

Minimization of Nitrogen Oxides from Fossil Fuel Power Plants using Swarm Intelligence Technique

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Abstract:- The pollutant from the fossil fuel plant threatening the entire world and ensure that the amount of emission such as sulfur dioxide (SO₂) and nitrogen oxides (NO_x) must be reduced. Hence it is necessary that the emission constraint must include in the economic dispatch problem and its objective is to minimize production cost with lowest emission. In this paper swarm intelligence technique has been proposed to solve an emission constrained economic dispatch problem. The performance of the proposed algorithm is tested on six unit test systems with various load demand and emission coefficients. The comparison of the simulation results prove that the proposed algorithm have a better performance than existing algorithms.

Keywords: Sulfur Minimization, Nitrogen Minimization, Emission Dispatch, Environmental dispatch, Swarm Intelligence.

1. INTRODUCTION

Due to the strict environment act the power industries must reduce the emissions from the fossil fuel power plants. The pollutant from the fossil fuel plant threatening the entire world and ensure that the amount of emission such as sulfur dioxide (SO₂) and nitrogen oxides (NO_x) must be reduced. Hence it is necessary that the emission constraint must combine with economic dispatch problem and its objective is to minimize production cost with lowest emission [1-4]. The mathematical approaches like Interactive Search (IS) approach, Newton – Raphson (NR) method, Non – Linear Programming (NLP), and Quadratic Programming (QP) have been applied to solve economic emission dispatch [5-9]. The classical methods may have difficulties in finding an optimal solution due to the longest execution time and presence of non – linear & discontinuity in the problem. The variety of artificial intelligence techniques and their hybrid versions has been applied to solve environmental emission dispatch problems [10-18]. Based on the shallow water theory named water evaporation optimization algorithm [19] have been applied to solve environmental economic dispatch problems.

Recently, inspired by the foraging behavior of honeybees, researchers have developed Artificial Bee Colony (ABC) algorithm for solving various optimization problems [20]. ABC is a relatively new population-based bio-inspired approach with the desirable characteristics such as robust and easy to implement. Further, ABC does not use any gradient – based information and it incorporates a flexible and well balanced mechanism to adapt to the global and local exploration abilities within a short computation time. This makes the algorithm efficient

in handling large and complex search spaces. In this paper, an ABC algorithm is proposed to determine the optimal solution for environmental economic dispatch problem.

2. PROBLEM FORMULATION

The reduction emission from fossil fuel fired power plants is essential for power industries due to clean Air Act Amendments of 1990 and the problem can be formulated as

The total emission of generation E_i can be

$$E_i = \alpha_i P_i^2 + \beta_i P_i + \gamma_i$$

(2.1)

E_i is the function of emissions in (Kg/h) and α_i , β_i and γ_i are the co-efficient of emission characteristics specific to each production unit.

3. SWARM INTELLIGENCE TECHNIQUE

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 SI 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 neighborhood of its current food source and evaluates its nectar amount (fitness). The i^{th} food source position is represented as X_i where $i=1, 2, \dots, N$ 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 $k \in \{1, 2, \dots, N\}$ and $j \in \{1, 2, \dots, D\}$ 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 SI: 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

4. SWARM INTELLIGENCE TECHNIQUE FOR ENVIRONMENT ECONOMIC DISPATCH

The proposed algorithm for solving EED 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 ($i=1, 2 \dots N$) 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.

5. SIMULATION 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 6 generating units test system given in [19] is studied and solved. The control parameters of SI algorithm are chosen as colony size 100, maximum cycle/generation number (MCN) 100, and limit value 30.

In order to show the effectiveness of the proposed ABC algorithm it has been tested on six generating unit system for the load demand of 700 MW, 800 MW, 900 MW, 1000 MW. The system particulars are available in the literature [19]. The simulation results obtained by the proposed as well as existing algorithms are presented in Table 5.1 & 5.2. The results shows that the proposed ABC algorithm achieves the minimized emission of NO_x for all load demands then existing algorithms. For the load demand of 700MW the proposed algorithm reaches the minimized emission value of 434.09 Kg/h, for 800MW the emission value is 548.54 Kg/h, for the load demand of 900MW it attain the value of 682.45 Kg/h and for the final load demand of 1000MW it obtain the better value of 837.45 Kg/h.

In all cases the proposed ABC algorithm achieves the competitive results with fully satisfies the system and problem constraints. The total production cost obtained by the proposed algorithm is also compared with existing techniques is also presented in Table 5.1. The comparison also shows that feasibility of the proposed algorithm reach better results in terms of least production cost. The

proposed algorithm have capability of online implementation for reduction of emission and production cost. From the comparison it is clear that ABC algorithm outperforms the existing algorithms.

Table 5.1 Optimal dispatches of proposed ABC and existing algorithms

Power Demand MW	Techniques	P ₁ (MW)	P ₂ (MW)	P ₃ (MW)	P ₄ (MW)	P ₅ (MW)	P ₆ (MW)	P _I (MW)
700	FA	80.1523	82.4019	113.9655	113.4758	163.4493	163.0944	16.53
	BA	80.1431	82.4033	113.9684	113.4763	163.4530	163.0950	16.53
	HYB	80.1506	82.4054	113.9570	113.4851	163.4436	163.0975	16.53
	WEO[19]	80.1439	82.4043	113.9657	113.4772	163.4471	163.0951	16.53
	ABC	80.1326	82.2178	113.8765	114.2367	164.2232	163.06537	17.75
800	FA	100.5399	103.7475	127.0118	126.3499	182.1959	181.7376	21.58
	BA	100.5295	103.7579	127.0076	126.3466	182.2088	181.7321	21.58
	HYB	100.5207	103.7662	127.0024	126.3547	182.1999	181.7385	21.58
	WEO[19]	100.5211	103.7511	127.0032	126.3518	182.2081	181.7382	21.57
	ABC	100.3456	103.4321	127.0023	127.2458	183.1076	181.6789	22.81
900	FA	120.9389	125.3301	140.1958	139.3394	201.0812	200.4822	27.36
	BA	120.9330	125.3313	140.1994	139.3392	201.0855	200.4791	27.36
	HYB	120.9357	125.3202	140.1992	139.3479	201.0706	200.4940	27.36
	WEO[19]	120.9362	125.3211	140.1993	139.3393	201.0808	200.4812	27.36
	ABC	120.7653	125.2455	141.1876	139.2212	202.0704	200.3271	28.81
1000	FA	125.0000	150.0000	156.2191	155.2644	224.0618	223.1839	33.73
	BA	125.0000	150.0000	156.2704	155.1559	224.0577	223.2458	33.73
	HYB	125.0000	150.0000	156.0719	155.2412	224.2263	223.1934	33.73
	WEO[19]	125.0000	150.0000	156.0792	155.2183	224.2173	223.2163	33.73
	ABC	125.0000	150.0000	157.05435	155.1789	224.1234	224.1221	35.47

Table 5.1 Comparison Results of Cost & Emission

Power Demand	Techniques	Cost (\$/hr)	Emission (Kg/h)
700 MW	FA	38101.09	434.13
	BA	38100.95	434.13
	HYB	38101.13	434.13
	WEO [19]	38100.72	434.12
	ABC	38100.65	434.09
800 MW	FA	43719.20	548.70
	BA	43719.15	548.70
	HYB	43719.14	548.70
	WEO [19]	43718.39	548.69
	ABC	43718.21	548.54
900 MW	FA	49650.29	682.62
	BA	49650.14	682.62
	HYB	49649.97	682.62
	WEO [19]	49649.53	682.61
	ABC	49649.34	682.45
1000 MW	FA	55456.64	837.77
	BA	55456.49	837.77
	HYB	55456.24	837.77
	WEO [19]	55456.12	837.76
	ABC	55456.08	837.45

6. CONCLUSION

The emission constrained economic load dispatch (ECELD) problem is a sub problem of an optimal power dispatch. In this paper emission constrained economic load dispatch problem is solved by using swarm intelligence technique named artificial bee colony algorithm. The simulation result of the proposed algorithm is compared with existing techniques. From the comparison it is clear that the proposed algorithm obtain the better results than existing algorithms for the load demands of 700MW, 800MW, 900MW, 1000MW. In all cases the proposed

algorithm clearly satisfies the system and problem constraints. The simulation results shows that the proposed algorithm have the ability to online implementation.

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