Large Scale Economic Load Dispatch by Clonal Selection Algorithm

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This paper presents a new optimization approach involving artificial immune system (AIS) applied to economic load dispatch (ELD) with non-smooth fuel cost functions. The approach utilizes the clonal selection principle and evolutionary approach wherein cloning of antibodies is performed followed by hypermutation. AIS utilizes the sum of total generation cost and penalty multiplier with violation of constraints as the objective function. The proposed method easily takes care of non-smoothness of cost function arising due to ramp rate limits, prohibited operating zones and valve point loading effects. To verify the robustness and superiority of the proposed AIS, it is applied in ELD problem with 40 generating units and the result reveals that the proposed AIS provides optimal solution as compared to the results of other existing techniques.

Keywords: Artificial immune system; Bacteria foraging; Clonal selection algorithm; Differential evolution; Valve point loadings

INTRODUCTION

Most of the power system optimization problems including economic load dispatch (ELD) have non-linear characteristics with heavy equality and inequality constraints that make the problem of finding the global optimum difficult using any mathematical programming and optimization techniques. Usually, the ELD problem is a sub-problem of unit commitment and a constrained optimization one. The fundamental requirement of ELD is to determine the optimal output of online generating units so as to meet the load demand at the minimum operating cost under various system constraints. Over the years, various mathematical methods and optimization techniques have been successfully employed to solve for ELD problems. The conventional methods are lambda iteration method, base point and participation factor method, gradient search method[1], etc. These numerical methods require the incremental cost curves to be monotonically increasing or piece wise linear. However, these methods have difficulties and are not suitable to address non-linear and discontinuous characteristics of actual practical problems. A dynamic programming method (DP) can solve such problems in different formulations[2]. However, this method suffers form massive computational burden for its large dimensionality when applied to practical size ELD problems.

In the past few years, stochastic search algorithms like simulated annealing (SA)[3], genetic algorithm (GA)[4-5], and evolutionary programming (EP)[6-7] may prove to be very efficient in solving complex power systems problems, but these heuristic methods do not always guarantee the globally optimal solution. In recent years, particle swarm optimization (PSO)[8-9] and bacterial foraging algorithm (BFA) have been successfully applied to ELD problems[10-11]. Quite promising results in terms fuel cost savings and speed of convergence are obtained by these techniques.

However, SA method employs a probabilistic approach in accepting candidate solutions in the search process and the solution get trapped by local optimum rather than at the global optimum. But, tuning its relevant control parameters is a difficult task. The recent research has identified few drawbacks of the stochastic methods like GA of its premature convergence causing degradation in performance and reduction its search capability and unsuitable when applied to highly epistatic objective functions. The main drawbacks of EP, GA and SA are their long execution time providing the optimal solutions.

Hybrid differential evolution[12] is a kind of stochastic optimization method successfully applied for solving ELD problems. The fittest of an offspring competes one-to-one with that of corresponding parent, which is different from other algorithms. This one-to-one competition gives rise to a faster convergence rate. Differential evolution[12] is the real coded GA combined with an adaptive random search using a normal random generator and also applied in various optimization problems.

This paper applies a recently proposed new algorithm from the family of evolutionary computations, known as artificial immune system (AIS)[13-14]. It has been applied to economic load dispatch with small power systems[15-16] without considering the valve-point loading effects. AIS is also considered as a promising optimization tool for complex real world problems. To show its efficiency and effectiveness the AIS methodology is applied to 40 generators with valve point loading effects along with various generator constraints. The results so obtained show its capability in solving ELD problems.

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This paper (re-modified) was received on June 2, 2009. Written discussion on the paper will be entertained till November 30, 2009.

PROBLEM DESCRIPTION

The ELD problem is about minimizing the fuel cost of generating units for a specified period of operation time so as to accomplish optimal dispatch among the committed units and in return satisfying the system constraints. Here, one model for ELD with non-smooth cost function is considered, as described in this paper.

ELD Problem with Non-smooth Cost Function

The prime objective of the ELD problem is to determine the most economic loadings of generators to minimize the generation cost such that the load demands in the intervals of the generation scheduling horizon can be met and simultaneously the operation constraints are satisfied. Here the optimization problem is expressed as

$$\text{Minimize } F = \sum_{i=1}^{m} f_i\left(P_i\right) \tag{1}$$

where *i* denotes the index of units; *m*, the total number of committed generators and P_i, the power output of i^{th} generator and *F* is total cost function of the system.

Power Balance Constraint

The total generation $\sum_{i=1}^{m}\left(P_i\right)$ should be equal to the total system demand P_D plus the transmission loss P_{Loss}. That is represented as

$$\sum_{i=1}^{m}\left(P_i\right) = P_D + P_{Loss} \tag{2}$$

To calculate the transmission loss, *B* coefficients method is used in general. The loss is represented by *B* coefficients as follows.

$$P_{Loss} = \sum_{i=1}^{m}\sum_{j=1}^{m} P_i B_{ij} P_j + \sum_{i=1}^{m} B_{0i} P_i + B_{00} \tag{3}$$

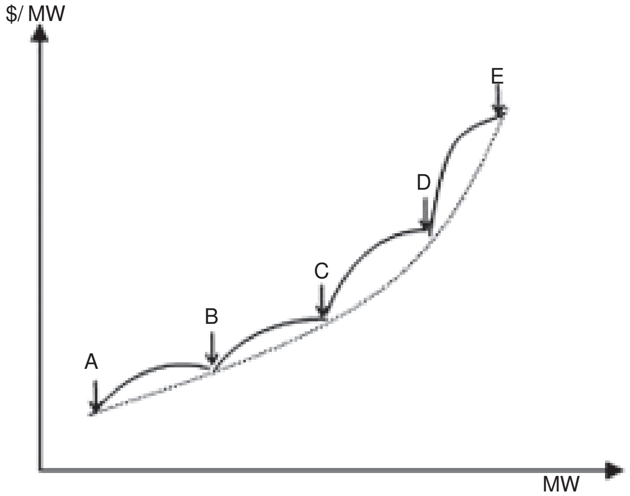

Figure 1 Example of cost function with five valves from A to E

The Generator Limits

The generation output of each unit should be between its minimum and maximum limits. This inequality constraint for each generator should be satisfied.

$$P_{i\,min} \le P_i \le P_{i\,max} \tag{4}$$

$P_{i\,min}$ and $P_{i\,max}$ are the minimum and maximum real power output of i^{th} generator.

Ramp Rate Limits

In ELD problems, the generator output is usually assumed to be adjusted smoothly and instantaneously. However, under practical circumstances ramp rate limit restricts the operating range of all the units for adjusting the generation operation between two operating periods. The inequality constraint due to the ramp rate limits[8] of unit due to the change in generation are given by the following constraint.

$$\text{Max}\left(P_{i\,min}, P_i^0 - D_{ri}\right) \le P_i \le \text{Min}\left(P_{i\,max}, P_i^0 + U_{ri}\right) \tag{5}$$

where, P_i and P_i^0 are the current and previous power output of i^{th} generator, respectively. U_{ri} and D_{ri} are the up-ramp and down-ramp limits of the i^{th} generator.

Prohibited Operating Zones

The input-output characteristics of modern units are inherently non-linear because of the steam valve point loadings[4]. The operating zones, due to valve point loading or vibration due to shaft bearing, is generally avoided in order to achieve best economy, called prohibited operating zones of a unit, which make the cost curve discontinuous in nature. The feasible operating zones of i^{th} unit having *k* number of prohibited operating zones are represented by

$$P_i \notin \left[P_{iL}^{pzk}, P_{iU}^{pzk}\right] \quad k = 1, 2, \ldots\ldots\ldots \tag{6}$$

$$P_i \le P_{iL}^{pzk} \text{ and } P_i \ge P_{iU}^{pzk} \tag{7}$$

where, P_{iL}^{pzk} and P_{iU}^{pzk} are the lower and upper limits of k^{th} prohibited zone for i^{th} unit.

Valve Point Loading Effects

Power plants commonly have multiple valves that are used to control the power output of the unit. The generators with multiple valve steam turbines possess a wide variation in the input-output characteristics[4]. The valve point effect introduces ripples in the heat rate curves and can not be represented by the polynomial function. Therefore, the actual cost curve is a combination of sinusoidal functions and quadratic functions represented by the equation (8). This type of problem is extremely difficult to solve with conventional gradient based techniques due to abrupt changes and discontinuities present in the incremental cost function.

In general, the cost function of i^{th} unit with valve point loading $f_i(P_i)$ is expressed as

$$f_i\left(P_i\right) = a_i + b_i P_i + c_i P_i^2 + \left| e_i \times \sin\left(f_i \times \left(P_{i\min} - P_i\right)\right)\right| \qquad (8)$$

where, a_i, b_i and c_i are the fuel-cost coefficients of the i^{th} unit and e_i, f_i are the constants of the i^{th} unit with valve point effects. The fitness function is evaluated as

$$\begin{aligned} fit = F + \lambda_1 \left| \sum_{i=1}^{m} \left(P_i\right) - P_D - P_{Loss} \right| \\ + \lambda_2 \left[\max\left(0, \max\left(P_{i\min}, P_i^0 - D_{ri}\right) - P_i\right) \right. \\ \left. + \max\left(0, P_i - \min\left(P_{i\max}, P_i^0 + U_{ri}\right)\right) \right] \end{aligned} \qquad (9)$$

where, λ_1 is the penalty multiplier of the power balance constraint and the penalty multiplier λ_2 for both ramp rate limit and prohibited operating zones violation constraints.

BRIEF OVERVIEW OF AIS

The natural immune system is accompanied by the evolution of immune systems of the species. The immune system defends the body from foreign pathogens that is able to recognize all cells within the body as either the self-cells or nonself-cells. It has a distributed task force that has the intelligence to take action from a local and global perspective using its network of chemical messengers for communication[14]. The biological process of the immune system need to be appreciated in order to understand the theoretical concept of artificial immune system. The body defense mechanism depends on action of antibodies to recognize and eliminate foreign cells called antigens. The antibodies are produced by lymphocytes through clonal proliferation. B-lymphocytes and T-lymphocytes are the two main components in the lymphocyte structure. The B-lymphocytes are the cells produced by the bone marrow and the T-lymphocytes are the cells produced by the thymus. A B-lymphocyte will produce only one antibody that is placed on its outer surface and acts as a receptor. Control mechanisms antibody productions are then regulated by the actions of T-lymphocytes.

The artificial immune system can produce various sets of antibodies with mechanism of antibody productions. However, an antibody can only specifically recognize a particular antigen. The portion on the antigen recognized by the antibody is called repitope that acts as an antigen determinant. Therefore each type of antibody has its specific antigen identifier called idiotope. When the receptor of a lymphocyte bound an antigen, it will receive triggering signal to activate clonal proliferation in order to form a large clone of the plasma cells. Since the lymphocytes can only make only one antibody, therefore the antibody secreted by the plasma cell will be identical to that which was originally acted as the lymphocyte receptor[14].

Clonal selection algorithm is implemented in artificial immune system by activating antibodies; proliferation and differentiation on the encounter of cells with antigens; maturation and diversification of antibody types by carrying out of affinity maturation process through random genetic changes; and removing those differentiated immune cells possess low affinity antigenic receptors. The objective function evaluation value and constraints satisfaction in the AIS optimization process is termed as affinity measures or fitness value. Higher is the satisfaction of constraints more is the affinity of the immune cells. Antigens represent constraints and the antibody-antigenic affinity refers to the extent of constraint satisfaction in the fitness function. In AIS the process of proliferation, maturation, and antigen-antibody interaction is repeated iteratively keeping in view with the fitness value of clones with higher affinity generate higher number of offsprings.

CLONAL SELECTION ALGORITHM

The clonal selection principle is an algorithm used by the immune system to describe the basic features of an immune response to an antigenic stimulus. The main features of the clonal selection principle includes as follows.

Initially a population of antibodies generated using binary strings. That is, the power output of each generating unit is encoded into a binary form and a string is formed. This paper refers lymphocytes as the antibody and makes no distinction between a B-cell and its antibody. Each binary string is checked for constraint violation and penalized in case of infeasibility with penalty proportional to the extent of constraint violation. Affinity is calculated via fitness or objective values. Each of the antibodies form the initial pool is copied into a fixed number of clones to generate a temporary population of clones. This population of clones is made to undergo maturation process through hypermutation mechanism. The hypermutation is carried out via affinity based hypermutation rate. Larger hypermutation rate is set for lower affinity clones and *vice-versa*. This is followed by their affinity evaluation and penalty in case of any constraint violation. A new population of the same size as initial population of antibodies is selected from the mutated clones and this completes the first iteration. In next iteration, this fresh population is made to undergo cloning and hypermutation as discussed above and likewise.

Proposed Clonal Algorithm for Economic Load Dispatch

The Implementation of clonal selection algorithm for solving economic load dispatch problem is according to the following procedures and summarized in the flowchart given in Figure 2.

Step 1

Initial population is formed by a set of antibodies. Each antibody contains *N* number of randomly generated binary strings, where *N* represents the number of generating units. Each binary string generated is decoded into actual value and tested for any constraints violation using equation (2) – equation (8). Only binary strings that satisfy the constraint are included in the population set.

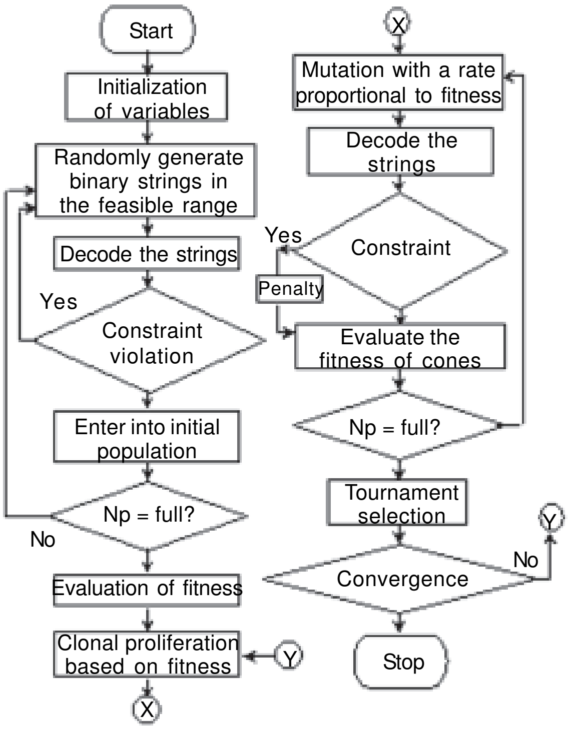

Figure 2 Flow chart of AIS algorithm

Step 2

The fitness value of each antibody in the population set is evaluated using equation (9).

Step 3

Individual antibodies in the population are cloned separately, giving rise to a temporary set of cloned individuals.

Step 4

The population of clones undergoes maturation process by implementing genetic operations, *ie*, mutation of cloned antibodies. The mutated clones are decoded and their fitness values are evaluated while satisfying constraints.

Step 5

A new population of the same size as the initial population is selected from the muted clones based on their fitness values for the next generation.

Step 6

The mutated clones are decoded into their real values followed by the evaluation of corresponding affinity for all the clones. Then tournament selection is done to select same number of mutated clones as there are in initial population.

Step 7

If the stopping criterion as the maximum number of iteration is reached, then print the result and stop; otherwise repeat steps (1) to (6).

RESULTS AND DISCUSSIONS

The proposed AIS optimization technique has been implemented in command line in Matlab 7.0 for the solution of economic load dispatch for 40 unit system with valve-point loading effects, generation limits, power loss, ramp rate limits and prohibited operating zones. The program was run on a 3.06 GHz, Pentium IV, with 256MB RAM PC. After a number of trials of run with different values of AIS parameters tuning, some of the key parameters are as detailed here.

Number of bits =16,

number of antibody in population = 20;

number of iterations = 2000,

probability of mutation = 0.02, and

the penalty multipliers $\lambda_1 = 100$ and $\lambda_2 = 10\ 000$.

Large populations give the algorithm more opportunities to find the desired solution since it can evaluate more thoroughly the feasible space at the expense of computational time. Small populations tend to converge to a solution faster than large populations but more susceptible towards local minima.

ELD with Non-smooth Cost Function

The program applied in test system with 40 generators with many constraints, such as, valve-point loading effect, generation limits, power loss, ramp rate limits and prohibited operating zones. The input data for 40 generators are given in this paper[7, 12]. Here, the total load demand for the 40 generator system is set as 10 500 MW.

Power System with Valve Point Loadings Only

The best cost for 40 generator system without losses by hybrid differential evolution (HDE) and also by self-tuning hybrid differential evolution (ST-HDE) was reported in this study[12] as 121813.26 $ and 121698.51 $, respectively. The best cost obtained out of 100 times running the program by the proposed AIS method for 40 generator system is 121482.004 $. The generation outputs and the corresponding costs of the best solution are provided in Table 1. The best solution provided among 100 trials, may not be the global solution but the results validating the heuristics applicability of the proposed algorithm for solving ELD problems. The Figure 3 depicts the convergence characteristics of AIS algorithm.

To observe the robustness and superiority of AIS has been applied and the obtained best result compared with relative frequency of other methods[7], such as, classical evolutionary programming (CEP), fast EP (FEP), modified FEP (MEP), improved FEP (IFEP) and modified PSO (MPSO)[9] and the solution quality of 100 trials were performed and the obtained statistical results are reported in Table 2. The proposed AIS method is a stochastic method where the solutions obtained may not be same at every run. When the program is run 100

Table 1 Best solution for 40 units system by valve-point effects only by AIS

Unit	P_{min}	P_{max}	Generation	Cost, $
1	36	114	114.0000	978.156
2	36	114	114.0000	978.156
3	60	120	97.4006	1190.562
4	80	190	179.7332	2143.552
5	47	97	87.8433	707.220
6	68	140	140.0000	1596.464
7	110	300	259.6016	2612.920
8	135	300	284.6009	2779.859
9	135	300	284.6075	2798.374
10	130	300	130.0000	2502.065
11	94	375	168.7998	2959.458
12	94	375	168.7999	2977.457
13	125	500	214.7598	3792.070
14	125	500	304.5196	5149.700
15	125	500	304.5196	5171.198
16	125	500	394.2794	6436.587
17	220	500	489.2794	5296.711
18	220	500	489.2796	5288.770
19	242	550	511.2795	5540.932
20	242	550	511.2794	5540.910
21	254	550	523.2795	5071.292
22	254	550	523.2796	5071.294
23	254	550	523.2796	5057.228
24	254	550	523.2794	5057.224
25	254	550	523.2795	5275.091
26	254	550	523.2794	5275.089
27	10	150	10.0000	1140.524
28	10	150	10.0000	1140.524
29	10	150	10.0000	1140.524
30	47	97	94.8883	821.479
31	60	190	190.0000	1643.991
32	60	190	190.0000	1643.991
33	60	190	190.0000	1643.991
34	90	200	175.5722	1769.756
35	90	200	200.0000	2043.727
36	90	200	200.0000	2043.727
37	25	110	110.0000	1220.166
38	25	110	110.0000	1220.166
39	25	110	110.0000	1220.166
40	242	550	511.2794	5540.930
Total generation and cost			10500.00	121482.004

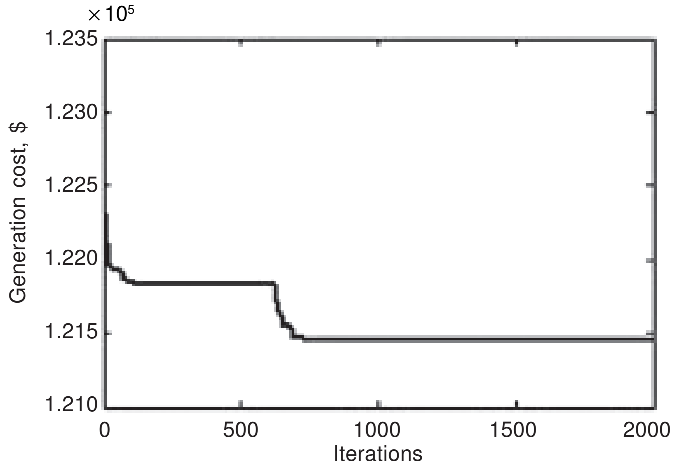

Figure 3 Convergence characteristics of AIS algorithm

times, the ranges of cost of the system obtained are classified into ten sub-ranges as shown in Table 2. The proposed AIS method provides all costs mostly in last three ranges, such as, 8th range (4 times), 9th range (31 times) and 10th range (65 times). The cost obtained by the AIS method lies in between 120 000 $ to 122 500 $ with 65 times in the 10th range. The best cost obtained out of 100 trials by various methods[12] is compared in Table 3.

Power System with Transmission Losses, Ramp Rate Limits, Prohibited Operating Zones and Valve-point Loading Effects

The proposed AIS method provides the best cost as 123 411.272 $ and worst cost as 124 313.244 $ out of 100

Table 2 Comparison of methods on relative frequency of convergence in the ranges of (k $) for 40 units system

Methods	126.5--127.0	126.0--126.5	125.5--126.0	125.0--125.5	124.5--125.0	124.0--124.5	123.5--124.0	123.0--123.5	122.5--123.0	120.0--122.5
Range	1	2	3	4	5	6	7	8	9	10
CEP[7]	10	4	-	16	22	42	4	2	-	-
EP[7]	6	-	4	2	10	20	26	24	6	-
MFEP[7]	-	-	-	-	-	14	26	50	10	-
IFEP[7]	-	-	2	-	4	4	18	50	22	-
MPSO[9]	-	-		-	-	-	-	-	53	47
BFA[10]	-	-	-	-	-	-	-		38	62
AIS	-	-	-	-	-	-	-	04	31	65

Table 3 Comparisons of simulation results of each method considering valve-point loading effects (40 units system)

CEP[7]	FEP[7]	MFEP[7]	IFEP[7]	MPSO[9]	BFA[10]	ST-HDE[12]	AIS
123488.290	122679.760	122647.570	122624.350	122252.625	121735.666	121698.510	121482.004

runs for 40 unit system by considering transmission losses, ramp rate limits, prohibited operating zones and valve-point loading effects. The best, average and worst cost of the proposed method is compared with DE, HDE and self-tuning HDE[12] methods and provided in Table 4. From the results, it is evident that the proposed AIS method appears to be best among all the reported methods. Table 5 provides the ramp rate, prohibited operating region data and also actual generated power of 40 units for the best cost of 123 411.272 $ by considering the above constraints.

Table 4 Comparison of different methods with transmission losses, ramp rate limits, prohibited operating zones and valve-point loading effects with a load demand of 10 500 MW

Methods	DE [12]	HDE [12]	ST-HDE [12]	AIS
P_{Loss}	119.9064	117.4074	117.74044	117.80
ΣP_g	10619.90	10617.40	10617.74	10617.80
Best cost	125074.40	123598.76	123496.02	123411.272
Average cost	127399.36	124210.34	124007.10	123886.547
Worst cost	129639.79	124855.80	124570.74	124313.244

Table 5 Best solution of 40 units system by considering transmission losses, ramp rate limits, prohibited operating zones and valve-point effects with a load demand of 10 500 MW

Unit	$P_{i\,\min}$	$P_{i\max}$	P_i^0	U_{ri}	D_{ri}	**Prohibited zones,** MW	Generation
1	36	114	100	114	114	–	110.8414
2	36	114	100	114	114	–	112.1604
3	60	120	90	120	120	–	120.0000
4	80	190	150	100	150	–	179.3632
5	47	97	80	97	97	–	93.1684
6	68	140	120	80	125	–	139.6557
7	110	300	280	165	200	–	299.9903
8	135	300	200	165	200	–	289.0102
9	135	300	230	165	200	–	284.5726
10	130	300	240	155	190	[130-150][200-230][270-299]	130.0000
11	94	375	210	150	185	[100-140][230-280][300-350]	94.0429
12	94	375	210	150	185	[100-140][230-280][300-350]	94.0000
13	125	500	230	206	235	[150-200][250-300][400-450]	125.0090
14	125	500	355	260	290	[200-250][300-350][450-490]	393.7394
15	125	500	350	186	215	–	484.5056
16	125	500	350	186	215	–	394.4071
17	220	500	460	240	270	–	489.2765
18	220	500	470	240	268	–	490.3992
19	242	550	500	290	315	–	511.2475
20	242	550	500	290	315	–	511.3917
21	254	550	510	335	360	–	523.1873
22	254	550	520	335	360	–	527.0917
23	254	550	520	335	362	–	523.1462
24	254	550	450	350	378	–	523.9341
25	254	550	400	350	380	–	523.6699
26	254	550	520	350	380	–	522.6462
27	10	150	20	95	145	–	10.0000
28	10	150	20	95	145	–	10.0402
29	10	150	25	98	145	–	10.0000
30	47	97	90	97	97	–	89.0178
31	60	190	170	90	145	–	188.5927
32	60	190	150	90	145	–	190.0000
33	60	190	190	90	145	–	190.0000
34	90	200	190	105	150	–	200.0000
35	90	200	150	105	150	–	199.9995
36	90	200	180	105	150	–	199.9154
37	25	110	60	110	110	–	108.2113
38	25	110	40	110	110	–	110.0000
39	25	110	50	110	110	–	110.0000
40	242	550	512	290	315	–	511.5669

CONCLUSION

This paper has employed a new approach using clonal selection based AIS algorithm to solve for economic load dispatch. The AIS has provided the best solution satisfying the constraints for the ELD problem with non-smooth cost function due to ramp rate limits, prohibited operating zones, power losses and valve-point effects. The results obtained by the proposed method were also compared to those obtained by evolutionary programming, MPSO, BFA and hybrid differential evolution methods. The AIS has shown its results better than the earlier best results when applied to large power systems in both the cases. Hence, the study shows that AIS could be a promising technique for solving complex optimization problems in power system operation.

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