www.ijaceeonline.com ISSN: 2456 - 3935
International Journal of Advances in Computer and Electronics Engineering
Volume 4, Issue 2, February 2019, pp. 6–16

Performance Analysis of Evolutionary Optimization Techniques for Economic Dispatch Problem

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Abstract: *This paper deals with comparisons of different evolutionary optimization techniques for the solution Economic Dispatch Problem (EDP) in power system. The main principle behind the evolutionary techniques is inspired by the biological evolution of the living organisms. Economic Dispatch problem deals with optimizing the operational cost of the online generators with fulfilling the consumer end power demand. Scheduling the practical generation units involves the complex limitations. Among these limitations valve point loading effect is included in this work for increased convolution. In this paper, the evolutionary optimization techniques such as the Real Coded Genetic Algorithm (RCGA), Binary Coded Genetic Algorithm (BCGA), Particle Swarm Optimization (PSO), Simulated Annealing (SA) and Artificial Immune System (AIS) are simulated for EDP for its performance analysis. These optimization algorithms are validated for three, thirteen and forty generating systems and their results are compared. From these results, the elite and the most suitable algorithm are found for solving the EDP.*

Keyword: *Artificial Immune System (AIS); Binary Coded Genetic Algorithm (BCGA); Economic Dispatch Problem (EDP); Evolutionary optimization Techniques; Particle Swarm Optimization (PSO); Real Coded Genetic Algorithm (RCGA); Simulated Annealing (SA).*

1. INTRODUCTION

In the power system operation and control, the generation sector cost optimization plays a vital role. If the cost of power generation increases, then the consumer tariff gets drastically hiked. Also the available fossil fuel gets depleted quickly. Among the fossil fuels, the coal is abundantly available and the amount of power produced is high. In this article, the coal power generating units are taken into account for the optimal operation. So for decreasing the tariff, the efficient utilization of coal generating units is the only solution. The efficient operation of these generating units is possible by the Economic dispatch problem. This EDP deals with determining the optimal power output of a certain set of generators to fulfill the system demand and other operational limitations with minimal operational cost.

Generally large turbo generators in coal fired thermal generating units have a set of valves at the inlet to the steam turbine. With the increase in power demand these valves are opened sequentially. The throttling loss in a valve is large, when it is just opened and is small when it is fully opened. This loss is termed as a valve point loading effect, which makes the cost curve highly nonlinear.

Over the recent years, the EDP is solved with the traditional mathematical methods include [linear programming (LP) [1], Dynamic Programming (DP) [2], Quadratic Programming (QP) [3].These methods are

Cite this paper:

S. Praveen, R. Vijay, G. Sathish, "Performance Analysis of Evolutionary Optimization Techniques for Economic Dispatch Problem", International Journal of Advances in Computer and Electronics Engineering, Vol. 4, No. 2, pp. 6-16, February 2019.

very good at solving the EDP, but if the nonlinearity of the problem increases, then the problem solving is complex and time consuming.

To overcome these hardships, the evolutionary meta-heuristics techniques [4] are widely used to solve ED Problems. The recent methods include Genetic Algorithm (GA) [5], Particle Swarm Optimization (PSO) [6], Simulated Annealing (SA) [7], Ant Colony Optimization (ACO) [8], Harmony Search (HS) [9], Cultural Algorithm (CA) [10], Artificial Immune System (AIS) [11], Biogeography Based Optimization (BBO) [12], Bat Motivated Optimization (BMO) [13], Bacterial Swarm Optimization [14,15] are proposed to solve the EDP

Genetic Algorithm (GA) mimics the Darwin's principle of natural selection and survival of the fittest which essentially attempt to emulate evolution in biological systems to compute solutions for optimization problems have been proved to be effective in solving the optimization problem, but it suffers from premature convergence and time consuming also fail to locate global solution.

The PSO is an evolutionary optimization tool of swarm intelligence field based on a swarm (population), where each member is seen as a particle, and each particle is a potential solution to the problem under analysis, has been found to robust in solving continuous nonlinear and linear optimization problem with less computation time and stable convergence characteristic than other heuristic optimization methods.

Simulated Annealing (SA) is having the ability to search for global solutions. It is a random search technique which exploits an analogy by the way in which a metal cools and freezes into a minimum energy crystalline structure. The annealing process and search for a minimum in more general system forms the basis of an optimization technique for combinatorial and other problems. It is probabilistic based method of accepting candidate's solutions in the search process. It suffers from setting the control parameters to achieve global optimum.

In order to get the qualitative solutions for problem related to EDP, algorithms like ACO, Harmony Search (HS) & Cultural Algorithm (CA) is proposed to solve the EDP with valve point loading. But these techniques have some shortcomings in convergence and stuck in local optima.

In this article, Artificial Immune System is simulated and compared with the above mentioned techniques for optimal operation and effectiveness. Artificial Immune System (AIS) [16] are adaptive systems inspired by theoretical immunology and observed immune functions, principles and models, which apply to complex problem domain. The immune system is highly complicated and appears to be precisely tuned to the problem of detecting and eliminating infections. It mimics the human immune system and follows the clonal selection or the clonal expansion principle. This process is used to explore new search regions and also escape from local optima. The recognition and learning capabilities of natural immune system provides the property of robustness, dynamism and adaptability to AIS based algorithm.

This paper considers three standard EDP problems, namely 3, 13 and 40 generating units with incremental fuel function, including a variable percentage of the maximum power being demanded with the valve-point loading effects.

2. PROBLEM FORMULATION

The objective of the ELD problem is to minimize the total fuel cost by adjusting the power output of each of the generators connected to the grid while satisfying the demand and other operational constraints which can be described mathematically as a minimization of the problem. The modeling is determined for the total fuel cost as the sum of the cost function of each generator.

The total fuel cost, which is the basic economic dispatch problem, can be described mathematically as a minimization of the problem.

$$F_t = \sum_{i=1}^{n} F_i\,(P_i) + m \times \{\max(0, (P_d - \sum P_i)\} \qquad (1)$$

Where $F_i(P_i)$ is the variation of fuel cost in \$ with generated Power (MW) which is the fuel cost equation of the i^{th} plant. It is given by

$$F_i(P_i) = a_i + b_iP_i + c_iP_i^2 \qquad (2)$$

To attain an exact and practical economic dispatch solution, the sensible operation of the ED problem must be examined with the valve point effects. Generally, to model the valve point effects, a rectified sinusoidal function is added to the input and output correlation. The power generating units with multi-valve steam turbines show a higher discrepancy in the fuel-cost functions. Figure 1 shows the ripple due to the valve-point, i.e., a cost function has higher order nonlinearity. Typically, the cost function taking into account the valve-point loadings of a generating unit is given in equation below

$$F_i(P_i) = a_i + b_iP_i + c_iP_i^2 + |e_i \sin f_i\ (P_{imin} - P_i)| \qquad (3)$$

The total fuel cost is to be reduced subject to the following constraints.

$$\sum_{i=1}^{n} P_i - P_d = 0 \qquad (4)$$

$$P_{imin} \le P_i \le P_{imax}; i = 1,2,..n \qquad (5)$$

Where a_i, b_i, c_i are the fuel cost coefficients of i^{th} generator,e_i and $f_i$are the fuel cost coefficients of the

ISSN: 2456 - 3935
International Journal of Advances in Computer and Electronics Engineering
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i^th unit with valve-points effects, $F_i(P_i)$ is the fuel cost of i^th generator, $/hr, F_t is the total fuel cost, $/hr, n is the number of generators, P_{imax} is the maximum generation limit of i^th generator, MW, P_{imin} is the minimum generation limit of i^th generator, MW, P_d is the system power demand, MW P_i is the real power output (MW) of i^th generator corresponding to time period t.

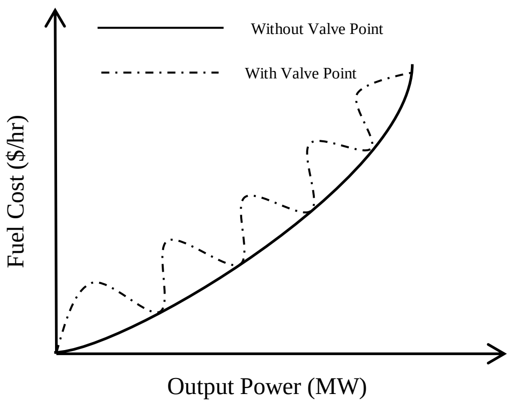

Figure 1 Incremental fuel cost versus power output steam turbine unit with valve point effect

3. ECONOMIC DISPATCH PROBLEM USING VARIOUS OPTIMIZATION ALGORITHMS

3.1 Economic Dispatch Problem Using RCGA and BCGA

For each problem of optimization in GA there are a large number of possible encodings. Although Binary coded Genetic Algorithm (BCGA) [17] is usually applied to power optimization problems. Real coded Genetic Algorithm (RCGA) [18] is a modified GA employing real valued vectors for representing chromosomes and its use of real valued representation in the GA has a several merits with optimization of function numerically over binary encoding. The efficiency of the RCGA is increased as there is no need to convert chromosomes to the binary, hence less memory is required and also there is no loss in precision by converting to binary or other values, and there is a great advantage to use different genetic operators. The procedure for BCGA is same as RCGA except for binary coding of chromosomes.

Step1: Initialize a population to generate the initial parent vectors of power outputs by choosing randomly RCGA by the implementation of probabilistic search, distributed uniformly in intervals within the limits and obtains a global optimum solution over a number of iterations.

Step2: The implementation of the RCGA is given below:
The initial population is obtained if equation (6) is satisfied. The fitness function is used to transform the cost function value into a measure of relative fitness. For representing the real valued function, the k^th chromosome C_k can be defined as follows:

$$C_k = [P_{k1}, P_{k2}, \ldots . P_{kn}] \quad (6)$$

where $k = 1,2, \ldots$ population size
Where P_{ki} represent output power of n^th generator of a k^th chromosome.

Step3: Reproduction, it involves formation of a mating pool by roulette wheel selection method.

Step4: Cross over, offspring's are created from the mating of two selected parents or mating pairs. It is thought that the crossover operator is mainly responsible for the global search property of the GA. A non-uniform arithmetic crossover operator was introduced into the RGA, which produces a complimentary pair of linear combinations produced from random proportions of the parents. The heuristic crossover operator generates a child that is a linear extrapolation away from the better parent along the direction of the vector joining the two parents. Two chromosomes, selected randomly for crossover, C_{igen} and C_{jgen}, may produce two offspring, $C_{igen}+1$ and $C_{igen}+1$, which is a linear combination of C_{igen} and C_{jgen} i.e.,

$$C_{igen} + 1 = a \times C_{igen} + (1-a)C_{jgen} \quad (7)$$

$$C_{jgen} + 1 = (1-a) \times C_{igen} + a)C_{jgen} \quad (8)$$

Where a is a randomly generated number in the range of [0, 1].

Step5: In the mutation process, the non-uniform mutation operator is used to inject new genetic material into the population and individually it is applied to each new structure. A given mutation involves random alteration of each gene with a small probability. Suppose that $C = (c_1, c_i, c_n)$ and $C_i \in [up_i, low_i]$ a gene to be mutated. Next, the gene, C_i', which results from non-uniform mutation can be defined as follows:

$$C_i' = C_i + d_i \times rand \quad (9)$$

Where $d_i = (P_{imax} - P_{imin}) \times mut\_scale$.
The value of mut_scale is normally set to 0.1 and $randn$ is normally distributed random numbers. The chromosomes which vi-

ISSN: 2456 - 3935
International Journal of Advances in Computer and Electronics Engineering
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olate constraints are given a penalty which will be added to the total fuel cost of those chromosomes. Hence the objective function value of chromosomes which have violated the constraints will be high. The penalty handling is shown in the procedure of PSO.

Step6: The parents and children created so in this iteration will compete with each other to form the next generation of chromosomes.

Step7: An elitist GA search is used and guarantees that the best solution obtained so far in the search is retained and used in the next generation, and thereby ensures no good solution in the previous generation can be lost in the search process.

Step8: Repeat steps 2-6 stop the process which maximum number of iterations has reached.

The important parameters in GA are tabulated in Table 1.

TABLE I GA PARAMETERS

Parameters	Size
Population size	50
Maximum no of iterations	500
Probability of cross over	0.8
Probability of mutation	0.1
Demand Penalty (m)	200

3.2 Particle Swarm Optimization (PSO)

Particle swarm optimization is a population based hypothetical optimization technique which can be applied for almost all non-linear complex optimizations in power system. It was aspired by the social behavior of organisms such as bird flocking and fish schooling and it utilizes a population based search procedure. According to the research results, birds find food by flocking hence all information is shared inside the flocking. This assumption is a basic concept of PSO. In PSO, each response is a particle and each particle in the search space regulates its flying velocity in agreement with its own flying velocity and its neighbors' flying velocity. The fitness values of all the particles are evaluated by the fitness function. The evaluated function is then optimized and has velocity, which directs the flying of particles. This operation is initialized by updating generations with a troop of random particles which search for optima.

Each particle is treated as a point in D dimensional space, and the ith particle is represented as

$$X_i = (x_{i1}, x_{i2}, \dots\dots x_{id}) \qquad (10)$$

The best former position of the ith particle is recorded and denoted as

$$P_{besti} = (P_{best1}, P_{best2}, \dots\dots P_{bestd}) \qquad (11)$$

The index of the best among the entire particle in the population is represented by the symbol G_{best}. The velocity (the rate of the position change) for particle is

$$V_i = (V_{i1}, V_{i2}, \dots\dots V_{id}) \qquad (12)$$

The reformed velocity and position of each particle can be calculated using the current velocity and the distance from P_{bestid} to G_{bestid} as shown in the following equations

$$V_{id}^{j+1} = W \times V_{id}^{j} + C_1 \times rand\,() \times (P_{best\,id} - X_{id}^{j}) + C_2 \times rand() \times (G_{best\,id} - X_{id}^{j}) \qquad (13)$$

Inertia weight factor

$$W = W_{max} - \frac{(W_{max} - W_{min}) \times iter}{iter_{max}} \qquad (14)$$

$$X_{id}^{j+1} = X_{id}^{j} + V_{id}^{t+1} \qquad (15)$$

The power outputs from each generator are taken as the particles of the PSO. Then the steps in the PSO algorithm for the economic dispatch problem are as follows:

Step1: In the Initial generations of particles and future updates of particles are generated in such a manner that the sum of the outputs of the particles equals power demand. Hence the demand is always satisfied, thus only feasible solutions are considered.

Step2: The particle velocities are generated randomly between maximum and minimum values of each particle.

Step3: Objective function values are calculated for each particle and penalties are assigned for those particles which do not satisfy the demand constraint. These values are assigned as P_{best} and minimum among these particles is assigned as G_{best}.

Step4: New velocities of the particles are evaluated using (13).

Step5: The position of each particles are modified using (15).

Step6: New objective function values are calculated for new positions of the particles. If the new values are better than previous P_{best} and G_{best} the new values are assigned to P_{best} and G_{best}.

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Step7: Repeat steps 2-6 and terminate if the maximum number of iterations are achieved.

The important parameters in PSO are tabulated in Table 2.

TABLE II PSO PARAMETERS

Parameters	Size
Population size	50
Maximum iterations	500
Wmin	0.4
Wmax	0.9
C1, C2	4
Vdmax	0.005*Pmax
Vdmin	-0.005*Pmax

3.3 Simulated Annealing

Simulated annealing (SA) is a random-search technique which exploits an analogy between the way in which a metal cools and freezes into a minimum energy crystalline structure (the annealing process) and the run in for a minimum in a general system; it forms the basis of an optimization technique for combinatorial and other problems. SA approaches the global maximization problem similar to the use of a bouncing ball that can bounce from valley to valley over mountains. The ball makes very high bounces at high "temperature", which enables it to bounce over any mountain to access any valley, given adequate bounces. The ball cannot bounce so high as the temperature declines and it can get trapped in relatively small ranges. A generating distribution generates valleys (states) to be explored and all the generating and acceptance distributions depend on the temperature and it has been proved that by carefully controlling the rate of cooling of the temperature, SA can reach the global optimum.

However, this requires infinite time and this problem is overcome by fast annealing and very fast simulated annealing (VFSR) or adaptive simulated annealing (ASA) since they are each in turn exponentially faster than SA. The major advantage of SA over other methods is an ability to avoid becoming trapped in local minima. Thus Simulated annealing (SA) is a random search approach which not only accepts changes that reduce the objective function, but also any changes that rises it. The latter is accepted with a probability

$$P = \exp\left(-\frac{\Delta f}{T}\right) \qquad (16)$$

Where Δf is the increase in f and T is the system "temperature" irrespective of the objective function involved.

The steps in Economic Load Dispatch Problem Using SA is given as

Step1: Create Initial solution (power outputs of the generators) and evaluate the fitness function.

Step2: Initialize the Temperature.

Step3: Generate new solution and access new solution.

Step4: Check whether new solution can be accepted with a probability.

Step5: Update Solution if probability is satisfied.

Step 6: Adjust temperature.

Step7: Repeat steps 2-5 until maximum iteration is reached.

The important parameters in SA are tabulated in Table 3.

TABLE III SA PARAMETERS

Parameters	Size
Initial temperature	100
Final temperature	0
Incremental decrease in Temperature	0.5
Maximum iterations	100

3.4 Artificial Immune System

Artificial Immune Systems (AIS) is a diverse area of research that attempts to bridge the division between immunology and engineering and is developed through the application of techniques such as mathematical and computational modeling of immunology. AIS are adaptive systems inspired by theoretical immunology applied to complex problem domain. The AIS system is more complex and appears to be precisely tuned to the problem of detecting and eliminating infections. AI has become known as an area of computer science and engineering that uses immune system metaphors for the novel creation of solutions. AIS is presently moving into an area of true interdisciplinary and one of genuine interaction between immunology, mathematics and engineering. Researchers have proved that it also provides a compelling example of a distributed information-processing system, which can be applied for designing better artificial adaptive systems. It has two selection principles the clonal selection or clonal expansion principle and negative selection. This process is used to explore new search regions and also escape from local optima. The recognition and learning capabilities of natural

ISSN: 2456 - 3935
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immune system provides the property of robustness, dynamism and adaptability to AIS based algorithm. The Proposed AIS Algorithm to solve EDP is given by the following steps:

In the Proposed Artificial immune system the new population is created by mutation operator. In this proposed algorithm a step wise linear decreasing mutation scale is introduced after some fixed number of iterations. The mutation for this algorithm is taken from real coded genetic algorithm i.e., specified in equation (9).

Step1: Generate randomly initial population (Power output of generators).

Step2: Find and sort objective values in ascending order by using equation (17)

Step3: Calculate affinity value (Affinity)

$$\text{Affinity} = \frac{1}{\text{objective function}} \tag{17}$$

Step4: Calculate the cloning rate of each of the anti-body using the following equation

$$\text{Rate of cloning} = \frac{\text{Affinity value} \times \text{Pop Size}}{\sum \text{Affinity value}} \tag{18}$$

Step5: Generate clones proportional to their cloning rate. (At this stage size of the population is increased)

Step6: Apply mutation process to each clone. In this algorithm a real mutation operator is used with step wise decreasing mutation scale is used i.e. after some fixed no of iterations mutation scale is decreased.

Step7: Compare the objective values of the mutated clone with the objective values of the original antibody and retain the best clone

Step8: Sort the mutated population in ascending order.

Step9: The population size is trimmed to original size by deleting the worst solutions.

Step10: Replace a percentage of R individuals with high objective values with randomly generated ones to introduce diversity.

Step11: Go back to step 2 until convergences occurs or after reaching a certain (predetermined) number of iterations.

The important parameters in AIS are tabulated in Table 4.

Table IV AIS PARAMETERS

Parameters	Size
Population size	50
Maximum no of iterations	500
Probability of mutation	0.75

4. RESULTS AND DISCUSSION

In this paper, the five optimization algorithms such as RCGA, BCGA, PSO, SA and AIS are used to solve EDP of thermal power plants with value point loading effects. The results for 3, 13 and 40 [19] generating unit test system with non-convex fuel cost functions are presented. For the implementation of EDP of these techniques a software program is written in MATLAB and they are executed using Intel core i5 processor @1.70 GHz with 4GB RAM.

The generating unit test system for a 3 unit system with the load demand of 850MW, a 13 unit system with the demand of 1800 MW, 2520MW & 2500MW and 40 unit systems with the load demand of 10500 MW is taken into consideration.

The power dispatch results of the considered generating system are simulated with above mentioned algorithms are shown in Table 5, 7, 9, 11 and 13 respectively. From these tables it is clear that the proposed AIS outperform the other techniques.

The best, worst and average results are trailed for 50 runs and the preeminent solution is given in the Table 6, 8, 10, 12 and 14. It is clear from the table 6 that the average values of the fuel cost of the proposed AIS technique are better than the others which shows the efficacy of the considered technique.

The optimum results of 3 unit system of AIS is 8218.8204$, a 13 unit system with 1800MW is 17972.8105$, 2520MW is 24137.8296$ and for 2500MW is 23948.8531$. The results for 40 unit system that of AIS is 121429.6627$.The average value for 3 unit system for that of AIS is 8219.7732$, a 13 unit system with 1800MW is 17986.1861$, for 2520MW is 24153.3883$ and of 2500MW is 23980.6673$. The average value of 40 unit system is 121791.3054$.To validate the optimum results 50 trail runs were made and the results were recorded.

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TABLE V RESULTS OF 3-UNIT SYSTEM WITH 850MW

Method/ Unit output	RGA	BGA	PSO	SA	AIS
P1	349.4736	349.627	349.4662	349.9628	349.7662
P2	400.0000	399.9998	400.0000	399.9996	400.0000
P3	100.5264	100.3726	100.5338	100.0378	100.2340
Total fuel cost ($)	8220.6892	8220.7025	8220.6884	8220.73	8218.8204
Total power generation(MW)	850.000	850.000	850.000	850.000	850.000

TABLE VI COST COMPARISON OF 3-UNIT SYSTEM WITH 850 MW

Total fuel cost ($)			
Method	**Best**	**Worst**	**Avg**
RGA	8220.6892	8225.6759	8223.3323
BGA	8220.7025	8221.1096	8221.3978
PSO	8220.6884	8228.3639	8224.5286
SA	8220.7300	8378.3282	8299.5084
AIS	8218.8204	8220.7260	8219.7732

TABLE VII RESULTS OF 13- UNIT SYSTEM WITH 1800MW

Method/ Unit output	RGA	BGA	PSO	SA	AIS
P1	628.0000	629.0000	448.7990	628.0000	628.3185
P2	299.0000	229.0000	302.5355	225.0000	297.5489
P3	224.0000	300.0000	299.1993	296.0000	224.3995
P4	60.0000	60.0000	109.8666	60.0000	60.0000
P5	60.0000	60.0000	60.0000	60.0000	109.8665
P6	60.0000	61.0000	109.8666	60.0000	60.0000
P7	60.0000	110.0000	60.0000	60.0000	109.8665
P8	60.0000	60.0000	109.8666	160.0000	60.0000
P9	159.0000	60.0000	109.8666	60.0000	60.0000
P10	40.0000	80.0000	40.0000	40.0000	40.0000
P11	40.0000	41.0000	40.0000	40.0000	40.0000
P12	55.0000	55.0000	55.0000	55.0000	55.0000
P13	55.0000	55.0000	55.0000	56.0000	55.0000
Total fuel cost($)	17987.9	18076.1	17975.3434	18019.6	17972.8105
Total power generation (MW)	1800	1800	1800	1800	1800

TABLE VIII COST COMPARISON OF 13-UNIT SYSTEM WITH 1800MW

Total fuel cost ($)					
Method	**RGA**	**BGA**	**PSO**	**SA**	**AIS**
Best	17987.9547	18076.1725	17975.3434	18019.6772	17972.8105
Worst	18265.5741	18008.0157	18140.2845	17978.5618	17999.5618
Avg	18167.7644	18042.0941	18057.8139	17999.1195	17986.1861

TABLE IX RESULTS OF 13- UNIT SYSTEM WITH 2520MW

Method/ Unit output	RGA	BGA	PSO	SA	AIS
P1	664.3178	628.3185	664.3183	628.3185	664.3181
P2	335.1984	299.1993	335.1941	299.1993	335.1828
P3	359.192	299.1993	359.1828	299.1993	359.1975
P4	179.7331	159.7331	129.8665	159.7331	129.8665
P5	146.7331	159.7331	146.7331	159.7331	146.7331
P6	117.8665	159.7331	167.7331	159.7331	167.7329
P7	159.8665	159.7331	159.8665	159.7331	159.8665
P8	135.0000	159.7331	135.0000	159.7331	135.0000
P9	135.0000	159.7331	134.9998	159.7331	135.0000
P10	55.1898	110.0844	86.34206	77.3999	86.3189
P11	87.7187	114.7998	56.59825	110.0844	56.6000
P12	56.5867	55.0000	56.58563	92.3999	56.5943
P13	87.5971	55.0000	87.58541	55.0000	87.5893
Total fuel cost ($)	24141.9514	24178.8346	24137.8623	24174.0762	24137.8296
Total power generation (MW)	2520.0000	2520.0000	2520.0000	2520.0000	2520.0000

TABLE X COST COMPARISON OF 13-UNIT SYSTEM WITH 2520MW

Total Fuel Cost in $					
Method	**RGA**	**BGA**	**PSO**	**SA**	**AIS [Prop.]**
Best	24141.9514	24178.8346	24137.8623	24174.0762	24137.8296
Worst	24487.7324	24421.7324	24358.9581	24300.7467	24168.9471
Avg.	24314.8419	24300.2835	24248.4102	24162.9581	24153.3883

TABLE XI RESULTS OF 13- UNIT SYSTEM WITH 2500MW

Method/ Unit output	RGA	BGA	PSO	SA	AIS
P1	664.3184	664.3183	664.3183	664.3183	664.3183
P2	260.3992	335.1785	260.3992	335.1977	260.3994
P3	359.1824	359.1876	359.1951	359.1922	359.1964
P4	179.7331	179.7331	179.7331	129.8665	179.7331
P5	146.7330	96.86642	146.7331	96.86646	146.7331
P6	167.7331	117.8665	167.7331	167.7331	167.7331
P7	159.8665	110.0000	159.8665	110.0000	159.8664
P8	134.9999	135.0000	135.0000	135.0000	135.0000
P9	135.0000	135.0000	135.0000	134.9999	135.0000
P10	55.18601	91.34222	91.35855	92.59365	91.31050
P11	56.58422	93.98903	56.5834	92.65454	56.59253
P12	92.72311	93.95845	56.57892	93.99277	56.57883
P13	87.54106	87.55988	87.50073	87.58488	87.53825
Total fuel cost($)	23949.1498	23967.9597	23948.8588	23964.0537	23948.8531
Total power generation (MW)	2500.0000	2500.0000	2500.0000	2500.0000	2500.0000

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TABLE XII COST COMPARISON OF 13-UNIT SYSTEM WITH 2500MW

Total Fuel Cost in $					
Method	**RGA**	**BGA**	**PSO**	**SA**	**AIS**
Best	23949.1498	23967.9597	23948.8588	23964.0537	23948.8531
Worst	24292.1476	24279.8475	24217.7463	24162.9581	24012.4816
Avg.	24120.6487	24123.9036	24083.3025	24063.5059	23980.6673

TABLE: XIII RESULTS OF 40- UNIT SYSTEM WITH 10500MW

Unit	AIS	Unit	AIS
1	113.9944	21	523.2794
2	110.9617	22	523.2794
3	97.39991	23	523.2794
4	179.7331	24	523.2794
5	90.1231	25	523.2794
6	140.0000	26	523.2794
7	259.5997	27	10.0000
8	284.5997	28	10.0000
9	284.5997	29	10.0000
10	130.0000	30	91.44074
11	94.0000	31	190.0000
12	168.7998	32	190.0000
13	214.7598	33	190.0000
14	394.2794	34	164.8370
15	394.2794	35	200.0000
16	304.5196	36	200.0000
17	489.2794	37	110.0000
18	489.2794	38	110.0000
19	511.2794	39	110.0000
20	511.2794	40	511.2794
Total fuel cost ($)			121429.6627
Total power generation (MW)			10500.0000

TABLE XIV COST COMPARISON OF 40-UNIT SYSTEM

Total Fuel cost in $					
Method	**RGA**	**BGA**	**PSO**	**SA**	**AIS**
Best	121519.3287	121568.6587	121493.1624	121524.0357	121429.6627
Worst	123852.7251	122382.9581	123252.5651	122632.6291	122152.9451
Avg	122686.0269	121975.5605	121922.8327	122078.3324	121791.3054

5. CONCLUSION

This paper proposes the Real Coded Genetic Algorithm, Binary Coded Genetic Algorithm, Particle swarm optimization, Simulated Annealing and Artificial Immune System technique to solve economic dispatch problem of 3, 13 and 40 generating unit test system with non-convex fuel cost function for different load demand. The above presented algorithm is simulated and validated for its performance. The best and average results clearly propose that the Proposed AIS gives better fuel cost than the other techniques. Further, it is applicable for distribution scheduling problem.

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Cite this paper:

S. Praveen, R. Vijay, G. Sathish, "Performance Analysis of Evolutionary Optimization Techniques for Economic Dispatch Problem", International Journal of Advances in Computer and Electronics Engineering, Vol. 4, No. 2, pp. 6-16, February 2019.