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MOABC ALGORITHM FOR ECONOMIC/ENVIRONMENTAL LOAD DISPATCH SOLUTION

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Abstract- This paper presents a Multi-objective Artificial BEE Colony (MOABC) algorithm for the solution of Economic/Environmental load Dispatch (EED) problem. The EED problem is a nonlinear constrained multi-objective optimization problem. Because, the three competing and non-commensurable fuel cost, system loss and pollutant emission objectives should be minimized simultaneously while satisfying certain system constraints. To cope with different solutions, Pareto dominance concept is used to generate and sort the dominated and non-dominated solutions in multi-objective optimization process. The effectiveness of the proposed method has been verified on IEEE 6-generator 30-bus test system. The numerical results demonstrate the great potential of the proposed MOABC approach to generate well distributed Pareto optimal non-dominated solutions of multi-objective EED problem. The comparison with the recently reported results using NSGA, NPGA, SPEA, MOPSO and MODE methods reveals the superiority of the proposed MOABC approach and confirms its capability for the solution of multi-objective EED problem in the real world power systems.

Keywords: MOABC, Environmental/Economic Load Dispatch, Pareto Optimal Solution, Transmission Loss.

I. INTRODUCTION

Economic Load Dispatch (ELD) problem is one of the main issues of power system operation and control. The goal of practical ELD problem is to determine the optimal schedule of output powers of online generating units to meet a fixed demand at minimum operating cost subject to operational constraints of the generators such as valve point loading effects, ramp rate limits, unit generating output limits and etc [1]. On the other hand, such as generation of electricity using fossil fuel leads to several contaminants as; SO_2, CO_2 and NO_x, into the atmosphere. These emissions have given rise to environmental concerns. In recent years, the pollution minimization due to the pressing public demand for clean air problem has attracted much attention for researchers. While, in some activities have done by countries as; the U.S. Clean Air Act amendments of 1990 and similar acts by European and Japanese governments, environmental constraints have topped the list of utility management concerns [2, 3]. Thus, it becomes important to perform the emission dispatch or include the emission constraints into the economic load dispatch for minimization of total cost as well as total emission. However, minimization of total cost and environmental pollution simultaneously are non-commensurable and contradictory in the nature and real system. Thus, the Environmental/Economic Dispatch (EED) problem is a highly nonlinear multi-objective optimization problem with heavy equality and inequality constraints.

Several methods and algorithms have been represented to solve the environmental economic power dispatch problems. In [2], the authors provided a summary of economic/environmental dispatching algorithms dating back to 1970 using conventional optimization methods. Several techniques to decrease the atmospheric emissions caused by fossil fuel have been reported and discussed in [3]. The authors suggested several equipments and methods to reduce pollution such as electrostatic precipitators, switching, placement of the generators and aged fuel-burners as the increase efficiency, clearing and gas Scrubbers.

Conventional technique such as linear programming technique has been proposed in [4] based on optimization procedures in which the objectives are considered one at a time. Therefore, the EED problem becomes more complex, makes not robustness and decreases the efficiency for practical applications. The EED optimization problem or multi-objective optimization problem in [5] was solved by using weighted-sum approaches to convert multiple objectives into a single goal. The weighted sum method is a direct way to convert multiple objectives into a single one with a set of Pareto-optimal solutions that can be obtained by varying the weights.

Multiple runs as many times as the number of desired Pareto-optimal solutions are disadvantage of this method. Furthermore, this method cannot be used to find Pareto-optimal solutions in problems having a non-convex Pareto-optimal front. To solve this problem, the ε-constraint method for multi-objective optimization was presented in [6].

In recent years, many Multi-objective Heuristics Optimization (MOHO) techniques like niched Pareto genetic algorithm [7], multi-objective evolutionary algorithm [8, 9], multi-objective Particle Swarm Optimization (MOPSO) [10, 11] and Multi-objective Differential Evolution (MODE) [12] algorithm have been represented for the EED problem optimization to find global or near global optimal solution. All the above MOHO techniques obtained impressive results, which confirm the potential of MOHOs for the solution of the real-world highly nonlinear constrained multi-objective optimization problems.

One of a novel evolutionary algorithm is Artificial Bee Colony (ABC) algorithm. The ABC algorithm is a typical swarm-based optimization method, in which the search algorithm is inspired by the intelligent foraging behavior of the honey bee swarm process [13]. Unlike the other heuristic techniques such as PSO, it carries out both global search and local search in each iteration process for significant probability increasing of the optimal solution finding and efficiently avoiding local optimum to a large extent. Also, it has less control parameters and a superior success rate since it does exploration and exploitation processes together proficiently. The main advantage of ABC algorithm is simple, robust and capable to solve multi-variable, multi-modal and difficult combinatorial optimization problems. In this paper, Multi-Objective Artificial Bee Colony (MOABC) is proposed to solve the environmental/economic power dispatch optimization problem. In general, changing standard single objective ABC to a MOABC needs redefinition of global and local best particles in order to obtain a front of optimal solutions. Thus, for non-dominance solutions sorting the Pareto archive maintenance approach and to ensure proper diversity amongst the solutions of the non-dominated solutions in Pareto archive maintenance the crowding distance method is used [14]. To illustrate the robustness of the proposed MOABC algorithm and their ability to provide efficient solution for the EED problem, it is tested on a IEEE 6-generator 30-bus test system in comparison with the performance of recently reported method in the litrature. The results evaluation reveals that the proposed MOABC algorithm achieves good solution for EED problem and is superior to other multi-objective methods.

II. EED PROBLEM

The environmental/economic power dispatch is one of the main issues of modern energy management system, which determines the optimal real power settings of generating units so minimized two competing objective functions, fuel cost and environmental pollution while satisfying several equality and inequality practical constrain of generators. In addition, the total system real power loss in the transmission network influence on EED problem for find best solution. Thus, the EED problem can be converted to a multi-objective optimization problem with three objective including cost, emission and transmission loss functions to improved active power dispatch simultaneously. This problem is formulated as:

A. Problem Objectives

1) Fuel cost minimization

The objective of ELD problem is to minimize the overall cost of generation units for a given load demand. This objective function is defined as follows:

$$F(P)=\sum_{i=1}^{N} a_i P_i^2 + b_i P_i + c_i \tag{1}$$

where, N is number of generator and F is the total fuel cost, a_i, b_i and c_i are cost coefficients and P_i is the real power output of the ith generator, respectively.

2) Emission minimization

Concerning environmental pollution caused by fossil fuel is important issue in the operation of modern power plants. The generation of electricity from fossil fuel releases several contaminants, such as Sulphur oxides, Nitrogen oxides and Carbon dioxide, into the atmosphere. The amount of pollutant emission is given as a function of generator output that is the sum of a quadratic and exponential function [11]:

$$E(P)=\sum_{i=1}^{N} 10^{-2}(\alpha_i + \beta_i P_i + \gamma_i P_i^2) + \xi_i \exp(\lambda_i P_i) \tag{2}$$

where ζ_i, λ_i, γ_i, α_i and β_i are coefficients of the ith generator emission characteristics.

3) Power loss minimization

In a small system through optimization of the EED problem, transmission losses will be ignored. In a large interconnected network where power is transmitted over long distances, one of the major and effective factors in the EED problem in modern network for optimum dispatch of generation is the transmission losses. Power flow can be described by Newton Raphson method as:

$$P_L(P)=\sum_{k=1}^{N_L} g_k [V_i^2 + V_j^2 - 2V_i V_j \cos(\theta_i - \theta_j)] \tag{3}$$

where, k is kth branches between bus i and j, i= 1, 2, …, N_D, j=1, 2, …, N_j. 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, V_i and V_j are the voltage magnitudes at bus i and j, θ_i and θ_j define voltage angles at bus i and j and g_k is the transfer conductance. P is active power in line i-j.

B. System Constraints

1) Equality constraints

The condition of equality constrain can be given by:

$$\sum_{i=1}^{N} P_i - P_D - P_{Loss} = 0 \tag{4}$$

where, P_D and P_{loss} are total demand and power loss, respectively.

2) Generation capacity constraints

For unflinching operation, the generator outputs and bus voltage is restricted by lower and upper limits as:

$$P_i^{\min} \le P_i \le P_i^{\max} \tag{5}$$

$$Q_i^{\min} \le Q_i \le Q_i^{\max} \tag{6}$$

$$v_i^{\min} \le v_i \le v_i^{\max} \tag{7}$$

where $P_i^{\min}$ and $P_i^{\max}$ are minimum and maximum active power of the ith generator.

3) Line flow constraints

This constrains can be described as:

$$\left|P_{Lf,k}\right| \le P_{Lf,k}^{\max} \quad k = 1, 2, ..., L \tag{8}$$

where $P_{Lf,k}$ is the real power flow of line k; $P_{Lf,k}^{\max}$ is the power flow up limit of line k and L is the number of transmission lines.

C. Problem Formulation

For considered all objective functions and practical constrains, the EED problem can be mathematically formulated as a nonlinear constrained multi-objective optimization problem. It can be expressed as:

$$\begin{aligned} &\min_{P_G}[F(P), E(P), P_L(P)] \\ &\text{subject to:} \\ &g(P) = 0 \\ &h(P) \le 0 \end{aligned} \tag{9}$$

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

III. MULTI OBJECTIVE PARTICLE SWARM OPTIMIZATION

A. ABC Overview

The ABC algorithm is a new member of swarm intelligence based on the food foraging behavior of honey-bees to solve multi-variable, multi-modal and difficult combinatorial optimization problems [13]. This algorithm is simple in concept, easy to implement and has fewer control parameters,

In the ABC algorithm, the colony of foraging artificial bees consists of three clusters (i.e. employed bees, onlookers and scouts). By an employed bee a food source is currently utilizing or ''employed". An onlooker is a bee that waiting on the dance area in the hive for making decision to select a food source from their food sources through the information contributed to employed bees. The scout is a bee which explores randomly the environment surrounding the hive for a novel food source. In the ABC approach, the first half of the colony consists of the employed artificial bees, and the second half includes the onlookers. Each food source has only one employed bee. Thus, the number of employed bees is equal to the number of food sources around the hive. The employed bee whose food source has been exhausted by the bees becomes a scout.

In the ABC, a possible solution to the optimization problem is represented with the position of a food source and the fitness (quality) of the solution is associated to the nectar amount of the associated food resource. Using a probability-based selection procedure onlookers are placed on the food sources. While the nectar amount of a food source increases, the probability value with which the food source is preferred by onlookers increases, too [15]. The main steps of the algorithm are given by: Initialize,

- REPEAT.

(a) Place the employed bees on the food sources in the memory;

(b) Place the onlooker bees on the food sources in the memory;

(c) Send the scouts to the search area for discovering new food sources.

- UNTIL (requirements are met).

This algorithm is an iterative process alike to the other swarm intelligence based methods. It starts with a randomly generated initial population of N solutions in a D-dimension space, where N and D denote the size of population and the number of parameters to be optimized, respectively. The ith food source is represented by $x_i = (x_{i1}, x_{i2}, \ldots, x_{iD})$ generated as follows:

$$x_{ij} = LB_j + \text{rand}(0,1) \times (UB_j - LB_j) \quad \text{for } j=1,2,...,D \text{ and } i=1,2,...,N \tag{10}$$

where, LB_j and UB_j are the lower and upper bounds for jth optimization parameter, respectively. These food sources are calculated (i.e. found the nectar amount) and randomly some better positions assigned to PS number of employed bees.

At this phase, an employed bee, x_i produces a revision in the solution in her memory depending on the local information with generate a novel food source (solution) x_{new} as follows:

$$x_{new}(j) = x_{ij} + r \times (x_{ij} - x_{kj}) \tag{11}$$

where, $k \in \{1, 2, \ldots, PS\}$ and $k \ne i$ and $j \in \{1, 2, \ldots, D\}$ are randomly selected indices. The r is a random number $\in (0, 1)$ which controls the production of neighbor food sources around x_{ij} and represents the comparison of two food positions visually by a bee. In the next stage, employed bee compares the new one against the current solution and memorizes the better one by means of a greedy selection mechanism.

After the completing search procedure by all employed bees, they contribute to the information obtained about the nectar of the food sources and their position with the onlooker bees on the dance area. An artificial onlooker bee evaluates the fitness information taken from all employed bees and chooses a food source x_i depending on the probability value corresponded to that food source, Prob_i, is given by [16]:

$$\text{Prob}_i = \frac{\text{Fit}_i}{\sum_{n=1}^{PS} \text{Fit}_n} \tag{12}$$

where, Fit_i is the fitness value of the ith food source.

If a food source position, x_i, cannot be further enhanced for some predetermined number of cycles (trials limit) then that food source is abandoned, the associating employed bee becomes a scout. The scout produces a new food source for replacing with x_i randomly using Equation (10).

These steps are repeated through a predetermined number of cycles, as Maximum Cycle Number (MCN), or until a termination criterion is satisfied [13, 15].

B. Multi Objective ABC (MOABC)

A lot of realistic life problems entail simultaneous optimization of some objective functions. In general, these functions are noncommensurable and often competing and conflicting objectives.

The application of a multi objective optimizer makes it possible to envisage the trade off among different conflicting objectives to direct the engineer in making his compromise and gives rise to a set of optimal solutions, in place of one optimal solution. The concept of Pareto dominance formulated by Vilfredo Pareto is used for the evaluation of the solutions [17]. This concept is defined as the follows:

For a multi objective optimization problem, a solution u_1 dominates u_2 if and only if:

$$\begin{aligned} &a)\ \forall\ i \in \{1,2,...,Mobj\} : f_i(x_1) \le f_i(x_2) \\ &b)\ \exists j \in \{1,2,...,Mobj\} : f_j(x_1) < f_j(x_2) \end{aligned} \tag{13}$$

where, *Mobj* is the dimension of the objective function. If x_1 dominates the solution x_2 then the x_1 is called the Non-Dominated (NOD) solution. The solutions that are nondominated within the whole search space are signified as Pareto-optimal and constitute the Pareto-optimal set. This set of optimal solutions is also known as Pareto optimal front.

Pareto dominance concept classifies solutions as dominated or non-dominated solutions and the "best solutions" are selected from the non-dominated solutions. The implemented algorithm is the non-dominated sorting PSO which is currently used in many other practical design problems.

To sort non-dominated solutions, the first front of the non-dominated solution is assigned the highest rank and the last one is assigned the lowest rank. When comparing solutions that belong to a same front, another parameter called crowding distance [14] is calculated for each solution.

The crowding distance is a measure of how close an individual is to its neighbors. Large average crowding distance will result in better diversity in the population. In order to investigate multi-objective problems, some modifications in the ABC algorithm were made. A multi-objective optimization algorithm must archive: guide the search towards the global Pareto-optimal front and maintain solution diversity in the Pareto-Optimal front.

C. Non-Dominated Sort

The initialized population is sorted based on non-domination. The fast sort algorithm as given in [14] is used here for NOD.

D. Crowding Distance

Once the non-dominated sort is complete, the crowding distance is assigned. As the individuals are selected based on rank and crowding distance all the individuals in the swarm are assigned a crowding distance value. Crowding distance is allocated front wise and comparing the crowding distance between two individuals in different front is meaningless. The algorithm as given in [14] is used here for the crowding distance.

The flowchart of the proposed MOABC algorithm is shown in Figure 1.

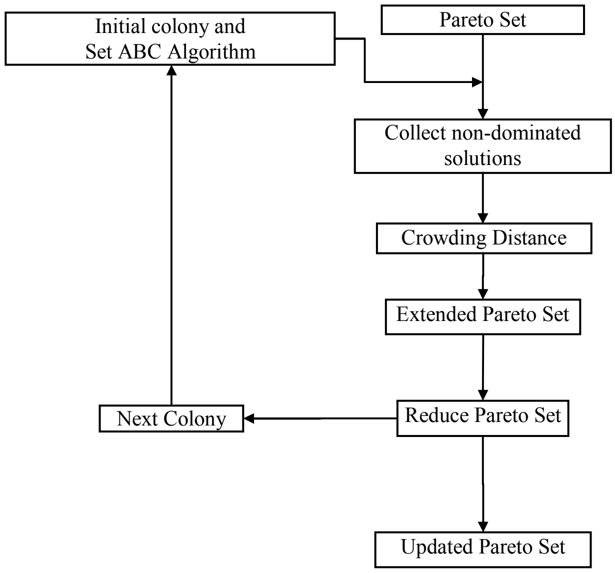

Figure 1. The flowchart of the proposed MOPSO algorithm

IV. RESULTS AND DISSCUSIONS

In order to illustrate the efficiency of the proposed MOABC algorithm for the solution of the EED problems, the IEEE 6-generator 30-bus is considered. The values of the fuel and emission coefficients of the IEEE 30-bus system are illustrated in Table 1. The line data and bus data of the system are given in [18]. The load of the IEEE 30-bus system was set to 2.834 pu on a 100MVA base.

The results obtained from the proposed method were compared in terms of the solution quality and computation efficiency with the Brent method [18] Non-Dominated Sorting Genetic Algorithm (NSGA) [18], Niched Pareto Generic Algorithm (NPGA) [7], Strength Pareto Evolutionary Algorithm (SPEA) [19], Multi-Objective Particle Swarm Optimization (MOPSO) [11] and Multi-Objective Differential Evolution (MODE) [12] in the literature.

The MOABC algorithm is implemented in Matlab software. In each test system, 30 independent runs were made for each of the optimization methods. To evaluate the potential of the proposed method on the test system, four different cases is considered as follows:

A. Case I

The cost function constraint is only considered. Here, the ABC algorithm implements as a single-objective optimization problem. The results using the proposed MOABC algorithm is in comparison with the recently reported methods is given in Table 2. The convergence of fuel cost while losses and emissions are not considered is shown in Figure 2.

B. Case II

The emission function is only considered. In this case, the ABC algorithm is employed as a single-objective optimization algorithm. The simulation result get from supposed algorithm compared with the NSGA, NPGA, SPEA, MOPSO and MODE approaches is presented in Table 3. The convergence of emission function while losses and fuel cost are not considered shown in Figure 3.

Table 1. Generator and emission coefficients of the IEEE 30-bus system (for all $P_{G\min} = 5$ MW and $P_{G\max} = 150$ MW)

No	λ	ζ	γ	β	α	c	b	a
P_{G1}	2.857	2.0e-4	6.490	-5.543	4.091	100	200	10
P_{G2}	3.333	5.0e-4	5.638	-6.047	2.543	120	150	10
P_{G3}	8.000	1.0e-6	4.586	-5.094	4.258	40	180	20
P_{G4}	2.000	2.0e-3	3.380	-3.550	5.326	60	100	10
P_{G5}	8.000	1.0e-6	4.586	-5.094	4.258	40	180	20
P_{G6}	6.667	1.0e-5	5.151	-5.555	6.131	100	150	10

Table 2. System best solution for case I

	SPEA	NPGA	NSGA	MOPSO	MODE	MOABC
P_{G1}	0.1279	0.1425	0.1447	0.1207	0.1332	0.1344
P_{G2}	0.3163	0.2693	0.3066	0.3131	0.2727	0.2873
P_{G3}	0.5803	0.5908	0.5493	0.5907	0.6018	0.6039
P_{G4}	0.9580	0.9944	0.9894	0.9769	0.9747	0.8854
P_{G5}	0.5258	0.5315	0.5244	0.5155	0.5146	0.5685
P_{G6}	0.3589	0.3392	0.3542	0.3504	0.3617	0.3551
Cost ($/h)	607.86	608.06	607.98	607.790	606.126	601.690
Emission (ton/h)	0.2176	0.2207	0.2191	0.2193	0.2195	0.2144

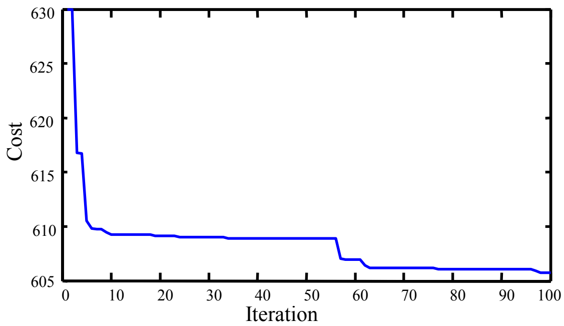

Figure 2. Cost function convergence

Table 3. System best solution for case II

	SPEA	NPGA	NSGA	MOPSO	MODE	MOABC
P_{G1}	0.4145	0.4064	0.3929	0.4101	0.39266	0.3142
P_{G2}	0.4450	0.4876	0.3937	0.4594	0.46256	0.1480
P_{G3}	0.5799	0.5251	0.5815	0.5511	0.56311	0.5019
P_{G4}	0.3847	0.4085	0.4316	0.3919	0.40309	0.6613
P_{G5}	0.5348	0.5386	0.5445	0.5413	0.5676	0.5246
P_{G6}	0.5051	0.4992	0.5192	0.5111	0.47826	0.4146
Cost ($/h)	644.77	644.23	638.98	644.740	642.849	611.969
Emission (ton/h)	0.1943	0.1943	0.1947	0.1942	0.1942	0.1989

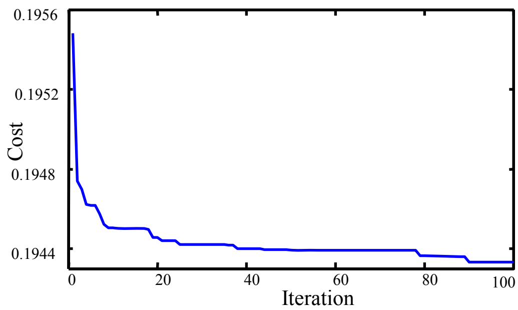

Figure 3. Emission function convergence

C. Case III

Two objective functions of fuel cost and emission is considered. In this sutation, the EED problem is handled as a bi-objective optimization problem where the fuel cost and pollutant emission are optimized simultaneously with the MOABC approach. The results using the proposed algorithm in comparsion with the recently reported methods are given in Table 4. The convergence of fuel cost while losses and emissions are not considered is shown in Figure 4. The distribution of the non-dominated solutions in Pareto optimal front using MOABC algorithm is shown in Figure 4.

D. Case IV

In this case, three objective functions i.e. emission, fuel cost and system loss are considered. Here, the EED problem is implemented as a multi-objective problem with conflicting nature. This case is more complex than the previous cases. In order to illustrate effectiveness of the proposed method it is compared with the MOPSO [11] and MODE [12], which have been applied to the EED problem with impressive success. The results of simulation are given in Table 5. The distribution of the non-dominated solutions in Pareto optimal front using the proposed MOABC is depicted in Figure 5.

Table 4. System best solution for case III

	SPEA	NPGA	NSGA	MOPSO	MODE	MOABC
P_{G1}	0.2752	0.2976	0.2935	0.2367	0.23555	0.3973
P_{G2}	0.3752	0.3956	0.3645	0.3616	0.34896	0.4633
P_{G3}	0.5796	0.5673	0.5833	0.5887	0.57001	0.5660
P_{G4}	0.6770	0.6928	0.6763	0.7041	0.72519	0.3996
P_{G5}	0.5283	0.5201	0.5383	0.5635	0.55357	0.5150
P_{G6}	0.4282	0.3904	0.4076	0.4087	0.42609	0.4973
Cost ($/h)	617.57	617.79	617.80	615.00	613.27	607.356
Emission (ton/h)	0.2001	0.2004	0.2002	0.2021	0.2026	0.1941

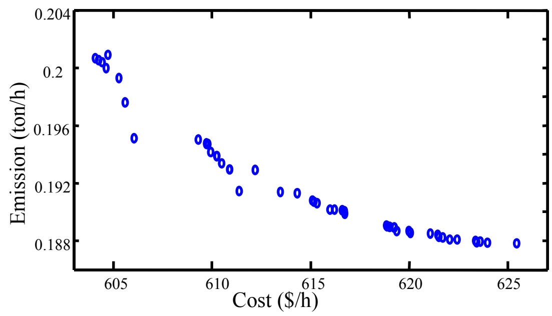

Figure 4. Pareto front using MOABC in case III

Table 5. System best solution for case IV

	MOPSO	MODE	MOABC
P_{G1}	0.39768	0.21207	0.2315
P_{G2}	0.41814	0.30659	0.3782
P_{G3}	0.64404	0.68878	0.6530
P_{G4}	0.75147	0.67937	0.6407
P_{G5}	0.44620	0.58218	0.5391
P_{G6}	0.48973	0.38691	0.3952
Cost ($/h)	614.913	614.170	612.3993
Emission (ton/h)	0.2081	0.2043	0.2010
System loss (MW)	2.8865	2.2009	2.0810

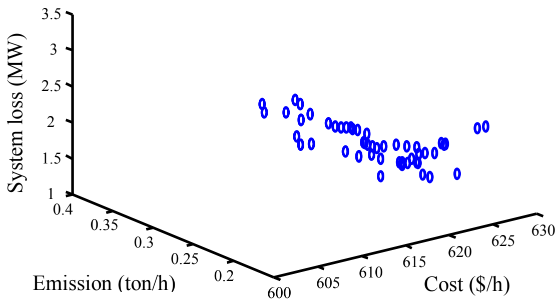

Figure 5. Pareto front using MOABC in case IV

From the above results in different comparative cases, it can be seen that the fuel cost, emission and transmission loss are reduced by using MOABC. These values are not negligible because of the continuous operations of power dispatch throughout the year as well as the numerous power plants worldwide. Thus, the proposed MOABC technique provided superior solutions for EED problem in comparison with the other reported methods in the literature.

V. CONCLUSIONS

A MOABC optimization technique has been successfully applied for the solution of the environmental/economic dispatch in power system in this paper. The proposed MOABC algorithm addresses a multi-objective version of the standard ABC technique and makes uses of its efficacy for the solution of multi-objective optimization problems. The EED problem has been formulated with competing fuel cost, environmental pollution (emission) and transmission losses objectives. To provide the selection mechanism between different objectives, the concept of Pareto dominance mechanism was employed. The comprehensive numerical results on IEEE 6 units 30 bus t test system confirm the successful implementation and efficiency of the proposed MOABC algorithm to solve multi-objective EED problem. The comparable studied that of the recent represented algorithms show the effectiveness of the proposed MOABC technique and their capability to provide superior quality solution and high computation efficiency. From these comparative studies, it is apparent that the MOABC can be successfully applied to solve EED problems in the real-world power systems.

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