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HYBRID DIFFERENTIAL EVOLUTION-AND-ELECTROMAGNETISM-LIKE ALGORITHM FOR TRANSMISSION LINE PROTECTION

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Abstract

In Planning of Special Protection Schemes (SPSs) in power systems, protecting of transmission corridor against undesired situations becomes an important challenge especially, arresting the transmission line overloading. In this paper, a Special Protection and Control Scheme (SPCS) based on Differential Evolution with Adaptive Mutation (DEAM) method to mitigate the line overloading issue has been presented. Optimal Generation Rescheduling strategy has been implemented as a corrective and control scheme taken by the SPCS and applied based on the minimum values of the Severity Index (SI) calculated in accordance to the load flow analysis in order to mitigate the line congestion problem. Different N-1 contingency conditions (transmission line outage) under both base and increased load demand situations are considered in this field of study. Simulation results of the DEAM algorithm on the IEEE 30-bus system are compared with those from the application of the conventional DE algorithm and the final results showed that the presented DEAM scheme offers better performance than DE in terms of less generation fuel cost under the considered situations.

Keywords: Differential evolution, Electromagnetism-like algorithm, Generation rescheduling, Special protection scheme, Transmission line overloading.

1. Introduction

Special protection Schemes (SPSs) also referred to Remedial Action Schemes (RASs) are developed to discover abnormal system conditions that contingency-associated and take pre-planned preventive actions for reliable system operations, not only isolation of faulted elements as taken in conventional protection schemes, but also to mitigate the consequences of the abnormal system conditions as well as keep acceptable performance. SPS actions comprise, changing in demand (load shedding), generation, and system configuration to ensure the stability and keep acceptable voltage and power flow [1]. Due to increasing complexity of utility operation in the last years according to different reasons such as the growth of demand, change in market conditions and increasing in power imports/exports between neighbouring countries, the transmission system has become more stressed resulting in transmission networks and other system components being worked near to their operational boundaries. Therefore, automated SPS schemes have been widely used by utilities in order to decrease probability of wide spread disturbances as well as to maximize the transaction capability of the transmission system, subsequently SPS schemes have proliferated [1].

Protecting of transmission grid from overloading (congestion) throughout extreme contingencies is a significant challenge that needs to be taken into consideration during implementing of SPS programs. The overloading issue of the network may worse according to load disturbances, line outage and/or transformer outage. The overloading situation of any transmission grid may lead to cascade line outages and system collapse. Thus, some remedial actions could be taken into consideration to avoid the overloading states, like generation rescheduling, line switching, installing phase shift transformers, and load shedding strategies [2].

Load shedding and generation rescheduling are the most widely applied corrective actions to alleviate the line congestion since building new transmission grid to meet N−1 contingency criteria is costly and time-consuming [2]. In general, the system impact studies and security assessment deal with N−1 contingency condition, which means loss of any one of the system components like line, generator, and transformer without loss of demand. The system impact studies require an evaluation of prior outage of N−1 contingency condition, and the post contingency loading is either above the risk limits or not to determine the operating constraints under various conditions.

2. Generation Rescheduling Scheme

To maintain a secure system operation, the transmission loading should be maintained within specific thermal limits, and if the power flow in line exceeds these limits, the line is said to be congested (overloaded). The overloading problem in a transmission line can happen according to sudden increase in load demand, unexpected line outages and sometimes failure of a power system component. Suitable preventive actions should be taken to effectively alleviate line overload in a minimum possible time as well as without violation of system constraints. One of the most generally used approaches for line overload mitigation is the rescheduling of generators in a power system [3].

Generation rescheduling strategy has been implemented by using several techniques based on optimal power flow for economy and security assessment. Pandiarajan K. and C. K. Babulal presented an application of hybrid Differential Evolution with Particle Swarm Optimization for line overload management.

Generation rescheduling is performed to remove the line overloads by reducing the severity index with a minimum rescheduling cost [3]. An Improved Differential Evolution algorithm to solve line overloading problem by generation rescheduling method has also been presented in [4].

In [5], a performed scheme based on neural network for prediction the line overloading amount and protecting the line from congestion by using generation rescheduling strategy due to N-1 contingency and sudden change in system demand has been presented. PSO algorithm has been proposed in [6] for overloading alleviation by applying rescheduling generation. Rescheduling has been done in an optimal power flow (OPF) to minimize the total line overload due to N-1 contingency and load variation. Genetic Algorithm considered as an optimization tool to solve the minimum load shedding issue in contingency conditions was proposed in [7]. The implemented method was utilized to identify the amount and location of load to be shed in addition to generation rescheduling in post contingency conditions. DE algorithm with its modified versions for optimal reactive power rescheduling problem has been resented in [8] and for optimum load shedding problem in [9] to enhance voltage stability in a power system.

3. Methodology

3.1. Problem formulation

The main objective of this work is to design a SPCS scheme to obtain an optimal real power rescheduling of the system generation units as a preventive action scheme in order to get the minimum generation fuel cost based on the price bids submitted by the generation companies along with minimizing of the severity of a post contingency condition formed by the transmission line outage under base as well as increased load events. This strategy (as a corrective action) generally mitigates the transmission line overloading issue that should subject to the system operating constraints during the normal and abnormal demand situations.

The minimizing criterion of the total generation cost from the system generation units is defined in the following formula:

$$FC_{Min} = \sum_{i=1}^{NG} (a_i + b_i P_{Gi} + c_i P_{Gi}^2) \quad \$/hr \tag{1}$$

where *FC* is the total generation fuel cost for the power generated within the power system and it is subjected to the system constraints represented by the equality and inequality constraints under the load flow analysis. a_i, b_i and c_i represent the system cost coefficients and these coefficients are adopted from [10]. P_{Gi} indicates the active power generated by generator *i* within a power system and these values can be calculated from the executed algorithm after applying the load flow analysis along with minimum severity index magnitudes and means that the line overloading problem has been mitigated due to the minimum severity values. *NG* is the number of generation units within a power system.

3.2. Severity index SI

The severity of an emergency state that is related to the line overloading issue can be expressed in terms of the severity index (*SI*) [5]. This index can be expressed as:

$$SI = \sum_{k=1}^{ovl} \left(\frac{S_{ij}}{S_{ij}^{max}} \right)^{2m} \tag{2}$$

S_{ij} is the line flow between bus i and j and can be obtained from the load flow analysis, where in this research, Newton-Raphson method has been utilized. S_{ij}^{max} is the line flow maximum limit, *ovl* is the set of the overloaded lines due to a contingency condition, and *m* represents an integer number.

Minimum severity index is taken as the objective function for the proposed algorithm along with the minimizing of the generation cost. In order to ensure a secure operating condition of any power system, the value of the severity index should be zero. The greater value of *SI*, the more critical contingency would be.The overloading management and the optimum generation rescheduling are generally subjected to the system constraints and these constraints are divided into equality and inequality constraints.

On one hand, equality constraints represent the expressions of the real and reactive power constraints during the power flow analysis. On the other hand, inequality constraints comprise the unit constraints and that means the active and reactive power min and max constrains, voltage constraints, and the line flow constraints [10].

The overall SPCS scheme operation based on the hybrid DEAM algorithm is shown in Fig. 1 such that this schem determines the optimal magnitudes of the active power generated in order to get the minimum generation rescheduling cost along with the minimum severity values and this considered as the objective function of the presented work.

4.Overview of The Hybrid DEAM Algorithm

Electromagnetism–like algorithm (EM) is a recently suggested algorithm based on a population set strategy and deals with nonlinear optimization issues [11]. In this algorithm, an attraction-repulsion concept of charges based on the Coulomb's law is utilized to move the individual vectors within a population set to the global optima. In the population set, the vectors via superior objective function attract others, while those who have inferior objective magnitudes repulse. EM algorithm has been performed in some applications reported in [11-13]. The overall details that belong to the EM method have been discussed in [11, 12].

Differential Evolution (DE) algorithm, is a population based algorithm that always resolves specific issues by enhancing its candidate solutions according to a predefined execution criteria. It is used for optimization with high performance and easy to understand and implement and introduced by Storn and Price in 1995 [14]. In this paper, a hybrid differential evolution and electromagnetis-like algorithm that generally denoted by DEAM has been performed in order to obtain the optimum generation values.

DEAM algorithm is usually similar to the conventional DE method except it employs the concept of the attraction–repulsion of the Electromagnetism–like approach and this idea is used to enhance the mutation mechanism of the DE algorithm [12]. The attraction operation principally exchanges the bad individual vectors within a population set with better individuals in each iteration in order to improve the convergence and the reliability (accuracy of the optimal solution) of DE algorithm [12, 13]. Mixed mutation strategies are utilized, where the first mutation strategy is undertaken by the normal DE and denoted by M_d. While the second concept is the mutation process that is utilized by EM algorithm and indicated by M_e [13]. Like other evolutionary algorithms, DEAM relies on an initial population set (*P*) that consists of *NP D*-dimensional individual vectors which are considered as a candidate solution to the optimization problem. This algorithm produces a population set of *NP* real valued individual vectors and every individual vector includes *D*

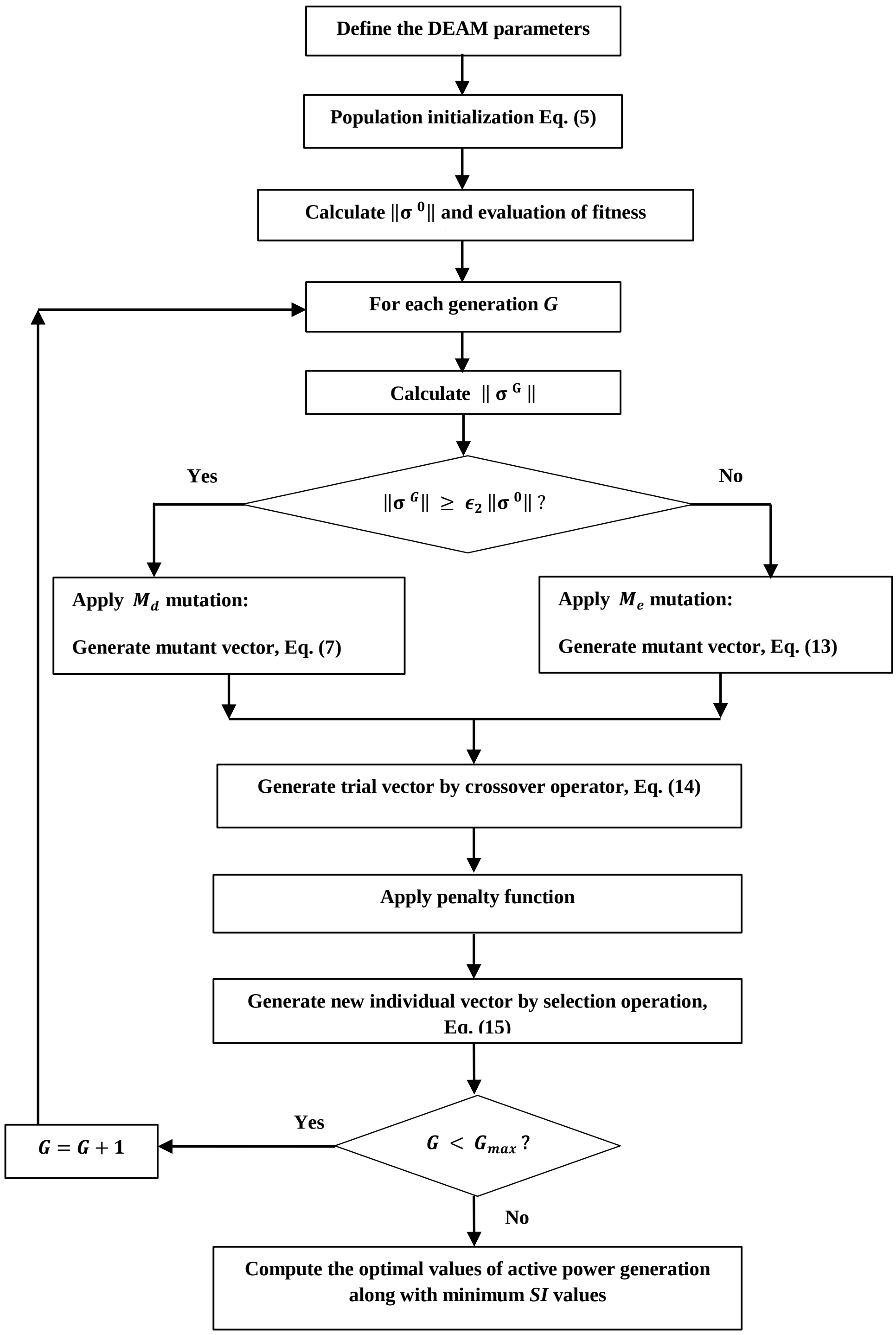

Fig. 1. General flowchart of the proposed algorithm.

parameters that represent the dimensionality of the optimization problem which needs to be optimized. The mutation, crossover, and selection steps are repeated for each iteration till the maximum number of iterations (G_{max}) is reached. The algorithm initiates a population set (P) of the real valued vectors $X_{i,G}$ as follows [15]:

$$P_{X,G} = [X_{1,G}, X_{2,G}, \dots\dots\dots, X_{i,G}] \quad (3)$$
$$X_{i,G} = [X_{j,i,G}] \quad (4)$$
where $j = 1, \dots.D, \quad i = 1, \dots.NP, \quad and \quad G = 0, 1, \dots G_{max}$

Each individual vector has a population index *i* that ranges from 1 to *NP*, where *NP* is the number of individuals (candidate solutions) to the optimization issue. The parameters within the vectors are indexed by *j* and ranges from 1 to *D*, where *D* is the dimension of the vector which represents, in this work, the number of generation units in the test system. $X_{i,G}$ is the target vector. The main steps of this algorithm are described as follows.

4.1. Initialization

In order to begin the optimization procedure, an initial population set (*P*) of *NP D*-dimentional real valued vectors are created and each of the parameter vector considers as a candidate solution to the optimization process. The inintial values of the *D* parameters are usually chosen randomly and distributed uniformly withiin the assumed search space between the boundaries that denoted by X_L and X_H, where X_L= [$X_{1,L}$, $X_{2,L}$,......., $X_{D,L}$] represent the lower limits of the serach space and X_H = [$X_{1,H}$, $X_{2,H}$,........., $X_{D,H}$] represent the upper limits as well. Thus the initial *j*th component of the *i*th population vector is initialized by the following formula:

$$X_{j,i,0} = X_{j,L,i} + rand[0,1](X_{j,H,i} - X_{j,L,i}) \quad (5)$$

where *rand* [0,1] is a random number distributed between 0 and 1.

4.2. Mutation

In this step, DEAM algorithm invoke either M_d or M_e mechanism in every iteration. The main criteria adopted in order to switch between both kinds of the mutation is based on the standard deviation of the row vectors of the population set *P* and discribed as follows:

$$Mutation = \begin{cases} M_e & if \quad \|\sigma^{G}\| < \epsilon_2 \|\sigma^{0}\| \\ M_d & otherwise \end{cases} \quad (6)$$

where $\|\sigma^{0}\|$ and $\|\sigma^{G}\|$ indicate to the norm of the vectors of the standard deviation belong to the row vectors for the initially generated and the current generation values respectively. ϵ_2 is a switching parameter which is implemented in order to switch between M_d and M_e operations and its value between 0 and 1. The magnitude of $\|\sigma^{G}\|$ is normally calculated at the beginning of each iteration. For each target vector ($X_{i,G}$), there is a mutant vector called also donor vector ($V_{i,G}$) generated due to M_d operator and can be expressed as:

$$V_{i,G} = X_{\alpha,G} + F(X_{\beta,G} - X_{\gamma,G}) \quad (7)$$

where $X_{\alpha,G}$, $X_{\beta,G}$ and $X_{\gamma,G}$ are vectors that randomly chosen among the population and they are different from the target vector. The indices $\alpha, \beta \; and \; \gamma$ are distinguished under the range from 1 to *NP*. The first vector $X_{\alpha,G}$ is called the base vector, and *F* represents the mutaion scaling factor and typically selected between 0 and 1. Whilst the M_e mutation is also based on three randomly selected vectors from the population. Unlike M_d, the value of the index of one of these chosen vectors may be the same index value of the current target vector [13].

The M_e operation utilizes the total force which is exerted on one of the individual vector for example $X_{\alpha,G}$ by the other two selected vectors $X_{\beta,G}$ and $X_{\gamma,G}$. Similar to the

EM algorithm, the force exerted on the vector $X_{\alpha,G}$ from $X_{\beta,G}$ and $X_{\gamma,G}$ is calculated based on the charges among the selected vectors and expressed as below:

$$q_{\alpha,\beta,G} = \frac{f(X_{\alpha,G}) - f(X_{\beta,G})}{f(X_{w,G}) - f(X_{b,G})} \tag{8}$$

$$q_{\alpha,\gamma,G} = \frac{f(X_{\alpha,G}) - f(X_{\gamma,G})}{f(X_{w,G}) - f(X_{b,G})} \tag{9}$$

$f(X)$ is the objective function for the individual vector X . $f(X_{b,G})$ and $f(X_{w,G})$ represent the best and worst magnitudes of the objective function for G^{th} iteration respectively, and G is the index that indicates the number of the current generation. Hence, the forces exerted on $X_{\alpha,G}$ by $X_{\beta,G}$ and $X_{\gamma,G}$ is calculated by:

$$F_{\alpha,\beta,G} = (X_{\beta,G} - X_{\alpha,G})q_{\alpha,\beta,G} \tag{10}$$

$$F_{\alpha,\gamma,G} = (X_{\gamma,G} - X_{\alpha,G})q_{\alpha,\gamma,G} \tag{11}$$

Subsequently, the resultant force exerted on $X_{\alpha,G}$ by $X_{\beta,G}$ and $X_{\gamma,G}$ is computed by:

$$F_{\alpha,G} = F_{\alpha,\beta,G} + F_{\alpha,\gamma,G} \tag{12}$$

After that, the mutant vector of the M_e mechanism is computed by:

$$V_{i,G} = X_{\alpha,G} + F_{\alpha,G} \tag{13}$$

4.3. Crossover

This stage of DEAM algorithm is the same of the crossover operation of DE algorithm. This process is usually used to increase the diversity of the population, where the donor vector $V_{i,G}$ and the target vector $X_{i,G}$ are both utilized to create a new vector named as the trial vector $U_{j,i,G}$ and can be expressed as:

$$U_{j,i,G} = \begin{cases} V_{j,i,G} & if \quad (rand \le CR \text{ } or \text{ } j = j_{rand}) \\ X_{j,i,G} & otherwise \end{cases} \tag{14}$$

CR denoted to the crossover control parameter that controls the diversity of the population and helps the algorithm to escape from the local optima and its range between 0 and 1. j_{rand} represents a randomly selected index to ensure that the trial vector $U_{i,G}$ obtains at least one element from $V_{i,G}$ and its range ∈ is [1, 2,…..*D*].

4.4. Selection and Evaluation

In order to keep the population size consistent during the following iterations, the selection procedure is normally conducted in order to detect either the current target vector $X_{i,G}$ or the trial vectors $U_{i,G}$ will be picked as a member to the next iteration ($G = G+1$). The selection creteria can be discribed as:

$$X_{i,G+1} = \begin{cases} U_{i,G} & if \quad J(U_{i,G}) < J(X_{i,G}) \\ X_{i,G} & otherwise \end{cases} \tag{15}$$

J(X) is the objective function to be minimized. The selection mechanism between these two vectors depends on the objective function magnitudes for the trial as well as the target vectors where the smaller one is chosen as a part into the next iteration. Therefore, the new population either gets better or remains consisten of the fitness function value, however never declines.

5. Results and Discussion

5.1. Simulated N-1 contingency conditions

To examine the effectiveness of the proposed DEAM based SPCS scheme, the algorithm has been tested on the IEEE 30-bus system and all the implemented data are adopted and reported in [10]. A Newton–Raphson method has been carried out to acheive the load flow analysis.

During the security assessment of a power system, line overloading risk may happen due to different reasons including line outage (i.e. line out of service). Therefore, *N*-1 contingency analysis is performed under both normal and abnormal load conditions in order to determine the harmful disturbance through the system operation. For each of the implemented case, pre and post contingency line flows are obtained from the load flow in order to identify which lines are overloaded according to a single line outage. As a result from the contingency analysis, the line outages between buses 1-2, 1-3, 3-4, 2-5 under base case as well as line 1-2 and 3-4 outages along with load increased at all system buses by 10%, in addition to line outage between buses 1-2 with increased load at bus 30 by 25% as well as line 1-3 outage with load increased at bus 8 by 25% have resulted in overloading of some other system lines.

The simulated line details along with their overloaded lines and related *SI* values before the generation rescheduling for both scenarios (i.e. base and increased load cases) are illustrated in Table 1. The line flow limits are adopted and taken from [10].

Table 1. Line outage details before generation rescheduling.

Line outage	Overloaded lines	Line flow (MVA)	Line limit (MVA)	Severity index (*SI*)
1-2	1-3	307.803	130	16.265
	2-4	65.592	65	
	3-4	279.121	130	
	4-6	174.058	90	
	6-8	36.362	32	
1-3	1-2	273.019	130	9.279
	2-4	86.154	65	
	2-6	92.759	65	
	6-8	33.188	32	
3-4	1-2	270.07	130	9.076
	2-4	84.916	65	
	2-6	91.805	65	
	6-8	32.928	32	
2-5	1-2	164.467	130	10.885
	2-4	74.604	65	
	2-6	102.858	65	
	4-6	124.097	90	
	5-7	110.189	70	
	6-8	33.317	32	
1-2 with increased load by 10%	1-3	369.586	130	22.580
	2-4	77.239	65	
	3-4	321.795	130	
	4-6	201.235	90	
	6-8	44.791	32	
3-4 with increased load by 10%	1-2	305.287	130	11.518
	2-4	93.888	65	
	2-6	101.556	65	
	6-8	38.874	32	
1-2 with increased load at bus 30 by 25%	1-3	312.86	130	16.854
	2-4	66.682	65	
	3-4	283.109	130	
	4-6	176.872	90	
	6-8	37.941	32	
1-3 with increased load at bus 8 by 25%	1-2	282.409	130	10.375
	2-4	89.188	65	
	2-6	96.427	65	
	6-8	40.136	32	

5.2. Optimization process of DEAM in generation rescheduling strategy

In order to maintain a secure system operation, the power flows in the lines should not exceed their permissible levels. Subsequently, appropriate corrective actions should be taken in order to alleviate the line congestion. The optimal magnitudes of the generation rescheduling are evaluated based on the combined DE and EM algorithms. The results are validated with the DE method for the same simulated cases in terms of the generation cost.

The power generated of the generation units are taken as the control variables from the proposed algorithm. Initially, a set of P_G values are produced by DEAM algorithm within their minimum and maximum boundaries. After that, these created P_G values are evaluated in the fitness function algorithm to obtain the related severity index magnitudes. Subsequently, this algorithm applies the specified mutation mechanism and the crossover to get the optimal fitness for all individual vectors. The control parameter setting regarding the mutation factor F and the crossover rate CR are taken as 0.8 and 0.5 respectively since these values are given the best results after executing many trials. The value of ϵ_2 is chosen to be 0.25 since the best magnitudes lie in the range between 0 and 0.4 [12]. Since the number of generation units is six, the value of the optimization problem (D) equals to six. The population size (*NP)* is selected within the range 5D to 10D [13]. Therefore, *NP* value is set to 30 for both algorithms and the maximum number of iterations (G_{max}) is set to be 50.

A corrective action scheme has been carried out by getting the optimum values of the power generated and these values are tabulated in Table 2 for DEAM and DE algorithms under base and increased load conditions. The generation rescheduling costs are also given in last column in addition to the total losses. It can be seen from the Table 2 that the hybrid DE and EM algorithms give less generation cost than DE in both system conditions for all the performed cases.

All the executed algorithms are performed for a maximum number of 50 iterations. The algorithms are conducted for at least 10 independent runs. The power generation values of the system are determined by the average magnitudes based on the total independent runs. The line details after the generation rescheduling strategy for the DEAM and DE based SPCS schemes are clarified in Table 3.

It is clear that the adopted power generated values from the executed algorithms are completely alleviated the line overloads and the resulted line flows are totally below their flow limits. Additionally, the resulted magnitudes of the severity index after applying the optimal generation values are completely reduced to zero which expressed that no more lines get overloaded after applying the generation rescheduling strategy which considered as a corrective action scheme and this means that the overloading problem in the transmission lines due to the emergency situation has been solved.

Table 2. Setting of the control variables.

Method	Line out of service	Active power generation (MW)						Power Losses (MW)	Generation cost ($/hr)
		PG1	PG2	PG5	PG8	PG11	PG13		
DEAM	1-2	126.70	44.98	42.00	31.07	21.10	30.34	12.48	877.46
	1-3	131.16	44.24	39.51	30.24	21.05	25.35	8.08	847.82
	3-4	129.00	42.62	35.31	30.61	21.03	32.38	7.49	844.80
	2-5	144.69	42.89	31.74	29.44	21.88	26.25	13.33	846.33

	1-2 with load increased by 10%	131.69	58.70	46.39	33.10	21.54	34.66	14.26	999.25
	3-4 with load increased by 10%	133.62	55.39	46.64	31.48	22.51	33.51	11.38	986.78
	1-2 with increased load at bus 30 by 25%	127.34	46.68	37.25	32.80	21.90	33.62	13.54	881.661
	1-3 with increased load at bus 8 by 25%	127.00	46.53	36.30	32.61	22.64	34.30	8.47	880.35
DE	1-2	124.87	46.12	41.53	30.97	20.19	32.97	12.82	880.96
	1-3	128.65	42.75	39.81	31.18	20.41	29.18	8.30	854.93
	3-4	129.07	42.62	35.31	30.81	21.02	32.61	7.92	846.79
	2-5	149.59	40.37	32.69	24.46	21.13	28.97	13.32	848.67
	1-2 with load increased by 10%	126.78	65.17	46.70	31.71	21.97	33.50	14.06	1003.17
	3-4 with load increased by 10%	133.14	55.34	45.62	32.25	20.77	36.46	11.83	988.08
	1-2 with increased load at bus 30 by 25%	126.44	44.84	40.11	32.27	21.88	33.71	13.17	887.85
	1-3 with increased load at bus 8 by 25%	129.61	45.66	39.73	30.18	21.36	32.96	8.60	884.19

Table 3. Overloaded line details after rescheduling for DEAM and DE based SPCS.

Line outage	Lines	Line limit (MVA)	DEAM		DE	
			Line flow (MVA)	*SI*	Line flo (MVA)	*SI*
1-2	1-3	130	125.745	0	123.144	0
	2-4	65	24.939		24.384	
	3-4	130	118.735		116.283	
	4-6	90	73.994		73.506	
	6-8	32	12.825		13.152	
1-3	1-2	130	129.138	0	128.068	0
	2-4	65	46.244		44.752	
	2-6	65	48. 774		47.477	
	6-8	32	6.631		7.040	
3-4	1-2	130	127.022	0	126.559	0
	2-4	65	42.929		42.758	
	2-6	65	46.288		46.112	
	6-8	32	8.048		8.085	

2-5	1-2	130	82.025	0	85.544	0
	2-4	65	43.203		43.368	
	2-6	65	58.730		59.528	
	4-6	90	68.905		71.591	
	5-7	70	69.255		69.689	
	6-8	32	11.515		12.509	
1-2 with increased load by 10%	1-3	130	129.190	0	124.888	0
	2-4	65	23.311		21.141	
	3-4	130	121.646		117.563	
	4-6	90	77.894		76.224	
	6-8	32	9.325		9.732	
3-4 with increased load by 10%	1-2	130	128.461	0	127.499	0
	2-4	65	47.864		47.139	
	2-6	65	51.396		50.865	
	6-8	32	5.584		5.228	
1-2 with increased load at bus 30 by 25%	1-3	130	126.145	0	125.361	0
	2-4	65	25.416			
	3-4	130	119.119		25.40	
	4-6	90	75.386		118.378	
	6-8	32	12.645		74.723	
					12.644	
1-3 with increased load at bus 8 by 25%	1-2	130	126.639	0	129.324	0
	2-4	65	44.485		45.869	
	2-6	65	47.971		49.416	
	6-8	32	9.509		10.626	

6. Conclusions

In this paper, a Special Protection and Control Scheme (SPCS) for transmission line overloading alleviation has been carried out. The proposed method was based on hybrid Differential Evolution and Electromagnetism-like and named as DEAM algorithm. This method is relieved the line overload issue under critical situations through the generation rescheduling strategy that considered as a remedial action scheme. Line overloads due to unexpected line outage (i.e. N-1 contingency) conditions under base and increased load are considered. Simulation results have been compared with those from DE algorithm and showed that the DEAM based scheme offers minimum generation cost than DE for all the proposed case studies.

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