



# Dynamic Economic Dispatch for Combined Heat and Power (Steam and Gas) Units Using Seeker and Bacteria Foraging Optimization Algorithms

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**To cite this article:**

Mohamed Ahmed Sadeek Mohamed. Dynamic Economic Dispatch for Combined Heat and Power (Steam and Gas) Units Using Seeker and Bacteria Foraging Optimization Algorithms. *American Journal of Engineering and Technology Management*. Vol. 1, No. 2, 2016, pp. 12-24. doi: 10.11648/j.ajetm.20160102.12

**Received:** July 13, 2016; **Accepted:** July 21, 2016; **Published:** August 6, 2016

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**Abstract:** In this paper, combined heat and power units are incorporated in dynamic economic dispatch to minimize total production costs considering realistic constraints such as ramp rate and spinning reserve limits effects over a short time span. Three evolutionary approaches, namely seeker optimization Algorithm (SOA), Seeker optimization with inertia weight factor (SOAIW) and Bacteria Foraging Optimization Algorithms (BFOA) are successfully implemented to solve the combined heat and power economic dispatch (CHPED) problem. These approaches have been tested on 12-generation units system with two steam, four gas and six cogeneration units. In addition, the performance tests are applied to measure the actual power output and the fuel consumption in every point tests for achieving different curves such as input/output, incremental heat rate and heat rate curves for the twelve units. The results of the four approaches are compared to obtain the best solution. The results show that the seeker optimization with improved inertia weight is able to achieve the best solution at less computational time.

**Keywords:** Combined Heat and Power Economic Dispatch (CHPED), Seeker Optimization Algorithm (SOA), Bacteria Foraging Optimization Algorithm (BFOA)

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## 1. Introduction

Combined heat and power unit (CHPU) known as cogeneration has the ability of creating simultaneous generation of two types of energy: useful heat and electricity. It improves efficiency and therefore, is more environmental friendly [1]. It also reduces the generation cost between 10 and 40% [2]. In Thermal Units, all the thermal energy is not converted into electricity and large quantities of energy are wasted in the form of heat [3]. CHPU uses the heat and can potentially achieve the energy conversion efficiency of up to 80% [4]. This means that less fuel needs to be consumed to produce the same amount of useful energy.

In order to utilize the CHPUs more efficiently, economic dispatch must be applied to achieve their optimal combination of power and heat output subject to system equality and inequality operational constraints. Hence, the combined heat and power economic dispatch (CHPED) problem is formulated as an optimization problem [5]. A practical CHPED problem should include ramp rate limits, spinning reserve to overcome the sudden fault in the system

and joint characteristic of electricity power heat which makes finding the optimal dispatching a challenging problem [6, 7].

In the recent researches, global optimization techniques like genetic algorithms (GA) [8], harmony search algorithm (HAS) [9], and particle swarm optimization (PSO) [10], have been applied for optimal tuning of CHPED based restructure schemes. These evolutionary algorithms are heuristic population-based search procedures that incorporate random variation and selection operators. Although, these methods seem to be good methods for the solution of CHPED parameter optimization problem, they have degraded efficiency to obtain global optimum solution when the system has a highly epistatic objective function (i.e. where parameters being optimized are highly correlated), and number of parameters to be optimized are large, then. In order to overcome these drawbacks, different modifications of particle swarm optimization approach are proposed for solution of the CHPED problem [10, 11, 12].

In this work, heat and power output of each generating unit and optimum fuel cost are obtained by using Three approaches; Seeker optimization Algorithm (SOA), Seeker optimization

Algorithm with inertia weight factor (SOAIW) and Bacteria Foraging Optimization Algorithms (BFOA). The results of the three approaches are compared. Simulation results show that the SOAIW approach is superior to the other existing methods.

## 2. CHPED Problem Formulation

The proposed CHPED problem is an optimization problem like economic load dispatch (ELD) problem, but it considers some types of production units such as pure heat units, cogenerating combined heat and power units. The cogeneration is a role to produce heat and power with feasible operation region according to Figure 1, where the boundary curve ABCDEF determines the feasible region. Along the boundary there is a trade-off between power generation and heat production delivered by the unit. It can be seen that along the curve AB the unit reaches maximum output power. On the contrary, the unit reaches maximum heat production along the curve CD. Therefore, power generation limits of cogeneration units are determined by combined functions incorporating the unit heat production, and vice versa [9]. Mathematically, the problem is formulated as:

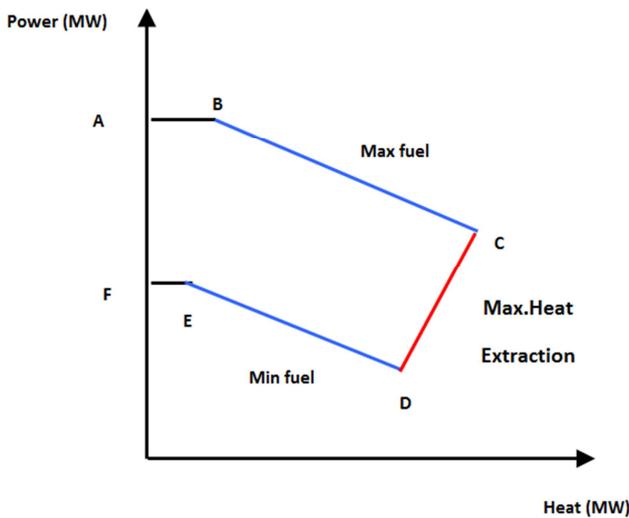


Figure 1. Typical heat-power region for cogeneration units.

### 2.1. Objective Function

Minimize:

$$\text{Cost} = \sum_{i=1}^{n_p} \alpha_i (p_i) + \sum_{j=1}^{n_c} \alpha_j (h_j p_j) \quad (1)$$

### 2.2. Constraints

#### 2.2.1. Equality Constraints

$$\sum_{i=1}^{n_p} p_i + \sum_{j=1}^{n_c} p_j = P_D \quad (2)$$

$$\sum_{i=1}^{n_c} h_i (p_j) = H_D \quad (3)$$

#### 2.2.2. Inequality Constraints

$$p_i^{\min} \leq p_i \leq p_i^{\max}, i = 1, \dots, n_p \quad (4)$$

$$p_j^{\min}(h_j) \leq p_j \leq p_j^{\max}(h_j), j = 1, \dots, n_c \quad (5)$$

$$h_j^{\min}(p_j) \leq h_j \leq h_j^{\max}(p_j), j = 1, \dots, n_c \quad (6)$$

where:

Cost: Total heat and power production cost,

$\alpha$ : Unit production cost,

$P$ : Unit power generation,

$h$ : cogeneration heat production,

$H_D$ : System heat demand,

$P_D$ : System power demand,

$n_p, n_c$  are the numbers of the of conventional power units and cogeneration units, respectively.

$p^{\min}$  and  $p^{\max}$  are the unit power capacity limits,

$h^{\min}$  and  $h^{\max}$  are the cogeneration heat capacity limits.

#### 2.3. In Addition, up and down Ramp Rate Limits can Be Formulated as

$$\max(P_i^{\min}, P_i^0 - DR_i) \leq P_i \leq \min(P_i^{\max}, P_i^0 + UR_i) \quad (7)$$

where,

$P_i$  is the output power at time 't',  $P_i^0$  is the initial output power,  $UR_i$  &  $DR_i$  are the ramp up & down rate limits of the  $i^{th}$  generator, respectively [13].

#### 2.4. Spinning Reserve Requirements

The Mid American Interconnected Network (MAIN) requires 1.1% of peak demand for regulation. MAIN's additional requirement for spinning reserve is 1.5% of it as peak demand. Thus, the total spinning reserve is allocated among as many units as is practical because it is easier to get the required rapid response by adjusting several units by small amounts rather than by adjusting a single unit by a large amount. The MAIN's non spinning reserve requirement is 1.9% of the peak demand [14].

## 3. Proposed Approaches of SOA

SOA is a population- based heuristic search algorithm. It regards optimization process as an optimal solution obtained by a seeker population. Each individual of this population is called a seeker. The total population is randomly categorized into three subpopulations. These subpopulations search over several different domains of the search space. All the seekers in the same subpopulation constitute a neighborhood. This neighborhood represents the social component for the social sharing of information.

### 3.1. Egotistic Behavior

Swarms (i.e., seeker population) are a class of entities found in nature which specialize in mutual cooperation among them

in executing their routine needs and roles. There are two extreme types of cooperative behavior. One, egotistic, is entirely pro-self and another, altruistic, is entirely pro-group

[15]. Every person, as a single sophisticated agent, is uniformly egotistic, believing that he should go toward his personal best position;  $\bar{I}_i$ , best through cognitive learning [16].

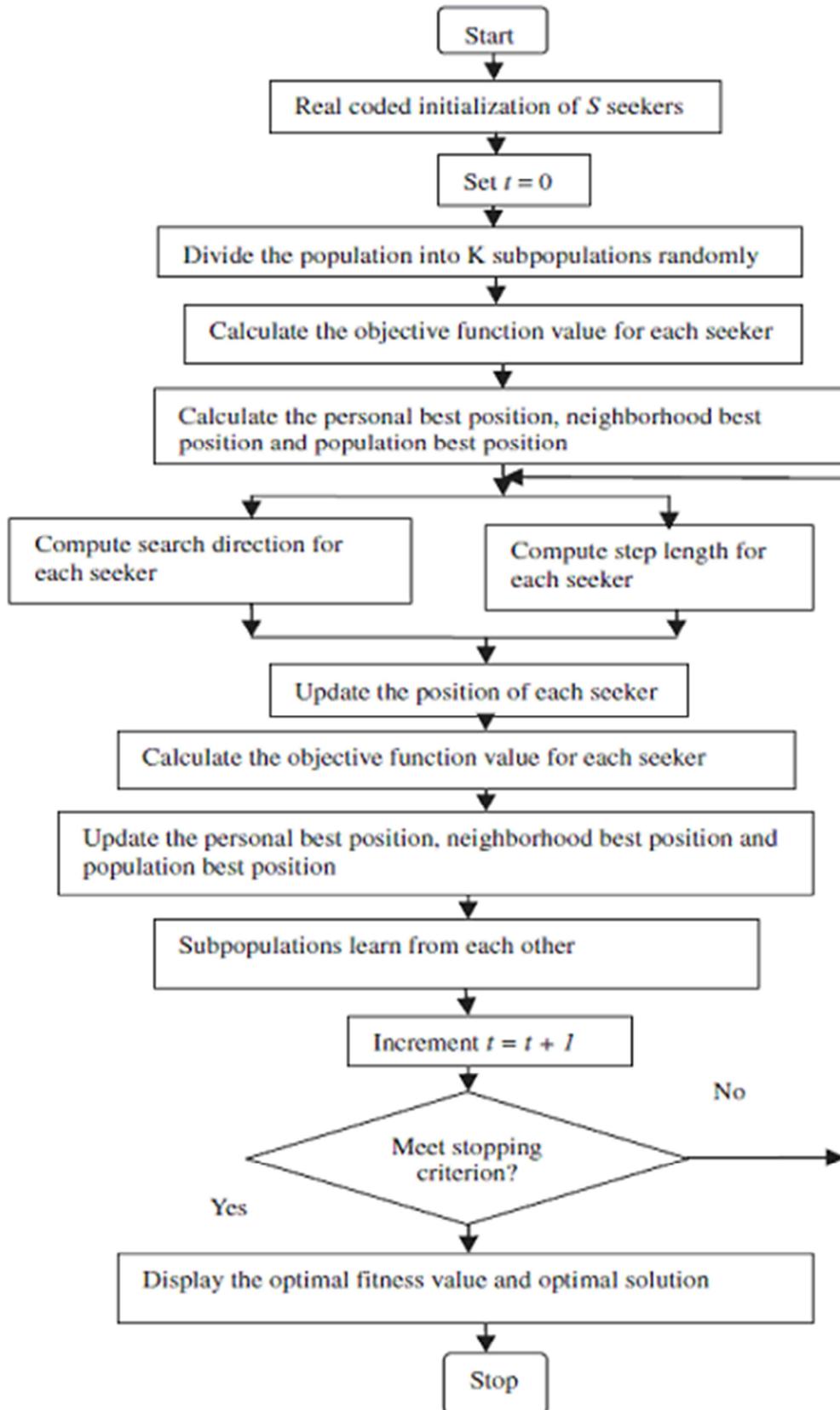


Figure 2. Flowchart of the seeker optimization algorithm [17].

### 3.2. Altruistic Behavior

The altruistic behavior means that the swarms co-operate explicitly, communicate with each other and adjust their behaviors in response to others to achieve the desired goal. Hence, the individuals exhibit entirely pro-group behavior through social learning and simultaneously move to the neighborhood's historical best position or the neighborhood's current best position. As a result, the move expresses a self-organized aggregation behavior of swarms. The aggregation is one of the fundamental self-organization behaviors of swarms in nature and is observed in organisms ranging from unicellular organisms to social insects and mammals [17]. The positive feedback of self-organized aggregation behaviors usually takes the form of attraction toward a given signal source. For a "black-box" problem in which the ideal global minimum value is unknown, the neighborhood's historical best position or the neighborhood's current best position is used as the only attraction signal source for the self-organized aggregation behavior.

### 3.3. Pro-activeness Behavior

Agents (i.e., seekers) enjoy the properties of pro-activeness: agents do not simply act in response to their environment; they are able to exhibit goal-directed behavior by taking the initiative. Furthermore, future behavior can be predicted and guided by past behavior [18]. As a result, the seekers may be pro-active to change their search directions and exhibit goal-directed behaviors according to the response to his past behaviors.

### 3.4. Steps of Seeker Optimization Algorithm

In SOA, a search direction  $\lambda_{ij}(t)$  and a step length  $\alpha_{ij}(t)$  are computed separately for each  $i^{\text{th}}$  seeker on each  $j^{\text{th}}$  variable at each time step  $t$ , two extreme types of cooperative behavior prevailing in swarm dynamics. One, egotistic, is entirely pro-self and another, altruistic, is entirely pro-group. Every seeker, as a single sophisticated agent, is uniformly egotistic. He believes that he should go towards his historical best position according to his own judgment. This attitude of  $i^{\text{th}}$  seeker may be modeled by an empirical direction vector

$\bar{\lambda}_{ij,ego}(t)$  as shown: [17].

$$\bar{\lambda}_{ij,ego}(t) = \text{sign} ( \bar{I}_{i,best}(t) - \bar{x}_i(t) ) \quad (8)$$

## 4. Seeker Optimization Algorithm with Inertia Weight Factor Approach (SOAIW)

In SOAIW the parameter  $\omega$  is used to decrease the step length with increasing time step so as to gradually improve the search precision. In the present experiments,  $\omega$  is linearly decreased from 0.9 to 0.1 [18].

## 5. The Bacteria Foraging Optimization Algorithm (BFOA)

During foraging of the real bacteria, locomotion is achieved by a set of tensile flagella. Flagella help an E.coli bacterium to tumble or swim, which are two basic operations performed by a bacterium at the time of foraging. When they rotate the flagella in the clockwise direction, each flagellum pulls on the cell. That results in the moving of flagella independently and finally the bacterium tumbles with lesser number of tumbling whereas in a harmful place it tumbles frequently to find a nutrient gradient. Moving the flagella in the counterclockwise direction helps the bacterium to swim at a very fast rate. In the above mentioned algorithm the bacteria undergoes chemotaxis, where they like to move towards a nutrient gradient and avoid noxious environment. Generally the bacteria move for a longer distance in a friendly environment. Figure 3 depicts how clockwise and counter clockwise movement of a bacterium take place in a nutrient solution.

When they get food in sufficient, they are increased in length and in presence of suitable temperature they break in the middle to form an exact replica of itself. This phenomenon inspired Passino to introduce an event of reproduction in BFOA. Due to the occurrence of sudden environmental changes or attack, the chemotactic progress may be destroyed and a group of bacteria may move to some other places or some other may be introduced in the swarm of concern.

This constitutes the event of elimination-dispersal in the real bacterial population, where all the bacteria in a region are killed or a group is dispersed into a new part of the environment [19].

Now suppose that we want to find the minimum of chemotactic " $J(\theta)$ ", where " $\theta$ " is the position of each bacteria at chemotactic step  $G$ -dimensional vector of real numbers, and we do not have measurements or an analytical description of the gradient " $\nabla J(\theta)$ ". BFOA mimics the four principal mechanisms observed in a real bacterial system: chemotaxis, swarming, reproduction, and elimination-dispersal to solve this non-gradient optimization problem.

Let us define a chemotactic step to be a tumble followed by a tumble or a tumble followed by a run. Let " $g$ " be the index for the chemotactic step. Let " $k$ " be the index for the reproduction step. Let " $L$ " be the index of the elimination-dispersal event. Also let [20-21].

$G$ : Dimension "position" of the search space,

$S$ : Total number of bacteria in the population,

$N_c$ : The number of chemotactic steps,

$N_s$ : The swimming length.

$N_r$ : The number of reproduction steps,

$N_e$ : The number of elimination-dispersal events,

$G_e$ : Elimination-dispersal probability,

$Y(e)$ : The size of the step taken in the random direction specified by the tumble.

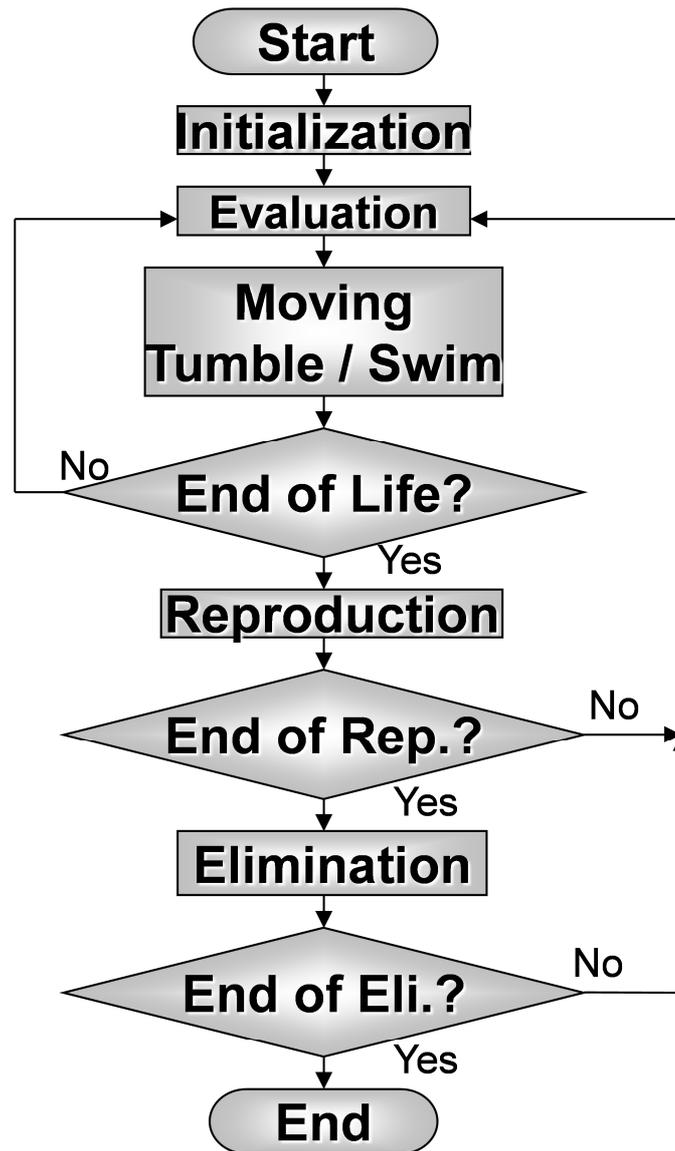


Figure 3. Flowchart of the BFOA algorithm [20-21].

## 6. Performance Tests

Testing and monitoring programs are developed to find out where the efficiency problems are and what improvements can be made. The objective of these performance tests is to provide uniform test methods to obtain the best points of the units operation (optimal power with maximum efficiency). In addition, they help determine the thermal performance and electrical output (capacity or efficiency) of heat cycle for electric power plants and cogeneration facilities according to the specifications [22, 23]. Twelve generation units (two steam units of Ayoun Mousa steam power plant, four gas units of West Damietta power plant and six cogeneration units of Damietta combined power plant) with data given in Appendix A are used in this study in order to assess the performance of the four approaches.

In this study, the performance tests are applied to measure the actual power output and the fuel consumption in every point tests to achieve different curves such as input/ output, incremental heat rate and heat rate curves for the 12 units. It has been proved that the intersection of both the hate rate and incremental heat rate curves occurs at the minimum heat rate value. The results of the performance tests for the 12 units are as follow:

- a) Power only units:  
- Two steam units

$$F(P_i) = \begin{bmatrix} 0.012 & -4.9588 & 2474.3 \\ 0.0105 & -4.4098 & 2431.7 \end{bmatrix} \times \begin{bmatrix} p_i^2 \\ p_i \\ 1 \end{bmatrix}$$

Limit:  $100 \leq p_i \leq 320$  and  $UR_i = 65$ ,  $DR_i = 100$

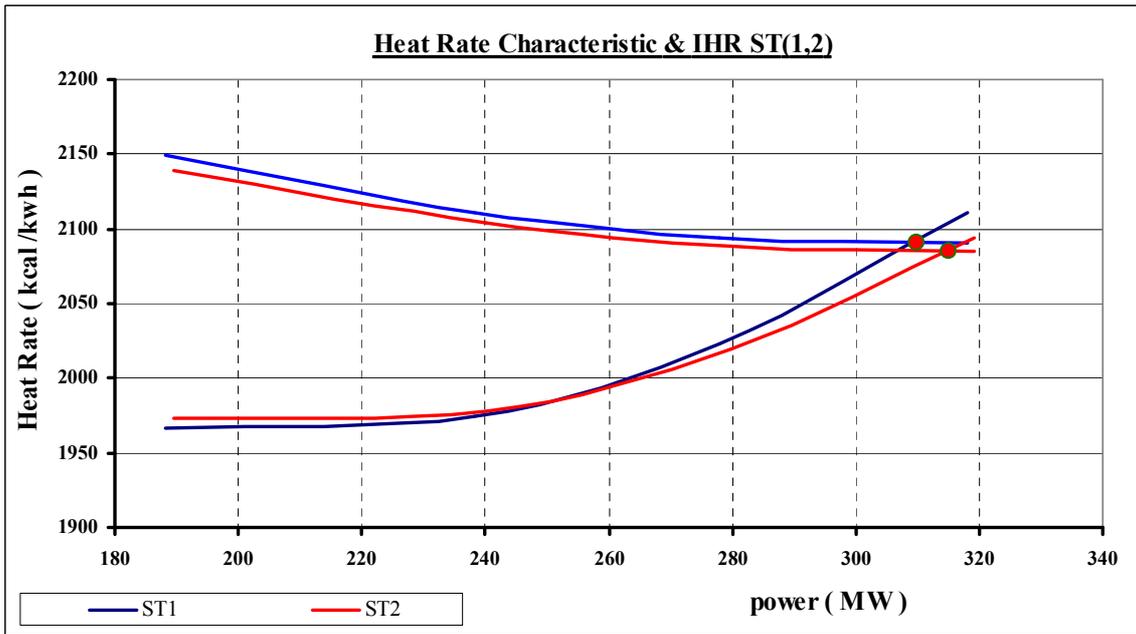


Figure 4. Illustrate performance test for 2 steam units.

The fuel costs of the two steam units according to Figure 4 can be expressed as:

b) Four gas units:

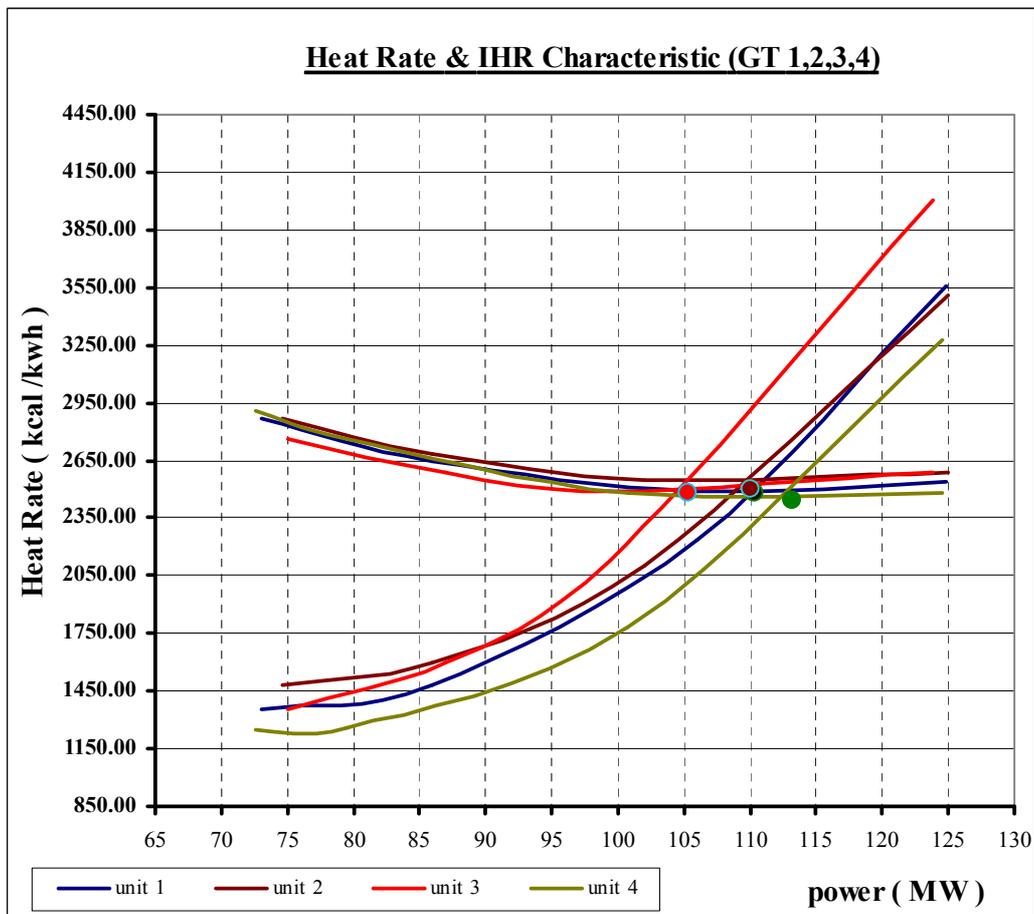


Figure 5. Illustrate performance test for 4 gas units.

From Figure 5 the fuel costs of the four gas units can be expressed as:

$$F(P_i) = \begin{bmatrix} 0.2794 & -61.625 & 5881.8 \\ 0.2574 & -56.929 & 5678.5 \\ 0.3098 & -65.22 & 5911.5 \\ 0.2809 & -63.592 & 6040 \end{bmatrix} \times \begin{bmatrix} p_i^2 \\ p_i \\ 1 \end{bmatrix}$$

Limit:  $64 \leq P_{GTi} \leq 125$ ,  $UR_i = 125$ ,  $DR_i = 125$

where,  $P_{GTi}$  is the power limits of gas units.

c) Cogeneration units:

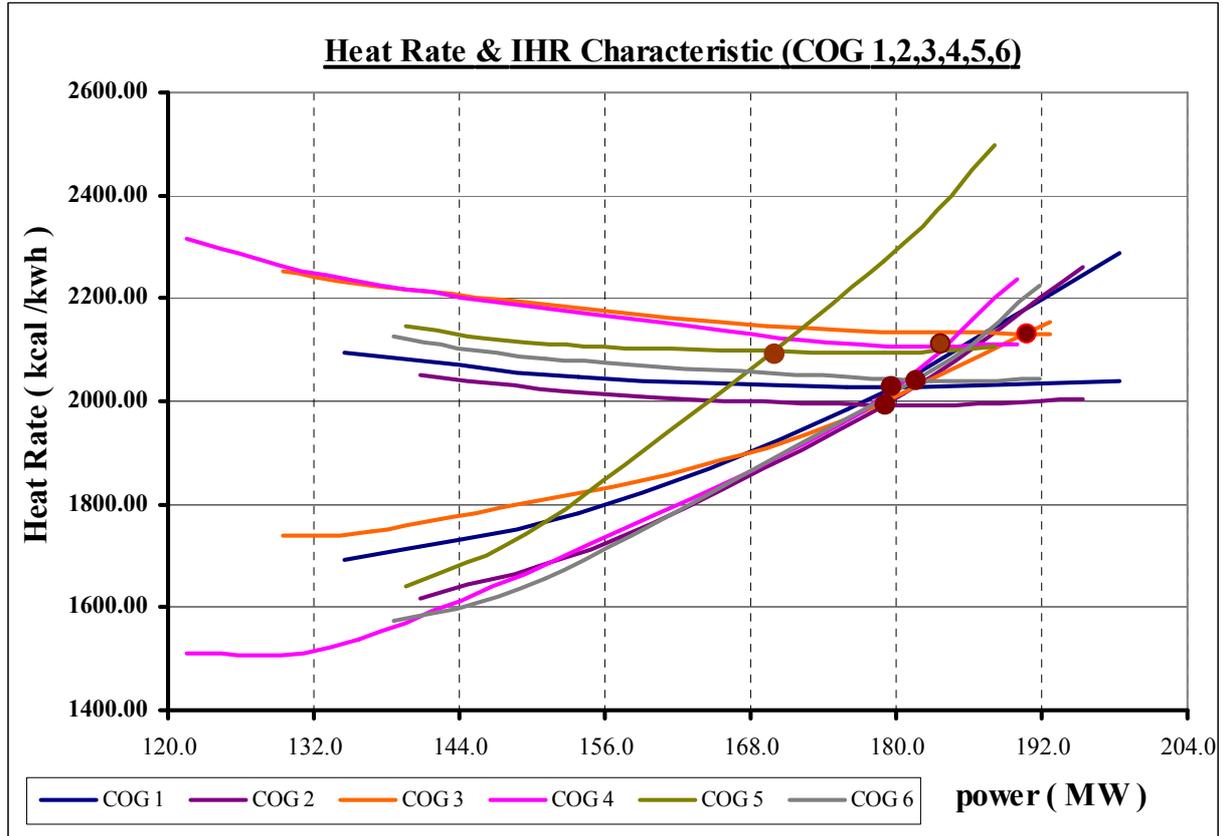


Figure 6. Illustrate performance test for 6 cogeneration units.

The combined heat and power cost equation is expressed as follow:

$$C_J(h_J, p_J) = a p_J^2 + b p_J + c h_J^2 + d h_J + e p_J h_J + f$$

where, a, b, c, d, e, and f are the combined heat and power cost equation coefficients and J is the number of cogeneration units.

Figure 6 shows the heat rate and incremental heat rate characteristics for cogeneration units. From this figure, the combined heat and cost is expressed as:

$$C_J(h_J, p_J) = \begin{bmatrix} 0.0999 & -23.922 & 0.0999 & -23.922 & 0.1998 & 3100.7 \\ 0.1215 & -29.022 & 0.1215 & -29.022 & 0.243 & 3293.2 \\ 0.0969 & -24.658 & 0.0969 & -24.658 & 0.1938 & 3306.7 \\ 0.1599 & -23.176 & 0.1599 & -23.176 & 0.3198 & 3909.3 \\ 0.1755 & -39.912 & 0.1755 & -39.912 & 0.351 & 3792.2 \\ 0.1383 & -33.512 & 0.1383 & -33.512 & 0.2766 & 3562.5 \end{bmatrix} \times \begin{bmatrix} p_J^2 \\ p_J \\ h_J^2 \\ h_J \\ p_J h_J \\ 1 \end{bmatrix} \cdot \text{Limit: } 64 \leq (P, H)_{\text{COG}J} \leq 200, \quad 64 \leq p_J \leq 140, \quad 0 \leq H_J \leq 68,$$

$UR_i = 60$ ,  $DR_i = 100$ .

where,

$(P, H)_{\text{COG}J}$ : total power and heat limits of cogeneration units,

$p_J$ : cogeneration power limits and  $H_J$ : cogeneration heat limits

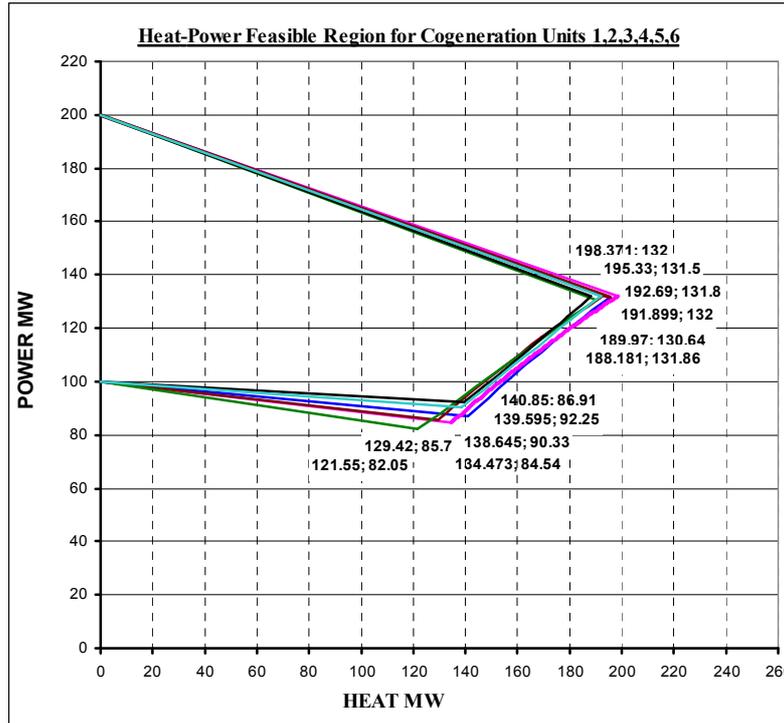


Figure 7. The heat-power operating region for 6 cogeneration units.

Figure 7 shows heat-power feasible region for the six cogeneration units. The maximum and minimum fuel is 200 and 100 MW; respectively.

## 7. Simulation Results

CHPED problem is solved using the SOA, SOAIW, and BFOA approaches. To assess the units efficiency when applying each approach, two case-study are proposed. First, the approaches are tested with a load demand equals to 2148 MW which is the reference of the performance test for the twelve generating units. Second, they are applied to a daily load curve. On both cases, twelve units (two steam, four gas and six cogeneration units) are used.

### 7.1. First Case Study

Figure 8 shows the convergence behavior of the SOA and the other two approaches for the twelve generating units at a load 2148 MW. It is shown that SOAIW approach can reach to the best solution with minimum cost. The convergence behavior of the SOAIW is the best.

Table 1 shows the comparison of the results of the performance of the three approaches at a load of 2148 MW. From these results, it can be seen that the results of SOAIW approach provides lower total operation cost at less computation time compared with those obtained from the other two approaches.

Therefore, SOAIW is more effective in providing better solutions and shows a more robust performance.

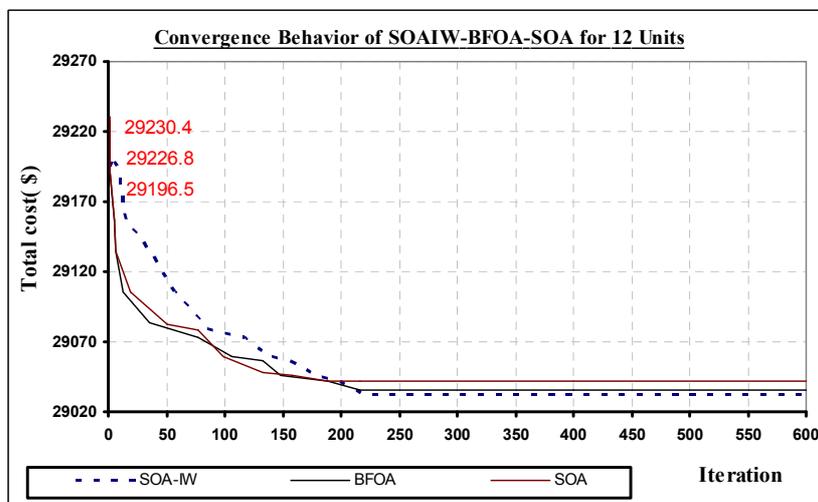


Figure 8. The convergence behavior of the SOA, SOAIW and BFOA for 12 units at load 2148MW.

Table 1. Comparison results between the SOA, SOAIW and BFOA approaches.

Units output	SOA	BFOA	SOA-IW
ST1	318.859	292.644	319.997
ST2	316.339	319.998	311.024
GA1	101.271	114.823	104.003
GA2	123.840	94.640	106.429
GA3	87.025	95.872	76.917
GA4	114.075	112.042	117.873
COG-P1	123.680	125.450	130.680
COG-H1	60.700	61.500	64.100
COG-P2	127.980	129.220	100.250
COG-H2	60.420	60.810	54.440
COG-P3	122.700	133.850	134.470
COG-H3	56.980	63.950	64.400
COG-P4	117.440	129.930	137.340
COG-H4	53.690	58.790	61.830
COG-P5	133.640	125.510	130.670
COG-H5	58.330	56.570	57.700
COG-P6	116.610	117.680	120.400
COG-H6	54.430	54.720	55.470
Total power (MW)	2148.000	2148.000	2148.000
Total heat (MW)	344.55	356.34	357.94
Total cost (\$/h)	29043.457	29039.763	29025.411
CPU Time (sec)	4.6	4.56	4.42

The total cost of SOAIW with heat and load demands (\$29025.41) is lower than those of SAO, and BFOA (\$29043.457 and \$29039.763, respectively). In addition, the total heat production which is the sum of the total heat production of the six cogeneration units (357.94 MW) is higher than those of the other approaches (344.55 MW and 356.34 MW; respectively). The same conclusion can be concluded from Figure 9.

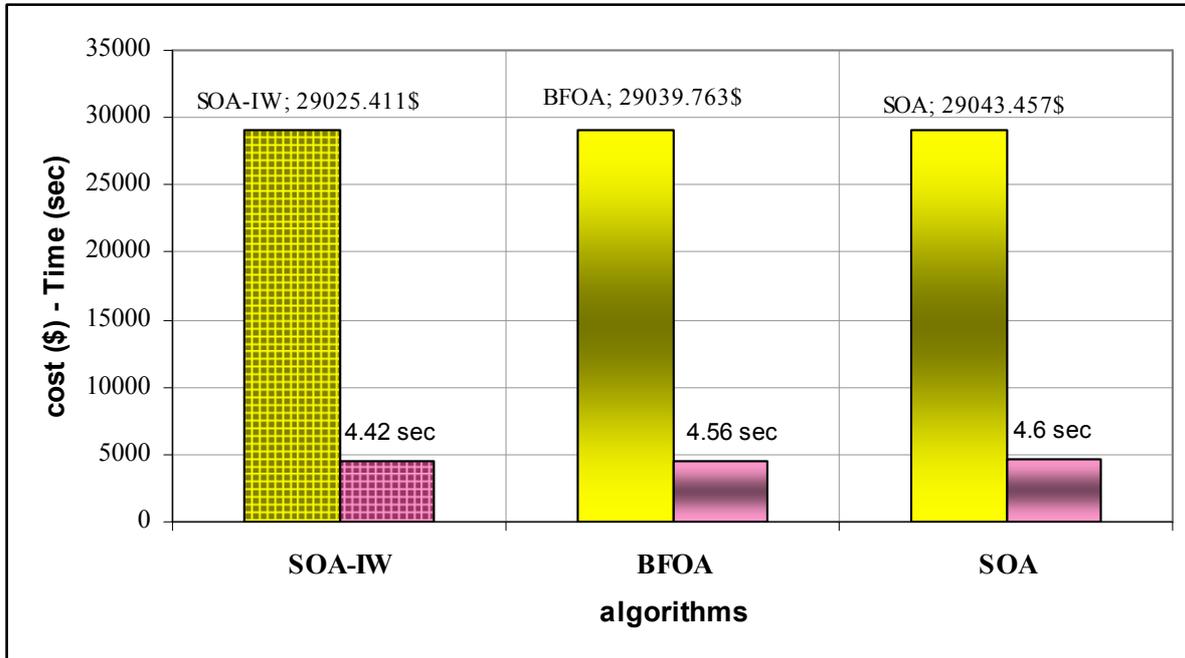


Figure 9. The comparison between SOA, SOAIW and BFOA methods for case 1.

7.2. Second Case Study

Figure 10 shows the daily load curve used in the study. The four approaches are applied to the twelve units and Figure 11 shows the comparison between the results. It is evident that the SOAIW algorithm has the advantage of cost saving that is around 1.00058 and 1.002016 times from SOA and BFOA, respectively.

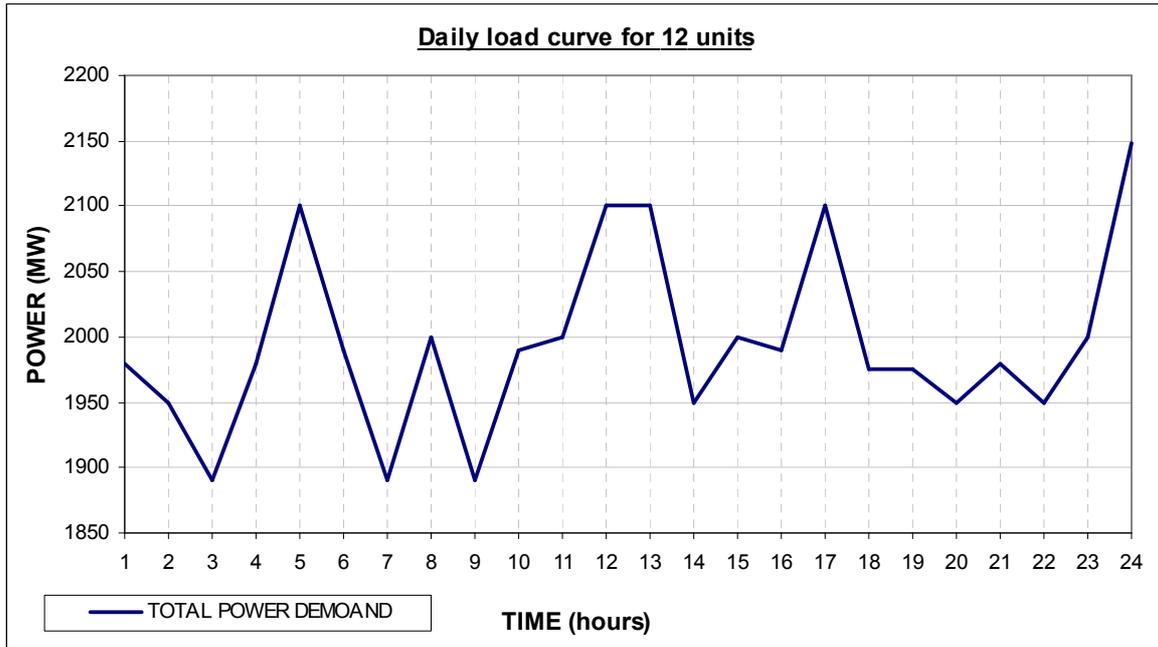


Figure 10. The daily load curve.

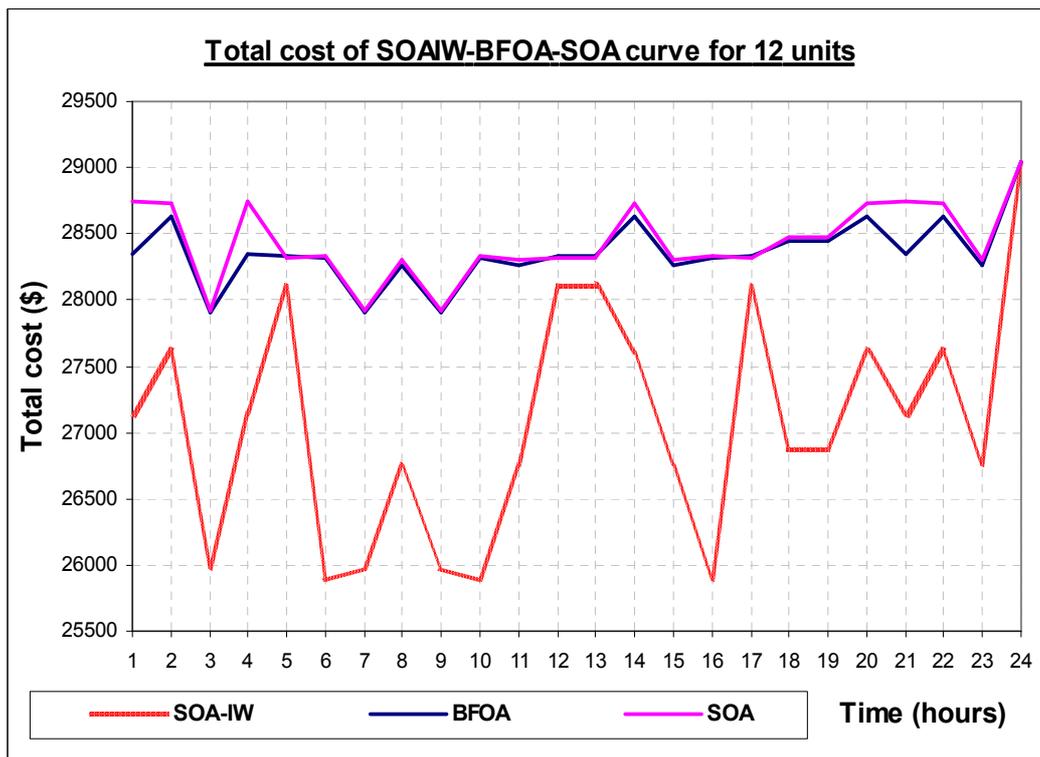


Figure 11. The total cost for 12 generation units of all approaches for case 2.

## 8. Conclusions

Comparative study based on SOA, SOAIW and BFOA approaches applied to solve CHPED problem has been presented. The approaches are tested on 12 generation units (two steam, four gas and six cogeneration units) taking into consideration the system and units constraints. The results of the Three approaches are compared. From the results, it is clear that SOAIW approach is more effective than other approaches discussed. This gives the best global optimum solution with less computation time than the SOA and BFOA techniques.

## Appendix A

The system data of twelve units (two steam, four gas and six cogeneration units) are used.

a) two steam units x 320 MW:

- Steam unit 1:

item	unit	Test1	Test2	Test3	Test4	Best point
Fuel (input)	(K cal/hr) x1000	664730	582015	502997	404351	647770
IHR	K cal /kwh	2110.89	2023.02	1974.08	1966.12	2090.09
Heat rate	K cal /kwh	2090.35	2094.18	2110.60	2149.43	2090.09
Power (output)	MW	318	277.92	238.32	188.12	309.925

- Steam unit 2:

item	unit	Test1	Test2	Test3	Test4	Best point
Fuel (input)	(K cal/hr) x1000	665668	584642	505425	405604	656558
IHR	K cal /kwh	2094.24	2020.01	1978.29	1973.07	2084.43
Heat rate	K cal /kwh	2084.51	2088.75	2104.01	2139.49	2084.44
Power (output)	MW	319.34	279.9	240.22	189.58	314.98

b) four gas units x 125 MW:

- Gas unit 1

item	unit	Test1	Test2	Test3	Test4	Best point
Fuel (input)	(K cal/hr) x1000	317324.7	263822.2	227770.346	209663.12	273909.9
IHR	K cal /kwh	3555.20	2235.32	1481.63	1351.32	2483.71
Heat rate	K cal /kwh	2542.67	2488.89	2648.49	2872.10	2483.77
Power (output)	MW	124.8	106	86	73	110.28

- Gas unit 2:

item	unit	Test1	Test2	Test3	Test4	Best point
Fuel (input)	(K cal/hr) x1000	323031.3	260072.6	230865.235	213659.53	278393.5
IHR	K cal /kwh	3511.88	2098.95	1596.01	1482.11	2497.74
Heat rate	K cal /kwh	2584.25	2549.73	2687.60	2864.07	2530.85
Power (output)	MW	125	102	85.9	74.6	110

- Gas unit 3:

item	unit	Test1	Test2	Test3	Test4	Best point
Fuel (input)	(K cal/hr) x1000	320071.9	247676.1	224654.549	207196.88	260931.5
IHR	K cal /kwh	4007.42	2134.01	1597.85	1356.38	2478.83
Heat rate	K cal /kwh	2585.40	2489.21	2582.24	2762.63	2478.92
Power (output)	MW	123.8	99.5	87	75	105.26

- Gas unit 4:

item	unit	Test1	Test2	Test3	Test4	Best point
Fuel (input)	(K cal/hr) x1000	308690.8	250392.3	219403.641	210814.23	276286.1
IHR	K cal /kwh	3275.93	1782.22	1254.95	1248.11	2440.70
Heat rate	K cal /kwh	2477.45	2484.05	2759.79	2903.78	2440.91
Power (output)	MW	124.6	100.8	79.5	72.6	113.19

c) six cogeneration units x 200MW:

- Cogeneration unit 1:

item	unit	Test1	Test2	Test3	Test4	Best point
Fuel (input)	(K cal/hr) x1000	404353.91	356572.29	315138.28	281644.22	363973.43
IHR	K cal /kwh	2286.44	1983.85	1784.71	1690.33	2026.6
Heat rate	K cal /kwh	2038.37	2027.09	2048.76	2094.43	2026.6
Power (output)	MW	132	116.95	100.36	84.54	
heat (output)	MW	198.371	175.904	153.819	134.473	179.595

- Cogeneration unit 2:

item	unit	Test1	Test2	Test3	Test4	Best point
Fuel (input)	(K cal/hr) x1000	391443.43	360134.47	316518.59	289141.83	357111.94
IHR	K cal /kwh	2260.04	2015.55	1733.91	1615.87	1993.39
Heat rate	K cal /kwh	2004.00	1993.48	2012.81	2052.78	1993.39
Power (output)	MW	131.5	120.6	101.34	86.91	
heat (output)	MW	195.33	180.66	157.25	140.85	179.148

- Cogeneration unit 3:

item	unit	Test1	Test2	Test3	Test4	Best point
Fuel (input)	(K cal/hr) x1000	410491.102	363411.374	304327.356	291457.797	406550.15
IHR	K cal /kwh	2153.21	1910.48	1746.90	1738.49	2130.2
Heat rate	K cal /kwh	2130.31	2145.03	2224.55	2252.11	2130.20
Power (output)	MW	131.8	116.6	91.8	85.7	
heat (output)	MW	192.69	169.42	136.80	129.42	190.851

- Cogeneration unit 4:

item	unit	Test1	Test2	Test3	Test4	Best point
Fuel (input)	(K cal/hr) x1000	401156.933	368562.154	302906.047	281493.663	387648.65
IHR	K cal /kwh	2237.59	1938.97	1537.40	1509.88	2109.6
Heat rate	K cal /kwh	2111.69	2114.38	2232.94	2315.85	2109.6
Power (output)	MW	130.64	119.6	92.05	82.05	
heat (output)	MW	189.97	174.31	135.65	121.55	183.752

- Cogeneration unit 5:

item	unit	Test1	Test2	Test3	Test4	Best point
Fuel (input)	(K cal/hr) x1000	396773.48	375003.52	319707.01	299629.20	355356.1
IHR	K cal /kwh	2496.34	2272.08	1772.19	1640.61	2079.110
Heat rate	K cal /kwh	2108.47	2094.51	2111.82	2146.42	2090.330
Power (output)	MW	131.86	124.34	101.61	92.25	
heat (output)	MW	188.181	179.041	151.389	139.595	170.00

- Cogeneration unit 6:

item	unit	Test1	Test2	Test3	Test4	Best point
Fuel (input)	(K cal/hr) x1000	392372.53	373151.982	314787.229	294693.019	370725.07
IHR	K cal /kwh	2224.51	2059.95	1656.48	1574.69	2039.92
Heat rate	K cal /kwh	2044.68	2039.99	2083.16	2125.52	2039.9212
Power (output)	MW	132	125.23	100.24	90.33	
heat (output)	MW	191.899	182.919	151.111	138.645	181.735

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