DEGL BASED OPTIMIZATION FOR PRACTICAL CONSTRAINED

ECONOMIC POWER DISPATCH PROBLEM

B.PADMANABHAN [1]   **SIVAKUMAR R.S** [2]

[1] M.E (Power Sys Engg), Sardar Raja College of Engineering, Alangulam, Tirunelveli Dist.
[2] M.E (Power Sys Engg), Anna University of Technology, Coimbatore.
padmanabhan_balu@yahoo.co.in [1]; sivakrs.88@gmail.com [2]

J.JASPER [3]
Associate Professor, Ponjesly College of Engineering, Nagercoil.
mailtojasper@gmail.com

Abstract - *In this paper a Differential Evolution with Global and Local Neighborhood (DEGL) was applied to Non – convex Economic Load Dispatch. Many nonlinear characteristics of the generator such as ramp rate limits, prohibited operating zone, and non-smooth cost functions are considered using the above presented method in practical generator operation. The feasibility of the method is demonstrated for three different systems, and it is compared with other DE variants in terms of the solution quality and computation efficiency. The experimental results show that the above method was indeed capable of obtaining higher quality solutions efficiently in ED problems.*

Index Terms— *Economic dispatch problem, Differential Evolution with Global and Local Neighborhood, Prohibited operating zones, valve-point loading effect.*

I. INTRODUCTION

SCARCITY of energy resources, increasing power generation cost and ever-growing demand for electric energy necessitates optimal economic dispatch in today's power systems. Economic Load Dispatch (ELD) is an important optimization task in power system operation. The main objective of Economic Load Dispatch is the allocation of power generation to different generating units so as to minimize the operating cost while satisfying various physical constraints. This makes the ELD problem a large-scale non-Linear constrained optimization problem. Typically, the cost function of each generator has been approximately represented by a single quadratic function where the valve-point effects and multiple fuels are usually ignored. This would be often introducing inaccuracy into the dispatch result.

Because of physical limitations of the power generators, a generating unit may have prohibited operating zones between the minimum and maximum power outputs. Generators that operate in these zones may experience amplification of vibrations in their shaft bearings, which should be avoided in practical application. On the other hand, due to the fact that unit generation output cannot be changed instantaneously, the unit in the actual operating processes is restricted by its ramp rate limit [3, 5]. Moreover, the units of real input–output characteristics include higher order non-linearities and discontinuities owing to the valve point effect, which has been modeled as a circulating commutated sinusoidal function in [6, 7]. The ED problem with the above considerations is usually a non-smooth/non-convex optimization problem [3, 4]. Conventional techniques offer good results but when the search space is non-linear and it has discontinuities they become very complicated with a slow convergence ratio and not always seeking to the optimal solution. The increase of the accuracy of the cost function usually results in higher nonlinear, non-smooth and non- convex function where the classical or gradient based methods cannot be applied [1].Therefore, the cost curve of a generator should not be too much simplified for practical power system operation. This kind of optimization problem is very hard, if not impossible, to solve using traditionally deterministic optimization algorithms.

Many mathematical assumptions-such as convex, quadratic, and differentiable objective and linear or linearized objective and constraints were required to simplify the problem. Hence the true global optimum of the problem could not be reached easily. New numerical methods are needed to cope with these difficulties, especially those with high-speed search to the optimal and not being trapped in local minima. An important goal in the economic dispatch area is the utilization of improved models for the generator production cost

curves, with the ability of capturing a better cost-power output relationship. As a result, cost functions that consider valve point loading effects [8]-[11], fuel switching [28], [29], [13], and prohibited operating zones [14]-[17] have been proposed. These improved models generally increase the level of complexity of the resulting optimization problem.

The economic dispatch problem has been solved via many traditional optimization methods, including: Gradient-based techniques, Newton method, Linear programming, and Quadratic programming. The Lagrangian multiplier method [1], which is generally used in the ED problem, is no longer directly applicable. Such classical optimization methods are highly sensitive to starting points and often converge to local optimum or diverge all together. Newton based algorithms have difficulty with handling a large number of inequality constraints [29]. Other methods like Lambda Iteration Method (LIM), Gradient Search (GS), Linear, Quadratic and Dynamic Programming (LP, QP, DP), and Newton Methods (NM), gained a lot of popularity in the last four decades.

Lin et al. [20] presented integrated evolutionary programming, Tabu search (TS) and quadratic programming (QP) methods to solve non-convex ED problems. This integrated artificial intelligence method also requires two-phase computations. Lin et al. developed an improved TS algorithm for ED with non-continuous and non-smooth cost functions, but the prohibited zones and system spinning reserve are relaxed in this work. Methods based on artificial intelligence techniques, such as artificial neural networks, have also been applied successfully and are reported for example in [17]. Similarly, EP has also successfully to solve for ED problems. However, its long execution time is its main disadvantage.

Differential Evolution developed by Storn and Price is one of the excellent evolutionary algorithms. Differential Evolution (DE) is one of the most recent population-based techniques. The DE algorithm has been applied to various fields of power system optimization. DE is an extremely powerful yet simple evolutionary algorithm that improves a population of individuals over several generations through the operators of mutation, crossover and selection. Differential evolution presents great convergence characteristics and requires few control parameters [21], [30], [31], which remain fixed throughout the optimization process and need minimum tuning.

The purpose of this paper is to present a solution methodology for the economic power dispatch problem using the Differential Evolution with Global and Local Neighborhood when non-convex, non-continuous and highly non-linear cost functions are used. This is the case when valve point loading effects, and prohibited operating zones are considered.

II. PROBLEM FORMULATION

The ELD problem is about minimizing the fuel cost of generating units for a specific period of operation so as to accomplish optimal generation dispatch among operating units and in return satisfying the system load demand, generator operation constraints with ramp rate limits and prohibited operating zones.

The objective of the classical economic dispatch is to minimize the total system cost by adjusting the power output of each of the generators connected to the grid. The total system cost is modeled as the sum of the cost function of each generator, which also intakes the generating limits. That is to operate each generator within the minimum and maximum values. The objective of ED is to determine the generation levels for all on-line units which minimize the total fuel cost, while satisfying a set of constraints

A. ECONOMIC DISPATCH (ED) PROBLEM FORMULATION

The fuel cost functions of the generating units are usually described by a quadratic function of power output. Thus the objective function is given as[23],

$$F_i(P_{gi}) = a_i P_i{}^2 + b_i P_i + c_i \quad \text{\$/hr} \qquad (1)$$

Where
  a_i, b_i, c_i - the fuel cost coefficients of the ith unit
  N- Number of generating units in the system
  $F_i(P_{gi})$ - total fuel cost

[1] Power balance constraint

$$\sum_{i=1}^{N} P_{gi} = P_D + P_{loss} \quad \text{MW} \qquad (2)$$

Where,
  P_D – Total power demand
  P_L – Total network losses

[2] Capacity limits constraints
  The generation outputs P_{gi} are restricted to be within the lower and upper operating limits $P_{g, min}$ and $P_{g, max}$

$$P_i^{\min} \leq P_i \leq P_i^{\max} \text{ For i= 1.....N} \qquad (3)$$

Where,

$P_i^{\min}$ – minimum generation limit

$P_i^{\max}$ – maximum generation limit

B. VALVE POINT EFFECT

Large steam turbine generators will have a number of steam admission valves that are opened in sequence to obtain ever–increasing output of the unit. As the unit loading increases the input to the unit increases and the incremental heat rate decreases between the opening points for any two valves.

This "valve point" effect which leads to non-smooth, non-convex input-output characteristics, to be solved using the heuristic techniques. The valve point effect is incorporated in ED problem by superimposing the sine component model on the quadratic cost curve which is given below [3],

$$F_i * (P_i) = F_i(P_i) + e_i \sin(f_i[P_i^{\min} - P_i]) \text{ \$/hr} \qquad (4)$$

Where

$F_i*(P_i)$–fuel cost if i^{th} unit with valve point effect

e_i, f_i – the fuel cost coefficients of the ith unit with valve point effect

C. RAMP RATE LIMITS

One of unpractical assumption that prevailed for simplifying the problem in many of the earlier research is that the adjustments of the power output are instantaneous. However, under practical circumstances ramp rate limit restricts the operating range of all the online units for adjusting the generator operation between two operating periods. The generation may increase or decrease with corresponding upper and downward ramp rate limits. The Ramp-Up and Ramp-Down rate limits of ith generator are given by,

As generation increases,

$$P_i - P_{i0} <= UR_i \qquad (5)$$

As generation decreases,

$$P_i - P_{i0} <= DR_i \qquad (6)$$

Otherwise we can written as,

$$\max(P_i^{\min}, P_{i0} - DR_i) <= P_i <= \min(P_i^{\max}, P_{i0} + UR_i) \quad (7)$$

Where,

P_i is the current output power

P_{i0} is the output power in the previous interval of the ith generator unit

UR_i is the up-ramp rate limit of the ith generator and

DR_i is the down-ramp rate limit of the ith generator

D. PROHIBITED OPERATING ZONES

The generating units may have certain ranges where operation is restricted on the grounds of physical limitations of machine components or instability e.g. due to steam valve or vibration in shaft bearings. Consequently, discontinuities are produced in cost curves corresponding to the prohibited operating zones. For unit with POZs, the feasible operating zones can be described as follows:

$$\begin{cases} P_i^{miin} \leq P_i \leq P_{i,1}^{LB} \\ P_{i,j-1}^{UB} \leq P_i \leq P_{i,j}^{LB} \, ... j = 2,3,........., NP_i \\ P_{i,j}^{UB} \leq P_i \leq P_i^{\max} \, ... j = NP_i \end{cases} \qquad (8)$$

III. DIFFERENTIAL EVOLUTION

The differential Evolution algorithm (DE) is a population based algorithm like genetic algorithm using the similar operators; crossover, mutation and selection. The main difference in constructing better solutions is that genetic algorithms rely on crossover while DE relies on mutation operators. This main operation is based on the differences of randomly sampled pairs of solutions in the population.

The algorithm uses mutation operation as a search mechanism and selection operation to direct the search toward the prospective regions in the search space. The DE algorithm also uses a non uniform crossover that can take child vector parameters from one parent more often than it does from other [23, 27]. By using the components of the existing population members to construct trial vectors, the recombination (crossover) operator efficiently shuffles information about successful combinations, enabling the search for a better solution space.

The highlights of Differential Evolution (DE) are,

- No derivatives are used
- Very few parameters to set
- A simple and apparently very reliable method. DE is reported [22]-[32] to be the only algorithm, which consistently found the optimal solution, and often with fewer function evaluations than the other direct search methods on benchmark nonlinear functions
- Simple vector subtraction to generate 'random' direction
- More variation in population (because solution has not converged yet) leads to more varied search over solution space
- Size and direction

The main steps of the DE algorithm are given below,

A. INITIALIZATION

Initialization generates initial population $\mathbf{P}_0$ which contains N_p individuals $\mathbf{x}^{0,}i$, $1 \le i \le N_p$.

$$X_j^{o,i} = b_j^L + \alpha_j^i(b_j^U - b_j^L) \quad 1 \le j \le N \quad (9)$$

Where, $[b_j^U, b_j^L]$ is the search space of the jth optimization parameter; α_j^i is a real random number but not necessarily uniform in the range [0, 1]

B. MUTATION

The mutation operator creates mutant vectors by perturbing a randomly selected vector x_a with the difference of two other randomly selected vectors x_b and x_c,

$$X_i^{(G)} = X_a^{(G)} + F.(X_b^{(G)} - X_c^G), \; i = 1,.....N_p \quad (10)$$

Where x_a, x_b and x_c are randomly chosen vectors among the N_P population, and $a \ne b \ne c$. x_a, x_b and x_c are selected a new for each parent vector. The scaling constant "F" is an algorithm control parameter used to adjust the perturbation size in the mutation operator and improve algorithm convergence.

C. CROSSOVER

The crossover operation generates trial vectors $x_i^{,,}$ by mixing the parameters of the mutant vectors $x_i^{,}$ with the target vectors x_i according to a selected probability distribution,

$$X_{j,i}^{"(G)} = \begin{cases} X_{j,i}^{'(G)} \;, \; if \; \rho_j \le C_R \; or \; j=q \\ X_{j,i}^{(G)} \;, \quad\quad otherwise \end{cases} \quad (11)$$

where i=1, …, N_P and j=1,…, D; q is a randomly chosen index $\in$ 1,…,N_P that guarantees that the trial vector gets at least one parameter from the mutant vector; ρ_j s a uniformly distributed random number within [0 , 1] generated anew for each value of j. The crossover constant C_R is an algorithm parameter that controls the diversity of the population and aids the algorithm to escape from local minima. $x_{j,i}^{'(G)}$ and $x_{j,i}^{"(G)}$ are the jth parameter of the ith target vector, mutant vector, and trial vector at generation G, respectively.

D. SELECTION

The selection operator forms the population by choosing between the trial vectors and their predecessors (target vectors) those individuals that present a better fitness are more optimal.

$$X_i^{(G+1)} = \begin{cases} X_i^{"(G)} \;, if \; f(X_i^{"(G)}) \le f(X_i^{(G)}) \\ X_i^{(G)} \;, \quad\quad otherwise \end{cases} \quad (12)$$

Where i=1.., N_P.

This optimization process is repeated for several generations, allowing individuals to improve their fitness as they explore the solution space in search of optimal values.

DE has three essential control parameters: the scaling factor (F), the crossover constant (C_R) and the population size (N_P). The scaling factor is a value in the range [0, 2] that controls the amount of perturbation in the mutation process. The crossover constant is a value in the range [0, 1] that controls the diversity of the population. The population size determines the number of individuals in the population and provides the algorithm enough diversity to search the solution space.

The most common method used to select control parameters is parameter tuning. Parameter tuning adjusts the control parameters through testing until the best settings are determined. Typically, the following ranges are good initial estimates: F = [0.5, 0.6], C_R = [0.75, 0.90], and N_P = [3*D, 8*D] in [38].

In order to avoid premature convergence, F or N_P should be increased, or C_R should be decreased. Larger values of F result in larger perturbations and better probabilities to escape from local optima, while lower C_R preserves more diversity in the population thus avoiding local optima.

E. DE STRATEGIES

Depending on the way the parent solutions are perturbed to generate a trial vector, there exist many trial vector generation strategies and consequently many DE variants.

- *DE/best/1*
- *DE/best/2*
- *DE/rand/1/bin*
- *DE/rand/2*
- *DEGL*

F.DEGL

Only in 2006, a new DE-variant, based on the neighborhood topology of the parameter vectors was developed to overcome some of the disadvantages of the classical DE versions. The authors in proposed a neighborhood-based local mutation operator that draws inspiration from PSO. For each member of the population a local mutation is created by employing the fittest vector in the neighborhood of that member and two other vectors chosen from the same neighborhood [26].

The model may be expressed as,

$$\vec{L}_i(t) = \vec{X}_i(t) + \lambda' \cdot (\vec{X}_{nbest}(t) - \vec{X}_i(t)) \\ + F' \cdot (\vec{X}_p(t) - \vec{X}_q(t)) \quad (13)$$

where the subscript nbest indicates the best vector in the neighborhood of $\vec{X}_i$ and p^{th}, q^{th} $(i - k, i + k)$.

A vector's neighborhood is the set of other parameter vector's that connected and it considers their experience when updating its position. The graph of interconnections is called the neighborhood structure. In the local model, whenever a parameter vector points to a good region of the search space, it only directly influences its immediate neighbors, its second degree neighbors will only be influence after those directly connected to them become highly successful themselves. Thus, there is a delay in the information spread through the population regarding the best position of each neighborhood. Therefore, the attraction to specific points is weaker, which prevents the population from getting trapped in local minima.

IV. SIMULATION RESULTS

This section presents the computation results of ED problem solved by Differential Evolution with Global and Local Neighborhood for 10, 13and 15 unit power systems. The non-smooth economic load dispatch (ELD) problem has been solved by variants of DE algorithm and is implemented by MATLAB program on Pentium IV, 3.00 GHz personal computer. In order to simulate the valve point effects of the generating units, a recurring sinusoid component is added with the objective function of fuel cost. However, many practical constraints of generators, such as ramp rate limits, prohibited operating zones, and power loss are also considered in the optimization process. The population size $N = 500$, the scaling factor $F = 0.9$ and the crossover factor $C = 0.9$ are considered for the study. These values were determined by parameter setting through trial and error method. Large number of population is used to allow the algorithm to search the solution space thoroughly but at the expense of computational time.

A. CASE STUDY I

This case study consisted of 10 thermal units of generation with the effects of valve-point loading, Ramp rate limits, Prohibited operating zones, equality and inequality constraints as in [2], [30]. In this case, the load demand expected to be determined was $P_D=2000MW$. The comparative results of DE are shown in the Table I.

Table I
CONVERGENCE RESULTS FOR 10
GENERATOR SYSTEMS
Load demand=2000MW

Unit MW	DE/best /1	DE/ best/2	DE/rand /1/bin	DE/ rand/2	DEGL
Unit 1	212.087	173.299	222.146	183.633	**195.193**
Unit 2	350.335	293.045	376.980	268.188	**286.109**
Unit 3	340	339.969	340	299.552	**340**
Unit 4	300	263.943	300	300	**300**
Unit5	243	243	243	243	**243**
Unit 6	160	160	160	160	**160**
Unit 7	130	130	130	130	**130**
Unit 8	120	120	120	120	**120**
Unit 9	80	80	80	80	**80**
Unit 10	142.503	274.902	106.151	293.549	**223.236**
P_{loss}	70.92	78.15	78.27	77.92	**77.53**
Fuel cost ($/hr)	126342. 398	126737. 619	128222. 622	127543.9 66	**124916.5 73**
Total power output	2077.92	2078.15	2078.27	2077.92	**2077.53**

B. CASE STUDY II

This case study consisted of 13 thermal units of generation with the effects of valve-point loading, Ramp rate limits, Prohibited operating zones, equality and inequality constraints as in [21]. In this case, the load demand expected to be determined was $P_D=1800MW$. The comparative results of DE are shown in the Table II.

Table II
CONVERGENCE RESULTS FOR 13
GENERATOR SYSTEMS
Load Demand=1800MW

Unit MW	DE/ best/1	DE/ best/2	DE/rand/ 1/bin	DE/ rand/2	DEGL
Unit 1	399.60	400.685	213.886	406.888	**226.501**
Unit 2	182.54	29.844	198.338	41.017	**337.490**
Unit 3	32.09	47.887	37.774	191.190	**192.635**
Unit 4	180	180	180	86.810	**83.926**
Unit 5	180	180	180	180	**180**
Unit 6	82.352	180	180	86.810	**82.593**
Unit 7	82.352	180	180	180	**180**
Unit 8	180	180	180	180	**180**
Unit 9	180	180	180	180	**83.170**
Unit 10	120	55.592	40	59.380	**57.139**
Unit 11	55.586	40	120	59.380	**55.173**
Unit 12	55	77.340	55	74.260	**71.030**
Unit 13	70.462	68.651	55	74.260	**70.336**
Fuelcost ($/hr)	16377. 271	16373.9 98	16652.9 74	16174.4 21	**16149.012**
Total power output	1800	1800	1800	1800	**1800**

C. CASE STUDY III

This case study consisted of 15 thermal units of generation with the effects of valve-point loading, Ramp rate limits, Prohibited operating zones, equality and inequality constraints as in [25]. In this case, the load demand expected to be determined was $P_D=2630MW$. The comparative results of DE with different strategies are shown in the Table III.

Table III
CONVERGENCE RESULTS FOR 15 GENERATOR SYSTEMS
Load Demand=2630MW

Unit MW	DE/ best/1	DE/ best/2	DE/rand/ 1/bin	DE/ rand/2	DEGL
Unit 1	399.304	455	431.846	455	**455**
Unit 2	455	455	455	455	**455**
Unit 3	130	130	130	130	**130**
Unit 4	130	130	130	130	**130**
Unit 5	198.054	236.935	260.659	235.371	**240.930**
Unit 6	460	460	460	460	**460**
Unit 7	465	465	465	465	**465**
Unit 8	60	60	60	60	**60**
Unit 9	25	25	25	25	**25**
Unit 10	25	25	25	28.742	**25**
Unit 11	80	80	80	77.764	**76.093**
Unit 12	75.636	80	80	80	**80**
Unit 13	85	25	25	25	**25**
Unit 14	15	15	15	15	**15**
Unit 15	15	15	15	15	**15**
Fuel cost ($/hr)	32913.4 56	32548.2 49	32665.3 76	32548.2 89	**32548.154**
Total Power Output	2630	2630	2630	2630	**2630**

From the table I, II and III it is proved that the fuel cost obtained by computation of DEGL method for economic dispatch problem with multiple constraints were lesser than the fuel cost obtained by other strategies of Differential Evolution.

V. CONCLUSION

This paper reported and compares the performance of different DE strategies to solve the ED problem with the generator constraints. The DE algorithm with Global and Local Neighborhood has been demonstrated to have superior features, including high-quality solution, stable convergence characteristic, and good computation efficiency. Many nonlinear characteristics of the generator such as ramp rate limits, valve-point effect, prohibited operating zones and non-smooth cost functions are considered for practical generator operation in this paper. The results show that the presented technique in DE was indeed capable of obtaining higher quality solution efficiently in ED problem.

VI. REFERENCES

(a) **Books:**

[1] A.J. Wood and B.F. Wollenberg, Power generation, Operation and Control. New York: Wiley, 1994.
[2] Chaturvedi, Soft Computing Techniques and its Applications in Electrical Engineering ISBN 978-3-540-77480-8 © 2008 Springer-Verlag Berlin Heidelberg

(b) **Periodicals:**

[3] B.Padmanabhan, Siva Kumar R.S, J.Jasper : 'Optimization of piecewise non-linear multi constrained Economic power dispatch problem using an Improved Genetic Algorithm', JEE Trans. Indus elect pow syst., 2010, 10, (3), pp. 106-112
[4] Lee, F.N., and Breipohl, A.M.: 'Reserve constrained economic dispatch with prohibited operating zones', IEEE Trans. Power Syst., 1993, 8, (1), pp. 246–254
[5] Chen, P.H., and Chang, H.C.: 'Large-scale economic dispatch by genetic algorithm', IEEE Trans. Power Syst., 1995, 10, (4), pp. 1919–1926
[6] T.Aruldoss Albert Victoire, A. Ebenezer Jeyakumar, " Reserve constrained Dynamic Dispatch of units with valve point effects", IEEE Trans. Power Syst., 2005, 20(3),pp. 1273-1282.
[7] D. C. Walters, G. B. Sheble, "Genetic Algorithm Solution Of Economic Dispatch With Valve Point Loading," IEEE Trans. Power Systems, Vol. 8, No. 3, pp. 1325-1332, August 1993.
[8] K. Wong, Y. Wong, "Genetic and genetic/simulated-annealing approaches to economic dispatch," IEEE Proceedings Gener, Trans and Distr, Vol. 141, No. 5, pp. 507-513, Sep 1994.
[9] H. Yang, P. Yang, C Huang, "Evolutionary Programming Based Economic Dispatch for Units with Non-Smooth Fuel Cost Functions," IEEE Trans. Power Systems, Vol. 11, No. 1, pp. 112-118, February 1996.
[10] J. Park; K. Lee; J. Shin; K. Lee, "A particle swarm optimization for economic dispatch with nonsmooth cost functions," IEEE Trans. On Power Systems, Vol. 20, No. 1, pp. 3442, Feb. 2005.
[11] C. E. Lin, G. L. Viviani, "Hierarchical Economic Dispatch for Piecewise Quadratic Cost Functions," IEEE Trans. Power Apparatus and Systems, Vol. PAS-103, No. 6, pp. I 1 70-1175, June 1984.
[12] W. Lin, F. Cheng, M. Tsay, "Nonconvex Economic Dispatch by Integrated Artificial Intelligence," IEEE Trans. on Power Systems, Vol. 16, No. 2, pp. 307-311, May 2001.
[13] K. Y. Lee, A. Sode Yone, J. Ho Park, "Adaptive Hopfield Neural Networks for Economic Load Dispatch," IEEE Trans. on Power Systems, Vol. 13, No. 2, pp. 519-526, May 1998.
[14] F. N. Lee, A. M. Breipohl, "Reserve Constrained Economic Dispatch With Prohibited Operating Zones,"

IEEE Trans. Power Systems, Vol. 8, No. 1, pp. 246-254, February 1993.

[15] J. Y. Fan, J. D. McDonald, "A Practical Approach to Real Time Economic Dispatch Considering Unit's Prohibited Operating Zones," IEEE Trans. Power Systems, Vol. 9, No. 4, pp. 1737-1743, November 1994.

[16] P. Chen, H. Chang, "Large-Scale Economic Dispatch by Genetic Algorithm," IEEE Trans. on Power Systems, Vol. 10, No. 4, pp. 1919-1926, November 1995.

[17] T. Jayabarathi. G. Sadasivam, V. Ramachandran, "Evolutionary Programming Based Economic Dispatch of Generators with Prohibited Operating Zones," Electric Power Systems Research, Vol. 52, No. 3, pp.261-266, December 1999.

[18] Chen CL, Chen N., "Direct search method for solving economic dispatch problem considering transmission capacity constraints". IEEE Trans Power Syst 2001;764–769.

[19] DosCoelho, Del de Almeida, Mariani V.C: 'Cultural Differential Evolution Approach to optimize the Economic dispatch of electrical energy using thermal generators', IEEE International Conference on EFTA 2008, pp 1378-1383.

[20] Lin, W.M., Cheng, F.S., and Tsay, M.T.: 'Nonconvex economic dispatch by integrated artificial intelligence', IEEE Trans. Power Syst., 2001, 16, (2), pp. 307–311

[21] Leandro dos Santos Coelho, Viviana Cocco Mariani, " Combining of Chaotic Differential Evolution and Quadratic Programming for Economic Dispatch Optimization with Valve-Point Effect," IEEE Trans. Power Syst., 2006, 21(2), 989-996.

[22] Storn, R., "System design by constraint adaptation and differential evolution," IEEE Trans. on Evolutionary Computation, Vol. 3, No. 1, 1999, pp. 22-34.

[23] F.Benhamida, Y.Ramdani, K.Madles : 'A Hopfield Neural Network solution to Economic Dispatch problem including Transmission Losses', JEE Trans. on Power electrical circuits., 2008, 8, (4), pp. 1-8

[24] Aniruddha Bhattacharya, Pranab Kumar Chattopadhyay, "A Modified Particle Swarm Optimization for solving the Non-convex Economic Dispatch", IEEE 2009.

[25] K.T. Chaturvedi, Manjareepandit, Laxmi Srivastava, "Self-Organizing Hierarchical Particle swarm optimization for non convex Economic Dispatch," IEEE Trans. Power Syst., 2008, 23(1), 1079-1087.

[26] Swagatam Das, Ajith Abraham, Uday K. Chakraborty & Amit Konar, "Differential Evolution using a Neighbourhood – based Mutaion operator" IEEE Trans. On Evolutionary Computation, Vol.13, No. 3, 2009, pp. 526-553.

(c) **Articles from published conference proceedings:**

[27] K. Wong, B. Lau, A. Fry, "Modelling Generator Input-Output Characteristcs with Valve-Point Loading Using Neural Networks," IEE 2nd International Conference on Advances in Power System Control Operation and Management, pp. 843-848, 7-10 Dec 1993.

[28] A. El-Gallad, M. El-Hawary, A. Sallam, A. Kalas, "Swarm Intelligence for Hybrid Cost Dispatch Problem," Canadian Conf. on Electrical and Computer Engineering, Vol. 2, pp. 753-757, 13-16 May 2001.

[29] J. Park, S. Yang, K. Mun, H. Lee, J. Jung, "An application of evolutionary computations to economic load dispatch with piecewise quadratic cost functions," The 1998 IEEE International Conference on Evolutionary Computation, Vol. 8, No. 3, pp. 289-294, 4-9 May 1998.

[30] K. Price, "Differential Evolution: A Fast and Simple NumericalOptimizer," Biennial Conference of the North American FuzzyInformation Processing Society. NAFIPS. 19-22 Jun 1996, pp. 524-527.

[31] R. Storn, "On the Usage of Differential Evolution for Function Optimization," Biennial Conference of the North American Fuzzy Information Processing Society. NAFIPS. 19-22 Jun 1996, pp. 519-523.

[32] R. Storn, and K. Price, "Minimizing the real functions of the ICEC'96 contest by differential evolution," Int. Conf. Evolutionary Computation, IEEE, 1996, pp.842-844.

B.Padmanabhan was born on June 26, 1989. He is doing his M.E. (Power Systems Engineering) degree in Sardar Raja College of Engineering, Tirunelveli Dist, TamilNadu, India.

His area of interest includes power system operation and control and Soft Computing Techniques.

Siva Kumar R.S was born on May 12, 1988. He is doing his M.E. (Power Systems Engineering) degree in Anna University of Technology, Coimbatore, TamilNadu, India.

His area of interest includes power system optimization and Artificial Intelligence.

J.Jasper was born on February 28, 1981. He is currently working toward the Ph.D. degree with the Faculty of Electrical Engineering, Anna University, Coimbatore, India.

He is presently an Associate Professor in the Department of Electrical Engineering, Ponjesly College of Engineering, Nagercoil, TamilNadu, India.

His major research interest includes power system operation, Distributed Generation, intelligent control and Electrical Machines.