# Transient Stability Constrained Optimal Power Flow Using Improved Particle Swarm Optimization

Tung The Tran and Dieu Ngoc Vo

***Abstract***— *This paper proposes an improved particle swarm optimization method for transient stability constrained optimal power flow (TSCOPF) problem. The transient stability constraint should be taken into consideration for the solution of the optimization problems in power systems. The formulas of TSCOPF are derived through the addition of rotor angle inequality constraints into optimal power flow relationships. The proposed IPSO is the particle swarm optimization with constriction factor and the particle's velocity guided by a pseudo-gradient. The pseudo-gradient is to determine the direction of the particles so that they can quickly move to optimal solution. The proposed method has been applied on WSCC 3-generator, 9-bus system, IEEE 30-bus systems. The obtained results using the IPSO are compared with those obtained using other modern techniques for performance examination.*

***Keywords***— **Improved particle swarm optimization, optimal power flow, transient stability.**

## 1. INTRODUCTION

Optimal power flow (OPF) is an important tool for power system operation, control and planning. It was first introduced by "Dommel and Tinney (1968)" [1]. OPF has become an important issue to the researchers over past two decades and has established its position as one of the main tools for optimal operation and planning of modern power systems. The objective of an OPF problem is to find the steady state operation point of generators in the system so as their total generation cost is minimized while satisfying various generator and system constraints such as generator's real and reactive power, bus voltage, transformer tap, switchable capacitor bank, and transmission line capacity limits. [1]In the OPF problem, the controllable variables usually determined are real power output of generators, voltage magnitude at generation buses, injected reactive power at compensation buses, and transformer tap settings.

OPF with transient stability constraints is an extension of the traditional OPF problems. In addition to the common constraints of OPF, the TSCOPF problems consider the dynamic stability constraints of power system. When any of a specified set of disturbances occurs, a feasible operation point should withstand the fault and ensure that the power system moves to a new stable equilibrium after the clear-ance of the fault without violating equality and inequality constraints even during transient period. These conditions for all of the specified credible contingencies are called as transient stability constraints. Transient stability constrained optimal power flow is an effective measure to coordinate the security and economic of power system. TSCOPF is a large-scale nonlinear optimization problem with both algebraic and differential equations developed by Sauer and Pai (1998) [2], Kundur (1994) [3].

The TSCOPF problem has been solved by several conventional methods such as: primal-dual interior-point method [4], linear programming (LP) [5], etc the conventional methods can find the optimal solution for an optimization problem with a very short time. However, the main drawback of these methods is that they are difficult to deal with non-convex optimization problems with non-differentiable objective. Moreover, these methods are also very difficult for dealing with large-scale problems due to large search space. Meta-heuristic search methods recently developed have shown that they have capability to deal with this complicated problem. Several meta-heuristic search methods have been also widely applied for solving the TSCOPF problem such as Evolutionary Programming (EP) [6], Genetic Algorithm (GA) [7], Artificial Bee Colony [8]... These meta-heuristic search methods can overcome the main drawback from the conventional methods with the problem not required to be differentiable. However, the optimal solutions obtained by these methods for optimization problems are near optimum and quality of the solutions is not high when they deal with large-scale problems; that is the obtained solutions may be local optimums with long computational time.

In 1995, Eberhart and Kennedy suggested a particle swarm optimization (PSO) method based on the analogy of swarm of bird flocking and fish schooling [9]. Due to its simple concept, easy implementation, and computational efficiency when compared with mathematical algorithm and other heuristic optimization techniques, PSO has attracted many attentions and been applied in various power system optimization problems such as economic dispatch, reactive power and voltage control, transient stability constrained optimal power flow and many others.

In this paper, a newly improved particle swarm optimization (IPSO) method is proposed for solving transient stability constrained optimal power flow problem. The proposed IPSO is the particle swarm

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optimization with constriction factor and the particle's velocity guided by a pseudo-gradient. The pseudo-gradient is to determine the direction for the particles so that they can quickly move to optimal solution. The proposed method has been tested on WSCC 3-generator, 9-bus system, IEEE 30-bus systems and the obtained results are compared to those from Differential Evolution (DE), Trajectory Sensitivities (TS), Time Domain Simulation (TDS), Genetic algorithm (GA), Evolutionary programming (EP).

## 2. PROBLEM FORMULATION

### 2.1. OPF formulation

The OPF problem was defined in the early 1960's as an extension of conventional economic dispatch to determine the optimal settings for control variables in a power network with respect to various constraints. The OPF is a static constrained nonlinear optimization problem, whose development has closely followed advances in numerical optimization techniques and computer technology. The OPF is a nonlinear optimization problem with nonlinear objective function and nonlinear constraints. The objective of the OPF problem is to minimize is to optimize the objective functions while satisfying several equality and inequality constraints [10]. Mathematically, the problem is formulated as follows:

$$\text{Min}\, f(x,u) \tag{1}$$

subject to

$$g(x,u) = 0 \tag{2}$$

$$h(x,u) \le 0 \tag{3}$$

where $f$ is the objective function to be minimized, $g$ is the set of equality constraints, and h is the set of inequality constraints. Vectors $x$ and $u$, the parameters of these functions, are called the state variable vector and control variable vector, respectively.

### 2.2. Objective function

The objective function is defined as the total fuel cost of the system with fuel cost curve approximated as a quadratic function of generator real power output:

$$Min\sum_{i=1}^{N_g} F_i(P_{gi}) = a_i + b_i P_{gi} + c_i P_{gi}^2 \tag{4}$$

where $P_{gi}$ is the real power output of generating units $i$; $N_g$ is the number of generating units; $a_i$, $b_i$ and $c_i$ are fuel cost coefficients of generating unit $i$.

### 2.3. Equality constraints

The equality in the OPF are defined as equality constraints:

$$P_{gi} - P_{di} = V_i \sum_{j=1}^{N_b} V_j [G_{ij}\cos(\delta_i - \delta_j) + B_{ij}\sin(\delta_i - \delta_j)]$$
$$i = 1,..., N_b \tag{5}$$

$$Q_{gi} + Q_{ci} - Q_{di} = V_i \sum_{j=1}^{N_b} V_j [G_{ij}\cos(\delta_i - \delta_j) + B_{ij}\sin(\delta_i - \delta_j)]$$
$$i = 1,..., N_b \tag{6}$$

where $N_b$ is the number of buses; $P_{di}$, $Q_{di}$ are the real and reactive power demands at bus $i$, respectively; $V_i$ is the voltage magnitude of the $i^{th}$ bus, $G_{ij}$ is the transfer conductance between bus $i$ and $j$ , $B_{ij}$ is the transfer susceptance between bus $i$ and $j$ , and $\theta_{ij}$ is the voltage angle difference between bus $i$ and $j$.

### 2.4. Inequality constraints

*a. Limits at generation buses*

$$P_{gi,\min} \le P_{gi} \le P_{gi,\max}\, ; i = 1,..., N_g \tag{7}$$

$$Q_{gi,\min} \le Q_{gi} \le Q_{gi,\max}\, ; i = 1,..., N_g \tag{8}$$

$$V_{gi,\min} \le V_{gi} \le V_{gi,\max}\, ; i = 1,..., N_g \tag{9}$$

*b. Capacity limits for switchable shunt capacitor banks*:

$$Q_{ci,\min} \le Q_{ci} \le Q_{ci,\max}\, ; i = 1,..., N_c \tag{10}$$

*c. Transformer tap settings constraints*

$$T_{k,\min} \le T_k \le T_{k,\max}\, ; k = 1,..., N_t \tag{11}$$

### 2.5. Transient stability constraints

The transient stability problem is explained through a range of algebraic equations. The oscillation equations of $i^{th}$ generator:

$$\dot{\delta}_i = \omega_i - \omega_0 \tag{12}$$

$$M_i \dot{\delta}_i = \omega_0 (P_{mi} - P_{ei} - D_i \omega_i) \tag{13}$$

where $\delta_i$ is the rotor angle of the $i^{th}$ generator, $\omega_i$ is the rotor speed of the $i^{th}$ generator, $M_i$ is the moment of inertia of the $i^{th}$ generator, $D_i$ is the damping constant of the $i^{th}$ generator, $P_{mi}$ is the mechanical input power of the $i$th generator, $P_{ei}$ is the electrical output power of the $i^{th}$ generator, and $\omega_0$ is the synchronous speed.

The position of the center of inertia (COI) is defined as follows:

$$\delta_{COI} = \frac{\sum_{i=1}^{N_g} M_i \delta_i}{\sum_{i=1}^{N_g} M_i} \tag{14}$$

The inequality constraints of the transient stability are formulated as follows:

$$\left|\delta_i - \delta_{COI}\right|_{\max} \le \delta_{\max} \qquad i = 1,..., N_g \tag{15}$$

## 3. 3. PSO ALGORITHMS FOR TSCOPF

### 3.1. Conventional Particle Swarm Optimization

Particle swarm optimization (PSO) provides a population-based search procedure in which individuals called particles change their position (state) with time. In a PSO system, particles fly around in a multidimensional search space. During the flight, each particle adjusts its position according to its own experience (personal best: pbest), and according to the experience of a neighboring particle (global best: gbest), leading to the best position encountered by itself and its neighbor [11]. The modified velocity and position of each particle are calculated:

$$v_{id}^{(k+1)} = v_{id}^{(k)} + c_1 \times rand_1 \times (pbest_{id}^{(k)} - x_{id}^{(k)}) + c_2 \times rand_2 \times (gbest_{id}^{(k)} - x_{id}^{(k)}) \quad (16)$$

$$x_{id}^{(k+1)} = x_{id}^{(k)} + v_{id}^{(k+1)} \quad (17)$$

where the constants $c_1$ and $c_2$ are cognitive and social parameters, respectively and $rand_1$ and $rand_2$ are the random values in [0, 1].

### 3.2. Concept of Pseudo-Gradient

The main idea of the pseudo-gradient is determining the direction of each individual in population based methods to solve non-convex optimization problems with non-differentiable functions [12]. The advantage of the pseudo-gradient is that it can provide a good direction in the search space of a problem without requiring the objective function to be differentiable.

For *n*-dimension optimal problem with non-differentiable function $f(x)$, the pseudo-gradient $g_p(x)$ is defined as follow [13]:

Supposed that $x_k = [x_{k1}, x_{k2}, \ldots, x_{kn}]$ is a point in the search space of the problem and it moves to another point $x_l$. There are two abilities for this movement by considering the value of the objective function at these two points.

If $f(x_l) < f(x_k)$, the direction from $x_k$ to $x_l$ is defined as the positive direction. The pseudo-gradient at point xl is determined by:

$$g_p(x_l) = [\delta(x_{l1}), \delta(x_{l2}), \ldots, \delta(x_{ln})]^T \quad (18)$$

where $\delta(x_{li})$ is the direction indicator of element xi moving from point k to point l defined by:

$$\delta(x_{li}) = \begin{cases} 1, \text{if } x_{li} > x_{ki} \\ 0, \text{if } x_{li} = x_{ki} \\ -1, \text{if } x_{li} < x_{ki} \end{cases} \quad (19)$$

If $f(x_l) \geq f(x_k)$, the direction from $x_k$ to $x_l$ is defined as the negative direction. The pseudo-gradient at point $x_l$ is determined by:

$$g_p(x_l) = 0 \quad (20)$$

From the definition, if the value of the pseudo-gradient $g_p(x_l) \neq 0$, it implies that a better solution for the objective function could be found in the next step based on the direction indicated by the pseudo-gradient $g_p(x_l)$ at point l. Otherwise, the search direction at this point should be changed due to no improvement of the objective function in this direction.

### 3.3. Improved Particle Swarm Optimization

The IPSO here is the PSO with constriction factor enhanced by the pseudo-gradient for speeding up its convergence process. The purpose of the pseudo-gradient is to guide the movement of particles in positive direction so that they can quickly move to the optimization.

In the PSO with constriction factor (Clerc & Kennedy, 2002) [14], the velocity of particles is determined as follows:

$$v_{id}^{(k+1)} = C \times \begin{bmatrix} v_{id}^{(k)} + c_1 \times rand_1 \times (pbest_{id}^{(k)} - x_{id}^{(k)}) \\ + c_2 \times rand_2 \times (pbest_{d}^{(k)} - x_{id}^{(k)}) \end{bmatrix} \quad (21)$$

$$C = \frac{2}{\left|2 - \varphi - \sqrt{\varphi^2 - 4\varphi}\right|}; \text{where } \varphi = c_1 + c_2, \varphi > 4 \quad (22)$$

The factor φ has an effect on the convergence characteristic of the system. But if the factor φ increases and makes the constriction *C* decrease producing diversification, it leads to slower convergence. Thus, the typical of factor φ is 4.1. PSO with constriction factor improved performance for a wide range of problems and was applied in various technical field.

For implementation of the pseudo-gradient in PSO, the two considered points corresponding to $x_k$ and $x_l$ in search space of the pseudo-gradient are the particle's position at iterations k and k+1 those are $x^{(k)}$ and $x^{(k+1)}$, respectively. Therefore, the updated position for particles in (17) is rewritten by:

$$x_{id}^{(k+1)} = \begin{cases} x_{id}^{(k)} + \delta(x_{id}^{(k+1)}) \times | v_{id}^{(k+1)} |, \text{ if } g_p(x_{id}^{(k+1)}) \neq 0 \\ x_{id}^{(k)} + v_{id}^{(k)}, \text{otherwise} \end{cases} \quad (23)$$

### 3.4. Implementation of IPSO for TSCOPF problem

The overall procedure of the proposed IPSO for solving the TSCOPF problem is addressed as follows:

Step 1: Input system data, contingency set; choose the controlling parameters for IPSO including number of particles NP, maximum number of iterations ITmax, cognitive and social acceleration factors $c_1$ and $c_2$

Step 2: Create initial particles' positions and velocities

Step 3: For each particle, calculate value of the dependent variables based on power flow solution and evaluate the fitness function $F_{pbestd}$. Determine the global best value of fitness function $F_{gbest}$

Step 4: Set pbest to the initial position for each particle and gbest for the best position of all particles. For transient stability violation evaluation (15), transient-stability simulation is used to produce the generator rotor responses. The maximum rotor angle deviation from the COI, among all generators and contingencies, is then used to compute a transient-stability penalty.

Step 5: Set the pseudo-gradient associated with particles to zero. Set iteration counter k = 1.

Step 6: Calculate new velocity $v^{(k)}_{id}$ and update position $x^{(k)}_{id}$ for each particle using (21) and (23), respectively.

Step 7: Solve power flow based on the newly obtained value of position for each particle.

Step 8: Evaluate fitness function for each particle with the newly obtained position. Compare the calculated FT to $FT_{pbest}$ to to update the best position of each particle.

Step 9: Pick up the best position of all particles to update the global best fitness function *FTgbest* and the global best position *gbest*

Step 10: Calculate the new pseudo-gradient for each particle based on its two latest positions corresponding to $x^{(k)}_{id}$ and $x^{(k-1)}_{id}$.

Step 11: If k < MAXITER, k = k + 1 and return to Step 6. Otherwise, stop.

A flowchart for overall procedure of the IPSO for solving the TSCOPF problem is also depicted in Fig 1.

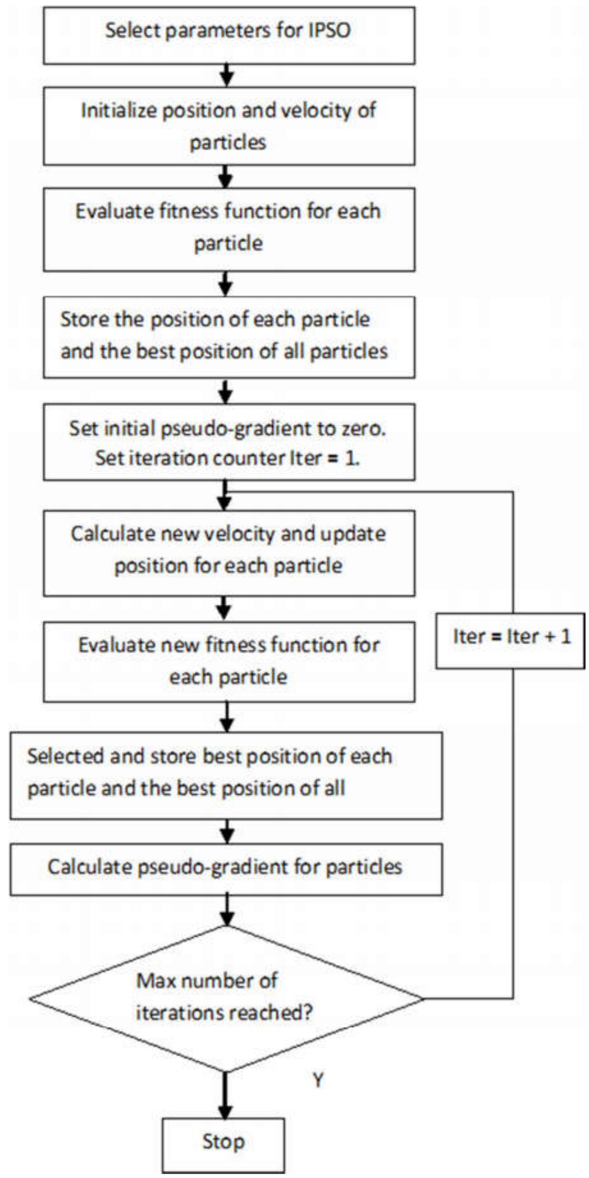


**Fig. 1. Flowchart of IPSO for TSCOPF problem.**

## 4. NUMERICAL RESULTS

The proposed IPSO is tested on WSCC 3-generator, 9-bus system, IEEE 30-bus systems. In all tested system, the upper and lower of voltage limits are set to 1.1pu and 0.95pu, respectively. The upper and lower of transformer tap changers are set to 1.1pu and 0.9pu, respectively. The transformer taps and switchable capacitor banks are discrete with a changing step of 0.01pu and 0.1MVar, respectively. The algorithm of this method was programmed by MATLAB R2009b in 2.4 GHz, i3, personal computer.

### *4.1. WSCC 3-generator, 9-bus system*

The WSCC 3-generator, 9-bus system is shown in Fig 2 and the system data are given in [2]. The upper and lower limits of all of the generator voltage magnitudes are set at 1.10 p.u. and 1.00 p.u., respectively. The upper and lower limits of the voltage magnitudes of the other buses are also set at 1.10 p.u. and 0.90 p.u., respectively. For this test system, the OPF and TSCOPF problems are solved for 2 fault cases. The step time of the integration is 10 ms for the transient stability simulation and the simulation period is taken into consideration as 5.0s. Here, $\delta_{max}$ is set to $200^0$ for the WSCC 3-generator, 9-bus system.

*Case 1:* There is no transient stability constraint in this optimization problem. The objective in this optimization problem is to minimize the total fuel cost of the entire power system to subject the generator constraints.

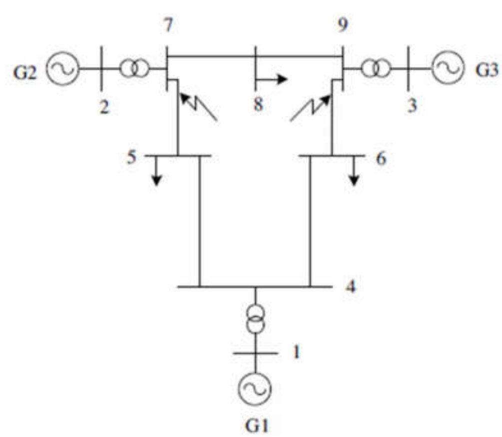


**Fig. 2. One-line diagram of the WSCC 3-generator, 9-bus system.**

The optimal power flow solution without transient stability limits has been obtained using IPSO. The main objective is to minimize the total fuel cost of the entire system. The results of the proposed algorithm are compared with the algorithms of: Differential Evolution (DE) [15], Trajectory Sensitivities (TS) [16], Time Domain Simulation (TDS) [17]. The comparison tables of the simulation results by different optimization techniques for Case 1 are given in Table1. From this table we can say that the value of the fuel cost obtained by the proposed algorithm is less than the results obtained from others in the above problem.

**Table 1: Comparision of simulation results for Case 1**

| Method | DE [15] | TS [16] | TDS [17] | IPSO |
|---|---|---|---|---|
| $P_{g1}$ (MW) | 105.94 | 106.19 | 105.94 | 106.11 |
| $P_{g2}$ (MW) | 113.04 | 112.96 | 113.04 | 114.26 |
| $P_{g3}$ (MW) | 99.29 | 99.20 | 99.24 | 96.60 |
| $V_{g1}$ *(p.u.)* | 1.05 | 1.00 | 1.05 | 1.035 |
| $V_{g2}$ *(p.u.)* | 1.05 | 1.00 | 1.05 | 1.029 |
| $V_{g3}$*(p.u.)* | 1.04 | 1.00 | 1.04 | 1.033 |
| FC ($/hr) | 1132.30 | 1132.59 | 1132.18 | 1131.75 |

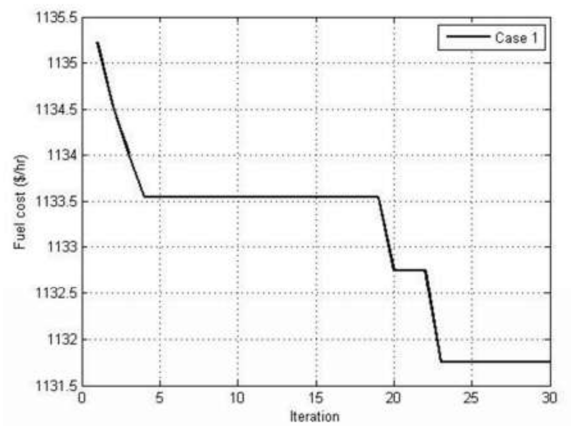


**Fig. 3. Convergence characteristics of IPSO for Case 1.**

*Case 2:* A 3-phase to ground fault at bus 7 and in line 7-5 in the system. The above fault was cleared by opening the contacts of the circuit breakers by 0.35 sec. The solution obtained from this case satisfies transient stability limit. The minimum fuel cost values and power generations are compared with other optimization methods Differential Evolution (DE) [15], Trajectory Sensitivities (TS)[16], Time Domain Simulation (TDS) [17] are given in Table 2; the convergence characteristics in Fig.4.

**Table 2: Comparision of simulation results for Case 2**

| Method | DE [15] | TS [16] | TDS [17] | IPSO |
|---|---|---|---|---|
| $P_{g1}$ (MW) | 130.94 | 170.20 | 117.85 | 116.61 |
| $P_{g2}$ (MW) | 94.46 | 48.94 | 103.50 | 105.89 |
| $P_{g3}$ (MW) | 93.09 | 98.74 | 96.66 | 93.29 |
| $V_{g1}$ *(p.u.)* | 0.9590 | 1.000 | 1.05 | 1.028 |
| $V_{g2}$ *(p.u.)* | 1.0139 | 1.000 | 1.05 | 1.068 |
| $V_{g3}$*(p.u.)* | 1.0467 | 1.000 | 1.04 | 1.056 |
| FC ($/hr) | 1140.06 | 1179.95 | 1134.01 | 1132.37 |

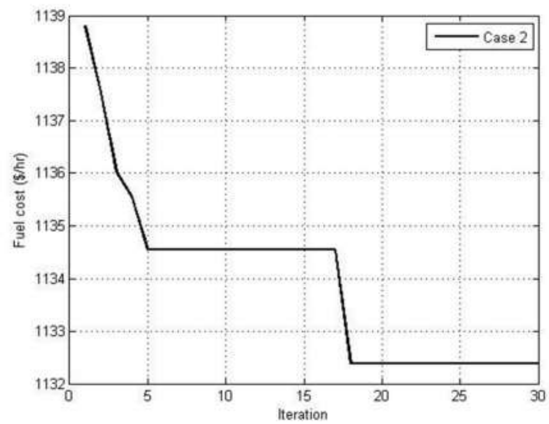


**Fig. 4. Convergence characteristics of IPSO for Case 2.**

*Case 3:* A 3-phase to ground fault at bus 9 and in line 9-6 in the system. The above fault was cleared at 0.3sec by opening the contacts of the nearby circuit breakers. Here also, the minimum fuel cost values and power generations are compared with other optimization methods: Differential Evolution (DE) [15], Trajectory Sensitivities (TS)[16], Time Domain Simulation (TDS) [17] given in Table 3. From there, it is observed that the fuel cost values and power generations obtained by the proposed method are less than those others. The convergence characteristic is shown in Fig 5.

**Table 3: Comparision of simulation results for Case 3**

| Method | DE [15] | TS [16] | TDS [17] | IPSO |
|---|---|---|---|---|
| $P_{g1}$ (MW) | 130.01 | 164.38 | 120.01 | 120.23 |
| $P_{g2}$ (MW) | 127.17 | 112.44 | 121.13 | 119.83 |
| $P_{g3}$ (MW) | 60.72 | 41.00 | 76.84 | 76.95 |
| $V_{g1}$ *(p.u.)* | 1.0495 | 1.000 | 1.05 | 1.019 |
| $V_{g2}$ *(p.u.)* | 1.0481 | 1.000 | 1.05 | 1.039 |
| $V_{g3}$*(p.u.)* | 1.0327 | 1.000 | 1.04 | 1.024 |
| FC ($/hr) | 1148.58 | 1179.95 | 1137.82 | 1135.25 |

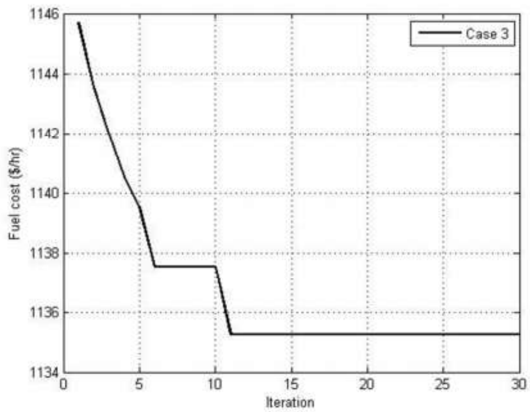


**Fig. 5. Convergence characteristics of IPSO for Case 3.**

### *4.2. IEEE 30-bus system*

The IEEE 30-bus test system contains 41 transmission lines, 6 generators, and 4 transformers, as shown in Figure 6. The system data were taken from [18] and the data for the generators in the test system are given in Table 3. The total active load and reactive load of the system is 189.2 MW and 107.2 MVar, respectively. Here, $\delta_{max}$ is set to $50^0$ for the IEEE 30-bus system.

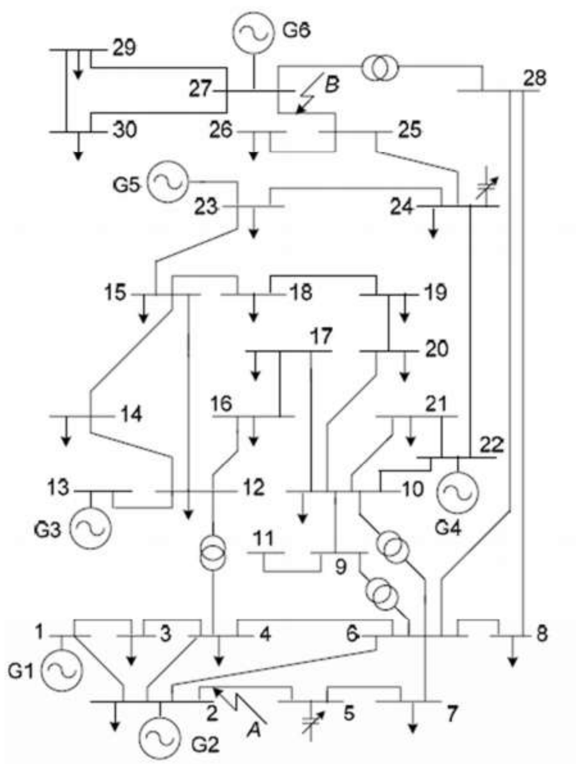

**Fig. 6. IEEE 30-bus system one-line diagram.**

The following fault case is studied for the test system:

*Case 4*: A 3-phase to ground fault at bus 2 and in line 2-5 in the system. The fault clearing time is taken as 0.18 s. The step time of the integration is at 10 ms for the transient stability simulation and the simulation period is taken into consideration as 5.0s. The obtained solutions are compared with other optimization methods: Genetic algorithm (GA) [7], Evolutionary programming (EP) [19]. From this Table 4 we can say that the value of the fuel cost obtained by the proposed algorithm is less than the results obtained from other two. The convergence characteristic is shown in Fig 7.

**Table 4: Comparision of simulation results for Case 4**

| Method | GA [7] | EP [19] | IPSO |
|---|---|---|---|
| $P_{g1}$ (MW) | 41.88 | 50.25 | 41.10 |
| $P_{g2}$ (MW) | 56.38 | 38.86 | 58.32 |
| $P_{g3}$ (MW) | 22.94 | 17.96 | 25.39 |
| $P_{g4}$ (MW) | 37.63 | 27.33 | 32.49 |
| $P_{g5}$ (MW) | 16.7 | 20.29 | 18.24 |
| $P_{g6}$ (MW) | 16.53 | 37.25 | 16.34 |
| $T1$ (buses 6–9) | 1.01 | 1.02 | 1.01 |
| $T2$ (buses 6–10) | 0.95 | 0.99 | 0.96 |
| $T3$ (buses 4–12) | 1.00 | 0.97 | 1.01 |
| $T4$ (buses 27 and 28) | 0.97 | 1.04 | 0.97 |
| FC ($/hr) | 585.62 | 585.83 | 585.10 |

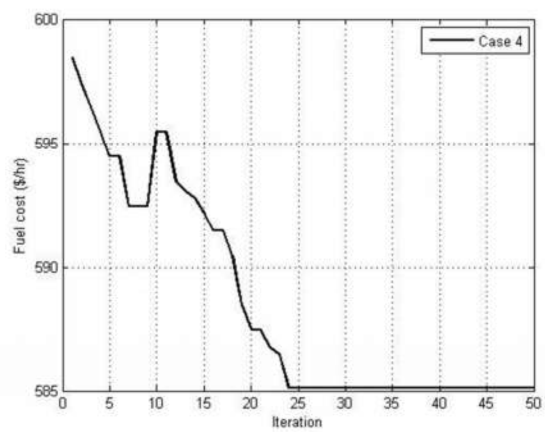


**Fig. 7. Convergence characteristics of IPSO for Case 4.**

## 5. CONCLUSION

The proposed IPSO method has been efficiently implement for solving the TSCOPF. The proposed IPSO method is a simple improvement from the PSO method with constriction factor by integrating the pseudo-gradient in to particle's velocity to enhance its search capability. The pseudo-gradient speeds up particles in search space in case they are on a right direction. Simulations are carried out with WSCC 3-generator, 9-bus system, IEEE 30-bus systems then compared with other methods. The results obtained by the proposed method outperform the other methods in terms of solution quality and computation efficiency. Therefore, the proposed PG-PSO could be a useful and favorable method for solving the non-differentiable problem in power systems.

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