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Estimation of fuel cost curve parameters for thermal power plants using the ABC algorithm

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Abstract: The solution accuracy of economic dispatch problems is associated with the accuracy of the fuel cost curve parameters. Therefore, updating of these parameters is a very important issue to further improve the final accuracy of economic dispatch problems. Estimating the parameters of the fuel cost curve may be the best solution for this issue. This paper presents an application of the artificial bee colony (ABC) algorithm to estimate the fuel cost curve parameters of thermal power plants. In the estimation problem, 1st-, 2nd-, and 3rd-order fuel cost functions are used, and the estimation problem is formulated as an optimization one. The ABC algorithm is used to solve this optimization problem by minimizing the total error in the estimated parameters. In this study, in order to evaluate the performance of the ABC algorithm, it is tested on 3 different cases that have 3 different fuel cost types, such as coal, oil, and gas. The results obtained from the proposed method are compared with the genetic algorithm, particle swarm optimization, and least square error methods reported previously in the literature. The results show that the ABC algorithm is stronger than the others at solving such a problem.

Key words: Fuel cost curve, parameter estimation, artificial bee colony algorithm

1. Introduction

The cost of electrical energy (MW) production is described with 3 main sources, namely facility construction, ownership cost, and operating costs. The operating cost is the most significant of these 3, and so the focus will be on the economics of the operation. The optimal power flow (OPF) and economic dispatch (ED) or economic/environmental dispatch (EED) have become the most important problems and commonly studied subjects for optimal and economic operation and planning processes of modern power systems [1–4]. These problems are formulated mathematically and aim to optimize a chosen objective function, such as fuel cost, while satisfying the operational constraints [5]. Hence, solution of these problems helps to save generating costs, especially in fossil fuel plants [6]. In the solving of these problems, the fuel cost curve is commonly represented by a linear, quadratic, or cubic function. Since the parameters of these functions are affected by many factors, such as the ambient operating temperature and aging of the generating units, one of the most important issues is to have an accurate estimate of the thermal unit fuel cost curve parameters. Thus, a realistic approximation of the fuel cost function to the actual cost curve by periodically estimating the cost function parameters is crucial in order to improve the final accuracy of the results in solving OPF or ED problems. Therefore, using a powerful and reliable estimation technique in estimation of the parameters of the fuel cost curve is a very important issue [7].

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In recent decades, some researchers have studied the estimation of fuel cost curve parameters using different techniques, such as conventional models or artificial intelligence (AI) and modern heuristic optimization algorithms. The research on the estimation of fuel cost curve parameters has only currently continued, so there are a limited number of studies in the literature on this subject. In early studies on this subject, researchers used static estimation techniques (least square error (LSE), Gauss–Newton, etc.) to solve estimation problems in power systems. Taylor and Huang [8] presented a study based on a recursive mathematical method in order to estimate the cost curves of the generating units in a thermal power system. El-Hawary and Mansour [9] proposed 4 algorithms, which were the LSE, Gauss–Newton method or Bard algorithm, Marquardt algorithm, and Powell regression algorithm, for the estimation of the parameters of the models used in the optimal economic operation of electric power systems. They compared all of these methods and reported that the methods gave almost the same values, but the Gauss–Newton method took the most computational time. Shoults and Mead [10] used the weighted least squares multiple linear regression method to calculate the coefficients of a cubic fuel cost input/output (I/O) curve. Chen and Postel [11] presented a methodology of online I/O curve identification based on the sequential regression technique implemented at the energy control center of the Southern California Edison Company. El-Shibini and Osman [12] developed a practical method to establish mathematical models for the fuel cost of thermal power stations in electrical power systems. Their new technique depended only on the operating records of the power stations, which are stored on a computer, and they used those records to estimate and continuously modify the fuel cost functions of the power stations. Soliman et al. [13] presented a study based on the least absolute value approximations for estimating the coefficients of a fuel cost I/O curve that exhibits nonmonotonically increasing characteristics. Liang and Glover [14] evaluated 2 polynomial curve-fitting methods: Gram–Schmidt orthonormalization and least-squares. They reported that the Gram–Schmidt method, which does require matrix inversion, gave more accurate fuel cost curves. These conventional static estimation models have been studied extensively and their numerical stabilities and computational efficiencies have been greatly improved by various techniques. However, in the presence of gross errors, these classical estimators remain weak in the field of state estimations.

Afterwards, researchers interested in dynamic estimation techniques, such as the Kalman filter and AI, due to these algorithms have some advantages such as being more accurate and more stable in predicting the state of the system. Soliman and Al-Kandari [15] presented the application of the well-known Kalman filtering algorithm for the online identification of the I/O curve of thermal power plants. They reported that the advantage of this approach is the capability of keeping track of the state of the thermal unit by making the coefficients of the I/O curve continuously adaptive to the real characteristic of the unit. Ferreira and Maciel Barbosa [16] proposed a square root filter (SRF) for dynamic state estimation instead of the Kalman filter. However, in [17], Shivakumar reported that the Kalman filter method has the disadvantage of not being able to handle large changes in the system, and the SRF technique is algebraically equivalent to the Kalman filter technique but is numerically more stable than the Kalman filter.

In recent years, AI techniques, such as artificial neural networks (ANN), and fuzzy logic (FL) and optimization techniques such as particle swarm optimization (PSO) and the genetic algorithm (GA), have been a great development. Thus, researchers have used these techniques in power system state estimation. Sinha and Mandal [18] modeled the dynamics of the power system more realistically using an ANN technique. Kumar and Srivastava [19] also used this technique for power system state forecasting. In general, the ANN is the superior method for solving the estimation problem, especially when the process model is not well-defined mathematically. However, the disadvantage of the ANN is the huge amount of data required for network training, which may not be available in some cases. FL [20] is one of the popular algorithms proposed by researchers for power system state estimation to decrease the computation time. However, its main disadvantage is that it is hard to create the fuzzy rules; doing so requires much experience. PSO and the GA are well known and widely used optimization algorithms in the field of power systems. El-Kantari and El-Naggar [21] used the GA and El-Naggar et al. [7] used the PSO method for estimating the parameters of thermal power plants' fuel cost function. Alrashidi et al. [22] proposed the PSO method to estimate the fuel cost function parameters of thermal power plants with valve point effects.

In this paper, a new metaheuristic optimization algorithm called the artificial bee colony (ABC) algorithm is proposed to estimate the fuel cost curve parameters of thermal power plants. The ABC algorithm was introduced by Karaboga in 2005 [23] and was developed by Karaboga and Basturk in 2007 [24]. It finds a possible solution for optimization problems with multivariable functions and is motivated by the foraging behavior of honeybees. There are some studies in the literature related to the ABC algorithm [25–36]. Karaboga and Akay reported in [36] that the ABC algorithm has a simpler and more flexible structure, has fewer control parameters, and produces better solutions than other optimization algorithms, such as PSO and GA. Because of this superiority of the ABC algorithm when compared to other heuristic techniques and the above disadvantages of the classical estimation methods, the ABC algorithm is used to solve the estimation problem defined in this paper.

In this study, the estimation problem of the fuel cost parameters is described as an optimization problem to minimize the total error in the estimated state parameters based on [7]. Smooth fuel cost functions are studied in 3 different cases. The ABC algorithm is used to find the optimal parameter estimation of the formulated optimization problem. The results obtained from the ABC algorithm are compared to the results reported in [7] and [21]. The comparison shows that the ABC algorithm produces better solutions than GA, PSO, and LSE algorithms in the solution of fuel cost curve parameter estimation in thermal power systems.

The rest of the paper is organized as follows: Section 2 defines the mathematical formulation of the fuel cost curve and in Section 3, the proposed approach of the ABC algorithm and its implementation to the problem under consideration are presented. Section 4 presents the experimental study results of the simulation and compares the results obtained from the ABC algorithm and the techniques reported in [7] and [21] for case studies of the estimation problem. Finally, the conclusion is illustrated in Section 5.

2. Mathematical model of the fuel cost curve

In OPF or ED problems, the cost function can be described as a smooth function. The smooth fuel cost function is defined by polynomial functions. However, if the generating units of the power plant have multivalve steam turbines, the fuel cost curve of the generators is very different when compared with the smooth functions. In this case, when valve point effects are considered, the fuel cost function is described as a nonsmooth cost function by adding sinusoidal functions. Since the valve point effect is not considered, the smooth fuel cost function is used in this study. The smooth fuel cost function is expressed as follows [7]:

$$FC_j(Pg_j) = a_{oj} + \sum_{i=1}^{N} a_{ij} + Pg_{ij} + r_j,\ j = 1, 2, ..M, \tag{1}$$

where FC_j is the fuel cost function of the jth unit, Pg_j is the electrical power output of the jth generator in MW, a_{ij} is the cost coefficient, r_j is the error related to the jth equation, N is the equation order (for linear it is 1, second-order it is 2, or cubic it is 3), and M is the total number of thermal generators in power system.

Smooth cost functions can be modeled as linear, quadratic, or cubic forms. In this case, the cost function is a 1st-, 2nd-, or 3rd-order equation. These different cost curves are illustrated in Figure 1 [7] and are formulated as follows:

Type 1: Linear form

N will be 1 and Eq. (1) will be in the form of:

$$FC_j(Pg_j) = a_{0j} + a_{1j}Pg_j + r_j. \tag{2}$$

Type 2: Quadratic form

N will be 2 and Eq. (1) will be in the form of:

$$FC_j(Pg_j) = a_{0j} + a_{1j}Pg_j + a_{2j}Pg_j^2 + r_j. \tag{3}$$

Type 3: Cubic form

N will be 3 and Eq. (1) will be in the form of:

$$FC_j(Pg_j) = a_{0j} + a_{1j}Pg_j + a_{2j}Pg_j^2 + a_{3j}Pg_j^3 + r_j, \tag{4}$$

where a_0, a_1, a_2, and a_3 are the fuel cost coefficients and Pg_j is the generated power of the jth unit.

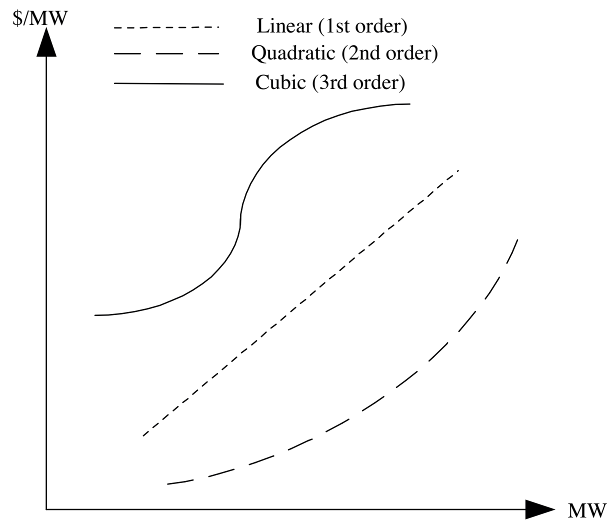

Figure 1. Three types of fuel cost function curves.

In this paper, the ABC algorithm is proposed to find an estimate of the coefficients of the fuel cost function for thermal generating units. The fuel cost energy function (FC$_{estimated}$) is calculated again at each cycle using these estimates. Next, the error for each measurement is minimized. Now the problem formulation is defined in a form so as to find an estimate for the fuel cost function coefficients that minimize the error ε_i. The error vector associated with each measurement is calculated by subtracting the actual and estimated values of the fuel function at each cycle, shown as follows [28]:

$$\varepsilon_i = FC_{i(actual)} - FC_{i(estimated)} \tag{5}$$

The ABC algorithm is used to find an estimate for the cost coefficients given in Eq. (5), minimizing ε_i, subjected to the equality and inequality constraints [28]. These constraints can be described as follows.

Equality constraint (power balance): According to this constraint, the total power generated must supply the total load demand and the transmission losses. It can be formulated as follows:

$$\sum_{i=1}^{n} Pg_i - (P_l + P_{loss}) = 0, \tag{6}$$

where Pg_i is the total power generated by the power system, P_l is the load demand, and P_{loss} is the transmission loses. In this study, P_{loss} is equal to 0.

Inequality constraint (maximum and minimum limits of the fuel cost coefficients): According to this constraint, fuel cost coefficients are constrained between the minimum and maximum limits. It can be formulated as follows:

$$C_{i\,\min} \leq C_i \leq C_{i\,\max}, \tag{7}$$

where C_i corresponds to the fuel cost coefficients and $C_{i\,\min}$ and $C_{i\,\max}$ are their minimum and maximum limits.

3. ABC algorithm

3.1. Overview of the ABC algorithm

The ABC algorithm is explained here based on [23–27,29–36]. The ABC algorithm is a metaheuristic optimization algorithm. It has been introduced by simulating the life processes and attitudes of honeybees in a colony. In the search process of the ABC algorithm, artificial bees modify their food positions with time in order to find the locations of food sources having a high nectar amount. Hence, they find the food source with the highest nectar amount. There are 3 types of bees in the colony of artificial bees, namely employed, onlooker, and scout bees. Employed bees exploit the food sources and give information about the nectar amount of the food source to the onlookers. The onlookers wait at the dancing area and decide which food source should be selected. The duty of a scout is to discover the new food sources. The number of employed bees is half of the colony and the other half of the colony consists of onlooker bees. Since only one employed bee is assigned for every food source, the number of employed bees corresponds to the number of solutions in the search space. In the ABC algorithm, while the employed and onlooker bees control the exploitation process, the scouts perform the exploration process. Performing both processes together makes the algorithm strong.

3.2. Implementation of the ABC algorithm for estimation of the fuel cost curve parameters problem

In the ABC algorithm, a possible solution to the optimization problem is represented by the position of a food source and the fitness of the associated solution is described by the nectar amount of this food source. Here, how the ABC algorithm works and its implementation for estimation of the fuel cost curve parameters problem are explained step by step.

Step 1: Input data.

In this step, the actual values of the fuel cost function, generation limits for each unit, and coefficient limits are read.

Step 2: Initialization of the ABC algorithm parameters.

In this step, the parameters of the ABC algorithm, such as the colony dimension, maximum cycle number (MCN), number of variables, and limit parameter, are initialized.

Step 3: Initialization of the population with a random solution.

In this step, a set of food sources (initial population of S solutions $x_i(i = 1, 2, \ldots S)$) is generated randomly by the bees and their nectar amounts are determined, where S corresponds to size of the employed bees. Each solution x_i is represented by a D-dimensional vector, where D corresponds to the number of parameters to be optimized.

Step 4: Evaluation of the fitness.

In this step, evaluation of the fitness function of each food source position corresponding to the employed bee in the colony is done using the error given in Eq. (5).

Step 5: Modification of the food source position and local selection by the employed bee.

In this step, an employed bee modifies the food source position, finds a new position (solution) using her visual information belonging to that source in her memory, and tests the nectar amount of the new source. In the ABC algorithm, the new food source found by the employed bee is described as follows:

$$v_{ij} = x_{ij} + \delta_{ij}(x_{ij} - x_{kj}), \quad k \in (1, 2, ..S), j \in (1, 2, ...D), \tag{8}$$

where k and j are randomly chosen indices and δ is a random number in the interval of [–1,1]. In fact, δ_{ij} gives a comparison between 2 sources found, the new and the old. After v_{ij} is produced and its fitness is evaluated, the comparison is done by the employed bees. According to the comparison, if the fitness value of the new food source is better than that of the old one, the new food source is kept in the memory and the old one is discarded; otherwise, the new one is discarded from the memory and the old one is kept. This selection is called local searching or greedy selection process in the ABC algorithm. In this process, if the new food source is selected instead of the old one, a limit count is set.

Step 6: Employ the onlookers for the selected sources and evaluate the fitness.

After completion of the local search process in Step 5 by the employed bees, they come back into the hive and share the nectar amount information of the sources with the onlooker bees waiting at the dancing area. In fact, these onlooker bees were called employed bees before going to the food source that they visited. In this step, onlooker bees make a new food source choice according to the information they took from the employed bees and the nectar amount is calculated. This process of choosing a food source depends on the probability value P_i associated with the fitness of that food source and is formulated as follows:

$$P_i = \frac{fit_i}{\sum\limits_{j=1}^{S} fit_j}, \tag{9}$$

where fit_i is the fitness value of the ith solution and S is the total number of food sources.

Step 7: Modification of the food source position by the onlookers.

In this step, the onlookers modify the food source position to find a new position (solution) using the visual information belonging to that source in their memory and check the nectar amount of the new source, just as in the case of the employed bee in Step 5. The greedy selection process is done again for the onlookers in this step. That is, if the fitness value of the new food source is better than that of the old one, the new food source is kept in the memory and old one is discarded; otherwise, the new one is discarded from the memory and the old one is kept.

Step 8: Abandon the exploited food sources.

This step is done according to the 'limit' parameter, which is a predetermined number of cycles for releasing the food source. In the ABC algorithm, a solution is abandoned when that solution can not improve further for the determined limit value. In this step, when the nectar amount is abandoned in this way, one of the employer bees is determined randomly as a scout bee to find a new food source. This process is described as follows:

$$x_i^j = x_{\min}^j + \beta(x_{\max}^j - x_{\min}^j), \quad j \in (1, 2, ...D), \tag{10}$$

where β is a random value in the interval of [0,1], and x_{min}^j and x_{max}^j are the minimum and maximum limits of the parameter to be optimized.

Step 9: Keep the position achieved so far and increase the counter of the cycle.

Step 10: Stopping of the global searching process.

In the ABC algorithm, steps 5 through 10 are repeated until the criterion is met. Next, this global searching process stops. The criterion is a predetermined cycle number called the MCN. The flow chart of the ABC algorithm is shown in Figure 2 [25].

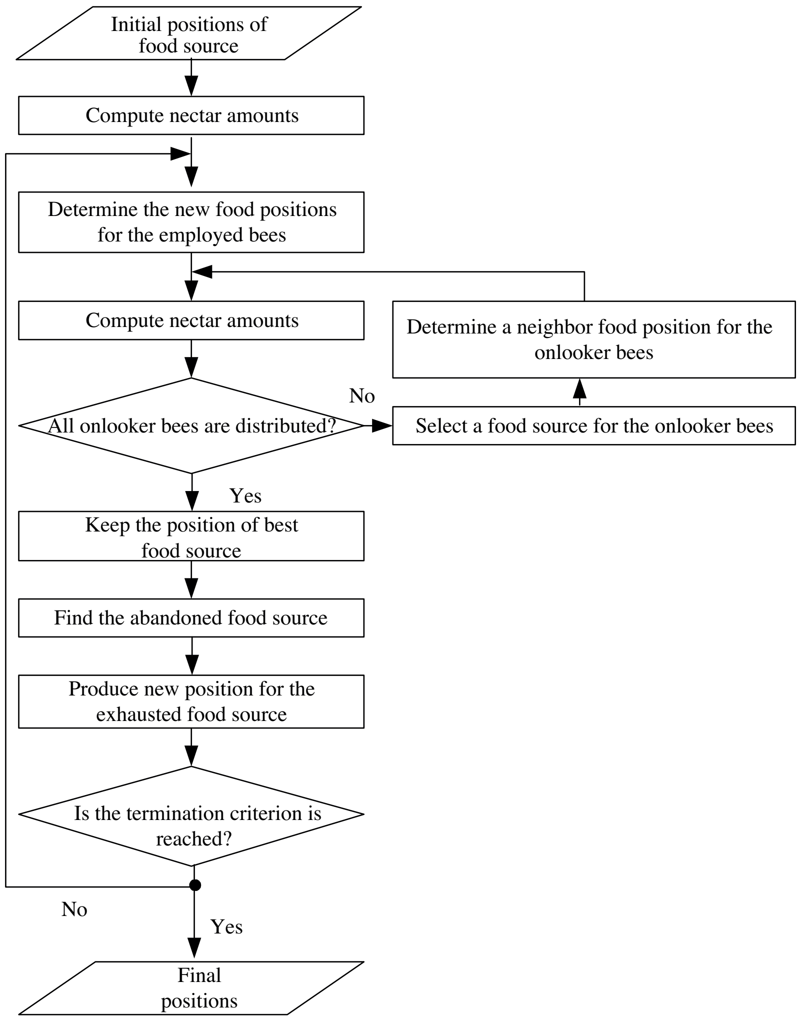

Figure 2. Flow chart of the ABC algorithm.

4. Experimental study and results

In this study, the steps of the algorithm explained above are implemented according to the flowchart given in Figure 2. The implementation of the algorithm and problem formulation is done using MATLAB. The algorithm is simulated on an Intel Core2 Duo processor with 2.2 GHz frequency and 2046 MB RAM. The parameters of the ABC algorithm for estimating the fuel cost parameter problem in this paper are described as shown in Table 1.

Table 1. Parameters of the ABC algorithm used in the simulation.

Values of the ABC algorithm	1st order	2nd order	3rd order
Colony dimension	20	20	20
MCN	400	400	400
Number of variables	2	3	4
Limit parameter	3000	3000	3000

In the experimental study, the ABC algorithm is applied to 5 test cases, which are described in Eqs. (2)–(4), to estimate the fuel cost parameters. The test cases and data were obtained from [7] and [21] in order to compare the results between those obtained from the ABC algorithm and those reported in [7] and [21]. The results obtained from the ABC algorithm are illustrated for each test case in Tables 2–11, comparing the results obtained from the GA reported in [21] and the PSO and LSE reported in [7].

Test case 1:

In this case, the linear fuel cost function described in Eq. (2) is used to estimate the parameters for 3 different thermal power plants with fuels such as coal, oil, and gas. Each power plant consists of 5 generating units with 10, 20, 30, 40, and 50 MW. In this test case, the results obtained from the proposed algorithm are compared to the PSO and LSE algorithms given in [7]. The estimated coefficients of the cost function (a_0 and a_1) with the ABC algorithm, PSO, and LSE are shown in Table 2, and the simulation results are shown in Table 3. In Table 3, the actual fuel cost data [7] for each unit; estimated fuel cost data obtained from the ABC algorithm, PSO [7], and LSE [7]; error values calculated from the difference between actual and estimated values; and total absolute error values for each algorithm are presented. As seen in Table 3, the ABC algorithm can reduce the total error by about 3.69 when compared with PSO and 6.32 when compared with the LSE for coal, by 4.52 when compared with PSO and 6.5 when compared with the LSE for oil, and by 4.37 when compared with PSO and 6.57 when compared with the LSE for gas, respectively. It is clearly seen according to these results that, for all of the fuel types, the estimated fuel cost values with the coefficients produced by the ABC algorithm are closer to the actual values.

Table 2. Estimated parameters of the linear cost function for test case 1.

Unit	Coefficients	Methods		
		ABC	PSO [7]	LSE [7]
1 (coal)	a_0	45.2120	63.236	63.236
	a_1	10.5600	10.190	10.170
2 (oil)	a_0	47.6520	66.001	66.160
	a_1	11.0310	10.570	10.631
3 (gas)	a_0	48.3990	66.002	66.700
	a_1	11.2210	10.780	10.830

Table 3. Simulation results for case study 1 (first-order model).

Unit	P (MW)	F_{actual} (GJ/h)	$F_{estimated}$ (GJ/h)			Error ($F_{estimated} - F_{actual}$)		
			Methods					
			ABC	PSO [7]	LSE [7]	ABC	PSO [7]	LSE [7]
1 (coal)	10	176.62	150.8120	161.905	164.936	25.8080	14.715	11.684
	20	256.40	256.4120	263.803	266.636	0.0120	7.403	10.236
	30	361.50	362.0120	365.702	368.336	0.5120	4.202	6.836
	40	467.60	467.6120	467.600	470.036	0.0120	0.000	2.436
	50	579.50	573.2120	569.498	571.736	6.2880	10.002	7.764
$\|\Sigma_{Error}\|$						32.6320	36.322	38.956
2 (oil)	10	184.75	157.9620	171.701	172.470	26.7880	13.049	12.280
	20	268.20	268.2720	277.400	278.780	0.0720	9.200	10.580
	30	377.70	378.5820	383.100	385.090	0.8820	5.400	7.390
	40	488.80	488.8920	488.800	491.400	0.0920	0.000	2.600
	50	606.00	599.2020	594.499	597.710	6.7980	11.501	8.290
$\|\Sigma_{Error}\|$						34.6320	39.151	41.140
3 (gas)	10	187.20	160.6090	173.802	175.000	26.5910	13.398	12.200
	20	272.80	272.8190	281.601	283.300	0.0190	8.801	10.500
	30	384.30	385.0290	389.401	391.600	0.7290	5.101	7.300
	40	497.20	497.2390	497.200	499.900	0.0390	0.000	2.700
	50	616.50	609.4490	604.999	608.200	7.0510	11.501	8.300
$\|\Sigma_{Error}\|$						34.4290	38.801	41.000

Test case 2:

In this test case, the power plant consists of 1 unit with 8 generators and the linear fuel cost function described in Eq. (2) is used to estimate the parameters for this power plant. In order to estimate the a_0 and a_1 parameters, the test data given in [21] were used. The estimated parameters produced by the ABC algorithm and GA [21] are given in Table 4. In Table 5, the actual fuel cost data [21] for each unit, estimated fuel cost data obtained from the ABC algorithm and GA [21], and percentage error values in the estimation process are presented. As seen in Table 5, the percentage errors produced by both algorithms for all of the generating units except for the unit with 165 MW are under 1%. However, the error values produced by the ABC algorithm are less than those of the GA for all generating units, except for the units with 150 and 165 MW. In addition, the percentage error values produced by the ABC algorithm reach 0 for 2 units, those with 75 MW and 120 MW. It is clearly seen according to these results that the resultant error is more acceptable than that of the GA. Thus, the linear fuel cost function approximates closer to the actual curve using the parameters produced by the ABC algorithm.

Table 4. Estimated parameters of the linear cost function for test case 2.

Coefficients	Methods	
	ABC	GA [21]
a_0	0.09734	0.087973
a_1	0.00896	0.0090778

Test case 3:

The quadratic fuel cost function described in Eq. (3) is used to estimate its parameters in this case for the same thermal power plants in test case 1. In this test case, the results obtained from the proposed algorithm are compared to those of the GA given in [21] and the PSO and LSE algorithms given in [7]. The estimated coefficients of the cost function (a_0, a_1, and a_2) with the ABC algorithm, GA, PSO, and LSE are shown in Table 6 and the simulation results are shown in Table 7. In Table 6, the actual fuel cost data [7,21] for each unit; estimated fuel cost data obtained from the ABC algorithm, GA [21], PSO [7], and LSE [7]; error values calculated from the difference between the actual and estimated values; and total absolute error values for each algorithm are presented. As seen in Table 7, the total error produced by the ABC algorithm is less than that of GA by about 5.84, PSO by about 0.3, and LSE by about 4.4 for coal; GA by about 6.62, PSO by about 1.71, and LSE by about 4.33 for oil; and GA by about 9.96, PSO by about 2.97, and LSE by about 4.45 for gas, respectively. It is clearly seen according to these results that the ABC algorithm produces a better solution for reducing the total error values than the others for all fuel types for this case. Therefore, the quadratic fuel cost function approximates closer to the actual curve using the parameters produced by the ABC algorithm.

Table 5. Simulation results for test case 2 (first-order model).

Unit P (MW)	F_{actual} (MBtu/h)	$F_{estimated}$ (MBtu/h)		Percentage of the error (%)	
		Methods			
		ABC	GA [21]	ABC	GA [21]
60	0.637	0.63467	0.63264	0.365714	0.684164
75	0.769	0.76900	0.76881	0	0.024832
90	0.901	0.90334	0.90498	–0.259168	–0.44131
105	1.034	1.03767	1.04114	–0.354686	–0.69085
120	1.172	1.17200	1.17731	0	–0.45312
135	1.301	1.30633	1.31348	–0.409850	–0.95909
150	1.453	1.44066	1.44965	0.848968	0.230910
165	1.602	1.57500	1.58581	1.685590	1.010485

Table 6. Estimated parameters of the quadratic cost function for test case 3.

Unit	Coefficients	Methods			
		ABC	GA [21]	PSO [7]	LSE [7]
1 (coal)	a_0	96.6046	100.3937	96.279	95.856
	a_1	7.5874	6.9761	7.592	7.374
	a_2	0.0414	0.0533	0.042	0.047
2 (oil)	a_0	101.5360	107.1688	101.000	100.710
	a_1	7.8779	7.7235	7.800	7.670
	a_2	0.0442	0.0467	0.046	0.049
3 (gas)	a_0	101.8179	116.3854	102.000	101.100
	a_1	8.0991	6.7342	7.900	7.881
	a_2	0.0439	0.0667	0.048	0.049

Test case 4:

In this test case, the cubic fuel cost function described in Eq. (4) is used to estimate its parameters for the same thermal power plants in test cases 1 and 3. In this test case, the results obtained from the proposed algorithm are compared to the PSO and LSE algorithms given in [7]. The estimated coefficients of the cost function (a_0, a_1, a_2, and a_3) with the ABC algorithm are shown in Table 8 and the simulation results are shown in Table 9. In Table 9, the actual fuel cost data [7] for each unit; estimated fuel cost data obtained from the ABC algorithm, PSO [7], and LSE [7]; error values calculated from the difference between the actual and estimated values; and total absolute error values for each algorithm are presented. As seen in Table 9, the total error produced by the ABC algorithm is less than that of PSO by about 3.21 and the LSE by about 4.9 for coal, PSO by about 0.3 and the LSE by about 5.81 for oil, and PSO by about 0.02 and the LSE by about 4.37 for gas, respectively. It is clearly seen according to these results that the ABC algorithm can reduce the total absolute error values more than the others for all fuel types for this test case. In this case, the cubic fuel cost function with the parameter values produced by the ABC algorithm can be computed as closer to the actual cost curve.

Table 7. Simulation results for test case 3 (second-order model).

Unit	P (MW)	F_{actual} (GJ/h)	$F_{estimated}$ (GJ/h) Methods				Error ($F_{estimated}$ – F_{actual})			
			ABC	GA [21]	PSO [7]	LSE [7]	ABC	GA [21]	PSO [7]	LSE [7]
1 (coal)	10	176.620	176.619	175.485	176.358	174.252	–0.001	–1.135	–0.262	–2.368
	20	256.400	264.913	261.236	264.765	261.968	8.513	4.836	8.365	5.568
	30	361.500	361.487	357.647	361.500	359.004	–0.013	–3.853	0.000	–2.496
	40	467.600	466.341	464.718	466.562	465.360	–1.259	–2.882	–1.038	–2.240
	50	579.500	579.475	582.449	579.952	581.036	–0.025	2.949	0.452	1.536
$\lvert\Sigma_{Error}\rvert$							9.81	15.655	10.117	14.208
2 (oil)	10	184.75	184.735	184.295	183.6	182.346	–0.015	–0.455	–1.150	–2.404
	20	268.2	276.774	272.449	275.4	273.862	8.574	4.249	7.200	5.662
	30	377.7	377.653	373.089	376.4	375.258	–0.047	–4.611	–1.300	–2.442
	40	488.8	487.372	485.729	486.6	486.534	–1.428	–3.071	–2.200	–2.266
	50	606	605.931	610.369	606	607.69	–0.069	4.369	0.000	1.690
$\lvert\Sigma_{Error}\rvert$							10.133	16.755	11.850	14.464
3 (gas)	10	187.2	187.799	188.648	185.78	184.824	0.599	1.448	–1.420	–2.376
	20	272.8	281.36	277.749	279.121	278.368	8.560	4.949	6.321	5.568
	30	384.3	384.301	378.441	382.022	381.732	0.001	–5.859	–2.278	–2.568
	40	497.2	496.022	492.473	494.484	494.916	–1.178	–4.727	–2.716	–2.284
	50	616.5	616.523	619.845	616.507	617.92	0.023	3.345	0.007	1.420
$\lvert\Sigma_{Error}\rvert$							10.361	20.328	12.742	14.216

In Figure 3, a variation of the total error according to the cycle number for this case is illustrated in order to show a sample of the convergence characteristic of the proposed algorithm. This graphic shows a good convergence; the proposed method arrives at the desired solution within the first 250 iterations.

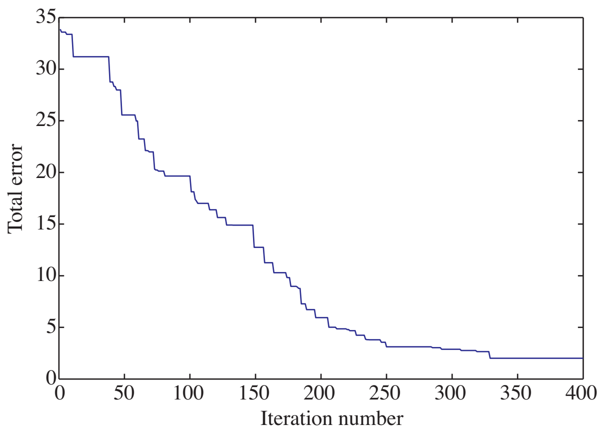

Figure 3. Convergence characteristic of the ABC algorithm for test case 4.

Table 8. Estimated parameters of the cubic fuel cost function for test case 4.

Unit	Coefficients	Methods		
		ABC	PSO [7]	LSE [7]
1 (coal)	a_0	124.5362	120.241	123.180
	a_1	3.4859	3.979	3.535
	a_2	0.1872	0.184	0.193
	a_3	–0.0015	−0.002	−0.002
2 (oil)	a_0	129.2351	130.278	128.640
	a_1	3.4859	3.542	3.746
	a_2	0.1872	0.200	0.199
	a_3	–0.0015	−0.002	−0.002
3 (gas)	a_0	126.0143	128.376	128.400
	a_1	3.8044	4.146	4.046
	a_2	0.1896	0.188	0.195
	a_3	–0.0015	−0.002	−0.002

Table 9. Simulation results for test case 4 (third-order model).

Unit	P (MW)	F_{actual} (GJ/h)	$F_{estimated}$ (GJ/h)			Error ($F_{estimated}$ – F_{actual})		
			Methods					
			ABC	PSO [7]	LSE [7]	ABC	PSO [7]	LSE [7]
1 (coal)	10	176.62	176.6152	176.806	176.227	0.0048	0.186	0.393
	20	256.40	257.1342	260.557	258.274	0.7342	4.157	1.874
	30	361.50	357.0932	361.951	359.721	4.4068	0.451	1.779
	40	467.60	467.4922	471.446	470.968	0.1078	3.846	3.368
	50	579.50	579.3312	579.500	582.415	0.1688	0.000	2.915
$\lvert\Sigma_{Error}\rvert$						5.4224	8.641	10.329
2 (oil)	10	184.75	184.7391	184.076	184.301	0.0109	0.674	0.449
	20	268.20	269.1631	268.200	269.562	0.9631	0.000	1.362
	30	377.70	373.5071	373.010	374.223	4.1929	4.690	3.477
	40	488.80	488.7711	488.863	488.084	0.0289	0.063	0.716
	50	606.00	605.9551	606.119	600.945	0.0449	0.119	5.055
$\lvert\Sigma_{Error}\rvert$						5.2407	5.547	11.059
3 (gas)	10	187.20	187.1883	187.101	186.804	0.0167	0.099	0.396
	20	272.80	274.6323	274.326	274.688	1.8323	1.526	1.888
	30	384.30	380.5613	381.000	382.452	3.7387	3.300	1.848
	40	497.20	497.1703	498.074	500.496	0.0297	0.874	3.296
	50	616.50	616.6593	616.500	619.220	0.1593	0.000	2.720
$\lvert\Sigma_{Error}\rvert$						5.7767	5.799	10.148

Test case 5:

In this test case, the cubic fuel cost function described in Eq. (4) is used to estimate its parameters for the same thermal power plants in test case 2 and the same data are used for the estimation of its a_0, a_1, a_2, and a_3 parameters. The estimated parameters produced by the ABC algorithm and GA [21] are given in Table 10. In Table 11, the actual fuel cost data [21] for each unit, estimated fuel cost data obtained from the ABC algorithm and GA [21], and percentage error values in the estimation process are presented. As seen in Table 11, for each unit, the maximum percentage error values produced by the ABC algorithm are less than those of the GA. The percentage errors produced by the ABC algorithm for the generating units with 75, 90, 105, 120, 150, and 165 MW are under 1%. Against this, the errors produced by the GA for the generating units with 105, 120, 150, and 165 MW are under the same error level. Moreover, while the error values produced by the ABC algorithm for 90, 105, and 120 MW are very close to 0, there is no error value close to 0 for the GA. These results demonstrate that the error values in the estimation of the cubic fuel cost function using the ABC algorithm are at more acceptable levels when compared with those of the GA. Therefore, the cubic fuel cost function approximates closer to the actual curve using the parameters produced by the ABC algorithm.

Table 10. Estimated parameters of the cubic fuel cost function for test case 5.

Coefficients	Methods	
	ABC	GA [21]
a_0	0.1824	0.1181
a_1	0.0074	0.008031
a_2	0.000005	0.0000063
a_3	0.000000016861239	0

Table 11. Simulation results for test case 5 (third-order model).

Unit P (MW)	F_{actual} (MBtu/h)	$F_{estimated}$ (MBtu/h)		Percentage of the error (%)	
		Methods			
		ABC	GA [21]	ABC	GA [21]
60	0.637	0.64811	0.62264	–1.74480	2.25432
75	0.769	0.77272	0.75586	–0.48325	1.70839
90	0.901	0.90128	0.89192	–0.03054	1.00777
105	1.034	1.03413	1.03081	–0.01285	0.30827
120	1.172	1.17163	1.17254	0.03152	−0.04608
135	1.301	1.31411	1.31710	–1.00767	−1.23770
150	1.453	1.46191	1.46450	–0.61335	−0.79147
165	1.602	1.61538	1.61473	–0.83512	−0.79479

5. Conclusion

In this paper, the ABC algorithm was applied to search for the optimal I/O curve parameters of thermal power plants. The behavior of the proposed algorithm under 3 different test cases for 3 different power plants with fuels such as coal, oil, and gas was also evaluated. The performance of the ABC algorithm was compared with the GA, PSO, and LSE methods. The results showed that the ABC algorithm is more robust and produces a lower error between the actual end estimated parameters compared to the others for all test cases. It is obvious that the ABC algorithm is a useful and powerful algorithm for solving such a problem.

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