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RESEARCH ARTICLE

# Hybrid Optimization Technique for Solving Combined Economic Emission Dispatch Problem of Power Systems

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## ABSTRACT

Mathematical optimization provides the best possible results to a problem. The latest trend in optimization, called hybrid optimization methods, combines two or more optimization techniques, deterministic and non-deterministic, with the aim of overcoming the limitation of one technique by the advantage(s) of the other technique(s). A hybrid particle swarm bat algorithm optimization technique that uses the frequency tuning technique of bat algorithm at the velocity updating stage in particle swarm optimization (PSO) was developed for avoiding premature convergence limitation of PSO using the potential of BA to escape being trapped at local optimum. Implementation of the developed optimization method for solving the combined economic emission dispatch problem of 28 Bus 7 Generators Nigeria power network showed that H-PS-BA optimization method performed better than PSO by 0.07%.

**Index Terms—**Bat algorithm, combined economic emission dispatch, hybrid optimization, non-deterministic optimization, particle swarm optimization.

## I. INTRODUCTION

The determination of the best desirable solution to a problem, known as optimization, is a commonly encountered mathematical problem in engineering. Numerous optimization routines have been evolved for solving different optimization problems. These methods are classified as deterministic, non-deterministic, and hybrid optimization procedures [1]. Different techniques of optimization have been deployed in solving electric power system problems. These methods include linear programming (LP), interior point method (IPM), and quadratic programming (QP) which all belong to the deterministic optimization class [2-5]. Non-deterministic methods of optimization such as bat algorithm (BA), artificial bee colony (ABC), genetic algorithm (GA), and particle swarm optimization (PSO) techniques were also employed for power system problem solutions [6,7].

A solution to complex power system problems using deterministic optimization methods was found to be difficult and expensive, the possibility of getting a global solution also decreases when the size of the problem increases, and the quality of global solution obtained cannot be guaranteed in the case of non-deterministic methods [8].

The realization of the fact that there is no perfect solution brought about the development of a successful trend in optimization: combination of different algorithms to form a hybrid. Hybrid optimization uses the superiority of a method to conquer the drawbacks of other methods [1,9]. Hybrid algorithms promise high-quality solutions and stability of convergence. They have a quick operation and are flexible in modeling compared to each separate technique [10].

The optimal allocation procedure of electrical energy production amidst participating generating units, satisfying all operational limitations while reducing generation cost, and the amount of emission produced simultaneously is termed combined economic emission dispatch (CEED) [12]. Combined economic emission dispatch has emerged as a very important optimization problem in contemporary deregulated power systems [13]. Optimal CEED problem (CEEDP) is necessitated because of shortage of resources, surging power generation costs, and soaring demands for electric energy [6]. Several elements influencing CEED include loss in transmission, characteristics of fuel consumption, valve point loading, ramp rate, prohibited zones of operation, and constraint conditions of the CEEDP [3,14,15].

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Different hybrid techniques of optimization have been evolved and applied to solve CEEDP in power systems. These include hybrid ABC-simulated annealing algorithm [16], hybrid firefly–bat algorithm [17], quantum-inspired PSO [18], hybrid ABC with fuzzy technique [19], and hybrid whale optimization algorithm with PSO [20]. The results of these works revealed that the hybrid algorithms solved the CEEDP more efficiently than the hybrid constituent methods applied separately.

This work develops a hybrid particle swarm bat algorithm (H-PS-BA) optimization technique which uses the frequency tuning technique of BA at the velocity updating stage of PSO to avoid premature convergence limitation of PSO. Particle swarm optimization is a favored and successful non-deterministic optimization method. It is robust with easy implementation but with limitations of premature convergence and it can be trapped at a local optimum [3]. The BA, however, is more efficacious in exploiting global best for determining feasible best solutions and has the ability to escape being trapped at a local minimum [11]. The developed optimization technique was employed to solve the CEEDP of Nigerian 28 bus 7 generators practical power network. This is one of the first configurations of the Nigerian deregulated power networks and its CEEDP has not been adequately considered [3].

## II. METHODOLOGY

### A. Particle Swarm Optimization

Particle swarm optimization, an organically motivated, community-based optimization method, was advanced and developed in 1995 by Kennedy and Eberhart [5,21]. The social behavior of birds thronging for food sets up the foundation for PSO. During birds' hunt for food, all bird tells one another the best food source it has discovered. Each bird then modifies its pathway in line with its best position and the group's best position.

In PSO, a separate bird is a particle having its own position and velocity in an n-dimensional search area, representing the position and velocity of a particle, respectively, with *x* and *y*. The *x* stands for the objective variable in the optimization. The velocity, *y*, denotes the step size the particle will move in subsequent iterations [22,23].

The position and velocity of ath particle are represented in n-dimensional search area as:

$$x_a = \left(x_{a1}, x_{a2}, \ldots, x_{an}\right) \tag{1}$$

$$y_a = \left(y_{a1}, y_{a2}, \ldots, y_{an}\right) \tag{2}$$

Each particle keeps a recollection of the present prime position discovered all the while and the present prime position established by all of the particles in the group denoted as *pbest* and *gbest* respectively in the n-dimensional search space and are given as follows:

$$pbest_a = \left(pbset_{a1}, pbest_{a2}, \ldots, pbest_{an}\right) \tag{3}$$

$$gbest_a = \left(gbset_{a1}, gbest_{a2}, \ldots, gbest_{an}\right) \tag{4}$$

The velocity of the ath particle is updated using the following equations:

$$y_{an}^{j} = wy_{an}^{j} + c_1 r_1 \left(pbest_{an}^{j} - x_{an}^{j}\right) + c_2 r_2 \left(gbest_{n}^{j} - x_{an}^{j}\right) \tag{5}$$

The position is updated by the following equation:

$$x_{an}^{j+1} = x_{an}^{j} + y_{an}^{j+1} \tag{6}$$

where,

$y_{an}^{j+1}$ = updated velocity of ath particle in n-dimensional space;

$w$ = inertial weight factor;

$y_{an}^{j}$ = velocity of ath particle at jth iteration;

$c_1, c_2$ = acceleration coefficients;

$r_1, r_2$ = random numbers [0,1];

$x_{an}^{j+1}$ = particle updated position for ath particle in n-dimensional space; and

$x_{an}^{j}$ = position of ath particle at iteration j.

Inertial weight factor helps in boosting the convergence rate of PSO algorithm speed based on descending linear function. Inertial weight factor is found using (7). The standard practice allocates the range between 0.4 ($w_{min}$) and 0.9 ($w_{max}$) [5].

$$\varphi = \varphi_{\max} - \left(\frac{\varphi_{\max} - \varphi_{\min}}{iter_{\max}}\right) iter \tag{7}$$

where,

$\phi_{\min}$ = minimum value of weighting factor;

$\phi_{\max}$ = maximum value of weighting factor;

iter = current iteration; and

$iter_{\max}$ = maximum number of iterations.

Figure 1 shows PSO algorithm flowchart. It highlighted steps in solving optimization problems using PSO.

### B. Bat Algorithm Optimization

Bat algorithm is an environment-inspired optimization technique that uses the echolocation behaviors of real bats and was introduced by Xin-She Yang in 2010 [24]. Bats were observed to be the only mammal with wings and are classified as microbats and megabats. The major difference between the classification is that microbats use echolocation [25]. Echolocation is a type of sound navigation and ranging (SONAR) technique that microbats use to locate their roosting crevices in the dark, avoid obstacles, and detect prey [7].

Echolocation of bats is a perceptual system where a series of loud ultrasound waves are sent out by bats to create echoes in their environment while the bats listen to the echoes. The position of food/prey is identified by bats based on the returned echoes with delays

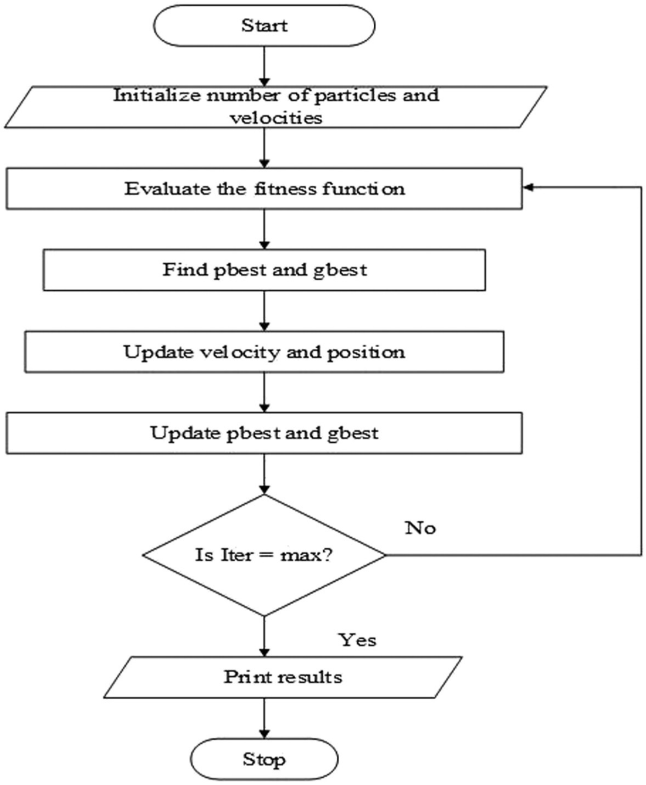


**Fig. 1.** Flowchart of particle swarm optimization algorithm.

and variations in sound levels [26,27]. The following assumptions were made to simplify the problem of BA [28]:

(i) Every microbat employs echolocation to decide distance and differentiate between food/prey and roadblock.
(ii) Individual microbat flies haphazardly with its own velocity and position having a constant frequency, different wavelength, and loudness to track prey.
(iii) Every microbat can modify, automatically, its wavelength or frequency of its discharged pulses. The pulse emission rate is modified depending on its closeness to its target.
(iv) Loudness is assumed to vary from maximum to minimum constant value.

Bat algorithm mimics the behavior of bats when they are hunting for food. Frequency-modulated signals are used by bats for distance perception. Each signal pulse can last little thousands of seconds (8–10 ms) within 25–100 kHz frequency range. The bats typically emit 10–20 of such pulses in a second. When bats are stalking, they can discharge over 200 pulses in a second [28]. For every idealized bat, the pulse frequency, velocity, and position at a particular time t are defined as follows [7]:

$$f_a = f_{\min} + \beta\left(f_{\max} - f_{\min}\right) \tag{8}$$

$$y_a^{t+1} = y_a^t + (x_a^t + x_{best}^t) f_a \tag{9}$$

$$x_a^t = x_a^t + v_a^{t+1} \tag{10}$$

where,

$f_{\min}$ = emitted pulse minimum frequency;

$f_{\max}$ = emitted pulse maximum frequency;

$\beta$ = a uniformly dispensed haphazard number between [0, 1];

$f_a$ = ath bat frequency;

$x_{best}^t$ = current foremost position at the time step t in the present population;

$t$ = current iteration number;

$y_a^t$ = velocity of ath bat;

$x_a^t$ = position of the ath bat.

Local random work is then used to execute a new search as follows:

$$x_{a(new)}^{t+1} = x_{best}^t + \xi A^t \tag{11}$$

where,

$\xi$ = uniformly distributed random number = $\xi\epsilon$niformly

$A^t$ = average loudness at time step $t$.

After the bats have succeeded in identifying prey, their loudness will be reduced and the pulse discharge rate will be shooting up. These features are described mathematically as follows:

$$A_a^{t+1} = \alpha A_a^t \tag{12}$$

$$r_a^{t+1} = r_a^0(1 - \exp(-\varphi t)) \tag{13}$$

where,

$r_a^0$ = initial emission pulse rate'

$\alpha$ = constant in the range of [0, 1]; and

$\phi$ and tant in the ran.

The step-by-step solution algorithm for optimization problems using BA is shown in Fig. 2.

**C. Development of Hybrid-Particle Swarm-Bat Algorithm Optimization technique**

Hybrid optimization method, H-PS-BA, was formulated and modeled in this work, and the developed H-PS-BA optimization technique was an embedded type hybrid algorithm that increases the diversity and avoids premature convergence by enhancing the PSO ability for local

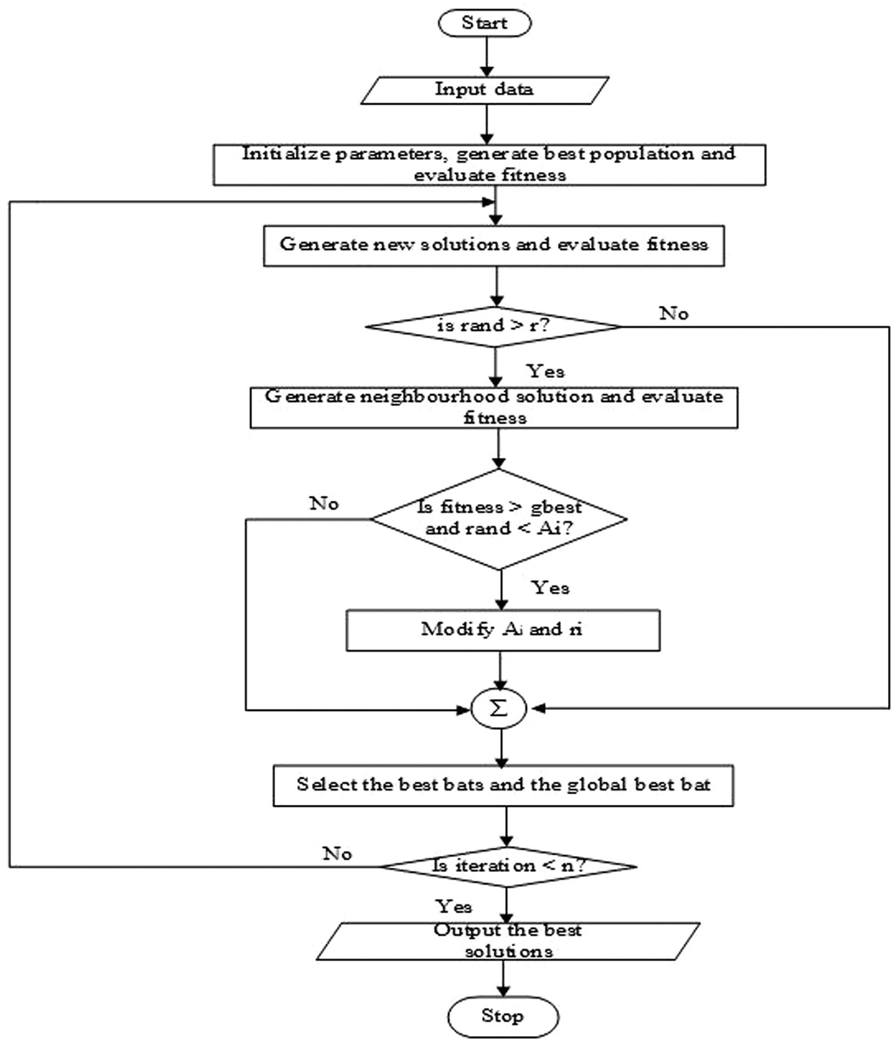


**Fig. 2.** Flowchart of bat algorithm.

search using the frequency tuning techniques of BA at the velocity updating stage of PSO algorithm. The algorithm combined the speedy convergence ability of PSO with the potential of BA to avoid local optimum.

Each microbat, for the original BA, sends out a pulse with a frequency value, $f_{min}$, and variable wavelength as represented in (8) above. In the developed H-PS-BA, two different pulses were assumed to be sent out by each bat in two separate directions, one toward the best bat (solution) and the other toward an erratically chosen bat. The frequencies of these introduced pulses were updated in equations (14) and (15) respectively in the direction of bat and in the direction of random bat.

$$f_{a1} = f_{min} + (f_{max} - f_{min}) * \beta_{a1}. \tag{14}$$

$$f_{a2} = f_{min} + (f_{max} - f_{min}) * \beta_{a2}. \tag{15}$$

where,

$f_{a1}$ = emission in the direction of best bat;

$f_{a2}$ = emission in the direction of random bat;

$f_{min}$ = minimum frequency;

$f_{max}$ = maximum frequency; and

$\beta_{a1}$ and $\beta_{a2}$ = random vectors between 0 and 1.

The velocity and position update equations of PSO given in (5) and (6) are given in (16) and (17), respectively:

$$y_{an}^{j+1} = wy_{an}^{j} + c_1 r_1 \left( pbest_{an}^{j} - x_{in}^{j} \right) + c_2 r_2 \left( gbest_{n}^{j} - x_{an}^{j} \right). \tag{16}$$

$$x_{an}^{j+1} = x_{an}^{j} + y_{an}^{j+1}. \tag{17}$$

where,

$y_{an}^{j+1}$ = updated velocity of ath particle in n-dimensional space;

$\Phi$ = inertial weight factor;

$y_{an}^{j}$ = velocity of ath particle at jth iteration;

$c_1,c_2$ = acceleration coefficients;

$r_1,r_2$ = random numbers [0,1];

$x_{an}^{j+1}$ = updated position of jth particle in n-dimensional space; and

$x_{an}^{j}$ = position of ath particle at iteration j.

Equation (16) is modified by introducing the Cartesian distance linking the bat position and local best position into the cognitive component of the equation and the Cartesian distance linking the best position and global position into the social component of the equation. The modification was formulated as follows:

Let $x_a$ = bat position

$Pbest_a$ = local best position

The Cartesian interval between the bat position $x_a$ and the local best position $pbest_a$ is given in (18):

$$PBEST_a = \sqrt{\sum_{k=1}^{N}\left(Pbest_a - x_a\right)^2} \tag{18}$$

where,

$PBEST$ = Cartesian interval between bat position and local best position;

$Pbest_a$ = local best position;

$X_a$ = bat position; and

$N$ = number of bats

Let $x_a$ = bat position

$Gbest_a$ = global best position

The Cartesian interval between the bat position and the global best position is given in (19):

$$GBEST = \sqrt{\sum_{k=1}^{N}\left(gbset_a - x_a\right)^2} \tag{19}$$

where,

$GBEST$ = Cartesian interval between bat position and local best position;

$Gbest_a$ = global best position;

$X_a$ = bat position; and

$N$ = number of bats.

The new velocity equation is given in (18).

$$y_a^{k+1} = w * y_a^k + \left(c_1 * \exp\left(-PBEST_a^2\right) * \left(pbest_a^k - x_a^k\right)\right) + \left(c2 * \exp\left(GBEST^2\right) * \left(gbest^k - x_a^k\right)\right). \tag{20}$$

Equation (20) ensures the removal of randomness in the velocity update and local and global bests were allowed to guide velocity and position updates. The H-PS-BA was finally developed by associating the pulse frequency of BA with the velocity update equation of PSO as given in (21) thereby ensuring the PSO ability to evade being trapped at local optimum.

$$y_a^{k+1} = w * y_a^k + \left(c_1 * \exp\left(-PBEST_a^2\right) * \left(pbest_a^k - x_a^k\right)\right) * f_{a1} + \left(c2 * \exp\left(GBEST^2\right) * \left(gbest^k - x_a^k\right)\right) * f_{a2}. \tag{21}$$

**D. Combine Economic Emission Dispatch Problem**

Thermal generator operation turns out various contaminants such as nitrogen oxide, sulfur oxide, and carbon oxide, released into the atmosphere. It is paramount to abate the production of contaminants by generators. This objective is realized by incorporating pollutant emissions reduction as an objective function [23].

The CEED problem's main goal is the simultaneous curtailment of the total fuel cost and amount of emission of generation in a power system. The objective function of CEEDP was modeled as follows [29]:

$$F_{total\,cost} = \sum_{i=1}^{N_g}\left[\left(a_i + b_i P_i + c_i P_i^2\right) + \left|e_i \sin\left(f_i\left(P_{i,\min} - P_i\right)\right)\right|\right] + h_i\left[\left(\alpha_i + \beta_i P_i + \gamma_i P_i^2\right) + \theta_i \exp\left(\delta_i P_i\right)\right] \tag{22}$$

Subject to:

$$\sum_{i=1}^{N_g} P_i = P_G = P_D + P_L \tag{23}$$

$$P_i^{\min} \le P_i \le P_i^{\max} \quad i = 1,2,...Ng \tag{24}$$

where,

$F_{total}$ = total fuel cost;

$F_i\,(P_i)$ = ith generating unit fuel cost;

$a_i,b_i,c_i$ = cost function coefficients function for generator i;

$P_i$ = output power of unit i;

$N_g$ = number of generators;

$E_{total}$ = total emission;

$E_i\,(P_i)$ = emission cost of ith generator;

$\alpha_i, \beta_i, \gamma_i$ = emission coefficients for generator i;

$P_D$ = total power demand of the system;

$P_G$ = total power generation of the system;

$P_L$ = total transmission loss of the system;

$P_i^{\min}$ = minimum power limit;

$P_i^{\max}$ = maximum power limit.

$$P_{\text{Loss}} = \sum_{i=1}^{N_g}\sum_{j=1}^{N_g} P_i M_{ij} P_j + \sum_{i=1}^{N_g} M_{oi} + M_{oo} \tag{25}$$

where,

$P_i$ = active power for ith generation unit;

$P_j$ = active power for jth generation unit;

$M_{00}$, $M_{ij}$, $M_{oi}$ = loss coefficient constant;

$F_{totalcost}$ = CEED's total fuel cost.

$$h_i = \frac{F_i\left(P_{i,\min}\right)}{E_i\left(P_{i,\max}\right)} = \frac{a_i + b_i P_{i,\min} + c_i P_{i,\min}^2 + e_i \sin\left(f_i\left(P_{i,\min} - P_i\right)\right)}{a_i + b_i P_{i,\max} + c_i P_{i,\max}^2 + \theta_i \exp\left(\delta_i P_i\right)} \tag{26}$$

The $h_i$ factor (price penalty factor) is utilized to harmonize emission costs and normal fuel costs [29]. The $h_i$ factor moves the definition of emission criterion, physically, from the weight of emission to cost of fuel for emission [29]:

The H-PS-BA optimization solution algorithm for CEED of power systems is given as follows:

Step 1: initialize parameters of PSO. Read power system data. The CEED dimension is the number of participating generators. The particles are generated between $P_{max}$ and $P_{min}$ haphazardly. The ith particle, for N number of units, is defined as:

$$P_i = \left[P_{i1}, P_{i2}, P_{i3}, \ldots, P_{iNg}\right]. \tag{27}$$

Step 2: generate initial velocities of the particles haphazardly in the following span:

$$\left[-y_i^{\max}, y_i^{\max}\right]. \tag{28}$$

Step 3: the objective function values of the particles are determined utilizing CEED objective function. Set the evaluated values as $P_{best}$.

Step 4: choose the best value among the $P_{best}$ as the $G_{best}$.

Step 5: calculate new velocities for all the dimensions in all particles using the hybridized velocity updating equations.

Step 6: check for constraints infringements on the lowest and highest values of the velocities.

$$\text{if } y_i^{new} > y_i^{\max}. \tag{29}$$

$$y_i^{new} = y_i^{\max}. \tag{30}$$

and

$$\text{if } y_i^{new} < y_i^{\min}. \tag{31}$$

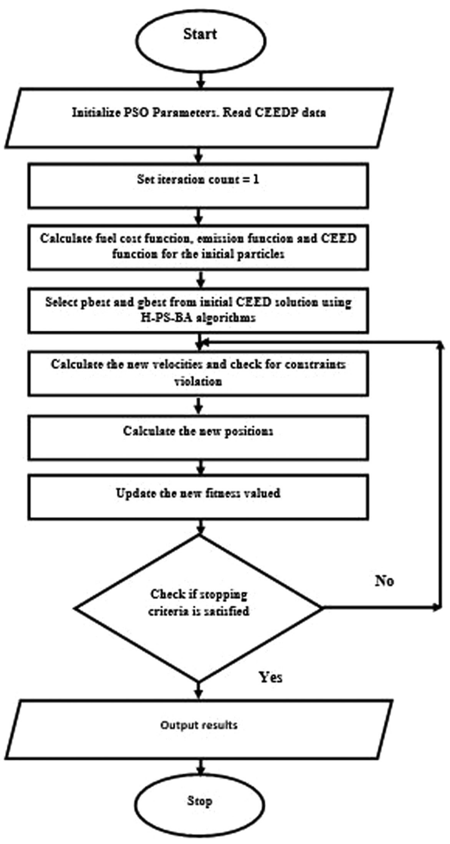


**Fig. 3.** Flowchart of H-PS-BA for CEEDP. H-PS-BA, hybrid-particle swarm-bat algorithm; CEEDP, combined economic emission dispatch problem.

$$y_i^{new} = y_i^{\min}. \quad (32)$$

Step 7: generator position in the particles is upgraded using (33):

$$P_i^{new} = P_i + y_i^{new}. \quad (33)$$

Step 8: determine, for the updated positions of particles, the objective function values. If the new value is superior to the previous $P_{best}$, the new value is set to $P_{best}$.

Step 9: $G_{best}$ for the population is updated.

Step 10: step 4 to step 10 is repeated until the maximum number of iterations

The step-by-step solution algorithm of CEEDP optimization solution using H-PS-BA is shown in Fig. 3.

## III. RESULTS AND DISCUSSION

The 28 bus 330 kV Nigerian network interconnects four thermal stations and three hydro stations to different load stations. Data for the network were acquired from National Control Center (NCC). The single-line diagram and generator data for the system are shown in Fig. 4 and Table I respectively. The shares of the hydro-generators in the total load demand of the network were taken to be fixed, while the shares of the thermal generators were evaluated [30]. The CEEDP solution was carried out using H-PS-BA optimization technique and conventional PSO to evaluate the whole generation cost of the system. The H-PS-BA and PSO techniques were subjected to same settings of parameters and data sets to allow result comparisons. The

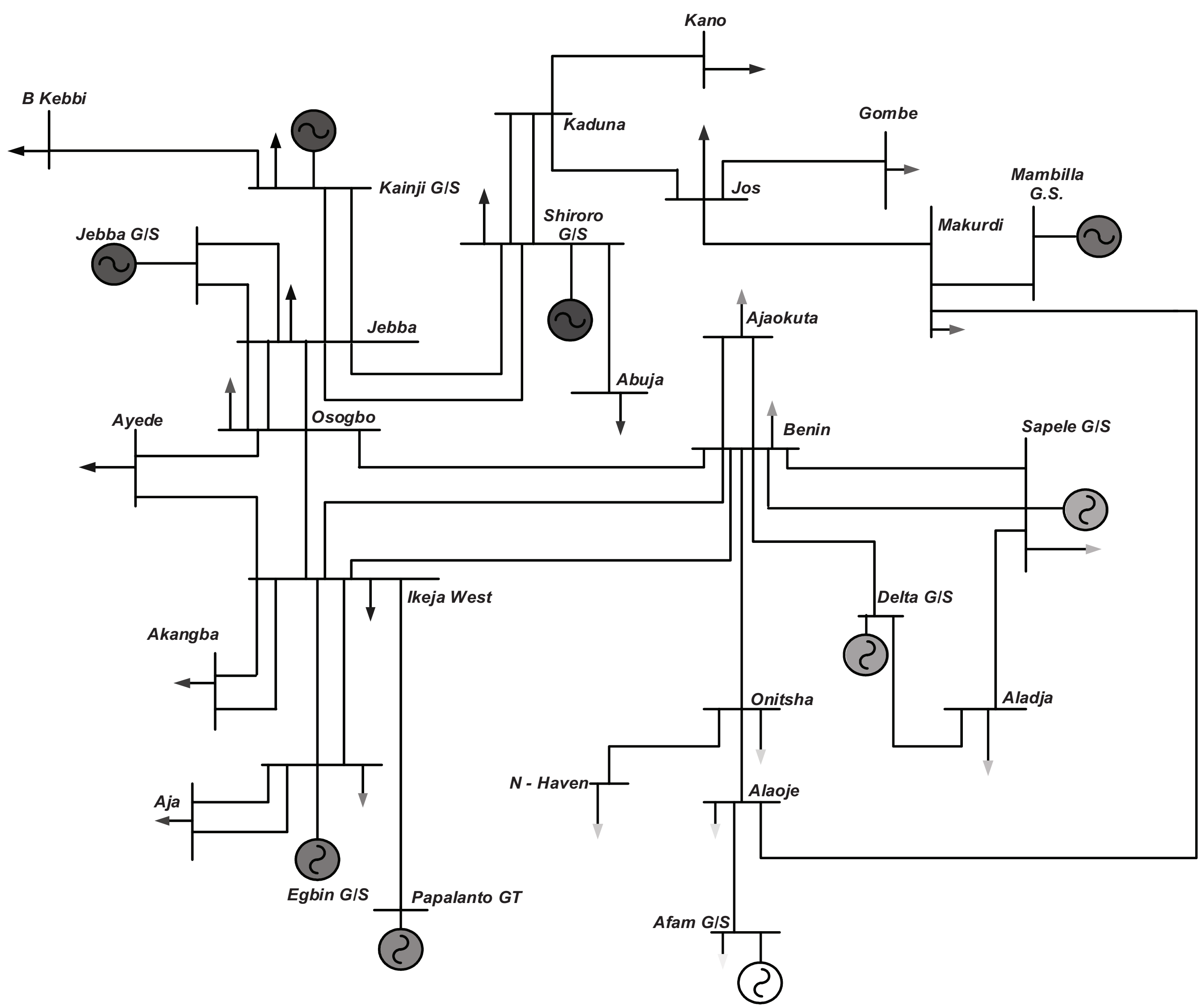


**Fig. 4.** Single line diagram of Nigerian 28 Bus 7 generator system.

**TABLE I.**
GENERATOR DATA FOR THE NIGERIAN 28 BUS 7 GENERATOR POWER SYSTEM

| Unit | $P_{min}$ (MW) | $P_{max}$ (MW) | a ($/h) | b ($/MWh) | c ($/(MW)²h) | d (($/h) | e (rad/MW) | α (lb/h) | β (lb/MWh) | γ (lb/(MW)²h) | µ (lb/h) | δ (1/MW) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| SAPELE | 137.5 | 550 | 0.1300 | 7.84 | 6929 | 0.00419 | 0.32767 | 13.8593 | 600 | 0.052 | 0.25475 | 0.01234 |
| DELTA | 75 | 300 | 1.2000 | 6.13 | 525.74 | 0.00419 | 0.32767 | 13.8593 | 260 | 0.028 | 0.25475 | 0.01234 |
| AFAM | 135 | 540 | 0.0920 | 56 | 1998 | 0.00683 | −0.54551 | 40.2669 | 450 | 0.084 | 0.24970 | 0.01200 |
| EGBIN | 275 | 1100 | 0.0310 | 13.10 | 12787 | 0.00683 | −0.54551 | 40.2669 | 850 | 0.094 | 0.24970 | 0.01200 |
| SHIRORO | 350 | 350 | 0.0130 | 6 | 29.23 | 0.00419 | 0.32767 | 13.8593 | 260 | 0.028 | 0.25475 | 0.01234 |
| KAINJI | 450 | 450 | 0.0012 | 5 | 28.74 | 0.00419 | 0.32767 | 13.8593 | 260 | 0.028 | 0.25475 | 0.01234 |
| JEBBA | 490 | 490 | 0.0011 | 3 | 93.36 | 0.00419 | 0.32767 | 13.8593 | 260 | 0.028 | 0.25475 | 0.01234 |

**TABLE II.**
PARAMETER SETTINGS

| S/No. | Parameters | Values |
|---|---|---|
| 1 | sws | 100 |
| 2 | mni | 1000 |
| 3 | $w_{min}$ | 0.4 |
| 4 | $w_{max}$ | 0.9 |
| 5 | $c_1$, $c_2$ | 2 |
| 6 | A’ | 0.9 |
| 7 | r | 0.1 |
| 8 | $Q_{min}$ | 0 |
| 10 | $Q_{max}$ | 2 |

parameter settings for the optimization techniques are shown in Table II.

The developed H-PS-BA optimization based on the CEEDP modeling was simulated using MATrix LABoratory (MATLAB 2018a) software. An HP EliteBook Revolve 810 G1 model, Intel (R) Core i5 HP Computer Laptop with a RAM of 4 GB and a speed of 1.90 GHz, was used for simulation run. The performance metric used in this work was the overall CEEDP cost of the system in $/h. This is the overall optimized cost of electricity generation by reducing total fuel cost and total emission charges concurrently and keeping load demand and other system equality and inequality constraints satisfied.

The results of real power allocations, economic and emission dispatches, and the CEED of the Nigerian system are shown in Table III. From the table, the real power distribution on each bus by each method is shown. The total power distribution for each optimization technique is the sum of power allocated and the loss generated. The H-PS-BA gave a system total loss higher than that of PSO by 0.22%. Increase in the loss is combined with the total energy generated by the system which in turn adds up to total cost of generation.

The table also revealed that total fuel cost of generation for economic dispatch was 109 740 $/h for PSO and 109 700 $/h for H-PS-BA optimization technique. This result showed that H-PS-BA optimization technique gave a lesser cost of fuel than PSO. Hybrid-particle swarm-bat algorithm performed better than PSO by 0.036 %. For emission dispatch, PSO gave emission output of 6255.9 kg/h, while for H-PS-BA optimization technique, the amount of total system emission was 6246.6 kg/h. Hybrid-particle swarm-bat algorithm optimization technique produced a reduced amount of emission when compared to the amount of emission produced by PSO. The H-PS-BA optimization technique performed better than PSO by 0.15 %.

The solution to the CEEDP gave a total CEED cost of 176 520 $/h and 176 390 $/h for using PSO and H-PS-BA optimization technique, respectively. The H-PS-BA gave a total overall generation cost that

**TABLE III.**
ECONOMIC DISPATCH, EMISSION DISPATCH, AND CEED OF NIGERIAN 28-BUS 7-GENERATOR SYSTEM FOR A DEMAND OF 2823.1 MW

| Generating Unit | PSO | H-PS-BA |
|---|---|---|
| SAPELE (MW) | 450.4634 | 439.5794 |
| DELTA (MW) | 75.0000 | 75.0000 |
| AFAM (MW) | 392.7547 | 382.4571 |
| EGBIN (MW) | 654.7837 | 676.0545 |
| SHIRORO (MW) | 350.0000 | 350.0000 |
| KAINJI (MW) | 450.0000 | 450.0000 |
| JEBBA (MW) | 490.0000 | 490.0000 |
| Loss (MW) | 39.9018 | 39.9910 |
| Total generation (MW) | 2863.0910 | 2863.0018 |
| **Fuel cost ($/h)** | **109 740** | **109 700** |
| **Emission (kg/h)** | **6255.9** | **6246.6** |
| **CEED ($/h)** | **176 520** | **176 390** |

CEED, combined economic emission dispatch; PSO, particle swarm optimization; H-PS-BA, hybrid-particle swarm-bat algorithm.

is lesser than what was obtained for using PSO. This result showed that H-PS-BA optimization technique performed better than PSO by 0.07%.

The convergence characteristic curve for the CEED of the Nigerian power system considered is given in Fig. 5. It can be remarked from the figure that the developed H-PS-BA optimization technique performed better than PSO with reference to minimizing the objective function of CEEDP of the system by converging to a lower generation cost than that of PSO.

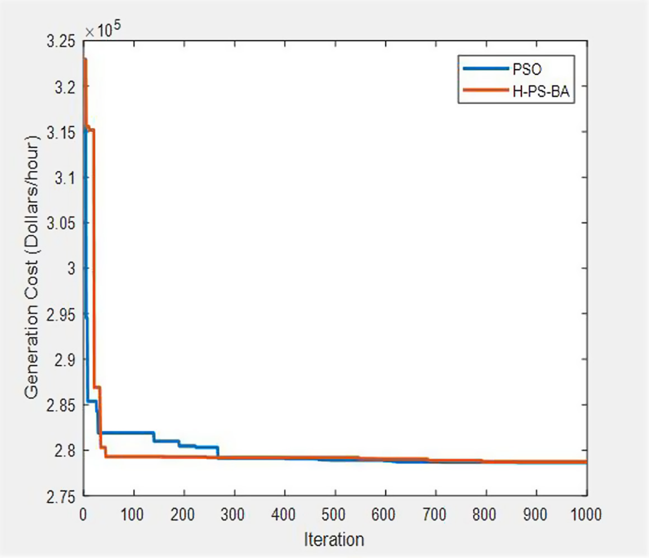


**Fig. 5.** Convergence characteristics of PSO and H-PS-BA for Nigerian 28-Bus 7-Generator Power System. PSO, particle swarm optimization; H-PS-BA, hybrid-particle swarm-bat algorithm.

## IV. CONCLUSION

This work developed an embedded type hybrid optimization technique, H-PS-BA optimization technique, that increased the diversity and avoid premature convergence of PSO. The H-PS-BA was employed to solve a paramount optimization problem in power system, the CEEDP, that needed to be solved accurately. The developed optimization technique was applied to solve CEEDP of Nigerian system. Results of the application were compared with the result obtained from using conventional PSO and it was shown that H-PS-BA gave a better performance than PSO by generating the lowest overall cost of generation. The H-PS-BA optimization technique was therefore concluded to be a better and more efficient optimization tool in solving mathematical optimization problems.

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