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Special Protection and Control Scheme for Transmission Line Overloading Elimination Based on Hybrid Differential Evolution/Electromagnetism-Like Algorithm

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Abstract – In designing System Protection Schemes (SPSs) in power systems, protecting transmission network against extreme undesired conditions becomes a significant challenge in mitigating the transmission line overloading. This paper presents an intelligent Special Protection and Control Scheme (SPCS) using of Differential Evolution with Adaptive Mutation (DEAM) approach to obtain the optimum generation rescheduling to solve the transmission line overloading problem in system contingency conditions. DEAM algorithm employs the attraction-repulsion idea that is applied in the electromagnetism-like algorithm to support the mutation process of the conventional Differential Evolution (DE) algorithm. Different N-1 contingency conditions under base and increase load demand are considered in this paper. Simulation results have been compared with those acquired from Genetic Algorithm (GA) application. Minimum severity index has been considered as the objective function. The final results show that the presented DEAM method offers better performance than GA in terms of faster convergence and less generation fuel cost. IEEE 30-bus test system has been used to prove the effectiveness and robustness of the proposed algorithm.

Keywords: Special protection scheme, N-1 contingency condition, Transmission line overloading, Generation rescheduling, Differential Evolution, Electromagnetism-like algorithm

Nomenclatures

P_i, Q_i	Active and reactive power injected into the system at bus *i*.
V_i, V_j	Bus voltage magnitude at buses *i* and *j*.
G_{ij}, B_{ij}	Self-conductance and susceptance of element *i-j*.
θ_{ij}	Voltage angle difference between bus *i* and *j*.
P_{Gi}, Q_{Gi}	Active and reactive power generated in bus *i*.
P_{Li}, Q_{Li}	Active and reactive power consumed in bus *i*.
$P_{Gi}^{min}, P_{Gi}^{max}$	Minimum and maximum limits of active power generated.
$Q_{Gi}^{min}, Q_{Gi}^{max}$	Minimum and maximum limits of reactive power generated.
V_i^{min}, V_i^{max}	Minimum and maximum limits of bus voltage magnitudes.
NB	Number of system buses.
NG	Number of generation units in power system.
NL	Number of transmission lines.
SI	Severity index
S_{ij}	Line flow between bus *i* and *j*.
S_{ij}^{max}	Line flow limit
ovl	Set of overloaded lines.
m	Integer exponent.

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1. Introduction

System Protection Schemes or Special protection Schemes (SPSs) also referred to as Remedial Action Schemes (RASs) are developed to discover abnormal system conditions and contingency- associated, and take pre-planned preventive actions for reliable system operations, other than isolation of faulted elements as taken in conventional protection schemes, to counteract the consequences of the abnormal system conditions, protect system integrity as well as keep acceptable performance [1]. SPS preventive actions comprise, changing in system demand (load shedding), changing in generation, and power system configuration to ensure system stability and meet acceptable voltage and power flow [2-4]. The triggering status of SPSs is usually applied by the occurrence of system perturbations like transient instability, voltage and/or frequency instability, and instability resulting from cascading line outages from the transmission network [3].

Due to increasing complexity of utility operation in the last years according to different reasons like the effects of growth in demand, increased size and complication of power systems, change in market conditions and increase in power imports/exports between neighbouring countries, the transmission system has become more stressed in its operation resulting in some transmission networks and other system components being worked near to their accepted operational boundaries. Thus, automated SPS programs have been widely applied 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], [4], [5].

The main purposes in constructing Special Protection Schemes are ensuring [6]:

- Operation of power systems within their operating limits.
- Increasing of a power system security during critical contingencies.
- Enhancing of the power system operating conditions within the activation of control schemes due to pre-determined corrective actions.

The protection of transmission infrastructure from overloading viewpoint throughout extreme contingencies is a significant issue which needs to be taken into consideration during designing of SPS schemes. The overloading problem of transmission network may worse according to load disturbances, transmission line outage and/or transformer outage. This issue may take place when there is no communication between system generation units and transmission grid [7]. The overloading situation of any transmission network may lead to cascading line outages and system collapse. Hence, some remedial actions could be taken into consideration to avoid the system overloading states, such as generation rescheduling, transmission line switching, phase shift transformers, demand side management and load shedding strategies [7]. Demand side management in which the load is changed by load shedding and generation rescheduling are the most widely utilized corrective actions to mitigate the line overloading where no additional reserves are needed.

The system impact studies and security assessment generally deal with N−1 contingency condition, which means loss of any one of the system components i.e. line, generator, and transformer without loss of demand. Therefore, it is determined whether or not the system operates in normal operating conditions and can resist these abnormal emergencies without any system limit violations [8]. 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 in order to determine the operating constraints under various conditions. The line overload problem based on protection and control can become a critical issue for prior outage of N−1 contingency conditions. Employing generation rescheduling and/or load shedding methods are the convenient corrective actions to avoid a system collapse in critical situations since building new transmission lines to meet N−1 contingency criteria is costly and time-consuming [9].

In this work, a hybrid Differential Evolution and Electromagnetism-like algorithm has been implemented to achieve the generation rescheduling plan due to the considered critical disturbances in order to relieve the line overloading issue based on the severity index criteria. In order to test the validation of the presented algorithm, IEEE 30-bus test system is used for the power flow solutions. Transmission line overloading due to sudden line outage with and without load disturbance is considered in this field of study.

2. Theoritical Background of Study

2.1 Generation rescheduling

To maintain a secure power system operation, the transmission grid loading should be maintained within specific thermal limits, and if the power flow in a specific line exceeds these limits, the line is said to be congested or 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. This could happen when there is miscommunication between the generation side and the transmission grid [10]. Alleviation of this critical situation is a crucial challenge in secure power system operation. Suitable preventive actions should be taken to effectively alleviate the line overloading 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 due to ease of control and no additional reserves are needed [11].

Generation rescheduling strategy has been applied by using several techniques based on optimal power flow for economy and security assessment. In [8], the authors presented a remedial action against the line overloads during the occurrence of contingencied based on the generation rescheduling plan and adjustment of phase-shifting transformers. The work proposed a GA based optimal power flow algorithm for determining the optimal magnitudes of active power generation and tested on IEEE-30 bus system.

Pandiarajan and Babulal presented an application from implementing a hybrid Differential Evolution with Particle Swarm Optimization (DEPSO) for transmission line overloading management [11]. Generation rescheduling is performed to remove the transmission line overloads by reducing the severity index magnitudes with a minimum rescheduling cost subjected to the system constraints. Simulation results were evaluated based on different N-1 contingency conditions.

An Improved Differential Evolution (IDE) algorithm to solve the line (congestion) overloading problem by the generation rescheduling method has also been presented in [12]. The solution was based on the generator sensitivity factor in order to select the most severe generators that should be rescheduled along with the voltage stability enhancement. The proposed method validated on the IEEE-30 bus system under base as well as increased load cases.

Balaraman and Kamaraj performed a scheme based on cascade back propogation neural network for prediction the line overloading amount and protecting the transmission line from the congestion issue by using the generation rescheduling concept due to N-1 contingency condition and sudden change in system demand [13]. Sharma S. and Laxmi S. conducted a technique based on cascade neural network to identify the overloaded lines in the power system and to predict the congestion amount in the identified overloaded lines [14]. The performed technique is evaluated for various generation/loading conditions and has been tested on the IEEE 14-bus system.

Line congestion management was also proposed, where the generators that participate in line overloads are chosen based on their sensitivity to the power flows in overloaded lines [15]. Generation rescheduling has been implemented using Particle Swarm Optimization (PSO) technique. PSO algorithm has also proposed in [16] for transmission overloading alleviation by applying rescheduling of system generation. Rescheduling has been done in an optimal power flow (OPF) aspect in order to minimize the total line overload. The same technique also presented in [18] for line congestion management with optimal generation rescheduling to relieve line overloads due to N-1 contingency and load variation.

Hagh M. Tarafdar *et al.* developed a version of Non-Dominated Sorting Genetic Algorithm which considered as an optimization tool to solve the minimum load shedding issue in system contingency conditions [17]. The implemented method was utilized to identify the amount and location of load to be shed in addition to generation rescheduling plan in post contingency conditions i.e. transmission line overloading and bus voltage violation. DE algorithm with its modified versions for optimal reactive power rescheduling problem has been presented in [19, 20] and for optimum load shedding problem in [21, 22] to enhance voltage stability in a power system.

It is obvious from the prior studies that the objectives of the generation rescheduling as well as load shedding strategies are:

- Mitigation of transmission line overload.
- Alleviation of bus voltage violation.
- Maintaining the desired level of voltage stability margins.

Thus, generation rescheduling and load shedding methods are the most effective and generally applied pre-planned actions taken by SPS to relieve the consequences of the critical power system conditions and contingency analysis to maintain suitable system performance and keep acceptable voltages or power flows.

3. Methodology

3.1 DEAM based SPCS

The main objective of the addressed DEAM based SPCS is to obtain an optimal rescheduling of real power generated in a power system in order to minimize the total generation fuel cost based on price bids exhibited by generation companies (GENCOs), in addition to minimizing the severity of post contingency conditions. This approach relieves the transmission grid overloading along with the system constraints during normal and abnormal system situations.

The minimization criterion of the total fuel cost in pre and post contingency conditions is defined as:

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

where *TC* represents the total generation fuel cost for modifying the real power generated of a power system in congestion management manner subjected to all system constraints. a_i, b_i and c_i are the system cost coefficients stated in Table 1 and adopted from [8, 23], P_{Gi} indicates the active power generated by generator *i*. The whole processing flow of the proposed hybrid Differential Evolution/Electromagnetism- like algorithm based SPCS is illustrated in Fig. 1 such that this SPCS determines the optimal values of active power generated along with the minimum severity index value that considered as the objective function as well as minimum generation rescheduling cost.

3.2 Severity Index (*SI*) formulation

The severity of an emergency situation that is associated with transmission line overloads can be characterized in terms of the severity index formula. This formula indicates the stressfulness on a power system in post contingency conditions [8, 13, 18] and can be expressed as follows:

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

The line flow is usually obtained from the load flow algorithm, where in this study, the Newton-Raphson method for load flow solution has been utilized. While computing the severity index values for the security assessment, only the overloaded lines have been considered during contingency analysis in order to avoid the masking effects [13]. In this work, the value of *m* has been fixed to 1 for the considered IEEE 30-bus test system. Furthermore, the value of *SI* should ideally be zero for a secure power system operation. The greater the value of *SI*, the more critical contingency would be.

3.3 Problem Formulation of DEAM Based SPCS's Constraints

In a power system contingency analysis, the primary task of the system operators is mitigating the line overloads.

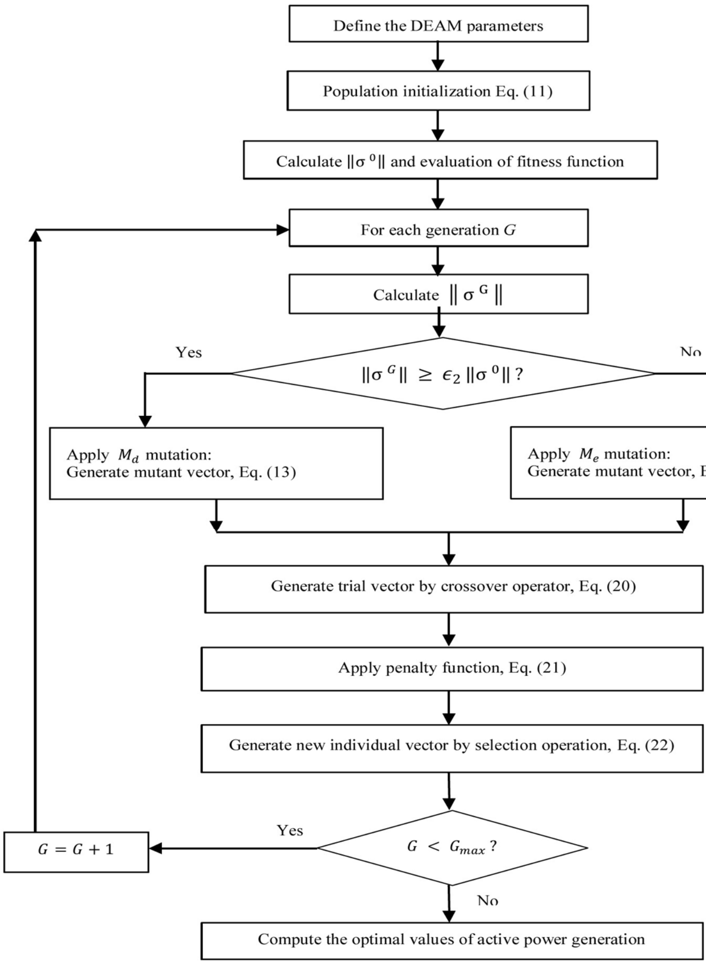

Fig. 1. General flowchart of the proposed DEAM based SPCS

Thus, a minimum value of the severity index has been taken as the objective function through this study along with minimum generation fuel cost. The minimization challenge and the optimal rescheduling of active power generation are subjected to the power system constraints as follows.

3.3.1 Equality constraints

The equality constraints represent the active and reactive power flow constraints and can be addressed as:

$$P_i = V_i \sum_{j=1}^{NB} V_j \left(G_{ij} \cos\theta_{ij} + B_{ij} \sin\theta_{ij}\right) \quad (3)$$

where: : $P_i = P_{Gi} - P_{Li}$

$$Q_i = V_i \sum_{j=1}^{NB} V_j \left(G_{ij}\, sin\, \theta_{ij} - B_{ij}\, cos\, \theta_{ij}\right) \quad (4)$$

where: $Q_i = Q_{Gi} - Q_{Li}$ for i = 1, …..NB

3.3.2 Inequality constraints

Inequality constraints illustrate the active and reactive power generation, voltage limits, as well as transmission line flow limits and represented as:

$$P_{Gi}^{min} \le P_{Gi} \le P_{Gi}^{max}\ i \in NG \quad (5)$$

$$Q_{Gi}^{min} \le Q_{Gi} \le Q_{Gi}^{max}\ i \in NG \quad (6)$$

$$V_i^{min} \le V_i \le V_i^{max}\ i \in NB \quad (7)$$

$$\left|S_{ij}\right| \le S_{ij}^{max}\ i = 1, \ldots . NL \quad (8)$$

Table 1. IEEE 30-bus generator data

Bus number*	Real power generation limits (MW)		Generation cost coefficients		
	min	max	a	b	c
1	50	200	0.0	2.0	0.00375
2	20	80	0.0	1.75	0.0175
5	15	50	0.0	1.0	0.0625
8	10	35	0.0	3.25	0.00834
11	10	30	0.0	3.0	0.025
13	12	40	0.0	3.0	0.025

*: Buses are where generators are located.

The real power generation limits thats related to the IEEE 30-bus test system are given in Table 1 as well as the generation cost coefficients that are adopted and taken from [23, 24].

4. The Proposed DEAM Algorithm

4.1 Overview of Electromagnetism-Like(EM) algorithm

Electromagnetism-like algorithm (EM) is a recently suggested algorithm based on a population set method [25], [26]. An attraction-repulsion concept is applied in this algorithm to move the individual vectors in a population set algorithm to the vicinity of the global optima. The vectors via superior objective values will attract others, whereas those with inferior objective values repulse. EM algorithm performed in some applications as in [25-29]. The general details of EM approach have been mentioned in [25, 27].

4.2 Overview of DEAM algorithm

Conventional Differential Evolution (DE) algorithm is a population set based direct search algorithm which solves problems by improving its solution according to predefined execution criteria. It is an algorithm used for optimization with high performance and is easy to understand and apply [32]. Storn and Price primarily introduced the DE algorithm in 1997 [31]. Like other evolutionary based algorithms, DE emplys of an initial population set which consists of *NP D*-dimensional individual vectors. These vectors that generated randomly are driven by a contraction operation toward the optimum values where these values satisfy the global minimization. In this work, a hybrid differential evolution and electromagnetis-like algorithm has been implemented in order to obtain the optimal values of active power generated.

DEAM algorithm is similar to the conventional DE approach except it employs the attraction-repulsion concept of the Electromagnetism-like algorithm in order to improve the mutation process of the conventional DE algorithm [28]. The attraction process principally exchanges bad individual vectors in a population set with better individuals for each iteration. The benefits from using DEAM algorithm are to improve the convergence of DE algorithm as well as improve its reliability (accuracy of optimal solution) [27, 28]. Mixed mutation strategies are utilized in this algorithm. The first mutation strategy is the mutaion used by the normal DE technique and denoted by M_d. Whereas the second concept is the mutation process that is utilized in the EM algorithm and indicated by M_e [29]. DEAM algorithm was tested on many test problems based on practical applications and has been utilized for extracting PV model parameters [25-29].

The proposed algorithm contains four simple stages: initialization, mutation operation, crossover operation, and lastly the selection process. DEAM algorithm is similar to the other population based algorithms where these algorithms rely on the initial population set (P) which is randomly generated and considered as a candidate solution to a particular optimization problem. This algorithm produces a population set of *NP* real valued individual vectors and every individual vector consists of *D* parameters that represent the dimensionality of the optimization problem and need to be optimized. Thus, this algorithm employs *NP D*-dimensional vectors as a population set in order to search the optimal values within the search region. The mutation, crossover as well as selection stages are repeated for each iteration until the maximum number of generations denoted by G_{max} is achieved or the desired fitness value is reached. The algorithm creates a population set of the real valued vectors $X_{i,G}$ as follows [33, 34]:

$$P_{X,G} = [X_{1,G}, X_{2,G}, \ldots] = [X_{i,G}] \tag{9}$$

$$i = 1, \ldots NP, and\ G = 0, 1, \ldots G_{max}$$

$$X_{i,G} = [X_{j,i,G}]\ and\ j = 1, \ldots D \tag{10}$$

Each individual vector has a population index i from 1 to *NP,* where *NP* is the number of individuals (candidate solutions) to the optimization problem. The parameters within the vectors are indexed by j and range from 1 to D, where D is the dimension of the individual vector which represents the number of generation units in the addressed power system in this study. $X_{i,G}$ is the target vector. G indicates the generation (i.e. iteartion) index to which a vector belongs. The main stages of this algorithm are described in details as follows:

4.2.1. Initialization

In order to start the optimization operation, an initial population set (P) consists of *NP D*-dimentional real valued vectors $X_{i,G} = [X_{1,i,G}, X_{2,i,G}, \ldots, X_{j,i,G} \ldots X_{D,i,G}]$ are created and each parameter vector represents a candidate solution to the optimization process. The initial values of the D parameters that represent the number of generation units are usually randomly selected and distributed uniformly in the search space. If the vector parameter has boundaries denoted by X_L and X_H, where $X_L = [X_{1,L}, X_{2,L}, \ldots, X_{D,L}]$ and $X_H = [X_{1,H}, X_{2,H}, \ldots, X_{D,H}]$ are the lower and upper limits of the search region respectively, then the initial jth component of the ith population vector is created by:

$$X_{j,i,0} = X_{j,L,i} + rand[0,1](X_{j,H,i} - X_{j,L,i}) \tag{10}$$

where *rand* [0,1] represents a random number which uniformly distributed between 0 and 1.

4.2.2 Mutation

In this stage, DEAM is invoked either M_d or M_e operation in every iteration. The main criteria adopted to switch between both kinds of the mutation process is based on the standard deviation of the row vectors of the population set P as follows:

$$Mutation = \begin{cases} M_e \; if \; \|\sigma^G\| < \epsilon_2 \|\sigma^0\| \\ M_d \; otherwise \end{cases} \quad (12)$$

where $\|\sigma^0\|$ and $\|\sigma^G\|$ represent the norm of the vectors of the standard deviation belong to the row vectors in the population set (P) for the initial generation and the current generation respectively. ϵ_2 is a switching parameter which is implemented to switch between M_d and M_e operations and its value $\epsilon_2 \in [0,1]$. The value of $\|\sigma^G\|$ is calculated at the beginning of each iteration. For each target vector $X_{i,G}$, there is a mutant vector (donor vector) $V_{i,G}$ which is generated due to M_d operation and described as:

$$V_{i,G} = X_{\alpha,G} + F\left(X_{\beta,G} - X_{\gamma,G}\right) \quad (13)$$

where $X_{\alpha,G}$, $X_{\beta,G}$ and $X_{\gamma,G}$ are vectors randomly chosen among the population and different from the target vector. α, β *and* γ are distinguished indices under the range from 1 to *NP*. The first vector $X_{\alpha,G}$ which is called the base vector, and F is a mutaion scaling factor and typically selected in the range between 0 and 1. Whilst the M_e mutation is also based on three distinguished vectors and randomly selected from the population set. Unlike M_d, however, the value of the index of one of these selected individual vectors could be the same index value of the current target vector [28]. The M_e process utilizes the total force exerted on one individual vector such as $X_{\alpha,G}$ by the other two selected vectors namely $X_{\beta,G}$ and $X_{\gamma,G}$. Similar to the EM algorithm, the force that exerted on the vector $X_{\alpha,G}$ by $X_{\beta,G}$ and $X_{\gamma,G}$ is calculated due to the charges between the selected vectors, and can be expressed as:

$$q_{\alpha,\beta,G} = \frac{f(X_{\alpha,G}) - f(X_{\beta,G})}{f(X_{w,G}) - f(X_{b,G})} \quad (14)$$

$$q_{\alpha,\gamma,G} = \frac{f(X_{\alpha,G}) - f(X_{\gamma,G})}{f(X_{w,G}) - f(X_{b,G})} \quad (15)$$

where $f(X)$ represents the objective function value for an individual vector X, $f\left(X_{b,G}\right)$ and $f\left(X_{w,G}\right)$ are the best and worst values of the objective function for G^{th} generation respectively. Additionally, G is the index which indicates the number of the current generation where G =1,2,... G_{max}. Thus, the forces exerted on $X_{\alpha,G}$ by $X_{\beta,G}$ and $X_{\gamma,G}$ is calculated by:

$$F_{\alpha,\beta,G} = \left(X_{\beta,G} - X_{\alpha,G}\right) q_{\alpha,\beta,G} \quad (16)$$

$$F_{\alpha,\gamma,G} = \left(X_{\gamma,G} - X_{\alpha,G}\right) q_{\alpha,\gamma,G} \quad (17)$$

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

$$F_{\alpha,G} = F_{\alpha,\beta,G} + F_{\alpha,\gamma,G} \quad (18)$$

After that, the donor vector of the M_e process is calculated as:

$$V_{i,G} = X_{\alpha,G} + F_{\alpha,G} \quad (19)$$

4.2.3. Crossover

This stage of DEAM algorithm is similar to the crossover process of the conventional DE algorithm. This step is performed to increase the diversity of the population, where in which the donor vector $V_{i,G}$ as well as the target vector $X_{i,G}$ are used to bring the trial vector $U_{j,i,G}$ and can be described by:

$$U_{j,i,G} = \begin{cases} V_{j,i,G} \; if \; (rand \le CR \; or \; j = j_{rand}) \\ X_{j,i,G} \; otherwise \end{cases} \quad (20)$$

where *CR* denoted to the crossover control parameter which controls the diversity of the population and assist the algorithm to escape from the local optima. Its range between 0 and 1. $j_{rand} \in [1,2,\ldots..D]$ represents a randomly selected index that ensures $U_{i,G}$ obtains at least one element from $V_{i,G}$.

A penalty function is implemented in order to avoid the violation of parameter limits and to ensure that the trial vector parameters lie within the allowable search region after the recombination process (mutation and crossover). Any vector parameter violates the permissible limits is replaced by a new value as:

$$U_{j,i,G} = X_{j,i,L} + rand[0,1]\left(X_{j,i,H} - X_{j,i,L}\right) \quad (21)$$

4.2.4. Selection

In order to keep the population size constant, the selection stage is used to detect either the current target vector $X_{i,G}$ or the trial vector $U_{i,G}$ will be chosen as a member to the next generation at (G = G+1). The selection mechanism can be addressed by the following formula:

$$X_{i,G+1} = \begin{cases} U_{i,G} \; if \; J\left(U_{i,G}\right) < J(X_{i,G}) \\ X_{i,G} \; otherwise \end{cases} \quad (22)$$

where $J(X)$ clarify the objective function that needs to be minimized. Thus, the selection operation between these two vectors depends on the objective function magnitudes where the smaller one is selected as a member in the population for the next generation. Therefore, the new population set either gets better or stays constant in terms of the fitness function value but never declines.

Lastly, the recombination process of the trial vectors (i.e. mutation and crossover) as well as the selection steps are repeated for every iteration till the prespecified maximum number of generation G_{max} is achieved. The pseudo code of the addressed DEAM algorithm is shown in Fig. 2.

Step 1:
Setting the control parameters magnitudes of DEAM algorithm:
Parameter limits [X_L,X_H], popoulation size *NP D*, maximum number of generations *Gmax*, crossover parameter *CR*, mutation factor *F*, and ϵ_2 .

Step 2:
Set the generation value G = 0 and randomly initialize a population set consisted from *NP* individual vectors and each individual vector uniformly distributed in the range [X_L, X_H] as:
$X_{j,i,0} = X_{j,L,i} + rand[0,1](X_{j,H,i} - X_{j,L,i})$
where j =1,2,....D , i =1,2,.......NP
Compute $\|\sigma^0\|$

Step 3:
Setting G = 1

$$fitness\_best = \min\left(f(X_{i,0})\right)$$

$$fitness\_worst = \max\left(f(X_{i,0})\right)$$

While $(G \leq G_{max})$ do:
Compute $\|\sigma^G\|$
for i = 1 to NP

Step 3.1 Mutation Step:
Create a mutant vector $V_{i,G}$
Select randomly three distinguished individual vectors $X_{\alpha,G}$,$X_{\beta,G}$ and $X_{\gamma,G}$ from the current population set.
$if\ \|\sigma^G\| \geq \epsilon_2 \|\sigma^0\|$

M_d **mutation step**
$V_{i,G} = X_{\alpha,G} + F(X_{\beta,G} - X_{\gamma,G})$
else
M_e **mutation steps**
$q_{\alpha,\beta,G} = \frac{f(X_{\alpha,G})-f(X_{\beta,G})}{f(X_{w,G})-f(X_{b,G})}$, $q_{\alpha,\gamma,G} = \frac{f(X_{\alpha,G})-f(X_{\gamma,G})}{f(X_{w,G})-f(X_{b,G})}$

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

$F_{\alpha,G} = F_{\alpha,\beta,G} + F_{\alpha,\gamma,G}$, $V_{i,G} = X_{\alpha,G} + F_{\alpha,G}$
end if

Step 3.2 Crossover Step:
Generate a trial vector $U_{j,i,G}$
Select j_{rand} randomly in the range [1,D]
for j = 1 to D

$if(rand \leq CR\ or\ j = j_{rand})$
$U_{j,i,G} = V_{j,i,G}$
else
$U_{j,i,G} = X_{j,i,G}$
end if
end for
Step 3.2.1 Penalty Function:
for j=1 to D
$if\ (U_{j,i,G} < X_{j,L,i})\ or\ (U_{j,i,G} > X_{j,H,i})$
$U_{j,i,G} = X_{j,L,i} + rand[0,1](X_{j,H,i} - X_{j,L,i})$
end if
end for

Step 3.3 Selection and evaluation:
Evaluate the trial vector $U_{j,i,G}$
$if\ f(U_{j,i,G}) < f(X_{j,i,G})$
$X_{i,G+1} = U_{i,G}$
else
$X_{i,G+1} = X_{i,G}$
end if
end for
Step 3.4 Generation Counter:
$G = G + 1$
end while

Fig. 2. Pseudo code of the performed DEAM algorithm

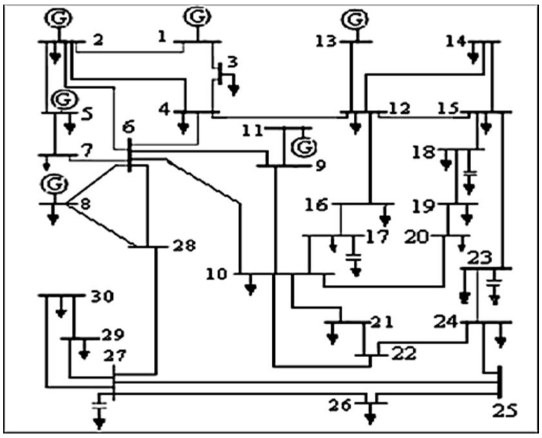

Fig. 3. Single line diagram of the IEEE 30-bus system [35]

5. Results and Discussion

In order to reveal the effectiveness of the proposed hybrid Differential Evolution and Electromagetism-like based SPCS scheme, the algorithm is validated on theIEEE 30-bus test system as shown in Fig. 3.

Simulation results of the presented algorithm are compared with those resulted from the Genetic Algorithm (GA) application in terms of the speed of convergence and the generation fuel cost. The executed approaches have been written in MATLAB software and carried out in an Intel core i3 2.2 GHz CPU, 2 GB RAM PC.

The utilized test system consists of six generator buses, twenty four load demand buses and fourty one transmission lines and the system data are adopted and taken from [23, 24] regarding the generators active power minimum and maximum limits, the transmission line parameters, and the system load demand. The total amount of active and reactive power of the load demand are 283.4 MW and 126.2 MVAR respectively. The minimum bus voltage limits for all system buses are maintained within 0.95 p.u and the maximum limits are 1.1 p.u for generator buses and 1.05 p.u for the remaining load buses through the application of the generation rescheduling plan which is considered as the remedial action scheme.

A.C power flow algorithm like Newton–Raphson method has been carried out to compute the parameters associated with each bus of the power system which comprise four parameters: bus voltage magnitude, voltage phase angle, active and reactive injected power. The parameters associated with each transmission line are: active and reactive power flows as well as line losses in a particular power system.

At any power system, transmission line overloading could occur due to different reasons including line outage. Hence, in this research, N-1 contingency analysis is performed under base and increased load demand conditions to identify the potential emergencies during the power system operation.

5.1 System contingency conditions

The system contingency analysis was conducted under both base and increased load situations in order to define the harmful disturbances in specific system conditions. For each of the implemented cases, pre and post contingency line flows are obtained from the power flow solution in order to determine which lines are overloaded due to a specific single line outage.

Thus, N-1 contingency analysis has been carried out under normal and abnormal system demand. From the contingency studies, the line outages 1-2, 1-3, 3-4, 2-5 under base load as well as line 1-2 and 3-4 outages under increased load at all system buses by 10% in addition to line 1-2 outage under increased demand at bus 30 by 25% and line 1-3 outage under increased load at bus 8 by 25% have resulted in overloading of some other transmission lines.

Table 2. Simulated line outage before rescheduling under base load conditions

Line outage	Overloaded lines	Line flow (MVA)	Line limit (MVA)	*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	

Table 3. Simulated line outage before rescheduling under increased load conditions

Line outage	Overloaded lines	Line flow (MVA)	Line limit (MVA)	*SI*
1-2 with increased load at all buses 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 at all buses 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	

The simulated line outage details for the carried out case studies with their affected overloaded lines before applying the generation rescheduling strategy for all scenarios under base and increased demand situations are tabulated in Table 2 and Table 3 respectively.

The line flow has been calculated by conducting full A.C power flow and the magnitudes of the severity index are evaluated for each scenario based on the severity index criterion. The transmission line flow limits are considered within the proposed algorithms and these limits are adopted and taken from the line data reported in [23].

5.2 DEAM application in generation rescheduling

To maintain a secure operation of a power system, the power flows in transmission lines should not exceed their allowable limits in both normal and abnormal system conditions. Subsequently, appropriate corrective actions should be taken to alleviate the transmission line overloads. The fundamental idea of this study is to alleviate the line overloading within the optimal rescheduling of active power generation during contingency conditions. The optimal value of the generation rescheduling has been evaluated based on the combined DE and EM based SPCS scheme as well as validated with GA based approach for the same simulation scenarios.

5.2.1 Optimization process of real power determination

The active power generated of the system generators are taken as the control variables for the proposed algorithm. At first, a set of P_G values are created randomly by DEAM algorithm within their minimum and maximum limits as given in Table 1 in such a way that the Eq. (5) is satisfied via its lower and upper boundaries.

After that, these created P_G values are evaluated in the fitness function algorithm to obtain the related severity index values. Subsequently, the proposed algorithm performs the specified mutation strategy and crossover operation in order to get a better and minimum fitness value for each individual vector within the population set.

The control parameter settings of the proposed SPCS regarding the mutation factor F and crossover factor CR are taken as 0.8 and 0.5 respectively. The good values of the parameter ϵ_2 lie between 0 and 0.4 [27]. In the present paper, ϵ_2 is selected to be 0.25 to obtain better results after many attempts.

Since the number of the system generators is six, the value of the optimization problem (D) equals to six. The population size (*NP*) is selected within the range 5D to 10D [30]. Thus, *NP* value is set to 30 which is the same population size in GA method. Moreover, in GA algorithm, the setting values of crossover probability and mutation probability are equal to 0.8 and 0.3 respectively according to many trials. The maximum number of iterations is set to

Table 4. Setting of control variables for base load cases

Hod	Line out of service	Active power generation (MW)						Power losses (MW)	Generation cost ($/hr)
		PG1	PG2	PG5	PG8	PG11	PG13		
	1-2	126.70	44.98	42.00	31.07	21.10	30.34	12.48	877.46
DEAM	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	126.77	43.51	42.27	27.5	22.48	33.81	12.94	882.74
GA	1-3	127.65	42.97	39.31	28.64	21.59	31.60	8.28	855.91
	3-4	129.99	42.16	34.74	29.34	21.98	33.40	8.11	847.04
	2-5	144.10	38.35	30.47	28.79	22.83	32.40	13.39	852.85

Table 5. Setting of control variables for increased load cases

Method	Line out of service	Active power generation (MW)						Power losses (MW)	Generation cost ($/hr)
		PG1	PG2	PG5	PG8	PG11	PG13		
DEAM	1-2 with increased load at all bus by 10%	131.69	58.70	46.39	33.10	21.54	34.66	14.16	999.25
	3-4 with increased load at all bus by 10%	133.62	55.39	46.64	31.48	22.51	33.51	11.14	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
GA	1-2 with increased load at all bus by 10%	130.03	60.15	47.18	31.25	24.01	33.92	14.75	1004.99
	3-4 with increased load at all bus by 10%	136.13	47.51	47.77	32.34	22.85	36.22	11.00	991.67
	1-2 with increased load at bus 30 by 25%	128.61	45.76	40.08	29.04	22.45	33.88	13.75	888.15
	1-3 with increased load at bus 8 by 25%	128.44	46.35	39.65	30.00	22.73	32.97	9.20	887.55

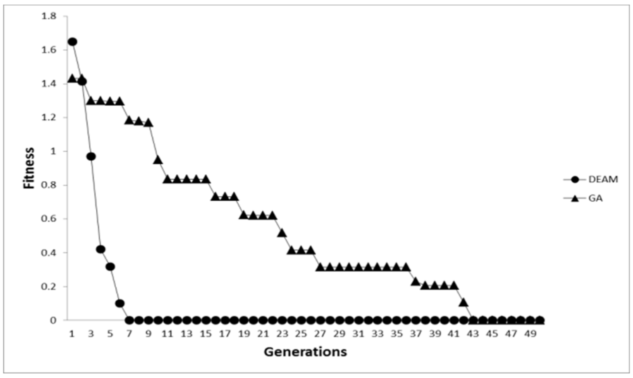

Fig. 4. Fitness convergence of line 1-2 outage

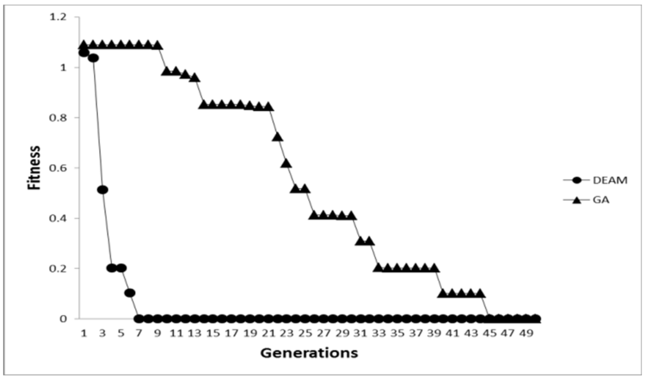

Fig. 5. Fitness convergence of line 1-3 outage

be 50 for both the executed algorithms.

The implemented fitness algorithm is the load flow solution in order to get the line flows for each simulated case and in turn evaluating the severity index values. Minimum severity index is taken as the objective function of the proposed approach. The optimal values of active power generated for each generation unit in the tested system and taken as the corrective action strategy are tabulated in Table 4 for the proposed DEAM as well as GA algorithms along with its specified line contingency under base load conditions. The results from the simulated 10% increased load cases at all buses along with line 1-2 and 3-4 outage as well as line 1-2 with increased load at bus 30 by 25% and line 1-3 with increased load at bus 8 by 25% are also shown in Table 5. The generation rescheduling cost for each implemented case study is also given in the last column within the Tables 4 and 5 respectively. It can be seen from the Table 4 as well as Table 5 that the hybrid DE and EM algorithm offers less generation rescheduling fuel cost than GA based approach for all the considered line outage simulation cases.

The applied algorithms are executed for a maximum number of 50 generations (iterations) and they have been forced to stop if the maximum number of generations is reached. In this paper, both algorithms are conducted for at least 10 independent test runs.

Active power generation magnitudes of the test system are determined as the average values based on the total independent test runs. The total system transmission losses for each line outage are also taken as the average and their values are depicted in Table 4 for the normal system demand as well as Table 5 for the increased system demand situations. The overloaded line details after rescheduling of the system generation units for DEAM and GA based

Table 6. Overloaded line details after rescheduling for DEAM and GA based SPCS

Line outage	Overloaded lines	Line limit (MVA)	DEAM		GA	
			Line flow (MVA)	*SI*	Line flow (MVA)	*SI*
1-2	1-3	130	125.745	0	125.732	0
	2-4	65	24.939		25.41	
	3-4	130	118.735		118.754	
	4-6	90	73.994		75.477	
	6-8	32	12.825		13.304	
1-3	1-2	130	129.138	0	127.244	0
	2-4	65	46.244		44.245	
	2-6	65	48. 774		47.251	
	6-8	32	6.631		7.850	
3-4	1-2	130	127.022	0	127.384	0
	2-4	65	42.929		42.677	
	2-6	65	46.288		46.163	
	6-8	32	8.048		8.422	
2-5	1-2	130	82.025	0	83.127	0
	2-4	65	43.203		40.128	
	2-6	65	58.730		55.383	
	4-6	90	68.905		67.608	
	5-7	70	69.255		68.666	
	6-8	32	11.515		12.777	
1-2 with increased load at all buses by 10%	1-3	130	129.190	0	127.852	0
	2-4	65	23.311		22.733	
	3-4	130	121.646		120.385	
	4-6	90	77.894		77.336	
	6-8	32	9.325		9.919	
3-4 with increased load at all buses by 10%	1-2	130	128.461	0	128.977	0
	2-4	65	47.864		45.643	
	2-6	65	51.396		49.087	
	6-8	32	5.584		5.470	
1-2 with increased load at bus 30 by 25%	1-3	130	126.145	0	127.242	0
	2-4	65	25.416		25.376	
	3-4	130	119.119		120.162	
	4-6	90	75.386		76.658	
	6-8	32	12.645		12.366	
1-3 with increased load at bus 8 by 25%	1-2	130	126.639	0	127.343	0
	2-4	65	44.485		45.405	
	2-6	65	47.971		48.905	
	6-8	32	9.509		10.856	

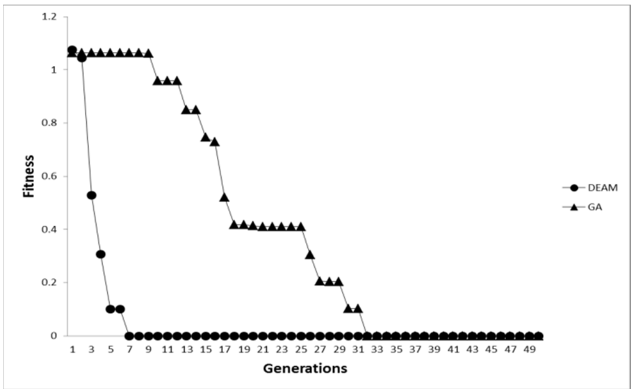

Fig. 6. Fitness convergence of line 3-4 outage

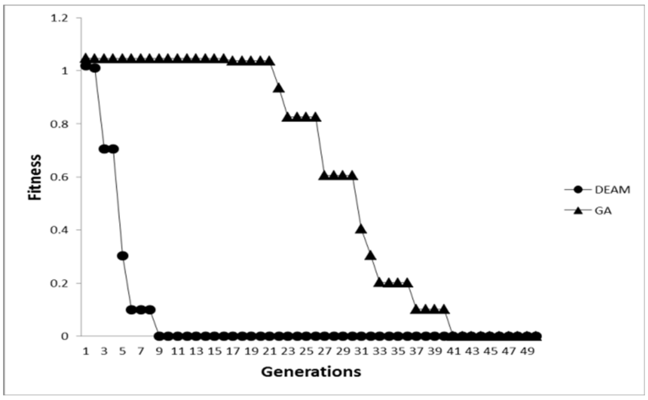

Fig. 7. Fitness convergence of line 2-5 outage

SPCS are illustrated in Table 6 for all the considered system conditions.

It can be seen from the Table 6 that the new power generated values by the performed algorithms are completely relieved the overloaded lines and the new line flows values are below their line flow limits. In addition to that, the new magnitudes of the severity index are completely reduced, where in the case of DEAM approach, from 16.265, 9.279, 9.076, and 10.885 for base load cases and 22.580, 11.518, 16.854, and 10.375 for increased load cases to zero which denoted that no more lines get overloaded after the generation rescheduling plan offered by the presented DEAM based SPCS. This means that the line overloading problem is completely solved. Similarly,

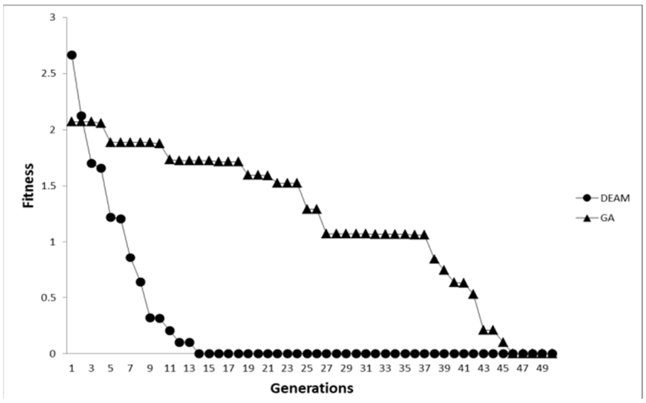

Fig. 8. Convergence of line 1-2 with 10% load increased

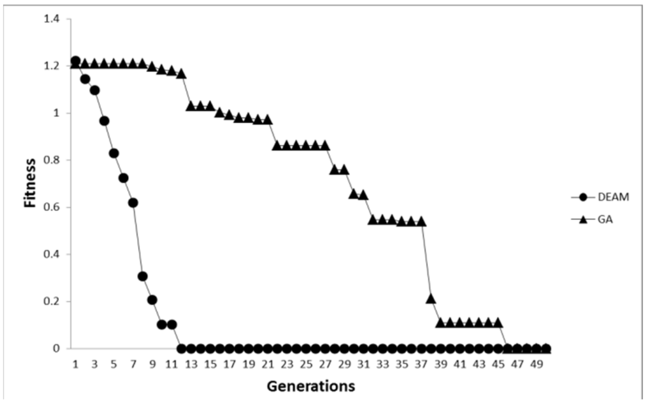

Fig. 9. Convergence of line 3-4 with 10% load increased

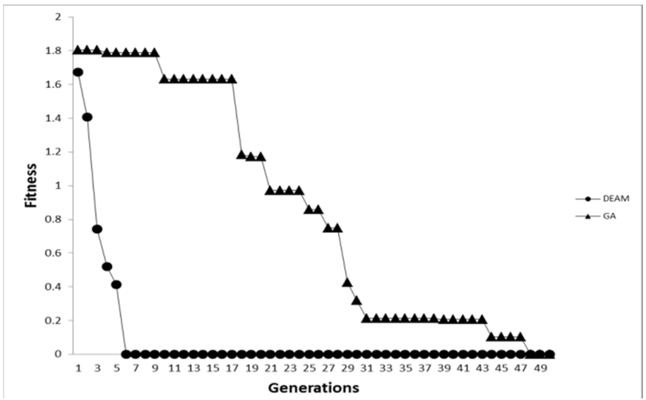

Fig. 10. Convergence of line 1-2 outage with load increased increased at bus 30 by 25%

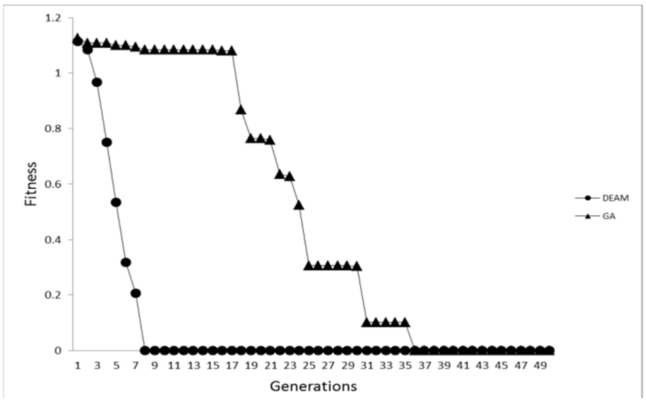

Fig. 11. Convergence of line 1-3 outage with load at bus 8 by 25%

the overloaded line details after rescheduling for the GA-based SPCS are also as shown in Table 6.

Fig. 4, 5, 6, and 7 for base load cases and 8, 9, 10, and 11 for increased load cases show the variations of the fitness function convergence for the specified simulated cases in this research work. These figures view the fitness convergence behaviour for the implemented DEAM based algorithm versus GA method. The fitness function values are taken as the average of the executed independent runs. Visually, it can be seen from the figures that the fitness behaviour of the proposed DEAM algorithm converges more rapidly than the fitness convergence of GA algorithm under both system conditions. During the first iterations, DEAM algorithm focuses on finding the appropriate solutions to the specified problem and the fitness values (i.e the severity index) are getting down to its minimum value close to zero.

6. Conclusion

In this research, a Special Protection and Control Scheme (SPCS) for transmission line overloading mitigation during critical contingencies has been proposed.

The proposed method is based on the Differential Evolution with Adaptive Mutation per iteration namely DEAM algorithm by combining the conventional version of DE algorithm with the attraction-repulsion idea of the EM mechanism. This method is proven to completely relieve the transmission line overloading problem along with minimum severity index under critical situations through the generation rescheduling strategy which considered as the preventive remedial action scheme. Line overloads according to unexpected line outage i.e. N-1 contingency condition under base case as well as increased demand are considered in this study. IEEE 30-bus system was used to demonstrate the validation of the DEAM based SPCS algorithm. Moreover, the numerical results have been compared with those of the Genetic Algorithm and showed that DEAM based method performs faster than GA in terms of the fitness convergence and offers minimum generation fuel cost for the considered case studies.

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