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Multiple objective particle swarm optimization technique for economic load dispatch*

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Abstract: A multi-objective particle swarm optimization (MOPSO) approach for multi-objective economic load dispatch problem in power system is presented in this paper. The economic load dispatch problem is a non-linear constrained multi-objective optimization problem. The proposed MOPSO approach handles the problem as a multi-objective problem with competing and non-commensurable fuel cost, emission and system loss objectives and has a diversity-preserving mechanism using an external memory (call "repository") and a geographically-based approach to find widely different Pareto-optimal solutions. In addition, fuzzy set theory is employed to extract the best compromise solution. Several optimization runs of the proposed MOPSO approach were carried out on the standard IEEE 30-bus test system. The results revealed the capabilities of the proposed MOPSO approach to generate well-distributed Pareto-optimal non-dominated solutions of multi-objective economic load dispatch. Comparison with Multi-objective Evolutionary Algorithm (MOEA) showed the superiority of the proposed MOPSO approach and confirmed its potential for solving multi-objective economic load dispatch.

Key words: Economic load dispatch, Multi-objective optimization, Multi-objective particle swarm optimization
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INTRODUCTION

The conventional economic load dispatch problem of power generation involves allocation of power generation to different thermal units to minimize the operating cost subject to diverse equality and inequality constraints of the power system. This makes the economic load dispatch problem a large-scale highly non-linear constrained optimization problem. However, as a result of public awareness of environmental protection, diverse emission compliance strategies have emerged (El-Keib *et al.*, 1994). These strategies include emission dispatching or trading, fuel switching and/or blend, installation of emission reduction equipment in the existing thermal plants, and retirement of old fuel-burning equipment or generating unit and replacement with cleaner and efficient one. Among these strategies, unit dispatch considering emission and cost minimization have received widespread attention due to its effective short-term results and smaller capital outlay.

In addition, the power system reactive power optimization directly influences the power system stability and power quality and achieves the objective of minimizing the total system real power loss in the transmission network. Thus, the economic load dispatch considering system loss can reasonably improve real and reactive power dispatch simultaneously. So, the economic load dispatch problem considering economic, environment and system loss can be handled as a multi-objective optimization problem with non-commensurable and contradictory objectives.

Many approaches and methods were proposed to solve multi-objective economic load dispatch problems. One feasible approach using conventional optimization method is to convert the multi-objective function into one with single objective by giving

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relative weighting values (Dhillon *et al*., 1993); but in the absence of sufficient information about the current operating conditions, asking the decision makers to articulate their preferences for the objectives in the form of weighting factors is not easy. Furthermore, this method cannot be used in problem having a non-convex Pareto-optimal front. The ε-constraint method developed by Hsiao *et al*.(1994) to avoid this difficulty optimizes the most preferred objective and considers the other objectives as constraints bounded by some allowable levels ε. The most obvious weaknesses of this approach are that it is time-consuming and tends to find weakly non-dominated solutions. A fuzzy multi-objective optimization technique for economic and emission dispatch (EED) problem was developed by Srinivasan *et al*.(1994), but the solutions produced are sub-optimal and the algorithm does not provide a systematic framework for directing the search towards the Pareto-optimal front. A fuzzy satisfaction-maximizing decision approach was successfully applied to solve the bi-objective EED problem (Huang *et al*., 1997), but extension of the approach to include more objectives is a very big problem. The multi-objective search technique for the multi-objective EED problem proposed by Das and Patvardhan (1998) is computationally complex and time-consuming. In addition, there is no effort to avoid the search bias to some regions in the problem space, which may result in premature convergence. This degrades the Pareto-optimal front so more efforts should be focused on preserving the diversity of the non-dominated solutions.

The use and development of heuristics-based multi-objective optimization techniques have significantly grown. Since they use a population of solutions in their search, multiple Pareto-optimal solutions can, in principle, be found in one single run. These models can be efficiently used to eliminate most of the difficulties of classical methods (Goldberg, 1989; Coello, 1999). Particle swarm optimization (PSO) method is one of heuristics-based optimization techniques and was successfully applied in diverse optimization tasks, but has seldom been applied multi-objective optimization so far.

The improved multiple objective particle swarm optimization (MOPSO) method proposed here to solve the economic load dispatch problem is relatively simple to implement, is population-based, uses an external memory (called "repository") and a geographically-based approach to maintain the diversity of sets of Pareto-optimal solutions (Knowles and Corne, 2000). A fuzzy-based mechanism is employed to extract the best compromise solution. In order to demonstrate the effectiveness of the proposed MOPSO approach, the IEEE 30-bus system is taken as the example. Objectives selected are economy, and minimal environmental impact and system loss.

PROBLEM FORMULATION

In this section, we shall formulate the optimization problems in power system economic load dispatch that have multiple non-commensurable objectives. In what follows, the performance indices together with the equality and inequality constraints pertaining to the power system optimization problems will be described.

Objectives

In optimizing economic load dispatch, the three most important evaluation indices economy, environment impact and total real power loss.

1. Minimization of fuel cost. The fuel cost of the system can be regarded as on essential criterion for economic feasibility. The fuel cost curve is assumed to be approximated by a quadratic function of generator real power output as

$$F_1 = \sum_{i=1}^{N} (a_i + b_i P_{Gi} + c_i P_{Gi}^2) \ (\$/\mathrm{h}) \qquad (1)$$

where, P_{Gi} is the real power output of an ith generator; N is the total number of generators; a_i, b_i, c_i, fuel cost curve coefficients of an ith generator, respectively.

2. Minimization of emission. The emission function can be presented as the sum of all types of emission considered, such as NO_x, SO_2, thermal emission, etc., with suitable pricing or weighting on each pollutant emitted. In the present study, only one type of emission (NO_x) is taken into account without loss of generality. The amount of NO_x emission is given as a function of generator output, that is, the sum of a quadratic and exponential function:

$$F_2 = \sum_{i=1}^{N}[10^{-2}(\alpha_i+\beta_i P_{Gi} + \gamma_i P_{Gi}^2) + \xi \exp(\lambda_i P_{Gi})] \quad (\text{ton/h}) \qquad (2)$$

where, α_i, β_i, γ_i, ξ_i, λ_i: coefficients of ith generator's NO_x emission characteristic.

3. Minimization of total real power loss. The power system reactive power optimization result directly influences the power system stability and power quality. The objective of the reactive power dispatch is to minimize the real power loss in the transmission network, which can be described as follows:

$$F_3 = \sum_{k\in N_E} P_{k\text{LOSS}} = \sum_{k\in N_E} g_{ij}(v_i^2 + v_j^2 - 2v_i v_j \cos\theta_{ij}) \qquad (3)$$

where, $k=(i,j)$; $i\in N_D$; $j\in N_j$. N_E is the set of numbers of network branches; N_D is the set of numbers of power demand bus; N_j is the set of numbers of buses adjacent to bus j, including bus j; g_{ij} is the conductance of the transmission line between buses i and j; θ_{ij} is voltage angle difference between buses i and j; v_i and v_j are voltage magnitude of bus i and j.

Constraints

1. Power balance constraints. The total power generation must cover the total demand P_D and the real power loss in the transmission lines P_{LOSS}. Hence,

$$\sum_{i=1}^{N} P_{Gi} - P_D - P_{LOSS} = 0 \qquad (4)$$

2. Generation capacity constraints. For stable operation, the generator outputs and bus voltage magnitudes are restricted by lower and upper limits as follows:

$$\begin{aligned} &P_{Gi\min} \le P_{Gi} \le P_{Gi\max} \quad && i=1,\ldots,N \\ &Q_{Gi\min} \le Q_{Gi} \le Q_{Gi\max} \quad && i=1,\ldots,N \\ &V_{i\min} \le V_i \le V_{i\max} \quad && i=1,\ldots,N \end{aligned} \qquad (5)$$

3. Security constraints. For secure operation, the transmission line loading S_l is restricted by its upper limits as

$$S_l \le S_{l\max} \qquad i=1,\ldots,n_l \qquad (6)$$

where n_l is the number of transmission lines.

Problem statement

After incorporating the above objectives and constraints into the problem, the problem can be mathematically formulated as a non-linear constrained multi-objective optimization problem as follows:

$$\min_{P_G}\{F_G, E_G, P_{LOSS}\} \qquad (7)$$

subject to:

$$h(x) = 0 \qquad (8)$$

$$g(x) \le 0 \qquad (9)$$

where g and h are the equality and inequality constraints respectively.

PSO AND MOPSO

PSO

Kennedy and Eberhart (1995) first introduced the PSO method driven by the social behavior of organisms such as fish (schooling) and bird (flocking). PSO, as an optimization tool, provides a population-based search procedure in which individuals called particles change their positions with time. In a PSO system, the group is a community composed of all particles, and all particles fly around in a multi-dimensional search space. During flight, each particle adjusts its position according to its own experience, and the experience of neighboring particles, making use of the best position encountered by itself and its neighbors. The swarm direction of each particle is defined by the set of particles neighboring the particle and its historical experience.

Let x and v denote a particle position and its corresponding flight velocity in a search space, respectively. Therefore, the ith particle is represented as $x_i=(x_{i1}, x_{i2}, \ldots, x_{id})$ in the d-dimensional search space. The best previous position of the ith particle is recorded and represented as $pbest_i=(pbest_{i1}, pbest_{i2}, \ldots, pbest_{id})$. The index of the best particle among all the particles in the group is represented by the $gbest=(gbest_1, gbest_2, \ldots, gbest_d)$. The flight velocity for particle i is represented as $v_i=(v_{i1}, v_{i2}, \ldots, v_{id})$. The modified velocity and position of each particle can be calculated using the current velocity and the distance from $pbest_i$ to $gbest$ as shown in the following formulas:

$$v_{id}^{(t+1)} = wv_{id}^{(t)} + c_1 r_1 (pbest_{id} - x_{id}^{(t)}) + c_2 r_2 (gbest_d - x_{id}^{(t)}) \quad (10)$$

$$x_{id}^{(t+1)} = x_{id}^{(t)} + v_{id}^{(t+1)},\ i = 1,2,\ldots,n,\ d = 1,2,\ldots,m \quad (11)$$

where w, c_1, $c_2 \geq 0$. n is the number of particles in a group; m is the number of members in a particle; w is the inertia weight factor; c_1 and c_2 are acceleration constants; r_1 and r_2 are two random numbers within the range [0,1]; $v_{id}^{(t)}$, $x_{id}^{(t)}$ are the velocity and the current of particle i in the dth-dimensional search space at iteration t, respectively.

MOPSO

In this paper, we improved the PSO method to facilitate a multi-objective approach. The important part in multi-objective particle swarm optimization (MOPSO) is to determine the best global particle for each particle i of the population. In the single-objective PSO, the global best particle is determined easily by selecting the particle with the best position. Since multi-objective optimization problems have a set of Pareto-optimal solutions as the optimum solutions, each particle of the population should use Pareto-optimal solutions as basis to select one of its global best particle (Parsopoulos and Vrahatis, 2002; Coello and Lechuga, 2003).

In this study, the proposed MOPSO method is inspired by more recent developments in the Multi-objective Evolutionary Algorithm (MOEA) literature. Two repositories are maintained in addition to the search population. One of the global best individuals found so far by the search process, and one containing a single local best for each member of the swarm (as in standard PSO). A truncated archive is used to store the global individuals. This archive uses the method from Knowles and Corne (2000) to separate the objective function space into a number of hypercubes (an adaptive grid), with the most densely populated hypercubes truncated if the archive exceeds its membership threshold. The archive also facilitates the selection of a global best for any particular individual (Fieldsend and Singh, 2002). The fitness value given to each hypercube that contains archive members is equal to dividing any number x>1 by the number of resident particles. Thus, a more densely populated hypercube is given a lower score. Selection of a global best for a particle is then based on roulette wheel selection of a hypercube first (according to its score), and then uniformly choosing a member of that hypercube.

After incorporating the above modifications, the detailed computational flow of MOPSO technique for economic load dispatch problem can be described in the following steps.

Step 1: Input parameters of system, and specify the lower and upper boundaries of each variable.

Step 2: Initialize randomly the speed and position of each particle and maintain the particles within the search space.

Step 3: For each particle of the population, employ the Newton-Raphson power flow analysis method to calculate power flow and system transmission loss, and evaluate each of the particles in the population.

Step 4: Store the positions of the particles that represent non-dominated vectors in the repository NOD.

Step 5: Generate hypercubes of the search space explored so far, and locate the particles using these hypercubes as a coordinate system where each particle's coordinates are defined according to the values of its objective function.

Step 6: Initialize the memory of each particle in which a single local best for each particle is contained (this memory serves as a guide to travel through the search space. This memory is stored in the other repository PBEST).

Step 7: Update the time counter t=t+1.

Step 8: Determine the best global particle *gbest* for each particle i from the repository NOD. First, those hypercubes containing more than one particle are assigned a fitness value equal to the result of dividing any number x>1 by the number of particles that they contain. Then, we apply roulette wheel selection using these fitness values to select the hypercube from which we will take the corresponding particle. Once the hypercube has been selected, we select randomly a particle as the best global particle *gbest* for particle i within such hypercube (Fieldsend *et al.*, 2003).

Step 9: Compute the speed and its new position of each particle using Eqs.(10) and (11), and maintain the particles within the search space in case they go beyond its boundaries.

Step 10: Evaluate each particle in the population by the Newton-Raphson power flow analysis method.

Step 11: Update the contents of the repository NOD together with the geographical representation of the particles within the hypercubes. This update consists of inserting all the currently nondominated locations into the repository. Any dominated locations from the repository are eliminated in the process. Since the size of the repository is limited, whenever it gets full, a secondary criterion for retention is applied: those particles located in less populated areas of objective space are given priority over those lying in highly populated regions.

Step 12: Update the contents of the repository PBEST. If the current position of the particle is dominated by the position in the repository PBEST, then the position in the repository PBEST is kept; otherwise, the current position replaces the one in memory; if neither of them is dominated by the other, one of them is randomly selected.

Step 13: If the maximum iterations $iter_{\max}$ are satisfied then go to Step 14. Otherwise, go to Step 7.

Step 14: Input a set of the Pareto-optimal solutions from the repository NOD.

Best compromise solution

Optimization of the above-formulated objective functions using MOPSO, yields not a single optimal solution, but a set of Pareto optimal solutions, in which one objective cannot be improved without sacrificing other objectives. For practical applications, however, we need to select one solution, which will satisfy the different goals to some extent. Such a solution is called best compromise solution. One of the challenging factors of the tradeoff decision is the imprecise nature of the decision maker's judgment.

Hence, the membership functions are introduced to represent the goals of each objective function (Niimura and Nakashima, 2003). Usually, a membership function for each of the objective functions is defined by the experiences and intuitive knowledge of the decision maker. In this work, a simple linear membership function was considered for each of the objective functions. The membership function is now defined as:

$$u_i = \begin{cases} 1 & F_i \le F_i^{\min} \\ \dfrac{F_i^{\max} - F_i}{F_i^{\max} - F_i^{\min}} & F_i^{\min} < F_i < F_i^{\max} \\ 0 & F_i \ge F_i^{\max} \end{cases} \quad (12)$$

where $F_i^{\min}$ is value of an original objective function i that is supposed to be completely satisfactory, and $F_i^{\max}$ is the value of the objective function that is clearly unsatisfactory to the decision maker. Therefore, the membership function represents the degree of achievement of the original objective function as a value between 0 and 1 with u_i=1 as completely satisfactory and u_i=0 as unsatisfactory. Such a linear membership function represents the decision maker's fuzzy goal of achievement, and at the same time scales the original objective functions with different physical units into the measure of 0~1. Fig.1 illustrates a typical shape of the membership function.

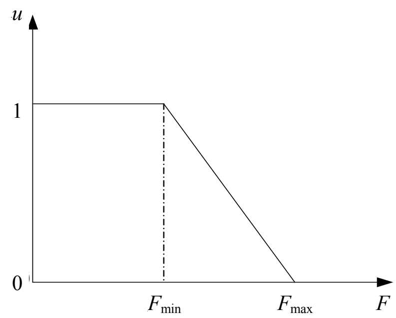

Fig.1 The membership function system

For each non-dominated solution k, the normalized membership function u^k is calculated as

$$u^k = \frac{\sum_{i=1}^{N_{\text{obj}}} u_i^k}{\sum_{k=1}^{M}\sum_{i=1}^{N_{\text{obj}}} u_i^k} \quad (13)$$

where M is the number of non-dominated solutions, and N_{obj} is the number of the objective functions. The function u^k in Eq.(13) can be represented as a fuzzy cardinal priority ranking of the non-dominated solutions. The solution that attains the maximum membership u^k in the fuzzy set can be chosen as the best compromise solution or that having the highest cardinal priority ranking.

Parameters of the proposed approach

The techniques and all simulations developed in this study were implemented on 4.0 GHz PC using MATLAB language. On all optimization runs, the population size *n* and the maximum number of iterations $iter_{max}$ were selected as 200 and 100, respectively. To determine the number of hypercubes that will be generated in objective function space, the number of divisions is recommended to be 30 to 50 according to much experience with MOPSO. Size of the repository is determined according to the number of non-dominated solutions.

RESULTS AND DISCUSSIONS

In this section, some numerical examples are provided to highlight the main features of the proposed MOPSO approach. The test system considered is shown in Fig.2 and was derived from the standard IEEE 30-bus 6-generator test system (detailed data given in Zimmerman and Gan, 1997). The values of the fuel and emission coefficients are given in Tables 1 and 2.

Initially, minimum and maximum values of each original objective function are computed in order to obtain the last compromise solution. Minimum values of the objectives are obtained by giving full consideration to one of the objectives and neglecting the others. In this study, we considered three objective functions. So, fuel cost, emission and system loss are optimized individually to obtain minimum values of the objectives. Owing to the conflicting nature of the objectives, emission and system loss have maximum values when fuel cost is minimum. The minimum and maximum values of the objectives are given in Table 3.

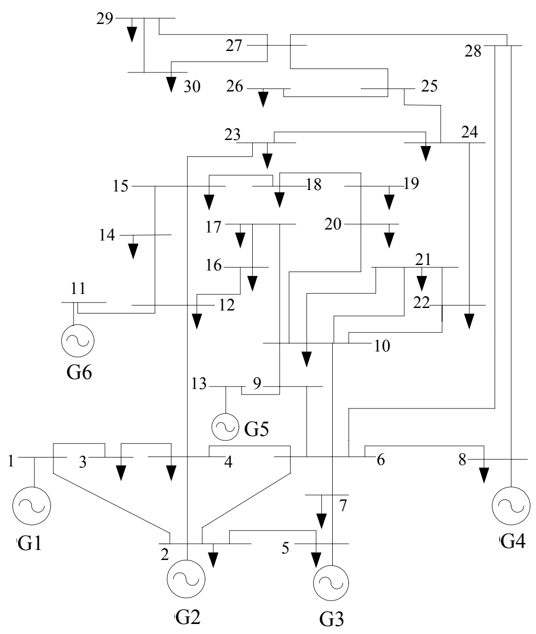

Fig.2 Single-line diagram of IEEE 30-bus test system

The two tests presented below are relevant to the solution of multi-objective economic load dispatch problem with two objective functions and three objective functions.

Fuel cost and emission

At first, we only considered two objective functions: fuel cost and emission. Economic emission load dispatch has received much attention in multi-objective economic dispatch research. For comparison, the Multi-objective Evolutionary Algorithm (MOEA) was applied to find the Pareto-optimal solutions. Crossover and mutation probabilities were

Table 1 The generating cost functions

Generator No.	$F = a + bP_G + cP_G^2$ (\$/h)			$P_{G\max}$ (MW)	$P_{G\min}$ (MW)
	a	b	c		
1	10	200	100	150	5
2	10	150	120	150	5
3	20	180	40	150	5
4	10	100	60	150	5
5	20	180	40	150	5
6	10	150	100	150	5

Table 2 The generating emission functions

Generator No.	$E = 10^{-2}(\alpha + \beta P_G + \gamma P_G^2) + \xi \exp(\lambda P_G)$ (ton/h)				
	α	β	γ	ξ	λ
1	4.091	–5.543	6.490	2.0e–4	2.857
2	2.543	–6.047	5.638	5.0e–4	3.333
3	4.258	–5094	4.586	1.0e–6	8.000
4	5.326	–3550	3.380	2.0e–3	2.000
5	4.258	–5.094	4.586	1.0e–6	8.000
6	6.131	–5.555	5.151	1.0e–5	6.667

Table 3 The minimum and maximum values of the objective

	MAX	MIN
Fuel cost (\$)	640.6426	606.6090
Emission (ton)	0.2248	0.1955
System loss (MW)	2.8758	1.7154

selected as 0.7 and 0.01, respectively. In the same objective functions and system network, MOEA and MOPSO were run to generate 100 non-dominated solutions. The Pareto-optimal front of MOEA is shown in Fig.3. The distribution of the non-dominated solutions in the Pareto-optimal front using the proposed MOPSO is shown in Fig.4. It is clear that the solutions are diverse and well distributed over the trade-off curve. Comparison of Figs.3 and 4 showed that the non-dominated solutions of the proposed MOPSO approach have better diversity characteristics and better non-dominated solutions.

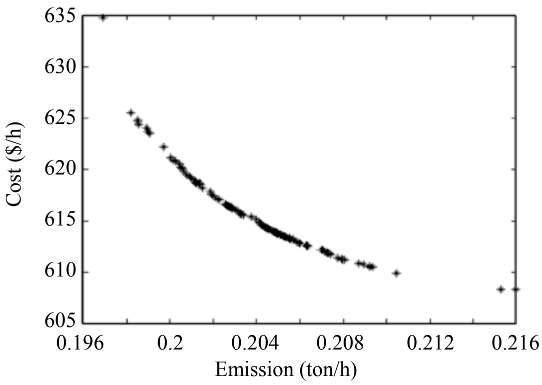

Fig.3 Pareto-optimal front using MOEA algorithm in case of tow objective functions

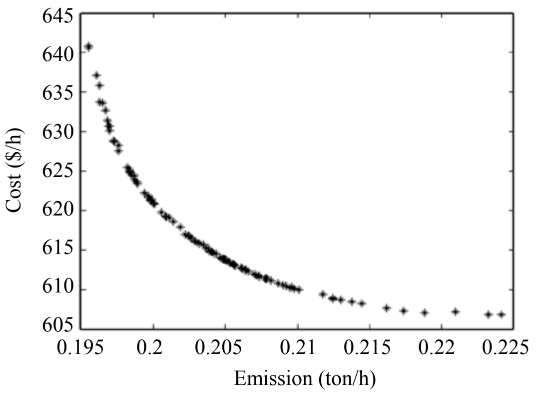

Fig.4 Pareto-optimal front using MOPSO algorithm in case of two objective functions

Figs.3 and 4 show the relationship (trade-off curve) of the fuel cost and emission objectives of non-dominated solutions obtained by MOEA and MOPSO approaches. By definition in multi-objective problems, a non-dominated solution is a feasible solution; at least one of whose objective values is better than the corresponding objective of all the other feasible solutions. The non-dominated solutions are those from which the multi-objective decision algorithm attempts to select the best compromise solution according to the preferences of the decision makers. Consequently, the two objectives of all the non-dominated solutions are located along the left and lower boundaries of the feasible domain as minimization is desired. The fuel costs of the non-dominated solutions thus appear to be inversely proportional to their emissions, as illustrated in Figs.3 and 4.

In Table 3, the membership functions given in Eqs.(12) and (13) are used to evaluate each member of the Pareto-optimal set. Then, the best compromise solution with maximum value of membership function can be extracted. This procedure was applied in both algorithms and the best compromise solutions are given in Table 4. It is quite evident that the proposed MOPSO approach yields better compromise solutions and higher degree of satisfaction.

Table 4 The best compromise solutions of the both algorithms

	MOEA	MOPSO
P_{G1}	43.6778	72.3630
P_{G2}	36.7739	36.7010
P_{G3}	57.0801	57.1720
P_{G4}	73.1756	74.6390
P_{G5}	53.4934	50.2620
P_{G6}	43.2479	43.4560
Fuel cost ($)	615.2835	614.9100
System loss (MW)	0.2038	0.2037

Fuel cost, emission and system loss

This case demonstrates the relationships between fuel cost, emission and system loss. This example is more complex than the previous case, because the size of the Pareto set is higher (150 non-dominated solutions) and the number of the objective functions is three. The distribution of the non-dominated solutions in Pareto-optimal front using the proposed MOPSO is shown in Fig.5 clearly showing the relationships among fuel cost, emission, and transmission. Because the three objective functions are naturally conflicting objectives, the attempt at decreasing fuel cost gives an operating point closer to the higher emission and the higher system loss. Thus, the best compromise solution is chosen from the set of Pareto optimal solutions in order to obtain the compromise operating point in the power system. The best compromise solution is given in Table 5.

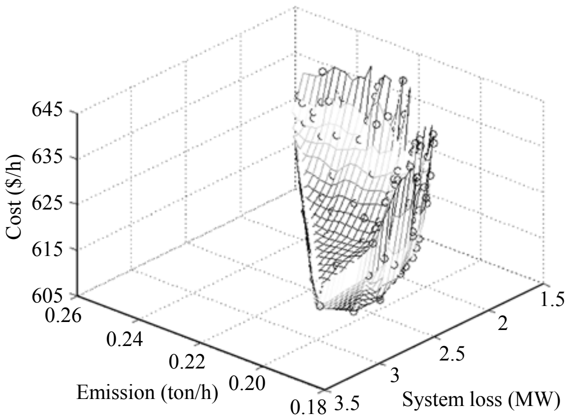

Fig.5 Pareto-optimal front using MOPSO algorithm in case of three objective functions

Table 5 The best compromise solutions using the MOPSO approach

Generator output (MW)	1	39.7680
	2	41.8137
	3	64.4044
	4	75.1466
	5	44.6203
	6	48.9729
Fuel cost ($)		614.9134
Emission (ton)		0.2081
System loss (MW)		2.8865

CONCLUSION

The MOPSO based approach presented in this paper was applied to economic load dispatch optimization problem formulated as multi-objective optimization problem with competing fuel cost, emission and system loss objectives. The proposed MOPSO approach has a diversity-preserving mechanism using an external memory (call "repository") and a geographically-based approach to find widely different Pareto-optimal solutions. Moreover, a fuzzy-based mechanism is employed to extract the best compromise solution from the trade-off curve. The results showed that the proposed MOPSO approach is efficient for solving multi-objective optimization problems where multiple Pareto-optimal solutions can be found in one simulation run. In addition, the non-dominated solutions in the obtained Pareto-optimal set are well distributed and have satisfactory diversity characteristics.

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