SYNOPSIS OF

OPTIMAL POWER FLOW SOLUTION USING DIFFERENTIAL EVOLUTION

A THESIS

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1 INTRODUCTION

Optimization refers to the study of problems where an objective function is minimized or maximized by systematically choosing the values of real and/or integer variables from within an allowed set. Many real world and theoretical problems may be modeled in the general framework of an optimization problem. Power system is one of the complex fields in electrical engineering, where optimization plays an important role. Some of the basic problems are Economic Load Dispatch (ELD), Unit Commitment (UC) and Optimal Power Flow (OPF). Solutions of power system optimization problems are difficult, due to the large size, complexity, wide geographical distribution and influence of many unexpected events. This situation is further aggravated by the presence of a large number of nonlinear equality and inequality constraints. Handling of all these constraints is a complicated task in traditional optimization methods like Lagrangian, gradient, Newton's methods. Most of the algorithms proposed for solving nonlinear optimization problems are not capable of making a distinction between local optimal solutions and global optimal solutions, and will treat the local solution as actual solutions to the original problem. It is therefore necessary to employ most efficient optimization methods to take full advantages in simplifying the formulation and implementation of the problem.

In recent years, heuristic methods are widely employed for solving such complex problems. Simulating these processes on a computer, results in stochastic optimization techniques that can often perform better than classical methods of optimization, when applied to difficult real world problems. These methods, though efficient, are time consuming. Various evolutionary techniques like Genetic Algorithm (GA), Evolutionary Programming (EP), Evolutionary Strategies (ES) and Particle Swarm Optimization (PSO), have been applied to power system optimization problems (Miranda *et al.*, 1998). Differential Evolution (DE) is a relatively new evolutionary algorithm proposed by Storn and Price (1997) which is simple, yet powerful, for solving complex optimization problems.

Practical optimization problems are often characterized by several non-commensurable and often competing objectives. The presence of multiple objectives in a problem, in principle, gives rise to a set of optimal solutions known as Pareto-optimal solution, instead of a single optimal solution (Coello, 1999). In the absence of any further information, it is not possible to decide which of these Pareto-optimal solutions is better than the other. Hence, the operator has to find as many Pareto-optimal solutions as possible from which the most suitable solution is chosen to meet a particular requirement. The use of true Multi-objective Optimization (MO) techniques in power system have advantages like: (a) it allows the management of different objectives, (b) it simplifies the decision making process, and (c) it gives indications on the consequences of the decision with respect to all the objective functions considered. In this way, the power system operator has several alternative solutions for decision making.

2 MOTIVATION

Constrained active and reactive OPF problems have complicated non-analytical, non-static and partially discrete formulations. A number of mathematical programming based techniques such as Linear Programming (LP), gradient method (Dommel and Tinney, 1968), Newton method (Sun *et al.*, 1984), Sequential Quadratic Programming (SQP) (Grudinin, 1998) and Interior Point Method (IPM) (Zhu and Xiong, 2003) have been proposed to solve the OPF problem. These methods rely on convexity to obtain the global optimal solution and as such are forced to simplify the relationships in order to ensure convexity. However the OPF problem is in general non-convex and as a result many local minima may exist. LP requires the objective function and constraints to be linear, which may lead to loss of accuracy. The gradient and Newton methods suffer from difficulty in handling inequality constraints. Conventional methods are not efficient in handling problems with discrete variables. In recent years, global optimization techniques such as GA (Devaraj and Yegnanarayana, 2006), Enhanced GA (Bakirtzis *et al.*, 2002), EP (Lai and Ma, 1997), ES (Das and Patvardhan, 2003), and PSO (Abido, 2002) have been proposed to solve the OPF problem.

Most realistic optimization problems require the simultaneous optimization of more than one objective function. Different mathematical techniques such as weighted summation, ϵ-constraint, and goal programming have been proposed to solve the MO active and reactive power dispatch problem (Dhillon *et al.*, 1994), (Muslu, 2004), (Chen, 1998), (Chen and Liu, 1994). Conventional optimization methods usually convert the multi-objective optimization problem to a single-objective optimization problem by emphasizing one particular Pareto-optimal solution at a time. For finding multiple solutions, such methods require multiple runs, finding a different solution at each simulation run. DE has the potential to achieve a true multi-objective optimization resulting in a set of Pareto optimal solutions.

In literature constraints were handled by use of a penalty function approach, i.e., the constraint violation is multiplied by a penalty coefficient and added to the objective function. Deb (2000) proposed a 'penalty parameterless' scheme to overcome the difficulty of choosing penalty coefficients for GA based constrained optimization problems. The penalty parameterless constraint handling technique can be effectively incorporated in DE as it uses pair-wise comparison for selection operator.

3 OBJECTIVES AND SCOPE

The objectives of this work are

1. developing DE based solution techniques for OPF problems with single and multiple objectives and comparing the performance and computational effectiveness of DE with other evolutionary and conventional techniques,

2. solving single objective OPF problems like (i) generation cost minimization considering network security and (ii) real power loss minimization with mixed integer variables, and

3. solving multi-objective OPF problems like (i) thermal dispatch with economic and emission objectives and (ii) volt-var optimization with real power loss in transmission lines and sum of voltage deviations at load buses as objectives.

Two-objective optimization, a subset of multi-objective optimization, is considered for this study, though the DE based solution technique can be extended to problems with more than two objectives.

4 Differential Evolution

DE is a simple population based, stochastic search evolutionary algorithm for global optimization and is capable of handling non-differentiable, non-linear, and multi-modal objective functions (Price *et al.*, 2005). The population of a DE algorithm is randomly initialized within the initial parameter bounds. The optimization process is conducted by means of three main operations: mutation, crossover and selection. In each generation, each individual of the current population becomes a target vector. For each target vector, the mutation operation produces a mutant vector, by adding the weighted difference between two randomly chosen vectors to a third 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. Generally the algorithm can be described in the following steps:

Step 1. An individual i in generation G is a multidimensional vector $\mathbf{x_i}^{\mathrm{G}} = (x_{i,1}, \ldots, x_{i,D})$. The population is initialized as

$$x_{i,k}^{\mathrm{G}} = x_{k_{min}} + rand(0,1) \times (x_{k_{max}} - x_{k_{min}}) \quad i \in [1, N_p], k \in [1, D] \tag{1}$$

where, N_p is the population size and D is the number of control variables. Each variable k in the individual is initialized within its boundaries $x_{k_{min}}$ and $x_{k_{max}}$.

Step 2. For every $i \in [1, \ldots, N_p]$ the weighted difference of two randomly chosen individuals $\mathbf{x_{r_2}}$ and $\mathbf{x_{r_3}}$, is added to another randomly selected individual $\mathbf{x_{r_1}}$ to build a mutated vector $\mathbf{v_i}$.

$$\mathbf{v_i} = \mathbf{x_{r_1}}^{\mathrm{G}} + F(\mathbf{x_{r_2}}^{\mathrm{G}} - \mathbf{x_{r_3}}^{\mathrm{G}}) \tag{2}$$

In Eq. (2), i, r_1, r_2 and r_3 are mutually different indices from the current generation. F is the step size which is chosen from the range [0, 2].

Step 3. The target vector $\mathbf{x_i}$ is mixed with the mutated vector $\mathbf{v_i}$ using the following scheme, to yield the trial vector $\mathbf{u_i}$.

$$\mathbf{u_i} = u_{i,k}^{\mathrm{G}+1} = \begin{cases} v_{i,k} & \text{if } rand_{k,i} \leq CR \text{ or } k = I_{rand} \\ x_{i,k}^{\mathrm{G}} & \text{if } rand_{k,i} > CR \text{ and } k \neq I_{rand} \end{cases} \tag{3}$$

where $rand_{k,i} \in [0,1]$ and I_{rand} is chosen randomly from the interval $[1, \ldots, D]$ once for each vector to ensure that at least one vector component originates from the mutated vector $\mathbf{v_i}$. Eq. (3) is applied for every vector component $i \in [1, \ldots, N_p]$, $k \in [1, \ldots, D]$. CR is the DE control parameter, called the Crossover Rate, and is a user defined parameter within range [0,1].

Step 4. Select the individuals for the next generation as follows:

$$\mathbf{x_i^{G+1}} = \begin{cases} \mathbf{u_i^{G+1}} & \text{if } f(\mathbf{u}_i^{\mathrm{G+1}}) \leq f(\mathbf{x}_i^{\mathrm{G}}) \\ \mathbf{x_i^{G}} & \text{otherwise} \end{cases} \tag{4}$$

For MO problems, the selection procedure differs from the basic DE algorithm. For the present work non-dominated sorting and ranking selection procedure developed by Deb *et al.* (2002) is used.

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

5 DESCRIPTION OF THE RESEARCH WORK

The OPF is a steady state, non-linear, and non-convex optimization problem, which schedules the power system controls to optimize an objective function while satisfying a set of nonlinear equality and inequality constraints (Dommel and Tinney, 1968). In general the OPF problem can be stated as

$$min \quad \mathbf{f}(\mathbf{x}, \mathbf{u}) \tag{5}$$

$$s.t. \quad \mathbf{g}(\mathbf{x}, \mathbf{u}) = 0 \tag{6}$$

$$\mathbf{h}(\mathbf{x}, \mathbf{u}) \leq 0 \tag{7}$$

$$\mathbf{x_{min}} \leq \mathbf{x} \leq \mathbf{x_{max}}, \quad \mathbf{u_{min}} \leq \mathbf{u} \leq \mathbf{u_{max}} \tag{8}$$

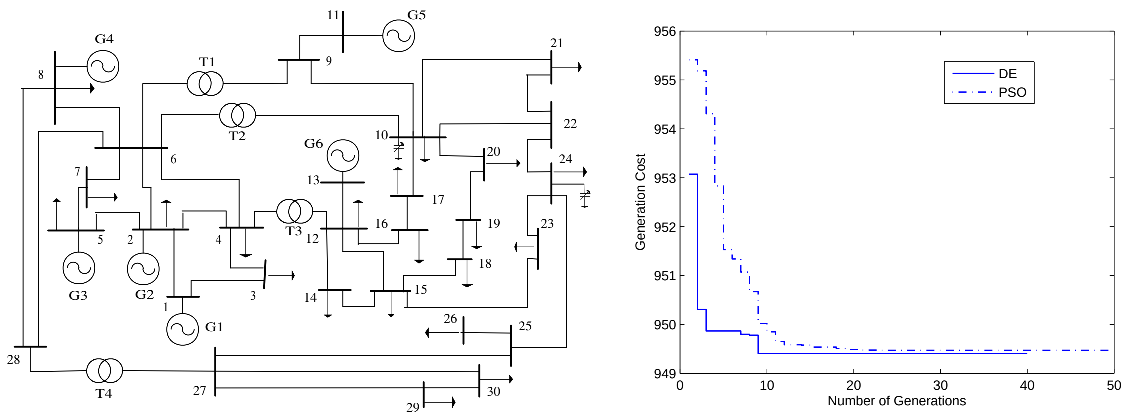
Here, $\mathbf{f}(\mathbf{x}, \mathbf{u})$ is the objective function that typically includes total generation cost (active power dispatch) or total losses in transmission system (reactive power dispatch), $\mathbf{g}(\mathbf{x}, \mathbf{u})$ represents nonlinear equality constraints (power flow equations) and $\mathbf{h}(\mathbf{x}, \mathbf{u})$ is the non-linear inequality constraints of vector arguments of $\mathbf{x}$ and $\mathbf{u}$. The vector $\mathbf{x}$ contains dependent variables consisting of bus voltage angles θ, load bus voltage magnitudes V_L, slack bus real power generation $P_{g,slack}$, and generator reactive power Q_g. The vector $\mathbf{u}$ consists of control variables like real power generation, P_g, generator terminal voltage, V_g, transformer tap ratio, t, and shunt compensation, Q_{sh}. Of the control variables P_g and V_g are continuous variables, while tap ratio of the tap changing transformer and reactive power output of shunt devices, Q_{sh}, are discrete variables.

5.1 Optimal Active Power Dispatch

The objective of Optimal Active Power Dispatch (OAPD) is to minimize the generation cost by adjusting the real power output of the committed generators. The generator cost curves are represented by quadratic functions and the total operating cost F_C in (\$/h) can be expressed as

$$F_C(P_g) = \sum_{i=1}^{N_g} (a_i + b_i P_{g_i} + c_i P_{g_i}^2) \tag{9}$$

where N_g is the number of thermal generators; a_i, b_i and c_i are the cost coefficients of the i^{th} generator; and P_{g_i} is the real power output of the i^{th} generator. OAPD problem was solved using the proposed method, PSO and SQP for standard IEEE 14, 30 and 57-bus systems. Fig. 1(a) shows the network diagram of IEEE 30-bus system and Fig. 1(b) shows the performance of the optimization technique in terms of cost with DE and PSO for the best run out of 30 trials on IEEE 30-bus system.



(a) Network Diagram (b) OAPD Convergence

Figure 1: IEEE 30-bus system

In order to verify the robustness of the proposed methodology simulation is carried out for 30 independent runs with different initial population. In each case, the best solution and CPU time were observed. The important statistical details like best, worst, average, standard deviation and variance, along with average CPU time, are listed in Table 1. It can be observed that DE algorithm is more robust and faster than PSO. To ensure a near optimum solution for any random trial, the standard deviation for multiple runs should be very low, which is satisfied better by DE, when compared to PSO. The minimum generating cost (best value) obtained by various techniques along with number of iterations taken, CPU time and number of load flows required are given in Table 2 for all the three test systems.

Table 1: OAPD - Statistical results for IEEE 30-bus system

Compared Item	DE	PSO
Min Cost ($/hr)	949.41	949.47
Max Cost ($/hr)	949.48	949.55
Average Cost ($/hr)	949.46	949.50
Standard Deviation	0.0215	0.0218
Average Iteration	40	49
Average CPU Time (s)	4.365	5.118

Table 2: OAPD - Comparison between DE, PSO and SQP for various test systems

Compared Item	IEEE 14-bus			IEEE 30-bus			IEEE 57-bus		
	DE	PSO	SQP	DE	PSO	SQP	DE	PSO	SQP
Min Cost ($/hr)	743.78	747.38	763.48	949.4	949.50	951.72	10719.56	10720.71	11303
No. of iteration	57	91	9	40	50	74	77	86	21
CPU time (s)	4.232	7.252	0.855	4.325	4.4	6.123	14.708	16.503	5.315
NLFE	1710	2730	NA	1200	1500	NA	2310	2580	NA

NLFE - No. of Load Flow Evaluations NA - Not Applicable

5.2 Optimal Reactive Power Dispatch

The Optimal Reactive Power Dispatch (ORPD) problem has significant influence on secure and economic operation of power systems. It is aimed at minimizing the active power loss in the transmission system by proper adjustments of reactive power variables under several security constraints. In ORPD it is assumed that the real power dispatch is performed separately and real power generation (except at the slack bus) is regarded as constant. Network losses, either for the whole network or for certain sections of network, are non-separable functions of dependent and independent variables. It is given as

$$P_{loss} = \sum_{k=1}^{N_l} g_k[(t_k V_i)^2 + V_j^2 - 2t_k V_i V_j cos\theta_{ij}] \tag{10}$$

where, g_k is the conductance of branch k connected between buses i and j; N_l is the number of transmission lines; t_k is the tap ratio of transformer k; V_i is the voltage magnitude at bus i; θ_{ij} is the voltage angle difference between buses i and j. To verify the effectiveness of the proposed DE based reactive dispatch optimization approach, simulation is carried out on standard IEEE 14, 30 and 57-bus systems and the results are compared with PSO and SQP. As in the previous case DE was found to be more robust as it gave minimum standard deviation among the solutions obtained from multiple random trials.

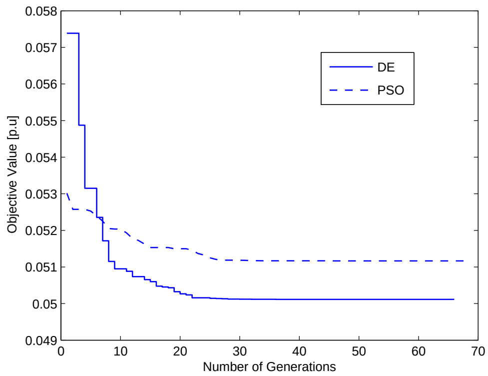


Figure 2: ORPD convergence for IEEE 30-bus system

Fig. 2 shows the objective function value (P_{loss}) plotted against number of generations obtained by DE and PSO. It can be observed that PSO settles to a sub-optimal value. The statistical details for 30 independent simulation runs are provided in Table 3. The minimum loss (best value) obtained by various techniques along with number of iterations taken, CPU time and number of load flow evaluations is given in Table 4 for all the three test systems.

Table 3: ORPD - Statistical results for IEEE 30-bus system

Compared Item	DE	PSO
Min P_{loss} (MW)	5.011	5.116
Max P_{loss} (MW)	5.022	5.218
Average P_{loss} (MW)	5.013	5.125
Standard Deviation	0.0026	0.0291
Average Iterations	66	69
Average CPU Time (s)	13.647	16.420

Table 4: ORPD - Comparison between DE, PSO and SQP for various test systems

Compared Item	IEEE 14-bus			IEEE 30-bus			IEEE 57-bus		
	DE	PSO	SQP	DE	PSO	SQP	DE	PSO	SQP
Min P_{loss} (MW)	13.239	13.250	13.246	5.011	5.116	5.043	25.048	25.305	26.010
No. of iteration	63	80	9	66	70	36	162	120	67
CPU time (s)	4.232	7.252	0.85	4.325	4.4	6.123	14.708	16.503	5.315
NLFE	1890	2400	NA	1980	2100	NA	4860	3600	NA

NLFE - No. of Load Flow Evaluations NA - Not Applicable

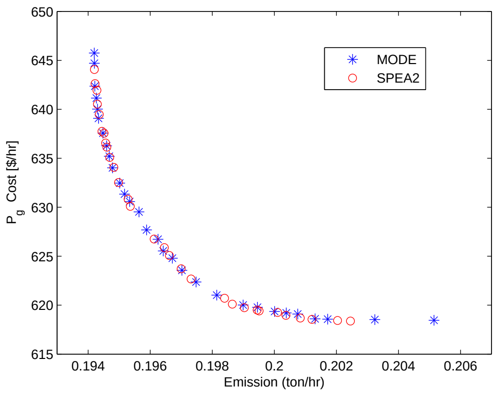
5.3 Economic Emission Dispatch

The environmental regulations have forced electric utilities to consider the environmental impact of generating plants in the normal operation of power systems. Under these circumstances, generation allocation is not only governed by the units capable of minimizing the total generation costs but also satisfying the emissions requirements (Abido, 2006). The economic-emission dispatch determines the real power allocation that reduces generation cost considering the amount of pollutant emission like sulphur oxides and nitrogen oxides. It is required to minimize two competing objective functions, generation cost and emission, while satisfying several equality and inequality constraints. The total generation cost is given in Eq. (9). The total emission F_E in (ton/h) of atmospheric pollutants such as sulphur oxides and nitrogen oxides caused by the operation of fossil fueled thermal generation can be expressed as

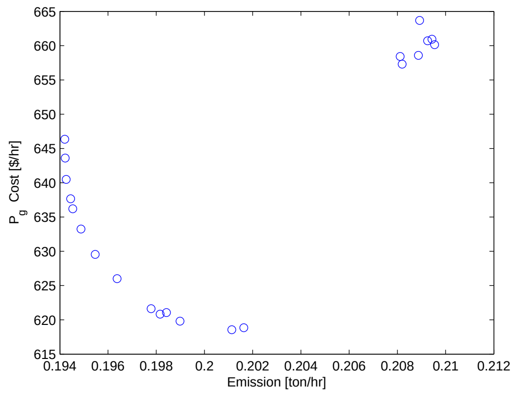
$$F_E(P_g) = \sum_{i=1}^{N_g}(\alpha_i + \beta_i P_{g_i} + \gamma_i P_{g_i}^2 + \zeta_i e^{\lambda_i P_{g_i}}) \tag{11}$$

where α_i, β_i, γ_i, ζ_i, and λ_i are coefficients of the i^{th} generator emission characteristics. To study the performance of economic emission dispatch using Multi-Objective Differential Evolution (MODE), simulations were performed on the standard IEEE 30-bus system with a population size of 30. To compare the results of the proposed approach for EED, the problem was also solved by the conventional weighted summation method and Strength Pareto Evolutionary Algorithm 2 (SPEA2) (Zitzler *et al.*, 2001). To generate a 30 non-dominated solutions with SPEA2 a main population size of 100 is used.

All the security constraints were considered while dispatching real power generation for Economic-Emission Dispatch (EED). Fig. 3(a) gives a comparison between the Pareto optimal solutions obtained by the MODE and SPEA2. It can be seen that with the proposed approach, solutions obtained are diverse and well distributed over the Pareto front. CPU time for MODE, SPEA2 and weighted summation method are 28.161, 82.862 and 122.8 seconds respectively.



(a) MODE & SPEA2 methods



(b) Weighted sum method

Figure 3: Pareto optimal solutions obtained for EED

Table 5: Minimum cost, minimum emission and best compromise solutions obtained by MODE and SPEA2 for EED

Control Variable	MODE			SPEA2		
	Min F_C	Min F_E	BCS	Min F_C	Min F_E	BCS
P_{g1}	0.1361	0.4184	0.3017	0.1701	0.4061	0.3085
P_{g2}	0.3455	0.4622	0.4019	0.3845	0.4546	0.3917
P_{g3}	0.7573	0.5441	0.5815	0.7074	0.5569	0.5621
P_{g4}	0.6016	0.3793	0.5967	0.6038	0.3872	0.5980
P_{g5}	0.5998	0.5520	0.5352	0.5762	0.5469	0.5384
P_{g6}	0.4162	0.5068	0.4436	0.4153	0.5107	0.4628
F_C ($/hr)	618.45	645.74	622.37	618.38	644.06	622.67
F_E (ton/hr)	0.2051	0.1942	0.1975	0.2051	0.1942	0.1973

BCS - Best Compromise Solution

The Pareto front given by weighted summation method after 30 simulation runs is shown in Fig. 3(b). It is clear that varying the weight coefficients in equal increments do not guarantee uniformly distributed solutions in the Pareto front. Further, all the non-dominated solutions cannot be obtained and some of the solutions obtained are inferior.

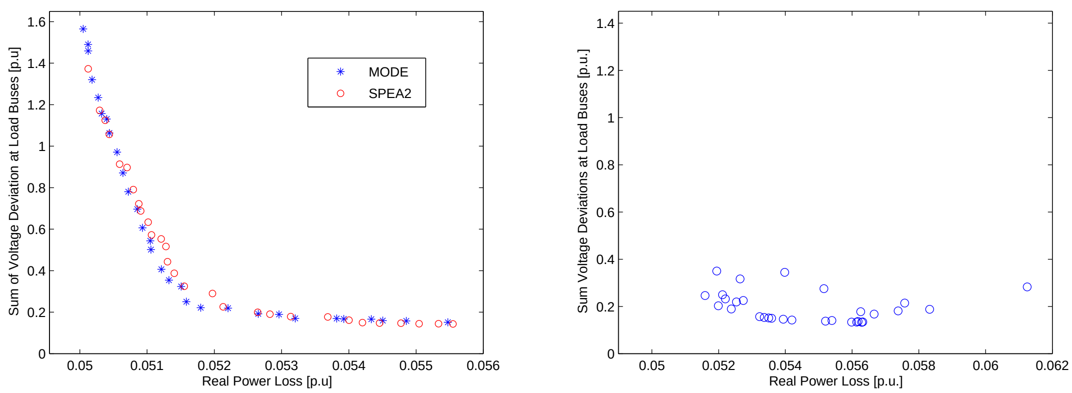
Once the set of Pareto optimal solutions is found, the compromise solution is chosen using a fuzzy function (Abido, 2006). Table 5 shows the control variable setting, F_C and F_E for minimum cost, minimum emission, best compromise solution obtained by MODE and SPEA2.

5.4 Multi-objective Volt-Var optimization

The ORPD problem is formulated as a non-linear constrained multi-objective optimization problem with active power loss in the transmission network and sum of load bus voltage magnitude deviations from specified nominal values as competing objectives. Network losses are non-separable functions of dependent and independent variables as given in Eq. (10). Bus voltage magnitude is one of the important security and service quality indexes. It is required to keep the voltage magnitude deviation of each load bus, from the specified nominal or reference value, as small as possible. Hence Voltage Deviation (VD) is taken as an objective given by

$$VD = \sum_{k=1}^{N_{PQ}} |V_k - V_k^{ref}| \tag{12}$$

where, V_k^{ref} is the specified reference value of the voltage magnitude at load bus k, which is usually set to 1.0 p.u. and N_{PQ} is the number of load buses.



(a) MODE & SPEA2 methods

(b) Weighted sum method

Figure 4: Pareto optimal solutions obtained for multi-objective volt-var optimization

Results for simulation carried out on standard IEEE 30-bus system are presented. Fig. 4(a) shows the performance comparison of MODE and SPEA2. Fig. 4(b) shows the Pareto front obtained by weighted summation method after 30 runs. CPU time taken by MODE, SPEA2 and weighted summation method for volt-var optimization are 58.424, 198.816 and 173.843 seconds respectively. Table 6 shows the control variable setting, F_C and F_E for minimum cost, minimum emission, best compromise solution obtained by MODE and SPEA2.

Table 6: Minimum loss, minimum deviation and best compromise solutions obtained by MODE and SPEA2 for volt-var optimization

Item	MODE			SPEA2		
	Min P_{loss}	Min VD	BCS	Min P_{loss}	Min VD	BCS
V_{G2}	1.0438	1.0409	1.0408	1.4025	1.0371	1.0427
V_{G5}	1.0235	1.0115	1.0214	1.0201	1.0112	1.0191
V_{G8}	1.0246	0.9971	1.0211	1.0230	0.9994	1.0207
V_{G11}	1.1000	1.0647	1.0363	1.0432	1.0153	1.0278
V_{G13}	1.1000	0.9983	1.0405	1.1000	1.0140	1.0440
T_{6-9}	0.9800	0.9100	0.9100	1.0100	0.9700	0.9500
T_{6-10}	1.1000	1.1000	1.1000	1.1000	1.0600	1.0600
T_{4-12}	1.0800	1.0900	0.9800	1.0600	1.0500	1.0100
T_{27-28}	1.0800	1.0500	1.0200	1.0800	1.0500	1.0300
Q_{C10}	0.3000	0.0800	0.1600	0.3000	0.1700	0.2200
Q_{C24}	0.0900	0.1400	0.1200	0.1200	0.1300	0.1200
P_{loss} (p.u.)	0.0501	0.0555	0.0516	0.0502	0.0541	0.0514
VD (p.u.)	1.5649	0.1512	0.2505	1.4175	0.1508	0.3451

BCS - Best Compromise Solution

6 CONCLUSIONS

Differential Evolution algorithm based single and multiple objective optimal power flow solutions have been proposed. Solutions to optimal active power and reactive power dispatch problems with single objectives like cost minimization and loss minimization have been developed. The problems are formulated as a mixed integer nonlinear optimization problems. Simulation results demonstrated the capability of DE to obtain better optimal solutions when compared to PSO and SQP. Also, DE took lesser number of iterations and function evaluations than PSO.

Multi-objective optimization using DE have been attempted to solve the economic emission dispatch and volt-var optimization problems. Economic emission problem has generation cost and emission of pollutants as non-commensurable objectives. Volt-var optimization has been formulated with real power loss in transmission lines and sum of voltage deviations at load buses from specified nominal values, as competing objectives. The results of the proposed approach show that it is efficient for solving multi-objective reactive power dispatch problem where multiple Pareto-optimal solutions can be found in single simulation run. The obtained Pareto-optimal solutions are well-distributed and have good diversity characteristics.

Compared to other population based optimization tools like GA and PSO, DE has fewer control parameters. Further, the penalty parameterless technique of handling inequality constraints employed in this work, for both single as well as multiple objective optimization problems, effectively eliminates the trial and error method of assigning penalty coefficients. This makes the optimization procedure independent of test system being used. DE based OPF was found to be more robust as it provided least standard deviation among the solutions obtained from multiple random trials.

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PROPOSED CONTENTS OF THE THESIS

1. INTRODUCTION
   1.1 Motivation
   1.2 Objective
   1.3 Scope of work
   1.4 Organization of the thesis

2. OPTIMAL POWER FLOW
   2.1 Introduction
   2.2 Types of OPF
   2.3 Mathematical Formulation
   2.4 Solution Methodologies
   2.5 Summary

3. EVOLUTIONARY ALGORITHMS
   3.1 Introduction
   3.2 Genetic Algorithm
   3.3 Particle Swarm Optimization
   3.4 Differential Evolution
   3.5 Constraint Handling
   3.6 Multi-objective Evolutionary Algorithms
   3.7 Summary

4. OPTIMAL ACTIVE POWER DISPATCH
   4.1 Introduction
   4.2 Problem formulation for cost minimization
   4.3 Implementation
   4.4 Simulation results
   4.5 Summary

5. OPTIMAL REACTIVE POWER DISPATCH
   5.1 Introduction
   5.2 Problem formulation for loss minimization
   5.3 Implementation
   5.4 Simulation results
   5.5 Summary

6. MULTI-OBJECTIVE THERMAL DISPATCH
   6.1 Introduction
   6.2 Problem formulation for optimal thermal dispatch with emission

PUBLICATIONS BASED ON THE THESIS

Journal Publications

1. M. Varadarajan and K. S. Swarup, "Network Loss Minimization with Voltage Security using Differential Evolution", *Electric Power System Research* In Press, Corrected Proof Available Online: 27 July 2007, http://dx.doi.org/10.1016/j.epsr. 2007.06.005.

2. M. Varadarajan and K. S. Swarup, "Volt-Var Optimization using Differential Evolution", *Electric Power Components and Systems* (Accepted for publication in vol. 36, no. 4, April 2008).

Conference Proceedings

1. M. Varadarajan and K. S. Swarup, "Volt-Var Optimization considering Voltage Security using Evolutionary Computing", *National Power Systems Conference (NPSC-2006)*, Dec. 22-24, IIT Roorkee.

2. M. Varadarajan and K. S. Swarup, "Optimal Reactive Power Dispatch using Differential Evolution Approach", *ICPS-2007*, Dec. 12-14, CPRI, Accepted.