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Optimal Operation of Tri-Generation Microgrids Considering Demand Uncertainties

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Abstract

Tri-generation microgrids, also known as combined cooling, heat and power (CCHP) microgrids, have the potential to suffice the collective thermal and electrical demands of the microgrid residents. However, the energy demand of microgrids cannot be accurately predicted. Therefore, in this paper, robust optimization-based modeling for optimal operation of tri-generation microgrids is proposed. Uncertainty in cooling, heat, and power demands and worst-case realizations of uncertainties are considered. Initially, a deterministic problem is formulated which is then transformed into a min-max robust counterpart. Finally, a tractable robust counterpart is formulated by using the dual of the inner sub-problem. The formulated model is capable of providing feasible solutions for all possible realizations of uncertainties in energy demands (within the uncertainty bounds). The final tractable robust counterpart is simulated in CPLEX and various uncertainty cases are simulated. Simulation results have proved the robustness and effectiveness of the proposed optimization strategy.

Keywords*: CCHP microgrids, demand uncertainty, microgrid operation, optimal operation, tri-generation microgrid, robust optimization*

1. Introduction

Microgrids (MGs) are expected to play a vital role in the transformation of the conventional passive distribution system to an active distribution network [1]. MGs have the potential to offer several benefits to both the utilities and the customers, which includes economic, technical, and environmental benefits. In this regard, combined heat and power (CHP) units are one of the most beneficial technologies. Waste heat is used to fulfill the heat load demands of the consumers and thus enhances the overall system efficiency. Tri-generation, also known as combined cooling, heat and power (CCHP), technologies are becoming more desirable and are even more economical due to their ability to suffice cooling, heat, and power demands [2]. The efficiency of tri-generation systems is up to 60-80%, which is considerably higher than those of conventional power systems. Penetration of distributed generators and demand response programs is increasing for achieving the fore-mentioned benefits from MGs. This enhanced penetration has imposed new challenges to the scheduling of microgrids [3]. Due to the significance of uncertainties associated with the energy demands of tri-generation microgrids, several researches have been conducted in the recent years.

Centralized energy management system (EMS) has been used for scheduling of tri-generation microgrids by [4]. Dynamic optimization and model predictive control have been for scheduling in day-ahead and real-time scheduling horizons. A method for optimizing all the three types of energies (electricity, heat, and cooling) and their usage in

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urban areas has been proposed by [5]. The developed optimization strategy has been tested in a southern Italian city. The authors in [6], have proposed a two-stage optimal planning algorithm for tri-generation microgrids. The objective of the formulation is to minimize both carbon emissions and life cycle operation cost of the microgrid. A review has been carried out by [7] on planning, scheduling, and control of CCHP systems. Due to the dependence of CCHP microgrid performance on design and energy management strategies of microgrids, those aspects have been focused by the authors. A study has been conducted in [8] for analyzing the impacts of wastes to energy conversion for CCHP applications. Both energy level and exergy analysis have been conducted to reveal the variation, quality, and quantity of energy in the operation of CCHPs. The authors in [9, 10] have evaluated the economic impacts of converting conventional power stations to CCHPs.

Various researches have been conducted for managing the uncertainties associated with load demands and renewable energy sources in microgrids. Sensitivity analysis has been used by authors in [11] for managing uncertainties in microgrids. Fuzzy logic-based optimization has been carried out by authors in [12]. A review of stochastic optimization techniques used for uncertainty management of microgrids has been carried out in [13]. Robust optimization has been used by authors of [14-15] for managing uncertainties associated with microgrids. Among the above-mentioned uncertainty management techniques, robust optimization and stochastic optimization have gained popularity among the microgrids energy management community. Robust optimization has the ability to provide immunity against the worst-case realization of uncertainty, in contrast to probabilistic immunity provided by stochastic optimization techniques. Detailed merits of robust optimization and demerits of stochastic optimization can be found in [14].

The models used for energy management of tri-generation microgrids, available in the literature, are either deterministic or are based on stochastic optimization. Similarly, most of the researches available in the literature on uncertainty management are focused on electrical energy management only. Consideration of uncertainties in demand of heat and cooling energies is equally important. Due to the coupling of these energies (cooling, heat, and electricity), uncertainty management of CCHP systems is more challenging and more desirable. Additionally, due to the complexity of stochastic optimization techniques and probabilistic guarantee of feasible solutions, these techniques are less attractive. Therefore, an attempt has been made in this paper to schedule the resources of microgrids considering uncertainties in CCHP demands using robust optimization.

In this paper, robust optimization-based modeling of CCHP microgrids has been carried out. Initially, a deterministic problem has been formulated which is based on mixed integer linear programming (MILP). Then a robust counterpart of the initial deterministic problem is formulated. The robust counterpart is a min-max problem and is non-linear. Therefore, dual of the inner sub-problem has been determined. Finally, a trackable robust optimization problem has been formulated. The final problem is mixed integer linear programming and has been implemented in CPLEX. Different uncertainty cases have been simulated to evaluate the feasibility of the proposed method. Uncertainty in electrical load only, uncertainty in heat load only, uncertainty in cooling load only, and uncertainty in all the three types of loads have been considered in the simulations.

2. Tri-Generation Microgrids and Demand Uncertainties

A typical tri-generation microgrid model is shown in Figure 1. Figure 1(a) shows the electricity, heating, and cooling networks, which are collectively termed as a physical network, of the tri-generation microgrid. It can be observed from Figure 1(a) that electricity demand of the microgrid can be fulfilled by using CHPs, renewable energy sources (DGs), utility grid, and battery energy storage system (BESS). Similarly, the excess of power can be traded with the utility grid or can be stored in the BESS. Heat

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energy demand of the microgrid can be fulfilled by using CHPs, heat only boilers (HOBs), and thermal energy storage system (TESS). Excess of heat will be wasted only when TESS is fully charged. The cooling demand of the microgrid can be fulfilled by using adsorption chillers (ACHs) or electric heat pumps (EHPs). The information/command flow of the tri-generation microgrid model, which is named as a cyber network, is shown in Figure 1(b). EMS will receive information from all components of the microgrid and time-of-use (TOU) price signals from the utility grid. After optimization, EMS will inform each component of the microgrid about its schedule.

The deterministic modeling of CHP/CCHP systems is straightforward. Detailed modeling of CHP systems can be found in [16]. However, the energy demand (cooling, heat, and electricity) of CCHP systems is uncertain in nature and it is difficult to accurately predict the energy demand. The uncertainty management becomes more challenging for CCHP systems due to mutual coupling of different energies (cooling, heat, and electricity). Therefore, due to merits of robust optimization, as stated in the previous section, robust optimization-based modeling of CCHP systems is carried out in this study. Detailed modeling is shown in the following section.

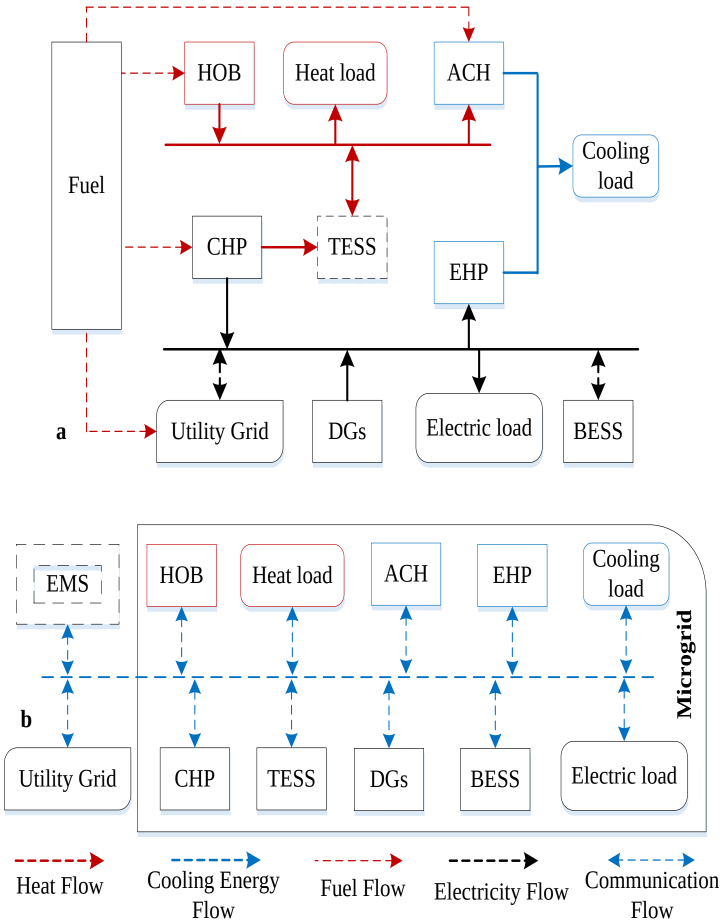

Figure 1. (a) Physical Network of Tri-Generation Microgrid System, (b) Cyber Network of Tri-Generation Microgrid System

3. Problem Formulation

The first step in the RO-based optimization is to formulate a deterministic model [14]. Then, the deterministic model is transformed to a min-max robust counterpart by using

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the uncertainty bounds. Finally, the robust counterpart is transformed to a tractable robust counterpart, which can be implemented by using commercial software like CPLEX.

3.1. Deterministic Model

3.1.1. Objective Function: The objective of the formulated model is to minimize the operation cost of CHP units (C_c^{CHP}), HOB units (C_h^{HOB}), and ACH units (C_a^{ACH}). In addition, the objective of the model is to maximize the profit for microgrid by trading electricity with the utility grid ($PR^{Buy}(t) \cdot P^{Buy}(t) - PR^{Sell}(t) \cdot P^{Sell}(t)$). The objective function of the formulated model is given by Equation (1).

$$min \sum_{t=1}^{T}\sum_{c=1}^{C}(C_c^{CHP} \cdot P_c^{CHP}(t)) + \sum_{t=1}^{T}\sum_{h=1}^{H}(C_h^{HOB} \cdot H_h^{HOB}(t)) + \sum_{t=1}^{T}\sum_{a=1}^{A}(C_a^{ACH} \cdot CO_a^{ACH}(t)) + \sum_{t}^{T}\left(PR^{Buy}(t) \cdot P^{Buy}(t) - PR^{Sell}(t) \cdot P^{Sell}(t)\right) \quad (1)$$

3.1.2. Energy Balancing: The electrical load demand ($P^{Load}(t)$) of microgrid can be fulfilled by using DGs, CHPs, trading with the utility grid, and charging/discharging ($P^{Dis}(t) - P^{Cha}(t)$) of BESS. BESS is taken as a load during charging phase the and as a source during discharging phase. EHP uses electricity as an input; therefore, it is taken as a load. Equation (2) shows the electrical energy balancing of the microgrid and Equation (3) shows the heat energy balancing of microgrid. Heat load demand ($H^{Load}(t)$) can be fulfilled by using HOBs, CHPs, and TESS ($H^{Dis}(t) - H^{Cha}(t)$). ACH uses heat energy as an input; therefore, it is taken as a load for heat energy balancing. The cooling load demand ($CO^{Load}(t)$) of the microgrid can be fulfilled by using EHPs ($CO_e^{EHP}(t)$) or ACHs ($CO_a^{ACH}(t)$), as given by Equation (4).

$$P^{Load}(t) = \sum_{d}^{D} P_d^{DG}(t) + \sum_{c}^{C} P_c^{CHP}(t) + P^{Buy}(t) - P^{Sell}(t) - P^{Cha}(t) + P^{Dis}(t) - \sum_{e}^{E} P_e^{EHP}(t) \quad (2)$$

$$H^{Load}(t) \le \sum_{h}^{H} H_h^{HOB}(t) + \sum_{c}^{C} H_c^{CHP}(t) - H^{Cha}(t) + H^{Dis}(t) - \sum_{a}^{A} H_a^{ACH}(t) \quad (3)$$

$$CO^{Load}(t) = \sum_{e}^{E} CO_e^{EHP}(t) + \sum_{a}^{A} CO_a^{ACH}(t) \quad (4)$$

$$H_c^{CHP}(t) = P_c^{CHP}(t).\ \eta_c \quad (5)$$

$$CO_a^{ACH}(t) = H_a^{ACH}(t).\ \eta_a \quad (6)$$

$$CO_e^{EHP}(t) = P_e^{EHP}(t).\ \eta_e \quad (7)$$

The electricity to heat conversion efficiency of a c–type CHP unit is given by (5), with an efficiency of η_c. The energy efficiency ratings of an a-type ACH unit (η_a) and an e-type EHP unit (η_e) are given by Equations (7) and (8), respectively.

3.1.3. BESS Modeling: The amount of energy, which can be charged at any time t ($P^{Cha}(t)$) can be determined by using Equation (8) and discharging by (9). The status-of-charge (SOC) of BESS at time t ($P^{SOC}(t)$) can be determined by using Equation (10). Finally, the bounds of BESS SOC are given by Equation (11). η_{Cha} and η_{Dis} are the charging and discharging losses of BESS.

$$0 \le P^{Cha}(t) \le \frac{P_{max}^{BESS} - P_{Cap}^{BESS}.P^{SOC}(t-1)}{\eta_{Cha}} \quad (8)$$

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$$0 \leq P^{Dis}(t) \leq \left(P_{Cap}^{BESS}.P^{SOC}(t-1) - P_{min}^{BESS}\right).\ \eta_{Dis} \tag{9}$$

$$P_{Cap}^{BESS}.P^{SOC}(t) = P_{Cap}^{BESS}.P^{SOC}(t-1) + P^{Cha}(t).\ \eta_{Cha} - \frac{P^{Dis}(t)}{\eta_{Dis}} \tag{10}$$

$$P_{min}^{BESS} \leq P_{Cap}^{BESS}.P^{SOC}(t) \leq P_{max}^{BESS} \tag{11}$$

3.1.4. TESS Modeling: The TESS model of the thermal storage tank is given by Equations (12)-(15) as developed in [16]. The TESS charging ($H^{Cha}(t)$) bounds are given by (12) and discharging ($H^{Dis}(t)$) bounds by (13). The SOC ($H^{SOC}(t)$) of TESS can be updated by using (14) and SOC bounds are given by (15). $H^{Loss}(t)$ is the thermal loss of the heat energy and it depends upon the time and type of material of tank.

$$H^{Cha}(t) \leq H_{max}^{TESS} - H_{Cap}^{TESS}.H^{SOC}(t-1) - H^{Dis}(t) \tag{12}$$

$$H^{Dis}(t) \leq H_{Cap}^{TESS}.H^{SOC}(t-1) + H^{Cha}(t) - H_{min}^{TESS} \tag{13}$$

$$H_{Cap}^{TESS}.H^{SOC}(t) = H_{Cap}^{TESS}.H^{SOC}(t-1) + H^{Cha}(t) - H^{Dis}(t) - H^{Loss}(t) \tag{14}$$

$$H_{min}^{TESS} \leq H_{Cap}^{TESS}.H^{SOC}(t) \leq H_{max}^{TESS} \tag{15}$$

3.2. Robust Counterpart

The second step is to formulate a robust counterpart of the deterministic problem. A general problem is considered for explaining the transformation process of RO, similar to [17]. Consider a deterministic linear problem (16)-(18). Matrix b is taken as the generation set for a given type of energy (cooling, heat, and electricity) and A is the energy demand. Uncertainty in A (demand) is considered in this study. In RO, upper and lower bounds of uncertainty are considered and scaled deviation (η_{ij}) is defined for each energy type. The upper and lower bounds can be determined by using methods suggested by [18].

$$min\, f(x) = cx \tag{16}$$

$$g(x) = Ax \leq b \tag{17}$$

$$l \leq x \leq u \tag{18}$$

The objective of RO is to provide a feasible solution for all possible realizations of uncertainties within the specified bounds. For a worst-case analysis, following problem is considered, Equations (19)-(21).

$$min\, cx \tag{19}$$

$$\sum_{j=1}^{n} a_{ij}x_j + max \sum_{j \in J_i} \hat{a}_{ij}\eta_{ij}x_j \leq b_j \tag{20}$$

$$l \leq x \leq u \tag{21}$$

It can be observed from Equation (20) that there is a *max* inside the energy balancing equation. It is known as sub-problem and next step is to determine the dual of the sub-problem. The sub-problem is given by Equations (22) and (23). Where, $\hat{a}_{ij}$ is the upper bound for ij[th] element of matrix A and Γ_i is the budget of uncertainty for i[th] element.

$$max \sum_{j \in J_i} \hat{a}_{ij}\eta_{ij}|x_j| \tag{22}$$

$$\sum_{j\in J_i}\eta_{ij} \leq \Gamma_i\,, \qquad 0 \leq \eta_{ij} \leq 1 \tag{23}$$

The dual of sub-problem shown above can be formulated as (24)-(26). z_i and p_{ij} are the dual variables of the sub-problem. In the same way, sub-problems can be determined for each energy type and corresponding duals can be formulated.

$$min\, z_i\Gamma_i + \sum_{j\in J_i} p_{ij} \tag{24}$$

$$z_i + p_{ij} \geq \hat{a}_{ij}y_j,\ |x_j| \leq y_j \tag{25}$$

$$z_i, p_{ij}, y_j \geq 0 \tag{26}$$

3.3. Tractable Robust Counterpart

The final step is to formulate a tractable robust counterpart using the dual of sub-problem developed in the previous section. The max portion of original robust problem ($max \sum_{j\in J_i} \hat{a}_{ij}\eta_{ij}x_j \leq b_j$) can be replaced by the dual of sub-problem. In this way, a final tractable solution can be obtained as given by Equation (27). The constraints for the final tractable robust counterpart are given by Equations (28)-(30).

$$min\, cx \tag{27}$$

$$\sum_{j=1}^{n} a_{ij}x_j + z_i\Gamma_i + \sum_{j\in J_i} p_{ij} \leq b_i \tag{28}$$

$$l_j \leq x_j \leq u_j,\ z_i + p_{ij} \geq \hat{a}_{ij}y_j \tag{29}$$

$$|x_j| \leq y_j,\ z_i, p_{ij}, y_j \geq 0 \tag{30}$$

4. Numerical Simulations

The microgrid model simulated in this study is similar to that of Figure (1). The analysis has been conducted for a 24-h scheduling horizon with a time interval of 1 hour. The uncertainty bounds for cooling, heat, and electrical energy demands are ±10%, ±15%, and ±20%, respectively. CPLEX has been used as an optimization tool and simulations have been carried out in Java environment.

4.1. Input Data

The hourly electrical, heat, and cooling demand of the microgrid along with TOU market price signals are tabulated in Table 1. The output of renewable generators is also taken as input and is also tabulated in Table 1. Table 2 shows the generation limits of tri-generation equipment along with their respective efficiencies and generation costs.

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Table 1. Hourly Energy Demand and Market Price Signals

Time Interval	Electrical Load	Heat Load	Cooling Load	Renewable Generation	Buying Price	Selling Price
1	359	219	50	20	80	70
2	367	260	60	23	80	70
3	389	289	89	28	80	70
4	337	239	37	32	80	70
5	367	307	67	39	80	70
6	353	333	103	50	80	70
7	398	388	108	55	100	80
8	427	397	117	60	100	80
9	469	369	129	69	100	80
10	498	388	138	68	100	80
11	513	313	143	70	100	80
12	568	360	168	75	130	100
13	597	297	197	80	130	100
14	512	212	212	80	130	100
15	519	219	219	74	130	100
16	507	247	227	73	130	100
17	468	268	268	61	130	100
18	435	285	235	50	130	100
19	412	312	212	31	100	80
20	498	348	198	35	100	80
21	447	347	147	28	100	80
22	439	389	139	33	100	80
23	327	327	127	20	80	70
24	308	308	47	18	80	70

Table 2. Parameters Related to Tri-Generation Equipment of Microgrid

	TESS	BESS	CHP	HOB	ACH	EHP
Max. (kW)	250	100	450	200	200	200
Min. (kW)	0	0	0	0	0	0
Efficiency (%)	98	η_{Chr} 98, η_{Dis} 98	η_c 75	η_b 100	η_a 85	η_e 125
Cost (Won)	-	-	98	67	25	-

4.2. Case 1: Uncertainty in Electrical Demand Only

In this case, nominal values of heat and cooling demand are considered while worst-case uncertainty for electrical demand is considered. In order to visualize the effect of uncertainty, both nominal (normal) and worst-case realization results of electrical demand are shown in Figures 2 and 3. It can be observed from Figure 2(a) that generation of CHP has been increased in time intervals 1-4. Figure 2(b) shows that more electricity has been bought from the utility grid to fulfill the uncertainty gap. Similarly, the amount of electricity sold to the utility grid has reduced in the peak price intervals. Due to the inconsideration of uncertainties in heating and cooling load demands, the change in commitment status of heating and cooling equipment is not prominent. However, due to the coupling of electrical and thermal energy, the commitment status of thermal equipment is also changed in some time intervals. During time interval 18 (Figure 2(c)), the output of HOB has been increased to increase the output of ACH. This will result in reduction of EHP output as shown in Figure 3. SOC of BESS and TESS is shown in Figure 2(d).

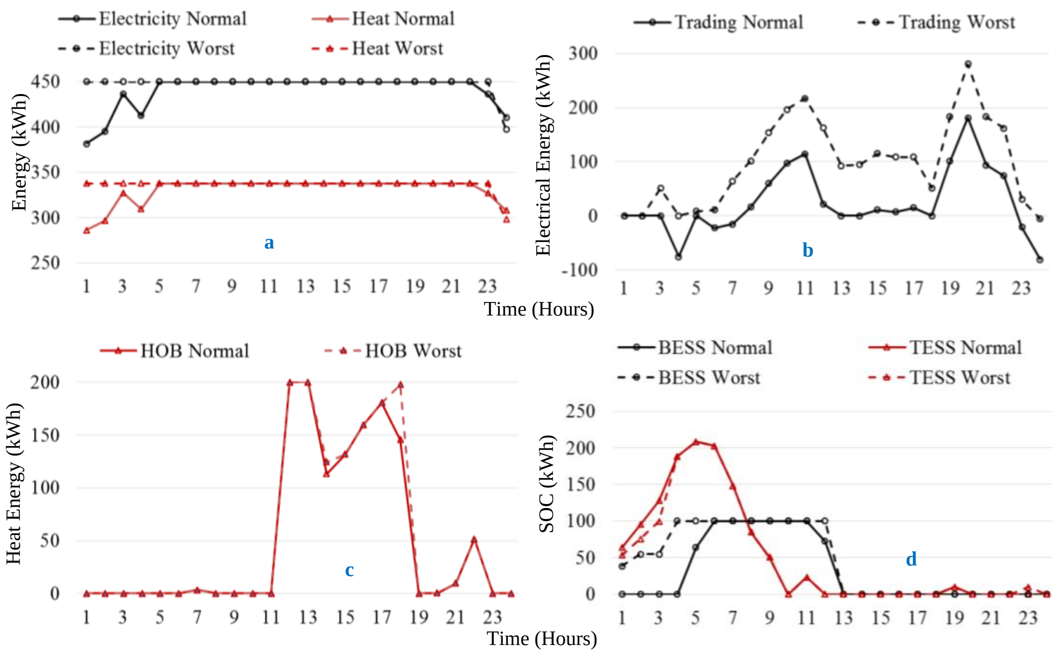

Figure 2. Commitment Staus of Tri-Generation Equipment in Case 1: (a) CHP; (b) Trading Amount; (c) HOB; (d) SOC of BESS and TESS

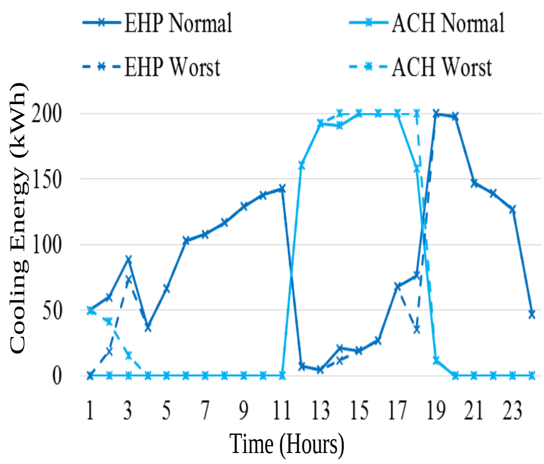

Figure 3. Commitment Staus EHP and ACH in Case 1

4.3. Case 2: Uncertainty in Heat Demand Only

In this case, nominal values of electrical and cooling energy demands are considered with uncertain heat load demand. Similar to the previous case, two cases (normal and

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worst) are considered in this case also. It can be observed from Figure 4(a) that generation of CHP has been increased to its fullest throughout the day to fulfill the thermal load demand. After fully operating the CHP, HOB output has also been increased in time intervals 7-11 and 13-24 as shown in Figure 3(c). Trading of electricity with the utility grid has not been drastically changed due to nominal values of electrical load demand for this case. However, during the time intervals 4, 6, 7, 23, and 24 power selling to utility has been reduced (Figure 4(b)) and electricity has been used to operate EHP. In order to fulfill the heat uncertainty gap, the output of ACH has been reduced during time intervals 12, 13, and 17 as shown in Figure 5. Due to unavailability of extra heat, TESS has not been fully used in this case as shown in Figure 3(d). BESS has been charged in the off-peak price intervals and discharged in the peak intervals to maximize the profit of microgrid as shown in Figure 3(d).

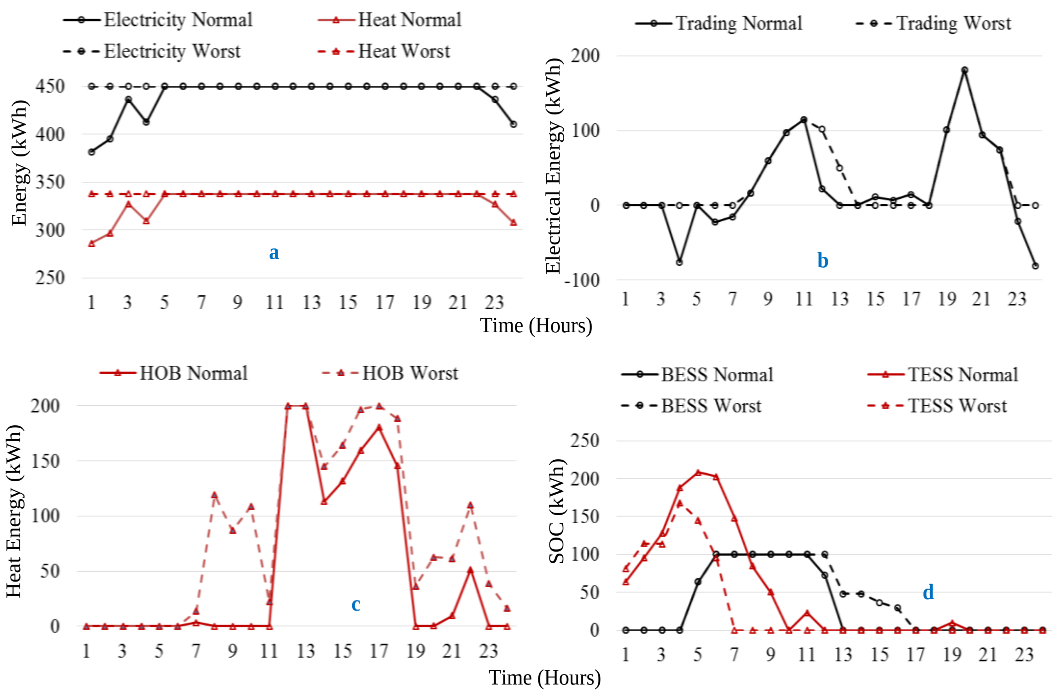

Figure 4. Commitment Staus of Tri-Generation Equipment in Case 2: (a) CHP; (b) Trading Amount; (c) HOB; (d) SOC of BESS and TESS

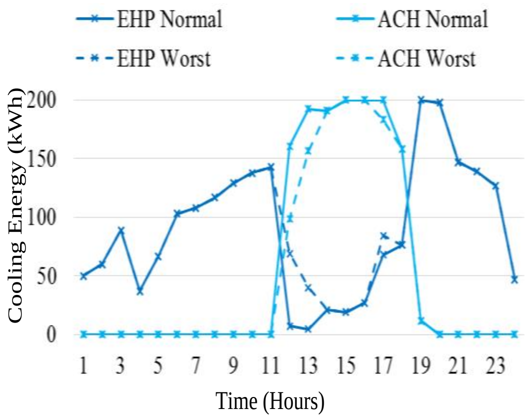

Figure 5. Commitment Staus EHP and ACH in Case 2

4.4. Case 3: Uncertainty in Cooling Demand Only

In this case, uncertainty in cooling energy demand is considered while electrical and heat loads are having nominal values. It can be observed from Figures 6 and 7 that the effect of cooling load uncertainty is lesser prominent as compared to previous two cases. It is due to the narrower uncertainty bound (±10%) for cooling uncertainty demand, which was ±15% and ±20% for heating and electricity demands. Figure 6(a) shows a minute change in the CHP output before and after considering the uncertainty in cooling demand. Similarly, trading with the utility grid has also changed slightly as depicted in Figure 6(b). During time intervals 18 and 20, the output of HOB has been increased (Figure b(c)) to operate ACH in order to fulfill the cooling demand uncertainty. During off-peak price intervals, the output of EHP has been increased and during peak price intervals, the output of ACH has been increased to fulfill the cooling load demand as depicted in Figure 7. The SOC of BESS and TESS showed a minute change in this case as depicted in Figure 6(d).

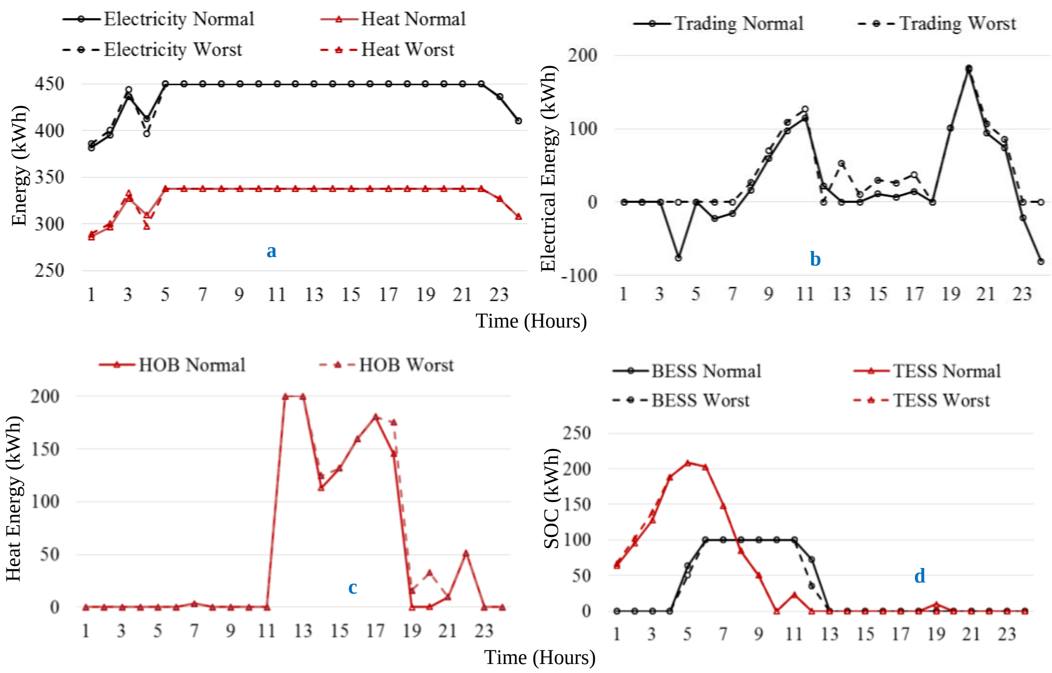

Figure 6. Commitment Staus of Tri-Generation Equipment in Case 3: (a) CHP; (b) Trading Amount; (c) HOB; (d) SOC of BESS and TESS

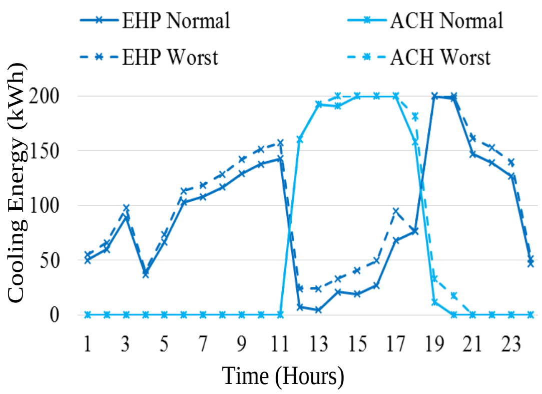

Figure 7. Commitment Staus EHP and ACH in Case 3

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4.5. Case 4: Uncertainty in all CCHP Demands

In the final case, uncertainty in all the three types of energy demands is considered. This is the worst possible case in the given framework of the simulated microgrid model. Due to the collective uncertainty in energy demands, the difference between the nominal case and the worst-case is more prominent as compared to the previous three cases. It can be observed from Figures 8(a) that CHP has been operated to its fullest throughout the day similar to Case 2. The difference in trading of electricity with the utility grid in this case is similar to that of Case 1. It can be observed from Figures 2(b) and 8(b). The change in commitment status of HOB, as depicted in Figure 8(c), is similar to that of Case 2, Figure 4(c). Similarly, the commitment status of ACH and EHP in this case is similar to that of Case 3. It can be verified from Figures 9 and 7. The SOC trend of BESS in this case is similar to that of Case 1 and TESS is similar to that of Case 2.

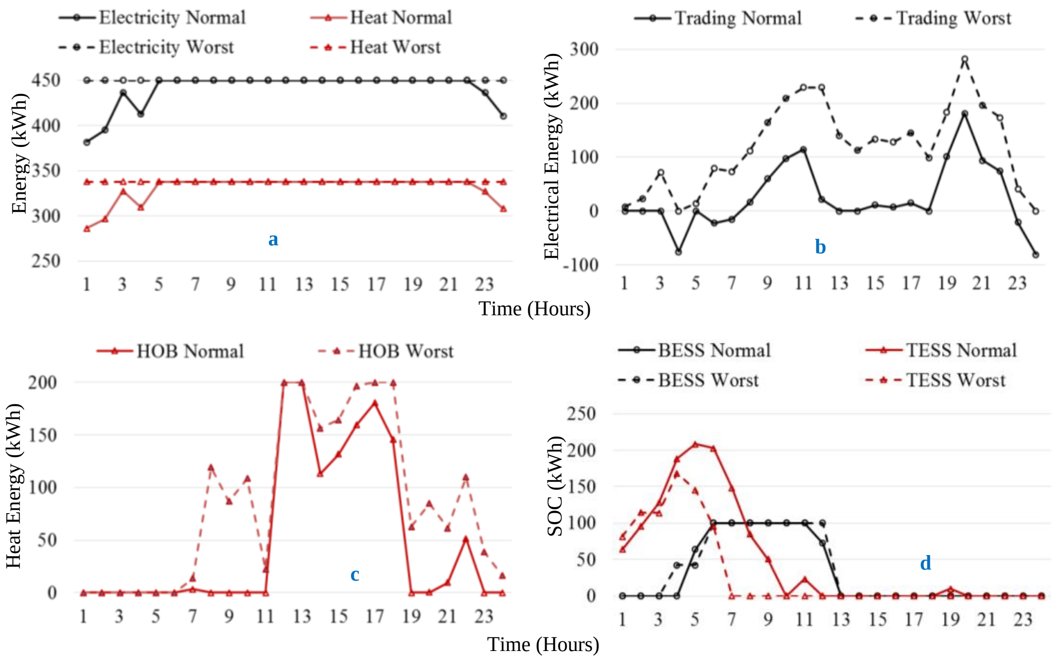

Figure 8. Commitment Staus of Tri-Generation Equipment in Case 4: (a) CHP; (b) Trading Amount; (c) HOB; (d) SOC of BESS and TESS

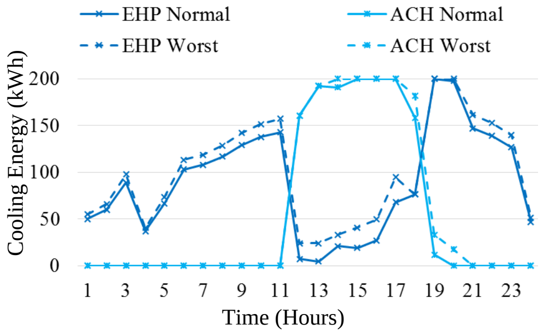

Figure 9. Commitment Staus EHP and ACH in Case 4

5. Conclusion

An RO-based energy management strategy for tri-generation microgrids is proposed in this paper. Given the uncertainty bounds, the proposed strategy is capable of providing feasible solutions for all possible realizations of uncertainties. The conservativeness of the solution can be controlled by deciding an acceptable value of budget of uncertainty. A tradeoff between the conservativeness of the solution and probability of feasible solution is required to assure an economic operation. Various uncertainty cases have been simulated in this study. It has been observed from simulation results that uncertainty in electrical demand influences the commitment status of heating and cooling equipment. Similarly, the influence of uncertainties in heating and cooling demands is also not limited to their respective sources' commitment status. The mutual coupling among the three energy demands in CCHP systems can be observed from the simulation results.

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