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Research paper

Salp swarm algorithm to combined economic and emission dispatch problems

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Abstract

The purpose of this paper is to present a Salp Swarm (SS) Algorithm for the solution of Combined Economic Emission Dispatch (CEED) problem. The production of electricity from the thermal power generation plants releases large containments of oxides of Nitrogen (NOx), Sulphur (SOx) and Carbon (COx) into the atmosphere. The CEED problem has been treated as a bi-objective optimization problem by taking economic and emissions simultaneously. SS algorithm is a recently suggested optimization algorithm based on swarming behaviour of salps when foraging and navigating in the oceans. To verify the robustness of the suggested SS algorithm is tested for CEED of two test systems with losses. All the results are carried out to demonstrate the effectiveness and validity of the scheme for practical applications. These study results have shown that the approach developed is efficient and suitable for real-time applications.

Keywords: *Economic Dispatch; Emission Dispatch; Transmission Losses; Mathematical Modeling, SALP Swarm Algorithm*

1. Introduction

Power system operating cost is minimized by the conventional Economic Dispatch (ED), which deals with the allocation of generation levels to the generating units to meet the required demand. Earlier many researchers have provided better solutions with different strategies for ED problem without taking emissions into account. However "Global Warming" concept attracted more attention to pollution minimization and the major contribution is from thermal power plants. The large quantities of emissions like NOx, SOx and COx are due to the burning of the fossil fuels such as coal, oil, gas, etc. used by the thermal plants. These emissions, have forced the utilities to take on various practices like the utilization of high-quality fuel, upgrading older plants with new and efficient plants, thus Emission Dispatch (EmD) is included as another objective to the conventional ED. EmD is much similar to the ED, but it extends to minimize only net emission level. Meeting both contradictory objectives by conventional ED or EmD is difficult hence CEED is considered an alternative strategy and it deals with minimizing the cost and emission simultaneously while reaching the system constraints.

Multiobjective ED problem can be solved either directly or through converting into the single-objective problem. Various approaches have been presented in the literature to solve different ED problems. Primarily Finnigan et al. [1] have solved ED problem by treating system pollutants as an additional constraint, Cadogan et al. [2] have utilized multiple-strategies for emissions and economic control of power generation, Kothari et al. [3] presented a computer-oriented technique for scheduling of thermal generation which results in the minimum NOx emission, power plants with higher effluent dispatches generates the power at lower cost than what they do under ED, Nanda et al. [4] has proposed a new computational technique using improved Box complex method and deals with the objective of obtaining minimum emission dispatch by proper scheduling and therefore resulting in raised operational costs. Granelli et al. [5] have solved dynamic dispatch by considering the emissions as a constraint, Nanda et al. [6] demonstrated EED problem for minimization of both cost and emission through the utilization of a several conflicting objective problems, Palanichamy et al. [7] have defined a new price penalty factor to account for emission and fuel costs. The objective function is defined in quadratic form and is used to solve the EED problem, Chang et al. [8] solved the economic and environmental objectives concurrently through linear combination and formed a single objective function by adjusting the weights, the trade-off between cost and emission was obtained, Song et al. [9] solved a fuzzy logic controller based genetic algorithm (FCGA) to solve the environmental, economic dispatch, Yalcinoz and Altun [10] solved EED through weighted sum method using genetic algorithms through arithmetic crossover, mutation and elitism, Harry et al. [11] solved EED dispatch problem using an elitist multiobjective evolutionary algorithm also known as the Non-dominated Sorting Genetic Algorithm - II (NSGA-II).

Many nature-inspired algorithms are implemented in the past to solve the ED problems such as Particle Swarm Optimization [12], Artificial Bee Colony optimization [13], Firefly algorithm [14], Cuckoo Search algorithm [15], Differential Search Algorithm [16], Bat algorithm [17], [18] and others in order to enhance the performance of ED problems.

This paper presents the application of SS Algorithm for the solution of CEED problem. The suggested methodology is utilized for solving CEED problems. The main intention of CEED is to simultaneously minimize both emission and cost of the unit while meeting the system constraints. In order to compute the effectiveness of the suggested algorithm, it has been implemented on two different test systems. Thus, the swarming behaviour of salps when navigating and foraging in the oceans can be efficiently extracted to optimize CEED problem. When simulation results are compared with other algorithms presented in the literature it proves the strength and effectiveness of the SS algorithm than other algorithms. This paper is structured as follows. Section 2 describes the mathematical modelling of ED problem with losses. The suggested SS Algorithm is described in section 3 and the description of test systems, results and comparisons of the proposed algorithm with other methods are presented in section 4. The final conclusion is presented in section 5.

2. Formulation of the problem

In this section, the formulation of economic, emission and combination of economic emission dispatch problem is presented.

a) Economic Dispatch (ED):

The classical ED problem has defined as finding the optimum power production, which minimizes the cost while satisfying the system constraints. The fuel cost function of every unit in a plant is described as a quadratic equation as follows.

$$F_i(P_i) = a_i P_i^2 + b_i P_i + c_i \ (\$/h) \tag{1}$$

Where ai, bi and ci are the cost coefficients of ith unit, the total cost function is described as follows.

$$F_T = \sum_{i=1}^{ng} F_i(P_i) \ (\$/h) \tag{2}$$

Where ng is a number of units.

b) Emission Dispatch (EmD):

The emission function of every unit is described as follows.

$$E_i(P_i) = \alpha_i P_i^2 + \beta_i P_i + \gamma_i \ (kg/h) \tag{3}$$

Where αi, βi and γi are the emission coefficients of ith unit

The total emission function is described as follows.

$$E_T = \sum_{i=1}^{ng} E_i(P_i) \ (kg/h) \tag{4}$$

Power balance constraint i.e. total generated power must be equal to total demand plus losses of the system are described as follows.

$$\sum_{i=}^{ng} P_i - (P_d + P_L) = 0 \tag{5}$$

Where Pd is demand (MW) and PL is losses (MW). The losses of the system are calculated through below formula with B – coefficients matrix.

$$P_L = \sum_{i}^{ng} \sum_{\substack{j=1 \\ j \neq i}}^{ng} P_i \ B_{ij} \ P_j \tag{6}$$

The inequality constraint i.e. power generated by any generating unit must lie in between its minimum and maximum specified powers are described as follows.

$$P_i^{\min} \le P_i \le P_i^{\max}$$

$$P_i^{min} \le P_i \le P_i^{max} \tag{7}$$

Where $P_i^{\min}$ and $P_i^{\max}$ are respectively the minimum and maximum power generation limits of ith unit.

Combined Economic Emission Dispatch (CEED):

The ED problem concentrates only on the minimization of cost and does not consider emissions. As emissions function i.e. EmD is included as another objective to the conventional ED. EmD is much similar to the ED, but it extends to minimize only net emission levels. From these it is concluded that we can operate the power system at lowest emission level or minimum cost and both cannot be satisfied simultaneously. In order to acheieve the same ED and EmD problems have to be solved as a bi-objective optimization problem while meeting necessary system constraints. This bi-objective problem is converted into single objective problem through price penalty factor. The new objective function is described as follows.

$$\text{Minimize } F = F_T + h_i \times E_T \tag{8}$$

Where h is price penalty factor ($/kg)

$$h_i = \frac{F_i(P_i^{\max})}{E_i(P_i^{\max})} \ (\$/h) \tag{9}$$

3. Modelling of salp swarm algorithm

Salp Swarm Algorithm (SSA), a new meta-heuristic algorithm suggested by Mirjalili [18] in 2017. Salps participate in the category of Salpidae and also have a transparent barrel-shaped body. Their cells are extremely a lot like jellyfish, where the normal water is pumped through their body as propulsion to go forward. Probably one of the most interesting tendencies of salps, which is their swarming tendency. In the profound oceans, salps often form a swarm called salp string. The root cause for this tendencies is not so clear so far, but some research workers consider for obtaining better locomotion utilizing fast coordinated changes and foraging.

The mathematical model for salp chains

The population of SS algorithm is split into two groupings such as leader and followers. The leader is the salp at the front of the chain, whereas the others of salps are believed as followers. As the name of these salps implies, the leader guides swarm and the followers follow one another.

Much like other horde-based techniques, the location of salps is bound to n-dimensional search space where n is the number of variables of a given problem. Thus, the location of most configurations is stored in a two-dimensional matrix called x. It is really likewise overlooked that there surely is a food source called F in the search space which is the swarm's target. To update the location of the leader the following formula is suggested.

$$x_j^1 = \begin{cases} F_j + c_1((ub_j - lb_j) \times c_2 + lb_j) & c_3 \ge 0 \\ F_j - c_1((ub_j - lb_j) \times c_2 + lb_j) & c_3 < 0 \end{cases} \tag{10}$$

Where x_j^1 shows the location of the leader in the jth dimension, Fj is the location of the food source in the jth dimension, ubj signifies the upper bound of jth dimension, lbj signifies the lower bound of j^{th} dimension, c1, c2 and c3 are random numbers. Eq. (10) demonstrates that the leader only changes its location with regards to the food source.

The coefficient c1 is the main parameter in SS algorithm because it balances exploration and exploitation thought as follows.

$$c_1 = 2e^{-(\frac{4l}{L})^2} \tag{11}$$

Where l is the current generation and L is the maximum number of generations.

The parameter c_2 and c_3 are random numbers uniformly generated in the range of [0-1]. In fact, they dictate the next location in j^{th} dimension must be towards positive infinity or negative infinity as well as the step size. To update the location of the followers, the following equations are utilized.

$$x_j^i = \frac{1}{2}(at^2 + v_0 t) \quad (12)$$

Where i≥2, x_j^i shows the location of ith follower salp in jth dimension, t is time, v0 is the initial speed, and $a = \frac{v_{final}}{v_0}$ where $v = \frac{x - x_0}{t}$

Because the time in optimization is the generation, the discrepancy between generations is equivalent to 1 and considering v0 = 0, this formula can be expressed as follows

$$x_j^i = \frac{1}{2}(x_j^i - x_j^{i-1}) \quad (13)$$

Where i≥2 and x_j^i shows the location of ith follower salp in jth dimension.

Salp chains can be simulated by Eq. (10) and (13).

Table 1 demonstrates how an SS algorithm begins by approximating the global optimum through initiatilizing multiple salps with random locations. After that, it calculates the fitness of ever salp, locates the salp with the best fitness, and assigns the location of the greatest salp to the changeable F_i as the source food to be chased by the salp chain. Meantime the coefficient c_1 is modified utilizing Eq. (11). For every dimension, the location of leading salp is modified utilizing Eq. (10) and the location of follower salps is modified using Eq. (13). If the salp goes beyond your search space, it'll be cut back on the limitations. All of the above steps except initialization are iteratively performed until satisfaction of an end condition.

Table 1: The pseudo code of the SS Algorithm:

Initialize the salp population i = 1, 2, . . . , n
Upper bounds ub
Lower bounds lb
Number of dimensions dim
Initialize the maximum number of generations itmax
Randomly initialize the locations of salps xi corresponding to the ub and lb
Define the fitness function F_i
Set t = 1 (counter initialization)
While (t < Max number of iterations)
Evaluate the fitness function of every salp location i.e. $F_i(x_i)$
Set the best salp location x_{best}
Update c_1 by using Eq. (11)
For (i=1; i≤ n) every salp
If (i= =1) then
Update the location of the leading salp using by Eq. (10)
Else
Update the location of the follower salp by Eq. (13)
End if
End for
If $F_n(x_i^t)$ is better than $F_n(x_{best})$ then
Update the location of the best salp
End if
Rank the salps and find the current best x_{best}
End while
Produce the best slap location

4. Results and discussions

The applicability and validity of the SS algorithm for practical applications is tested on various test systems. The obtained best solution in 100 runs is compared with the results obtained using the SS algorithm. All the programs are implemented with MATLAB (2010a) and the system configuration is core i3 processor with 2. 0 GHz speed and 4 GB RAM.

4.1. The setting of SS Algorithm Parameters:

The parameters for the SS algorithm considered here are: n = 20; c_1 is calculated using an Eq. (12), c_2 and c_3 are the random generations. The SS algorithm, stopping criteria is based on maximum-iterations=100.

4.2. Numerical solutions

Test system 1: The test system consists of three thermal generating units [10]. All the data, such as the cost and emission coefficients and operating limits are pasted in table 2 and loss coefficients in table 3. Only one type of pollutant (i.e. NOx emission) is considered. The test system has conducted for two different demands of 500 MW and 700 MW. Simulation results of CEED problem for the demand of 500 MW and 700 MW are obtained from the SS algorithm and compared with other algorithms such as BA and ABC and tabulated in table 4, from the table 4 it is clear that the SS algorithm give the less fuel cost, emission and total operating cost than BA for different load demands like 500 MW and 700 MW.

Table 2: Fuel Cost and Emission Coefficients of the Test System 1

Unit	Fuel cost coefficients			NO_x Emission coefficients			P_{min} (MW)	P_{max} (MW)
	a_i	b_i	c_i	α_i	β_i	γ_i		
G_1	0.03546	38.30553	1243.53110	0.00683	-0.5455	40.26690	35	210
G_2	0.02111	36.32782	1658.56960	0.00461	-0.5116	42.89553	130	325
G_3	0.01799	38.27041	1356.65920	0.00461	-0.5116	42.89553	125	315

Table 3: Losses Coefficients of Test System 1

0.00007	0.000025	0.000030
0.000030	0.000069	0.000032
0.000025	0.000032	0.000080

Table 4: Comparison of Results for the Test System 1

Demand	h ($/kg)	Outputs	ABC	BAT	SSA
500 MW	44.788	P1 (MW)	128.8494	128.8496	128.8417
		P2 (MW)	191.4610	192.5606	192.5612
		P3 (MW)	191.3687	190.2657	190.2705
		Power Output (MW)	511.6791	511.6759	511.6735
		Loss (MW)	11.6791	11.6759	11.6735
		Fuel cost ($/h)	25494.904	25493.991	25493.858
		Emission (kg/h)	311.125	311.133	311.1306
		Total Cost ($/h)	39429.646	39426.551	39426.4652
700 MW	47.82	P1 (MW)	182.6259	182.6477	182.6481
		P2 (MW)	270.3542	271.2396	271.2369
		P3 (MW)	270.3541	269.4426	269.4423

	Power Output (MW)	723.3342	723.3299	723.3274
	Loss (MW)	23.3342	23.3299	23.3274
	Fuel cost ($/h)	35462.826	35462.501	35462.3747
	Emission (kg/h)	354.628	651.505	651.5004
	Total Cost ($/h)	66617.903	66617.505	66617.1228

The convergence curve, the tendency of proposed SS algorithm based strategy for different demands of 500 MW and 700 MW are plotted in figures 1 and 2. It shows that the method converges in fewer cycles [17] thereby possessing
high-quality convergence property and resulting in less operating cost.

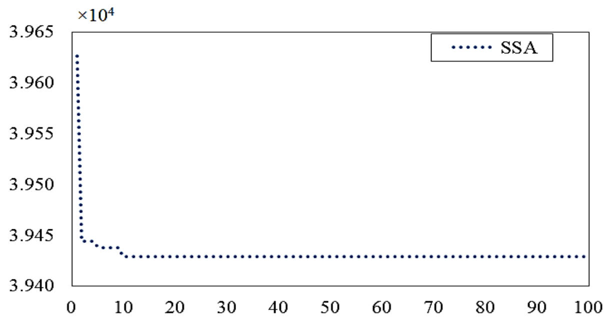

Fig. 1: Convergence Curve of SS Algorithm for Test System 1 for P_d = 500 MW.

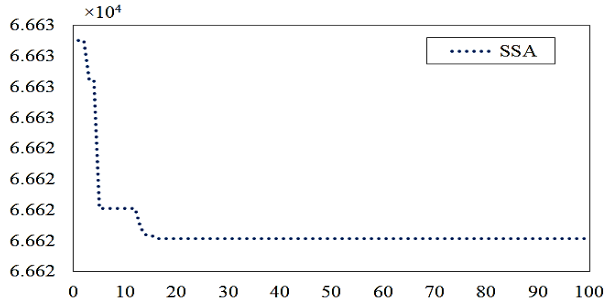

Fig. 2: Convergence Curve of SS Algorithm for Test System 1 for P_d = 700 MW.

Test system 2: The test system consists of six thermal generating units [10]. All the data, such as the cost and emission coefficients and operating limits are pasted in Table 5 and loss coefficients in Table 6. Only one type of pollutant (i.e. NOx emission) is considered. The test system has been conducted for two different power demands of 500 MW and 900 MW.
Simulation outcomes of CEED problem for the demand of 500 MW and 900 MW are obtained from the SS algorithm are compared with other algorithms such as BA and ABC and tabulated in table 7, from the table 7 it is clear that the SS algorithm give the less fuel cost, emission and total operating cost than BA for different load demands like 500 MW and 900 MW.

Table 5: Fuel Cost and Emission Coefficients of the Test System 2

Unit	Fuel cost coefficients			NO_x Emission coefficients			P_{min} (MW)	P_{max} (MW)
	a_i	b_i	c_i	α_i	β_i	γ_i		
G_1	0.15247	38.53973	756.79886	0.00419	0.32767	13.85932	10	125
G_2	0.10587	46.15916	451.32513	0.00419	0.32767	13.85932	20	150
G_3	0.02803	40.39655	1049.9977	0.00683	-0.54551	40.26690	35	125
G_4	0.03546	38.30552	1243.5311	0.00683	-0.54551	40.26690	35	210
G_5	0.02111	36.32782	1658.5596	0.00461	-0.51116	42.89553	130	325
G_6	0.01799	38.27041	1356.6592	0.00461	-0.51116	42.89553	125	325

Table 6: Losses Coefficients of Test System 2

0.000140	0.000017	0.000015	0.000019	0.000026	0.000022
0.000017	0.000060	0.000013	0.000016	0.000015	0.000020
0.000015	0.000013	0.000065	0.000017	0.000024	0.000019
0.000019	0.000016	0.000017	0.000071	0.000030	0.000025
0.000026	0.000015	0.000024	0.000030	0.000069	0.000032
0.000022	0.000020	0.000019	0.000025	0.000032	0.000085

Table 7: Comparison of Results for the Test System 2

Demand	h ($/kg)	Outputs	ABC	BA	SSA
		P1 (MW)	33.2772	33.2703	33.48344
		P2 (MW)	26.8596	26.85061	26.48023
		P3 (MW)	89.8963	89.91347	90.07591
		P4 (MW)	90.4832	90.48638	90.73406
		P5 (MW)	135.6435	135.6411	135.6835
500	43.898	P6 (MW)	132.7744	132.7620	132.4784
		Power Output (MW)	419.0379	419.01039	508.9356
		Losses (MW)	8.9343	8.9339	8.9356
		Fuel cost ($/h)	27613.0000	27612.7490	27611.9866
		Emission (kg/h)	263.0120	263.0060	263.0438
		Total Cost ($/h)	39156.9000	39158.199	39159.0816
		P1 (MW)	92.3185	92.3288	92.16276
		P2 (MW)	98.3707	98.3100	98.2785
		P3 (MW)	150.1997	150.1132	150.702
		P4 (MW)	148.5549	148.5586	149.0059
900	47.822	P5 (MW)	220.4051	220.4007	219.8209
		P6 (MW)	218.1615	218.1267	218.0282
		Power Output (MW)	928.0104	927.8380	927.9982
		Losses (MW)	28.0087	28.0089	27.9982
		Fuel cost ($/h)	47045.3000	48350.163	48347.2656
		Emission (kg/h)	693.7910	693.772	693.865

Total Cost ($/h)	81527.6000	81527.793	81526.5045

The convergence curve, tendency of proposed SS algorithm based strategy for different demands of 500 MW and 900 MW are plotted in figures 3 and 4. It shows that the method converges in fewer cycles [17] thereby possessing high-quality convergence property and resulting in very less operating cost.

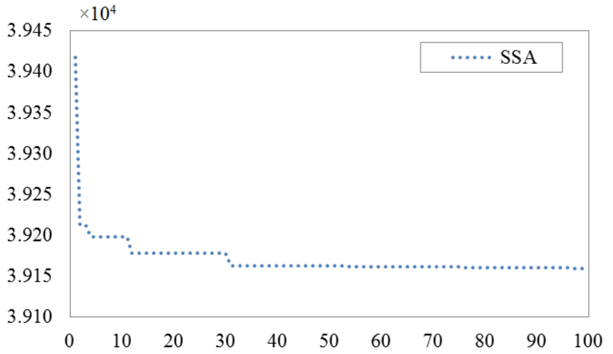

Fig. 3: Convergence Curve of SS Algorithm for Test System 2 for P_d = 500 MW.

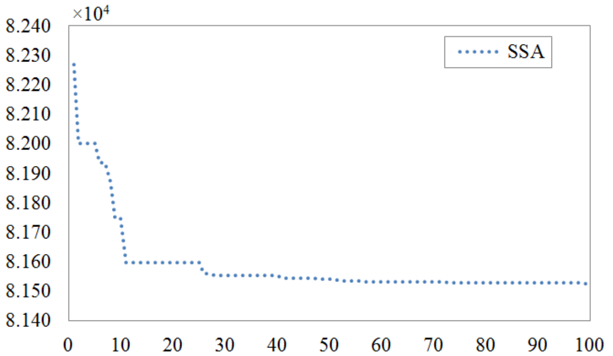

Fig. 4: Convergence Curve of SS Algorithm for Test System 2 for P_d = 900 MW.

5. Conclusion

In this paper, a new SS algorithm is implemented. In order to present the effectiveness of the algorithm, it is implemented to CEED with three and six thermal generating units. The simulation results obtained from the proposed SS algorithm were compared to those obtained by BA and ABC. The comparison gives that SS algorithm performs better than the above-mentioned methods. The SS algorithm has simple to implement, greater features and quality of solutions, stable convergence characteristics and high-quality computational efficiency. Therefore, these simulation results show that SS algorithm is a promising technique for solving complicated problems in power system.

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