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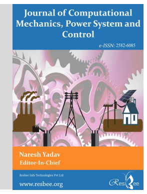

HGAGWO: A Multi-Objective Optimal Positioning and Sizing of Fuel Cells in DG Systems

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Abstract: Nowadays, Distribution System has experienced several important changes because of the implementation of smart grid technology and incorporation of distributed and renewable energy resources. Generally, optimal incorporation of Distributed Generators and reconfiguration of the radial network have optimistic impacts on the power system. In this paper, localization, and determination of fuel cells challenges are addressed in order to connect with Distributed Generation (DG) systems. Hence, to overcome this challenge dual-phase approach is exploited. In the first phase, the Neural Network (NN) is utilized for determining the optimal position. In the second phase, the hybrid Genetic Algorithm (GA) and Grey Wolf Optimization (GWO) is exploited to determine the optimal sizing of fuel cells. In addition, the proposed technique is simulated in four IEEE bus systems, which is compared over traditional methods namely GA, Particle Swarm Optimization (PSO), and GWO. The results exhibit the performance analysis of the proposed technique and conventional techniques.

Keywords: Distributed generation; optimal sizing; fuel cells; neural network; optimization techniques

Nomenclature

Abbreviations	Descriptions
NN	Neural Network
MOO	Multi-Objective Optimization
PV	Photovoltaic
ALO	Ant Lion Optimizer
DS	Distribution System
THD	Total Harmonic Distortion
OPAS	Optimal Placement And Sizing
RDS	Radial Distribution System
VPI	Voltage Profile Index
DG	Distributed generation
DN	Distribution Networks
BIBC	Bus Current Injection To Branch Current
GA	Genetic Algorithm
VP	Voltage Profile
APL	Active Power loss
UM	Unified Model
BCBV	Branch Current To Bus Voltage
PSO	Particle Swarm Optimization
NN	Neural Network
SOO	Single-Objective Optimization
VSI	Voltage Stability Index
GWO	Grey Wolf Optimization
WCA	Water Cycle Algorithm

1.Introduction

Generally, DG is represented as a miniature-scale spotted electric power source, which situated close to the loads [12]. Various DG techniques are exploited namely PV cells, wind turbines, small fuel cells, biomass, hydro, micro-turbines, etc. Comprehensively, DGs have been worked in the DSs taking into account of procedural benefits for the power grids namely minimization of power loss, enhancement of VP as well as system protection, consistency enhancement, and energy effectiveness expansion. Furthermore, the energy-critical situation occurred because of the shortage of the existing energy

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provisions namely natural gas and petroleum, as well as the complete benefit to climate amend and global warming that pushed all the stakeholders jointly with distributed companies administrators [13] [14] [15]. This is used to focus on the complete service of the DG techniques with the employ of environmentally approving renewable energy resources. In the DG techniquees, the investment can provide a real possibility to stay the load sequence using the gainful, low-carbon, high-efficiency ability to increase substitutes [16]. Incorporation and installation of DGs in DS may offer various economic, technical, and environmental advantages. The advantages of environmental are the minimization of emission levels and pollution in the system. Moreover, it aims to minimize the operational costs as much as possible and to augment the proceeds of all system contributors.

In many works, OPAS of DG units in the DN is considered [17] [18] [19]. In the literature, several approach principles are evaluated for the optimal planning issue of DG units for example to minimize reactive power control, system power losses, Voltage Profile improvement, enhancement of system security and improvement of consistency, and wear out the potential of the DG diffusion [20]. Through defining a proper objective function, the OPAS of DG units can be attained that should be constructed for multi or single-objective.

Numerous works of literature have presented the study of OPAS of DGs [9] [10] [11]. In a DN, to increase the VS and decrease real power losses, an invasive weed optimization-based technique was presented in [9]. At multi-load levels to reduce the APL [10] presented a technique for OPAS of a DG. In [11] an approach, which exploits the programming technique and GA [24], was presented. Moreover, in [12] multi-objective techniques were exploited for OPAS of DG units. For this reason, a multi-objective technique was presented in [22] with regards to DGs uncertainty and power quality [25].

The main objective of this paper is to present a dual-phase methodology to determine the optimal location and sizing. Here, the neural network is exploited in the first phase for determining the optimal location of the fuel cells. Subsequently, in the second phase, the hybridization of GA and GWO technique is utilized to determine the optimal sizing of the fuel cells. The rest of the paper is organized as follows: Section 2 describes the literature review of the paper. Section 3 states the mathematical model of optimal sizing and siting for DG's. Section 4 defines the optimal location and sizing using proposed approach. Section 5 describes the results and discussions. Section 6 states the conclusion of the paper.

2. Literature Review

In 2018, Doudou N. Luta, Atanda K. Raji [1], presented hybrid energy storage integrating with a hydrogen fuel cell, a supercapacitor also experimented. Here, the main aim was to discover the best size of a complex energy storage system of a commercial load that was contributed from photovoltaic panels. The appropriate structural design was exploited on the basis of its cost efficiency and technical viability. Here, the analysis based on the sensitivity for the hydrogen storage projected costs was performed to calculate the effect of the Levelized cost of energy and the hydrogen on the system cost.

In 2018, Jamila Snoussi et al [2] worked on the advancement of fuel cell hybrid electric vehicles. Therefore, optimal sizing of the hybrid energy storage systems presented in this paper. It was performed by taking into consideration of the energy management technique on the basis of the frequency-separation. Through a multiobjective grey wolf optimizer, the optimal solutions were calculated for different load profiles.

In 2017, Hongxia Zhan et al [3] developed an optimal DG positioning technique to increase the dissemination DG level in DN without changing the original relay security strategies. Here, the Genetic algorithm was exploited in order to identify the OPAS of DG in DN. Experimental analysis studies were performed on a three-feeder test DN and an extensively exploited 33-node test system to exhibit the efficiency of the proposed technique.

In 2018, Adel A. Abou El-Ela et al [4] presented a WCA for OPAS of DGs. Here, the main objective of the proposed technique was to achieve economic, technical, as well as environmental advantages. In addition, various objective functions such as reducing voltage deviation, power losses, total emissions generated through generation sources, total electrical energy cost, and voltage stability index enhancement were contemplated.

In 2018, Mohammad Jafar Hadidian-Moghaddam et al [5] developed a novel optimization technique to resolve the optimal siting and sizing issue of DG in a DS. By means of considering various objectives, the optimization issue was resolved by exploiting a novel ALO. These objectives were the minimization of acquired energy cost from the upstream network because of the reliability enhancement, DGs power generation, and minimization of application cost for DGs, DS losses and bus voltage divergence. By means of MOO and an SOO aforementioned issue was solved.

In 2019, Ashokkumar Lakum and Vasundhara Mahajan [6] worked on the impact of DG penetration on the OPAS of APF. To put the possible buses the New nonlinear Load Position on the basis of the APF current injection (NLPCI) technique was presented for the position of APF with the nonlinear load and DG. To identify the active power filter optimal size, the GWO was exploited. The outcome demonstrates that the active power filter size needed with the addition of DG and the nonlinear load was better than the nonlinear load.

In 2017, A.M. Abd-el-Motaleb and Sarah Kazem Bekdach [7] discussed the study of the optimal sizing of DG in a hybrid power system. By exploiting the autoregressive moving average technique, the wind speed and load demand suspicions were modeled and utilizing the chronological "Monte Carlo" experimentation the system affirms were chronologically sampled. In addition, an objective mode on the basis of the self-adapted evolutionary scheme in the amalgamation of the Fischer– Burmeister technique was presented. To attain the least possible investment cost, the performance of the proposed optimization resolver was demonstrated in computationally.

In 2019, Faheem Ud Din et al [8] presented Genetic Algorithm as a resolving tool to discover the optimal size of DG and optimal reconfiguration of the network in an unreliable load environment. Here, the main objective was to reduce Total Harmonic Distortion (THD) and line losses and to enhance the system voltage profile. Concurrently, this was performed by OPAS of DG and optimal reconfiguration of the network. Here, the effect of total harmonic distortion on the power factor was also calculated. By analysis of the network based on the sensitivity, the position buses for DG were established. According to the network topology, backward/ forward sweep technique and the fast harmonic load flow analysis on the basis of the BIBC and BCBV matrix were developed.

3.Mathematical Model of Optimal Sizing and Siting for DG's

3.1Objective Function

(a)Power Loss Index (PLI):

In reference to the problem on DG, the Active Power Loss connected with the DS give out as the objective model, which needs to experience the reduction and they are denoted in eq. (1) and (2).

$$f_1 = \min(P_{loss}) \tag{1}$$

$$P_{loss} = \sum_{i=1}^{N_B}\sum_{j>1}^{N_B}\{Y_{ij}\}\left[V_{vi}^2 + V_i^2 - 2V_{vi}V_{vj}\cos(\delta_{vi} - \delta_{vj})\right] \tag{2}$$

A system showing improved performances will certainly experience minimum loss. Therefore, the real and reactive power loss indices are represented in eq. (3) and (4), correspondingly. In eq. (3), the P_{LDG} denotes the complete real power losses that are generated in the DG availability and P_L represents the complete real power losses that appear in require of DG. In eq. (4), Q_{LDG} denote the complete real and the reactive power losses and. Furthermore, Q_L represents the complete reactive power losses. These losses can be reduced while the DGs are subjected to position or sizing in any best way.

$$ILP = \frac{[P_{LDG}]}{[P_L]} \tag{3}$$

$$ILQ = \frac{[Q_{LDG}]}{[Q_L]} \tag{4}$$

(b) Voltage Stability Index (VSI):

The power system ability is to uphold the voltages on several network buses in permitted restrictions, and then the disturbance application is referred to as the VS. Generally, instability occurs because of the system's incapability in portrait the loads with sufficient reactive power. The VSI that corresponds to the RDS is obtained through signifying a simple power flow technique.

$$I(v) = \frac{V(s)\angle\delta(s) - V(v)\angle\delta(v)}{r(v) + jx(v)} \tag{5}$$

where,

$$r(v) = \mathrm{Re\,al}\left[(V_v\angle\delta_v - V_s\angle\delta_s)/I(v)\right] \tag{6}$$

$$x(v) = \mathrm{Im\,ag}\left[(V_v\angle\delta_v - V_s\angle\delta_s)/I(v)\right] \tag{7}$$

$$P(v) - jQ(v) = V^*(v)I(v) \tag{8}$$

By eq. (5)-(8), we obtain eq. (9)

$$\left.\begin{array}{r}|V(v)|^4-\left(|V(s)|^2-2P(v)r(v)-2Q(v)x(v)\right)|V(v)|^2\\+\left(P^2(v)+Q^2(v)\right)\left(r^2(v)+x^2(v)\right)\end{array}\right\}=0 \tag{9}$$

Let,

$$b(v)=\left(|V(s)|^2-2P(v)r(v)-2Q(v)x(v)\right) \tag{10}$$

$$c(v)=\left(P^2(v)+Q^2(v)\right)\left(r^2(v)+x^2(v)\right) \tag{11}$$

Using eq. (10) and (11), eq. (9) can be indicated as eq. (12)

$$|V(v)|^4-b(v)|V(v)|^2+c(v)=0 \tag{12}$$

Eq. (12) indicates the load flow convergence in the RDS might occur at the condition,

$$b(m)^2-4.0c(m)\geq 0 \tag{13}$$

Substitution of eq. (10) and eq. (11) in eq. (13) obtains eq. (14).

$$\left.\begin{array}{r}|V(s)|^4-4.0\left(P(v)x(v)-Q(v)r(v)\right)^2\\-4.0\left(P(v)r(v)+Q(v)x(v)\right)|V(s)|^2\end{array}\right\}\geq 0 \tag{14}$$

Let,

$$VSI(m)=\left\{\begin{array}{l}|V(s)|^4-4.0\left(P(v)x(v)-Q(v)r(v)\right)^2\\-4.0\left(P(v)r(v)+Q(v)x(v)\right)|V(s)|^2\end{array}\right. \tag{15}$$

The RDS is established to function in a steady way if the given form is fulfilled.

$$VSI(v)\geq 0,\quad \text{for}\ v=2,3,\ldots,N_B \tag{16}$$

This index suggests dual advantages such as (a) the complete measurement of VSI requires a single load practice, and (b) in a real-time situation, provides the capability to attain suitable speed for the measurements. Once the VSI related to every single node in the network is resolute, the voltage stability measurement apprehensive with the complete system is performed. The node behavior of a maximized sensitivity level is the one that possesses the minimum value of VSI .

Subsequently, a new index entailing on the whole VSI, which correspond to the whole DN stated in eq. (17).

$$OVSI=\sum_{m=2}^{NB}\left[VSI(v)\right] \tag{17}$$

When $OVSI$ assumes a maximum value the network is established to show a higher voltage stability limit.

(c) Voltage Profile:

The performance of the network and nodal voltages not including the primary node obtain improved remarkably, while the DSs are connected with the DG. Eq. (18) states the voltage profile definition regarding the IVD index. Here, NN states the number of nodes; $V_{no\min al}$ presumes a value of 1.00 p.u. and 1.03 p.u. for the RDS connecting 69 and 38 nodes, correspondingly.

$$IVD=\max_{i=2}^{NN}\left(\frac{\left|\overline{V}_{no\min al}\right|-\left|\overline{V}_i\right|}{\left|\overline{V}_{no\min al}\right|}\right) \tag{18}$$

Generally, $(V_{\min}\leq V_i\leq V_{\max})$ states that each bus has its limit of voltage. Because of this technical restraint, a small and a satisfactory limit of IVD value can be attained.

(d) Power flow constraints:

The eq. (19) and (20) states the nonlinear power flow that provides as the equality constraints that are exploited to achieve the conservation of the complete real and the reactive powers, which are connected with the DS.

$$P_{gni}=P_{dni}-V_{ni}\sum_{j=1}^{N}V_{nj}Y_{nj}\cos\left(\delta_{ni}-\delta_{nj}-\theta_{nj}\right) \tag{19}$$

$$Q_{gni}=Q_{dni}-V_{ni}\sum_{j=1}^{N}V_{nj}Y_{nj}\cos\left(\delta_{ni}-\delta_{nj}-\theta_{nj}\right) \tag{20}$$

(e) Line flow constraints:

At distinct network compartments, the power flow is significantly changed with the amalgamation of DGs in the system. To preserve the line flow, the maximum care is necessary within the suitable restrictions, hence that the issue of line overloading is prohibited from happening. The line flows are established to descend in the suitable restrictions, while the IC index embraces a value, which is lesser than one. If the value of the IC index goes beyond unity, after that the line flows are certain to need control. Using eq. (21), determination of the IC can be done.

Where, $\overline{S_{ij}}$ indicates the flow of MVA regarding the line, which connects the bus j and i ; $\overline{CS_{ij}}$ represents the MVA ability connected with line i and j; At last, NL represents for the number of lines.

$$IC = \max_{i=1}^{NL}\left(\frac{\left|\overline{S_{ij}}\right|}{\left|\overline{CS_{ij}}\right|}\right) \tag{21}$$

(f) UM:

As the line flow and the power flow restraints can be contemplated in the creation of the solution pool, the UM comprises the loss of power, VSI and VP.

Therefore, in eq. (22) the derived UM is represented, where, λ_1 λ_2 and λ_3 is chosen.

$$\sum_i \lambda_i = 1$$

$$F^{obj} = \lambda_1 P_{loss} + \lambda_2 OVSI + \lambda_3 IVD + \{[\max(\min(V_i) - V_{max}),0] + [\max((V_{min}) - \min(V_i)),0]\}\beta_1 + \left\{\max\left(\left|\min(S)\right| - \left|S^{max}\right|\right),0\right\}\beta_2 \tag{22}$$

By the proposed technique, this UM is set as the objective function that needs to be resolved hence that the best position of the fuel cells and their sizing can be evaluated.

4. Optimal Location and Sizing Using Proposed Technique

As demonstrated in fig. 1, the proposed dual phase technique, the NN [22] recognizes data from the DS and the number of fuel cells to be deployed to calculate the best position, whereas the fuel cells are to be located. Once the best position is determined, the best size apprehensive with the fuel cell is calculated by the proposed HGAGWO. The proposed technique obtains the outcomes from the examination on power flow, stability, and VP, as well as the information with respect to the optimal position, for solving the optimal size of the fuel cell.

4.1 Neural Network for Optimal Location

The NN gets a training library for the fuel cells degree that needs to be connected as well as the corresponding positions. Prior to network training, the position of fuel cells whereas they are appropriate to reduce the loss that is evaluated by the proposed technique. Therefore, the objective model for determining the optimal location is indicated in eq. (23).

$$B_d^* = \arg\min_{B_d} P^{loss} \tag{23}$$

Therefore, the best positions for deviating degree of fuel cells are estimated and the library is formulated as $[\overline{F}B_d]$, while the B_d indicates the best position of the buses whereas the fuel cells to be conn and $\overline{F}$ indicate the degree of fuel cells to be connected in the system. The $\overline{F}$ represents a column vector of dimension $N_f \times 1$ to indicate N_f a number of fuel cells and B_d represents the binary matrix of dimension $N_f \times N_f$ in that unit values indicates the fuel cell association and zeros denote no fuel cell association. B_d is formulated whereas that $\sum_{f=1}^{N_f} B_d(f) = \overline{F}(f)$, in such a way f indicates the f^{th} degree of fuel cell association.

In eq. (24), the training library is subjected to the NN for training and the NN learns the library exploiting the nonlinear model whereas ω represents the network weights to be calculated and N_H indicates the number of hidden neurons. The adopted NN feeds forward by nature and the training is carried out by utilizing the backpropagation algorithm.

$$B_d(f) = \omega_0 + \sum_{h=1}^{N_H} \frac{1}{1 + \exp\left(-\overline{F}\omega_h\right)} \tag{24}$$

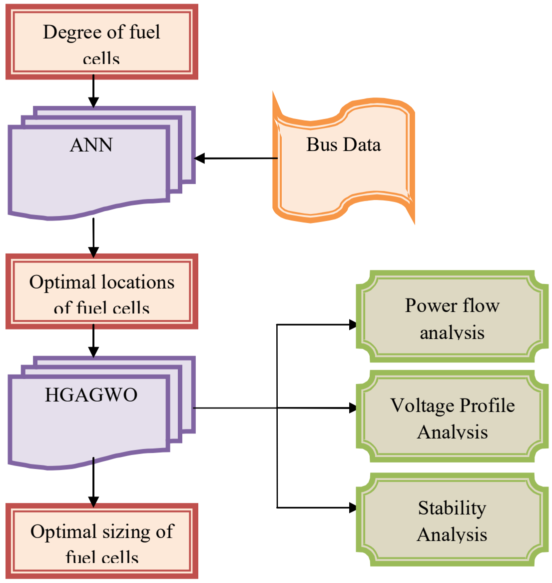

Fig. 1. *Systematic Diagram of optimal location and sizing using the proposed technique*

4.2 Conventional Genetic Algorithm

To interpret the adaptive processes of natural systems, the GA is developed [14]. Usually, GA is connected with the exploit of a binary demonstration although currently, one can locate GA, which exploits other types of demonstrations. Generally, by mating, the parents (individuals), as well as a mutation operator the GA, applies a crossover operator, which arbitrarily mutates the individual contents to endorse variety to produce a new offspring.

A probabilistic chosen is exploited by GA, which is initially the proportional selection. The substitute (survival was selected) is generational, namely, by the offsprings, the parents are reinstated systematically. The operator of the crossover is on the basis of the uniform crossover or n-point when the mutation is a bit flipping.

Selection operator: In GA, the selection phase is significant to select the individuals from the population for the crossover operator. There are several types of selection operator namely elitist selections, tournament selection, roulette wheel selection, and rank selection.

Crossover operator: Generally, GA exploits a crossover operator to select solutions with a probability C_p to arbitrarily alter an individual and endorse diversity. The population substitute is generational, which is to say, by the offsprings, the parents are substituted methodically. There are various kinds of crossover namely two-point crossover, single-point crossover, uniform crossover, arithmetical crossover, and so forth.

Mutation operator: In GA, the major task of the mutation is to enhance the exploration procedure of the technique as well as evade the convergence of premature in the population by connecting a random number from (0, 1) with every gene in every individual in the population P and mutating the gene that their connected number is lesser than M_p.

4.3 Conventional GWO Algorithm

GWO is a population-based metaheuristic technique that emulates the hunting process and leadership hierarchy of grey wolves in nature [20]. Here, the mathematical representations of the encircling tracking, social hierarchy, and attacking prey are presented.

In GWO, α represented as the first fittest solution, the second and the third fittest solutions are represented as β and δ, correspondingly.

The remaining solutions are indicated by ω. In GWO technique, the hunting process is done by ϕ, μ and ζ. The ω solutions pursue these three wolves. Eq. (25) and (26) represents the mathematical representation of the encircling behavior.

$$E = \left| K \cdot Z_p(t) - L \cdot Z(t) \right| \tag{25}$$

$$Z(t+1) = Z_p(t) - L \cdot E \tag{26}$$

Where, t represents the current iteration, Z_p indicates the location vector of the prey, L and K are coefficient vectors, and Z represents the grey wolf location vector. Eq. (27) and (28) is exploited to calculate the vectors L and K.

$$L = 2l \cdot r_1 - l \tag{27}$$

$$K = 2 \cdot r_2 \tag{28}$$

where components of l are linearly minimized from 2 to 0 against the iterations course, and r_1 and r_2 are random vectors in (0, 1).

Generally, the operation of hunting is performed by the ϕ . The μ and ζ may intermittently contribute to hunting. In the mathematical representation of grey wolves hunting behavior, the ϕ, μ and ζ have an enhanced idea regarding the possible position of prey.

The first three optimal solutions are stored and the other agent is forced to update their locations on the basis of the position of the optimal search agents.

$$E_\alpha = \left| K_1 \cdot Z_\phi - Z \right| \tag{29}$$

$$E_\beta = \left| K_1 \cdot Z_\mu - Z \right| \tag{30}$$

$$E_\delta = \left| K_1 \cdot Z_\zeta - Z \right| \tag{31}$$

$$Z_1 = Z_\phi - L_1 \cdot (E_\phi) \tag{32}$$

$$Z_2 = Z_\mu - L_1 \cdot (E_\mu) \tag{33}$$

$$Z_3 = Z_\zeta - L_1 \cdot (E_\zeta) \tag{34}$$

$$Z(t+1) = \frac{Z_1 + Z_2 + Z_3}{3} \tag{35}$$

By attacking the prey, the grey wolves terminate the hunt while the prey impedes moving. The vector L is an arbitrary value in the interval $[-2l, 2l]$, whereas l is minimized from 2 to 0 against the course of iterations. While $|L| < 1$, the wolves attack in the direction of the prey indicates an exploitation procedure. In GWO, the exploration procedure is used for the location ϕ, μ and ζ, which deviates from each other to explore for prey and congregates to attack prey. The exploration process is mathematically modeled using L arbitrary values >1 or <-1 to force the search agent to deviate from the prey. While $|L| > 1$, the wolves are obliged to deviate from the prey to discover more appropriate prey.

4.4 Proposed HGAGWO Algorithm for Optimal Sizing

In this paper, a hybrid technique by integrating the GA and the GWO technique the optimal sizing of fuel cells is performed [21]. The performance analysis exhibits that the combination of the two techniques enhances the performance of the proposed technique. The proposed HGAGWO technique is performed on the basis of three procedures that formulate it potent and capable to resolve the reduction of the possible energy function.

By generating the initial population randomly the proposed technique begins and applies the GWO that has a better capability to balance among the exploitation and the exploration phase. The GWO technique assists the proposed technique to explore the search space and use the capable area that has a better solution nevertheless, in the large scale optimization issues.

In addition, this proposed technique is exploited to conquer a few issues that are foisted by minimizing in size and complication of the optimization issues. Here, the proposed technique is to guarantee better coverage of the search space as well as an enhanced convergence to the global optima through the dimension of the issue maximizes. The proposed technique attains this by partitioning the population into sets of partitions. Each partition comprised a certain amount of individuals and is observed as a subspace in the search procedure. Choosing several subspaces preserves search diversity.

(a) Role of GA operators:

In the proposed technique, GA operators (crossover, mutation) are applied. It is because to maximize the diversity of the search and evade the traditional GWO technique premature convergence.

The proposed technique exploits an enhanced arithmetic crossover operation is stated in algorithm 1.

Algorithm 1: Pseudo code of cross over operation
Cross over (p^1, p^2)
Arbitrarily select $\lambda \in (0,1)$
Two offspring $o^1 = (o^1_1, \ldots.. o^1_D)$ and $o^2 = (o^2_1, \ldots.. o^2_D)$ are generated from parents $p^1 = (p^1_1, \ldots.. p^1_D)$ and $p^2 = (p^2_1, \ldots.. p^2_D)$
Where, $c^1_i = \lambda p^1_i + (1-\lambda) p^2_i$
$c^2_i = \lambda p^2_i + (1-\lambda) p^1_i$
$i = 1 \ldots\ldots E$
Return

Algorithm 2: Pseudo code of Proposed HGAGWO
Initialize the initial values of the population size n, coefficient vectors L and K, parameter a, crossover probability C_p, mutation probability M_p partition number N_p, number of solutions in each partition μ, number of variables in each partition u, and the maximum number of iterations Max_{itr}.
Initialize $t = 0$
for $(i = 1; i \leq n)$ do
Produce an first population $Z_i(t)$ arbitrarily
For each search agent $f(Z_i)$, estimate the fitness function
end for
repeat
Apply the eq. (35) on the whole population
Selection operator is applied for the GA on the complete population $Z(t)$
Partition the population $Z(t)$ into N_p sub-partitions, where each sub-partition $Z'(t)$ size is $u \times \mu$
for $(i = 1; i \leq N_p)$ do
As stated in Algorithm 1, use the arithmetical crossover on each sub-partition $Z'(t)$
end for
On the whole population $Z(t)$, apply the GA mutation operator
In the population $Z(t)$, update the solutions
Set $t = t + 1$
until $(t \geq Max_{itr})$
Generate an optimal solution.

5. Results and Discussions

5.1 Experimental Procedure

By utilizing fuel cells, the proposed DG technique was implemented in MATLAB. Moreover, the simulation was performed in four IEEE standard bus systems namely 9, 12, 33 and 69 bus test systems. Here, the cost models associated with the voltage stability, power loss, and VP and the final cost model have been studied. Therefore, attained results were compared over three conventional techniques namely GA, PSO, and GWO. In the following sub-sections, the ensuing values were analyzed.

5.2 Performance Analysis of Test Case 1

Table 1 summarizes the performance analysis of Test case 1 for IEEE 9 bus system. It is well known the first objective model is considered as power loss, the second objective model is considered as VP and the third objective model is considered as voltage stability. Here, the proposed HGAGWO technique is 0.71%, 0.9%, and 1.02% better than the PSO, GA and GWO algorithm regarding the first objective model. The proposed technique is 14% and 16% better than the GWO algorithm while resolving the second and third objective functions. With respect to the iteration 1000 and population size 100, the proposed technique is 6% and 4% superior to the conventional GA and PSO regarding the first objective model. Likewise, the proposed technique is 4% and 8% better than the traditional PSO regarding the second and third objective model. This shows each objective model has done the proposed technique to rule in the cumulative objective model of all the conventional techniques.

Table 1. *Comparison analysis of IEEE 9 Bus System*

Methodology	Functions	GA	PSO	GWO	HGAGWO
Iteration =100 and population size =10	Objective model 1	1442.23	1412.22	1422.21	1402.12
	Objective model 2	1623.21	1621.11	1634.34	1610.11
	Objective model 3	1121.212	1021.214	1102.222	1001,021
	Total Cost	1821.210	1815.101	1802.219	1789.210
Iteration =1000 and population size =100	Objective model 1	189.2123	167.2132	183.4123	122.3210
	Objective model 2	123.12	121.23	128.11	119.10
	Objective model 3	112.11	110.123	122.13	102.23
	Total Cost	717.22	772.23	737.23	707.12

5.3 Performance Analysis of Test Case 2

In Table 2, the proposed technique individually performs superior to the conventional techniques with significant percentage enhancement regarding the population size 10 and iteration 100 as well as population size 100and iteration 1000. Since, 13% of performance enhancement is verified for objective model 1 over GWO technique, 16% enhancement in objective model 2 and 18% in objective model 3. On average 19% of performance enhancement has been evident by the proposed technique with respect to the GWO technique.

Table 2. *Comparison analysis of IEEE 12 Bus System*

Methodology	Functions	GA	PSO	GWO	HGAGWO
Iteration =100 and population size =10	Objective model 1	154.22	178.21	167.21	145.21
	Objective model 2	145.23	143.32	165.23	112.23
	Objective model 3	189.22	193.24	184.23	176.22
	Total Cost	254.23	276.24	278.22	233.43
Iteration =1000 and population size =100	Objective model 1	132.234	176.234	189.456	122.567
	Objective model 2	124.126	176.235	184.989	114.675
	Objective model 3	117.345	147.955	135.677	104.23
	Total Cost	345.234	323.432	310.212	301.232

5.4 Performance Analysis of Test Case 3

In Table 3, the proposed technique has recorded good performance enhancement over the conventional algorithms for population size 10 and iteration 100 as well as population size 100 and iteration 1000. Here, the performance analysis summarizes the proposed technique is superior to the conventional technique. The enhancement is recorded as 12%, 19% and 20% for the three objective model, correspondingly.

Table 3. *Comparison analysis of IEEE 33 Bus System*

Methodology	Functions	GA	PSO	GWO	HGAGWO
Iteration =100 and population size =10	Objective model 1	321.221	342.123	363.287	302.123
	Objective model 2	234.342	231.213	214.234	210.232
	Objective function 3	212.454	246.23	267.89	209.189
	Total Cost	390.123	378.127	345.645	320.145
Iteration =1000 and population size =100	Objective model 1	456.232	443.257	490.563	490.236
	Objective model 2	567.874	578.904	546.765	520.234
	Objective model 3	672.234	426.9	616.4	410.56
	Total Cost	616.4	612.64	634.5	614.5

5.5 Performance Analysis of Test Case 4

As same as the first three cases, the proposed technique is superior to all the given existing techniques, which is mentioned in Table 4. For objective model 1, the proposed technique obtains an enhanced outcome of about 3% against the conventional GWO technique, 8% for objective model 2 and 10% for objective model 3. The average performance enhancement for the three objective models is estimated as 15% when the performance enhancement regarding the total cost model is about 20%.

Table 4. Comparison analysis of IEEE 69 Bus System

Methodology	Functions	GA	PSO	GWO	HGAGWO
Iteration =100 and population size =10	Objective model 1	190.8	714.2	186.3	936.9
	Objective model 2	0.132	0.0199	0.190	0.076
	Objective function 3	26.75	26.44	26.74	26.32
	Total Cost	134.22	136.57	134.34	134.5
Iteration =1000 and population size =100	Objective model 1	26.63	26. 73	26.64	26. 61
	Objective model 2	75.14	72.44	78.67	72.87
	Objective model 3	14.92	15.92	12.57	10.32
	Total Cost	75.04	88.77	72.79	72.89

6.Conclusion

To determine the OPAS of fuel cells a dual-phase technique was proposed in this paper. In addition, the proposed DG technique exploiting fuel cells was simulated in MATLAB. The simulation was performed in four IEEE standard bus systems namely 9, 12, 33 and 69 bus test systems. At first, the performance of the proposed technique was analyzed to determine the fuel cells by the iterations. Then, the reduced cost values acquired from each optimization technique was calculated. Moreover, the reduced cost values have integrated the cumulative cost and the individual cost models. Further, the experimental analysis exhibits that the proposed technique was superior to the existing techniques by considering individual objective models namely voltage stability, power loss, as well as VP. This shows that the proposed technique has increased power flow and the system stability.

Compliance with Ethical Standards

Conflicts of interest: Authors declared that they have no conflict of interest.

Human participants: The conducted research follows the ethical standards and the authors ensured that they have not conducted any studies with human participants or animals.

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