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Evaluation of the performance of different firefly algorithms to the economic load dispatch problem in electrical power systems

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Abstract

The planning, operation and control of electric power systems has attracted the attention of many researchers. Thus, effort is put in improving the efficiency of generation and operation of power plants. Economic load dispatch (ELD) is crucial since it is required to schedule committed generating units so as to meet load demand at minimum operating cost. In addition to satisfying all system equality and inequality constraints as well as limitations imposed on the generating units during operation. To solve the economic load dispatch problem, traditional and intelligent techniques were applied. Researchers have shown interest in utilizing metaheuristic methods to solve complex optimization problems in real life applications. In this paper, three alternatives of firefly algorithms are applied to solve the nonlinear ELD problem. A comparative study is carried out on the solution of ELD problem using those recent variants and the classical firefly algorithm for different test cases. Efficiency is evaluated by comparing best solutions obtained in terms of execution time, fuel cost and power loss.

Keywords: Economic load dispatch, Firefly algorithm, Modified firefly, Memetic firefly, and Variable step size firefly

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1. Introduction

The operation and planning of electric power generation system is significant in the electric industry. Generation, transmission and distribution of electric power should be done efficiently, economically and optimally. The need to reduce the running charges of the electric energy became important due to the rise in fuel cost, expansion of the interconnected power systems and limited availability of generating units. Economic load dispatch (ELD) is a fundamental issue because as the power systems expand and cost of fuel increase, the need for determining optimal power output from generating units and minimizing operational cost grows. Economic load dispatch is the allocation of output power of the committed generating units optimally. This is done by generating optimum power, satisfying load demand and considering other operational system equality and inequality constraints. The ELD problem is a non-convex optimization problem since the input/output of generating units in real life are highly non-smooth and nonlinear. In addition, prohibited operating zone, ramp rate limits and multi-fuel options are usually considered. Since the objective is for the solution to converge to superior results in a reduced amount of time putting into consideration system constraints, choosing the appropriate optimization approach is important (Zhu et al., 2015).

Traditional mathematical optimization techniques like Linear Programming (LP) (Dhamanda et al., 2013), Quadratic Programming (QP) (Benhamida et al., 2013), Lambda Iteration (Lin et al., 1992), and Newton method (Jabr et al., 2000) were applied to solve the ELD problem. They have the advantage of being simple and fast. Nevertheless, they depend on initial points; sometimes they converge to the neighboring local optimal solution or even diverge. In addition, the solution of non-convex ELD problems is difficult and the computational effort it requires is enormous. To overcome the limitations of the traditional optimization techniques, metaheuristic methods were developed. These intelligent metaheuristic methods have shown fruitful success in solving the toughest nonlinear non convex optimization problems reaching feasible optimal solutions. Therefore, they have taken over conventional methods, becoming the best alternative choice for researchers in solving the ELD problem to ensure global solution with least computational effort. Examples of these intelligent metaheuristic methods are Simulated Annealing (SA) (Panigrahi et al., 2006), Differential Evolution (DE) (Noman and Iba, 2008), Genetic Algorithm (GA) (Sahoo et al., 2014), Particle Swarm Optimization (PSO), Ant Colony optimization (ACO), and Firefly Algorithm (FFA) (Moustafa et al., 2016).

The FFA is a developing optimization technique that is simple with a great ability to converge to optimum solutions faster than other intelligent methods (Subramanian and Thanushkodi, 2013; Younes, 2013). As a result, it is very useful when used in real time application making it suitable in solving the ELD problem. However, when dealing with complex optimization problems, the FFA shows deficiency in reaching global optima. It also doesn't save better-quality previous solutions and the parameters are not dynamic and the tuning of such parameters has proven to be a difficult task. It is a challenging task to solve complex optimization problems. Consequently, it is necessary to develop and enhance the optimization techniques. Although FFA has been widely applied to solve benchmark functions and numerous practical problems and has shown promise in finding optimal solutions, it has limitations in finding global optimum, especially when the complexity of the problem increases. Therefore, it became essential to propose modifications to the FFA and combining it with other intelligent techniques and creating new hybrids, hence, obtain efficient and reliable solutions (Fister et al., 2013). Modifications include and not restricted to: adding memory, varying parameters of the algorithm throughout the iterations and altering the updating formula for the fireflies. New variants of FFA were proposed and implemented to solve benchmark functions, engineering design problems, economic load dispatch problems and so on (Kazemzadah-Parsi, 2014; FisterJr et al., 2012, Yu et al., 2015; Farhani et al., 2011; Gandomi et al., 2013; Yu et al., 2014). Some of these new versions of firefly algorithm recently developed, but not yet applied to solve the ELD problem like modified firefly algorithm(MFA), memeticfirefly algorithm (MFFA) and variable step size firefly algorithm (VSSFA) (Kazemzadah-Parsi, 2014; FisterJr et al., 2012, Yu et al., 2015). In this paper, these three variants are applied to solve the nonlinear ELD problem. A comparative study was carried out on the solution of ELD problem using those recent variants and the classical FFA for different test cases. Efficiency was evaluated by comparing best solutions obtained in terms of execution time, fuel cost and power loss.

2. Problem Formulation

The objective of the nonlinear ELD optimization problem is to minimize cost while satisfying the load demand and other operational system equality and inequality constraints (Zhu et al., 2015).

2.1 Objective function- cost function

Minimize

$$F_T = F(P_i) = \sum_{i=1}^{N_g} F_i(P_i) \ \$/hr \tag{1}$$

$$F_i(P_i) = a_i + b_i P_i + c_i {P_i}^2 \ \$/hr \tag{2}$$

where

F_T: Total Quadratic cost function; it could be also a cubic function

P_i: Real power generated

N_g: Number of generation busses

a_i, b_i, c_i : Fuel cost coefficients for i^{th} unit

2.2 Constraints

The objective function must be minimized while considering the following constraints:

1) Equality constraint- Energy balance equation

$$\sum_{i=1}^{N_g} P_i = P_D + P_L \tag{3}$$

$$P_L = \sum_{i=1}^{N_g} \sum_{j=1}^{N_g} P_i B_{ij} P_j \tag{4}$$

where

P_D = Load demand

P_L= Power transmission losses

B_{ij}= Loss coefficients (constants)

P_i, P_j = Active power injection at the i^{th} and j^{th} generators

In some cases, power losses are neglected and the active power balance equation becomes:

$$\sum_{i=1}^{N_g} P_i = P_D \tag{5}$$

2) Inequality constraint- Generating limits

Generated active power should lie between minimum and maximum operational values

$$P_i^{min} \le P_i \le P_i^{max} \tag{6}$$

where

P_i= Power output from generator (i)

P_i^{min} = Minimum permitted power output by generator (i)

P_i^{max} = Maximum permitted power output by generator (i)

3. Firefly Algorithm

Firefly algorithm is a recent nature based metaheuristic developed by Yang to solve the continuous optimization problems. The idea behind FFA is that fireflies emit light produced by chemical reactions. The light flashing behavior attracts fireflies to each other for mating purposes (Yang, 2008).

To simulate such idyllic behavior, some rules must be followed:

a) Fireflies are assumed to be unisex. Attraction of fireflies doesn't depend on their sex, but depend only on their brightness.
b) The brightness of a firefly is determined by the objective function
c) Attractiveness is directly proportional to brightness and both are inversely proportional to distance

Using Firefly algorithm in optimization problems, light intensity and brightness represents the objective function and the attraction and movement towards the brightest firefly resembles reaching optimal solution. The factors affecting the algorithm are light intensity, attractiveness, distance, and movement and are given by:

$$Light\ intensity\ I(r) = I_0 e^{-\gamma r^2} \quad (7)$$
$$Attractiveness\ \beta(r) = \beta_0 e^{-\gamma r^2} \quad (8)$$

where I_0 and β_0 are the initial light intensity and initial brightness, respectively.

This distance between firefly i and firefly j is represented as:

$$r_{ij} = \|x_i - x_j\| = \sqrt{\sum_{k=1}^{d} (x_{ik} - x_{jk})^2} \quad (9)$$

The formula that controls the fireflies' movement is given by:

$$x_i^{t+1} = x_i^t + \beta_0 e^{-\gamma r_{ij}^2}(x_j^t - x_i^t) + \alpha(rand - 0.5) \quad (10)$$

where t is the number of current iteration, α[0,1]is the randomization parameter and γ[0,∞) is the coefficient of absorption. The first term is the current position of the firefly i, the second term is due to attraction towards a brighter firefly j and the last term represents the random walk of the firefly.

A. Variants of Firefly Algorithm

Since FFA was developed, it has become a popular optimizer. It has been widely applied to solve benchmark functions and numerous practical problems. Although the FFA has shown promise in finding optimal solutions, it has limitations in finding the global optimum, especially when the complexity of the problem increases. In recent studies, major improvements and changes were applied to the FFA to enhance its performance. New variants of FFA were proposed and implemented to solve benchmark functions, engineering design problems and so on (Kazemzadah-Parsi, 2014; FisterJr et al., 2012; Yu et al., 2015; Farhani et al., 2011; Gandomi et al., 2013; Yu et al., 2014).

Gaussian firefly was developed by (Farhani et al., 2011). Gaussian distribution was used to control the random movement of fireflies so they are directed to the global solution. Firefly with chaos was proposed by (Gandomi et al., 2013). Chaos was introduced to FFA for a more efficient global optimization. Wise step size firefly algorithm was developed by (Yu et al., 2014). Parameter α is controlled by global best position and vary dynamically with iterations. Modified firefly algorithm was presented by (Kazemzadah-Parsi, 2014). The updating formula is adjusted, memory is added and newborn fireflies are added in each iteration. Memetic firefly was developed by (FisterJr et al., 2012). It was applied to combinatorial problems. Instead of having fixed parameters α and β, these parameters are dynamically fine-tuned and the random movement is scaled as well. Variable step size firefly algorithm was used by (Yu et al., 2015). Parameter α varies dynamically with the iterations.

B. Modified Firefly Algorithm

Modified firefly algorithm was presented by (Kazemzadah-Parsi, 2014). Updating formula is adjusted, memory is added and newborn fireflies are added in each iteration.
Three new modifications were suggested: adding memory, newborn fireflies and updating formula.

a) Adding memory: Two approaches are considered in the adding memory modification.

   1. (m_1) high quality solution fireflies are not updated and transferred to the following iterations. The rest of the fireflies ($n - m_1$) are updated using a new updating formula discussed later.

2. (m_2) high quality solution fireflies are copied and saved from the current iteration. In the next iteration, (m_2) low quality solution fireflies are exchanged by the (m_2) high quality solution fireflies saved from the preceding iteration.
In our work only the second approach is implemented.

b) Newborn fireflies: (k) low quality solution fireflies are exchanged by (k) randomly generated fireflies within the search space.

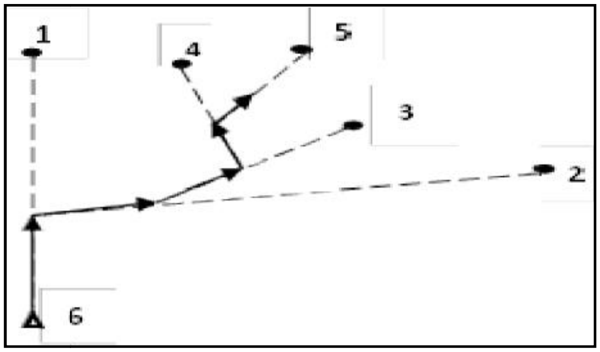

Figure 1. Schematic diagram that shows the zigzag path that firefly (6) takes to approach the five more luminous fireflies than itself. Its location is updated in five steps.

c) Updating formula: The strategy implemented by the original firefly algorithm is that the fireflies to reach the optimum solution by taking steps towards the brightest firefly, then a step towards the second bright and so on. The fireflies approached brighter ones in a zigzag like path.

Depending on the value of objective function, the six fireflies arranged. Firefly (1) is the most luminous and firefly (6) is the least luminous. In the first iteration to update the location of firefly (6), it approaches firefly (1) since it is the brightest. During the second iteration, firefly (6) approaches firefly (2) since it is the second bright, and thus; its location is updated. During the upcoming iterations, the former steps are repeated until there no fireflies brighter than firefly (6) as shown in Figure1. The number of steps each firefly takes to update its location is equal to the number of more luminous fireflies than itself.

This approach is ineffective, requires more computational time and affects the performance of the algorithm negatively.The modification to this time consuming approach suggests that a point representing the general overall location of the more luminous fireflies is calculated as shown in Figure 2. The representation proposed in our study is to calculate the mean location of the more luminous fireflies. This mean point (P_i) that represents the mean coordinates of fireflies more luminous than firefly (i) is given by the following formula:

$$P_i = \frac{1}{i-1} \sum_{k=1}^{i-1} x_k \quad (11)$$

$$r_i = \|P_i - x_i\| \quad (12)$$

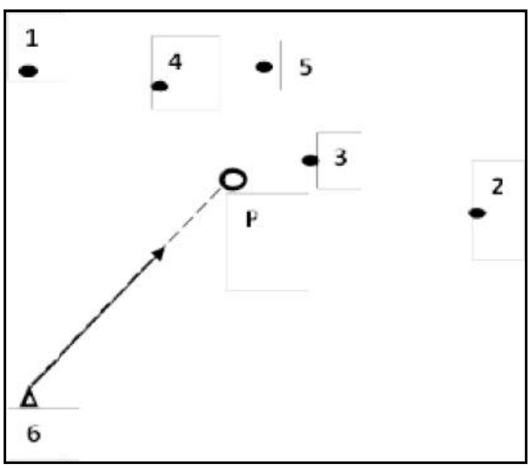

Figure 2. Schematic diagram illustrating the mean point (P) that represents the mean coordinates of fireflies more luminous than firefly (6). Its location is updated in only one step

and thus changing the updating formula with a scaled random movement to be:

$$x_i^{t+1} = x_i^t + \beta\left(P_i^t - x_i^t\right) + \alpha\varepsilon \tag{13}$$

with $\beta=\beta_0 e^{-\gamma r_i^2}$, $\varepsilon=(rand-0.5)*(U-L)$
where U and L are the upper and lower bounds of the search space, respectively.

C. Memetic Firefly Algorithm

Memetic firefly was developed by (Fister et al., 2012). The MFFA was applied on combinatorial problems. Instead of having fixed parameters α and β, these parameters are dynamically fine-tuned and the random movement is scaled as well. Memetic algorithm (MA) attains the balance between diversity and intensity of solution in search space. Diversification (randomness) allows fireflies to wander in search space and not cluster near local optima. Intensification allows fireflies to smoothly converge to the global optimal solution. Such balance utilizes global and local search to obtain optimal solutions effectively. MFFA combines the balance of search in memetic algorithms and the superiority of firefly algorithm compared to other methods. Memetic firefly algorithm can solve problems with high dimensions and various strategies were proposed. High diversification can lead to inefficient search and high intensification can lead to converging prematurely.

α is adjusted dynamically by:

$$\alpha = \alpha\left(\frac{1}{9000}\right)^{\frac{1}{t}} * (U-L) \tag{14}$$

where
α is initially set to 0.2
t = number of current iteration
U = upper bound of the search space
L = lower bound of the search space.
β changes in the range [0.2,1] using this formula:

$$\beta = \beta_{min} + (\beta_0 - \beta_{min})e^{-\gamma r_{ij}^2} \tag{15}$$

where $\beta_{min}=0.2$ and $\beta_0=1$

and thus changing the updating formula with a scaled random movement to be:

$$x_i^{t+1} = x_i^t + \beta\left(x_j^t - x_i^t\right) + \alpha(rand - 0.5) \square (U-L) \tag{16}$$

where U and L are the upper and lower bounds of search space, respectively.

D. Variable Step Size Firefly Algorithm

Variable step size firefly algorithm was used by (Yu et al., 2015). Parameter α varies dynamically with the iterations. The parameters of the firefly algorithm are kept fixed. The balance between global and local search is controlled by the randomization parameter or step size α. Such balance is affected by keeping this parameter unchangeable. The initial iterations should encourage exploring possible solutions in the search space. Therefore, a larger α initially is required to evade local optimum. As the iterations go on, a smaller α is more appropriate to exploit the neighborhood of prospective solutions. The decreasing of step size α as iterations proceed guarantees convergence to global optimal solution efficiently. In the variable step size firefly algorithm (VSSFA), step size α is adjusted dynamically as iterations progress.
The step size α formula given by the following formula:

$$\alpha(k) = \frac{0.4}{1+exp^{(0.005*(k-MaxGeneration))}} \tag{17}$$

where
k: the current iteration
MaxGeneration: the total number of iterations.

4. Test and Results

The FFA and its three variants explained in the preceding chapter are applied on the ELD problem of three units systems. The number of fireflies, maximum number of iterations, light absorption coefficient and initial brightness are the same for the firefly algorithm and its variants. The randomization parameter is different for each application. Memory and newborn parameters are given for the MFA. Minimum brightness is given for the MFFA. The best and mean solutions and standard deviation of twenty independent runs are calculated in each application. The best solutions, time of execution and the statistical results were evaluated and analyzed. Comparisons of the results obtained by firefly algorithm, its variants and other techniques mentioned in literature were carried out (Reddy and Reddy, 2012; Sudhakaran et al., 2007; Tiwari et al., 2013).

Table 1. Parameters for firefly algorithm and its variants

Parameters	Values for different algorithms			
	FFA	*MFA*	*VSSFA*	*MFFA*
MaxGeneration	150	150	150	150
n	25	25	25	25
α	0.2	0.2	Varies with iterations	Initially α=0.2 but decreases with iterations
γ	1	1	1	1
β_0	1	1	1	1
β_{min}	NA	NA	NA	0.2
m_1	NA	0	NA	NA
m_2	NA	1	NA	NA
k	NA	1	NA	NA

The cost functions to be minimized for the three thermal units are given as follows:

$$F_1 = 561 + 7.92P_1 + 0.001562{P_1}^2 \ \$/hr \tag{18}$$
$$F_2 = 310 + 7.85P_2 + 0.001940{P_2}^2 \ \$/hr \tag{19}$$
$$F_3 = 78 + 7.97P_3 + 0.004820{P_3}^2 \ \$/hr \tag{20}$$

Real power limits:

$$100 \le P_1 \le 600 \tag{21}$$
$$100 \le P_2 \le 400 \tag{22}$$
$$40 \le P_3 \le 200 \tag{23}$$

$$P_D + P_L = P_1 + P_2 + P_3 \tag{24}$$

Loss coefficient B_{ij}

$$B_{ij} = \begin{bmatrix} 0.000075 & 0.000005 & 0.0000075 \\ 0.000005 & 0.000015 & 0.00001 \\ 0.0000075 & 0.00001 & 0.000045 \end{bmatrix}$$

4.1 Transmission losses not included

The power distribution, cost and time for the best solution obtained by the different approaches for different power demands are given in the Tables (2–7). The reliability analyses for twenty independent runs are given in the Tables (8 – 13).

The comparisons between best cost and time of execution for the FFA, its variants and GA are given in Table (14) and Figures (3 – 4).

Table 2. Solution for power demand = 450MW

	FFA	**MFA**	**VSSFA**	**MFFA**
P1	210.9323	205.5350	202.7603	204.1462
P2	178.5729	183.0785	183.7123	183.7871
P3	60.4947	61.3865	63.5275	62.0667
Cost	4652.5	4652.4	4652.5	4652.4
Time(seconds)	0.498447	0.078653	0.524861	0.217412

Table 3. Solution for power demand = 585MW

	FFA	**MFA**	**VSSFA**	**MFFA**
P1	266.6992	269.3735	267.6083	267.2763
P2	238.3142	233.6227	234.6370	234.5635
P3	79.9866	82.0038	82.7547	83.1602
Cost	5821.6	5821.6	5821.6	5821.6
Time(seconds)	0.514214	0.078843	0.533350	0.212202

Table 4. Solution for power demand = 600MW

	FFA	**MFA**	**VSSFA**	**MFFA**
P1	275.6610	276.3577	271.5320	276.2698
P2	242.0674	239.6248	244.0853	239.4353

P3	82.2716	84.0175	84.3827	84.2950
Cost	5953.2	5953.1	5953.2	5953.1
Time(seconds)	0.509636	0.077439	0.532048	0.199898

Table 5. Solution for power demand = 700MW

	FFA	MFA	VSSFA	MFFA
P1	326.3860	323.1222	320.9296	322.6530
P2	275.7047	278.1399	276.2013	277.9427
P3	97.9093	98.7379	102.8691	99.4043
Cost	6838.7	6838.6	6838.7	6838.6
Time(seconds)	0.508926	0.079287	0.552621	0.207671

Table 6. Solution for power demand = 800MW

	FFA	MFA	VSSFA	MFFA
P1	366.1402	368.0085	372.5973	368.5635
P2	318.9648	317.0630	314.0788	316.6006
P3	114.8950	114.9284	113.3239	114.8359
Cost	7738.8	7738.8	7738.8	7738.8
Time(seconds)	0.515501	0.078750	0.545341	0.212810

Table 7. Solution for power demand = 900MW

	FFA	MFA	VSSFA	MFFA
P1	413.4513	415.4486	414.8906	416.6916
P2	355.9829	354.6639	352.8460	353.4335
P3	130.5658	129.8874	132.2634	129.8749
Cost	8653.6	8653.6	8653.6	8653.6
Time(seconds)	0.517866	0.079307	0.555965	0.214578

The cost of fuel and time of execution is minimal for both the MFA and MFFA. However, the time of execution for the MFA is less than that of the MFFA. Time of execution of VSFFA is maximal in this case.

Table 8. Reliability analysis for power demand = 450MW

	FFA	MFA	VSSFA	MFFA
Best	4652.5	4652.4	4652.5	4652.4
Mean	4654.57	4652.4	4653.945	4653.02
SD	2.342535738	0	1.4964783	0.900643

Table 9. Reliability analysis for power demand = 585MW

	FFA	MFA	VSSFA	MFFA
Best	5821.6	5821.6	5821.6	5821.6
Mean	5824.465	5812.6	5823.495	5822.045
SD	1.9107108	0	1.5669195	0.9389103

Table 10. Reliability analysis for power demand = 600 MW

	FFA	MFA	VSSFA	MFFA
Best	5953.2	5953.1	5953.2	5953.1
Mean	5955.05	5953.12	5953.965	5953.425
SD	1.6410844	0.0410391	0.7125012	0.7946366

Table11. Reliability analysis for power demand = 700MW

	FFA	MFA	VSSFA	MFFA
Best	6838.7	6838.6	6838.7	6838.6
Mean	6839.92	6838.6	6840.025	6838.7
SD	1.8019288	0	1.3633839	0.2655679

Table 12. Reliability analysis for power demand = 800MW

	FFA	MFA	VSSFA	MFFA
Best	7738.8	7738.8	7738.8	7738.8
Mean	7742.865	7738.8	7742.175	7739.03
SD	2.9462331	0	2.120793	0.6009641

Table 13. Reliability analysis for power demand = 900MW

	FFA	MFA	VSSFA	MFFA
Best	8653.6	8653.6	8653.6	8653.6
Mean	8656.5011	8653.6	8656.085	8653.605
SD	3.2084989	0	2.3611494	0.0223607

The result obtained by MFA is the most stable and the FFA is the least stable. MFFA is more stable than VSSFA.

Table 14. Comparing cost for different power demands with Genetic Algorithm

Power demand	GA	FFA	MFA	VSSFA	MFFA
585	5827.5	5821.6	5821.6	5821.6	5821.6
700	6877.2	6838.7	6838.6	6838.7	6838.6
800	7756.8	7738.8	7738.8	7738.8	7738.8

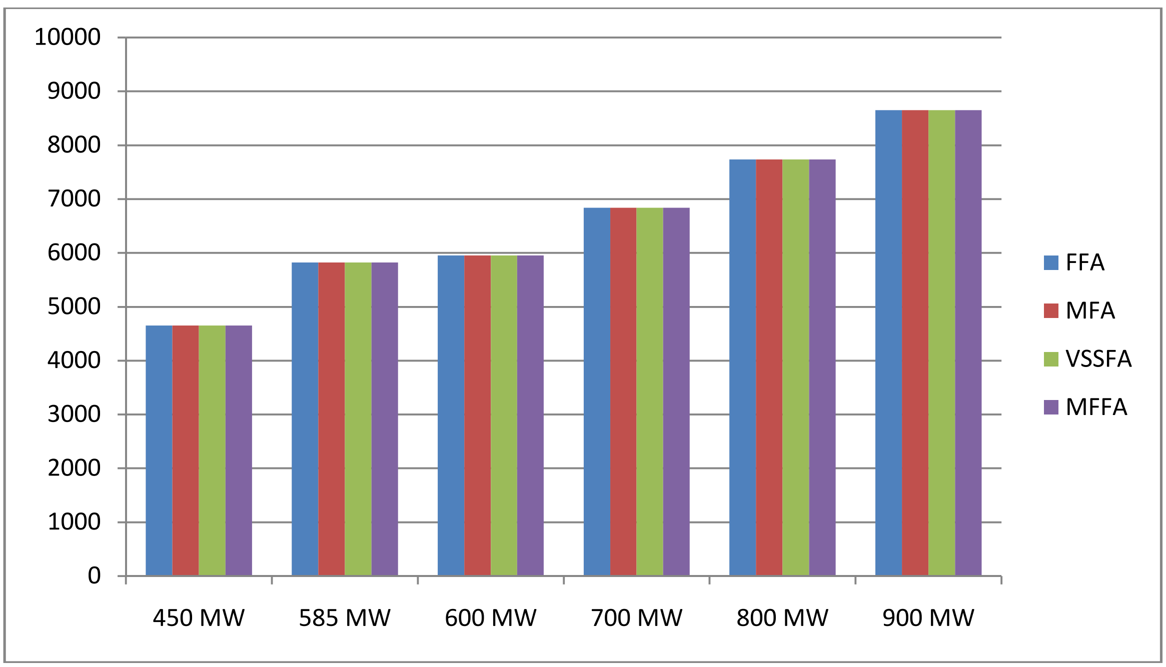

Figure 3. Comparing cost for different power demands

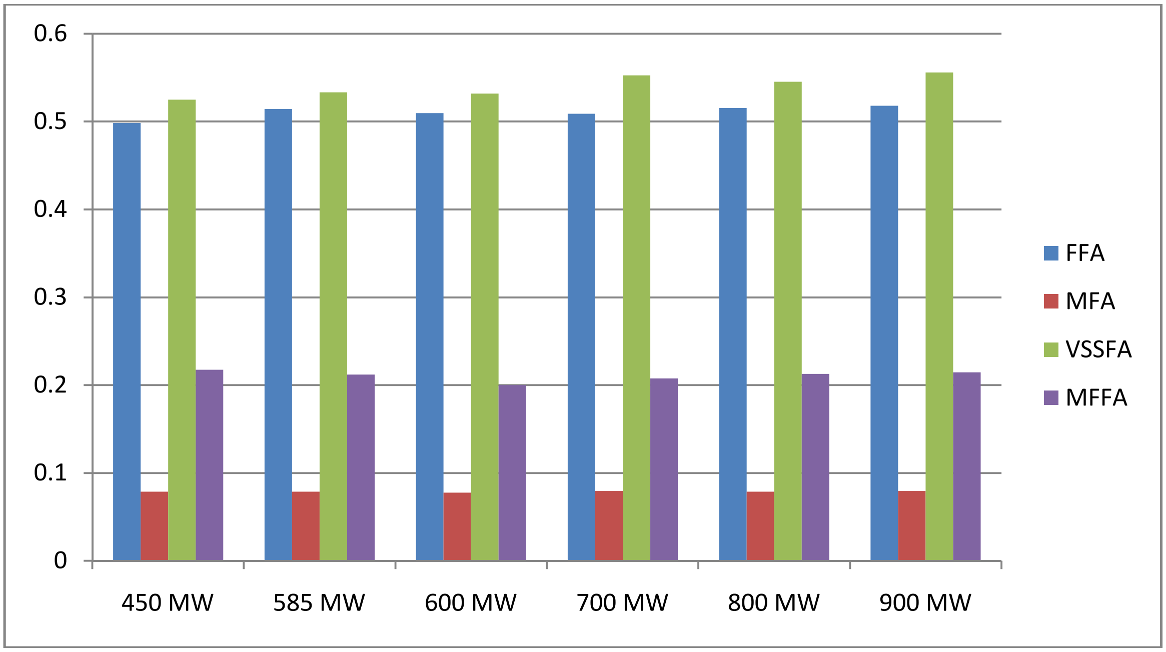

Figure 4. Comparing time for different power demands

As shown in the above table and figures FFA achieves better solution than GA in terms of minimum cost. The difference in cost between FFA and its variants is not significant. However, the MFA is almost 6.5 times faster than the FFA. The MFFA is almost 2.5 times faster than FFA.

4.2 Transmission losses included

The power distribution, cost, time and power losses for the best solution obtained by the different approaches for different power demands are given in the Tables (15 –18). The reliability analyses for twenty independent runs are given in the Tables (19 – 22). The comparisons between best cost time of execution and power losses of FFA, its variants and PSO are given in Tables (23 – 24) and Figures (5 – 7).

Table 15. Solution for power demand = 585MW

	FFA	MFA	VSSFA	MFFA
P1	229.8586	233.1711	227.2825	232.9819
P2	265.1271	268.1007	273.4247	267.9658
P3	96.9115	90.6825	91.0920	91.0032
Ploss	6.8971	6.0667	6.7993	6.9509
Cost	5887.3	5887.0	5887.2	5887.0
Time(seconds)	2.410235	0.344904	2.710710	0.603812

Table 16. Solution for power demand = 600MW

	FFA	MFA	VSSFA	MFFA
P1	241.6172	238.4055	233.3197	235.0256
P2	272.9669	275.0288	281.1677	277.9416
P3	92.8020	93.8673	92.6692	94.2434
Ploss	7.3861	6.3111	7.1566	7.2106
Cost	6022.3	6022.3	6022.4	6022.3
Time(seconds)	2.461330	0.358319	2.625015	0.661870

Table 17. Solution for power demand = 700MW

	FFA	MFA	VSSFA	MFFA
P1	282.9725	279.9986	276.4951	27808975
P2	312.8414	318.9859	316.2038	320.3834
P3	114.3339	111.0446	117.2554	110.7102
Ploss	10.1477	8.8288	9.9543	9.9911

Cost	6935.1	6934.9	6935.2	6934.9
Time(seconds)	2.443697	0.330166	2.692303	0.622944

Table 18. Solution for power demand = 800MW

	FFA	**MFA**	**VSSFA**	**MFFA**
P1	319.7665	319.8415	316.4809	318.4764
P2	363.9400	365.1622	366.1312	366.1738
P3	129.4296	128.1260	130.4087	128.4306
Ploss	13.1361	11.7293	13.0208	13.0808
Cost	7867.5	7867.4e	7867.5	7867.4
Time(seconds)	2.422965	0.324316	2.608767	0.752689

The minimum fuel cost and least execution time are achieved by both the MFA and MFFA. However, MFA is faster than MFFA. The best solution obtained by VSSFA is the worst in terms of execution time and minimum cost.

Table 19. Reliability analysis for power demand =585MW

	FFA	**MFA**	**VSSFA**	**MFFA**
Best	5887.3	5887.0	5887.2	5887.0
Mean	5890.245	5887.09	5888.865	5887.375
SD	2.5351165	0.0307794	1.5218669	1.1433446

Table 20. Reliability analysis for power demand =600MW

	FFA	**MFA**	**VSSFA**	**MFFA**
Best	6022.3	6022.3	6022.4	6022.3
Mean	6025.5	6022.3	6024.245	6022.625
SD	3.6103652	0	1.493662	0.6239728

Table 21. Reliability analysis for power demand =700MW

	FFA	**MFA**	**VSSFA**	**MFFA**
Best	6935.1	6934.9	6935.2	6934.9
Mean	6937.745	6934.915	6936.75	6935.13
SD	2.3209515	0.0366348	1.2492103	0.6375116

Table 22. Reliability analysis for power demand =800MW

	FFA	**MFA**	**VSSFA**	**MFFA**
Best	7867.5	7867.4e	7867.5	7867.4
Mean	7869.84	7867.4	7869.935	7867.915
SD	3.5845282	0	2.4009373	0.5294237

The variants of firefly algorithm are more stable the FFA. MFA is the more stable than MFFA and MFFA is more stable than VSFFA.

Table 23. Comparing cost for different power demands with particle swarm algorithm

Power demand	**PSO**	**FFA**	**MFA**	**VSSFA**	**MFFA**
585	5889.9	5887.3	5887.0	5887.2	5887.0

Table 24. Comparing loss for different power demands with particle swarm algorithm

Power demand	**PSO**	**FFA**	**MFA**	**VSSFA**	**MFFA**
585	6.9661	6.8971	6.0667	6.7993	6.9509

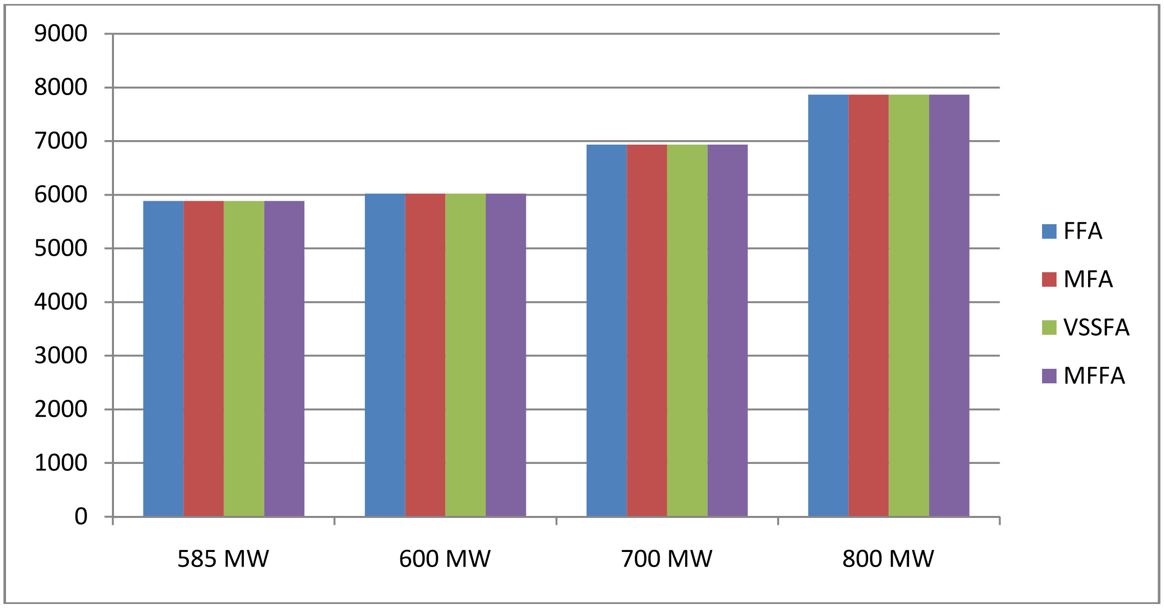

Figure 5. Comparing cost for different power demands

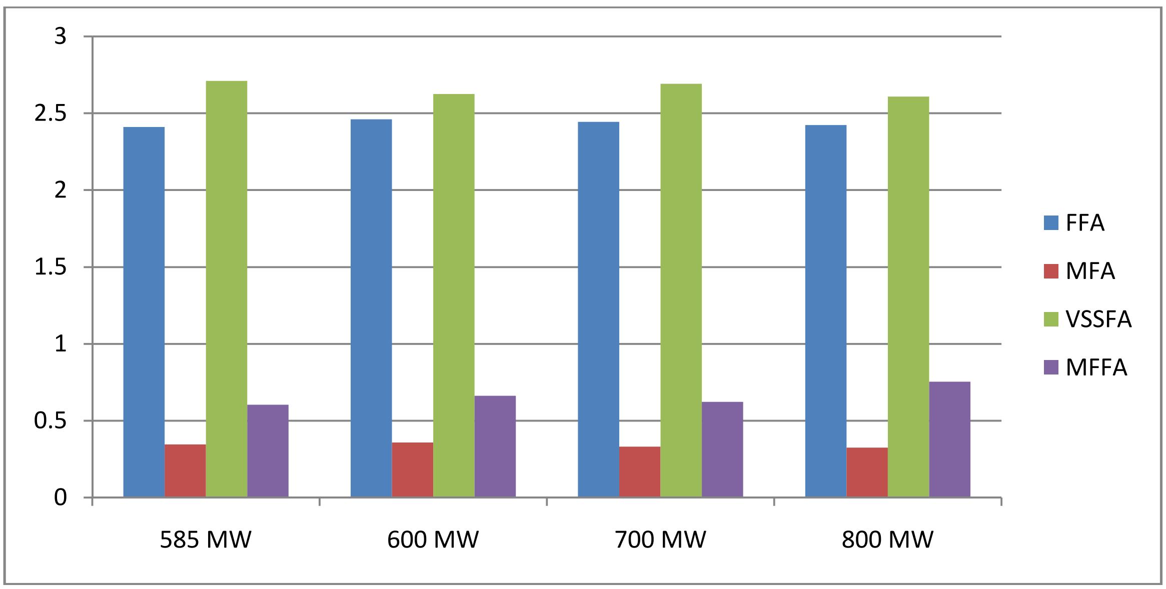

Figure 6. Comparing time for different power demands

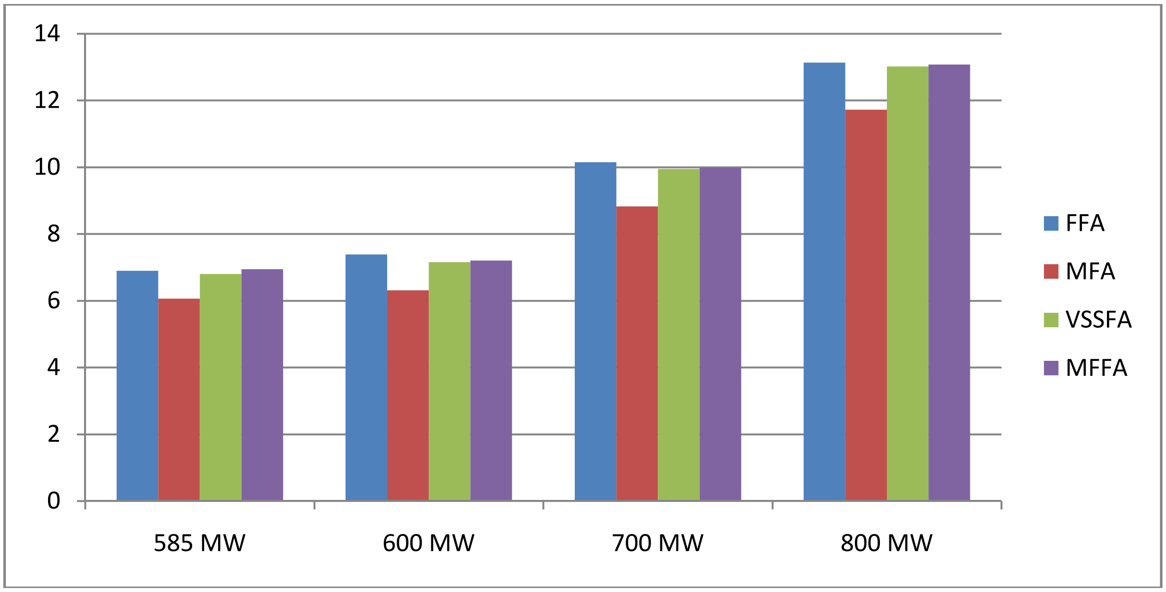

Figure 7. Comparing losses for different power demands

As shown in the above table and figures FFA achieves better solution than PSO in terms of minimum cost and execution time. The MFA outperforms the other approaches in terms of execution time and power loss. The MFA is almost 7.4 times faster than the FFA. The MFFA is almost 3.6 times faster than FFA. The VSSFA is the slowest but has less power losses compared to MFFA and FFA.

5. Conclusions

Since its development, firefly algorithm was utilized to solve many complex optimization problems. It was applied in the solution of economic load dispatch problem. When compared to other techniques, it has shown its superiority in achieving high quality solutions. Because FFA has some disadvantages, several modifications were proposed. In this study, three novel enhancements of FFA: modified firefly algorithm, Memetic firefly algorithm and variable step size firefly algorithmwere implemented to solve the ELD problem. The results show that the MFA capability of reaching global optimal solutions in the minimal execution time and with least transmission losses. It is superior to FFA and the other two variants. The MFFA algorithm was more successful in comparison to the FFA and VSSFA in terms of getting better solutions faster. The ELD problem is a fundamental issue. The need to generate optimum power and satisfy all system constraints in the least amount of time is important. With the noticeable difference in execution time of almost 6.5-7.5 speed gain than that of the FFA, the MFA is the most suitable method of solution of the economic load dispatch problem. It generates optimum power, at minimum operating cost and minimum transmission losses.

Nomenclature

F_T	Total cost function
a_i, b_i, c_i	Fuel cost coefficients for i^{th} unit
E_T	Total Emission cost function
α_i, β_i, γ_i, δ_i, η_i	Emission coefficients for i^{th} unit
N_g	Number of generation busses
e_i, f_i	Fuel cost coefficients for i^{th} unit considering valve pointeffects
P_i,	Real power output from generator (i)
P_i^{min}	Minimum permitted real power output by generator (i)
P_i^{max}	Maximum permitted real power output by generator (i)
P_i^0	Preceding power output from generator (i)
P_D	Load demand
P_L	Power transmission losses
B_{ij}	Loss coefficients (constants)
UR_i	Up ramp rate limit by generator (i)
DR_i	Down ramp rate limit by generator (i)
$P_{i,k}^{lower}$	Lower limit of k^{th} prohibited operation zones for generator (i)
$P_{i,k}^{upper}$	Upper limit of k^{th} prohibited operation zones for generator (i)
PZ_i	Number of allowed operating zones for generator (i)
Q_i	Reactive power output from generator (i)

Q_i^{min}	Minimum permitted reactive power output by generator (i)
Q_i^{max}	Maximum permitted reactive power output by generator (i)
δ_i	Phase angle of bus (i)
δ_i^{min}	Minimum phase angle of bus (i)
δ_i^{max}	Maximum phase angle of bus (i)
I_0	Initial light intensity
β_0	Initial brightness
t	Number of current iteration
α	Randomization parameter
γ	Light absorption coefficient
U	Upper bound
L	Lower bound
n	Number of fireflies

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