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GWO-based estimation of input-output parameters of thermal power plants

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ABSTRACT

The fuel cost curve of thermal generators was very important in the calculation of economic dispatch and optimal power flow. Temperature and aging could make changes to fuel cost curve so curve estimation need to be done periodically. The accuracy of the curve parameters estimation strongly affected the calculation of the dispatch. This paper aims to estimate the fuel cost curve parameters by using the grey wolf optimizer method. The problem of curve parameter estimation was made as an optimization problem. The objective function to be minimized was the total number of absolute error or the difference between the actual value and the estimated value of the fuel cost function. The estimated values of parameter that produce the smallest total absolute error were the values of final solution. The simulation results showed that parameter estimation using gray wolf optimizer method further minimized the value of objective function. By using three models of fuel cost curve and given test data, parameter estimation using grey wolf optimizer method produced the better estimation results than those estimation results obtained using least square error, particle swarm optimization, genetic algorithm, artificial bee colony and cuckoo search methods.

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1. INTRODUCTION

The planning and operation of the power system requires an economic dispatch review. One important factor in solving economic dispatch problems is the fuel cost curve of thermal generators. The fuel cost curve function or the heat characteristic curve expresses the input-output relationship of a thermal generator. This fuel cost function is influenced by the temperature and aging of the generator units and affects the shape of fuel cost curve, so the estimating the fuel cost curve needs to be evaluated periodically [1].

An accurate estimation of thermal unit input-output curve coefficients is important for solving economic dispatch or optimal power flow problems. The accuracy of the estimated coefficients affects the final accuracy of the dispatch process. Fuel cost functions can be represented by mathematical models. Several mathematical models have been made, but in general, there are two main models for representing fuel costs function, i.e. smooth model and non-smooth model.

Several methods have been proposed and implemented to solve estimation problems in power systems including estimation of fuel cost curve of thermal generator. Some of these techniques are based on static estimation and dynamic estimation technique. Several static estimation techniques, such as least square error (LSE), Gauss-Newton, Bard algorithm, Marquardt algorithm dan Powell regression [2], linear regression [3] and linear sequential regression technique [4], least absolute value [5], and Gram-Schmidt orthonormalization [6] have been proposed and implemented in estimating the fuel cost curve parameters. Most of these estimation techniques can improve computational efficiency and numerical stability, but the resulting errors are still large and reduce the accuracy of the estimation process. Kalman filter is one of the dynamic estimation techniques which have the advantage of being able to update the fuel cost curve parameter estimation using new measurement data. The disadvantage of this technique, as well as other dynamic filters, is that it requires large data to achieve a better solution [7-9].

Meta-heuristic optimization methods have become popular to solve many optimization problems in many fields of study. Evolutionary algorithm-based metaheuristic methods such as artificial neural networks (ANN), genetic algorithm (GA) and Differential evolution (DE) can solve optimization problems with non mathematical model function and many non-smooth optimization problems with non-convex and discontinues function. One of the drawbacks using ANN-based methods is the huge amount of data required for network training, which may not be available in some cases [10]. The GA method has been used to estimate parameters of a smooth and non-smooth fuel cost curve but the resulting estimation error still large [11]. The more accurate results of parameter estimation with smooth and non-smooth fuel cost curves have been proposed and implemented using the DE method [12] and improved DE method [13].

Metaheuristic methods based on swarm intelligence such as particle swarm optimization (PSO), artificial bee colony (ABC), and cuckoo search (CS) are more robust and eases of use also can solve optimization problem with many types of objective function with small data. All of these methods had been already used to succesfully solve many optimization problems in power systems [14-16]. In estimating the parameters of the fuel cost curve, the ABC method [17] is more accurate than the PSO method [18, 19] and the CS method [20], with a smaller estimation error. Grey wolf optimizer (GWO) is one of metaheuristic optimization methods based on the prey hunting mechanism of a group of grey wolf. The various optimization problems in power systems have been solved by the GWO method and provided better results than those results obtained using some other optimization methods [21-23].

The main objective of this paper is introducing a new method based on grey wolf optimizer for estimating input-output parameters of thermal generator unit. GWO is relatively new method based on swarm intelligence and already have better final solution compared to PSO. In this paper, estimation of input-output parameters of fuel cost curve is formulated as an optimization problem. The main goal of this works is to minimize total absolute error of estimated fuel cost function. GWO is used to find the parameters of fuel cost curve and different study cases are presented to validate the proposed approach.

This paper is organized as follows: section 2 is general overview of grey wolf optimizer. Section 3 is research method, which consist of modeling the fuel cost curve and estimating input-output parameter of fuel cost curve. Section 4 is results and analysis, which consist of simulation results of estimating parameters using GWO for each case with three thermal generators with different fuel types.

2. GREY WOLF OPTIMIZER (GWO)

Grey-Wolf Optimizer (GWO) is a relatively new metaheuristic algorithm that first introduced by S. Mirjalili et al. [24]. GWO mimics the leadership hierarchy and hunting mechanism of grey wolves in nature. Using the hierarchy of wolves, GWO implements three main steps of hunting, i.e. searching, encircling and attacking prey. There are four types of wolfs, i.e. alpha, beta, delta and omega for simulating the hierarchy of leadership. This hierarchy influences the final solution in hunting prey and in this algorithm, alpha is considered to be a best solution, followed by beta, delta and omega.

Encircling prey process can be described in equation as follows:

$$\vec{D} = \left|\vec{C} \cdot \vec{X}_p(t) - \vec{X}(t)\right| \tag{1}$$

$$\vec{X}(t+1) = \vec{X}_p(t) - \vec{A} \cdot \vec{D} \tag{2}$$

where t is current iteration, $\vec{X}$ is position vector of grey wolf, $\vec{X}_p$ is position vector of prey and $\vec{A}$ and $\vec{C}$ are coefficients vector that calculated by following equations:

$$\vec{A} = 2\vec{a} \cdot \vec{r}_1 - \vec{a} \tag{3}$$

$$\vec{C} = 2 \cdot \vec{r}_2 \tag{4}$$

where $\vec{r}_1$ and $\vec{r}_2$ are random vectors between 0 and 1 and $\vec{a}$ is set decrease linearly from 2 to 0 during iteration process. During hunting process, three best solutions obtained so far are saved and the other search agents (including omega) update their positions according to position of the best search agents. The score and position of three search agents (i.e. alpha, beta, and delta) is updated using in (5-7), respectively:

$$\vec{D}_\alpha = \left|\vec{C}_1 \cdot \vec{X}_\alpha - \vec{X}\right| \quad (5)$$

$$\vec{D}_\beta = \left|\vec{C}_2 \cdot \vec{X}_\beta - \vec{X}\right| \quad (6)$$

$$\vec{D}_\delta = \left|\vec{C}_3 \cdot \vec{X}_\delta - \vec{X}\right| \quad (7)$$

The position vector of prey with respect to alpha, beta and delta wolves is calculated using in (8-10), respectively. The best position of prey in the next iteration is calculated by taking average values of prey position with respect to alpha, beta and delta wolves as written in (11).

$$\vec{X}_1 = \vec{X}_\alpha - \vec{A}_1 \cdot \vec{X}_\alpha \quad (8)$$

$$\vec{X}_2 = \vec{X}_\beta - \vec{A}_2 \cdot \vec{X}_\beta \quad (9)$$

$$\vec{X}_3 = \vec{X}_\delta - \vec{A}_3 \cdot \vec{X}_\delta \quad (10)$$

$$\vec{X}(t+1) = \frac{\vec{X}_1+\vec{X}_2+\vec{X}_3}{3} \quad (11)$$

The ability of searching and attacking prey of grey wolfs represent the ability of exploration and exploitation of this algorithm. These all are identified by values of A, where A<1 is attacking and A>1 is searching.

3. RESEARCH METHOD

3.1. Modeling of the fuel cost curve

The fuel cost curve of thermal generator can be expressed as an input-output relationship, which is between the total cost per hour or the total amount of energy used per hour and output of active power. In this study, the fuel cost curve is considered to be a smooth curve model. The fuel cost curve for the thermal generator unit *n* as a function of output active power can be modeled by a polynomial function which expressed in the following form:

$$F_n(P_n) = a_{0n} + \sum_{m=1}^{L} a_{mn} P_n^m + r_n n \quad n = 1,2,\ldots,N \quad (12)$$

where F_n is the fuel cost function of nth generator, P_n is active power generated by the nth thermal generator, a_{on} and a_{mn} are the nth generator curve coefficients, r_n is error associated with the nth equation, N is number of thermal generators, and L is equation order.

In this study, there are three models for representing fuel cost function:

Model 1. First order polynomial model or linear model.

In this case, (12) will be in the form:

$$F_n(P_n) = a_{0n} + a_{1n}P_n + r_n \quad (13)$$

Model 2. Second order polynomial model or quadratic model.

In this case, in (12) will be in the form:

$$F_n(P_n) = a_{0n} + a_{1n}P_n + a_{2n}P_n^2 + r_n \quad (14)$$

Model 3. Third order polynomial model or cubic model:

In this case, in (12) will be in the form:

$$F_n(P_n) = a_{0n} + a_{1n}P_n + a_{2n}P_n^2 + a_{3n}P_n^3 + r_n \quad (15)$$

All three-models are considered as a discrete system and in state space form can be written as:

$$Z_n = f_n(P_n, X_n) + R_n \tag{16}$$

where Z_n is a fuel cost vector for the nth generator, X_n are parameter vector to be estimated (a_0, a_1, a_2, a_3) for nth generator, R_n is error vector associated with Z_n. Then, associated error with each measurement can be calculated as:

$$r_n = F_{n(actual)} - F_{n(estimated)} \tag{17}$$

The problem is formulated as to find an estimate for parameter vector X that minimize error vector R.

3.2. Estimation of fuel cost curve parameter using grey wolf optimizer (GWO)

Estimation of input-output parameters of fuel cost curve using GWO is performed as an optimization problem. The objective function to be minimized is sum of absolute error between actual cost and estimated cost. The objective function of nth generator is the sum of absolute error of (17) and can be written as:

$$F_{obj,n} = \sum_{k=1}^{M} \left| F_{k,n(actual)} - F_{k,n(estimated)} \right| \tag{18}$$

where k is vector of input data which consists of energy used in GJ/h and its corresponding active power output in MW, and M is number of total data.

Number of search dimension depends on curve model. For linear model, the search dimension is 2, for quadratic model, the search dimension is 3 and for cubic model, the search dimension is 4. Position of each search agent is evaluated each iteration to find the value of objective function and the estimated value of fuel cost. Three best values of fitness are saved as score value, i.e. alpha score, beta score and delta score. Position of each search agent is then updated in next iteration. These procedures are performed until the maximum iteration is reached. The best solution and best position obtained at maximum iteration is considered to be the final solution.

The algorithm for finding estimated values of fuel cost curve parameters using GWO is explained step by step as follows:

- Initialize the number of each search agent, the maximum number of iterations, and the upper and lower limit of the search for parameters. Scores and initial positions of each search agent, alpha, beta and delta are set to infinity for this minimization problem.
- Set the number of search dimensions according to the cost curve model and the initial iteration.
- Calculate the estimated cost value, $F_{estimated}$, for each search agent.
- Calculate the total absolute error for each search agent according to (18).
- If the absolute error is smaller than the previous value, then the score and positions of each search agent are stored. If the absolute error is greater than the previous value, then the score and positions of each search agent are deleted.
- Continue steps 3, 4 and 5 for the next search agent until the number of search agents is reached.
- Update the position of each search agent according to (8-11).
- Continue step 3 to 7 for the next iteration.
- If the iteration has reached the maximum iteration, the procedure is stopped. Print the results of alpha scores and alpha position X_α.

This procedure is repeated for other generators and other fuel cost curve models. The algorithm described above is illustrated by the flow chart as shown in Figure 1.

4. RESULTS AND ANALYSIS

The algorithm is described above and illustrated by the flowchart in Figure 1 is implemented using MATLAB. Simulation using GWO is performed using practical data from [2]. These data are used to estimate parameters of three model of fuel cost curve. For each case, simulation is performed for 1000 iterations with the lower bound and upper bound values of each parameter are set between -200 and 200. Number of search agents used in this simulation is 20. Simulation is performed by different trials and 50 best trials are saved for each case. The results obtained for each case are then compared to the results obtained using other methods.

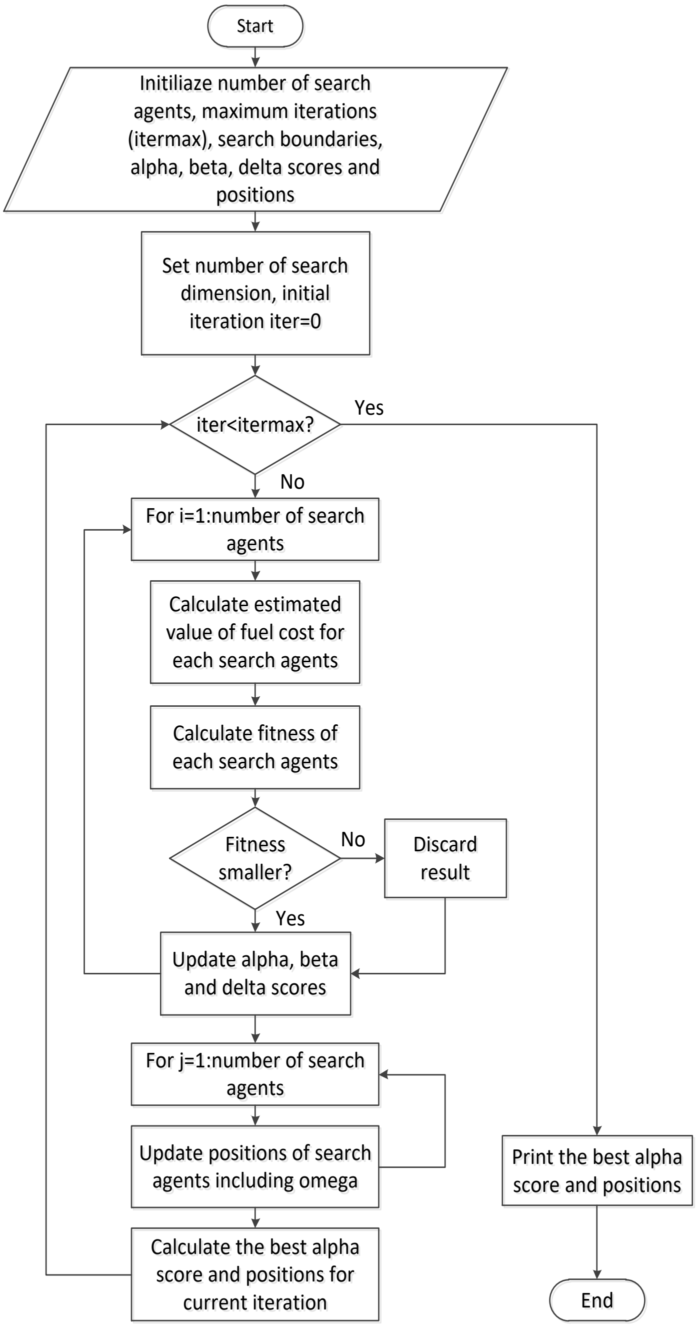

Figure 1. Flow chart of the GWO algorithm

4.1. Case study 1

In this case, linear model of fuel cost function described in (13) is used for estimating two parameter coefficients (a_0 and a_1) of thermal generator cost curve. The estimation results using GWO are compared to the results obtained using the LSE, PSO, ABC and CS methods. The estimated coefficient value, the estimated generator cost function values and the estimated error values using the GWO and the estimation results using LSE, PSO, ABC and CS are shown in Table 1, Table 2 and Table 3, respectively. As seen from Table 3, estimation of fuel cost curve parameter using GWO can more minimize total absolute error values compared to those results obtained using four other methods. The GWO method achieves convergence to the minimum value of the objective function for more than 200 iterations in the case of generator unit 1, as shown in Figure 2.

Table 1. Estimated parameters for case study 1 (linear model)

Unit	Coefficients	Methods				
		LSE	PSO	ABC	CS	GWO
1 (Coal)	a_0	63.236	63.236	45.2120	43.566	45.2008
	a_1	10.170	10.190	10.5600	10.597	10.5600
2 (Oil)	a_0	66.160	66.001	47.6520	62.559	47.6006
	a_1	10.631	10.570	11.0310	10.655	11.0300
3 (Gas)	a_0	66.700	66.002	48.3990	62.889	48.4004
	a_1	10.830	10.780	11.2210	10.860	11.2200

Table 2. Estimated fuel cost function for case study 1 (linear model)

Unit	P (MW)	F_{actual} (GJ/h)	$F_{estimated}$ (GJ/h)				
			LSE	PSO	ABC	CS	GWO
	10	176.62	164.936	161.905	150.812	149.532	150.800
	20	256.40	266.636	263.803	256.412	255.498	256.400
1 (coal)	30	361.50	368.338	365.702	362.012	361.464	361.999
	40	467.60	470.036	467.600	467.612	467.430	467.599
	50	579.50	571.736	569.498	573.212	573.396	573.199
	10	184.75	172.470	171.701	157.962	169.109	157.900
	20	268.20	278.780	277.400	268.272	275.659	268.200
2 (oil)	30	377.70	385.090	383.100	378.582	382.209	378.500
	40	488.80	491.400	488.800	488.892	488.759	488.800
	50	606.00	597.710	594.499	599.202	595.309	599.101
	10	187.20	175.000	173.802	160.609	171.498	160.600
	20	272.80	283.300	281.601	272.819	280.097	272.800
3 (gas)	30	384.30	391.600	389.401	385.029	388.696	385.000
	40	497.20	499.900	497.200	497.239	497.295	497.200
	50	616.50	608.200	604.999	609.499	605.894	609.400

Table 3. Estimated error for case study 1 (linear model)

Unit	P (MW)	F_{actual} (GJ/h)	Error = $\lvert F_{ectual} - F_{estimated} \rvert$				
			LSE	PSO	ABC	CS	GWO
	10	176.62	11.684	14.715	25.808	27.088	25.820
	20	256.40	10.236	7.403	0.012	0.902	0.000
1 coal)	30	361.50	6.836	4.202	0.512	0.036	0.500
	40	467.60	2.436	0.000	0.012	0.170	0.001
	50	579.50	7.764	10.002	6.288	6.104	6.301
Σ error			38.956	36.322	32.632	34.301	32.622
	10	184.75	12.280	13.049	26.788	15.641	26.850
	20	268.20	10.580	9.200	0.072	7.459	0.000
2 (oil)	30	377.70	7.390	5.400	0.882	4.509	0.800
	40	488.80	2.600	0.000	0.092	0.041	0.000
	50	606.00	8.290	11.501	6.798	10.691	6.900
Σ error			41.140	39.151	34.632	38.341	34.550
	10	187.20	12.200	13.398	26.591	15.702	26.600
	20	272.80	10.500	8.801	0.019	7.297	0.000
3 (gas)	30	384.30	7.300	5.101	0.729	4.396	0.700
	40	497.20	2.700	0.000	0.039	0.095	0.000
	50	616.50	8.300	11.501	7.051	10.606	7.100
Σ error			41.000	38.801	34.429	38.096	34.400

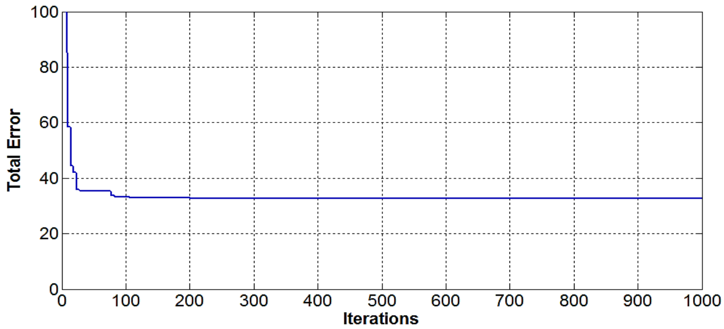

Figure 2. Convergence characteristic for case study 1 (linear model) of generator unit 1

4.2. Case study 2

In this case, three parameters coefficients (a_0, a_1 and a_2) of fuel cost function with quadratic model as described in (14) are estimated. The same thermal power plants data in case study 1 are used in this case. The results obtained using GWO are compared to the results obtained using LSE, PSO, ABC, CS, GA and DE methods. The estimated parameter coefficients using GWO and the other methods are shown in Table 4. The estimated value of fuel cost function and the total absolute error between actual value and estimated value of fuel cost function obtained from each method are shown in Table 5 and Table 6, respectively. As seen in Table 6, the total absolute errors obtained using GWO are smaller than those results obtained using the PSO, LSE, GA, ABC and CS methods, but still slightly larger than the total absolute errors obtained using the DE method. It is clear that the GWO method produces a better solution than the solution obtained using the LSE, PSO, GA, ABC and CS methods, although it is still less accurate than the solution obtained using the DE method. In this case, for generator unit 1, GWO method requires more than 900 iterations to achieve convergence to the best minimum value of the objective function as shown in Figure 3.

Table 4. Estimated parameters for case study 2 (quadratic model)

Unit	Coefficients	Methods						
		LSE	PSO	GA	ABC	CS	DE	GWO
1 (Coal)	a_0	95.856	96.279	100.3937	96.6046	96.540	96.6000	96.5936
	a_1	7.374	7.592	6.9761	7.5874	7.575	7.5880	7.5879
	a_2	0.047	0.042	0.0533	0.0414	0.042	0.0414	0.0414
2 (Oil)	a_0	100.710	101.000	107.1688	101.5360	100.887	101.53125	101.5306
	a_1	7.670	7.800	7.7235	7.8779	7.890	7.8800	7.8800
	a_2	0.049	0.046	0.0467	0.0442	0.045	0.044188	0.0442
3 (Gas)	a_0	101.100	102.00	116.3854	101.8179	99.239	101.8125	101.8110
	a_1	7.881	7.900	6.7342	8.0991	8.138	8.1000	8.1002
	a_2	0.049	0.048	0.0667	0.0439	0.045	0.043875	0.0439

Table 5. Estimated fuel cost function for case study 2 (quadratic model)

Unit	P (MW)	F_{actual} (GJ/h)	$F_{estimated}$ (GJ/h)						
			LSE	GA	PSO	ABC	CS	DE	GWO
1 coal)	10	176.62	174.252	175.485	176.358	176.619	176.480	N/A	176.613
	20	256.40	261.968	261.236	264.765	264.913	264.800	N/A	264.914
	30	361.50	359.004	357.647	361.500	361.487	361.500	N/A	361.497
	40	467.60	465.360	464.718	466.562	466.341	466.580	N/A	466.360
	50	579.50	581.036	582.449	579.952	579.475	580.040	N/A	579.504
2 (oil)	10	184.75	182.346	184.295	183.600	184.735	184.248	N/A	184.750
	20	268.20	273.862	272.449	275.400	276.774	276.525	N/A	276.806
	30	377.70	375.258	373.089	376.400	377.653	377.718	N/A	377.700
	40	488.80	486.534	485.729	486.600	487.372	487.827	N/A	487.431
	50	606.00	607.690	610.369	606.000	605.931	606.851	N/A	606.000
3 (gas)	10	187.20	184.824	188.648	185.780	187.799	185.145	N/A	185.780
	20	272.80	278.368	277.749	279.121	281.360	280.111	N/A	279.121
	30	384.30	381.732	378.441	382.022	384.301	384.137	N/A	382.022
	40	497.20	494.916	492.473	494.484	496.022	497.223	N/A	494.484
	50	616.50	617.920	619.845	616.507	616.523	619.369	N/A	616.507

Table 6. Estimated error for case study 2 (quadratic model)

Unit	P (MW)	F_{actual} (GJ/h)	Error = $\lvert F_{ectual} - F_{estimated} \rvert$						
			LSE	GA	PSO	ABC	CS	DE	GWO
1 coal)	10	176.62	2.368	1.135	0.262	0.001	0.140	0.000	0.067
	20	256.40	5.568	4.836	8.365	8.513	8.400	8.5200	8.514
	30	361.50	2.496	3.853	0.000	0.013	0.000	0.000	0.004
	40	467.60	2.240	2.882	1.038	1.259	1.020	1.240	1.240
	50	579.50	1.536	2.949	0.452	0.025	0.540	0.000	0.004
Σ error			14.208	15.655	10.117	9.810	10.100	9.760	9.769
2 (oil)	10	184.75	2.404	0.455	1.150	0.015	0.502	0.000	0.000
	20	268.20	5.662	4.249	7.200	8.574	8.325	8.606	8.606
	30	377.70	2.442	4.611	1.300	0.047	0.018	0.000	0.000
	40	488.80	2.266	3.071	2.200	1.428	0.973	1.368	1.369
	50	606.00	1.690	4.369	0.000	0.069	0.851	0.001	0.000
Σ error			14.464	16.755	11.850	10.133	10.669	9.975	9.975
3 (gas)	10	187.20	2.376	1.448	1.420	0.599	2.055	0.000	0.000
	20	272.80	5.568	4.949	6.321	8.560	7.311	8.563	8.562
	30	384.30	2.568	5.859	2.278	0.001	0.163	0.000	0.001
	40	497.20	2.284	4.727	2.716	1.178	0.023	1.187	1.188
	50	616.50	1.420	3.345	0.007	0.023	2.869	0.000	0.000
Σ error			14.216	20.328	12.741	10.361	12.421	9.750	9.751

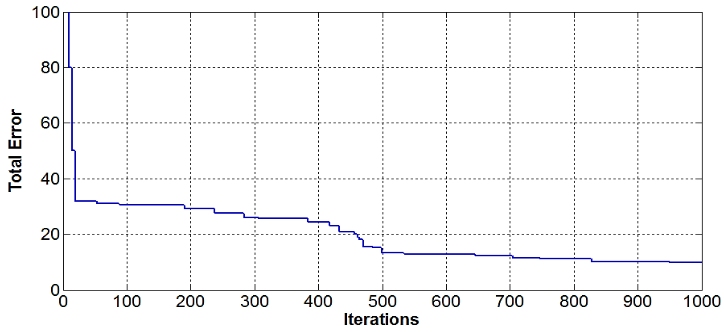

Figure 3. Convergence characteristic for case study 2 (quadratic model) of generator unit 1

4.3. Case study 3

In this case, four parameters (a_0, a_1, a_2 and a_3) of fuel cost function using cubic model as described in (15) are estimated. The thermal generator data used in this case are the same as the data used in case study 1 and case study 2. The results obtained using GWO are compared to the results obtained using LSE, PSO, ABC, and DE methods. The results of estimated parameter of fuel cost curves obtained by using GWO method and the LSE, PSO, ABC, DE methods are shown in Table 7.

Table 7. Estimated parameters for case study 3 (cubic model)

Unit	Coefficients	Methods				
		LSE	PSO	ABC	DE	GWO
1 (Coal)	a_0	123.180	120.241	124.5362	127.0667	127.3003
	a_1	3.535	3.939.	3.4859	3.1187	3.0794
	a_2	0.193	0.184	0.1872	0.1999	0.2021
	a_3	-0.002	-0.002	-0.0015	-0.0016	-0.0017
2 (Oil)	a_0	128.640	130.278	129.2351	132.5000	132.7809
	a_1	3.746	3.542	3.4859	3.3325	3.2672
	a_2	0.199	0.200	0.1872	0.2059	0.2094
	a_3	-0.002	-0.002	-0.0015	-0.00166	-0.0017
3 (Gas)	a_0	128.400	128.376	126.0143	132.3333	131.0319
	a_1	4.046	4.146	3.8044	3.6250	3.8076
	a_2	0.195	0.188	0.1896	0.2024	0.1962
	a_3	-0.002	-0.002	-0.0015	-0.0016	-0.0016

The estimation results of fuel cost functions, absolute errors and total absolute errors either using the GWO method or using the LSE, PSO, ABC and DE methods are shown in Table 8 and Table 9, respectively. As seen from Table 9, estimating parameter using the GWO can produce total absolute errors smaller than those obtained using the LSE, PSO, and ABC methods. But the total number of absolute errors obtained using GWO method is still greater than the results obtained using the DE method.

Table 8. Estimated fuel cost function for case study 3 (cubic model)

Unit	P (MW)	F_{actual} (GJ/h)	$F_{estimated}$ (GJ/h)				
			LSE	PSO	ABC	DE	GWO
1 (coal)	10	176.62	174.227	176.806	176.615	N/A	176.648
	20	256.40	258.274	260.557	257.134	N/A	256.478
	30	361.50	359.721	361.951	357.093	N/A	356.854
	40	467.60	470.968	471.446	467.492	N/A	467.840
	50	579.50	582.415	579.500	579.331	N/A	579.500
2 (oil)	10	184.75	184.301	184.076	184.739	N/A	184.686
	20	268.20	269.562	268.200	269.163	N/A	268.218
	30	377.70	374.223	373.010	373.507	N/A	373.119
	40	488.80	488.084	488.863	488.771	N/A	489.129
	50	606.00	600.945	606.119	605.955	N/A	605.991
3 (gas)	10	187.20	186.804	187.101	187.188	N/A	187.166
	20	272.80	274.688	274.326	274.632	N/A	273.162
	30	384.30	382.452	381.000	380.561	N/A	379.638
	40	497.20	500.496	498.074	497.170	N/A	497.211
	50	616.50	619.220	616.500	616.659	N/A	616.500

Table 9. Estimated error for case study 3 (cubic model)

Unit	P (MW)	F_{actual} (GJ/h)	Error = | $F_{ectual} - F_{estimated}$ | LSE	PSO	ABC	DE	GWO
	10	176.62	0.393	0.186	0.0048	0.000	0.028
	20	256.40	1.874	4.157	0.7342	0.000	0.078
1 coal)	30	361.50	1.779	0.451	4.4068	4.854	4.646
	40	467.60	3.368	3.846	0.1078	0.002	0.240
	50	579.50	2.915	0.000	0.1688	0.004	0.000
Σ error			10.329	8.641	5.422	4.860	4.992
	10	184.75	0.449	0.674	0.0109	0.000	0.064
	20	268.20	1.362	0.000	0.9631	0.000	0.018
2 (oil)	30	377.70	3.477	4.690	4.1929	4.825	4.581
	40	488.80	0.716	0.063	0.0289	0.000	0.329
	50	606.00	5.005	0.119	0.0449	0.000	0.010
Σ error			11.059	5.547	5.421	4.825	5.002
	10	187.20	0.396	0.099	0.0167	0.000	0.034
	20	272.80	1.888	1.526	1.8323	0.000	0.362
3 (gas)	30	384.30	1.848	3.300	3.7387	4.917	4.662
	40	497.20	3.296	0.874	0.0297	0.000	0.011
	50	616.50	2.720	0.000	0.159	0.000	0.000
Σ error			10.148	5.799	5.777	4.917	5.069

The convergence characteristic of simulation for generator unit 1 shows that GWO method is able to achieve optimal fitness values in more than 500 iterations as shown in Figure 4. The total number absolute errors for three-unit thermal generators obtained with this model are much lower than those obtained in case study 1 and 2. This means that the third order or cubic model is more suitable for representing fuel cost curve of thermal generator [25].

From the results, the GWO-based method is able to minimize the total number of absolute errors better than the LSE, PSO, ABC and CS methods so that the estimated value of the fuel cost function is closer to the actual value of fuel cost function. Although the total number of absolute errors obtained is still greater than that value obtained using the DE method, the GWO method can be the one of the best option tools for estimating the parameter of fuel cost curve of thermal generating units. The GWO method takes about 1.5 seconds to converge with the current simulation parameters.

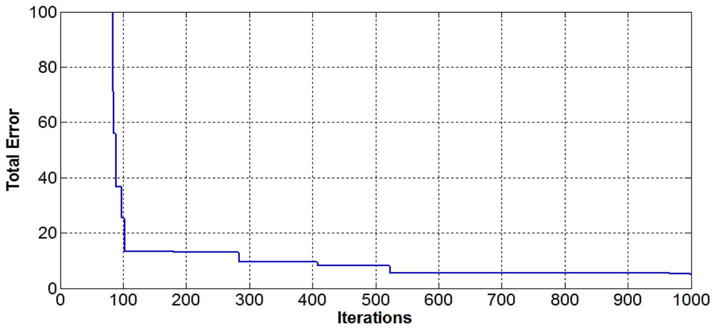

Figure 4. Convergence characteristic for case study 3 (cubic model) of generator unit 1

5. CONCLUSION

Estimation of the input-output curve or fuel cost curve parameters of thermal generator using the grey wolf optimizer (GWO) method is presented in this paper. Three models of fuel cost curves with three thermal generators with different fuels type have been tested using this method. The estimated parameter is obtained by minimizing the total number of absolute error between the actual value and the estimated value of the generator fuel cost function. The test results show that the GWO method is more accurate for estimating parameter of the input-output curve of thermal generator units by producing smaller total absolute errors compared to those obtained using LSE, PSO, GA, ABC and CS methods and slightly less accurate compared to those obtained using DE method.

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