Multi-area Environmental Economic Dispatch with Reserve Constraints Using Enhanced Particle Swarm Optimization

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Abstract

In this paper, the multi-area environmental economic dispatch (MAEED) problem with reserve constraints is solved by proposing an enhanced particle swarm optimization (EPSO) method. The objective of MAEED problem is to determine the optimal generating schedule of thermal units and inter-area power transactions in such a way that total fuel cost and emission are simultaneously optimized while satisfying tie-line, reserve, and other operational constraints. The spinning reserve requirements for reserve-sharing provisions are investigated by considering contingency and pooling spinning reserves. The control equation of the particle swarm optimization (PSO) is modified by improving the cognitive component of the particle's velocity using a new concept of a preceding experience. In addition, the operators of PSO are dynamically controlled to maintain a better balance between cognitive and social behavior of the swarm. The effectiveness of the proposed EPSO has been investigated on four areas, 16 generators and four areas, 40 generators test systems. The application results show that EPSO is very promising to solve the MAEED problem.

Keywords : contingency spinning reserve, multi-area economic-emission dispatch, particle swarm optimization, pooling spinning reserve, tie-line capacity

1. Introduction

Modern power systems are large, with multiple control areas interconnected through tie-lines. Each control area has its own load and generation. Areas of individual utility are interconnected through tie-lines to operate with maximum reliability, reserve sharing, improved security, and less production cost than when operated as an isolated area [1]. In an interconnected power system, several generation companies join to form a power pool with an aim to gain economic benefits in their operations. The benefits of the pool depend on several factors such as the characteristics of a pool, types of interconnections, tie-line limits, and spinning reserve requirements. The regulatory bodies have enforced certain norms to keep a definite amount of generation in each area as a contingency spinning reserve to meet its own contingencies and a definite amount of generation in the area as pooling reserve. The economic benefit of the pool also depends on how the pooling reserve is handled. Moreover, regulatory bodies have also imposed limits and penalties on the emission of pollutants due to environmental concerns. Therefore, multi-area economic dispatch (MAED) with the consideration of emission, transmission capacity constraint, and reserve sharing is more practical in the context of modern power systems.

Some early efforts to attempt the MAED problem can be briefly stated as follows: Sharma *et al.* [2] formulated the MAED problem with area spinning reserve constraints and without the consideration of emission. They established that more economy can be achieved using reserve sharing. Shoults *et al.* [3] suggested import and export constraints between areas that can be analyzed on a daily, monthly, and annual basis. Romano *et al.* [4] formulated the economic dispatch problem with line flow constraints and spinning reserves using the linear optimization program and solved using the Dantzig-Wolfe decomposition principle. Desell *et al.* [5] described an application of linear programming to transmission-constrained generation production cost analysis in power system planning. Wang and Shahidehpour [6] proposed a decomposition approach to non-linear multi-area generation scheduling with tie-line constraints using expert systems. The authors showed the efficiency of their proposed approach by testing it on a four-area system, with each area consisting of 26 units [7]. In recent years, modern artificial intelligence–based techniques have shown potential to solve such complex combinatorial constrained optimization problems due to their ability to obtain global or near-global optima. Jayabarathi *et al.* [7] solved MAED problems with tie-line constraints using evolutionary programming. Chen and Chen [8] presented direct search method for solving economic dispatch problem considering transmission capacity constraints. Manoharan *et al.* [9] proposed covariance matrix-adapted evolutionary strategy for a multi-area dispatch where a Karush Kuhun Tucker (KKT) optimality criterion is applied to guarantee the optimal convergence. Zhu [10] presented a new non-linear optimization neural network approach to study security-constrained interconnected multi-area dispatch problems. Basu [11] employed artificial bee colony optimization with a variety of system constraints. However, effluent emissions from thermal units have not been given serious consideration by these attempts. In the recent past, the optimal multi-area environmental economic dispatch (MAEED) problem has been attempted by Wang and Singh [12]. They formulated the problem by considering tie-line transfer capacities and area spinning reserve sharing to ensure security and improved reliability, respectively. But the norms of regulatory bodies enforce utilities to keep a definite amount of reserve, *i.e.*, contingency spinning reserve, in each area to meet out their own contingencies. From the literature survey, it is found that MAED with the consideration of emission, tie-line constraints, and spinning reserve requirement has not been attempted.

In the light of the above discussion, a new formulation of economic emission dispatch is proposed in this paper by extending the economic dispatch problem to an MAEED problem with the consideration of transmission capacity constraints and with a new reserve sharing approach. This formulation increases the complexity of the dispatch problem that arises due to conflicting nature of cost and emission objectives, stringent area power balance constraints, tie-line constraints, and area spinning reserve constraints, in addition to the other operational constraints [2]. The proposed formulation is solved using an improved particle swarm optimization (PSO)-based method proposed in this paper. A new concept is also proposed to share spinning reserve requirement, which results in substantial saving in overall spinning reserve requirement.

PSO is a swarm intelligence-based meta-heuristic optimization technique that has shown its proven potential to solve diverse engineering optimization problems. Researchers are attracted toward this technique due to its simplicity, convergence speed, and robustness. However, PSO has an inherent tendency of local trapping. Several modified versions of PSO have been reported in the recent past to enhance its performance by modulating inertia weight [13–17], improving cognitive and social behavior [14, 17–20], using constriction factor approach [21, 22], modifying the control equation of the PSO [13, 16, 20, 23–27], or squeezing the search space [26, 27], etc. However, some of these versions of PSO require exhaustive experimentations for parameter setting and some additional mechanism to avoid local trapping. Some others employed empirical formulae to regulate particle's velocity in order to maintain a better balance between cognitive and social behavior of the swarm.

In this paper, an improved variant of PSO, *i.e.*, EPSO, is proposed by exponentially varying inertia weight, cognitive, and social components of particles' velocities in such a way that a proper balance is maintained between cognitive and social behaviors of the swarm throughout the computational process. For this purpose, the concept of preceding experience and exponentially varying constriction functions are suggested, which are not yet reported in the literature. A constraint handling algorithm is also proposed especially to deal with inter-area constraints related to inter-exchange of power, tie-line constraints, and spinning reserve requirements. A new scheme for inter-area spinning reserve sharing is proposed to cater contingency reserve requirements of each area.

The proposed method effectively regulates the velocity of particles during their flights so as to enhance its exploration and exploitation potentials. The economic and environmental objectives of ED problem are combined in a fuzzy framework to solve this multi-objective optimization problem. The effectiveness of the proposed method has been investigated on two four-areas test systems of different dimensions considering various operational constraints such as valve-point loading effects, power balance, tie-line capacity, and spinning reserves. The performance of the proposed method is compared with other established methods.

2. Problem Formulation

A large interconnected power system is generally composed of different areas or zones based on various criteria such as geographical, operational, planning, and organizational. Each of these areas is interconnected to its neighboring areas through tie-lines. Each area has its own generation, load, and spinning reserve. These areas were planned for exchange of operational surpluses among different control areas. From a market point of view, these areas are decentralized. However, for technical reasons, there is one independent system operator (ISO) that imposes certain operational restrictions on these control areas for the purpose of grid security such as tie-line constraints and total spinning reserve constraints. In a deregulated power system, generally different power generation companies of different areas pool together with the objective to achieve the most economical generation policy that could supply the local demands without violating certain operational constraints imposed by the ISO. The proposed approach assumed that there is pooling of different generation companies of different areas to achieve the common goal of maximizing their profits. The aim of the MAEED is therefore to dispatch the generators of a power pool for the forecasted load in such a fashion that optimizes the fuel cost and pollutant emissions from thermal units while satisfying operational constraints, contingency reserve constraints, and transmission capacity constraints. In the proposed formulation, the non-contingency reserved is shared. The mathematical formulation of MAEED is described further.

2.1. Generator Fuel Cost Function

The generator cost function is generally considered as quadratic when valve-point effects are neglected. However, large turbine generators usually have a number of fuel admission valves that are operated in sequence to meet out the increased generation. The opening of a valve increases the throttling losses rapidly and thus the incremental heat rate rises suddenly. This valve-point effect introduces ripples in the heat-rate curves and can be modeled as sinusoidal function in the cost function. Therefore, the objective function for the MAED problem may be stated as to minimize the following:

$$F(P_{Gmj}) = \sum_{m=1}^{M}\sum_{j=1}^{N_{Gm}}(a_{mj} + b_{mj}P_{Gmj} + c_{mj}P_{Gmj}^2) + |e_{mj}\sin(f_{mj}(P_{Gmj}^{\min} - P_{Gmj}))| \tag{1}$$

where a_{mj}, b_{mj}, c_{mj} are the cost coefficients, and e_{mj} and f_{mj} are the valve point effect coefficients of the jth generator in area m, P_{Gmj} is the real power output of the jth generator in area m, $P^{\min}{}_{Gmj}$ is the minimum generation limit of the jth generator in area m, M is the number of areas, and N_{Gm} is the number of generating units in the system in area m.

2.2. Pollutant Emission Function

The pollutant emission produced by thermal plants can be expressed as a sum of a quadratic and an exponential function as follows:

$$E(P_{Gmj}) = \sum_{m=1}^{M}\sum_{j=1}^{N_{Gm}}\alpha_{mj} + \beta_{mj}P_{Gmj} + \gamma_{mj}P_{Gmj}^2 \tag{2}$$

where, α_{mj}, β_{mj}, and γ_{mj} are the emission coefficient of the jth generator in area m.
Subject to the following constraints.

2.3. Power Balance Constraints

In area m, the total power generation of all generators must be equal to the area power demand P_{Dm} with the consideration of imported and exported power [1] and can be stated as follows:

$$\sum_{j=1}^{N_{Gm}} P_{Gmj} = P_{Dm} + \sum_{k,k\neq m} P_{Tmk}; m \in M \tag{3}$$

where P_{Dm} is the power demand of area m; P_{Tmk} is the tie-line real power transfer from area m to area k. P_{Tmk} is positive when power flows from area m to area k and is negative when power flows from area k to area m.

2.4. Generator Constraints

For stable operation, power output of each generator is restricted within its minimum and maximum limits. The generator power limits are expressed as follows:

$$P_{Gmj}^{\min} \leq P_{Gmj} \leq P_{Gmj}^{\max} \tag{4}$$

where $P^{\min}{}_{Gmj}$and$P_{Gmj}{}^{\max}$ are the minimum and maximum generation limits of the jth generator in area m.

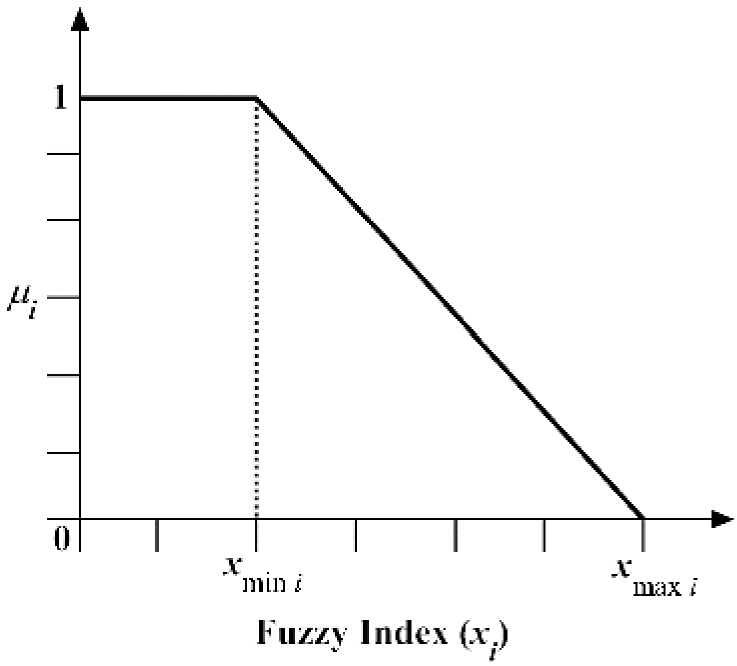

Figure 1 The conventional trapezoidal fuzzy membership function.

2.5. Tie-line Capacity Constraints

The transfer of real tie-line power P_{Tmk} from area *m* to area *k* should not exceed the maximum tie-line limit for security consideration and it is expressed as below:

$$-P_{Tmk}^{\max} \leq P_{Tmk} \leq P_{Tmk}^{\max} \tag{5}$$

where $P^{\max}{}_{Tmk}$is the maximum tie-line power limit from area *m* to area *k*.

2.6. Area Spinning Reserve Constraints

In a power pool, generally a fixed reserve is kept in each area to meet the contingency requirement of that area. This reserve may be called as contingency spinning reserve of the area. In addition, a pooling spinning reserve is also kept to meet the emergency requirement of the power pool such as loss of generation in any area of the pool. This pooling spinning reserve can either be kept in one area as a supplementary reserve or it may be contributed by multiple areas of the pool. When this reserve is kept in each area, the total specified spinning reserve in each area is the sum of contingency reserve and supplementary reserve of that area. In Ref. [12], the contingency reserve of an area and contribution of that area to pool reserve are combined and termed as specified/required spinning reserve of that area. However, if only contingency reserve of an area is kept as specified reserve of that area and the pool reserve is shared among all areas of the pool, it may result in less spinning reserve requirement in each area and thereby reducing the overall reserve requirement of the pool. It is therefore proposed that the spinning reserve requirement of an area *i* should satisfy the following equation:

$$\sum_{j=1}^{N_{Gm}} S_{mj} \geq S_{cm} + S_{pm} + \sum_{k,k\neq m} RC_{mk} \tag{6}$$

where S_{mj} is the available reserve on the *j*th unit of *m*th area, S_{cm} is the contingency spinning reserve in the *m*th area, S_{pm} is the pooling spinning reserve in the *m*th area, and RC_{mk} is the pool reserve contributed from area *m* to area *k*.

2.7. Multi-objective Formulation in Fuzzy Framework

In fuzzy domain, each objective is associated with a membership function. The membership function indicates the degree of satisfaction of the objective. The trapezoidal fuzzy function, as shown in Figure 1, provides a linear and continuous relationship between the fuzzy membership function and the fuzzy index of the concern objective and assigns any membership value between 0 and 1 to the objectives. The conventional trapezoidal fuzzy membership function [28–31] is used to combine various objectives.
Mathematically,

$$\mu_i = \begin{cases} 1; \ x_i \leq x_{\min i} \\ Mx_i + C; \ x_{\min i} \leq x_i \leq x_{\max i} \\ 0; \ x_i \geq x_{\max i} \end{cases} \tag{7}$$

The lower and upper bounds of the desired objective are $x_{\min i}$ and $x_{\max i}$, respectively, and can be varied according to the preferences of different operators. If $x_i \leq x_{\min i}$, a unity membership value and if $x_i \geq x_{\max i}$, a zero membership value is assigned. The coefficients M and C are decided by the lower and upper bounds of the fuzzy index x_i and are given by

$$M = -1/(x_{max\ i} - x_{min\ i})$$

$$C = x_{max\ i}/(x_{\max\ i} - x_{\min\ i}) \tag{8}$$

$$C = x_{max\ i}/(x_{\max\ i} - x_{\min\ i}) \tag{9}$$

Now a single objective function can be used to solve this MAEED problem as to

$$\text{Max}\ \mu = (\mu_1 \mu_2)^{1/2} \tag{10}$$

where μ_1 and μ_2 denote fuzzy membership functions for the fuel cost and pollutant emission, respectively, and μ is the overall fuzzy membership function for two objectives.
Subject to the generator constraints defined by (3)–(6).

3. Proposed EPSO

The conventional PSO is initialized with a population of random solutions and searches for optima by updating particle positions. The velocity of the particle is influenced by three components, namely, initial, cognitive, and social components. Each particle updates its previous velocity and position vectors according to the following model of [32].

$$\begin{aligned} v_i^{k+1} &= Wv_i^k + C_1 \times rand_1() \times \frac{pbest_i^k - s_i^k}{\Delta t} \\ &\quad + C_2 \times rand_2() \times \frac{gbest^k - s_i^k}{\Delta t} \\ s_i^{k+1} &= s_i^k + v_i^{k+1} \times \Delta t \end{aligned} \tag{11}$$

$$\begin{aligned} &\quad + C_2 \times rand_2() \times \frac{gbest^k - s_i^k}{\Delta t} \\ s_i^{k+1} &= s_i^k + v_i^{k+1} \times \Delta t \end{aligned} \tag{12}$$

where v_{ik} is the velocity of ith particle at kth iteration, $rand_1()$ and $rand_2()$ are random numbers between 0 and 1, s_i^k is the position of ith particle at kth iteration, C_1, C_2 are the acceleration coefficients, $pbest_i^k$ is the best position of ith particle achieved based on its own experience, $gbest^k$ is the best particle position based on overall swarm experience, Δt is the time step, usually set to 1 sec, and W is the inertia weight and is allowed to decrease linearly as follows:

$$W = W_{\min} + \frac{(W_{\max} - W_{\min}) \times (itr_{\max} - itr)}{itr_{\max}} \tag{13}$$

where $W_{\min}$ and $W_{\max}$ are the respective minimum and maximum bounds of the inertia weight, $itr_{\max}$ is the maximum number of iterations, and itr is the current iteration.

For better performance of PSO, the particles must fly with higher velocities during the early flights to enhance global search and should gradually slow down during later flights of the journey to improve the local search. Therefore, with appropriate regulation of particle's velocity, the performance of PSO can be improved. This requires a proper balance between cognitive and social behaviors of the swarm. Initially, the cognitive component must dominate over the social component to ensure global exploration of the search space. However, during the later part of the journey, the social component must dominate over the cognitive one so as to divert all particles toward the global best to improve the local exploitation. This is essential for a good balance between exploration and exploitation as suggested by [10].

In the conventional PSO, only the initial velocity component is regulated by inertia weight. However, the cognitive and social behavior of the swarm, though randomized to ensure diversity, is statically controlled by assigning constant values to acceleration coefficients. These cognitive and social components of velocity are added in the regulated initial velocity component to decide the movement of particles. This probably causes uncontrolled particle velocities during the whole computation process and thus results in insufficient exploration and exploitation of the search space. As a consequence, the conventional PSO inherently exhibits poor convergence due to local trapping. Therefore, a modified control equation is suggested for dynamically regulating particle's velocity by suggesting suitable exponential constriction functions ζ_1 and ζ_2. Moreover, the cognitive and social components are modified by considering the preceding experience. The suggested control equation for the proposed EPSO may be expressed as

$$\begin{aligned} v_i^{k+1} \quad = \quad & W \times v_i^k + \zeta_1 \times C_{1b} \times rand_1() \times \frac{pbest_i^k - s_i^k}{\Delta t} \\ & +(1 - \zeta_1) \times C_{1p} \times rand_2() \times \frac{s_i^k - ppreceding_i^k}{\Delta t} \\ & +\zeta_2 \times C_2 \times rand_3() \times \frac{gbest^k - s_i^k}{\Delta t} \end{aligned} \tag{14}$$

where C_{1b} and C_{1p} are acceleration coefficients representing cognitive behavior for the best and preceding experiences and $ppreceding_i^k$ is the preceding position of the ith particle for the kth iteration. In the proposed method, the inertia weight is modified to regulate the tradeoff between the global exploration and the local exploitation of the swarm. The preceding experience has been added to improve the cognitive component. Further, dynamic acceleration coefficients have been introduced using constriction functions to regulate the cognitive and social behaviors of the swarm. These proposed modifications are discussed in the following sections.

3.1. Inertia Weight Update

The trend of linear modulation of inertia weight of [33] is followed to solve optimization problems using PSO by many researchers till date [23, 24, 34, 35]. For large-scale optimization problems, there exist a large number of local optima in the close vicinity of the global optima. Therefore, the exploitation potential of the search algorithm should be sufficient to obtain better solutions. Therefore, the inertia weight has been intuitively varied exponentially with respect to iterations. Modulations suggested to update the inertia weight is governed by the following relation:

$$W = \exp\left(-\eta \log_e \left(W_{\max}/W_{\min}\right)\right); \;\; \eta = itr/itr_{\max} \tag{15}$$

3.2. Updating Preceding Experience

The cognitive behavior was split in [24] by considering also the worst experience in addition to the best experience of the particle to provide some additional diversity, but it results in poor local exploitation unless supported by a local random search. Therefore, the concept of the preceding experience is suggested where the current fitness of each particle is compared with its fitness value in the preceding iteration, and if it is found less, it will be treated as the preceding experience. The preceding experience of the particle produces much less diversity than the worst experience and thus can provide better exploration and exploitation of the search space without employing any additional local random search or else.

3.3. Dynamic Control of Acceleration Coefficients

The cognitive and social behaviors introduced in the conventional PSO play an important role in searching the promising area where the global optima may exist and thereafter approaching toward the global optima. In conventional PSO, these behaviors are governed by static acceleration coefficients. However, many researchers [14, 17–20, 36] suggested that these acceleration coefficients must be dynamically controlled with iterations to regulate particle's velocity during the whole computation process. In the present work, following the logic of dynamic inertia weight, the acceleration coefficients are dynamically controlled by introducing two exponential constriction functions ζ_1 and ζ_2. These constriction functions dynamically regulate the cognitive and social behaviors of the swarm, thus limiting particles' velocities during their whole course of the flight and are proposed as

$$\zeta_1 = \exp(-\mu\eta)$$
$$\zeta_2 = k_c \exp(\mu\eta) \tag{16}$$

(17)

The constriction functions help to maintain the dynamic behaviors of cognitive and social components. In the beginning, the cognitive component dominates over the social one. As the iterations proceed, the cognitive component drops sharply, whereas the social component builds up gradually. After a certain iteration count, they attain same values. Let these components become equal when η is η_t, and then the constriction factor k_c is given by

$$k_c = C_{1b} \exp(-2\mu\eta_t))/C_2 \tag{18}$$

Beyond η_t, the social component dominates over the cognitive component till the end of the search. Let it become k_s when the iteration count is exhausted, and is given by

$$k_{\mathrm{s}} = k_{\mathrm{c}} C_2 \exp(\mu) \tag{19}$$

From (18) and (19)

$$k_{\mathrm{s}} = C_{1b} \exp(\mu (1 - 2\eta_t)) \tag{20}$$

Interestingly, k_{s} is independent of C_2, but it is the function of C_{1b}. In the light of [16], k_{s} cannot be more than C_{1b} and thus η_t should be more than 0.5. Further, the cognitive component will not be perceptible for μ to be five or more [37]. The coefficients of exponents terms μ and the constriction factor k_{c} dynamically govern the cognitive and social components of particles' velocities. Therefore, both are responsible to maintain a proper balance between cognitive and social behavior of the swarm during the whole course of the flight. For the given values of static acceleration coefficients, both μ and η_t can be optimized to determine the optimal value of k_{s} using (20) and then the optimal value of k_{c} can be obtained using (18). These alterations in the control equation of the conventional PSO regulates particles' velocities without any additional formulation as reported in many improved versions of PSO [19, 27, 38, 39], yet preserving diversity due to the stochastic nature of cognitive and social behaviors of the swarm.

3.4. Particle Encoding and Initialization

The solution of an MAED problem is the set of the most optimal generations and the connected tie-lines of that area for the desired objective (s) bounded by certain operational constraints. In the proposed PSO, the particles are encoded in real numbers as the set of current generations and the connected tie-lines of that area in MW, as shown in Figure 2.

$$\begin{array}{cccccccc}
P_{G11} & P_{G12} & \cdots & P_{G1j} & \cdots & \cdots & P_{G1N} \\
P_{G21} & P_{G22} & \cdots & P_{G2j} & \cdots & \cdots & P_{G2N} \\
P_{Gm1} & P_{Gm2} & \cdots & P_{Gmj} & \cdots & \cdots & P_{GmN} \\
P_{T12} & P_{T13} & \cdots & P_{T23} & \cdots & \cdots & P_{Tmk}
\end{array}$$

Figure 2 Particle encoding for the proposed EPSO.

The initial population is randomly created with predefined number of particles to maintain diversity. Each of these particles satisfies the problem constraints defined by (3)–(6). Infeasible particles, whenever appeared, are corrected employing a constrained handling algorithm as described later in the section. The fitness of each particle is evaluated using (10) and then *pbest*, *ppreceding*, and *gbest* are initialized. The initial velocity of particles is assumed to be zero.

3.5. Constrained Handling

The velocity and position update may create infeasible solutions. In the proposed method, infeasible individuals are not rejected but are corrected to feasible ones using a constrained handling algorithm. For this purpose, the generations of all generators are adjusted by their respective bounded generation limits, tie-line, and area spinning reserve constraints as given in Eqs. (3)–(6). If the generations are lesser or greater than minimum or maximum generation level, then the corresponding generation is set at minimum or maximum bound limits as in (4). Similarly, if the transfer of real tie-line power from area *i* to area *k* exceeds its limit, then the corresponding tie-line power is set at tie-line bound limits as in (5) for security consideration. For area spinning reserve constraint, every area has to fulfill its respective reserve requirement as per (6), and if not satisfied, then the difference amount of reserve is distributed equally among all generating units and the connected tie-lines of that area till it is satisfied. The power balance error is calculated using (3). The error in the power is also equally distributed among all generators and the procedure is repeated till the error is reduced to a predefined mismatch value, say 0.001 MW.

3.6. Elitism and Termination Criterion

In stochastic-based algorithms like PSO, the solution with the best fitness in the current iteration may be lost in the next iteration. Therefore, the particle with the best fitness is kept preserved for the next iteration. The algorithm is terminated when either all particles reach to the global best position or the predefined maximum iteration number is reached.

4. Simulation Results and Discussion

The proposed algorithm is tested on two test systems, *i.e.*, four areas, 16 generators system and four areas 40 generators system. The value of acceleration coefficients C_{1b}, C_{1p}, and C_2 for these test systems are taken as 1.6, 0.4, and 2.0, respectively, as in [24]. The value of maximum and minimum bounds of the inertia weight is taken as 0.9 and 0.1, respectively. The swarm size and maximum iteration count have been obtained after usual tradeoff. A swarm size of 20 and 100 is taken for these test systems, respectively, and the maximum iteration count is taken as 1000 and 2500. The proposed algorithm has been developed using MATLAB and the simulations have been carried on a personal computer of Intel i5, 3.2 GHz, and 4 GB RAM.

To determine the optimal value of k_s, several experimentations have been performed by varying μ and η_t in the expected range [5, 5.5] and [0.5, 0.75] for test system 1. The results obtained for MAED on the basis of average fuel cost and its standard deviation (STD) after100 independent trials of EPSO are presented in Table 1. The table shows that the optimal value of k_s is 0.2 and the corresponding values of μ and η_t are found to be 5.2 and 0.70, respectively. The proposed EPSO is now applied on each test systems with following three different cases.

Table 1 Optimizing k_s

k_s	**Average fuel cost ($/hr)**	**STD**
0.1	2144.714787	0.006806
0.2	2143.824856	0.006575
0.3	2144.749566	0.006837
0.4	2146.536661	0.006939
0.5	2152.244788	0.008060

1. Case 1: Without inter-area aid
2. Case 2: Inter-area aid with reserve sharing
3. Case 3: Inter-area aid with proposed reserve sharing

In case 1, all areas are assumed not be interconnected by tie-lines and every area has to individually satisfy its own reserve requirement. In case 2, the areas are interconnected and individual area reserves are mutually shared, whereas in case 3, the areas are interconnected and reserve sharing is allowed while keeping intact the contingency and pooling spinning reserve constraints. The application results obtained by the proposed PSO after 100 independent trials are presented and compared with other existing population-based techniques.

4.1. Test System 1

This system consists of four areas, each with four thermal units and the transmission losses are neglected. All the four areas are interconnected through six tie-lines as shown in Figure 3. The detailed data of this system may be referred from [12]. The system base MVA is considered as 100 MVA. The area power demand is 0.3, 0.5, 0.4, and 0.6 p.u., respectively. The minimum and maximum limits of tie-lines are considered as in [12].

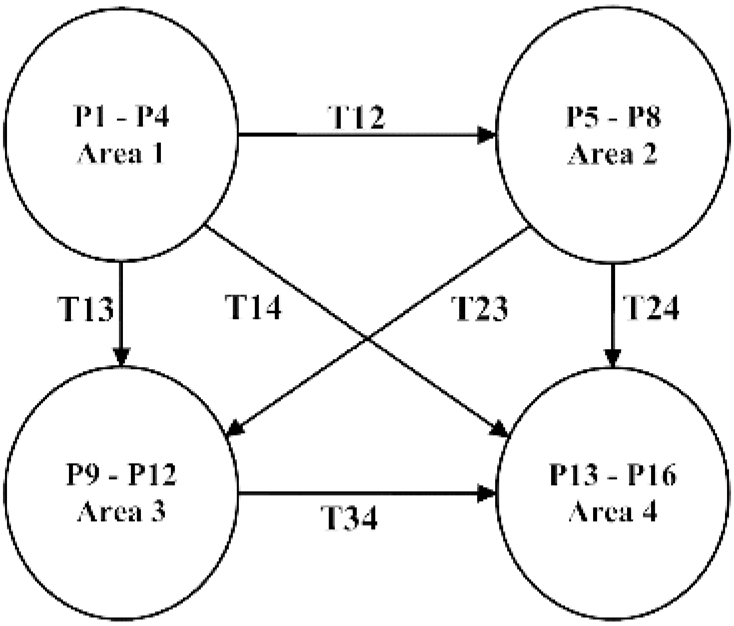

Figure 3 Four areas 16 generators system for test system 1.

For case 1, the value of specified spinning reserve of each area is 30% of area power demand as in [12]. To show the effectiveness of the proposed EPSO, it is applied for MAED of this system. The minimum fuel cost obtained using EPSO is found to be 2143.824 $/hr, which is better than 2181.261 $/hr, obtained by the differential evolution with chaotic sequences (DEC2) of [2]. The proposed method is then applied for MAEED problem for this system. The optimal fuel cost and emission obtained are 2172.522 $/hr and 2.997 ton/hr, respectively. The method of [12] provides Pareto solutions for this system with fuel cost variation from 2191.140 $/hr to 2191.270 $/hr and corresponding emission variation from 3.749 ton/hr to 3.692 ton/hr. From this result, it is clear that the proposed method provides a much better solution for both the objectives in comparison to the existing method [12]. Thus, the proposed EPSO has found a solution that dominates over the Pareto front generated by the MOPSO of [12]. This verifies the effectiveness of the proposed EPSO.

For case 2, the specified spinning reserve requirement for each area is taken same as in case 1. The MAEED problem is solved using EPSO. The best solution obtained provides a fuel cost and emission as 2165.7987 $/hr and 2.8329 ton/hr, respectively. The Pareto optimal solutions obtained by [12] shows extreme end solutions for fuel cost as 2166.8200 $/hr and 2178.2000 $/hr. The corresponding emissions are obtained as 3.3152 ton/hr and 3.2301 ton/hr, respectively. Thus, the proposed method provides a better solution than the existing method [12]. It may also be observed that the fuel cost is reduced from 2172.522 $/hr to 2165.7987 $/hr and the emission is reduced from 2.997 ton/hr to 2.8329 ton/hr when inter-area flow of power is allowed.

For case 3, the proposed inter-area reserve sharing is employed by considering the contingency spinning reserve in each area, and the pooling reserve is contributed by all areas. The contingency spinning reserve for each area is taken as 7% of its power demand and the pooling spinning reserve is taken as 30% of the power demand of area 4, having the highest loading. For this case, the proposed method provides fuel cost and emission as 2164.8558 $/hr and 2.4304 ton/hr, respectively, which are less than that obtained in case 2. This result highlights the importance of reserve sharing as proposed in this paper. Since this reserve sharing approach is new, no comparison results are available in the literature.

Table 2 Contingency, pooling spinning, and available reserves for case 3

Reserve	**Area 1**	**Area 2**	**Area 3**	**Area 4**
Contingency spinning reserve (p.u.)	0.0210	0.0350	0.0280	0.0420
Pooling spinning reserve (p.u.)	0.1800			
Available reserve (p.u.)	0.0618	0.1940	0.7938	0.5067

Table 2 provides a quick reference to check the validity of the reserve sharing constraints imposed for the solution obtained. The table shows that the available reserve for each area is more than its respective contingency spinning reserve requirement. It can also be seen from the table that the sum of available reserves is maintained higher than the sum of contingency and pooling spinning reserve requirement. It can also be observed from the table that the total reserve to be maintained in case 3 is 0.306 p.u., whereas in case 2 it was 0.54 p.u. Thus, the proposed inter-area reserve sharing scheme provides significant reduction in the spinning reserve requirements. The optimal generating schedule and the corresponding tie-line flows obtained by the proposed method for MAEED may be referred from Table 3. It can be observed from the table that the optimal solution satisfied all the problem constraints.

Table 3 Optimal generation schedule for test system 1

Case 1		Case 2		Case 3	
Unit	Power (MW)	Unit	Power (MW)	Unit	Power (MW)
1,1	0.128330	1,1	0.120000	1,1	0.119800
1,2	0.100000	1,2	0.060000	1,2	0.098700
1,3	0.025700	1,3	0.110000	1,3	0.089900
1,4	0.045876	1,4	0.110000	1,4	0.119900
2,1	0.159713	2,1	0.188600	2,1	0.169500
2,2	0.120000	2,2	0.117600	2,2	0.116700
2,3	0.108913	2,3	0.132400	2,3	0.129100
2,4	0.111280	2,4	0.103600	2,4	0.140700
3,1	0.085696	3,1	0.066000	3,1	0.089900
3,2	0.079593	3,2	0.063700	3,2	0.076100
3,3	0.085660	3,3	0.080900	3,3	0.101200
3,4	0.148953	3,4	0.194100	3,4	0.139000
4,1	0.110000	4,1	0.094300	4,1	0.110000
4,2	0.157307	4,2	0.100500	4,2	0.079300
4,3	0.145921	4,3	0.128300	4,3	0.083400
4,4	0.186672	4,4	0.125300	4,4	0.130700
T1,2	—	T1,2	0.001000	T1,2	0.001000
T1,3	—	T1,3	0.001000	T1,3	0.001200
T1,4	—	T1,4	0.098100	T1,4	0.126200
T2,3	—	T2,3	0.003400	T2,3	0.001700
T2,4	—	T2,4	0.039800	T2,4	0.055000
T3,4	—	T3,4	0.009000	T3,4	0.009000

4.2. Test System 2

This is a four-area 40 units generating system [11], with non-convexity in the cost function due to valve-point loading effect and transmission losses being neglected. Each area consists of 10 generating units and all four areas are interconnected through six tie-lines as shown in Figure 4. The figure also shows area power demands as a percentage of the total power demand (PD) of 10,500 MW. The area-wise fuel cost coefficient data may be referred from [11] and the pollutant emission coefficient data is taken from [40]. The tie-line limit from area 1 to area 2, from area 1 to area 3, and from area 2 to area 3 or vice versa is taken as 200 MW and that for the remaining each tie-line is taken as 100 MW.

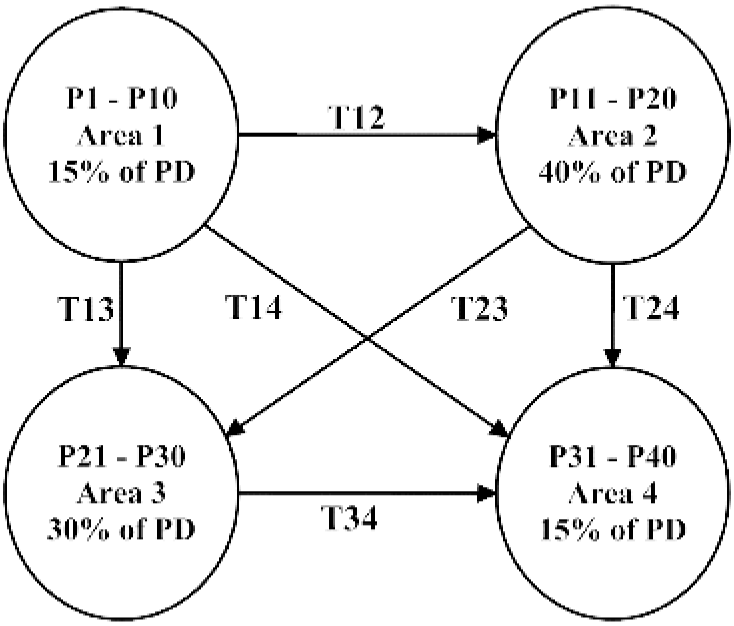

Figure 4 Four area 40 generators system for test system 2.

For case 1 and case 2, the specified spinning reserves for each area are assumed as 20% of its power demand. For case 3, the contingency spinning reserve for each area is considered as 7% of its power demand and the pooling spinning reserve is assumed as 25% of power demand of area 2. The best results obtained using EPSO for these cases are presented in Table 4. It can be observed from the table that both fuel cost and emission reduce in case 2 than in case 1 and it further reduces in case 3. In fact, the proposed reserve sharing scheme causes a reduction of 1.154% in fuel cost and 5.132% in emission as compared with case 2. The Pareto fronts stored in the archive for both test systems are shown in Figure 5. The figure shows very closely spaced non-dominated set of solutions for each test system. The Pareto fronts obtained are not exactly hyperbolic in shape because the MAEED problem is solved in fuzzy framework.

Table 4 Simulation results obtained using EPSO for all cases of test system 2

Case	Fuel cost ($/hr)	Emission (ton/hr)
1	129324.92	106.5239
2	128519.35	87.6159
3	127036.79	83.1192

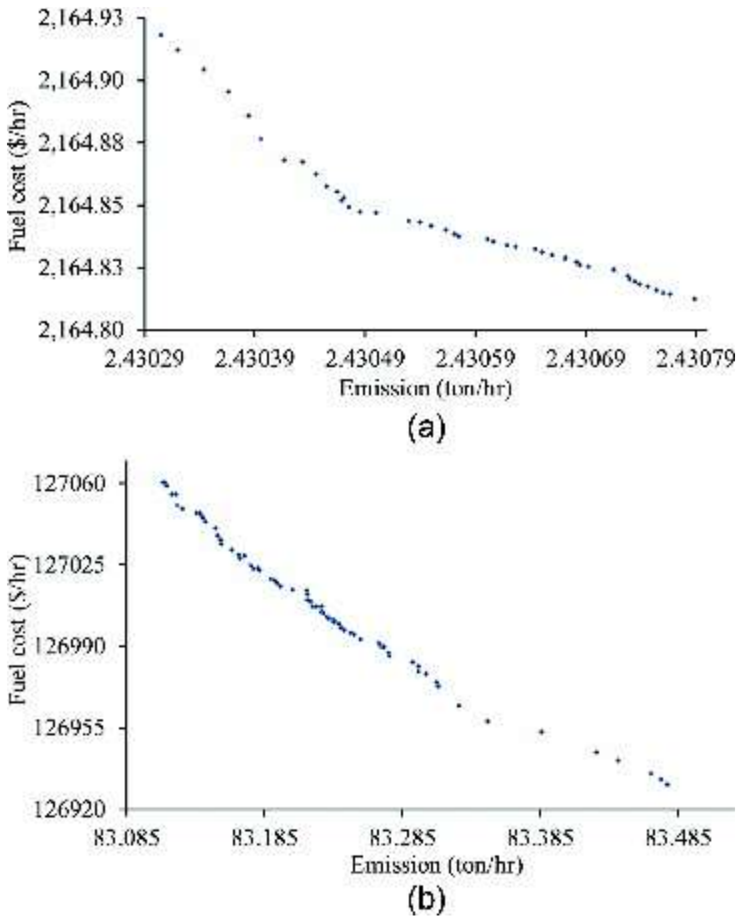

Figure 5 Pareto front for (a) Test system 1 (b) Test system 2.

Table 5 provides the contingency, pooling spinning, and available reserves for the solution obtained using EPSO. The table shows that the available reserve for each area obtained by the optimal solution is over and above than its respective contingency spinning reserve requirement. It can also be seen from the table that the sum of available reserve of all areas is maintained higher than the sum of pooling and contingency spinning reserves of all areas. The optimal generating schedule and the corresponding tie-line flows obtained for MAEED of case 3 is presented in Table 6. It can be observed from the table that the optimal solution satisfied all the problem constraints.

Table 5 Contingency, pooling spinning, and available reserves for case 3

Reserve	**Area 1**	**Area 2**	**Area 3**	**Area 4**
Contingency spinning reserve (MW)	110.25	294	220.5	110.25
Pooling spinning reserve (MW)	1050			
Available reserve (MW)	183.58	802.54	1060.89	175.00

Table 6 Optimal generating schedule and tie-line flows for case 3

Area, Unit	Power (MW)	Area, Unit	Power (MW)	Area, Unit	Power (MW)
1,1	113.9981	2,7	475.2723	4,3	177.8161
1,2	113.9987	2,8	475.8056	4,4	200.0000
1,3	119.9993	2,9	436.8372	4,5	200.0000
1,4	179.7417	2,10	438.1827	4,6	200.0000
1,5	96.9987	3,1	439.9741	4,7	106.6446
1,6	136.9723	3,2	439.7863	4,8	105.8255
1,7	299.9984	3,3	441.0615	4,9	106.9335
1,8	299.9988	3,4	441.5426	4,10	421.6155
1,9	299.7135	3,5	441.0398	T1,2	181.5195
1,10	130.0032	3,6	438.4807	T1,3	134.9021
2,1	318.0953	3,7	15.6718	T1,4	−99.9991
2,2	317.5724	3,8	15.7586	T2,3	128.9781
2,3	402.4054	3,9	15.7953	T2,4	−100.0000
2,4	394.4399	3,10	97.0000	T3,4	−100.0000
2,5	394.4111	4,1	178.1622	–	–
2,6	394.4364	4,2	178.0009	–	–

From the application results of the proposed method and its comparison with existing method, it is clear that the proposed method is computationally very efficient and is capable of solving large and complex economic dispatch problems. This is due to the modifications suggested in the conventional PSO. To highlight the sequential impact of modifications suggested in inertia weight, cognitive and social behaviors of the proposed EPSO, Table 7 is presented. The table classifies ‘a’ as the conventional PSO, ‘b’ refers ‘a’ with exponential modulations in inertia weight, ‘c’ refers ‘b’ with preceding experience, and ‘d’ refers the proposed EPSO for the sake of convenience.

Table 7 Sequential modifications in the proposed EPSO

Parameter	*a*	*b*	*c*	*d*
W	Linear	Exponential	Exponential	Exponential
C_{1b}	2.0	2.0	1.6	1.6
C_{1p}	Not existing	Not existing	0.4	0.4
C_2	2.0	2.0	2.0	2.0
k_s	Not existing	Not existing	Not existing	0.1

A comparison of the set of convergence characteristics for PSO and its variants used to solve the MAEED problem for test system 2 is shown in Figure 6. This figure shows convergence for the best and average fitness, respectively. It can be observed from Figure 6(a) that subsequent modifications in the inertia weight, cognitive, and the social component in the control equation of the conventional PSO, the convergence characteristics are progressively improved by avoiding more and more local trappings. It can also be observed from the figure that except EPSO, the initial shape of convergence is more or less same. It happens because the constriction functions suggested in the cognitive and social components of particle's velocity play key role for better convergence in EPSO. A similar conclusion may be drawn from Figure 6(b). It can be observed from the figure that in EPSO alone, the particles do not identify the probable area of global optima during early iterations. In fact, if the promising area with global optimum is identified at the earlier stages of the optimization, there is a possibility of missing that area without exploitation [24]. Therefore, the EPSO offers advantage to exploit this region meticulously and thus converges to global or near-global optima.

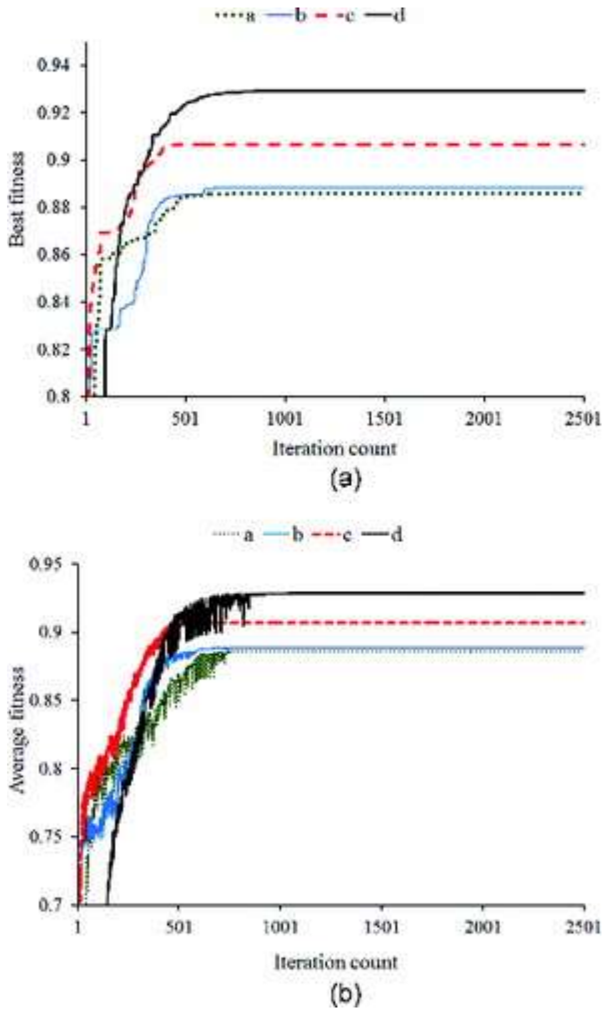

Figure 6 Convergence characteristics for (a) best fitness (b) average fitness for test system 2.

5. Conclusions

The MAEED problem with reserve constraint provides more economy in power generation, if area spinning reserves are also shared mutually among the interconnected areas, keeping their respective contingency spinning reserves intact. However, the system security imposes restrictions on the inter-area power transactions through tie-lines, making MAEED highly complex combinatorial constrained optimization problem. In addition, complexity arises due to the stringent area power balance constraints, tie-line constraints, and area reserve constraints. In addition, the cost and emission objectives of thermal plants are conflicting in nature, which further increases the complexity of the problem. In this paper, an EPSO method has been proposed to solve the complex MAEED problem. Attempts have also been made to overcome the drawbacks of the existing PSO methods by proposing EPSO method. In EPSO, the control parameters are allowed to vary with iterations in such a fashion that ensures a proper balance between cognitive and social behavior of the swarm and thus improves exploration and exploitation potentials of the PSO. This results in better convergence, higher solution quality, and stronger robustness. The application of the proposed method is investigated on two standard test generating systems with different scenarios of spinning reserve requirements for reserve sharing provisions by considering contingency and pooling spinning reserves. It has been found that the proposed reserve sharing scheme not only curtails the total reserve requirement of the system but also reduces fuel cost and pollutant emission of thermal units. The application results show that the proposed method is consistently efficient and is not trapped in local minima. It is noteworthy that EPSO does not require additional mechanism to avoid local trapping or to bound particle's velocities or squeezing the search space. Moreover, it is independent of the initial state of particles in the search space. The comparison and application results show that the proposed method is capable of producing a better solution than the other existing methods.

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