Hybrid Optimization Techniques for Enhancing Optimal Flow of Power Systems

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Abstract
Hybrid optimization techniques have been extensively utilized for solving optimal power flow problems in distribution systems integrated with or without renewable energy systems, with load uncertainty. Particle swarm optimization (PSO) is integrated with Gray wolf optimizer (GWO) to create a hybrid algorithm, HPSOGWO. HPSOGWO is implemented to augment the optimal power flow solutions of IEEE-30 bus and IEEE-62 bus systems. Five objective functions are considered to investigate the power quality of the hybrid algorithm. The proposed algorithm strength is justified by a comparative study with each individual algorithm. The suggested algorithms provide different accuracy results in small and large scale distributed systems, which indicates their drawbacks in certain systems. The system is solved using MATLAB.

Keywords:
Optimal power flow ; Hybrid optimization techniques ; Exploration and exploitation abilities

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1. Introduction

Recently, several modern optimization techniques have been improved. The joint objective of these techniques is the detection of the most optimal solution and convergence performance. Hence, every algorithm inspired by nature must be contained from exploration and exploitation to guarantee the best global solution.

Exploration involves a search method to obtain a better solution in a large area, which is a global search. When searching for a solution via the method, it is the most suitable to utilize exploitation because it impacts a small area, and it is a local search. Eventually, all modern techniques strive to achieve an equilibrium between the capacity to explore and exploit the situation to search the most appropriate solution and performance in the search space [1].

Particle swarm optimization (PSO) has been implemented for nonlinear optimization issues such as a stochastic method. Kennedy and Eberhart reported that PSO essentially simulates social behavior [2,3]. Due to its convergence speed, reliability, simplicity, and capacity to pinpoint global and optimal solutions, PSO is the best option.

Recently, Mirjalili et al. developed another method known as grey wolf optimizer (GWO), which has been created as per the hunting method and hierarchy exhibited by grey wolves [4]. GWO has been successfully implemented to optimize key metrics from coding algorithms [10]. In addition, GWO can be employed for solving optimizing key values in feature subset selection [11], time forecasting [12], optimum power flow issues [13], economic dispatch issues [14], flow-shop scheduling issues [15], and an optimal double-layer grid design [16]. Several algorithms were created to augment the convergence performance of GWO, e.g., parallelized GWO [17, 18], binary GWO [19], integration of DE with GW^O [20], hybrid GWO with genetic algorithm (GA) [21], hybrid DE with GWO[22], and hybrid GWO using the elite opposition-based learning strategy and simplex method[23].

The no-free lunch theorem[24] for optimization permits researchers to search or develop fresh algorithms and augment the quality of the existing ones, indicative of the lack of a single technique that can address all issues.

In addition to PSO, several hybrids exist, such as the particle swarm optimization with gravitational search algorithm (PSO-GASE)[5,6], particle swarm optimization with dragonfly algorithm (PSODA) [7], particle swarm optimization with firefly algorithm (PSOFA)[8], and particle swarm optimization with multi-verse optimizer (PSOMVO)[9].

Port-Hamiltonian algorithm was implemented for optimizing the power flow of multi-terminal DC networks. The technique is utilized for offshore wind integration grid in the North Sea and the interconnection with the network dynamic is examined using numerical simulations[25]. Moth swarm algorithm incorporated with gravitational search algorithm for optimal power flow considering the wind energy system. The technique is tested with IEEE 30-bus, IEEE 57-bus, and IEEE 118-bus integrated with and without wind energy system. The results approved the efficiency and accuracy of the techniques [26].

An interline current flow controller (CFC) is utilized for decreasing the operating cost of hybrid AC/DC, mesh grids using elimination the congestion within the DC lines. The technique is implemented in a case studies of 5-terminal AC/DC meshed grid. This leads to improving the optimal power flow of the studied system, considering the load uncertainty and different configuration of the transmission system [27]

Hybrid modified imperialist competitive algorithm with sequential quadratic programming is employed to solve the constrained of the optimal power flow problem of hybrid power system integrated with renewable energy system. The techniques suggested is evaluated and tested using three benchmark systems which are IEEE 30-bus, IEEE 57-bus and IEEE 118-bus power systems integrated with few PV system and wind energy system[28].

The solution of optimal power flow problem of distribution systems using decentralized saddle-point dynamics [29].

In this study, a new hybrid (HPSOGWO)

that uses both PSO and GWO is examined. The following five functions are included:

1. Minimization of Active Power Transmission Loss
2. Minimization of Fuel Costs related to Generation
3. Maximization of Margin for Reaction Power Reserve
4. Minimization of Reactive Power Transmission Loss
5. Minimization of Emission Index

2. Problem Formulation

2.1. General OPF Problem Formulation

The mathematical formula of the OPF problem is as follows:

$$\text{Minimize } F(x, u)$$

$$\text{Subject to } g_E(x, u) = 0$$

$$go(x, u) \leq 0$$

$$go(x, u) < 0$$

Several control variables for this problem are defined as follows:

$$u = [Q_c^T \ \ TC^T \ V_G^T \ \ P_G^T]$$

where

u = control variables

QC = reactive power supplied by all shunt reactors

TC = magnitude of transformer load tap changer

VG = magnitude of voltage at generator buses

PG = active power generated at generator buses

$$x = [V_L^T \ \ \theta^T \ \ P_{SG} \ \ Q_G^T \ ]$$

where

x = state variables

V_L = magnitude of voltage at load buses

θ = voltage angles of all buses excluding the slack bus”

P_{SG} = active power generated at the slack bus

Q_G = reactive power generated at all generator units

N_L = number of load buses

N_G = number of generator buses

The OPF problem, i.e., the optimization problem, is outlined as maximizing or minimizing the objective function, where the problem is put through a series of equality and inequality restrictions.

3.Problem Objectives

3.1.Fuel Cost Minimization

The economic distribution of a load is defined among the different generators of a system, and the variable operating costs must be presented as the active power generated at each generator in a system. Hence, the fuel cost is the essential cost in a thermal or nuclear unit. Then, the fuel cost must be presented as active power generated at each generator in a system. In addition, other costs, such as operation and maintenance costs, can be presented as the power output. Fixed costs such as the capital cost, depreciation, etc. are not included in the fuel cost.

The curve for fuel cost is thought to be estimated by the quadric function of the active power generated by each unit in a system as follows:

$$F_1 = \sum_{i=1}^{NG} (a_i + b_i P_{Gi} + c_i P_{Gi}^2) \quad (1)$$

where

P_{Gi} = active power generated at an ith generator in a system

N_G= number of generators in a system

a_i, b_i, c_i = fuel cost coefficients of an ith generator in a system.

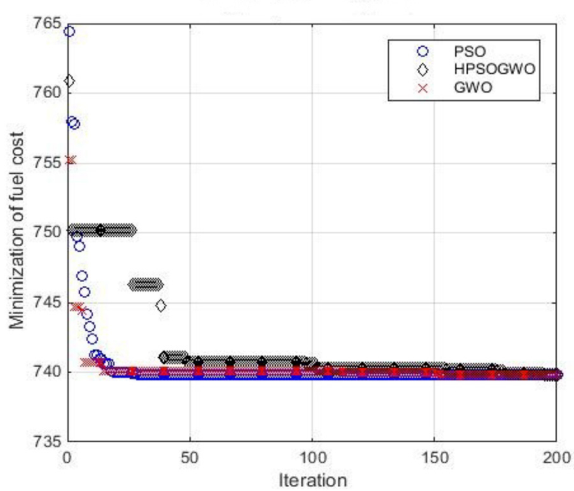

Fig. 1. Generated fuel cost minimization for a 30-bus IEEE system

3.2. Emission Minimization

The function of emissions can be summarized as all types of the considered emissions, such as NOx, SO2, and thermal emissions. As shown in the equation, emissions in terms of their amount are highlighted as the function of the active power, which is generated at each generator in a system, and it is expressed as the sum of quadratic and exponential functions:

$$F_2 = \sum_{i=1}^{NG} [10^{-2} * (\alpha_i + \beta_i P_{Gi} + \gamma_i P_{Gi}^2) + \epsilon_i \exp(\lambda_i P_{Gi})] \quad (2)$$

where

$\alpha_i, \beta_i, \gamma_i, \lambda_i$ and ϵ_i are the emission characteristic coefficients of the ith generator.

3.3 Total Active Power Loss Minimization

The term PL represents the total I2R loss in the transmission lines and transformers of the system. From equation (3), the total active power loss equals the sum of the generated active power at each generator in a system subtracted by the sum of the active power at each load bus in a system; hence, PLoss must be greater than zero."

$$F_3 = \sum_{i=1}^{N} P_l = \sum_{i=1}^{NG} P_{Gi} - \sum_{i=1}^{Nd} P_{di} \quad (3)$$

3.4 *Reactive Power Transmission Loss Minimization*

This resulted in the increase in the voltage stability margin and augmentation of the transportation system from real power out of sources to sinks in a network, and QLoss can be either positive or negative.

$$F_4 = \sum_{i=1}^{N} Q_i = \sum_{i=1}^{NG} Q_{Gi} - \sum_{i=1}^{Nd} Q_{di} \quad (4)$$

1.1. Reactive Power Reserve Margin Maximization

Reactive power reserve margin maximization leads to the minimization of the reactive power losses and improvement of the voltage stability and the generator's capacity to aid the bus voltage under augmented system disturbances or load conditions. The speedy sources (reactive) include FACTs, generators, and synchronous condensers.

$$F_5 = \sum_{i=1}^{NG} \frac{Q_i^2}{Q_{imax}} \quad (5)$$

4. Problem Constraints

4.1. Equality constraints

The equality constraint condition can be expressed as follows:

$$\sum_{i=1}^{NG} P_{Gi} - P_D - P_{Loss} = 0 \quad (6)$$

$$\sum_{i=1}^{NG} Q_{Gi} - Q_D - Q_{Loss} = 0 \quad (7)$$

4.2. Inequality constraints

• Constraints of generation capacity

The generator outputs and bus voltage are restricted by min and max limits as follows:

$$P_{Gi}^{min} \le P_{Gi} \le P_{Gi}^{max}$$

$$Q_{Gi}^{min} \le Q_{Gi} \le Q_{Gi}^{max}$$

$$Q_i^{min} \le Q_i \le Q_i^{max}$$

$$v_i^{min} \le v_i \le v_i^{max}$$

• Constraints of line flow

$$\left|P_{Lf,k}\right| \le P_{Lf,k}^{max} \qquad k = 1,2,\ldots\ldots,L$$

Where, $P_{Lf,k}$ is the active power flow of line k, $P_{Lf,k}^{max}$ is the active power flow high limit of line k, and L is the number of transmission lines.

5. Optimization Techniques

The mathematical model for each optimization technique is explained in this section.

5.1. Particle Swarm Optimization (PSO)

In 1995, Kennedy and Eberhart proposed PSO [2,3], which is inspired by the social behavior of different animals, birds, and insects. PSO looked at elements such as the schooling of fish or flocking of birds.
The word particle is concerned with a single unit, i.e., a bird in a swarm or a bee from a colony. Each piece comes together with its own intelligence into a collective, building a group or the hive mind.
When one particle or unit locates a path to food, others will swarm and instantly follow even if they are located far from the swarm. This is based on hive intelligence, which is a technique that stems more from behavior than genetics, where algorithms

are known as evolution-based processes. It is where a population of the unit or particles are put into use to solve optimization issues. Each exhibits two essential characteristics: velocity and position.
The particles are present in the search space, and they can be in the best possible spot when examined in terms of the objective function. The particles can be updated to a better position, and their velocities are estimated by equations 9 and 10. This perspective is gained from hive or swarm behavior to augment global optimization function solutions [30].

These mathematical equations are as follows:

$$\omega = \omega_{\max} - k * \frac{\omega_{\max} - \omega_{\min}}{\text{Maxite}} \tag{8}$$

$$V_{i,j}^{k+1} = \omega * V_{i,j}^{k} + c_1 * r_1 * \left(Pbest_{i,j}^{k} - X_{i,j}^{k}\right) + c_2 * r_2 * \left(Gbest_{i,j}^{k} - X_{i,j}^{k}\right) \tag{9}$$

$$X_{i,j}^{k+1} = X_{i,j}^{k} + V_{i,j}^{k+1} \tag{10}$$

where N represents the population size, and dimension D is presented as $X=[X_1,X_2,\ldots,X_N]^T$, where T is a transpose operator. Each particle is presented as $Xi = (I = 1,2,\ldots.,N)$ is presented as $X=[I,I_{i,2},\ldots.,I]\ ]$. In addition, the initial velocity of the population is indicated as $V=[V_1,V_2,\ldots,V_N]^T$.Thus, the velocity of each particle in a population $Xi(i = 1,2,\ldots, N)$ is presented as $V = [V_{i,1},V_{i,2},\ldots,V_{i,D}]$. The index i mutates from 1 to N, whereas the index j mutates from 1 to D."

5.2 Grey Wolf Optimizer (GWO)

Mirjalili et al. were the first to develop the GWO algorithm, which is essentially inspired by the leadership hierarchy and hunting methods of grey wolves [4]. The wolves in question are thought to be at the top of the food chain and live as a collective.
The study examined four species, including (α), beta (β), delta (δ), and omega (ω), respectively, in terms of the simulation patterns of the leadership hierarchy and basic GWO parameters.

In terms of the GWO design, as per the hierarchy of the wolves, alpha (a) is designated as the best solution. The second and third best solutions are designated as beta (β) and delta (δ), respectively. The remaining candidate solutions are designated as (ω). The WHO algorithm simulates the behavior of the wolves during hunting in three stages: chasing, hunting, and tracking the prey, in addition to attacking the target. This behavior is considered during the design of GWO, which can be expressed as follows:

$$\vec{D} = \left|\vec{C}.\overrightarrow{X_P}(t) - \vec{X}(t)\right| \tag{11}$$

$$\vec{X}(t+1) = \overrightarrow{X_P}(t) - \vec{A}.\vec{D} \tag{12}$$

where (t) is the present iteration, Xp is the prey position vector, D, A, and C are coefficient vectors, and X is the GWO vector. A and C are calculated as follows:

$$\vec{A} = 2\vec{a}.\vec{r_1} - \vec{a} \quad (13)$$

$$\vec{C} = 2.\vec{r_2} \quad (14)$$

The hunting behavior of the grey wolves is simulated assuming that alpha (α), beta (β), and delta (δ) have enhanced knowledge of the prey site that is likely to be targeted, which can be explained as follows:

$$\vec{D_\alpha} = |\vec{C_1}.\vec{X_\alpha} - \vec{X}|, \vec{D_\beta} = |\vec{C_2}.\vec{X_\beta} - \vec{X}|, \vec{D_\delta} = |\vec{C_3}.\vec{X_\delta} - \vec{X}| \quad (15)$$

$$\vec{X_1} = \vec{X_\alpha} - \vec{A_1}.(\vec{D_\alpha}) \quad (16)$$

$$\vec{X_2} = \vec{X_\beta} - \vec{A_2}.(\vec{D_\beta}) \quad (17)$$

$$\vec{X_3} = \vec{X_\delta} - \vec{A_3}.(\vec{D_\delta}) \quad (18)$$

$$\vec{X}(t+1) = \frac{\vec{X_1} + \vec{X_2} + \vec{X_3}}{3} \quad (19)$$

At $|A| < 1$, the wolves are forced to attack the prey, where A is a random value. Searching for the prey is the exploration ability, while attacking the prey is the exploitation ability. At $|A| > 1$, the wolves are forced to diverge from the prey.

6. A New Hybrid Algorithm

Several hybridization techniques for heuristic techniques. Talbi [31-32] reported the hybridization of two or more techniques. HPSOGWO is the combination of GWO and PSO, where the strengths of both techniques are put into place during exploration when the Pbest value of PSO is switched with that of GWO. In terms of HPSOGWO, the position of the first three agents is updated in the equation for the search space (15), with an additional inertia constant (ω) to control the exploration and exploration within the search space. The equation that results from this modification is expressed as follows:

$$\vec{D_\alpha} = |\vec{C_1}.\vec{X_\alpha} - \omega * \vec{X}|, \vec{D_\beta} = |\vec{C_2}.\vec{X_\beta} - \omega * \vec{X}|, \vec{D_\delta} = |\vec{C_3}.\vec{X_\delta} - \omega * \vec{X}| \quad (20)$$

where ω denotes the inertia weight. For combining PSO and GWO, the updated equation and velocity can be expressed as follows:

$$V_{i,j}^{k+1} = I * V_{i,j}^{k} + c_1 * r_1 * (X_I - X_{i,j}^{k}) + c_2 * r_2 * (I - X_{i,j}^{k}) + c_3 * r_3 * (I_3 - X_{i,j}^{k}) \quad (21)$$

$$X_{i,I}^{k+1} = I + V_{i,j}^{k+1} \quad (22)$$

Basic steps of HPSOGWO

STEP 1: Create an initial population (agents) or (grey wolves).

STEP 2: Initialize a, A, C, and ω equations (8, 13, 14).

STEP 3: Perform fitness evaluation of each agent.

STEP 4: Calculate the position of the grey wolf. Xα, Xβ, and Xδ equations (20) and (16–18).

STEP 5: Update the velocity and position equations (21, 22).

STEP 6: Repeat STEPS 2–5 until the stop criteria is reached.

STEP 7: Stop.

7. Results and Discussion

Figure 3 and Figure 4 show the results for the 30-bus 6-generator and 62-bus 19-generator IEEE systems, respectively. The total active power demands for the 30-bus and 62-bus systems are 283.4 MW and 2,912 MW, respectively, and their corresponding total reactive power demands are 126.2 MVar and 1,269 MVar. Five OPFs are individually implemented as one objective function during the process optimization by using PSO, GWO, and HPSOGWO and compared (Table I and Table II):

F1 Fuel Cost Minimization
F2 Emission Minimization
F3 Total Active Power Loss Minimization
F4 Reactive Power Transmission Loss Minimization
F5 Reactive Power Reserve Margin Maximization

NO.	PSO	GWO	HPSOGWO
F1	739.8271	739.8284	739.8568
F2	2.0637E–04	2.0485E–04	2.0491E–04
F3	8.8753	16.7702	5.1
F4	–15.8380	–11.2374	–16.7756
F5	1.2414E-41	6.0820E–58	7.6379E–18
Percentage	66.67%	63.33%	70%

Table 1. Values of the Five Functions (OPFs) by PSO, GWO, and HPSOGWO for a 30-bus IEEE System

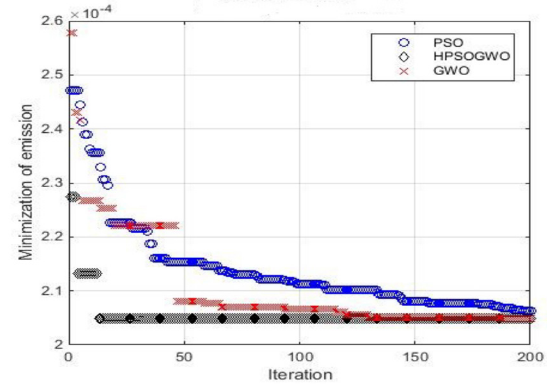

Fig. 2. Emission index minimization for a 30-bus IEEE system

NO.	PSO	GWO	HPSOGWO
F1	2342.3	2343.7	2361.6
F2	0.397	0.395	0.393
F3	547.8	572.6	566.6
F4	437.9	457.5	450.9
F5	5.28E–18	5.68E–24	7.77E–09
Percentage	80%	60%	60%

Table 2. Values of the Five Functions (OPFs) by PSO, GWO, and HPSOGWO for a 62-bus IEEE System

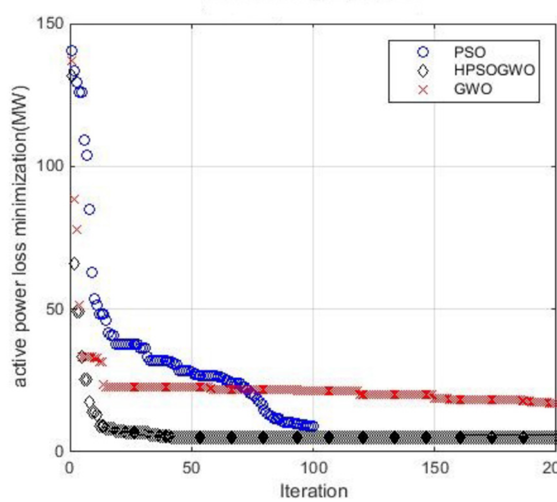

Fig. 3. Active power loss minimization for 30-bus IEEE system

Table 1 summarizes the best optimal solutions, convergence performance, and best statistical values achieved by HPSOGWO for five function values. The performances of GWO and PSO are satisfactory, but neither can match up to that of HPSOGWO: "HPSOGWO is more reliable in providing superior quality results with reasonable iterations and prevents the premature convergence of the search process to a local optimal point and provides superior exploration of the search course."

Table II summarizes the best optimal solutions, convergence performance, and best statistical values achieved by PSO for five function values. The performances of HPSOGWO and GWO are the same, GWO only exhibits the best optimal solution for the maximization of reactive power reserve margin, and HPSOGWO only exhibits the best optimal solution for the minimization of emissions.

Parameters	Quantity
Population size	100
Number of iterations	200

Table 3. Standard Values of All the Used Algorithms

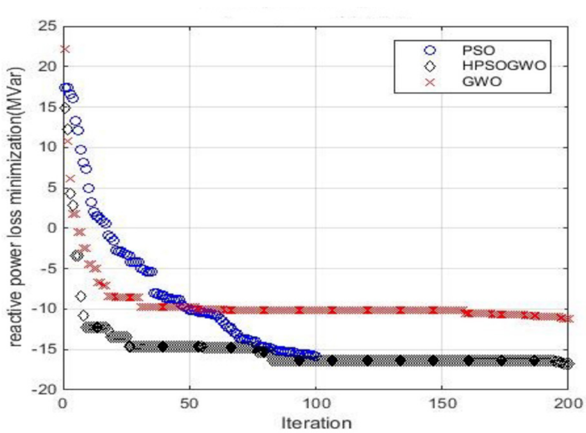

Fig. 4. Reactive power loss minimization for a 30-bus IEEE system

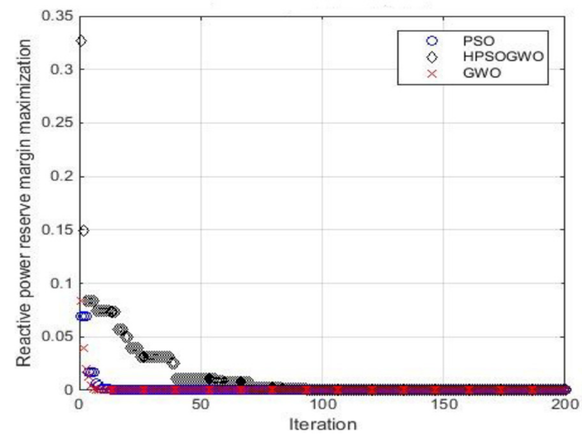

Fig. 5. Reactive power reserve margin maximization "for 30-bus IEEE system

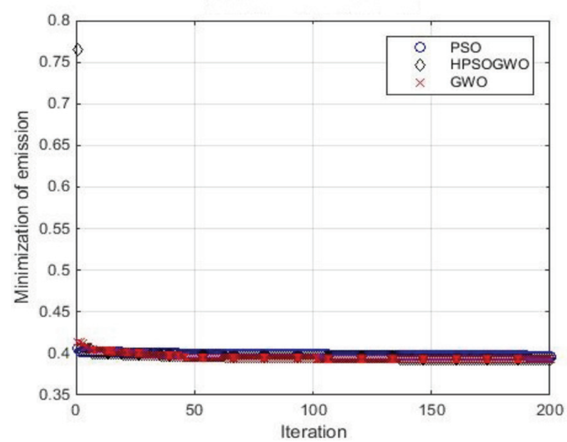

Fig. 6. Generation fuel cost minimization for a 62-bus IEEE system

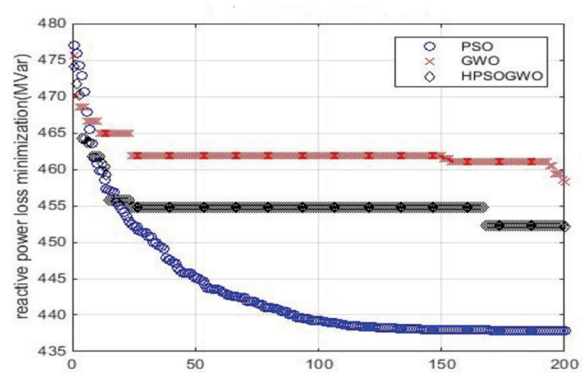

Fig. 7. Emission index minimization for a a62-bus IEEE system

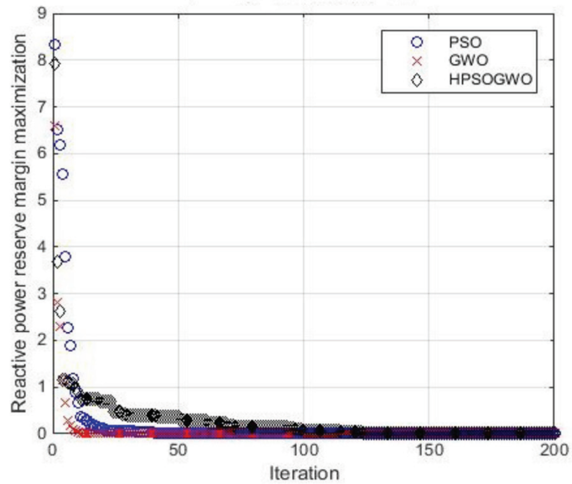

Fig. 8. Active power loss minimization for a 62-bus IEEE system

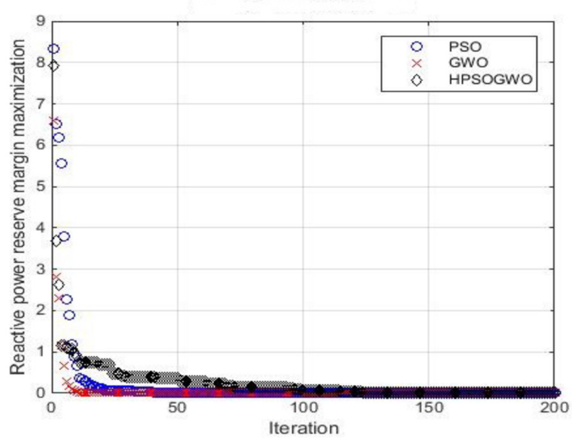

Fig. 10. Reactive power reserve margin maximization for a 62-bus IEEE system

8. Conclusions

The hybrid optimization technique comprising two algorithms, i.e., PSO and GWO, respectively, was outlined in this study for different scenarios. The quality of this technique was examined using two 30-bus [33] and 62-bus IEEE systems [34] with different cases. Five objective functions were considered to investigate whether the proposed algorithm was of a desired quality. Furthermore, the hybrid algorithm was compared with PSO and GWO. Results revealed that compared to

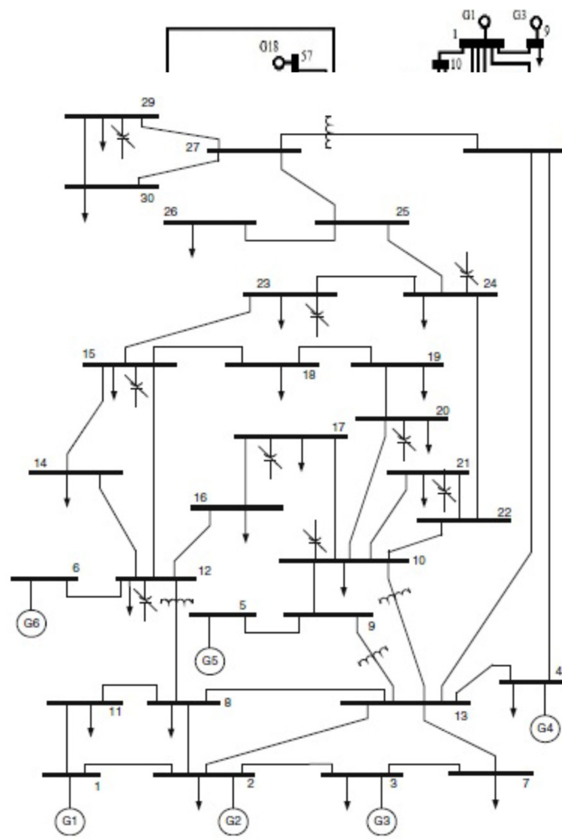
Fig. 11. Single-line diagram of a 30-bus IEEE test system

GWO, PSO and HPSOGWO afford better results by a low number of iterations and high-quality solutions. The suggested hybrid algorithms mostly provide very good results and high accuracy but not in all cases, due to nature of each optimization algorithm

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