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OPTIMAL REACTIVE POWER DISPATCH USING IMPROVED CHAOTIC PSO ALGORITHM WITH THE WINGBEAT FREQUENCY

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Abstract

The importance of reactive power to the economy and security of power systems cannot be overemphasized. For instance, Transmission losses increase when reactive power is unevenly distributed on transmission network; and power quality is affected as well. The cheapest way of reducing these transmission lines losses is via reactive power dispatch approach. This study therefore proposes an Improved Chaotic Particle Swarm Optimization algorithm (ICPSO) with the primary aim of reducing real power transmission line losses while adhering to system constraints. Although the traditional PSO has a fast convergence speed, it falls easily into local optimum and it is slow at the later stage of convergence. The ICPSO is proposed in this research to overcome these shortcomings. The approach combines PSO with chaotic map which increases particles' diversity, allowing particles to explore the search region more; and a wingbeat frequency component which helps to sustain the rate of convergence of particles. MATPOWER 7.1 in MATLAB 2019a environment was utilized for the implementation. The purported algorithm was examined on IEEE14 and IEEE30 Test Beds respectively. When tried out on IEEE14 Test bed, real power loss was reduced from 13.393 MW to 12.260 MW; whereas real power transmission line loss was brought down from 17.557 MW to 15.977 MW when tried out on IEEE30 Test Bed. In terms of reducing real power transmission lines losses, the simulation results show that the proposed approach performs better when compared with other algorithms.

Keywords: *Optimal Reactive Power Dispatch, Particle Swarm optimization Algorithm, Logistic based chaotic map, Wingbeat Frequency, Real power transmission lines losses*

1. Introduction

Power losses on transmission lines have assumed a very high embarrassing dimension, impeding economic growth of countries. Although system losses are inevitable, they can be at least minimized. One of the leading causes of these losses experienced in electric power grids (EPG) is the uneven distribution of reactive power. This has been a challenge age long. Some of the ways of minimizing losses on power systems, specifically on transmission lines include a redesign, replacement of equipment that are improperly sized, enhancement of conductors' quality etc. However, these approaches require huge financial investments and are not cost effective.

The cheapest way of achieving the objective of minimizing losses on EPG's transmission lines is via optimal reactive power dispatch (ORPD) approach. This approach which is complicated and non-linear, entails the adjustment of control variables for example reactive power output of shunt compensators, transformer tap ratio, generator voltages so as to reduce real power losses, or minimize total voltage deviation or to enhance voltage stability. With the continuous growth and expansion of power networks, ORPD has become even more critical to the guaranteed economy, safety and reliability of power systems. Extensive efforts have been made to utilize conventional optimization techniques for ORPD.

Conventional approaches such as Integer method, interior point method, decomposition technique, mixed integer programming, Newton-based approach, gradient-based algorithm, dynamic programming, quadratic programming, non-linear programming, and linear programming and so on were utilized in [1-15]. In spite of the ability of these conventional methods to converge excellently, exhibiting their strong points in handling linear constraints and differentiable objective functions ORPD problems, they fall into local optimum easily and cannot effectively handle problems with non-continuous and undifferentiated objective functions, in addition to variables that are discrete. Besides, they require too high computational time. So, they are not suitable for solving ORPD problems [16].

Particle Swarm optimization (PSO) algorithm is amongst the most potent optimization methods that has been utilized and still being used for the solution of ORPD problem. Despite its fast convergence speed and its ease of implementation, it suffers from two major problems namely its easy drift into local optimum and its lacking in the convergence velocity at the last phase of convergence. In the attempt to proffer solution to these two major shortcomings, several variants and improvements have been put forward to the traditional PSO; which include the introduction of linearly decreasing inertia weightiness and constricting factor into the PSO velocity equation in [17-28], the use of a sinusoidally changing inertia weight technique in [29], the division of existing initial swarm into different sub-swarms in [30], the introduction of a new component of inertia called speed component to maintain particles' speed in [31], and the combination of PSO with other algorithms in [32-41]. A lot of these proposed improvements either suffer from too high computational time and computational complexity due to too many added parameters and even still fall easily into local optimum. Besides, a lot of them only considered improving particles' diversity, failing to give serious attention to the convergence speed at the later stage of convergence.

Therefore, this study is focused on presenting an Improved Chaotic PSO that combines PSO with logistic based chaotic map to enhance particles' initial positions, a chaotic linearly decreasing inertia weight to improve particles' diversity and a wing-beat frequency component to maintain convergence speed and then using the proposed technique to minimize transmission losses. The IEEE14 and IEEE30 test beds have been employed for the verification of the proposed approach and results of simulation show that the proposed technique is more effective in minimizing transmission losses and maintaining convergence speed with a favorable CPU time.

The rest of the paper is organized as follows. The materials and methods that were employed for the optimal reactive power dispatch so as to minimize real power transmission lines losses in EPG are presented in section 2. Section 3 is devoted to the development and implementation of the proposed Improved Chaotic PSO algorithm that incorporated wingbeat frequency in the MATPOWER 7.1 in MATLAB 2019a environment. In this section, the simulation results and discussions are also showcased. Finally, in section 4, some conclusions are demoed.

2. Materials and Methods

2.1. Problem Formulation of ORPD

The yardstick for the choice of the ORPD problems relies on application area, classification and details of the network under considerations; such as, quantity and origins of reactive power, EPG's security issues, the stratum of transmission line losses, and so on. The major objective of ORPD is to achieve minimum real power losses. This research is therefore, solely concerned about the minimization of transmission line losses. Generally, ORPD problem is divided into three parts [16][42][43] and can be described as follows:

Minimize: $f(x,u)$, objective function

Subject to: $g(x,u) = 0$, equality constraints

$h(x,u) \leq 0$, inequality constraints (1)

Usually in optimization problems (OP), for the sake of the conveniences, constrained OP are transformed into unconstrained OP by the addition of penalty terms [44], as described in

$$F(x,u) = f(x,u) + \Omega \quad (2)$$

where, $F(x,u)$ is objective function to be minimized with penalty function Ω added, and $f(x,u)$ is the objective function without adding penalty function. x denotes the vector of dependent variables; which includes [45], the voltage V_L at the load bus, reactive power Q_G at the generator bus and the loading capacity S_L of the transmission line. u represents the vector of control variables; which includes, the voltage V_G at generator bus, tap settings of Transformers T, and Shunt VAR compensation Q_C.

The fitness function f is the minimizing line losses while adhering to system constraints and it is given as:

$$f(x,u) = min\{P_{loss}\} = min\sum_{br=1}^{N_T} G_{br}[V_i^2 + V_j^2 - 2V_iV_j\cos(\delta_i - \delta_j)] \quad (3)$$

where, br is the branch between buses i and j, P_{loss} is active power loss; V_i *and* V_j are the voltage magnitudes at bus i and j respectively; G_{br} is line conductance of branch $i-j$; N_T is total number of lines; δ_i and δ_j are voltage angles at buses i and j respectively.

The determination of the objective function in Eq. (3) is subject to equality and inequality constraints. The power balance equations form equality constraints [46]; and they are basically defined as

$$P_{Gi} - P_{Di} - V_i\sum_{br=1}^{N_B} V_j[G_{br}\cos(\delta_i - \delta_j) + B_{br}\sin(\delta_i - \delta_j)] = 0 \quad (4)$$

$$Q_{Gi} - Q_{Di} - V_i\sum_{br=1}^{N_T} V_j[G_{br}\sin(\delta_i - \delta_j) + B_{br}\cos(\delta_i - \delta_j)] = 0 \quad (5)$$

where, P_{Gi} and Q_{Gi} are the respective active and reactive power generations at bus i; P_{Di} and Q_{Di} are the respective active and reactive power load demands at bus i; B_{br} is the mutual susceptance of line br; N_B is the total number of buses.

On the other hand, generators, transformers tap settings, and shunt var compensators constraints form inequalities constraints in the ORPD problems. The minimum V_{minGi} and maximum V_{maxGi} voltages; and the minimum Q_{minGi} and maximum Q_{maxGi} reactive power output of the generating unit i^{th} constitute the generators constraints [46], and they are expressed as

$$V_{minGi} \leq V_{Gi} \leq V_{maxGi} \quad i = 1,2,\dots,N_G \quad (6)$$

$$Q_{minGi} \leq Q_{Gi} \leq Q_{maxGi} \quad i = 1,2,\dots,N_G \quad (7)$$

The minimum T_{minGi} and maximum T_{maxGi} of transformers tap setting limits of i^{th} transformer form transformer constraints [46]; and they are expressed as

$$T_{minGi} \leq T_{Gi} \leq T_{maxGi} \quad i = 1,2,\dots,N_T \quad (8)$$

Whereas, the minimum Q_{minCi} and maximum Q_{maxCi} of the VAR injection limits of i^{th} shunt compensator form the shunt var compensators constraints [46]; and they are expressed as

$$Q_{minCi} \leq Q_{Ci} \leq Q_{maxCi} \quad i = 1,2,\dots,N_C \quad (9)$$

2.2 Penalty Function

It is evident from subsection 2.1 that there are many constraints to be dealt with, for the line losses in an EPG to be minimized. And it is well known that when too many constraints are added to power flow optimization problems, a solution may not be attained. To solve non-linear OP, the most common approach is the use of penalty functions [45] to transform a constrained OP into an unconstrained OP; so as to ensure power system security. Thus, in this study, the inequality constraints selected (that is, bus voltages, transformer tap settings, and shunt compensators) were made penalty function; and added to the fitness function, and as such, Eq. (3) becomes:

$$F(x,u) = P_{loss} + \lambda_v\sum_{k=1}^{N_B}(V_i - V_i^{lim})^2 + \lambda_c\sum_{k=1}^{N_B}(Q_{ci} - Q_{ci}^{lim})^2 + \lambda_T\sum_{k=1}^{N_B}(T_i - T_i^{lim})^2 \quad (10)$$

where λ_v, λ_c, λ_T are the penalty factors associated with V_i^{lim}, Q_{ci}^{lim}, T_i^{lim} as expressed in [46] as:

$$V_i^{lim} = \begin{cases} V_i^{lim};\ if\ V_i < V_i^{min} \\ V_i^{lim};\ if V_i > V_i^{max} \end{cases} \quad (11)$$

$$Q_{ci}^{lim} = \begin{cases} Q_{ci}^{lim};\ if\ V_i < Q_{ci}^{min} \\ Q_{ci}^{lim};\ if V_i > Q_{ci}^{max} \end{cases} \quad (12)$$

$$T_i^{lim} = \begin{cases} T_i^{lim};\ if\ T_i < T_i^{min} \\ T_i^{lim};\ if T_i > T_i^{max} \end{cases} \quad (13)$$

The quadratic penalty functions were used in this study due to its ability in controlling constraints effectively.

2.3 Standard PSO Algorithm

PSO is a population-based algorithm that mimics the social and cooperative behavior of species, such as, flock of birds, and school of fishes that are searching for nutrients. In the algorithm, a bird, flock of birds, and nutrients are represented by a particle, swarm, and the global optimum respectively. The PSO is being employed because it possesses fast convergence velocity, easy implementation, and requires few parameters for its implementation.

The position, and the rate at which the position of a particle in a given swarm changes at a given time, can best be described by velocity and position vectors [18] [28];

$$U_{ln}^{(k+1)} = \gamma\left(wU_{ln}^{(k)} + \frac{1}{\Delta t}\left(c_1r_1(P_{bestln} - X_{ln}^{(k)}) + c_2r_2(G_{bestl} - X_{ln}^{(k)})\right)\right) \quad (14)$$

$$X_{ln}^{(k+1)} = X_{ln}^{(k)} + U_{ln}^{(k+1)}\Delta t \quad (15)$$

With these two vectors, the fitness of each particle is obtained; and particles are able to reach global or near global optimum.

In Eq. (14), w is a linearly decreasing inertia weight factor; and is defined by [28] as the

$$w = w_{max} - \left(\frac{w_{max} - w_{min}}{maximum\ iteration}\right) \times iteration \quad (16)$$

In Eq. (14) through (16), γ is a constriction factor [18]; and has a value of 0.729, $U_{ln}^{(k+1)}$ indicates the rate at which l^{th} particle is changing its position lately at a given time in the n^{th} d-dimension, at the k^{th} iteration, w is linearly decreasing inertia weight factor, c_1 is the individual learning or cognitive acceleration factor, c_2 is the social learning or acceleration factor, r_1, r_2 are numbers between [0,1] that are brought into existence indiscriminately, P_{best} denotes the individual best location of the l^{th} particle as regards self-experience, G_{best} represents the global best location of the swarm, $X_{ln}^{(k)}$ is the position of the l^{th} particle, in the n^{th} d-dimension at the k^{th} iteration, k is the iteration index, Δt is the time difference, w_{min} is the initial value of inertia weight factor, w_{max} is the final value of inertia weight factor, A large w encourages global search, while a small inertia w fosters local search [28].

2.4 The Improved Chaotic PSO Method

The proposed Improved Chaotic PSO (ICPSO) presented in this study unites the merits of the standard PSO and a logistic based chaotic map. The fast convergence ability of PSO is combined with chaotic sequence which increases particles diversity, and the introduction of a wingbeat frequency component which helps to control search pace. Therefore, the proposed algorithm entails the use of a chaotic inertia weight and the addition of a wingbeat frequency component to the PSO's velocity equation. These two improvements made to the standard PSO are elucidated as follows:

2.4.1 The Use of a Chaotic Inertia Weight: The use of a chaotic inertia weight w_{ch} instead of a linearly decreasing inertia weight is suggested in this study, so as to allow particles that enter into local optimum, to jump out of it; and explore the search region the more. To achieve this goal, we employed a simple logic map [47]; which is expressed in this study as

$$w_{ch} = w^{k+1} = \mu w^k(1 - w^k) \tag{17}$$

In Eq. (17), μ is a determinant factor that checks whether a particle with w stabilizes at a fixed value, or vibrates within a bounded successiveness of values, or acts chaotically in an irregular manner. And it has the values that range from 0 to 4 [47]. In this research, we are interested in chaotic state, and in line with [47], which reveals that a chaotic state will be attained whenever $\mu = 4.0$; consequently, Eq. (17) therefore becomes

$$w_{ch} = w^{k+1} = 4w^k(1 - w^k) \tag{18}$$

In this study, the w is updated iteratively using

$$w = w_{min} + (w_{max} - w_{min}) \times w_{ch} \tag{19}$$

Eq. (16) is a linearly decreasing inertia weight factor equation; whereas, Eq. (19) is the chaotically transformed inertia weight factor equation.

2.4.2 Incorporation of a wingbeat frequency parameter: The introduction of chaotic sequence poses a challenge; the velocity of convergence of PSO is affected. As particles' diversity increase, velocity of convergence suffers, thereby increasing computational time. This obstacle is assumed to be due to non-incorporation of the particle's wing-beat frequency into different type of PSO algorithms; which have being proposed by previous researchers for solving different kind of issues in the EPG. To that effect, the wing-beat frequency is therefore considered in this study.

The wingbeat frequency f_{ref} is an important parameter that needs to be considered in the development of PSO algorithm; because it is a principal determinant factor of the swarm's energetic outlay during the swarm trajectory [48-51]. To that effect, the parameter is accounted for in this study by making use of an equation derived and validated by [51]; which is expressed as:

$$f_{ref} = 1.08\left(m^{1/3}g^{1/2}b^{-1}s^{-1/4}\rho^{-1/3}\right) \tag{20}$$

In Eq. (20), $b\ and\ s$ are the wing span and area of the l^{th} particle respectively, g is the acceleration due to gravity, which is a constant and is taken as $9.81\ ms^{-2}$, and ρ is an air density, another constant, which is taken as $1.21\ kgm^{-3}$ [51], and m denotes mass of the particle; and it makes up of total mass of the body (m_{tot}) of the particle, and mass of the wings (m_{wng}) of the particle. In a situation where m_{wng} is not known, according to [52], it can be approximated by using

$$m_{wng} = 0.112 m_{tot}^{0.11} \tag{21}$$

It should be noted that the choice of the values of m, b and s in Eq. (20) is particle dependent.

With the incorporation of ICPSO wingbeat frequency $(Freq(l) = \frac{1}{\Delta t})$, the improved velocity equation for the proposed algorithm is:

$$U_{ln}^{(k+1)} = 0.729\left(w_t U_{ln}^{(k)} + \left(c_1 r_1\left(P_{bestln} - X_{ln}^{(k)}\right) + c_2 r_2\left(G_{bestl} - X_{ln}^{(k)}\right)\right) \times Freq(l)\right) \tag{22}$$

And the improved position equation

$$X_{ln}^{(k+1)} = X_{ln}^{(k)} + \left(U_{ln}^{(k+1)}/Freq(l)\right) \tag{23}$$

where,

$$Freq(l) = f_{ref\_min} + \beta\left(f_{ref\_min} - f_{ref\_max}\right) \tag{24}$$

In Eq. (24),

$$f_{ref\_min} = 1.08\left({m_{wng}}^{1/3}g^{1/2}b^{-1}s^{-1/4}\rho^{-1/3}\right) \tag{25}$$

$$f_{ref\_max} = 1.08\left({m_{tot}}^{1/3}g^{1/2}b^{-1}s^{-1/4}\rho^{-1/3}\right) \tag{26}$$

In Eq. (24), β is a uniform random number between 0 and 1; which determines the rate at which the particle is flapping its wings. It will be 0, if the wings of the particle are not flapped; but 1, when its wings are being flapped at highest rate.

2.4.3 Procedure for the Realization of the ICPSO algorithm: Fig. 1 presents the flow chart for the realization of ICPSO algorithm; which is realized in twelve (12) steps, as explained in pseudo-code viz:

Step 1: Declare the

a) initial and final values of k; i.e., $k = 0$, and $k_{max} = 250$;
b) values of X_{min}, X_{max}, U_{min}, U_{max}, w_{min}, w_{max}, N, μ, and d;
c) physical features of a particle in the swarm: m_{tot}, m_{wng}, s, b, and, ρ;
d) limits of all the control variables of the Test Bed;

Step 2: Evaluate the two components of the wing-beat frequency; f_{ref_min} and f_{ref_max} using Eq. (25) and Eq. (26) respectively.

Step 3: Load the Bus and Branch data of the Test Bed

Step 4:

a) Generate randomly particles $x_{ln}|_{l=1:N}^{n=1:d}$

b) Is $n > d$? If the answer is yes, go to Step 5

c) $n = n + 1$: go to Step 4a)

Step 5: Run load flow, evaluate and store line losses of the Test Bed for each x_{ln} generated

Step 6: Are the control variables obtained in Step 5 within their limits? If the answer is affirmative, go to Step 8

Step 7: Invoke Penalty factor

Step 8:

a) Compute the fitness value of the particle in the d dimension;

b) Store each fitness value as a particle personal best position, P_{bestln}

c) Rank all the P_{bestln} and pick the $min\{P_{bestln}\}$ as the Global best solution for the l^{th} particle, G_{bestl}

Step 9: Update the velocity by

a) evaluating w chaotically using Eq. (17) through Eq. (19)

b) generating randomly $\beta \in \{0,1\}$

c) evaluating $Freq(l)$ by using result obtained in Step 9b) in Eq. (24);

d) using Eq. (22)

e) checking the limits of the velocity viz:

If $U_{ln}^{k+1} > U_{max}$, then, $U_{ln}^{k+1} = U_{max}$;

If $U_{ln}^{k+1} < U_{min}$, then, $U_{ln}^{k+1} = U_{min}$

Step 10:

a) Update the position by using Eq. (23)

b) Check the limits of the position viz:

If $X_{ln}^{k+1} > X_{max}$, then, $X_{ln}^{k+1} = X_{max}$;

If $X_{ln}^{k+1} < X_{min}$, then, $X_{ln}^{k+1} = X_{min}$

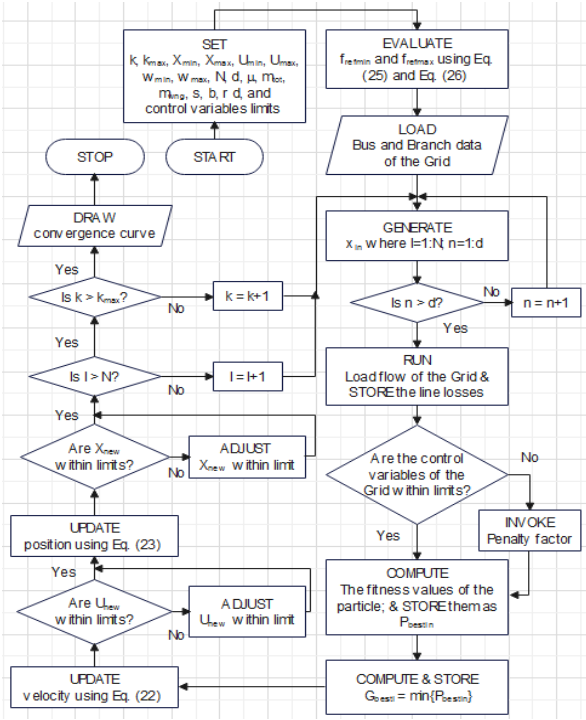

Fig. 1: Flowcharting for implementing the proposed ICPSO

Step 11: Stopping Criteria

a) Is $l > N$? If the answer is Yes, go to step 11c)

b) $l = l + 1$: go to Step 4

c) Is $k > k_{max}$? If the answer is Yes, go to step 11e)

d) $k = k + 1$: go to Step 4

e) Draw a complete convergence curve

Step 12: Stop

3. Modelling, Simulation Results, and Discussion

3.1 Modelling

In this study, the proposed ICPSO algorithm that incorporated wing-beat frequency was developed and implemented in the MATPOWER 7.1 in MATLAB 2019a environment using Fig. 1. In this contribution, it is assumed that the swarm of interest is *Pteropodidae Rousettus* (specie of Bat); in which each particle of the swam has the following feature:

$m_{tot} = 0.104\ kg, m_{wng} = 0.0130\ kg, b = 0.530\ m$, and $s = 0.0465\ m^2$ [52].

3.2 Simulations

With the intention of ascertaining and authenticating the effectiveness of the proposed ICPSO in minimizing real power transmission losses, it was verified on IEEE14 and IEEE30 test beds. Simulations were run three different times on each Test bed at different time. The simulation results were juxtaposed with the results obtained using conventional PSO and other algorithms.

3.2.1 Simulations on IEEE14 Test Bed: Fig. 2 depicts a single line diagram of IEEE14 Test Bed. Table 1 gives information about the test bed while the limits of control variables for the test bed are presented in Table 2. In total, nine (9) control variables, as shown in Table 4, were considered and used for the reduction of real power losses.

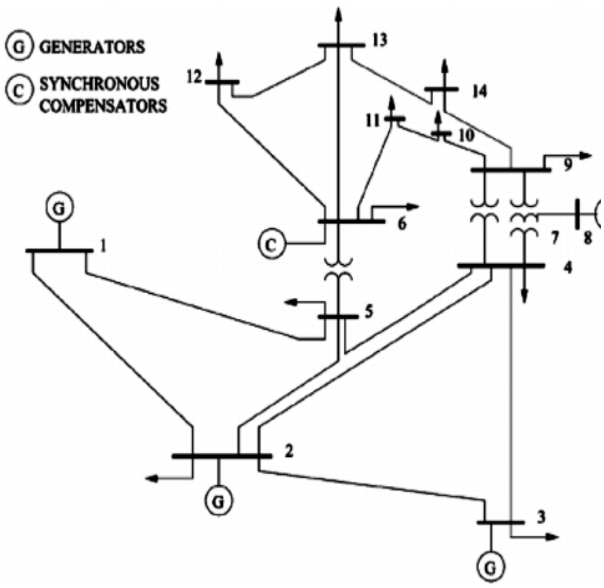

Fig 2: Single line diagram of IEEE14 Test Bed

Table 1: Components of IEEE14 Test Bed

Component	Number
Bus	14
Generator	5
Branch	30
Transformer tap	3
Shunt Var Compensator	1

Table 2: Limits of control variables for IEEE14 Test Bed

Control Variable	Minimum	Maximum
Generator Voltage (V_G)	0.95 pu	1.10 pu
Transformer Tap position (T_K)	0.90 pu	1.10 pu
Shunt Capacitance (Q_C)	0 MVAr	20 MVAr

The convergence trends of PSO and ICPSO algorithms after 250 iterations when verified on the IEEE14 Test Bed are presented in Figs 3 and 4 respectively; which show that the PSO and proposed ICPSO algorithms start converging at about 40th and 25th iterations respectively.

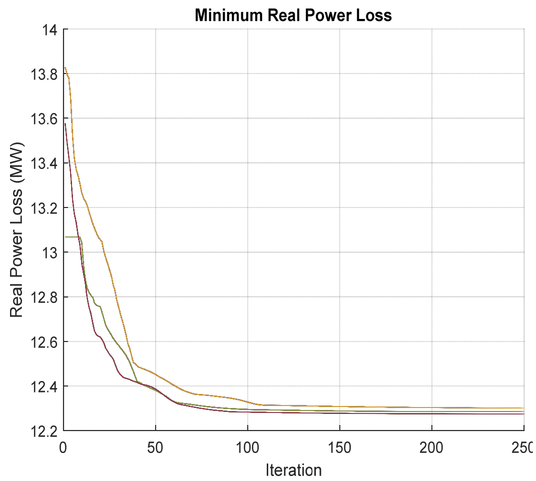

Fig.3: The convergence trend of the PSO on IEEE14 Test Bed

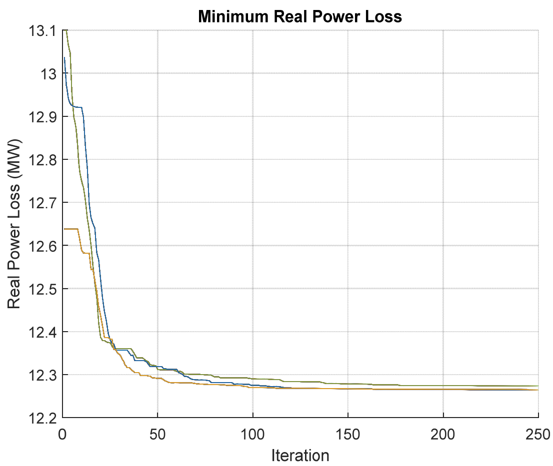

Fig 4: The convergence trend of the ICPSO on IEEE14 Test Bed

Table 3 presents comparison among the results attained using the proposed approach and that achieved by other algorithms. It is clear from the table that the proposed ICPSO performs better than all other algorithms utilized in previous studies, by achieving a minimum real power loss of **12.260 MW**; whereas the standard PSO, PSO [23], CBA-IV [46], and PSO [53] achieved minimum losses of 12.275 MW, 12.270 MW, 12.292 MW and 12.360 MW respectively.

Table 3: Comparison of the results on IEEE14 Test Bed

Algorithm	Best MW Loss	Worst MW Loss	MW Mean	% Reduction
NEWTON RAPHSON (BASE CASE)	-	-	13.393	-
PSO [23]	12.270	-	-	8.38
CBA-IV [46]	12.292	12.309	12.304	8.22
PSO	12.275	12.303	12.288	8.25

PSO [53]	-	-	12.360	7.71
ICPSO	**12.260**	**12.270**	**12.265**	**8.42**

Table 4 shows the values of the control variables before and after carrying out optimization exercise on the IEEE14 Test Bed; and it reveals that the control variable limits are strictly adhered to, when the proposed technique is adopted.

Table 4: Values of control variable pre and post optimization for IEEE14 Test Bed

Control Variables	Base Case	PSO	ICPSO
V_{g1}	1.06	1.10	1.10
V_{g2}	1.05	1.08	1.09
V_{g3}	1.01	1.05	1.06
V_{g6}	1.07	1.03	1.10
V_{g8}	1.09	1.03	1.10
T_{4-7}	0.98	1.02	0.98
T_{4-9}	0.97	1.01	0.98
T_{5-6}	0.93	1.02	1.01
Qc_9	19.00	20.00	19.99

3.2.2 Simulations on IEEE30 Test Bed: Fig. 5 depicts a one line diagram of IEEE30 Test Bed. Table 5 gives information about the IEEE30 Test Bed, while Table 6 presents the limits of control variables for the Test Bed. In total, as shown in Table 8, twelve (12) control variables were considered and used for the reduction of real power losses on the Test bed.

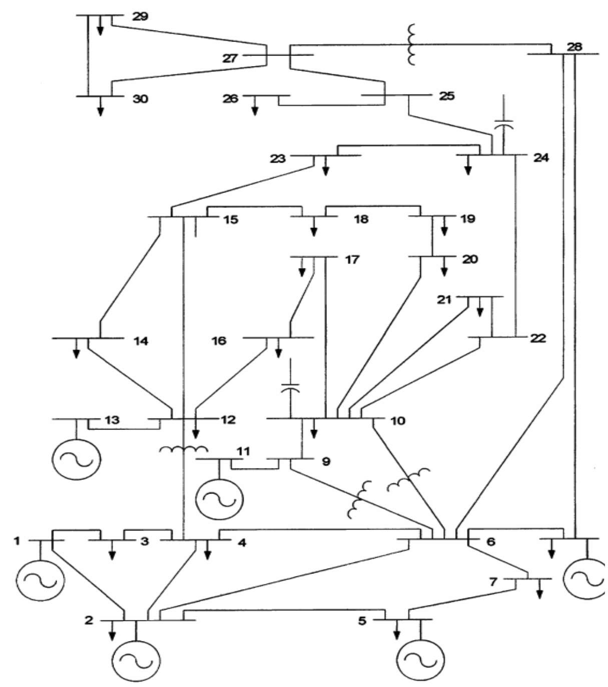

Fig 5: A one line diagram of IEEE30 Test Bed

Table 5: Components of IEEE30 Test Bed

Component	Number
Bus	30
Generator	6
Branch	41
Transformer tap	4

Table 6: The limits of control variables for IEEE30 Test Bed

Control variable	Minimum	Maximum
Generator Voltage (V_G)	0.95 pu	1.10 pu
Transformer Tap position (T_K)	0.90 pu	1.10 pu
Shunt Capacitance (Q_C)	0 MVAr	20 MVAr

The convergence trends of PSO and ICPSO algorithms after 250 iterations when verified on IEEE30 Test Bed are presented in Figs. 6 and 7 respectively. It is evident from convergence curves that the PSO and ICPSO algorithms on the IEEE30 Test bed start converging at about 45th and 15th iterations respectively.

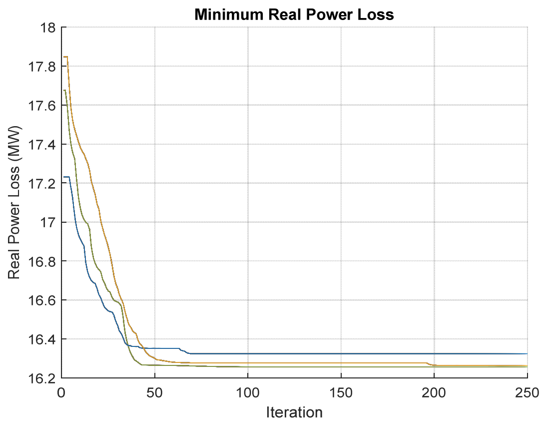

Fig. 6: The convergence trend for IEEE30 Test Bed when PSO algorithm was used

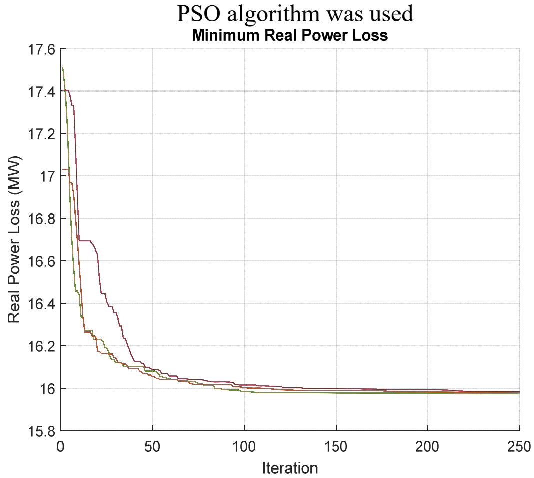

Fig. 7: The convergence trend for IEEE30 Test Bed when proposed ICPSO algorithm was used

Table 7 presents comparison among the results attained using the proposed approach and that achieved by other algorithms.

Table 7: Comparison of Simulation results on IEEE30 Test Bed

Algorithm	Best MW Loss	Worst MW Loss	MW Mean	% Reduction
Newton Raphson (Base Case)	-	-	17.557	-
PSO	16.258	16.325	16.292	7.21
HPSOBAT [41]	16.059	16.169	16.125	8.53
ICPSO	**15.977**	**15.984**	**15.981**	**8.98**

It is clear from the Table 7 that the proposed ICPSO performs better than the standard PSO algorithm and even when compared with other algorithms utilized in previous studies, achieving a minimum real power loss of **15.977 MW**; whereas the standard PSO and HPSOBAT [41] achieved minimum losses of 16.258 MW and 16.059 MW respectively.

Table 8 shows the values of the control variables pre and post optimization of IEEE30 Test Bed; and it reveals that the control variable limits are strictly adhered to, when the proposed technique is adopted.

Table 8: The values of the control variables pre and post optimization of IEEE30 Test Bed

Control Variables	Base Case	PSO	ICPSO
V_{g1}	1.06	1.10	1.10
V_{g2}	1.05	1.06	1.09
V_{g5}	1.01	1.04	1.05
V_{g8}	1.01	1.08	1.06
V_{g11}	1.08	1.04	1.09
V_{g13}	1.07	1.05	1.10
T_{6-9}	0.98	1.02	1.01
T_{6-10}	0.97	1.06	0.99
T_{4-12}	0.93	1.04	0.99
T_{27-28}	0.97	1.02	0.97
Qc_{10}	19.00	14.3	11.61
Qc_{24}	4.30	12.4	12.76

4. Conclusions

In this study, the proposed ICPSO algorithmic rule has been purported for the solving of ORPD perturbation. The approach entails the combination of PSO with a logistic based chaotic map to improve particles initial position and diversity; and the introduction of a wing-beat frequency component to maintain particles' convergence velocity. The major objective is the minimization of transmission line losses while adhering to system constraints. Simulation results were obtained when the algorithm was verified on IEEE14 and IEEE30 Test Beds respectively to validate the effectiveness of the proposed technique. The results obtained reveal that the proposed ICPSO algorithm starts converging as early as possible; and it performs better than the standard PSO and other algorithms compared with in term of minimization of the real power losses on EPGs.

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