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Solution for CEED using Hybrid (Firefly-De) Algorithm

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Abstract: This project develops efficient algorithms by using firefly and differential evolution algorithm to minimize Economic Dispatch, NO_x Emission Dispatch and Combined Economic and Emission Dispatch problems in thermal power plant. The thermal power plants pollute air, soil and water. Due to this, the present energy production processes are not ecologically clean. The combination of fossil fuels gives rise to particulate materials and gaseous pollutants apart from discharge of heat to water courses. The three principal gaseous pollutants, namely carbon-dioxide, oxides of sulfur and nitrogen cause detrimental effects on human beings. This harmful ecological effects caused by the emission of particulate and gaseous pollutants can be reduced by adequate distribution of load between the plants of a power system. But, this leads to a noticeable increase in the operating cost of the plants. For successful operation of the system subject to ecological and environmental constraints, algorithms have been proposed for minimum cost, minimum NO_x emission and combined economic and emission dispatches. These are based upon quadratic type objective function and the solution gives the optimal dispatch directly. In the present work, a price penalty factor is introduced which blends the emission cost with normal fuel cost. This avoids the use of two classes of dispatching and the need to switch over between them.

Index Terms: Firefly Algorithm (FFA), Differential Evolution (DE).

1. INTRODUCTION

The Resource scheduling problem is divided into two stages, the commitment stage and the constrained economic dispatch stages. The OPF constraints that are relevant to the active power such as transmission capacity constraints, different types of emission requirements (i.e. SO2 and NOx), emission caps for certain areas of the system and the total system emission as well as fuel constraints are considered in the formulation of the commitment stage to ensure the feasibility of the constrained economic dispatch stage. In the constrained economic dispatch, constraints corresponding to transmission capacity, load and reserve requirements as well as generating unit limits are incorporated. To obtain fast and efficient solutions, the constrained economic dispatch problem is decomposed into sub problems, each corresponding to constrained economic dispatch of committed units at a given period.

Economic power dispatch is a common problem pertaining to the allocation of the amount of power to be generated by different plants in the system on an optimum economy basis. Some of the states in India expertise severe power shortage for which optimization of fuel costs are not of current interest during peak load periods. But during lean load periods, economic dispatch reduced fuel cost and line losses. The existing energy production processes are not ecologically clean. For instance thermal power plants pollute air, soil and water. The combustion of fossil fuels gives rise to particulate materials and gaseous pollutants apart from discharge of heat to water courses. The particulate materials do not cause a serious problem in air contamination but the three principal gaseous pollutants, namely, carbon-dioxide, oxides of nitrogen and sulfur cause detrimental effects on human beings. So, when distributing load between the stations, the planner should not only strive for minimizing the system generation costs but also take in to account the impact of each station on the environment under a particular load. Minimum cost can no longer be the goal of operation if society is to have a clean atmosphere. Minimum emission dispatching is one method in which all power supplying authorities and consumers have within their grasp to meet the problems of air pollution.

Optimization of cost of generation has been formulated based on classical ELD with emission and line flow constraints. The detailed problem is as follows.
For a given power system network, the optimization cost of generation is given by the following equation:

$$\text{Min } F(P_G) = C_t + h*E(P_G) \text{ \$/hour} \qquad [1.1]$$

$F(P_G)$ = CEED cost in \$/hour
C_t = Total generation cost \$/hour
$E(P_G)$ = Total emission in ton/hour
h= price penalty factor in \$/ton

Bi – objective problem converted into single objective by using penalty factor (h) CEED used to find a generating pattern to minimize generating cost and emission. Generating cost and Emission are function of real power generation.The objective of the project work is to find the minimum generating cost, subjected to equality constraint of power balance equation and inequality constraint of control and depended variables

Several strategies to reduce the atmospheric emissions have been proposed and discussed [1]. These include installation of pollutant cleaning equipment such as gas scrubbers and electrostatic precipitators, switching to low emission fuels, replacement of the aged fuel-burners and generator units with cleaner and more efficient ones.

In the first part of this project, the new conventional algorithm is applied to minimum cost, minimum emission and combined minimum cost and minimum emission. So, the combined economic and emission dispatch gives a closer reduced cost compared to separate minimum cost and minimum emission dispatches. In the second part of the project, hybrid algorithm is implemented to solve the above mentioned three dispatch models and the results are compared with the solutions obtained from the firefly algorithm and differential evolution algorithm . The results proved that the hybrid Algorithm approaches provide a global optimal solution than the conventional method.

1.1 ECONOMIC AND EMISSION DISPATCH

The EED problem is a highly nonlinear and a multimodal optimization problem. Therefore, conventional optimization methods that make use of derivatives and gradients, in general, not able to locate or identify the global optimum. On the other hand, many mathematical assumptions such as analytic and differential objective functions have to be given to simplify the problem. Furthermore, this approach does not give any information regarding the trade-offs involved. Hybrid algorithm is used to minimize the both economic and emission dispatch problem and the hybrid algorithm such as differential evolution and firefly algorithm.

1.2 FIREFLY ALGORITHM

Thousands of fireflies lives together and communicate them with flashing light. They communication has two fundamental functions they are attract prey and attract mating partner**.** Firefly is unisex and attracted by another firefly in spite of sex Firefly moves towards brightest if no brighter one then firefly moves randomly in solution space Brightness of firefly is decreased with increased distance. Main reasons for reduction in attractiveness are absorption factors in nature are implemented by using absorption coefficient.

1.3 DIFFERENTIAL EVOLUTION

Differential Evolution was first proposed over1994-1996 by Storn and Price at Berkely. The ability of DE is to optimize nonlinear, non-continuous and non-differential real world problems. Compare to other population based Meta heuristic algorithms, DE emphasis on Mutation than Recombination or Crossover. It mutate vector with a help of randomly selected a pair of vector in the same population.

The mutation guides the vector towards the global optimum. The distribution of the difference between randomly sampled vectors is determined by the distribution of these vectors. The distribution of the vector is mainly determined by the corresponding objective function. This enables DE function robustly and more as a generic global optimizer.

DE works on population of vectors, where vector is a group of decision variables. Selection of decision variable is based on their impact on the problem to be optimized. These decision variables need to be encoded and set of initial values are chosen from the solution space. By mutation and recombination new vectors are created. The selection process selects the best vectors based on the selection criterion. DE is inherent minimization problem and suitable for cost minimization of OPF problem.

2. POWER PLANT EMISSIONS & DISPATCHING STRATEGIE

2.1 INTRODUCTION

The generation of electricity from fossil fuel releases several contaminants, such as sulfur oxides, nitrogen oxides and carbon dioxide, in to the atmosphere. Reducing atmospheric pollution will be one of the major challenges for electric utilities over the next few decades. The US Clean Air Act Amendments mandates a significant reduction of NO_x and SO_2 emissions from 1980 levels [8]. The 1990 amendments to the Clean Air Act have renewed emphasis on emission dispatching strategies. The emission dispatching strategies developed in the 1970's can be divided into two categories:

(1) Methods minimizing emissions and

(2) Methods minimizing cost subject to emission constraints.

Each will play a role in the future. The first category includes both minimization of stack exit emissions and ground level concentrations. The first technical papers published on emission dispatching [9] [10] are related to the first category. Some algorithms minimize total emissions while others reduce emissions in a certain geographical region, or at a point, to a specified value. This later group requires the use of an emission dispersion model, which is generally considered both inaccurate and computationally intensive. Costs that are minimized include various combinations of: (1) fuel cost (2) Emission taxes, and (3) emission worth. Both single and multiple objective [11] [12] approaches have been developed.

2.2 Power Plant Emissions

The two primary power plant emissions from a dispatching perspective are sulfur dioxide (SO_2) and nitrogen oxides (NO_x). Figure 1 will aid in the following explanation. SO_2 is dependent on the amount of fuel burned. The sulfur enters the boiler as a part of the fuel.

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During the combustion process, some of the sulfur unites with oxygen from the fuel and the combustion air to form SO_2. The remaining sulfur becomes a part of the bottom ash in the boiler. If stack gas clean up equipment (a scrubber for example) is present, most of the SO_2 is removed. The remaining SO_2 exits the stack as an emission. Fuel blending, fuel switching and scrubbers are the primary methods for reducing the amount of SO_2 emitted.

NO_x emissions are more complex. There are two sources of nitrogen that combine with oxygen from the fuel and the combustion air to produce NO_x. The first source is nitrogen in the air that produces an emission called thermal NO_x. The second source is nitrogen in the fuel that produces an emission called fuel NO_x. The total NO_x produced during combustion is the sum of the thermal NO_x and the fuel NO_x. In coal, there is no apparent correlation between the amount of fuel-bound nitrogen and the fuel NO_x produced [13].

Although NO_x is usually composed of 95% NO and 5% NO_2, normally NO_x is calculated as if it were 100% NO_2 [13]. NOx output is much more difficult to predict than SO_2, because of the impact of the amount of excess air and the combustion temperature profile throughout the boiler. Stack gas clean up equipment may remove a portion of the NO_x from the stack gas before it exits the stack. Low NO_x burners, temperature control, fuel gas recirculation, selective catalytic reduction, and turning of fuel air ratios among the different burners are the primary methods for reducing the amount of NO_x produced.

Another by-product of the combustion of coal is ash. The resultant ash either becomes a part of the bottom ash or is contained in the stack gas as fly ash. Furnace type and coal type determines how much ash there is and how much of that becomes fly ash. Electrostatic precipitators, dust collectors, fabric filters and wet scrubbers have been used successfully to remove fly ash from the stack gas. Although not usually considered in emission dispatching, the amount of fly ash emitted may be calculated and presented along with the corresponding SO_2 and NO_x values.

2.3 Emission Models

Emission models may be classified as either operation-related or startup related, which include startup, thermal cooling and banking. The most recent amendments to the Clean Air Act will require inclusion of startup related emissions.

Emission dispatching techniques require operation-related emission output models that depend on unit's output. Two possible model types exits. The first (an input-output model) is based on fuel consumption while the second (an output-output model) is based on stack emission measurements. The stacks of existing power plants are not currently instrumented to measure the emissions of SO_2 and NO_X. Thus, models based on fuel consumption will initially be required. As instrumentation is installed as required by the Clean Air Amendments, modeling will be based on stack emission measurements because of its greater accuracy.

For SO2, the input-output may be defined as the amount of fuel consumed as a function of power output multiplied by a constant. This constant includes

(1) The percent of sulfur in the fuel,
(2) The high heating value of the fuel,
(3) The percent of fuel that becomes bottom ash as opposed to becoming SO_2 in
the stack gas,
(4) The ratio of molecular weight of SO_2 to sulfur, and
(5) The efficiency of stack gas cleanup equipment present.

In equation form, this may be represented as

$$SO_{2EO} = (0.01 * SC_{FC}) * (F(p) * 10^6) / (HHV * 2000)$$
$$(64/14) * (0.01 * SGC_{SO2}) (1.01 * EFF_{SO2}) \qquad \ldots(2.1)$$

where SO_{2EO} is actual SO_2 stack output in tons per hour, F (p) is fuel consumption in millions of Btu's per hour as a function of unit's net power output in megawatts, SC_{FC} is sulfur content of the fuel in percent, SGC_{SO2} is stack gas component of SO_2 in percent as opposed to the bottom ash content, EFF_{SO2} is stack gas clean up equipment SO_2 efficiency in percent and HHV is high heating value of the fuel in Btu's.

For fuel NOx, a similar input-output model may be defined and represented as

$$NOXF_{EO} = (0.01 * NC_{FC}) * (F(p) * 10^6) / (HHV * 2000)$$
$$(46/14) * (0.01 * SGC_{NOX}) \qquad \ldots(2.2)$$

where $NOXF_{EO}$ is fuel NO_X production in tons per hour before any stack gas clean up equipment, NC_{FC} is nitrogen content of the fuel in percent, SGC_{NOX} is stack gas component of NO_X in percent as opposed to the bottom ash content.

Thermal NOx determination is more complex as it depends on

(1) combustion time,
(2) combustion temperature, and
(3) the nitrogen and oxygen concentrations.

Hence, the present concentrates on nitrogen oxides (NO_x),and here thermal NO_X is assumed to be dependent on the power output of the unit. But with the stack gas clean up equipment scrubber, most of the SO_2 is removed.

2.4 Dispatching Strategies

Dispatching algorithms seek to minimize some objective function subject to a set of constraints. Ignoring emission considerations, the most common objective function to minimize is the total operating cost. The corresponding set of constraints includes:

(1) The total generation must equal the total system load plus any transmission losses, and

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(2) Each individual generating unit must operate between minimum and maximum power output limits.
This type of optimization is commonly called economic dispatch and may be summarized mathematically as

$$\text{Minimize: } \sum_{i=1}^{N} (F_i (P_i)*FP_i \qquad \text{[Eq.2.3]}$$

Subject to:

$$\sum_{i=1}^{N} P_i=P_{load}+P_{losses} \qquad \text{[Eq.2.4]}$$

$$P_{iMin}<=P_i<=P_{iMax} \quad i=1, 2\text{----}, N \qquad \text{[Eq.2.5]}$$

Transmission losses may be represented in one of four ways:
(1) Being ignored or considered as included in the system load,
(2) Being represented by a single transmission loss polynomial that depends on the daily peak load and is used with constant penalty factors for each generating unit,
(3) Being represented by the transmission loss matrix equation that used with loss matrix penalty factors or reference bus penalty factors, and
(4) Being represented by a full power flow network representation.

The inclusion of emission considerations in dispatch scheduling modifies either (1) objective function, or (2) the set of constraints (including addition of more constraints). The various single control area emission strategies for a single period to be discussed are summarized in.These dispatching strategies are ignored since the 1990 amendments to the Clean Air Act place limits on emission at the stack exit.

3. FORMULATION OF DISPATCHING STRATEGIES

3.1 PROBLEM FORMULATION

This section develops the formulation of objective function and constraints for economic dispatch, minimum NO_X emission dispatch and combined economic and emission dispatch methods [1].

3.1.1 Economic Dispatch

The fuel cost of a thermal plant can be regarded as an essential criterion for economic feasibility. The fuel cost curve is assumed to be approximated by a quadratic function of generator active power output as

$$C_t = \sum_{i=1}^{ng} \alpha_i + \beta_i P_{Gi} + \gamma_i P_{Gi}^2 + \left|\zeta_i \sin\left[\lambda_i\left(P_{Gi}^{\min} - P_{Gi}\right)\right]\right| \qquad \text{[Eq.3.1]}$$

The economic dispatch problem is defined as to minimize

$$C_t = \sum_{i=1}^{ng} \alpha_i + \beta_i P_{Gi} + \gamma_i P_{Gi}^2 + \left|\zeta_i \sin\left[\lambda_i\left(P_{Gi}^{\min} - P_{Gi}\right)\right]\right| \qquad \text{[Eq.3.2]}$$

where
i=1,2,3………..n

$F_t$is the total fuel cost in the system ($/hr), P_{Gi} the power output of i[th] generating unit (MW), α_i, β_i, γ_i the fuel cost coefficients of i[th] unit, and N is the number of thermal units. This is subject to

(1) The operating constraints, that is, plant capacity constraints

$$P_{Gi(\min)} \le P_{Gi} \le P_{Gi(\max)}$$
$$i = 1,2,3\text{........}n \quad \text{......... [Eq.3.3]}$$

Where $P_{Gi(min)}$ is the minimum power output of i[th] unit (MW), and $P_{Gi(max)}$ the maximum power output of i[th] unit (MW);

(2) The system demand constraint

$$\sum_{i=1}^{N} P_i = P_D + P_L \qquad \text{[Eq.3.4]}$$

Where P_D is the total system power demand (MW), and P_L the total transmission losses (MW) calculated by average loss formula coefficients.

3.1.2 Minimum NO_X Emission Dispatch

The economic dispatch is well recognized and will minimize total fuel cost while meeting total load plus transmission losses and generator limit constraints. Emission constraints may be violated. Minimum emission strategy can be implemented by direct substitution of an incremental emission curve for an incremental cost curve in a conventional economic dispatch algorithm.

The amount of NOx is given [1] [2] [3] as a function of generator output, that is, the sum of quadratic and exponential functions. This complex function is successfully approximated into a simple quadratic function of the form

$$E(P_G) = \sum_{i=1}^{ng} 10^{-2}(a_i + b_i P_{Gi} + c_i P_{Gi}^2) + d_i \exp(e_i P_{Gi}) \qquad \text{[Eq.3.5]}$$

where N is the number of thermal units and E_i the NO_X emission of i[th] unit (ton/hr).
The minimum NOx emission dispatch problem is defined as to minimize

$$E(P_G) = \sum_{i=1}^{ng} 10^{-2}(a_i + b_i P_{Gi} + c_i P_{Gi}^2) + d_i \exp(e_i P_{Gi}) \qquad \text{[Eq.3.6]}$$

Where E_i is the total NO_x emission (ton/hr), P_{Gi} the power output of the i[th] generator (MW); a_i,b_i,c_i, d_i, e_i the NO_xemission coefficients of i[th] unit and N the number of thermal units. This is subject to the generating unit constraint Eq.3.3 & load constraint Eq.3.4.

The minimum NO_X emissions are possible by proper generator scheduling which may cause a further fuel expense and the increase in operating cost.

3.1.3 Combined Economic & Emission Dispatch

In minimizing total emission, local constraints may become intolerable, necessitating a shift away from minimum total emission to meet local constraints. So the problem of choosing the least cost generating schedule with environmental objectives still remains and so a combined economic and environmentally satisfied dispatch method is rather sensible than separate minimum emission as well as cost dispatches.

The NOx emissions of the thermal units are given by

$$E(P_G) = \sum_{i=1}^{ng} 10^{-2}(a_i + b_i P_{Gi} + c_i P_{Gi}^2) + d_i \exp(e_i P_{Gi}) \quad \text{[Eq.3.7]}$$

The emissions are converted into monetary units by inventing a price. That is, the emission costs are blended with the normal fuel costs with the use of the price factor defined as the price penalty factor h. This avoids the problem of dispatching and need to switchover between them. After the introduction of the price penalty factor, the total operating cost of the system is the cost of fuel plus the implied cost of NOx emission. So, the combined economic emission dispatch problem is defined as to minimize

$$\text{Min } F(P_G) = C_t + h*E(P_G) \text{ \$/hour} \quad \text{[Eq.3.8]}$$

where h = price penalty factor (\$/ton), which is the cost incurred to reduce 1 kg of NO_x emission output. This is subject to the generating unit constraint Eq.3.3 & load constraint Eq.3.4.

3.2 Operating Constraints

The active power generation of the generators is restricted to lie within the given minimum and maximum limits which are determined by the permissible extremes of operating conditions. Pi must fall within the minimum and maximum limits.

3.2.1 Lower Generation Limit

At optimum dispatch, if the optimum generation of the j^{th} plant goes below its lower limit P_{jmin},then the j^{th} plant is allowed to generate power equal to P_{jmin}.The remaining (n-1) plants are allowed to share the power P_D' in Eq.3.14 where

$$P_D' = P_D \; (P_{jmin} - P^2_{jmin} B_{jj}) \quad \text{....... [Eq.3.9]}$$

The values of σ_1, σ_2 and σ_3 are calculated for the remaining (n-1) plants excluding the j^{th} plant to give a new value of λ.

3.2.2 Upper Generation Limits

At optimum dispatch, if the optimum generation of the j^{th} plant goes above its upper limit P_{jmax}, then the j^{th} plant is allowed to generate power equal to P_{jmax}.The remaining (n-1) plants are allowed to share the power P_D'

$$P_D' = P_D \; (P_{jmax} - P^2_{jmax} B_{jj}) \quad \text{...... [Eq.3.10]}$$

The values of σ_1, σ_2 and σ_3 are calculated for the remaining (n-1) plants excluding the jth plant to give a new value of λ.

3.3 PRICE PENALTY FACTOR

A price penalty factor (h) is a price factor which blends the emission costs with the normal fuel costs. This avoids the use of two classes of dispatching and need to switch over between them. After the introduction of the price penalty factor, the total operating cost of the system is the cost of fuel plus the implied cost of NO_x emission.

This value is calculated as follow for a system operating with a load of PD MW

(1) The average cost of each generator is evaluated at its maximum output, that is,

$$\frac{F_i(Pg_{i2\max})}{Pg_{i\max}} = \frac{\alpha_i Pg_{i\max} + \beta_i Pg_{i\max} + \gamma_i}{Pg_{i\max}}, \$/Mwh \quad \text{[Eq.3.11]}$$

(2) The average NOx emission of each generator is evaluated at its maximum output, that is,

$$\frac{E_i(Pg_{i\max})}{Pg_{i\max}} = \frac{a_i Pg_{i2\max} + b_i Pg_{i\max} + c_i}{Pg_{i\max}}, ton/Mwh \quad \text{[Eq.3.12]}$$

(3) By dividing the average cost of each generator by its average NOx emission, the price penalty factor is,

$$\frac{F_i(Pg_{i\max})/Pg_{i\max}}{E_i(Pg_{i\max})/Pg_{i\max}} = \frac{\alpha_i Pg_{i\max}{}^2 + \beta_i Pg_{i\max} + \gamma_i)}{a_i Pg_{i\max}{}^2 + b_i Pg_{i\max} + c_i)} = h_i, (\$/ton) \quad \text{Eq.3.13]}$$

(4) Obtained h_i is arranged in ascending order,

(5) The maximum capacity of each unit ($P_{gi\ max}$) is added one at a time, starting from the smallest h_i unit, until $\sum P_{i\max} \geq P_D$.

(6) At this stage, h_i associated with the last unit in the process is the price penalty factor g (\$/ton) for the given load.

It has been tested and found that the price penalty factor works out well for all load levels of the system. Once the value of h is fixed the optimization is similar to that discussed in the above section.

A numerical example of the computational procedure of propsed modified price penalty factor is explained as follows:

i.The ratio between the maximum fuelcost and emission cost of three generating units were found and arranged in ascending order

h_i = [h_3 h_2 h_1]

h_i = [1.1909 2.6221 3.1057]

ii.The corresponding maximum limits of generating units are given by
$P_{i,max}$ = [180 150 200]

iii.m is formed by adding maximum capacity of the units one by one
m = [180 330 330]

iv.For a load P_0 MW, add the elements of m, one at a time, starting from the smallest $h_i$unit until $\sum m > P_D$.
For P_D = 259MW, (180+330)MW > 259MW

v. The modified price penalty factor $h_m$is computed by interpolating the values of h_i, for last two units by satisfying the corresponding load demand.
i.e,h_m = 1.1909 + ((2.6221 – 1.1909)/(330 – 180)*(259 - 180)
therefore h_m = 1.9446

4. FIREFLY ALGORITHM

4.1 FIREFLY INTRODUCTION

Rhythmic flashing light of fireflies induce to develop firefly algorithm by Xin-She Yang at Cambridge University in 2007. Thousands of fireflies lives together and communicate them with flashing light. They communication has two fundamental functions they are attract prey and attract mating partner. Communication is established based on frequency and duration of light. Mating partners produce synchronised flash lights which brings together for mating. Physics inverse square law states that intensity of light decreases with distance from the light source. This makes the visual of firefly light is limited to some distance.

4.2 BASIC DESCRIPTION

Firefly algorithm (FA) mimics firefly's intelligent technique to find optimal solution for engineering problems. For optimization flashing light is formulated based on objective function. Brightest firefly is the most optimal solution for the problem under consideration. A firefly is set of control variables of the problem considered. Brightness of the firefly is calculated by evaluating the objective function to be optimized. This algorithm used for maximization or minimization problem. FA has idealization as compared to natural firefly, they are

- Firefly is unisex and attracted by another firefly in spite of sex
- Firefly moves towards brightest if no brighter one then firefly moves randomly in solution space
- Brightness of firefly is affected by problem nature

General form FA optimization is a maximization of objective function subjected to constraints. FA moves fireflies towards global optimal solution spot through iteration by iteration. A firefly is a set of control variable and its light intensity is objective function or fitness value of the firefly. The process of FA are create or initialize fireflies, find brightness of firefly, move each firefly towards brightest one, find global brightest to give optimal solution. General form of FA optimization is maximize objective function, subjected to equality function and inequality function as given below,

Minimize $C_t = \sum_{i=1}^{NG} f_i(P_G)$ \$/hr (4.1)

Subject to: $g(|V|, \delta)=0$ (4.2)

$X_{min} \leq X \leq X_{max}$ (4.3)

Where,

C_t is total generating cost in \$/hr
$g(|V|, \delta)$ is power flow balance equation
X is a set of control variable
X_{min}, X_{max} are minimum and maximum value of control variable

4.3 FIREFLY BASED CEED

To optimize CEED problem the control variables, real power generation, generator bus voltages and transformer tap position are considered. The limits on these control variables form prime constraints in addition to power balance condition. Actual values of these control variables are used to form a firefly. These fireflies form population and initialized randomly from the solution space and then evolution is carried out using its brightness and distance from brightest firefly.

4.3.1 Encoding

Encoding is the process of converting set of control variables in CEED into firefly for optimization. Ability of FA is to operate on floating point and mixed integer makes ease of encoding. Final iteration of FA gives global bright firefly which is the optimal solution of CEED. For the evolution and better convergence fitness function is most important as follows.

4.3.2 Fitness function

An appropriate fitness function (brightness) is vital for evolution and convergence of FA. It is an CEED objective functions and penalty functions if any. FA evaluates brightness for each firefly in the population. Objective function value for a firefly is called brightness of the firefly. FA makes a firefly to move towards brighter firefly in the population. Distance moved and brightness of each firefly is calculated and best firefly (global best) is calculated in the iteration. Improvement in solution is achieved iteration by iteration and final iteration provides global best optimal solution to CEED.

4.3.3 Attractiveness

Firefly moves towards more attractiveness. This attractiveness of considered firefly with others is calculated using the function. This attractiveness is decreases with increase in distance between fireflies. Main reasons for reduction in attractiveness are absorption factors in nature are implemented by using absorption coefficient. This function is monotonically decreasing function given below the equation 4.4.

$$\beta = \beta_0 \exp(-\gamma r^2) \qquad (4.4)$$

Where,
β is attractiveness of a firefly
β_0 is initial attractiveness
γ is absorption coefficient
r is distance between fireflies

4.3.4 Distance
Distance between fireflies i and j is calculated using Cartesian distance as given below the equation 4.5

$$r_{ij} = \| x_i - x_j \| = \sqrt{\sum_{k=1}^{d} (x_{i,k} - x_{j,k})^2} \qquad (4.5)$$

In 2-dimensional solution space the distance between i and j fireflies may calculated as follows the equation 4.6

$$r_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \qquad (4.6)$$

4.3.5 Movement
Movement of i^{th} firefly towards j^{th} brighter firefly is based attractiveness and distance between them as given below

$$x_i^{k+1} = x_i^k + \beta_0 * \exp(-\gamma r^2) * (x_j^k - x_i^k) + \alpha * \varepsilon_i \qquad (4.7)$$

Where the left side first term is initial position of i^{th} firefly, second term gives attractiveness towards j^{th} firefly and third term introduce random movement in i^{th} firefly. Initial attractiveness β_0 is taken as 1.0; absorption coefficient γ is taken as 0.9. Randomising coefficient α rang in between 0 and 1, in this work it is taken as 0.2; ε_i is randomization vector ranges from 0 to 0.5.

4.3.6 Stopping criteria
Fireflies moves randomly and try to attract towards brighter firefly. FA improves problems' solution iteration by iteration and the iteration has to be stopped either the problem is converged or iteration reached its maximum value. Stopping of iteration is important to provide solution for time complexity. In this project work maximum number of 100 iterations is considered as stopping criteria.

4.4 ALGORITHM FOR FIREFLY ALGORITHM
Step 1: Firefly is a set of control variables in CEED
Step 2: Initialise fireflies in the population within solution space
Step 3: CEED objective function is used to find brightness of firefly
Step 4: Attractiveness of firefly with other fireflies is calculated
Step 5: Distance between fireflies is calculated
Step 6: firefly i is moved towards firefly j using equation 4.7
Step 7: Rank the fireflies and find the current global best

4.5 MERITS & LIMITATIONS OF FIREFLY ALGORITHM
FA has advantages over other optimization techniques some of the merits of FA are listed below,

- FA is promising intelligent algorithm to find global optima
- Automatic subdivision and random reduction.
- Ability to solve complex function optimization
- Population based search technique
- Objective fitness function may be static or non-stationary
- Solves nonlinear, multimodal problems
- Solves continuous or discontinuous functions

FA has some limitation they are
- Large population size makes slower convergence
- Knowledge on problem domain is essential
- Mutation is not present in FA

Despite the limitations, FA is one of the most efficient algorithms in modern optimization to solve nonlinear, non convex and discontinuous optimization problem.

5. DIFFERENTIAL EVOLUTION

5.1 INTRODUCTION
Differential Evolution was first proposed over1994-1996 by Storn and Price at Berkely . The ability of DE is to optimize nonlinear, non-continuous and non-differential real world problems. Compare to other population based Meta heuristic algorithms, DE emphasis on Mutation than Recombination or Crossover. It mutate vector with a help of randomly selected a pair of vector in the same population. The mutation guides the vector towards the global optimum. The distribution of the difference between randomly sampled vectors is determined by the distribution of these vectors. The distribution of the vector is mainly determined by the corresponding objective function. This enables DE function robustly and more as a generic global optimizer. DE works on population of vectors, where vector is a group of decision variables. Selection of decision variable is based on their impact on the problem to be optimized. These decision variables need to be encoded and set of initial values are chosen from the solution space. By mutation and recombination new vectors are created. The selection process selects the best vectors based on the selection criterion. DE is inherent minimization problem and suitable for cost minimization of OPF problem.

5.2 BASIC DESCRIPTION
DE has good convergence characteristic and use real value control variables hence no need of encoding and decoding. Set of control variables which decide problem solution forms a vector. Set of vector forms population, evolves iteration by iteration to converge into optimal solution. Random variation in vectors used for the evolution. The

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basic operations in DE are encoding real world problem into DE optimization problem, mutation, recombination and selection. DE select a vector called target vector and it undergone mutation and recombination process results trail vector. Selection procedure selects either target or trail vector based on their fitness. General form of DE optimization is given below,

Minimize $C_t = \sum_{i=1}^{NG} f_i(P_G)$ \$/hr (5.1)

Subject to: $g(|V|, \delta)=0$ (5.2)

$X_{min} \leq X \leq X_{max}$ (5.3)

Where,

C_t is total generating cost in \$/hr

$g(|V|, \delta)$ is power flow balance equation

X is a set of control variable

X_{min}, X_{max} are minimum and maximum value of control variable

5.3 DE BASED OPF

To optimize OPF problem the control variables, real power generation, generator bus voltages and transformer tap position are considered. The limits on these control variables form prime constraints in addition to power balance condition. Actual values of these control variables are used in vectors. Vectors form population and initialized randomly from the solution space and then evolution is carried out using mutation and recombination and selection process.

5.3.1 Encoding

Encoding is the process of converting set of control variables in OPF into vector of DE optimization problem. Ability of DE is to operate on floating point and mixed integer makes ease of encoding. Final value of vector gives optimal values of control variables is the optimal solution of OPF. For the evolution and better convergence fitness function is most important as follows.

5.3.2 Fitness Function

An appropriate fitness function is vital for evolution and convergence of DE. It is an OPF objective functions and penalty functions if any. DE evaluates fitness function for each vector in the population. Objective function value for a vector is called fitness for the vector. DE generate a trail vector for a target vector using mutation and recombination, greater fitness vector among target and trail vector is considered for next generation.

5.3.3 Mutation

Mutation is emphasised than recombination. The objective of mutation is to enable search diversity in the parameter space as well as to direct the existing vectors with suitable amount of parameter variation in a way that will lead to better results at a suitable time. It keeps the search robust and explores new areas in the search domain. Target vector is selected based on fitness function to find mutated vector by using randomly selected vector from the population other than target vector. Four types of commonly used mutation are

DE/rand/1/ bin: $X_{r1}^{mutated} = X_{r1}+SF*(X_{r2} – X_{r3})$ (5.4)

DE/rand/2/bin: $X_{r1}^{mutated} = X_{r1}+SF*(X_{r2} – X_{r3})+SF*(X_{r4} – X_{r5})$ (5.5)

DE/best/1/bin: $X_{r1}^{mutated} = X_{best}+SF*(X_{r1} – X_{r2})$ (5.6)

DE/best/2/ bin: $X_{r1}^{mutated} = X_{best}+SF*(X_{r1} – X_{r2})+SF*(X_{r3} – X_{r4})$ (5.7)

Where,

X_{r1} is target vector

$X_{r1}^{mutated}$ is mutated vector

X_{best} is the best optimal solution in the population

SF is scaling factor

r1 to r5 are random vector position in population

$r1\neq r2\neq r3\neq r4\neq r5$

First two mutation rules given in equation 5.4 and 5.5 are called random vector mutation rule, next two mutation rule are called best vector based mutation rule. Appropriate scaling factor should be decided based on problem domain and its range from 0 to 1. High value of scaling factor may decrease in convergence speed but escapes from local minima.

Equation 5.4 is used to generate mutated vector for target vector using target vector, scaling factor and other two randomly selected vectors from the population. To induce more diversity four more random vectors are used as given in equation 5.5. In these two equation target vector and other randomly selected vectors are used. To reinforce best vector in the population equations 5.6 and 5.7 are used. Equation 5.6 makes diversity from the best vector using scaling factor, target vector and one randomly selected vector in the population. Equation 5.7 uses best vector, scaling factor, target vector and three more randomly selected vectors to generate mutated vector. In this work scaling factor is taken as 0.7.

5.3.4Recombination

Recombination or crossover generates trail vector from target and mutated vector. The name recombination is most appropriate since it recombines either mutated or target vector particles (control variables) based on crossover constant. This process reinforces prior successes in the current population. Two types of commonly used recombination are Binomial recombination and Exponential recombination. Binomial recombination is simplest and most frequently used recombination. CR is crossover constant ranges from 0 to1. In this work crossover constant CR is taken as 0.2. Large value of CR speeds up convergence and low value is good for separable problem.

$$X^{trail} = \begin{cases} X^{mutated} \ if \ (rand) \leq CR \\ X^{target} \ if \ (rand) > CR \end{cases} \quad (5.8)$$

X1	rand (1) > CR	X1		Y1
X2		Y2	rand (2) ≤ CR	Y2
X3	rand (3) > CR	X3		Y3
X4		Y4	rand (4) ≤ CR	Y4
X5		Y5	rand (5) ≤ CR	Y5
X6	rand (6) > CR	X6		Y6

Figure 6.1 Binomial mutation rule representation

5.3.5 Selection

One to one selection process is used in DE, this process decides either same vector (target) is to keep or trail vector is to use for next iteration. X is a vector, and k represents iteration number. X^k is target vector in current population and X^{k+1} is a selected vector for next iteration. For initial start, vectors are initialised by random values of control variables in the solution space using the equation 6.9 and rand (0, 1) is the function generates a random number in between 0 and 1. Fitness of target vector and trail vector is computed using fitness function. Target vector is replaced by trail vector if the fitness of trail vector is greater than the target vector. The condition for selection is given in equation 5.10 below.

$$X^0 = X_{min} + rand(0,1)*(X_{max} - X_{min}) \quad (5.9)$$

$$X^{k+1} = \begin{cases} X^{trail} & if \; f(trail) < f(target) \\ X^{target} & if \; f(target) \le f(trail) \end{cases} \quad (5.10)$$

Selection process is repeated for every vector in the population to maintain population size same for all iterations.

5.3.6 Stopping criteria

DE improves problems' solution iteration by iteration and the iteration has to be stopped either the problem is converged or iteration reached its maximum value. Stopping of iteration is important to provide solution for time complexity. In this project work maximum number of 100 iterations, is considered as stopping criteria.

5.4 ALGORITHM FOR DIFFERENTIAL EVOLUTION

The procedure for DE to solve OPF is given below

Step 1: Control variables of OPF is selected as particles of a vector

Step 2: Initialise vectors in the population within solution space

Step 3: OPF objective function is taken as fitness function of DE

Step 4: Target vector is selected and mutated to get mutated vector

Step 5: Crossover is done on mutated vector to get trail vector

Step 6: Selection process decides existence or replacement of target vector with trail vector

Step 7: Next iteration population is generated using selection process

Step 8: Repeat step 4 to step 7 till stopping criterion is satisfied

Step 9: Print the optimal result after stopping criterion is satisfied

5.6 MERITS & LIMITATIONS OF DIFFERNTIAL EVOLUTION

DE has advantages over other optimization techniques some of the merits of DE are listed below,

- DE is a minimizing optimization problem
- Ability to solve complex function optimization
- Objective fitness function may be static or non-stationary
- Solves linear or nonlinear functions
- Solves continuous or discontinuous functions

DE has some limitation they are

- Large population size makes slower convergence
- Low value of scaling factor may struck to local minima
- Low value of crossover constant decreases convergence speed

Despite the limitations, DE is one of the most efficient algorithms in modern optimization to solve nonlinear, non convex, discontinuous and noisy optimization problem.

5.7 CONCLUSION

DE is efficient minimization optimization intelligent algorithm, emphasis mutation and converges to global optimal value. DE is vector based algorithm and control variables may be used as real values. Selection of vector particle, population size, scaling factor and crossover constant are important for good convergence. Control variables values are taken as real values, objective function of OPF is taken as fitness function of DE. In this chapter DE implementation is explained using algorithm and flowchart. DE replacement scheme of target vector is inferior hence firefly algorithm is used to solve OPF in next chapter.

6. RESULTS AND GRAPHS

6.1 GENERAL

This chapter deals with complete explanation of MATLAB. In this chapter complete analysis of MATLAB and it is explained. The waveforms obtained in MATLAB are shown in table.

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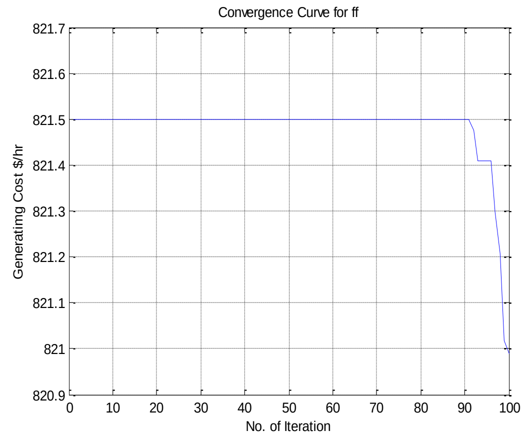

Fig.6.3.1 Economic dispatch for FFA

From this graph economic cost is identified and the generating pattern is given below in the table 6.3.1

Table 6.3.1 Economic dispatch for FFA

S. No.	Generator Bus	Generation (MW)	Min. Limit (MW)	Max. Limit (MW)
1	1	214.754	50	200
2	2	28.3389	20	80
3	5	17.1237	15	50
4	8	11.3221	10	55
5	11	11.3221	10	30
6	13	13.3221	12	40

Generation Cost = 820.988 $/Hr
Emission = 0.238064 ton/Hr
CEED Cost = 820.988 $/Hr

From the table 6.3.1 shows the generating cost is **820.988 $/Hr**

6.3.2 Emission Dispatch for Firefly Algorithm

Emission dispatch for firefly algorithm graph shows the emission value for generation and table value is detailed discussed and the voltage distribution is also explained in the table 6.3.2 and the graph is shown in the fig 6.3.2

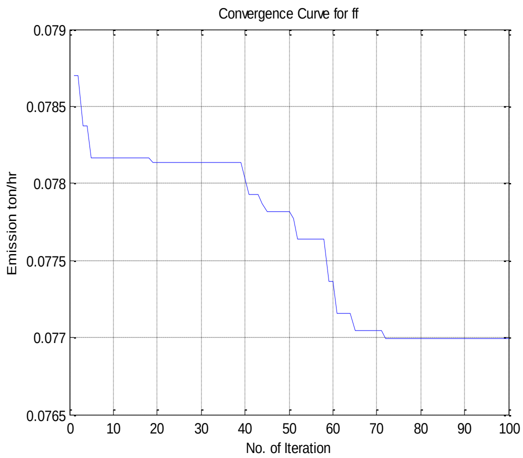

Fig.6.3.2 Emission dispatch for FFA

Table 6.3.2 Emission dispatch for FFA

S. No.	Generator Bus	Generation (MW)	Min. Limit (MW)	Max. Limit (MW)
1	1	92.5207	50	200
2	2	70.9999	20	80
3	5	24.4567	15	50
4	8	47.1996	10	55
5	11	15.4273	10	30
6	13	38.5762	12	40

Generation Cost = 868.502 $/Hr
Emission = 0.0769901 ton/Hr
CEED Cost = 1294.42 $/Hr

From this table 6.3.2 shows the emission is about **0.0769901 ton/Hr**

6.4 DIFFERIENTIAL EVOLUTION

6.4.1 Economic Dispatch for Differential Evolution algorithm

Economic dispatch for DE algorithm gives the economical curve for the generation which produces the minimum cost value

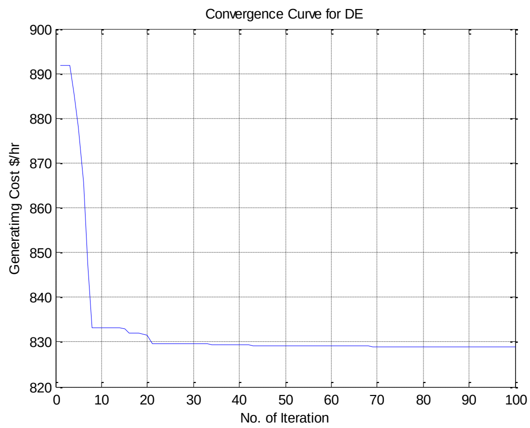

Fig.6.4.1 Economic dispatch for DE algorithm

Tabulated value is given in the table 7.4.1 which shows the value of generating cost and the combined cost also

Table 6.4.1 Economic dispatch for DE algorithm

S. No.	Generator Bus	Generation (MW)	Min. Limit (MW)	Max. Limit (MW)
1	1	133.042	50	200
2	2	60	20	80
3	5	35	15	50
4	8	30	10	55
5	11	10	10	30
6	13	22	12	40

Generation Cost = 828.833 $/Hr
Emission = 0.101069 ton/Hr
CEED Cost = 828.833 $/Hr

From the table shows the value of economic cost is about **828.833 $/Hr**

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6.4.2 Emission Dispatch for Differential Evolution Algorithm

Emission dispatch curve shows the emission curve for the differential algorithm and the curve shows in fig.6.4.2

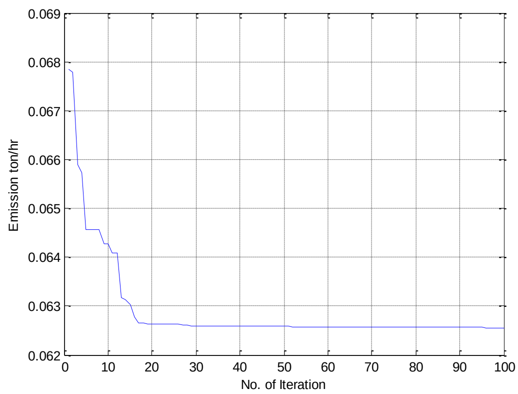

Fig.6.4.2 Emission dispatch for DE algorithm

Table 6.4.2 Emission dispatch for DE algorithm

S. No.	Generator Bus	Generation (MW)	Min. Limit (MW)	Max. Limit (MW)
1	1	51.2514	50	200
2	2	60	20	80
3	5	50	15	50
4	8	55	10	55
5	11	30	10	30
6	13	40	12	40

Generation Cost = 1001.12 $/Hr
Emission = 0.0625606 ton/Hr
CEED Cost = 1050.67 $/Hr

From this table 6.4.2 shows the generation pattern and the value of minimized emission is about **0.0625606 ton/Hr**

6.5 HYBRID FIREFLY AND DE ALGORITHM

6.5.1 Economic Dispatch

Economic dispatch for the hybrid firefly and differential evolution is given by combining the both algorithms. By combining the algorithm we can get the better result by comparing the individual results. Economic curve is shown in the fig 6.5.1

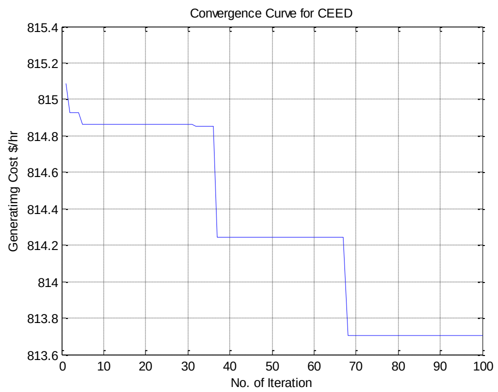

Fig.6.5.1 Economic dispatch for FFA-DE

Table 6.5.1 Economic dispatch for FFA-DE

S. No.	Generator Bus	Generation (MW)	Min. Limit (MW)	Max. Limit (MW)
1	1	159.886	50	200
2	2	51.1593	20	80
3	5	26.5239	15	50
4	8	10.852	10	55
5	11	17.8265	10	30
6	13	25.924	12	40

Generation Cost = 813.705 $/Hr
Emission = 0.129316 ton/Hr
CEED Cost = 813.705 $/Hr

From this table 6.5.1 shows the value of minimized economic dispatch value and the generating pattern is given.

6.5.2 Emission Dispatch for Hybrid FF-DE Algorithm

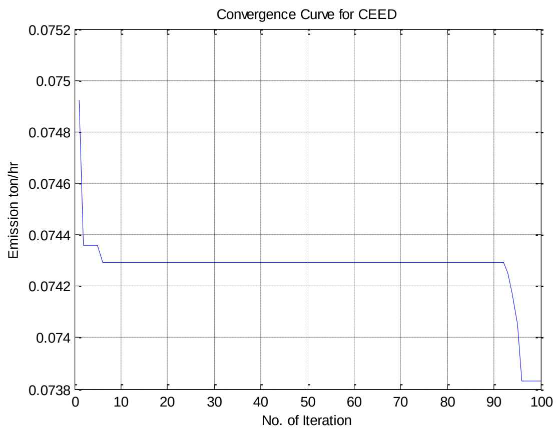

Fig 6.5.2 shows the emission curve for the hybrid algorithm

Table 6.5.2 Emission dispatch for FFA-DE

S. No.	Generator Bus	Generation (MW)	Min. Limit (MW)	Max. Limit (MW)
1	1	82.5561	50	200
2	2	78.4283	20	80
3	5	30.134	15	50
4	8	45.3716	10	55
5	11	21.9579	10	30
6	13	30.3248	12	40

Generation Cost = 878.885 $/Hr
Emission = 0.0738313 ton/Hr
CEED Cost = 1241.31 $/Hr

From the table 6.5.2 shows the minimized value for the hybrid generation and it produces the best result which compared to individuals.

7. COMPARISON RESULTS

The method, CEED using hybrid algorithm like Firefly and Differential evolution and the test system consists of IEEE 30 Bus it consists of 6 generators, 4 Transformers and 30 bus.

7.1 COMPARISON OF CONVERGENCE CURVE

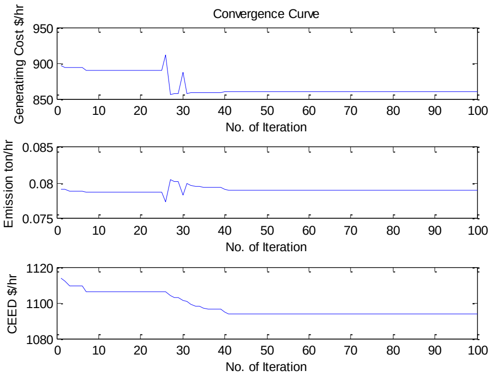

Fig.7.1 CEED graph for Firefly algorithm

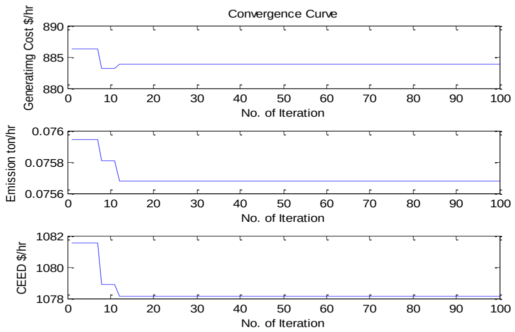

Fig.7.2 CEED graph for DE algorithm

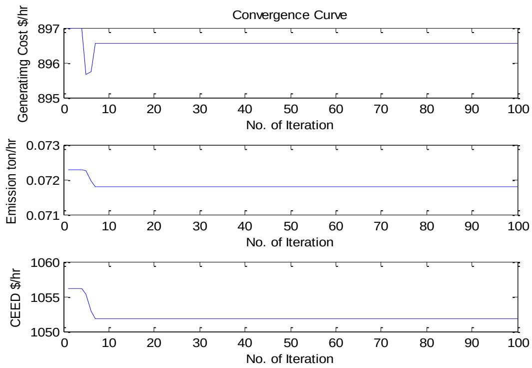

Fig.7.3 CEED graph for FIREFLY-DE

7.2 VOLTAGE MAGNATITUDE FOR FIREFLY-DE

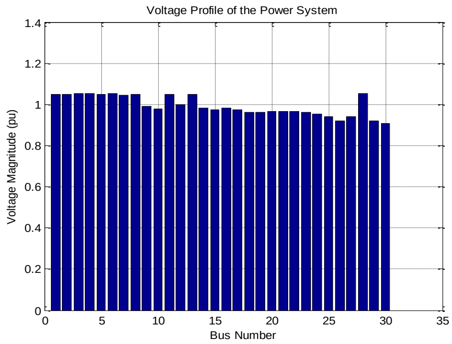

Fig.7.4 CEED Voltage magnitude

7.3 COMPARISON TABLES

Table 7.1 CEED table for FFA

S. No.	Generator Bus	Generation (MW)	Min. Limit (MW)	Max. Limit (MW)
1	1	100.026	50	200
2	2	66.4019	20	80
3	5	25.2542	15	50
4	8	34.0939	10	55
5	11	25.3074	10	30
6	13	38.2712	12	40

Generation Cost = 859.869 $/Hr
Emission = 0.0789889 ton/Hr
CEED Cost = 1093.95 $/Hr

From the above table 7.1 shows the value of CEED for firefly algorithm and the fig.7.1 indicates the curve for the firefly which is given in the table

Table 7.2 CEED table for DE algorithm

S. No.	Generator Bus	Generation (MW)	Min. Limit (MW)	Max. Limit (MW)
1	1	98.7254	50	200
2	2	52.6653	20	80
3	5	42.04	15	50
4	8	26.9796	10	55
5	11	28.4483	10	30
6	13	39.4768	12	40

Generation Cost = 883.898 $/Hr
Emission = 0.0756798 ton/Hr
CEED Cost = 1078.15 $/Hr

Table 7.3 CEED table for FIREFLY-DE

S. No.	Generator Bus	Generation (MW)	Min. Limit (MW)	Max. Limit (MW)
1	1	88.1157	50	200
2	2	54.6262	20	80
3	5	47.2118	15	50
4	8	52.6524	10	55
5	11	17.287	10	30
6	13	27.9577	12	40

Generation Cost = 896.561 $/Hr
Emission = 0.0717958 ton/Hr
CEED Cost = 1051.83 $/Hr

TABLE: 1

ALGORITHM	GENERATING COST $/Hr	EMISSION ton/Hr	CEED COST $/Hr
FIREFLY	859.869	0.07898	**1093.95**
DIFFERENTIAL EVOLUTION	883.898	0.07567	**1078.15**
FIREFLY-DE	896.561	0.07179	**1051.83**

8. CONCLUSION

An algorithm has been developed for the determination of the global or near-global optimal solution for the Combined Economic and Emission Dispatch (CEED). The hybrid algorithm of Firefly and Differential Evolution has been tested for the IEEE 30 Bus system with six generating units and thirty bus in that one bus has slack bus. The result obtained from the CEED is compared with the Firefly and DE algorithm. The result obtained from the CEED which gives the better result of CEED cost which compared to the firefly and DE. The convergence curves are shown in the chapter 7 and the combined table and graph is analyze in the chapter 8 which shows the minimized value of the CEED in the FIREFLY-DE algorithm.

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