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A Simulation Analysis of Optimal Power Flow using Differential Evolution Algorithm for IEEE-30 Bus System

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***Abstract*—This paper presents application of Differential Evolution (DE) Algorithm for solution of optimal power flow. As conventionally we use gradient based methods for optimal power flow. But conventional methods sometimes give local optimum values. And if problem is non-linear mix-integer type then it is very difficult to get the optimum solution. Therefore evolutionary techniques are applied for such problems. In this paper a IEEE-30 bus system is used for testing of effectiveness of the algorithm.**

***Keywords*—Optimal Power Flow, Differential Evolution**.

I. Introduction

The field of optimization has been the focus of much attention nowadays. Optimization techniques and concepts are not limited to any particular discipline and are playing an increasingly important role in the solution and modeling of engineering, economic, design and scientific systems. Optimization is the process through which the best possible values of decision variables are obtained under the given set of constraints and in accordance to a selected optimization objective function. The best value would give the smallest objective function value for a minimization problem or the largest objective function value for a maximization problem. In terms of real world applications, the objective function is often a representation of some physically significant measure such as profit, loss, utility, risk or error. Hence optimizing the system or design to make it as effective or functional as possible is an important part of the overall application.

In recent years, optimization algorithms have received increasing attention by the research community in the Power System. Scientifically, the field of optimization algorithms is a highly relevant research area, because these algorithms can find approximate solutions to problems where no analytic method exists, e.g. for solving non-linear differential equations or problems where finding even an approximate solution is tedious. Optimization algorithms have a very broad range of application, since many problems in power system can be formulated as an optimization task where the objective is to minimize or maximize a given objective function. For example, such algorithms can often be used to improve the quality of generation, to lower the product cost, or increase efficiency in transmission and scheduling – related problems.

In this context, even a few percent improvement of existing solution may give the system engineers great bit of advantage. Hence, optimization techniques can be an important key to success. In contrast to the algorithmic approach, the manual search of a solution with a slight improvement is often tedious, if not impossible, because manual optimization requires a great deal of insight and patience.

Furthermore, manual optimization often limits the scope of the search process to what the human expert is trained to consider as a good solution. Conversely, optimization algorithms automate the search and are not biased in scope regarding the solutions. The wide range of real-world optimization problems and the importance of finding good approximate solution have lead to a great variety of optimization techniques.

The Optimal Power Flow (OPF) has been frequently solved using classical optimization methods. The OPF has been usually considered as the minimization of an objective function representing the general cost and/or the transmission loss. The constraints involved are the physical laws governing the power generation-transmission systems and the operating limitations of the equipments. Effective optimal power flow is limited by (i) the high dimensionality of power systems and (ii) the incomplete domain dependent knowledge of power system engineers. The first limitation is addressed by numerical optimization procedures based on successive linearization using the first and the second derivatives of objective functions and their constraints as the search directions or by linear programming solutions to imprecise models [1-4]. The advantages of such methods are in their mathematical underpinnings, but disadvantages exist also in the sensitivity to problem formulation, algorithm selection and usually converge to a local minimum [5]. The second limitation, incomplete domain knowledge, preludes also the reliable use of expert systems, where rule completeness is not possible. The OPF problem has been solved via many traditional optimization methods, including: Gradient-based techniques, Newton methods, Linear Programming and Quadratic Programming. Most of these techniques are not capable of solving effectively, Optimization Problems with a non-convex, non-continuous and highly nonlinear solution space.

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In recent years, new optimization techniques based on the principles of natural evolution, and with the ability to solve extremely complex optimization problems, have been developed.

Optimal Power Flow (OPF) was firstly introduced by Carpentiers as a network constrained economic dispatch [Carpentiers, 1962] and formulated by Dommel and Tinny as optimal power flow [Dommel and Tinny, 1968]. The main purpose of OPF is to operate the system at the most economic state while satisfying specified security constraints. OPF has great meaning for power system operation and development especially in the modern society where human beings depend much more on electricity. Power system security analysis is composed of both static and dynamic security analysis. However, most previous research works concern only about maintaining static security in the OPF problem; few can effectively deal with dynamic security constraints despite the recognition of its great importance.

Due to the rapid increase of electricity demand and the deregulation of electricity markets, power systems tend to operate more closely to stability boundaries and as a consequence, many instability problems occurred in many countries recently. Huge losses and expensive costs in these events give good evidence that dynamic stability under large disturbances is still the most serious threat for the development of modern power systems. Among various dynamic security analyses, transient stability is one of the most essential and important assessments. Huge attentions have been paid on power system transient stability analysis by engineers and researchers all these years.

There are two possible approaches to solving optimization problems, namely: deterministic and stochastic. Deterministic methods exploit the underlying mathematical structure of the problem for solving specific problem types. These methods are mathematically concrete and extremely effective within their scope. The majority of deterministic methods are focused on local optimization and those deals specifically with global optimization problems are fairly limited. Following are the deterministic optimization methods Linear Programming (LP) Method, Newton-Raphson (NR) Method, Quadratic Programming (QP) Method, Nonlinear Programming (NLP) Method, and Interior Point (IP) Method.

Search methods or heuristic methods or stochastic methods represent a broad class of computational global optimization strategies that use novel approaches to intelligent search for optimal values. They are often inspired by physical processes, natural evolution and stochastic events.

Even though these methods are unorthodox and have a minimal mathematical basis or convergence guarantee, they have nonetheless proven themselves as effective and practical global optimization strategies. Most of these methods are aimed at solving global optimization problems.

Some of these methods are Genetic Algorithms (GA), Evolutionary Programming (EP), Evolutionary Strategies (ES), Simulated Annealing Algorithm, Ant Colony Optimization (ACO), Particle Swarm Optimization (PSO), Tabu Search Algorithms and Differential Evolution Algorithm (DEA).

II. Differential Evolution Algorithm

A differential evolution algorithm (DEA) is an evolutionary computation method that was originally introduced by Storn and Price in 1995. Furthermore, they developed DEA to be a reliable and versatile function optimizer that is also readily applicable to a wide range of optimization problems. DE is a simple population based, stochastic search evolutionary algorithm for optimization and is capable of handling non-differentiable, non-linear and multi-model objective functions. Differential evolution improves a population of candidate solution over several generations using the mutation, crossover and selection operators in order to reach an optimal solution. Differential evolution presents great convergence characteristics and requires few control parameters, which remain fixed throughout the optimization process and need minimum tuning [9, 10]. Differential evolution solves real valued problems based on the principles of natural evolution [11-15].

DE uses a population of floating point encoded individuals and mutation, crossover and selection operators to explore the solution space in search of global optima. DE is a novel evolution algorithm as it employs real-coded variables, instead of a binary or a gray representation. DE typically relies on *mutation* as the search operator and uses *selection* to direct the search towards the prospective regions in the feasible region.

The optimization process is carried by means of three main operations:

- Mutation,
- Crossover and
- Selection.
  - In each generation, each parameter vector or individual of the current population becomes a target vector.
  - For each target vector, the mutation operation produces a new parameter vector (called mutant vector), by adding the weighted difference between two randomly chosen vectors to a third (also randomly chosen) vector.

- The crossover operation generates a new vector (called trial vector), by mixing the parameters of the mutant vector with those of the target vector.
- If the trial vector obtains a better fitness value than the target vector, then the trial vector replaces the target vector in the next generation.

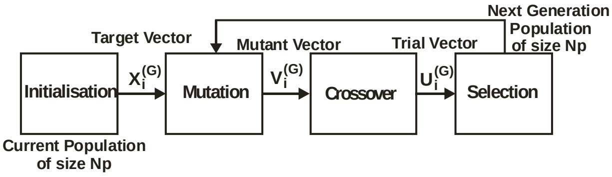

Figure – 1 Steps of Differential Evolution Algorithm

General Optimization Process of DE Algorithm

The general scheme of DE method is quite similar to other evolutionary algorithms. At every generation G, DE maintains a population $P^{(G)}$ of size Np vectors consisted of floating point encoded individuals or candidate solutions to the problem, which evolves throughout the optimization process to find global solutions as shown in equation (1).

$$P^{(G)} = [\ X1^{(G)} \ \ldots\ldots\ Xi^{(G)},\ldots\ldots\ XNp^{(G)}\ ] \quad \ldots\ldots\ldots (1)$$

Each individual or candidate solution Xi, is a D-dimensional vector that contains as many parameters as the problem decision parameters, D, to be optimized.

$$Xi^{(G)} = [\ X1,\ i^{(G)} \ \ldots\ldots\ Xj,\ i^{(G)}\ ,\ldots XD,\ i^{(G)}\ ] \quad \ldots\ldots\ldots (2)$$

Where $i = 1, 2, 3, \ldots.$ Np; $j = 1, 2, 3, \ldots\ldots$ D; G = generation or iteration number.

The Differential Evolution optimization process is conducted by means of the following operations:

I. Initialization

The first step in the DE optimization process is to create an initial population of candidate solutions by assigning random values to each decisions parameter of each individual of the population.

Such values must lie inside the feasible bounds of the decision variable and can be generated by equation (3). In case a preliminary solution is available, adding normally distributed random deviations to the nominal solution often generates the initial population.

$$X\ j,i^{(G=0)} = X\ j^{min} + \lambda\ j\ (X\ j^{max} - X\ j^{min}) \quad \ldots\ldots\ldots (3)$$

Where i = 1,2, …... Np; j = 1,2, ….. D;

Xj^{min} & Xj^{max} = Lower & Upper Bound of the jth decision parameter respectively.

λj = Uniformly Distributed Random Number within [0,1] generated a new for each value of j.

$X\ ji^{(G=0)}$ = Initial value (G=0) of the jth parameter of the ith individual vector.

Once every vector of the population has been initialized, its corresponding fitness value is calculated and stored for future reference.

II. Mutation

After the population is initialized, the operators of mutation, crossover and selection create the population of the next generation $P^{(G+1)}$ by using the current population $P^{(G)}$. At every generation G, each vector in the population has to serve once as a target vector $Xi^{(G)}$. For each target vector, a mutant vector $Vi^{(G)} = [\ V1,\ i^{(G)} \ \ldots\ldots\ VD,\ i^{(G)}\ ]$ is generated by perturbing a randomly selected vector (Xa) with difference of two other randomly selected vectors (Xb & Xc).

$$Vi^{(G)} = Xa^{(G)} + F\ (Xb^{(G)} - Xc^{(G)}) \quad \ldots\ldots\ldots\ldots\ldots\ldots (4)$$

Where $Xa^{(G)}$, $Xb^{(G)}$ and $Xc^{(G)}$ are randomly chosen vectors from the set {1,2, …… Np} and subjected to the condition that $a \neq b \neq c \neq i$. $Xa^{(G)}$, $Xb^{(G)}$ and $Xc^{(G)}$ are selected anew for each parent vector. F is a user-defined constant known as the "scaling mutation factor", which is typically chosen from within the range [0, 2].

III. Crossover

In order to increase the diversity of the perturbed parameter vectors, the crossover operation is used. The crossover operation generates trial vectors ($Ui^{(G)}$) by mixing the parameters of mutant vectors ($Vi^{(G)}$) with the target vectors ($Xi^{(G)}$) according to selected probability distribution like binomial or exponential.

$$U_{j,i}^{(G)} = \begin{cases} V_{j,i}^{(G)} & \text{if} \quad \lambda j \leq CR \quad \text{or } j = q \\ X_{j,i}^{(G)} & \text{otherwise} \end{cases} \quad \ldots\ldots\ldots (5)$$

Where λj is a uniformly distributed random number within the range [0,1] generated anew for each value of j. CR is known as the Crossover Rate Constant and is a user-defined parameter within the range [0, 1]. The index q is randomly chosen from the interval [1,….. D], which ensures that the trial vector ($Ui^{(G)}$) gets at least one parameter from the mutant vector ($Vi^{(G)}$). When CR=1, for example, every trial vector parameter comes from $Vi^{(G)}$. On the other hand, if CR=0, all but one trial vector parameter comes from the target vector to ensure that $Xi^{(G)}$ differs from $Xi^{(G+1)}$ by at least one parameter.

IV. Selection

Finally, the selection operator is applied in the last stage of the DEA procedure. The selection operator chooses the vectors that are going to compose the population in the next generation.

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This operator compares the fitness of the trial vector and the corresponding target vector and selects the one that provides the best solution. The fitter of the two is then allowed to advance into the next generation according to equation (6).

$$X_{j,i}^{(G+1)} = \begin{cases} U_{j,i}^{(G)} & \text{if } f(U_{j,i}^{(G)}) < f(X_{j,i}^{(G)}) \\ X_{j,i}^{(G)} & \text{otherwise} \end{cases} \quad \ldots\ldots\ldots\ldots (6)$$

This optimization process is repeated for several generations, allowing individuals to improve their fitness as they explore the solution space in search for optimal value. The overall optimization process is stooped whenever maximum number of generation is reached or other predetermined convergence criterion is satisfied.

V. Stopping Criteria

An important aspect for a stochastic algorithm is deciding when to stop the algorithm. We know that stochastic methods converge with a probability of 1 to an optional value as time goes to infinity. However upholding such a convergence guarantee is impractical. Therefore the user will need to decide on some preset conditions that will terminate the algorithm. Deciding on what stopping criteria to use is dependent on many factors such as the application of the algorithm, accuracy required, cost and time constraints. Some of the most common stopping criteria used for the DE algorithm include:

- A preset number of maximum generations
- The difference between the best & worst function values in the population is very small.
- The best function value has not improved beyond some tolerance value for a predefined number of generations.
- The distance between solution vectors in the population is small.

Selection of Control Parameters

DE has three essential control parameters: the population size Np, the weight applied to the random differential or the scaling factor F and the crossover constant CR. Proper selection of control parameters is very important for algorithm success and performance. The optimal control parameters are problem specific. Therefore, the set of control parameters that best fit each problem have to be chosen carefully. The most common method used to select control parameters is parameter tuning. Parameter tuning adjusts the control parameters through testing until the best settings are determined.

The population size determines the number of individuals in the population and provides the algorithm enough diversity to search the solution space.

Originally suggested value for the scaling factor F was in the range [0, 2]. However, empirical testing has shown that for most problems the optimal value for F is in the range [0.4, 1]. Scaling factor F controls the amount of perturbation in the mutation process. The crossover constant, CR, is a value in the range [0, 1] and is used to control the diversity of the population.

In order to avoid premature convergence, F or Np should be increased, or CR should be decreased. Larger values of F result in larger perturbations and better probabilities to escape from local optima, while lower Cr preserves more diversity in the population thus avoiding local optima.

III. Optimal Power Flow

The set of optimization problems in electrical power system engineering is known collectively as optimal power flow (OPF). In 1962, Carpentier introduced OPF as an extension to the problem of economic dispatch (ED) of generation in electrical power systems. Carpentier's key contribution was the inclusion of the electrical power flow equations in the ED formulation. Today, the defining feature of OPF remains the presence of power flow equations in the set of equality constraints.

In general, OPF includes any optimization problem which seeks to optimize the operation of an electric system (specifically, the generation and transmission if electricity) subject to the physical constraints imposed by electrical laws and engineering limits on the decision variables.

The objective of an Optimal Power Flow (OPF) algorithm is to find steady state operation point which minimizes generation cost, loss etc. while maintaining an acceptable system performance in terms of limits on generators real and reactive powers, line flow limits, output of various compensating devices etc.

The optimal power flow is a power flow problem in which certain controllable variables are adjusted to minimize an objective function such as the cost of active power generation or the losses, while satisfying physical and operating limits on various controls, dependent variables and function of variables. The types of controls that an optimal power flow must be able to accommodate are active and reactive power injections, generator voltages, transformer tap ratios and phase shift angles. In other words, the optimal power flow problem seeks to find an optimal profile of active and reactive power generations along with voltage magnitudes in such a manner as to minimize the total operating costs of a thermal electric power system, while satisfying network security constraints.

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An Optimal Power Flow (OPF) function schedules the power system controls to optimize an objective function while satisfying a set of nonlinear equality and inequality constraints. The equality constraints are the conventional power flow equations; the inequality constraints are the limits on the control and operating variables of the system. Mathematically, the OPF can be formulated as a constrained nonlinear optimization problem.

System Variables

In OPF, the decision variables are often partitioned into a set of control (independent) variables "u" and a set of state (independent) variables "x". At each search step, the OPF algorithm fixes "u" and derives "x" by solving a conventional PF. To analyze the power system network, there is a need of knowing the system variables. They are:

I. *Control variables "u" (Pg & Qg)*: The real and reactive power generations are called control variables since they are used to control the state of the system.
II. *Disturbance variables "p" (Pd & Qd)*: The real and reactive power demands are called demand variables since they are beyond the system control and hence considered as uncontrolled or disturbance variables.
III. *State variables "x" (*V*& δ)*: The bus voltage magnitude *V*& its phase angle δ dispatch the state of the system. These are dependent variables that are being controlled by control variables.

IV. Problem Formulation

The OPF problem is an optimization problem that determines the power output of each online generator that will result in a least cost system operating state. In general, OPF problem can be formulated in the following form:

Minimize f (u, x) …………………….............… (7)

subject to $g(u, x) = 0$

$h(u, x) \leq 0$

where, – u is the set of controllable variables in the system;

– x is the set of state variables;

– f (u, x) is the objective finction;

– g (u, x) & h (u, x) are respectively the set of equality and inequality constraints.

Cost Function: The objective of the OPF is to minimize the total system cost by adjusting the power output of each of the generators connected to the grid. The total system cost is modeled as the sum of the cost function of each generator. The generator cost curves are modeled with smooth quadratic functions, given by:

$$\text{Minimize } F_T = \sum_{i=1}^{NG} F_i(P_{gi}) = \sum_{i=1}^{NG} (a_i + b_i P_{gi} + c_i P_{gi}^2) \quad \text{…..…..(8)}$$

Where, Fr = Fuel cost of the system;

Fi = Fuel cost of the ith generating unit of the system;
Pgi = Real power generated in the ith generating unit;
NG = Number of generators;
ai, bi, ci = Cost coefficients of the ith generator.

Equality Constraints: The equality constraint is represented by the power balance equation that reduces the power system to a basic principle of equilibrium between total system generation and total system loads. Equilibrium is only met when the total system generation equals the total system load demand (PD) plus system losses (PL).

$$\sum_{i=1}^{NG} P_{gi} - P_D - P_L = 0 \quad \text{………………………..…… (9)}$$

Where, Pgi = Real power generated at ith bus;
NG = Number of generator buses.

Inequality Constraints: For static load flow equations solution to have practical significance, all the state and control variables must be within the specified limits. These limits are represented by specifications of power system hardware and operating constraints, and are described as follows:

– Limits on real power generation

$P_{gi}^{min} \leq P_{gi} \leq P_{gi}^{max}$ (i = 1, 2, …… NG)

– Limits on reactive power

$Q_{gi}^{min} \leq Q_{gi} \leq Q_{gi}^{max}$ (i = 1, 2, …… NG)

– Limits on voltage magnitudes

$|V_i|^{min} \leq |V_i| \leq |V_i|^{max}$ (i = 1, 2, …… NB)

The limit arises due to the fact that power system equipments are designed to operate at fixed voltage within the allowable variations of ± (5 – 10) % of rated values.

V. System Investigated (IEEE – 30 Bus System)

The IEEE 30 Bus Test case represents a portion of the American Electric Power System (in the Midwestern US) as of December, 1961, which is made available to the electric utility industry as a standard test case for evaluating various analytical methods and computer programs for the solution of power system problems.

The IEEE - 30 bus power system model as shown in Figure 2. We have considered a modal system of IEEE – 30 bus system for simulation of the suggested method. The specification of the IEEE-30 Bus system is described in the table -1 & table – 2 [14].

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The proposed algorithm has been implemented on IEEE-30 bus power system model. We have tested the performance of the proposed algorithm with effectiveness under different load conditions. For consideration we had vary the load from 100% to 140% for the base load.

Table – 1
System Description Of Case Study

S. N.	Variables	IEEE 30 Bus System
1	Buses	30
2	Branches	41
3	Generators	6
4	Generator buses	6
5	Shunt Reactors	2
6	Tap changing transformers	4

Table – 2
Generator Operating Limts & Fuel Cost Coeefifients

S. No.	Generation at bus #	P_{gi}^{min} (MW)	P_{gi}^{max} (MW)	ai (Rs/h)	bi (Rs/MWh)	ci (Rs/MWh)
1	1	50	200	0	2.00	0.00375
2	2	20	80	0	1.75	0.01750
3	5	15	50	0	1.00	0.06250
4	8	10	35	0	3.25	0.00830
5	11	10	30	0	3.00	0.02500
6	13	12	40	0	3.00	0.02500

TABLE – 3
Bus Load Data Of The IEEE – Bus System

Bus	Load (MW)	Bus	Load (MW)	Bus	Load(MW)
01	0.0	11	0.0	21	17.5
02	21.7	12	11.2	22	0.0
03	2.4	13	0.0	23	3.2
04	7.6	14	6.2	24	8.7
05	94.2	15	8.2	25	0,0
06	0.0	16	3.5	26	3.5
07	22.8	17	9.0	27	0.0
08	30.0	18	3.2	28	0.0
09	0.0	19	9.2	29	2.4
10	5.8	20	2.2	30	10.6

Table – 4
Parameter Values Of DE Algorithm

Poplation Size, Np	20	Mutation Probablity, F	0.8
Maximum no. of Generations, itermax	100	Crossover Probabilty Constant, CR	0.8

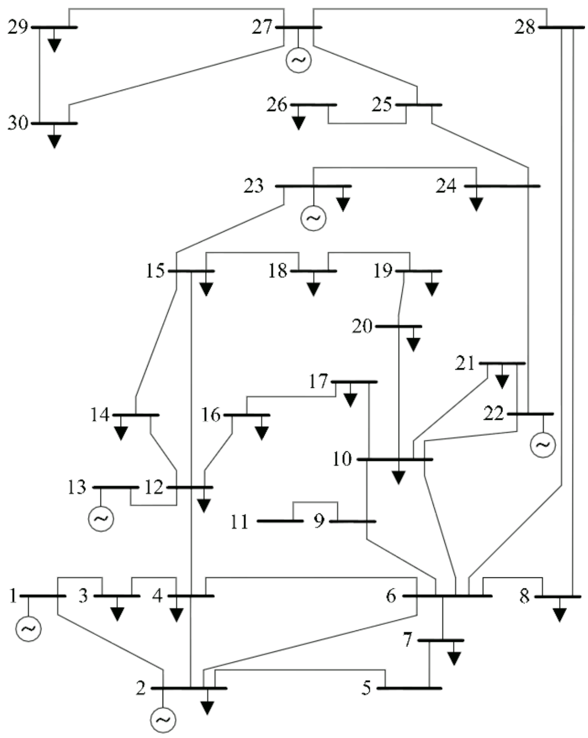

Figure - 2 Single line diagram of the IEEE 30-bus test system

VI. SIMULATION AND RESULTS

Optimal Power flow (OPF) is allocating loads to plants for minimum cost while meeting the network constraints. It is formulated as an optimization problem of minimizing the total fuel cost of all committed plant while meeting the network (power flow) constraints. The simulations were performed using MATLAB software.

We have considered the variation of the product cost with respect to the number of iterations for two cases, one with 100% load and other with 140% load. In both the cases, as number of iterations increases the optimal value of cost function converges and settles at a constant minimum value after a certain number of iterations. Under normal conditions it settles to the minimum in lesser number of iterations, whereas it took more number of iterations under stressed conditions.

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The analysis of the different plots and the simulation of the results so obtained, it is clear that differential evolutions algorithm is working effectively in case of the stressed conditions too.

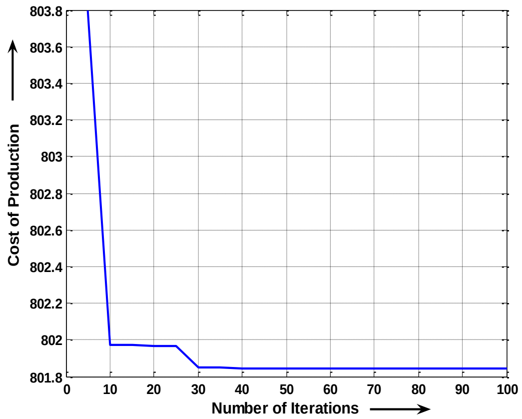

Figure-3 Cost of Production Vs No. of Iterations at 100% Load

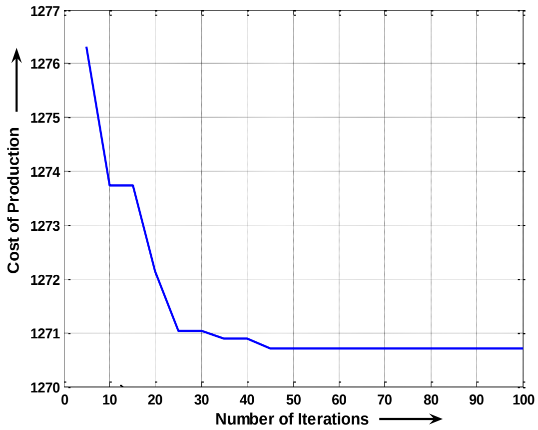

Figure-4 Cost of Production Vs No. of Iterations at 140% Load

Table – 5
Variation In Minimum Cost At Different Iterations

Number of Iterations	Cost of Production at 100% Load in Rs/MWh	Cost of Production at 140% Load in Rs./MWh
5	803.794	1276.320
10	801.975	1273.731
15	801.975	1273.731
20	801.966	1272.147
25	801.966	1271.042
30	801.852	1271.042
35	801.852	1270.885
40	801.846	1270.880
45	801.844	1270.712
50	801.843	1270.712
55	801.843	1270.710
60	801.843	1270.709
65	801.843	1270.707
70	801.843	1270.706
75	801.843	1270.706
80	801.843	1270.706
85	801.843	1270.706
90	801.843	1270.706
95	801.843	1270.706
100	801.843	1270.706

VII. CONCLUSION

The result is showing that DE algorithm is efficiently working in stressed conditions also as the load increases up to 140 %. This shows that DE algorithm can perform well even at large systems also. If we compare the conventional method it is very clear that DE is simple and can be applied to mix-integer problems also.

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