OPTIMIZATION OF PIECEWISE NON-LINEAR MULTI CONSTRAINED ECONOMIC POWER DISPATCH PROBLEM USING AN IMPROVED GENETIC ALGORITHM

B. Padmanabhan, R. S. SivaKumar, J. Jasper

Ponjesly College of Engineering, Nagercoil, India
padmanabhan_balu@yahoo.co.in, shiross912@yahoo.com, mailtojasper@gmail.com

Abstract: *In this paper, a more realistic formulation of the Economic Dispatch problem is proposed, which considers practical constraints and non linear characteristics. The proposed ED formulation includes ramp rate limits, valve loading effects, equality and inequality constraints, which usually are found simultaneously in realistic power systems. This paper presents a novel Genetic Algorithm to solve the economic load dispatch (ELD) problem of thermal generators of a power system. This method provides an almost global optimal solution, since they don't get stuck at local optimum. The proposed method and its variants are validated for the two test systems consisting of 3 and 10 thermal units whose incremental fuel cost functions takes into account the valve-point loading effects.*

Keywords: *Economic load Dispatch, Genetic Algorithm, Valve-point loading, Ramp rate limits, Roulette selection*

1. INTRODUCTION

Economic Load Dispatch (ELD) seeks "the best" generation for the generating plants to supply the required demand plus transmission losses with the minimum production cost. Improvement in scheduling the units output can lead to significant cost savings. In traditional ELD problems, the cost function of each generator is approximately represented by a simple quadratic function and is solved using mathematical programming based on several optimization techniques such as dynamic programming, Linear programming, homogenous linear programming and quadratic programming methods[1],[2]-[4]. However none of these methods may be able to provide an optimal solution and they usually get stuck at a local optimum. Normally the input-output characteristic of modern generating units are highly non-linear in nature due to valve-point effect [19]-[22], ramp-rate limits, Fuel switching [14]-[15] etc, having multiple local minimum points in the cost function. To overcome such difficulties many heuristic search algorithms, such as Genetic algorithm [5], Differential Evolution [6], Tabu search [7, 8], etc., have been proposed to solve ELD problem. These techniques can be used to search the global optimum with any type of objective function and constraints. In this paper, two ED problem for 3 and 10 thermal units with a non smooth fuel cost function [9] are employed to demonstrate the performance of the proposed method. This paper employs genetic algorithm to solve the non convex and non smooth cost function.

The rest of this paper is organized as follows: Section II describes the formulation of an ED problem; while section III explains the standards in GA. Section IV then details the procedure of handling the GA. Section V gives the flow chart. Section VI gives the Data's and Section VII gives the results of the optimization. Section VIII outlines our conclusion and future research.

2. PROBLEM DESCRIPTION

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. It can be formulated as follows:

2.1. 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:
Minimize:

$$F_i(P_i) = a_i P_i^2 + b_i P_i + c_i \qquad (1)$$

where

a_i, b_i, c_i – the fuel cost coefficients of the ith unit
N- Number of generating units in the system
P_i – output generation of ith unit.
1. Power balance constraint:

$$\sum_{i=1}^{N} P_i = P_D + P_L \qquad (2)$$

where

P_D – Total power demand

P_L – Total network losses

2. Capacity limits constraints:

$$P_i^{\min} \leq P_i \leq P_i^{\max} \qquad (3)$$

where

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

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

2.2. 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 [10], however, when a valve is first opened, the throttling losses increases rapidly and the incremental heat rate rises suddenly. This is "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,

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

where

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

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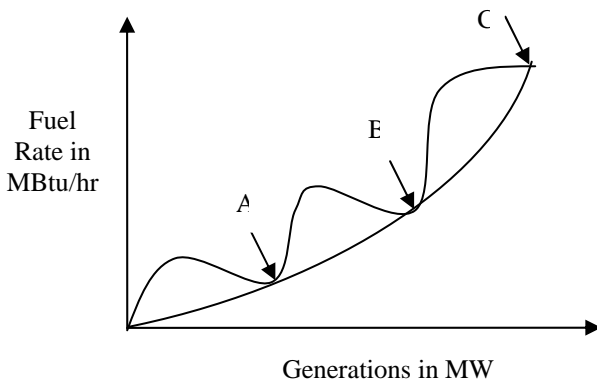

Fig. 1 – Valve point curve

2.3. 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

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

and

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

Where Pi is the current output power and Pi0 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.

3. OPTIMIZATION USING GENETIC ALGORITHM

3.1. BASIC FUNDAMENTALS OF GA

Genetic Algorithm (GA) is a search algorithm based on the conjecture of natural selection and genetics. The features of genetic algorithm are different from other search techniques in several aspects.

- First, the algorithm is a multi-path that searches many peaks in parallel, and hence reducing the possibility of local minimum trapping.
- Secondly, GA works with a coding of parameters instead of the parameters themselves. The coding of parameter will help the genetic operator to evolve the current state into the next state with minimum computations.
- Thirdly, GA evaluates the fitness of each string to guide its search instead of the optimization function.
- Three basic operators of GA are reproduction, crossover, and mutation

3.2. BASIC OPERATORS OF GA

Reproduction: A mechanism by which the most highly fit members in a population is selected to pass on information to the next population of members. It effectively selects the fittest of the springs in the current population to be used in generating the next population. In this way, relevant information concerning the fitness of a string is passed along to successive generations.

Crossover: A mechanism by which strings can exchange information, possibly creating more highly fit strings in the process and allowing the exploration of new regions of the search space.

Mutation: It ensures that a string position will never be fixed at a certain value for all time.

3.3. ALGORITHM FOR GA

1. Code the problem variables into binary strings.
2. Randomly generate initial population strings. Tossing of a coin can be used.

3. Evaluate fitness values of population members
4. If solution available among the population?
   then Stop, else Continue.
5. Select highly fit strings as parents and produce offspring's according to their fitness.
6. Create new string by mating current offspring. Apply crossover and mutation operators to introduce variations and form new strings.
7. New springs replace existing one.
8. GOTO step 4 and repeat
9. Stop.

4. IMPLEMENTATION OF GA

4.1. CODING:

Implementation of problem in a genetic problem starts from the parameter encoding. It is carefully done to utilize the genetic algorithm's ability to efficiently transfer information between chromosome strings and objective function of the problem. Binary coded strings 1s and 0s are used.

4.2. FITNESS FUNCTION:

Genetic algorithm mimics the survival of the fittest principle of nature to make a search process. Therefore, the Genetic Algorithm problems are naturally suitable for maximization problems. Minimization problems are usually converted into the maximization problems using some suitable transformations, The fitness function for maximization problem is given by f(x) =F(x) and for minimization f(x)=[1/1+F(x)].

In order to emphasize the best chromosome and speed up the convergence of the evolutionary process, fitness function is normalized into the range between 0 and 1. The fitness function of the ith chromosome is given by

$$f_i(x) = 1/[1 + k((F_i(x)/F) - 1)] \qquad (8)$$

where

$F_i(x)$ is the solution corresponding to the ith chromosome

f_i^{min} is the solution of the highest ranking chromosome

k is the scaling constant

4.3. REPRODUCTION

The reproduction genetic algorithm operator selects the good strings in a population and forms a matting pool. The commonly used selection operator is the proportionate reproduction operator where a string is selected from the mating pool with a probability proportional to its fitness. The probability of selecting the ith string is

$$p_i = f/\sum_{j=1}^{L} f_i \qquad (9)$$

where

L is the population size

f_i is the fitness function of the ith population

This selection scheme is implemented by using the roulette-wheel [11] with its circumference marked for each string proportionate to the string's fitness.

4.4. COMPETITION AND SELECTION

Each individual in the combined population has to compete with some other individuals to have a chance to be copied to the next generation. The score of each trial vector after stochastic competition is given by

$$w_i = \sum_{n=1}^{L} w_n \qquad (10)$$

4.5. CROSSOVER OPERATOR

In crossover the information is exchanged among stings of the mating pool to create new strings. In the crossover operator the good substrings from parent strings will be combined to form a better child offspring. There are three forms of crossover:
- One point crossover
- Uniform crossover
- Multi point crossover

The effect of crossover may be detrimental or beneficial. The crossover has three distinct sub-steps, namely:
- Slice each of parent in the substrings
- Exchange a pair of corresponding substrings of parents
- Merge the two respective substrings to form offspring.

4.6. MUTATION

Mutation is the important operator, because newly created individuals have no new inheritance information and the number of alleles is decreasing. This process results in the contraction of the population to one point. Diversity is necessary to search a big part of the search space. It is achieved by the mutation.

Mutation operator changes 1to 0 and vice versa with a small mutation probability. The bit-wise mutation is performed bit-by-bit by flipping the coin with required probability. In general, mutation probability is fixed throughout the whole search processing. However a small fixed mutation probability can only result in a premature convergence, while the search with a large fixed mutation probability will not converge.
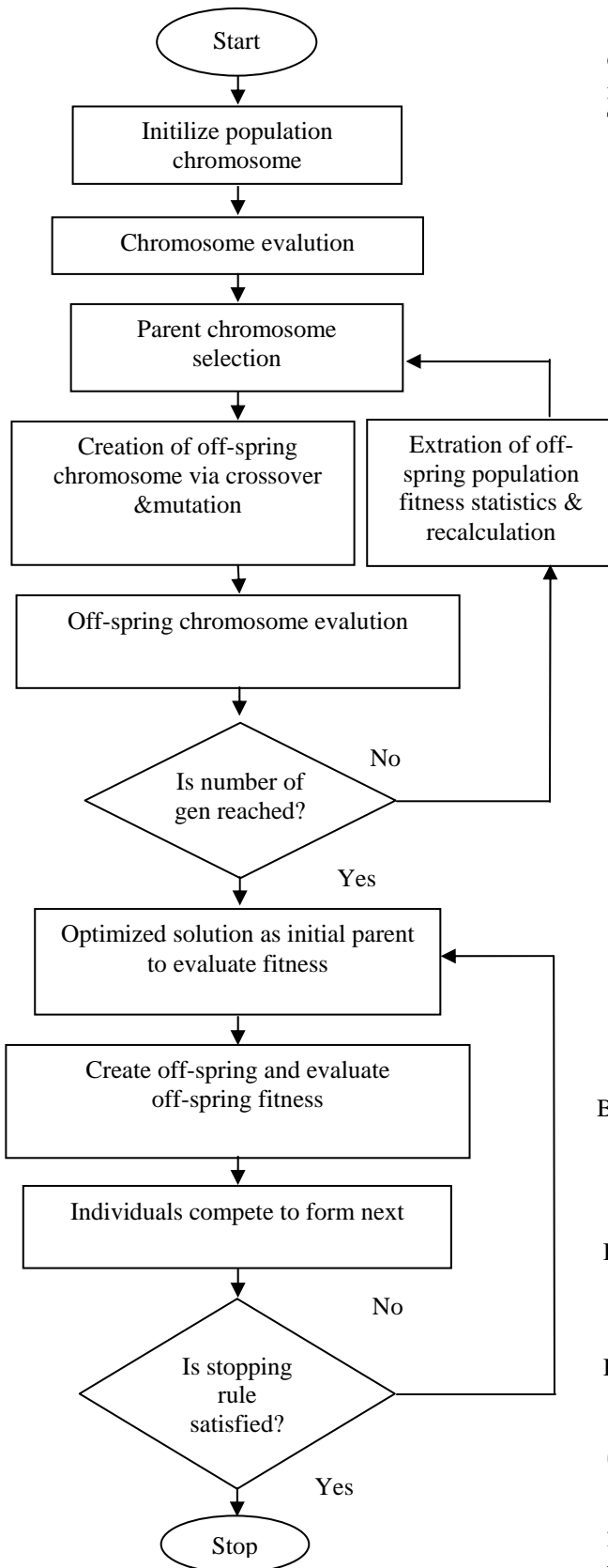
5. FLOW CHART

Fig. 2 – Flowchart for Genetic Algorithm.

6. DATA'S AND RESULT

6.1. TEST CASE I

3-generator System: The unit characteristics data are given in Table 1,2 and 3. The load demand is 850MW. The B loss coefficients are given in the Table 4.[12]

Table 1. Capacity and Cost Co-Efficient

Quantities	Unit-1	Unit-2	Unit-3
a_i	0.004820	0.001940	0.001562
b_i	7.97	7.85	7.92
c_i	78	310	562
P_{imin}	50	100	100
P_{imax}	200	400	600

Table 2. Valve-Point Loading

Quantities	Unit-1	Unit-2	Unit-3
e_i	150	200	300
F_i	0.063	0.042	0.0315

Table 3. Ramp Rate Limits

Unit	P_{io}	UR_i	DR_i
1	170	50	90
2	350	80	120
3	440	80	120

Table 4. B-Coefficients

$$B = \begin{bmatrix} 0.0006760 & 0.0000953 & -0.0000507 \\ 0.0000953 & 0.0005210 & 0.0000901 \\ -0.0000507 & 0.0000901 & 0.0002940 \end{bmatrix} MW^{-1}$$

$$B_0 = \begin{bmatrix} -0.07660 & -0.00342 & 0.01890 \end{bmatrix}$$

$$B_{00} = \begin{bmatrix} 4.0357 \end{bmatrix} MW$$

6.2. TEST CASE II

10-generator Systems: The load demand is 2000MW. The unit characteristics data are given in the Table 5, 6 and 7. The system B loss coefficients are given in the Table 8.

323

Table 5. Capacity AND Cost Co-Efficient

Unit	a_i	b_i	c_i	Pimin	Pimax
1	0.1524	38.5379	786.7988	150	470
2	0.1058	46.1591	451.3251	135	470
3	0.0280	40.3965	1049.9977	73	340
4	0.0354	38.3055	1243.5311	60	300
5	0.0211	36.3278	1658.5696	73	243
6	0.0179	38.2704	1356.6592	57	160
7	0.0121	36.5104	1450.7045	20	130
8	0.0124	36.5104	1450.7045	47	120
9	0.1090	39.5804	1455.6056	20	80
10	0.1295	40.5407	1469.4026	10	455

Table 6. Valve-Point Loading

Quantities	e_i	f_i
Unit-1	450	0.041
Unit-2	600	0.036
Unit-3	320	0.028
Unit-4	260	0.052
Unit-5	280	0.063
Unit-6	310	0.048
Unit-7	300	0.086
Unit-8	340	0.082
Unit-9	270	0.098
Unit-10	380	0.094

Table 7. Ramp Rate Limits

Quantities	Pio	URi	DRi
Unit-1	90	80	120
Unit-2	400	80	120
Unit-3	100	70	105
Unit-4	95	65	100
Unit-5	80	60	90
Unit-6	105	60	100
Unit-7	100	130	130
Unit-8	90	100	120
Unit-9	40	80	80
Unit-10	40	80	120

Table 8. B-Coefficients

$$B = 1 \times 10^{-4} \begin{pmatrix} 49 & 14 & 15 & 15 & 16 & 17 & 17 & 18 & 19 & 20 \\ 14 & 45 & 16 & 16 & 17 & 15 & 15 & 16 & 18 & 18 \\ 15 & 16 & 39 & 10 & 12 & 12 & 14 & 14 & 16 & 16 \\ 15 & 16 & 10 & 40 & 14 & 10 & 11 & 12 & 14 & 15 \\ 16 & 17 & 12 & 14 & 35 & 11 & 13 & 13 & 15 & 16 \\ 17 & 15 & 32 & 10 & 11 & 36 & 12 & 12 & 14 & 15 \\ 17 & 15 & 14 & 11 & 13 & 12 & 38 & 16 & 16 & 18 \\ 18 & 16 & 14 & 12 & 13 & 12 & 16 & 40 & 15 & 16 \\ 19 & 18 & 16 & 14 & 15 & 14 & 16 & 15 & 42 & 19 \\ 20 & 18 & 16 & 15 & 16 & 15 & 18 & 16 & 19 & 44 \end{pmatrix} \text{MW}^{-1}$$

$$B0 = \begin{bmatrix} 0.0000 & 0.0000 & 0.0000 & 0.0000 & 0.0000 & 0.0000 & 0.0000 & 0.0000 & 0.0000 & 0.0000 \end{bmatrix}$$

$$B00 = \begin{bmatrix} 0.00000 \end{bmatrix}$$

Table 9. Convergence Results for 3 Generating Units With Valve Point Effect & Losses

PD = 850MW
No. of Trials = 50
No. of Population = 5
Crossoverrate=0.8; MutRate=0.001

Quantities	Res-1	Res-2	Res-3
P1(MW)	148.67	146.75	146.56
P2(MW)	297.33	293.5	293.12
P3(MW)	428.88	422.5	421.87
F1(Rs/hr)	1379.5	1379.4	1379.4
F2(Rs/hr)	2643.1	2588.5	2584.3
F3(Rs/hr)	4487.5	4388	4377.7
Ploss(MW)	13.361	13.159	13.139
Total Gen(MW)	874.88	862.76	861.55
Total Fuel Cost(Rs/hr)	8510.1	8355.9	8341.4
CPU Time(sec)	6.25	6	6.0313
Best Trial	13	28	50

Table 10. Convergence Results for 10 Generating Units With Valve Point Effect

PD = 2000MW
No. of Trials = 50
No. of Population = 5
Crossoverrate=0.8; MutRate=0.001

Unit power output	Optimal Values by GA
P1(MW)	225.6242
P2(MW)	233.7826
P3(MW)	330
P4(MW)	300
P5(MW)	242
P6(MW)	160
P7(MW)	130
P8(MW)	118
P9(MW)	80
P10(MW)	245.9484
Total Power Output(MW)	2065.3552
Ploss(MW)	56.872
Total Generation Cost(Rs/h)	125975.5063
CPU time(sec)	23.547
Best Trial	47

7. CONCLUSION

In this paper, a comprehensives ED model including ramp rate limits, valve loading effects and transmission losses together is presented. In this method, the genetic algorithm method is found best suited for the fuel cost functions of non-smooth, non-continuous valve point curves. The proposed

GA can provide a more diverse search of solution space and so better optimum solutions with low computation burden can be found. The research work is under way in order to incorporate more security issues of power system in the ED model with other constraints.

8. REFERENCES

[1] A. J. Wood and B. F. Wollenberg. *Power generation, Operation and Control*. New York: Wiley, 1994.

[2] C. E. Lin and G. L. Viviani. Hierarchical economic dispatch for piecewise quadratic cost functions. *IEEE Trans. Power App.Syst.*, June 1984. Vol. PAS-103, No. 6, pp. 1170-1175.

[3] S. Granville. Optimal reactive dispatch through interior points methods. *in Proc, IEEE Summer Meeting*, Seattle, WA, 1992, Paper No. 92 SM 416-8 PWRS.

[4] Z. X. Liang and J. D. Glover. A zoom feature for a programming solution to economic dispatch including transmission losses. *IEEE Trans.Power Syst.*, Aug 1992. Vol. 7, No. 3, pp. 544-550.

[5] A. G. Bakirtzis, P. N. Biskas, C. E. Zoumas, and V. Petridis. Optimal power flow by enchanced genetic algorithm. *IEEE Trans. Power systems*, May 2002, Vol. 17, No. 2, pp. 229-236.

[6] J. Yurevich and K. P. Wong. Evolutionary programming based optimal power flow algorithms. *IEEE Trans. Power Syst.*, November 1999, Vol. 14, No. 4, pp. 1245-250.

[7] T. Kulworawanichpong and S. Sujitjorn. Optimal power flow using Tabu search. *IEEE Power Engineering Review*, June 2002, Vol. 22, pp. 37-40.

[8] M. A. Abido. Optimal power flow using tabu search algorithm. *Electric Power Components and Systems*, May 2002, Vol. 30, No. 5, pp. 469-483.

[9] N. Sinha, R. Chakrabarti, and P. K. Chatto-padhyay. Evolutionary programming techniques for economic load dispatch. *IEEE Trans.Evol.Comput.*, Feb. 2003, Vol. 7, No. 1, pp.83-94.

[10] H. T. Yang, P. C. Yang and C. L. Huang. Evolutionary programming based Economic Dispatch for units with non-smooth fuel cost functions. *IEEE Trans. Power Systems*, Feb. 1996, Vol. 11, No. 1, pp. 112-118.

[11] D. E. Goldberg. *Genetic Algorithm in Search, Optimization and Machine learning*. Reading MA: Addison-Wesley, 1989.

[12] C. T. Su, C. T. Lin. New Approach with a Hopfield modeling framework to economic dispatch of power system. *IEEE Transactions Power Systems*, 15(2) (2000) 541-545.

[13] C. S. Chang, and W. Fu. Stochastic multiobjective generation dispatch of combined heat and power system. *IEEE proceedings-Generation, Transmission and Distribution*, 1998, Vol. 145 (5), pp. 583-591.

[14] A. El-Gallad, M. El-Hawary, A. Sallam, A. Kalas. Swarm intelligence for hybrid cost dispatch problem. *Canadian Conf. on Electrical and Computer Engineering*, 13-16 May 2001, Vol. 2, pp. 753-757.

[15] W. Lin, F. Cheng, M. Tsay. Nonconvex Economic Dispatch by Integrated Artificial Intelligence. *IEEE Trans. on Power Systems*, May 2001, Vol. 16, No. 2, pp. 307-311.

[16] 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*, 4-9 May 1998, Vol. 8, No. 3, pp. 289-294.

[17] K. Y. Lee, A. Sode Yone, J. Ho Park. Adaptive Hopfield Neural Networks for Economic Load Dispatch. *IEEE Trans. on Power Systems*, May 1998, Vol. 13, No. 2, pp. 519-526.

[18] IEEE Committee Report. Present Practices in the Economic Operation of Power Systems. *IEEE Transactions on Power Apparatus and Systems*, Vol. PAS-90, July/August 1971, pp. 1768-1775.

[19] D. C. Walters, G. B. Sheble. Genetic algorithm solution of economic dispatch with valve point loading. *IEEE Trans. Power Systems*, August 1993, Vol. 8, No. 3, pp. 1325-1332.

[20] K. Wong, Y. Wong. Genetic and genetic/simulated-annealing approaches to economic dispatch. *IEEE Proceedings Gener., Trans. and Distr.*, Sep 1994, Vol. 141, No. 5, pp. 507-513.

B. Padmanabhan *was born on June 26, 1989. He is doing his final year B.E. degree electrical engineering in Ponjesly College of Engineering, Nagercoil, TamilNadu, India.*

His area of interest includes power system optimization, and Electrical Machines.

R.S. SivaKumar *was born on May 12, 1988. He is doing his final year B.E degree electrical engineering in Ponjesly College of Engineering, Nagercoil, TamilNadu India.*

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

J. Jasper *was born on February 28, 1981. He received the B.E. degree electrical engineering in 2003 from C.S.I Institute of Technology, Manonmanium Sundaranar University, TamilNadu, India, and the M.E. degree in electrical enginee-ring in 2005 from Annamalai University,* *Chidambaram, India. He is currently working toward the Ph.D. degree with the Faculty of Electrical Engineering, Anna University, Coimbatore, India.*

He is presently a Senior Lecturer in the Department of Electrical Engineering, Ponjesly College of Engineering, Tamilnadu, India.

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