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Solving Dynamic Optimal Power Flow Problems using DE and IMDE Algorithms

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Abstract: This paper proposes an intersect mutation differential algorithm to solve the dynamic optimal power flow (DOPF) problem with the prohibited zones, valve-point effects, ramp rate and security constraints. The proposed method uses a novel direction to improve the global search ability of differential evolution algorithm. The dynamic optimal power flow problem is solved under multi-period conditions. Also, the prohibited zones, nonlinear characteristics of the alternative current power flow as well as technical constraints, such as transmission constraints, are all considered for the realistic operation. These features make the DOPF as a complicated nonlinear and non-convex optimization problem. This proposed intersect mutation differential evolution algorithm is applied for solving the DOPF problem on an IEEE 30-bus test system to illustrate the application of the proposed modeling framework. The results obtained on the IEEE 30-bus system are also compared with the results reported in the literature.

Keywords: Optimal power flow, dynamic optimal power flow, differential evolution; intersect mutation differential evolution, ramp rate constraint; prohibited zones. security constraints.

1. INTRODUCTION

Optimal power flow (OPF) calculation has been a challenging task to operate a modern power system in an efficient way. It determines optimal control variables and system quantities for optimal power system planning and operation. The OPF calculations have also become necessary to compensate the system for continually changing load demand and provide energy of a high quality[1]. The optimal power flow optimizes different objective functions simultaneously satisfying the physical, operational and security constraints under the given period and load conditions.

In general, OPF can be defined as a non-linear, non convex, multi-dimensional and large-scale numerical problem. In the practical power system operation, the power demand is continually changed during the entire day, therefore, it has become necessary to solve the OPF problem in each hour considering economic and security aspects and is termed as dynamic optimal power flow (DOPF). The DOPF is actually the extended formulations of the original OPF problem and it is more difficult to solve because of its large dimensionality[2].

In the literature, several classical techniques have been developed and used for solving the optimal power flow problems. Gradient based method [3], non-linear programming [4], linear programming (LP) [5,6], quadratic programming (QP) [7], Newton-based method [8,9], sequential unconstrained minimization technique [10] and interior point methods (IPMs) [11] have been successfully implemented and have proved their capabilities for solving the optimal power flow problems.

Carpentier [3], proposed the first solution technique for solving the OPF problem and was naed as the reduced gradient method. Dommel and Tinney [4] presented the formulation of optimal power flow based on Kuhn–Tucker optimality criterion using a combination of the gradient method with independent variables and penalty functions. Abou El-Ala and Abido [5] and Mota-Palomini [6] proposed the linear programming method (LP) for getting the results in fast and secure ways than the nonlinear programming method. In addition, quadratic programming (QP) based approaches are proposed by Burchett [7] and Newton based optimal power flow methods are used and applied successfully by Sun [8] and Santos [9].
All the classical optimization methods presented in the literature require an acceptable initial point as the quality of solutions highly depends on the initial settings. Due to the disadvantages of the classical methods and with the development of the population based optimization methods, the use of population methods for solving the optimal power flow problems has rapidly grown during the last decades. The population based optimization methods do not use the derivative information, and have the ability to overcome trap in a local minimum, and cope with large-scaled non-linear problems[12].

The most popular methods in this field such as genetic algorithm (GA) [13], enhanced genetic algorithm (EGA) [14], evolutionary programming (EP) [15,16], simulated annealing (SA) [17], particle swarm optimization (PSO) [18], differential evolution (DE) [19], stochastic weight trade-off particle swarm optimization (SWT-PSO) [20],

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biogeography-based (BBO) and quasi-oppositional biogeography-based optimization (QOBBO) [21,22], gravitational search algorithm (GSA) [23], harmony search algorithm (HS) [24], artificial bee colony algorithm (ABC) [25], modified imperialist competitive algorithm(MOMICA) [26] and many more Grey Wolf Optimizer (GWO) [27–31] have been proposed to solve the different OPF problems.

Differential evolution (DE) is a simple and very powerful evolutionary algorithm (EA) introduced by Storn and Price [32]. With the advantages of simplicity, fast convergence and less parameter, DE has been used in many areas. Most researchers focus on choosing suitable control parameter values, and have done a lot of impressive works [33–40]. From the literatures mentioned above, one can see that the focus of these researches was the setting of the components, but the self-adaption strategies were becoming more and more complicated.

Although, in the literature, there are few proposed methods for novel improvement of DE, such as [41–43], the simulation results showed that there were many spaces for improvement. In this paper, we propose a new DE algorithm, called intersect mutation differential evolution (IMDE) algorithm with better experimental results. The remainder of this paper is organized as follows: Section 2 describes the formulation of DOPF problems. Section 3 explains the DE and IMDE algorithms, Section 4 gives the implementation steps of both DE and IMDE algorithms and Section 6 gives the numerical examples of solving the DOPF problem. Finally Section 6 explains the conclusions.

2. PROBLEM FORMULATION OF DYNAMIC OPTIMAL POWER FLOW

The main objective function of the DOPF is the minimization of the total fuel cost over total time horizon. The adjustable system quantities such as controllable real power generations, controllable voltage magnitudes, and transformer tap ratios are taken as control variables in the proposed scheme. Accordingly, the objective function of the DOPF problem can be written as follows:

$$Min \quad F(\mathbf{X}) = \sum_{t=1}^{T}\sum_{i=1}^{N} F_{it}(P_{it}) \quad (\$) \tag{1}$$

where $F(\mathbf{X})$ is the total generating cost over the whole dispatch period, T is the number of intervals in the scheduled horizon, N is the number of generating units, and $F_{it}(P_{Git})$ is the fuel cost in terms of its real power output P_{Git} in megawatts at time t. Considering the valve-point effects, the fuel cost function of i^{th} thermal generating unit is expressed as the sum of a quadratic and a sinusoidal function in the following form

$$F_{it}(P_{it}) = a_i P_{it}^2 + b_i P_{it} + c_i + \left| \ e_i \sin(f_i (P_{i\min} - P_{it})) \ \right| \quad (\$/h) \tag{2}$$

where a_i, b_i and c_i are cost coefficients,

e_i and f_i are constants from the valve point effect of the i^{th} generating unit.

$$\mathbf{X} = [\mathbf{P_G}, \mathbf{V_G}, \mathbf{T_{TP}}, \mathbf{Q_c}]_{1*NV} \tag{3}$$

$$\mathbf{P_G} = \left[P_{G1}, P_{G2}, ..., P_{GNg-1} \right]_{1*((N_g-1)*T} \tag{4}$$

$$P_{Gi} = \left[P_{Gi,1}, P_{Gi,2}, ..., P_{Gi,t}, ..., P_{Gi,T} \right]_{1*T} \tag{5}$$

$$\mathbf{V_G} = \left[\mathbf{V_{G1}}, \mathbf{V_{G2}}, ..., \mathbf{V_{gNg}} \right]_{1*(Ng*T)} \tag{6}$$

$$V_{Gi} = \left[V_{Gi,1}, V_{Gi,2}, ..., V_{Gi,t}, ..., V_{Gi,T} \right]_{1*T} \tag{7}$$

$$\mathbf{T_{TP}} = [\mathbf{T_{TP1}}, \mathbf{T_{TP2}}, ..., \mathbf{T_{TPNtran}}]_{1*(NT*T)} \tag{8}$$

$$T_{TPi} = [T_{TPi,1}, T_{TPi,2}, ..., T_{TPi,t}, ..., T_{TPi,T}]_{1*T} \tag{9}$$

$$NV = (N_{tran} + N_{cap} + N_{gen} + (N_{gen} - 1)) * T \tag{10}$$

This objective function minimizes the total system generation cost, where $F(\mathbf{X})$ is the total generation cost, X is the control vector of the presented problem, $\mathbf{P_G}$ is a vector related to the power generation of all generator except slack generator. $\mathbf{P_{Gi,t}}$ is the real power generation of i^{th} unit at t^{th} interval, $\mathbf{V_G}$ is a vector related to the voltage of

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generator bus (PV buses), and $\mathbf{V_{Gi,t}}$ is the voltage magnitude of i^{th} generator at t^{th} interval, $\mathbf{T_{TP}}$ is a vector related to the tap of transformers and $\mathbf{T_{TPi,t}}$ is the tap of i^{th} transformer at t^{th} interval, which is a discrete control variable, meanwhile, it is considered as continuous variable in this paper.

Similarly, Ng is the total number of generation units, NT is the number of tap transformers, and T is the number of intervals, respectively. NV is the number of control variable in the proposed optimization problem.

The minimization of the generation cost is subjected to the following equality and inequality constraints:
Prohibited operating zones. Units can have prohibited operation regions due to faults in the machines themselves or the associated auxiliaries, such as boilers, feed pumps etc.
Generators ramp rate: The ramp rate is the amount of load you can add to the turbine per unit of time.
Real power balance constraint: The total generation should be able to satisfy the given load demand at any interval.
AC power flow equalities: The power flow constraints are satisfied by running the load flow solution techniques.
The inequality constraints: For the safety purposes of the generating units as well as the stable operation of the system, all the generating units are firmly limited to operate within their minimum and maximum generation capacity;
System spinning reserve constraint: A minimum system spinning reserve is required to be considered to satisfy the system load demand and be responsible for any frequency changes due to load fluctuations in real-time systems
Security constraints: The OPF security constraints ensure that the optimal solution is secure, preventively secure or correctively secure with respect to the steady operational state of the power system. Modeled security constraints are upper and lower bounds on all variables except voltage phases, and upper bounds on specified branch-current magnitudes referred to as transmission thermal-limit constraints.

3. OVERVIEW OF OPTIMIZATION ALGORITHMS

3.1 Differential evolution algorithm

DE uses mutation and crossover to generate new individuals. One population consists of NP individuals. One individual $X_{i,G}$ consists of D variables which are constrained by search range. The initial individuals are randomly determined, then mutation and crossover are used to generate the new individuals and selection is applied to determine whether the new individual or the original one will survive into the next generation[43].
Mutation: According to the strategy DE/rand/1/bin, the mutation vector $v_{i,G+1}, i=(1,2,3,...,NP)$, is generated by using three randomly chosen target vectors $x_{r1,G}, x_{r2,G}, x_{r3,G}$ and a mutation parameter F . The formula is represented as:

$$v_{i,G+1} = x_{r1,G} + F(x_{r2,G} - x_{r3,G}), \quad r1 \neq r2 \neq r3 \neq i \tag{11}$$

From the formula above, we can see that it contains 4 vectors, so the number of population (NP) must be at least 4. F > 0 is a mutation control parameter which affects the disturbance added by two individuals.
Crossover: Crossover means to swap the dimensions between the target vectors and its offspring mutant vector controlled by crossover parameter CR. Usually the binomial crossover is accepted, which is described as:

$$u_{i,G+1}^{j} = \begin{cases} v_{i,G+1}^{j} & if\ r(j) \leq CR\, or\ j = n_j \\ x_{i,G}^{j} & otherwise \end{cases} \tag{12}$$

where $u_{i,G+1}^{j}$ means the jth number of trial vector $u_{i,G+1}$, $r(j)$ is a random number between [0, 1], and n_j is a randomly generated dimension to make sure that at least one dimension of the trial
vector is closed from the mutant vector.
Selection: The operation of selection determines whether the trail vector or the target vector survives into the next generation on the basis of the vectors' fitness. Greedy selection is used:

$$x_{i,G+1} = \begin{cases} u_{i,G+1}^{j} & if\ f(u_{i,G+1}) < f(x_{i,G}) \\ x_{i,G} & otherwise \end{cases} \tag{13}$$

where $f(u_{i,G+1})$ and $f(u_{i,G})$ are the objectives of $u_{i,G}$ and $x_{i,G}$ and $f(u_{i,G+1}) < f(x_{i,G})$ is used to solve minimization problems.

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3.2 IMDE algorithm

Most researchers proposed different ways on choosing suitable control parameter values of differential evolution [29–36]. In this section, a novel direction to improve the global search ability of DE is proposed. There are two different processes put forward to obtain the next generation. There are only a few modifications in mutation operation between them, since most operations of these two processes are in common.

The first process: Novel mutation and crossover operations for the worse part and the better part are different. For the better part, mutate the vectors with one individual (wr1) chosen from the worse part and two individuals (br1 and br2) chosen from the better part, as the formula below shows:

$$v_{i,G+1} = x_{wr1,G} + F(x_{br2,G} - x_{br3,G}), \quad br1 \neq br2 \neq wr1 \neq j \tag{14}$$

Also with the aim to improve the searching ability, some changes are made for the crossover operation. This novel operation is described as:

$$u^j_{i,G+1} = \begin{cases} v^j_{i,G+1} & if \ f(v_{i,G+1}) \leq f(x_{i,G}) \, or \, if \ r(j) \geq CR \, or \ j = n_j \\ x^j_{i,G} & otherwise \end{cases} \tag{15}$$

For the worse part, mutate the vectors with one individual (br1) chosen from the better part and two individuals (wr1 and wr2) chosen from the worse part, as the formula below shows:

$$v_{i,G+1} = x_{br1,G} + F(x_{wr1,G} - x_{wr2,G}), \quad br1 \neq wr1 \neq wr2 \neq j \tag{16}$$

Then:

$$u^j_{i,G+1} = \begin{cases} v^j_{i,G+1} & if \ r(j) \leq CR \, or \ j = n_j \\ x^j_{i,G} & otherwise \end{cases} \tag{17}$$

And there are no changes to selection operation.

The second process: The 1st process use the individuals in the worse part to search for wilder regions with the aim to improve global search ability. So in the second process, use another novel mutation operation which is similar to the strategy DE/current-best/1/bin.

For the second process, the formula changed to:

The better part:

$$v_{i,G+1} = x_{wr1,G} + F(x_{wr1,G} - x_{br2,Gw}), \quad br1 \neq wr1 \neq wr2 \neq j \tag{18}$$

$$u^j_{i,G+1} = \begin{cases} v^j_{i,G+1} & if \ f(v_{i,G+1}) \leq f(x_{i,G}) \, or \, if \ r(j) \geq CR \, or \ j = n_j \\ x^j_{i,G} & otherwise \end{cases} \tag{19}$$

$$u^j_{i,G+1} = \begin{cases} v^j_{i,G+1} & if \ f(v_{i,G+1}) \leq f(x_{i,G}) \, or \, if \ r(j) \geq CR \, or \ j = n_j \\ x^j_{i,G} & otherwise \end{cases} \tag{20}$$

The worse part:

$$v_{i,G+1} = x_{br1,G} + F(x_{wr1,G} - x_{br2,Gw}), \quad br1 \neq wr1 \neq wr2 \neq j \tag{21}$$

$$u^j_{i,G+1} = \begin{cases} v^j_{i,G+1} & if \ r(j) \leq CR \, or \ j = n_j \\ x^j_{i,G} & otherwise \end{cases} \tag{22}$$

4. IMPLEMENTATION STEPS OF DE AND IMDE ALGORITHMS ON DOPF PROBLEM

In this section, the application of DE and IMDE on the DOPF problem is presented step by step.

DE Algorithm: The details of the DE based optimization algorithm are as follows

Step. 1 Generate an initial population randomly within the control variable bounds.

Step. 2 For each individual in the population, run power flow algorithm such as Newton- Raphson method, to find the operating points.

Step. 3 Evaluate the fitness of the individuals

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Step. 4 Perform differentiation (mutation) and crossover to create offspring from parents.
Step. 5 Perform Selection between parent and offspring. While using the penalty method of constraint handling the following criteria are enforced while selecting the individuals for the next generation. Any feasible solution is preferred to any infeasible solution. Among two feasible solutions, the one having better objective function value is preferred.
Step. 6 Store the best individual of the current generation.
Step. 7 Repeat steps 2 to 6 till the termination criteria is met (maximum number of generations).

IMDE Algorithm: The working steps of the proposed IMDE are shown as follows:
Step 1: Initialization. Set the generation number G = 0. Randomly initialize a population of NP target individuals
Step 2: Evaluate each target individual rank individuals according to the fitness in descending order.
Step 3: Generate NP trial individuals. For i = 1 to NP repeat the Steps 3.1–3.2.
Step 3.1: For 1st process for worse part, generate a mutant vector using formula (14); for better part, generate a mutant vector using formula (15).
Step 3.2: for worse part, generate a trial vector using formula (16); for better part, generate a trail vector using formula (17).
Step 4: Selection for next generation. Determine the members of the target population using the formula (13).
Step 5: Increment the generation G = G + 1. If G does not equal to the maxing number of generation, go to Step 2; otherwise, stop iteration.
The difference between 2nd process and 1st process is at Step 3, so in 2nd process we only need to do some changes to Step 3:
Step 3.1: For 2nd process
for worse part, generate a mutant vector using formula (18);
for better part, generate a mutant vector using formula (20).
Step 3.2: for worse part, generate a trial vector using formula (21);
for better part, generate a trail vector using formula (22).

5. SIMULATION RESULTS

To demonstrate the performance of the proposed DE and IMDE algorithms, these methods have been applied on the IEEE 30-bus test system. Detailed data about 30-bus IEEE test system can be obtained from [44]. The IEEE 30-bus system consists of six generators connected at buses 1, 2, 5, 8, 11, and 13, where the bus 1 is treated as the slack bus. The lower and upper voltage magnitude limits of all buses are set to 0.95 and 1.1 p.u. respectively. The system's single-line diagram is shown in Figure 1. This test system has two shunt compensator capacitors installed at buses 10 and 24.. Also, this system has four tap changing transformers connected between the buses 6–9, 6–10, 4–12, and 27–28, and their lower and upper limits are set to 0.9 and 1.1 p.u. respectively. All generators' cost coefficients, power generation limit, ramp rates, and prohibited zones are taken from [2] for the IEEE 30-bus test system.

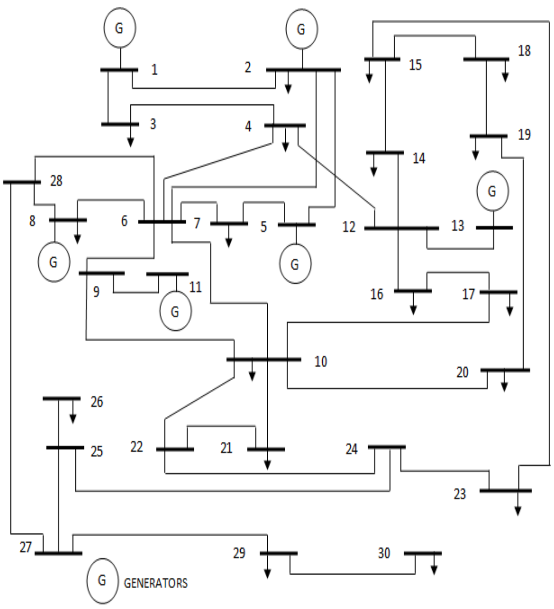

Figure 1. Single-line diagram of IEEE 30-bus test system

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In this paper, MATLAB programming codes for both the DE and the IMDE dynamic optimal power flow algorithms are developed and incorporated together for the simulation purposes. In the implementation of the algorithms, several parameters have been tuned for optimal search process and have been extracted from many computer experiments. The settings of the proposed algorithm are as follows: Number of populations is set to 100 and the maximum number of iteration is 400 for the test system.

In this case, all the constraints such as the valve-point effect, ramp rate, and prohibited zones are considered simultaneously. Fig. 2 shows the variation of fitness function against the number of generations during the DE and IMDE evolutionary process. From this figure it is clearly seen that the convergence property of the IMDE method is better than those achieved by the DE algorithm. Fig. 3 shows the best real power generation levels of each generator during each period.

The results of implementing DOPF over the IEEE 30-bus test system using the proposed DE and IMDE algorithms along with the other methods reported in the literature are presented in Tables 1. The results show the superiority of the proposed method over other methods. The cost obtained by the proposed technique is found to be less than the existing results while satisfying all the equality and inequality constraints. From Table 1, it can be inferred that the proposed algorithms can converge to the better solution, which proves the ability of the proposed algorithm for solving the complex DOPF problems. Figure 4 compares the real power loss obtained after optimization with the proposed DE and IMDE methods on the 30-bus test system. According to Fig.4, the real power loss of the system in each period with the proposed IMDE algorithm is higher than DE due the further reduction in the cost of generation.

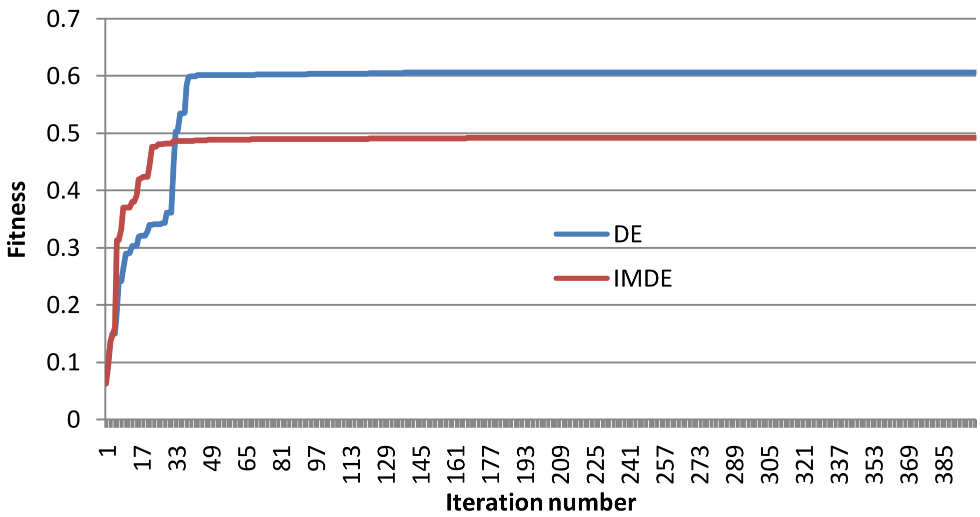

Figure 2: Convergence of fitness function of the IEEE 30-bus system

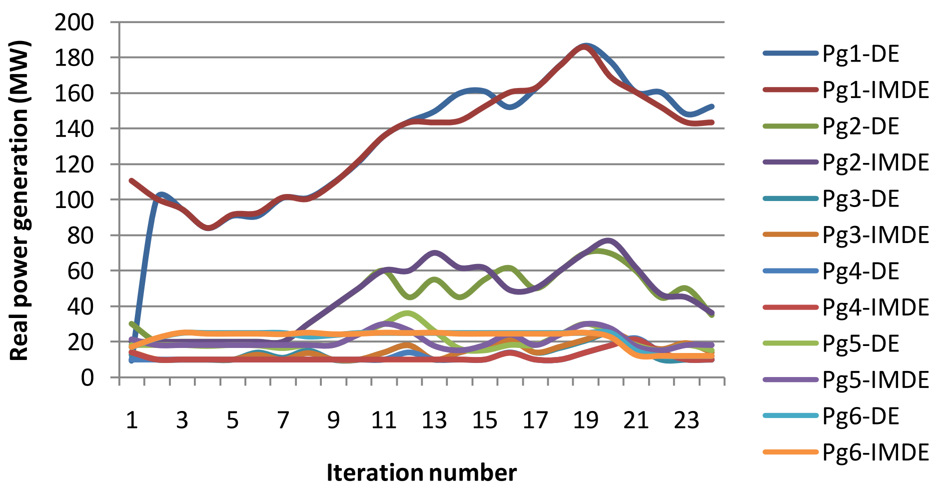

Figure 3: Real power generation levels of IEEE 30-bus system

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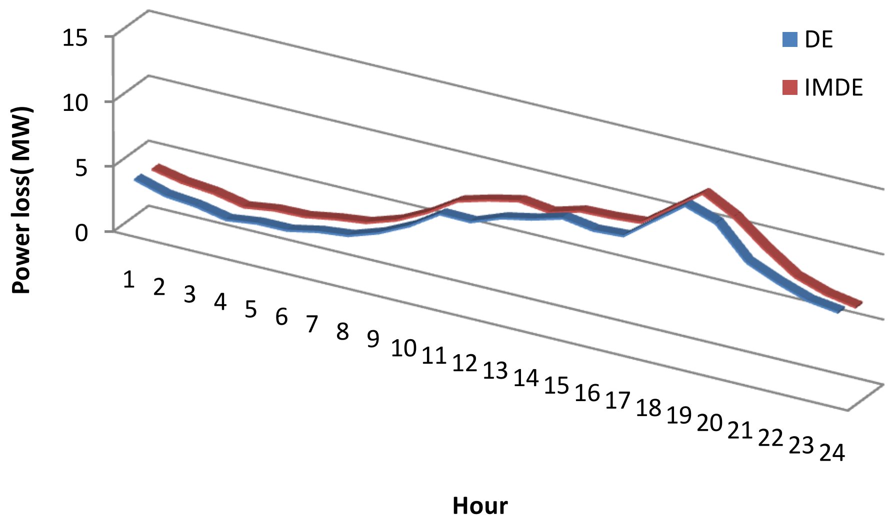

Figure 4: Real power loss of the IEEE 30-bus system

Table 1 Comparing generation cost obtained with different algorithms on IEEE 30-bus system

Method	Cost($/24h)
SA[2]	16,703.81
PSO[2]	16,619.92
PSO-SA[2]	16,486.85
Proposed DE	16,506.00
Proposed IMDE	16,471.00

6. CONCLUSION

This paper has been proposed two population based techniques to solve the dynamic optimal power flow problems such as differential evolution and intersect mutation differential evolution. The simulation results have shown the superiority of the proposed algorithms over the previous methods reported in the literature. The proposed DOPF which, is a complex, non-convex, non-smooth, and nonlinear optimization problem with constraints like ramp rate, prohibited zones, and valve-point effect has been formulated and solved effectively. Despite the complicated structure of the DOPF problem, the results prove the applicability and validity of the proposed techniques as efficient tools for solving complicated problems such as DOPF. The results have been compared with those obtained by other evolutionary algorithms reported in the literature. It is seen from the comparisons that the proposed methods such as differential evolution and intersect mutation differential evolution algorithms provide better solutions.

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