Multi Objective Optimization of Environmental Constrained Economic Dispatch Problem

B. Srinivasa Rao[1], and K. Vaisakh[2]

[1]*V R Siddhartha Engineering College, Vijayawada-520007, A.P., India*
[2]*AU College of Engineering, Visakhapatnam-530003, A.P, India*

ABSTRACT

This chapter deals with implementation of multi objective optimization methods for solving economic emission dispatch (EED) problem of thermal power generators. Four different evolutionary algorithms such as non-dominated sorting genetic algorithm-II (NSGA-II), multi-objective particle swarm optimization (MOPSO), multi-objective differential evolutionary algorithm (MODE) and multi-objective adaptive clonal selection algorithm (MOACSA) have been presented to solve EED problem. In all these methods a non-dominated sorting technique along with crowded distance ranking is used to find and manage the pareto optimal front. Here three different objectives namely cost, NO_X emission and loss are considered for optimization. In formulation of EED problem for multi-objective optimization various operational constraints in addition to power demand equality constraints are taken into consideration. An IEEE 30-bus 6 unit test system is considered to show the efficiency of the presented methods in solving MOEED problem. The results are compared with two and three objective case studies by using these four algorithms namely NSGA-II, MOPSO, MODE and MOACSA methods.

Keywords: Multi-objective optimization, economic emission dispatch, clonal selection algorithm

1. INTRODUCTION

Traditionally ED problem [1-4] plays vital role in optimal operation of power system. It is referred as the process of allocation of generation to various generating units available such that cost of generation is optimum subject to several equality and inequality constraints. However, with increase in public awareness over the environmental pollution caused by thermal plants, EED problem [5, 6] has drawn much more attention for a good dispatch scheme forn great economical benefit, and reduced pollutants emission.

Various investigations on EED have been reported in the literature till date. A direct approach using conventional methods is, to convert multi-objective EED (MOEED) problem into an equivalent single objective problem [7, 8] by treating emission as constraint. However this method fails in getting complete trade-off curve between cost and emission due to approximation model.

Later a linear programming based optimization technique is proposed in [9] to solve EED problem by considering only one objective at any point of time. But this method requires high computation time and it also fails in giving precise information about complete trade-off curve between cost and emission. In other direction, Zahavi et al. converted MOEED problem to a single objective problem with linear combination of different objectives as a weighted sum [10], in which a set of Pareto-optimal solutions are attained with different weights. Unfortunately, this method demands multiple runs to get Pareto-optimal solutions and not suitable for problems having a non-convex Pareto front.

In recent years many biological inspired [11], swarm intelligence [12] and artificial intelligent based techniques [13] are developed and applied successfully to solve EED problems. The AIS's with intrinsic characteristics [14] are capable to make these methods more appropriate for MOO. Recently, AIS based algorithm is used to solve combined heat and power ED problem by Basu [15]. In this article a new artificial immune system based adaptive clonal selection algorithm (ACSA) is presented in addition to three standard algorithms namely NSGA-II, MOPSO and MODE. All these four methods are applied to solve multi-objective EED problem.

2. MATHEMATICAL FORMULATION OF EED PROBLEM

The mathematical formulation of EED problem treated as MOOP. In literature, this MOOP formulation is defined well and is presented briefly in this section. The general MOOP is composed of control variables set, objective functions, several equality and inequality constraints that are functional relations.

3. PROBLEM OBJECTIVE FUNCTIONS:

In this chapter, three different objectives are considered for illustrating various multi-objective optimization methods. These objective functions are minimization of fuel cost, NO_X emission and real power transmission loss.

Minimization of fuel cost

The ED problem is defined as minimization of the total fuel cost by satisfying various equality and inequality constraints. The total fuel cost function of generator units can be denoted as:

$$F_1 = \sum_{i=1}^{NG} FC_i\left(P_{Gi}\right) = \sum_{i=1}^{NG} a_i + b_i P_{Gi} + c_i P_{Gi}^{\,2} (\$/h) \tag{1}$$

where a_i, b_i *and* c_i are the quadratic fuel cost coefficients pertain to i^{th} generator; P_{Gi} is generating real power output of ith generator; NG is the total generator units.

Minimization of NO_X emission

Thermal units operating with fossil-fuels may release environmental pollutant emissions due to burning of fuels for production of electrical power. The emission function includes sum of all type of emissions like sulphur oxides SO_X and nitrogen oxides NO_X. The emission produced by each thermal unit denoted as a quadratic function in terms generator power output. Therefore the objective function represents minimization of NO_X or SO_X emission may be mathematically modelled as:

$$F_2 = \sum_{i=1}^{NG} (\alpha_i P_{Gi}^2 + \beta_i P_{Gi} + \gamma_i) + \xi_i e^{\lambda_i P_{Gi}} \tag{2}$$

where α_i, β_i, γ_i, ξ_i and λ_i are emission coefficients of the ith thermal unit.

Minimization of real power loss

Active power transmission loss P_L is also treated as one objective function, since the loss reduction is an efficient way to decrease the generation cost and increases the social welfare. This objective function denoted as:

$$F_3 = P_L = \sum_{k=1}^{NL} g_k [V_i^2 + V_j^2 - 2V_i V_j \cos(\delta_i - \delta_j)] \tag{3}$$

where g_k is the conductance of a transmission line k connected between buses i and j; V_i, V_j are the voltage magnitudes at bus i and j respectively; δ_i and δ_j are the phase angles of voltages at bus i and j respectively.

Problem Constraints

The OPF problem has to satisfy both equality and inequality constraints. The operating limits of system are assumed as inequality constraints, while load flow equations are equality constraints.

Equality constraints

The equality constraint represents real power balance equilibrium condition it must satisfy always for any power system network, i.e.

$$\sum_{i=1}^{NG} P_{Gi} - P_D - P_L = 0 \tag{4}$$

Here P_D is total active power demand in the system. And P_L is total transmission losses which can be calculated by using the NR load flow method.

Inequality constraints

The inequality constraints representing the system operating limits as follows.

Generation constraints: Generator voltages, real power outputs and reactive power outputs are restricted by their lower and upper bounds as follows:

$$V_{Gi}^{\min} \leq V_{Gi} \leq V_{Gi}^{\max}, \quad i = 1, \ldots, NG \tag{5}$$

$$P_{Gi}^{\min} \leq P_{Gi} \leq P_{Gi}^{\max}, \quad i = 1, \ldots, NG \tag{6}$$

$$Q_{Gi}^{\min} \leq Q_{Gi} \leq Q_{Gi}^{\max}, \quad i = 1, \ldots, NG \tag{7}$$

Transformer constraints: Transformer tap settings are restricted by their minimum and maximum limits as follows:

$$T_i^{\min} \leq T_i \leq T_i^{\max}, \quad i = 1, \ldots, NT \tag{8}$$

where   NT – Number of tap changing transformers

Shunt VAR constraints: Reactive power injections at buses are restricted by their minimum and maximum limits as:

$$Q_{Ci}^{\min} \leq Q_{Ci} \leq Q_{Ci}^{\max}, \quad i = 1, \ldots, NC \tag{9}$$

where NC – Number of shunt compensators

Security constraints: These include the limits of voltage magnitudes at load buses and transmission line loadings as follows:

$$V_{Li}^{\min} \leq V_{Li} \leq V_{Li}^{\max}, \quad i = 1, \ldots, N_{PQ} \tag{10}$$

$$S_{li} \leq S_{li}^{\max}, \quad i = 1, \ldots, NL \tag{11}$$

4. CONSTRAINTS HANDLING TECHNIQUE

In optimization process there is possibility of violation of inequality constraints results in infeasible solution. When too many constraints are imposed in problem there is a chance to get no solution satisfying all of them. In order to solve this problem a penalty factor is added to objective function corresponding to different security constraints like load bus voltage limits, line flow limits and reactive power generation limits. If all the security constraints are satisfied then the penalty function value will be zero. All security constraint violations are handled as sum of all penalties which is added to one of the objective function is given by

$$\text{Jpen} = J_{LF} + J_{BV} + J_{Qg} \tag{12}$$

Penalty function for line flow violations,

$$J_{LF} = Kp \sum_{i=1}^{NL} (\left| S_{li} \right| - S_{li}^{\lim})^2 \tag{13}$$

Penalty function for load bus voltage violations,

$$\begin{aligned} J_{BV} &= K_v \sum_{i=1}^{N_{PQ}} (V_{li} - V_{max})^2, \; if \; V_{li} > V_{max} \; \text{ or } \\ &= K_v \sum_{i=1}^{N_{PQ}} (V_{min} - V_{li})^2, \; if \; V_{li} < V_{min} \end{aligned} \tag{14}$$

Penalty function for reactive power generation violation

$$\begin{aligned} J_{Qg} &= K_q \sum_{i=1}^{NG} (Q_{Gi} - Q_{max})^2, \; if \; Q_{Gi} > Q_{max} \; \text{ or } \\ &= K_q \sum_{i=1}^{NG} (Q_{min} - Q_{Gi})^2, \; if \; Q_{Gi} < Q_{min} \end{aligned} \tag{15}$$

where Kp, Kv and Kq are the corresponding scaling factors for penalty functions.

5. MULTI-OBJECTIVE OPTIMIZATION

In real world, any multi-objective optimization problem consists of several objective functions that are needed to optimize simultaneously with certain equality constraints along with inequality constraints. This MOOP can be formulated mathematically as:

$$Min \; F(x) = [f_1(x), f_2(x),\dots f_i(x)] \qquad i = 1, 2, \cdots, N \tag{16}$$

$$\text{subject to} : \left\{ g_j(x) = 0, \; h_k(x) \le 0 \right\} \quad j = 1, 2, \cdots, J; \;\; k = 1, 2, \cdots, K;$$

where f_i, h_k and g_j are i^{th} objective function, k^{th} inequality constraint and j^{th} equality constraint respectively. x - represents a decision vector; N, K & J are number of multiple objectives, inequality and equality constraints.

Best Compromise Solution

After having the Pareto-optimal set, a fuzzy-based mechanism is applied to extract a the best compromise solution. Due to imprecise nature of the decision maker's judgment, the ith objective function of a solution in the Pareto-optimal set, F_i, is represented by a membership function μ_i defined as

$$\mu_i = \begin{cases} 1, & F_i \le F_i^{min}, \\ \dfrac{F_i^{max} - F_i}{F_i^{max} - F_i^{min}}, & F_i^{min} < F_i < F_i^{max}, \\ 0, & F_i \ge F_i^{max}. \end{cases} \quad (17)$$

where F_i^{max} and F_i^{min} are the maximum and minimum values of the ith objective function respectively.

Particle swarm optimization (PSO)

Recently a new evolutionary computational intelligence technique called particle swarm optimization (PSO), has been proposed and introduced [16] to solve optimization problems. This technique combines social psychology principles in socio-cognition human agents and evolutionary computations. PSO has been motivated by the behavior of organisms such as fish schooling and bird flocking. Generally, PSO is characterized as simple in concept, easy to implement, and computationally efficient. Unlike the other heuristic techniques, PSO has a flexible and well-balanced mechanism to enhance the global and local exploration abilities.

Differential Evolution (DE)

In the recent past, power full EA such as differential evolution (DE) techniques are employed for power system optimization problems. DE, developed by Storn et al. [17], is a numerical optimization approach that is simple to implement, significantly faster and robust. These methods, when used with real-valued parameters, optimize non-differentiable and nonlinear continuous space problems. One of the significant features of DE is that it utilizes the variation of sampled object vectors pairs obtained at random to conduct mutation operation than using probability function like other EAs.

Genetic Algorithm

Genetic algorithm (GA) is a directed random search method used to find global minimum solution in huge multidimensional search area. For the first time, Holland proposed GA [18] and is effectively applied to many optimization problems [19]. GA makes use of genetic operators to progressively develop fitness of population and control individuals in a solution population over numerous generations. Generally, all the optimization parameters are considered as binary numbers .The GA optimization uses a random numbers generator to generate random initial population. This method is useful when optimization problem prior knowledge is unavailable.

Clonal Selection Algorithm

With the growth of computational intelligence in recent years, the branch of AIS has greatly influencing the engineering applications. The AIS based algorithms are developed using biological principles such as clone generation, proliferation and maturation. These principles are mimicked then included into an AIS based algorithm termed as the clonal selection algorithm (CSA) [20, 21]. The clonal selection algorithm (CSA) named CLONALG, was proposed by Leandro and Fernando [22] is population based stochastic technique. This CSA is more extensively used artificial immune based optimization method in pattern recognition and multimodal optimization problems with binary representation of variables.

Implementation of MOACSA for EED Problem

This section deals with step by step procedure of the MOACSA method for solving EED problem with consideration of transmission loss, generation limits and all security constraints.

Generate randomly distributed antibodies of initial population with size $(N_{pop} \times N)$ and store them in archive X .

$$X = \left[X_1 \ X_2 \ldots X_i \ldots X_{N_{pop}} \right]^T \tag{18}$$

where, $X_i = \left[P_G \quad V_G \quad Tap \quad Q_c \right]_{1xN}$

All elements of vector X_i is set of decision variables called as molecules of particular antibody. The vector consists of these antibodies population to be evaluated and is denoted by:

$$\left.\begin{aligned}
P_G &= \begin{bmatrix} P_{G1} \ P_{G2} \ldots P_{Gi} \ldots P_{G_{NG}} \end{bmatrix} \\
V_G &= \begin{bmatrix} V_{G1} \ V_{G2} \ldots V_{Gi} \ldots V_{G_{NG}} \end{bmatrix} \\
Tap &= \begin{bmatrix} T_1 \ T_2 \ldots T_i \ldots T_{NT} \end{bmatrix} \\
Q_C &= \begin{bmatrix} Q_{C1} \ Q_{C2} \ldots Q_{Ci} \ldots Q_{C_{NC}} \end{bmatrix}
\end{aligned}\right\} \tag{19}$$

For each antibody satisfy the equality and inequality constraints. That means adjust the sum of P_{Gi} values in an antibody equal to total load demand, P_D, i.e.. $\sum_{i=1}^{NG} P_{Gi} = P_D$

Run NR load flow program for each antibody and calculate the transmission losses, slack bus power and line flows.

Evaluate the affinity for each antibody which is nothing but objective function values.

Cost function, F_1 evaluating from eq. 1

NO_x emission function, F_2 estimated from eq. 2

Loss P_L estimated from eq. 3

The initial population is sorted using non-dominated sorting technique described in section 1.3.1 and then assign crowding distance [23].

Set iteration counter $k := 0$

$k = k + 1$

Select the best population N_{sel} of antibodies which gives non-dominated solution from the archive X_{nds} and store them at an archive X_{best} for cloning and maturate operation.

Cloning of population set $C = [C_1 \ C_2 \cdots C_i \cdots C_{N_{sel}}]$, where C_i represents number of copies of ith antibody from X_{best}

The population of clones undergoes somatic hyper maturation results in new antibody is given by:

$$C_{new}(i) = C(i) + \alpha_i * (R_{d1} - R_{d2}) * \max(f_i) \tag{20}$$

where R_{d1} and R_{d2} are two randomly generated numbers in the range of 1 to N and α_i is mutation rate and given as:

$$\alpha_i = \exp(-f_i \rho) \tag{21}$$

where ρ controls decay of exponential function, f_i is normalized antigenic affinity over the interval (0,1).

$$f_i = \frac{F_i}{\sum\limits_{i=1}^{N_{sel}} F_i} \tag{22}$$

where F_i is the fitness or affinity of ith best population

Again each molecule of new mutated antibody is tested for any constraint violation.

Recalculate the affinity of all mutated clones as in 4th step and sorted again based on non-dominated sorting.

Modify the acceleration factor $cc = cc \times \gamma$ where γ value lies in between 0.5 to 1.1.

Check for stopping criterion. If the iterations are reaches to maximum go to next step, otherwise go to step 7.

Obtain Pareto optimal set of solutions from final iteration.

Step1: The best compromised solution is obtained from Pareto optimal front using fuzzy membership function approach.

6. SIMULATION RESULTS

The proposed multi-objective optimization algorithms presented in this chapter are tested on 6-unit IEEE 30-bus test system. This system has 6 generators, 41 transmission lines, 4 transformers and 9 reactive power injections at various buses. The detailed data of the test system is available in [24]. The generator voltage limits, transformer taps and Qshunts are assumed to have their upper and lower limits as shown in Table 1.

Table 1: Limits of Control variables

Variables	Vgs	Taps	Qshunts
Min	0.95	0.9	0
Max	1.1	1.1	0.05

For this test system three objectives, namely fuel cost, emission and loss have been considered for optimization. For comparison purpose the simulations carried out on test system for Tri-objective optimization (Fuel cost, NO_x emission and loss)

This MOEED problem has also been solved by implementing four different algorithms namely MOACSA, NSGA-II, MOPSO and MODE and results are compared. The control parameters of all the four algorithms are given in Table 2.

Table 2: Control parameters of various algorithms used for computation

MOACSA	NSGA-II	MOPSO	MODE
Population = 50	Population = 50	Population = 50	Population = 50
Best pop = 40	No. of gen = 200	No. of gen = 200	No. of gen = 200
No. of iterations= 200	Crossover = 5	C1 = 2	Crossover = 0.98
Clonal size factor= 1	Mutation = 50	C2 = 2	FF = 0.5
cc = 0.8971	Tournament= 2		Tournament= 1

Tri objective optimization:

This case study is an example of three-dimensional multi-objective optimization of EED problem with all security constraints. Here, three objectives are optimized simultaneously by all the four methods. The Pareto fronts of various methods are indicated in Fig. 1 for case-ii. The optimal settings of control variables along with function are tabulated in Table 3 for case-ii. The best compromised solution with each method for tri-objective optimization is given in Table 4.
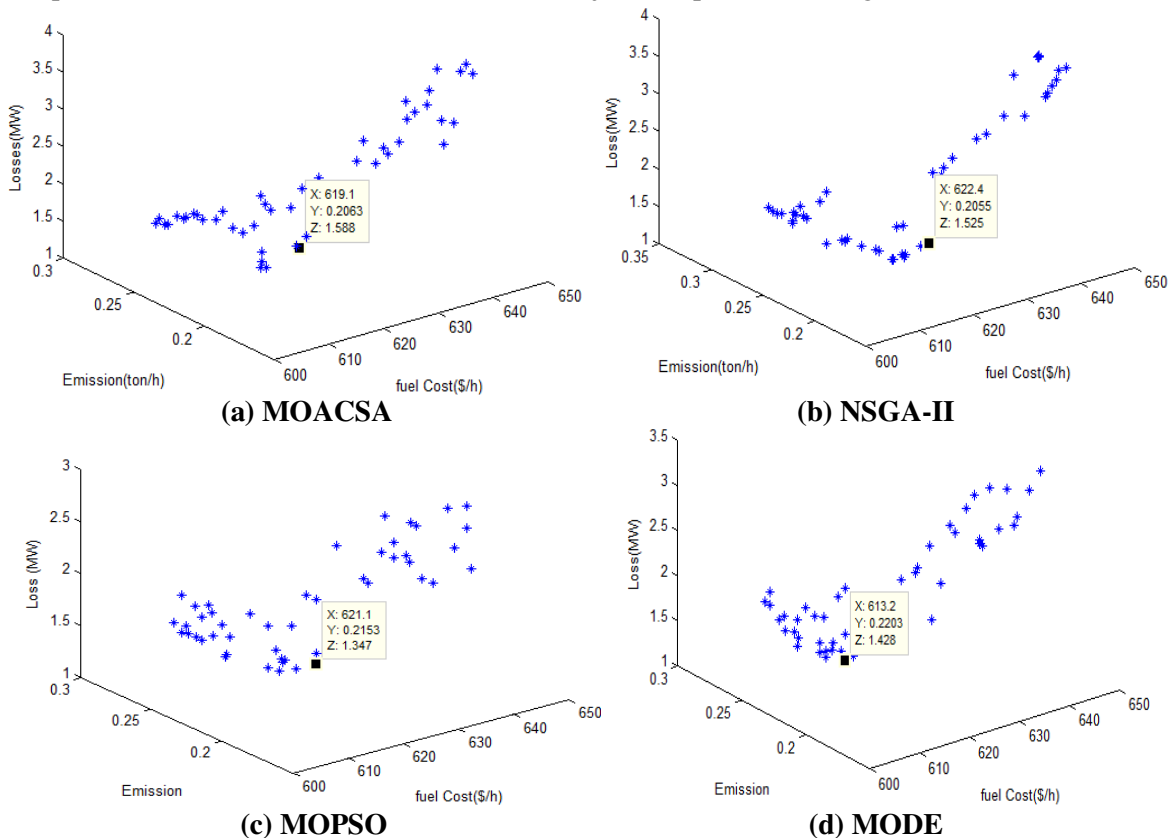
Fig. 1: Pareto optimal front of test system with cost, emission and loss as objectives (case-ii)

Table 3: Optimal solution of test system with various methods for cost, emission and loss objectives (case ii)

Method	MOACSA			NSGA-II			MOPSO			MODE		
Variables	Min. Cost	Min. emission	Min. loss	Min. cost	Min. emission	Min. loss	Min. cost	Min. emission	Min. loss	Min. cost	Min. emission	Min. loss
P_{G1} (MW)	11.1752	41.2880	6.2139	11.1706	40.6724	6.2721	11.4414	39.3378	6.3699	12.1408	42.4797	6.2734
P_{G2} (MW)	29.7040	46.2594	31.7717	30.4959	46.3320	32.6688	30.5673	47.4179	24.2273	29.4058	44.4386	24.1763
P_{G3} (MW)	49.8639	54.5698	40.6684	48.6156	54.3400	45.4479	49.2656	55.6444	36.0631	50.2645	54.6859	50.3077
P_{G4} (MW)	98.4056	39.2474	73.9788	99.6893	39.0773	68.7522	99.7133	38.2066	82.1996	99.3312	41.2023	73.6692
P_{G5} (MW)	60.8407	54.1692	98.4977	60.0850	54.7380	99.8029	58.8156	54.3895	99.8895	58.6216	51.9644	98.6881
P_{G6} (MW)	35.2904	51.4756	33.4835	35.3764	51.6968	31.7282	35.7228	51.5777	36.0205	35.6772	51.3260	31.5587
V_1 (p.u.)	1.0165	1.0383	1.0500	1.0458	1.0439	1.0479	1.0155	1.0295	1.0194	1.0600	1.0595	1.0600
V_2 (p.u.)	1.0138	1.0145	1.0500	1.0451	1.0226	1.0470	1.0215	1.0201	1.0157	1.0599	1.0535	1.0541
V_3 (p.u.)	1.0240	0.9792	1.0474	1.0482	1.0027	1.0495	1.0209	1.0021	1.0229	1.0571	1.0588	1.0595
V_4 (p.u.)	1.0500	0.9866	1.0500	1.0622	1.0913	1.0484	1.0489	1.0052	1.0409	1.0600	1.0444	1.0600
V_5 (p.u.)	1.0040	0.9523	1.0466	1.0354	0.9895	1.0467	1.0098	0.9708	1.0139	1.0600	1.0546	1.0555
V_6 (p.u.)	1.0486	1.0187	1.0500	1.0417	1.0928	1.0651	1.0214	1.0385	1.0398	1.0405	1.0360	1.0600
T_1	0.9584	1.0447	0.9873	0.9600	1.0578	0.9647	0.9944	1.0302	0.9796	1.0628	1.1000	1.0239
T_2	1.0400	0.9773	1.0353	1.0008	1.0756	1.0130	0.9890	0.9699	0.9686	0.9326	0.9049	0.9190
T_3	0.9475	0.9616	0.9478	1.0587	0.9012	1.0099	0.9856	0.9575	0.9812	1.0587	1.1000	1.0327
T_4	0.9595	0.9624	0.9606	0.9847	0.9530	0.9846	0.9779	1.0375	0.9784	0.9821	0.9784	0.9830
Q_{c10} (p.u)	0.0500	0.0013	0.0500	0.0456	0.0202	0.0393	0.0368	0.0269	0.0308	0.0146	0.0009	0
Q_{c12} (p.u)	0.0134	0.0070	0.0500	0.0159	0.0344	0.0385	0.0260	0.0311	0.0196	0.0421	0.0500	0.0500
Q_{c15} (p.u)	0.0427	0.0203	0.0500	0.0500	0.0097	0.0142	0.0215	0.0282	0.0211	0.0447	0.0345	0.0500
Q_{c17} (p.u)	0.0500	0.0500	0.0460	0.0254	0.0392	0.0352	0.0282	0.0342	0.0320	0.0500	0	0.0500
Q_{c21} (p.u)	0.0500	0.0109	0.0500	0.0186	0.0065	0.0324	0.0291	0.0220	0.0396	0.0143	0.0286	0.0383
Q_{c22} (p.u)	0.0371	0.0351	0.0368	0.0167	0.0344	0.0476	0.0238	0.0344	0.0134	0.0361	0.0365	0.0140
Q_{c23} (p.u)	0.0500	0.0460	0.0500	0.0024	0.0331	0.0498	0.0172	0.0317	0.0307	0.0347	0.0049	0.0195
Q_{c24} (p.u)	0.0039	0.0098	0.0390	0.0153	0.0412	0.0275	0.0368	0.0200	0.0407	0.0430	0.0500	0.0500
Q_{c29} (p.u)	0.0341	0.0254	0.0386	0.0349	0.0400	0.0384	0.0223	0.0187	0.0298	0.0273	0.0044	0.0178
Cost($/h)	**604.6608**	646.2704	616.7591	**604.9608**	645.7921	619.0763	**605.0620**	645.4718	616.1043	**604.8634**	642.8147	617.0217
Emission	0.2434	**0.1942**	0.2249	0.2211	**0.1942**	0.2224	0.2477	**0.1942**	0.2354	0.2475	**0.1943**	0.2264
Loss (MW)	1.8798	3.6094	**1.2139**	2.0400	3.4565	**1.2721**	2.1260	3.1739	**1.3699**	2.0411	2.6970	**1.2734**
$\sum P_{Gi}$(MW)	285.28	287.0094	284.6139	285.440	286.86	284.67	285.5260	286.5739	284.7699	285.44	286.10	284.67

Table 4: Best compromise solution of test system with various methods for tri-objectives

Variables	MOACSA	NSGA-II	MOPSO	MODE
P_{G1} (MW)	22.2703	25.8574	11.1516	15.7933
P_{G2} (MW)	31.6977	33.9013	29.8121	30.1736
P_{G3} (MW)	46.0220	49.3873	44.2015	51.0804
P_{G4} (MW)	61.4704	56.5892	76.0960	61.7237
P_{G5} (MW)	84.8146	85.1319	90.0778	96.4820
P_{G6} (MW)	38.7134	34.0577	33.4891	29.4941
V_1 (p.u.)	1.0360	1.0507	1.0177	1.0600
V_2 (p.u.)	1.0366	1.0482	1.0151	1.0585
V_3 (p.u.)	1.0447	1.0534	1.0248	1.0599
V_4 (p.u.)	1.0435	1.0389	1.0482	1.0568
V_5 (p.u.)	1.0500	1.0379	1.0205	1.0533
V_6 (p.u.)	1.0479	1.0447	1.0358	1.0600
T_1	0.9508	0.9570	0.9841	1.0386
T_2	1.0932	1.0171	0.9742	0.9072
T_3	0.9720	1.0085	0.9757	0.9984
T_4	0.9527	0.9836	0.9753	0.9999
Q_{c10} (p.u)	0.0208	0.0381	0.0273	0.0179
Q_{c12} (p.u)	0.0333	0.0403	0.0210	0.0500
Q_{c15} (p.u)	0.0190	0.0176	0.0203	0
Q_{c17} (p.u)	0	0.0341	0.0325	0.0256
Q_{c21} (p.u)	0.0264	0.0303	0.0360	0.0064
Q_{c22} (p.u)	0.0500	0.0500	0.0146	0.0378
Q_{c23} (p.u)	0.0007	0.0500	0.0293	0.0196
Q_{c24} (p.u)	0.0417	0.0241	0.0391	0.0285
Q_{c29} (p.u)	0.0500	0.0365	0.0261	0.0229
Cost($/h)	619.0551	622.4143	613.1925	621.0733
Emission	0.2063	0.2055	0.2203	0.2153
Loss (MW)	1.5883	1.5248	1.4281	1.3469
$\sum P_{Gi}$(MW)	284.9883	284.9248	284.8281	284.7469

7. CONCLUSIONS

In this chapter four types of multi-objective optimization methods namely MOPSO, MODE, NSGA-II and MOACSA are presented to solve MOEED problem. The main target of the proposed methods is to find Pareto optimal set of solutions for power system control that satisfy both security and operational constraints simultaneously. The most important privilege of all the four methods is obtaining Pareto optimal front allowing the system operator to use their order of preference in selecting best solution for implementation. The feasibility of all the four methods for

solving MOEED problem is tested on standard IEEE 30-bus test system for two and three objective case studies. In two objective case studies only cost and emission objectives are considered with different operational constraints. While in three objective cases fuel cost, emission and loss objectives are considered with all security constraints.

REFERENCES

[1] Jeyadevi, S., et al. "Solving multiobjective optimal reactive power dispatch using modified NSGA-II." *International Journal of Electrical Power & Energy Systems*33.2 (2011): 219-228.

[2] Cai, Jiejin, et al. "Chaotic particle swarm optimization for economic dispatch considering the generator constraints." Energy Conversion and Management 48.2 (2007): 645-653.

[3] Coelho, Leandro dos Santos, and Chu-Sheng Lee. "Solving economic load dispatch problems in power systems using chaotic and Gaussian particle swarm optimization approaches." International Journal of Electrical Power & Energy Systems 30.5 (2008): 297-307.

[4] Srinivasa Reddy, A., and K. Vaisakh. "Shuffled differential evolution for economic dispatch with valve point loading effects." International Journal of Electrical Power & Energy Systems 46 (2013): 342-352.

[5] Zahavi, Jacob, and Lawrence Eisenberg. "An application of the Economic-environmental power dispatch." Systems, Man and Cybernetics, IEEE Transactions on 7.7 (1977): 523-530.

[6] King, T. Denise, M. E. El-Hawary, and Ferial El-Hawary. "Optimal environmental dispatching of electric power systems via an improved Hopfield neural network model." Power Systems, IEEE Transactions on 10.3 (1995): 1559-1565.

[7] Palanichamy, C., and N. Sundar Babu. "Analytical solution for combined economic and emissions dispatch." Electric Power Systems Research 78.7 (2008): 1129-1137.

[8] Tuan, TQuoc, et al. "Emergency load shedding to avoid risks of voltage instability using indicators." Power Systems, IEEE Transactions on 9.1 (1994): 341-351.

[9] Farag, Ahmed, Samir Al-Baiyat, and T. C. Cheng. "Economic load dispatch multiobjective optimization procedures using linear programming techniques."Power Systems, IEEE Transactions on 10.2 (1995): 731-738.

[10] Zahavi, Jacob, and Lawrence Eisenberg. "Economic-Enviromental Power Dispatch." Systems, Man and Cybernetics, IEEE Transactions on 5 (1975): 485-489.

[11] Hota, P. K., A. K. Barisal, and R. Chakrabarti. "Economic emission load dispatch through fuzzy based bacterial foraging algorithm." *International Journal of Electrical Power & Energy Systems* 32.7 (2010): 794-803.

[12] Cai, Jiejin, et al. "A multi-objective chaotic ant swarm optimization for environmental / economic dispatch." International Journal of Electrical Power & Energy Systems 32.5 (2010): 337-344.

[13] Jacob Raglend, I., et al. "Comparison of AI techniques to solve combined economic emission dispatch problem with line flow constraints." *International Journal of Electrical Power & Energy Systems* 32.6 (2010): 592-598.

[14] Coello, Carlos A. Coello, and Nareli Cruz Cortés. "Solving multiobjective optimization problems using an artificial immune system." *Genetic Programming and Evolvable Machines* 6.2 (2005): 163-190.

[15] Basu, M. "Artificial immune system for combined heat and power economic dispatch." *International Journal of Electrical Power & Energy Systems* 43.1 (2012):1-5.

[16]   Kennedy, J.: The Particle Swarm: Social Adaptation of Knowledge. In: Proceedings of the 1997 IEEE international Conference on Evolutionary Computation ICEC 1997, Indianapolis, Indiana, USA, pp. 303–308 (1997)

[17]   Price, Kenneth V., Rainer M. Storn, and Jouni A. Lampinen. "Differential evolution a practical approach to global optimization." (2005).

[18]   Holland, John H. Adaptation in natural and artificial systems: An introductory analysis with applications to biology, control, and artificial intelligence. U Michigan Press, 1975.

[19]   Caponetto, R., et al. "Genetic algorithms and applications in system engineering: a survey." Transactions of the Institute of Measurement and Control 15.3 (1993):143-156.

[20]   De Castro, Leandro N., and Fernando J. Von Zuben. "Learning and optimization using the clonal selection principle." Evolutionary Computation, IEEE Transactions on 6.3 (2002): 239-251.

[21]   De Castro, Leandro Nunes, and Fernando José Von Zuben. "Artificial immune systems: Part II–A survey of applications." FEEC/Univ. Campinas, Campinas, Brazil (2000).

[22]   Burnet, F. M. "Clonal selaection and after." Theoretical Immunology 63 (1978): 85.

[23]   Rahman, Titik Khawa Abdul, Saiful Izwan Suliman, and Ismail Musirin. "Artificial immune-based optimization technique for solving economic dispatch in power system." Neural Nets. Springer Berlin Heidelberg, 2006. 338-345.

[24]   Lee, K. Y., Y. M. Park, and J. L. Ortiz. "A united approach to optimal real and reactive power dispatch." Power Apparatus and Systems, IEEE Transactions on 5 (1985): 1147-1153.