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Application of nature-inspired algorithm for solving large- scale optimal power flow problem

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Abstract
The conventional techniques for solving optimal power flow (OPF) problems usually become comparatively less effective, and the computational difficulties increase significantly with increasing network size and complexity. To overcome the shortcomings of the conventional techniques, nature-inspired methods like the particle swarm optimization (PSO) method have been developed and applied to OPF problems in the recent years. This paper is hinged on the need to adopt these heuristic approaches in solving power flow problems in the Nigeria power system. This was demonstrated in this thesis, by implementing the conventional Newton Raphson method and a nature-inspired method, the particle swarm optimization technique in the IEEE 14 Bus network and validating the efficacy of the results gotten from the two methods on the Nigeria 330kV 52-Bus network to show the superior performance of the PSO technique. The results from the implementation of the PSO algorithm showed that the total active power and reactive power losses were substantially reduced to 175.1MW and 81.4MVAR and the system time of convergence was faster and occurred after 2 iterations at 2.03seconds. Thus it could be seen that the PSO algorithm have proved to exhibit a superior performance for optimisation of a large power system at a better speed of convergence when compared with the Newton Raphson method.
Keywords: Conventional, Particle, Swarm, Optimisation, Nature-inspired, Algorithm, Convergence.

1. Introduction

The difficulty of solving optimal power flow (OPF) problems increases significantly with increasing network size and complexity. Recent industrial developments have greatly increased electric power system complexity. In prior decades, utilities had relatively few generators compared to the numbers introduced today by the advent of independent power producers and uncertainties in demand response programs add variables to the load side of OPF problems. There are many conventional OPF solution methods that exist: bus admittance matrix, Gauss-Seidel iterative algorithm, Newton-Raphson method, linear and non-linear programming, gradient-based method, dynamic programming, interior point method, Lambda iteration, fast-decoupled algorithms, and integer programming. These methods have distinct mathematical characteristics, computational requirements and varying considerably in their adaptability to the modelling and solution requirements of different power system applications. These conventional OPF techniques are based on mathematical formulations which have to be simplified in order to get an optimal solution. 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 stagnation, slow computational time (especially if the number of variables is large) and expensive in computing large power system solutions (Mota-Palomino & Quintana 2016).

To overcome the shortcomings of conventional techniques, nature-inspired methods have been developed and applied to OPF problems in the recent past. The major advantages of these methods include: fast convergence rate, appropriate for solving non-linear optimization problems, ability to find global optimum solutions, suitable for solving multi-objective optimization problems, pertinent in finding multiple optimal solutions in a single simulation run and versatile in handling constraints (Mandal & Roy 2013).

Nonetheless, since the objective function of reactive power dispatch problem is not convex, many local optima exist. Therefore, the linear programming method is very likely to get trapped into one of these local optima and cannot achieve a global optimal solution. Moreover, linear programming ignores the higher-order terms, so the accuracy of the results can also be affected (Biskas et al. 2005). The quadratic programming method is another method that can be used to solve the reactive power dispatch problem (Nanda, Kothari & Srivastava 2015). Quadratic programming is more adaptable to the nonlinear characteristic of reactive power dispatch problem than linear programming. The disadvantage is that quadratic programming does not work very well for the high dimensional problems, as the dimension increases the computation time would increase dramatically. The OPF provides a useful support to the operator to overcome many difficulties in the real time control and operation planning of power systems (Xia & Chan 2006). Depending on the specific objectives and constraints, there are different OPF formulations. The typical objectives of OPF problems are minimization of the total fuel cost, minimization of the transmission loss, maximization of the degree of security of a system, or a combination of some of them. Most researches concentrated only on power problems involving very small equations whose matrices can be conveniently handled manually (Arrillaga & Arnold 1994). With the advent of digital computers, the solutions to power problems were reduced to sets of algorithms solved by computers.

The first of these methods was the Gauss-Seidel iterative algorithm using the nodal-admittance matrix method, with the first successful computer program developed by Ward and Hale in 1956 (Arrillaga & Arnold 1994). Like the bus admittance matrix method, the Gauss-Seidel iterative algorithm was simple in structure, with lower memory requirement and less computational time per iteration. But the major problem was the slow rate of convergence, therefore large number of iterations are needed, especially in large systems where the algorithm was discovered to be obsolete, as the number of iterations required for a solution was found to be relatively high. The need to study power problems for large systems became necessary with the increase in high voltage interconnections between systems. A more successful algorithm and the most universally acceptable replacement for the Gauss-Seidel method was the Newton-Raphson method. It was found to be very suitable for large-scale power systems, with more degree of accuracy, convergence after a few iterations, which are independent on the system size. However, it was a difficult solution technique, as calculations were complex, hence more computer time per iteration was involved, and large computer memory required.

Other traditional mathematical optimisation methods include: Linear and non-linear programming, gradient-based method, dynamic programming, interior point method, Lambda iteration, fast-decoupled algorithms, and integer programming (Kumar & Alwarsamy 2011), (Chukwu, Ahiakwo & Nanim 2007), (Mehdinejad et. al 2016). In most of these algorithms, optimality of solutions was mathematically formulated, and could be applied to large-scale problems. They have no problem-specific parameters, and most of them have high computational efficiency, with ease of implementation. However, solutions obtained using them have their inherent implementation limitations. The solutions for large-scale systems are not very simple. Many of the techniques fail to get optimal solutions, with a possibility of being stuck in local optima (Xia & Elaiw 2010), (Lenin & Reddy 2014), (Lenin, Reddy & Kalavathi 2016).

Linear programming encounters poor computation efficiency; while dynamic programming suffers from the curse of dimensionality, a process whereby the dimensions of the economic load dispatch (ELD) problem become too large that it requires massive computational effort (Santos & Da Costa, 2015). These problems affect their application to practical generator problems with ramp rates, valve-point effects and prohibited operating zones constraints. The conventional methods of optimal power flow are hugely challenged with poor convergence and stagnation, slow computational time for large number of variables and expensive in computing large power system solutions. The development of evolutionary techniques and their hybrids has ameliorated these challenges (Vlachogiannis & Lee 2016), (Zhao, Guo & Cao 2015), Singh, Mukherjeeb, & Ghoshal, 2015). This paper is hinged on the need to adopt these heuristic approaches in solving dispatch and power flow problems in the Nigeria power system. In this paper, a nature-inspired algorithm, particle swarm optimisation method was used to solve OPF problems in the Nigeria power system so as to overcome the difficulties of using the mathematical methods.

2.0 Material and methods

The power flow optimization problem was solved by implementing the Particle Swarm Optimization (PSO) algorithm in MATPOWER 7.1 toolbox. A modified MATPOWER code utilizing particle swarm optimization algorithm was developed to solve the power flow problem in the power systems. The Particle Swarm Optimization method results would be compared with the conventional Newton Raphson method for the IEEE-14 bus network and validated on the Nigeria 52-bus power system so as to show the effectiveness of the PSO in solving power flow problems.

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 (Bratton & Kennedy 2007):

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

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

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

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 (Bratton & Kennedy 2007):

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

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

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

$$x_{d+1} = x_d + V_{d+1} \quad (2.5)$$

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)*:

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

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:

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

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

Eq. (3.6) is used under the constraint that $Ø \geq 4$. If $Ø < 4$, then all particles would slowly spiral toward and around the best solution in the searching space without convergence guarantee, but if $Ø > 4$, then all particles are guaranteed to converge quickly (Bratton & Kennedy 2007):
2.1.6 Individual best $P_{best\ i}$ and Global best G_{best} :

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

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.

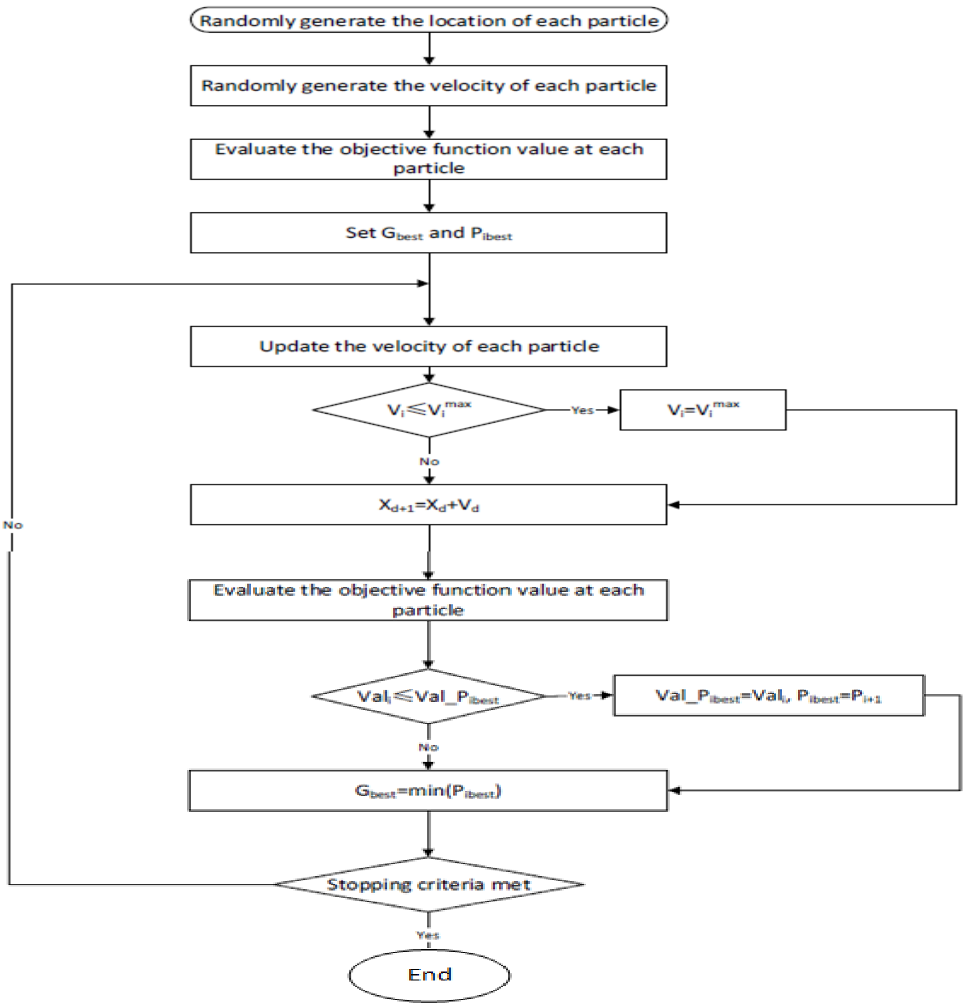

Fig 2.1: Flow Chart of the PSO Technique

2.2 The Newton-Raphson procedure is as follow:

Step 1: Choose the initial values of the voltage magnitudes $|V|^{(0)}$ of all n_p loads buses and n-1 angles $\delta^{(0)}$ of the voltages of all the buses except the slack bus.
Step 2: Use the estimated $|V|^{(0)}$and $\delta^{(0)}$ to calculate a total n-1 number of injected real power $P_{calc}^{(0)}$ and equal number of real power discrepancy $\Delta P^{(0)}$.
Step 3: Use the estimated $|V|^{(0)}$ and $\delta^{(0)}$ to calculate a total n_p number of injected reactive power $Q_{calc}^{(0)}$ and equal number of real power discrepancy $\Delta P^{(0)}$.
Step 4: Use the estimated $|V|^{(0)}$ and $\delta^{(0)}$ to formulated the Jacobian matrix $J^{(0)}$.
Step 5: Solve the load flow problem for $\delta^{(0)}$ and $\Delta|V|^{(0)} \div \Delta|V|^{(0)}$.
Step 6: Obtain the updates from:

$$\boldsymbol{\delta}^{(\mathbf{1})} = \boldsymbol{\delta}^{(\mathbf{0})} + \Delta\boldsymbol{\delta}^{(\mathbf{0})} \tag{2.10}$$

$$|V|^{(1)} = \Delta|V|^{(0)} + \left[\frac{\Delta|V|^{(0)}}{|V|^{(0)}}\right] \tag{2.11}$$

Step-7: Check if all the mismatches are below a small number. Terminate the process if yes. Otherwise go back to step-1 to start the next iteration with the updates given by (1) and (2).
The result can be found in a form of linear system of equations that can be expressed as:

$\begin{bmatrix} \Delta\theta \\ \Delta|V| \end{bmatrix} = J^{-1} \begin{bmatrix} \Delta P \\ \Delta Q \end{bmatrix}$ Here, ΔP and ΔQ are called mismatch equation.

Where,

$$\Delta P_i = -P_i + \sum_{k=1}^{N} |V_i||V_k|(G_{ik}cos_{ik} + B_{ik}sin\theta_{ik}) \quad (2.12)$$

$$\Delta Q_i = -Q_i + \sum_{k=1}^{N} |V_i||V_k|(G_{ik}sin_{ik} - B_{ik}cos\theta_{ik}) \quad (2.13)$$

and J is a matrix of partial derivatives known as a Jacobian Matrix:

$$J = \begin{bmatrix} \frac{\partial\Delta P}{\partial\theta} & \frac{\partial\Delta P}{\partial|V|} \\ \frac{\partial\Delta Q}{\partial\theta} & \frac{\partial\Delta P}{\partial|V|} \end{bmatrix} \quad (2.14)$$

The sets of linear equations are solved to determine the next guess (*m+1*) of voltage magnitude and angles based on:

$$\theta^{m+1} = \theta^{m} + \Delta\theta \quad (2.15)$$

$$|V|^{(m+1)} = |V|^{(m)} + \Delta|V| \quad (2.16)$$

This iteration process continues until a stopping condition is met. A typical stopping condition is to end the iteration process if the standard of the iterative conditions is under a standard value.

3.0 Results and Discussions

The superior performance of the Particle Swarm Optimisation (PSO) method over the Newton Raphson method for power flow optimisation was first verified on IEEE 14 bus system and then was validated on the extended Nigeria 52-bus power system.

3.1 Optimal Power Flow Results of the IEEE 14 Bus Network with the Conventional Newton Raphson Method

The runpf function can calculate the power flow of the IEEE 14 bus network In MATLAB 7.10 environment as shown in Figure 4.5 below.

```
Newton's method power flow (power balance, polar) converged in 2 iterations.

Converged in 0.98 seconds
================================================================================
|     System Summary                                                           |
================================================================================

How many?                How much?              P (MW)            Q (MVAr)
---------------------    -------------------  -------------  -----------------
Buses              14     Total Gen Capacity     772.4           -52.0 to 148.0
Generators          5     On-line Capacity       772.4           -52.0 to 148.0
Committed Gens      5     Generation (actual)    272.4              82.4
Loads              11     Load                   259.0              73.5
  Fixed            11       Fixed                259.0              73.5
  Dispatchable      0       Dispatchable          -0.0 of -0.0      -0.0
Shunts              1     Shunt (inj)             -0.0              21.2
Branches           20     Losses (I^2 * Z)        13.39             54.54
Transformers        3     Branch Charging (inj)     -               24.4
Inter-ties          0     Total Inter-tie Flow     0.0               0.0
Areas               1

                          Minimum                      Maximum
                 -------------------------  --------------------------------
Voltage Magnitude   1.010 p.u. @ bus 3          1.090 p.u. @ bus 8
Voltage Angle     -16.03 deg   @ bus 14         0.00 deg   @ bus 1
P Losses (I^2*R)             -                  4.30 MW    @ line 1-2
Q Losses (I^2*X)             -                 13.12 MVAr  @ line 1-2
```

Figure 3.1. Optimal Power Flow Results of System Summary for IEEE 14 bus network

Figures 3.1 shows the optimal power flow results for the IEEE 14 bus network using the conventional Newton Raphson method. The total active power loss and reactive power loss are 13.393MW and 54.54MVAR respectively. Bus 1 is assigned as the slack bus. Bus 3 has the minimum voltage magnitude of 1.010p.u while bus 8 has the maximum voltage magnitude of 1.090p.u. The minimum voltage angle of -16.03deg was seen at bus 14 while the maximum voltage angle of 0.000deg was in bus 1. The maximum line active and reactive power loss was 4.3MW and 13.12MVAR at line 1 to 2.

3.2 Case 2- Optimal Power Flow Results of the IEEE 14 bus network with the PSO Algorithm

The results below show the implementation of the PSO algorithm for the optimal power flow in the IEEE 14 bus network. The system Summary of the Optimal Power Flow Results for the IEEE 14 bus network using the PSO method is shown in figure 3.2 below.

```
MATPOWER Version 7.1, 08-Oct-2020 -- AC Optimal Power Flow
  AC OPF formulation: polar voltages, power balance eqns
MATPOWER Interior Point Solver -- MIPS, Version 1.4, 08-Oct-2020
 (using built-in linear solver)
Converged!

Converged in 0.20 seconds
Objective Function Value = 8081.53 $/hr
================================================================================
|     System Summary                                                           |
================================================================================

How many?                How much?              P (MW)            Q (MVAr)
---------------------    -------------------  -------------  -----------------
Buses              14     Total Gen Capacity     772.4           -52.0 to 148.0
Generators          5     On-line Capacity       772.4           -52.0 to 148.0
Committed Gens      5     Generation (actual)    268.3              67.6
Loads              11     Load                   259.0              73.5
  Fixed            11       Fixed                259.0              73.5
  Dispatchable      0       Dispatchable          -0.0 of -0.0      -0.0
Shunts              1     Shunt (inj)             -0.0              20.7
Branches           20     Losses (I^2 * Z)         9.29             39.16
Transformers        3     Branch Charging (inj)     -               24.3
Inter-ties          0     Total Inter-tie Flow     0.0               0.0
Areas               1
```

Figure 3.2. Optimal Power Flow Results of System Summary for IEEE 14 bus network using the PSO method

Implementing the PSO method as shown in Fig 3.2, can be seen that the total active power loss and reactive power loss for the IEEE 14 bus network were reduced to 9.287MW and 39.16MVAR respectively. The maximum voltage magnitude of 1.060 p.u was seen in Bus 1, while Bus 4 has the minimum voltage magnitude of 1.014 p.u. The minimum voltage angle was -14.27deg. at Bus 14 while the maximum voltage angle was in bus 1. The maximum power loss of 2.90MW and 8.86MVAR was seen on line 1-2.

Table 3.1. Comparison of the Real Power Loss at Each Branch

Branch Number	From Bus To Bus	Conventional NR Method	PSO Optimized
1	1-2	4.298 MW	2.902MW
2	1-5	2.763 MW	2.051MW
3	2-3	2.323 MW	1.344MW
4	2-4	1.677 MW	1.285MW
5	2-5	0.904 MW	0.737MW
6	3-4	0.373 MW	0.099MW
7	4-5	0.514 MW	0.331MW
8	4-7	0 .000MW	-0.000MW
9	4-9	0 .000MW	0.000MW

10	5-6	0 .000MW	0.000MW
11	6-11	0.055 MW	0.049MW
12	6-12	0.072 MW	0.072MW
13	6-13	0.212 MW	0.208MW
14	7-8	0 .000MW	0.000MW
15	7-9	0 .000MW	0.000MW
16	9-10	0.013 MW	0.015MW
17	9-14	0.116 MW	0.131MW
18	10-11	0.013 MW	0.010MW
19	12-13	0.006 MW	0.006MW
20	13-14	0.054 MW	0.047MW

3.3 Case 3- Optimal Power Flow Results of the Nigeria 52 Bus Network with the Conventional Newton Raphson Method

The runpf function can calculate the power flow of the Nigeria 52 bus network in MATLAB 7.10 environment as shown in Figure 3.3 below.

```
MATPOWER Version 7.1, 08-Oct-2020 -- AC Power Flow (Newton)

Newton's method power flow (power balance, polar) converged in 5 iterations.

Converged in 3.57 seconds
================================================================================
|     System Summary                                                           |
================================================================================

How many?                How much?              P (MW)            Q (MVAr)
---------------------    -------------------  -------------  -----------------
Buses             52     Total Gen Capacity     9000           -235.0 to 6750.0
Generators        17     On-line Capacity       9000           -235.0 to 6750.0
Committed Gens    13     Generation (actual)    7255.6             3668.1
Loads             51     Load                   6870.4             3530.3
  Fixed           51       Fixed                6870.4             3530.3
  Dispatchable     0       Dispatchable          -0.0 of -0.0       -0.0
Shunts             0     Shunt (inj)             -0.0               21.2
Branches          51     Losses (I^2 * Z)        385.2              183.4
Transformers       0     Branch Charging (inj)     -                24.4
Inter-ties         0     Total Inter-tie Flow     0.0                0.0
Areas              1
```

Fig 3.3: Optimal Power Flow Results of System Summary for Nigeria 52 bus network

The Optimal power result of the Nigeria 52 Bus power system using the conventional Newton Raphson method is shown in Fig 3.3. 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.

3.4 Case 4- Optimal Power Flow Results of the Nigeria 330kV 52 Bus network with the PSO Algorithm

The PSO algorithm was implemented in the Nigeria 52 Bus power network and the results are shown below. The system summary for Nigeria 52 bus network with the PSO method is shown in Fig 3.4:

```
MATPOWER Version 7.1, 08-Oct-2020 -- AC Optimal Power Flow
  AC OPF formulation: polar voltages, power balance eqns
MATPOWER Interior Point Solver -- MIPS, Version 1.4, 08-Oct-2020
 (using built-in linear solver)
Converged in 2 iterations!

Converged in 2.03 seconds
Objective Function Value = 51.85 $/hr
================================================================================
|     System Summary                                                           |
================================================================================

How many?                How much?              P (MW)            Q (MVAr)
---------------------    -------------------  -------------  -----------------
Buses             52     Total Gen Capacity     9000          -235.0 to 6750.0
Generators        17     On-line Capacity       9000          -235.0 to 6750.0
Committed Gens    13     Generation (actual)    7045.5              3566.1
Loads             51     Load                   6870.4              3530.3
  Fixed           51       Fixed                6870.4              3530.3
  Dispatchable     0       Dispatchable        -0.0 of -0.0         -0.0
Shunts             0     Shunt (inj)           -0.0                 21.2
Branches          51     Losses (I^2 * Z)       175.1               81.4
Transformers       0     Branch Charging (inj)    -                 24.4
Inter-ties         0     Total Inter-tie Flow   0.0                 0.0
Areas              1
```

Fig 3.4: Optimal Power Flow Results of System Summary for Nigeria 52 bus network with the PSO method

Implementing the PSO method as shown in Fig 3.4, 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 12.4MW and 1.3MVAR was seen on line 1-2.

Table 2.2 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	1.01

4.0. Conclusion

The results from the Optimal Power Flow for IEEE 14 bus network with the conventional Newton Raphson method in Fig. 3.1 showed that the total active and reactive power losses were 13.39MW and 54.54MVAR respectively. There was convergence after 2 iterations at 0.98 seconds. The voltage profile was between the minimum value of 1.010p.u and a maximum of 1.090p.u with a voltage angle of -16.03deg. The maximum line active and reactive power losses were 4.3MW and 13.12MVAR at line 1 to 2. When the Particle Swarm Optimisation algorithm was implemented on the IEEE 14 bus network for Optimal Power Flow solution as shown in Fig. 3.2, the total active power and reactive power losses were reduced to 9.29MW and 39.16MVAR. The system time of convergence was faster after 1 iteration at 0.20seconds. Also, the maximum line active and reactive power losses on line 1 to 2 were reduced remarkably to 2.902MW and 8.86MVAR respectively. These have shown that the system was better optimised with the PSO algorithm than the conventional method.

This was also validated on the Nigeria 330kV 52-Bus network where the total active and reactive power losses were 385.2MW and 183.4MVAR respectively when the Optimal Power Flow solution was done with the conventional

Newton Raphson method as shown in Fig 3.3. The convergence was after 5 iterations at 3.57seconds. The maximum line active and reactive power losses were 30.4MW and 8.52MVAR at line 3 to 4. When the PSO algorithm was implemented on the Nigeria 330kV 52-Bus network as shown in Fig. 3.4, it was seen to be better optimised. The total active power and reactive power losses were substantially reduced to 175.1MW and 81.4MVAR. The system time of convergence was faster and occurred after 2 iterations at 2.03seconds. Also, the maximum line active and reactive power losses on line 1 to 2 were reduced greatly to 12.4MW and 1.30MVAR respectively. Thus, it could be seen that the PSO algorithm have proved to exhibit a superior performance for optimisation of a large power system at a better speed of convergence when compared with the conventional method.

5.0 Recommendation

Further study should be done on the effects of DG incorporation to the optimal power flow solution with the PSO method. Other, metaheuristic methods like genetic algorithm and bee colony optimisation methods should be compared to ascertain the most effective for power flow solution with DG integration in the Nigeria power system.

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