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Multi-objective Environmental/Economic Dispatch Using Interactive Artificial Bee Colony Algorithm

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ABSTRACT

In this research a multi-objective Interactive Artificial Bee Colony (MOIABC) is applied for Environmental/ Economic Power Dispatch (EED) problem. The EED problem is the scheduling of generators which fulfill the load demand of the power plants using fossil fuel and also making combined production, in order for them to perform with minimum cost and emission. Thus, by environmental dispatch, emissions can be reduced by dispatch of power generation to minimize emissions. The proposed technique has been carried out on the IEEE 30- and 118-bus test system. The results demonstrate the capability of the proposed MOIABC approach to solve of multi-objective EED problem. The comparison reported results with MODE and other techniques reveals the superiority of the proposed MOIABC approach and confirms its potential for solving other power systems multi-objective optimization problems.

KEYWORDS: Environmental/economic power dispatch, IABC, Minimum cost and emission, Multi-objective optimization.

1. INTRODUCTION

The population rapid increase in world, widespread economic activities and the targeted improvements in the living standards result in a continuously increasing demand for energy services. Contrary to this increase in energy demand, the reduction of the energy sources requires the economic distribution of the produced energy. Hence, a lot of researchers made studies over the suitable power values produced by the generators depending on the fuel costs. In these studies, they produced successful results by using various optimization algorithms [1]. Despite the fact that traditional classical economic can optimize the fuel cost of the generators, it still cannot produce a solution for the environmental pollution due to the excessive emission of fossil fuels.

The classical Economic Load Dispatch (ELD) problem is to operate electric power systems so as to minimize the total fuel cost. This single objective can no longer be considered alone due to the environmental concerns that arise from the emissions produced by fossil fueled electric power plants. Indeed, the clean air act amendments have been applied to reduce SO2 and NOx emissions from such power plants. Hence, emissions can be reduced by dispatch of power generation to minimize emissions instead of or as a supplement to the usual cost objective of economic dispatch [2].

The EED problem is a multi-objective problem with conflicting objectives because pollution is conflicting with minimum cost of generation. A summary of environmental/ economic dispatch techniques dating back to 1970 by using conventional optimization methods was reviewed in [3]. The problem of EED in [4] is reduced to a single objective problem by treating the emission as a constraint with a permissible limit. However, this formulation has a severe difficulty in getting the trade-off relations between cost and emission.

The EED problem is formulated mathematically as a nonlinear constrained multi-objective problem with competing and non-commensurable objectives of fuel cost, emission and system loss. Consequently, single objective and conventional optimization methods that make use of derivatives and gradients, in general, are not able to locate or identify the global optimum. Furthermore, there are many mathematical assumptions such as analytic and differential objective functions that have to be given to simplify the problem. Moreover, this approach does not give any information regarding the trade-offs involved [5].

Various techniques have been proposed to solve this multi-objective problem whereby most researchers have concentrated on the deterministic problem. Accordingly, in “[6], [7], [8]” use multi-objective Genetic Algorithm (GA), hierarchical system approach [2], fuzzified multi-objective particle swarm optimization algorithm [9], fuzzy linear programming “[10], [11]”, fast Newton-Raphson algorithm [12], linear programming [13].

Also Artificial Bee Colony (ABC) is one of the heuristic algorithms that find a possible solution for optimization problems with multi-variable functions and it is motivated by the foraging behavior of honeybees. ABC is improved based on inspecting the behaviors of real bees on finding nectar and sharing the information of food sources to the bees in the hive [14]. There are a lot of studies which present that ABC has been used for solving different optimization problems [15]. Also ABC has a lot of advantages (more simple and flexible and has less control

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parameters) and it is different from other heuristic algorithms, such as particle swarm optimization (PSO), GA and Differential Evolution (DE) [16].These characteristics of the ABC, make it feasible and powerful.

According to the operation and the structure of the ABC, it should be noted that the operation of the agent, e.g. the artificial bee, can only move straight to one of the nectar sources of those are discovered by the employed bees. Nevertheless, this characteristic may narrow down the zones of which the bees can explore and may become a drawback of the ABC. Therefore, in this research an interactive strategy by considering the universal gravitation between the artificial bees for the ABC to retrieve the disadvantages is applied.

In this research, a multi-objective Interactive Artificial Bee Colony (IABC) is proposed to solve the environmental/ economic power dispatch problem. This newly technique makes ABC technique, more flexible and powerful. The proposed algorithm runs on the IEEE 30- and 118-bus test systems and the results are compared with techniques which are presented in [17]. The achieved numerical results of the proposed technique demonstrate the feasibility of the proposed technique to solve the multi-objective EED problem.

I. Problem Statement

It is clear that, in solution to an environmental/economic dispatch problem gives active power generations for all generation units that minimize the total cost rate, which is the summation of the total thermal cost rate and the total emission cost rate. According to this fact that, the power system stability and power quality are influenced by power system reactive power optimization, it should be noted that the ELD, considering system loss can reasonably improve real and reactive power dispatch simultaneously [6]. Hence, the ELD problem should be considered as a multi-objective optimization problem which is based on economic, environment and system loss. The EED problem can be formulated as follows:

I.1. Problem Objectives

Fuel cost minimization: The cost curves of generators are presented by quadratic functions. Also the total fuel cost $F(P_G)$ *($/h)* is presented as:

$$F(P_G) = \sum_{i=1}^{N} a_i + biP_{Gi} + c_i P_{Gi}^2$$

(1)

Where,

N= the number of generators

a_i, b_i, c_i= the cost coefficients of the i_{th} generator

P_{Gi} = the real power output of the i_{th} generator

$$P_G = [P_{G1}, P_{G2}, ..., P_{GN}]^T$$

P_G = the vector of real power output generator

I.2. Emission Minimization

The emission function can be described as the sum of all types of emission considered, such as SO_2, NO_x , and thermal emission, with suitable pricing or weighting on each pollutant emitted. In this study, only one type of emission (NO_x) is taken into account without loss of generality [9]. The amount of NO_x emission is defined as a function of generator output, that is, the sum of a quadratic and exponential function:

The conventional ELD problem can be found by the amount of active power to be generated by units at minimum fuel cost, but it is not considered as the amount of emissions released from burning fossil fuels. The total amount of emission such as SO_2 or NO_x depends on the amount of power generated by unit [10]. The NO_x emission amount which is, the sum of a quadratic and exponential function is given as:

$$E(P_G) = \sum_{i=1}^{N} 10^{-2}(a_i + \beta i P_{Gi} + \gamma_i P_{Gi}^2) + \xi_i \exp(\gamma_i P_{Gi}) \tag{2}$$

Where, α_i, β_i, γ_i, ζ_i and λ_i are the coefficients of i_{th} generator emission characteristics.

Total real power loss's minimization:

The objective of the reactive power dispatch is to minimize the real power loss in the transmission network. Also it can be determined by means of a power flow solution exactly and can be presented as:

$$P_L(P_G) = \sum_{K=1}^{NL} g_k [V_i^2 + V_j^2 - 2ViVj \cos(\theta i - \theta j)] \tag{3}$$

Where,

K= the network branches that connects bus i to j $(i=1,2,\ldots,ND/\ j=1,2,\ldots,N_j)$

N_D= the set of numbers of power demand bus

N_j = the set of numbers of buses adjacent to bus j

N_L = the set of numbers of network branches (transmission lines)
V_i, V_j = the voltage magnitudes at bus i and j
g_k = the transfer conductance between bus i and j
θ_i , θ_j = the voltage angles at bus i and j, respectively

I.3. Problem Constrains

Generation constraints: The upper and lower constrains of generator outputs and bus voltage magnitudes are presented as:

$$P_{Gi}^{\min} \leq P_{Gi} \leq P_{Gi}^{\max} , i = 1,..., N$$
$$Q_{Gi}^{\min} \leq Q_{Gi} \leq Q_{Gi}^{\max} , i = 1,..., N$$
$$V_{Gi}^{\min} \leq V_{Gi} \leq V_{Gi}^{\max} , i = 1,..., N$$
(4)

$P_{Gi}^{\min}$, $P_{Gi}^{\max}$ = the minimum and maximum real power output of the i_{th} generator, respectively
$Q_{Gi}^{\min}$, $Q_{Gi}^{\max}$ = the minimum and maximum active power output of the i_{th} generator, respectively
$V_{Gi}^{\min}$, $V_{Gi}^{\max}$ = the minimum and maximum voltage magnitude of the i_{th} transmission line, respectively.

Also the power balance constraint is expressed as:

$$\sum_{i=1}^{N} P_{Gi} - P_D - P_L = 0$$
(5)

The line loading constrain is explain as:

$$S_{li} \leq S_{li}^{\max} , i = 1,..., N_L$$
(6)

Where, S_{li}^{max} is maximum power flow through the i_{th} transmission line.

I.4. Problem formulation

According to the above equations, the mathematical formulation of multi-objective optimization problem is presented as:

$$\min_{PG} [F(P_G), E(P_G), P_L(P_G)]$$
(7)

Subject to: $g(P_G)=0$ and $h(P_G) \leq 0$
Where, g and h = the equality and inequality constraints, respectively.

II. Molto-objective Interactive Artificial Bee Colony

II.1. Artificial Bee Colony Technique

The Artificial Bee Colony (ABC) algorithm is proposed by Karaboga [14] in 2005, and the performance of the ABC is analyzed in 2007 [15]. The foraging bees are classified into three group; employed bees, onlookers and scout bees. All bees that are currently exploiting a source of food are known as employed. The employed bees exploit the food source and they carry the information about the food source back to the hive and share this information with onlooker bees. Onlookers bees are waiting in the hive for the achieved information to be shared by the employed bees about their discovered food sources and scout bees will always be searching for the new food sources near the hive. Employed bees share the achieved information about food sources by dancing in the designated dance area inside the hive. The nature of this dance is proportional to the nectar content of the food source just exploited by the dancing bee. Onlooker bees watch the dance and choose a food source according to the probability proportional to the quality of that food source. Therefore, appropriate food sources attract more onlooker bees compared to the bad ones. Whenever a source of food is exploited completely, all the employed bees associated with it abandon the food source, and become scout. Scout bees can be visualized as performing the job of exploration, whereas, employed and onlooker bees can be visualized as performing the job of exploitation [16].

In the meta-heuristic ABC technique, the number of employed bees is equal to the number of food sources which is also equal to the number of onlooker bees. There is just one employed bee for each food source whose first position is randomly generated. Each employed bee, at each iteration of the algorithm determines a new neighboring food source of its currently associated food source by the following equation, and computes the nectar amount of this new food source:

$$v_{ij} = z_{ij} + \theta_{ij} (z_{ij} - z_{kj})$$
(8)

Where, Θ_{ij} is a random number between [-1, 1]. If the nectar amount of this new food source is more than that of its currently associated food source, then this employed bee moves to this new food source, otherwise it continues with the old one. After all employed bees complete the algorithm search process; they share the information about their food sources with onlooker bees [18]. An onlooker bee evaluates the nectar data taken from all employed bees and chooses a food source with a probability related to its nectar amount by this equation. This method, known as roulette wheel selection method, provides better candidates to have a greater chance of being selected:

$$p_i = \frac{fit_i}{\sum_{n=1}^{SN} fit_i}$$

(9)

Where, fit_i is the fitness value of the solution i which is proportional to the nectar amount of the food source in the position i and SN is the number of food sources which is equal to the number of employed bees. Pseudo code for ABC algorithm:

- Initialize
- Repeat.
- Move the employed bees onto their food source and evaluate the fitness
- Move the onlookers onto the food source and evaluate their fitness
- Move the scouts for searching new food source
- Memorize the best food source found so far
- Until (termination criteria satisfied)

II.2. Interactive Artificial Bee Colony

An Interactive ABC (IABC) optimization algorithm for solving EED problem has been proposed in this research. The algorithm maps the forager bee's path improvement mechanism to pick new coordinates. The forager bee is directed by scout bee which calculates the fitness values of all possible neighboring coordinates. Unfortunately, in ABC the original design of the onlooker bee's movement only considers the relation between the employed bee, which is selected by the roulette wheel selection, and the one selected randomly. Hence, it is not strong enough to maximize the exploitation capacity. The IABC is proposed by employing the Newtonian law of universal gravitation [18]. The universal gravitations between the onlooker bee and the selected employed bees are exploited which is described as:

$$F_{12} = G\,\frac{m_1 m_2}{r_{21}^2}\,\hat{r}_{21}$$

(10)

Where,
F_{12} = the gravitational force heads from the object 1 to the object 2
G = the universal gravitational constant
m_1, m_2 = the masses of the objects
r_{21} = the separation between the objects

$$\hat{r}_{21} = \frac{r_2 - r_1}{\left| r_2 - r_1 \right|}$$

In this technique, the mass m_1 is substituted by the parameter. The mass, m_2, is substituted by the fitness value of the randomly selected employed bee and is denoted by the symbol, fit_i.

The process of the IABC can be described in five steps as:

- **Initialization:** Spray n_e percentage of the populations into the solution space randomly, and then calculate their fitness values, which are called the nectar amounts, where ne represents the ratio of employed bees to the total population. Once the mentioned populations are positioned into the solution space, they are called the employed bees.
- **Move the Onlookers:** Compute the probability of selecting a food source by equation of fitness value, select a food source to move to by roulette wheel selection for every onlooker bees and then determine the nectar amounts of them.
- **Move the Scouts:** If the fitness amount of the employed bees do not be improved by a continuous predetermined number of iterations, which is called *'limit'*, those food sources are abandoned, and these employed bees become the scouts.
- **Update the Best Food Source Found So Far:** Memorize the appropriate fitness value and the position, which are found by the bees.

- **Termination Checking:** Check if the value of the iterations satisfies the termination condition. If the termination condition is satisfied, terminate the program and output the results; otherwise go back to the Step 2.

III. NUMERICAL RESULTS

III.1. IEEE 30-bus test system

In this research the IEEE 6-generator 30-bus test system and IEEE 14-generator 118-bus test system are considered as case studies for solving the EED problem using the proposed IABC technique. The values of the fuel and emission coefficients of the IEEE 30-bus system are given in “Table 1”. The line data and bus data of the system are presented in [19]. Also, the load of the IEEE 30-bus system was set to 2.834 pu on a 100MVA base. The values of the fuel and emission coefficients of the IEEE 118-bus system is given in “Table 2”, and the load of this system was set to 950MW “[20], [21]”.

To demonstrate the effectiveness of the proposed IABC, the multi-objective EED problem with two objective functions of fuel cost is considered in case one. Case two is the emission objective function. Case 3 is the fuel cost and emission together. Also three objective functions of fuel cost, emission and system loss are considered which is called case four.

“**Table 1.** The values of the fuel and emission coefficients of the IEEE 118-bus system.”

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

“**Table 2.** Generator and emission coefficients of the IEEE 118-bus system..”

P_{Gmin} (MW)	P_{Gmax} (MW)	γ	β	α	*c*	*b*	*a*	*NO*
50	300	23.333	−1.500	0.016	0.50	189	150	P_{G1}
50	300	21.022	−1.820	0.031	0.55	200	115	P_{G2}
50	300	22.050	−1.249	0.013	0.60	350	40	P_{G3}
50	300	22.983	−1.355	0.012	0.50	315	122	P_{G4}
50	300	21.313	−1.900	0.020	0.50	305	125	P_{G5}
50	300	21.900	0.805	0.007	0.70	275	70	P_{G6}
50	300	23.001	−1.401	0.015	0.70	345	70	P_{G7}
50	300	24.003	−1.800	0.018	0.70	345	70	P_{G8}
50	300	25.121	−2.000	0.019	0.50	245	130	P_{G9}
50	300	22.990	−1.360	0.012	0.50	245	130	P_{G10}
50	300	27.010	−2.100	0.033	0.55	235	135	P_{G11}
50	300	25.101	−1.800	0.018	0.45	130	200	P_{G12}
50	300	24.313	−1.810	0.018	0.70	345	70	P_{G13}
50	300	27.119	−1.921	0.030	0.60	389	45	P_{G14}

Actually the fuel cost, emission and system loss objectives are optimized individually to explore the extreme points of the tradeoff surface in all cases. Hence, the basic DE for this case has been implemented as the problem becomes a single-objective optimization problem. The minimum and maximum objective values of case studies when optimized individually for all cases are presented in “Table 3” and “Table 4”, respectively.

“**Table 3.** The minimum and maximum objective values of IEEE 30-bus system.”

Objective	*Fuel cost ($)*	*Emission (ton)*	*System loss (MW)*
MAX	646.335	0.22635	3.6061
MIN	606.03	0.19418	1.7176

“**Table 4.** The minimum and maximum objective values of IEEE 118-bus system.”

Objective	*Fuel cost ($)*	*Emission (ton)*	*System loss (MW)*
MAX	4571.350	152.613	10.059
MIN	4420.801	25.248	8.531

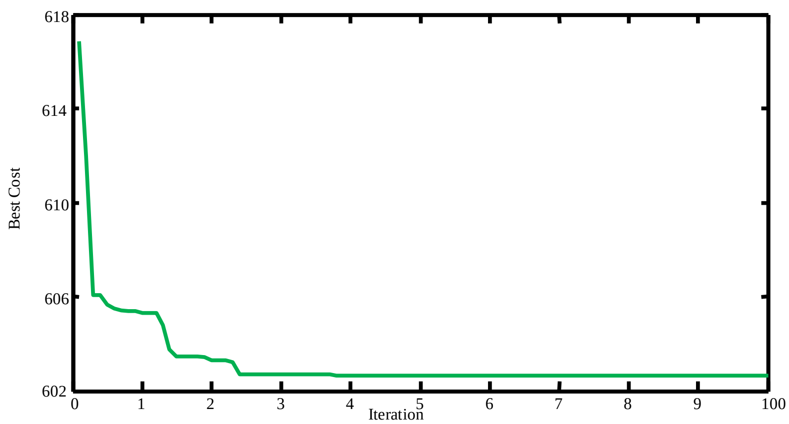
The effectiveness of the proposed IABC algorithm for solving the EED problem is compared with the MODE [17], NSGA [19], NPGA [22], SPEA [23] and MOPSO [24]. The results of best cost and best emission solutions achieved by IABC are compared with other techniques which are given in “Table 5” and “Table 6”, respectively. It is obvious that, the proposed IABC obtains the best cost and best emission compared to other techniques. Also the trend of objective function variation of cost function and variation of emission function are presented in "Figure 1" & "Figure 2" respectively.

"**Table 5.** IEEE 30-bus system best solutions out of ten runs for cost of MOIABC, Case 1."

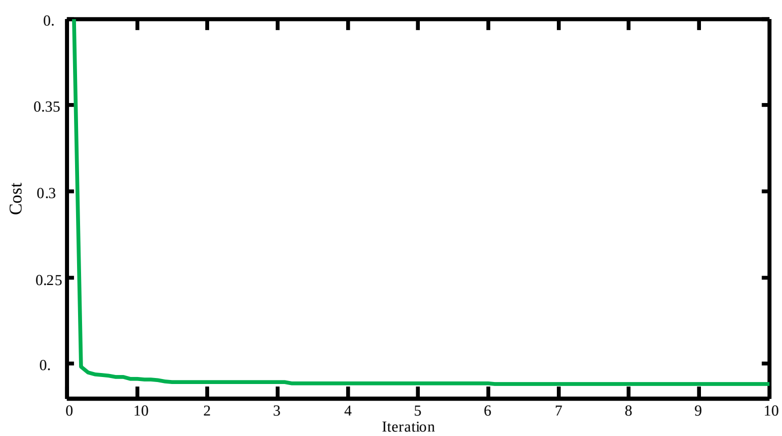
SPEA	*NPGA*	*NSGA*	*MOPSO*	*MODE*	*MOIABC*	*No. Gen*
0.1279	0.1425	0.1447	0.1207	0.1332	0.1903	P_{G1}
0.3163	0.2693	0.3066	0.3131	0.2727	0.3260	P_{G2}
0.5803	0.5908	0.5493	0.5907	0.6018	0.4356	P_{G3}
0.9580	0.9944	0.9894	0.9769	0.9747	0.8832	P_{G4}
0.5258	0.5315	0.5244	0.5155	0.5146	0.5922	P_{G5}
0.3589	0.3392	0.3542	0.3504	0.3617	0.4067	P_{G6}
607.86	608.06	607.98	607.790	606.126	602.6306	*Cost ($/h)*
0.2176	0.2207	0.2191	0.2193	0.2195	0.1975	*Emission (ton/h)*
0.0332	0.0337	0.0346	0.0333	0.0247	3.1383e-005	*Mismatch power*

"**Table 6.** IEEE 30-bus system best solutions out of ten runs for emission of MOIABC, Case 2."

SPEA	*NPGA*	*NSGA*	*MOPSO*	*MODE*	*MOIABC*	*No. Gen*
0.4145	0.4064	0.3929	0.4101	0.39266	0.3977	P_{G1}
0.4450	0.4876	0.3937	0.4594	0.46256	0.3990	P_{G2}
0.5799	0.5251	0.5815	0.5511	0.56311	0.4522	P_{G3}
0.3847	0.4085	0.4316	0.3919	0.40309	0.5613	P_{G4}
0.5348	0.5386	0.5445	0.5413	0.5676	0.6168	P_{G5}
0.5051	0.4992	0.5192	0.5111	0.47826	0.4213	P_{G6}
644.77	644.23	638.98	644.740	642.849	626.1005	*Cost ($/h)*
0.1943	0.1943	0.1947	0.1942	0.1942	0.1880	*Emission (ton/h)*
0.0300	0.0314	0.0294	0.0309	0.0333	0.0143	*Mismatch power*



"**Figure 1.** Objective function variation of cost function."

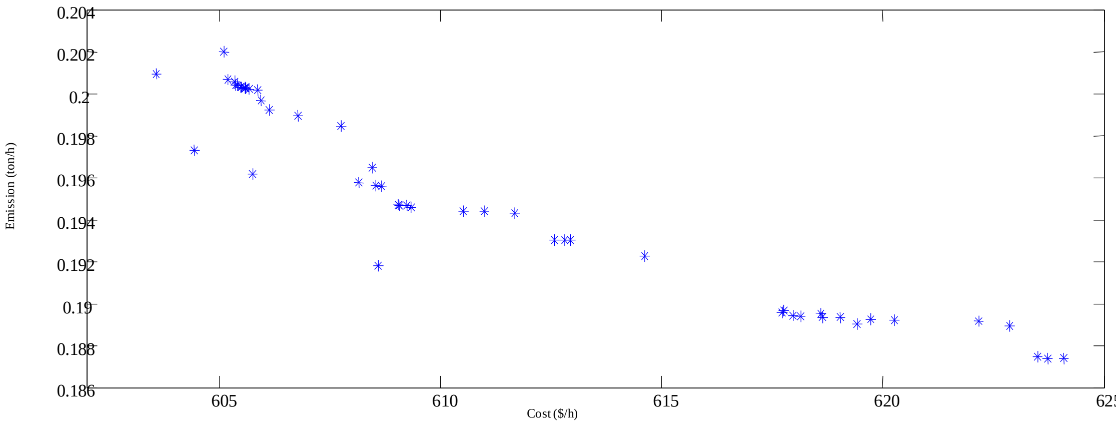


"**Figure 2.** Objective function variation of emission function."

Moreover, the best compromise solution of the proposed MOIABC in case 3 is presented in "Table 7". Also a typical Pareto front of case 3 and 4 obtained by MOIABC is shown in "Figure 3" and "Figure 4", respectively [25]. For case 4, the solutions of MODE, MOPSO and MOIABC are presented in “Table 8”. The Pareto front of this case is presented in “Figure 4”.

“**Table 7.** IEEE 30-bus system best compromise solutions of MOIABC, case 3.”

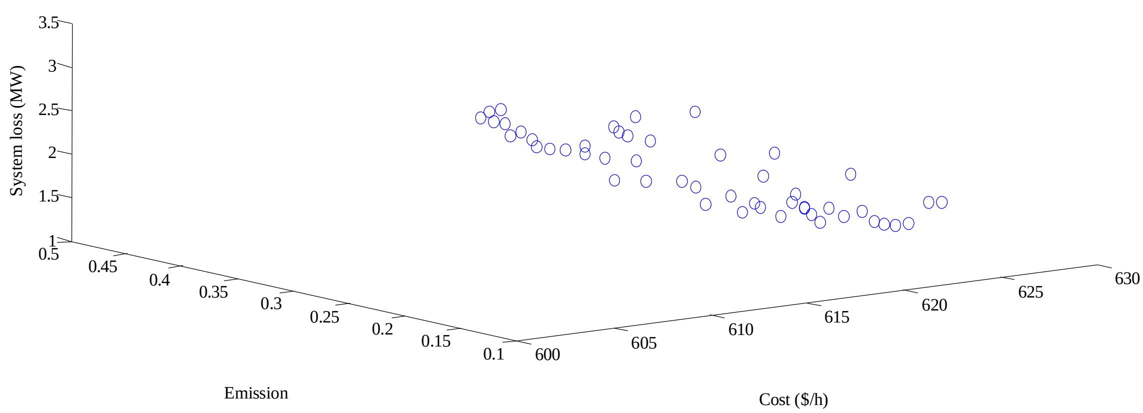
SPEA	*NPGA*	*NSGA*	*MOPSO*	*MODE*	*MOIABC*	*No. Gen*
0.2752	0.2976	0.2935	0.2367	0.23555	0.1760	P_{G1}
0.3752	0.3956	0.3645	0.3616	0.34896	0.3421	P_{G2}
0.5796	0.5673	0.5833	0.5887	0.57001	0.7103	P_{G3}
0.6770	0.6928	0.6763	0.7041	0.72519	0.7171	P_{G4}
0.5283	0.5201	0.5383	0.5635	0.55357	0.5283	P_{G5}
0.4282	0.3904	0.4076	0.4087	0.42609	0.3646	P_{G6}
617.57	617.79	617.80	615.00	613.27	608.5227	*Cost ($/h)*
0.2001	0.2004	0.2002	0.2021	0.2026	0.1956	*Emission (ton/h)*
0.0295	0.0298	0.0295	0.0293	0.0254	0.0045	*Mismatch power*



“**Figure 3.** IEEE 30-bus system Pareto front using MOIABC in Case 3.”

“**Table 8.** IEEE 30-bus system best compromise solutions of MODE , MOPSO and MOIABC, Case 4.”

MOPSO	*MODE*	*MOIABC*	*No. Gen*
0.39768	0.21207	0.2408	P_{G1}
0.41814	0.30659	0.3142	P_{G2}
0.64404	0.68878	0.7804	P_{G3}
0.75147	0.67937	0.6265	P_{G4}
0.44620	0.58218	0.5475	P_{G5}
0.48973	0.38691	0.3316	P_{G6}
614.913	614.170	615.2530	*Cost ($/h)*
0.2081	0.2043	0.1954	*Emission (ton/h)*
2.8865	2.2009	1.7768	*System loss (MW)*
0.3133	0.0219	0.0070	*Mismatch power*



"**Figure 4.** IEEE 30-bus system Pareto front using MOIABC in Case 4."

III.2. IEEE 118-bus test system

In this case study, a standard IEEE 14-generator 118-bus test system "[20], [21]" is considered. Since the network branches data is not available in the existing literature, transmission loss for this system is calculated using the Kron's loss formula [21].

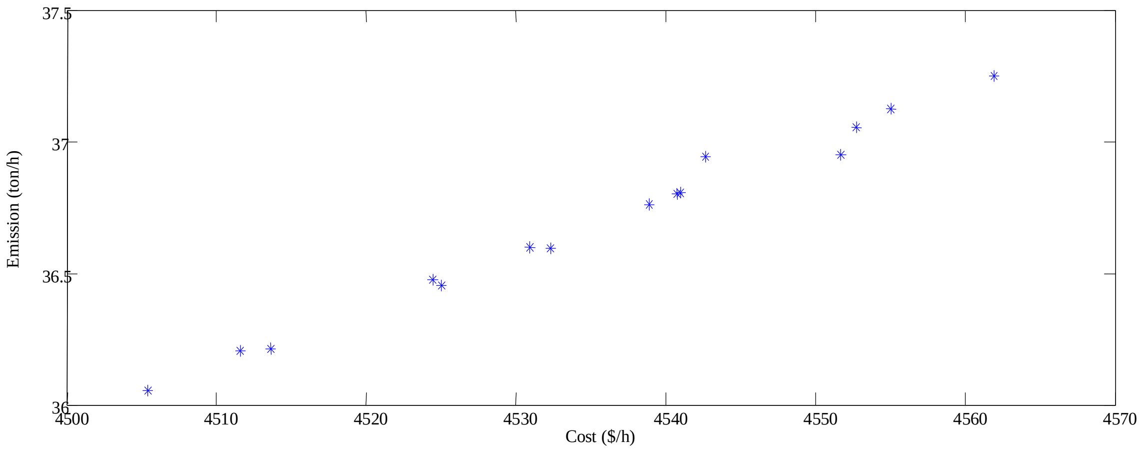
In this case study, two cases is considered as a test functions. For Case 1, the bi-objective optimization problem with cost and emission objectives is considered. And for Case 2, the transmission losses PL is regard as the third objective. In this regard, the best compromise solution of case 1 and 2 are presented in "Table 9" and "Table 10", respectively. The results of the proposed algorithm are compared with PSO based Weighted Aggregation (WA) approach and a Multi-objective Evolutionary Algorithm (MOEA), fuzzified multi-objective particle swarm algorithm (FMPSO) and MODE [17]. It is clear that the proposed MOIABC algorithm is superior than other compared techniques. Also a typical Pareto front of IEEE 118-bus test system obtained by MOIABC is shown in "Figure 5" and "Figure 6", respectively.

"**Table 9.** IEEE 118-bus system best compromise solutions from different algorithms, Case 1."

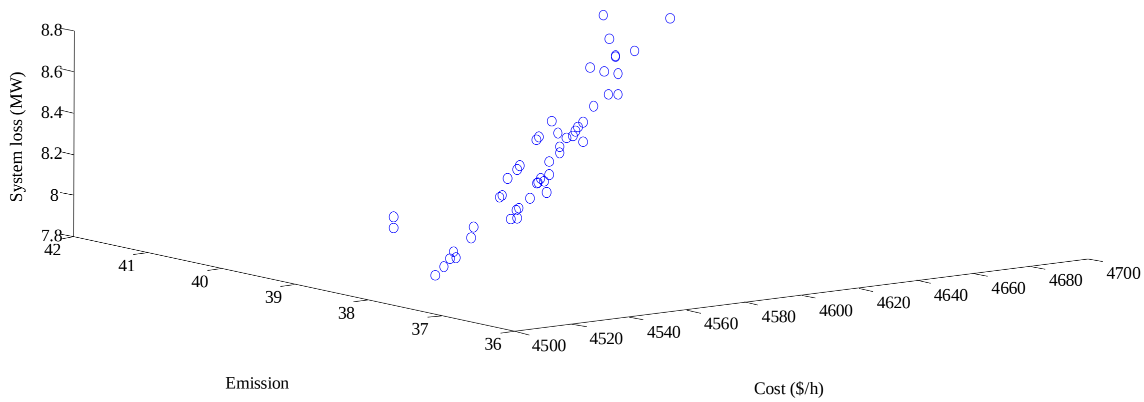
WA	*MOEA*	*FMPSO*	*MODE*	*MOIABC*	*No. Gen*
91.1562	81.6684	94.5703	82.1555	78.9346	*PG1*
109.584	108.597	105.728	50.4606	69.2084	*PG2*
51.4286	50.3574	50.992	68.8527	57.5399	*PG3*
50.1945	50.0378	50.0	83.5687	62.7127	*PG4*
68.3609	88.2061	75.7894	68.1255	81.4834	*PG5*
90.6869	89.5116	84.6362	50.0254	67.8076	*PG6*
53.5931	50.0	53.3723	65.3001	62.4491	*PG7*
56.4637	51.6133	54.8911	66.7923	84.6177	*PG8*
77.0796	82.3149	83.6218	75.7799	61.9143	*PG9*
51.234	54.5174	52.5273	95.4330	81.1730	*PG10*
87.3122	84.3849	79.5150	50.4028	70.7583	*PG11*
110.159	112.184	106.104	87.1779	60.1542	*PG12*
55.1502	51.427	58.1926	65.6425	55.8518	*PG13*
50.722	50.408	50.1546	50.1148	55.9838	*PG14*
4558.0	4565.1	4548.6	4508.5	4505.421	*Cost ($/h)*
39.2491	39.7978	38.0501	37.3536	36.1432	*Emission (ton/h)*
53.1249	55.2278	50.0946	9.8317	0.5889	*Mismatch power*

"**Table 10.** IEEE 118-bus system best compromise solutions of MODE and MOIABC, Case 2."

MODE	*MOIABC*	*No. Gen*
70.9094	52.1022	P_{G1}
51.1464	59.3140	P_{G2}
69.1604	71.9158	P_{G3}
77.3742	62.1448	P_{G4}
68.9120	65.7374	P_{G5}
50.5830	62.7551	P_{G6}
72.0363	50.1560	P_{G7}
69.6698	79.7264	P_{G8}
73.4252	56.3872	P_{G9}
101.0704	83.8212	P_{G10}
53.8714	95.7814	P_{G11}
86.9146	82.3573	P_{G12}
64.1231,	74.2873	P_{G13}
50.1213	54.1363	P_{G14}
4524.9	4506.005	*Cost ($/h)*
37.629	3.731402	*Emission (ton/h)*
9.3301	7.962371	*System loss (MW)*
9.3984	0.6225	*Mismatch power*



"**Figure 5.** IEEE 118-bus system Pareto front using MOIABC in Case 1."



"**Figure 6.** IEEE 118-bus system Pareto front using MOIABC in Case 2."

According to the achieved numerical results, it is clear that all cases the results of the proposed technique are better. In addition, the close agreement of the results shows clearly the capability of the proposed approach to handle multi-objective optimization problems as the best solution of EED problem for each objective in case studies.

IV. Conclusion

In this research, the EED optimization problem formulated as multi-objective optimization problem with competing objectives of fuel cost, emission and system loss. This difficult optimization problem is solved by using the MOIABC algorithm. Actually, ABC is developed based on inspecting the behaviors of real bees on finding nectar and sharing the information of food sources to the bees in the hive. The achieved numerical results of the proposed technique demonstrate the feasibility of the proposed technique to solve the multi-objective EED problem. The IEEE 30- and 118-bus test systems were used to investigate the effectiveness of the proposed MOIABC approach. The proposed technique is compared with other MOEAs, such as NPGA, NSGA, SPEA, MOPSO and MODE. It is obvious that, the proposed technique achieve appropriate results is power systems. Hence, the MOIABC gives lower cost for several cases in two test systems.

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