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Research Article

Dispatching a 19-Unit Indian Utility System Using a Refined Differential Evolution Algorithm

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This paper presents a differential evolution with neighborhood based mutation (DE-NM) technique to solve Dynamic Economic Dispatch (DED) problem with valve point effects and multiple fuel options. A new mutation scheme based on neighborhood topology is presented with an aim to achieve the cost reduction together satisfying the dynamic behavior of the generating units over the considered time period. The neighborhood based mutation (NM) balances the exploration and exploitation of the search effort of differential evolution (DE) technique. The NM method enhances the convergence speed and the performance of the DE technique. The performance of the DE-NM is tested on a 10-unit and a real public Indian utility system with 19 generating units. Both the test systems are illustrated under different load patterns. The dispatch results obtained using the proposed method for the Indian system have considerably reduced the operating cost and optimized its operation.

1. Introduction

Dynamic economic dispatch (DED) is a vital task in the economic operation of modern power system [1, 2]. The DED is defined as the optimal allocation of the predicted load profile among the online generators for a specific period of time. The objective of DED is to minimize the total fuel cost over the whole scheduling period subjected to practical and technical constraints. In DED the generation schedule is greatly affected due to ramp rate limits [3]. This ramp rate constraint sets a limit on the rate of change of electrical power output for the safe operation of the generating units. Thus the DED problem is a practical formulation in real-time power system problem.

Actual DED formulation mainly depends on the representation of the fuel cost curve of the generators. Several conventional methods [4–6] such as lambda iteration, base point participation factor, Newton method, gradient method and Dynamic programming (DP) [7] is used to solve the DED problem by assuming the fuel cost curve of the generators piecewise linear and non-monotonically increasing. But, in practical generation the fuel cost curve is non-linear and non-convex because of valve point effect [8], multiple fuel option [9] and operational constraints such as prohibited operating zones [10], spinning reserves [11]. Thus makes the above conventional methods fail to solve for quality solution.

To overcome the drawback in the conventional methods, heuristic techniques were introduced. Recently, artificial intelligence techniques such as Artificial Neural Network (ANN) [12], genetic algorithm (GA) [8], evolutionary programming (EP) [13], simulated annealing (SA) [14], particle swarm optimization (PSO) [15], differential evolution (DE) [16], modified differential evolution (MDE) [17], and hybrid algorithm (HA) [18, 19] are widely used to solve the DED problem. All the techniques have yielded success to certain extent, but they suffer from premature convergence, local trapping of the problem, and setting the control parameter.

Combining deterministic techniques with evolutionary algorithms (EAs) is a promising alternative to solve highly nonlinear and nonconvex cost functions. Probabilistic methods do not always guarantee discovering the global optimum solution in finite time since updating their candidate's position in the solution space requires probabilistic rules. Therefore, fine tuning of the above techniques was applied for every improvement in the solution. Plenty of literature work has been done on the fine tuning of above methods. To be concise, a few are included in the reference. Hybridization of EP with SQP (EP-SQP) [20], PSO with SQP (PSO-SQP) [21], and chaotic differential evolution with SQP (DEC-SQP) [22] are few examples.

Differential evolution proposed by Storn and Price is one of the EA widely used in solving power system optimization problems. DE has got many advantages such that it is simple and easy to understand, and it can handle integer and discrete optimization, ease of use, fast convergence and robustness. In addition, DE is good at exploring the search space and locating the region of global optimum. Like other EAs, DE performance decreases as search space dimensionality increases. Also, DE is sensitive to the choice of the control parameters and it is difficult to adjust them for different problems [23]. Such contradictions in adjusting the control parameters can be overcome by self-adaptive techniques [24]. Hybridization of DE with other heuristic or local different algorithms is considered as an alternate direction of improvement of classical DE.

From the literature [22–25], it can be observed that the main modifications, improvements, and developments on DE focus on adjusting control parameters in self-adaptive manner and or hybridization with other local search techniques. Very few enhancements have been implemented to modify the standard mutation strategies or to propose new mutation rules so as to enhance the total search ability of DE and to overcome the problems of stagnation or premature convergence [25]. In addition, DE is good at exploring the search space but slow at exploitation of solution [26]. In this paper DE algorithm with a neighborhood based mutation (DE-NM) [27] is developed for solving the DED problem. The new mutation scheme utilizes a concept of neighborhood of each population member. The neighborhood based mutation (NM) balances both the exploration and exploitation process to enhance the search ability of DE.

The significant contribution of this paper is optimum generation schedule of an Indian utility system for three different load patterns. The Indian utility system consists of 19 generating units with the fuel cost function taking into account the valve-point effect and multiple fuel option. The DED problem of the Indian utility system is solved conventionally by priority list method where the generating units are allowed to run at full load to meet the demand. Also, real time constraints, such as ramp rate limits, prohibited operating zones, and so forth, are not taken into account in the solution. In recent years pilot attempts are taken to implement various artificial techniques in the operation and control of Indian power system. One such attempt is presented in this paper to solve the DED problem with valve point loading, ramp rate limits, prohibited operating zones, multiple fuel options, and spinning reserve.

This paper is organized as follows: DED problem is formulated in Section 2. Sections 3 and 4 give a detailed description of the DE-NM. Section 5 describes the implementation of DE-NM to DED problem. Analysis of DE-NM method with two systems is provided in Section 6 and Section 7 outlines the conclusion.

2. Problem Formulation

The objective function of DED problem is to minimize the total production cost of power over a given dispatch period, while satisfying various constraints. The objective function is formulated as

$$\text{Minimize,}\ \ F_T = \sum_{h=1}^{H}\sum_{i=1}^{N} F_{ih}\left(P_{ih}\right). \tag{1}$$

Generally, the generator cost function is usually expressed as a quadratic polynomial as

$$F_{ih}\left(P_{ih}\right) = a_i P_{ih}^2 + b_i P_{ih} + c_i. \tag{2}$$

For accurate nonconvex models of the objective function, the DED problem with valve point effects has to be considered by superimposing a rectified sinusoid component in the traditional quadratic fuel cost function as formulated in

$$F_{ih}\left(P_{ih}\right) = a_i P_{ih}^2 + b_i P_{ih} + c_i + \left| e_i \sin\left(f_i \left(P_{ih}^{\min} - P_{ih} \right)\right)\right|. \tag{3}$$

Similarly practical generating units are supplied with multiple fuel sources and the cost functions of these units are represented with few or several piecewise quadratic functions. Such a cost function is called as a hybrid cost function and each segment of the hybrid cost function gives some information about the fuel burnt. The hybrid cost function is formulated as

$$F_{ih}\left(P_{ih}\right) = \begin{cases} a_{i,1}P_{ih}^2 + b_{i,1}P_{ih} + c_{i,1}, & \text{fuel 1}, \quad P_{ih}^{\min} \le P_{ih} \le P_{ih,1} \\ a_{i,2}P_{ih}^2 + b_{i,2}P_{ih} + c_{i,2}, & \text{fuel 2}, \quad P_{ih,1} < P_{ih} \le P_{ih,2} \\ \quad \vdots & \\ a_{i,k}P_{ih}^2 + b_{i,k}P_{ih} + c_{i,k}, & \text{fuel } k, \quad P_{ih,k-1} < P_{ih} \le P_{ih}^{\max}. \end{cases} \tag{4}$$

For more accurate dispatch results, the valve point effect and the multiple fuel options are integrated into the basic quadratic cost function. Thus the basic quadratic cost function given in (2) with N generating units and N_F fuel options for each unit is formulated as

$$\begin{aligned} F_{ih}\left(P_{ih}\right) &= a_{i,k}P_{ih}^2 + b_{i,k}P_{ih} + c_{i,k} \\ &\quad + \left| e_{i,k} \sin\left(f_{i,k}\left(P_{ih,k}^{\min} - P_{ih}\right)\right)\right| \\ &\text{if } P_{ih,k}^{\min} \le P_{ih} \le P_{ih,k}^{\max},\ \text{fuel option } k, \\ &\qquad k = 1, 2, \ldots, N_F. \end{aligned} \tag{5}$$

The objective function as given in (1) is subjected to the following equality and inequality constraints.

The power output from all the generating units must satisfy the total demand and the transmission losses of the system. The equality constraint is formulated as

$$\sum_{i=1}^{N} P_{ih} = P_{Dh} + P_{\text{Loss},h}. \tag{6}$$

The transmission loss is expressed in a quadratic form as

$$P_{\text{Loss},h} = \sum_{m=1}^{N} \sum_{n=1}^{N} P_{mh} B_{mn} P_{nh}. \quad (7)$$

The real power output of each generating unit is limited by the maximum and minimum power limit of the units. It is formulated as

$$P_i^{\min} \le P_{ih} \le P_i^{\max}. \quad (8)$$

The operating range of the generating units is restricted by their ramp rate limits. This is formulated as

$$\begin{aligned} P_{ih} - P_{i(h-1)} &\le \text{UR}_i \quad \text{if generation increases,} \\ P_{i(h-1)} - P_{ih} &\le \text{DR}_i \quad \text{if generation decreases.} \end{aligned} \quad (9)$$

Thus (8) is modified as

$$\max\left(P_i^{\min}, P_{i(h-1)} - \text{DR}_i\right) \le P_{ih} \le \min\left(P_i^{\max}, P_{i(h-1)} + \text{UR}_i\right). \quad (10)$$

Physical limitations of power plant components restrict the operation of generating units in certain operating regions known as prohibited zones. The power generated by each unit should lie either above or below the prohibited zones. Thus the feasible operating zones for the generating units are formulated as

$$\begin{aligned} P_i^{\min} &\le P_{ih} \le P_{i,1}^{l}, \\ P_{i,j-1}^{u} &\le P_{ih} \le P_{i,j}^{l} \quad j = 2, 3, \dots, n, \\ P_{i,n}^{u} &\le P_{ih} \le P_i^{\max}. \end{aligned} \quad (11)$$

The spinning reserve constraint considering the prohibited operating zones is formulated as

$$\begin{aligned} &\sum_{i=1}^{N} S_{ih} \ge S_R, \\ &S_{ih} = \begin{cases} \min\left\{\left(P_i^{\max} - P_{ih}\right), S_i^{\max}\right\}, \\ \quad \text{for units without prohibited zones} \\ 0, \quad \text{otherwise.} \end{cases} \end{aligned} \quad (12)$$

From (12) it is shown that a unit with prohibited operating zones does not contribute to the spinning reserve of the system. This is because the prohibited zones severely restrict the generating unit's flexibility to regulate system load.

3. Neighborhood Based Mutation (NM)

The optimization process in DE involves three basic operations such as mutation, crossover, and selection. Mutation in DE is a special kind of differential operator which is used to generate mutant or donor vectors. Actually it is the process of mutation, which demarcates one DE scheme from another. The rate of convergence of DE as well as its accuracy can be improved largely by applying different mutation strategies. Storn and Price proposed many DE variants applicable to different problems [28]. In this paper a new DE variant, based on neighborhood topology of the parameter vectors, is presented to improve the convergence characteristics of DE [29]. This concept of neighborhood topology is borrowed from the PSO algorithm.

3.1. Neighborhood Model. A graph of interconnection of vectors is called as neighborhood structure. The vectors in the neighborhood structure are assumed to be arranged in a circular fashion. Consider a DE population $P = [\vec{X}_1, \vec{X}_2, \dots, \vec{X}_{\text{NP}}]$ where each, $\vec{X}_i$ is a D-dimensional parameter vector. For every $\vec{X}_i$ a neighborhood of radius K is defined which consists of vectors $\vec{X}_{i-K}, \dots \vec{X}_i, \dots, \vec{X}_{i+K}$. K is a nonzero integer from 0 to $(\text{NP} - 1)/2$. A proper balance between exploration and exploitation is necessary for efficient and effective operation of DE. Two kinds of neighborhood mutation models are presented to control the exploration and the exploitation process. One is local mutation model which has a greater tendency to locate the optimal solution of the objective function but needs more iteration. Second is global mutation model which rapidly converges to the optimal solution of the objective function but suffers from premature convergence problem.

3.1.1. Local Neighborhood Mutation Model. For each vector $\vec{X}_i$ of the population, a local donor vector is created by employing the best vector in the neighborhood of that member. In this mutation model each vector is mutated using the best position found so far in the neighborhood of it and not in the entire population. The local donor vector $\vec{L}_{i,G}$ is created as

$$\vec{L}_{i,G} = \vec{X}_{i,G} + \alpha \cdot \left(\vec{X}_{n\_\text{best}_i,G} - \vec{X}_{i,G}\right) + \beta \cdot \left(\vec{X}_{p,G} - \vec{X}_{q,G}\right), \quad (13)$$

where the subscript n_best_i indicates the best vector in the neighborhood of $\vec{X}_{i,G}$ and $\vec{X}_{p,G}$ and $\vec{X}_{q,G}$ are two randomly chosen vectors from the same neighborhood, that is, $p, q \in [i-k, i+k]$ with $p \ne q \ne i$.

3.1.2. Global Neighborhood Mutation Model. Similarly, the global donor vector is created by using the best vector of the entire population. The global donor vector $\vec{g}_{i,G}$ is created as

$$\vec{g}_{i,G} = \vec{X}_{i,G} + \alpha \cdot \left(\vec{X}_{g\_\text{best},G} - \vec{X}_{i,G}\right) + \beta \cdot \left(\vec{X}_{r1,G} - \vec{X}_{r2,G}\right), \quad (14)$$

where the subscript g_best indicates the best vector in the entire population at generation G and $\vec{X}_{r1,G}$ and $\vec{X}_{r2,G}$ are two randomly chosen vectors from the population, that is, $r_1, r_2 \in [1, \text{NP}]$ with $r_1 \ne r_2 \ne i$.

The local mutation model favours exploration since all the vectors of the population are biased by different individuals. Global mutation model favours exploitation since all the vectors of the population are biased by the same individual.

The two mutation operators are then combined using a new parameter called weight factor $w \in (0,1)$ to form the actual mutation model of the presented DE algorithm.

$$\vec{V}_{i,G} = w \cdot \vec{g}_{i,G} + (1-w) \cdot \vec{L}_{i,G}. \quad (15)$$

4. DE with Neighborhood Based Mutation

DE begins with a population of NP D-dimensional parameter vectors representing the candidate solutions. The ith vector of the population at the current generation is given as

$$\vec{X}_{i,G} = [x_{1,i,G}, x_{2,i,G}, \ldots, x_{D,i,G}]. \quad (16)$$

The vector $\vec{X}_{i,G}$ is known as target or parent vector. G represents the subsequent generation and it is given by $G = 1, 2, \ldots, G_{\max}$. The initial population (i.e., $G = 0$) is randomly created by covering the entire search space as much as possible within prescribed minimum and maximum bounds. The jth component of the ith target vector is created as

$$x_{j,i,0} = x_{j,\min} + \operatorname{rand}(0,1) \cdot \left(x_{j,\max} - x_{j,\min}\right), \quad (17)$$

where rand$(0,1)$ is a uniformly distributed random number lying between 0 and 1 and is obtained independently for each component of the ith vector. Each target vector of the population is subjected to mutation, crossover, and selection which are explained in the following subsections.

4.1. Mutation. After initialization, DE creates a donor vector $\vec{V}_{i,G}$ corresponding to each target vector $\vec{X}_{i,G}$ in the current generation through mutation. In this method the actual donor vector is created with the help of global and neighborhood mutation models.

For each member a global and local donor vector is created using (13) and (14). After creating the global and local donor vector they are combined using a weight factor w using (15).

4.2. Crossover. In crossover operation few components of the donor vector are exchanged with target vector to form a trial vector $\vec{U}_{i,G} = [u_{1,i,G}, u_{2,i,G}, \ldots, u_{D,i,G}]$. Two kinds of crossover schemes—exponential and binomial crossovers—can be used in DE. In this paper, binomial crossover is performed on each of the D variables whenever a randomly picked number between 0 and 1 is less than or equal to the Cr value. The number of parameters inherited from the donor has a binomial distribution. The scheme is outlined as

$$u_{j,i,G} = \begin{cases} v_{j,i,G}, & \text{if } \left(\operatorname{rand}_{i,j}(0,1) \le \mathrm{Cr}\right) \\ x_{j,i,G}, & \text{otherwise,} \end{cases} \quad (18)$$

where rand$_{i,j}(0,1) \in [0,1]$ is a uniformly distributed random number for each jth component of the ith parameter vector.

4.3. Selection. To keep the population size constant over subsequent generations, the next step of the algorithm calls for selection to determine whether the target or the trial vector survives to the next generation, that is, at $G = G + 1$.

The selection operation is given as

$$\vec{X}_{i,G+1} = \begin{cases} \vec{U}_{i,G}, & \text{if } f\left(\vec{U}_{i,G}\right) \le f\left(\vec{X}_{i,G}\right), \\ \vec{X}_{i,G}, & \text{if } f\left(\vec{U}_{i,G}\right) \ge f\left(\vec{X}_{i,G}\right), \end{cases} \quad (19)$$

where $f(\vec{X}_i)$ is the function to be minimized. So if the new trial vector yields an equal or lower value of the objective function than that of target vector, then it replaces the corresponding target vector in the next generation. Otherwise the target vector is retained in the next generation. Hence the population either gets better (with respect to the minimization of the objective function) or remains the same in fitness status but never deteriorates.

The three operations are repeated until a stopping criterion is met which is usually the maximum generation, that is, $G_{\max}$.

5. Implementation of DE-NM for DED Problem

Step 1 (initialization of the population). For a population of size NP and dimension D, an initial vector (target vector) $X_{ij,G}$ is randomly generated. D represents the number of decision variables to be optimized. In DED problem D represents the number of generating units (i.e., N) to be considered. The vector X_{ij} is the real power output (i.e., P_{ij}) of jth unit of the ith population randomly generated within the operating limits using (8). The population is represented in a matrix form as

$$\text{Population} = \begin{bmatrix} \vec{X}_{11} & \vec{X}_{12} & \vec{X}_{13} & \cdots & \vec{X}_{1D} \\ \vec{X}_{21} & \vec{X}_{22} & \vec{X}_{23} & \cdots & \vec{X}_{2D} \\ \vdots & \vdots & & & \vdots \\ \vec{X}_{\mathrm{NP}1} & \vec{X}_{\mathrm{NP}2} & & \cdots & \vec{X}_{\mathrm{NP}D} \end{bmatrix}. \quad (20)$$

Each component of the ith individual in the population is randomly generated such that the component is uniformly distributed within the minimum and maximum power limits of the generating units. The generation of the jth component of the ith individual is given by (17).

Step 2 (handling the generation limit constraints). In Step 1 the power output from each generator is limited to be within minimum and maximum power limits. For the generator with ramp rate limits, the minimum and the maximum power limits are adjusted by using (10). Also, during the recombination and mutation operation, the power output of a generator can go above or below the maximum and minimum limits. Therefore, to restrict the P_i to be within the generating limit, a strategy is defined as follow:

$$P_{ij} = \begin{cases} P_i^{\min} & \text{if } P_{ij} < P_i^{\min}, \\ P_i^{\max} & \text{if } P_{ij} > P_i^{\max}, \\ P_{ij} & \text{otherwise.} \end{cases} \quad (21)$$

Step 3 (mutation operation). Consider the following.

Step 3.1. A neighborhood structure of radius K is created for each X_{ij} vector.

Step 3.2 (local neighborhood model). In this model a donor vector is created using the best position found so far in a small neighborhood of it and not in entire population. The mutated vector $\vec{L}_{i,G}$ is known as local donor vector and it is obtained using (13).

Step 3.3 (global neighborhood model). In this model a globally best vector $X_{\text{best},G}$ of the entire population is used for mutating a population member. The global donor vector $\vec{g}_{iG}$ is obtained using (14).

Both the local and global donor vectors are combined using (15) to obtain the actual donor vector $V_{i,G}$ of the presented technique.

Step 4 (recombination (crossover)). Recombination is employed to generate a trial vector U_i by replacing certain components of X_i with corresponding components of donor vector V_i. The trial vector by crossover operation is obtained using (18).

Step 5 (evaluation of fitness function). The evaluation function is computed from (1) and the generator cost function $F_i(P_i)$ used is the cost function considering the valve point effect and multiple fuel option as given in (5). The power balance and the prohibited operating zone constraints are included in the evaluation function by adding a penalty term to the objective function. The power balance constraint is considered without including the transmission losses for simplicity.

Consider

$$f(P_{ih}) = \sum_{i=1}^{N} F_{ih}(P_{ih}) + \lambda \cdot \left[\sum_{i=1}^{N} P_{ih} - P_{Dh}\right]^2 + \gamma \cdot \left[\sum_{i=1}^{n} v_i^R\right], \quad (22)$$

where λ is the penalty parameter for not satisfying the load demand and γ represents the penalty for a unit loading falling within a prohibited operating zone. v_i^R is the violation of the prohibited zone constraint for the ith unit which is defined as

$$v_i^R = \begin{cases} 1, & \text{if } P_i \text{ violates the prohibited zones,} \\ 0. \end{cases} \quad (23)$$

Step 6 (selection). Members to constitute the population of next generation $(G+1)$ are decided by (14). The new vector $X_{i,(G+1)}$ is selected based on the comparison of fitness value of both X_i and U_i.

Step 7 (verification of stopping criterion). Set the generation count $G = G + 1$. Go to Step 3 until stopping criterion is met which is usually maximum generation count $G_{\max}$.

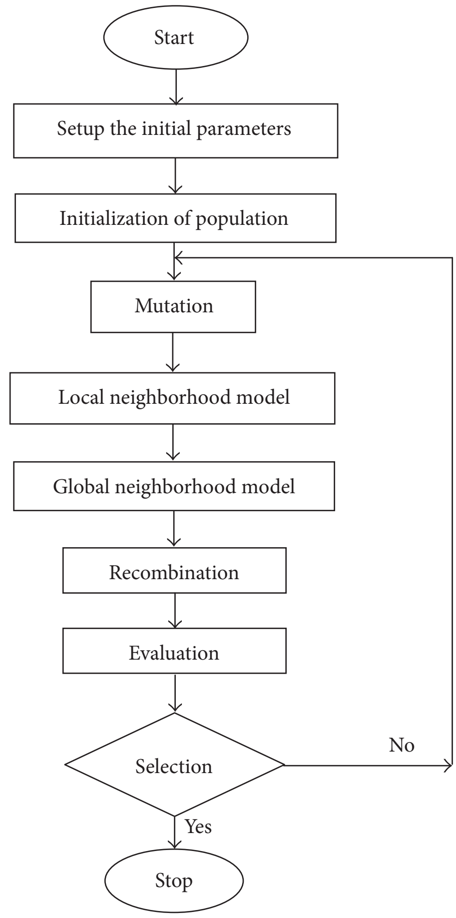

FIGURE 1: Flowchart for DE-NM approach for DED.

5.1. Flowchart for DE-NM Approach for DED. See Figure 1.

6. Test Results and Analysis

6.1. Description of the Test Systems. In this section two case systems are studied using DE-NM method. The fuel cost functions of the two systems are nonconvex considering valve point effect and multiple fuel option in its fuel cost.

Three different load patterns are applied for both these systems to demonstrate the robustness of the proposed solution technique as well as to show the effectiveness in scheduling for different load patterns (situations). The simulation horizon for all the three load patterns is taken as 24 hr with a dispatch interval of 1 hr. The coding is written using the MATLAB 7 programming language and executed in a personal computer machine.

6.2. Parameter Selection. DE-NM consists of four new parameters in addition to F and CR as in classical DE. They are α, β, w, and K. The role of α and β same as that of F. Thus, the number of parameters reduced by considering $\alpha = \beta = F$. The most important parameter in DE-NM is the weight factor w, which controls the balance between the exploration and exploitation capabilities. To obtain the balance, value of w

Table 1: Best power generation schedule obtained by DE-NM for case study 1.

Hour	Unit									
	1 (MW)	2 (MW)	3 (MW)	4 (MW)	5 (MW)	6 (MW)	7 (MW)	8 (MW)	9 (MW)	10 (MW)
1	168.862	177.000	250.000	250.000	240.000	166.000	250.000	180.570	243.000	250.000
2	163.886	177.000	250.000	250.000	234.691	163.000	250.000	173.854	253.000	250.000
3	165.705	177.000	250.000	250.000	235.047	160.543	250.000	178.591	253.000	250.000
4	165.826	177.000	250.000	250.000	240.000	163.000	250.000	181.576	249.509	250.000
5	172.019	177.000	250.000	250.000	457.000	150.375	250.000	183.538	252.999	247.372
6	192.564	177.000	269.658	265.000	451.287	196.324	250.000	249.687	302.656	254.658
7	181.538	177.000	253.465	253.465	446.999	180.580	250.000	246.700	218.376	250.000
8	172.014	177.000	250.000	250.000	457.000	163.000	250.000	176.040	249.509	250.000
9	171.935	177.000	250.000	250.000	240.000	153.000	250.000	183.521	253.000	250.000
10	170.438	177.000	250.000	250.000	240.000	163.000	250.000	176.607	253.000	246.927
11	179.939	177.000	253.528	253.528	457.000	174.322	250.000	191.455	273.573	250.000
12	165.807	177.000	250.000	250.000	234.616	163.000	250.000	180.585	251.231	247.169
13	178.362	177.000	251.413	251.413	457.000	161.753	250.000	190.465	270.278	250.000
14	205.211	177.000	250.000	250.000	457.000	163.000	282.078	254.494	345.626	264.559
15	205.220	177.000	310.646	265.000	457.000	224.225	277.774	254.494	406.509	273.310
16	194.144	177.000	274.350	265.000	457.000	199.127	262.903	250.463	304.055	246.630
17	178.354	177.000	261.510	261.510	457.000	162.985	250.000	247.775	266.450	246.924
18	167.277	177.000	250.000	250.000	233.617	163.000	250.000	179.579	253.000	246.382
19	163.876	177.000	250.000	250.000	451.287	163.000	250.000	177.557	248.712	250.000
20	171.953	177.000	250.000	250.000	235.047	160.543	250.000	184.512	253.000	250.000
21	168.889	177.000	250.000	250.000	234.691	163.000	250.000	181.563	253.000	250.000
22	178.361	177.000	252.512	252.512	240.000	171.466	250.000	192.440	263.232	246.630
23	165.864	177.000	250.000	250.000	240.000	156.074	250.000	183.479	253.000	246.925
24	176.904	177.000	250.000	250.000	457.000	158.553	250.000	181.986	251.996	250.000

is usually selected from the range $[0, 1]$. It is adapted online during the execution of the algorithm by a linear increment scheme; that is, it is initialized with 0 and increased up to 1. Since w starts with 0, it favors the exploration process during the initial stage and on getting promoted to 1 it favors the exploitation process. The linear increment scheme is given by

$$w_G = \frac{G}{G_{\max}}. \tag{24}$$

In this paper, the neighborhood size equal to 10% of the total population size of 100 is considered. The value for both α and β is taken as 0.8 and crossover rate $\mathrm{Cr} = 0.9$. The DE-NM is applied to both the case studies for 30 independent trials (1000 iterations per trial) with the selected parameters.

6.3. Case Study 1. In this test case, a 10-unit system is optimized to meet three different load patterns. The level of fluctuation of the three different load patterns is given in Figure 2. The peak demand for load pattern 1, pattern 2, and pattern 3 is 3208 MW, 2460 MW, and 3210 MW, respectively. The system data and the related constraints for this case study are given in [30]. The complete generation schedule for load pattern 2 corresponding to the minimum generation cost obtained by DE-NM is presented in Table 1. Table 2 gives the fuel type chosen by the units for the corresponding best generation schedule obtained. The fuel chosen by the units for all three load patterns is given in Table 2. The table format represents the fuel type chosen by an unit for pattern 1 and it is followed by fuel type for the same unit for patterns 2 and 3, respectively.

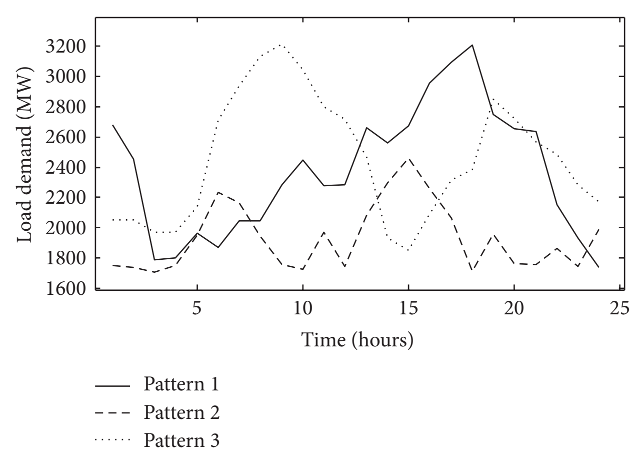

Figure 2: Load demand patterns for case study 1.

The best cost obtained by the DE-NM method considering spinning reserve for pattern 1 is \$10649.68, for pattern 2 is \$8103.326, and for pattern 3 is \$11054.83. The worst cost obtained by the DE-NM method for pattern 1 is

Table 2: Fuel switching of generators for case study 1.

Hour	Unit									
	1	2	3	4	5	6	7	8	9	10
1	2, 1, 1	1, 1, 1	1, 1, 1	3, 3, 2	3, 3, 1	3, 1, 1	2, 1, 1	3, 2, 2	3, 1, 1	1, 1, 1
2	2, 1, 1	1, 1, 1	1, 1, 1	3, 3, 2	3, 3, 1	3, 1, 1	1, 1, 1	3, 3, 2	3, 1, 1	1, 1, 1
3	1, 1, 1	1, 1, 1	1, 1, 1	2, 3, 2	1, 3, 1	1, 1, 1	1, 1, 1	2, 2, 2	1, 1, 1	1, 1, 1
4	1, 1, 1	1, 1, 1	1, 1, 1	2, 2, 2	1, 3, 1	1, 1, 1	1, 1, 1	2, 2, 2	1, 1, 1	1, 1, 1
5	1, 1, 1	1, 1, 1	1, 1, 1	3, 2, 2	1, 3, 3	1, 1, 1	1, 1, 1	3, 3, 2	1, 1, 1	1, 1, 1
6	1, 1, 2	1, 1, 1	1, 1, 1	3, 3, 3	1, 3, 3	1, 3, 1	1, 1, 1	2, 3, 3	1, 3, 1	1, 1, 1
7	1, 1, 2	1, 1, 1	1, 3, 1	3, 3, 3	3, 3, 3	1, 3, 1	1, 3, 1	2, 3, 3	1, 3, 1	1, 1, 1
8	1, 1, 2	1, 1, 1	1, 2, 1	2, 3, 2	3, 3, 3	1, 3, 1	1, 3, 1	2, 3, 2	1, 3, 1	1, 2, 1
9	2, 1, 2	1, 1, 1	1, 2, 1	3, 3, 2	1, 3, 1	3, 3, 1	1, 3, 1	3, 3, 2	3, 3, 1	1, 2, 1
10	2, 1, 2	1, 1, 1	1, 2, 1	3, 3, 2	3, 3, 1	3, 3, 1	1, 3, 1	3, 3, 2	1, 3, 1	1, 3, 1
11	2, 1, 2	1, 1, 1	1, 1, 1	3, 3, 1	3, 3, 3	3, 3, 1	1, 3, 1	3, 3, 2	1, 3, 1	1, 1, 1
12	2, 1, 2	1, 1, 1	1, 1, 1	3, 3, 2	3, 3, 1	3, 3, 1	1, 1, 1	3, 3, 2	1, 3, 1	1, 1, 1
13	2, 1, 2	1, 1, 1	1, 1, 1	3, 3, 3	3, 3, 3	3, 3, 1	1, 1, 1	3, 3, 2	3, 3, 1	1, 1, 1
14	2, 2, 1	1, 1, 1	1, 1, 1	3, 2, 3	3, 3, 3	3, 1, 1	1, 1, 1	3, 2, 3	3, 1, 1	1, 1, 1
15	2, 2, 1	1, 1, 1	1, 1, 1	3, 3, 3	3, 1, 3	3, 3, 3	1, 1, 1	3, 2, 3	3, 1, 1	1, 1, 1
16	2, 1, 1	1, 1, 1	2, 1, 1	3, 2, 3	3, 3, 3	3, 1, 1	2, 1, 1	3, 3, 3	3, 1, 1	1, 1, 1
17	2, 1, 1	1, 1, 1	2, 1, 1	3, 3, 2	3, 3, 3	3, 3, 1	3, 1, 1	3, 3, 3	3, 1, 1	1, 1, 1
18	2, 1, 2	1, 1, 1	2, 1, 1	3, 3, 2	3, 3, 1	3, 3, 1	3, 1, 1	3, 3, 2	3, 1, 1	2, 1, 1
19	2, 1, 2	11, 1	1, 3, 1	2, 3, 2	3, 3, 3	3, 3, 1	2, 3, 1	3, 3, 2	3, 3, 1	1, 1, 1
20	2, 1, 2	1, 1, 1	1, 1, 1	2, 3, 2	3, 3, 1	3, 3, 1	1, 1, 1	3, 3, 2	3, 3, 1	1, 1, 1
21	2, 1, 2	1, 1, 1	1, 1, 1	2, 3, 2	3, 3, 1	3, 3, 1	1, 1, 1	3, 3, 2	3, 3, 1	1, 1, 1
22	1, 1, 2	1, 1, 1	1, 1, 1	2, 3, 3	3, 3, 1	1, 3, 1	1, 1, 1	3, 3, 2	1, 3, 1	1, 1, 1
23	1, 1, 1	1, 1, 1	1, 1, 1	2, 3, 2	1, 3, 1	1, 3, 1	1, 1, 1	3, 3, 2	1, 1, 1	1, 1, 1
24	1, 1, 1	1, 1, 1	1, 1, 1	2, 3, 2	1, 3, 3	1, 1, 1	1, 1, 1	2, 3, 2	1, 1, 1	1, 1, 1

$11952.07, pattern 2 is $9163.973, and pattern 3 is $12036.89. The average cost of pattern 1, pattern 2, and pattern 3 for all the 30 trials is $11451.82, $9711.448, and $11497.85. Figures 3(a), 3(b), and 3(c) shows the distribution of the cost obtained for load patterns 1, 2, and 3, respectively. A straight line passing through each distribution area denotes the average cost. The percentage of producing quality solutions by DE-NM is above 60% as seen from Figure 4.

6.4. A Short Overview of the Indian Utility System. Indian power system is a geographically dispersed network of generators. For ease of operation, the entire Indian power system has been divided into five regions, namely, Northern Region (NR), Western Region (WR), Southern Region (SR), Eastern Region (ER), and North Eastern Region (NER). While NR, WR, ER, and NER are interconnected as a single grid, the SR had not been interconnected with the national grid. This prevents the SR from receiving benefits from national power market. The SR covering 6, 51,000 Sq. Km of area comprises the states of Andhra Pradesh, Karnataka, Kerala, Pondicherry and Tamil Nadu. The Indian utility system considered in this paper belongs to the state of Tamil Nadu. The Electricity Board of Tamil Nadu state was recently restructured and the board is in the move of handing over transmission and distribution to the private operators.

The South Indian network comprises of 19 thermal units, located at various parts of the state of Tamil Nadu. Since the system under consideration belongs to the state department, the technical data of the system cannot be published is available with the corresponding author, and will be provided on request. Also the data of system network is approximated neglecting several local feeder data this work neglects estimation of transmission losses for simplicity. Even then, as per the board's advice, this work assumes a uniform 20% loss in the transmission and hence it is added to the 24-hour load demand data for scheduling.

6.5. Case Study 2. This system involves a standard Indian utility system with 19 units. All the 19 units include nonlinear characteristics such as valve point effect, ramp rate limit, multiple fuels, prohibited operating zones and spinning reserve constraint. This system is applied for three different load patterns as shown in Figure 5. The demand for each hour includes approximately 20% of transmission losses. A generation schedule is obtained using the DE-NM method where each unit contributes to the demand and the transmission loss. The maximum demand for pattern 1 is 4400 MW, for pattern 2 is 4186 MW, and for pattern 3 is 4173 MW. Table 3 gives the best generation schedule obtained by the DE-NM method for pattern 2. Few units in the system are provided with multiple fuel option. The fuel types include 1, 2, 3, 4, 5

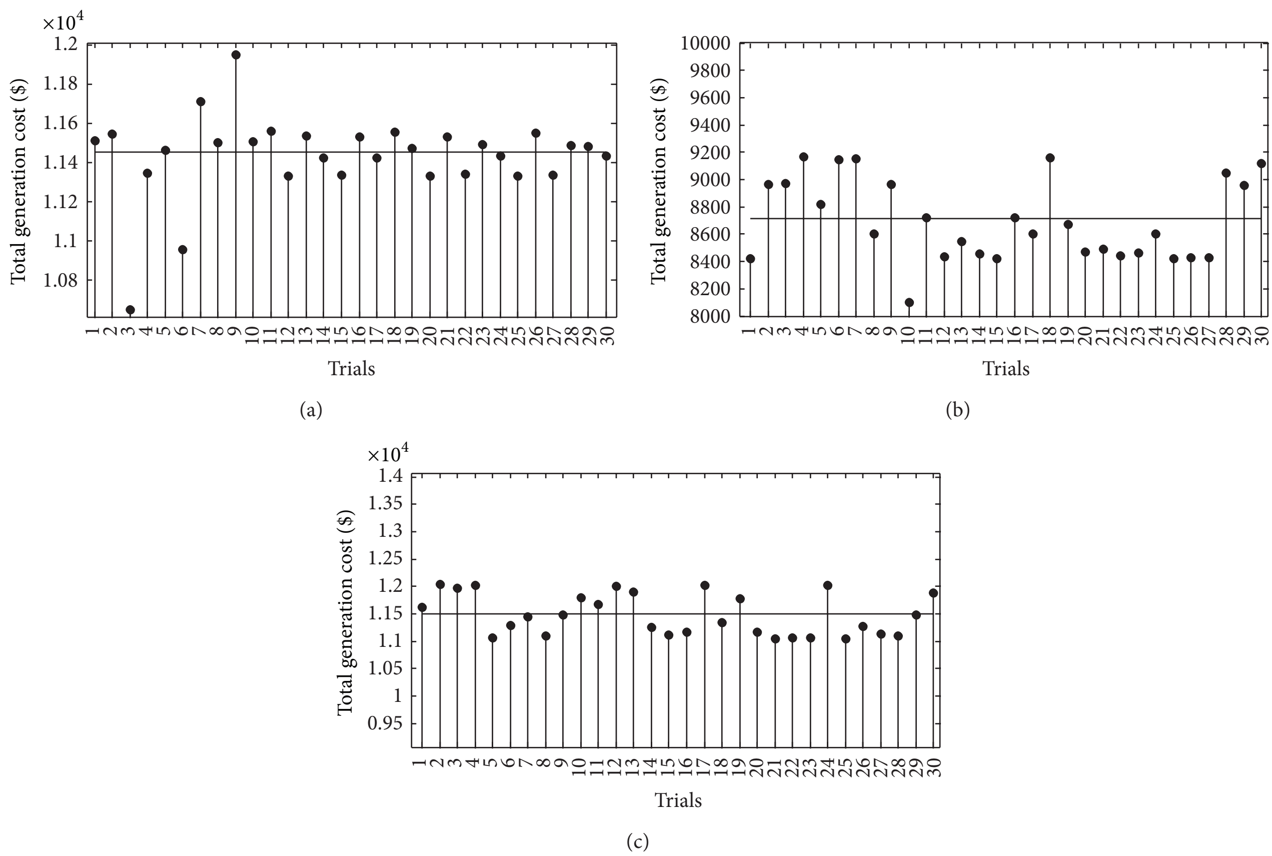

Figure 3: (a) Cost distribution obtained by DE-NM for case study 1 with pattern 1. (b) Cost distribution obtained by DE-NM for case study 1 with pattern 2. (c) Cost distribution obtained by DE-NM for case study 1 with pattern 3.

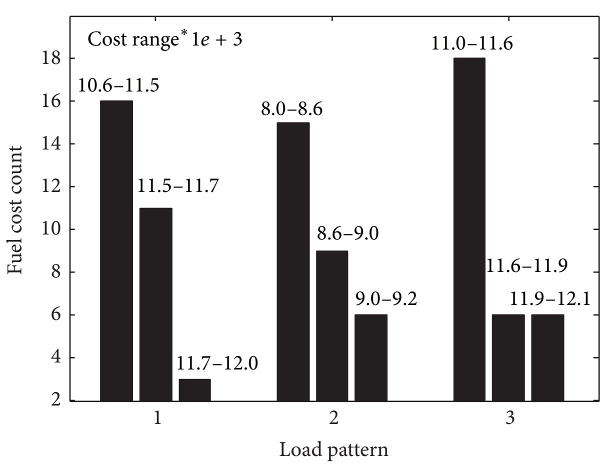

Figure 4: Frequency of convergence for case study 1.

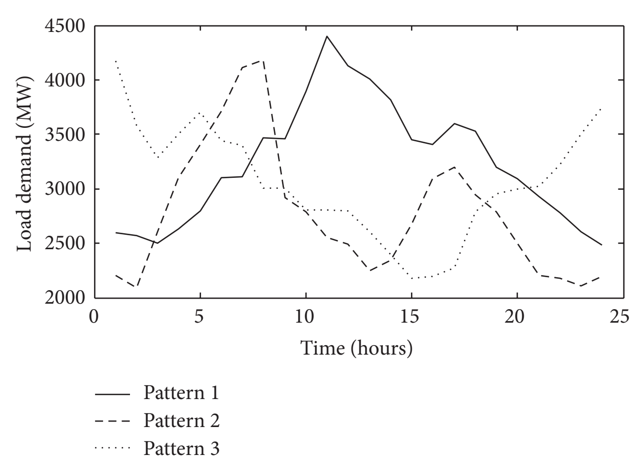

Figure 5: Load demand patterns for case study 2.

and 6. Table 4 shows the fuel switching for units 3, 5, 7, 13, and 19 and all the remaining units utilize fuel 1 for every hour of time interval.

The best cost obtained by the DE-NM method for pattern 1, 2, and 3 is \$404122.623, \$324962.343, and \$372140.528, respectively. The worst cost for pattern 1 is \$40565.659, pattern 2 is \$341440.818, and pattern 3 is \$374405.694. Figures 6(a), 6(b), and 6(c) shows the cost distribution for the system with pattern 1, pattern 2, and pattern 3, respectively. The straight line running through the cost distribution area represents the average cost. The average cost for pattern1 is 405515.7524, pattern 2 is \$334321.1071, and pattern 3 is \$33109.9977. The percentage of producing quality solutions by DE-NM for the system is above 70% as seen from

Table 3: Best power generation schedule obtained by DE-NM for case study 2.

Hour	Power output (MW)									
	1	2	3	4	5	6	7	8	9	10
1	126.623	176.332	126.942	25.000	113.750	340.000	166.554	150.000	242.127	15.000
2	124.189	165.000	144.530	08.000	146.176	340.000	177.498	138.874	254.528	15.000
3	127.640	161.742	140.000	25.000	177.500	334.685	177.500	152.687	283.000	15.000
4	132.015	287.062	368.136	25.000	175.995	340.000	177.499	165.069	260.000	40.000
5	148.315	421.843	400.000	25.000	177.500	340.000	174.898	193.407	280.290	40.000
6	227.936	438.000	440.000	25.000	177.500	340.000	176.290	321.681	302.381	40.000
7	292.692	438.000	400.000	25.000	177.499	363.000	177.499	452.292	516.598	40.000
8	300.000	438.000	400.000	25.000	177.500	371.145	177.499	500.000	532.465	40.000
9	120.045	204.725	374.718	25.000	177.500	338.122	177.499	144.607	283.000	40.000
10	129.676	196.189	202.088	25.000	177.500	340.000	177.500	153.581	257.593	40.000
11	125.834	137.702	136.903	25.000	177.499	340.000	177.499	152.633	254.420	15.000
12	126.297	149.825	140.000	25.000	177.497	335.679	177.484	294.088	238.824	15.000
13	131.871	176.309	129.436	25.000	177.499	340.000	177.499	137.506	234.751	15.000
14	119.616	177.057	103.519	25.000	177.499	340.000	177.499	142.830	260.000	15.000
15	124.985	165.000	290.000	25.000	177.499	340.000	177.499	152.687	249.272	40.000
16	114.362	309.274	337.442	25.000	177.499	340.000	177.499	152.334	239.253	40.000
17	126.154	324.1193	377.603	25.000	177.499	340.000	177.499	158.274	254.610	40.000
18	126.332	308.015	275.423	25.000	166.567	340.000	177.499	152.908	258.483	40.000
19	125.370	187.353	288.980	25.000	177.499	340.000	177.499	123.743	260.000	15.000
20	129.077	185.934	140.000	22.658	177.499	338.663	177.499	129.939	260.000	15.000
21	103.540	154.576	301.215	25.000	167.760	332.659	177.500	149.915	267.546	15.000
22	128.134	151.202	140.000	08.000	177.499	340.000	157.499	151.103	250.829	15.000
23	118.221	165.000	140.000	08.000	177.499	331.385	168.524	147.996	291.043	15.000
24	131.233	165.000	140.000	25.000	176.952	340.000	177.493	142.536	250.797	15.000
Hour	Unit (MW)									
	11	12	13	14	15	16	17	18	19	
1	050.036	75.000	177.499	56.908	032.620	80.000	80.000	079.895	460.000	
2	050.000	40.000	130.805	95.000	043.997	15.000	80.000	073.000	420.219	
3	150.000	75.000	177.500	95.000	049.824	80.000	80.000	230.000	443.210	
4	150.000	75.000	177.499	95.000	141.701	80.000	80.000	230.000	473.308	
5	150.000	75.000	177.500	95.000	220.000	80.000	80.000	230.000	466.529	
6	150.000	75.000	177.500	95.000	220.000	80.000	80.000	230.000	483.000	
7	150.000	75.000	177.499	95.000	220.000	80.000	80.000	230.000	491.740	
8	150.000	75.000	177.499	95.000	220.000	80.000	80.000	230.000	487.647	
9	050.000	75.000	177.499	95.000	187.521	80.000	80.000	230.000	430.000	
10	150.000	75.000	171.776	95.000	121.250	80.000	80.000	230.000	460.000	
11	150.000	75.000	177.499	81.780	040.653	80.000	80.000	230.000	469.862	
12	079.616	75.000	177.488	87.838	036.233	80.000	80.000	111.209	460.000	
13	050.000	25.000	177.499	65.000	041.758	80.000	80.000	092.411	460.000	
14	108.595	75.000	177.499	65.000	044.047	80.000	80.000	087.993	460.000	
15	150.000	75.000	177.499	95.000	028.027	80.000	80.000	184.753	433.063	
16	150.000	75.000	177.499	95.000	182.323	80.000	80.000	230.000	480.285	
17	150.000	75.000	177.499	95.000	198.027	80.000	80.000	230.000	483.000	
18	150.000	75.000	177.499	95.000	094.367	80.000	80.000	230.000	466.193	
19	150.000	75.000	177.499	95.000	091.068	80.000	80.000	230.000	464.949	
20	150.000	75.000	177.499	31.432	035.402	80.000	80.000	230.000	438.682	
21	060.000	75.000	113.750	65.000	044.040	80.000	80.000	073.000	460.000	
22	150.000	75.000	112.426	35.000	044.592	80.000	80.000	073.000	380.409	
23	50.000	75.000	113.750	94.352	033.301	15.000	44.215	073.000	460.000	
24	50.000	75.000	177.499	95.000	044.034	45.000	16.283	050.000	454.875	

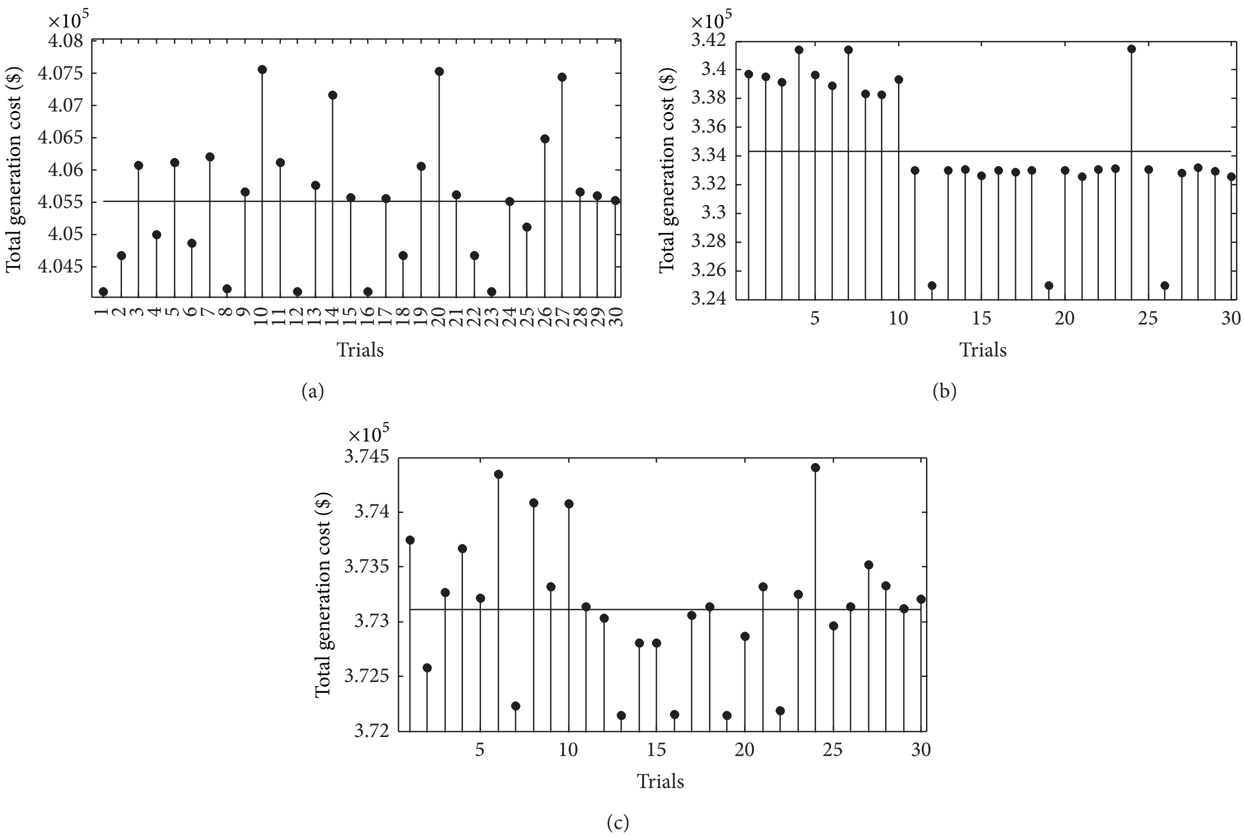

Figure 6: (a) Cost distribution obtained by DE-NM for case study 2 with pattern 1. (b) Cost distribution obtained by DE-NM for case study 2 with pattern 2. (c) Cost distribution obtained by DE-NM for case study 2 with pattern 3.

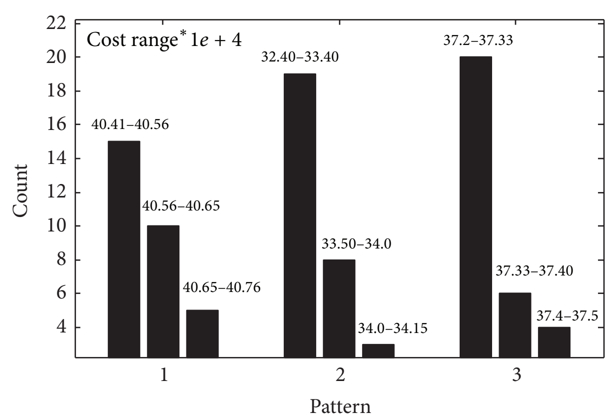

Figure 7: Frequency of convergence for case study 2.

Figure 7. Table 5 clearly shows the computational time of the three patterns for both the test systems. Table 6 presents the relationship between k, computation time, and result quality for a 10-unit system.

7. Conclusion

A maiden attempt has been taken to apply Differential Evolution with Neighborhood based Mutation (DE-NM) method to solve Dynamic Economic Dispatch (DED) problem including ramp rate effects, prohibited operating zones, spinning reserve, and multiple fuel options under a single frame. To show the effectiveness of the DE-NM method, an Indian utility system and a 10-unit system are presented to solve the DED problem for a given load profile. The results show that DE-NM is efficient in handling the constraints and it is applicable to larger systems. Due to enormous transmission lines in the Indian utility system, a proper model

Table 4: Fuel switching of generators for case study 2.

Hour	Unit (MW)				
	3	5	7	13	19
1	1, 1, 2	2, 4, 2	2, 6, 2	2, 2, 2	1, 1, 2
2	2, 1, 2	2, 4, 2	2, 2, 2	2, 1, 2	1, 1, 1
3	1, 1, 2	2, 2, 2	2, 2, 2	2, 2, 2	1, 1, 1
4	1, 2, 2	2, 2, 2	2, 2, 2	6, 2, 2	1, 1, 1
5	2, 2, 2	2, 2, 2	2, 2, 2	2, 2, 2	1, 1, 1
6	2, 2, 2	2, 2, 2	2, 2, 2	2, 2, 2	1, 1, 1
7	2, 2, 2	2, 2, 2	6, 2, 2	2, 2, 6	1, 1, 1
8	2, 2, 2	2, 2, 2	2, 2, 2	2, 2, 2	2, 1, 1
9	2, 2, 2	2, 2, 2	2, 2, 2	2, 2, 2	1, 1, 1
10	2, 1, 2	2, 2, 2	2, 2, 2	2, 2, 2	1, 1, 1
11	2, 1, 2	2, 2, 2	2, 2, 2	2, 2, 2	2, 1, 1
12	2, 1, 2	2, 2, 2	2, 2, 6	2, 2, 2	2, 1, 1
13	2, 1, 1	2, 2, 2	2, 2, 2	2, 2, 2	1, 1, 1
14	2, 1, 1	2, 2, 2	2, 2, 2	2, 2, 2	2, 1, 1
15	2, 2, 1	2, 2, 2	2, 2, 2	2, 2, 2	1, 1, 1
16	2, 2, 1	2, 2, 2	2, 2, 2	2, 2, 2	2, 1, 1
17	2, 2, 1	2, 2, 2	2, 2, 2	2, 2, 1	2, 1, 1
18	2, 2, 2	2, 6, 2	2, 2, 6	2, 2, 2	1, 1, 1
19	2, 2, 2	2, 2, 2	2, 2, 2	2, 2, 2	1, 1, 1
20	2, 1, 2	2, 2, 2	2, 2, 2	2, 2, 2	1, 1, 1
21	2, 2, 2	2, 2, 2	2, 2, 2	2, 1, 2	1, 1, 1
22	2, 1, 2	2, 2, 2	2, 6, 6	6, 1, 2	1, 1, 1
23	1, 1, 2	2, 2, 2	2, 6, 2	2, 1, 2	1, 1, 1
24	1, 1, 2	2, 2, 2	2, 2, 2	2, 2, 2	1, 1, 1

Table 5: Computation time for both systems for 1000 iterations with a population size of 100.

10-unit system		19-unit system	
Load pattern	Sec	Load pattern	Sec
1	13.581	1	32.939
2	12.121	2	33.782
3	11.465	3	34.566

Table 6: Relationship between k, computation time, and result quality for a 10-unit system.

	k	Time in Sec	Cost range
Pattern 1	10%	13.581	11640–11500
	20%	96.32	11583–11472
	30%	1134.15	11953–11678
Pattern 2	10%	12.121	8600–8000
	20%	89.56	8578–7926
	30%	985.23	8927–8712
Pattern 3	10%	11.465	11600–11000
	20%	73.42	11578–11215
	30%	921.73	11827–11749

for including the losses is still under the search. The search ability of the DE-NM is improved by striking proper balance between exploration and exploitation process. The simulation results show that the DE-NM method is capable of producing solutions which are near optimal and has stable converging characteristics.

Nomenclature

F_T:	Total fuel cost of the system ($)
$F_{ih}(P_{ih})$:	Incremental fuel cost function ($/h)
P_{ih}:	Real power output of the ith unit at the hth interval (MW)
N:	Number of generating units
H:	Number of intervals in the given time period
a_i, b_i, and c_i:	Cost coefficients of the ith generating unit
e_i and f_i:	Constants from the valve point of the ith generating unit
$P_{ih}^{\min}/P_{ih}^{\max}$:	Minimum/maximum limit of the real power of the ith unit at hth interval (MW)
N_F:	Number of fuel options for each generating unit
P_{Dh}:	Power demand at the hth interval (MW)
$P_{\text{loss},h}$:	Power loss at the hth interval (MW)
B_{mn}:	Transmission loss coefficients
UR_i/DR_i:	Up/down ramp rate limits of the ith unit (MW)
$P_{i(h-1)}$:	Power generated by the ith unit at the $(h-1)$th interval (MW)
n:	Number of generators with prohibited operating zones
$P_{i,n}^u/P_{i,n}^l$:	Upper/lower limit of the nth prohibited zone for ith generating unit
S_{ih}:	Spinning reserve contribution of the ith generating unit at the hth interval (MW)
S_R:	System spinning reserve requirement (MW)
$S_i^{\max}$:	Maximum spinning reserve contribution of the ith generating unit (MW)
NP:	Total number of population
α and β:	Scaling factors
w:	Scalar weight
$G_{\max}$:	Maximum generation count
Cr:	Crossover rate.

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

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