Dynamic Economic Load Dispatch Using Bee Swarming Optimization Algorithms

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***Abstract*: In this paper Dynamic Economic Dispatch (DED) problem in power system using Bee Swarming Optimization (BSO) algorithm is proposed. The Dynamic Economic Dispatch (DED) is the latest development in ELD and the main objective of DED is a minimization of total fuel cost subject to various system constraints. The DED problem considers the limits on the generating ramping rate to maintain the life of generation equipment. The feasibility of the proposed BSO algorithm is tested on 9 generating unit and results are compared with existing techniques. The numerical simulation results showed that the proposed BSO algorithm was indeed capable of obtaining higher quality of solutions efficiently in dynamic economic dispatch problems.**

***Keywords*: Dynamic Economic Load Dispatch, Ramp Rate Limit, Bee Swarming Optimization, Swarm Intelligence, Spinning Reserve.**

1. Introduction

Economic dispatch problem is one of the fundamental issues in power system operation. In essence, it is an optimization problem and its objective is to reduce the total generation cost of units, while satisfying constraints. Previous efforts on solving economic dispatch problems have employed various mathematical programming methods and optimization techniques. These conventional methods include the lambda–iteration method, and the gradient method. [1], [2]. In these numerical methods for solution of economic dispatch problems, an essential assumption is that the incremental curves of the units are monotonically increasing piecewise-linear functions. Unfortunately, this assumption may render these methods infeasible because of its nonlinear characteristics of a generator include discontinuous prohibited zones, ramp rate limits, and cost functions which are not smooth or convex. Furthermore, for a large-scale mixed-generating system, the conventional method has oscillatory problem resulting in a longer solution time. A dynamic programming method for solving the economic dispatch problem with valve-point modeling had been presented by [1], [2]. However, the dynamic programming method may cause the dimensions of the economic dispatch problem to become extremely large, thus requiring enormous computational efforts.

In order to make numerical methods more convenient for solving economic dispatch problems, artificial intelligent techniques, such as the Hopfield neural networks[22-23], have been successfully employed to solve economic dispatch problems for units with piecewise quadratic fuel cost functions and prohibited zones constraint [3], [4]. However, an unsuitable sigmoidal function adopted in the Hopfield model may suffer from excessive numerical iterations, resulting in huge calculations.

In the past decade, a global optimization technique known as genetic algorithms or simulated annealing, which is a form of probabilistic heuristic algorithm, has been successfully used to solve power optimization problems such as feeder reconfiguration and capacitor placement in distribution system [1], [5], [7]. The genetic algorithm method is faster than the simulated annealing method because the genetic algorithm has parallel search techniques, which emulate natural genetic operations. Due to its high potential for global optimization, genetic algorithm has received great attention in solving economic dispatch problems. In some genetic algorithm applications, many constraints including network losses, ramp rate limits, and valve-point zone were considered for the probability of the proposed method.

The genetic algorithm model that employed units' output as the encoded parameter of chromosome to solve economic dispatch problem for valve-point discontinuities has been presented in [5]. The genetic algorithm method that used the system incremented cost as encoded parameter for solving economic dispatch that can take into account network losses, ramp rate limits, and valve-point zone have been presented in [8]. An integrated parallel genetic algorithm incorporating simulated annealing and tabu search techniques that employed the generator's output as the encoded parameter has been discussed in [9]. For an efficient genetic algorithm method used the real-coded representation scheme, arithmetic crossover, mutation, and elitism in the genetic algorithm to solve more efficiently the economic dispatch problem, and it can obtain a high-quality solution with less computation time [10].

Though the genetic algorithm methods have been employed successfully to solve complex optimization problems, recent research has identified some deficiencies in genetic algorithm performance. This degradation in efficiency is apparent in applications with highly epistatic objective functions (i.e., where the parameters being optimized are highly correlated) the crossover and mutation operations cannot ensure better fitness of offspring because chromosomes in the population have similar structures and their averages fitness is high toward the end of the evolutionary process has been presented in [11], [16]. Moreover, the premature convergence of genetic algorithm degrades its performance and reduces its search capability that leads to a higher probability toward obtaining a local optimum [11].

The particle swarm optimization is one of the modern heuristic algorithms, it was developed [13] and [17] through simulation of a simplified social system, and has been found to be robust in solving continuous nonlinear optimization problems. The particle swarm optimization technique can generate high-quality solutions within shorter calculation time and stable convergence characteristic than other stochastic methods have been proposed in [14]–[17]. Although the particle swarm optimization seems to be sensitive to the tuning of some weights or parameters, many researches are still in progress for providing its potential in solving complex power system problems [16]. The particle swarm optimization for reactive power and voltage control considering voltage security assessment. The feasibility of their method is compared with the reactive tabu system and enumeration method on practical power system, and has shown promising results [18]. The use of hybrid particle swarm optimization method for solving efficiently the practical distribution state estimation problem presented in [19].

In this article, bee swarming optimization algorithm solving the dynamic economic dispatch problem in power system is proposed. The proposed method considers the real power balance, real power generation limits, and ramp-up and ramp-down rates limit constraints. An example from the literature is solved by the proposed method, and the solution is compared with some other methods to prove the validity and effectiveness of the proposed technique.

2. Problem formulation

The dynamic economic dispatch problem is concerned with minimizing the overall cost of N dispatchable generating units over the whole scheduling period, H, subjected to some operating constraints.

$$\text{Minimize} \quad F_T = \sum_{h=1}^{H} \sum_{i=1}^{N} F_i(P_{ih}) \tag{1}$$

Where

$$F_i(P_{ih}) = a_i \times P_{ih}{}^2 + b_i \times P_{ih} + c_i \tag{2}$$

Subjected to the real power balance, real power generation limits, and ramp-up and ramp-down rates as in Eqs. (3) – (6) respectively;

i) Power balance

$$\sum_{i=1}^{N} P_{ih} = L_h + P_{Loss-h} \quad \forall h \in [1,2,\ldots\ldots H] \tag{3}$$

Transmission losses can be modeled either by running a complete load flow analysis to the system or by using the B-coefficients method. In the B-coefficients method, the transmission losses are expressed as a quadratic function of the generation level of each generator as follows

$$P_{Loss-h} = \sum_{i=1}^{n} \sum_{j=1}^{n} P_{ih}\, B_{ij}\, P_{jh} \tag{4}$$

ii) Generator limit

$$P_{i-min} \le P_{ih} \le P_{i-max} \quad \forall i \in [1,2,\ldots N], \ \forall h \in [1,2,\ldots. H] \tag{5}$$

iii) Ramping rate limit

To avoid undue thermal stresses on the boiler and the combustion equipment, the rate of change of the output power of each thermal unit must not exceed a certain ramp limit rate during increasing or decreasing the power output of each unit. This can be mathematically as follows

$$RDR_i \le P_{ih} \le RUR_i \ \forall i \in [1,2,\ldots N], \forall h \in [1,2,\ldots. H] \tag{6}$$

A. Bee swarming optimization algorithm

The foraging bees are classified into three categories; employed bees, onlookers and scout bees. All bees that are currently exploiting a food source are known as employed. The employed bees exploit the food source and they carry the information about food source back to the hive and share this information with onlooker bees. Onlookers bees are waiting in the hive for the information to be shared by the employed bees about their discovered food sources and scouts bees will always be searching for new food sources near the hive. Employed bees share information about food sources by dancing in the designated dance area inside the hive. The nature of dance is proportional to the nectar content of food source just exploited by the dancing bee. Onlooker bees watch the dance and choose a food source according to the probability proportional to the quality of that food source. Therefore, good food sources attract more onlooker bees compared to bad ones. Whenever a food source is exploited fully, all the employed bees associated with it abandon the food source, and become scout. Scout bees can be visualized as performing the job of exploration, whereas employed and onlooker bees can be visualized as performing the job of exploitation.

In the BSO algorithm, each food source is a possible solution for the problem under consideration and the nectar amount of a food source represents the quality of the solution represented by the fitness value. The number of food sources is same as the number of employed bees and there is exactly one employed bee for every food source. This algorithm starts by associating all employed bees with randomly generated food sources (solution). In each iteration, every employed bee determines a food source in the neighbor- hood of its current food source and evaluates its nectar amount (fitness). The i^{th} food source position is represented as X_i where i=1, 2, …, N is a D-dimensional vector. The nectar amount of the food source located at X_i is calculated by using the Eq. (7). After watching the dancing of employed bees, an onlooker bee goes to the region of food source at X_i by the probability p_i defined in Eq. (8).

$$fit_i = \frac{1}{1+f_i} \tag{7}$$

$$p_i = \frac{fit_i}{\sum_{n=1}^{N} fit_n} \tag{8}$$

The onlooker finds a neighborhood food source in the vicinity of X_i by using the Eq. (9)

$$v_{ij} = x_{ij} + \phi_{ij}(x_{ij} - x_{kj}) \tag{9}$$

Where $k \in \{1,2,......N\}$ and $j \in \{1,2,......D\}$ are randomly chosen indexes. Although k is determined randomly, it has to be different from i. ϕ_{ij} is a random number between [-1, 1]. If its new fitness value is better than the best fitness value achieved so far, then the bee moves to this new food source abandoning the old one, otherwise it remains in its old food source. When all employed bees have finished this process, they share the fitness information with the onlookers, each of which selects a food source according to probability given in Eq. (8). With this scheme, good food sources will get more onlookers than the bad ones. Each bee will search for better food source around neighborhood patch for a certain number of cycles (limit), and if the fitness value will not improve then that bee becomes scout bee.

It is clear from the above explanation that there are three control parameters used in the basic BSO: The number of the food sources which is equal to the number of employed or onlooker bees (N), the value of limit and the maximum cycle number (MCN). Parameter-tuning, in meta-heuristic optimization algorithms influences the performance of the algorithm significantly. Divergence, becoming trapped in local extrema and time-consumption are such consequences of setting the parameters improperly. The SI, algorithm, as an advantage has few controlled parameters. Since initializing a population "randomly" with a feasible region is sometimes cumbersome, the SI algorithm does not depend on the initial population to be in a feasible region. Instead, its performance directs the population to the feasible region sufficiently [24].

1) Bee swarm optimization algorithm for dynamic economic dispatch

The proposed algorithm for solving DED problem is summarized as follows.

Step 1: Read the system data.
Step 2: Initialize the control parameters of the algorithm.
Step 3: An initial population of N solution is generated for each solution X_i (i=1, 2 … N) is represented by a D-dimensional vector.
Step 4: Evaluate the fitness value of each individual in the colony.
Step 5: Produce neighbor solutions for the employed bees and evaluate them.
Step 6: Apply the selection process.
Step 7: If all onlooker bees are distributed, go to step 10. Otherwise, go to the next step.
Step 8: Calculate the probability values p_i for the solutions X_i.
Step 9: Produce neighbor solutions for the selected onlooker bee, depending on the p_i value and evaluate them.
Step 10: Determine the abandoned solution for the scout bees, if it exists and replace it with a completely new randomly generated solution and evaluate them.
Step 11: Memorize the best solution attained so far.
Step 12: Stop the process if the termination criteria is satisfied. Otherwise, go to step 3.

3. Results and discussion

Software package implementing the new proposed technique is developed using Intel(R) Core(TM)^2 Duo CPU, 2.10 GHz processor. To illustrate the validity and effectiveness of the proposed technique, the 9 generating units' test system given in [25] is studied and solved. The control parameters of SI algorithm are chosen as colony size 200, maximum cycle/generation number (MCN) 50, and limit value 40.

In order to show the effectiveness of the proposed BSO algorithm it has been tested on nine generating unit system for the load demand of 1055 MW, 1057 MW, 1058 MW, 1062 MW, 1071 MW, 1099 MW. The system particulars are available in the literature [25] and also presented in Table 1 and Table 2. The simulation results obtained by the proposed as well as existing algorithms are presented in Table 3. The simulation results show that proposed algorithm clearly satisfies the load demand and system constraints. It is evident from the comparison the proposed algorithm achieves the better results than existing algorithms.

Table 1
Cost Coefficients of Test System

Unit No.	A ($/h)	B ($/MWh)	C ($/MWh^2)
1	550	8.10	0.00028
2	309	8.10	0.00048
3	290	7.82	0.00056
4	250	7.74	0.00324
5	240	7.75	0.00324
6	220	7.76	0.00324
7	200	7.78	0.00334
8	180	8.5	0.00312
9	126	8.6	0.00284

Table 2
Power and ramp rate limit

Unit no.	P_{min} (MW)	P_{max} (MW)	D_j (MW/h)	R_j (MW/h)
1	50	680	80	70
2	50	360	50	40
3	60	300	50	40
4	60	240	45	35
5	55	200	45	35
6	40	180	40	35
7	40	160	40	35
8	30	150	35	30
9	55	120	35	30

4. Conclusion

In power industry markets optimal generation dispatch can save millions of dollars per year in production costs. The objective of DED problem is to find an optimal combination of power generation units that minimize the overall generation cost subject to meet out system constraints fully. Recently swarm intelligence techniques play a vital role to solve an engineering optimization problem. In this paper a swarm intelligence technique has been used to solve the DED problem. The simulation results are compared with existing algorithms. The results show that the proposed algorithms achieve the better results and have the capability to online implementation.

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