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Optimal Design of a Combined Cooling, Heating, and Power System and Its Ability to Adapt to Uncertainty

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Abstract: To realize the best performances of the distributed energy system (DES), many uncertainties including demands, solar radiation, natural gas, and electricity prices must be addressed properly in the planning process. This study aims to study the optimal sizing and performances of a hybrid combined cooling, heating, and power (CCHP) system under uncertainty in consideration of the operation parameters, including the lowest electric load ratio (LELR) and the electric cooling ratio (ECR). In addition, the ability of the system to adapt to uncertainty is analyzed. The above works are implemented separately under three operation strategies with multi-objectives in energy and cost saving, as well as CO_2 reducing. Results show that the system with optimized operation parameters performs better in both the deterministic and uncertain conditions. When the ECRs in the summer and in mid-season as well as the LELR are set at 50.00%, 50.00%, and 20.00% respectively, the system operating in the strategy of following the electric load has the best ability to adapt to uncertainty. In addition, among all the uncertainties, the single uncertain natural gas price and the single uncertain heating demand have the smallest and largest effects on the optimal design respectively.

Keywords: CCHP system; stochastic programming; operation parameters; uncertainty

1. Introduction

In recent years, the energy system is on its way to be transformed to meet the requirements of energy saving and environment protection. In this way, many distributed energy systems (DESs) including the CHP (combined heating and power) system, the CCHP (combined cooling heating and power) system, and other hybrid systems can be planned for commercial buildings, residential districts, and industry parks because of their efficient, economic, and environmental performances. At the design stage of a DES for a building, some parameters, such as the estimated energy demands, natural resources, and energy prices, are regarded as the fixed values. Nevertheless, at the operation stage in the real application, all these parameters fluctuate with different uncertain characteristics, which can cause a worse performance than the expected one. Therefore, the uncertainty must be handled in both the planning and operation [1].

Many authors have implemented works on tackling the uncertainty in DES planning with different methods, including fuzzy programming [2], robust optimization [3], and stochastic programming [4]. In the fuzzy approach, Moradi et al. [5] used fuzzy programming to deal with the uncertain electrical and thermal demands as well as the natural gas and electrical power prices in a CHP system.

Considering the uncertainty in load demand and fuel cost, Mavrotas et al. [6,7] proposed a fuzzy mathematical framework to plan an energy system. Zhou et al. [8] employed a fuzzy interval possibilistic model to handle the CO_2 emission factor uncertainty in a sustainable electrical power system. Lu et al. [9] addressed the uncertainties of energy price and CO_2 emission factors in the energy system with an interval-fuzzy possibilistic programming model. Based on a life cycle assessment, Li et al. [10] employed a fuzzy rough set to deal with the uncertainties existing in natural resources to evaluate the environmental impact for a distributed renewable energy system. In the robust approach, Majewski et al. [11] addressed the uncertain data of energy demands and the prices in a CCHP system based on a proposed robust model. Luo et al. [12] carried out robust design work for a CCHP system accounting for uncertain demands and photovoltaic output power. Niu et al. [13] planned a renewable cooling resource in a robust way considering demands and renewable energy uncertainties. Based on the minimax regret criterion, Yokoyama et al. [14] carried out robust optimal design works for a gas turbine co-generation system in consideration of uncertain energy demands. Roberts et al. [15] carried out a robust sizing for an energy system in a probabilistic scenario-based way, accounting for uncertain demands and natural resources. In the stochastic approach, Mavromatidis et al. [16] employed the stochastic model in planning for a distributed energy system while considering uncertain energy prices, emission factors, demands, and solar radiation. Incorporating long term uncertainties of loads and prices, Onishi et al. [17] used a stochastic model to get the optimal design for a tri-generation system. Afzali et al. [18] employed a stochastic method to deal with uncertain demands and energy prices when planning an energy system for an urban community. Yang et al. [19] accounted for uncertainties of demands, solar radiation, wind speed, and energy prices in the planning work for CCHP systems. Vaderobli et al. [20] addressed the uncertainties of weather and cost in a renewable energy system with stochastic optimization.

Most of the above works presented for a CHP or CCHP system focus only on the optimal sizing under uncertainty while ignoring the optimization of operation parameters, such as the lowest electric load ratio and the electric cooling ratio. In the deterministic optimization for a CCHP system [21], the operation parameters have apparent effects on the system performance and design. In uncertain optimization, however, it needs further research about how these operation parameters influence the optimal design for a CCHP or CHP system and the ability of the system to adapt to uncertainty. Based on these, the works in this study mainly lie in the following aspects: (1) the effects of multi-uncertainties on a CCHP system planning is researched; (2) the effects of operation parameters on the ability of the system to adapt to uncertainty is investigated; and (3) the effects of a single uncertainty in generated scenarios on system planning is analyzed. This study is composed of six sections. Section 2 presents a system description about the system structure, the operation strategies, and system performances. Section 3 shows the optimization under uncertainty, including the stochastic programming method, the proposed model, and algorithm. Section 4 provides the information about the hotel and case set. Section 5 implements the results from the analysis, and Section 6 concludes the paper.

2. System Description

2.1. System Configuration

The planned hybrid CCHP system in this study is shown in Figure 1. The technical and economic parameters can be found in Appendix A.1. In the system, the energy balances are as follows:

(1) Cooling energy balance:

$$Q_C = Q_{EC} + Q_{AC} \tag{1}$$

(2) Heating energy balance:

$$Q_H = (Q_{HRS} + Q_{GB} + Q_{SHC} - Q_{HSTin} + Q_{HSTout} - Q_{ACin}) \cdot \eta_{HE} \tag{2}$$

(3) Electric energy balance:

$$E = E_{GT} + E_{PV} + E_{grid} - E_{EC} \tag{3}$$

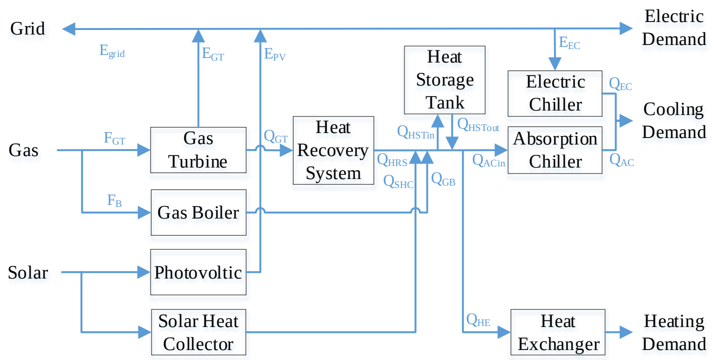

Figure 1. The hybrid combined cooling, heating, and power (CCHP) system configuration.

2.2. Operation Strategy

Following the thermal load (FTL) [22], following the electric load (FEL) [23], and following the hybrid electric-thermal load (FHL) [24] are the three basic operating strategies for a CCHP system. When the CCHP system operates in FTL, the gas turbine (GT) gives priority to meet the heating demand. When the system operates in FEL, the gas turbine (GT) gives priority to meet the electric demand. In both of these two strategies, the unmet heating and electric demands are covered by a gas boiler (GB) and a state grid, respectively. When the system operates in FHL, if the heat-to-electric ratio of the GT is in part B of Figure 2, the system operates in FEL, or else it operates in FHL. The specific logic of the strategies is defined in Appendix A.2.

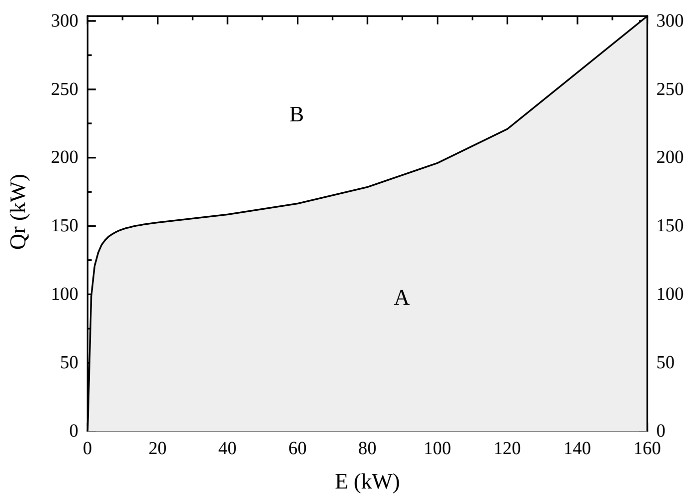

Figure 2. Heating and electric output in the gas turbine.

2.3. System Performance

The integrated performance (IP), which is composed of the annual total cost saving (ATCS), the primary energy saving (PES), and the carbon dioxide emission reduction (CDER), is used as an objective in the presented study, which is expressed by [25,26]:

$$IP = \omega_1 \cdot ATCS + \omega_2 \cdot PES + \omega_3 \cdot CO2ER, \tag{4}$$

where $ATCS$, PES, and $CO2ER$ are denoted by f_1, f_2, and f_3 respectively, and then the integrated performance is described as:

$$IP = \omega_1 \cdot f_1 + \omega_2 \cdot f_2 + \omega_3 \cdot f_3, \tag{5}$$

where $\omega_i = \frac{1}{3}(i = 1, 2, 3)$ are the weights of each criterion. The specific formulations of ATCS, PES, and CDER are shown in Appendix A.3.

3. Optimization under Uncertainty

3.1. Two-Stage Stochastic Programming

The two-stage stochastic programming problem [4] is used to handle the uncertainty in the planning process. Its basic mathematical model is shown as follows:

Stage 1:

$$\min_{x \in X}\{g(x) := c^T x + E[Q(x, \xi)]\}, \tag{6}$$

Stage 2:

$$\begin{aligned} &\min_{y} q^T y, \\ &s.t.\, Tx + Wy \le h, \end{aligned} \tag{7}$$

where $x \in \mathbb{R}^n$ is the decision variable or the here-and-now variable in the first stage, while $y \in \mathbb{R}^n$ is the process variable or the wait-and-see variable in the second stage, and $\xi = (q,\ T,\ W,\ h)$ denotes the uncertain factors in the second stage.

After sampling, the above problem can be solved. Monte Carlo sampling is one of the sampling techniques used to simulate the future situation of uncertain factors. Based on the given probability distribution, N samples of uncertainty are generated, which is $\xi = (\xi_1, \xi_2, \ldots, \xi_n)$. Combining with the sample average approximation (SAA) method, the expectation function $q(x) = E[Q(x, \xi)]$ in Equation (1) transforms into:

$$\bar{q}_N(x) = \frac{1}{N}\sum_{j=1}^{N} Q(x, \xi_j), \tag{8}$$

which then turns the two-stage problem into:

$$\min_{x \in X}\{g(x) := c^T x + \frac{1}{N}\sum_{j=1}^{N} Q(x, \xi_j)\}. \tag{9}$$

3.2. Stochastic Programming Model for the CCHP System

To divide the optimization problem into two stages, the integrated performance is transformed as follows:

$$IP = \omega_1 \cdot f_1 + \omega_2 \cdot f_2 + \omega_3 \cdot f_3 = \omega_1 \cdot (1 + C \cdot f_{11} + C \cdot f_{12}) + \omega_2 \cdot f_2 + \omega_3 \cdot f_3, \tag{10}$$

where C is the constant, while f_{11} and f_{12} are the investment cost and operation cost of the CCHP system, respectively.

According to the transformed integrated performance and the basic process of optimization, the two-stage stochastic programming model is created as follows:

Stage 1:

$$\begin{aligned} &\max_{d} \tfrac{1}{3}\{1 + C \cdot f_{11}(d) + E[C \cdot f_{12}(d, \xi) + f_2(d, \xi) + f_3(d, \xi)]\}, \\ &s.t.\, \varphi^d(d) = 0, \\ &\psi^d(d) \le 0, \end{aligned} \tag{11}$$

Stage 2:

$$\begin{aligned} &\max_{o} \left[f_{12}(d,\xi,o) + f_2(d,\xi,o) + f_3(d,\xi,o) \right], \\ &s.t. \, \varphi^o(d,\xi,o) = 0, \\ &\quad \psi^o(d,\xi,o) \leq 0. \end{aligned} \tag{12}$$

where d is the design variable, including the optimal capacity of each equipment and operation parameters; o is the operation variable, including the gas consumption and electricity consumption; ξ is the uncertainty, including uncertain demands, energies prices, and solar radiation; φ^d and ψ^d are equality and inequality constraints for the design variables, respectively; and φ^o and ψ^o are the equality and inequality constraints for the operation variables, respectively. In addition, the uncertainties of demands, solar radiation, and the natural gas and grid electricity prices are addressed in the model; their probability distributions are shown in Appendix A.4.

3.3. Optimization Algorithm

To solve the nonlinear problem, the artificial bee colony (ABC) algorithm [27] is employed in this study. The basic process to realize stochastic programming optimization by the ABC is depicted in Figure 3 while the process of the ABC is presented in Algorithm 1.

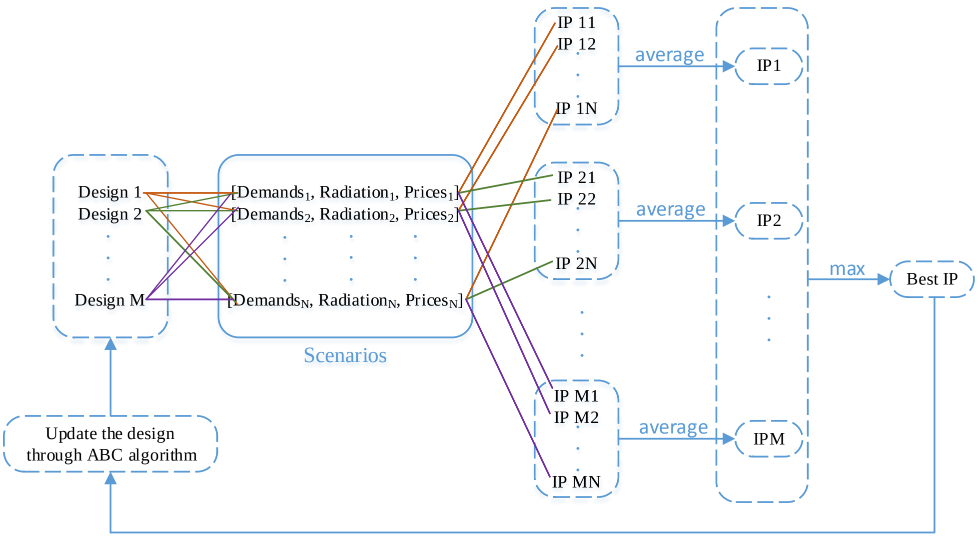

Figure 3. Stochastic programming process by the artificial bee colony (ABC) algorithm.

Algorithm 1: ABC algorithm optimization process.

Input: Economic and technical parameters, scenarios of demands, solar radiation, and energy prices
  Step 1: Generate all food sources and variables randomly.
  Step 2: Evaluate the fitness of all foods according to the fitness function, given by Equation (4).
Repeat
  Step 3: Employ bee search:
  Compute the objectives of all scenarios and update the food source according to the best IP.
  Step 4: Onlooker bee search:
  Compute the objectives of all scenarios and update the food source according to the best IP.
  Step 5: If trail number > limit, then go to step 6. Otherwise, go to step 7.
  Step 6: Scout bee search:
  Generate a new food source and replace the old one if the new one is better.
  Step 7: Record the best food source.
Until: Max iteration > ε
Output: Optimal capacities, LELRs, and ECRs

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4. Case Study

4.1. Hotel Description

The U.S. Department of Energy [28] simulated demands for different types of buildings, which include hotels, schools, and hospitals. In this study, a large hotel that is located at Ohio State University (shown in Figure 4) is used to implement the study. The local climate is a temperate continental climate. July is on average the warmest month, the average high and low temperatures of which are 30.0 and 17.8 °C, respectively; January is on average the coolest month, the average high and low temperatures of which are 2.8 and −7.2 °C, respectively [29]. Some information about the hotel is shown in Table 1. Figure 5a,b shows the demands and solar radiation, respectively. The U.S. Energy Information Administration [30,31] provides the natural gas and grid electricity prices, which are 5.99 dollars per thousand cubic feet and 9.94 cents per kilowatt hour, respectively.

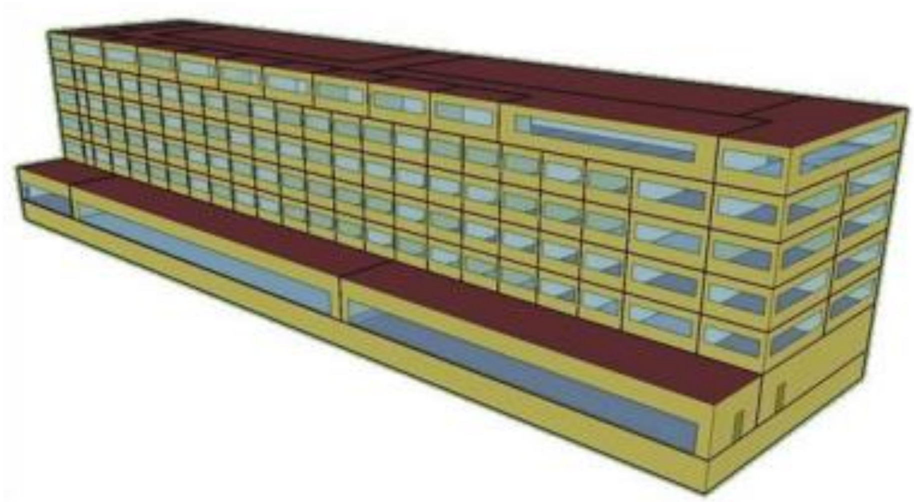

Figure 4. Large hotel at Ohio State University used in the study.

Table 1. Hotel description.

Item	Description
Building type	Large hotel
Orientation	Faces south
Roof area	1147.5 m^2
Total area	11,345 m^2
Occupancy	65%
Aspect ratio	Ground floor: 3.79 (86.56 m × 22.86 m) All other floors: 5.07 (86.56 m × 17.07 m)
Number of floors	1 basement, 6 above-ground floors
Window fraction	East: 24.5%; West: 24.5%; South: 36.7%; North: 26.0%
Exterior walls	Concrete blocks, wall insulation, and gypsum board

4.2. Simulation Cases

To investigate the effects of electric cooling ratios in the summer (ECR_S) and in mid-season (ECR_M) as well as the lowest electric load ratio (LELR) on system planning, several cases were set in this paper, which are depicted in Table 2. Cases 1–3 were implemented under the deterministic condition, in which the operation parameters are given as 50%, 50%, and 20% [32] respectively in case 1; only the ECRs were optimized in case 2, while the two kinds of parameters were optimized in case 3. Cases 4–6 were carried out under an uncertain condition; the results of the cases were then compared to that of case 1 to study the effect of operation parameters on the ability of the system to adapt uncertainty. In addition, the parameters of the ABC algorithm of cases 1–6 are presented in Appendix A.5.

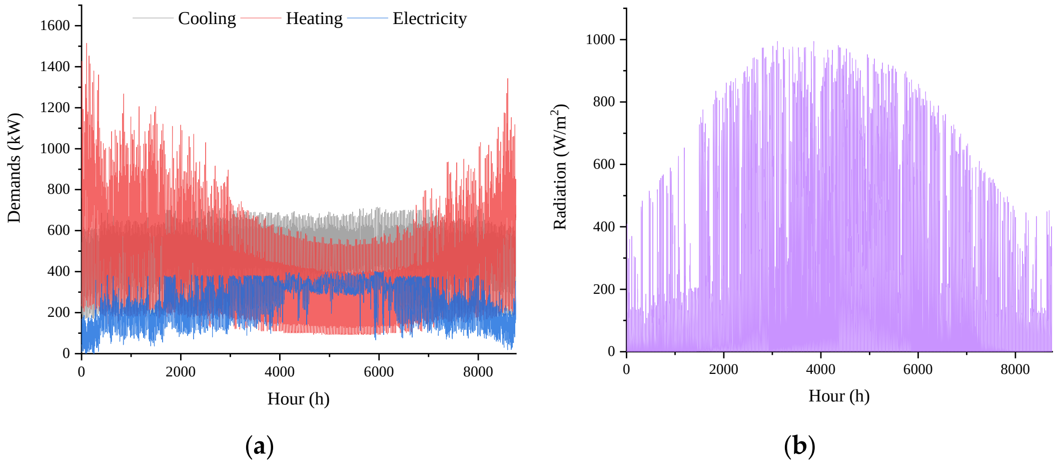

Figure 5. (**a**) Annual demands of the hotel; (**b**) Annual solar radiation.

Table 2. Simulated cases.

Case	ECRs		LELR		DET	UN
	Given	Optimized	Given	Optimized		
1	√		√		√	
2		√	√		√	
3		√		√	√	
4	√		√			√
5		√	√			√
6		√		√		√

5. Results and Analysis

5.1. Result of Deterministic Conditions

Tables 3 and 4 show the system performances and the optimal design of cases 1–3, respectively. It can be seen from Table 3 that following the electric load (FEL) is the best operation strategy for cases 1–3, and the integrated performance (IP) is 36.00%, 36.63%, and 36.67% respectively. In addition, case 3 performs best among the three strategies on the whole with 33.29% of PES, 47.62% of CDER, and 29.10% of ATCS because the optimal lowest electric load ratio (LELR) and the electric cooling ratios in the summer (ECR_S) and in mid-season (ECR_M) are optimized. Table 4 shows that the LELR, ECR_S, and ECR_M of case 3 in FEL are 5.75%, 37.74%, and 60.38% respectively. Figure 6 presents the annual fuel consumption, the CO_2 emission, and the cost of cases 1–3 when the system operates in the best operation strategy (FEL); it can be seen that the annual values of case 3 are 1.1114×10^7 kW, 2.4732×10^9 g, and 3.6047×10^5 dollars, respectively.

Table 3. System performances of deterministic cases.

Strategy	Case	PES	CDER	ATCS	IP
FTL	1	25.90%	37.38%	22.71%	28.66%
	2	26.09%	38.93%	23.70%	29.57%
	3	26.18%	39.02%	23.73%	29.64%
FEL	1	32.34%	46.72%	28.95%	36.00%
	2	33.25%	47.54%	29.11%	36.63%
	3	33.29%	47.62%	29.10%	36.67%
FHL	1	27.21%	38.46%	23.37%	29.68%
	2	27.53%	40.66%	24.77%	30.99%
	3	27.63%	40.73%	24.81%	31.05%

Table 4. Optimal design of deterministic cases in FEL.

Strategy: FEL		Case		
		1	**2**	**3**
GT	kW	1475	1490	1500
AB	kW	1477	1476	1475
PV	m^2	1478	1315	1347
SHC	m^2	0	162	130
EC	kW	357	267	269
AC	kW	357	447	444
HE	kW	1514	1514	1514
HST	kW	1174	1750	1786
LELR	%	20.00	20.00	5.75
ECR_S	%	50.00	37.36	37.74
ECR_M	%	50.00	59.57	60.38

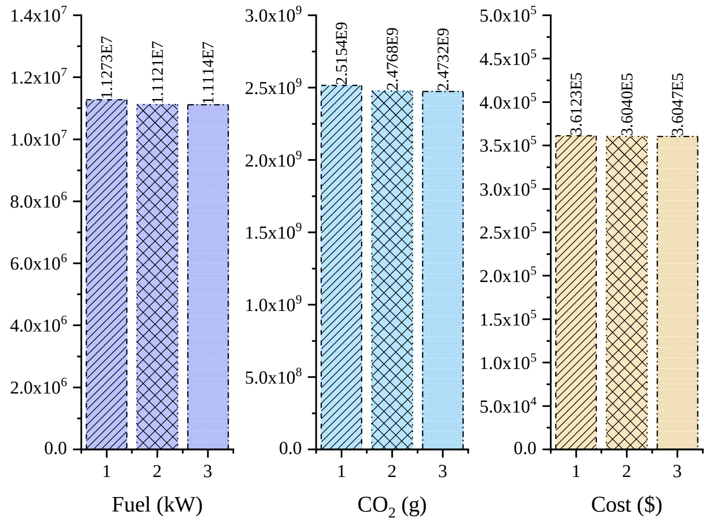

Figure 6. Fuel consumption, CO_2 emission, and cost of the deterministic cases in following the electric load (FEL).

5.2. Result of Uncertain Conditions

5.2.1. Effect of Multi-Uncertainties to System Planning

Uncertainties of demands, solar radiation, and energy prices are handled in cases 4–6, the system performances of which are shown in Table 5. It can be seen that the performances of uncertain cases 4–6 are similar to those of deterministic cases 1–3. Case 6 with optimized LELR and ECRs in FEL are best while 33.17% of the primary energy, 47.48% of CO_2, and 31.24% of the total cost are reduced annually. To be specific, Figure 7 depicts that the system operating in the best operation strategy (FEL) of case 6 consumes 1.1134×10^7 kW natural gas, generates 2.4797×10^9 g CO_2, and costs 3.8708×10^5 dollars annually, and all the values are the lowest among the three uncertain cases.

Table 6 presents the optimal design of uncertain cases 4–6. To analyze the ability of the system to adapt to uncertainty, the results of the uncertain cases 4–6 and the deterministic cases 1–3 are compared; the cascade color table is shown in Table 7, which is based on the absolute deviation of the cases. It can be seen that on the whole, case 4 performs best to handle uncertainty with the lowest fluctuation of optimal design while the capacities of case 6 deviates from case 3 most significantly among the three uncertain cases.

Table 5. System performances of uncertain cases.

Strategy	Case	PES	CDER	TCS	IP
FTL	4	25.59%	37.06%	23.89%	28.85%
	5	25.66%	38.35%	25.04%	29.68%
	6	25.73%	38.45%	25.11%	29.76%
FEL	4	32.21%	46.58%	31.09%	36.62%
	5	33.12%	47.39%	31.23%	37.24%
	6	33.17%	47.48%	31.24%	37.30%
FHL	4	27.01%	38.20%	24.56%	29.92%
	5	27.09%	40.07%	26.24%	31.13%
	6	27.19%	40.19%	26.32%	31.23%

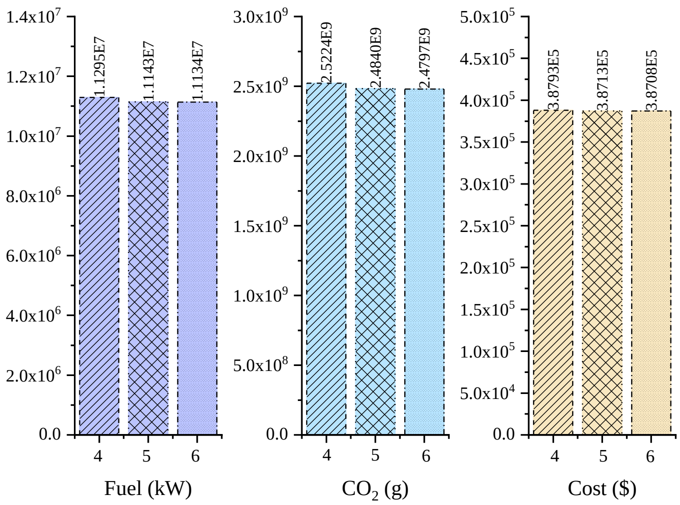

Figure 7. Fuel consumption, CO_2 emission, and cost of the uncertain cases in FEL.

Table 6. Optimal design of uncertain cases in FEL.

Strategy: FEL		Case		
		4	5	6
GT	kW	1491	1511	1521
AB	kW	1645	1636	1632
PV	m^2	1477	1334	1406
SHC	m^2	0	144	72
EC	kW	439	331	342
AC	kW	439	547	536
HE	kW	1637	1637	1637
HST	kW	1284	1901	1943
LELR	%	20.00	20.00	2.00
ECR_S	%	50.00	37.70	61.28
ECR_M	%	50.00	60.59	38.92

Table 7. The absolute deviation of optimal design between uncertain cases 4–6 and their deterministic cases 1–3.

Strategy: FEL	GT	AB	PV	SHC	EC	AC	HE	HST	LELR	ECR_S	ECR_M
	kW	kW	m^2	m^2	kW	kW	kW	kW	%	%	%
D_{4-1}	16	167	0	0	82	82	123	110	0.00	0.00	0.00
D_{5-2}	21	159	19	19	64	100	123	151	0.00	0.35	1.01
D_{6-3}	21	156	58	58	72	92	123	157	3.75	23.54	21.46

Note: In each column of Tables 7, 10 and 11, the deeper the green is, the more effects it has while the deeper the red, the fewer effects.

5.2.2. Effect of a Single Uncertainty to System Planning

The previous section shows that the ability of case 6 in tackling multi-uncertainties is the worst among the uncertain cases, but it has the best performances in efficient, environmental, and economic factors when the system operates in FEL. Therefore, this part analyzes the effect of a single uncertainty of case 6 in relation to the system planning in FEL.

Table 8 depicts the optimal design while Table 9 shows the optimal operation and cost under the different single uncertainties of case 6. It can be seen from Table 8 that the case under the single uncertain natural gas price has the largest LELR (6.34%), while all the other single uncertainties make the lowest electric load ratio decline into around 2.00%.

Table 8. Optimal design under case 3 and the single uncertain cases.

Strategy: FEL		Case						
		3	**Un_GP**	**Un_EP**	**Un_Solar**	**Un_C**	**Un_H**	**Un_E**
GT	kW	1500	1499	1516	1499	1500	1502	1501
AB	kW	1475	1475	1474	1475	1483	1633	1474
PV	m2	1347	1346	1352	1325	1358	1379	1374
SHC	m2	130	132	125	152	120	98	103
EC	kW	269	269	268	266	334	273	276
AC	kW	444	445	446	447	544	441	437
HE	kW	1514	1514	1514	1514	1514	1637	1514
HST	kW	1786	1792	1807	1778	1821	1865	1825
ECR_S	%	37.74	37.67	37.50	37.29	38.06	38.22	38.70
ECR_M	%	60.38	60.31	60.40	59.69	60.46	61.09	61.10
LELR	%	5.75	6.34	0.00	1.96	1.94	1.78	2.12

Table 9. Operation and costs under case 3 and the single uncertain cases.

Strategy	Case	Gas	Electricity	CO_2 Emission	Operation	Investment
		kW	**kW**	**g**	**Dollar**	**Dollar**
FEL	3	10,806,665	98,873	2,473,175,048	226,734	133,732
	Un_GP	10,806,559	98,849	2,473,128,748	237,571	133,749
	Un_EP	10,837,186	89,363	2,470,684,094	227,592	134,374
	Un_Solar	10,811,792	97,942	2,473,401,674	226,744	141,699
	Un_C	10,800,111	102,746	2,475,482,955	226,987	136,974
	Un_H	10,808,245	98,475	2,473,137,795	226,726	135,394
	Un_E	10,773,825	113,526	2,480,134,837	227,531	133,942

To study the degree of effects of every single uncertainty on system planning, the color cascade tables are created, as shown in Tables 10 and 11, which are based on the absolute deviation between the single uncertain cases and the referenced case 3. On the whole, the tables show that the single uncertain heating demand has the largest effects on the optimal design but has the smallest effects on the operation and costs. In addition, the single uncertain natural gas price has the smallest effects on the optimal design, while the single uncertain electric demand has the biggest effects on the operation and costs.

To be specific, the single uncertain natural gas price has maximal influences only on the operation cost; the single uncertain grid electricity price has maximal influences on the capacity of GT and LELR; the single uncertain solar radiation has maximal influences only on the investment cost; the single uncertain cooling demand has maximal influences on the capacities of EC and AC; the single uncertain heating demand has maximal influences on the capacities of AB, PV, SHC, HE, and HST; and the uncertain electric demand has maximal influences on ECR_S, ECR_M, natural gas consumption, grid electricity consumption, and CO_2 emission.

Table 10. The absolute deviation of optimal design between the single uncertain cases and case 3.

Strategy: FEL	GT	AB	PV	SHC	EC	AC	HE	HST	ECR_S	ECR_M	ELR
Delta	kW	kW	m^2	m^2	kW	kW	kW	kW	%	%	%
$D_{GP\text{-}3}$	1	0	1	2	0	1	0	6	0.07	0.07	0.59
$D_{EP\text{-}3}$	16	1	5	5	1	2	0	14	0.24	0.02	5.75
$D_{Solar\text{-}3}$	1	0	22	22	3	3	0	8	0.45	0.69	3.79
$D_{C\text{-}3}$	0	8	11	11	65	100	0	35	0.32	0.08	3.8
$D_{H\text{-}3}$	2	157	32	32	3	3	123	79	0.48	0.71	3.97
$D_{E\text{-}3}$	1	1	27	27	7	7	0	39	0.96	0.72	3.62

Table 11. The absolute deviation of optimal operation and cost between the single uncertain cases and case 3.

Strategy: FEL	Gas	Electricity	CO_2 Emission	Operation	Investment
Delta	kW	kW	g	Dollar	Dollar
$D_{GP\text{-}3}$	107	24	46,299	10,837	16
$D_{EP\text{-}3}$	30,521	9510	2,490,953	858	642
$D_{Solar\text{-}3}$	5127	931	226,627	10	7967
$D_{C\text{-}3}$	6554	3874	2,307,908	254	3242
$D_{H\text{-}3}$	1580	397	37,253	8	1661
$D_{E\text{-}3}$	32,840	14,654	6,959,789	797	210

6. Conclusions

In this paper, the planning work of a hybrid CCHP system under uncertainty is implemented for a large hotel. In particular, the electric cooling ratios and the lowest electric load ratio are optimized in the proposed stochastic programming model, in which the uncertain demands (cooling, heating, and electric), the solar radiation, and the energy prices (natural gas and grid electricity) are addressed. All the above works aim to (1) obtain the optimal design for the CCHP system, including optimal capacities, operation parameters, and operation strategy; (2) investigate the ability of the system to adapt to uncertainty; and (3) study the effects of a single uncertainty on system planning. All the processes can be applied in the fields of energy system planning, and the main conclusions obtained are as follows:

- When the operation parameters, including the electric cooling ratios and the lowest electric load ratio, are optimized, the hybrid CCHP system performs best in both the deterministic and uncertain conditions.
- When multi-uncertainties are tackled, following the electric load is the best operation strategy for the system with optimized operation parameters in which the PES, CDER, TCS, and IP are 33.17%, 47.48%, 31.24%, and 37.30% respectively.
- The hybrid CCHP system has the best ability to adapt to uncertainty with the given electric cooling ratio (50.00%) and the lowest electric load ratio (20.00%).
- All the single uncertainties make electric cooling ratios fluctuate in varying degrees; meanwhile except for the uncertain natural gas price, the others make the lowest electric load ratio drop into around 2.00%.
- On the whole, the single uncertain natural gas price has minimal influences on the system optimal design while the single uncertain heating demand has the largest effects on the optimal design but has the smallest effects on system operation and costs.

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Abbreviations

ABC	Artificial bee colony algorithm
AC	Absorption chiller
ATCS	Annual total cost saving
CCHP	Combined cooling heating and power system
CDER	Carbon dioxide emission reduction
CHP	Combined heating and power system
D	Absolute delta
d	Design variable
DES	Distributed energy system
DET	Deterministic case
E	Electricity
EC	Electric chiller
ECR_M	Electric cooling ration in mid-seasons
ECR_S	Electric cooling ration in summer
LELR	Lowest electric load ratio
EP	Grid electricity price
F	Fuel
f	Part load ratio
FEL	Following the electric load
FHL	Following hybrid electric-thermal load
FHL	Following the thermal load
GB	Gas boiler
GP	Natural gas price
GT	Gas turbine
H	Heat
HE	Heat exchanger
HRS	Heat recovery system
HST	Heat storage tank
i	Number of employed bees
IP	Integrated performance
LELR	Lowest electric load ratio
N	Number of samples
o	The operation variable
PES	Primary energy saving
P V	Photovoltaic
SAA	Sample average approximation
SES	Separated energy system
SHC	Solar heat collector
SP	Stochastic programming
UN	Uncertain case
Greek symbols	
η	The efficiency
λ	Electric cooling ratio
ω	The weight
ψ	Inequality constraints
ε	Stopping criterion
φ	Equality constraints
ξ	Uncertainty sample

Subscripts

in	Input energy
out	Output energy

Appendix A

This part includes the technical and economic parameters in Appendix A.1, the logic of the three operation strategies in Appendix A.2, the specific formulation of system performances in Appendix A.3, the probability distribution of uncertainty in Appendix A.4, and the parameters of the ABC algorithm of cases 1–6 in Appendix A.5.

Appendix A.1 Technical and Economic Parameters

Table A1. CO_2 emission factor.

	Natural Gas	Grid Electricity	Source
Value (g/kWh)	220	968	[33]

Table A2. Efficiency and unit price of the facilities in the hybrid CCHP system.

Facility	GT	HE	GB	AC	EC	PV	SHC	HST	
								Charging	Discharging
Efficiency	0.3 [1]	0.8	0.8	0.7	3	0.1444 [2]	0.615	0.9	0.9
Source	[34]					[35]		[36]	
Unit price (Yuan/kW) [3]	6800	200	300	1200	970	14,575	4006	230	
Source	[34]					[36]		[37]	

[1] $\eta_{GT} = 0.1283 \cdot f_{GT}^3 - 0.6592 \cdot f_{GT}^2 + 0.7945 \cdot f_{GT} + 0.003$ [38]; $\eta_{GT} = 0.3$ is the efficiency of GT at full load; f_{GT} is the part load factor of GT. [2] $\eta_{PV} = -0.0237 \cdot f_{PV} + 0.1681 \cdot f_{PV}^{0.1078}$ [35]; $\eta_{PV} = 0.1444$ is the efficiency of PV at full load; f_{PV} is the part load factor of PV. [3] 7.0249 Yuan = 1 U.S. dollar.

Appendix A.2 The Logic of the Three Operation Strategies

(1) FTL

if H_demand ≥ H_GT_max + H_SHC + H_HST
the unmet heat demand is covered by gas heater,
the unmet electric demand is covered by grid.
else if H_SHC + H_HST ≤ H_demand < H_GT_max + H_SHC + H_HST
if ELR_GT ≥ LELR
the unmet electric demand is covered by grid.
else
the unmet heat demand is covered by gas heater,
the unmet electric demand is covered by grid.
else if H_SHC ≤ H_demand < H_SHC + H_HST
the unmet electric demand is covered by grid.
else
the unmet electric demand is covered by grid.
end

(2) FEL

if E_demand ≥ E_GT_max + E_PV
the unmet electric demand is covered by grid
the unmet heating demand is covered by gas heater
else if E_PV ≤ E_demand < E_GT_max + E_PV
if ELR_GT ≥ LELR
the unmet heating demand is covered by gas heater.
else
the unmet electric demand is covered by grid
the unmet heating demand is covered by gas heater
else
the unmet electric demand is covered by grid
the unmet heating demand is covered bygas heater
end

(3) FHL

if heat − to − electric ratio of GT is at area B
GT operates in FEL
else
GT operates in FTL
end

Appendix A.3 System Performance

The specific formulation of each performance is shown as follows:

(1) Annual total cost saving (ATCS, f_1)

$$f_1 = \frac{ATC_{SES} - ATC_{CCHP}}{ATC_{SES}},$$

where ATC_{SES} and ATC_{CCHP} are the annual total cost of the separated energy system and the CCHP systems, respectively. Moreover, the annual total cost of CCHP is composed of facility investment (f_{11}) and operation cost (f_{12}), therefore:

$$f_1 = 1 - \frac{f_{11} + f_{12}}{ATC_{SES}} = 1 - \frac{f_{11}}{ATC_{SES}} - \frac{f_{12}}{ATC_{SES}},$$

denotes $-\frac{1}{ATC_{SES}}$ as C, then:

$$f_1 = C \cdot f_{11} + C \cdot f_{12}.$$

(2) Primary energy saving (PES, f_2)

$$f_3 = \frac{F^{SES} - F^{CCHP}}{F^{SES}},$$

where F_{SES} and F_{CCHP} are the energy consumption of the separated energy system and the CCHP systems, respectively.

(3) Carbon dioxide emission reduction (CDER, f_3)

$$f_3 = \frac{CDE_{SES} - CDE_{CCHP}}{CDE_{SES}},$$

where CED_{SES} and CDE_{CCHP} are CO_2 emission from the separated energy system and the CCHP systems, respectively.

Appendix A.4 Probability Distribution of Uncertainty

Table A3. The probability distribution of demand.

Demands	Time	Distribution	σ	Source
Cooling Heating Electric	00:00–23:00	$N(\mu, \sigma^2)$	10.2%μ	[39–41]

Table A4. The probability distribution of solar radiation.

Month	Time	Distribution	σ	Source
November–April	9:00–15:00 16:00–8:00	$N(\mu, \sigma^2)$	12%μ 25%μ	[19,41,42]
May–October	9:00–15:00 16:00–8:00		3%μ 8%μ	

Table A5. The probability distribution of natural gas and electricity prices.

Price	Distribution	Parameters			Source
		Min	Middle	Max	
Natural gas	Triangular	0.833 × Price	1.083 × Price	1.167 × Price	[19,33]
Electricity	Uniform	0.882 × Price	-	1.225 × Price	

Appendix A.5 Parameters in the ABC Algorithm

Table A6. Parameters of the ABC algorithm.

<table>
<tr><th>Variables</th><th>Value</th><th colspan="3">Case</th></tr>
<tr><td>Colony</td><td>100</td><td rowspan="6">1&4</td><td rowspan="8">2&5</td><td rowspan="9">3&6</td></tr>
<tr><td>Food source</td><td>50</td></tr>
<tr><td>Max cycle</td><td>200</td></tr>
<tr><td>GT</td><td>[0,2000] kW</td></tr>
<tr><td>PV area</td><td>[0,1477] m^2</td></tr>
<tr><td>HST</td><td>[0,3000] kW</td></tr>
<tr><td>ECR_S</td><td>[0,1]</td><td></td></tr>
<tr><td>ECR_M</td><td>[0,1]</td><td></td></tr>
<tr><td>LELR</td><td>[0,1]</td><td></td><td></td></tr>
</table>

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