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Transmission Line Management Using Hybrid Differential Evolution with Particle Swarm Optimization

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This paper proposes an application of hybrid differential evolution with particle swarm optimization (DEPSO) for transmission line management in power system network. Generation rescheduling is performed to reinstate the system from abnormal to normal operating condition. The identification of overloaded lines is based on computation of overload factor (OLF). The objective of the proposed approach is to alleviate the transmission line overload by reducing severity index (SI) subjected to the power balance, voltage and generator limit constraints. The effectiveness of the proposed approach is demonstrated for different contingency cases in IEEE 30 and IEEE 118 bus systems in MATLAB environment and their results are compared with other evolutionary algorithms like Particle swarm optimization (PSO) and Differential evolution (DE). The results show DEPSO approach well proves its ability to remove the line overloads with a minimum rescheduling cost.

Keywords: Generation Rescheduling; Particle Swarm Optimization; Differential Evolution, Severity Index; Overload Management.

1. Introduction

Overloading of a transmission network in a power system can occur due to the lack of coordination between generation and transmission utilities or as a result of unexpected contingencies such as sudden increase of load demand, outage of transmission lines, transformers, generators, etc. When overloading in a power system occurs, protection and control actions are required to stop the power system's degradation. The aim of corrective control strategy is to avoid cascading outages or system collapse, and to maintain system reliability. The possible corrective control actions to relieve the overload are real power generation rescheduling, phase shifting transformers, line switching and load shedding. The use of phase shifting transformers, line switching and load shedding leads to additional reserves and interruption of power supply. The real power generation rescheduling is the most widely used control for network overload alleviation because of ease of control and require no additional reserves.

In [1], the authors' proposed a directed acyclic graph concept for the computation of generator rescheduling dispatch. The real power transfer between generator and loads were analyzed using graph theory approach. This approach uses the concept of 'reach of a generator' and 'generator area and links' and maintains secured operating state of the power system ignoring optimality of the operating points. In [2], the authors' proposed an use of genetic algorithm (GA) and multi-objective genetic algorithm (MOGA) to alleviate the violations of the overloaded lines and minimize the transmission line losses for different operating conditions. The minimization of transmission power losses and power flows in critical lines were considered as major objectives. In [3] the authors' proposed an application of multi-objective genetic algorithm (MOGA) to solve the security enhancement problem. The decision variables considered were generator active power,

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generator bus voltage magnitude and the reactance of thyristor controlled series capacitors (TCSC). The TCSC locations were identified based on the computation of line overload sensitivity Index (LOSI). In [4], the authors' proposed, particle swarm optimization with time-varying acceleration coefficients (PSO-TVAC) approach for optimal congestion management. The redispatched generators were selected based on the large magnitude of generator sensitivity. In [5], the authors' proposed, fuzzy inference based generator active power rescheduling for network congestion under normal/contingency conditions. The network congestions were managed using counter flow information obtained from the tracing of network virtual flows due to various sources. In [6], the authors' proposed an alleviation of overloads by redispatch of generators with minimum rescheduling cost. The optimal rescheduling of active powers of generators were selected based on the generator sensitivity to the congested line, utilizing fuzzy adaptive bacterial foraging (FABF) algorithm. In [7], the authors' proposed, multi-objective particle swarm optimization (MOPSO) method for overload management in a power system. The overloads in a transmission network were alleviated by generation rescheduling and/or load shedding of participating generators and loads. This method provides a very close sub-optimal solution for smooth as well as non smooth objective functions, even though it does not guarantee in global optimal solution. In [8], the authors' proposed a particle swarm optimization based corrective strategy to alleviate the line overloads. The participation of generators were selected using generator sensitivities to the power flow on overloaded lines. The convergence of the PSO algorithm depends on the appropriate selection of particle size, inertia weight and maximum velocity of particles. The proper choice of these parameters is required to get the superior results. In [9], the authors' proposed a direct method for alleviation of line overloads. The participating generators were selected on the basis of sensitivities of the generation buses to the overloaded lines and costs of generation at those buses. The changes in generation and load shedding schedule were computed by considering cost and sensitivity to line currents. In [10], the authors' proposed an application of DEPSO algorithm to solve the maximum loadability problem. The results were compared with multi agent hybrid particle swarm optimization (MAHPSO) and DE. The algorithm improves the loadability margin with less number of iterations by consuming more time per iteration when compared to other algorithms. In [11], the authors' proposed a fuzzy logic based approach to alleviate the network overloads by generation rescheduling. The generation shift sensitivity factor (GSSF) was used to recommend the changes in generation. The approach removes the overloaded lines in the considered test cases but could not remove the overload completely. In [12], the authors' proposed fuzzy logic based real power rescheduling of generators to remove the overloads in a transmission line. The vulnerability index (VI) and GSSF indices were used to alleviate an overload by enhancing the security margin in terms of reduced losses, increased loadability and reactive reserve margin. In [13], the authors' proposed, modern optimization technique of optimal effective localized area (OELA) to dispatch the optimal active power at different operating conditions. In [14], the authors' proposed a contingency constrained economic load dispatch (CCELD) dispatch using improved particle swarm optimization (IPSO) to alleviate transmission line overloads. The line overloads were relieved through rescheduling of generators with minimum fuel cost and minimum severity index. In [15], the authors' proposed a graphical user interface (GUI) based on a genetic algorithm to determine the optimal location and sizing parameters of multi type FACTS devices for power flow reduction on overloaded lines in a transmission network .

In this paper an application of hybrid differential evolution with particle swarm optimization for transmission line overload management in power system network is presented with illustrated example.

The organization of the paper is as follows: Section 2 presents the optimization problem formulation for overload alleviation. Sections 3 and 4 explain the overview of PSO and DE. In section 5 the algorithm of DEPSO in solving the overload management problem is presented. The simulation results for different contingency cases in IEEE 30 and IEEE 118 bus systems are presented in section 6. Finally, conclusions are given in Section 7.

2. Problem formulation

The objective of the proposed method is to alleviate the transmission line overload by reducing severity index.

2.1. Objective function

Minimize

$$SI_l = \sum_{l \in Lo}^{n} \left(\frac{s_l}{s_l^{\max}} \right)^{2m} \tag{1}$$

where,

$s_l =$ flow in line l (MVA), $s_l^{\max}$ = rating of the line l (MVA), $L_o =$ set of overloaded lines, $m =$ integer exponent =1(Assumed).

2.2. Constraints

2.2.1. Equality constraints

Generation/load balance Equation

$$\sum_{i=1}^{N_G} (P_{Gi}) - \sum_{i=1}^{N_D} (P_{Di}) - P_L = 0 \tag{2}$$

2.2.2. Inequality Constraints

(i) Voltage constraints

$$V_{i,\min} \le V_i \le V_{i,\max} \tag{3}$$

(ii) Generator constraints

$$P_{Gi,\min} \le P_{Gi} \le P_{Gi,\max} \tag{4}$$

3. Overview of particle swarm optimization

PSO is a simple and efficient population-based optimization method [16]. PSO simulates the behaviors of bird flocking. It uses a number of agents (particles) that constitute a swarm moving around in the search space looking for the best solution. Each particle is treated as a point in an N-dimensional space which adjusts its “flying” according to its own flying

experience as well as the flying experience of other particles. All of particles have fitness values, which are evaluated by the fitness function to be optimized, and have velocities, which direct the flying of the particles.
PSO is initialized with a group of random particles (solutions) and then searches for optima by updating generations. In every iteration, each particle is updated by two "best" values such as particle best ($pbest$) and global best ($gbest$). After finding the two best values, the particle updates its velocity and positions using the following equation (5) and (6).

$$V_i^{(u+1)} = w * V_i^{(u)} + C_1 * rand(\ ) * (\ pbest_i - p_i^{(u)}\ ) + C_2 * rand(\ ) * (\ gbest_i - p_i^{(u)}\ ) \tag{5}$$

$$P_i^{(u+1)} = P_i^{u} + V_i^{(u+1)} \tag{6}$$

where,
The term $rand(\ ) * (\ pbest_i - p_i^{(u)})$ is called particle memory influence.
The term $rand(\ ) * (\ gbest_i - p_i^{(u)})$ is called swarm influence.
$V_i^{(u)}$ is the velocity of i_{th} particle at iteration u must lie in the range.

$$V_{\min} \le V_i^{(u)} \le V_{\max} \tag{7}$$

The parameter $V_{\max}$ determines the resolution, or fitness, with which regions are to be searched between the present position and the target position. If $V_{\max}$ is too high, particles may fly past good solutions. If $V_{\min}$ is too small, particles may not explore sufficiently beyond local solutions. The constants C_1 and C_2 pull each particle towards $pbest$ and $gbest$ positions. Suitable selection of inertia weight W provides a balance between global and local explorations, thus requiring less iteration on average to find a sufficiently optimal solution. In general, the inertia weight W is set according to the following equation.

$$W = W_{\max} - \left[\frac{W_{\max} - W_{\min}}{ITER_{\max}} \right] \times ITER \tag{8}$$

where,
W = inertia weighting factor, $W_{\max}$ = maximum value of weighting factor, $W_{\min}$ = minimum value of weighting factor, $ITER_{\max}$ = maximum number of iterations, $ITER$ = current number of iteration.

4. Overview of differential evolution

Differential Evolution is a stochastic direct search optimization method, which can be used to minimize nonlinear and non-differentiable continuous space functions with real-valued parameters. It was first proposed by Storn and Price. DE also relies on initial random population generation, which is then improved using selection, mutation, and crossover repeated through generations until the convergence criterion is met [17].

4.1 Differential Evolution Algorithm Optimization Process

4.1.1 Initialization

In the first step of the Differential Evolution Algorithm optimization process, the population of candidate solutions must be initialized. Typically, each decision parameter in every vector of the initial population is assigned a randomly chosen value from within its corresponding feasible bounds.

$$x_{j,i}^{(G=0)} = x_j^{\min} + rand_j(0,1).(x_j^{\max} - x_j^{\min}) \tag{9}$$

where,
$i = 1,..., N_p \quad j = 1,..., D$

$x_{j,i}^{(G=0)}$ is the initial value $(G = 0)$ of the j^{th} parameter of the i^{th} individual vector.

$x_j^{\min}$ and $x_j^{\max}$ are the lower and upper bounds of the j^{th} decision parameter respectively.

4.1.2 Mutation

The Differential Evolution Algorithm optimization process is carried out by applying the following three basic genetic operations; mutation, recombination (also known as crossover) and selection. After the population is initialized, the operators of mutation, crossover and selection create the population of the next generation $P(G+1)$ by using the current population $P(G)$ .The mutation operator generates mutant vectors $(V_i^{(G)})$ by perturbing a randomly selected vector (X_{r1}) with the difference of two other randomly selected vectors (X_{r2} and X_{r3}) .

$$V_i^{(G)} = X_{r1}{}^{(G)} + F(X_{r2}{}^{(G)} - X_{r3}{}^{(G)}), i = 1,..., N_p \tag{10}$$

where,
$r1, r2, r3$ are randomly chosen vector indices, which $r1, r2, r3 \in [1,..., N_p]$

F is a user-defined constant known as the “scaling mutation factor”, which is typically chosen from within the range (0,1).

4.1.3 Crossover

Crossover operation helps to increase the diversity among the mutant parameter vectors. At the generation G, the crossover operation creates trial vectors (U_i) by mixing the parameters of the mutant vectors (V_i) with the target vectors (x_i) according to a selected probability distribution.

$$U_i^{(G)} = U_{j,i}{}^{(G)} = \begin{cases} V_{j,i}{}^{(G)} & if\ rand_j(0,1) \le CR \\ x_{j,i}{}^{(G)} & otherwise \end{cases} \tag{11}$$

where,
CR is the crossover probability, which is usually selected from within the range (0,1).
$rand_j$ is a uniformly distributed random number within the range (0,1) generated a new for each value of j.

4.1.4 Selection

The selection operator chooses the vectors that are going to compose the population in the next generation. This operator compares the fitness of the trial vector and the corresponding target vector and selects the one that provides the best solution. The fitter of the two vectors is then allowed to advance into the next generation according to equation (12).

$$X_i^{(G+1)} = \begin{cases} U_i^{(G)} & \text{if } f(U_i^{(G)}) \le f(X_i^{(G)}) \\ X_i^{(G)} & \text{otherwise} \end{cases} \tag{12}$$

5. DEPSO based Generation Rescheduling

DE is a simple evolutionary algorithm and uses the differential information for further search. The differential information results instability in performance. PSO has been applied widely since it can converge quickly but easily got stuck in local optima. The combination of DE and PSO (termed DEPSO) that makes up their disadvantages [18]. The inclusion of PSO phase along with DE creates a perturbation in the population, which in turn helps in maintaining diversity of the population and producing a good optimal solution.

5.1. Proposed DEPSO Algorithm

The step by step procedure of DEPSO algorithm is given below.

Step 1: Calculate SI using equation (1) in order to rank the severity of the contingency.
Step 2: Outage is created for the line having highest SI and compute OLF for all lines using the following equation.

$$OLF_l = \frac{S_l}{S_l^{\max}} \tag{13}$$

Step 3: If there is no overloads then stop the process otherwise identify the number of overloaded lines.
Step 4: Generate initial parent population P of individuals using equation (9) and compute fitness values SI_i.
Step 5: Apply mutation to generate new individuals using equation (10) and compute fitness values $SI1_i$.
Step 6: Apply crossover to generate new individuals using equation (11) and compute fitness values $SI2_i$.
Step 7: Apply selection operator to select the best value of next generation using equation (12).
Step 8: Update the mutation and crossover and form a new population P of individuals.
Step 9: Check for maximum number of generations.

Step 10: Compute best population P of individuals, enters the PSO phase, Select the PSO parameters such as inertia weight, acceleration coefficients, particle size and maximum number of generations (G_{max}).
Step 11: Evaluate particles fitness using equation (1).
Step 12: Update the particle velocity and position using equation (5) and (6).
Step 13: Repeat the step 11 and 12 until the maximum generations is reached.
Step 14: Obtain latest global best position, reschedule the generators accordingly and compute SI, OLF of all lines.
The above procedure is illustrated in figure 1.

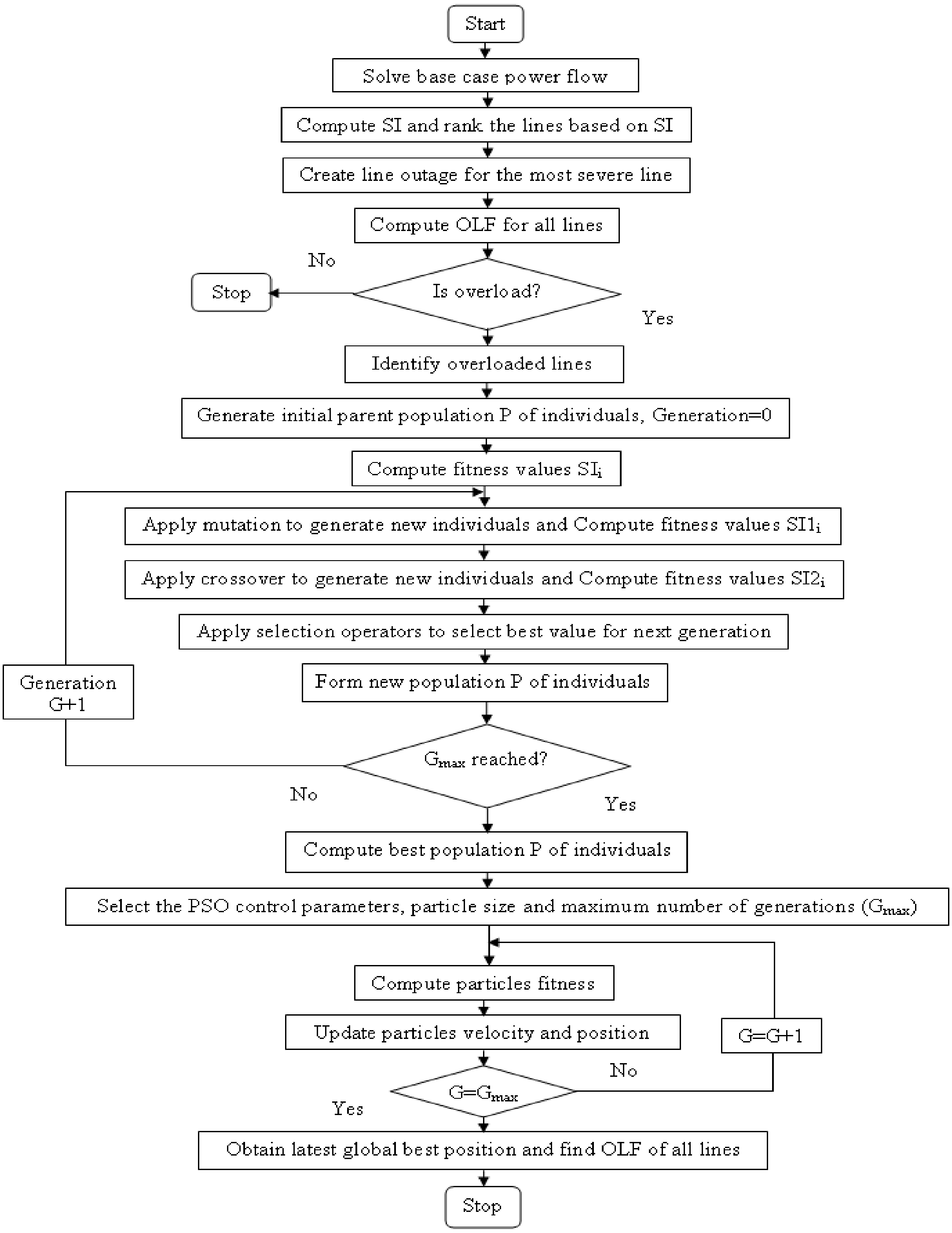

Fig.1 Flow chart of proposed DEPSO Algorithm

6. Simulation Results

Three different cases are considered for the simulation study The simulation studies are performed on system having 2.27 GHz Intel 5 processor with 2 GB of RAM in MATLAB environment. The proposed DEPSO based generation redispatch approach is applied to alleviate line overload for different contingency cases namely Case A and Case B in IEEE 30 bus system and Case C in IEEE 118 bus system. The results such as OLF of all overloaded lines, power loss, SI and generation rescheduling cost of all three cases are compared with PSO and DE based approaches. The power flow is obtained using MATPOWER software [19]. The transmission line limits for IEEE 30 bus system and IEEE 118 bus system are taken from [20, 21]. The proposed approach is applied for 25 independent runs and the final parameters are selected based on minimum objective value as well as rescheduling cost.

6.1. Overload Alleviation in IEEE 30 Bus System

6.1.1. Case A: Line 2-5 outage

In this case, the DEPSO algorithm is applied to alleviate transmission line overload under contingency condition in the IEEE 30 bus system. Contingency ranking are carried out under base-load conditions to identify the harmful contingencies. It is found that line outage 2-5 is one of the severe contingencies. As a consequence of line 2-5 outage, lines 1-2, 2-4, 2-6, 4-6, 5-7 & 6-8 get overloaded. The parameter setting for PSO and DE is shown in table 1. The overloaded line details before rescheduling is shown in table 2. Table 3 presents the control variable setting for overload management. The overloaded line details after rescheduling is shown in table 4. Figure 2 illustrates rescheduling cost of generators to alleviate line overload for independent test runs. Figure 3 illustrates contribution of generators by different approaches for overload management.

Table 1: Parameter settings for PSO and DE

PSO	DE
No. of particles=20	No. of particles=20
C1=C2=2	Mutation factor=0.3
Inertia weight=Wmax=0.9 Wmin=0.4	Crossover probability=0.6
Maximum Generations=100	Maximum Generations =100

Table 2: Overloaded Line Details before rescheduling

Outage line	Overloaded lines	Power Flow (MVA)	Line flow limit (MVA)	OLF	Amount of Power violation (MVA)	Total power violation (MVA)	Power Loss (MW)	SI
2-5	1-2	165.4421	130	1.2726	35.4421	160.2603	32.823	11.0064
	2-4	74.6652	65	1.1487	9.6652			
	2-6	102.9619	65	1.5840	37.9619			
	4-6	123.6755	90	1.3742	33.6755			
	5-7	110.1006	70	1.5729	40.1006			
	6-8	35.4150	32	1.1067	3.4150			

Table 3: Control variable setting for corrective action

Generator Bus Number	PSO	DE	DEPSO
	Generated Real Power (MW)		
1	138.83	141.22	142.16
2	52.04	51.26	50.95
5	33.69	33.23	33.05
8	23.35	23.02	22.90
11	20.68	20.42	20.32
13	26.95	26.59	26.44

Table 4: Overloaded Line Details after rescheduling

Method	Outage line	Overloaded lines	Power Flow (MVA)	OLF	Power Loss (MW)	SI	Generation Cost ($/hr)
PSO	2-5	1-2	77.0442	0.5926	12.129	0	845.20
		2-4	45.1419	0.6945			
		2-6	61.2479	0.9423			
		4-6	70.9532	0.7884			
		5-7	68.4823	0.9783			
		6-8	10.1664	0.3177			
DE		1-2	78.6793	0.6052	12.336	0	843.52
		2-4	45.4659	0.6995			
		2-6	61.7376	0.9498			
		4-6	71.6763	0.7964			
		5-7	69.0218	0.9860			
		6-8	10.2817	0.3213			
DEPSO		1-2	79.3228	0.6102	12.419	0	842.89
		2-4	45.5932	0.7014			
		2-6	61.9300	0.9528			
		4-6	71.9604	0.7996			
		5-7	69.2339	0.9891			
		6-8	10.3307	0.3228			

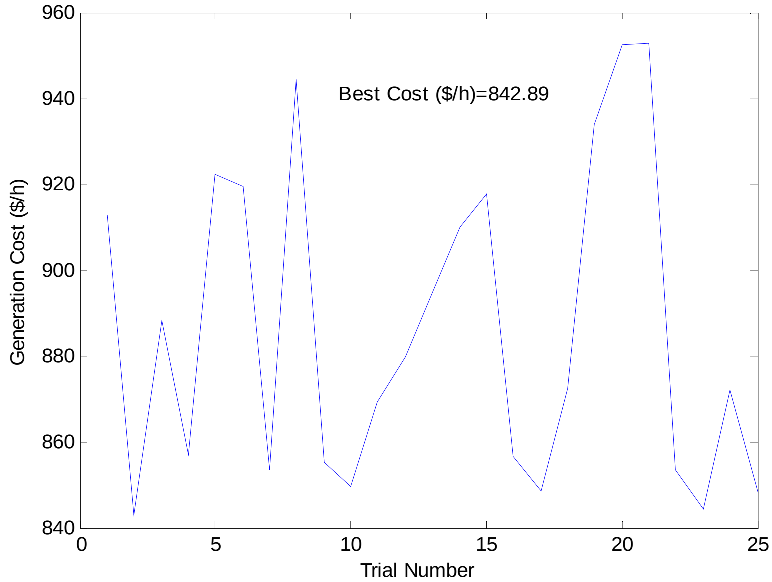

Fig. 2 Generation cost versus independent test runs of proposed approach

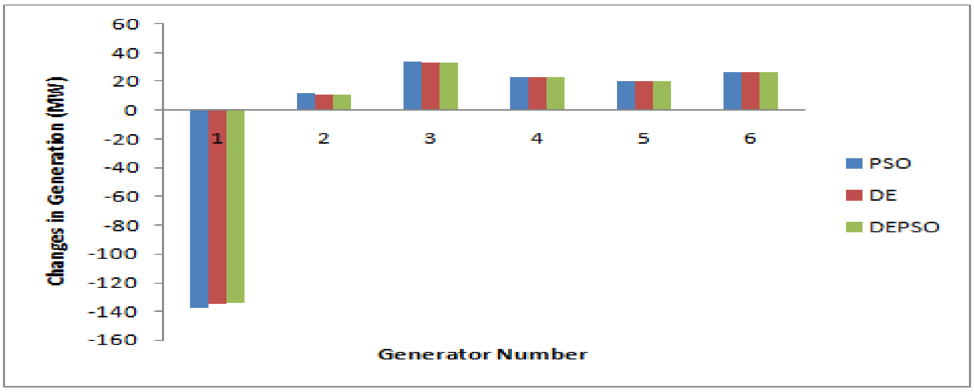

Fig. 3 Contribution of Generators for overload management

In the considered outage case, all the three approaches relieved all the six overloaded lines. Among the six overloaded lines, the OLF of most overloaded line 2-6 is 1.5840 and that after rescheduling is reduced to 0.9423, 0.9498 and 0.9528 using PSO, DE and DEPSO approaches respectively. Similarly, the power loss is reduced from 32.823 MW to 12.129, 12.336 and 12.419 and also the severity index is completely reduced from 11.0064. The time taken per iteration in PSO, DE and DEPSO based approaches are 0.1206 seconds, 0.1126 seconds and 0.2325 seconds respectively. From table 3 and 4, it is clear that DEPSO based generation rescheduling approach could able to remove the line overloads with a minimum changes in generation and minimum rescheduling cost of 842.89 $/h at 2nd trial, when compared to other approaches.

6.1.2. Case B: Line 1-3 outage

In this case, an outage is created in line 1-3. As a consequence of line 1-3 outage, lines 1-2, 2-4, 2-6, 6-8 get overloaded. The overloaded line details before rescheduling is shown in table 5. Table 6 presents the control variable setting for overload management and table 7 presents overloaded line details after rescheduling. Figure 4 illustrates rescheduling cost of generators to alleviate line overload for independent test runs. Figure 5 illustrates contribution of generators by different approaches for overload management.

Table 5: Overloaded Line Details before rescheduling

Outage line	Overloaded lines	Power Flow (MVA)	Line flow limit (MVA)	OLF	Amount of Power violation (MVA)	Total power violation (MVA)	Power Loss (MW)	SI
1-3	1-2	274.0264	130	2.1079	144.0264	196.1237	26.987	9.4474
	2-4	86.1203	65	1.3249	21.1203			
	2-6	92.7203	65	1.4265	27.7203			
	6-8	35.2567	32	1.1018	3.2567			

Table 6: Control variable setting for corrective action

Generator Bus Number	PSO	DE	DEPSO
	Generated Real Power (MW)		
1	121.29	125.75	128.99
2	56.80	55.33	54.26
5	36.47	35.61	34.98
8	25.33	24.72	24.27
11	22.27	21.78	21.42
13	29.17	28.49	27.99

Table 7: Overloaded Line Details after rescheduling

Method	Outage line	Overloaded lines	Power Flow (MVA)	OLF	Power Loss (MW)	SI	Generation Cost ($/hr)
PSO	1-3	1-2	121.8660	0.9374	7.934	0	848.87
		2-4	46.7420	0.7191			
		2-6	50.0383	0.7698			
		6-8	7.2447	0.2264			
DE		1-2	126.4216	0.9725	8.266	0	844.46
		2-4	47.6311	0.7328			
		2-6	51.0019	0.7846			
		6-8	7.7314	0.2416			
DEPSO		1-2	129.7288	0.9979	8.512	0	841.38
		2-4	48.2763	0.7427			
		2-6	51.7011	0.7954			
		6-8	8.1016	0.2532			

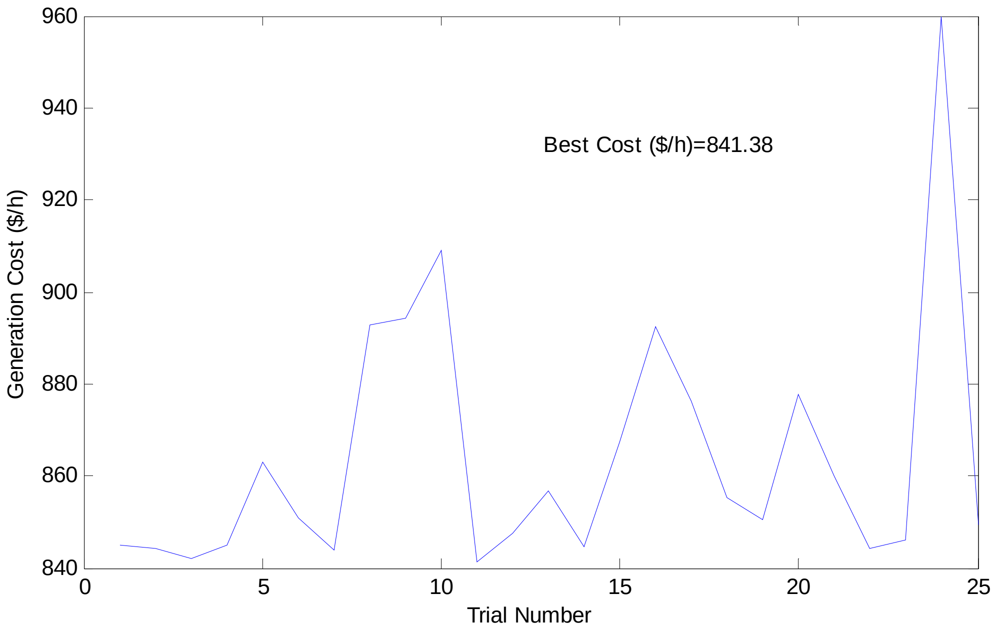

Fig. 4 Generation cost versus independent test runs of proposed approach

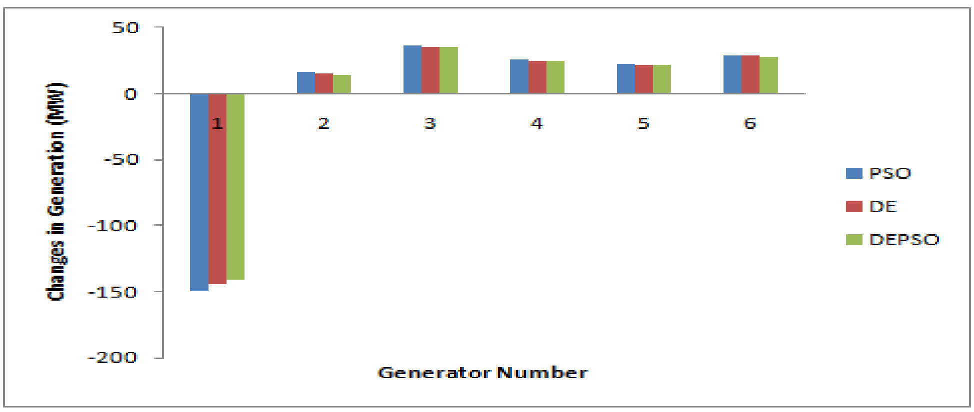

Fig.5 Contribution of Generators for overload management

In the considered outage case, all the four overloaded lines are relieved. Among the four overloaded lines, the OLF of most overloaded line 1-2 is 2.1079 and that after rescheduling is reduced to 0.9374, 0.9725 and 0.9979 using PSO, DE and DEPSO approaches respectively. Similarly, the power loss is reduced from 26.987 MW to 7.934, 8.266 and 8.512 and also the severity index is completely reduced from 9.4474. The time taken per iteration in PSO, DE and DEPSO based approaches are 0.1199 seconds, 0.1124 seconds and 0.2296 seconds respectively. From table 6 and 7, it is clear that DEPSO based generation rescheduling approach could able to remove the line overloads with a minimum rescheduling cost of 841.38 $/h at 11th trial, when compared to other approaches.

6.2. Overload Alleviation in IEEE 118 Bus System

6.2.1. Case C: Line 8-5 outage

In this case, the DEPSO algorithm is applied to alleviate transmission line overload under contingency condition in IEEE 118 bus system. Contingency analysis is conducted under base load conditions to identify the harmful contingencies. From the contingency analysis it is found that the line outage 8-5 is the most severe one, and results in overloading on five other lines. The overloaded lines are 12-14, 13-15, 12-16, 15-17 and 16-17. Line 16-17 is found to be loaded heavily beyond its maximum limit of 130 MW. The total power violation is found to be 77.6254 MVA. The amount of generation rescheduling for alleviating the overload of 77.6254 MVA are computed and their details are shown in table 8, table 9 and table 10.

Table 8: Overloaded Line Details before rescheduling

Outage line	Overloaded lines	Power Flow (MVA)	Line flow limit (MVA)	OLF	Amount of Power violation (MVA)	Total power violation (MVA)	Power Loss (MW)	SI
8-5	12-14	107.2030	100	1.0720	7.2030	77.6254	197.029	6.3471
	13-15	103.0672	100	1.0307	3.0672			
	12-16	143.6514	130	1.1050	13.6517			
	15-17	223.4804	200	1.1174	23.4804			
	16-17	160.2231	130	1.2325	30.2231			

Table 9: Control variable setting for corrective action

Generator Bus Number	PSO	DE	DEPSO	Generator Bus Number	PSO	DE	DEPSO
	Generated Real Power (MW)				Generated Real Power (MW)		
10	370.96	395.76	395.80	65	304.16	320.17	323.76
12	175.08	170.42	151.64	66	259.50	284.91	255.90
25	271.42	218.54	210.10	69	654.99	737.20	745.98
26	280.57	280.72	270.00	80	388.39	381.66	433.12
31	63.91	43.50	24.85	87	48.52	65.74	28.19
46	83.66	32.63	75.75	89	452.66	439.18	503.70
49	171.08	165.51	201.20	100	262.80	274.38	231.06
54	98.94	54.20	79.73	103	96.26	63.76	69.41
59	162.81	173.41	171.19	111	98.06	88.30	63.48
61	142.15	206.10	165.40				

Table 10: Overloaded Line Details after rescheduling

Method	Outage line	Overloaded lines	Power Flow (MVA)	OLF	Power Loss (MW)	SI	Generation Cost ($/hr)
PSO	8-5	12-14	69.9779	0.6998	143.917	0	148750
		13-15	75.1073	0.7511			
		12-16	100.9520	0.7765			
		15-17	198.9040	0.9945			
		16-17	120.2794	0.9252			
DE		12-14	72.0448	0.7204	154.098	0	147740
		13-15	76.6762	0.7668			
		12-16	102.6607	0.7897			
		15-17	196.5525	0.9828			
		16-17	121.9227	0.9379			
DEPSO		12-14	79.8597	0.7986	158.267	0	139000
		13-15	82.5909	0.8259			
		12-16	110.7935	0.8523			
		15-17	196.8924	0.9845			
		16-17	129.6500	0.9973			

Figure 6 illustrates rescheduling cost of generators to alleviate line overload for independent test runs. Figure 7 illustrates contribution of generators by different approaches for overload management.

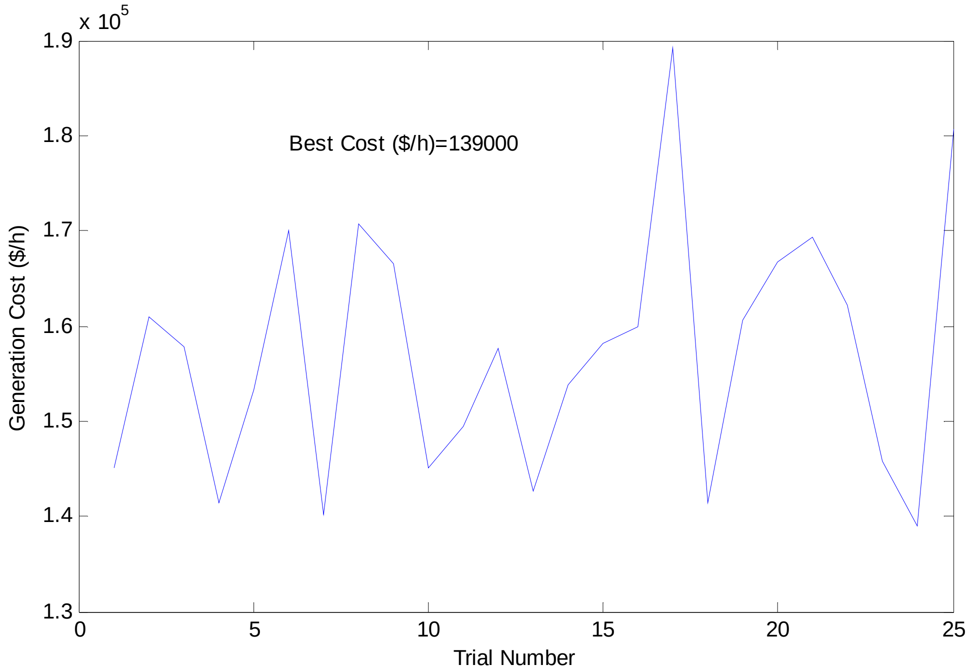

Fig. 6 Generation cost versus independent test runs of proposed approach

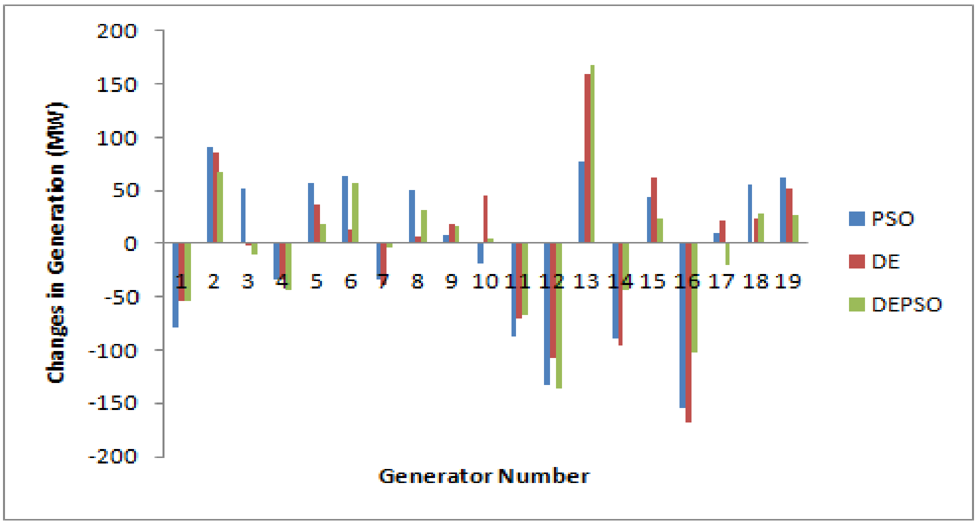

Fig.7: Contribution of Generators for overload management

In the considered outage case, PSO, DE and DEPSO based approaches relieved all the five overloaded lines. The time taken per iteration in PSO, DE and DEPSO based approaches are 0.2371 seconds, 0.2124 seconds and 0.4370 seconds respectively. Among the five overloaded lines, the OLF of most overloaded line 16-17 is 1.2325 and that after rescheduling is reduced to 0.9252, 0.9379 and 0.9973 using PSO, DE and DEPSO approaches respectively. Similarly, the power loss is reduced from 197.029 MW to 143.917, 154.098 and 158.267 and also the severity index is completely reduced from 6.3471. From table 9 and 10, it is clear that DEPSO based generation rescheduling approach could able to remove the line overloads with a minimum rescheduling cost of 139000 \$/h at 24th trial, when compared to other approaches.

7. Conclusion

This paper has proposed an hybrid differential evolution with particle swarm optimization based generation rescheduling approach for transmission line management in a contingent power network. N-1 contingency analysis is carried out to identify the most severe lines and those lines are selected for outage. Line overloads due to unexpected line outage under base load conditions are considered. The overloaded lines are relieved through rescheduling of generators with minimum severity index as well as overload factors. The effectiveness of the methods is demonstrated for all possible line contingencies in IEEE 30 bus system and IEEE 118 bus system. The two cases namely Case A and case B for IEEE 30 bus system and one case namely Case C for IEEE 118 bus system are presented and their results are compared with other evolutionary algorithms like Particle swarm optimization and Differential evolution. All the approaches could able to remove the transmission line overloads for all considered cases. However, DEPSO based generation rescheduling approach remove the line overloads with minimum rescheduling cost of 842.89 \$/h, 841.38 \$/h and 139000 \$/h respectively when compared to other approaches.

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