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Multi-criteria Optimization of a CCHP System Using Balanced Tree Growth Algorithm

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ABSTRACT

The main idea of this paper is to multi-criteria optimal designing of a combined cooling, heat and power (CCHP) system in an industrial unit by considering cooling loads, electricity, and heating. Different scenarios such as selling scenarios, no-selling scenario, as well as the possibility of electricity selling with identical capacities of the gas engine have been utilized. Because of the complexity of this problem, a new developed metaheuristic methodology, called Balanced Tree Growth Algorithm (BTGA) is designed and utilized. Relative Annual Benefit (RAB) as a multi-criterion function along with a gas engine is utilized as the primary mover during the optimization. Final simulation indicate that the proposed approach has well results toward the method from the literature. The results also specified that however using of the proposed configuration gives suitable results for different scenarios, selling scenario is more profitable.

Keywords: *Multi-criteria optimization; CCHP; Balanced Tree Growth Algorithm; Relative annual benefit*

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1. INTRODUCTION

Conventional power plants usually generate electricity through an inefficient process [1]. A fossil fuel such as gasoline, coal, or natural gas releases heat energy in a large furnace during the combustion process [2]. This heat is used to boil and evaporate water to turn the steam from a turbine, to move the turbine of the generator, and to generate electricity by rotating the generator [3]. The problem with this cycle is that a lot of energy is wasted at each stage [4]. Boiled water, which is supposed to start the turbine, has to be cooled in very large cooling towers in the open air, which in turn causes a lot of energy to be lost [5-7]. One of the best alternative forcovering this issue is to utilize the Combined Cooling, Heating, and Power (CCHP) system.

Simultaneous generation based on CCHP using one type of input fuel makes significant energy savings possible and, in many cases, a key alternative to separate thermal and electrical energy generations because of its high value of energy performance, reduced pollution emissions and increased robustness. However, it seems necessary to have a correct assessment in order to examine the economic justification of investment in these power plants according to various conditions such as the type and volume of energy demand at the place of consumption and also the characteristics of operation parameters [8].

If we prevent the combustion of any amount of fossil fuels, we have prevented the production of large amounts of carbon dioxide and its entry into the atmosphere, which in itself slightly reduces the intensity of global warming [9-14]. Reducing the combustion of fossil fuels helps reduce air pollution and related problems, as well as reducing acid rain and water pollution. Replacing older power plants with much smaller cogeneration plants reduces

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our dependence on centralized power grids and our vulnerability to global power outages [15, 16]. These power plants, like conventional power plants, run on any fuel such as oil, gas or biomass [17-19]. The CCHP systems not only increase the energy consumption performance, but also decreases the fuel consumption and they have a big effect on declining emissions [12, 20]. Recently, with the advancement of technology, the progress and development of CCHP systems and the economic benefits of this energy conversion process as well as reduction of investment costs, has led to a broad approach of major energy consumers for using this technology [21, 22]. Accordingly, higher energy efficiency of these systems can decrease the need for fuel and so, indirectly decreases the environmental pollution by up to 50% on a large scale, a step towards the restructured electricity industry development and the advantage of the products distributing [23-25]. The main parts of a CCHP system including initial actuator, generator, heating energy exchanger, and managing system [26-28]. All through the generation process of the compressor, the chemical energy in the fuel is released based on a main actuator like turbine or engine to be converted into the mechanical output power of the generated shaft [29-31]. This power is then employed for swiveling the drive shaft and for energy generation [32]. The system is then used the wasted heat energy of the output gases of the initial actuator to recover it for using them in cooling and heating based on chiller and heat exchangers, respectively. Fig. (1) represents the main formation of the considered CCHP system.

Different works have been done in this area in the literature. for instance, Li et al. [33] proposed a CCHP and a ground source heat pump (GSHP) coupling system with to increase the system efficiency. The results were then compared with the system in the absence of heat exchanger. To achieve optimal solution to the algorithm, it is compared with separated generation (SG) system, based on simple GA (SGA) and quantum GA (QGA) for a hotel building. The results showed that QGA gives better achievements than the SGA in solving of the energy system configuration.

Zeng et al. [34] proposed an off-design optimization model for a CCHP-GSHP using carbon tax. The optimization includes 13 decision variables based on environment criteria, economy criteria, and energy criteria. They used a hybrid Particle Swarm Optimization (PSO) algorithm to resolve the problem. For indicating the system efficiency, the method was applied to a case study and the results indicate the superiority of the proposed CCHP-GSHP system toward a reference system. Finally, a sensitivity analysis was performed based on the electricity and natural gas price.

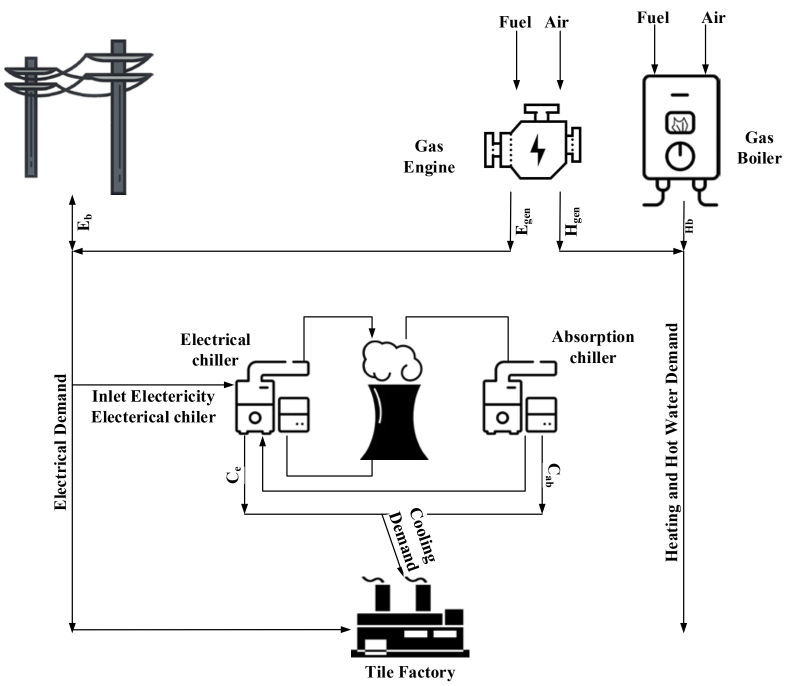


Fig. 1. The main formation of the analyzed CCHP plant

Cao et al. [27] introduced a multi-criteria approach for environment, economic, and thermodynamics assessment of a CCHP system with a 5kW PEMFC stack as the primary mover. The paper introduced improved emperor penguin optimization (IEPO) algorithm to optimize the performance of the system. During the simulation, energy and exergy analysis was permed on the annual cost, and pollutant emission reduction. The results were compared with another work from the literature to indicate the superiority of the proposed algorithm.

Zhi et al. [35] proposed another optimal solution for designing of a CCHP system along with a 5 kW proton exchange membrane stack as the primary mover. They proposed Improved Butterfly Optimization Algorithm (IBOA) to increase the system efficiency. for performance analysis of the system, it is assessed in different terms of pollutant emission reduction, exergy and energy, and annual cost. Simulation results showed that using the proposed algorithm increases the system efficiency in different terms in comparison with other methods from the literature.

Cao et al. [36] presented an optimal methodology for optimizing the energy flow of a CCHP system by considering the power consumption reduction. The method was optimized based on Developed Owl Search Algorithm (DOSA) applied to a building in Kerman, Iran. The results of the method were compared with some other algorithms and the results indicated the higher performance of the suggested technique compared with others.

Although, several works were proposed in the field of CCHP systems optimization, most of them lacks studies on the cogeneration design combined with industrial units along with economic, environmental, thermodynamic analyzes. Furthermore, most of the illustrated metaheuristics have their specific shortcomings from local optimum trapping to premature convergence. The main idea behind this study is to propose a new optimization algorithm with the least shortcoming and a cost function based on environmental analyzes, economic, and thermodynamic.

2. SYSTEM MODELING

In this study, the method analysis has been performed in energy, environmental and economic terms of view. All of these assessments are important in the CCHP systems performance analysis. In the following, the methods of system analysis are clarified.

2.1. Economic analysis of the System

The first analysis is to assess the system cash flow for system economic performance analysis. The assessment of a CCHP system contains fuel costs, initial investment costs, and operation and maintenance costs. The initial cost of the system can be addressed by the following formulation [37]:

$$C_i = \alpha \times C \tag{1}$$

where, C signifies the capital investment cost (\$/kW), and α describes the capital recovery factor which is achieved as follows [12, 38]:

$$\alpha = \frac{i \times (1+i)^n}{(1+i)^n - 1} \tag{2}$$

where i signifies the system interest rate.

Also, the annual salvage cost of the system, A, is achieved as follows:

$$A = \frac{S_v \times (1+i)^n}{(1+i)^n - 1} \tag{3}$$

where S_v describes the salvage value in the current year that is regularly measured as a percentage of the system initial cost.

Finally, by considering the above formulations, the equivalent uniform annual cost is defined as follows:

$$AC_{eu} = C_i + S_v \tag{4}$$

The main information of the cost for the system including the initial costs, salvage value of equipment and the maintenance costs is given in Table 1.

2.2. System analysis in terms of first law of thermodynamics

Because of the inconsistency of the heating, cooling, and electrical loads and also water requirements with time at the studied place, the equipment of the CCHP have time-dependent. To do so, sometimes, the equipment should run in *partial load* (loads with sizer less than the nominal load of equipment). Changing the operation

Table 1. The required parameters of the optimal 4E investigation

Notation	Parameter	Value	Unit
ε_{NOx}	NOx emission factor	6.853	\$/kg
ε_{CO}	CO emission factor	0.02086	\$/kg
ε_{CO2}	CO2 emission factor	0.024	\$/kg

Table 2. Technical specifications

Parameter	Value
η_c^{ab}	0.7
η_n^{b}	90
η_c^{co}	3

point in the equipment to the partial load make its technical parameters like fuel consumption, heat loss, and efficiency varying. Here, all of the characteristics for the equipment have been measured by assuming the partial load.

The total heat generated of the CCHP system (H_g) equals to the sum of extracted heat from lubrication, exhaust, and the cooling water process in the gas engine. By considering this assumption, the technical features of the absorption chillers, compression, and the boiler are given below:

$$\frac{\eta_b}{\eta_n^b} = -0.6249 \times L_p^2 + 1.525 \times L_p + 0.0951 \tag{5}$$

$$\frac{\eta_c^{co}}{\eta_n^{co}} = -0.819 \times L_p^2 + 1.1819 \times L_p \tag{6}$$

$$\frac{\eta_c^{ab}}{\eta_n^{ab}} = L_p \times \left(0.75 \times L_p^2 + 0.0195 \times L_p\right)^{-1} \tag{7}$$

where, L_p signifies the partial load (%), η_n^b and η_b describe the nominal load and the partial load efficiencies of the boiler, respectively; η_n^{co} and η_c^{co} represent the nominal load and the partial load efficiencies of the comprador; and η_c^{ab} and η_n^{ab} describe the partial load and the nominal load efficiencies of the absorption chiller. The following assumptions have been considered for the present study (Table 2).

Also, the fuel consumption is achieved by the following [39]:

$$f_{con} = \frac{E_n}{\eta_{nom} \times LHV} \tag{8}$$

Where, η_{nom} describes the nominal efficiency and achieved as follows:

$$\eta_{nom} = 9.73 \times 10^{-7} \times E_n + 0.375 \tag{9}$$

2.3. Economic analysis of the System

The present study uses three environmental criterion including NOx, CO, and CO2 emissions. The equation for the presented parameters is given below:

$$m_E^k = \sum_{j=1}^{T} \left(\psi_E^k \times E_j\right) \times \tau_j \tag{10}$$

$$m_{C_{ab}}^k = \sum_{j=1}^{T} \left(\psi_H^k \times C_{ab,j}\right) \times \tau_j \tag{11}$$

$$m_H^k = \sum_{j=1}^{T} \left(\psi_H^k \times H_j\right) \times \tau_j \tag{12}$$

$$m_{C_c}^k = \sum_{j=1}^{T} \left(\frac{\psi_E^k \times C_{c,j}}{COP_c}\right) \times \tau_j \tag{13}$$

where, τ describes the time period of a month (hr), COP describes the coefficient of performance (%), k describes the pollutant type (i.e. NOx, CO, and CO2), ψ signifies the emission factor for all types of energies, j defines the month, and m represents the pollutant mass (Kg). Table 1 tabulates the CCHP emission factor and the traditional (trad) systems.

3. OBJECTIVE FUNCTION

For analyzing of the system in terms of economic, environmental, and energy, the Relative Annual Benefit (RAB) has been utilized. The RAB is an indicator to determine the difference between the annual cost of traditional system and the system in providing the electricity loads. Optimization of the system depends to minimizing the RAB function which is achieved as follows:

$$RAB = TAC_{tr} - TAC_{sys} \tag{14}$$

where, TAC_{tr} describes the costs and incomes of the traditional system and is estimated as:

$$TAC_{tr} = \sum_{j=1}^{T} \left[E_b \times p_e + m_f \times p_f + \sum_{k=1}^{3} \left(m_{tr}^k \times \varepsilon_k\right) \right] \times \tau \sum_{=1}^{L} \left(p_m + EUAC\right)_l \times NC_l \times n_l \tag{15}$$

where, E_b signifies the electricity of the boiler, p_m describes the maintenance costs, p_e defines the electricity purchase, p_f represents the fuel consumption, m defines the mass flow rate, l describes the type of equipment, n determines the quantity of equipment, ε describes emissions' fines.

Furthermore, the annual cost of the CCHP system, TAC_{sys} similarly with a difference in the electricity and equipment sale of the system is obtained by the following:

$$TAC_{sys} = \sum_{j=1}^{T} \left[\begin{array}{l} E_b \times p_e - E_s \times p_e^s + m_f \times p_f \\ + \sum_{k=1}^{3} \left(m_{CCHP}^k \times \varepsilon_k \right) \end{array} \right] \times \tau \sum_{l=1}^{L} \left(p_m + EUAC \right)_l \times NC_l \times n_l \tag{16}$$

where, E_s describes the grid selling electricity and p_e^s defines the unit price of the grid selling electricity.

4. THE CASE STUDY

The optimization process is performed to an industrial factory placed in Naning, the center of the Guangxi Zhuang placed in southern china with coordinates 22°49′00″N 108°19′39″E. The idea is to optimize the CCHP generation system of the factory to progress its efficiency. The required electricity of the factory, E_D, includes its different loads such as lighting, and cooling energy for compression chiller has been purchased from the grid and the required heating is supplied by fuel consumption in the boiler. Fig. (2) shows different load deliveries for the case study.

5. THE SYSTEM POLICY

In the traditional system in the case study, the nominal capacity of the boiler and electric chiller show the maximum cooling and heating, respectively. This policy can be assessed by the following:

$$H_b = H_D \quad if \quad C_{ab} = 0 \tag{17}$$

$$E_b = E_D + C_D \times COP_c \tag{18}$$

$$C_C = C_D \tag{19}$$

where, H_b and H_D are the heat for boiler and the demand.

Once using the absorption chiller, the boiler is also utilized for supplying the required heat for cooling of the demand (C_D). Here, the maximum cooling indicates the chiller nominal capacity and the needed total heating for the factory though the needed heat for the absorption chiller determines the boiler nominal capacity as follows:

$$C_{ab} = C_D \quad if \ E_C = 0 \tag{20}$$

$$E_b = E_D \tag{21}$$

$$H_b = H_D + C_D \times COP_{ab} \tag{22}$$

The primary mover of the studied CCHP system is gas engine which supplies the required electricity demand for the lightening (E_D) and the compression chiller (E_C). If the building required energy demand is more than the generated electricity by the prime mover (E_g), the deficiency will be provided by purchasing the electricity from the distribution system. In this study, the value of the sold electricity to the distribution system (E_s) is assumed zero, i.e.

$$E_s = 0 \quad if \quad E_g < \left(E_C + E_D \right) \tag{23}$$

$$E_b = E_C + E_D - E_g \tag{24}$$

In contrast, if the building required energy

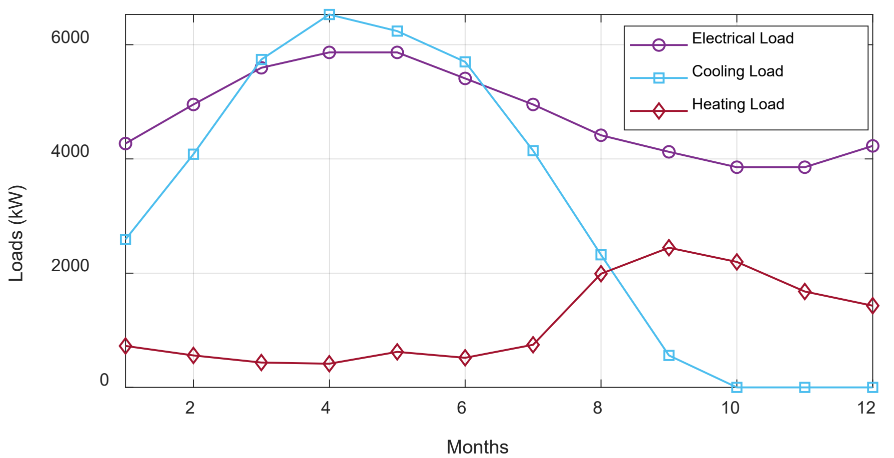


Fig. 2. Different load deliveries for the case study

demand is less than the generated electricity by the prime mover, the system can sell the extra electricity to the distribution system, i.e.

$$\begin{cases} E_s = E_g - E_C - E_D & if \quad E_g > (E_C + E_D) \\ E_b = 0 \end{cases} \tag{25}$$

The required heating demand (H_D) is supplied by the wasted heat from the boiler by transferring it toward the absorption chiller. In the event that the required heating energy is not supplied by the absorption chiller, the compression chiller will be used for supplying the deficiency. This policy can be illustrated as follows:

$$H_b = 0 \quad if \; H_g > H_D \tag{26}$$

$$C_{ab} = \left(H_g - H_D\right) / COP_{ab} \tag{27}$$

$$C_C = C_D - C_{ab} \tag{28}$$

If the heat demand of the building is higher than the produced heat by the prime mover, the supplementary heating has been supplied by the boiler and the required cooling has been provided by the compression chiller (C_c), i.e.

$$H_b = 0 \quad if \; H_g > H_D \tag{29}$$

$$C_{ab} = \left(H_g - H_D\right) / COP_{ab} \tag{30}$$

$$C_C = C_D - C_{ab} \tag{31}$$

Due to the complexity of this problem, using classic optimization may not give proper solution in a logical time. Therefore, in the following, a new optimization methodology is introduced.

6. THE BALANCED TREE GROWTH ALGORITHM

6.1. The concept of the algorithm

This algorithm is a bio-inspired optimization algorithm which is inspired by the trees competition for obtaining nutrients and light. The Tree Growth Algorithm (TGA) divides the trees population into four separate phases. The first phase is called best trees group which includes a number of well trees that have good potential because of growth favorable conditions, i.e. they receive enough amount of light and the main competition among them is to focus on the food during the competition. Due to the slow growing of the trees, the better trees are taller and smoother with older age. Accordingly, by growing the age of the trees, the rate of growth has been decreased meaningfully rather than before and their focus changes to receive the food in roots. In the other phase that is called light group competition, some trees attempt to move to distance between the adjacent best trees with different angles to meet the light. The other group that is called the remove and replace group, the trees that have grown low, have been replaced by new candidate by planting new trees. The last phase which is called the reproduction group, belongs to the best trees. In this phase, due to the favorable growth of these trees, they commence to multiply and generate new plants. Due to the growing close to the mother tree, the offspring receive some special factors. The mathematical model of the algorithm is described briefly as follows:

Step 1) Initializing: in this step, the initial population of trees has been generated randomly in the range of upper and lower bounds

Step 2) Fitness evaluation: during this step, the fitness value for each tree has been achieved by evaluation based on the considered function.

Step 3) Find the optimized tree. In other words, this step finds the minimization, the optimized tree is the one which gives the minimum value for the objective function and contrariwise. Here, T_g^j is the global best at j^{th} iteration.

Step 4) Let N_1 local better solutions. During the process, several local searches are searched for the solutions as if the new solutions have better results, replace them.

$$T_i^{j+1} = r \times T_i^j + \frac{1}{\gamma} \times T_i^j \tag{32}$$

where, r is a random variable with standard uniform distribution in the range [0,1], that owing to light satisfaction by the trees, its roots are trained to transfer and engage food that growth at a rate of T_i^j units and γ describes the reduction rate of power for trees based on reduced food around, high growth, and aging.

Step 5) Move N_2 number of solutions to distance between the near best solutions under diverse α angles. To do so, first, the distance between the selected trees and others should be found as follows:

$$d_i = \sqrt{\left(\sum_{i=1}^{N_1+N_2} \left(T_{N_2}^j - T_i^j\right)^2\right)} \tag{33}$$

Such that,

$$d_i = \begin{cases} d_i \ if \ T_{N_2}^j \neq T_i^j \\ \infty \ if \ T_{N_2}^j = T_i^j \end{cases} \quad (34)$$

Afterward, two solutions including x_1 and x_2 with minimal distance, d_i to obtain a linear combination among the trees. This process can be formulated as follows:

$$y = \lambda \times x_1 + (1-\lambda) \times x_2 \quad (35)$$

where, λ defines a random variable with standard uniform distribution in the range [0,1].

For moving this tree between two neighbor trees with an $\alpha_i = U(0,1)$ angles, the following equation is utilized:

$$T_{N_2}^j = T_{N_2}^j + \alpha_i \times y \quad (36)$$

Step 6) Remove N_3 numbers of worse solutions and replace random values instead of them

Step 7) Generate N numbers of new population, where $N = N_1 + N_2 + N_3$.

Step 8) Generate N_4 numbers of new solution and changing them by the mask operator based on the best solution, randomly and then added to the new population, i.e.

$$new\ population = new\ population + N_4 \quad (37)$$

Step 9) Sorting the new population and selecting N numbers of them as the initial population of the next iteration which is performed based on tournament, roulette wheel, or the best solution.

Step 10) if stopping criteria is met, end the algorithm and display the results. If not so, repeat the algorithm from step 3.

6.2. Balanced Tree Growth Algorithm (BTGA)

The Tree Growth Algorithm (TGA) is a new and well-organized metaheuristic algorithm that can be utilized in different areas for solving the optimization problems [40, 41]. However, if there is an unbalanced trade-off between the exploitation and the exploration of the algorithm, it may result premature convergence with low accuracy. To resolve this shortcoming in the TGA, the local search plan is utilized by considering an elite tree in each iteration. First, the elite tree with best cost is found the search space. Afterward, N_l number of trees are selected. Then, other trees move their root toward the elite tree to form new trees instead of N_3 numbers of removed trees; in this case, by considering ν as radius in growth space,

$$T_{N_3}^j = T_{N_3}^e \times (2 \times \delta \times \nu + (1-\nu)); \ i = 1,2,\ldots,m \quad (38)$$

where, $T_{N_3}^e$ describes i^{th} variable amount for the elite tree, and $T_{N_3}^j$ represents the i^{th} variable value for the j^{th} new population. The new population is defined by a row vector as follows:

$$T_{N_3}^j = \left[x_i^j, x_2^j, \ldots, x_m^j\right]; \ s = 1,2,\ldots,N_l \quad (39)$$

where, δ signifies a random value between 0 and 1. Then, the new results should be checked and modified to guarantee the best value between the minimum value ($\underline{x}$) and maximum value ($\overline{x}$) as follows:

$$T_{N_3}^j = \begin{cases} \underline{x} \ if \ x_i^s < \underline{x} \\ \overline{x} \ if \ x_i^s > \overline{x} \end{cases} \quad (40)$$

And the cost value for all new trees are evaluated to obtain the best tree with the best cost.

The second modification in the algorithm that is used for resolving the premature convergence is to use chaos mechanism. Chaos mechanism is a conception for defining of the sensitive systems which are affected by any small changes. The applications of this mechanism is increasing day by day in the optimization field [12, 21]. This mechanism can be utilized for refining the algorithm in terms of convergence speeds [42, 43]. The typical definition of the chaos mechanism is as follows:

$$X_{i+1}^j = f\left(X_i^j\right), j = 1,2,\ldots,d_m \quad (41)$$

where, $f\left(X_i^j\right)$ determines the generator function of the mechanism, and d_m signifies the map dimension. In this study, Tent map has been employed for modifying the local better solutions as follows:

$$T_i^{j+1} = p^q \times T_i^j + \frac{1}{\gamma} \times T_i^j \quad (42)$$

where,

$$P^{q+1} = \begin{cases} 1.43 \times P^q, & P_i^q < 0.7 \\ 3.33 \times \left(1-P^q\right), & P_i^q \geq 0.7 \end{cases} \quad (43)$$

6.3. Algorithm validation

In this subsection, the experimentation of the suggested BTGA for four standard test functions is described for evaluating the proposed algorithm's efficiency. For indicating the superiority of the presented method, it has been compared with four renowned optimization algorithms including Emperor Penguin Optimizer (EPO)[44], Spotted Hyena Optimizer (SHO) [45], Multi Verse Optimizer (MVO) [46], and the basic TGA [40]. The parameter settings of the suggested BTGA and the competitor metaheuristics are indicated in Table 3.

The mathematical formulation of the test functions are as follows.

1) Generalized Rosenbrock's Function:

$$F_1(x) = \sum_{i=1}^{d}\left[100\times\left(x_{i+1}-x_i^2\right)^2+\left(x_i-1\right)^2\right] \tag{44}$$

where,

$$-30 \le x_i \le 30;\ F_1^{min} = 0;\ d = 30 \tag{45}$$

2) Generalized Rastrigin's function:

$$F_2(x) = \sum_{i=1}^{d}\left[x_i^2 - 10\times\cos\left(2\times\pi\times x_i\right)+10\right] \tag{46}$$

where,

$$-5.12 \le x_i \le 5.12;\ F_2^{min} = 0;\ d = 30 \tag{47}$$

3) Hartman's Family:

$$F_3(x) = -\sum_{i=1}^{4} c_i \times \exp\left(-\sum_{j=1}^{d} a_{ij}\times\left(x_j - p_{ij}\right)^2\right) \tag{48}$$

where,

$$0 \le x_i \le 1;\ F_3^{min} = -3.32;\ d = 3;\ c_i = [1, 1.2, 3, 3.2];$$

$$p_{ij} = \begin{bmatrix} 0.37 & 0.12 & 0.27 \\ 0.47 & 0.44 & 0.75 \\ 0.11 & 0.87 & 0.55 \\ 0.40 & 0.57 & 0.88 \end{bmatrix} \tag{49}$$

4) Shekel's Foxholes Function:

$$F_{21}(x) = -\sum_{i=1}^{d}\left[\left(x_i - a_i\right)\times\left(x_i - a_i\right)^T + c_i\right]^{-1} \tag{50}$$

where,

$$0 \le x_i \le 10;\ F_3^{min} = -10.1532;\ d = 4;\quad c_i = [0.1, 0.2, 0.2, 0.4];\ a_i = [4, 1, 8, 6] \tag{51}$$

The simulations have been performed based on MATLB R2017b environment on the Microsoft Windows 10 using 64-bit Core i-7 processor with 2.60 GHz and 16 GB main memory. The minimum value (min), maximum value (max), average value (mean), and standard deviation value (Std) of the best optimal solution are mentioned in Table 2. For the test functions, all of the compared metaheuristics uses 45 independent runs with 200 iterations and 100 search agents. Table 4 tabulate the simulation results of the algorithms.

It is observed from Table that, the suggested BTGA gives the minimum value for the functions that accordingly gives the best accurate results than the other compared algorithms. Furthermore, minimum value of the standard deviation value of the function shows that the proposed BTGA has the highest consistency and reliability over different runs.

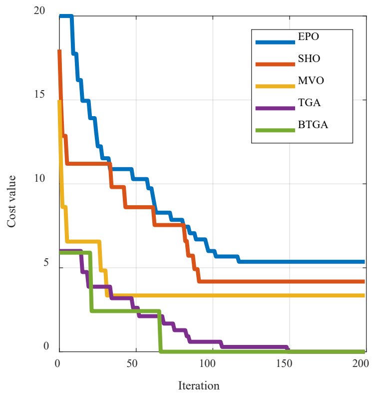
For more validation, convergence analysis is performed. The main purpose behind the convergence analysis is to determine the suggested BTGA behavior. The candidates explore the whole solution space and changes quickly during the initial step of the optimization. Fig. (3) shows the

Table 3. The parameter settings of the suggested BTGA and the competitor metaheuristics

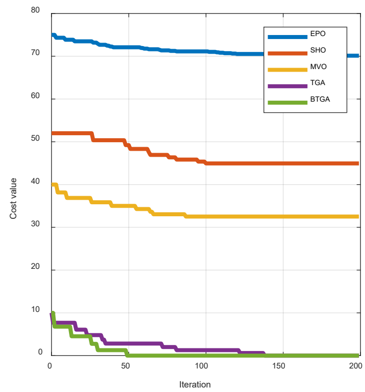
Algorithm	Parameter	Value	Algorithm	Parameter	Value
EPO [44]	$\vec{A}$	[-1.5, 1.5]	TGA [40]	N_1	10
	Temperature value (T')	[1, 1000]		N_2	15
	M	2		N_4	10
	f	[2, 3]		γ	0.8
	Function S()	[0, 1.5]		λ	0.5
SHO [45]	l	[1.5, 2]	MVO [46]	Traveling distance rate	[0.6, 1]
	$\vec{M}$	[0.5, 1]		Wormhole existence prob.	[0.2, 1]
	$\vec{h}$	[5, 0]			

Table 4. The comparison results of the algorithms for the test functions

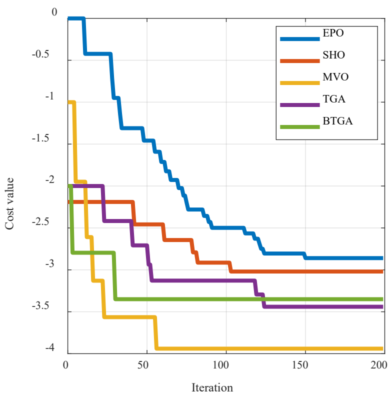
Algorithm	indicator	F_1	F_2	F_3	F_4
EPO [44]	Min	5.36	70.13	-2.86	-5.32
	Max	7.53	150.22	-1.83	-2.39
	Mean	6.91	93.82	-2.27	-4.06
	std	4.69	46.76	2.14	2.47
SHO [45]	Min	4.18	44.94	-3.02	-5.03
	Max	5.72	68.35	-0.01	-1.38
	Mean	4.93	53.16	-2.24	-2.53
	std	4.68	30.59	3.18	3.96
MVO [46]	Min	3.35	32.52	-3.94	-5.16
	Max	5.67	45.82	-1.06	-2.85
	Mean	4.19	19.91	-2.45	-3.34
	std	3.20	11.66	2.26	3.61
TGA [40]	Min	0.00	0.00	-3.44	-9.37
	Max	6.31	30.07	-2.57	-6.68
	Mean	4.86	9.41	-2.95	-8.39
	std	4.13	7.79	1.68	3.18
BTGA	Min	0.00	0.00	-3.35	-10.22
	Max	5	15.24	-2.01	-8.84
	Mean	4.98	11.50	-5.87	-9.29
	std	3.26	5.37	1.38	1.19



(F1)



(F2)



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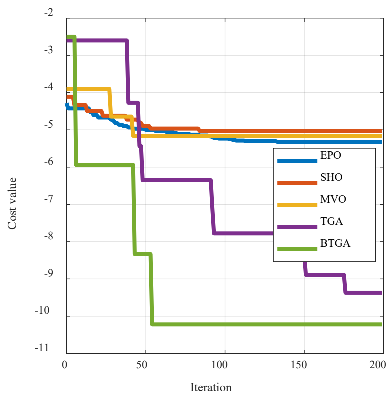

(F4)

Fig. 3. The convergence profile for all compared algorithms on the standard test functions

convergence profile for all compared algorithms on the standard test functions.

As can be observed from Fig. (1), the suggested BTGA has the best convergence behavior toward the others.

At can be observed, at first iterations, the algorithm can be converged more rapidly in the solution space because of its improved mechanism. The final convergence of the algorithm indicates that the proposed BTGA keeps a proper trade-off between exploitation and exploration to achieve the global optimal point. This reveals that the results give different behaviors of BTGA which indicate better success rate of BTGA toward the other compared algorithms.

7. OPTIMIZATION STRATEGY

This section clarifies the method of using the suggested BTGA for the multi-criteria optimization (environmental, energy, and economic) of the studied CCHP. The parameters for designing contain the annual prime movers' capacity, the number of the prime movers, the cooling capacity of chillers, the partial load, and the boiler heating prime movers' capacity in three scenarios including selling scenarios, no-selling scenario, and the possibility of electricity selling with similar capacities of the gas engine. The Relative Annual Benefit (RAB) is used for optimal designing of the parameters based on the proposed BTGA. The limitations of the design parameters are tabulated in Table 5.

In this study, the Balanced Tree Growth Algorithm as a multi-objective optimizer is employed for optimal parameters designing by maximizing the value of the following cost function [47]:

$$Max\,RAB = \left(n_j \times E_n\right) \tag{51}$$

where, j stands for the Number of Equipment. Subject to the following (Table 6).

For implementing of the algorithm to optimal determination of the CCHP parameters in the factory, the proposed BTGA has been utilized. the algorithm is used due to the complexity, nonlinearity, discrete, and non-differentiable features of the RAB indicator. The optimization strategy of the studied CCHP system is explained below.

During the optimization, the operating range of the CCHP equipment presents the solution space. In other words, each tree includes the capacity for the CCHP equipment. The selected trees in the

Table 5. The limitations of the design parameters

Parameters	Values	Unit
The changes in the heating capacity of the boiler	00	kW
The changes in the partial load of prime movers	60	%
The changes in the nominal capacity of prime movers	50	kW
The changes in the cooling capacity of the compression chiller	20 to 100	kW
The changes in the cooling capacity of the absorption chiller	0 to 6000 0 to 8000	kW

Table 6. The constraints and conditions optimization

Parameter	Value	The constraint details
Gas engine capacity	$E_{nom} < 6500$	Efficiency and cost limitations
Partial load	$PL > 22$	Efficiency limitation
The outlet temperature of the boiler exhaust	$T < 119.5$	Environmental limitation
The outlet temperature of the prime mover exhaust	$T < 146.3$	
Population	97	Convergence
The probability of gene combination	0.78	
Scaling	Random	
Selection	Uniform	
Termination criterion	10^{-5}	-
Mutation type	-	Limitation dependent
Initial mutation rate	0.004	Mutation type limitation
Minimum mutation rate	0.0004	

BTGA for this case study should maximize the cost function. therefore, the inverse of the cost function has been utilized. Afterward, the cost function in each iteration has been described and then the cost value for al trees is evaluated. The new iteration is formed after implementing algorithm operators to the current iteration. For method verification, the results of the optimization with RAB objective function based on the gas engine prime movers are compared with the method from [48]. Fig. (4) compares the simulation results of the study with Sanaye et al. [48].

The results show that the proposed method has a satisfying agreement with the results in the high capacity of the gas engine. Then, the optimization results are conferred based on three different scenarios: selling, selling with similar capacities, and no-selling. Furthermore, the parameters of the design contain the number and the nominal prime movers' capacity, the capacity of absorption, backup boiler, and compression chillers are taken and debated. The results show that however using the proposed configuration gives proper results for all scenarios, selling scenario is more gainful. Table 7 indicates the optimal productivity of the scenarios.

Table 7. optimal productivity of the scenarios

Strategy	Optimal profitability ($/year)
No-selling	1.1374×10^6
Electricity sold to the grid	1.2658×10^6
Electricity sold to the grid with similar capacities	1.2443×10^6

The results of the parameters optimizing for no-selling and selling scenarios are tabulated in Table 7. As is observed, the gas engine quantity for the initial prime movers in both strategies is identical. In addition, however, the prime movers' capacity is not equal in low capacities, but it is equal in high capacities. The prime movers' capacity is higher in selling scenario.

Absorption chillers and electric chillers are utilized for providing the required demand of the cooling in the no-selling scenario. Here, electric

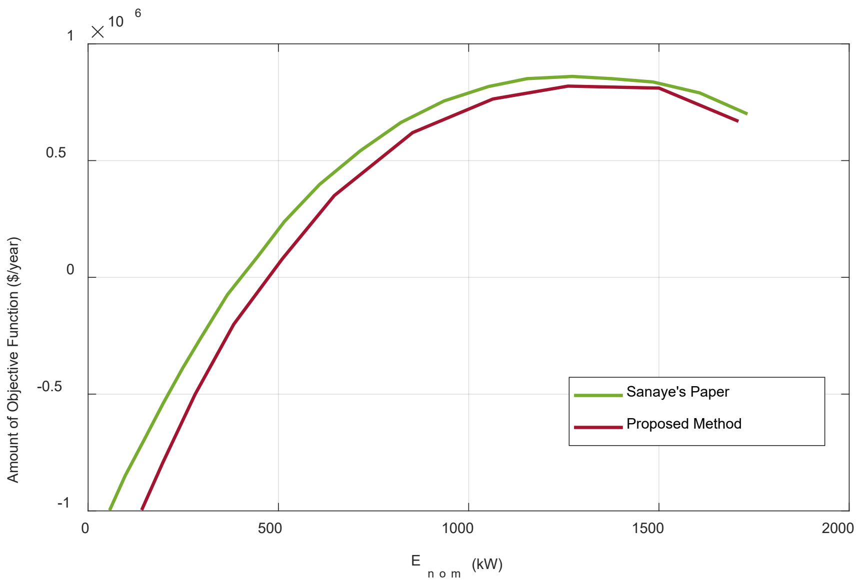

Fig. 4. The comparison results of the study of the with those achieved by Sanaye et al. [48]

Table 8. The results of the parameters optimizing for selling and no-selling scenarios

Strategy	Selling	No-selling	Unit
Capacity for backup boiler	4700	0	kW
Capacity for electric chiller	0	2700	kW
Number of prime movers	2	2	-
Nominal prime movers' capacity	5200-800	5200-600	kW
Absorption chiller capacity	7500	5000	kW

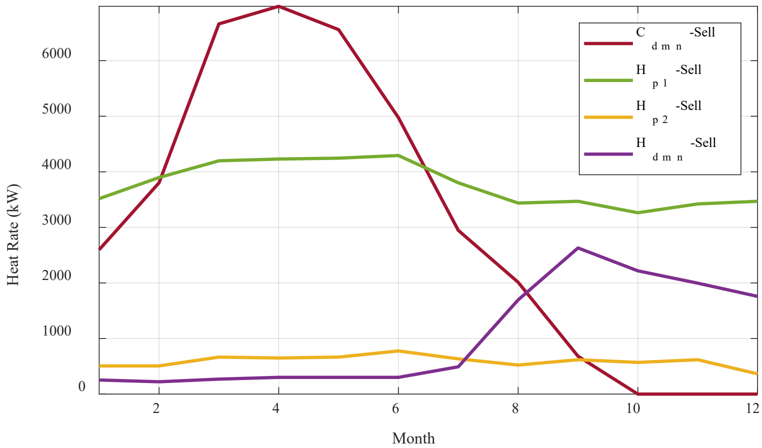

Fig. 5. Thermal efficiency profile of the system during the optimal mode of selling scenario

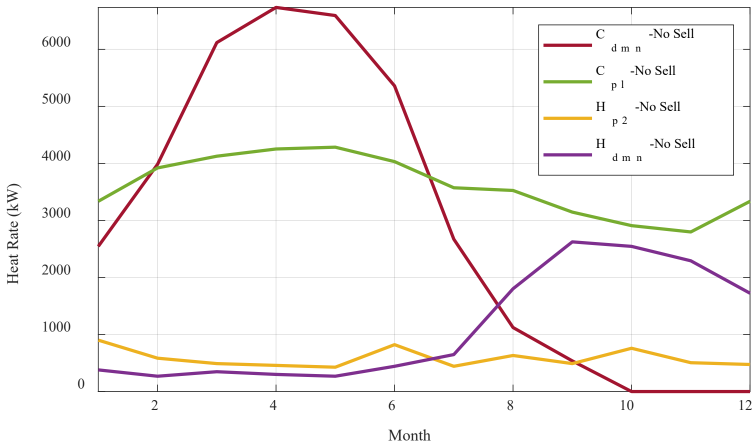

Fig. 6. Thermal efficiency profile of the system during the optimal mode of no-selling scenario

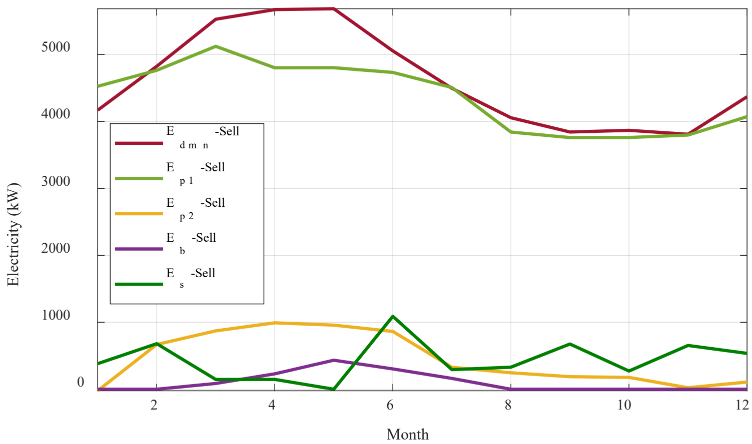

Fig. 7. Electrical efficiency profile of the system during the optimal mode of selling scenario

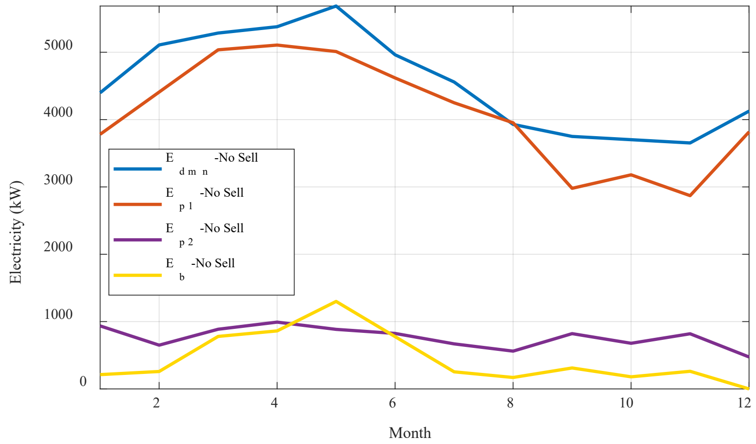

Fig. 8. Electrical efficiency profile of the system during the optimal mode of no-selling scenario

Table 9. indicates the optimal efficiency of the two aforementioned strategies

Strategy	With similar capacities	With different capacities	Unit
Parameter setting	Optimal value		
Capacity of backup boiler (kW)	5400	4700	kW
Quantity of prime movers	1	2	-
Capacity of absorption chiller (kW)	7500	7500	kW
Capacity electric chiller (kW)	0	0	kW
Nominal capacity of prime movers (kW)	5200	5200-800	kW

chiller provides about 25% of the cooling load. Furthermore, the backup boiler capacity is zero for no-selling scenario, though it equals 5000 kW in the selling scenario. For more clarification of these two scenarios, the thermal and electrical performance profiles are shown in Figs. (5) to (8).

With more analysis the above figures, it can be dedicated that the selling scenario with no similar capacities requires electricity purchasing with a maximum of one third than the other scenarios for 5 months. Since, in the no-selling scenario, the amount of the heat generated by the movers is higher than the required heat demand by the building, there is no need for the backup boiler in the system.

For hot seasons, the required heat of the absorption chiller for cooling of the building is supplied by wasted heat that is the difference between the heat generation in the building and the required heat. Therefore, the maximum absorption chiller capacity is determined by the maximum wasted heat. Consequently, during the selling scenario with no similar capacities, the heat produced by the primary movers in the hot seasons gives higher amount than the heat demand in the building. The surplus heat is then utilized for cooling the building based on the absorption chiller.

During the no-selling scenario, about one fourth of the cooling demand is supplied by electric chillers which is due to the low amount of heat loss extracted from the primary movers such that and the absorption chillers can't resist the total cooling load. Table 8 indicates the optimal efficiency of the two aforementioned strategies. As stated by the results, the selling scenario with no similar capacities is more efficient. Also, it is observed that the selling scenario with similar capacities has more efficiency toward the no-selling scenario.

It is remarkable that the selling scenario with different capacities and two primary movers has the best efficiency. The wasted heat during the similar capacities and selling scenario gives lower efficiency than the boiler higher capacity. The thermal and electrical performance of the selling scenario with similar and different capacities are shown in Fig. (9) and Fig. (10).

As can be observed from Fig. (9), during the optimal mode, we need to purchase a maximum of about 1050 kW electricity from the distribution

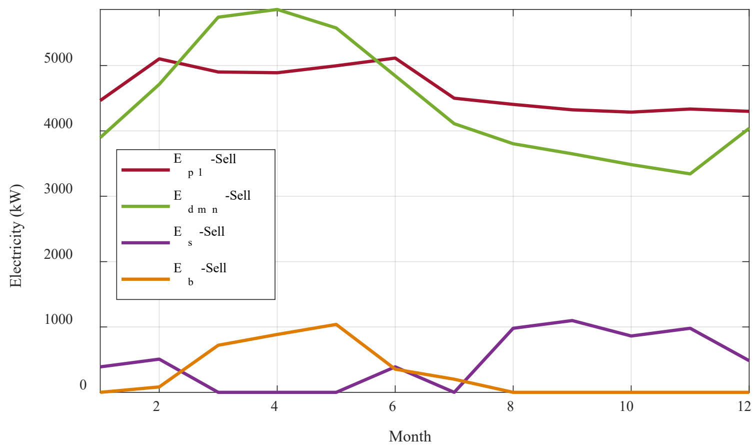

Fig. 9. The system electrical efficiency in optimal mode in the similar capacities and selling scenario

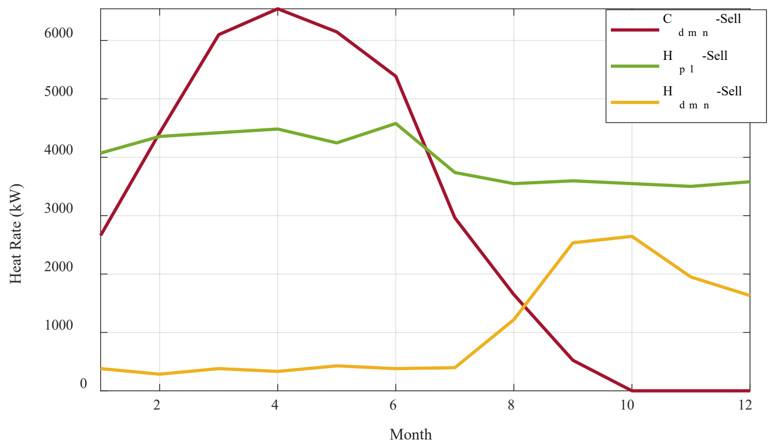

Fig. 10. The system thermal efficiency in the optimal mode in the similar capacities and selling scenario

network in months 3 to 5. Furthermore, we can sell electricity to the distribution network in other months with a maximum of about 1100 kW.

8. CONCLUSION

This paper presented an optimization design for a combined cooling, heating and power (CCHP) system in a factory in terms of environmental, energy, and economic. Optimization includes different parameters of annual prime movers' capacity, the cooling capacity of chillers, the number of the prime movers, the partial load, and the boiler heating prime movers' capacity in three scenarios including selling scenarios, no-selling scenario, and the possibility of electricity selling with similar capacities of the gas engine. Due to the complexity of this problem, a new improved metaheuristic methodology, called Balanced Tree Growth Algorithm (BTGA) was utilized. Also, the Relative Annual Benefit (RAB) is used for optimal designing of the parameters. Final results show good results for the proposed methodology. The results indicated that although utilizing of the presented configuration gives appropriate results for different scenarios, selling scenario is more gainful.

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