22

Reserve-Constrained Multiarea Environmental/Economic Dispatch Using Enhanced Particle Swarm Optimization

Lingfeng Wang and Chanan Singh
Department of Electrical and Computer Engineering,
Texas A&M University College Station
USA

1. Introduction

Development of the power dispatch problem can be divided into several stages. The traditional economic dispatch (ED) has only one objective for minimizing fuel costs (Lee, et al., 1998). With the increasing awareness of environmental protection in recent years, environmental/economic dispatch (EED) is proposed as an alternative to achieve simultaneously the minimization of fuel costs and pollutant emissions (Abido, 2003; Talaq, et al., 1994). At the same time, only limited work has been carried out to deal with the multiarea economic dispatch (MAED), where power is dispatched within multiple areas (Chen & Chen, 2001; Jayabarathi, et al., 2000; Streiffert, 1995; Wang & Shahidepour, 1992; Yalcinoz & Short, 1998; Zhu, 2003). In this chapter, we further extend the concept of EED into the MAED scenario and a new concept termed multiarea environmental/economic dispatch (MAEED) is proposed by also minimizing the pollutant emissions in the MAED context. The MAEED problem is first presented and then an enhanced multiobjective particle swarm optimization (MOPSO) algorithm is developed to handle the MAEED problem. PSO has turned out to be capable of dealing with a variety of complex engineering optimization problems like MAEED considered in this study. In the problem formulation, the tie-line transfer capacities are treated as a set of design constraints to increase the system security. Furthermore, area spinning reserve requirements are also incorporated in order to ensure the system reliability. Reserve-sharing scheme is used to enable the area without enough capacity to meet its reserve demand. A four-area test power system is then used as an application example to verify the effectiveness of the proposed method through numerical simulations. A comparative study is also carried out to illustrate the different solutions obtained based on different problem formulations.

The remainder of the chapter is organized as follows: In Section 2, the MAEED problem is formulated. The inner working of the particle swarm optimization (PSO) algorithm is discussed in Section 3. In Section 4, the proposed method for optimal MAEED is presented. Simulation results and analysis are given in Section 5. Finally, conclusions are drawn and future research directions are suggested.

Source: Swarm Intelligence: Focus on Ant and Particle Swarm Optimization, Book edited by: Felix T. S. Chan and Manoj Kumar Tiwari, ISBN 978-3-902613-09-7, pp. 532, December 2007, Itech Education and Publishing, Vienna, Austria

2. Problem Formulation

The optimal MAEED problem can be modeled as a bi-criteria optimization problem. The two conflicting objectives, i.e., operational costs and pollutant emissions, should be minimized simultaneously while fulfilling certain system constraints.

2.1 Design objectives

- Objective 1: Minimization of operational costs

The generator cost curves are represented by quadratic functions. The total \$/h fuel cost $FC(P_G)$ can be represented as follows:

$$FC(P_G) = \sum_{j=1}^{N} \sum_{i=1}^{M_j} a_{ij} + b_{ij} P_{G_{ij}} + c_{ij} P_{G_{ij}}^2 \tag{1}$$

where N is the number of areas, M_j is the number of generators committed to the operating system in area j, a_{ij}, b_{ij}, c_{ij} are the cost coefficients of the i-th generator in area j, and $P_{G_{ij}}$ is the real power output of the i-th generator in area j. P_{A_j} is the vector of real power outputs of generators in area j and defined as

$$P_{A_j} = [P_{G_{1j}}, P_{G_{2j}}, \ldots, P_{G_{M_j j}}] \tag{2}$$

Thus,

$$P_G = [P_{A_1}, P_{A_2}, \ldots, P_{A_N}] \tag{3}$$

Another operational cost in MAEED is the transmission cost $TC(P_T)$ for power transfer between areas. It can be expressed as follows:

$$TC(P_T) = \sum_{j=1}^{N-1} \sum_{k=j+1}^{N} f_{jk} P_{T_{jk}} \tag{4}$$

where $P_{T_{jk}}$ is the tie line flow from area j to area k, f_{jk} is the transmission cost coefficient relevant to $P_{T_{jk}}$. P_T is the vector of real power transmission between areas and defined as

$$P_T = [P_{T_{1,2}}, \ldots, P_{T_{1,N}}, P_{T_{2,3}}, \ldots, P_{T_{2,N}}, \ldots, P_{T_{N-1,N}}] \tag{5}$$

As a result, the total operational costs can be calculated as

$$F_1 = FC(P_G) + TC(P_T) \tag{6}$$

- Objective 2: Minimization of pollutant emissions

The SO_2 and NO_x emissions can be approximated by a quadratic function of the generator output:

$$F_2 = \sum_{j=1}^{N} \sum_{i=1}^{M_j} \alpha_{ij} + \beta_{ij} P_{G_{ij}} + \gamma_{ij} P_{G_{ij}}^2 \tag{7}$$

where α_{ij}, β_{ij}, and γ_{ij} are coefficients of the i-th generator emission characteristics in area j.

2.2 Design constraints

There are three kinds of constraints considered in the problem, i.e, the generation capacity of each generator, area power balance, and tie line transfer limits.

- Constraint 1: Generation capacity constraint

For normal system operations, real power output of each generator is restricted by lower and upper bounds as follows:

$$P_{G_{ij}}^{min} \leq P_{G_{ij}} \leq P_{G_{ij}}^{max} \tag{8}$$

where $P_{G_{ij}}^{min}$ and $P_{G_{ij}}^{max}$ are the minimum and maximum power produced by generator *i* in area *j*.

- Constraint 2: Area power balance constraint

In area *j,* the total power generation must cover the total demand P_{D_j} with the consideration of imported and exported power. The power transmission loss is not considered in this study. This relation can be expressed as

$$\sum_{i=1}^{M_j} P_{G_{ij}} = P_{D_j} + \sum_{k,k\neq j} P_{T_{jk}}, j = 1, 2, \ldots, N. \tag{9}$$

- Constraint 3: Area spinning reserve constraint

In area *j*, the spinning reserve requirement should be satisfied through multiarea reserve sharing:

$$\sum_{i=1}^{M_j} P_{S_{ij}} \geq P_{S_{Req_j}} + \sum_{k,k\neq j} P_{RC_{jk}}, j = 1, 2, \ldots, N \tag{10}$$

where the spinning reserve of unit *i* in area *j* $P_{S_{ij}}$ equals to $P_{G_{ij}}^{max} - P_{G_{ij}}$, $P_{S_{Req_j}}$. is the required spinning reserve in area *j*, and $P_{RC_{kj}}$ is the reserve contribution from area *k* to area *j*.

A new vector P_{RC} is defined here to represent the reserve sharing between areas:

$$P_{RC} = [P_{RC_{1,2}}, \ldots, P_{RC_{1,N}}, P_{RC_{2,3}}, \ldots, P_{RC_{2,N}}, \ldots, P_{RC_{N-1,N}}]. \tag{11}$$

- Constraint 4: Tie line constraint

The transfer including both generation and reserve from area *j* to area *k* should not exceed the tie line transfer capacities for security consideration:

$$P_{T_{jk,min}} \leq P_{T_{jk}} + P_{RC_{jk}} \leq P_{T_{jk,max}} \tag{12}$$

where $P_{T_{jk,min}}$ and $P_{T_{jk,max}}$ specify the tie-line transmission capability.

In summary, the objective of MAEED optimization is to minimize F_1 and F_2 simultaneously subject to the constraints (8), (9), (10), and (12).

3. Particle Swarm Optimization

Particle swarm optimization (PSO) is inspired from the collective behavior exhibited in swarms of social insects (Kennedy & Eberhart, 1995). It has turned out to be an effective optimizer in dealing with a broad variety of engineering design problems. In PSO, a swarm is made up of many particles, and each particle represents a potential solution (i.e., individual). PSO algorithms are global optimization algorithms and do not need the operations for obtaining gradients of the cost function. Initially the particles are randomly generated to spread in the feasible search space. A particle has its own position and flight velocity, which keep being adjusted during the optimization process. The update equations determine the position of each particle in the next iteration. Let $k \in \mathbb{N}$ denote the generation number, let $N \in \mathbb{N}$ denote the swarm population in each generation, let $x_i(k) \in \mathbb{R}^M$, $i \in \{1,..., N\}$, denote the i-th particle of the k-th iteration, let $v_i(k) \in \mathbb{R}^M$ denote its velocity, let $c_1, c_2 \in \mathbb{R}_+$ and let $r_1(k)$, $r_2(k) \sim U(0,1)$ be uniformly distributed random numbers between 0 and 1, let w be the inertia weight factor, and let $\chi \in [0,1]$ be the constriction factor for controlling the particle velocity magnitude. Then, the update equation is, for all $i \in \{1,..., N\}$ and all $k \in \mathbb{N}$,

$$\begin{aligned} v_i(k+1) &= \chi * (wv_i(k) + c_1 r_1(k)(pbest_i(k) - x_i(k)) \\ &+ c_2 r_2(k)(gbest(k) - x_i(k))), \end{aligned} \tag{13}$$

$$x_i(k+1) = x_i(k) + v_i(k+1), \tag{14}$$

where $Vi(0) \triangleq 0$ and

$$pbest_i(k) \triangleq \operatorname{argmin}_{x \in \{x_i(j)\}_{j=0}^{k}} f(x), \tag{15}$$

$$gbest(k) \triangleq \operatorname{argmin}_{x \in \{\{x_i(j)\}_{j=0}^{k}\}_{i=1}^{N}} f(x). \tag{16}$$

Hence, $pbest_i(k)$ is the position that for the i-th particle yields the lowest cost over all generations, and $gbest(k)$ is the location of the best particle in the entire population of all generations. The inertia weight w is considered to be crucial in determining the PSO convergence behavior. It regulates the effect of the past velocities on the current velocity. By doing so, it controls the wide-ranging and nearby search of the swarm. A large inertia weight facilitates searching unexplored areas, while a small one enables fine-tuning the current search region. The inertia is usually set to be a large value initially in order to achieve better global exploration, and gradually it is reduced for obtaining more refined solutions. The term $c_1r_1(k)(pbest_i(k) - x_i(k))$ is relevant to cognition since it takes into account the particle's own flight experience, and the term $c_2r_2(k)(gbest(k) - x_i(k))$ is associated with social interaction between the particles. Therefore, the learning factors c_1 and c_2 are also known as *cognitive acceleration constant* and *social acceleration constant,* respectively. The constriction factor χ should be chosen to enable appropriate particle movement steps. Under the guidance of these two updating rules, the particles will be attracted to move toward the best position found thus far. That is, the optimal or near-optimal solutions can be sought out due to this driving force.

4. The Proposed Solution Method

PSO-based approaches have shown advantages in resolving a wide variety of engineering optimization problems in terms of simplicity, convergence speed, and robustness (Kennedy & Eberhart, 2001). In this study, an enhanced particle swarm optimization algorithm (i.e., MOPSO) is proposed and it is then applied to deal with the MAEED problem.

4.1 Encoding scheme

The first step in defining a PSO algorithm is to connect the "real world" to the "PSO world", that is, to build a bridge between the practical problem and the problem solver by which the optimization is performed. Encoding is to define a mapping from the phenotypes onto a set of genotypes. In PSO, each particle flying in the search space is a potential solution. The power output of each generating unit and the tie line flow is selected as the position of the particle in each dimension to constitute the individual, which is a potential solution for the MAEED problem. The position values in all dimensions are all real-coded and the *i*-th individual P_i can be represented as follows:

$$P_i = [P_G, P_{RC}, P_T], \qquad i = 1, 2, \ldots, PS \tag{17}$$

where *PS* is the population size.

4.2 Constraints handling

Constraints lie at the heart of all constrained engineering optimization applications. Practical constraints, which are oftentimes nonlinear and non-trivial, confine the feasible solutions to a small subset of the entire design space. There are several prime approaches which can be applied to treat the constrained optimization problems, i.e., feasibility preservation, penalty functions, repair functions, restricting search to the feasible region, decoder functions, and other hybrid approaches (Eiben & Smith, 2003). Since PSO is essentially an unconstrained optimization algorithm, the constraints handling scheme needs to be incorporated into it in order to deal with the constrained power dispatch problem. Here a straightforward constraint-checking procedure is added. A feasible solution needs to satisfy all the constraints. Thus, for each potential solution, once a constraint is violated, it is not necessary to test its validity against other constraints anymore, which may be very many or highly complicated. In doing so, the overall time consumption is not proportional to the number of computational iterations and the computation time is significantly reduced. Furthermore, this approach is easy to implement as no pre-processing measures and complex numerical manipulations are needed. Since the individual fitness evaluation and its constraints are dealt with in a separate fashion, the approach can be commonly used in other optimization applications. In the selection of Pareto-optimal solutions, when any two individuals are compared, their constraints are examined first. If both satisfy the constraints, the concept of Pareto-dominance is then applied to determine which potential solution should be chosen. If both are infeasible solutions, then they are not qualified to be stored in the archive. If one is feasible and the other is not, the feasible dominates. Though this scheme is simple, it turns out to be quite effective in guaranteeing the feasibility of the non-dominated solutions throughout the optimization run.

4.3 Guides selection

A challenging task in applying PSO to handle multi-objective problems is to design a scheme for choosing both local and global guides for each particle in the swarm. Unlike single objective (SO) problems, there are no explicit concepts on how personal and global best positions can be identified in multi-objective (MO) problems. In the single-objective PSO, the global best particle can be readily found by choosing the particle with the best position. In MO optimization problems, the optimum solutions are Pareto-optimal. Thus, each particle should select the globally best particle based on the Pareto-optimal concept.

Oftentimes, the key task in MOPSO is to determine the best global search guide for each particle in the population. A fuzzification mechanism is introduced to the proposed multi-objective particle swarm optimization algorithm for the selection of global best position *gbest*. Here we interpret *gbest* not just as a point but as an area, and each point in the area has different possibilities of being chosen as the $gbest$. The fuzzification formula used in the study is $N(gbest, std^2)$, which represents a set of normally distributed particles with $gbest$ as their mean value and std as standard deviation. First, in each iteration, the original $gbest$ is selected from the archive, which is however not used directly to update the particle speed and position. Instead, an area around it is randomly generated based on the normal distribution. Then, tournament selection is applied to choose the $gbest$ from this area, which will be used to update the particle speed and position. It is obvious that large std values will result in large generated selection regions. Furthermore, in tournament selection, local competition is used to determine survivors. In this study, binary tournament selection is used where the individual with the higher fitness in the group of two individuals is selected, and the other is removed. This selection scheme can be deemed as an effective measure to increase the population diversity during the optimization process.

4.4 Archiving

The major function of the archive is to store a historical record of the non-dominated solutions found along the heuristic search process. The archive interacts with the generational population in each iteration so as to absorb superior current non-dominated solutions and eliminate inferior solutions currently stored in the archive. The non-dominated solutions obtained at every iteration in the generational population (swarm) are compared with the contents of archive in a one-per-one basis. A candidate solution can be added to the archive if it meets any of the following conditions:

- There is no solution currently stored in the archive;
- The archive is not full and the candidate solution is not dominated by or equal to any solution currently stored in the archive;
- The candidate solution dominates any existing solution in the archive;
- The archive is full but the candidate solution is non-dominated and is in a sparser region than at least one solution currently stored in the archive.

4.5 Optimization procedure

The computational flow of the proposed optimization procedure is laid out as follows:

- Step 1: Specify the lower and upper bound generation power of each unit as well as the tie-line transfer limits; specify the area loads and reserves.
- Step 2: Randomly initialize the individuals of the population.
- Step 3: Evaluate each individual P_i in the population based on the concept of Pareto-dominance.
- Step 4: Store the non-dominated members found thus far in the archive.
- Step 5: Initialize the memory of each particle where a single local best $pbest$ is stored. The memory is contained in another archive.
- Step 6: Increase the iteration counter.
- Step 7: Choose the personal best position $pbest$ for each particle based on the memory record; Choose the global best $gbest$ from the fuzzi-fied region using binary

tournament selection. The niching and fitness sharing mechanism is also applied throughout this process for enhancing solution diversity (Wang & Singh, 2007).

- Step 8: Update the member velocity v of each individual P_i, based on (13) as follows:

$$\begin{aligned} v_{id}^{(t+1)} &= w * v_i^{(t)} + c_1 * \mathrm{rand}() * (pbest_{id} - P_{id}^{(t)}) \\ &+ c_2 * \mathrm{Rand}() * (gbest_d - P_{id}^{(t)}), \\ & \quad i = 1, \ldots, PS; d = 1, \ldots, (GN + 2 * TLN) \end{aligned} \tag{18}$$

where GN is the total number of generators, and TLN is the number of tie lines.

- Step 9: Modify the member position of each individual P_i, based on (14) as follows:

$$P_{id}^{(t+1)} = P_{id}^{(t)} + v_{id}^{(t+1)} \tag{19}$$

- Step 10: Update the archive which stores non-dominated solutions according to the four selection criteria as discussed earlier.
- Step 11: If the current individual is dominated by the $pbest$ in the memory, then keep the $pbest$ in the memory; Otherwise, replace the $pbest$ in the memory with the current individual.
- Step 12: If the maximum iterations are reached, then go to Step 13. Otherwise, go to Step 6.
- Step 13: Output a set of Pareto-optimal solutions from the archive as the final solutions for further decision-making selection.

5. An Application Example

In this study, a four-area test system is used to investigate the effectiveness of the proposed MOPSO algorithm. There are four generators in each area with different fuel and emission characteristics, which are shown in Table 1 and Table 2, respectively. The tie-line transfer limits are shown in Table 3. The system base is 100 MVA. The area loads are 0.3, 0.5, 0.4, and 0.6 p.u., respectively. The area spinning reserve is 30% of the load demand in each area. The transmission cost is not considered in simulations since it is normally small as compared with the total fuel costs.

In the simulations, after some trials, both the population size and archive size are set to 100, and the number of generations is set to 500. The constants c_1 and c_2 are both chosen as 1. The inertia weight factor w decreases linearly during the optimization run according to

$$w = w_{max} - \frac{w_{max} - w_{min}}{iter_{max}} \times iter \tag{20}$$

where $iter_{max}$ is the number of generations and $iter$ is the current number of iterations. In the first 200 generations, the $gbest$ is fuzzified using a large standard deviation to generate a region around the $gbest$ according to Gaussian distribution. In the remaining 300 generations, its value is decreased. This makes sense since, similar to the choice of w values, initial large standard deviation enables global search while the following small standard deviation facilitates local exploration using small movement in each iteration. The minimum fuel costs and minimum emissions obtained with and without inter-area aid are shown in Table 4 and Table 5, respectively. It should be noted that the negative values of tie-line flow $P_{T_{jk}}$, where $k > j$, indicate that the flow is sent from area k to area j.

Generator ij	a_{ij}	b_{ij}	c_{ij}	$P_{G_{ij}}^{min}$	$P_{G_{ij}}^{max}$
$G_{1,1}$	150	189	0.50	0.0005	0.14
$G_{1,2}$	115	200	0.55	0.0005	0.10
$G_{1,3}$	40	350	0.60	0.0005	0.13
$G_{1,4}$	122	315	0.50	0.0005	0.12
$G_{2,1}$	125	305	0.50	0.0005	0.25
$G_{2,2}$	70	275	0.70	0.0005	0.12
$G_{2,3}$	70	345	0.70	0.0005	0.20
$G_{2,4}$	70	345	0.70	0.0005	0.18
$G_{3,1}$	130	245	0.50	0.0005	0.30
$G_{3,2}$	130	245	0.50	0.0005	0.30
$G_{3,3}$	135	235	0.55	0.0005	0.30
$G_{3,4}$	200	130	0.45	0.0005	0.30
$G_{4,1}$	70	345	0.70	0.0005	0.11
$G_{4,2}$	45	389	0.60	0.0005	0.20
$G_{4,3}$	75	355	0.60	0.0005	0.30
$G_{4,4}$	100	370	0.80	0.0005	0.30

Table 1. Fuel cost coefficients and generator capacities (p.u.)

Generator ij	a_{ij}	b_{ij}	c_{ij}
$G_{1,1}$	0.016	-1.500	23.333
$G_{1,2}$	0.031	-1.820	21.022
$G_{1,3}$	0.013	-1.249	22.050
$G_{1,4}$	0.012	-1.355	22.983
$G_{2,1}$	0.020	-1.900	21.313
$G_{2,2}$	0.007	0.805	21.900
$G_{2,3}$	0.015	-1.401	23.001
$G_{2,4}$	0.018	-1.800	24.003
$G_{3,1}$	0.019	-2.000	25.121
$G_{3,2}$	0.012	-1.360	22.990
$G_{3,3}$	0.033	-2.100	27.010
$G_{3,4}$	0.018	-1.800	25.101
$G_{4,1}$	0.018	-1.810	24.313
$G_{4,2}$	0.030	-1.921	27.119
$G_{4,3}$	0.020	-1.200	30.110
$G_{4,4}$	0.040	-1.400	22.500

Table 2. Pollutant emissions coefficients (p.u.)

Tie line *jk*	$P_{T_{jk}}^{min}$	$P_{T_{jk}}^{max}$
$P_{T_{1,2}}$	0.001	0.060
$P_{T_{1,3}}$	0.001	0.040
$P_{T_{1,4}}$	0.001	0.200
$P_{T_{2,3}}$	0.001	0.035
$P_{T_{2,4}}$	0.001	0.055
$P_{T_{3,4}}$	0.001	0.009

Table 3. Tie-line transfer limits (p.u.)

Generation/objectives	w/ inter-area aid (p.u.)	w/o inter-area aid (p.u.)
$P_{G_{1,1}}$	0.1320	0.1074
$P_{G_{1,2}}$	0.0649	0.0943
$P_{G_{1,3}}$	0.1201	0.0503
$P_{G_{1,4}}$	0.1128	0.0533
$P_{G_{2,1}}$	0.2047	0.2507
$P_{G_{2,2}}$	0.0657	0.0671
$P_{G_{2,3}}$	0.1316	0.0980
$P_{G_{2,4}}$	0.1503	0.0846
$P_{G_{3,1}}$	0.0572	0.1083
$P_{G_{3,2}}$	0.0971	0.1646
$P_{G_{3,3}}$	0.0663	0.0662
$P_{G_{3,4}}$	0.2278	0.0622
$P_{G_{4,1}}$	0.0759	0.0754
$P_{G_{4,2}}$	0.1123	0.1587
$P_{G_{4,3}}$	0.0520	0.1071
$P_{G_{4,4}}$	0.1402	0.2604
$P_{T_{1,2}}$	-0.0316	-
$P_{T_{1,3}}$	-0.0088	-
$P_{T_{1,4}}$	0.1699	-
$P_{T_{2,3}}$	-0.0320	-
$P_{T_{2,4}}$	0.0516	-
$P_{T_{3,4}}$	0.0048	-
Mininium cost (\$/hour)	2166.82	2191.14
Emission (ton/hour)	3.3152	3.7493

Table 4. Minimum fuel costs with and without inter-area aid

Generation/objectives	w/ inter-area aid (p.u.)	w/o inter-area aid (p.u.)
$P_{G_{1,1}}$	0.1277	0.1089
$P_{G_{1,2}}$	0.0625	0.0940
$P_{G_{1,3}}$	0.1188	0.0500
$P_{G_{1,4}}$	0.0945	0.0500
$P_{G_{2,1}}$	0.1684	0.2464
$P_{G_{2,2}}$	0.0677	0.0676
$P_{G_{2,3}}$	0.1891	0.1022
$P_{G_{2,4}}$	0.1604	0.0852
$P_{G_{3,1}}$	0.0619	0.1089
$P_{G_{3,2}}$	0.0722	0.1659
$P_{G_{3,3}}$	0.0901	0.0658
$P_{G_{3,4}}$	0.1948	0.0619
$P_{G_{4,1}}$	0.0900	0.0794
$P_{G_{4,2}}$	0.1172	0.1639
$P_{G_{4,3}}$	0.0595	0.1075
$P_{G_{4,4}}$	0.1498	0.2512
$P_{T_{1,2}}$	-0.0469	-
$P_{T_{1,3}}$	-0.0020	-
$P_{T_{1,4}}$	0.1427	-
$P_{T_{2,3}}$	-0.020	-
$P_{T_{2,4}}$	0.0499	-
$P_{T_{3,4}}$	-0.0089	-
Minimum emission (ton/hr)	3.2301	3.6923
Fuel cost ($/hour)	2178.20	2191.27

Table 5. Minimum emissions with and without inter-area aid

From the simulation results, it is evident that both fuel costs and emissions of the MAEED with inter-area aid dominate those of the separate areas case. Thus, it is desirable to connect the multiple areas for achieving lower fuel costs and emissions while satisfying the load demands of different areas. Based on the above simulation results, we can find that except for area 1, other three areas are all capable of satisfying the reserve requirements by themselves. Only area 1 needs reserve sharing from other area in order to cover the additional power for reserve satisfaction. Here, it is assumed that the reserve sharing scheme is applied unless the capacity in the area cannot fulfill the area reserve demand itself. Table 6 illustrates the reserve sharing for the minimum cost and minimum emission cases. $P_{RCG_{i,j}}$ represents the reserve contribution from generator G_{ij}. Again, the negative values of reserve sharing $P_{RC_{jk}}$ where $k > j$, indicate that the reserve is sent from area k to area j when needed.

From the simulation results, we can appreciate that when the area spinning reserve requirements are considered, higher operational costs and higher emissions are inevitably caused for achieving higher power system reliability.

Reserve combination	Minimum cost solution (p.u.)	Minimum emission solution (p.u)
$P_{S_{1,1}}$	0.0080	0.0123
$P_{S_{1,2}}$	0.0351	0.0375
$P_{S_{1,3}}$	0.0099	0.0112
$P_{S_{1,4}}$	0.0072	0.0255
$P_{RCG_{2,1}}$	0.0005	0.0005
$P_{RCG_{2,2}}$	0.0005	0
$P_{RCG_{2,3}}$	0.0005	0
$P_{RCG_{2,4}}$	0.0005	0
$P_{RCG_{3,1}}$	0.0070	0.0012
$P_{RCG_{3,2}}$	0.0007	0
$P_{RCG_{3,3}}$	0.0080	0.0008
$P_{RCG_{3,4}}$	0.0100	0.0010
$P_{RCG_{4,1}}$	0.0005	0
$P_{RCG_{4,2}}$	0.0005	0
$P_{RCG_{4,3}}$	0.0006	0
$P_{RCG_{4,4}}$	0.0005	0
$P_{RC_{1,2}}$	-0.0020	-0.0005
$P_{RC_{1,3}}$	-0.0257	-0.0030
$P_{RC_{1,4}}$	-0.0021	0

Table 6. Reserve sharing for enabling area 1 to satisfy the reserve demand

6. Concluding Remarks

In this chapter, a new concept termed multiarea environmental/economic dispatch (MAEED) is proposed, and an enhanced multiobjective particle swarm optimization (MOPSO) algorithm is used to derive a set of Pareto-optimal solutions. The tie-line transfer limits between areas are considered to ensure the power system security. Also, the area spinning reserve requirements are incorporated in order to increase the system reliability. A comparison is made between the solutions obtained from different problem formulations. In this work, reserve sharing is only applied when there exists an area without sufficient generation capacity for reserve requirement fulfillment. In the future work, the reserve can be simultaneously scheduled with the generation. Moreover, the power flow in each area can be considered to further increase the system security. Other issues such as transmission losses, transmission costs, and buying and selling policies between areas can also be considered in MAEED problems.

7. References

Abido, M. A. (2003). Environmental/economic power dispatch using multiobjective evolutionary algorithms, *IEEE Transactions on Power Systems,* Vol. 18, No. 4, pp. 1529-1537.

Chen, C.-L. & Chen, N. (2001). Direct search method for solving economic dispatch problem considering transmission capacity constraints, *IEEE Trans. on Power Systems,* Vol. 16, No. 4, pp. 764-769.

Eiben, A. E. & Smith, J. E. (2003). *Introduction to Evolutionary Computing,* Springer-Verlag.

Jayabarathi, T.; Sadasivam, G. & Ramachandran, V. (2000). Evolutionary programming-based multi-area economic dispatch with tie line constraints, *Electric Machines and Power Systems,* Vol. 28, pp. 1165-1176.

Kennedy, J. & Eberhart, R. (1995). Particle swarm optimization, *IEEE Proceedings of the International Conference on Neural Networks,* Perth, Australia, pp. 1942-1948.

Kennedy, J. & Eberhart, R. (2001). *Swarm Intelligence,* Morgan Kauf-mann Publishers, San Francisco.

Lee, K.Y.; Yome, A.S. & Park, J.H. (1998). Adaptive Hopfield neural networks for economic load dispatch, *IEEE Transactions on Power Systems,* Vol. 13, No. 2, pp. 519-526.

Streiffert, D. (1995). Multi-area economic dispatch with tie line constraints, *IEEE Trans. on Power Systems,* Vol. 10, No. 4, pp. 1946-1951.

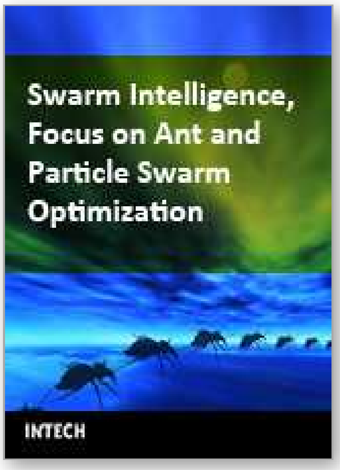
Talaq, J. H.; EI-Hawary, F. & EI-Hawary, M. E. (1994). A summary of environmental/economic dispatch algorithms, *IEEE Transactions on Power Systems,* Vol. 9, No. 3, pp. 1508-1516.

Wang, C. & Shahidepour, S. M. (1992). A decomposition approach to non-linear multi-area generation scheduling with tie line constraints using expert systems, *IEEE Trans, on Power Systems,* Vol. 7, No. 4, pp. 1409-1418.

Wang, L. F. & Singh, C. (2007). Environmental/economic power dispatch using a fuzzified multi-objective particle swarm optimization algorithm, *Electric Power Systems Research,* in press.

Yalcinoz, T. & Short, M. J. (1998). Neural neworks approach for solving economic dispatch problems with transmission capacity constraints, *IEEE Trans. Power Systems,* Vol. 13, No. 2, pp. 307-313.

Zhu, J. Z. (2003). Multiarea power systems economic power dispatch using a nonlinear optimization neural network approach, *Electric Power Components and Systems,* Vol. 31, No. 6, pp. 553-563.



Swarm Intelligence, Focus on Ant and Particle Swarm Optimization

Edited by FelixT.S.Chan and Manoj KumarTiwari

ISBN 978-3-902613-09-7
Hard cover, 532 pages
Publisher I-Tech Education and Publishing
Published online 01, December, 2007
Published in print edition December, 2007

In the era globalisation the emerging technologies are governing engineering industries to a multifaceted state. The escalating complexity has demanded researchers to find the possible ways of easing the solution of the problems. This has motivated the researchers to grasp ideas from the nature and implant it in the engineering sciences. This way of thinking led to emergence of many biologically inspired algorithms that have proven to be efficient in handling the computationally complex problems with competence such as Genetic Algorithm (GA), Ant Colony Optimization (ACO), Particle Swarm Optimization (PSO), etc. Motivated by the capability of the biologically inspired algorithms the present book on "Swarm Intelligence: Focus on Ant and Particle Swarm Optimization" aims to present recent developments and applications concerning optimization with swarm intelligence techniques. The papers selected for this book comprise a cross-section of topics that reflect a variety of perspectives and disciplinary backgrounds. In addition to the introduction of new concepts of swarm intelligence, this book also presented some selected representative case studies covering power plant maintenance scheduling; geotechnical engineering; design and machining tolerances; layout problems; manufacturing process plan; job-shop scheduling; structural design; environmental dispatching problems; wireless communication; water distribution systems; multi-plant supply chain; fault diagnosis of airplane engines; and process scheduling. I believe these 27 chapters presented in this book adequately reflect these topics.