POLİTEKNİK DERGİSİ

JOURNAL of POLYTECHNIC

ISSN: 1302-0900 (PRINT), ISSN: 2147-9429 (ONLINE)
URL: http://dergipark.org.tr/politeknik

Investigation the success of semidefinite programming for the estimating of fuel cost curves in thermal power plants

Termik santrallerde yakıt maliyet eğrilerinin tahmini için yarı-kesin programlamanın başarısının araştırılması

***Yazar(lar) (Author(s))**: Ugur GUVENC[1], Huseyin BAKIR[2], Serhat DUMAN[3]*

ORCID[1]: 0000-0002-5193-7990

ORCID[2]: 0000-0001-5473-5158

ORCID[3]: 0000-0002-1091-125X

Bu makaleye şu şekilde atıfta bulunabilirsiniz(To cite to this article): Guvenc U., Bakir H. and Duman S., "Investigation the success of semidefinite programming for the estimating of fuel cost curves in thermal power plants", ***Politeknik Dergisi***, 24(1): 247-254, (2021).

Erişim linki (To link to this article): http://dergipark.org.tr/politeknik/archive

DOI: 10.2339/politeknik.645827

Investigation the Success of Semidefinite Programming for the Estimating of Fuel Cost Curves in Thermal Power Plants

Highlights

- *SDP method has been proposed for fuel cost function parameter estimation problem.*
- *First, second and third order fuel cost curve functions.*
- *Power plants with different fuel types such as coal, oil, and gas.*
- *Comparison results are in favor of SDP.*

Graphical Abstract

- *Parameter estimation is an optimization problem in which the optimal values of the unknown parameters should be estimated.*
- *This paper presents a new and accurate method for estimating the parameters of thermal power plants fuel cost function.*

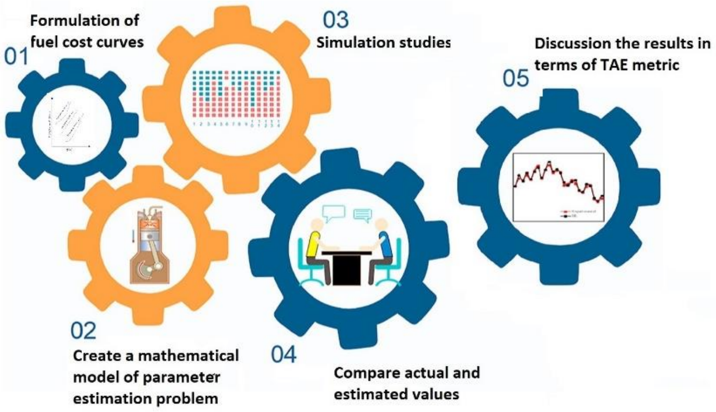

Figure. Paper flowchart

Aim

The main goal of this paper is to optimize the fuel cost function coefficients of thermal generation units.

Design & Methodology

A semidefinite programming (SDP) method was proposed for the estimation of fuel cost functions' parameters in thermal power plants. The parameter estimation problem was designed as a minimization problem, where the objective function is the total absolute error (TAE). The coefficients of fuel cost curve functions are found for first, second, and third-order models. Different fuel types such as coal, oil and gas were taken into consideration in the simulation studies.

Originality

The first study applying the SDP method for estimating the parameters of the fuel cost function in thermal power plants.

Findings

The results achieved from the semidefinite programming method were compared with that of particle swarm optimization (PSO), artificial bee colony (ABC), crow search algorithm (CSA) and least error square (LES) methods, respectively. The results clearly demonstrate that SDP outperforms other techniques based on the total absolute error parameter. It has been observed that the higher the complexity (degree) of the fuel cost function, the higher the performance of the SDP.

Conclusion

The results showed that the SDP method is more robust and produces a lower error compared to the other methods. It is obvious that the SDP is a useful and powerful method for solving such a problem.

Declaration of Ethical Standards

The author(s) of this article declare that the materials and methods used in this study do not require ethical committee permission and/or legal-special permission.

Investigation the Success of Semidefinite Programming for the Estimating of Fuel Cost Curves in Thermal Power Plants

Research Article / Araştırma Makalesi

Ugur GUVENC[1*], Huseyin BAKIR[2], Serhat DUMAN[3]

[1]Faculty of Technology, Department of Electrical and Electronics Engineering, Duzce University,Duzce, Turkey
[2]Dogus Vocational School of Higher Education, Department of Mechatronics, Dogus University, Istanbul, Turkey
[3]Faculty of Engineering and NaturalSciences, Department of Electrical Engineering, Bandirma Onyedi Eylul University,Bandirma, Turkey

(Geliş/Received : 12.11.2019 ; Kabul/Accepted : 13.03.2020)

ABSTRACT

Accurate estimation of fuel cost curve parameters in thermal power plants is of great importance because these parameters directly influence the economic dispatch calculations. In this paper, a semidefinite programming (SDP) approach was proposed for the estimation of fuel cost functions' parameters in thermal power plants. The parameter estimation problem was designed as a minimization problem, where the objective function was accepted as the total absolute error (TAE) in the study. Also, linear, quadratic, and cubic fuel cost functions were used to estimate the fuel cost parameters. Different fuel types such as coal, oil and gas were preferred for simulation studies. The results achieved from the semidefinite programming method were compared with that of particle swarm optimization (PSO), artificial bee colony (ABC), crow search algorithm (CSA) and least error square (LES) methods, respectively. The performance of the methods were compared according to the TAE parameter. Simulation results showed that SDP method is more successful than other methods considered in this paper. Clearly, the present paper showed that SDP has a higher potential to solve parameter estimation problems.

Keywords: Fuel cost function, parameter estimation problem,semidefinite programming.

Termik Santrallerde Yakıt Maliyet Eğrilerinin Tahmini için Yarı-Kesin Programlamanın Başarısının Araştırılması

ÖZ

Termik güç santrallerinde, yakıt maliyet eğrisi parametreleri ekonomik dağıtım hesaplamalarını doğrudan etkilediği için bu parametrelerin doğru tahmin edilmesi büyük önem taşımaktadır. Bu çalışmada, termik santrallerdeki yakıt maliyet fonksiyonu parametrelerinin tahmini için yarı kesin programlama (YKP) yaklaşımı önerildi. Parametre tahmin problemi, amaç fonksiyonunun toplam mutlak hata (TMH) olarak kabul edildiği bir minimizasyon problemi olarak tasarlandı. Ayrıca, yakıt maliyet eğrisi parametrelerini tahmin etmek için doğrusal, ikinci dereceden ve kübik yakıt maliyet fonksiyonları kullanıldı. Simülasyon çalışmaları için kömür, petrol ve gaz gibi farklı yakıt türleri tercih edildi. Yarı kesin programlama yönteminden elde edilen sonuçlar sırasıyla parçacık sürüsü optimizasyonu (PSO), yapay arı kolonisi (YAK), karga arama algoritması (KAA) ve en küçük hata karesi (EKHK) yöntemleriyle karşılaştırıldı. Yöntemlerin performansı TMH parametresine göre karşılaştırılmıştır. Simulasyon sonuçları YKP yönteminin bu makalede dikkate alınan diğer yöntemlerden daha başarılı olduğu gösterdi. Bu makale YKP'nin parametre tahmin problemlerini çözme potansiyelinin yüksek olduğunu açıkça gösterdi.

Anahtar Kelimeler: Yakıt maliyet fonksiyonu, parameter tahmin problemi,yarı-kesin programlama.

1. INTRODUCTION

Economic load dispatch (ELD) is crucial in power system planning and operation. The aim of ELD is to operate generators that produce energy in a power plant with minimum fuel costs, simultaneously, while satisfying the operational constraints and load demand [1]. The ELD problem can be devised as an optimization problem aimed at minimizing the fuel cost function. In ELD problem the fuel cost function is commonly represented by a linear, quadratic, or cubic function [2, 3]. Accurate estimation of fuel cost function parameters is critical in solving the ELD problem. Many algebraic models are being recommended for the fuel cost curve. Generally, fuel cost functions are represented by two essential classifications: smooth and non-smooth. [3-5].

In the literature, fuel cost curve parameters were estimated using heuristic optimization algorithms, artificial intelligence techniques, and traditional models. In [3], the particle swarm optimization (PSO) method

** Sorumlu yazar(Corresponding Author)*
e-posta : ugurguvenc@duzce.edu.tr

was presented for the fuel cost curve parameter estimation problem. In [4], a new differential evolution (DE) algorithm was proposed for the fuel cost parameter estimation problem. In [5], the authors proposed an improved differential evolution (IDE) algorithm for the parameter estimation problem. Ref. [6] presented an implementation of the artificial bee colony (ABC) algorithm to estimate the fuel cost curve parameters of thermal power plants (TPP). In [7], the crow search algorithm (CSA) was recommended for estimating the fuel cost curve parameters for TPP with and without the valve point effect. In [8], a new approach was proposed for parameter estimation based on the cuckoo search (CS) algorithm. The authors submitted the teaching-learning based optimization (TLBO) algorithm to estimate the fuel cost curve parameters in Ref. [9]. In [10], four algorithms were used to estimate the coefficients of the fuel cost curves. A new practice to solve the parameter estimation problem using a cuckoo search (CS) based algorithm was proposed in Ref. [11].

SDP has recently received much attention for various problems solution in power system analysis. Some applications are: In [12], it has been shown that SDP can effectively solve high dimension, non-smooth power system problems. In [13], the authors used an SDP method to solve the economic emission dispatch (EED) problem. Ref. [14] emphasized the success of SDP for optimal power flow problems. In [15], SDP was used to solve the renewable microgrid state estimation and its stabilization problem. In [16], the solution of the multi-objective optimal power flow problem was realized by SDP. It has been proved that SDP method is successful in solving complex problems with high number of variables.

The aim of this study is to present a new method based on semidefinite programming in order to estimate the fuel cost curve coefficients in TPP with high reliability. The parameter estimation problem was designed as a minimization problem, where the objective function is the total absolute error. In this paper, the smooth fuel cost functions are taken into consideration. Different study cases are presented to confirm the effectiveness of the proposed approach.

The rest of the paper is organized as follows: problem formulation is explained in Section 2. Following this, the main structure of the SDP is introduced in Section 3. In Section 4, the effectiveness of the SDP method was confirmed by comparisons with different optimization algorithms and traditional methods. Finally, we conclude in Section 5.

2. FORMULATION OF THE PROBLEM

The operating characteristic of TPP is represented by fuel cost functions. The fuel cost curve for the thermal generating unit (i) can be expressed by a polynomial function that relates its fuel cost to its real power output (MW) as [4, 5]:

$$F_i(P_{ti}) = a_{0i} + \sum_{j=1}^{L} a_{ji} P_{ti}{}^{j} + r_i \quad j = 1,2,\dots,N \tag{1}$$

where F_i is the fuel cost of the ith generator, P_{ti} is the output power generated by the ith thermal unit, a_{0i} and a_{ji} are the cost coefficients for generator i, r_i is the error associated with the ith equation, L is the polynomial order. N is the number of generation units.

In this paper, three different cost fuel functions were used.

Model 1: Linear fuel cost function

$$F_i(P_{ti}) = a_{0i} + a_{1i}P_{ti} + r_i \tag{2}$$

Model 2: Quadratic fuel cost function

$$F_i(P_{ti}) = a_{0i} + a_{1i}P_{ti} + a_{2i}P_{ti}{}^2 + r_i \tag{3}$$

Model 3: Cubic fuel cost function

$$F_i(P_{ti}) = a_{0i} + a_{1i}P_{ti} + a_{2i}P_{ti}{}^2 + a_{3i}P_{ti}{}^3 + r_i \tag{4}$$

where a_{0i}, a_{1i}, a_{2i} and a_{3i} are the fuel cost coeficients to be estimated and P_{ti} is the generated power of the ith unit [3].

Fig. 1 shows different smooth fuel cost curves. Entry to the unit is the total cost per hour F($/hr) and output is the net electrical power output of the unit P(MW) [7].

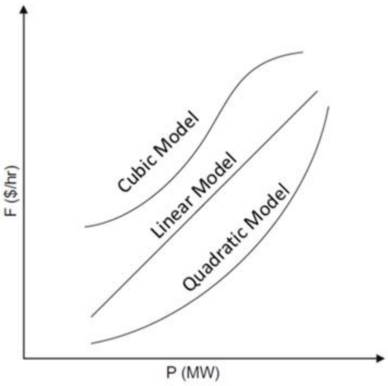

Figure 1. Convex fuel cost curves

A set of nonlinear equations of the parameter estimation problem can be formulated as follows [5]:

$$Z_i = f_i(P_i, X_i) + r_i \tag{5}$$

where Z_i is a vector of actual values of generation costs, X_i is the fuel cost parameters $(a_{0i}, a_{1i}, a_{2i}, a_{3i})$ to estimate for the ith generator and r_i is the error vector.

$$r_i = F_{i(actual)} - F_{i(estimated)} \tag{6}$$

The objective function is to minimize the total absolute error (TAE), subject to the equality and inequality constraints [7].

$$minimize\ \ TAE = \sum |r_i| \tag{7a}$$

$$subject\ to:\ \sum_{i=1}^{n} P_i = P_D + P_L \tag{7b}$$

$$C_i{}^l \leq C_i \leq C_i{}^u \tag{7c}$$

where P_i is the total power generation, P_D is the load demand, P_L is the transmission losses. Transmission losses are not considered ($P_L = 0$). $C_i{}^l$ and $C_i{}^u$ are the lower and upper bounds of fuel cost coefficients for the ith unit.

3. SEMIDEFINITE PROGRAMMING

Semidefinite programming is one of the most popular convex optimization methods. One of the main superiority of convex optimization is that whenever the problem is convex, the solution is globally optimal. Even when the problem is non-convex, SDP relaxation of the problem provides a good computable related to the optimal value [17, 18].

In heuristic methods, the parameter setting is required for optimum result, SDP does not have such an obligation [19, 20]. SDP is a generalization of the linear program (LP) in which the vector variables are modified by matrix variables and the element-wise non-negativity by positive semidefiniteness of the matrices [21, 22]. In this paper, an optimization problem is characterized by using primal SDP form [12]:

$$minimize < A_0, X > \tag{8a}$$

$$subject\ to\ < A_i, X > = b_i\ ,\ \ i = 1, \ldots, m \tag{8b}$$

$$X \geq 0 \tag{8c}$$

The related dual SDP problem is:

$$maximize < b, y > \tag{9a}$$

$$subject\ to \sum_{i=1}^{m} y_i A_i \leq A_0 \qquad y \in R^m \tag{9b}$$

where $X \in S^n$ is the decision variable $b \in R^m$ and $A_0, A_i \in S^n$. S^n is the set of all symmetric matrices in R^{nxn}. The inner product between two matrices $X, Y \in S^n$ is defined as $< X, Y >= Trace(XY) = \sum_{i=1}^{n} \sum_{j=1}^{n} X_{ij} Y_{ij}$ [17].

The addition of a semidefinite matrix variable in the direct formulation of some problems as SDP does not all the time produce a convex SDP problem. Reasons adduced for this include possible non-convexity in the objective function or in the constraints. Thus, the resulting SDP problem is rough to solve to global optimality. The relaxation of the SDP problem means that the non-convex constraints are embedded in a larger convex constraint set [12]. Contemplate the problem with non-convex constraint set K.

$$f^* = \min_{x \in K} f(x) \tag{10}$$

Given that there exists a convex set K' such that $K \subset K'$. The relaxed problem becomes:

$$f_* = \min_{x \in K'} f(x) \tag{11}$$

4. NUMERICAL RESULTS

The SDP approach for solving the fuel cost curve parameter estimation problem, have been tested using data published in [6]. The problem was solved in MATLAB environment using CVX with SDTP3 solver [23]. CVX is a modeling system used in MATLAB to solve convex optimization problems.

In this section, the proposed approach was applied to three different fuel cost functions, and the results obtained from the simulation studies were compared with other results in the literature, namely: Particle Swarm Optimization (PSO) [3], Artificial Bee Colony (ABC) [6], Crow Search Algorithm (CSA) [7], Least Error Square (LES) [10].

Table 1. Estimated fuel cost coefficients for the linear model

First-order model			
System	Method	Parameters	
		a_0	a_1
Unit 1 (Coal)	PSO	60.006	10.190
	ABC	45.212	10.560
	CSA	45.200	10.560
	LES	63.236	10.170
	SDP	45.200	10.560
Unit 2 (Oil)	PSO	66.051	10.570
	ABC	47.652	11.031
	CSA	47.600	11.030
	LES	66.160	10.631
	SDP	47.600	11.030
Unit 3 (Gas)	PSO	66.002	10.780
	ABC	48.399	11.221
	CSA	48.400	11.220
	LES	66.700	10.830
	SDP	48.400	11.220

Table 2. Simulation results for the linear model

First-order model													
System	P (MW)	F_{actual} (GJ/h)	PSO $F_{estimated}$ (GJ/h)	ABC $F_{estimated}$ (GJ/h)	CSA $F_{estimated}$ (GJ/h)	LES $F_{estimated}$ (GJ/h)	SDP $F_{estimated}$ (GJ/h)	Error PSO	Error ABC	Error CSA	Error LES	Error SDP
Unit 1 (Coal)	10	176.62	161.905	150.812	150.800	164.936	150.800	14.715	25.080	25.820	11.684	25.820
	20	256.40	263.803	256.412	256.400	266.636	256.400	-7.403	-0.012	0.000	10.236	0.000
	30	361.50	365.702	362.012	362.000	368.336	362.000	-4.202	-0.512	-0.500	6.836	0.500
	40	467.60	467.600	467.612	467.600	470.036	467.600	0.000	-0.012	0.000	2.436	0.000
	50	579.50	569.498	573.212	573.200	571.736	573.200	10.002	6.288	6.300	7.764	6.300
∑Error								36.332	32.632	32.620	38.956	32.620
Unit 2 (Oil)	10	184.75	171.701	157.962	157.900	172.470	157.900	13.049	26.788	26.850	12.280	26.850
	20	268.20	277.400	268.272	268.200	278.780	268.200	-9.200	-0.072	0.000	10.580	0.000
	30	377.70	383.100	378.582	378.500	385.090	378.500	-5.400	-0.882	0.800	7.390	0.800
	40	488.80	488.800	488.892	488.800	491.400	488.800	0.000	-0.092	0.000	2.600	0.000
	50	606.00	594.499	599.202	599.100	597.710	599.100	11.501	6.798	6.900	8.290	6.900
∑Error								39.151	34.632	34.550	41.140	34.550
Unit 3 (Gas)	10	187.20	173.802	160.609	160.600	175.000	160.600	13.398	26.591	26.600	12.200	26.600
	20	272.80	281.601	272.819	272.800	283.300	272.800	-8.801	-0.019	0.000	-10.50	0.000
	30	384.30	389.401	385.029	385.000	391.600	385.000	-5.101	-0.729	-0.700	-7.300	0.700
	40	497.20	497.200	497.239	497.200	499.900	497.200	0.000	-0.039	0.000	-2.700	0.000
	50	616.50	604.999	609.449	609.400	608.200	609.400	11.501	7.051	7.100	8.300	7.100
∑Error								38.801	34.429	34.400	41.000	34.400

4.1. Case 1: Linear Cost Function

In this case, the SDP method was applied to estimate the fuel cost function parameters of the quadratic model. The fuel cost coefficients computed by SDP and the results by techniques noted in this study are provided in Table 1. Actual fuel cost data for each unit; the estimated fuel cost values and total absolute error values obtained by PSO, ABC, CSA, LES and SDP methods are shown in Table 2. From Table 2, it can be noticed that SDP and CSA reach a minimum total absolute estimation error for each unit. SDP and CSA give the least objective function (32.620 GJ/h) compared to PSO (36.332 GJ/h), ABC (32.632 GJ/h), and LES (38.956 GJ/h) for unit 1. In other words, SDP and CSA are 10.216%, 0.036%, and 16.264% less than the results of PSO, ABC, and LES respectively. For unit 2, SDP and CSA reach a minimum total absolute estimation error (34.550 GJ/h) compare to PSO (39.151 GJ/h), ABC (34.632 GJ/h), and LES (41.140 GJ/h). Briefly, SDP and CSA are 11.751%, 0.236%, and 16.018% less than the results of PSO, ABC, and LES respectively. Total absolute estimation error obtained with SDP and CSA methods for unit 3 is 34.400 GJ/h. SDP and CSA reduced the total error by 11.342%, 0.084%, and 16.097% respectively, compared to PSO, ABC, and LES.

4.2. Case 2: Quadratic Cost Function

The fuel cost coefficients obtained by SDP and the results by techniques considered in this study are reported in Table 3. The simulation results for the quadratic fuel cost function are presented in Table 4. From Table 4, it is clear that the SDP and CSA methods give the minimum objective function value 9.760 GJ/h, 9.975 GJ/h, 9.750 GJ/h for coal, oil and gas unit respectively. The minimum total absolute error of unit 1 obtained by SDP and CSA is 9,760 (GJ/h). In other words, SDP and CSA are 0.357 (GJ/h), 0.050 (GJ/h), and 4.448 (GJ/h) less than the results of PSO, ABC, and LES respectively. For unit 2, SDP and CSA give the least objective function value 9.975 (GJ/h). Also, SDP and CSA reduced the total absolute error by 1.875 (GJ/h), 0.158 (GJ/h), and 4.489 (GJ/h) respectively, compared to PSO, ABC, and LES. For unit 3, SDP and CSA reach the least objective function value 9.750 (GJ/h) compare to other methods. The result obtained using the SDP method reduced the error value by 2.991 (GJ/h), 0.611 (GJ/h) and 4.466 (GJ/h) respectively, compared to PSO, ABC, and LES. It is seen that SDP can reduce the total absolute error significantly.

Table 3. Estimated fuel cost coefficients for the quadratic model

First-order model				
System	Method	Parameters		
		a_0	a_1	a_2
Unit 1 (Coal)	PSO	96.279	7.592	0.042
	ABC	96.604	7.587	0.041
	CSA	96.600	7.588	0.041
	LES	95.856	7.374	0.047
	SDP	96.600	7.588	0.041
Unit 2 (Oil)	PSO	101.000	7.800	0.046
	ABC	101.536	7.877	0.044
	CSA	101.531	7.880	0.044
	LES	100.710	7.670	0.049
	SDP	101.531	7.880	0.044
Unit 3 (Gas)	PSO	102.000	7.900	0.048
	ABC	101.817	8.099	0.043
	CSA	101.812	8.100	0.043
	LES	101.100	7.881	0.049
	SDP	101.812	8.100	0.043

Table 4. Simulation results for the quadratic model

First-order model												
System	P (MW)	F_{actual} (GJ/h)	PSO $F_{estimated}$ (GJ/h)	ABC $F_{estimated}$ (GJ/h)	CSA $F_{estimated}$ (GJ/h)	LES $F_{estimated}$ (GJ/h)	SDP $F_{estimated}$ (GJ/h)	Error PSO	ABC	CSA	LES	SDP
Unit 1 (Coal)	10	176.62	176.358	176.619	176.620	174.252	176.620	0.262	0.001	0.000	2.368	0.000
	20	256.40	264.765	264.913	264.920	261.968	264.920	-8.365	-8.513	-8.520	-5.568	8.520
	30	361.50	361.500	361.487	361.500	359.004	361.500	0.000	0.013	0.000	2.496	0.000
	40	467.60	466.562	466.341	466.360	465.360	466.360	1.038	1.259	1.240	2.240	1.240
	50	579.50	579.952	579.475	579.500	581.036	579.500	-0.452	0.025	0.000	-1.536	0.000
∑Error								10.117	9.810	9.760	14.208	9.760
Unit 2 (Oil)	10	184.75	183.600	184.735	184.750	182.346	184.750	1.150	0.015	0.000	2.404	0.000
	20	268.20	275.400	276.774	276.806	273.862	276.806	-7.200	-8.574	-8.606	-5.662	8.606
	30	377.70	376.400	377.653	377.700	375.258	377.700	1.300	0.047	0.000	2.442	0.000
	40	488.80	486.600	487.372	487.431	486.534	487.431	2.200	1.428	1.369	2.266	1.368
	50	606.00	606.000	605.931	606.000	607.690	606.000	0.000	0.069	0.000	-1.690	0.000
∑Error								11.850	10.133	9.975	14.464	9.975
Unit 3 (Gas)	10	187.20	185.780	187.799	187.200	184.824	187.200	1.420	-0.599	0.000	2.376	0.000
	20	272.80	279.121	281.36	281.362	278.368	281.362	-6.321	-8.560	-8.562	-5.568	8.562
	30	384.30	382.022	384.301	384.300	381.732	384.300	2.278	-0.001	0.000	2.568	0.000
	40	497.20	494.484	496.022	496.012	494.916	496.012	2.716	-1.178	1.188	2.284	1.187
	50	616.50	616.507	616.523	616.500	617.920	616.500	-0.007	-0.023	0.000	-1.420	0.000
∑Error								12.741	10.361	9.750	14.216	9.750

4.3. Case 3: Cubic Cost Function

In this case, the cubic fuel cost function, which has a more complex structure than other fuel cost functions, was preferred to demonstrate the effectiveness of the proposed approach. Table 5 presents the estimated coefficients of the cost function obtained using considered methods for case 3. In Table 6, the actual fuel cost data for each unit; estimated fuel cost data obtained from the noted methods in this paper; error values calculated from the difference between actual and estimated values; and total absolute error values for each algorithm are presented. Total absolute error values from the PSO, ABC, CSA, LES, and SDP methods are 8.641, 5.422, 4.862,10.329 and 4.853 GJ/h for unit 1. As the simulation results show, the minimum objective value obtained by the SDP method is better than others. That is, the SDP is 43.837%, 10.494%,0.185%, and 53.015% lower than compared with the results of the PSO, ABC, CSA, and LES algorithms. For unit 2, the obtained simulation results from the PSO, ABC, CSA, LES, and SDP methods are 5.547, 5.240, 4.841, 11.059 and 4.825 GJ/h, respectively. The SDP method is 0.722, 0.415, 0.016, and 6.234 GJ/h lower than the results of PSO, ABC, CSA, and LES, respectively. In other words, the proposed method is 13.016%, 7.919%, 0.332%, and 56.370% lower than the results of the methods specified in Table 6, respectively. For unit 3, the simulation results of the PSO, ABC, CSA, LES, and SDP methods are 5.799, 5.776, 4.935, 10.148 and 4.916 GJ/h, respectively.

The SDP method is 0.883, 0.863, 0.019, and 5.232 GJ/h less than the results of PSO, ABC, CSA and LES, respectively. Also, the proposed method is 15.226%, 14.889%, 0.385%, and 51.556% lower than those of the other algorithms, respectively. Simulation results proved that SDP method is more successful than PSO, ABC, CSA and LES methods in estimating the parameters of cubic cost function.

Table 5. Estimated fuel cost coefficients for the cubic model.

First-order model					
System	Method	Parameters			
		a_0	a_1	a_2	a_3
Unit 1 (Coal)	PSO	120.241	3.979	0.184	-0.002
	ABC	124.536	3.485	0.187	-0.001
	CSA	127.036	3.122	0.199	-0.001
	LES	123.180	3.535	0.193	-0.002
	SDP	127.066	3.118	0.199	-0.001
Unit 2 (Oil)	PSO	130.278	3.542	0.200	-0.002
	ABC	129.235	3.485	0.187	-0.001
	CSA	132.463	3.336	0.205	-0.001
	LES	128.640	3.746	0.199	-0.002
	SDP	132.500	3.332	0.205	-0.001
Unit 3 (Gas)	PSO	128.376	4.146	0.188	-0.002
	ABC	126.014	3.804	0.189	-0.001
	CSA	132.428	3.608	0.203	-0.001
	LES	128.400	4.046	0.195	-0.002
	SDP	132.333	3.625	0.202	-0.001

Table 6. Simulation results for the cubic model

First-order model												
System	P (MW)	F_{actual} (GJ/h)	PSO $F_{estimated}$ (GJ/h)	ABC $F_{estimated}$ (GJ/h)	CSA $F_{estimated}$ (GJ/h)	LES $F_{estimated}$ (GJ/h)	SDP $F_{estimated}$ (GJ/h)	Error				
								PSO	ABC	CSA	LES	SDP
Unit 1 (Coal)	10	176.62	176.806	176.615	176.617	176.227	176.620	-0.186	-0.004	0.003	0.393	0.000
	20	256.40	260.557	257.134	256.405	258.274	256.400	-4.157	-0.734	-0.005	-1.874	0.000
	30	361.50	361.951	357.093	356.649	359.721	356.646	-0.451	4.406	4.851	1.779	4.853
	40	467.60	471.446	467.492	467.597	470.968	467.600	3.846	0.107	0.003	-3.368	0.000
	50	579.50	579.500	579.331	579.500	582.415	579.500	0.000	0.168	0.000	-2.915	0.000
∑Error								8.641	5.422	4.862	10.329	4.853
Unit 2 (Oil)	10	184.75	184.076	184.739	184.744	184.301	184.750	0.674	0.010	0.006	0.449	0.000
	20	268.20	268.200	269.163	268.213	269.562	268.200	0.000	-0.963	-0.013	-1.362	0.000
	30	377.70	373.010	373.507	372.896	374.223	372.875	4.690	4.192	4.804	3.477	4.825
	40	488.80	488.863	488.771	488.816	488.084	488.800	-0.063	0.028	-0.016	0.716	0.000
	50	606.00	606.119	605.955	605.998	600.945	606.000	-0.119	0.044	0.002	5.055	0.000
∑Error								5.547	5.240	4.841	11.059	4.825
Unit 3 (Gas)	10	187.20	187.101	187.188	187.200	186.804	187.200	0.099	0.016	0.000	0.369	0.000
	20	272.80	274.326	274.632	272.800	274.688	272.800	-1.526	-1.832	0.000	-1.888	0.000
	30	384.30	381.000	380.561	379.421	382.452	379.383	3.300	3.738	4.879	1.848	4.916
	40	497.20	498.074	497.170	497.256	500.496	497.200	-0.874	0.029	-0.056	-3.296	0.000
	50	616.50	616.500	616.659	616.500	619.220	616.500	0.000	-0.159	0.000	-2.720	0.000
∑Error								5.799	5.776	4.935	10.148	4.916

5. CONCLUSION

In this paper, the SDP algorithm was applied to find the optimal fuel cost curve parameters of thermal power plants. The parameter estimation problem has been expressed as an optimization problem where the objective is to minimize the total absolute error. To evaluate the success of the proposed method, three different test cases were evaluated for three different power plants with different fuel types such as coal, oil, and gas. The performance of the SDP method was compared with the PSO, ABC, CSA and LES methods. The simulation results showed that the SDP algorithm is more robust and produces a lower error between the actual and estimated parameters compared to the others for all test cases.

DECLARATION OF ETHICAL STANDARDS

The author(s) of this article declare that the materials and methods used in this study do not require ethical committee permission and/or legal-special permission.

REFERENCES

[1] Güvenç U., Sönmez Y., Duman S., and Yörükeren N.,''Combined economic and emission dispatch solution using gravitational search algorithm'', Scientia Iranica, 6: 1754-1762, (2012).

[2] Daycock C., DesJardins R., and Fennell S., "Generation cost forecasting using on-line thermodynamics models", ***Electric Power*** , 5–7, (2004).

[3] El-Naggar K. M., AlRashidi M. R., and Al-Othman A. K., " Estimating the input–output parameters of TPP using PSO", ***Energy Conversion and Management,*** 7: 1767-1772, (2009).

[4] Sayah S., and Hamouda A., "Novel application of differential evolution algorithm for estimating fuel cost function of thermal generating units," ***In 2015 Third World Conference on Complex Systems (WCCS)***, 1-6, (2015).

[5] Sayah S., and Hamouda A., " Efficient method for estimation of smooth and nonsmooth fuel cost curves for TPP," ***International Transactions on Electrical Energy Systems***, 3:1-14, (2018).

[6] Sönmez Y., "Estimation of fuel cost curve parameters for TPP using the ABC algorithm," ***Turkish Journal of Electrical Engineering & Computer Sciences***, 21: 1827-1841, (2013).

[7] Askarzadeh A., and Gharibi M., " Accurate estimation of cost function parameters for TPP using a novel optimization approach," ***Energy Sources, Part A: Recovery, Utilization, and Environmental Effects***, 24: 2986-2999, (2018).

[8] AlRashidi M. R., El-Naggar K. M., and AlHajri M. F., " Estimation of fuel cost function characteristics using Cuckoo search," ***In International Conference on Computer Science, Data Mining & Mechanical Engineering***, Bangkok, Thailand, (2015).

[9] Durai S., S.Subramanian, and S. Ganesan, " Preferred Economic Dispatch of Thermal Power Units," ***Journal of Power and Energy Engineering***, 11: 47-69, (2015).

[10] El-Hawary M. E., and Mansour S. Y., "Performance evaluation of parameter estimation algorithms for economic operation of power systems," ***IEEE Transactions on Power Apparatus and Systems***, 3: 574-582,1982.

[11] AlRashidi M. R., El-Naggar K. M., and AlHajri M. F., "Convex and non-convex heat curve parameters estimation using cuckoo search," ***Arabian Journal for Science and Engineering***, 3:873-882, (2015).

[12] Alawode K. O., Jubril A. M., Kehinde L. O., and Ogunbona P. O., ''Semidefinite programming solution of economic dispatch problem with non-smooth, non-convex cost functions,'' ***Electric Power Systems Research***, 164: 178-187, (2018).

[13] Jubril A. M., Olaniyan O. A., Komolafe O. A., and Ogunbona P. O., ''Economic-emission dispatch problem: A semi-definite programming approach'', ***Applied Energy***, 134: 446-455, (2014).

[14] Bai X., Wei H., Fujisawa K., and Wang Y., ''Semidefinite programming for optimal power flow problems,'' ***International Journal of Electrical Power & Energy Systems***, 30: 383-392, (2008).

[15] Rana M. M., Li L., and Su S. W., ''Controlling the renewable microgrid using semidefinite programming technique,'' ***International Journal of Electrical Power & Energy Systems***, 84,: 225-231, (2017).

[16] Davoodi E., Babaei E., and Mohammadi-ivatloo B., ''An efficient covexified SDP model for multi-objective optimal power flow'', ***International Journal of Electrical Power & Energy Systems***,102: 254-264, (2018).

[17] Boyd S., and Vandenberghe L., "Semidefinite programming relaxations of non-convex problems in control and combinatorial optimization," ***In Communications, Computation, Control, and Signal Processing***, 279-287. Springer, Boston, (1997).

[18] Jubril A. M., Adediji A. O., and Olaniyan O. A., "Solving the combined heat and power dispatch problem: A semi-definite programming approach," ***Electric Power Components And Systems***, 12: 1362-1376, (2012).

[19] Molzahn D. K., Lesieutre B. C., and DeMarco C. L., "A sufficient condition for global optimality of solutions to the optimal power flow problem", ***IEEE Transactions on Power Systems***, 2: 978-979, (2013).

[20] Zhu Y., Jian J., Wu J., and Yang L., "Global optimization of non-convex hydro-thermal coordination based on semidefinite programming", ***IEEE Transactions on Power Systems***, 4: 3720-3728, (2013).

[21] Vandenberghe L., and Boyd S., "Semidefinite programming", SIAM review, 1: 49-95, (1996).

[22] Overton M. and Wolkowicz H., "Semidefinite programming", Mathematical Programming, 1: 105-109, (1997).

[23] CVX Research Incorporated, CVX: Matlab Software for Disciplined Convex Programming, version 2.1, (2019 July).