Solution of Non-Convex and Dynamic Economic Load Dispatch Problem of Small Scale Power Systems using Dragonfly Algorithm

Vikram Kumar Kamboj
Department of Electrical Engineering,
DAV University, Jalandhar,
Punjab, India

Pawanpreet Singh
M.Tech Research Scholar, Electrical Engineering
Department, DAV University,
Jalandhar

Ashutosh Bhadoria
Department of Electrical Engineering,
DAV University, Jalandhar,
Punjab, India

S. K. Bath
Department of Electrical Engineering, GZS Campus
College of Engineering & Technology,
Bathinda, Punjab

***Abstract*—Dragonfly algorithm is a novel intelligence optimization technique, which simulates the static and dynamic swarming behaviours of dragonflies in environment. Exploration and exploitation in dragonfly algorithm is achieved by modelling the social interaction of dragonflies in navigating, searching for foods and avoiding enemies when swarming dynamically or statistically. This paper presents the application of dragonfly algorithm for the solution of non-convex and dynamic economic load dispatch problem of electric power system. The performance of dragonfly algorithm is tested for economic load dispatch problem of six IEEE benchmarks of small scale power systems and the results are verified by a comparative study with Lambda Iteration Method, Particle Swarm Optimization (PSO) algorithm, Genetic Algorithm (GA), Simulated Annealing(SA), Artificial Bee Colony (ABC), Evolutionary Programming (EP) and Grey Wolf Optimizer(GWO). Comparative results show that the performance of Dragonfly algorithm is better than recently developed GWO algorithm and other well known heuristics and meta-heuristics search algorithms.**

Keywords—* *Economic Load Dispatch Problem (ELDP), Dragonfly Algorithm (DA), Grey Wolf Optimizer (GWO)

I. INTRODUCTION

In modern power system networks, there are various generating resources like thermal, hydro, nuclear etc. Also, the load demand varies during a day and attains different peak values. Thus, it is required to decide which generating unit to turn on and at what time it is needed in the power system network and also the sequence in which the units must be shut down keeping in mind the cost effectiveness of turning on and shutting down of respective units. The entire process of computing and making these decisions is known as unit commitment (UC). The unit which is decided or scheduled to be connected to the power system network, as and when required, is known to be committed unit. Unit commitment in power systems refers to the problem of determining the on/off states of generating units that minimize the operating cost for a given time horizon. Electrical power plays a pivotal role in the modern world to satisfy various needs. It is therefore very important that the electrical power generated is transmitted and distributed efficiently in order to satisfy the power requirement. Electrical power is generated in several ways. The most significant crisis in the planning and operation of electric power generation system is the effective scheduling of all generators in a system to meet the required demand. The Economic Load Dispatch (ELD) problem is the most important optimization problem in scheduling the generation among thermal generating units in power system.

Economic dispatch in electric power system refers to the short-term discernment of the optimal generation output of various electric utilities, to meet the system load demand, at the minimum possible cost, subject to various system and operating constraints viz. operational and transmission constraints. The Economic Load Dispatch Problem (ELDP) means that the electric utilities (i.e. generator's) real and reactive power are allowed to vary within certain limits so as to meet a particular load demand within lowest fuel cost. The ultimate aim of the ELD problem is to minimize the operation cost of the power generation system, while supplying the required power demanded. In addition to this, the various operational constraints of the system should also be satisfied. The problem of ELD is usually multimodal, discontinuous and highly nonlinear. Although the cost curve of thermal generating units are generally modelled as a smooth curve, the input-output characteristics are nonlinear by nature because of valve-point loading effects, Prohibited Operating Zones (POZ), ramp rate limits etc.

In recent years, various evolutionary, heuristic and meta-heuristics optimization algorithms have been developed simulating natural phenomena such as: Genetic Algorithm(GA) [1], Ant Colony Optimization (ACO) [2], Particle Swarm Optimization[3], Simulating Annealing(SA)[4], Gravitational Local Search (GLSA) [5], Big-Bang Big-Crunch (BBBC) [6], Gravitational Search Algorithm (GSA) [7], Curved Space Optimization (CSO) [8], Charged System Search (CSS) [9], Central Force Optimization (CFO) [10], Artificial Chemical Reaction Optimization Algorithm (ACROA) [11], Black Hole (BH)

[12] algorithm, Ray Optimization algorithm(ROA) [13], Small-World Optimization Algorithm (SWOA) [14], Galaxy-based Search Algorithm (GbSA) [15], Shuffled Frog Leaping Algorithm(SFLA)[16], Snake Algorithm[17], Biogeography Based Optimization[18], Marriage in Honey Bees Optimization Algorithm (MBO) [19] ,Artificial Fish-Swarm Algorithm (AFSA) [20] , Termite Algorithm (TA)[21] , Wasp Swarm Algorithm(WSA) [22] , Monkey Search Algorithm(MSA) [23] , Bee Collecting Pollen Algorithm (BCPA) [24] , Cuckoo Search Algorithm (CSA) [25], Dolphin Partner Optimization (DPO)[26] , Firefly Algorithm[27], Krill Herd (KH) algorithm [28] , Fruit fly Optimization Algorithm (FOA) [29], Distributed BBO[30]. Out of these heuristics evolutionary search algorithm, some of these are used to solve Economic Load Dispatch Problem(ELDP), Combined Economic Load Dispatch Problem(CELDP), Dynamic Economic Dispatch Problem(DEDP) and Combined Economic Emission Dispatch (CEED) and are reported in numerous literatures as: Evolutionary Programming [31], Particle Swarm Optimization[32], Genetic Algorithm[32,33], Improved Genetic Algorithm[34], Adaptive PSO and Chaotic PSO[35], cardinal Priority ranking based Decision making[36], Gravitational Search Algorithm[37, 42, 45], Biogeography Based Optimization[38, 39, 44], Intelligent Water Drop Algorithm[40], Hybrid Harmony Search Algorithm[41], Firefly Algorithm[43], Cuckoo Search Algorithm[46, 54], Biogeography Based Optimization[44], Differential harmony Search[47], Hybrid Particle Swarm Optimization and Gravitational Search Algorithm[48], Differential Evolution[49], Modified Ant Colony Optimization[50], Modified Harmony Search[51], Hybrid GA-MGA[52], Artificial Bee Colony[53]. Although no optimization algorithm can perform general enough to solve all optimizations problems, each optimization algorithm have their own advantages and disadvantages. The limitations of some of these well known optimization algorithms are listed below:

The major limitations of the numerical techniques and dynamic programming method are the size or dimensions of the problem, large computational time and complexity in programming. The mixed integer programming methods for solving the economic load dispatch problem fails when the participation of number of units increases because they require a large memory and suffer from great computational delay. Gradient Descent method is distracted for Non-Differentiable search spaces. The Lagrangian Relaxation (LR) approach fails to obtain solution feasibility and solution quality of problems and becomes complex if the number of units are more. The Branch and Bound (BB) method employs a linear function to represent fuel cost, start-up cost and obtains a lower and upper bounds. The difficulty of this method is the exponential growth in the execution time for systems of a large practical size. An Expert System (ES) algorithm rectifies the complexity in calculations and saving in computation time. But it faces the problem if the new schedule is differing from schedule in database. The fuzzy theory method using fuzzy set solves the forecasted load schedules error but it suffers from complexity. The Hopfield neural network technique considers more constraints but it may suffer from numerical convergence due to its training process. The Simulated Annealing (SA) and Tabu Search (TS) are powerful, general-purpose stochastic optimization technique, which can theoretically converge asymptotically to a global optimum solution with probability one. But it takes much time to reach the near-global minimum. Particle swarm optimization (PSO) has simple concept, easy implementation, relative robustness to control parameters and computational efficiency[55], although it has numerous advantages, it get trapped in a local minimum, when handling heavily constrained problems due to the limited local/global searching capabilities [56, 57]. Differential Evolution (DE) algorithm has the ability to find the true global minimum regardless of the initial parameters values and requires few control parameters. It has parallel processing nature and fast convergence as compared to conventional optimization algorithm. Although, it does not always give an exact global optimum due to premature convergence and may require tremendously high computation time because of a large number of fitness evaluations. The Biogeography Based Optimization (BBO) is an efficient algorithm for Power System optimization, which does not take unnecessary computational time and is good for exploiting the solutions. The solutions obtained by BBO algorithm does not die at the end of each generation like the other optimization algorithm, but the convergence becomes slow for medium and large scale systems. Gravitational Search algorithm has the advantages to explore better optimized results, but due to the cumulative effect of the fitness function on mass, masses get heavier and heavier over the course of iteration. This causes masses to remain in close proximity and neutralise the gravitational forces of each other in later iterations, preventing them from rapidly exploiting the optimum [55]. Therefore, increasing effect of the cost function on mass, masses get greater over the course of iteration and search process and convergence becomes slow. To overcome the limitation of GSA, Seyedali Mirjalili [55] proposed an Adaptive gbest-Guided Gravitational Search algorithm (AgGGSA), in which the best mass is archived and utilised to accelerate the exploitation phase, enriching the weakness of GSA. Grey wolf Optimizer (GWO) is a recently developed powerful evolutionary algorithm proposed by Seyedali Mirjalili [57] and has the ability to converge to a better quality near-optimal solution and possesses better convergence characteristics than other prevailing techniques reported in the recent literatures. Also, GWO has a good balance between exploration and exploitation that result in high local optima avoidance, but the computation of GWO algorithm becomes slow, when applied to economic dispatch problem of medium and large scale power system. To overcome the drawbacks of GWO algorithm, recently developed intelligence Dragonfly Algorithm (DA), developed by Seyedali Mirjalili [59], is tested for the solution of non-convex and dynamic economic load dispatch problem of electric power system.

II. ECONOMIC LOAD DISPATCH PROBLEM FORMULATION

The scheduling of electric utilities along with the distribution of the generation power which must be planned to meet the load demand for a specific time period represents the Unit Commitment Problem (UCP). Economic Load

Dispatch Problem (ELDP) refers the optimal generation schedule for the generation system to deliver the required load demand plus transmission loss with the optimal generation fuel cost. Noteworthy economical benefits can be achieved by searching a better solution to the Economic Load Dispatch Problem (ELDP). The economic dispatch problem is defined so as to optimize the total operational cost of an electric power system while meeting the total load demand plus transmission losses within utilities generating limits [56]. The overall objective of Economic Load Dispatch Problem (ELDP) of electric power system is to plan the devoted (Committed) electric utilities outputs so as to congregate the load demand at optimal operating cost while satisfying all generating utilities constraints and various operational constraints of the electric utilities. The economic load dispatch problem (ELDP) is a constrained optimization problem and it can be mathematically expressed as follows [56]:

$$\min[FC(P_n)] = \sum_{n=1}^{U} (\alpha_n P_n^2 + \beta_n P_n + \gamma_n) \quad \text{\$/Hour} \tag{1}$$

subject to:

(i) The energy balance equation:

$$\sum_{n=1}^{U} P_n = P_{Demand} + P_{Loss}. \tag{2}$$

(ii) The inequality constraints:

$$P_n^{\min} \le P_n \le P_n^{\max} \qquad (n = 1, 2, 3, \dots, U). \tag{3}$$

where, α_n, β_n and γ_n are cost coefficients.

P_{Demand} is Load Demand.

P_{Loss} is power transmission Loss.

U is the number of generating units.

P_n is real power generation and will act as decision variable.

The most simple and approximate method of expressing power transmission loss, P_{Loss} as a function of generator powers is through George's Formula using B-coefficients and mathematically can be expressed as [56]:

$$P_{Loss} = \sum_{n=1}^{U} \sum_{m=1}^{U} P_{g_n} B_{nm} P_{g_m} \quad \text{MW} \tag{4}$$

where, P_{g_n} and P_{g_m} are the real power generations at the n^{th} and m^{th} buses respectively.

B_{nm} is the loss coefficients which are constant under certain assumed conditions and U is the number of generating units.

The constrained Economic Load Dispatch Problem can be converted to unconstrained ELD Problem using Penalty of definite value, which can be mathematically expressed as:

$$\min[FC(P_n)] = \sum_{n=1}^{U} F_n(P_n) + 1000 * \left| \left(\sum_{n=1}^{U} P_n - P_{Demand} - \sum_{n=1}^{U} \sum_{m=1}^{U} B_{nm} P_n P_m \right) \right| \tag{5}$$

The equation (5) represent the unconstrained economic load dispatch problem including penalty factor of $\sum_{n=1}^{U}\sum_{m=1}^{U} B_{nm} P_n P_m$. The complete unconstrained economic load dispatch problem having (U-1) variables can be represented as:

$$\min[FC(P_n)] = \sum_{n=1}^{U} (\alpha_n P_n^2 + \beta_n P_n + \gamma_n) + 1000 * \left| abs\left(\sum_{n=1}^{U} P_n - P_{Demand} - \sum_{n=1}^{U} \sum_{m=1}^{U} B_{nm} P_n P_m \right) \right| \tag{6}$$

The complete unconstrained economic load dispatch problem with valve point effect having (U-1) variables can be represented as:

$$\min[FC(P_n)] = \sum_{n=1}^{U} \left(\alpha_n P_n^2 + \beta_n P_n + \gamma_n + \left| (\delta_n \times \sin(\varepsilon_n \times (P_n^{\min} - P_n)) \right| \right) + 1000 * abs\left(\sum_{n=1}^{U} P_n - P_{Demand} - \sum_{n=1}^{U} \sum_{m=1}^{U} B_{nm} P_n P_m \right) \tag{7}$$

III. DRAGONFLY ALGORITHM AND MATHEMATICAL FORMULATION

Dragonfly Algorithm (DA) is a novel intelligence optimization technique proposed by Seyedali Mirjalili [59], which simulates the behaviours of dragonflies stationary and energetic swarming in environment .Exploration and exploitation in dragonfly algorithm is obtained by imitating the social communication of dragonflies in navigating, searching for foods and avoiding enemy when swarming statistically or energetically. The exploration and exploitation in dragonfly algorithm is achieved by following steps:

- Separation: This refers to the static smash avoidance of the individuals from other individuals in the Neighbourhood.
- Alignment: which indicates velocity similar of individuals to that of other individuals in neighbourhood?
- Cohesion: which refers to the inclination of individuals towards the centre of the mass of the neighbourhood? The main function of any swarm is endurance, so all of the individuals should be attracted towards food sources and distracted outward enemies. Considers these two behaviours, there are five main factors in position updating of individuals in swarms. The behaviours of each is mathematically modelled as follows: The separation process in dragonfly algorithm can be updated as follows:

$$S_i = -\sum_{J=1}^{N} X - X_J \tag{8}$$

Where, N is the number of neighbouring individuals, X is the current individual position, X_J is the position J-th neighbouring individual.

Alignment process in dragonfly algorithm can be updated using following recursive relation:

$$A_i = \frac{\sum_{J=1}^{N} V_J}{N} \tag{9}$$

where, V_J shows the velocity of J-th neighbouring individual.

The cohesion in dragonfly algorithm is calculated as follows:

$$C_i = \frac{\sum_{J=1}^{N} X_J}{N} - X \qquad (10)$$

Where, X is current individual position, N is the number of neighbourhoods' and X_J is the position of J-th neighbouring individual.

Attraction towards a food source is calculated as follows:

$$F_i = X^+ - X \qquad (11)$$

Where, X is the current individual position and X^+ position shows the food source.

Interruption outwards an enemies is calculated as follows

$$E_i = X^- + X \qquad (12)$$

Where, X is the current individual position and X^- shows the position of the enemy.

For updating the position of imitation dragonflies in search space and imitate their activities, two vectors are considered: step (ΔX) and position (X). The step vector is similar to velocity vector of PSO algorithm shows the direction of the movement of the dragonflies and mathematically defined as follows:

$$\Delta X_{t+1} = (sS_i + aA_i + cC_i + fF_i + eE_i) + w\Delta X_t \qquad (13)$$

Where, s shows the separation weight, S_i indicates of the separation of i-th individual, a is the alignment weight, A_i is alignment of the i-th individual, c is indicates the cohesion weight, C_i is the cohesion of the i-th individual, f is the food factor, F_i is the i-th individual food source , e is indicate the enemy factor, E_i is the position of enemy of the i-th individual, w is indicate the inertia weight, and t is indicate the iteration counter.

After calculating the step vector, the position vectors are calculated as follows

$$X_{t+1} = X_t + \Delta X_{t+1} \qquad (14)$$

To improve the uncertainty, stochastic behaviour and exploration of the synthetic dragonflies, they are essential to fly around the search space using a unsystematic walk (Levy flight) when there is no neighbouring solutions obtain. In this condition, the position updating dragonflies is using the following equation:

$$X_{t+1} = X_t + Levy(d) \times X_t \qquad (15)$$

Where, t is indicating the current iteration, and d is indicating the dimension of the position vectors.

The Levy flight is calculated as follows:

$$Levy(x) = 0.001 \times \frac{r_1 \times \sigma}{|r_2|^{1/\beta}} \qquad (16)$$

Where, r_1 and r_2 are two random numbers in [0,1], b is a constant and σ is calculated as follows:

$$\sigma = \left(\frac{\Gamma(1+\beta) \times \sin(\prod \beta / 2)}{\Gamma(\frac{1+\beta}{2}) \times \beta \times 2^{(\frac{\beta-1}{2})}} \right) \qquad (17)$$

```
Initialize the dragonflies population (X_i) and step vectors (ΔX_i); (i ∈ 1,2,3,4,...,n)
While the end condition is not satisfied
        Calculate the objective values of all dragonflies
        Update the food source and enemy using eqn.(11) and (12)
        Update w, s, a, c, f and e
        Calculate S, A, C, F and E using eqns.(8) to (12)
        Update neighboring radius
    if a dragonfly has at least one neighboring dragonfly
        Update velocity vector using eqn.(13)
        Update position vector using eqn.(14)
          else
            Update position vector using eqn.(15)
    end if
            Check and correct the new positions based on the boundaries of variables
end while
```

Fig.1: PSEUDO code for Dragonfly algorithm

IV. TEST SYSTEMS, RESULTS AND DISCUSSION

In order to show the effectiveness of the dragonfly algorithm for economic load dispatch Problem, four benchmark test system of small scale power systems having standard IEEE bus systems have been taken into consideration. The performance of the proposed dragonfly algorithm is tested in MATLAB 2013a (8.1.0.604) software on Intel® core™ i-5-3470S CPU@ 2.90 GHz, 4.00 GB RAM system. The PSEUDO code for Dragonfly algorithm is mentioned in Fig.1

A. *Test System-I: 3-Generating Unit System considering transmission losses*

The first test system consists of 3-Generating units with a load demand of 150 MW [60]. Test data of 3-Generating Unit System are taken from [60], Loss Coefficients Matrices are used to calculate the corresponding Transmission losses. The algorithm is tested for 250 iterations and The corresponding results are compared with lambda iteration method [60] and Particle Swarm Optimization (PSO) [60] and Grey Wolf Optimizer (GWO)[59]. Table-I shows that optimal fuel cost for 3-unit generating model for 150MW load demand using GWO and DA algorithm is **1597.4815** Rs./hour, power loss using DA is **2.3420 MW** and Iteration time for DA algorithm is **4.322344 seconds,** which shows the superiority of DA algorithm over GWO and population based PSO algorithm. For 3-generating units system, DA completely converges in 58 iterations and takes Iteration time of **3.463332 seconds** while GWO algorithm takes 92 iterations for convergence and converges times of **4.761541 seconds.**

B. *Test System-II: 3-Generating Unit System without transmission losses*

The second test system also consisting of 3-Generating Unit System [58] is tested for two different load demands of 850 MW and 1050 MW including transmission losses. The corresponding results are compared with lambda iteration method [58], Genetic Algorithm (GA)[58], Particle Swarm Optimization(PSO)[58,60], Artificial Bee Colony(ABC)[58] and Grey Wolf Optimizer(GWO) [61]. Table-II shows the comparison of results with different methodologies and it is found that optimal value of fuel cost obtained by DA is much less that lambda iteration, GA, PSO, ABC and GWO. The convergence curve of test case-II is shown in Fig.2 (b)-(c).

C. Test System-III: 5-Generating unit system considering valve point effect

The third test system consists of 5-Generating Unit System [58] is tested for load demand of 730 MW. Valve point effect is taken into consideration, but transmission losses are neglected while calculating optimal fuel cost. The results obtained by ALO algorithm are compared with lambda iteration method [58], Genetic Algorithm (GA)[58], Particle Swarm Optimization(PSO)[58], APSO[58], Artificial Bee Colony(ABC)[58], Evolutionary Programming(EP)[58] and Grey Wolf Optimizer(GWO) [61]. Table-IV shows the comparison of results with different methodologies and it is found that optimal value of fuel cost obtained by DA is much less that lambda iteration, GA, PSO, APSO, ABC, EP and GWO. The convergence curve of test case-III is shown in Fig.3 (a).

D. Test System-IV: 6-Generating Unit System without valve point effect.

The fourth test case consists of 6-Generating unit System without valve point loading [60]. The results of 6-generating units systems are tested for load demands of 600 MW, 700 MW, 800 MW, 900 MW and 1000MW and are shown in Table-V and effectiveness of ALO for 6-generating unit system is compared with lambda iteration method [60], particle swarm optimization (PSO)[60] and Grey Wolf Optimizer(GWO)[61]. Corresponding analysis of results (Table-V) shows that DA algorithm yields better fuel cost and power loss as compared to Lambda-Iteration Method, Particle Swarm Optimization Algorithm and Grey Wolf Optimizer. Also, the convergence of proposed algorithm is much better than these algorithms. The convergence curve of test case-IV is shown in Fig.3 (b). Another test benchmark of 6-generating units is tested for load demand of 1263 MW and experimentally it is found that the results obtained by DA are much better than FA[65], BBO[66], ABC[66], SOH-PSO[67], NMPSO[68], PSO-LRS[70], NPSO-LRS[70], DE[65], GA[69] and SA[65].

E. Test System-V: 13-Generating unit system considering valve point effect

The fifth test system consists of 13-Generating Unit System [64] is tested for load demand of 2520 MW. Valve point effect is taken into consideration, but transmission losses are neglected while calculating optimal fuel cost. The results obtained by Dragonfly algorithm are compared with Simulated Annealing [64] and Genetic Algorithm (GA) [64]. Table-VI shows the comparison of results with GA, SA and it is found that optimal value of fuel cost obtained by DA is much less than Simulated Annealing (SA) and Genetic Algorithm (GA). The convergence curve of test case-IV is shown in Fig. 2(a).

F. Test System-VI: 20-Generating unit system considering valve point effect

The sixth test system consists of 20-Generating Unit System [71] is tested for load demand of 2500 MW considering transmission losses. The results obtained by Dragonfly algorithm are compared with ABC [72], ABCNN [71], BBO [73], LI [74], HM [75], QP [76] and GAMS [76]. Table-VIII shows the comparison of results with ABCNN, BBO, LI, HM, QP, GAMS and it is found that optimal value of fuel cost obtained by DA is much less than these well known heuristics algorithms.

Table-I: Economic Load Dispatch for 3-Generating Units System (Load Demand=150MW)

Method	Load Demand	P1 (MW)	P2(MW)	P3(MW)	Fuel Cost (Rs./h)	P_{loss} (MW)	No. of Iteration	Elapsed Time(Seconds)
Lambda Iteration [60]	150 MW	33.4401	64.0974	55.1011	1599.9	2.66	250	NA
PSO [60]	150 MW	33.0858	64.4545	54.8325	1598.79	2.37	250	NA
GWO	150 MW	30.4998	64.6208	54.8994	1597.4815	2.3444	250	4.761541
DA[Proposed Method]	150 MW	32.8101	64.595	54.9369	1597.4815	2.3420	250	4.322344

Table-II: Economic Load Dispatch for 3-Generating Units System (Load Demand=850MW)

Method	Load Demand	Generation Scheduling			Fuel Cost (Rs./h)	Best Cost	Average Cost	Worst Cost	Iteration Time(sec.)
		U1	U2	U3					
Lambda Iteration	850 MW	382.258	127.419	340.323	8575.68	---	---	---	---
GA	850 MW	382.2552	127.4184	340.3202	8575.64	---	---	---	---
PSO	850 MW	394.5243	200	255.4756	8280.81	---	---	---	---
ABC	850 MW	300.266	149.733	400	8253.1	---	---	---	---
DA[Proposed Method]	850MW	300.266	149.733	400	8253.1052	8253.1052	8253.1052	8253.1052	9.3128

Table-III: Economic Load Dispatch for 3-Generating Units System (Load Demand=1050MW)

Method	Load Demand	Generation Scheduling			Cost(Rs./Hour)	Best Cost	Average Cost	Worst Cost	Iteration Time(sec.)
		U1	U2	U3					
Lambda Iteration	1050 MW	487.5	162.5	400	10212.459	---	---	---	---
GA	1050 MW	487.498	162.499	400	10212.44	---	---	---	---
PSO	1050 MW	492.699	157.3	400	10123.73	---	---	---	---
ABC	1050 MW	492.6991	157.301	400	10123.73	---	---	---	---
DA[Proposed Method]	1050MW	492.69	157.3	400	10123.7347				9.3281

Table-IV: Economic Load Dispatch for 5-Generating Units (Load Demand=730 MW)										
Method	Load Demand	Units Generation Scheduling					Cost(Rs./Hour)	Best	Average	Worst
		U1	U2	U3	U4	U5				
Lambda Iteration	730 MW	218.028	109.014	147.535	28.38	272.042	2412.709	---	---	---
GA	730 MW	218.0184	109.0092	147.5229	28.37844	227.0275	2412.538	---	---	---
PSO	730 MW	229.5195	125	175	75	125.4804	2252.572	---	---	---
APSO	730 MW	225.3845	113.02	109.4146	73.11176	209.0692	2140.97	---	---	---
EP	730 MW	229.803	101.5736	113.7999	75	209.8235	2030.673	---	---	---
ABC	730 MW	229.5247	102.0669	113.4005	75	210.0079	2030.259	---	---	---
DA[Proposed Method]	730MW	229.5196	102.91	112.72	75	209.83	2029.823	2029.823	2076.946	2124.07

Table-V: Economic Load Dispatch for 6-Generating Units										
Comparison of Results for 6-Generating Units System										
Load Demand	Methods	P1(MW)	P2(MW)	P3(MW)	P4(MW)	P5(MW)	P6(MW)	Fuel Cost(Rs./h)	P_{loss}	Iteration Time(Sec.)
600 MW	Lambda Iteration	23.7909	10.22	95.25	10.12309	202.967	181.34	32132.29	14.7988	---
	PSO	23.8602	10	95.6394	100.7081	202.8315	181.1978	32094.72	14.2373	---
	DA	23.8705	10	95.6365	100.7078	202.8302	181.1922	32094.6783	4.23721	11.818428
700 MW	Lambda Iteration	28.29	10.0901	118.9873	118	230.2372	213.9068	36912.32	19.5114	---
	PSO	28.29	10	118.9583	118.6747	230.763	212.7449	36912.22	19.43	---
	DA	28.2991	10	119.0333	118.6142	230.7032	212.7813	36912.1448	19.431	11.863085
800 MW	Lambda Iteration	32.9521	14.7126	141.5988	136.0345	258.1009	243.8011	41897.25	27.5	---
	PSO	32.586	14.4839	141.5475	136.0435	257.6624	243.0073	41896.7	25.33	---
	DA	32.6006	14.4782	141.5441	136.0404	257.6578	243.0098	41896.6286	25.3309	11.937735
900 MW	Lambda Iteration	36.9889	22.1821	163.01	153.2168	284.1482	273.0581	47045.32	32.6131	NA
	PSO	36.848	21.0774	163.9304	153.263	284.1696	272.7301	47045.25	31.98	NA
	DA	36.8638	21.0785	163.9289	153.2192	284.243	272.6538	47045.1565	31.9873	11.89715
1000 MW	Lambda Iteration	40.3969	28.1002	187	171.2136	310.721	303.1006	52362.07	40.5323	NA
	PSO	41.1657	27.7786	186.5604	170.5795	310.8297	302.568	52361.65	39.4821	NA
	DA	41.1849	27.8074	186.061	170.7025	311.2873	302.4481	52361.1604	39.4912	11.81442

Table-VII: Economic Load Dispatch for 6-Generating Units (Load Demand=1263 MW)													
Unit Power Output	DA	FA[65]	BBO[66]	AB[65]C	SOH-PSO[67]	New MPSO[68]	PSO[69]	PSO-LRS[70]	NPSO[70]	NPSO-LRS[70]	DE[65]	GA[69]	SA[65]
P1(MW)	500	445.08	447.3997	438.65	438.21	446.71	447.5	447.444	447.4734	446.96	400	474.81	447.08
P2(MW)	154.1458	173.08	173.2392	167.9	172.58	173.01	173.32	173.343	173.1012	173.3944	186.55	178.64	173.18
P3(MW)	236.4782	264.42	263.3163	262.82	257.42	265	263.47	263.3646	262.6804	262.3436	289	262.21	263.92
P4(MW)	135.1084	139.59	138.0006	136.77	141.09	139	139.06	139.1279	139.4156	139.512	150	134.28	139.06
P5(MW)	151.2559	166.02	165.4104	171.76	179.37	165.23	165.48	165.5076	165.3002	164.7089	200	151.9	165.58
P6(MW)	98.4635	87.21	87.07979	97.67	86.88	86.78	87.13	87.1698	87.9761	89.0162	50	74.81	86.63
Total Power Output	1275.5419	1275.4	1275.446	1275.57	1275.55	1275.7	1276.1	1275.95	1275.95	1275.94	1275.55	1276.03	1275.47
Total Transmission loss(MW)	12.4519	12.4	12.446	12.57	12.55	12.958	12.9571	12.9471	12.947	12.9361	12.55	13.022	12.47
Total Generation Cost($/Hour)	15406.5198	15443	15443.0963	15445.4	15446.02	15447	15450	15450	15450	15450	15452	15459	15466
Iteration Time	11.9101	11.52	0.0325	2.82	0.0633	0.0379	0.06	NA	NA	NA	6.2	0.22	62.02

Table-VIII: Economic Load Dispatch for 20-Generating Units (Load Demand=2500 MW)

Unit	DA	ABCNN[71]	ABC[72]	BBO[73]	LI[74]	HM[75]	QP[76]	GAMS[76]
P1	600	599.9972	599.882	513.0892	512.7805	512.7804	600	512.782
P2	133.7124	172.4309	172.866	173.3533	169.1033	169.1035	200	169.102
P3	50	50	106.993	126.9231	126.8898	126.8897	50	126.891
P4	50	50	63.1275	103.3292	1028657	102.8656	56.92	102.891
P5	92.724	115.8288	70.9701	113.7174	113.6836	113.6836	94.28	113.683
P6	31.986	39.5509	52.1022	73.06694	73.571	73.5709	33.72	73.572
P7	125	120.0216	119.142	114.9843	115.2878	115.2876	125	115.29
P8	50	71.7034	50	116.4238	116.3994	116.3994	60.24	116.4
P9	106.8898	129.4382	76.3559	100.6948	100.4062	100.4063	103.28	100.405
P10	49.941	30	102.403	99.99979	106.0267	106.0267	79.49	106.027
P11	263.5682	2304784	263.905	148.977	150.2395	150.2395	221.14	150.239
P12	407.4554	469.0286	362.23	294.0207	292.7648	292.7647	347.05	292.766
P13	160	104.1452	123.52	1195754	119.1154	119.1155	127.38	119.114
P14	72.7019	80.0902	47.7657	30.54786	30.834	30.8342	60.29	30.832
P15	90.3428	59.3637	56.4597	116.4546	115.8057	115.8056	116.7	115.805
P16	35.0882	34.0204	34.0936	36.22787	36.2545	36.2545	36.25	36.254
P17	33.1827	41.623	31.4734	66.87943	66.859	66.859	30	66.859
P18	46.9723	30	30	88.54701	87.972	87.972	58.21	87.967
P19	83.53	55.3963	118.464	1,009,802	100.8033	100.8033	85.52	100.8033
P20	30	30	30	54.2725	54.305	54.305	30	54.305
Total Power Output	2513.0945	2513.1164	2511.8	2592.1011	2591.967	2591.967	2515.48	2591.976
Total Transmission loss(MW)	13.0945	13.1163	11.7527	92.1011	91.967	91.9669	15.48	91.967
Total Generation Cost($/Hour)	60427.444	60446.377	60540	62456.779	62456.639	62456.634	62456.63	62456.63

Table-VI: Economic Load Dispatch for 13-Generating Units (Load Demand=2520 MW)
ELD for 13-units test system using DA

Unit	Generated Power(MW)	Unit	Generated Power(MW)
1	1166.877271	8	60.03842743
2	303.8276937	9	109.8665501
3	299.7904073	10	40
4	60	11	40
5	109.8665501	12	55
6	60	13	55
7	159.7331001		

Comparison of Results

Method	Cost(Rs./Hour)
SA[64]	24970.91
GA[64]	24398.23
DA[Proposed Method]	24386.86

I. CONCLUSIONS

In this research paper, application of Dragonfly algorithm is presented for the solution of non-convex and dynamic economic load dispatch problem of electric power system. Performance of ALO algorithm is tested for small scale power plants. The effectiveness of proposed Dragonfly algorithm is tested with the standard IEEE bus system consisting of 3, 5 and 6 generating units model considering transmission losses (Power Loss) and valve point effect.

The results obtained show that Dragonfly algorithm have been successfully implemented to solve different ELD problems moreover, Dragonfly algorithm is able to provide very spirited results in terms of minimizing total fuel cost and lower transmission loss. Also, convergence of Dragonfly algorithm is very fast as compared to Lambda Iteration Method, Particle Swarm Optimization (PSO) algorithm, Genetic algorithm (GA), APSO, Artificial Bee Colony (ABC), and Grey Wolf Optimizer (GWO) for small scale power systems. Also, It has been observed that the Dragonfly algorithm has the ability to converge to a better quality near-optimal solution and possesses better convergence characteristics than other widespread techniques reported in the recent literatures. It is also clear from the results obtained by different trials show that the Dragonfly algorithm shows a good balance between exploration and exploitation that result in high local optima avoidance.

Thus, this algorithm may become very promising for solving some more complex power system optimizations problems such as: Economic Load Dispatch for quadratic and cubical cost function, Single and Multi-objective Economic Load Dispatch including valve point effect, Economic Load Dispatch incorporating wind Power , Economic Load Dispatch incorporating Solar Power, Hydro-Thermal and Wind-Thermal Scheduling of electric power system. Thermal Scheduling incorporating Smart Grids, Hydro-Thermal Scheduling incorporating Smart Grids, Single and Multi Objective Unit Commitment Problem formulation, Multi-Objective and Multi-Area Unit Commitment Problem

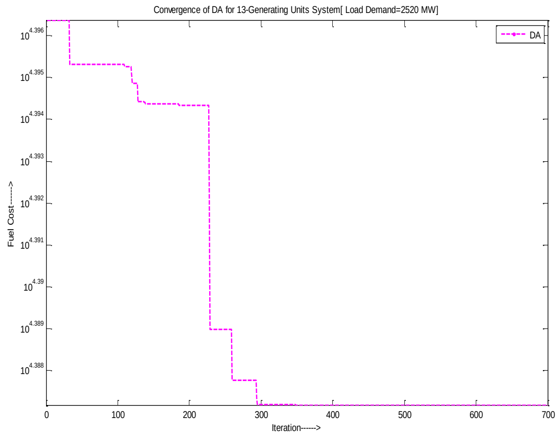

Fig.2(a): Convergence of DA for 13-Generaing unit System

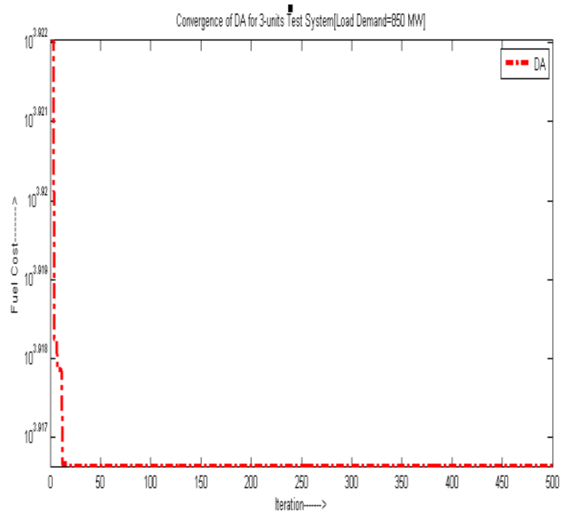

Fig.2(b): Convergence of DA Algorithm for 3-Generating Units test system [load demand = 850MW]

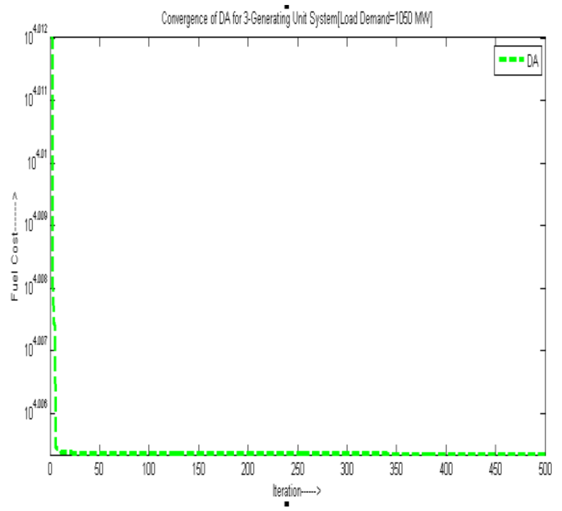

Fig.2(c): Convergence of DA Algorithm for 3-Generating Units test system [load demand = 1050MW]

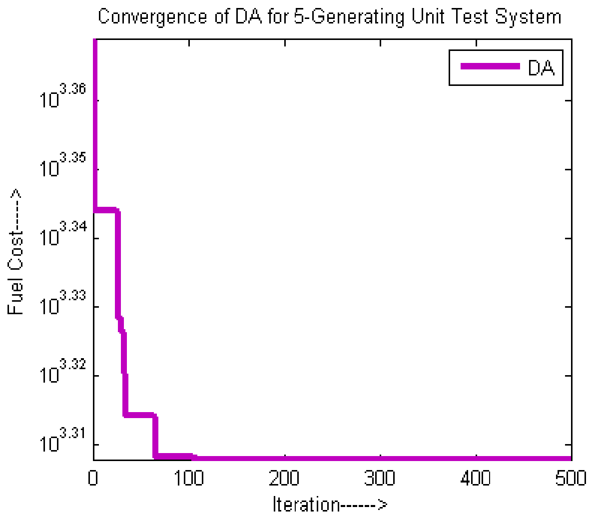

Fig.3(a): The convergence curve of test case-III

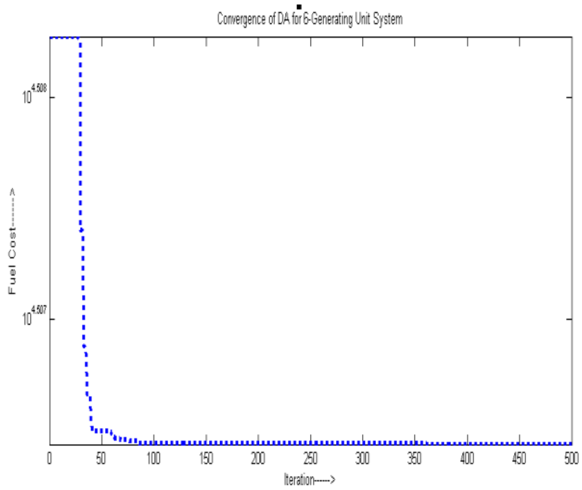

Fig.3(c): The convergence curve of test case-IV

REFERENCES

[1] E. Bonabeau, M. Dorigo, and G. Theraulaz, Swarm intelligence: from natural to artificial systems: OUP USA, 1999.
[2] M. Dorigo, M. Birattari, and T. Stutzle, "Ant colony optimization," Computational Intelligence Magazine, IEEE, vol.1, pp. 28-39, 2006.
[3] J. Kennedy and R. Eberhart, "Particle swarm optimization," in IEEE International Conference on Neural Networks Proceedings, pp. 1942-1948, 1995.
[4] S. Kirkpatrick, D. G. Jr., and M. P. Vecchi, "Optimization by simulated annealing," science, vol. 220, pp. 671-680, 1983.
[5] B. Webster and P. J. Bernhard, "A local search optimization algorithm based on natural principles of gravitation," in Proceedings of the 2003 International Conference on Information and Knowledge Engineering (IKE'03), Las Vegas, Nevada, USA, pp. 255-261, 2003.
[6] O. K. Erol and I. Eksin, "A new optimization method: big bang–big crunch," Advances in Engineering Software, vol. 37, pp. 106-111, 2006.
[7] E. Rashedi, H. Nezamabadi-Pour, and S. Saryazdi, "GSA: a gravitational search algorithm," Information sciences, vol. 179, pp. 2232-2248, 2009.
[8] F. F. Moghaddam, R. F. Moghaddam, and M. Cheriet, "Curved Space Optimization: A Random Search based on General Relativity Theory," arXiv preprint arXiv:1208.2214, 2012.
[9] A. Kaveh and S. Talatahari, "A novel heuristic optimization method: charged system search," Acta Mechanica, vol. 213, pp. 267-289, 2010.
[10] R. A. Formato, "Central force optimization: A new metaheuristic with applications in applied electromagnetics," Progress In Electromagnetics Research, vol. 77, pp. 425-491, 2007.
[11] B. Alatas, "ACROA: Artificial Chemical Reaction Optimization Algorithm for global optimization," Expert Systems with Applications, vol. 38, pp. 13170-13180, 2011.
[12] A. Hatamlou, "Black hole: A new heuristic optimization approach for data clustering," Information sciences, 2012.
[13] A. Kaveh and M. Khayatazad, "A new meta-heuristic method: Ray Optimization," Computers & Structures, vol. 112, pp. 283-294, 2012.
[14] H. Du, X. Wu, and J. Zhuang, "Small-world optimization algorithm for function optimization," in Advances in Natural Computation, ed: Springer, pp. 264-273, 2006.
[15] H. Shah-Hosseini, "Principal components analysis by the galaxy-based search algorithm: a novel metaheuristic for continuous optimisation," International Journal of Computational Science and Engineering, vol. 6, pp. 132-140, 2011.
[16] Xue-hui L., Ye Y. and Xia L., "Solving TSP with Shuffled Frog-Leaping Algorithm", IEEE Proc. 8th International Conference on Intelligent Systems Design and Applications(ISDA'08), Kaohsiung, vol. 3, pp. 228- 232, 26- 28 Nov. 2008.
[17] Fang H., Kim J. and Jang J., "A Fast Snake Algorithm for Tracking Multiple-Objects", Journal of Information Processing Systems, vol.7, no. 3, pp. 519- 530, Sep. 2011.
[18] Simon D., "Biogeography-Based Optimization", IEEE Transactions on Evolutionary Computation, vol. 12, no. 6, pp. 702- 713, Dec. 2008.

[19] H. A. Abbass, "MBO: Marriage in honey bees optimization-A haplometrosis polygynous swarming approach," in Proceedings of the 2001 Congress on Evolutionary Computation, pp. 207-214, 2001.
[20] X. Li, "A new intelligent optimization-artificial fish swarm algorithm," Doctor thesis, Zhejiang University of Zhejiang, China, 2003.
[21] M. Roth, "Termite: A swarm intelligent routing algorithm for mobile wireless ad-hoc networks," 2005.
[22] P. C. Pinto, T. A. Runkler, and J. M. Sousa, "Wasp swarm algorithm for dynamic MAX-SAT problems," in Adaptive and Natural Computing Algorithms, ed: Springer, pp. 350-357, 2007.
[23] A. Mucherino and O. Seref, "Monkey search: a novel metaheuristic search for global optimization," in AIP conference proceedings, pp. 162, 2007.
[24] X. Lu and Y. Zhou, "A novel global convergence algorithm: bee collecting pollen algorithm," in Advanced Intelligent Computing Theories and Applications. With Aspects of Artificial Intelligence, ed: Springer, pp. 518-525, 2008.
[25] X.-S. Yang and S. Deb, "Cuckoo search via Lévy flights," in World Congress on Nature & Biologically Inspired Computing, NaBIC 2009, pp. 210-214, 2009.
[26] Y. Shiqin, J. Jianjun, and Y. Guangxing, "A Dolphin Partner Optimization," in WRI Global Congress on Intelligent Systems, GCIS'09, pp. 124-128, 2009.
[27] X.-S. Yang, "Firefly algorithm, stochastic test functions and design optimisation," International Journal of Bio-Inspired Computation, vol. 2, pp. 78-84, 2010.
[28] A. H. Gandomi and A. H. Alavi, "Krill Herd: a new bio-inspired optimization algorithm," Communications in Nonlinear Science and Numerical Simulation, 2012.
[29] W.-T. Pan, "A new fruit fly optimization algorithm: taking the financial distress model as an example," Knowledge-Based Systems, vol. 26, pp. 69-74, 2012.
[30] Khokhar B., Parmar K.P.S. and Dahiya S., "Application of Biogeography-based Optimization for Economic Dispatch Problems", International Journal of Computer Applications (0975 – 888), vol. 47, no.13, pp. 25- 30, June 2012.
[31] Sinha, Nidul, R. Chakrabarti, and P. K. Chattopadhyay. "Evolutionary programming techniques for economic load dispatch." IEEE Transactions on Evolutionary Computation, vol. 7, no. 1, pp: 83-94, 2003.
[32] Gaing, Zwe-Lee. "Particle swarm optimization to solving the economic dispatch considering the generator constraints." IEEE Transactions on Power Systems, vol. 18, no. 3, pp: 1187-1195, 2003.
[33] Chiang, Chao-Lung. "Improved genetic algorithm for power economic dispatch of units with valve-point effects and multiple fuels." IEEE Transactions on Power Systems, vol. 20, no. 4, pp:1690-1699, 2005.
[34] Devi, A. Lakshmi, and O. Vamsi Krishna. "combined Economic and Emission dispatch using evolutionary algorithms-A case study." ARPN Journal of engineering and applied sciences 3, no. 6, pp:28-35, 2008.
[35] Kumar, K. Sathish, R. Rajaram, V. Tamilselvan, V. Shanmugasundaram, S. Naveen, and IG Mohamed Nowfal Hariharan T. Jayabarathi. "Economic dispatch with valve point effect using various PSO Techniques." Vol. 2, no. 6, pp:130-135, 2009.
[36] Singh, Lakhwinder, and J. S. Dhillon. "Cardinal priority ranking based decision making for economic-emission dispatch problem." International Journal of Engineering, Science and Technology 1, no. 1, pp:272-282, 2009.
[37] Duman, S., U. Güvenç, and N. Yörükeren. "Gravitational search algorithm for economic dispatch with valve-point effects." International Review of Electrical Engineering 5, no. 6, pp:2890-2895, 2010.
[38] Bhattacharya, Aniruddha, and Pranab Kumar Chattopadhyay. "Solving complex economic load dispatch problems using biogeography-based optimization." Expert Systems with Applications 37, no. 5, pp:3605-3615, 2010.
[39] Bhattacharya, Aniruddha, and P. K. Chattopadhyay. "Application of biogeography-based optimization for solving multi-objective economic emission load dispatch problems." Electric Power Components and Systems, vol. 38, no. 3, pp:340-365, 2010.
[40] Rayapudi, S. Rao. "An intelligent water drop algorithm for solving economic load dispatch problem." International Journal of Electrical and Electronics Engineering, vol. 5, no. 2, pp:43-49, 2011.
[41] Pandi, V. Ravikumar, and Bijaya Ketan Panigrahi. "Dynamic economic load dispatch using hybrid swarm intelligence based harmony search algorithm." Expert Systems with Applications, vol. 38, no. 7, pp:8509-8514, 2011.
[42] Swain, R. K., N. C. Sahu, and P. K. Hota. "Gravitational search algorithm for optimal economic dispatch." Procedia Technology 6, pp: 411-419, 2012.
[43] Yang, Xin-She, Seyyed Soheil Sadat Hosseini, and Amir Hossein Gandomi. "Firefly algorithm for solving non-convex economic dispatch problems with valve loading effect." Applied Soft Computing, vol. 12, no. 3 pp: 1180-1186, 2012.
[44] Rajasomashekar, S., and P. Aravindhababu. "Biogeography based optimization technique for best compromise solution of economic emission dispatch." Swarm and Evolutionary Computation, vol. 7, pp : 47-57, 2012.
[45] Güvenç, U., Y. Sönmez, S. Duman, and N. Yörükeren. "Combined economic and emission dispatch solution using gravitational search algorithm." Scientia Iranica, vol. 19, no. 6, pp: 1754-1762, 2012.
[46] Adriane, B. S. "Cuckoo Search for Solving Economic Dispatch Load Problem." Intelligent Control and Automation, vol. 4, pp: 385-390, 2013.
[47] Wang, Ling, and Ling-po Li. "An effective differential harmony search algorithm for the solving non-convex economic load dispatch problems." International Journal of Electrical Power & Energy Systems, vol. 44, no. 1, pp: 832-843, 2013.
[48] Dubey, Hari Mohan, Manjaree Pandit, B. K. Panigrahi, and Mugdha Udgir. "Economic Load Dispatch by Hybrid Swarm Intelligence Based Gravitational Search Algorithm." International Journal Of Intelligent Systems And Applications (Ijisa), vol. 5, no. 8, pp: 21-32, 2013.
[49] Ravi, C. N., and Dr C. Christober Asir Rajan. "Differential Evolution technique to solve Combined Economic Emission Dispatch." In 3rd International Conference on Electronics, Biomedical Engineering and its Applications (ICEBEA'2013), pp. 26-27, January 2013.
[50] Gopalakrishnan, R., and A. Krishnan. "An efficient technique to solve combined economic and emission dispatch problem using modified Ant colony optimization." Sadhana, vol. 38, no. 4, pp: 545-556, 2013.
[51] SECUI, Dinu Călin, Gabriel Bendea, and Cristina HORA. "A Modified Harmony Search Algorithm for the Economic Dispatch Problem." Studies in Informatics and Control, vol. 23, no. 2, pp: 143-152, 2014.
[52] Kherfane, R. L., M. Younes, N. Kherfane, and F. Khodja. "Solving Economic Dispatch Problem Using Hybrid GA-MGA." Energy Procedia, vol. 50, pp: 937-944, 2014.
[53] Aydin, Dogan, Serdar Ozyon, Celal Yaşar, and Tianjun Liao. "Artificial bee colony algorithm with dynamic population size to combined economic and emission dispatch problem." International journal of electrical power & energy systems, vol. 54, pp: 144-153, 2014.
[54] Thao, Nguyen Thi Phuong, and Nguyen Trung Thang. "Environmental Economic Load Dispatch with Quadratic Fuel Cost Function Using Cuckoo Search Algorithm." International Journal of u-and e-Service, Science and Technology, vol. 7, no. 2, pp: 199-210, 2014.
[55] Seyedali Mirjalili, Andrew Lewis, Adaptive gbest-guided gravitational search algorithm, Neural Computing and Applications, vol. 25, issue 7-8, pp.1569-1584, December 2014.
[56] Dhillon, J. S. and Kothari, D. P., Power System Optimization (2nd edition), New Delhi, INDIA, Prentice Hall India, 2010.
[57] Seyedali Mirjalili, Seyed Mohammad Mirjalili, Andrew Lewis, "Grey Wolf Optimizer", Advances in Engineering Software, vol. 69, pp: 46–61, 2014.
[58] Bestha Mallikarjuna, K Harinath Reddy, O Hemakeshavulu, "Economic Load Dispatch with Valve-Point Result Employing a Binary Bat Formula", International Journal of Electrical and Computer Engineering (IJECE)(ISSN: 2088-8708), vol. 4, no. 1, pp. 101-107, Feburary 2014.
[59] Seyedali Mirjalili, "Dragonfly algorithm: a new meta-heuristic optimization technique for solving single-objective, discrete, and multi-objective problems", Neural Comput & Applic, DOI 10.1007/s00521-015-1920-1.
[60] A. J. Wood and B. F. Wollenberg, Power Generation, Operation and Control, 2nd ed. New York, NY, USA: Wiley, 1996.
[61] V.K. Kamboj, S.K. Bath, J.S. Dhillon, "Solution of Non-Convex Economic Load Dispatch Problem Using Grey Wolf Optimizer", Neural Computing and Applications, DOI: 10.1007/s00521-015-1934-8.
[62] Seyedali Mirjalili, Seyed Mohammad Mirjalili, Abdolreza Hatamlou, "Multi-Verse Optimizer: a nature-inspired algorithm for global optimization", Neural Computing and Applications, DOI:10.1007/s00521-015-1870-7, March 2015.

[63] Seyedali Mirjalili,Dragonfly algorithm: a new meta-heuristic optimization technique for solving single-objective, discrete, and multi-objective problems, Neural Computing and Applications, DOI: 10.1007/s00521-015-1920-1, 2015.

[64] T. A. A. Victorie, A. E. Jeyakumar, Hybrid PSO-SQP for economic dispatch with valve-point effect, Electric Power Systems Research, vol. 71, pp. 51-59, 2004.

[65] R.Subramanian, K.Thanushkodi ,"An Efficient Firefly Algorithm to Solve Economic Dispatch Problems", International Journal of Soft Computing and Engineering (IJSCE) ISSN: 2231-2307, vol. 2, issue 1, March 2013.

[66] Aniruddha Bhattacharya, Member, IEEE, and Pranab Kumar Chattopadhyay," Biogeography-Based Optimization for Different Economic Load Dispatch Problems", IEEE Transactions On Power Systems, vol. 25, no. 2, May 2010.

[67] K. T. Chaturvedi, M. Pandit, and L. Srivastava, "Self-organizing hierarchical particle swarm optimization for nonconvex economic dispatch," IEEE Transactions on Power Systems, vol. 23, no. 3, p. 1079, Aug. 2008.

[68] C.-C. Kuo, "A novel coding scheme for practical economic dispatch by modified particle swarm approach," IEEE Transactions on Power Systems, vol. 23, no. 4, p. 1825, Nov. 2008.

[69] Z.-L. Gaing, "Particle swarm optimization to solving the economic dispatch considering the generator constraints," IEEE Trans. Power Syst., vol. 18, no. 3, pp. 1187–1195, Aug. 2003.

[70] I. Selvakumar and K. Thanushkodi, "A new particle swarm optimization solution to nonconvex economic dispatch problems," IEEE Trans. Power Syst., vol. 22, no. 1, pp. 42–51, Feb. 2007.

[71] D.Karaboga,C.Qzturk,Neural Networks Training by Artificial Bee Colony Algorithm on Pattern Classification, Neural Network World, vol. 19, no. 3, pp: 279-292, 2009.

[72] D.Karaboga,B.Akay, A Comparative Study of Artificial Bee Colony Algorithm, Applied Mathematics and Computational, 214, pp: 108-132, 2009.

[73] Bhattacharya, P.K. Chattopadhyay, "Biogeography-based optimization for different economic load dispatch problems," IEEE Trans. on Power Systems, vol. 25, pp. 1064- 1077, May 2010.

[74] Su,C.T.& Lin,C.T., "New approach with a Hoplfield modelling framework to economic dispatch", IEEE Transactions on Power System, vol. 15, no. 2, pp:5 41-545, 2000.

[75] Ching-Tozong Su and Chien _Tung Lin, New Approach with a Hopefield Modelling Framework to Economic Dispatch, IEEE Transactions on Power Systems, vol. 15, no. 2, pp. 541-545, 2000

[76] Bisen, Devender, et al. "Solution of Large Scale Economic Load Dispatch Problem Using Quadratic Programming and GAMS; A Comparative Analysis. ,"Journal of Information and Computing Science vol. 7.3, pp:200-211, 2012.