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Swarm intelligence technique for solving optimal power flow problem in the Nigeria power system

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Abstract

This paper deals on the implementation of the particle swarm optimization method for solving power flow problems in the Nigeria power system. The difficulty of solving optimal power flow (OPF) problems increases significantly with increasing network size and complexity. Some of the weakness of the conventional methods include: limited ability in solving real-world large scale optimization problems, weakness in handling constraints, poor convergence and slow computational time. The results gotten by implementing the Particle Swarm Optimization (PSO) algorithm in Nigeria 330kV 52-Bus network show that the total active power and reactive power losses were substantially reduced to 0.03MW and 0.05MVAR. The system time of convergence was faster at 0.5seconds. Also, the maximum line active and reactive power losses on line 1 to 2 were reduced greatly to 0.00MW and 0.01MVAR respectively. These show that the system was better optimized with the PSO algorithm than the conventional method.

Keywords: Swarm; Particle; Optimization; Optimal; Constraints; Variable; Convergence

1. Introduction

One of the most significant optimization problems in electric power systems is Optimal Power Flow (OPF) which is used to determine an optimal operating condition for power systems while considering the limitations of the equipments and other operating constraints [1,2]. With the ever rising demand in power, expansion of the power grid and the resulting increase of the constraint variables, the traditional mathematical programming method is prone to the problem of dimensionality disaster. These classical techniques such as LaGrange based methods, linear programming (LP), non-linear programming (NLP) and quadratic programming (QP) methods present some limitations in their implementation. One of such limitations is that there exist the possibility for these approaches to be caught at the local minima when the cost functions are non-convex or piecewise discontinuous in the functional space.

Furthermore, treatments of operational constraints are very difficult using the classical approach. The primary objective of OPF is to obtain the optimal state of the control variables by minimizing an objective function for a particular power system while keeping all constraints (equality and inequality constraints) within limits [3]. These classical techniques such as LaGrange based methods, linear programming (LP), non-linear programming (NLP) and quadratic programming (QP) methods present some limitations in their implementation. new heuristic techniques have been developed to circumvent the above stated limitations and used to solve many global optimization problems in science and engineering. These methods include: Genetic Algorithm (GA)], Bat Algorithm (BA), Seeker Optimization Algorithm (SOA), Particle Swarm Optimization (PSO), Differential Evolution (DE), Bacterial Foraging Optimization (BFO), Differential Evolution (DE) [4,5,6].

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The methods involving PSO as proposed by [7] involved the solution of the reactive power and voltage control problem. The voltage security was evaluated using the power flow and contingency analysis methods. The control problem was formulated as a mixed-integer non-linear optimization problem. This work concluded that the PSO technique has a comparable or superior convergence rate and stability for several difficult optimization problems. However, it suffered premature convergence when the parameters were not chosen correctly. Author [8] developed Fletcher's Quadratic Programming to solve the OPF problem. The algorithm decoupled the OPF problem into sub-problems with two different objective functions: minimization of generation cost and minimization of active power transmission line losses. This problem in [9] by proposing a penalty based discretization technique which eliminated combinatorial search in providing a near optimal discrete solution. An Interior Point Method (IPM) technique based on the primal dual method to solve the OPD problem in large scale power systems was presented [10]. In the problem formulation, the inequality constraints were eliminated by incorporating them as a logarithmic barrier function. Owning to the obvious advantages of the PSO technique, this paper would explore the applications in solving the OPF problems in the Nigeria power system and the result from the PSO technique compared with conventional classical optimisation methods.

2. Material and methods

The power flow optimization problem was solved by implementing the Particle Swarm Optimization (PSO) algorithm in MATPOWER 5.1 toolbox. A modified MATPOWER code utilizing particle swarm optimization algorithm was developed to solve the power flow problem in the power systems. The results gotten with the Particle Swarm Optimization method would be compared with the conventional Newton Raphson method so as to show the effectiveness of the PSO in solving power flow problems in the Nigeria 52-bus power system.

2.1. Fundamental Equations for PSO Algorithm

2.1.1. Particle $X_i(k)$

A candidate solution represented by a *d*-dimensional real-valued vector, where *d* is the number of optimized parameters; at iteration *k*, the *ith* particle $X_i(k)$ can be described as [11]:

$$x_i(k) = [x_{i1}(k), x_{12}(k), \dots\dots, x_{id}(k)] \dots\dots (2.1)$$

2.1.2. Population

This is a set of *N* particles at iteration *k*.

$$\text{Pop}(k) = [X_1(k), X_2(k), \dots\dots.. X_N(k)] \dots\dots \;(2.2)$$

Where *N* represents the number of candidate solutions.

2.1.3. Particle velocity $V_i(k)$:

The velocity of the moving particles represented by a *d*-dimensional real-valued vector; at iteration *k*, the *ith* particle $V_i(k)$ can be described as [11]:

$$V_i(k) = [V_{i1}(k), V_{i2}(k), \dots\dots.., V_{id}(k)] \dots. (2.3)$$

Where $V_{id}(k)$ is the velocity component of the *ith* particle with respect to the *dth* dimension.

$$V_{d+1} = k * \left(w * V_d + \varphi_1.rand(x) * (P_{best} - x_d) + \varphi_2.rand(x) * (g_{best} - x_d)\right) \dots\dots (2.4)$$

$$x_{d+1} = x_d + V_{d+1} \;\dots. (2.5)$$

Where,
w is the inertia weight factor,
$\varphi_1$and φ_2 are acceleration factors,
rand () is a random value between 0 and 1.
k is the constriction factor.

2.1.4. Inertia weight w(k)

$$(w) = w_{max} - \frac{(w_{max} - w_{min})}{iter_{max}} * iter \dots\dots..(2.6)$$

Where $iter_{max}$ is the maximum number of iterations and iter is the current number of iterations.

2.1.5. Constriction Factor χ

The velocity update equation with the constriction factor can be expressed as follows:

$$V_{ij}^{k+1} = \chi\left[w * V_{ij}^{k} + c_1 * r_1\left(P_{best\ ij}^{k} - X_{ij}^{k}\right) + c_2 * r_2 * (G_{best\ ij}^{k} - X_{ij}^{k})\right] \dots..(2.7)$$

$$\text{With } \emptyset = \emptyset_1 + \emptyset_2;\ \emptyset_1 = c_1 r_1; \emptyset_2 = c_2 r_2 \dots\dots..(2.8)$$

Eq. (3.6) is used under the constraint that $\emptyset \geq 4$. If $\emptyset < 4$, then all particles would slowly spiral toward and around the best solution in the searching space without convergence guarantee, but if $\emptyset > 4$, then all particles are guaranteed to converge quickly [11].

2.1.6. Individual best $P_{best\ i}$ and Global best G_{best}

$$P_{best\ i} = [P_{best\ i1}, P_{best\ i2}, \dots, P_{best\ id}] \dots\dots\dots. (2.9)$$

While Global best G_{best} is the best position among all of the individual best positions achieved thus far.

2.1.7. Stopping criteria

The search process will be terminated whenever one of the following criteria is satisfied.

- The number of iterations since the last change of the best solution is greater than a pre-specified number.
- The number of iterations reaches the maximum allowable number.

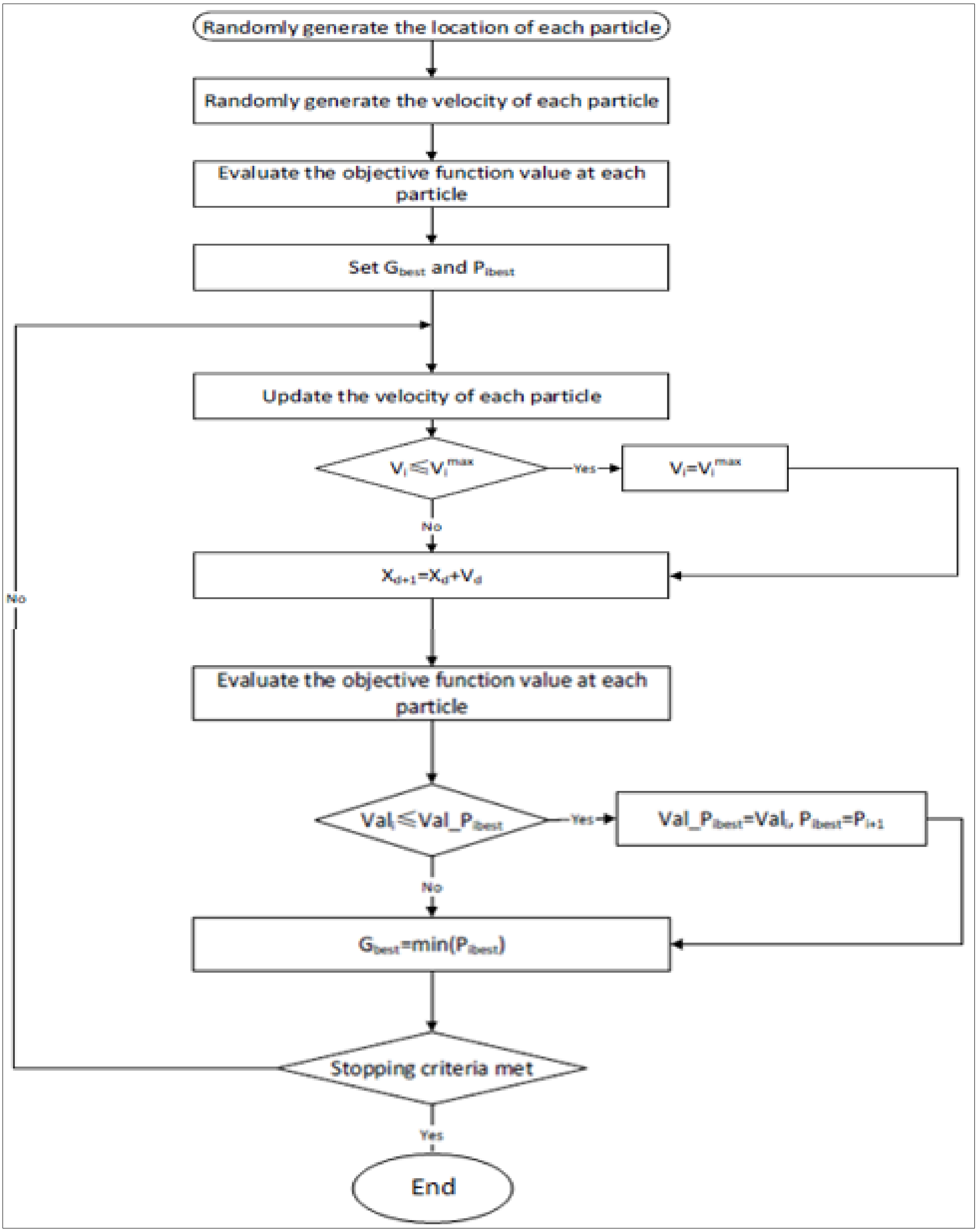

Figure 1 Flow Chart of the PSO Technique

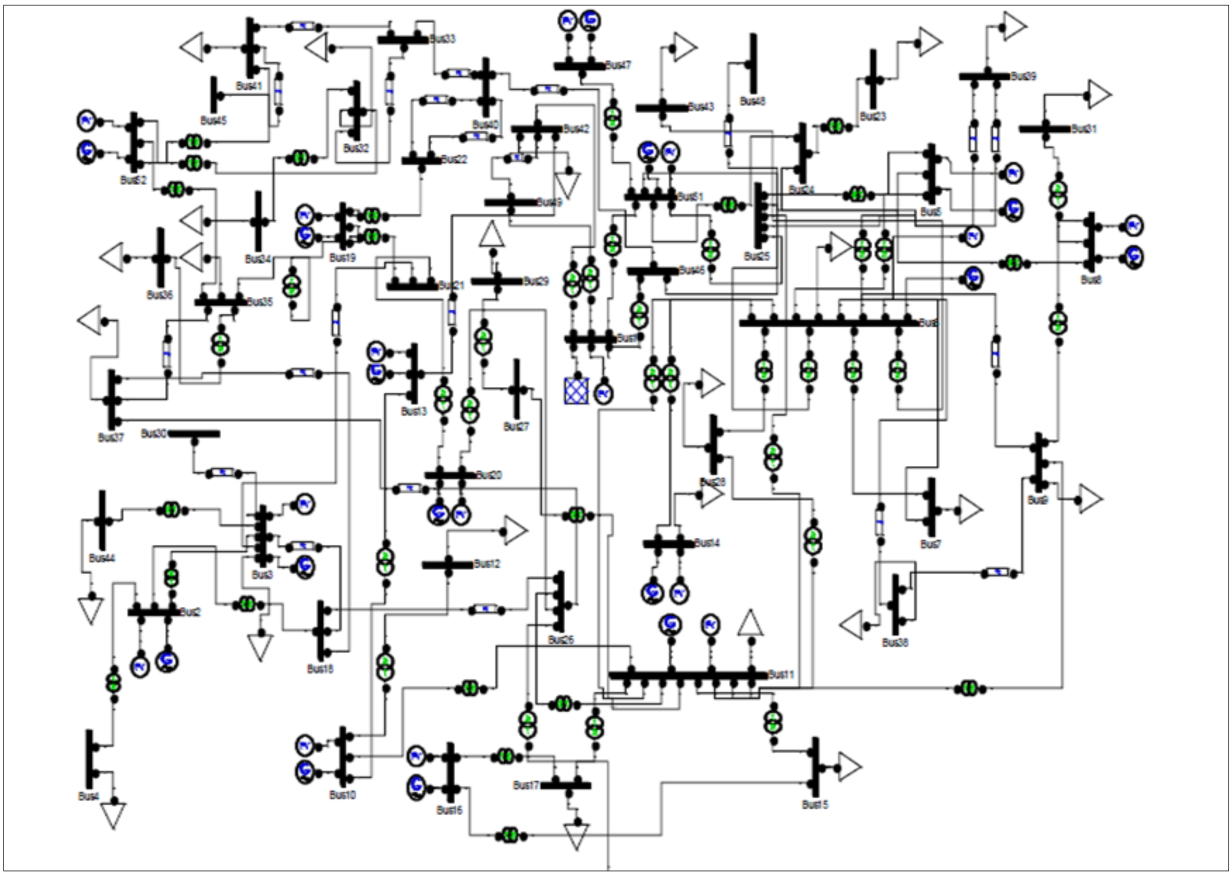

Figure 2 The Nigeria Power System in Simulink simulation model

3. Results and discussion

The result of the implementation of the PSO method is shown below depicting the total active power loss and reactive power loss for the Nigeria 330kV 52-Bus power network.

Table 1 Comparison of the Real Power Loss at Each Branch of the Nigeria 52 Bus Power System

Branch Number	From Bus	To Bus	Conventional NR Method (MW)	PSO Optimized (MW)
1	1	2	22.1	12.4
2	2	3	10.3	5.30
3	3	4	30.4	5.80
4	4	5	18.5	6.40
5	5	6	19.0	3.32
6	6	7	7.5	2.01
7	7	8	3.35	3.50
8	8	9	6.5	3.65
9	9	10	6.45	3.21
10	10	11	13.8	7.63
11	11	12	12.3	6.82
12	12	13	10.2	5.10
13	13	14	10.5	5.25

14	14	15	10.3	5.13
15	15	16	15.7	7.50
16	16	17	4.55	2.44
17	17	18	7.50	3.56
18	18	19	9.30	4.87
19	3	20	15.5	4.57
20	4	21	8.15	3.56
21	5	22	0.00	0.00
22	22	23	2.10	0.00
23	23	24	1.28	0.00
24	24	25	0.00	0.00
25	26	26	0.00	0.00
26	26	27	0.00	0.00
27	23	28	0.00	0.00
28	24	29	0.00	3.21
29	7	30	11.4	5.52
30	30	31	15.2	6.11
31	31	32	12.3	0.00
32	32	33	10.6	0.00
33	33	34	0.00	0.00
34	34	35	0.00	0.00
35	35	36	0.00	0.00
36	36	37	0.00	4.30
37	37	38	0.00	3.20
38	30	39	0.00	3.50
39	35	40	3.20	6.53
40	8	41	7.10	3.50
41	9	42	2.50	6.34
42	10	43	5.50	7.14
43	11	44	12.4	1.22
44	12	45	0.00	2.35
45	14	46	13.1	3.18
46	46	47	12.8	1.21
47	47	48	9.22	3.01
48	46	49	2.45	5.32
49	15	50	5.90	4.15
50	17	51	10.4	2.10
51	23	52	5.25	1.07
Total			**385.20**	**175.1**

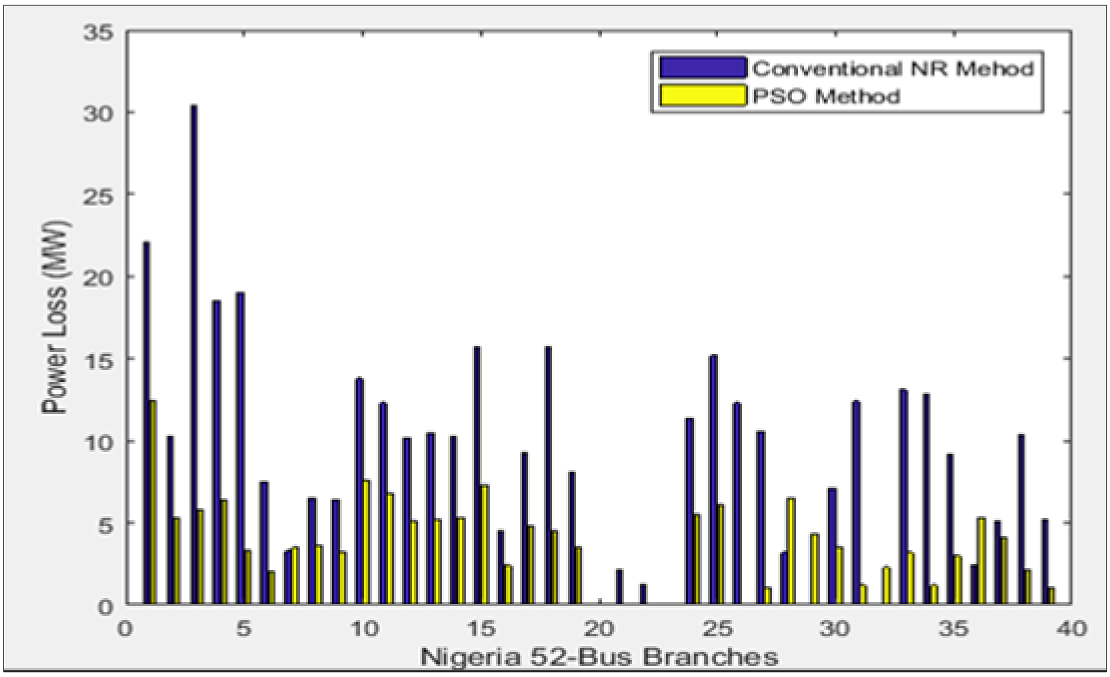

Figure 3 Bar graph of the comparison of the Real Power Loss at Each Branch on the Nigeria 52-Bus Branches

The Optimal power result of the Nigeria 52 Bus power system using the conventional Newton Raphson method is shown in Table 1 and Fig 3. The total active power loss and reactive power losses were 385.2MW and 183.4MVAR respectively. Bus 16 has the minimum voltage magnitude of 0.908p.u while bus 1 has the maximum voltage magnitude of 1.000p.u. The minimum voltage angle of -0.80deg was seen at but 14 while the maximum voltage angle was in bus 1. The maximum line power losses of 30.4MW and 8.52MVAR were seen on line 3 to 4. For the implementation of the PSO method it can be seen that the total active power loss and reactive power loss for the Nigeria 330kV 52-Bus power network were reduced to 175.1MW and 81.4MVAR respectively. The maximum voltage magnitude of 1.000p.u was seen in Bus 3, while Bus 19 has the minimum voltage magnitude of 0.969p.u. The minimum voltage angle was -0.87deg. at Bus 19 while the maximum voltage angle was 0.000p.u in bus 1. The maximum line power loss of line 1-2 was significantly reduced to 12.4MW and 1.3MVAR.

4. Conclusion

The application and implementation of the particle swarm optimization for optimal power flow solution in the Nigeria power system has a faster time of convergence and less computational time. The PSO algorithm yields optimal settings of the control variables of the test power systems and reduced the active power transmission line losses. The algorithm simulations demonstrated the effectiveness and superiority of the PSO method over the Newton-Raphson method as it outperformed the conventional method for all system parameters optimization and was found to be more accurate, robust and efficient.

Compliance with ethical standards

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Disclosure of conflict of interest

The authors declare no conflicts of interest regarding the publication of this paper.

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