# Effectiveness of Adaptive Differential Evolutionary Approach for Economic Load Dispatch

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**ABSTRACT: The economic distribution of the load is an important optimization problem in the power system. The economic transport is the short-term determination of the optimal performance of a number of power plants to cover the system load at the lowest possible cost, given the conditions of transport and operation. The problem of economic accounting is solved by a special computer software that should take into account the operational and system constraints of the available resources and the corresponding transmission capacities. In this paper, a black hole optimization algorithm(BH) and adaptive differential evolutionary (ADE) algorithm is utilized to solve the optimal power flow problem considering the generation fuel cost and minimizing the power losses as an objective functions. The IEEE 30-Bus systems are used to illustrate performance of these algorithm. The simulation is performed on variable load i.e. 200MW, 250MW, and 300MW. The respective losses are evaluated using ADE algorithm as well as BH algorithm. From result analysis it is concluded that ADE algorithm is better than BH algorithm with respect to amount of power loss in MW.**

**KEYWORDS: Economic Load Dispatch, Optimal Power Flow, Differential Evolution, Black Hole.**

## I. INTRODUCTION

Electricity became a vital commodity in our modern times. Almost every other commodity around us relies on electricity, from light systems, heating, cooling, water systems, communication, and transportation to a wide range of industrial processes. More than fifteen percent of energy consumed worldwide refers to electricity, but this percent is much higher in developed countries and tends to increase. Moreover, electricity consumption is highly correlated with the economic growth. In the past three decades, the electricity consumption worldwide almost tripled as a consequence of economic growth.

The vital impact of electricity on our daily lives is especially noticed when sudden interruptions in the continuous electricity supply occur. Moreover, sudden, uncontrolled, wide-scale power outages may result in high societal and economic threats [1].

Electricity is usually produced by large power plants which use coal, heavy fuel oil, natural gas, hydro or nuclear fission as primary energy source and transform it into electrical power. Besides these technologies which have been used in power systems for decades, renewable energy sources such as wind, solar thermal and solar photovoltaics, biomass and micro-hydro are increasingly being utilized into the modern power systems. Each of the technologies mentioned above have a couple of economic, technical and societal advantages and disadvantages. The fossil fuel and nuclear technologies, on one hand, have the disadvantages of using finite resources with unequal distribution of fuel supplies between regions (creating possibilities for exercising political influence), and they are pollutant (emission of greenhouse gases or nuclear waste).

However, they have economic and technical disadvantages, such as that they are still more expensive than conventional generation and they are mostly less controllable since their primary energy cannot be controlled (with the exception of hydro, geothermal and biomass). Therefore, the integration of renewable energy sources into the power system poses technical and economic challenges [2].

## II. RELATED WORK

In general, the power generation problem is based on three different sets of decisions which are dependent on the length of the planning time horizon. The first set consists of the long-term decisions (years) where the decision variables to be determined are the capacity, type, and number of power generators (units) to own. In the medium term (days to months), one needs to decide how to schedule (commit) the existing units for the planning horizon. And finally, in the short term (minutes to hours), the goal is to efficiently determine the amount of power that each committed unit need to produce in order to meet the real-time electricity demand. In general, the long-term problem is identified as the power expansion problem, the medium-term problem is identified as the unit commitment (UC) problem, and the short-term problem is called the economic dispatch (ED) or generator allocation problem. Note that the mid-term problems may refer also to the maintenance scheduling, when the time horizon is in the range of one year. In this case, the short-term problems refer to both UC and ED, and their time horizon is in the range of weeks to minutes [4].

Palaniyappan et al. [1] proposed an approach to solve the distribution of economic burdens with CO2 reduction in thermal power plants by using the Firefly algorithm. The six-generation system simulation concluded that the proposed method reduces global warming while minimizing fuel consumption.

Subramanian et al. [2] proposed an efficient and reliable firefly algorithm to solve the economic problem of load distribution. The proposed method was applied to six generation systems and the results were compared with other population-based techniques, such as simulated annealing, genetic algorithm, differential evolution, particle swarm optimization and artificial bee colonies optimization.

Mansor et al. [3] presented a technique for the optimization named immuno-logarithmic evolutionary programming to solve the problem of non-convex economic distribution. The technique proposed is to developed and to improve the global optima search process in order to solve the problem of non-convex economic distribution. The implementation of the IEEE 14-bus reliability test system.

Uma Sharma et al. [4] proposed a genetic algorithm (GA) method for the solution of a problem of distribution of the thermal load of the thermal generator. This suggested method has been implemented on 3 generators and 6 generators and the system should be considered as a system without loss of data.

Gaurav Gupta and Sachin Goyal [5] contributed to the search for an optimal solution to the problem of DELD using the proposed solution technique, based on the particle swarm optimization technique (PSO). The PSO is used to find the optimal production program for all the generator sets in order to provide energy to the load at the minimum operating cost and minimum fuel consumption, while satisfying all the constraints of the system, such as: valve point effect, ramp speed limits and transmission losses. The simulation is performed on a system of 5 generators on the 24 hour horizon.

## III. ECONOMIC LOAD DISPATCH

Economic transport is the method to determine the most efficient, economical and reliable operation of an electrical system by allocating the available energy generation resources to provide the system load. The main objective is to minimize the total cost of production taking into account the operational constraints of the available production resources. In terms of shipping costs, the required load request is distributed among the production units available to minimize operating costs.

The economic planning of the generators aims at guaranteeing at all times the optimal combination of the generator connected to the system to satisfy the load demand. The problem of the distribution of economic burdens has two distinct phases. This is the online presentation and commitment of the units [5-7].

The goal is to minimize total production costs (including fuel costs, emissions, operating / maintenance costs and net loss costs) while respecting the following operating costs:

- System load demand
- Downward-and-upward regulating margin requirements of the system
- Lower and upper economic limits of each generating unit
- Maximum ramping rate of each generating unit
- Unit's restricted operating zones (up to three restricted zones per unit)
- Emission allowance of the system (SO2, CO2, NOx) Network security constraints (maximum mW power flows of transmission lines)

*Basic Mathematical Formulation*

Consider n generators in the same system or turn them off electrically to neglect online losses. Let C1, C2, ..., Cn be the operating costs of the individual units for the corresponding power outputs P1, P2, ..., Pn. If C is the total cost of ownership of the complete system and PR is the total power received by the system bus and transmitted to the load it will be, then,

$$C = C_1 + C_2 + \cdots \ldots \ldots + C_n = \sum_{i=1} C_i \qquad \text{(i)}$$

$$P_R = P_1 + P_2 + \cdots \ldots . + P_n = \sum_{i=1} P_i \qquad \text{(ii)}$$

Equation (i) and (ii) can be minimized as:

$$C = \sum_{i=1}^{n} C_i \qquad \text{(iii)}$$

$$P_R - \sum_{i=1}^{n} P_i \quad \text{(iv)}$$

The above equation shows that if transmission losses are neglected, the total demand PR at any instant must be met by the total generation. The above equation is the equality constraint. This a constrained minimizing problem. This problem can be solved by using Lagrangian multiplier technique.

$$C^* = C + \lambda f \quad \text{(v)}$$

where f is the equality constraint equation given by:

$$P_R = \sum_{i=1}^{n} P_i = f(P_1, P_2, \dots\dots P_n) = 0 \quad \text{(vi)}$$

And λ is the Lagrange multiplier. Combination of equations (1.5) and (1.6) gives:

$$C^* = C + \lambda(P_R - \sum_{i=1}^{n} P_i) \quad \text{(vii)}$$

Equation (vii) can be solved for minimum by determining the partial derivate of the function C* on variable Pi and equating it equal to zero.

$$\frac{\partial C^*}{\partial P_i} = \frac{\partial C}{\partial P_i} + \lambda \frac{\partial}{\partial P_i}(P_R - \sum_{i=1}^{n} P_i) = 0 \quad \text{(viii)}$$

$$\frac{\partial C^*}{\partial P_i} = \frac{\partial C}{\partial P_i} + \lambda(1-0) = 0 = 0 \quad \text{(ix)}$$

$$\frac{\partial C}{\partial P_i} = \lambda \quad \text{(x)}$$

Since $C_i$ is a function of $P_i$ only. The partial derivates become full derivates, that is,

$$\frac{\partial C_i}{\partial P_i} = \frac{\partial C_i}{\partial P_i} \quad \text{(xi)}$$

Therefore, the condition for optimum operation is

$$\frac{\partial C_1}{\partial P_1} = \frac{\partial C_2}{\partial P_2} = \cdots \dots . = \frac{\partial C_n}{\partial P_n} = \lambda \quad \text{(xii)}$$

Since the $\frac{dC_i}{dP_i}$ is the increment cost generation for the generator. The equation above shows that the criterion of the most economical load distribution in a plant is that all the units must operate with the same additional cost as the fuel. This is known as the principle of the same criterion λ or principle of the same additional cost for the economic operation.

The simplest economic problem in load distribution is the absence of losses in the transmission line. For this reason, total demand is the sum of all generations. It is assumed that a cost function is known for each installation. The problem is determining the actual energy production. For each plant, the total cost of ownership is as low as possible and production remains in the lower and upper generations. Let us suppose that there is a station with GN generators engaged and that the request for active load (Pl) is provided. The production of active energy (Pgt) for each generator must be allocated to minimize the total cost. The optimization problem can then be specified as:

$$Minimize\ F(P_{gt}) \quad \text{(xiii)}$$

## IV. METHODOLOGY

Evolutionary algorithms (EA) were used frequently in the engineering optimization methods to overcome the weakness of the conventional methods in finding the global optimal solution while satisfying the different constraints.

### A. Mathematical Formulation

The general formulation of the optimal power flow optimization problem can be stated as follows:

$$\begin{gathered} \min f(x,u) \\ \text{s.t } g(x,u) = 0 \end{gathered} \quad \text{(xiv)}$$

$$\text{and } h(x,u) \leq 0$$

where f is the OPF objective function

g is the equality constraints

h is the inequality constraints

x and u are the system state and control vectors respectively.

The state variable can be represented as:

$$x_t = [P_{g1} Q_{g1} \ldots \ldots Q_{gn} V_{l1} \ldots \ldots V_{lny} S_{l1} \ldots \ldots S_{lnz}] \quad \text{(xv)}$$

where $P_{g1}$ is the slack bus generator output power

$Q_g$ is the generator output reactive power

$V_l$ is the PQ bus voltages

$S_l$ is the transmission line power flow

nx,ny and nz are the number of generator units, the number of PQ buses, and the number of transmission lines respectively.

$$U_t = [V_{g1} V_{gnx} P_{g1} \ldots \ldots P_{gnx} T_1 \ldots \ldots V_{nt} Q_{c1} \ldots \ldots Q_{cnc}] \quad \text{(xvi)}$$

The control vector is shown in (4.3), where the Vg is the voltage at controlled buses

Pg is the generator real output power

T is the transformers tap changers setting

Qc the output reactive power generated by the shunt compensator

nt and nc are the number of tap changing transformers and number of shunt compensators.

*B. Adaptive Differential Evolutionary Algorithm*

The differential evolution algorithm (DEA) is technically simple; Scalable population-based algorithm (EA), highly efficient with limited parameter optimization problems [10]. DEA applies an avid selection process with implicit elitic characteristics.

The Differential Evolution Algorithm (DEA) is a simple population-based stochastic parallel search algorithm for global optimization capable of handling non-differentiable, non-linear and multimodal objective functions. In DEA, the population is composed of true vectors of dimension D, which corresponds to the number of design parameters. The size of the population is defined with the parameter Np. The initial population is equally distributed in the research space.

$$x_{i,k}^G = x_{kmin} + rand[0,1] * (x_{kmax} - x_{kmin}) \quad \text{(xxii)}$$

Where, $i \in [1, N_p]$ and k$\in [1, D]$

Every variable k in a single i of the generation G is initialized within its limits $x_{kmin}$ and $x_{kmax}$. For each generation, two operators, mutations and crosses (recombination) are applied to each individual, creating the new population. Thus, a selection phase takes place during which each individual of the new population is compared with the corresponding individual of the elderly population and the best of them is selected as a member of the new generation population. In the following, the evolutionary operators are briefly described.

*Crossover*

Following the mutation phase, the crossover (recombination)operator is applied on the population. For each mutant vector$V_i^{G+1}$, a trail vector, $U_i^{G+1} = (u_{i1}^{G+1}, u_{i2}^{G+1}, \ldots, u_{iD}^{G+1})$is generated, with

$$\begin{aligned} u_{j,i}^{G+1} &= v_{j,i}^{G+1} \quad if\ (rand_j \leq CR)\ or\ (j = I_{rand}) \\ &= X_{j,i}^{G} \quad if\ (rand_j > CR)\ and\ (j \neq I_{rand}) \end{aligned} \quad \text{(xxiii)}$$

where rand$_j \epsilon [0,1]$ and $I_{rand}$ is chosen randomly from the interval [1……D] once for each vector to ensure that at least one vector component originates from the mutated vector $v_i$. CR is the DE control parameter that is called the crossover rate and is a user defined parameter within range [0,1]. Equation is applied for every vector component I $\epsilon$ [1………Np], j $\epsilon$ [1,….,D].

*Selection*

To decide whether the vector $U_i^{G+1}$ should be a member of thepopulation comprising the next generation, it is compared to thecorresponding vector $X_i^G$.

$$X_i^{G+1} = U_i^{G+1} \text{ if } f(U_i^{G+1}) < f(X_i^G) \quad \text{(xxiv)}$$

All solutions in the population have the same chances of being selected as parents, regardless of their fitness score. If the parent is even better, he remains in the population, which includes the characteristic of elitism.

*Termination Criteria*

The iterative process can be interrupted if one of the following criteria is satisfied: an acceptable solution has been reached, a condition is met without further improvements, the control variables are set to a stable state or a predefined number of iterations is performed. In most cases, it is not easy to verify that the resulting solution is the most acceptable. In this work, iterations are interrupted if the results remain constant for a fixed number of generations or if the maximum number of generations is reached, depending on the event that occurs first.

Algorithm : (Adaptive Differential Evolutionary)

1: Initialize the number of population NP, the maximum number of evolution, maximum iteration, scale factor and cross-factor

2: Initialize the population pop.

3: Update the scaling factor of each individual according to the above formula

4: Update the cross-factor of each individual according to the above formula

5: Perform the following behavior: Mutation, Crossover and Selection, and produce a new generation of individuals.

6: Until the termination criterion is met.

## V. RESULT ANALYSIS

In this research work IEEE 30-bus system is used for optimal power generation. In this test system, the proposed algorithm has been utilized to solve the OPF problem with fuel cost minimization objective functions.

*A. Fuel Cost Minimization*

In this case, the objective is to minimize the total fuel cost of the generation units as follows:

$$J_1 = W_{cost} + LR_{cost} + \sum_{i=1}^{N_x} f_i(P_i) \quad \text{(xxv)}$$

$$f_i(P_i) = a_i + b_i P_i + c_i P_i^2 \quad \text{(xxvi)}$$

Where fi(Pi) is the fuel cost of generation unit i,

$N_x$ is the number of generator units

$P_i$ is the out power of generation unit i

ai, bi and ci are the fuel cost coefficients.

$W_{cost}$ is the total cost of wind power generation and LR cost is the total cost of load reduction.

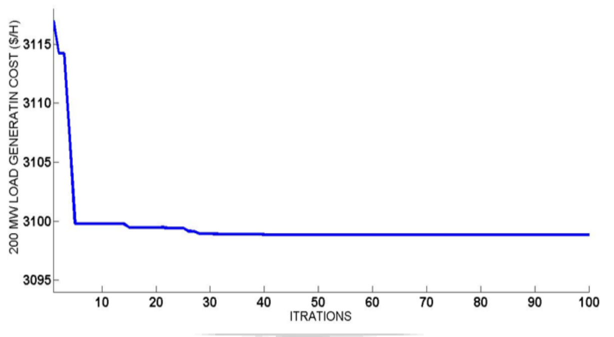


**Figure 1: Convergence Characteristic for 200 MW Load (ADE)**

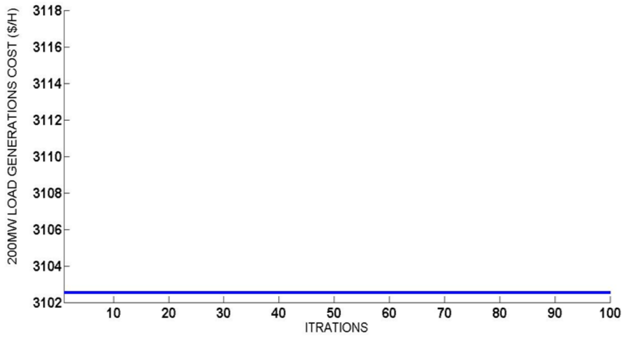


**Figure 2: Convergence Characteristic for 200 MW Load (BH)**

Figure 1 and 2 represents the convergence characteristic graph for 200 MW load with ADE algorithm as well as BH algorithm. From graph it is concluded that convergence characteristic of ADE algorithm shows better performance with respect to BH algorithm.

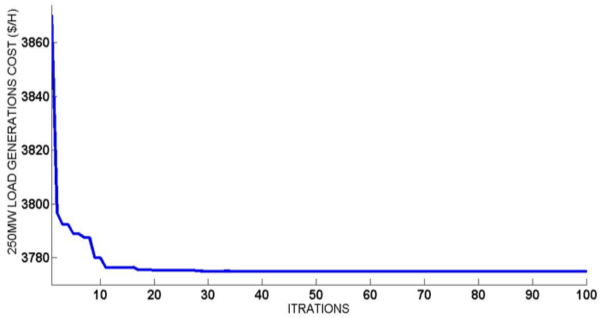


**Figure 3: Convergence Characteristic for 250 MW Load (ADE)**

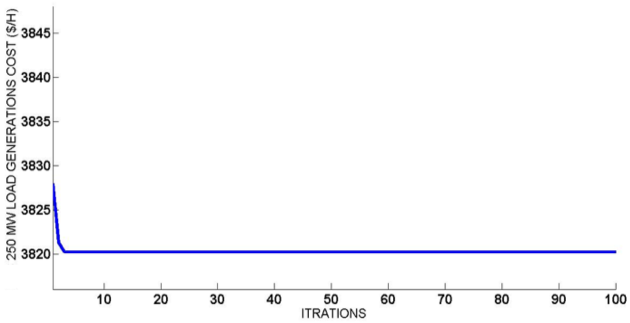


**Figure 4: Convergence Characteristic for 250 MW Load (BH)**

Figure 3 and 4 represents the convergence characteristic graph for 250 MW load with ADE algorithm as well as BH algorithm. From graph it is concluded that convergence characteristic of DE algorithm shows better performance with respect to BH algorithm.

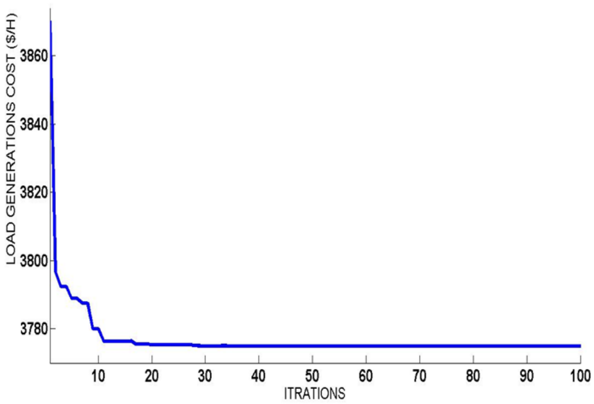


**Figure 5: Convergence Characteristic for 300 MW load (DE)**

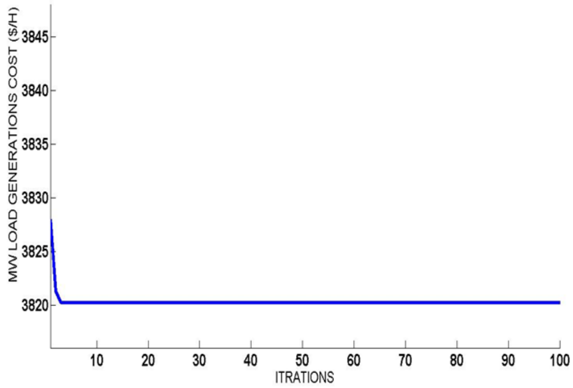


**Figure 6: Convergence Characteristic for 300 MW Load (BH)**

Figure 5 and 5 represents the convergence characteristic graph for 300 MW load with ADE algorithm as well as BH algorithm. From graph it is concluded that convergence characteristic of ADE algorithm shows better performance with respect to BH algorithm.

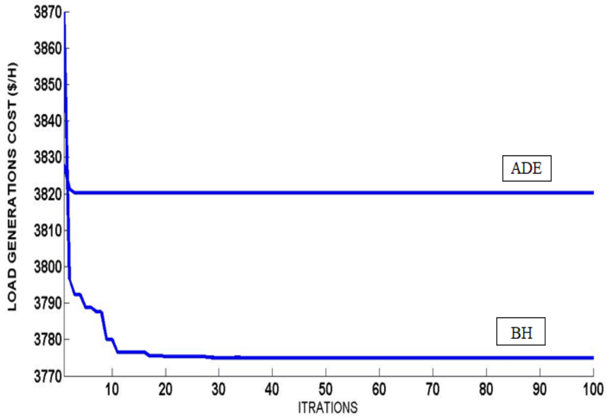


**Figure 7: Comparative Convergence Graph**

Figure 8 and figure 9 is demonstrates the fuel cost optimization with respect to power losses and execution time by applying ADE and BH algorithm. The simulation is performed on variable load i.e. 200MW, 250MW and and 300 MW The respective losses are evaluated using ADE algorithm as well as BH algorithm. From result analysis it is concluded that ADE algorithm is better than BH algorithm with respect to amount of power loss in MW.

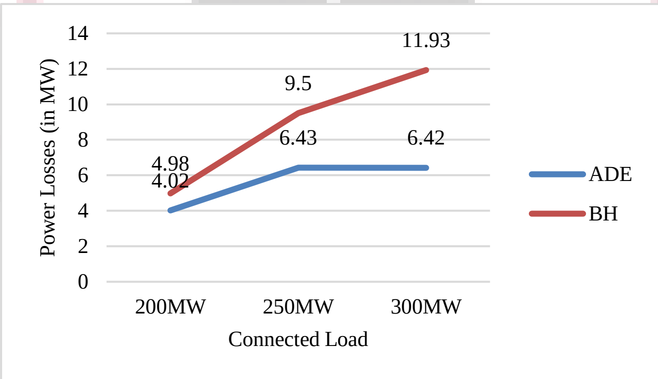


**Figure 8: Comparative Power Losses**

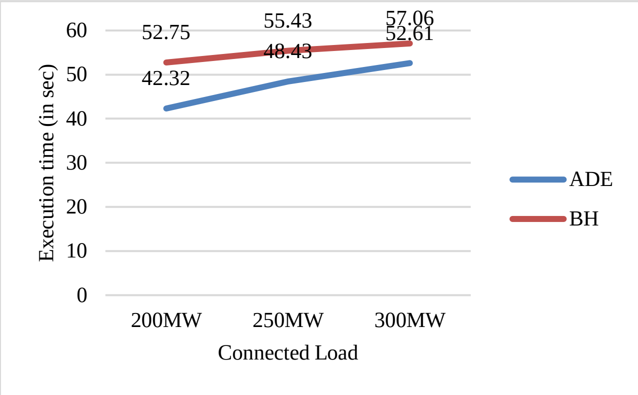


**Figure 9: Comparative Execution Time**

## VI. CONCLUSION

In this paper generator scheduling is done using are taking for IEEE 30 bus system for generator scheduling various load are consider for generator scheduling ADE and BH algorithm optimization applied so as to total cost of generation should be minimum in the work it is found that ADE is given minimum cost of generation load for 200 MW, 250MW and 300 MW and black hole algorithm is given for load 200 MW, 250MW and 300 MW by considering 100 iterations are each load . It is observed that differential evolutionary is performing better than black hole algorithm. In this respect of number of iterations as well as generation cost the result are shown in the table form as well as graphical form.

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