Extended Dynamic Economic Environmental Dispatch using Multi-Objective Particle Swarm Optimization

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Abstract: The purpose of this paper is to present the extended version of the conventional DEED to overcome the ramp rate violations when its optimal solutions for one period (normally one day) are implemented repeatedly and periodically over consequent dispatch periods to meet the periodic load demands. This dynamic dispatch problem, which is referred to as EDEED, is a multi-objective optimization problem which **simultaneously** minimizes both fuel cost and pollutants emission while satisfying a set of constraints. A multi-objective particle swarm optimization (MOPSO) method has been applied in this article for solving EDEED problem. The performance of the proposed method has been evaluated on the 10-unit test system with non-smooth fuel cost and emission level functions in comparison with those methods reported in the literature.

Keywords: Extended dynamic economic emission dispatch, multi-objective optimization, particle swarm optimization, ramp rate violations, Pareto-dominance concepts.

1. Introduction

One of the major interests in recent years is the reducing of the fuel cost in electric-power-generating plants. Dynamic economic dispatch (DED) is a real-time power system problem which is used to determine the production levels of scheduled units over a short-term time span to meet the load demand at minimum operating cost under various system and operating constraints [1]. However, several thermal generators must be committed in order to satisfy the varying load demand and according to fast growing power demand the quantity of coal burnt is also increasing. And this leads to an increasing release of several contaminants such as carbon dioxide (CO₂), sulfur oxides (SO_x) and nitrogen oxides (NO_x) into the atmosphere. The Clean Air Act Amendments of 1990 [2] have forced the electric utilities to modify their design or operational strategies to reduce pollution emissions. Therefore, the thermal electrical power plants not only take into consideration the economic dispatch problem, but also consider the emission dispatch problem simultaneously; such problem

is referred to as economic and environmental power dispatch (EED) problem [3,4].

Taking into account the importance of DED and EED as well as their shortcomings, the coupling dynamic model that is called dynamic economic emission dispatch (DEED) should be studied [5]. DEED is a crucial task in the operation and planning of power system, which is used to schedule optimally the committed generating units' outputs over a certain period of time considering multiple objectives, generators' ramp rate limits and predicted load demands. So it is closer to the practical, but it is more difficult to be solved due to the high-dimensional and multiple objectives.

The emission can be considered into the dynamic economic dispatch problem following three main research directions [3]. The first direction is to reduce the DEED by treating the emission as a constraint with a pre-specified limit and minimizing the fuel cost [6,7]. In this situation, the model is equivalent to the DED and the result is not conducive to scientific decision making [5]. The second research direction is to convert the DEED problem to a single objective problem by linear combination of different objectives as a weighted sum [8,9]. The third direction is to consider the emission as another objective where both emission and cost are minimized simultaneously [10-12].

Recently, price penalty factor [13], fuzzy satisfying method [10] and goal-attainment method [9,14], are used respectively to simplify the dynamic dispatch problem and to convert the model into a single objective optimization problem. All of these methods yield meaningful results, but the set of Pareto-optimal solutions is hard to get since different weights are used in different runs of the single objective optimization algorithm [15]. In addition to these literatures, a non-dominated sorting genetic algorithm II (NSGA-II) has been successfully applied to solve the DEED problem as a true multi-objective problem and good results have been achieved in [11]. An improved bacterial foraging algorithm (IBFA) has been proposed in [8] for solving the DEED problem by converting the multi-objective optimization problem into a single objective optimization. A group search optimizer with multiple producers (GSOMP) has been developed in [12] in order to solve the DEED problem. A modified adaptive multi-objective differential evolutionary algorithm (MAMODE) that includes expanded double selection and adaptive random restart operators has been proposed for solving the DEED problem in [5].

Each heuristic optimization techniques, such as genetic algorithm (GA), Tabu search (TS), simulated annealing (SA), particle swarm optimization (PSO), has its own advantages and disadvantages; however particle swarm has gained a lot of attention in recent years and it's a very suitable algorithm for such problems [16]. In addition, PSO algorithm is relatively simple and easy to be implemented in computer simulations, since its working mechanism only involves two fundamental updating rules, and it has fewer operators to adjust in the implementation [17]. It has the ability to handle non-smooth and nonconvex economic power dispatch problem [18,19]. However, the dispatch problem was formulated as a mono-objective optimization model with the fuel cost as the only objective considered for optimization. Thus, to render the standard PSO capable of dealing with multi-objective optimization problem with non-commensurable and contradictory objectives, some modifications become necessary. However, in this paper, the original PSO algorithm is modified and improved in order to handle a multi-objective optimization of the Dynamic dispatch problem. The Pareto-dominance concept is employed to extend the approach to solve multi-objective problems.

The load demand is assumed to be periodic over a dispatch period of one day. This periodic assumption is made to reflect the cyclic consumption behavior and seasonal changes [20]. Then, the obtained optimal solutions of the DEED problem over the dispatch interval are to be implemented not only for the first day but also for all the other week days. Sometimes, these solutions cannot be implemented repeatedly and periodically over other periods, since a ramp rate violation may occur when the optimal solution of the DEED problem over the first day is simply implemented in the next day [21]. This problem will be resolved in this paper by introducing more constraints and thus formulating a new version of the classical DEED problem [20,22], which is called extended DEED problem.

The present paper is organized as follows: section 2 formulates the extended dynamic economic and emission dispatch (EDEED) problem. The determination of generation levels of the remaining generator is presented in section 3. In Section 4, the proposed method using MOPSO to solve EDEED is detailed. Simulation results are outlined, discussed and compared with MAMODE [5], IFBA [8] and RCGA/NSGA-II [11] methods in Section 5. The last section presents the concluding remarks.

2. Problem formulation

The present formulation treats extended dynamic economic emission dispatch (EDEED) problem as a multi-objective mathematical programming problem which simultaneously minimize the fuel cost and pollutions emission over the whole dispatch periods while satisfying various constraints. Generally the problem is formulated as follows

A. Problem objectives

A.1. Minimization of fuel cost

The fuel cost function for each thermal generating unit in the system, considering the valve-point effect, can be modeled as the sum of a quadratic and a sinusoidal function. Therefore, the total fuel cost (F_t) over the whole dispatch period is expressed as [11,17]

$$\min \left(F_t = \sum_{t=1}^T \sum_{i=1}^N C_i(P_i^t) = \sum_{t=1}^T \sum_{i=1}^N \left[a_i + b_i P_i^t + c_i (P_i^t)^2 + |d_i \sin(e_i (P_i^{\min} - P_i^t))| \right] \right) \quad (1)$$

where a_i , b_i , c_i are the cost coefficients of thermal unit i , d_i , e_i are the valve-point coefficients of i th unit, P_i^t is the real power output of i th unit during time interval t ; $C_i(P_i^t)$ is the generation cost for unit i to produce P_i^t at time t , $P_i^{\min}$ is the minimum generation limits for i th unit, N is the number of generating units and T is the number of intervals in the scheduled horizon.

A.2. Minimization of emission

The total emission (E_t) of atmospheric pollutants such as sulphur oxides SOx and nitrogen oxides NOx, caused by the operation of fossil-fueled thermal power generation can be expressed as [8,11]

$$\min \left(E_t = \sum_{t=1}^T \sum_{i=1}^N E_i(P_i^t) = \sum_{t=1}^T \sum_{i=1}^N \left[\alpha_i + \beta_i P_i^t + \gamma_i (P_i^t)^2 + \xi_i \exp(\lambda_i P_i^t) \right] \right) \quad (2)$$

where α_i , β_i , γ_i , ξ_i , λ_i are the emission coefficients of i th unit and $E_i(P_i^t)$ is the amount of emission from unit i from producing power P_i^t .

A.3. Constraints

- Real power balance constraints

Hourly power balance considering network transmission losses is given by

$$\sum_{i=1}^N P_i^t = P_D^t + P_{loss}^t \quad ; \quad t \in T \quad (3)$$

where P_D^t , P_{loss}^t are the load demand and the transmission line losses at the time interval t .

The transmission losses can be calculated using the results of load flow problem or Kron's loss formula known as B-matrix coefficients developed by Kron and adopted by Kirchmayer [23]. The latter method is used in this paper to determine the transmission losses which are given by

$$P_{loss}^t = \sum_{i=1}^N \sum_{j=1}^N P_i^t B_{ij} P_j^t \quad ; \quad t \in T \quad (4)$$

where B_{ij} is the transmission loss coefficient.

Generation limits of units

$$P_i^{\min} \leq P_i^t \leq P_i^{\max} \quad ; \quad i \in N ; t \in T \quad (5)$$

where $P_i^{\min}$, $P_i^{\max}$ are the lower and upper generation limits for i th unit.

- Generating unit ramp rate limits

Depending on the load demand at time period t , the output power change rate of each thermal unit i must be in an acceptable range to avoid undue stresses on the boiler and

combustion equipments [24]. The generator constraints due to ramp rate limits of generating units are given as follows

$$\begin{cases} P_i^t - P_i^{t-1} \leq UR_i \\ P_i^{t-1} - P_i^t \leq DR_i \end{cases} ; i \in N ; t = 2, \dots, T. \quad (6)$$

$$-DR_i \leq P_i^1 - P_i^T \leq UR_i ; i \in N \quad (7)$$

where UR_i , DR_i are the ramp-up and the ramp-down rate limits of the i th unit.

Considering ramp rate limits of units, generator capacity limits (5) can be rewritten as follows

$$\begin{cases} P_i^{\min} \leq P_i^t \leq P_i^{\max} & ; i \in N & \text{if } t = 1 \\ \max(P_i^{\min}, P_i^{t-1} - DR_i) \leq P_i^t \leq \min(P_i^{\max}, P_i^{t-1} + UR_i) & ; i \in N & \text{Others} \end{cases} \quad (8)$$

Generally, over each time interval the conventional DEED problem is solved under static and dynamic constraints (constraints (3)–(6)). Since the demand is periodic, the obtained solution of the DEED must be implemented for all the week days. Sometimes the ramp rate constraint may be violated when the thermal units change their generation levels from the last hour in a day to the first hour of the next day. In order to avoid such a problem, the classical DEED problem must be extended by including the constraint (7). The new version of this dynamic dispatch problem will be referred to as EDEED.

3. Determination of remaining generator level

Assuming that the power loading of $(N-1)$ generators are specified, the power level of N^{th} generator (i.e. the remaining generator) is given by

$$P_N^t = P_D^t + P_{\text{loss}}^t - \sum_{i=1}^{N-1} P_i^t ; t \in T \quad (9)$$

The transmission loss P_{loss}^t is a function of all generating units including that of the dependent unit and it is given by

$$P_{\text{loss}}^t = B_{NN} \left(P_N^t \right)^2 + \left(2 \sum_{i=1}^{N-1} B_{Ni} P_i^t \right) P_N^t + \sum_{i=1}^{N-1} \sum_{j=1}^{N-1} P_i^t B_{ij} P_j^t ; t \in T \quad (10)$$

After substituting the value of P_{loss}^t from (10) into (9) and rearranging, equation (9) becomes

$$B_{NN} \left(P_N^t \right)^2 + \left(2 \sum_{i=1}^{N-1} B_{Ni} P_i^t - 1 \right) P_N^t + \left(P_D^t + \sum_{i=1}^{N-1} \sum_{j=1}^{N-1} P_i^t B_{ij} P_j^t - \sum_{i=1}^{N-1} P_i^t \right) = 0 ; t \in T \quad (11)$$

The value of the loading of the dependent generating unit (i.e. N^{th}) can be easily calculated by solving Eq. (11) using standard algebraic method and must satisfy the constraints (5) and (6).

4. Multi-Objective Particle Swarm Optimization

A. Multi-objective optimization

The general minimization problem of N_{obj} objective functions associated with a number of equality and inequality constraints can be defined as follows:

$$\text{Minimize } f_i(x) \quad i = 1, \dots, N_{obj} \quad (12)$$

$$\text{Subject to } \begin{cases} g_j(x) = 0 & j = 1, \dots, J \\ h_k(x) \leq 0 & k = 1, \dots, K \end{cases} \quad (13)$$

where f_i is the objective function, x is the decision vector, g_j is the j^{th} equality constraint and h_k is the k^{th} inequality constraint.

In a minimization problem, a solution u_1 dominates another solution u_2 , if and only if:

$$f_i(u_1) \leq f_i(u_2) \quad \forall i \in \{1, 2, \dots, N_{obj}\} \quad (14)$$

$$f_j(u_1) < f_j(u_2) \quad \exists j \in \{1, 2, \dots, N_{obj}\} \quad (15)$$

A solution u_1 , is said to be *Pareto optimal*, if it is not dominated by any other solution u_2 in the solution space. Then the solution u_1 is called the *non-dominated solution*. The set of all feasible non-dominated solutions constitutes the *Pareto-optimal set*, and for a given Pareto-optimal set, the corresponding objective function values in the objective space is called the *Pareto front*.

B. Overview of PSO

The concept of PSO is inspired from the social behavior of animals, such as birds in flocks or fish in schools, as well as on swarm theory. It was first proposed by Kennedy and Eberhart in 1995 [26] as new heuristic method. In PSO, each individual of the swarm represents a potential solution which moves through a multi-dimensional search space to look for a potential solution by learning itself history experience and the experience of its neighbors. In a physical D -dimensional search space, the potential solution can be represented by the particle's position vector $X_i(t) = (x_{i1}(t), x_{i2}(t), \dots, x_{id}(t), \dots, x_{iD}(t))$. The position, $X_i(t)$, of the i^{th} particle is adjusted by a stochastic velocity $V_i(t) = (v_{i1}(t), v_{i2}(t), \dots, v_{id}(t), \dots, v_{iD}(t))$. Thus, the particle will change its position and velocity according to the following equations

$$v_{ij}(t+1) = \omega \cdot v_{ij}(t) + c_1 \cdot r_1 \cdot (pbest_{ij}(t) - x_{ij}(t)) + c_2 \cdot r_2 \cdot (gbest_j(t) - x_{ij}(t))$$

$$i = 1, 2, \dots, N_p \quad ; \quad j = 1, 2, \dots, D \quad (16)$$

$$x_{ij}(t+1) = x_{ij}(t) + v_{ij}(t+1) \quad i = 1, 2, \dots, N_p \quad ; \quad j = 1, 2, \dots, D \quad (17)$$

where $pbest_{ij}(t)$ is the personal best position of the i^{th} particle at generation t , $gbest_j(t)$ represents the global best position among all particles at generation t , ω is the inertia weight factor that determines the influence of the velocity of the previous iteration to update the velocity, c_1 and c_2 are acceleration coefficients which control the effect of the personal and global best particles and r_1 and r_2 are independently uniformly distributed random variables within the range $[0,1]$. The inertia weight ω is linearly decreasing as the iterations proceed and can be calculated using Eq.(18).

$$\omega = \omega_{\max} - \frac{\omega_{\max} - \omega_{\min}}{iter_{\max}} \cdot iter \quad (18)$$

where ω_{max} , ω_{min} are the initial and the final weights, $iter$ is the current iteration number and $iter_{max}$ is the maximum iteration number.

C. MOPSO method

The original version of PSO can only be applied to single objective optimization tasks. However, with the adaptation of Pareto-optimal concepts, PSO can be used to solve the multi-objective optimization problem effectively. Modifying standard PSO to a multi-objective PSO needs a redefinition of global and local best particles to find a set of different optimal solutions. In MOPSO, there is no absolute global optimum, but rather a set of non-dominated solutions. The MOPSO approach is based on the essential idea of the use of an external repository in which every particle will file its flight experiences after each flight cycle [27]. In this method, the explored search space must be divided into a number of hypercubes. Each hypercube, which is interpreted as a geographical region, receives a fitness value depending on the number of particles that lie in it. Thereafter, the selection of a global best for a particle is based on roulette wheel selection of a hypercube.

C.1. Representation of Basic elements of MOPSO :

The technical terms of the proposed MOPSO method are defined and represented as follows:

Particle, P_{Gi} : In this study, the power output of the first $(N-1)$ generators constitute the decision variables of the optimization problem. Thus, each power output is selected as a gene. These genes are real coded and they constitute a particle which represents a candidate solution for the EDEED problems. The i^{th} particle P_{Gi} can be represented by the following vector $P_{Gi} = [P_{i1}, P_{i2}, \dots, P_{id}, \dots, P_{i(N-1)}]$. The generation power output P_{id} of the d^{th} unit at i^{th} particle is represented as the position of the i^{th} particle with respect to the d^{th} dimension. The power of the N^{th} unit is calculated using eq(11).

Population, POP: It is a set of N_p particles, i.e., $POP = [P_{G1}, \dots, P_{GNp}]^T$. The dimension of a population (swarm) is $N_p \times (N-1)$.

Particle velocity, $V_i(t)$: At generation t , the i^{th} particle velocity $V_i(t)$ can be described as $V_i(t) = [v_{i1}(t), v_{i2}(t), \dots, v_{i(N-1)}(t)]$. This vector drives the optimization process, that is, it determines the direction in which a particle needs to move to enhance its current position.

Personal best position, $pbest$: the personal best position or the local leader represents the best solution found by the i^{th} particle itself so far. It can be described as $pbest = [pbest_{i1}, pbest_{i2}, \dots, pbest_{i(N-1)}]$.

Global best position, $gbest$: represents the position of the best particle of the entire swarm. The global best position is represented by $gbest = [gbest_1, gbest_2, \dots, gbest_{(N-1)}]$.

C.2. Main Algorithm.

The algorithm of the MOPSO for EDEED problem can be described in the following steps.

- Step1:** Specify the lower and upper limits of generation power of each thermal generator as well as the range of security level.
- Step 2:** Initialize the particles of the population with random positions and velocities in the feasible search space.
- Step 3:** Compute the transmission loss using B-coefficient loss formula for each individual P_{Gi} of the population POP.
- Step 4:** Based on the concept of Pareto-dominance, each individual P_{Gi} will be evaluated in the population POP.
- Step 5:** Store the non-dominated solutions found in the archive REP.
- Step 6:** Produce the hypercubes by dividing the so far explored search space, and place the individuals using these hypercubes as a coordinate system where each individual's coordinates are defined according to the values of its objective function.
- Step 7:** Initialize the memory of each particle in which a single local best $pbest$ is stored. The memory is contained in the other archive PBEST.
- Step 8:** Increment iteration counter.
- Step 9:** Select the best global particle $gbest$ for each particle i from REP.

Step 10: Update the speed and position of each particle using Eqs (16) and (17). If the position and speed of a new particle violate their limits in any dimension, then they should be modified accordingly in order to stay within the search space.

Step 11: Evaluate each particle in the population.

Step 12: Update the contents of *REP* together with the geographical representation of the particles within the hypercubes.

Step 13: Update the contents of *PBEST*.

Step 14: If any stopping criterion is satisfied, then go to Step 15. Otherwise, go to Step 8.

Step 15: Output a set of Pareto-optimal solutions from *REP* as the final solutions.

C.3. Best compromise solution.

After obtaining the Pareto-optimal set of non-dominated solutions, it is practical to select one solution as the best compromise solution from all non-dominated solutions that satisfy the criterion of the decision maker. Due to imprecise nature of the decision maker's judgment, each objective F_i is represented by a membership function defined as [4]

$$\mu_i = \begin{cases} 1, & F_i \leq F_i^{\min}, \\ \frac{F_i^{\max} - F_i}{F_i^{\max} - F_i^{\min}}, & F_i^{\min} < F_i < F_i^{\max}, \\ 0, & F_i \geq F_i^{\max}, \end{cases} \quad (20)$$

where $F_i^{\max}$ and $F_i^{\min}$ are the maximum and minimum values of the i^{th} objective function F_i , respectively. Then, the normalized membership function μ^k for each non-dominated solution k , is calculated as

$$\mu^k = \frac{\sum_{i=1}^{Nobj} \mu_i^k}{\sum_{k=1}^M \sum_{i=1}^{Nobj} \mu_i^k} \quad (21)$$

where M is the number of non-dominated solutions. The best compromise solution is the one having the maximum membership μ^k

5. Simulation results

$$B_{ij} = 10^{-6} \times \begin{pmatrix} 49 & 14 & 15 & 15 & 16 & 17 & 17 & 18 & 19 & 20 \\ 14 & 45 & 16 & 16 & 17 & 15 & 15 & 16 & 18 & 18 \\ 15 & 16 & 39 & 10 & 12 & 12 & 14 & 14 & 16 & 16 \\ 15 & 16 & 10 & 40 & 14 & 10 & 11 & 12 & 14 & 15 \\ 16 & 17 & 12 & 14 & 35 & 11 & 13 & 13 & 15 & 16 \\ 17 & 15 & 12 & 10 & 11 & 36 & 12 & 12 & 14 & 15 \\ 17 & 15 & 14 & 11 & 13 & 12 & 38 & 16 & 16 & 18 \\ 18 & 16 & 14 & 12 & 13 & 12 & 16 & 40 & 15 & 16 \\ 19 & 18 & 16 & 14 & 15 & 14 & 16 & 15 & 42 & 19 \\ 20 & 18 & 16 & 15 & 16 & 15 & 18 & 16 & 19 & 44 \end{pmatrix} \quad (22)$$

In order to verify the feasibility and effectiveness of the proposed MOPSO method for solving EDEED problem, a ten-unit test system with non-smooth valve-point effects cost and emission level functions is studied in this section. The transmission losses, ramp rate constraints including the additional constraint (7) and generation limits are considered in this system. The technical data of the units, as well as the demand of the system are taken from [11] and are given in [Tables A.1 and A.2 in Appendix A](#). The transmission loss formula coefficients for the ten unit test system are given by Eq. (22).

A. Parameters setting

The proposed method is implemented using Matlab 7.9.0 (R2009b) on an Intel® core™ i3, 2.4 GHz, and 4.0 of RAM personal computer. In all optimization runs, the proposed MOPSO technique is applied with a population size and maximum iteration count of 100 and 300, respectively. The maximum size of the Pareto-optimal set was selected as 100 solutions. If the number of non-dominated Pareto optimal solutions in global best set and local best set exceeds the respective bound, the clustering technique is used. The MOPSO control parameters are $c_1 = 2.05$, $c_2 = 2.05$, $\omega_{max} = 0.9$ and $\omega_{min} = 0.4$. The dispatch horizon T is chosen as one day with 24 intervals ($T=24$) where each interval is assumed to be 1h.

B. Computational results and comparison

The EDEED problem for the test system is carried out to determine the hourly generation schedule using MOPSO for the minimum fuel cost case, minimum emission case and compromising minimum fuel cost and emission case. Then, the corresponding results are listed in [Table 1](#). Results show that when the best cost dispatch is taken into account, the system is faced with the minimum amount of cost for a 24h time interval, where it is 2471050 \$. On the other hand by considering the best emission, the system is operated at its lowest amount of emission, where it is 292380 lb. For the compromising minimum fuel cost and emission case, the fuel cost and pollutant emission obtained by the proposed method can be reduced about 2512170 \$ and 300040 lb, respectively.

The generation of each unit over 24h for the best compromise solution is shown in Figure 1. It can be seen that the generators 5, 6, 7, 8, 9 and 10 reach their maximum production from a total load demand greater than or equal to 1258 MW since they are the least powerful machines, but the generated power by the committed units 1, 2, 3 and 4 follow the profile of load demand P_D and work with their full capacities in peak demand times.

Table 1: Optimal solutions of ten-unit test system obtained by MOPSO technique for minimum cost, minimum emission and best compromise solution.

	minimum fuel cost	minimum emission	best compromise solution
daily cost (10^6 \$)	2.471050	2.586330	2.512170
Daily Emission (10^5 lb)	3.23020	2.92380	3.00040
Daily Loss (MW)	1290.9	1313.5	1299.2

Figure 1. Generation of each unit during 24 hours.

The ramp up/ramp down values of each unit for each hour in the optimization problem of the EDEED is shown in Figure 2. It can be seen that the unit ramp rate constraints and in particular the constraint (7) have been respected. However, for the conventional DEED problem, from the obtained simulation results of the ten-unit system using MAMODE [5], IFBA [8] and RCGA/NSGA-II [11] methods, it is clearly seen that the ramp rate constraint between the last hour in a day and the first hour of the next day of some generating units is violated. Therefore, these optimal solutions cannot be implemented repeatedly every day to meet the periodic load demand. Table 2 summarizes the violations occurred of the last constraint when solving the classical DEED problem using the previous methods reported in the literature for the case of the best compromise solution. In order to remedy this problem, the classic DEED problem must be extended by adding the constraint (7).

Table 2. Violations of the unit ramp rate constraint (constraint (7)) for the conventional DEED problem using MAMODE, IFBA and RCGA/NSGA-II.

Method	generating units i	optimal solution P_i^1 (MW)	optimal solution P_i^T (MW)	Ramp rate constraint $P_i^1 - P_i^T$ (MW)
MAMODE[5] (see Table 6)	5	83.1300	205.08	$-121.9500 < -DR_5 = -50$
IFBA[8] (see Table 9)	7	93.0603	129.5904	$-36.5301 < -DR_7 = -30$
RCGA/NSGA-II[11] (see Table 3)	4	116.6711	178.9356	$-62.2645 < -DR_4 = -50$
	5	80.5442	151.9618	$-71.4176 < -DR_5 = -50$
	9	58.5082	24.0029	$34.5053 > UR_9 = 30$

Figure 2. The ramp up/ramp down values of:
(a) units 1, 2, 3; (b) units 4, 5, 6; (c) units 7, 8, 9, 10

To show the advantages of the proposed MOPSO method, the simulation results obtained from the proposed method are compared with those of other methods available in the literature MAMODE[5], IFBA[8] and RCGA/NSGA-II[11] in Table 3. The results of the proposed method are in bold. It is clear to see from the Table 3 that the proposed method produces much better results than those reported in literature.

Table 3. Comparison of the simulation results for different methods.

	Best cost		Best emission		Best compromise	
	Cost ($\times 10^6$ \$)	Emission ($\times 10^5$ lb)	Cost ($\times 10^6$ \$)	Emission ($\times 10^5$ lb)	Cost ($\times 10^6$ \$)	Emission ($\times 10^5$ lb)
Proposed MOPSO	2.471050	3.23020	2.586330	2.92380	2.512170	3.00040
MAMODE[5]	2.492451	3.15119	2.581621	2.95244	2.514113	3.02742
IBFA[8]	2.481733	3.27501	2.614341	2.95833	2.517116	2.99036
RCGA/NSGA-II[11]	2.5168	3.1740	2.6563	3.0412	2.5226	3.0994

6. Conclusion

In this paper, multi-objective particle swarm optimization (MOPSO) has been successfully applied to solve the extended version of the classical dynamic economic emission dispatch (EDEED) problem. The dynamic dispatch problem has been formulated as multi-objective optimization problem with competing fuel cost and emission objectives under the system and practical operation constraints over a certain period of time. The EDEED problem represents the practical meaning of optimal operation and control of online generation units to meet the demand of power system networks. Since the demand and constraints are periodic, the optimal solutions of the EDEED are successfully implemented repeatedly and periodically without causing ramp rate violations when the thermal units change their generation levels from the last hour in a day to the first hour of the next day. The comparison of the total generation cost and the emission for EDEED problems obtained by the proposed method with those obtained by the other methods such as RCGA/NSGA-II, IFBA and MAMODE for 10-unit system, demonstrated the superiority and feasibility of the proposed method.

Appendix A

See Tables A.1 and A.2.

Table 1. Hourly load profile for 10-unit system for 24 h

Hour	1	2	3	4	5	6	7	8	9	10	11	12
Load (MW)	1036	1110	1258	1406	1480	1628	1702	1776	1924	2022	2106	2150
Hour	13	14	15	16	17	18	19	20	21	22	23	24
Load (MW)	2072	1924	1776	1554	1480	1628	1776	1972	1924	1628	1332	1184

Table 2. data for 10-unit system

Unit	a	b	c	d	e	α	β	γ	ξ	λ	P_{min}	P_{max}	UR	DR
1	786.7988	38.5397	0.1524	450	0.041	103.3908	-2.4444	0.0312	0.5035	0.0207	150	470	80	80
2	451.3251	46.1591	0.1058	600	0.036	103.3908	-2.4444	0.0312	0.5035	0.0207	135	470	80	80
3	1049.9977	40.3965	0.0280	320	0.028	300.3910	-4.0695	0.0509	0.4968	0.0202	73	340	80	80
4	1243.5311	38.3055	0.0354	260	0.052	300.3910	-4.0695	0.0509	0.4968	0.0202	60	300	50	50
5	1658.5696	36.3278	0.0211	280	0.063	320.0006	-3.8132	0.0344	0.4972	0.0200	73	243	50	50
6	1356.6592	38.2704	0.0179	310	0.048	320.0006	-3.8132	0.0344	0.4972	0.0200	57	160	50	50
7	1450.7045	36.5104	0.0121	300	0.086	330.0056	-3.9023	0.0465	0.5163	0.0214	20	130	30	30
8	1450.7045	36.5104	0.0121	340	0.082	330.0056	-3.9023	0.0465	0.5163	0.0214	47	120	30	30
9	1455.6056	39.5804	0.1090	270	0.098	350.0056	-3.9524	0.0465	0.5475	0.0234	20	80	30	30
10	1469.4026	40.5407	0.1295	380	0.094	360.0012	-3.9864	0.0470	0.5475	0.0234	10	55	30	30

7. References

- [1]. M. Elaiw, X. Xia, A. M. Shehata, "Dynamic Economic Dispatch Using Hybrid DE-SQP for Generating Units with Valve-Point Effects", *Mathematical Problems in Engineering*, Vol. 2012, 10 pages, 2012.
- [2]. El-Keib AA, Ma H, Hart JL, "Economic dispatch in view of the clean air act of 1990", *IEEE Trans Power Syst*, Vol. 9, No. 2, pp. 972–978, 1994
- [3]. M.A. Abido, "Environmental/economic power dispatch using multiobjective evolutionary algorithms", *IEEE Transactions on Power Systems* Vol. 18, No. 4, pp. 1529–1537, 2003.
- [4]. M.A. Abido, "Multiobjective particle swarm optimization for environmental/economic dispatch problem", *Electric Power Systems Research* Vol. 79, pp. 1105–1113, 2009.
- [5]. X. Jiang, J. Zhou, H. Wang, Y. Zhang, "Dynamic environmental economic dispatch using multiobjective differential evolution algorithm with expanded double selection and adaptive random restart", *Electrical Power and Energy Systems* Vol. 49, pp. 399–407, 2013.
- [6]. G.P. Granelli, M. Montagna, G.L. Pasini, P. Marannino, "Emission constrained dynamic dispatch", *Electric Power Systems Research* Vol. 24, No. 1, pp. 56–64, 1992.
- [7]. Y.H. Song, I.K. Yu, "Dynamic load dispatch with voltage security and environmental constraints", *Electric Power Systems Research* Vol. 43, pp. 53–60, 1997.
- [8]. P. Nicole, T. Anshul, T. Shashikala, P. Manjaree, "An improved bacterial foraging algorithm for combined static/dynamic environmental economic dispatch", *Applied Soft Computing* Vol. 12 (2012) pp. 3500–3513.
- [9]. M. Basu, "Particle swarm optimization based goal-attainment method for dynamic economic emission dispatch", *Electric Power Components and Systems*, Vol. 34, 1015–1025, 2006.
- [10]. M. Basu, "Dynamic economic emission dispatch using evolutionary programming and fuzzy satisfied method", *Int. J. Emerging Elect. Power Syst*, Vol. 8, No.4, pp. 1–15, 2007.
- [11]. M. Basu, "Dynamic economic emission dispatch using nondominated sorting genetic algorithm-II", *International Journal of Electrical Power & Energy Systems* Vol. 30, No. 2, pp. 140–149, 2008.
- [12]. C.X. Guo, J.P. Zhan, Q.H. Wu, "Dynamic economic emission dispatch based on group search optimizer with multiple producers", *Electric Power Systems Research*, Vol. 86, pp.8–16, 2012.
- [13]. R. Bharathi, M.J. Kumar, D. Sunitha, S. Premalatha, "Optimization of combined economic and emission dispatch problem – a comparative study", *Power Eng. Conf. IPEC Int 2007*, pp. 134–139, 2007.
- [14]. Bahmanifirouzi B, Farjah E, Niknam T, "Multi-objective stochastic dynamic economic emission dispatch enhancement by fuzzy adaptive modified theta particle swarm optimization", *J Renew Sustain Energy*, Vol. 4, No. 2, 023105, 2012;
- [15]. K. Deb, "Multi-Objective Optimization Using Evolutionary Algorithms", *Technical Report. John Wiley and Sons, USA 2001*.
- [16]. Mahor, V. Prasad, S. Rangnekar. Economic dispatch using particle swarm optimization: A review. *Renewable and Sustainable Energy Reviews*, Vol.13, No.8. pp. 2134–2141, 2009.
- [17]. A.M. Elaiwa, X. Xiab, A.M. Shehatac, "Hybrid DE-SQP and hybrid PSO-SQP methods for solving dynamic economic emission dispatch problem with valve-point effects", *Electric Power Systems Research*, Vol. 103, pp. 192–200, 2013.
- [18]. A. Safari, H. Shayeghi, "Iteration Particle Swarm Optimization Procedure for Economic Load Dispatch with Generator Constraints", *Expert System with Applications* Vol. 38, No.5, pp. 6043-6048, 2011.

- [19]. C.K. Panigrahi, P.K. Chattopadhyay, R. Chakrabarti, "Load Dispatch and PSO Algorithm for DED Control", *International Journal of Automation and Control*, Vol. 1, pp. 195-206, 2007.
- [20]. X. Xia, J. Zhang, A. Elaiw, "An application of model predictive control to the dynamic economic dispatch of power generation", *Control Engineering Practice* Vol. 19, No. 6, pp. 638-648, 2011.
- [21]. X. Xia, J. Zhang, A. Elaiw, "A model predictive control approach to dynamic economic dispatch problem", *In IEEE Bucharest PowerTech Conference*, 2009.
- [22]. M. Elaiw, X. Xia, A.M. Shehata, "Minimization of Fuel Costs and Gaseous Emissions of Electric Power Generation by Model Predictive Control", *Mathematical Problems in Engineering*, Vol. 2013, 15 pages, 2013.
- [23]. A.Y. Abdelaziz, M.Z. Kamh, S.F. Mekhamer, M.A.L. Badr, "A hybrid HNN-QP approach for dynamic economic dispatch problem", *Elect. Power Syst. Res*, Vol. 78, No. 10, pp. 1784-1788, 2008.
- [24]. B. Mohammadi-ivatloo, A. Rabiee, M. Ehsan, "Time-varying acceleration coefficients ipso for solving dynamic economic dispatch with non-smooth cost function", *Energy Conversion and Management*, Vol. 56, pp. 175-183, 2012.
- [25]. E. Zitzler, L. Thiele, "Multiobjective evolutionary algorithms: A comparative case study and the strength pareto approach", *IEEE Transactions on Evolutionary Computation*, Vol. 3, No.4, pp. 257-271, 1999.
- [26]. J. Kennedy, RC. Eberhart, "Particle swarm optimization", *In: Proceedings of the IEEE international conference on neural networks*, Piscataway, NJ: IEEE Service Center, pp. 1942-1948, 1995.
- [27]. C. A. Coello Coello, G. T. Pulido, and M. S. Lechuga, "Handling multiple objectives with particle swarm optimization", *IEEE Transactions on Evolutionary Computation* Vol. 8, No. 3, pp. 256-279, 2004.
- [28]. J.E. Fieldsend, , R.M. Everson, S. Singh, "Using unconstrained elite archives for multi-objective optimization", *IEEE Transactions on Evolutionary Computation*, Vol. 7, No. 3, pp. 305-323, 2003.

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