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ORPD in highly stressed system-A comparative study using DE and BAT algorithm

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***Abstract*— Optimal reactive power dispatch (ORPD) is a complex optimization problem in which we try to "optimally" set the values of control variables like reactive power output of generators (generator bus voltages), tap ratios of transformers and reactive power output of shunt compensators like capacitors etc. to minimize the total transmission active power losses while satisfying a given set of constraints. In this paper solution of ORPD problem is done by stochastic population based search algorithms like differential evolution (DE) and BAT algorithms. The numerical results clearly show that DE algorithm gives better results required to reach global best solution. In order to illustrate the effectiveness of the proposed algorithm, it has been tested on highly stressed modified IEEE 300-bus test system.**

***Index Terms*— reactive power dispatch, optimization, active power loss, metaheuristics.**

I. Introduction

Power system operators ensure the quality and reliability of supply to the customers by maintaining the load bus voltages in their permissible limits. Any changes to the system configuration or in power demands can result in higher or lower voltages in the system. This situation can be improved by the operator by reallocating reactive power generations in the system, i.e., by adjusting transformer taps, changing generator voltages, and by switching VAR sources. Also, it is possible to minimize the system losses by reactive power redistributions in the system. Thus, it is a twofold objective function: firstly, to minimize the system losses and to improve the voltage profiles. The concept of reactive power optimization and the classic method for reactive power dispatch explained here. Then it addresses Differential evolution algorithm, and particle swarm optimization and their practical application in reactive power optimization.

In the past two decades, the problem of reactive power control for improving economy and security of power system operation received much attention. Power system operators ensure the quality and reliability of supply to the customers by maintaining the load bus voltages in their permissible limits. Any changes to the system configuration or in demands can affect voltage levels in the system. This situation can be improved by reallocating reactive power generations in the system, *i.e.* by adjusting transformer taps, varying generator voltages and by switching on/off static var compensators. In addition, the system losses can be minimized by redistribution of reactive power in the system.

In general, reactive power dispatch (RPD) is a complex combinatorial optimization problem for a large scale power system involving nonlinear and discontinuous functions having multiple local minima. The aim of the RPD problem is to minimize the network real power loss and improve voltage profiles by regulating generator bus voltages, switching and changing transformer tap-settings. To solve the RPD problem, a number of conventional optimization techniques have been proposed. They include gradient-based methods, non-linear programming (NLP), quadratic programming (QP), linear programming (LP) and interior point methods. Several evolutionary computation techniques such as genetic algorithms (GA), evolutionary programming (EP) and swarm intelligence have been applied to solve the optimal RPD problems. However, these approaches only result in a single optimal solution. An improved multi-objective generalized differential evolution (I-GDE3) approach to solve optimal reactive power dispatch (ORPD) with multiple and competing objectives is proposed in this article. The objective functions are minimization of real power loss and bus voltage profile improvement. For maintaining good diversity, the concepts of simulated binary crossover (SBX) based recombination and dynamic crowding distance (DCD), are implemented in the GDE3 algorithm [1].

A differential evolution algorithm based OPF for reactive power dispatch and voltage control in power system planning and operation studies is proposed. The problem is formulated as a mixed integer nonlinear optimization problem. Compared to PSO, DE has fewer control parameters (population size, step size and crossover rate). Further, the penalty parameter less technique of handling inequality constraints effectively eliminates the trial and error method of assigning penalty coefficients and also makes the process system independent [5]. The proposed DE approach has been evaluated on IEEE 14, IEEE 30, and IEEE 118-bus systems and the results were compared with that obtained using PSO and SQP.

The Differential Evolution method (DE) for minimizing continuous space functions has been introduced and shown to be superior to Adaptive Simulated Annealing (ASA) as well as the Annealed Nelder & Mead approach (ANM) [4]. A new heuristic approach for minimizing possibly nonlinear and non differentiable continuous space functions is presented. By means of an extensive test bed, which includes the De Jong functions, it will be demonstrated that the new method converges faster and with more certainty than Adaptive Simulated Annealing as well as the Annealed Nelder & Mead approach, both of which have a reputation for being very powerful. The performance of particle swarm optimization using an inertia weight is compared with performance using a constriction factor [6]. Five benchmark functions are used for the comparison. It is concluded that the best approach is to use the constriction factor while limiting the maximum velocity V_{max} to the dynamic range of the variable X_{max} on each dimension. This approach provides performance on the benchmark functions superior to any other published results known by the authors. Constrained active and reactive OPF problems have complicated formulations. A number of mathematical programming based techniques such as randomly search method Differential Evolution (DE) Algorithm and Bat Algorithm have been proposed to solve the OPF problem.

We organize this paper as follows: in the next section (Section II), basics of reactive power dispatch and also contain reactive power economic dispatch. ORPD problem formulation is discussed in Section III. In Section IV, algorithms used for optimization, which are DE and BA used for global best solution of ORPD. Simulation results and comparative study of two algorithms are discussed in section V. Finally, conclusion is made in Section VI.

II. Reactive Power Dispatch

A. Reactive Power Balance

The voltage profile of power system operation is determined by reactive power balance in the system. That is,

$$\sum_{i=1}^{NG} Q_{Gi} + \sum_{j=1}^{NC} Q_{Cj} = \sum_{K=1}^{ND} Q_{dk} + Q_L \quad (1)$$

Where,

Q_{Gi} : The reactive power generation of generator i

Q_{Cj} : The reactive power generation of the VAR compensation device j such as capacitor, SVC, etc.

Q_{dk} : The reactive power load at load bus k

Q_L : System reactive power loss. It includes the reactive power loss of transformer and transmission lines.

According to the experience of practical operations, the reactive power loss of transformer can be computed with the following approximated formula,

$$Q_{LT} = \frac{I_0\%}{100} S_N + \frac{V_s\%S^2}{100S_N}\left(\frac{V_N}{V}\right)^2 \quad (2)$$

Where,

Q_{LT} : The reactive power loss of the transformer

S_N : The rated MVA power of the transformer

V_N : The rated voltage of the transformer

$V_S\%$: The short- circuit voltage of the transformer

$I_0\%$: The no- load current of the transformer

V : The operation voltage of the transformer

The reactive power loss of transmission line ij can be computed as below:

$$Q_{Ll} = \frac{P_t^2 + Q_t^2}{V_t^2} X - \frac{V_i^2 + V_j^2}{2} B \quad (3)$$

Where,

Q_{Ll}: The reactive power loss of the transmission line

P_i: The real power at end i of the line

Q_i: The reactive power at end i of the line

V_i: The voltage at end i of transmission line ij

V_j: The voltage at end j of transmission line ij

X: The reactance of the line

B: The equivalent susceptance of the line (to ground)

B. Reactive Power Economic Dispatch

The purpose of the reactive power economic dispatch is to make the system real power loss minimal through determining the reactive power output of each reactive power source under the constraint condition of the system load demands.

The system real power loss can be represented as below:

$$P_L = P_L(P_1, P_2, \dots, P_n, Q_1, Q_2, \dots, Q_n) \quad (4)$$

For the classic reactive power dispatch problem, the real power outputs of the generators are already known, and the constraint is reactive power balance equation, that is,

$$\sum_{i=1}^{M} Q_{Gi} = Q_D + Q_L \quad (5)$$

For simplification, QG in equation (5) includes all reactive power sources such as generator, capacitor, SVC, etc.

III. ORPD Problem Formulation

Optimal reactive power dispatch is a complex optimization problem in which we try to "optimally" set the values of control variables like reactive power output of generators (generator bus voltages), tap ratios of transformers and reactive power output of shunt compensators like capacitors etc. to minimize the total transmission active power losses while satisfying a given set of constraints [2]. We have used basic Differential Evolution (DE) algorithm for minimizing the following objective function (6).

$$min \sum_{k \epsilon Ng} P_{kloss} = \sum_{k \epsilon Ng} g_k \left(v_i^2 + v_j^2 - 2v_i v_j \cos \Theta_{ij}\right) \qquad (6)$$

Where,

$k = (i, j)$; $i \in N_B$ (Total no. of buses)

$j = N_i$ (No. of buses adjustment to bus i, including bus i)

$\sum_{k \epsilon Ng} P_{kloss}$ = Total active power losses in the transmission system

g_k = Conductance of branch k (pu)

v_i, v_j = voltage magnitude (pu) of bus i and j respectively

Θ_{ij} = load angle difference between bus i and j (rad)

Subject to,

Equality constraints:

Active power flow balance equations at all buses excluding slack bus

$$P_{gi} - P_{di} - v_i \sum_{j \epsilon Ni} v_i \left(g_{ij} \cos \Theta_{ij} + B_{ij} \sin \Theta_{ij}\right) = 0$$

Reactive power flow balance equations at all PQ buses (load buses)

$$Q_{gi} - Q_{di} - v_i \sum_{j \epsilon Ni} v_i \left(g_{ij} \sin \Theta_{ij} + B_{ij} \cos \Theta_{ij}\right) = 0$$

Inequality constraints:

Reactive power generation limit for each generator bus

$$Q_{gi}^{min} \leq Q_{gi} \leq Q_{gi}^{max}, i \in N_g$$

Voltage magnitude limit for each bus

$$v_i^{min} \leq v_i \leq v_i^{max}, i \in N_B$$

Transformer tap-setting constraint

$$T_k^{min} \leq T_k \leq T_k^{max}$$

Power flow limit constraint of each transmission line

$$S_l \leq S_l^{max}$$

Static square penalty function is used to handle inequality constrains. So the Augmented objective function (fitness function) would be as equation (7),

$$F_P = \sum_{k \epsilon Ng} P_{kloss} + Penalty\ Function \qquad (7)$$

Where,

$$Penalty\ Function = k_1 \sum_{i=1}^{N_G} f\left(Q_{gi}\right) + k_2 \sum_{i=1}^{N} f\left(v_i\right) + k_3 \sum_{i=1}^{N_G} f\left(S_{lm}\right)$$

k_1, k_2, k_3 = 10,000

$$f(x) = \begin{cases} 0 & if\ x^{min} \leq x \leq x^{max} \\ (x - x^{max})^2 & if\ x > x^{max} \\ (x^{min} - x)^2 & if\ x < x^{min} \end{cases}$$

IV. ALGORITHMS USED FOR OPTIMIZATION

The aim of optimization is to determine the best-suited solution to a problem under a given set of constraints. Several researchers over the decades have come up with different solutions to linear and non-linear optimization problems. Mathematically an optimization problem involves a fitness function describing the problem, under a set of constraints representing the solution space for the problem. Unfortunately, most of the traditional optimization techniques are centered around evaluating the first derivatives to locate the optima on a given constrained surface. Because of the difficulties in evaluating the first derivatives, to locate the optima for many rough and discontinuous optimization surfaces, in recent times, several derivative free optimization algorithms have emerged. The optimization problem, now-a-days, is represented as an intelligent search problem, where one or more agents are employed to determine the optima on a search landscape, representing the constrained surface for the optimization problem.

In evolutionary computation, differential evolution (DE) is a method that optimizes a problem by iteratively trying to improve a candidate solution with regard to a given measure of quality. Such methods are commonly known as metaheuristics as they make few or no assumptions about the problem being optimized and can search very large spaces of candidate solutions. The algorithm is inspired by biological and sociological motivations and can take care of optimality on rough, discontinuous and multimodal surfaces [3]. The main advantages of differential evolution are: (1) no major restrictions apply to the error function i.e, non-differentiable transfer functions may be used; (2) there are no major restrictions on the regularization methods; (3) convergence to a global minimum can be expected (but the time needed for convergence can be intolerable); (4) easy tuning of the algorithm parameters (mainly the size of population); (5) the linear time and space complexity of the algorithm can be established.

Also In this paper, we intend to propose a metaheuristic method, namely, the Bat Algorithm (BA), based on the echolocation behavior of bats. The capability of echolocation of micro bats is fascinating as these bats can find their prey and discriminate different types of insects even in complete darkness. We will first formulate the bat algorithm by idealizing the echolocation behavior of bats. We then describe how it works and make comparison with other existing algorithms. Finally, we will discuss some implications for further studies [13].

A. Procedure DE

Generally, the algorithm can be described in the following steps:

Step 1) Initialization: At the very beginning of a DE run, problem independent variables are initialized in their feasible numerical range. Therefore, if the j^{th} variable of the given problem has its lower and upper bound as x_{kmin} and x_{kmax} , respectively, then the j^{th} component of the i^{th} population members may be initialized as, An individual *i* in generation G is a multidimensional vector x_i^G = ($x_{i,1}$, ... , $x_{i,D}$).

$$x_{i,k}^G = x_{kmin} + rand(0,1) \cdot (x_{kmax} - x_{kmin})$$

$i \in [1, NP], k \in [1, D]$

where,

NP is the population size and

D is the number of control variables.

Each variable k in the individual is initialized within its boundaries x_{kmin} and x_{kmax}.

Step 2) Mutation For every i ∈ [1, 2,…, NP] the weighted difference of two randomly chosen individuals X_{r2} and X_{r3}, is added to another randomly selected individual X_{r1} to build a mutated vector v_i.

$$v_i = x_{r1}^G + F(x_{r2}^G - x_{r3}^G)$$

Where, i, r1, r2 and r3 are mutually different indices from the current generation. F is the step size which is chosen from the range [0, 2].

Step 3) Crossover The target vector x_i is mixed with the mutated vector v_i using the following scheme, to yield the trial vector u_i

$$u_i = u_{i,k}^{G+1} = \begin{cases} v_{i,k} & if\ rand_{k,i} \leq CR\ or\ k = I_{rand} \\ x_{i,k}^G & if\ rand_{k,i} > CR\ and\ k \neq I_{rand} \end{cases}$$

Where, $rand_{k,i}$ ∈ [0, 1] and I_{rand} is chosen randomly from the interval [1, 2,. . . ,D], CR is the DE control parameter, called the Crossover Rate, and is a user defined parameter within range [0,1].

Step 4) Selection Select the individuals for the next generation a follows:

$$x_i^{G+1} = \begin{cases} u_i^{G+1} & if\ f(u_i^{G+1}) \leq f(x_i^G) \\ x_i^G & OTHERWISE \end{cases}$$

Step 5) Repeat the mutation, crossover and selection operators until termination criteria, such as maximum number of generation is met.

B. Procedure Bat Algorithm

If we idealize some of the echolocation characteristics of microbats, we can develop various bat-inspired algorithms or bat algorithms. For simplicity, we now use the following approximate or idealized rules:

1. All bats use echolocation to sense distance, and they also ‘know’ the difference between food/prey and background barriers in some magical way;
2. Bats fly randomly with velocity v_i at position x_i with a fixed frequency f_{min}, varying wavelength λ and loudness A_0 to search for prey. They can automatically adjust the wavelength (or frequency) of their emitted pulses and adjust the rate of pulse emission r ϵ [0, 1], depending on the proximity of their target;
3. Although the loudness can vary in many ways, we assume that the loudness varies from a large (positive) A_0 to a minimum constant value A_{min}.

V. SIMULATION RESULTS

The DE and BA approach for optimal reactive power dispatch algorithms are tested on standard IEEE 300 bus test systems. For coding used test_bed_opf [17] and a comparative study of Both DE and BA [13], employing a constriction coefficient, was done to verify the performance of the DE and BAT algorithm. The DE and BAT algorithm is implemented using MATLAB running on Core i3-2350M CPU PC. We have used MATPOWER [8] software, version 3.2 for executing load flow analysis for each particle. DE and BA parameters used for the simulation are summarized in Table 2. Number of individuals in a population for each test system is decided by experimentation. Table 1 contains test system.

A. ORPD test case – IEEE 300 bus system

Objective: Minimize the total active power transmission losses while fulfilling constraints (associated to nodal balance of power, nodal voltages, allowable branch power flows, and generator reactive power capability) for normal (non-contingency), and selected N-1 conditions.

Constraints: 651 for non-contingency conditions, and 950 for each N-1 condition.

Optimization variables: 145, comprising 69 continuous variables associated to generator bus voltage set-points, 62 discrete variables associated to stepwise adjustable on-load transformers’ tap positions, and 14 binary variables associated to switchable shunt compensation devices.

Considered contingencies (N-1 conditions): outages at branches 187, 176 and 213.

Number of function evaluations: 300000.

By running the simulation which made of MATLAB code for both algorithms obtained results in the form of continuous, discrete and binary variables as seen from figure 1 to figure 6.

Table 1: Test system

Item/System		IEEE 300 Bus System
Generators		69
Loads		201
Lines/cables		304
Transformers	Step wise	62
	Fixed tap	45
Shunt Compensation	Binary on/off	14
	Step wise	0
	Continuous	0

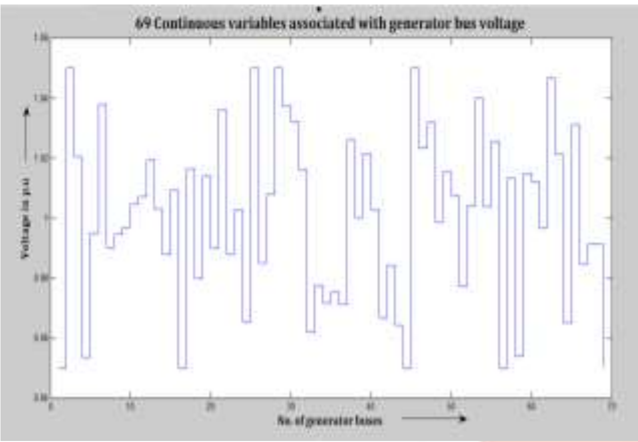

Fig 1: Output of 69 continuous variables of IEEE 300 bus system with DE

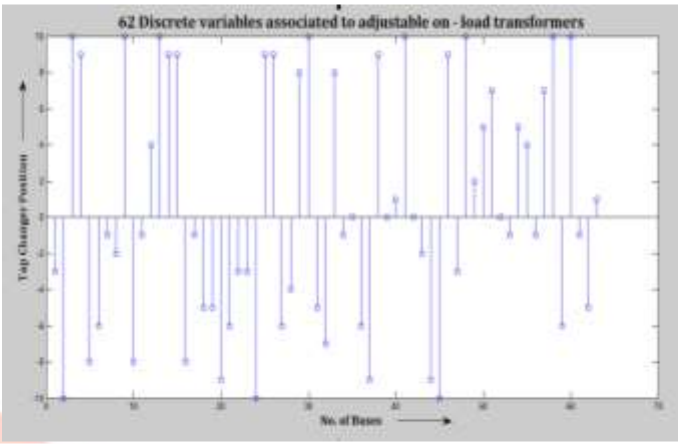

Fig 2: Output of 62 continuous variables of IEEE 300 bus system with DE

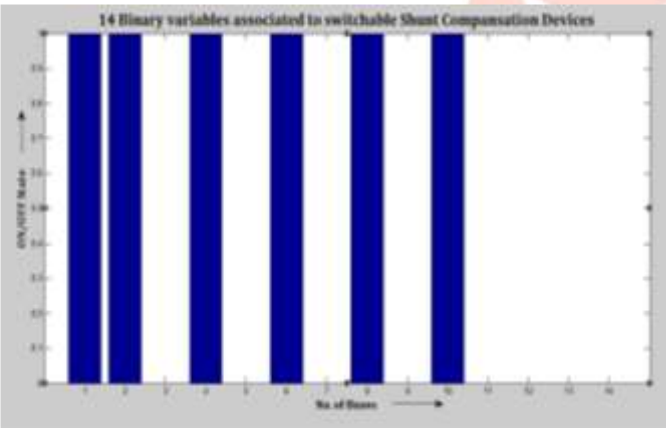

Fig 3: Output of 14 Binary variables of IEEE 300 bus system with DE

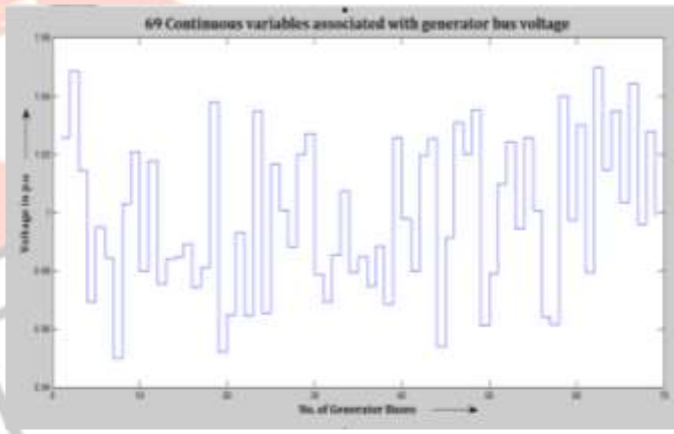

Fig 4: Output of 69 Continuous variables of IEEE 300 bus system with BA

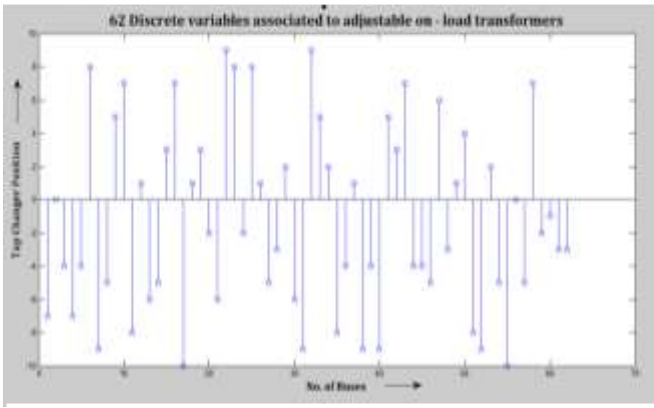

Fig 5: Output of 62 Discrete variables of IEEE 300 bus system with BA

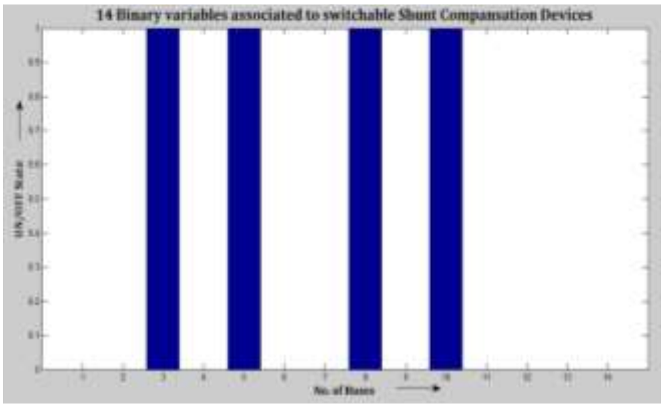

Fig 6: Output of 14 Binary variables of IEEE 300 bus system with BA

B. Comparison between DE and BA

Number of individuals in a population for test system is decided based on trial simulation run. The results, which follow, are the best solutions over 31 independent trials. Results obtain using differential evolution and bat algorithm for ORPD and compare results in Table - 2. Also observing control variables of IEEE 300 bus system in Figure. After running MATLAB code observation take as below in Table 2.

Comparisons of continuous, discrete and binary variables are observed from figure 7 to figure 9.

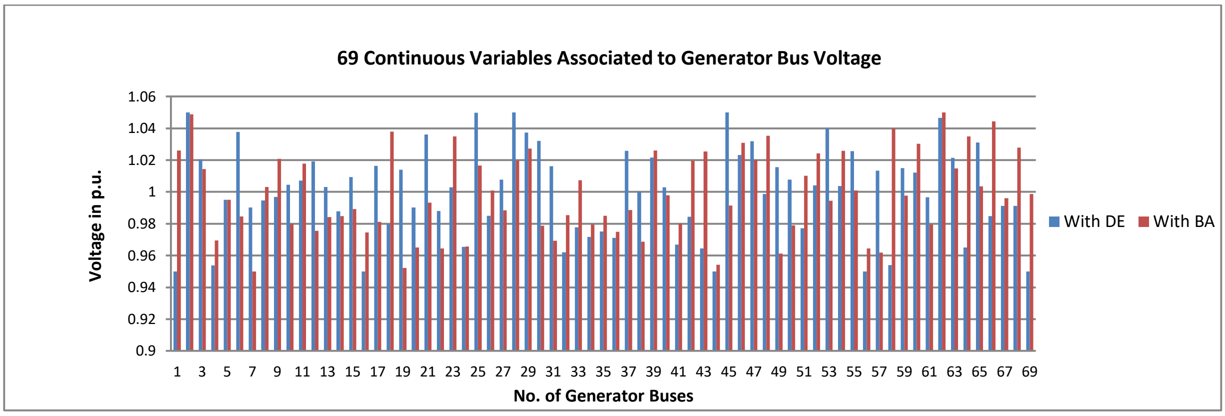

Fig 7: Comparison of 69 Continuous variables of IEEE 300 bus system

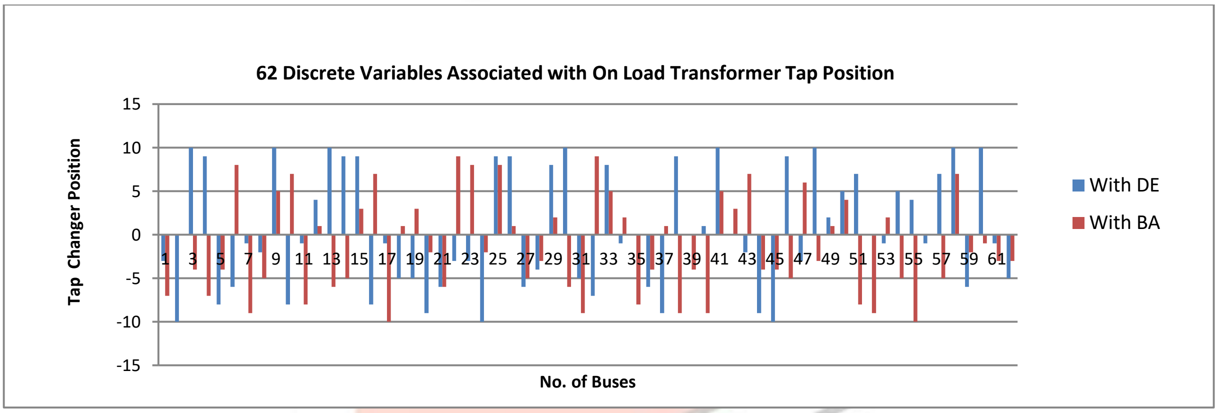

Fig 8: Comparison of 62 Discrete variables of IEEE 300 bus system

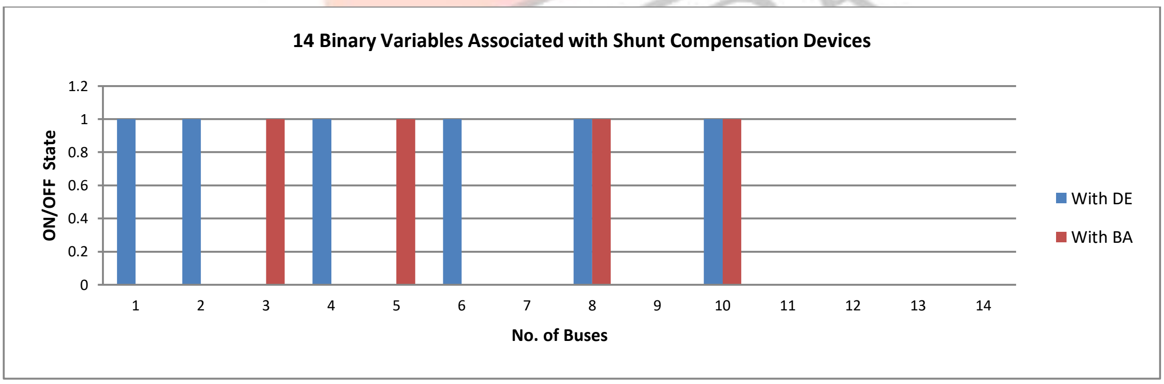

Fig 9: Comparison of 14 Binary variables of IEEE 300 bus system

Table 2: Comparison of Active Power loss obtained with two Different Algorithms

Loss	With DE	With BA
Active power loss (Ploss) MW in IEEE 300 Bus System	**440 MW**	**460.8 MW**

VI. Conclusion

In this paper, a multi objective ORPD problem with conflicting objectives such as total active power losses minimization and bus voltage profile improvement while fulfilling constraints associated to equality and inequality constraints. Results obtain using differential evolution and bat algorithm for ORPD, compare both results and also observing control variables of IEEE 300 bus system, which gives comparative study of problem and found that DE is better than BA. DE has some advantages likes no major restrictions apply to the error function, convergence to a global minimum for objective function can be expected within limit and space complexity of the algorithm can be established.

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