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Cost–Performance Optimization of a Renewable Energy Resources Based Multimicrogrid System

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Abstract:

The growing energy demand, the increase in its price, and the increasing pollution worldwide are considered large problems that need unusual solutions. To overcome these problems, it is necessary to search for innovative solutions using renewable resources and energy management of the energy systems. Energy management means reducing the operating, maintenance, and generation costs of the system and enhancing system performance with methods such as power loss reduction and stability enhancement and alleviating the harmful emissions to the environment. Thus, the energy management of a micro-grid has become one of the most vital aspects of the power or energy system all over the world. The objective of this paper is to optimize a multiobjective problem of a renewable energy resources (RER) based multimicrogoid (MMG) system considering the output variation of the photovoltaic (PV) and wind Turbine (WT) as renewable energy resources and variation of the load demand and electricity prices. In this paper three microgrids (MGs) are connected with IEEE 33- bus distribution system each MG consists of a PV and WT. A three objective functions are modeled for this system to optimize the total annual cost, the voltage deviation and the voltage stability index (cost – performance multiobjective function). The optimization problem is solved with particle swarm optimization (PSO) technique for the system with and without RER. A comparison is carried out with two other optimization techniques, mountain gazelle optimization (MGO) and gorilla troop optimization (GTO). The results of the simulation show that the system cost is considerably reduced and the performance optimized

1. Introduction

It is expected that in 2030 the energy demand will increase by 12% due to the fast increment of the load demand [1]. In [2] the increasing demand for energy and its prices with increasing gas emissions are considered as big challenges that needs applicable solutions. The key solution for this challenges is by using RER and optimization techniques for energy management (EM) to optimize total system cost, power losses, gas emissions, system reliability and stability. MG optimization is to minimize the installation and maintenance and operation cost and electricity prices [3]. In [4] used EM to optimize operation of PV and WT as major resources of a MG with an energy storage system (ESS) as backup system. In [5], the method of Latin Hypercube Sampling (LHS) is used to manipulate the uncertainties of the PV and WT and solved the optimization technique for EM. In [6], used more than one type of WT generators and power converters to study the system with fault incidence. In [7] studied the standalone MG performance during faults with different types of load. In [8] accomplished a thorough review to study the types of optimizations algorithms that are used to optimize the MG operation with PV and WT as RERs, in this review it is concluded that the reliability of the system is increased when using ESS with PV and WT. In [9], a multiobjective particle swarm optimization (MOPSO) is used for energy management optimization of a microgrid to minimize the cost and emission. In [10] used the modified bacterial foraging optimization (MBFO) for EM of a MG with WT and ESS and the uncertainties of the WT has been considered. In [11], applied (MBFO) for optimal operation of a MG ith WT as RER and ESS to optimize the total cost and gas emission. In [12] used a fuzzy self-adaptive particle swarm optimization (FSAPSO) algorithm for optimal operation of a MG with PV, WT, battery energy storage system (BESS) and fuel cell (FC) unit. In this study the objective functions are the cost and gas emission. In [13], applied the modified honey bee Mating optimization (MHBMO) technique to optimize the cost. In [14] applied the optimization technique of Efficient Salp Swarm Algorithm (ESSA) for optimal operation of a MG and cost reduction with RERs and ESS. In [15] used the Ant-Lion Optimizer (ALO) technique to optimize the total cost of a MG with RERs and ESS. In [16], implemented the Moth Flame Optimization (MFO) to minimize the losses of the MG. In [17], used the Symbiotic Organisms Search (SOS) for optimal operation of a MG with RERs. In [18], used the convex method to optimize the size and location of BESS and total cost. In [19] used Moth-flame Optimization (MFO) technique in a standalone MG to optimize the cost and size and location of BESS considering life cycle cost of the components. In [20], used equilibrium optimizer (EO) for optimizing RERs location optimization considering uncertainties of the RERs. In [21] used fuzzy logic grey wolf optimization (FLGWO) to optimize a MG with RERs and ESS. In [22] used a day-ahead scheduling to optimize the cost and power factor for a hybrid MG. In [23] used multi agent system of a three layer for optimal operation of a distributed energy resources. From literature review, it is concluded that the MG optimization problem is nonlinear and non-convex therefore it is a complex issue. So choosing a suitable optimization algorithm to solve the problem is an important and difficult issue. According to the above literature review, the gaps that have been filled by this paper are as follows: the optimization problem of MGs is considering both of economic and techno issue of the system and reducing the power loss in system which is greatly affecting cost- performance of the MGs. The main contribution of this paper are as follows:

PSO algorithm is used to optimize the cost – performance of a MMG system, the simulated system is optimized with connected RERs and compared with the system simulation without RERs, two other optimization techniques MGO and GTO are used to optimize the system and compared with the results of the PSO optimization algorithm to validate the results of the optimization.

The paper sections are arranged as: Section 2 gives the formulation of the problem. Section 3 explains the types of optimization techniques. Section 4 gives the simulation results. Section 5 is the conclusion.

2. Formulation of the Problem

In this paper, a multi objective function model is considered to optimize the operation of a three MGs connected to IEEE33 bus system, each MG consists of renewable energy resources of Photovoltaic (PV) and wind turbine (WT), a multi objective function is solved with satisfying the system constraints, which can be formulated as follows:

2.1 Multiobjective Functions

2.1.1 Optimization of the Cost

The total annual cost consists of the annual cost of energy loss (Co_{loss}), the cost of buying electric energy from the main grid (Co_{Grid}), PV units cost (Co_{PV}) and WT cost (Co_{WT}), and it can be modelled as the following:

$$Co = min(Co_{Grid} + Co_{loss} + Co_{PV} + Co_{WT}) \tag{1}$$

The details of (1) are given in (2) – (10) as follow:

$$Co_{Grid} = 365 \times K_{Grid} \times \sum_{h=1}^{24} P_{Grid(h)} \tag{2}$$

$$Co_{Loss} = 365 \times K_{Loss} \times \sum_{h=1}^{24} P_{Total\_loss(h)} \tag{3}$$

$$Co_{PV} = Cost_{PV}^{inst.} + Cost_{PV}^{O\&M} \tag{4}$$

$$Co_{PV}^{inst.} = CF \times K_{PV} \times P_{sr} \tag{5}$$

J. of Advanced Industrial Technology and Application Vol. 5 No. 1 (2024) p. 45-56

$$Co_{PV}^{O\&M} = K_{PV}^{O\&M} \times \sum_{h=1}^{24} P_{PV(h)} \quad (6)$$

$$Co_{WT} = Cost_{WT}^{inst.} + Cost_{WT}^{O\&M} \quad (7)$$

$$Co_{WT}^{inst.} = CF \times K_{WT} \times P_{wr} \quad (8)$$

$$Co_{WT}^{O\&M} = K_{WT}^{O\&M} \times \sum_{h=1}^{24} P_{WT(h)} \quad (9)$$

$$CF = \frac{\beta_{PV,WT} \times (1+\beta_{PV,WT})^{NP_{PV,WT}}}{(1+\beta_{PV,WT})^{NP_{PV,WT}} - 1} \quad (10)$$

where K_{Grid} is cost of buying energy ($/KWh) from the grid, $P_{Grid(h)}$ is power bought from grid, K_{Loss} is cost of energy loss ($/KWh), $P_{Total\_loss(h)}$ is hourly total power loss, $Cost_{PV}^{inst.}$ is cost of installation of PV unit, CF is factor of capital recovery, K_{PV} is cost of buying of PV unit ($/kW), P_{sr} is rated power of PV unit., $Cost_{PV}^{O\&M}$ is cost of operation and maintenance of PV units, $K_{PV}^{O\&M}$ is cost of operation and maintenance ($/KWh) of PV unit, $P_{PV(h)}$ is hourly output power of PV unit, $Cost_{WT}^{inst.}$ is cost of installation of WT, $Co_{WT}^{O\&M}$ is cost of operation and maintenance of wind turbine, K_{WT} is buying cost of WT ($/kW), P_{wr} is rated power of WT unit, $K_{WT}^{O\&M}$ is cost of operation and maintenance ($/KWh) of WT unit, $P_{WT(h)}$ is hourly output power of WT unit, $\beta_{PV,WT}$ is interest rate of capital investment of installed PV or WT, $NP_{PV,WT}$ is PV unit or WT lifetime, The output power of PV units and WT are determined by (11) and (12) [24]:

$$P_{PV} = \begin{cases} P_{sr}\left(\dfrac{{G_s}^2}{G_{std} \times X_c}\right) & for\ 0 < G_s \le X_c \\ P_{sr}\left(\dfrac{G_s}{G_{std}}\right) & for\ X_c \le G_s \le G_{STD} \\ P_{sr} & G_{STD} \le G_s \end{cases} \quad (11)$$

G_s is the solar irradiance; G_{std} is the standard solar irradiance (1000 W/m^2) , X_c is a certain irradiance point, it is assigned as 120.

$$P_{WT}(\omega) = \begin{cases} 0 & for \quad \omega < \omega_i\ and\ \omega > \omega_o \\ P_{wr}\left(\dfrac{\omega - \omega_i}{\omega_r - \omega_i}\right) & for \quad (\omega_i \le \omega \le \omega_r) \\ P_{wr} & for \quad (\omega_r < \omega \le \omega_o) \end{cases} \quad (12)$$

Where ω_r is the rated speed of wind; ω_o is the cutout speed of wind; ω_i is the cut in speed of wind.

2.1.2 Optimization of Voltage Profile

The technical performance of the system is maximized by optimizing the voltage profile and this will be represented by minimizing the voltage inclination, this can be formulated as:

$$\sum VD = \sum_{h=1}^{24}\sum_{n=1}^{NB} |(V_n - 1)| \quad (13)$$

V_n is the voltage of the n^{th} bus, NB is the number of buses in the gird

2.1.3 Optimization of Voltage Stability Index

The optimization of the stability can be carried out by maximizing the voltage stability index (VSI) which is the third objective function of this optimization problem [25]:

$$VSI_n = |V_n|^4 - 4(P_nX_{nm} - Q_nR_{nm})^2 - 4(P_nX_{nm} + Q_nR_{nm})|V_n|^2 \quad (14)$$

$$\sum VSI = \sum_{h=1}^{24}\sum_{n=1}^{NB} VSI_n \quad (15)$$

where R_{nm} and X_{nm} are the resistance and reactance respectively of the branches between bus m and bus n. P_n and Q_n are the active and reactive power at bus n, respectively. The multiobjective function can be modelled as following:

$$F = W_1F_1 + W_2F_2 + W_3F_3 \tag{16}$$

$$F_1 = \frac{Co_{RERs}}{Co_{Base}} \tag{17}$$

$$F_2 = \frac{VD_{RERs}}{VD_{Base}} \tag{18}$$

$$F_3 = \frac{1}{VSI_{RERs}} \tag{19}$$

The values of W_1, W_2 and W_3 are 0.5, 0.25 and 0.25, respectively [26], the Base subscript is indicating the base case or without RERs, and RERs subscript indicating the system with renewable energy resources.

2.2 The Constraints of the System

2.2.1 Inequality Constraints

In this section the formulation of the inequality constraints of the system is derived as follows:

$$\boldsymbol{V_{min} \leq V_n \leq V_{max}} \tag{20}$$

$$\boldsymbol{P_{sr} + P_{wr} \leq \sum_{i=1}^{NB} P_{D,i}} \tag{21}$$

$$\boldsymbol{PF_{min} \leq PF \leq PF_{max}} \tag{22}$$

$$\boldsymbol{I_n \leq I_{max,n} \qquad n = 1,2,3 \ldots, NT} \tag{23}$$

Where, V_{min} is the minimum value of the voltage, V_{max} is the maximum value of the voltage, P_D is the active power demand. $I_{max,n}$ is the maximum current at the n^th^ branch, PF_{min} and PF_{max} are the minimum and maximum limits of the WT power factor, respectively, NT is the number of transmission lines.

2.2.2 Equality Constraint

In this section the formulation of the equality constraints of the system is derived as follows:

$$\boldsymbol{P_S + P_{PV} + P_{WT} = \sum_{i=1}^{NT} P_{loss,i} + \sum_{i=1}^{NB} P_{D,i}} \tag{24}$$

$$\boldsymbol{Q_S + Q_{WT} = \sum_{i=1}^{NT} Q_{loss,i} + \sum_{i=1}^{NB} Q_{D,i}} \tag{25}$$

Where, P_S and Q_S are the active and reactive power supplied by the grid respectively. Q_D is the load demand reactive power.

3. Types of Optimization Techniques

3.1 PSO Algorithm [27]

The motion of the birds to search food is evolved to PSO algorithm which is a population based heuristic process. The solutions are inspired from the scattered random particles in a given problem space. The vectors for position X and velocity V of the ith particle located in a d-dimensional space are mathematically represented as follows:

$$V_j(k+1) = w(k)\,V_j + c_1 r_1 (Pbest_j(k) - V_j(K)) + c_2 r_2 (Gbest_j(k) - X_j(K)) \tag{26a}$$

$$X_j(k+1) = X_{j(k)} + V_j(k+1) \tag{26b}$$

$r1$ and $r2$ are the uniform random numbers between 0 and 1, $w(k)$ is the weighting factor that process the effect of past velocities on current velocity, $Gbest(k)$ is the best global position at iteration k, $Pbestj(k)$ is the best location of particle j during iteration k, and c_1 and c_2 are social scaling parameters such that $c_1 = c_2 = 2$.

3.2 GTO Algorithm [28]

Gorillas live in groups called troops. GTO generally follows the following rules to search for a solution:
1. The space of GTO optimization algorithm consists of three kinds of solutions, where X is known as the gorillas' position vector, the GX as the gorilla candidate position vectors and the silverback which is the best solution found in each iteration.
2. Just one silverback in entire population is selected for optimizing the operation.
3. X, GX, and silverback solutions are simulating the social life of gorilla in nature accurately.

$$GX\ (t+1) = \begin{cases} (UB - LB) \times r_1 + LB & rand \leq\ p \\ (r_2 - C) \times X_r + L \times H & rand \geq 0.5 \\ X(t) - L \times \left(L \times \left(X(t) - GX_r(t)\right) + r_3 \times \left(X(t) - GX_r(t)\right)\right) & rand < 0.5 \end{cases} \tag{27}$$

$GX(t+1)$ is the next position vector in the next t iteration. $X(t)$ is the current vector of the position. r_1, r_2, r_3, and $rand$ are random values ranging from 0 to 1. p is a parameter that has to be assigned in range 0-1 in previous to starting optimization. UB and LB are respectively the upper and lower bounds. Xr is one member in the group randomly selected from the entire population. GXr is one of the position vectors randomly selected and includes the positions updated in each phase. C, L, and H are calculated using (28), (29), and (30), respectively.

$$C = F\ \times (1 - \frac{It}{MaxIt}) \tag{28}$$

$$L\ = C \times l \tag{29}$$

$$H = Z \times X\,(t) \tag{30}$$

$$Z = [\,-C, C\,] \tag{31}$$

$$F = cos\,(2 \times r_4) + 1 \tag{32}$$

Where It is the current iteration, $MaxIt$ is the total iterations. L is determined from (29). I is a random value in the range of −1 and 1. Z is a random value determined from (31). $-C$, C *and* F are estimated from (32). *cos* is cosine function. r_4 is random values ranging from 0 to 1.

3.3 MGO Algorithm [29]

MGO technique solves optimization problem by four main parts of the life of mountain gazelles: bachelor male herds, maternity herds, territorial solitary males, and migration to search for food. Each gazelle (Xi) can be a member in one of bachelor male herds, maternity herds and territorial solitary males while solving the optimization problem.

3.3.1 Territorial Solitary Males

The adult male territory is modeled in (33).

$$TSM = male_{gazelle} - \left|\left(ri_1 \times BH - ri_2 \times X(t)\right) \times F\right| \times Cof_r \tag{33}$$

Where $male_{gazelle}$ is the position vector of the best global solution (adult male). The parameters ri_1 and ri_2 are random integers 1 or 2. BH is the young male herd coefficient vector, determined by (34). F is calculated by (35). $Cofr$ is a randomly selected coefficient vector, it is to increase the capability of searching, determined by (36).

$$BH = X_{ra} \times r_1 + M_{pr} \times r_2\,, \quad ra = \frac{N}{3} \dots . N \tag{34}$$

Xra is a random solution (young male) in the interval of ra. Mpr is the average number of search agents, it is randomly assigned. N is the total number of gazelles. r_1 and r_2 are random values between 0 and 1.

$$F = N_1(D) \times \exp(2 - Iter \times (\frac{2}{MaxIter})) \tag{35}$$

N_1 is a random number from the standard distribution. *MaxIter* is the total number of iterations, and *Iter* is the current number of iteration.

$$Cof_1 = f(x) = \begin{cases} (a+1) + r_3, \\ a \times N_2(D), \\ r_4(D), \\ N_3(D) \times N_4(D)^2 \times \cos((r_4 \times 2) \times N_3(D)) \end{cases} \tag{36}$$

a is determined by (37). r_3, r_4, are random numbers in the range 0 - 1. N_2, N_3 and N_4 are random numbers in the normal range and dimensions of the optimization problem. *cos is* the cosine function.

$$a = -1 + Iter \times \left(\frac{-1}{MaxIter}\right) \tag{37}$$

MaxIter is the total iterations and *Iter* is the current iteration.

3.3.2 Maternity Herds

They are playing an important role in life cycle of mountain gazelles, as they generate solid male gazelles. $Male_{gazelles}$ assists in delivery of young males intending to possess females. This behavior can be modelled by (38).

$$MH = (BH + Cof_1) + (ri_3 \times male_{gazelle} - ri_4 \times X_{rand}) \times Cof_1 \tag{38}$$

BH is the vector of the impact factor of young males, determined by (34). ri_3 and ri_4 are integer and random numbers 1 or 2. $Male_{gazelle}$ is the global solution in the current iteration. X_{rand} is the vector position of a gazelle that is randomly chosen from the entire population.

3.3.3 Bachelor Male Herds

As young male gazelles are fighting the male gazelles to dominate and control the female gazelles. This can be modelled by (39).

$$BMH = (X(t) - D) + (ri_5 \times male_{gazelle} - ri_6 \times BH) \times Cof_r \tag{39}$$

$X(t)$ is the position of the gazelle vector in the current iteration, D is determined by (40), ri_5 and ri_6 are integers 1 or 2 that are chosen randomly. $Male_{gazelle}$ *is* the position of the global solution.

$$D = (|X(t)| + |male_{gazelle}|) \times (2 \times r_6 - 1) \tag{40}$$

r_6 is a random number between 0 and 1.

4. Simulation Results

The PSO technique is used to solve cost –performance optimization problem of a three MGs connected to a distribution system, each MG includes PV and WT as shown in figure 1. The cost optimization as a first objective function is to optimize the total annual cost as given in (1) by minimizing buying energy from the grid and the total cost of PV and WT units. Sizing and location optimization of the three MGs has been carried out. Performance optimization includes the second and third objective functions to optimize the buses voltage profile and the voltage stability index of the system respectively. The system is simulated without RER and compared to the system with RER. The optimization problem of the system is compared with MGO and GTO algorithms for validating the effectiveness of the PSO method. The tested system is IEEE 33-bus, the specifications of the system are given in Table 1. The simulated system coefficients of the cost and constraints listed in Table 2. The hourly solar irradiance, hourly wind speed [32], hourly load demand and hourly electricity prices [33] are shown in figures (2, 3, 4, 5) respectively.

J. of Advanced Industrial Technology and Application Vol. 5 No. 1 (2024) p. 45-56

Fig. 1 *PVs and WTs of connected MGs*

Table 1 *IEEE 33- bus system specification*

Parameter	Value
No. of branches	32
No. of buses	33
Minimum voltage at bus	0.90378 @ bus 18
Active load (kW)	3715.000
Reactive power (Kvar)	2300.000
Active Power losses (kW)	210.972
Reactive Power losses (Kvar)	143.117
VD $(\mathrm{p.u})$	1.8046
VSI $(\mathrm{p.u})$	25.5393

Table 2 *Constraints of the system and cost coefficients*

Parameter	Value
PV Cost [30]	
Cost of buying PV unit ($\boldsymbol{K_{PV}}$)	770 $/kW
Cost of operation and maintenance of PV unit ($\boldsymbol{K_{PV}^{O\&M}}$)	0.01 $/kWh
Interest rate of capital investment of the installed PV ($\boldsymbol{\beta_{PV}}$)	10%
PV lifetime ($\boldsymbol{NP_{PV}}$)	20
WT Cost [30]	
Cost of buying WT ($\boldsymbol{K_{WT}}$)	4000 $/kW
Cost of operation and maintenance of WT ($\boldsymbol{Co_{WT}^{O\&M}}$)	0.01 $/kWh
Interest rate of capital investment of the installed WT ($\boldsymbol{\beta_{WT}}$)	10%
WT lifetime ($\boldsymbol{NP_{WT}}$)	20
Cost coefficients	
Cost of energy loss ($\boldsymbol{K_{Loss}}$) [31]	0.06 $/kWh
System constraints	
Voltage bounds	$\boldsymbol{0.95\ p.u \le V \le 1.5\ p.u}$
Limits of PV size	$\boldsymbol{0 \le PV \le 1720\ kW}$
Limits of WT size	$\boldsymbol{0 \le P_W \le 2000\ kW}$
Limits of power factor of the WT	$\boldsymbol{0.6 \le P.F \le 1}$

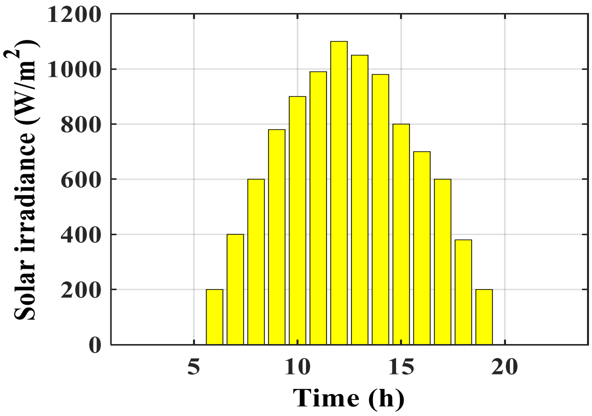

Fig. 2 *Solar irradiance*

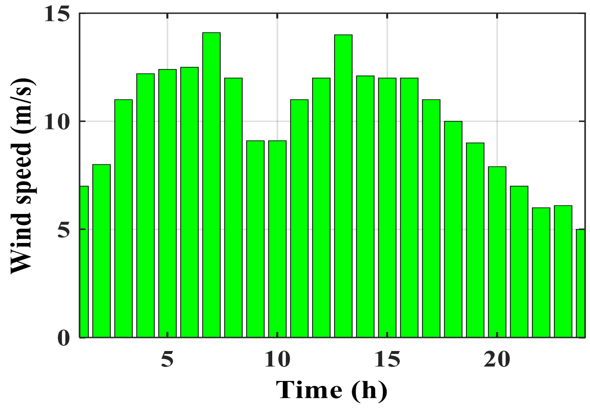

Fig. 3 *Wind speed*

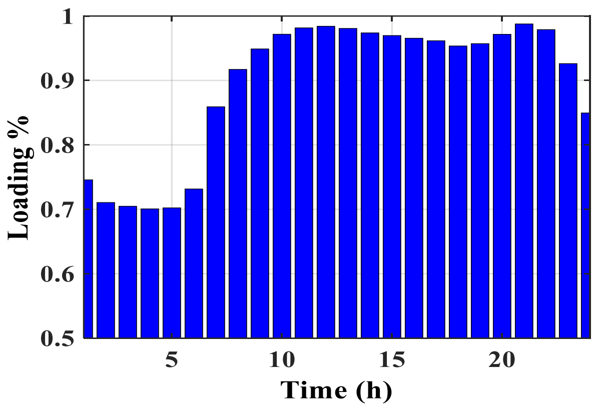

Fig.4 *Load profile*

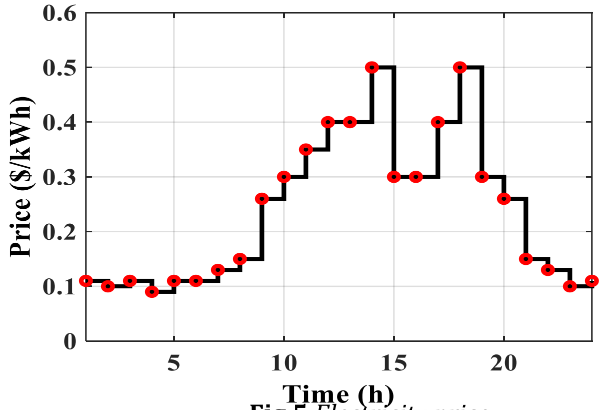

Fig.5 *Electricity price*

4.1 Simulation Results with PSO

PSO technique is used to solve the optimization problem and system is simulated with and without RER. Figure 6 shows the simulation result of the PVs output power i.e. PV_1, PV_2, and PV_3 of the three MGs. Figure 7 shows the output power of WT1, WT2, and WT3. The power loss is minimized with RER as compared to the power loss without RER as shown in figure 8. As given in table 3, using PSO technique gives optimized location of the $MGs_{(1,2,3)}$ at buses 18, 21, and 31respectively as shown in figure 9, the total annual cost, voltage deviation summation and the voltage stability index of the system simulated using PSO technique are 4.3010E+06 USD, 31.8119 p.u. and 654.1861 p.u. as compared to the system simulation results without RER of 7.65393E+06 USD, 38.3756 and 629.0769 respectively.

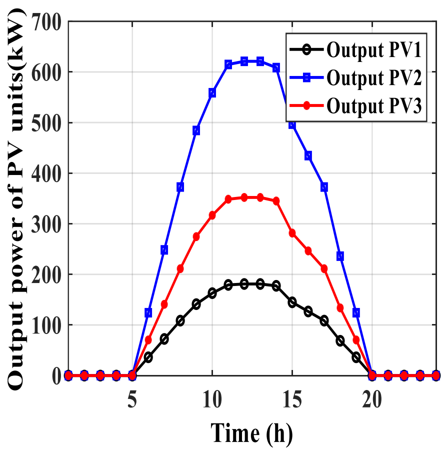

Fig. 6 *PVs output power*

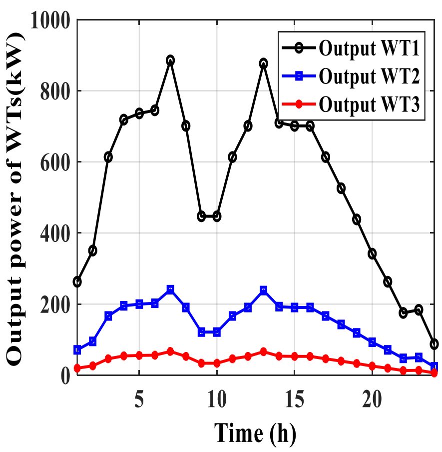

Fig. 7 *WTs output power*

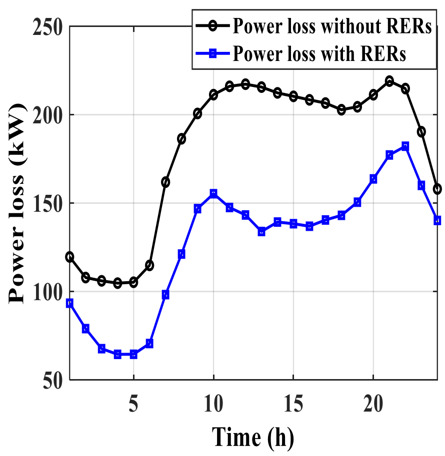

Fig. 8 *Comparison of power loss*

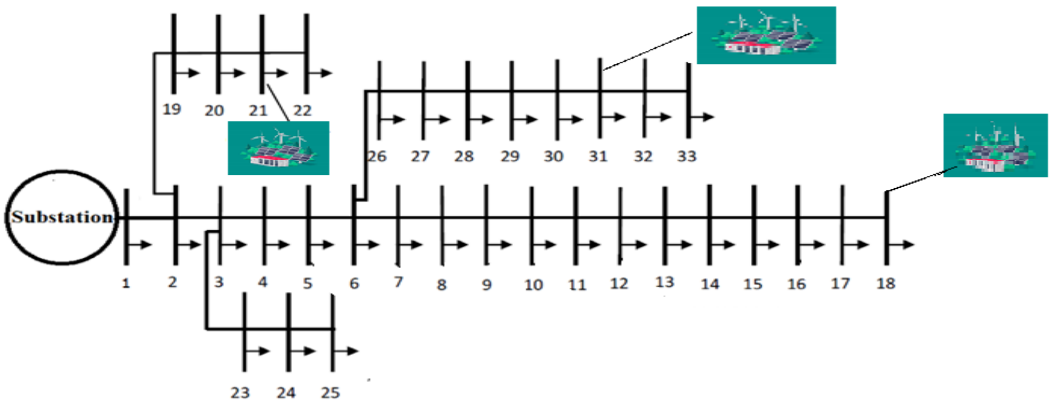

Fig. 9 *Microgrids location using PSO technique*

4.2 4.2 Simulation Results with GTO

GTO technique is used to solve the optimization problem and system is simulated with and without RER. Figure 10 shows the simulation result of the PVs output power i.e. PV_1 , PV_2 , and PV_3 of the three MGs. Figure 11 shows the output power of WT_1, WT_2, and WT_3. The power loss is minimized with RER as compared to the power loss without RER as shown in figure 12. As given in table 3, using GTO technique gives the optimized location of the $MGs_{(1,2,3)}$ at buses 2, 7, and 26 respectively as shown in figure 13, the total annual cost, voltage deviation summation and the voltage stability index of the system simulated using GTO technique are 5.4666E+06 USD, 34.7227 p.u. and 641.2149 p.u. respectively.

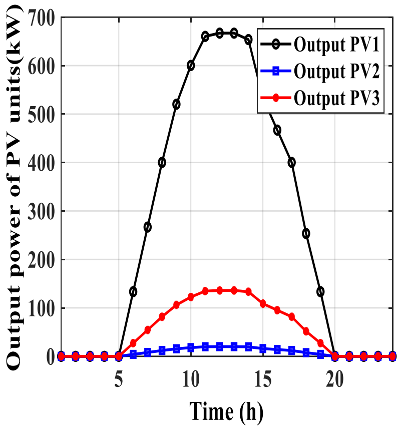

Fig.10 *PVs output power*

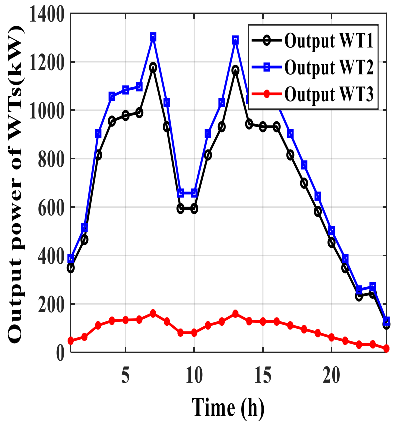

Fig.11 *WTs output power loss*

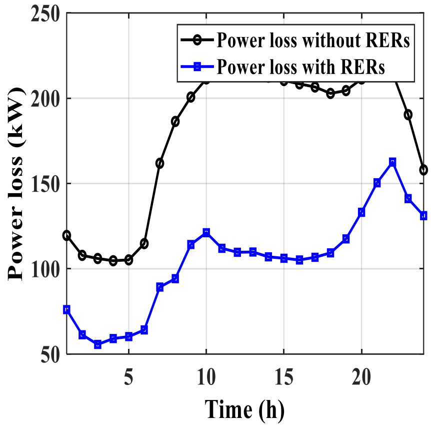

Fig.12 *Comparison of power*

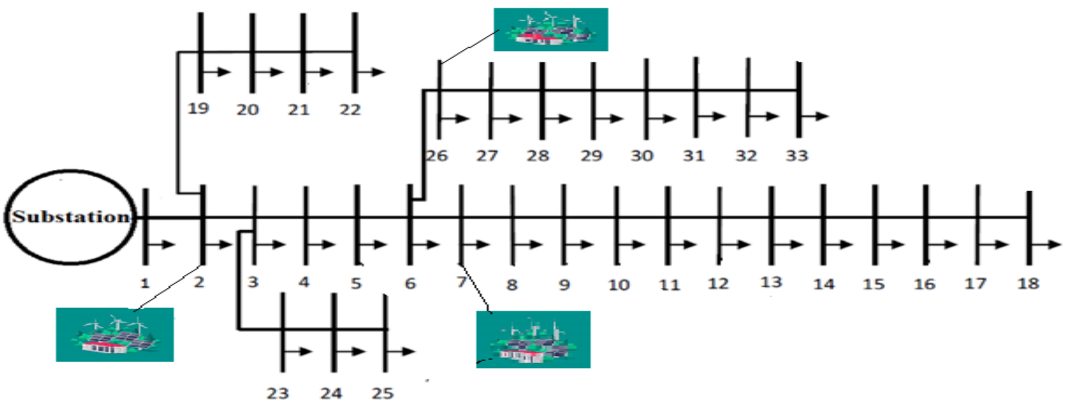

Fig. 13 *Microgrids location using GTO technique*

4.3 Simulation Results with MGO

GTO technique is used to solve the optimization problem and the system is simulated with and without RER. Figure 14 shows the simulation result of output power of PV_1, PV_2, and PV_3 of the three microgrids. Figure 15 shows the output power of WT_1, WT_2, and WT_3. The power loss is minimized with RER as compared to the power loss without RER as shown in figure 16. As given in table 3, using MGO technique gives the optimized location of $MGs_{(1,2,3)}$ at buses 15, 25, and 33 as shown in figure 17, the total annual cost, voltage deviation summation and voltage stability index of the system MGO technique are 4.3451E+06 USD, 20.6649 p.u. and 692.7072 p.u. respectively.

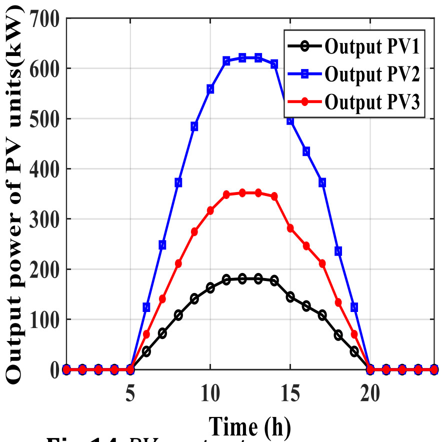

Fig.14 *PVs output power*

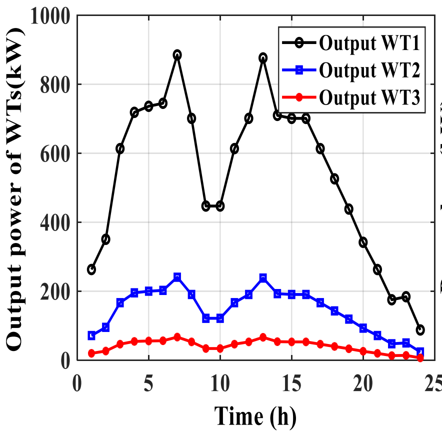

Fig.15 *WTs output power*

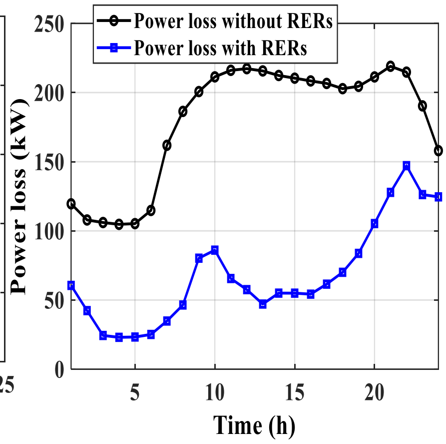

Fig.16 *Comparison of power loss*

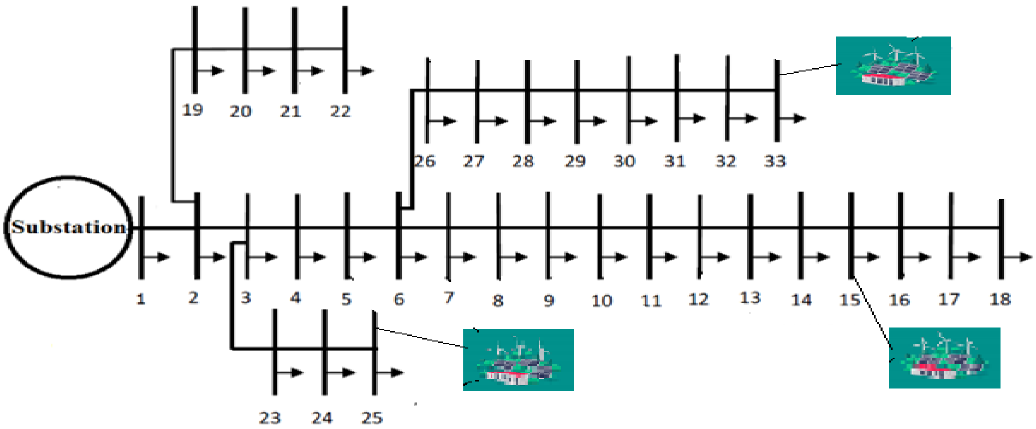

Fig. 17 *Microgrids location using MGO technique*

Table 3 *Results of MMG optimization with PSO, GTO, and MGO techniques*

Item	Without RERs	PSO	GTO	MGO
Loss of Energy (KWh)	1.4759E+06	1.1160E+06	1.2399E+06	0.7533E+06
Cost of total annual energy loss (USD	8.85518E+04	6.6964E+04	7.4397E+04	4.5202E+04
Purchased Power from grid (KW)	3.05390E+06	1.5584E+06	2.1384E+06	1. 4585E+06
Total annual purchased energy cost (USD)	7.56538E+6	3.1722E+06	4.8049E+06	3.0502E+06
Microgrids optimal location	--	18, 21, 31	2, 7, 26	25, 15, 33
Microgrid 1				
Optimal siz PV (kW), WT (kW), PF	--	1651, 1180, 0.8	20, 40, 0.7	446, 1030, 1
Microgrid 2				
Optimal size PV (kW), WT (kW), PF of	--	311, 194, 0.668	144, 715, 1	711, 898, 0.7
Microgrid 3				
Optimal size PV (kW), WT (kW), PF of	--	51, 188, 0.6215	20, 20, 0.7	368, 114, 0.8923
Total cost of PVs and WTs (USD)	0	0.1459E+06	0.5872E+06	0.1523E+06

∑VD (p.u.)	38.37576	31.8119	34.7227	20.6649
∑VSI (p.u.)	629.0769	654.1861	641.2149	692.7072
Total annual cost (USD)	7.65393E+06	4.3010E+06	5.4666E+06	4.3451E+06

5. Conclusion

In this study, a multi objective function is solved with optimal integration of solar PVs and WTs based multi-microgrid IEEE 33 –bus distribution system. A three optimization algorithms PSO, GTO and MGO are used to solve this multi objective function with satisfying the system constraints and considering the variation of solar irradiance, wind speed, demand load and electricity prices. The suggested optimization techniques solved and optimized the proposed multi-objective function in calculating the total annual cost, the sum of voltage deviation and the voltage stability index. The three optimization technique have optimized the size and location of microgrids. The multi –objective function is considered as techno- economic objective function as it is intending to minimize the voltage deviation of the buses and maximizing the voltage stability index in one hand whereas in other hand is to minimize the total annual cost of the system by reducing the power purchased from grid, reducing the power loss and minimizing the cost of operation and maintenance of the microgrids. The system is simulated without RER and with RER, to calculate the total annual cost, voltage stability index and voltage deviation of the system. Table 3 shows, a cost reduction of 43.84 %, 28.57 %, and 43.23 %, voltage stability index enhancement of 3.99 %, 1.92 % and 10.11 % and voltage deviation decrement of 17.1 %, 9.5 % and 20.09 % using PSO, GTO and MGO optimization techniques respectively,

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Conflict of Interest

Authors declare that there is no conflict of interests regarding the publication of the paper.

Author Contribution

The authors confirm contribution to the paper as follows: ***study conception and design:*** *Adel Ridha Othman, Ziyodulla Yusupov, Muhammet Tahir Guneser;* ***data collection:*** *Adel Ridha Othman, Ziyodulla Yusupov, Muhammet Tahir Guneser;* ***analysis and interpretation of results:*** *Adel Ridha Othman, Ziyodulla Yusupov, Muhammet Tahir Guneser;* ***draft manuscript preparation:*** *Adel Ridha Othman, Ziyodulla Yusupov, Muhammet Tahir Guneser. All authors reviewed the results and approved the final version of the manuscript.*

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