MAXIMUM LOADING ENHANCEMENT BY DIFFERENTIAL EVOLUTION PARTICLE SWARM OPTIMIZATION BASED OPTIMAL POWER FLOW SOLUTION

By

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ABSTRACT

Maximum Loadability Limit (MLL) is the margin between the operating point of the system and the maximum loading point. The enhancement of maximum loadability limit of power system can be formulated as an optimization problem, which consists of two steps namely computing MLL and the optimum cost of generation for MLL. This paper proposes a Differential Evolution Particle Swarm Optimization (DEPSO) algorithm for solving the optimal power flow problem for MLL enhancement with voltage stability constraint. The DEPSO employs features of both differential evolution (DE) and Particle Swarm Optimization (PSO) for the development of hybrid algorithm. The feasibility of the proposed approach was tested on IEEE 30-, 57-bus test systems. Case studies were investigated to test and validate the robustness of the proposed method in finding optimal solution. Simulation results demonstrate that the DEPSO provides very remarkable results compared to original DE,PSO and other methods reported in the literature recently.

Keywords: Differential Evolution, Optimal Power Flow, Particle Swarm Optimization, Generation Cost, Voltage Stability Index.

INTRODUCTION

In the present day modern power systems, an important tool for power system operators both in planning and operating stages is Optimal Power Flow (OPF). The main purpose of an OPF is to determine the optimal operating state of a power system and the corresponding settings of control variables for economic operation, while at the same time satisfying various equality and inequality constraints. The equality constraints are the power flow equations, while the inequality constraints are the limits on control variables and the operating limits of power system dependent variables. The OPF problem, in general, is a large-scale highly constrained nonlinear non-convex optimization problem.

1. Literature Review

Many mathematical programming techniques [1-10] such as Linear Programming [LP], nonlinear programming (NLP), Quadratic Programming (QP), Newton method, and Interior Point Methods (IPM) have been applied to solve the OPF problem successfully. However, these classical optimization methods are limited in handling algebraic functions. Usually, these methods rely on the assumption that the fuel cost characteristic of a generating unit is a smooth, convex function. However, there are situations where it is not possible, or appropriate, to represent the unit's fuel cost characteristics as convex function.

The problem of voltage stability is one of the main concerns in the operation of power system. There are different approaches to estimate the voltage stability of the systems. Estimating the maximum loadability limit of power system is one of the approaches. Maximum loadability limit is the margin between the operating point of the system and the maximum loading point. The maximum loadability limit problem has been formulated as a non-linear optimization problem. Various mathematical techniques to solve maximum loadability limit can be categorized as,

- Continuation Power Flow method (CPF),

- Successive Quadratic Programming (SQP),
- Interior Point method (IP),
- Repetitive Power Flow Solution.

If the system is already near the maximum loading point, the continuation power flow technique [11] may face some convergence problems. The SQP [12] approach uses the second order derivatives to improve the convergence rate. These methods become too slow as the number of control variables becomes very large. Interior point methods [12] are computationally efficient.

However, if the step size is not chosen properly, the sub-linear problem may have a solution that is infeasible in the original non-linear domain. Another technique is the repetitive power flow solution [13] by increasing the load on the system in some direction in steps and solving the load flow at each step until the load flow solution diverges. The divergence of the load flow [14] does not represent the maximum loading point. In general, conventional optimization methods are not able to locate global optimum, can only lead to a local optimum and sometimes result in divergence.

In the recent past, evolutionary techniques have been developed to solve MLL problem. The premature convergence of genetic algorithm (GA) [15] degrades its performance and reduces its search capability, which leads to a higher probability towards obtaining a local optimum. The Particle Swarm Optimization (PSO) technique [16-17] can generate high quality solutions within short calculation time and have more global searching ability at the beginning of the run and a local search near the end of the run. A Hybrid Particle Swarm Optimization (HPSO) [18] adds breeding and subpopulation process of GA to PSO. It can jump from the current searching point into the effective area directly by the breeding and subpopulation process to reach a better optimum solution than the standard PSO.

Recently, power full evolutionary algorithm such as Differential Evolution (DE) technique is employed for power system optimization problems. Differential evolution, developed by Storn and Price [19], is a numerical optimization approach that is simple, easy to implement, significantly faster and robust. DE combines simple arithmetic operators with the classical operators of crossover mutation and selection to evolve from a randomly generated starting population to a final solution. The fittest of an offspring competes one-to-one with that of corresponding parent, which is different from the other evolutionary algorithms. This one-to-one competition gives rise to faster convergence rate.

In this paper, an efficient Differential Evolution Particle Swarm Optimization (DEPSO) based approach is proposed to solve the OPF problem to enhance the maximum loadability limit with voltage stability constraints. The proposed DEPSO method has been applied on IEEE 30-, and IEEE 57-bus standard test systems. Simulation results demonstrate that the DEPSO algorithm is superior to the original DE and PSO and provides very remarkable results compared to those reported in the literature.

The remainder of the paper is organized as follows Section 1 describes the formulation of an optimal power flow problem, while section 2 explains the DEPSO approach. Section 3 details the procedure of proposed DEPSO and Section 4 presents the results of the proposed optimization methods to solve the case studies of optimal power flow problems on IEEE 30–bus and IEEE 57- bus test systems. Last section outlines the conclusion.

1. Problem Formulation

The main goal of OPF is to optimize a certain objective subject to several equality and inequality constraints. The problem can be mathematically modeled as follows,

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

subject to

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

$$h_{min} \leq h(x,u) \leq h_{max} \tag{3}$$

where vector x denotes the state variables of a power system network that contains the slack bus real power output (P_{G1}), voltage magnitudes and phase angles of the load buses ($Vi,\delta i$) and generator reactive power outputs (Q_G) Vector u represents control variables that consist of real power generation levels (P_{GN}) and generator voltages magnitudes ($|V_{GN}|$) transformer tap setting (T_K) and reactive power injections (Q_{CK}) due to volt-amperes reactive (VAR) compensations; i.e.,

$$u = [P_{G2}.......P_{GN}, V_{G1}.......V_{GN}, T_1.......T_{NT}, Q_{C1}.......Q_{CS}] \quad (4)$$

Where

N = number of generator buses,

NT = number of tap changing transformers

CS = number of shunt reactive power injections.

The OPF problem has two categories of constraints:

1.1. Objective functions

The first objective is to maximize the active power load applied to the transmission network. The second objective is to find the optimal power flow solution for the maximum loadability limit.

Objective I:

$$\text{Maximize } F_1 = \lambda \quad (5)$$

Where λ is the loading factor, which represents the increase in the system load from base case without violating the voltage limit. The load at all the load buses are increased in steps from base case to maximum loading point until the load flow solution diverges, whose load model is given as below:

$$P_{Di} = P_{Di,0}(1 + K_i) \quad (6)$$

Objective II:

$$Minimize\ F_2 = \sum_{j=1}^{n} F_{cj}(P_j) \quad (7)$$

Where $F_{cj}(P_j)$ is the fuel cost function of unit j and P_j is the real power generated by the unit j, The fuel cost function of the generating unit j is given by

$$F_{ci}(P_{gi}) = a_i P^2_{gi} + b_i P_{gi} + _{ci} \quad (8)$$

Where a_i, b_i and c_i are the fuel cost coefficients of generating unit I.

The maximization of the above function is subjected to number of constraints;

Equality Constraints,

1. These are the sets of nonlinear power flow equations that govern the power system, i.e,

$$P_{Gi} - P_{Di} - \sum_{j=1}^{n} |V_i||V_j||Y_{ij}| \cos(\theta_{ij} - \delta_i + \delta_j) = 0 \quad (9)$$

$$Q_{Gi} - Q_{Di} + \sum_{j=1}^{n} |V_i||V_j||Y_{ij}| \sin(\theta_{ij} - \delta_i + \delta_j) = 0 \quad (10)$$

where P_{gi} and Q_{gi} are the real and reactive power outputs injected at bus I respectively, and P_{Di} and Q_{Di} are the real and reactive power outputs injected at bus P_{Di} and Q_{di} and elements of the bus admittance matrix are represented by $|Y_{ij}|$ and θ_{ij}.

2. Power balance constraints,

$$P_{d,\max} = \sum_{j=1}^{n} P_j - P_L \quad (11)$$

where $P_{d,max}$ is the maximum loadability limit and P_L is the transmission loss.

Inequality Constraints: These are the set of constraints that represent the system operational and security limits like the bounds on the following:

3. Generators real outputs

$$P_{Gi}^{\min} \le P_{Gi} \le P_{Gi}^{\max}, i = 1, \ldots, N \quad (12)$$

4. Voltage magnitudes at each bus in the network

$$V_i^{\min} \le V_i \le V_i^{\max}, i = 1, \ldots, NL \quad (13)$$

5. Transformer tap settings

$$T_i^{\min} \le T_i \le T_i^{\max}, i = 1, \ldots, NT \quad (14)$$

6. Reactive power injections due to capacitor banks

$$Q_{Ci}^{\min} \le Q_{Ci} \le Q_{Ci}^{\max}, i = 1, \ldots, CS \quad (15)$$

7. Transmission lines loading

$$S_i \le S_i^{\max}, i = 1, \ldots, nl \quad (16)$$

Since voltage instability occurs when the system attains low voltages at load buses, the voltage stability L-index [20] is incorporated as an inequality constraint.

8. Voltage stability index

$$Lj_i \le Lj_i^{\max}, i = 1, \ldots, NL \quad (17)$$

9. Real power load limit

$$P_{L,k} \le P_{L,k}^{\max} \quad for \quad k = 1,2,.....,L \quad (18)$$

The maximization of objective function I and minimization of objective function II are simultaneously obtained by incorporating them in the fitness functions as follows:

$$fit = F_1 + \sum_{k=1}^{L} K_p (P_{L,K} - P_{L,K}^{\max})^2 + \left(1 \Big/ \left(F_2 + \sum_{j=ng+1}^{nb} K_v (V_j - V_j^{\lim})^2 + \sum_{j=ng+1}^{nb} K_l (L_j - L_j^{\lim})^2)\right)\right) \quad (19)$$

where λ_{vi} and $\lambda_{L,K}$ are the penalty factors.

$V_i^{\lim}$ and $L_j^{\lim}$ are defined as

$$\left.\begin{aligned} V_i^{\lim} &= V_i^{\max} \quad for \quad V_i > V_i^{\max} \\ V_i^{\lim} &= V_i^{\min} \quad for \quad V_i < V_i^{\min} \\ L_j^{\lim} &= L_j^{\max} \quad for \quad L_j > L_j^{\max} \end{aligned}\right\} \quad (20)$$

In the maximum loadability problem, the equality constraints are satisfied by running the power flow program. The generator bus real power generations (P_{gi}), generator terminal voltages (V_{gi}), transformer tap settings (T_i), the reactive power generation of capacitor bank (Q_{ci}), are the control variables and they are self-restricted by the representation itself. The active power generation at the slack bus (P_{gs}), load bus voltages (V_{li}), real power loads ($P_{l,k}$), and line flows (S_l), and voltage stability (L_j) index are state variables which are restricted through penalty function approach.

2. Algorithm

2.1. Particle Swarm Optimization

Particle swarm optimization is an evolutionary algorithm developed by Eberhart and Kennedy in 1995 [21]. It is a population based search algorithm and is inspired by the observation of natural habits of bird flocking and fish schooling. In PSO, a swarm of particles moves through a D dimensional search space. The particles in the search process are the potential solutions, which move around the defined search space with some velocity until the error is minimized or the solution is reached, as decided by the fitness function.

The particles reach to the desired solution by updating their position and velocity according to the PSO equations. In PSO model, each individual is treated as a volume-less particle in the D-dimensional space, with the position and velocity of i^{th} particle represented as:

$$X_i = (x_{i1}, x_{i2}, \ldots, x_{iD}) \quad (21)$$

$$V_i = (V_{i1}, V_{i2}, \ldots, V_{iD}) \quad (22)$$

$$V_{id} = \omega * V_{id} + c_1 * rand_1() * (P_{id} - X_{id}) + c_2 * rand_2() * (P_g - X_{id}) \quad (23)$$

$$X_{id} = x_{id} + V_{id} \quad (24)$$

These particles are randomly distributed over the search space with initial position and velocity. They change their positions and velocity according to (23) and (24) where c_1 and c_2 are cognitive and social acceleration constants, $rand_1()$ and $rand_2()$ are two random functions uniformly distributed in the range of [0,1] and ω is the inertia weight introduced to accelerate the convergence speed of PSO [21].

Vector $P_i = (P_{i1}, P_{i2}, \ldots, P_{iD})$ is the best previous position (the position giving the best fitness value) of particle i called the pbest, and vector $P_g = (P_{g1}, P_{g2}, \ldots, P_{gD})$ is the position of the best particle among all the particles in the population and is called the gbest. X_{id}, V_{id}, P_{id} are the d^{th} dimension of vector of X_i, V_i, P_i

2.2. Differential Evolution

Differential evolution was introduced by Storn and Price in 1995 [22-23]. It is yet another population based stochastic search technique for function minimization. In DE, the weighted difference between the two population vectors is added to a third vector and optimized using selection, crossover and mutation operators as in GA. Each individual is first mutated according to the difference operation. This mutated individual, called the offspring, is then recombined with the parent under certain criteria such as crossover rate. Fitness of both the parent and the offspring is then calculated and the offspring is selected for the next generation only if it has a better fitness than the parent [24].

2.3. Differential Evolution Particle Swarm Optimization

A hybrid of DE and PSO gives a new method of optimization called the differential evolution particle swarm optimization [25]. In DEPSO, new offspring is created by the mutation of the parent. In this paper gbest has been taken as the parent and a Gaussian distribution has been considered. For mutation, 4 particles are randomly chosen from the population. The weighted error between these particles' positions is used to mutate the parent and create an offspring [26-27]. The mutation takes place according to (25).

If (rand() < CR OR d == k)

then
$$T_{id} = P_{gd} + \delta_{2,d} \quad (25)$$

$$\delta_{2,d} = \frac{(P_{1,d} - P_{2,d}) + (P_{3,d} - P_{4,d})}{2} \quad (26)$$

where $\delta_{2,d}$ is the weighted error in different dimensions, T_{id} is the offspring and P_{gd} is the gbest position of the parent. The mutation takes place under the condition when a random number between [0,1] is less than the reproduction rate CR or the particles position in any one randomly chosen dimension, k is mutated. This ensures that offspring is never same as the parent. Then the fitness of the offspring is evaluated and the offspring replaces the parent only if it has a better fitness than the parent, otherwise the parent is retained for the next iteration [25]. Basic flowchart for DEPSO is given in Figure 1.

3. Algorithm for Optimum Cost of Generation for MLL using DEPSO

The objective function is to maximize the load and to minimize the cost of generation using HPSO. Load is assumed as the particle to be optimized. Either maximum number of iterations or the maximum value of load without violating the voltage constraints is set as a stopping criterion.

Following is the DEPSO algorithm for optimal power flow for MLL of power system.

Step 1: Input parameters of system and algorithm and specify the lower and upper boundaries of each variable.

Step 2: Generate n number of particles, i.e., the parameters to be optimized.

Step 3: Evaluate the fitness value of each particle based on the Newton–Raphson power flow analysis.

Step 4: Update the time counter $t = t + 1$.

Step 5: Execute PSO operator on the particles.

Step 6: Update the velocity of each particle in PSO.

Step 7: Perform the breeding and subpopulation process to replace the worst particles, i.e., particles with low fitness value according to the Eqs. (11) and (12). Breeding is performed between two best parents.

Step 8: If one of the stopping criteria is satisfied, then go to Step 9. Otherwise go to Step 4.

Step 9: Output the particle with the maximum fitness value in the last generation.

4. Simulation Results and Discussion

4.1. Results of IEEE 30-bus Test System

The proposed algorithm was implemented in MATLAB computing environment with Pentium-IV, 2.66 GHz computer with 512 MB RAM. The standard IEEE 30-bus test system was used to test effectiveness of DEPSO approach. The test system consists of six generating units interconnected with 41 branches of a transmission network with a total load of 283.4 MW and 126.2 Mvar as shown in Figure 2. The bus data and the branch data are taken from the ref. [48]. The original system has two capacitors banks installed at bus 5 and 24 with ratings of 19 and 4 MVAR respectively. These capacitor banks are not considered in this work, rather the shunt injections are

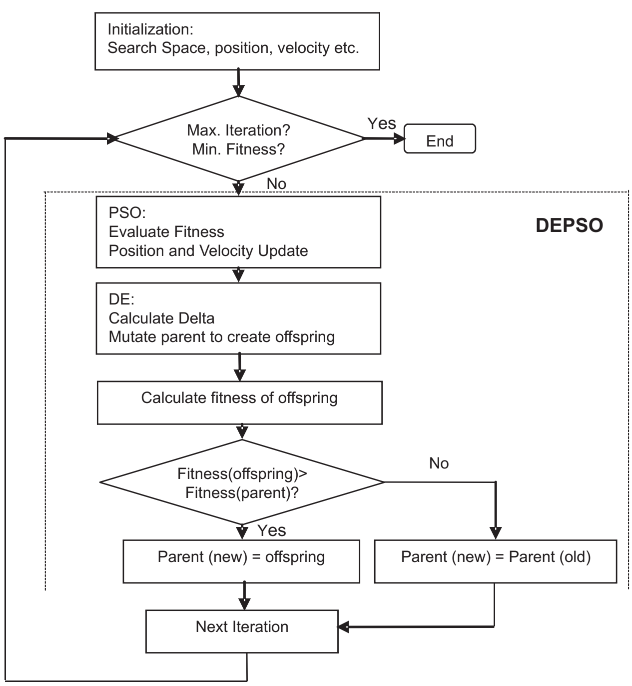

Figure 1. Basic Flowchart showing the DEPSO Algorithm

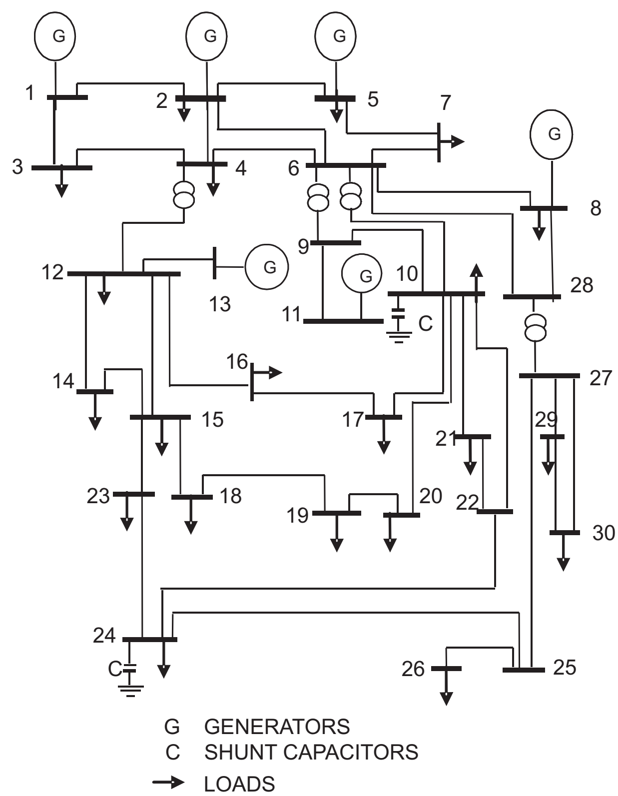

Figure 2. Single Line Diagram of IEEE 30-Bus Test System

provided at buses 10, 12, 15, 17, 20, 21, 23, 24 and 29 as given in [49]. In this case study, bus 1 is considered as the swing bus.

The maximum and minimum values for the generator voltage and tap changing transformer control variables are 1.1 and 0.9 in per unit respectively. The maximum and minimum voltages for the load buses are considered to be 1.05 and 0.95 in per unit. The line flow limits are taken from [48]. The voltage stability index is considered from [50]. In this simulation study, minimization of fuel cost objective with voltage stability constraint is considered to test the performance of the proposed algorithm. The objective function is augmented with the equality, inequality, and voltage stability constraints.

In the case study, two sets of 20 test runs for solving the OPF problem, were performed; the first set DEPSO/PSO based economic dispatch algorithm and the second one DEPSO/PSO based OPF.

Nowadays the interconnected power systems are being operated under stressed conditions which impose threat to voltage stability due to low voltages. Hence, the voltage stability index is incorporated as an inequality constraint in the OPF problem. The proposed method uses L-index to assess how far is the threat to the system from voltage instability [20].

The initial load, total generations and power losses for modified IEEE 30 bus system are given as follows: (Figures 3-6, Table 1).

Parameter		Economic Dispatch		OPF	
		DEPSO	PSO	DEPSO	PSO
Real Powers settings	P_{G1}	0.5689	0.5689	0.5598	0.5613
	P_{G2}	0.7216	0.7216	0.7251	0.7237
	P_{G3}	0.2551	0.2551	0.2758	0.2803
	P_{G4}	0.2621	0.2621	0.2748	0.2749
	P_{G5}	0.2551	0.2551	0.2718	0.2671
	P_{G6}	0.5500	0.5500	0.5500	0.5500
Voltages settings	V_{G1}	-	-	1.0685	1.0696
	V_{G2}			1.0644	1.0644
	V_{G3}			1.0995	1.1000
	V_{G4}			1.0443	1.0420
	V_{G5}			1.0573	1.0529
	V_{G6}			1.0656	1.0666
Tap settings	Tap-1	-	-	0.9700	1.0300
	Tap-2			1.0200	0.9300
	Tap-3			1.0500	1.0500
	Tap-4			1.0900	1.0900
Shunt comp	Q_{SVC2}	-	-	0.0600	0.0600
	Q_{SVC1}			0.1200	0.1200
Cost ($/hr.)		854.6571	854.6571	873.9358	873.9534
P Loss(p.u.)		-	-	0.0444	0.0444
Lj^2sum		-	-	0.0501	0.0502

Table 1. Optimal Settings of Control Variables for IEEE 30-Bus System (λ=1.381)

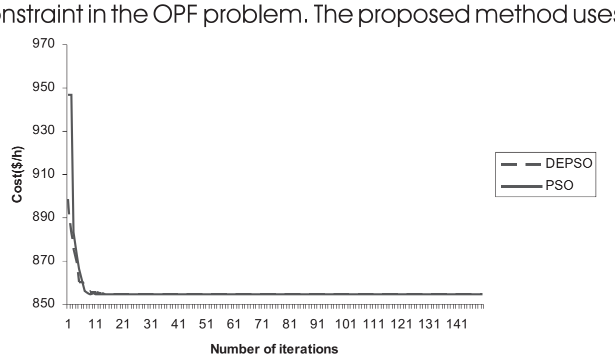

Figure 3. Convergence of Cost of Generation for IEEE 30-Bus System (Economic Dispatch)

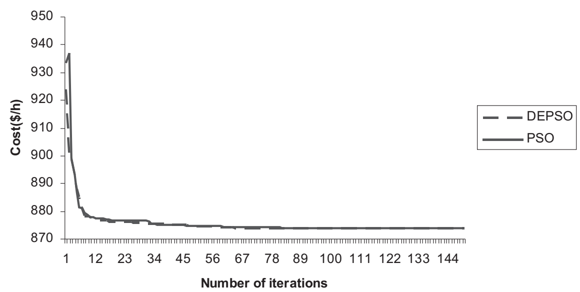

Figure 4. Convergence of Cost of Generation for IEEE 30-Bus System (OPF)

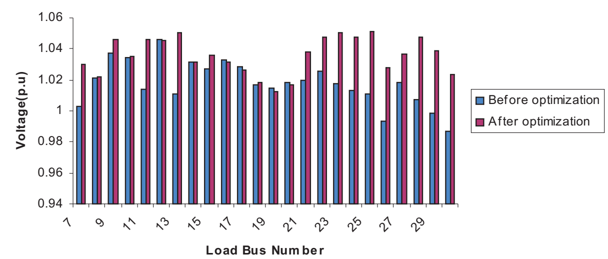

Figure 5. Bus Voltage Profiles for IEEE 30-Bus System

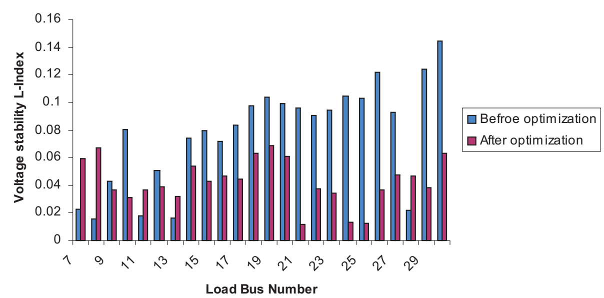

Figure 6. Voltage Stability Indices for IEEE 30-Bus System

P_{load} = 1.8920 p.u.; Q_{load} = 1.0720 p.u.; $\sum P_G$ = 1.9164 p.u.; $\sum Q_G$ = 1.0041p.u.; P_{loss} = 0.0244 p.u.; Q_{loss} = 0.0899 p.u.;

Maximum loadability limit for modified IEEE 30-bus system by DEPSO OPF solution is 2.6129 p.u.

4.2. IEEE 57-Bus System Results

The proposed algorithms for solving optimal power flow problems for MLL enhancement are applied on IEEE 57-bus system as shown in Figure 7. The system data is taken from [29]. The network consists of 80 branches, 7 generator buses, 50 load buses, and seventeen tap changing transformers. The possible shunt reactive power source installation buses are 18, 25 and 53. The continuous control variables in this study are treated same as in the previous case studies. All load bus voltages are required to be maintained within the range of 0.95–1.1 p.u.

The initial load, total generations and power losses for IEEE 57 bus system are given as follows: (Figures 8-11, Table 2).

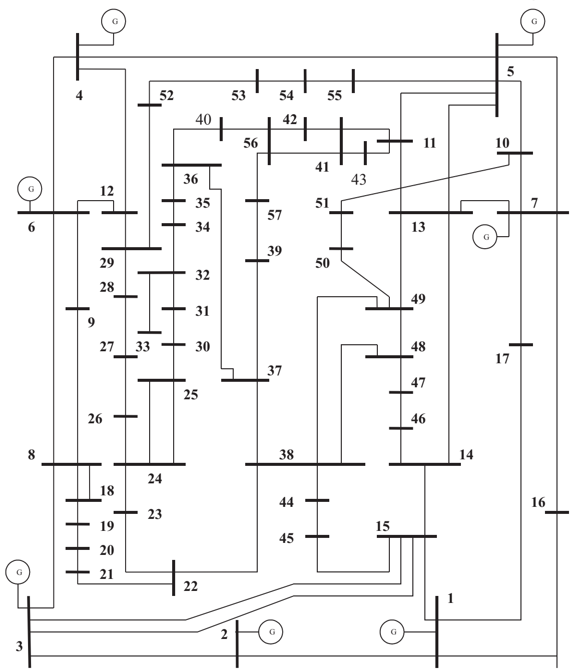

Figure 7. Network Diagram of IEEE 57-Bus System

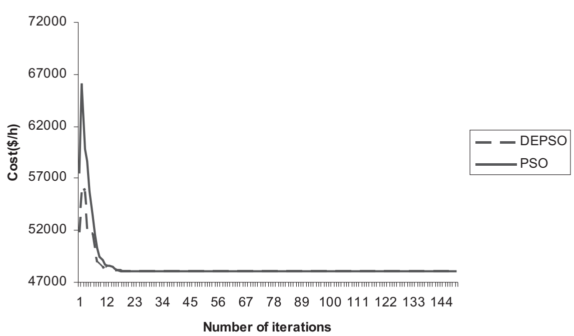

Figure 8. Convergence of Cost of Generation for IEEE 57-Bus System (Economic Dispatch)

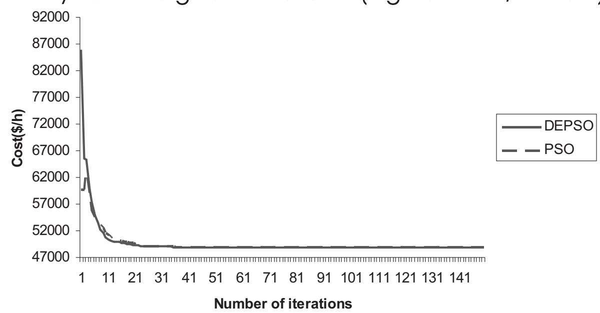

Figure 9. Convergence of Cost of Generation for IEEE 57-Bus System (OPF)

Parameter		Economic Dispatch		OPF	
		DEPSO	PSO	DEPSO	PSO
Real Powers settings	P_{G1}	1.3987	1.3986	1.4568	1.4659
	P_{G2}	0.8507	1.0000	1.0000	1.0000
	P_{G3}	0.4340	0.4340	0.4698	0.4628
	P_{G4}	5.5000	5.5000	5.5000	5.5000
	P_{G5}	0.8507	0.8507	1.0000	1.0000
	P_{G6}	1.0000	0.8507	0.8133	0.8114
	P_{G7}	4.1000	4.1000	4.1000	4.1000
Voltages settings	V_{G1}			1.0718	1.0563
	V_{G2}			1.0769	1.0606
	V_{G3}	-	-	1.0639	1.1518
	V_{G4}			1.1000	1.0880
	V_{G5}			1.0866	1.0716
	V_{G6}			1.0718	1.0663
	V_{G7}			1.0625	1.0494
Tap settings	Tap-1			1.0500	0.9800
	Tap-2			0.9900	0.9800
	Tap-3			1.0000	1.0200
	Tap-4			0.9200	0.9000
	Tap-5			0.9000	1.0000
	Tap-6			1.0400	1.0300
	Tap-7			0.9900	0.9900
	Tap-8			0.9700	0.9700
	Tap-9	-	-	0.9900	0.9800
	Tap-10			0.9800	0.9700
	Tap-11			0.9700	0.9600
	Tap-12			1.0000	0.9800
	Tap-13			0.9400	0.9300
	Tap-14			1.0300	0.9800
	Tap-15			0.9900	1.0800
	Tap-16			1.0100	1.0000
	Tap-17			1.0200	1.0000
	Q_{SVC1}			0	0
	Q_{SVC2}	-	-	0.1200	0.1200
	Q_{SVC3}			0.0600	0.1200
Cost ($/hr.)		48049	48049	48915	48916
P Loss(p.u.)		-	-	0.2058	0.2060
Lj^2sum		-	-	1.1969	1.1430

Table 2. Optimal Settings of Control Variables for IEEE 57-Bus System (λ=1.130)

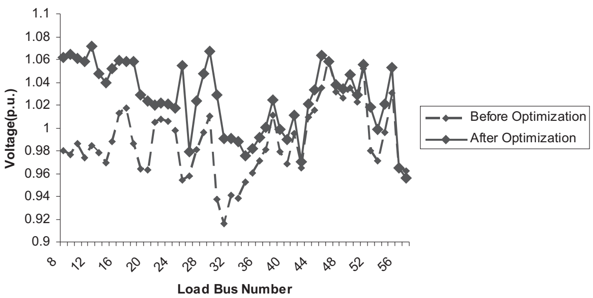

Figure 10. Bus Voltage Profiles for IEEE 57-Bus System

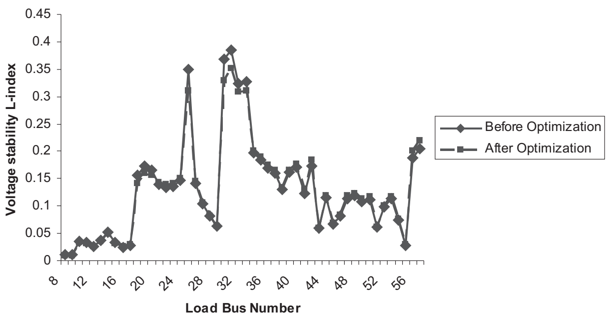

Figure 11. Voltage Stability Indices for IEEE 57-Bus System

Algorithm		Pdmax (p.u)	Percentage rise of MLL (%)	Convergence iteration number/time(s)
IEEE 30-bus system	PSO[30]	2.601001	5.7489	37/61.3615
	HPSO[30]	2.603455	5.8487	24/39.8020
	DEPSO	2.612900	5.8841	11/25.1235
IEEE 57-bus system	PSO[30]	14.039	2.035	39/67.2340
	HPSO[30]	14.062	2.2021	29/58.1046
	DEPSO	14.125	2.2120	15/30.2456

Table 3. Comparison of MLL for Modified IEEE 30- and 57-Bus Test Systems

$P_{load} = 12.5$ p.u.; $Q_{load} = 3.364$ p.u.; $\sum P_G = 12.7866$ p.u.; $\sum Q_G = 3.2108$ p.u.; $P_{loss} = 0.27864$ p.u.; $Q_{loss} = 1.2167$ p.u.;

Maximum loadability limit for IEEE 57-bus system by DEPSO OPF solution is 14.1250 p.u.13.759 p.u.

For comparison purposes, MLL and optimum cost of generation of modified IEEE 30 bus, and IEEE 57 bus systems are tabulated in Table 3. From Table 3, it can be observed that MLL by DEPSO is greater than HPSO and PSO with less convergence time. The convergence characteristics for DEPSO and PSO for modified IEEE 30 bus and IEEE 57 bus systems are given in Figures 3–4, and 8-9 respectively. DEPSO converges faster than PSO for modified IEEE 30 bus system, and IEEE 57 bus systems. From Tables 1–3, it is observed that the optimum cost of generation by DEPSO is less than HPSO and PSO with less computation time. The bus voltage profiles and voltage stability indices for DEPSO for modified IEEE 30 bus and IEEE 57 bus systems are given in Figures 5–6, and 10-11 respectively. On the whole, it is clear that DEPSO converges at better optimum solution with less execution time.

Conclusion

In this paper, a novel differential evolution particle swarm optimization (DEPSO) approach has been presented for solving the OPF problem with voltage stability constraint with different inequality constraints for maximizing the loadability. The DEPSO algorithm effectively solves the OPF problem with loading factor and voltage stability constraints. The results clearly indicate that better solutions are obtained using this approach when compared with other methods reported in the literature. Simulation results show that the DEPSO is superior to the original PSO and DE algorithms with regard to the convergence to the global optimum. The proposed approach has been successfully and effectively implemented to find the optimal settings of the control variables of the IEEE 30 and 57 –bus test systems.

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