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Firefly Algorithm Based Power Economic Dispatch of Generators Using Valve Point Effects and Multiple Fuel Options

Sreelekha V, Riya Scaria
Electrical and Electronics Engineering , FISAT,Angamaly,Kerala,India

Abstract*—The major issue in power system is power economic dispatch (PED) problem. Mainly it is an optimization problem and to reduce total generation cost of units is its main objective, while satisfying constraints. Most of the classical problem formulation in PED problem presents deficiencies due to the simplicity of the cost models. Here, the power economic dispatch problem formulation takes in to account of non-smooth fuel cost function due to valve point effects and multiple fuel options and making this to a real world problem. This paper introduces a solution to this power economic dispatch problem using Dr. Xin-She Yang developed firefly algorithm. The proposed approach has been examined and tested with the numerical results of PED problems with ten-generation units including valve-point effects and multiple fuel options. The test results clearly show the effectiveness of proposed approach for solving PED problems. Also we will compare the proposed firefly algorithm with Self-Adaptive Differential Evolution (SDE) algorithm in order to reveal that it is capable of getting good quality optimal solutions with proper adjustment of parameters.

Index Terms—**Firefly Algorithm, Multiple fuels, Power Economic Dispatch, Valve-point effects.**

I. INTRODUCTION

The main objective of power economic dispatch problem is to allocating loads to different generators economically as well as satisfying system constraints, while minimizes the generation fuel cost of the plant. Thus PED problem come under the category of large-scale non- linear constrained optimization problem. Many conventional techniques are employed for this problem, but when the search space is non-linear and it has discontinuities they become very complicated with a slow convergence ratio and no guarantee for seeking to the optimal solution. New numerical methods are come forward to overcome these problems, particularly those with high-speed search to the optimal and not being trapped in local minima. Solving nonlinear PED problems without any restriction on the shape of the cost curves, the stochastic search algorithms such as genetic algorithm (GA), evolutionary programming (EP) [1] , simulated annealing (SA), and particle swarm optimization (PSO) [2] may prove to be very effective. These heuristic methods often provide a fast and reasonable solution (suboptimal nearly global optimal solution) ,but these are not provide any guarantee discovering the globally optimal solution in finite time. In simulated annealing, setting of control parameters is a difficult task and convergence speed is slow in a real system applications. In order to solve complex optimization problems, GA methods have been employed successfully, but recent research has identified some deficiencies in GA performance. The premature convergence of GA decreases its performance and reduces its search capability that attains a higher probability toward obtaining a local optimum. To solve optimization problems, EP seems a better method. EP method produce solutions that is just near global optimum one, when applied to problems consisting of more number of local optima. However, GA and EP take long simulation time in order to obtain solution for such problems. Hybrid methods also introduced for this problems [3],[4],[5],[6]. The generation cost function for power plants can be modeled using a segmented piecewise quadratic function. The generating units with multi-fuel sources (coal, nature gas, or oil), arrive to the problem of determining the most economic fuel to burn. Some studies of the PED problem, such as genetic algorithm(GA),evolutionary programming (EP), Tabu search ,dynamic programming(DP) and the particle swarm optimization (PSO) with the SQP method (PSO-SQP) ,consider valve-point effects only ,while some other methods such as hierarchical method (HM), Hopfield Neural Network (HNN), adaptive Hopfield neural network (AHNN),taken only the multi-fuel options [7]. By considering the PED problem with both valve point effects and multi-fuel options is the only way to obtain more accurate and realistic solution [8]. Self- adaptive differential evolution (SDE) is one of the new generation of evolutionary algorithm (EA), developed by Storn and Price [9],[10] , applied for PED problems including valve-point effects and multiple fuels. But SDE does not always provide exact global optimum and involve crucial control parameters such as population size. A new algorithm that belongs to the category of biology-inspired meta-heuristic algorithms [11],[12] is the firefly algorithm which is based on the flashing light of fireflies. In the firefly algorithm, the objective function of a given optimization problem is associated with this flashing light or light intensity which helps the swarm of fireflies to move to brighter and more attractive locations in order to obtain efficient optimal solutions[11]. This paper presents how the recently developed firefly algorithm can be used to solve the optimal power flow problem including both valve point effects and multiple fuels. This algorithm has many advantages like

- High convergence rate.

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- Ever agent i.e. firefly works individually and finds a better position for itself in consideration with its current position as well as the position of other agents. Though, it escapes from the local optima and attains a global optimum in less number of iterations.
- Robust.

The comparison of results from SDE algorithm shows firefly algorithm provides global optimal or near global optimal solutions for realistic PED problems with reasonable execution time.

II. PED PROBLEM FORMULATION

The PED problem is defined as to minimize the total operating cost of the power system by scheduling the loads to different generators economically while simultaneously satisfying all unit and system equality and inequality constraints. The fuel cost objective is to minimize the total fuel cost operating cost of all committed plants can be stated as follow [13]:

$$Minimize F_T = \sum_{i=1}^{n} Fi(Pi) \quad (1)$$

Where Fi(Pi) represents fuel cost function of i[th] generator , Pi is the i[th] unit power output, n is the number of generators in the system. For the i[th] generator, the fuel cost is defined as

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

Where the fuel cost coefficients of generator i are a_i, b_i and c_i.

While minimizing the total fuel cost, the total power generation must satisfy the total required demand (power balance).

$$\sum_{i=1}^{n} Pi = P_D \quad (3)$$

Where is PD the total required demand in MW.

Also there is a generator capacity constrain in which power generation should lie between maximum and minimum limits and this inequality constraints is represented by

$$MinP_i \le P_i \le MaxP_i \quad (4)$$

where Min P_i and MaxP_i are the lower and upper limit of the i[th] generator's out power P_i in MW.

Practically, the objective function of the PED problem contains non-differential points due to the effects of valve point loading and multiple fuel options. Thus the objective function should be a set of non-smooth cost functions. The realistic PED operation takes part both valve point effects and multiple fuels in which objective function is represented as a set of piecewise superposition of sinusoidal functions and quadratic functions [10].

A. PED Problem Considering Only the Valve-Point Effects

Smooth quadratic functions are commonly used to model the generators to relate power output to production cost. This simplifies the power economic dispatch problem. For practical cases, quadratic representations do not model properly generators, so more accurate models are required to get better solutions. Power plants commonly composed of multiple valves to control the output. When steam inlet valves are first opened, there will be a sudden increase in losses which introduce ripples in cost function. This is known as valve point loading. The fuel cost function with valve point effect which will result non-linear, non-smooth and non-convex cost function [10].

$$F_i(P_i) = a_i P_i^2 + b_i P_i + c_i + \left| e_i * \sin(f_i (P_i^{\min} - P_i)) \right| \quad (5)$$

where e_i, f_i are the fuel cost coefficients of i[th] unit considering valve point effects.

B. PED Problem Considering Only the Multi-Fuel Options

The multi-fuel sources are practically used by dispatching units, in which each unit should be represented with several piecewise quadratic functions which shows the effects of fuel type changes, and generator must select the most economic fuel to burn. A generator with *k* fuel options the cost function curve is divided into *k* discrete regions between minimum and maximum bounds [10]. The fuel cost function expressed as:

$$F_i(P_i) = \begin{cases} a_{i1} P_i^2 + b_{i1} P_i + c_{i1}, \ fuel1, P_i^{\min} \le P_i \le P_{i1} \\ a_{i2} P_i^2 + b_{i2} P_i + c_{i2}, \ fuel2, P_{i1} \le P_i \le P_{i2} \\ . \\ . \\ a_{ik} P_i^2 + b_{ik} P_i + c_{ik}, \ fuelk, P_{ik-1} \le P_i \le P_i^{\max} \end{cases} \quad (6)$$

Where a_{ik},b_{ik},c_{ik} are the cost coefficients of i[th] unit with fuel type k.

C. PED Problem considering both Valve Point Effect and Multi-Fuel Options

The realistic modeling of PED problem should involve both valve-point effects and multiple fuel options in the problem formulation [10]. Therefore, the total cost function should combine (5) with (6) and is formulated as follows:

$$F_i(P_i) = \begin{cases} a_{i1} P_i^2 + b_{i1} P_i + c_{i1} + \left| e_{i1} * \sin(f_{i1} (P_{i1}^{\min} - P_{i1})) \right|, \\ \quad fuel1, P_i^{\min} \le P_i \le P_{i1} \\ a_{i2} P_i^2 + b_{i2} P_i + c_{i2} + \left| e_{i2} * \sin(f_{i2} (P_{i2}^{\min} - P_{i2})) \right|, \\ \quad fuel2, P_{i1} \le P_i \le P_{i2} \\ . \\ . \\ a_{ik} P_i^2 + b_{ik} P_i + c_{ik} + \left| e_{ik} * \sin(f_{ik} (P_{ik}^{\min} - P_{ik})) \right|, \\ \quad fuelk, P_{ik-1} \le P_i \le P_i^{\max} \end{cases}$$

III. FIREFLY ALGORITHM

The Firefly Algorithm (FA) developed by Dr. Xin-She Yang is a nature-inspired algorithm which is based on the flashing behavior of fireflies [11],[12]. The firefly algorithm possess many similarities with other swarm intelligence algorithms such as Particle Swarm Optimization (PSO) [14], Bacterial Foraging (BFA) algorithm, and Artificial Bee

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Colony algorithm (ABC), it is much simpler both in implementation and concept [15],[16],[17]. Its major advantage includes that it is based on the global communication among the the fireflies and it uses mainly real random numbers [11],[16], and as a result, it seems more effective in optimal power flow problems.

According to flashing characteristics of real fireflies, the firefly algorithm has three idealized rules [16],[17].They are:

1. All fireflies are unisex in nature so that they will move towards more attractive and brighter fireflies regardless of their sex.

2. Attractiveness is proportional to their brightness which decreases as the distance from the other firefly increases due to the fact that the air absorbs light. If there is not present a brighter or more attractive firefly than a particular one, it will select random movement.

3. The value of the objective function of a given problem is used to determine the brightness or light intensity of a firefly. The light intensity is proportional to the value of the objective function, in case of maximization problems.

A. Attractiveness Function

Attractiveness function of a firefly is a monotonically decreasing function in the firefly algorithm [11].

$$\beta(r)=\beta_0 * \exp(-\gamma r^n), \text{ with } n \geq 1 \quad (8)$$

where, r represents the distance between any two fireflies, the initial attractiveness at r = 0 is β_0 and γ is an light absorption coefficient[15].

B. Distance between Fireflies

Cartesian or Euclidean distance is defined as the distance between any two fireflies i and j, at positions x_i and x_j , [11][15]respectively.

$$r_{ij}=\left\|X_i - X_j\right\| = \sqrt{\sum_{k=1}^{d}(X_{i,k}-X_{j,k})^2} \quad (9)$$

Where $x_{i,k}$ gives the k^{th} component of the spatial coordinate x_i of the i^{th} firefly and d gives the number of dimensions.

C.Movement Function

The movement of a firefly *i* towards more attractive firefly *j* is given by:

$$Xi = Xi + \beta(r)*(Xj - Xi) + \alpha*(rand - \frac{1}{2}) \quad (10)$$

where the first element is the firefly's current position, the second term is used for considering a firefly's attractiveness to adjacent fireflies, and the third element shows the random movement of a firefly if there is no any brighter ones. The α is a randomization parameter, while rand is a random number generator uniformly distributed in the space [0, 1]. In this implementation of the algorithm, choose of β_0 = 1.0, α = [0, 1] and the absorption coefficient γ =1.0 guarantees a quick convergence of the algorithm to the optimal solution [11],[15],[17].

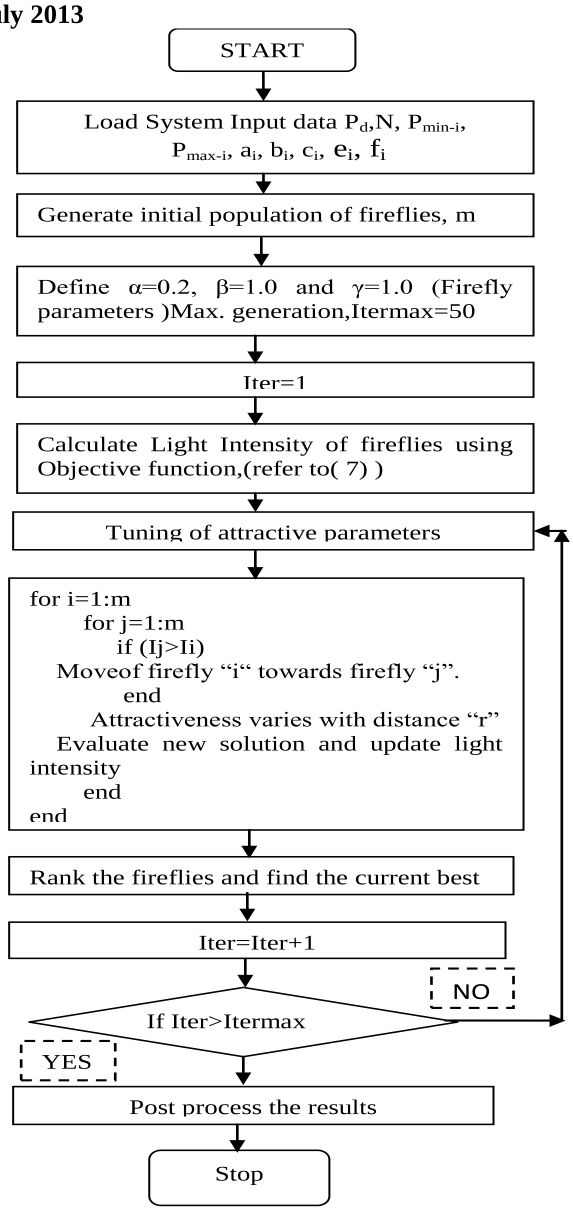

Fig 1.Flowchart of the FA based PED Problem

The convergence of the algorithm is obtained when m ≥ *n* for any large number of fireflies (m), where n is the number of local optima of an optimization problem [12]. However, it is under search a formal proof of the convergence of the algorithm that the algorithm will attain global optima when $m \rightarrow \infty$and $t \geq 1$.The proper choice of the number of iterations together with the selection of parameters γ, β, α, and m depends on the nature of the given optimization problem as this affects the convergence of the algorithm. If population size increases the computational time also increases [11].

Based on the absorption coefficient γ, there are two special cases, one with $\gamma \rightarrow \infty$ [12] and other with $\gamma \rightarrow 0$.In the case $\gamma \rightarrow 0$, the light intensity does not decrease with distance *r* between two fireflies increases and the attractiveness coefficient is constant $\beta=\beta_0$.So firefly can be seen anywhere, optimum can be easily reached .In case $\gamma \rightarrow \infty$, attractiveness coefficient is the Dirac delta function $\beta(r) \rightarrow \delta(r)$. In this attractiveness is almost zero, fireflies cannot see each other and they move

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Volume 3, Issue 1, July 2013

randomly [16],[17]. Fig.1 demonstrates the flowchart of the firefly algorithm based optimal power flow.

IV. NUMERICAL SIMULATION RESULTS

The proposed firefly algorithm has been implemented in Matlab 2010 programming language [18] and MS Windows 7 as an operating system. The solutions obtained through the FA are compared with SDE algorithm [10]. In this paper, PED problem considering both valve point effects and multiple fuel options is studied for ten generating units. The system data is shown in the Table I [10]. In this simulation, the values of the control parameters chosen are: $\gamma = 1.0$, $\beta_{0=}1$, and m = 20. The values of the fuel cost coefficients, the power limits of each generator and the total power load demand are supplied as inputs to the firefly algorithm. Problem is conducted for different demands such as 2400 MW, 2500 MW, 2600 MW and 2700 MW. The power output of each generator, the fuel type used by each generator, the fuel cost, and computational time are considered as outputs of the proposed Firefly algorithm. The initial solution of the given problem is given as:

$$X_j = rand * (upper - lower) + lower \qquad (11)$$

where x_j gives the new solution of j[th] firefly, rand is a random number generator uniformly distributed in the space [0,1], while upper and lower are the upper range and lower range of the j[th] firefly, respectively. After this evaluation, algorithm enters to the main loop [11].

Table II, III, IV, & V shows the comparison of optimal dispatch of generating units for various system demands. Fig.2 shows the convergence characteristics of the FA for a demand of 2400MW.

TABLE I. System Data for 10 Unit System Considering Valve-Point Effects and Multiple Fuels

Unit	Generation Min P1 P2 Max F1 F2 F3	Fuel Type	Cost coefficients a_i	b_i	c_i	e_i	f_i
1	100 196 250 1 2	1	.2176e-2	-.3975e0	.2697e2	.2697e-1	-.3975e1
		2	.1861e-2	-.3059e0	.2113e2	.2113e-1	-.3059e1
2	50 114 157 230 2 3 1	1	.4194e-2	-.1269e1	.1184e3	.1184e0	-.1269e2
		2	.1138e-2	-.3988e-1	.1865e1	.1865e-2	-.3988e0
		3	.1620e-2	-.1980e0	.1365e2	.1365e-1	-.1980e1
3	200 332 388 500 1 3 2	1	.1457e-2	-.3116e0	.3979e2	.3979e-1	-.3116e1
		2	.1176e-4	.4864e0	-.5914e2	-.5914e-1	.4864e1
		3	.8035e-3	.3389e-1	-.2875e1	-.2876e-2	.3389e0
4	99 138 200 265 1 2 3	1	.1049e-2	-.3114e-1	.1983e1	.1983e-2	-.3114e0
		2	.2758e-2	-.6348e0	.5285e2	.5285e-1	-.6348e1
		3	.5935e-2	-.2338e1	.2668e3	.2668e0	-.2338e2
5	190 338 407 490 1 2 3	1	.1066e-2	-.8733e-1	.1392e2	.1392e-1	-.8733e0
		2	.1597e-2	-.5206e0	.9976e2	.9976e-1	-.5206e1
		3	.1498e-3	.4462e0	-.5399e2	-.5399e-1	.4462e1
6	85 138 200 265 2 1 3	1	.2758e-2	-.6348e0	.5285e2	.5285e-1	-.6348e1
		2	.1049e-2	-.3114e-1	.1983e1	.1983e-2	-.3114e0
		3	.5935e-2	-.2338e1	.2668e3	.2668e0	-.2338e2
7	200 331 391 500 1 2 3	1	.1107e-2	-.1325e0	.1893e2	.1893e-1	-.1325e1
		2	.1165e-2	-.2267e0	.4377e2	.4377e-1	-.2267e1
		3	.2454e-3	.3559e0	-.4335e2	-.4335e-1	.3559e1
8	99 138 200 265 1 2 3	1	.1049e-2	-.3114e-1	.1983e1	.1983e-2	-.3114e0
		2	.2758e-2	-.6348e0	.5285e2	.5285e-1	-.6348e1
		3	.5935e-2	-.2338e1	.2668e3	.2668e0	-.2338e2
9	130 213 370 440 3 1 3	1	.1554e-2	-.5675e0	.8853e2	.8853e-1	-.5675e1
		2	.7033e-2	-.4514e-1	.1530e2	.1423e-1	-.1817e0
		3	.6121e-3	-.1817e-1	.1423e2	.1423e-1	-.1817e0
10	200 362 407 490 1 3 2	1	.1102e-2	-.9938e-1	.1397e2	.1397e-1	-.9938e0
		2	.4164e-4	.5084e0	-.6113e2	-.6113e-1	.5084e1
		3	.1137e-2	-.2024e0	.4671e2	.4671e-1	-.2024e1

TABLE II. Comparison Of Dispatch Results Of 10 Unit Sample System for P_D=2400 MW

Unit	P_D=2500 MW SDE Fuel Type	SDE Gen	FA Fuel Type	FA Gen
1	2	205.2313	2	205.4449
2	1	207.7488	1	205.7707
3	1	263.3244	1	265.5267
4	3	235.3396	3	236.5638
5	1	258.8721	1	258.5717
6	3	236.2802	3	235.1407
7	1	270.7378	1	272.7144
8	3	235.6083	3	236.2052
9	1	331.4680	1	330.3627
10	1	255.3914	1	253.6992
TGC ($/hour)	526.3232		526.3099	
Simulation Time(s)	22.28		12. 478300	

TABLE III. Comparison Of Dispatch Results Of 10 Unit Sample System for P_D=2500 MW

Unit	P_D=2400 MW SDE Fuel Type	SDE Gen	FA Fuel Type	FA Gen
1	1	189.1794	1	190.0957
2	1	202.5519	1	202.0569
3	1	255.5954	1	252.4342
4	3	231.4428	3	233.0701
5	1	242.5304	1	242.8688
6	3	234.4029	3	232.0505
7	1	250.3072	1	252.0507
8	3	232.5178	3	234.5932
9	1	321.5026	1	321.5106
10	1	239.9736	1	239.2692
TGC ($/hour)	481.8628		481.7862	
Simulation Time(s)	21.39		12. 405080	

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TABLE IV. Comparison Of Dispatch Results Of 10 Unit Sample System for P_D=2600 MW

Unit	P_D=2600MW			
	SDE		FA	
	Fuel Type	Gen	Fuel Type	Gen
1	2	218.2263	2	216.5416
2	1	211.7117	1	211.7131
3	1	276.7690	1	280.6472
4	3	239.3707	3	239.3857
5	1	275.6483	1	273.0872
6	3	240.1769	3	238.6329
7	1	285.9984	1	283.7824
8	3	238.1582	3	238.8904
9	1	341.8984	1	344.7556
10	1	272.0419	1	272.5639
TGC ($/hour)	574.5388		574.4334	
Simulation Time(s)	22.08		11.947726	

TABLE V. Comparison Of Dispatch Results Of 10 Unit Sample System for P_D=2700 MW

Unit	P_D=2700MW			
	SDE		FA	
	Fuel Type	Gen	Fuel Type	Gen
1	2	218.9403	2	218.5837
2	1	212.7204	1	212.2071
3	1	282.6327	1	280.6631
4	3	239.7738	3	238.8482
5	1	277.4606	1	276.0391
6	3	240.1769	3	240.3822
7	1	287.2932	1	290.1790
8	3	239.9082	3	239.9677
9	3	426.0885	3	428.5225
10	1	275.0054	1	274.6071
TGC ($/hour)	623.9225		623.8606	
Simulation Time(s)	21.92		12.470234	

It is clear from the characteristic that the solution by FA is converged to high quality solutions at the early iterations. The results proved that the proposed FA algorithm provides higher-quality optimal solution with reasonable computation time. It is also observed that the proposed firefly algorithm is very fast and accurate while satisfying constraints at various power load levels. The algorithm provides optimal solution in time less than that provide by SDE algorithm.

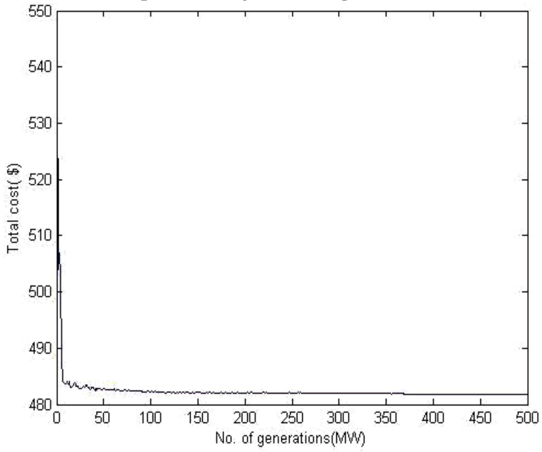

Fig 2. Convergence Characteristics of Firefly Algorithm for 10-unit System

V.CONCLUSION

A firefly algorithm for solving the PED problem with non-smooth cost functions considering valve point effects and multiple fuels are presented in this paper. The feasibility of the proposed method for solving PED problems was presented with considering nonlinearities due to valve-point effects and multiple fuel options. The comparison of the results with SDE algorithm reported in the literature shows the superiority of the proposed method and its potential for solving non-smooth PED problems in a power system.

VI. ACKNOWLEDGMENT

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AUTHOR'S PROFILE

Sreelekha V was born in 1989 in Kerala, India. She received Bachelor of Technology from M.G University Kerala, India in 2011.She is doing Master of Technology from M.G University Kerala, India. She is currently researching in the field of Power Electronics and Power Systems.

Riya Scaria was working as a Assistant professor in FISAT, Angamaly, Kerala, India. She received Bachelor of Technology from M.G University, Kerala, India and M.E degree in Power Systems Engineering from Annamalai University, Annamalainagar, Tamilnadu, India.