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Combined Heat and Power Units Sizing and Energy Cost Optimization of a Residential Building by Using an Artificial Bee Colony Algorithm

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ABSTRACT Battery manufacturing and recycling are expensive; combined heat and power (CHP) units are optimal for residential premises. CHP units can enhance energy efficiency and reduce energy costs, but appropriately sized units must be chosen. Here, we optimize CHP unit sizing to minimize the energy costs of residential areas. Sizing is based on both the electricity and heat loads; it is possible to optimally rate the various types of CHP units. We compare an artificial bee colony (ABC) optimization method to a genetic algorithm (GA) when various strategies are adopted. Electricity and heat loads are considered together when sizing CHP units and optimizing costs using the ABC algorithm and the GA. The optimization outcomes are compared to a base case; the ABC method performs better than the GA. The average daily energy cost savings possible using the ABC method were higher for all three seasons (by 25.9, 4.4, and 10.8% respectively) compared to those possible when residential premises lacked CHP units.

INDEX TERMS Artificial bee colony, cost-benefit analysis, CHP unit size optimization, energy conversion, genetic algorithm, residential building automation.

NOMENCLATURE

ABBREVIATIONS

GA	Genetic Algorithm
PSO	Particle Swarm Optimization
LP	Linear Programming
MILP	Mixed Integer Linear Programming
DP	Dynamic Programming
ABC	Artificial Bee Colony
RB	Rule-Based
PDPg	Probabilistic Dynamic Planning
TAC	Total Annual Cost
CE	Carbon Emission
LCA	Life Cycle Assessment
DRP	Demand Response Program

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I. INTRODUCTION

A. MOTIVATION

Combined heat and power (CHP) units are valuable in that their carbon emissions are very low, in addition to other features that render them superior to other energy-generation units [1]. The output efficiencies of CHP units are

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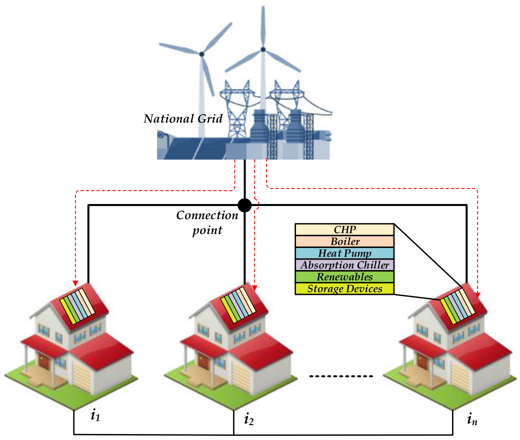

FIGURE 1. **A CHP unit -based DER.**

significantly higher and the emissions are much lower than those of other devices [2]. Climate variation/unpredictability affects CHP units' performance only minimally [3]. In [4], it was shown that the cost of CHP units is decreasing [5]. Hence, CHP units with kW ratings are being installed in residential areas.

Profitable but environmentally responsible energy generation poses significant challenges for metropolitan systems. Optimal sizing of distributed energy resources (DERs), residential energy hubs, and energy plants is crucial. Figure 1 shows the basic concept of a DER used to evaluate various optimization techniques that seek to increase energy plant efficiency via optimal sizing and good technological management.

B. PREVIOUS STUDIES

Various previous approaches will now be briefly described. Use of a dynamic programming (DP) method to optimize both the sizing of CHP units and plant operation was presented in [6]. DP is commonly applied to optimize the control and energy management of hybrid energy plants. The objective is to reduce primary energy consumption by optimizing both CHP unit size and hybrid plant operation. The authors of [7] used a model predictive control (MPC) algorithm for a photovoltaic (PV) system that was combined with storage and CHP units to reduce operation costs. Tests were performed using various storage systems such as batteries and heat pumps. The operational costs were reduced by 7.3% when an optimized algorithm (compared to rule-based control) was used. A dynamic method for structural sizing of domestic energy hubs was proposed in [8]; the system featured a CHP unit, a boiler, a PV system, and electrical and heat storage systems. The objective of the work (which employed a Monte-Carlo simulation method and a DP approach) was to minimize both the capital costs and operating costs (OCs) during planning. The authors of [9] presented two multi-objective models aiding DER design; it sought to satisfy regional needs in terms of cooling, heating, and electricity. Two primary methods of DER design that considered both total annual costs (TACs) and carbon emissions (CEs) as objective functions were tested and implemented.

The study described in [9] was similar to that in [6] but the storage systems differed. A genetic algorithm (GA) optimization technique was employed to reduce primary energy consumption (by about 12%) over the entire cycle of a hybrid plant. Mathematical programming was employed in [11] to optimize the design and planning of a fourth-generation heating model that met energy exchange and on-site generation requirements. The principal objective was to explore the impact of energy exchange among buildings and to ensure that the system had adequate capacity. The optimization framework of [12] sought to ensure satisfactory operation of a CHP system located in an ambiguous environment (thus subject to demand response events). The system featured a gas turbine, storage systems, a heat pump, and boilers. A price-based demand program was applied to improve system economy by changing the energy expenditure as required. Sizing of a CHP system and optimization of the day-to-day energy costs for a building fitted with only a CHP system was discussed in [13], using the GA optimization technique. Both electricity and heat loads served as sizing criteria when optimizing the ratings of different types of CHP units.

Although CHP systems are more efficient and less polluting than battery energy storage systems (BESSs), their capital and maintenance costs are significantly higher. It is unclear whether BESSs are economical for residential buildings; CHP units and grids provide electricity on demand and CHP units and gas boilers heat on demand. BESSs were not evaluated in [14], but other factors that impact cost, efficiency, CHP unit rating, and CHP unit type were considered. The electrical efficiency of a CHP unit is one-fourth of its rating when it operates at 10% of the rated value. Furthermore, the heating efficiency also decreases under low-input operation [1]. Small CHP unit ratings are indicators of high efficiency and low emissions when delivering residential loads. However, small units cannot respond to increased load demands even when operating at full rated power, which is expensive. Therefore, large units are essential when power demand is high. Thus, appropriate CHP unit sizing is critical to ensure high efficiency and low costs.

To achieve a good CHP rating, sizing is the most critical step in optimization; however, the desired outcomes may differ. Specific design criteria must be applied. CHP unit sizing involves evaluation of both CHP unit type and the load demand. Here, we analyze two types of CHP units, a fuel cell (FC) and a gas engine (GE). The efficiency of the FC is higher [15]. The rated electric:heat efficiency ratio is 33% for a FC but 74% for a GE [16]. Residential loads usually feature both heat and electricity demands. These are considered individually during sizing because their patterns differ. The authors of [4] and [17] suggested that the use of heat demand as a sizing criterion was optimal, given the high thermal efficiency of a CHP system. In [4], the sale of electricity back to the grid was considered. Such sales are rather challenging, given the high standards that apply when selling electricity to utility grids, which are owned by government organizations [17]. Because of this, and the non-availability of energy-recording meters in most residential premises, we do not consider energy export to a grid below.

In [18], multi-microgrid agent-based energy management of DERs in smart islanded energy-hub (EH) system is proposed by using the primal-dual method of multipliers (PDMM) approach. This EH modeling combines CHP units and electric vehicles (EVs) with renewable energy resources (RERs). But this work is only concentrated on the application of the residential load of a single house. In [19], modified social spider optimization (MSSO) approach is applied for the training process of generative adversarial networks (GAN) by employing deep learning for RER based control of the matrix converter. But this approach is not applied for CHP unit's optimization. Although in [20], PSO and ABC algorithms are used together to optimize artificial neural network (ANN) based energy efficient buildings. But no details and specific applications of CHP units are demonstrated. In [21], multiple heuristic optimization algorithms (including GA and ABC) are used with machine learning-based controllers for energy-efficient buildings. But CHP units are not chosen for the analysis. In [22], CHP units are considered with the application of GA and ABC algorithms by applying different optimal cycle modes, including CHP mode. But the objectives are entirely different from micro gas turbine units, and superior performance with GA is achieved.

C. CONTRIBUTIONS

Various methods have been used for CHP system sizing, including a maximum rectangle (MR) method; GA; linear programming (LP); dynamic programming (DP); MPC; and nonlinear programming (NLP). LP requires linearization of all constraints, at the cost of loss of accuracy during optimization; NLP methods may become trapped in local minima. The MR method considers the average load demand rather than the maximum demand when seeking to fully exploit CHP ratings [4]. GA is a powerful optimization tool when multivariable non-linear objectives are set, and can be used to minimize daily costs. Here, we use both GA and an artificial bee colony (ABC) algorithm. Our principal contributions are:

- ABC algorithm is not implemented in the literature studies for different sizing criteria of two types of CHP units.
- New algorithms are emerging over a period of time. Still, the authors only considered the impact of the ABC algorithm over GA for the specific problem of a rural residential house in Pakistan. The base paper was selected in our study for all the input data, and we checked the performance of the ABC algorithm.
- We use the GA and the ABC algorithm to optimize CHP system sizing.
- Use of the ABC algorithm reduces the computational burden.
- The reductions in optimal and minimum costs afforded by the ABC method are investigated.
- We use different CHP units and load types when establishing the most feasible sizing criteria identifying optimal CHP units.
- Our DER model features various technological modules that can operate in any residential building to fulfil the load demands of prosumers (end-users). Such demands may include hot water, cooling, and electricity.

II. CHP SIZING AND SYSTEM OPTIMIZATION

Subsection 2.1 shows how to use GA methodology to optimize costs; subsection 2.2 indicates how to employ the ABC method to optimize the daily energy costs of different types of CHP units. Table 1 compares the various optimization methods, and shows that the GA and the ABC algorithm are superior. Table 2 compares previous studies to our study. Figure 2 shows a flow chart of our optimization methodology. The ABC algorithm flow chart checks CHP units and solves the problem based on heat or electricity optimization criteria. Two types of CHP units that are available in the market are investigated in this work. ABC search mechanism in this work criteria is based on the feedback mechanism. The first iteration is done with random generation of 100 population size. The next step involves the selection of the best solution out of 100 possible solutions. The subsequent step re-iterates the process so that the values of the next 99 randomly generated populations will surround the neighbor value of the previous best solution. This feedback-based population criteria and solution mechanism guarantee the converging to the global optima.

The residential demand in terms of an objective function assuring everyday cost minimization can be expressed as:

$$F(t) = \sum_{t=1}^{t=1440} P_{Eimp}(t) \times C_e(t) + P_{Gimp}(t) \times C_{gas}(t) + P_{CHPimp}(t) \times C_{gas}(t) \tag{1}$$

where $F(t)$ is the everyday energy cost in Pakistani Rupees (PKR), $C_e(t)$ is the electricity price, $C_{gas}(t)$ is the gas price, $P_{Eimp}(t)$ is electricity imported from the grid, $P_{Gimp}(t)$ is the gas imported for the boiler, and $P_{CHPimp}(t)$ is the gas imported for the CHP system. The equality constraints that fulfil the requirements for both electricity and heat are:

$$P_E(t) = P_{Eimp}(t) + \eta_{CHPE} \times P_{CHPimp}(t) \tag{2}$$

$$P_H(t) = P_{Gimp}(t) \times \eta_B + \eta_{CHPH} \times P_{CHPimp}(t) \tag{3}$$

where $P_E(t)$ is the electricity energy requirement and $P_H(t)$ the heat energy requirement of the residential area. η_{CHPE} is the electricity output efficiency and η_{CHPH} the heat output efficiency of the CHP unit. η_B is the conversion efficiency of gas heat to boiler heat. The inequality constraints of the system are:

$$\eta_{CHPEmin} \leq \eta_{CHPE} \leq \eta_{CHPEmax} \tag{4}$$

$$\eta_{CHPHmin} \leq \eta_{CHPH} \leq \eta_{CHPHmax} \tag{5}$$

TABLE 1. A comparison of optimization algorithms.

Algorithm	Advantages	Disadvantages
GA	• Applicable to both linear and nonlinear optimizations • Can handle both discrete and continuous objective functions	• The computational time is high for complex problems • A global optimum cannot be assured
PSO	• Applicable to both linear and nonlinear optimizations • Can handle both discrete and continuous objective functions • Convergence is rapid	• Parameter initialization is difficult • A global optimum cannot be assured
LP/MILP	• Implementation is simple. • Applicable to both discrete and continuous objective functions • High accuracy	• Applicable to linear optimization only • The computation time is high
DP	• Applicable to both linear and nonlinear optimizations • Applicable to both discrete and continuous objective functions • Well-suited to complex systems	• Applicable only when the results can be delivered in steps
ABC	• Implementation is simple • Flexible and robust • A local optimum is assured • Can process cost objectives	• Secondary information is lacking • Updated fitness analysis is required if the initial parameters change • Cannot evaluate a large number of objective functions • Sequential processing is slow

TABLE 2. A comparison of optimization methods.

Ref	Demand-side management	Load-dependent CHP unit conversion: Efficiencies are calculated	Planned components (CHP)	ABC vs. GA
[6]	Yes	No	No	No
[7]	No	No	Yes	No
[8]	Yes	No	Yes	No
[9]	No	No	Yes	No
[10]	No	Yes	Yes	No
[11]	Yes	Yes	No	No
[12]	Yes	Yes	No	No
Present work	Yes	Yes	Yes	Yes

$$P_{CHPimp}(t) = 0$$

$$\zeta \times P_R \leq P_{CHPimp}(t) \leq P_R \quad (6)$$

$$P_{Eimp}(t) \geq 0 \quad (7)$$

$$P_{Gimp}(t) \geq 0 \quad (8)$$

Equations (4) and (5) impose restrictions on the output efficiencies of electricity and heat, and Equation (6) describes the switching and feasible operational modes of the CHP system. P_R is the rated capacity of the CHP system and the scaling factor is expressed as ζ (set to 10%). All scenarios were simulated using both the GA and the ABC algorithm to minimize daily costs; this ultimately yielded optimal ratings for the CHP units. Here, electricity and heat are only imported from the grid; the power flow directions are thus greater than zero in Equations (7) and (8). The output efficiencies of the CHP unit in terms of both electricity and heat are:

$$\eta_{CHPE} = \zeta_{CHPE} \times (11.67 \times \log\left(\frac{P_{CHPimp}(t)}{P_R}\right) \times 100) - 0.06459 \times \left(\frac{P_{CHPimp}(t)}{P_R}\right) \times 100) - 18.76) \quad (9)$$

$$\eta_{CHPH} = \zeta_{CHPH} \times (0.1256 \times \left(\frac{P_{CHPimp}(t)}{P_R}\right) \times 100) - 82.32 \times \left(\frac{P_R}{P_{CHPimp}(t)}\right) \times 100) - 28.73) \quad (10)$$

where ζ_{CHPE} is the coefficient of the CHP unit's electricity output efficiency and ζ_{CHPH} is the equivalent for heat. The ζ_{CHPE} and ζ_{CHPH} values are 0.783 and 1.610, respectively, for a GE and 1.298 and 1.187, respectively, for an FC.

As can be seen in (2), (3), (9), and (10), the problem is both non-convex and highly non-linear, and thus cannot be solved by optimization techniques (e.g., LP, quadratic programming) that guarantee global optima. It is possible to render the

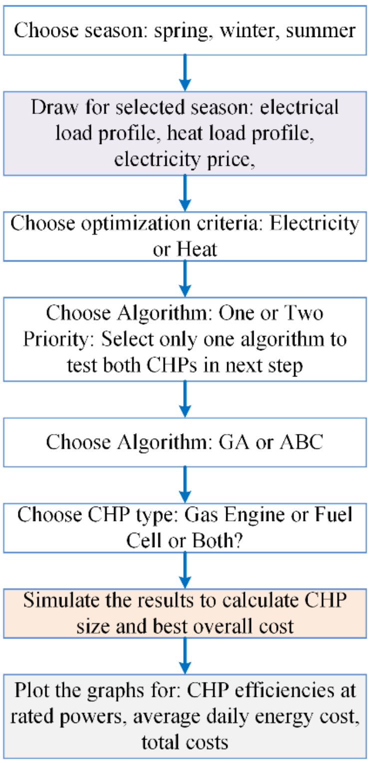

FIGURE 2. A flow chart of GA and ABC optimization.

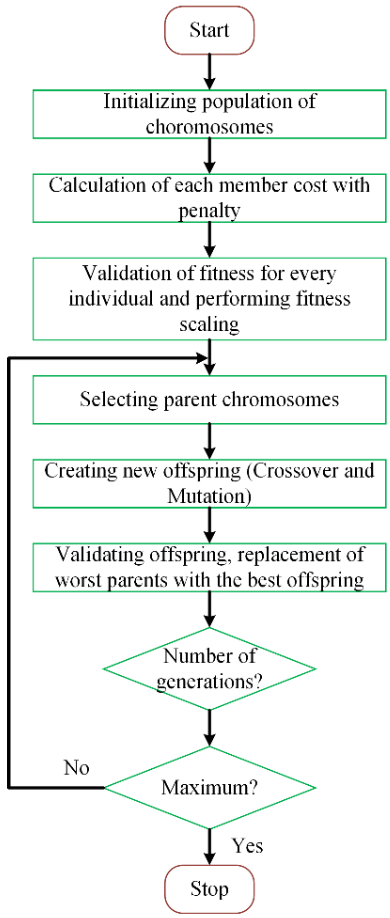

FIGURE 3. Flow chart showing implementation of the GA optimization algorithm [9].

problem convex, but the high-level non-linearity would create large modeling errors. We thus use and compare the heuristic ABC and GA optimization techniques.

A. OPTIMIZATION OF COSTS USING A GA

The GA was developed in 1970; this is a probabilistic, intelligent searching algorithm that exploits biological development during optimization. It is simple to implement, and mathematical modeling is not required. If a multi-objective problem must be solved, a GA can show the trade-offs between all conflicting objective functions [19]. GAs effectively handle both non-linear and non-continuous objective functions [20]. GAs differ significantly from other optimization techniques in that GAs seek a parallel population of points and use a probabilistic rather than a deterministic approach. GAs can solve both constrained and unconstrained optimization problems [21].

GAs feature four steps, thus chromosome evaluation, selection, crossover, and mutation. The chromosomes are termed solution candidates (variables). A schematic of GA optimization is shown in the flow chart of Figure 3. A combination of single entities is treated as a population; the population size is the number of such entities. During selection, high-quality entities are preferred and low-quality entities are dropped. The scale (fitness) values represent the outcomes of analyses that determine the optimal results. Finally, the two most essential components are crossed; mutation is now employed to produce new solution sets within a predefined search space. The net production (offspring) survive because they perform best in the defined environment. The algorithm terminates the search for optimization if a solution is acceptable. Here, the population size was set to 7, the crossover fraction to 0.8, and iteration ceased at 100 generations (the termination criterion). GAs typically require considerable computation time to develop accurate and feasible solutions; the population size and generation number are the principal factors affecting the time required, and thus the calculation efficiency.

The steps used when employing a GA algorithm for CHP unit sizing and cost optimization are:

1) Initialize a population of N chromosomes in a solution space (the search space).
2) Determine an objective function for each chromosome by reference to relevant genes (the decision variables).
3) Select chromosomes by reference to the "survival of the fittest" and enter them into a mating pool. The most popular selection approach is the roulette wheel.
4) Apply crossover values (with probabilities) to all offspring genes. Thus, randomly select two chromosomes (parents) when creating two offspring.
5) Trigger mutations by reference to probability considerations. A random number within an acceptable range is selected when mutation proceeds.

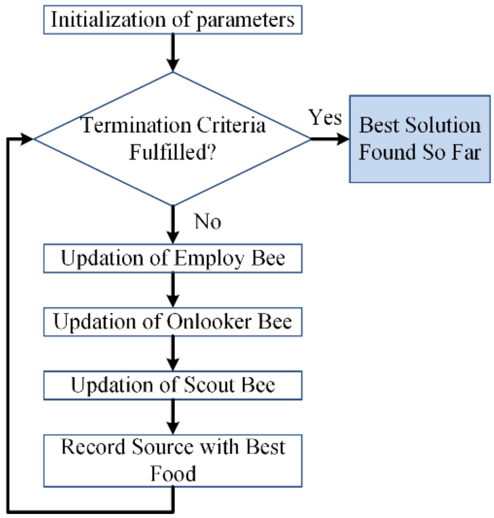

FIGURE 4. Flow chart for implementation of the ABC optimization algorithm.

6) Evaluate the offspring by calculating objective functions for each of their chromosomes.
7) Replace the poorest chromosomes of the parents and offspring with newly identified better chromosomes before selecting the next-generation population.
8) Repeat steps 4 to 7 until the maximum number of generations (iterations) is attained. The best chromosomes at that time constitute the optimal solution.

B. OPTIMIZATION OF COSTS USING THE ABC ALGORITHM

ABC algorithms were developed in 2005 in [22] to solve numerical optimization problems [23]. The drivers were the intelligence and behaviors of honey bees [24]. The ABC algorithm is a powerful and intelligent optimization technique that handles constrained and non-constrained optimization problems [25]. A flow chart of the ABC algorithm is shown in Figure 4. There are three sets of bees: employed, onlooker, and scout bees [25]. Half of all bees are employed and the other half are onlookers. Each employed bee exploring a food source also scouts for unused food. The solution is a food source position and the nectar quantity reflects the solution quality. The number of possible solutions is the number of employed or onlooker bees.

The initial factor considered by the ABC algorithm are the number of food points (NFP), which equals the total number of bees. Random numbers create initial populations yielding solutions when the following relationship among random positions is in play [23]:

$$X_{ab} = X_{b,\min} + rand \times \left(X_{b,\max} - X_{b,\min}\right),$$
$$a = 1, 2, \ldots NFP, \ \ b = 1, 2, \ldots, J \tag{11}$$

where X_{ab} is the a^{th} population of the b^{th} vector and the NFP is 5. $X_{b,min}$ and $X_{b,max}$ are the minimum and maximum boundaries of the b^{th} vector, and *rand* is a random number from 0 to 1. The fitness function is:

$$Fitness_a = Obj\left(X_{ab}\right) + \sum_{m=1}^{M} \lambda_{eq,m} \left|h\left(X_{ab}\right)\right|^2 + \sum_{n=1}^{N} \lambda_{ineq,n} \left|g\left(X_{ab}\right) - g_{\lim}\right|^2 \tag{12}$$

where *Obj* is the objective function and the equality and inequality constraints are represented by $h(X_{ab})$ and $g(X_{ab})$ respectively. The penalty factors abbreviated as $\lambda_{\text{eq,m,}}$ and $\lambda_{\text{ineq,n}}$ can be adjusted during optimization. g_{lim} is defined as follows:

$$g_{\lim} = \begin{cases} X_b & if\ X_{b,\min} \le X_b \le X_{b,\max} \\ X_{b,\min} & if\ X_b < X_{b,\min} \\ X_{b,\max} & if\ X_b > X_{b,\max} \end{cases} \tag{13}$$

The steps used when employing the ABC algorithm for CHP unit sizing and cost optimization are:

1) Initialize the solution population X (the food source positions).
2) Calculate the nectar values of this population employing a fitness function.
3) Develop neighboring solutions for employed bees using random numbers and validate these as in step 2.
4) Apply a selection procedure.
5) Go to step 9 when dealing with distributed onlooker bees; otherwise go to step 6.
6) Calculate the probability values of the solutions.
7) Develop neighboring solutions for nominated onlooker bees based on the above values. Use random numbers and re-apply step 2.
8) Apply step 4.
9) Determine abandoned solutions for scout bees if possible, and replace these with an entirely new solution calculated via (11). Evaluate these as in step 2.
10) Save the best solution obtained to this point.
11) Stop and print the results if the maximum number of iterations is attained. Otherwise, repeat step 3.

The value of the penalty factor can be increased if one or more variables might create a violation. This ensures that the solution is feasible.

III. CASE STUDY

The data is taken from [12] in which only maximum rectangle (MR) and GA were implemented while the ABC algorithm was tested on this data with the application of this case study in Pakistan. We used a CHP system to service a terraced domestic building in Pakistan occupied by four people. The building is located in a rural area (Murree Punjab). Both heat and electricity are required; the weather can be cold. Murree (which is hilly) is one of the most popular tourist areas in Pakistan. In the time of British India, many prominent Britons were born there. As the summer is pleasant, the Government of Pakistan maintains a retreat in this region, which is frequently visited by foreign dignitaries including heads of

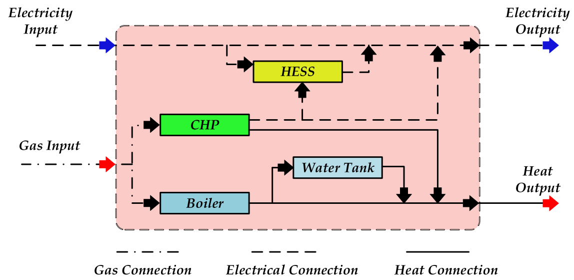

FIGURE 5. Schematic of the energy flow in a smart building.

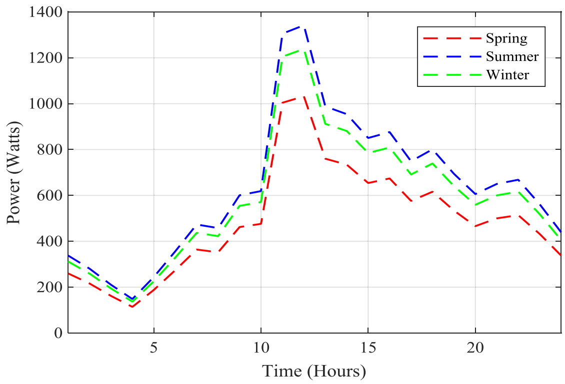

FIGURE 6. The electrical energy demands over a typical day.

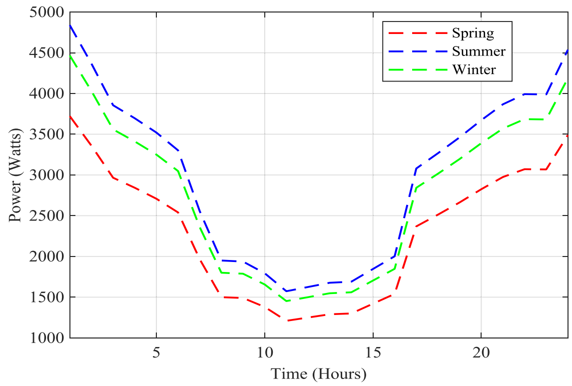

FIGURE 7. Heat (thermal) energy demands over a typical day.

states [26]. The co-ordinates are 33°54′ 3″ N and 73° 23′ 4″ E. The residence features one double room, four single rooms, a drawing room, two bathrooms, and one kitchen. The total area is 160 m^2. Figure 5 shows a schematic of the energy flow in a typical smart building. The model of [27] is used to generate random numbers indicating daily electricity utilization; the model of [28] defines daily heat utilization. In Pakistan, gas costs about 10 PKR/kWh; the electricity tariff is that of [32]. The tariff is dynamic, varying on a half-hourly basis. Figures 6, 7, and 8 show the daily energy demands for electricity and heat, and the prices in the three seasons, respectively. Figure 8 shows the time-of-use (TOU) electricity prices. Figures 6–8 present our simulation of the optimization problem.

IV. OPTIMIZATION RESULTS

The coefficients of energy needs are variables that depend on the weather, as shown in Table 3 [13]. The electrical

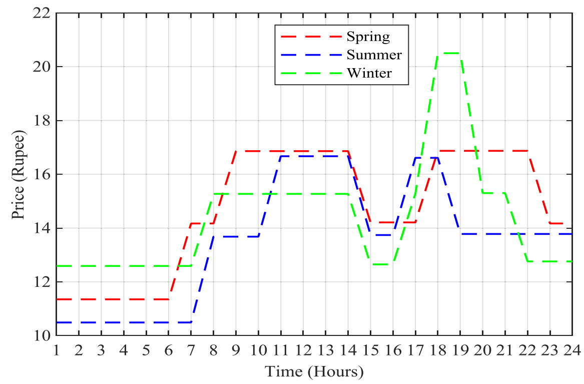

FIGURE 8. Daily time-of-use (TOU) electricity prices for the three seasons.

TABLE 3. The energy requirement coefficients of the three seasons.

Parameter	Spring	Summer	Winter
Electrical	1	1.3	1.2
Thermal	1	1.3	1.2

TABLE 4. The installed components.

Component	Capacity (kW)
Grid	1.31
Boiler	5.50
CHP	4.76

requirement in summer is 1.3-fold that in spring. The components installed at commencement of analysis, and the basic energy costs, are shown in Table 4 [13].

A. COST OPTIMIZATION FOR OPTIMAL CHP RATING

By applying the strategies outlined in subsections 2.1 and 2.2 of section 2, optimizations (CHP output efficiencies and costs) are obtained for all three seasons. Figure 9a–d show the GA- based CHP efficiencies for every minute of the day. Figure 10a–d show the ABC-based CHP efficiencies for every minute. Using Equations (9) and (10), it can be shown that the electricity efficiency contains logarithmic terms; the heat efficiency is more linear than the electricity efficiency. The electricity load efficiency increases logarithmically as the load increases; the heat efficiency does not. As shown in Figure 6, as the electricity load increases from hours 10 to 15, the efficiency at that time also increases markedly, as shown in Figures 10 and 12. However, the efficiency of the heat load is relatively even because efficiency does not increase logarithmically. The performance of the ABC algorithm is better than that of GA, as shown in Figures 10 and 12; the ABC efficiency of Figure 12 is much higher.

Figure 11 compares the costs imposed by the two algorithms over the three seasons. From Fig. 11, we can see that heat dependent ABC criteria has less cost for both the gas engine and fuel cell. In comparison, the opposite scenario is observed for GA based electricity-dependent fuel cell. However, the cost of gas engine electricity-dependent

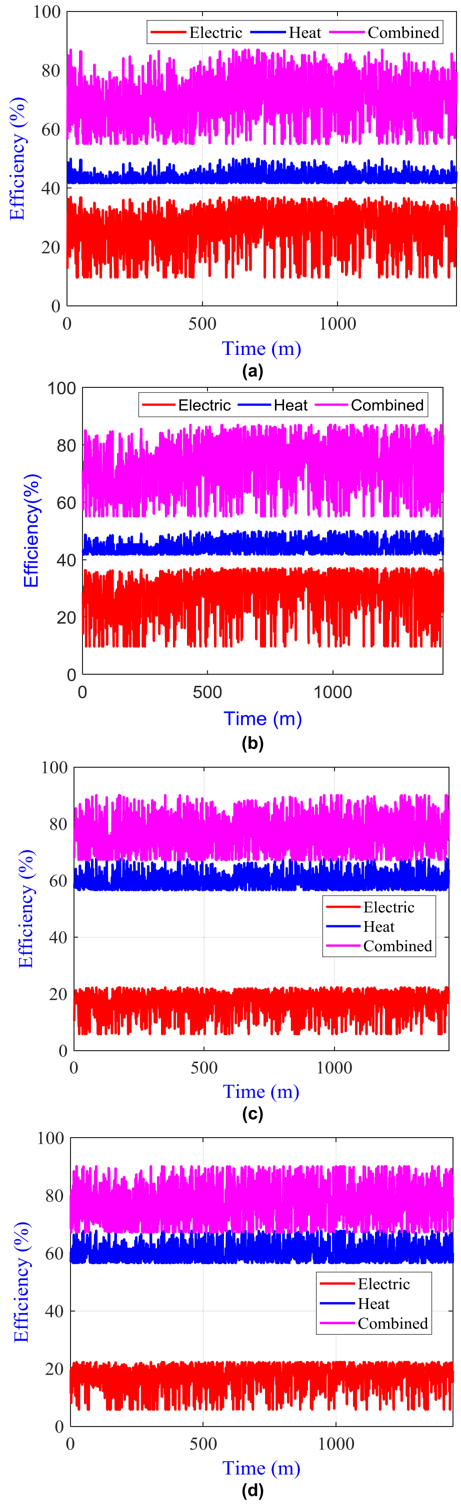

FIGURE 9. GA minutes-based efficiencies for a typical day (a) FC (heat dependent); (b) FC (electricity-dependent); (c) GE (heat dependent); (d) GE (electricity-dependent).

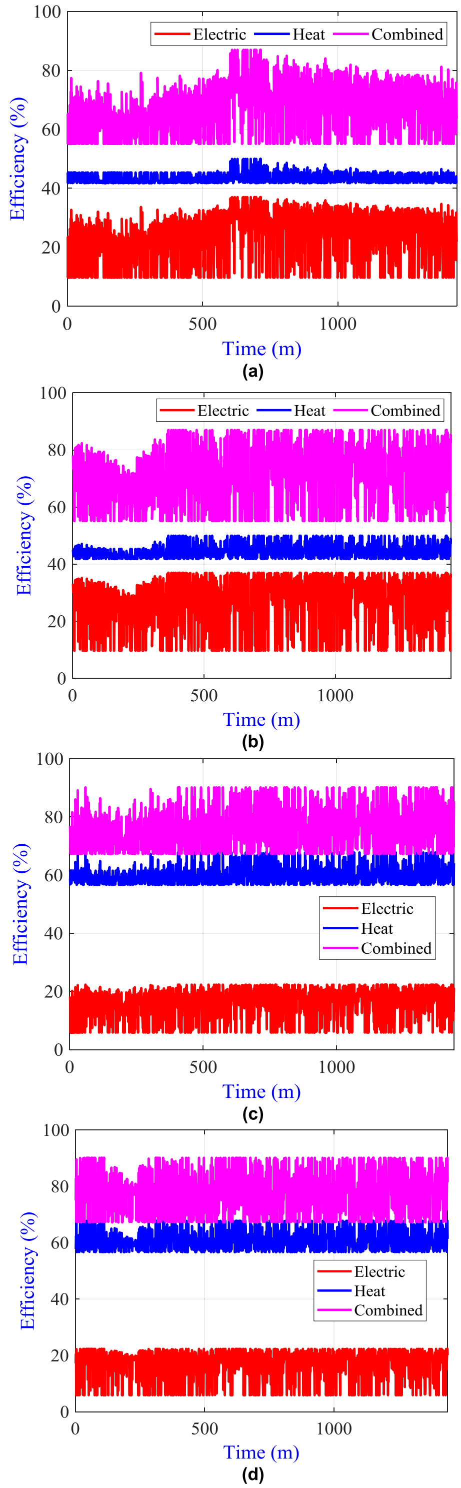

FIGURE 10. ABC minutes-based efficiencies for a typical day (a) FC (heat dependent); (b) FC (electricity-dependent); (c) GE (heat dependent); (d) GE (electricity-dependent).

criteria is almost the same for both GA and ABC algorithms. Table 5 gives detailed information on CHP ratings and costs for all seasons based on both sizing criteria. Table 6 and Figure 12 detail the computational burdens imposed when solving the objectives of each scenario. The optimal sizing results yielded by both GA and the ABC method using heat as the sizing criterion are shown in Table 7. The primary energy consumptions are listed in Table 8. A comparison of optimal installed components with heat as a sizing criterion is shown in Table 9. The comparison between the optimization

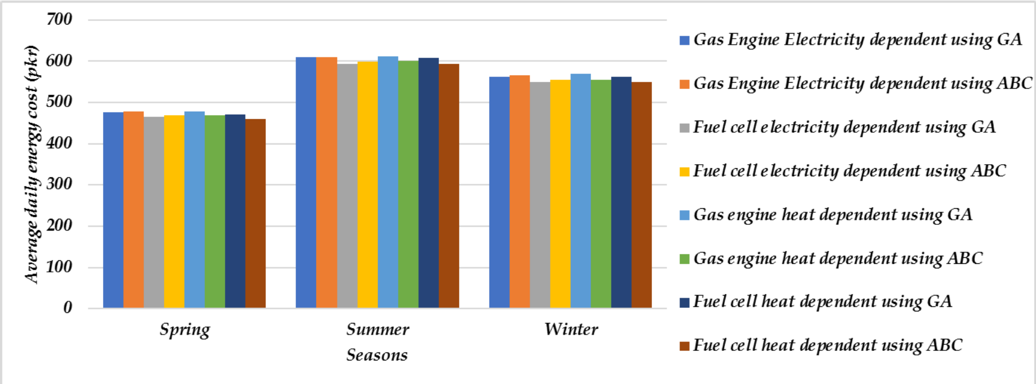

FIGURE 11. Electricity prices in different seasons.

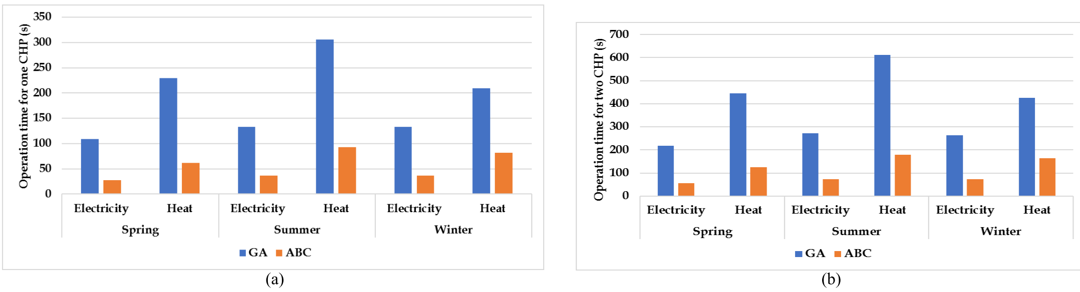

FIGURE 12. The simulation time (a) for one CHP and (b) for two CHP.

TABLE 5. Comparison of operational costs.

Season	Criteria	CHP	Best rated CHP (W)		Best Cost at rated CHP	
			GA	ABC	GA	ABC
Spring	Electricity	Gas Engine	1000	1000	476.1179	478.5480
		Fuel Cell	1000	1000	465.5958	469.5524
	Heat	Gas Engine	2000	2000	478.3178	469.5140
		Fuel Cell	2000	2500	471.1076	460.5319
Summer	Electricity	Gas Engine	1000	1250	609.5626	610.5753
		Fuel Cell	1250	1250	594.3494	599.1951
	Heat	Gas Engine	2000	3000	611.8046	600.6212
		Fuel Cell	2000	2000	608.0600	592.7170
Winter	Electricity	Gas Engine	1250	1250	562.9217	566.4327
		Fuel Cell	1250	1250	548.6436	554.1960
	Heat	Gas Engine	2500	2500	570.0811	555.1767
		Fuel Cell	1500	3000	563.0740	548.7939

methods and the present work is presented in Table 10. However, eight subplots for two figures (namely Fig. 9 and Fig. 10) are necessary to show four different cases for both algorithms. These four cases are (a) FC (heat dependent); (b) FC (electricity-dependent); (c) GE (heat dependent); (d) GE (electricity-dependent).

B. COST OPTIMIZATION FOR OPTIMAL CHP RATING

We used a GA to size both types of CHP units.

1) FUEL CELL CHP UNIT

Figure 13 shows the CHP unit's installation ratings and everyday costs using heat as the sizing criterion. The cost falls as the CHP unit's rating increases to 2,000 W, which is thus the optimal CHP unit rating. Figure 14 shows the CHP unit's installation rating and everyday costs using electricity as the sizing criterion. The cost falls as the CHP unit's rating increases to 2,000 W, which is thus the optimal CHP unit's rating.

2) GAS ENGINE CHP UNIT

Figure 13 shows the CHP unit's installation ratings and everyday costs using heat as the sizing criterion. The cost falls as the CHP unit's rating increases to 2,000 W, which is thus the optimal CHP unit's rating. Figure 13 compares the average daily energy costs of FC and GE CHP units with different

TABLE 6. Comparison of simulation time.

Scenario	Sizing Criteria	No. of CHP	Processing time	
			GA	ABC
Spring	Electricity	One	1m 49s	0m 28s
		Two	3m 38s	0m 55s
	Heat	One	3m 49s	1m 02s
		Two	7m 26s	2m 04s
Summer	Electricity	One	2m 13s	0m 37s
		Two	4m 32s	1m 13s
	Heat	One	5m 06s	1m 33s
		Two	10m 11s	2m 58s
Winter	Electricity	One	2m 13s	0m 37s
		Two	4m 24s	1m 14s
	Heat	One	3m 29s	1m 22s
		Two	7m 05s	2m 43s

TABLE 7. Comparison of sizing optimization (sizing criteria: heat).

Method	Season	P_{CHP-GE}(W)	P_{CHP-FC}(W)
GA	Spring	2000	2000
	Summer	2000	2000
	Winter	2500	1500
ABC	Spring	2000	2500
	Summer	3000	2000
	Winter	2500	3000

TABLE 8. Comparison of consumption (sizing criteria: heat).

Parameter	Season	GA	ABC
Primary energy consumption [kWh]	Spring	4078.9	4038.9
	Summer	5322.4	5240.1
	Winter	4933.2	4844.3
Computation time [m]	Spring	7.4	2.1
	Summer	10.2	2.9
	Winter	7.1	2.7

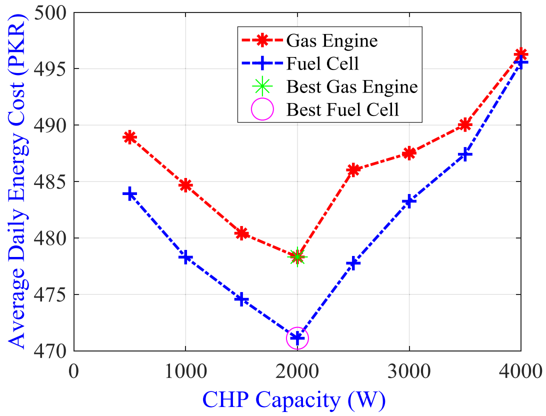

FIGURE 13. GA based comparison of the daily cost of a residential house (heat criteria).

capacities, using the heat criterion. Figure 14 shows the CHP unit's installation ratings and everyday costs using electricity as the sizing criterion. Figure 14 shows that the costs fall as the CHP unit's rating increases to 1,000 W, which is thus the optimal CHP unit's rating. Figure 14 compares the average daily energy costs of FC and GE CHP units of various capacities using the electricity criterion.

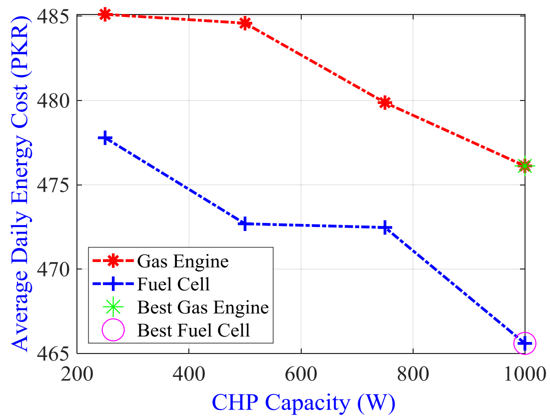

FIGURE 14. GA based comparison of the daily cost of a residential house (electricity criteria).

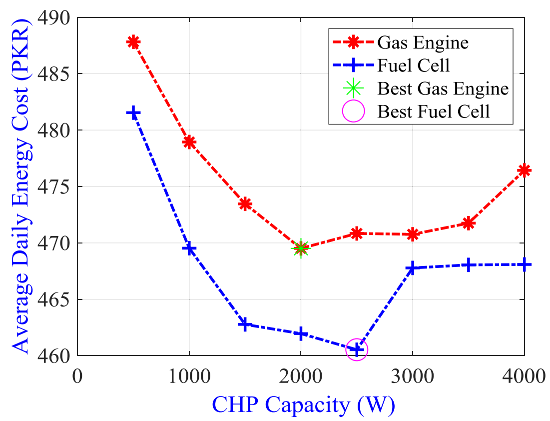

FIGURE 15. ABC based comparison of everyday cost of a residential house for erecting of fuel cell CHP vs. gas engine CHP using heat criteria.

C. OPTIMAL CHP UNIT'S RATING AND COST MINIMIZATION USING THE ABC ALGORITHM

Here, we use the ABC algorithm to determine the optimal sizes of both types of CHP units.

1) FUEL CELL CHP UNIT

Figure 15 shows the CHP unit's installation ratings and everyday costs using heat as the sizing criterion. The cost falls as

TABLE 9. **Comparison of Results of optimal installed components (sizing criteria: heat).**

Season	Total cost (PKR)			Installed components (kW)		
	Base Case	GA	ABC	Components	GA	ABC
Spring	636.1	471.1	460.5	Grid	0.988	1.03
				Boiler	4.18	4.23
				CHP	2.00	2.50
Summer	633.9	608.1	592.7	Grid	1.31	1.34
				Boiler	5.40	5.50
				CHP	2.00	2.00
Winter	633.9	567.4	548.9	Grid	1.24	1.24
				Boiler	5.01	5.08
				CHP	2.50	2.50

TABLE 10. **Comparison between the optimization methods.**

Ref	Region	Methodology	Primary energy saving (%)
[6]-2019-H. Bahlawan	Italy	DP vs (traditional, GA)	24 (traditional), 5.4 (GA)
[7]-2019-T. M. Kneiske	Germany	MPC vs. RB	7.3 (RB)
[8]-2019-S. Senemar	-	PDPg (DPg, DSM)	4 (DPg), 11 (DSM)
[9]-2019-H. Bahlawan	Italy	Three seasons: GA vs (LCA, traditional)	1st season: 4 (LCA), 2nd & 3rd season:14 & 17 (traditional)
[10]-2019-M. Sameti	Switzerland	Three seasons: MILP	25, 11, 40 (MILP)
[11]-2019-M. Majidi	-	Three seasons: Traditional vs. (Robust, DRP)	9.84, 30.66, 30.88 (Robust); 9.76, 31.84,32.26 (DRP)
[12]-2017-D. Yu	UK	GA vs. traditional	13 (traditional)
Present work	Pakistan	Three seasons: Traditional vs. (GA, ABC)	25.9, 4.4,10.8 (GA); 27.6, 6.8,13.7 (ABC)

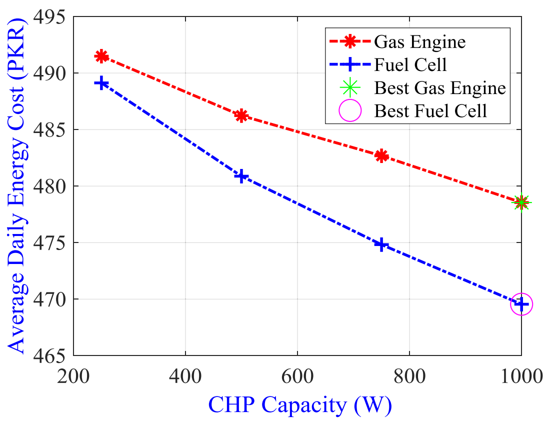

FIGURE 16. **ABC based comparison of everyday cost of a residential house for erecting of fuel cell CHP vs. gas engine CHP electricity criteria.**

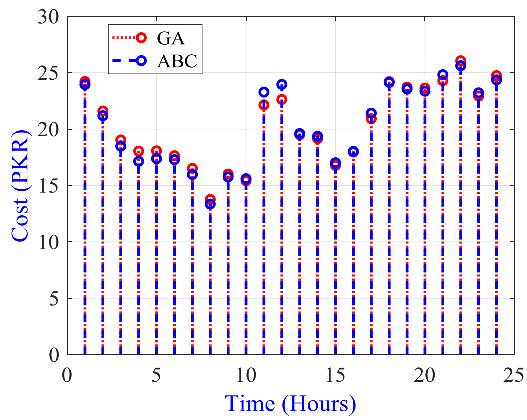

FIGURE 17. **Hourly Total Costs of GA and ABC (Rated gas engine CHP capacity = 2000).**

the CHP unit's rating increases to 2,500 W, which is thus the optimal rating. Figure 16 shows the CHP unit's installation ratings and everyday costs using electricity as the sizing criterion. The cost falls as the CHP unit's rating increases to 1,000 W, which is thus the optimal rating.

2) GAS ENGINE CHP UNIT

Figure 15 shows the CHP unit's installation ratings and everyday costs using heat as the sizing criterion. The cost falls as the CHP unit's rating increases to 2,000 W, which is thus the optimal rating. Figure 15 compares the average daily energy costs of FC and GE CHP units of different capacities, using the heat criterion. Figure 16 shows the CHP unit's installation ratings and everyday costs using electricity as the sizing criterion. The cost falls as the CHP unit's rating increases to 1,000 W, which is thus the optimal rating. Figure 16 compares the average daily energy costs of FC and GE CHP units of different capacities, using the electricity criterion.

D. COMPARISON OF THE GA AND ABC METHODOLOGIES

Figure 17 shows the total hourly costs of a GE CHP unit with a capacity of 2,000 W; the convergence curve is shown in Figure 18. Figure 19 shows the total hourly costs of an FC CHP unit with a capacity of 2,500 W; the convergence curve is shown in Figure 20. The optimal sizes of FC- and GE-based CHP units are 2,500 W and 2,000 W respectively. Figures 17 and 18 show the results for a 2,000-W GE CHP unit when the GA and the ABC algorithm are employed. Figures 19 and 20 compare the results when the

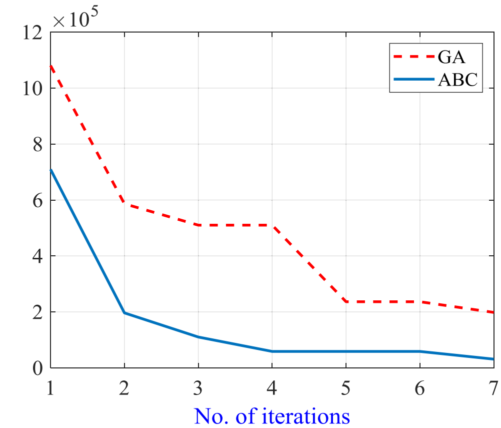

FIGURE 18. Convergence Curve of GA and ABC (Rated gas engine CHP capacity = 2000).

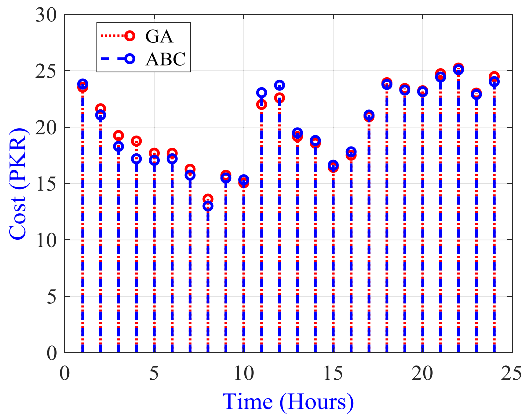

FIGURE 19. Hourly Total Costs of GA and ABC (Rated fuel cell CHP capacity = 2500).

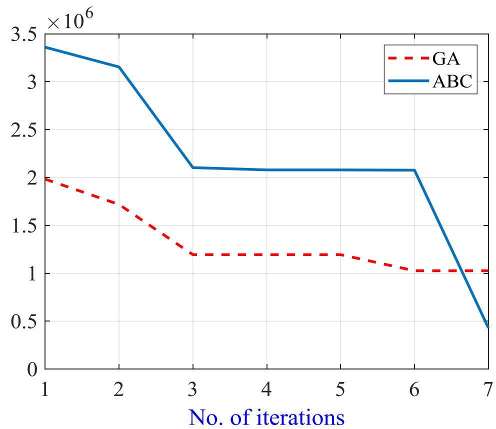

FIGURE 20. Convergence Curve of GA and ABC (Rated fuel cell, CHP = 2500 Watt).

GA and the ABC algorithm are used to analyze the 2,500-W FC CHP unit.

V. CRITICAL ANALYSIS AND DISCUSSION

We list the nine highlights of our study:

(1) Better results are obtained when the heat rather than the electricity demand serves as the sizing criterion for CHP units because the average heat requirement is significantly greater than the electricity requirement throughout the year. Therefore, use of the heat requirement for sizing identifies optimal FC and GE CHP units. It is not helpful to employ the electricity requirement as the sole sizing criterion because a GE CHP unit exhibits a high heat to power ratio; such a CHP unit will produce more unnecessary heat.

(2) When the the ABC algorithm was used for CHP unit sizing with the heat demand as the sizing criterion, the cost:benefit ratios were always better than those afforded by the GA because the ABC algorithm selects a CHP unit rating that fulfils most load demands imposed over the entire year. The CHP unit with the maximum rating is chosen. Although the primary energy saving is not as good as that afforded by the GA; the capital (investment) cost savings are marked.

(3) The simulations showed that simultaneous evaluation of all objectives (operating and capital costs, and efficiency) was rather complicated. Higher-capacity CHP units afforded better primary energy savings, but cost more and were less efficient than lower-capacity CHP units because the higher-capacity CHP units require more electrical energy at peak hours. If this energy is delivered by smaller CHP units, costs are reduced. Also, higher-capacity CHP units contribute only low inputs to the rated power ratios; the CHP units function at low input power (which is the prime cause of poor efficiency). Most CHP power is not utilized effectively; the capital cost is thus high.

(4) The greatest energy-savings were evident in winter, followed by summer and spring. Energy-savings in spring were low because of the heat demand; the CHP unit's heat output relative to electricity consumption was thus also low. To enhance energy saving, the capacity of the CHP unit could be lowered, also reducing costs during other seasons. However, energy storage will be needed to deliver the peak hour loads

(5) The computational burden with the ABC algorithm is significantly shorter than GA, which shows the proposed ABC methodology's superior performance with a faster response.

(6) The minute-based efficiencies (Figures 9 and 11) of the GA and the ABC algorithm show that both afford high resolution. It is clear that the ABC algorithm exhibits less oscillation and greater stability, especially when heat serves as the sizing criterion.

(7) As the ABC is a heuristic search algorithm, the results contain an element of randomness. Convergence curves are commonly used to select the best solutions of such algorithms [30]; we drew such curves. Figures 20 and 22 show that the ABC algorithm was better than the GA. When selecting the final solution, we considered the average of 10 optimizations; 5 or even 3 optimizations may be adequate if the variations in random numbers are negligible.

(8) We selected CHP unit capacities with base loads in mind. The maximum base load was 1 kW (Fig. 7); a CHP capacity of 1 kW was thus the lower limit, rendering it simple to derive an optimal value.

(9) Fig. 20 shows the convergence for FC based CHP. The authors are agreed with the concern that ABC convergence in the FC case is not reached yet. But the comparison with GA shows that GA convergence behavior is constant after the 6th iteration while the ABC convergence trend clearly indicates the effectiveness of the ABC algorithm over GA. This convergence trend can also be proved from Fig. 18. Since the number of iterations is set to 7 in the simulation analysis, comparative analysis in Fig. 20 still validates the ABC algorithm's superior performance over GA.

(10) The problem is not stochastic, and the only deterministic problem with pure deterministic data with non-uncertainties is considered in this work.

VI. CONCLUSION

We compared, and optimized the performances of GE- and FC-based CHP units. We compared the use of the GA and the ABC algorithm to these ends. We explored the computational burdens imposed by the GA and the ABC methods. The use of both heat and electricity criteria to optimize objective functions yielded impressive results. Employment of the electricity criterion alone will not size a CHP unit optimally, since the heat requirement is significantly greater than the electrical demand; we thus employed both heat and electricity standards. We first used the GA for CHP unit sizing. The simulation suggested that, optimally, an FC-based CHP unit should have a capacity of 2,500 W and a GE-based CHP unit a rating of 2,000 W. The daily cost minimizations are 25.9% those of the base cases. ABC algorithm optimizations yielded daily cost minimizations 27.6% those of the base cases, thus about 1.7% more than afforded by the GA when the heat demand served as the CHP unit sizing criterion. The ABC algorithm was superior to the GA because the former algorithm afforded a better cost:benefit ratio and increased energy efficiency. Furthermore, the ABC method makes more use of CHP units' ratings; cheap energy can be delivered on specific days. In summary:

- We used the GA and ABC algorithm for CHP unit sizing.
- The computational burden imposed by the ABC algorithm was much less than that of the GA.
- The optimization cost of the ABC algorithm was lower than that of the GA.
- Simulations of different GE and FC CHP units using the heat and electricity criteria yield feedback allowing engineers, scientists, and system planners to select optimal CHP units.

In future, we will explore whether the FC lifetime impacts performance. We will simulate savings over a 5,000-h period (the life of an FC) and price the various 1,000-W FCs. This analysis will give deep insight to see whether the FC's price is higher or lower compared to the savings. This work's limitations will be handled as future work that will also combine the CHP study of this work with the already published V2G integrated RER microgrid [33] for multi-microgrid RER-based energy hub (EH) system. Future work also includes testing of new and latest algorithms with single and multi-microgrid energy-hub systems. The community load for multiple households (microgrid clusters) will also be a part of future work.

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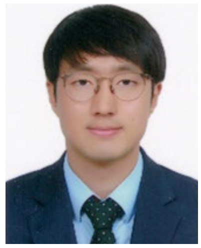

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