

Environmental/Economic Power Dispatch Problem /renewable energy Using firefly algorithm

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Abstract— Exploitation and development of renewable energy such as solar and wind energy is a very important alternative to reduce gas emissions, reduce the bill for power generation. This paper examines the implications of renewable energy deployment in power generation with the classical energy system, managed by an intelligent method, to minimize the cost of production of electric energy and also reduce the emission of gases. Simulation results on the 10 units power system prove the efficiency of this method thus confirming its capacity to solve the environmental/economic power dispatch problem with the renewable energy.

Keywords— *Economic Power Dispatch (EPD); renewable energy; environmental, an intelligent method*

I. INTRODUCTION

Electricity is regarded as the invention that changed the world; some centuries ago the world was in total darkness. Currently electricity is virtually present in all our activities. With the advanced technology on the one hand, and population growth on the other hand, these two factors have made the world a voracious and ravenous appetite for electricity. Most predictions to ensure the growth of energy consumption in developed countries in the compositions to about 1% per year, but for developing countries, consumption now exceeds 5% per year [1]. With the increasing negative effects of fossil fuel combustion on the environment in addition to limited stock of fossil fuel have forced many countries to inquire into and change to environmentally friendly alternatives that are renewable to sustain the increasing energy demand. Energy policy plays a vital role to mitigate the impacts of global warming and crisis of energy availability [2]. The problem which has received much attention. It is of current interest of many utilities and it has been marked as one of the most operational needs. In traditional economic dispatch, the operating cost is reduced by the suitable attribution of the quantity of power to be produced by different generating units. However the optimal production cost can not be the best in terms of the environmental criteria. Recently many countries throughout the world have concentrated on the reduction of the quantity of pollutants from fossil fuel to the production of electrical energy of each unit. The gaseous pollutants emitted by the power stations cause harmful effects with the human beings and the environment like the sulphur dioxide (SO₂), nitrogen oxide (NO_x) and the carbon dioxide (CO₂), etc. Thus,

the optimization of production cost should not be the only objective but the reduction of emission must also be taken into account. Considering the difference in homogeneity of the two equations, the equation of the cost of fuel given in \$/hr, and the equation of emission of gases to the production of electrical energy given in Kg/hr. Algeria has substantial resources and inexhaustible renewable energy ie solar radiation exceptional covers an area of 2,381,745 km², with over 3000 hours of sunshine per year and the existence of significant wind energy potential. Moreover, these energies are clean, renewable and are used where they are and their decentralized nature is well suited to the state of scattered areas of low population density. Consequently, they can contribute to environmental protection, reduce the emission of greenhouse gases, particularly a successful CO₂ reduction, and to combat global warming, be considered as a future alternative to conventional energy, increased energy independence and preservation of raw materials. Our work revolves around two main axes: the injection of the maximum power produced from renewable energy sources in the Algerian network. Optimal management of power produced by conventional power plants by an improved firefly algorithm (FFA). Simulation results on the 10 units power system prove the efficiency of this method thus confirming its capacity to solve the environmental/economic power dispatch problem with the renewable energy.

II. PROBLEM FORMULATION AND OPTIMIZATION WITH THE SOLAR ENERGY AND WIND ENERGY

1) Solar Energy

The maximum power provided by a solar panel is given by the following characteristic [3]:

$$P_s = P_1 \cdot E_c \cdot [1 + P_2 \cdot (T_j - T_{jref})] \quad (1)$$

E_c is solar radiation, T_{jref} is the reference temperature of the panels at 25°C, T_j is the cells junction temperature (°C), P_1 represent the characteristic dispersion of the panels and the value for one panel is included enters 0.095 to 0.105 and the parameter $P_2 = 0.47\%/^{\circ}\text{C}$; is the drift in panels temperature [3].

The addition of one parameter P_3 to the characteristic, gives more satisfactory results:

$$P_s = P_1 \cdot [1 + P_2 \cdot (T_j - T_{jref})] \cdot (P_3 + E_c) \quad (2)$$

This simplified model makes it possible to determine the maximum power provided by a group of panels for solar radiation and panel temperature given, with only three constant parameters P_1 , P_2 and P_3 and simple equation to apply. A thermal solar power station consists of a production of solar system of heat which feeds from the turbines in a thermal cycle of electricity production.

B. Wind energy

The power contained in the form of kinetic energy, P (W), the wind is expressed by:

$$P = \frac{1}{2} \cdot \rho \cdot A \cdot v^3 \quad (3)$$

with:

A is the area traversed by the wind (m^2); ρ is the density of air ($= 1.225 kg/m^3$) and v is the wind speed (m/s).

The wind generator can recover some of this wind power and represents the power produced by wind generator:

$$P_{el} = \frac{1}{2} \cdot \rho \cdot C_e \cdot A \cdot v^3 \cdot 10^{-3} \quad (4)$$

C_e is the efficiency factor, which depends on the wind speed and the system architecture [4].

C. Economic Dispatch

Optimization of cost of generation has been formulated based on classical OPF with line flow constraints. The detailed problem is given as follows [5].

$$F = \text{Min} \sum_{i=1}^{NG} f(P_{Gi}) \quad (5)$$

The cost function $f(P_{Gi})$ is usually expressed as a quadratic polynomial [6].

$$f(P_{Gi}) = a_i P_{Gi}^2 + b_i P_{Gi} + c_i \quad (6)$$

The minimization the daily total cost of active power generation may be expressed by:

$$F = \text{Min} \sum_{i=1}^{24} \sum_{i=1}^{NG} f(P_{Gi}) \quad (7)$$

The minimum value of the above objective function has to be found out by satisfying the following constraints [7]:

$$\sum_{i=1}^{NG} P_{Gi} + \sum_{k=1}^{NGk} P_{GRk} - P_D - P_L = 0 \quad (8)$$

The generation capacity of each generator has some limits and it can be expressed as [8]:

$$P_{Gi}^{\min} \leq P_{Gi} \leq P_{Gi}^{\max} \quad (9)$$

In minimizing the cost, the equality constraint (power balance) and inequality constraint (power limits) should be

satisfied. The transmission loss can be represented by the B-coefficient method as

$$P_L = \sum_i \sum_j P_{Gi} B_{ij} P_{Gj} \quad (10)$$

Where B_{ij} is the transmission loss coefficient, P_i, P_j are the power generation of i th and j th units. The B-coefficients are found through the Z-bus calculation technique.

Where

$P_{Gi}^{\min}, P_{Gi}^{\max}$: Lower and upper limit of active power generation at bus i

a_i, b_i, c_i the cost coefficients of the i th generator.

P_{Gi} : The power output of generator i in MW;

P_D : Active power load total

P_{Gi} : Active power generation at bus i

P_{GRk} : Active power renewable generation at bus k

P_L : Real losses

NG : Number of thermal generators connected in the network.

NGR : Number of renewable generator

D. Minimization of pollutants emission

The most important emissions considered in the power generation industry due to their effects on the environment are sulfur dioxide (SO_2) and nitrogen oxides (NO_x) [9]. These emissions can be modeled through functions that associate emissions with power production for each unit [10, 11]. One approach to represent SO_2 and NO_x emissions is to use a combination of polynomial and exponential terms [12]:

$$EC(P_g) = \sum (\alpha_i P_{gi}^2 + \beta_i P_{gi} + \gamma_i) + \varepsilon_i \exp(\lambda_i P_{gi})$$

$$P_L = 0 \quad (11)$$

where

$\alpha_i, \beta_i, \gamma_i, \varepsilon_i$ and λ_i are coefficients of the i th generator emission characteristics..

The bi-objective combined economic emission dispatch problem is converted into single optimization problem by introducing price penalty factor h as follows.

Minimise $F = FC + h \cdot EC$

Subjected to the power flow constraints of equations [13]. The price penalty factor h blends the emission with fuel cost and F is the total operating cost in \$/h. The price penalty factor h_i is the ratio between the maximum fuel cost and maximum emission of corresponding generator.

$$h_i = \frac{FC(P_{gi}^{\max})}{EC(P_{gi}^{\max})}$$

The following steps are used to find the price penalty factor for a particular load demand

1. Find the ratio between maximum fuel cost and maximum emission of each generator.
2. Arrange the values of price penalty factor in ascending order.
3. Add the maximum capacity of each unit P_{gi}^{\max} one at a time, starting from the Smallest h_i unit until $\sum P_{gi}^{\max} \geq P_d$
4. At this stage, h_i associated with the last unit in the process is the price penalty factor h for the given load.

The above procedure gives the approximate value of price penalty factor computation for the corresponding load demand. Hence a modified price penalty factor (hm) is introduced in this work to give the exact value for the particular load demand. The first two steps of h computation remain the same for the calculation of modified price penalty factor. Then it is calculated by interpolating the values of h_i corresponding to their load demand values.

III. FIREFLY ALGORITHM (FFA)

Fireflies (lightning bugs) use their bioluminescence to attract mates or prey. They live in moist places under debris on the ground, others beneath bark and decaying vegetation.

Firefly Algorithm (FFA) was developed by Xin-She Yang at Cambridge University in 2007. It uses the following three idealized rules: 1) All fireflies are unisex so that a firefly will be attracted to other fireflies regardless of their sex. 2) Attractiveness is proportional to their brightness; thus for any two flashing fireflies the less brighter will move towards the brighter one. The attractiveness is proportional to the brightness and they both decrease as their distance increases. If there is no brighter firefly than a particular one it will move randomly. 3) The brightness of a firefly is affected or determined by the landscape of the objective function. On the first rule, each firefly attracts all the other fireflies with weaker flashes [14]. All fireflies are unisex so that one firefly will be attracted to other fireflies regardless of their sex. Secondly, attractiveness is proportional to their brightness which is reversely proportional to their distances. For any two flashing fireflies, the less bright one will move towards the brighter one. The attractiveness is proportional to the brightness and they both decrease as their distance increases. If there is no brighter one than a particular firefly, it will move randomly. Finally, no firefly can attract the brightest firefly and it moves randomly. The brightness of a firefly is affected or determined by the landscape of the objective function. For a maximization problem the brightness can simply be proportional to the value of the objective function. Other forms of brightness can be defined in a similar way to the fitness function in genetic algorithms based on these three rules.

1) Attractiveness

In the firefly algorithm there are two important issues: the variation of light intensity and the formulation of the

attractiveness. For simplicity, we can always assume that the attractiveness of a firefly is determined by its brightness which in turn is associated with the encoded objective function [15]. In the simplest case for maximum optimization problems, the brightness I of a firefly at a particular location x can be chosen as $I(x)$ corresponding to $f(x)$. However, the attractiveness β is relative; it should be seen in the eyes of the beholder or judged by the other fireflies [16]. Thus, it will vary with the distance r_{ij} between firefly i and firefly j . In addition, light intensity decreases with the distance from its source and light is also absorbed in the media so we should allow the attractiveness to vary with the degree of absorption. In the simplest form, the light intensity $I(r)$ varies according to the inverse square law $I(r) = I_s / r^2$ where I_s is the intensity at the source. For a given medium with a fixed light absorption coefficient, the light intensity I varies with the distance r [17].

That is $I = I_0 e^{-\gamma r}$, where I_0 is the original light intensity. In order to avoid the singularity at

$r = 0$ in the expression $I(r) = I_s / r^2$ the combined effect of both the inverse square law and absorption can be approximated using the following Gaussian form:

$$I(r) = I_0 e^{-\gamma r^2} \quad (12)$$

Sometimes we may need a function which decreases monotonically at a slower rate. In this case we can use the following approximation:

$$I(r) = \frac{1}{1 + e^{r^2}} I_0 e^{-\gamma r^2} \quad (13)$$

At a shorter distance, the above two forms are essentially the same. This is because the series expansions about $r = 0$ have the form:

$$e^{-\gamma r^2} \approx 1 - \gamma r^2 + \dots, \quad \frac{1}{1 + e^{r^2}} \approx 1 - \gamma r^2 + \dots, \quad (14)$$

and are equivalent to each other up to the order of $O(r^3)$.

Since a firefly's attractiveness is proportional to the light intensity seen by adjacent fireflies, we can now define the attractiveness β of a firefly by:

$$\beta(r) = \beta_0 e^{-\gamma r^2} \quad (15)$$

where β_0 is the attractiveness at $r = 0$. As it is often faster to calculate $1 / (1 + r^2)$ than an exponential function, the above expression, if necessary, can conveniently be replaced by

$$\beta = \frac{\beta_0}{1 + e^{r^2}}. \quad \text{Equation (9) defines a characteristic distance}$$

$\Gamma = \frac{1}{\sqrt{\gamma}}$ over which the attractiveness changes significantly from β_0 to $\beta_0 e^{-1}$.

In the implementation, the actual form of attractiveness function $\beta(r)$ can be any monotonically

decreasing function such as the following generalized form:

$$\beta(r) = \beta_0 e^{-\gamma r^m} \text{ with } m \geq 1 \quad (16)$$

For a fixed γ , the characteristic length becomes $\Gamma = \gamma^{-1/m} \rightarrow 1$ as $m \rightarrow \infty$.

Conversely, for a given length scale Γ in an optimization problem, the parameter γ

can be used as a typical initial value. That is $\gamma = \frac{1}{\Gamma^m}$.

2) Distance and Movement

The distance between any two fireflies i and j at x_i and x_j is the Cartesian distance given by [18] as follows:

$$r_{ij} = |x_i - x_j| = \sqrt{\sum_k^d (x_{i,k} - x_{j,k})^2} \quad (17)$$

Where x_{ik} is the k -th component of the spatial coordinate x_i of i -th firefly as shown in fig.2 the movement of a firefly i is attracted to another more attractive firefly j is determined by

$$x_{i+1} = x_i + \beta_0 e^{-\gamma r_{ij}^2} (x_j - x_i) + \alpha \left(\text{rand} - \frac{1}{2} \right) \quad (18)$$

Where the first term is the current position of a firefly, the second term is used for considering a firefly's attractiveness to light intensity seen by adjacent fireflies and the third term is used for the random movement of a firefly in case there are not any brighter ones. The coefficient α is a randomization parameter determined by the problem of interest, while rand is a random number generator uniformly distributed in the space $[0, 1]$. As we will see in this implementation of the algorithm, we will use $\beta_0 = 0.1$, $\alpha \in [0, 1]$ and the attractiveness or absorption coefficient $\gamma = 1.0$ which guarantees a quick convergence of the algorithm to the optimal solution (see figure 1).

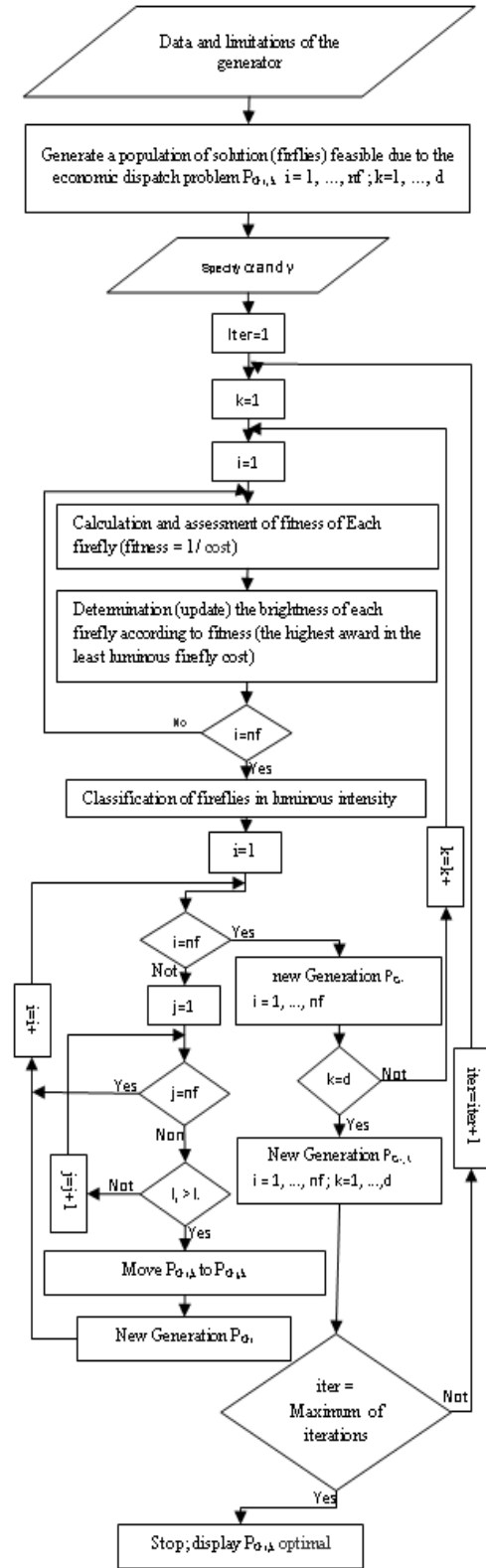


Fig. 1. Flow chart for EPD using Firefly algorithm.

IV. SIMULATION RESULTS

The new firefly algorithm (FFA) was coded in the MATLAB environment. The test was performed on the Algerian 59-bus system. This network consists of 59 buses, 10 generators, 36 loads of 684.10 MW and 83 branches. Table 2 shows the technical parameters of the 10 generators. These parameters were determined by curve fitting techniques based on real test data, with PL=19.6490MW. To demonstrate the effectiveness of the proposed technique, two different cases have been considered, as follows:

Case1: calculate the total cost and emission to Algerian electrical network without renewable energy.

Case 2: Minimize the total cost function and the emission, with renewable energy.

It is noticed that the proposed method (FFA) gives reduction in fuel cost and the emission in case 1 without renewable energy (Table III). The convergence profiles of the best solution for the fuel cost, the emission, the fuel cost and the emission are shown in Fig. 2, 3,4 and 5, respectively. from Table 4 taking into account the renewable-energy (case 2), we can notice that the optimization has been greatly improved (see figures 6,7,8 and 9). It is noticed also from these figures that the convergence of the proposed approach (FFA) is promising , we got the results after only 50 iterations.

TABLE I. POWER GENERATION LIMITS COST COEFFICIENT DATA OF COMPARISON OF GENERATING UNITS OF 10-UNIT SYSTEM.

Bus No	Power limit (MW)		Cost Coefficients		
	P_{Gi}^{min} (Mw)	P_{Gi}^{max} (MW)	a_i	b_i	c_i
1	8	72	0.0085	1.50	0
2	10	70	0.0170	2.50	0
3	30	510	0.0085	1.50	0
4	20	400	0.0085	1.50	0
5	15	150	0.0170	2.50	0
6	10	100	0.0170	2.50	0
7	10	100	0.0030	2.00	0
8	15	140	0.0030	2.00	0
9	18	175	0.0030	2.00	0
10	15	140	0.0030	2.00	0
11	0	30	/	/	/
12	0	10	/	/	/

TABLE II. EMISSION CO-EFFICIENT DATA OF GENERATING UNITS OF 10-UNIT SYSTEM.

Bus No	Emission Coefficients				
	α_i	β_i	γ_i	γ_i	λ_i
1	4.091	-5.554	6.490	2.00e-04	2.857

2	2.543	-6.047	5.638	5.00e-04	3.333
3	4.258	-5.094	4.586	1.00e-06	8.000
4	5.326	-3.550	3.380	2.00e-03	2.000
5	4.258	-5.094	4.586	1.00e-06	8.000
6	6.131	-5.555	5.151	1.00e-05	6.667
7	4.091	-5.554	6.490	2.00e-04	2.857
8	2.543	-6.047	5.638	5.00e-04	3.333
9	4.258	-5.094	4.586	1.00e-06	8.000
10	5.326	-3.550	3.380	2.00e-03	2.000

TABLE III. BEST COMPROMISE OUTPUT FOR 10 GENERATOR SYSTEM (CASE 1)

	minimum cost	minimum emission	minimum cost and emission
P_{G1} (MW)	27.651275	34.905620	63.912720
P_{G2} (MW)	10.236654	44.582265	28.630876
P_{G3} (MW)	98.577976	78.694207	150.449182
P_{G4} (MW)	164.521511	134.069683	137.938443
P_{G5} (MW)	25.823325	68.474983	19.607090
P_{G6} (MW)	10.010182	32.812131	17.749961
P_{G7} (MW)	67.760025	51.259948	78.499539
P_{G8} (MW)	129.423035	105.642829	112.362983
P_{G9} (MW)	83.473542	119.680957	23.007701
P_{G10} (MW)	85.693984	33.202681	71.361280
P_{GR1} (MW)	0.00	0.00	0.00
P_{GR2} (MW)	0.00	0.00	0.00
P_D (MW)	684.10	684.10	684.10
P_L (MW)	19.1715	19.3253	19.4198
Cost (\$/h)	1723.830137	1781.153845	1744.324163
Emission (ton/h)	0.454346	0.381361	0.401380
T (s)	0.82813	0.78125	0.81250

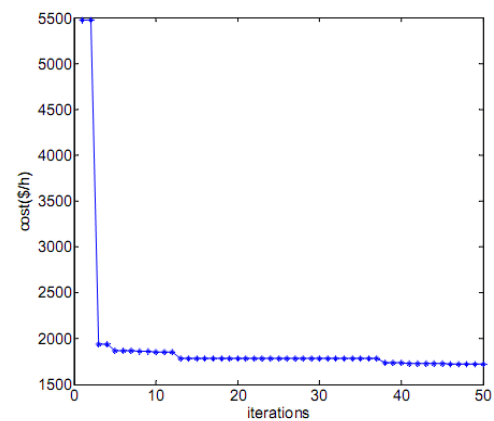


Fig. 2. Convergence characteristic for fuel cost minimization for case 1 (minimum cost)

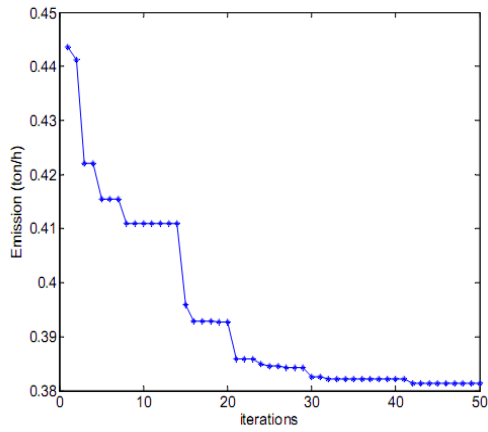


Fig. 3. Convergence characteristic for emission minimization for case 1 (minimum emission)

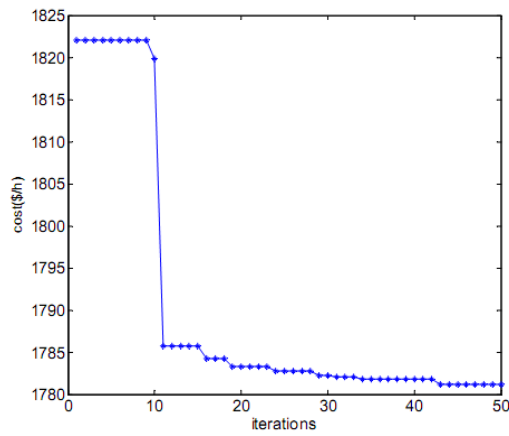


Fig. 4. Convergence characteristic for fuel cost minimization for case 1 (minimum cost and emission)

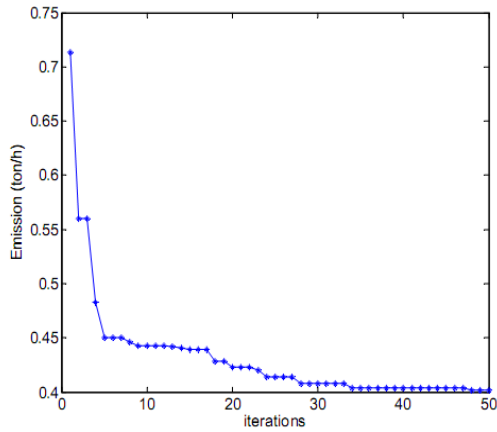


Fig. 5. Convergence characteristic for emission minimization for case 1 (minimum cost and emission)

TABLE IV. BEST COMPROMISE OUTPUT FOR 10 GENERATOR (CASE 2)

	<i>minimum cost</i>	<i>minimum emission</i>	<i>minimum cost and emission</i>
$P_{G1}(MW)$	35.126728	26.927115	44.607584
$P_{G2}(MW)$	40.630506	51.606233	41.527364
$P_{G3}(MW)$	112.232408	81.774188	58.197489
$P_{G4}(MW)$	109.720341	54.829520	116.908146
$P_{G5}(MW)$	23.952401	35.894921	45.133375
$P_{G6}(MW)$	24.829224	67.783741	17.569297
$P_{G7}(MW)$	53.465187	95.082396	15.254955
$P_{G8}(MW)$	122.255830	92.478793	128.300546
$P_{G9}(MW)$	46.207456	84.254893	149.534607
$P_{G10}(MW)$	94.906182	72.301011	45.194946
$P_{GR1}(MW)$	30.000000	30.000000	30.000000
$P_{GR2}(MW)$	10.000000	10.000000	10.000000
$P_D(MW)$	684	684	684
$P_L(MW)$	19.3263	10.2572	18.2283
Cost (\$/h)	1644.965062	1680.608566	1658.962885
Emission (ton/h)	0.362192	0.290030	0.31325
T(s)	0.98438	1.024581	1.01563

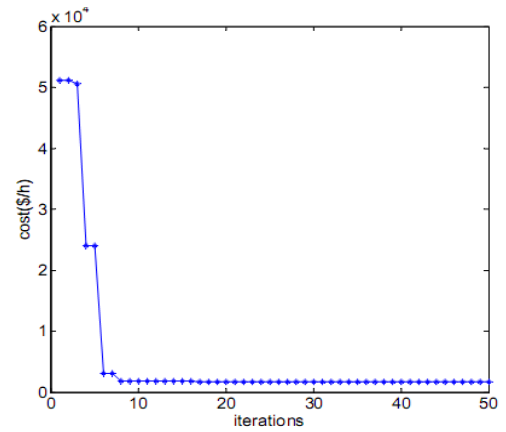


Fig. 6. Convergence characteristic for fuel cost minimization for case 2 (minimum cost)

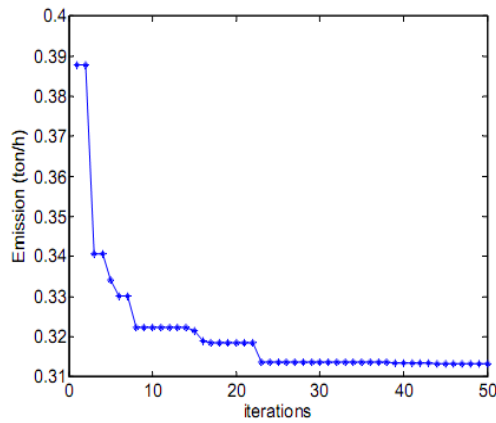


Fig. 7. Convergence characteristic for emission minimization for case 2 (minimum emission)

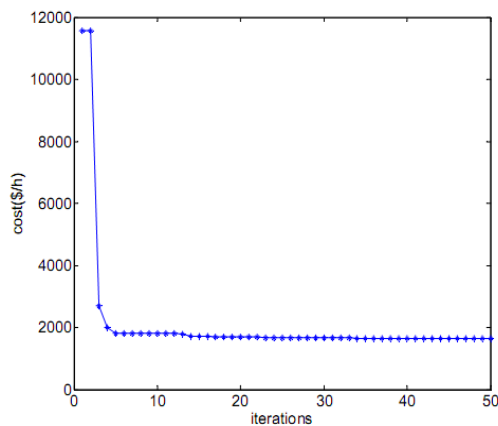


Fig. 8. Convergence characteristic for fuel cost minimization for case 2 (minimum cost and emission)

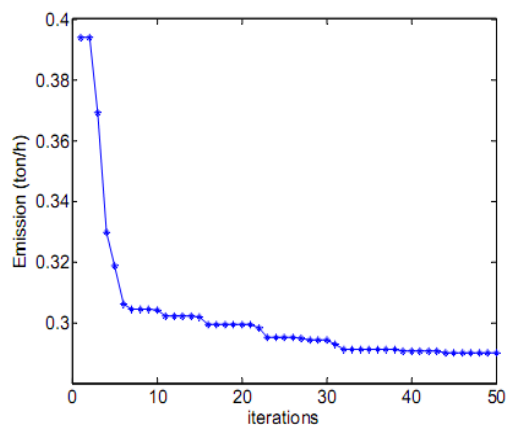


Fig. 9. Convergence characteristic for emission minimization for case 2 (minimum cost and emission)

V. CONCLUSION

Most of the countries are investing in renewable energy technology to meet emission target and increase the share of power from renewable energy sources. our work strengthens the idea and gives a method for the integration of renewable energies in the classical system.

REFERENCES

- [1] Muneer T, Asif M, Munawwar S. Sustainable production of solar electricity with particular reference to the Indian economy. *Renewable and Sustainable Energy Reviews* 2005;9:444-73
- [2] R. Saidur, M.R. Islam, N.A. Rahim, K.H. Solangi, A review on global wind energy policy, *Renewable and Sustainable Energy Reviews* 2010;14: 1744–1762
- [3] Faisal A. Mohamed, Heikki N. Koivo., (2007), Online Management of Micro Grid with Battery Storage Using Multiobjective Optimization, *POWERENG* 2007, April 12-14,
- [4] Nadine May. Eco-balance of a Solar Electricity Transmission from North Africa to Europe. Diploma Thesis, Faculty for Physics and Geological Sciences, Technical University of Braunschweig; 2005
- [5] O. Alsac, J. Bright, M. Prais, and B. Stott, "Further developments in LP-based optimal power flow," *IEEE Transactions on Power Systems*, Vol. 5, 1990, pp. 697-711.
- [6] J. Nanda, D. P. Kothari, and S. C. Srivastava, "New optimal power-dispatch algorithm using Fletcher's quadratic programming method," in *Proceedings of the IEE*, Vol. 136, 1989, pp. 153-161.
- [7] R. D. Zimmerman, C. E. Murillo-Sanchez, and R. J. Thomas, "Matpower's extensible optimal power flow architecture," *Power and Energy Society General Meeting, 2009 IEEE*, July 26-30 2009, pp. 1-7.
- [8] H. W. Dommel, "Optimal power dispatch," *IEEE Transactions on Power Apparatus and Systems*, Vol. PAS93, 1974, pp. 820-830.
- [9] Basu M. Dynamic economic emission dispatch using nondominated sorting genetic algorithm– II. *Electr Power Energy Syst* 2008;30(2):140–9.
- [10] Jiang X, Zhou J, Wang H, Zhang Y. Dynamic environmental economic dispatch using multi-objective differential evolution algorithm with expanded double selection and adaptive random restart. *Int J Electr Power Energy Syst* 2013;49:399–407.
- [11] Zhang R, Zhou J, Mo L, Ouyang S, Liao X. Economic environmental dispatch using an enhanced multi-objective cultural algorithm. *Electr Power Syst Res* 2013;99:18–29
- [12] Basu M. Economic environmental dispatch using multi-objective differential evolution. *Appl Soft Comput* 2011;11(2):2845–53.
- [13] Provas Kumar Roy, Sudipta Bhui, "Multi-objective quasi-oppositional teaching learning based optimization for economic emission load dispatch problem", *Electrical Power and Energy Systems* 53 (2013) 937–948.
- [14] Fraga .H. (2008)., Firefly luminescence: A historical perspective and recent developments, *Journal of Photochemical & Photobiological Sciences*, vol. 7, pp. 146–158.
- [15] Yang .X.S., (2009). Firefly algorithms for multimodal optimization, *Stochastic Algorithms: Foundations and Applications Lecture Notes in Computer Sciences*, vol. 5792, pp. 169–178.
- [16] Yang .X. S., "Firefly algorithm, stochastic test functions and design optimisation, *International Journal of Bio-Inspired Computation*, vol. 2 n. 2, pp. 78–84, 2010.(13)
- [17] S. X. Yang, "Firefly Algorithm", *Engineering Optimization*. Hoboken, New Jersey: Wiley, 2010, pp. 221-230.
- [18] Xin-She Yang, "Firefly Algorithm", *Engineering Optimization: An Introduction with Metaheuristic Applications*, pp 221-230, Wiley, 2010.