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http://penerbit.uthm.edu.my/ojs/index.php/ijie ISSN : 2229-838X e-ISSN : 2600-7916 The International Journal of Integrated Engineering

# **Scheduling of Multiple Energy Consumption in The Smart Buildings with Peak Demand Management**

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DOI: https://doi.org/10.30880/ijie.2023.15.04.027 Received 29 July 2023; Accepted 4 September 2023; Available online 28 August 2023

Abstract: The global energy crisis and the depletion of fossil fuels have become pressing concerns, leading experts to search for alternative solutions. This paper presents an analysis of the day-ahead operation of the multi-carrier energy system (MCES) with the aim of minimizing operational costs, reducing pollution emissions, and maximizing consumers' comfort. The authors propose an optimal scheduling strategy called energy demand curtailment (EDCS), which aims at efficiently managing electrical energy consumption. Additionally, they consider an on-site generation strategy (OGS) for consumers to operate their own energy storages. Both EDCS and OGS are modeled based on demand-side management (DSM). To optimize these strategies and achieve their objectives, fuzzy logic is employed as an optimization approach along with objective functions. Finally, two scenarios are examined through numerical simulations to illustrate the effectiveness of this approach in optimizing energy utilization in MCE.

Keywords: Day-ahead operation, multi-carrier energy system (MCES), optimal scheduling strategy, fuzzy logic, demand-side management (DSM)

# 1. Introduction

# **1.1 Motivation and Context**

In recent years, the most noteworthy advancements in energy generation involve the creation of energy hub (EH) systems that possess multiple capabilities and objectives to satisfy the demand for energy through various forms of

energy carriers, concurrently [1]. These EH systems consist of a range of energy resources or multi-carrier energies such as gas, electricity, and thermal power in order to fulfill different requirements within a specific region. However, employing an energy hub with diverse sources presents several challenges relating to economic feasibility and environmental impact on existing energy systems [2].

Nomenclature			
t, T	Time index	Hour	
bo, BO	Boiler index	_	
b, B	Battery index	-	
chp,CHP	CHP index	-	
$\alpha, \beta, \lambda$	Cost factors of other fuels for feed DGs	\$/kW	
δ,γ,ζ	Cost factors of other fuels for feed CHP units for heat generation	\$/kW	
σ, <i>κ</i> , <i>ν</i>	Emission factors of DGs and EC	g/kW	
$P_{bat}$ , $P_{EC}$	Power of battery and Electrical generation from EC	kW	
$arOmega_{EC}$	Electrical price in EC	\$/kW	
$arOmega_{GP}$	Gas price in NGC	\$/m <sup>3</sup>	
$P_{GAS}$ , $D_{GAS}$	Gas generation from NGC and Gas demand	m <sup>3</sup>	
$D_E$ , $D_H$	Electrical and Heat demands	kW	
$D_{EDCS}$	Value of energy demand curtailment strategy (EDCS)	kW	
$P_{CHP}$	Electrical generation by CHP	kW	
$H_{CHP}$	Heat generation by CHP	kW	
$H_{BO}$	Heat generation by boiler	kW	
$C_{EC}, C_{NGC}$	EC and NGC operation cost	\$	
$C_{EDCS}, C_{CHP}, C_{BO}$	Operation cost of EDCS, CHP and boiler	\$	
$E_{CHP}, E_{BO}, E_{EC}$	Emission generation by CHP, boiler and EC	kg	
$\eta_{dis}$ ,	Battery's Efficiency in discharge mode	%	
$\eta_{ch}$	Battery's Efficiency in charge mode	%	
$\mu_{dis}$ , $\mu_{ch}$	Binary variables of battery in discharge and charge modes	-	

Within such intricate energy systems, characterized by technical issues like economic constraints and environmental consequences, numerous loads have the potential to actively participate in optimizing the distribution of available energy. By incorporating demand-side management (DSM) strategies during operation periods, these loads can effectively bridge any gaps between supply and demand [3]. DSM represents a novel approach embraced by smart grids which focus on monitoring consumers' activities related to their consumption patterns [4]. This strategy is capable of effectively managing variations in the overall magnitude of energy demands. The utilization of DSM in EH can be referred to as "smart EH". Within this smart EH, all resources and loads are outfitted with real-time information systems and sophisticated sensors to ensure efficient coordination during operation. Figure 1 illustrates the architecture of the proposed smart EH grid. The key components within this system are outlined below:

1) Utilities: Natural gas and electrical companies are classified as utilities, with the electrical company (EC) and natural gas company (NGC) serving as primary sources of energy generation. The EC offers varying electricity prices throughout the day.

2) Energy hub management system (EHMS) and distributed generators (DGs): The EHMS possesses the capability to optimize energy consumption through economic signals, effectively communicating this information to consumers. DGs consist of boiler units and combined heat and power (CHP) units that utilize natural gas and other fuels for generating energy.

3) Consumers: Within residential areas, consumers account for a significant amount of energy consumption. To control their loads, consumers adopt a DSM approach by implementing controllable devices.

4) Energy storage devices: Electrical storage systems (ESSs), serve as the primary form of storing energy. These systems can meet electrical loads during peak-hours when there is a high demand for electricity due to elevated prices.



Fig.1 - Architecture of the proposed smart EH

# **1.2 Literature Review**

In this particular subsection, the examination of prior research on EH systems have been undertaken as part of a comprehensive literature review. In [5] explores the scheduling of energy for MCE while employing a risk approach in order to reduce generation costs amid uncertain energy prices. The authors of [6] focused on real-time energy management for micro energy systems outfitted with EH technology, factoring in the availability index of resources involved in energy generation through an iterative algorithm. In [7], the modeling of energy planning is presented by employing a multi-step standardized approach along with DSM strategies aided by coupling matrix techniques. In [8] introduce a proposed probabilistic optimization model aimed at maximizing profits within an energy hub system operating within competitive energy markets. In [9], the authors examine the modeling of value-at-risk with consideration given to DSM implementation. This analysis aims to reduce generation costs with demand uncertainty. In [10] discusses energy optimization in smart buildings through local generation as a means to minimize costs and emissions. In [11], the operation of an energy hub system is explored to increase reliability in meeting demands by utilizing a power-to-gas (P2G) system. In [12], probabilistic energy flow within an energy hub system is investigated using an online dictionary-learning approach to decrease overall energy costs. Authors in [13] propose DSM modeling for energy management through households' time slot scheduling in smart homes, taking into account both MCE system operations and energy prices within the energy market. Finally, in [14], researchers focus on energy scheduling within an energy hub equipped with storage systems such as ice storage conditioners and compressed air devices. Their objective is to achieve a reduction in environmental emissions during long-term operations.

#### **1.3 Novelties**

This paper presents a study of multi-objective operation in energy scheduling for energy Harvesting (EH) systems, specifically focusing on Day-Ahead demand side management (DSM) strategies. These strategies encompass the energy demand curtailment strategy (EDCS) and onsite generation strategy (OGS), which aim to minimize operational costs, reduce emission pollution, and enhance consumer comfort. To meet local demand within EH systems, the OGS utilizes a battery energy storage system. The authors propose solving this multi-objective optimization problem using fuzzy methodology. As such, this paper's notable contributions and innovations can be summarized as follows:

1) Introducing a multi-objective operation framework for smart EH systems' energy scheduling.

2) Incorporation of improving consumer comfort, reducing operational costs, and alleviating emission pollution within a multi-objective function.

3) Presentation of the EDCS and OGS as DSM strategies.

- 4) Utilization of a battery energy storage system to implement the OGS capabilities.
- 5) Adoption of fuzzy methodology as an optimization technique in addressing these objectives.

#### 2. DSM Modeling

The DSM approaches are structured in the following manner:

The EDCS modeling is devised to facilitate involvement in DSM strategy through demand curtailment. The EDCS model takes shape as follows:

$$C_{EDCS}(t) = D_{EDCS}(t) \times \Omega_{EC}(t) \qquad t = 1, 2, ..., T$$
<sup>(1)</sup>

The EDCS is formulated than energy prices at peak demand. Also, in equation (2), bound of the EDCS is formulated.

$$0 \le D_{EDCS}(t) \le D_{EDCS}^{\max} \tag{2}$$

The OGS is proposed considering meet local electrical demand using battery storage systems. The modeling battery storage system is as follow [15]:

$$\begin{cases} P_{bat}(t) / \eta_{dis} \leq P_{bat}^{\max} \times \mu_{dis}(t) & Disch \quad P_{bat}(t) \geq 0\\ P_{bat}(t) \times (-\eta_{ch}) \leq P_{bat}^{\max} \times \mu_{ch}(t) & Charg \quad P_{bat}(t) \leq 0 \end{cases}$$
(3)

The modeling of the battery storage system, operating in both discharging and charging modes, is encapsulated by equation (3). It should be noted that the battery cannot undergo simultaneous charge and discharge processes. Consequently, the impracticability of executing both operations simultaneously is expressed through equation (4) formulation.

$$\mu_{dis}\left(t\right) + \mu_{ch}\left(t\right) \le 1 \tag{4}$$

# 3. Objectives Modeling

In this particular section, we proceed to model the objective functions encompassing operation costs, emission pollution, and consumers' comfort as our primary objectives.

#### 3.1 Frist Objective

The primary objective is to minimize the operational cost of the system.

$$\min f_{1} = \sum_{t=1}^{T} \left\{ C_{EC}(t) + C_{NGC}(t) + \sum_{chp=1}^{CHP} C_{CHP}(t, CHP) + \sum_{bo=1}^{BO} C_{BO}(t, BO) + C_{EDCS}(t) \right\}$$
(5)

Where:

$$C_{EC}(t) = \Omega_{EC}(t) \times P_{EC}(t) \qquad \forall t$$
(6)

$$C_{NGC}(t) = \Omega_{GP}(t) \times P_{GAS}(t) \qquad \forall t$$
<sup>(7)</sup>

$$C_{CHP}(t, CHP) = \left\{ \alpha P_{CHP}^{2}(t, CHP) + \beta P_{CHP}(t, CHP) + \lambda \right\}$$
$$+ \left\{ \delta H_{CHP}^{2}(t, CHP) + \gamma H_{CHP}(t, CHP) + \xi \right\}$$

$$+\left\{\Omega_{GP}(t)\times(H_{CHP}(t,CHP)+P_{CHP}(t,CHP))\right\} \qquad \forall t,CHP$$
(8)

$$C_{BO}(t,BO) = \left\{ \alpha H_{BO}^{2}(t,BO) + \beta H_{BO}(t,BO) + \lambda \right\}$$
$$+ \left\{ \Omega_{GP}(t) \times (H_{BO}(t,BO)) \right\} \qquad \forall t,BO$$
(9)

The costs of the EC and NGC can be formulated according to equations (6) and (7), respectively. Both the CHP and boiler units are supplied with natural gas as well as other fuels. Equations (8) and (9) enable us to model the operation costs of the CHPs and boilers, respectively.

#### 3.2 Second Objective

The second objective function serves to minimize the emission generation caused by DGs and EC:

$$\min f_{2} = \sum_{t=1}^{T} \left\{ \sum_{bo=1}^{BO} E_{BO}(t, BO) + \sum_{chp=1}^{CHP} E_{CHP}(t, BO) + E_{EC}(t) \right\}$$
(10)

Where:

$$E_{BO}(t,BO) = \left\{ \varpi H_{BO}^2(t,BO) + \kappa H_{BO}(t,BO) + \nu \right\} \quad \forall t,BO$$
<sup>(11)</sup>

$$E_{CHP}(t, CHP) = \left\{ \varpi P_{CHP}^2(t, CHP) + \kappa P_{CHP}(t, CHP) + v \right\} \quad \forall t, CHP$$
(12)

$$E_{EC}(t) = \left\{ \varpi P_{EC}^{2}(t) + \kappa P_{EC}(t) + \nu \right\} \qquad \forall t$$
(13)

Equations (11) -(13) pertain to the emission of pollutants caused by boilers, CHPs, and EC.

#### **3.3 Third Objective**

The endeavor to enhance consumers' comfort is regarded as a tertiary aim.

$$\max f_{3} = 1 - \left[ \frac{\sum_{t=1}^{T} |\Psi(t) - \Psi^{OP}(t)|}{\sum_{t=1}^{T} \Psi(t)} \right]$$
(14)

At time t,  $\Psi$  represents the initial consumption of both electrical and thermal energies, while  $\Psi_{OP}$  signifies the aspired level of energy consumption during that same period.

#### 4. Constraints

The constraints of the EH are as follow:

$$\sum_{chp=1}^{CHP} P_{CHP}(t, CHP) + \sum_{b=1}^{B} P_{bat}(t) + P_{EC}(t) = D_{E}(t) - D_{EDCS}(t) \quad \forall t$$
(15)

$$\sum_{chp=1}^{CHP} H_{CHP}(t, CHP) + \sum_{bo=1}^{BO} H_{BO}(t, BO) = D_H(t) \qquad \forall t$$
(16)

$$P_{GAS}(t) - \sum_{chp=1}^{CHP} P_{CHP}(t, CHP) - \sum_{bo=1}^{BO} H_{BO}(t, BO) = D_{GAS}(t) \quad \forall t$$
(17)

$$0 \le P_{CHP}(t, CHP) \le P_{CHP}^{\max} \qquad \forall t, CHP$$
(18)

$$0 \le H_{CHP}(t, CHP) \le H_{CHP}^{\max} \qquad \forall t, CHP$$
<sup>(19)</sup>

$$0 \le H_{BO}(t, BO) \le H_{BO}^{\max} \qquad \forall t, BO$$
<sup>(20)</sup>

The constraints (15) - (17) model the energy balance limitations for electricity, heat, and natural gas. In addition, the boundaries of energy generation for DGs are formulated by constraints (18) - (20), respectively.

#### 4.1 Fuzzy Solution Method

The multi-objective optimization approach utilizes the fuzzy solution method to solve the given problem. The fuzzy constraints, represented by equations (21) -(25), are proposed in order to find solutions for the objectives. In this particular method, the extreme points of each function are presented in equations (21) -(23). Utilizing these equations, the minimum rates of objective functions can be calculated by approaching each function individually as a minimization level and iterating through the extreme points. On the other hand, solving for other functions is done with regards to the obtained solution in order to determine their maximum rates. Equation (24) allows for normalization of objectives and acquisition of membership functions ( $\mu$ ). Ultimately, equation (25) is used to select both an optimal and best solution based on its maximum membership function [16].

 $f < f^{\min}$ 

$$f_1^{\min} = f_1(x_1), f_1^{\max} = \max\{f_1(x_2), f_1(x_3)\}$$
(21)

$$f_2^{\min} = f_2(x_2), f_2^{\max} = \max\left\{f_2(x_1), f_2(x_3)\right\}$$
(22)

$$f_{3}^{\min} = f_{3}(x_{3}), f_{3}^{\max} = \max\{f_{3}(x_{1}), f_{3}(x_{2})\}$$
(23)

$$\mu_{i} = \begin{cases} \frac{f_{i}^{\max} - f_{i}}{f_{i}^{\max} - f_{i}^{\min}} & f_{i}^{\min} \leq f \leq f_{i}^{\max} \\ 0 & f_{i} \geq f_{i}^{\max} \end{cases}$$
(24)

$$\max \mu_{i} = \max \{\min(\mu_{1}, \mu_{2}, \mu_{3})\}$$
(25)

In the optimization, x and fi represent the pinnacle of solutions and the i-th objective function, respectively.

#### 5. Simulation and Case Studies

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In this section, we delve into the examination of the proposed approach and methodology through numerical simulation in the GAMS optimization software. The ensuing results are subsequently analyzed based on two scenarios outlined below:

Scenario A) The day-ahead optimal operation of EH without consideration of the OGS and EDCS. Scenario B) The day-ahead optimal operation of an energy hub inclusive of OGS and EDCS.

It is important to note that Figure 1 portrays the Energy Hub (EH) system which encompasses various demands such as thermal, electrical, and natural gas needs alongside two boiler units and two CHP units for a 24-hour ahead operational basis. The consumption of natural gas generated by NGC occurs within consumers, Boiler 1, and CHP 1. Conversely, other fuels act as fuel sources for Boiler 2 and CHP 2. Tables 1 and 2 provide economic and emission information pertaining to boilers and CHPs respectively; while Table 3 details the energy limits associated with DGs. Notably, the cost per unit volume in NGC stands at \$14 [17] [18]. Figure 2 showcases thermal, electrical, and gas-based energy demands whilst operating under specified parameters. Finally, the assumed power value for battery utilization in OGS amounts to approximately 30 kW [19]. The battery's efficacy in the process of charging and discharging is estimated at 90% and 95% respectively [20]. Additionally, electrical tariffs within the EC during hours 1-8 are set at 65\$/kW, while during hours 9-18 they rise to a value of 80\$/kW. Finally, from hours 19 to 24 the rates peak at an amount equal to 98\$/kW [21] [22]. It is noteworthy that the EDCS system has the capability to reduce maximum power demand by as much as 90 kW.

Parameters	α (\$/kW <sup>2</sup> )	β (\$/kW)	λ (\$)	δ (\$/kW <sup>2</sup> )	γ (\$/kW)	ξ (\$)
Units						
Boiler 2	53.4	85.3	110.5	-	-	-
CHP 2	53.3	83.6	105.4	45.4	75.5	95.4

Table 1 - Economic information of Boiler 2 and CHP 2 with other fuels cost factors

Parameters	<del>ர</del> (g/kW <sup>2</sup> )	к (g/kW)	v (g)	
Units				
Boiler 1	43.3	45.3	55.5	
Boiler 2	50.4	52.4	58.4	
CHP 1	48.3	50.4	53.8	
CHP 2	52.5	58.6	65.4	
EC	86.3	75.4	120.3	



#### Fig. 2 - Energies demand

# 5.1 Results

In accordance with the proposed scenarios, scenario A involves optimizing energy without taking into account EDCS and OGS. Within this scenario, objective functions such as operational cost, emission pollution, and consumer comfort are optimized under the constraints of an energy hub system. The fuzzy method is utilized to achieve optimization. In Fig. 3, it can be observed that the best solution on the Pareto frontier has a maximum membership value of 0.354. This optimal solution attributes a value of \$433224.3 to operational cost (the first objective), 6221.301kg to emission pollution (the second objective) and demonstrates a consumer comfort level of 76.3% (the third objective).

The breakdown of operation costs reveals that EC accounts for 39.6%, NGC accounts for 41.3%, and DGs account for 19.1%. Furthermore, emissions generated by EC amount to 3883 kg while DGs contribute an additional 2337 kg in emissions. It is evident that the EC and NGC exhibit significant values in terms of cost and emissions generated within the EH system. The NGC, facing a high demand for natural gas from consumers, incurs the highest operational expenses compared to the EC and DGs.

To illustrate this further, Table 4 presents energy scheduling data involving electrical and heat energies in scenario A. As depicted, during periods of peak demand and elevated electrical prices, power generation by the EC is completely utilized by consumers. Furthermore, all DGs constantly operate throughout each hour with substantial energy production. It should be noted that these DGs are able to achieve their operation while maintaining lower costs and emissions than those associated with the EC.



Fig. 3 - Pareto frontier and the best solution in scenario A

Hour	Electri	cal generat	ted (kW)	Heat generated (kW)			
	CHP 1	CHP 2	EC	Boiler 1	Boiler 2	CHP 1	CHP 2
1	125	120	139.5	100	120	0	110
2	125	120	301.1	80	120	14.5	70
3	125	120	279.1	3.1	120	0	110
4	125	120	273.1	55	120	70.7	110
5	125	100	20	15.4	120	100	110
6	125	120	228.7	0	120	100	80
7	125	120	86.3	100	120	0	110
8	125	120	80.7	100	120	0	100
9	125	120	471.2	100	120	100	21
10	125	120	311.1	0	120	100	82
11	125	120	336.5	0	120	100	64
12	125	120	361.1	100	120	10	55
13	125	120	335.4	32.9	120	6	110
14	125	120	232.1	0	120	100	17
15	125	120	143.1	0	120	100	6
16	125	120	134.6	0	120	100	60
17	125	120	176.5	23	120	100	76
18	125	120	559.4	100	120	10	90
19	125	120	491.4	100	120	100	15
20	125	120	489.7	100	120	100	110
21	125	120	419	90	120	100	15
22	125	120	286.1	50	120	0	30
23	125	120	254.2	50	120	50	50
24	125	120	245.3	100	120	20	110

Table 4 - Energy scheduling in scenario A

In the context of Scenario B, optimal energy scheduling takes into account both OGS and EDCS with all objective functions. In this scenario, the utilization of OGS involves the implementation of a battery storage system in order to meet the electrical demand within the energy hub. The involvement of both EDCS and OGS in this particular scenario is contingent upon the prevailing electrical prices within EC.

The role of EDCS is primarily focused on reducing the consumption of electrical energy during periods when electricity prices are high. On the other hand, OGS operates by charging during times when electricity prices are low and discharging during peak demand intervals marked by high electricity charges.

Fig.4 illustrates a graph that showcases how EDCS affects the profile of electrical demand over time. It demonstrates that with EDCS activated, there is a noticeable decrease in electrical demand specifically during instances when electrically charged rates are at their highest points.

With these adjustments made due to EDCS strategies being implemented, it has been observed that there is an overall reduction in total electrical demand equalling 836.4kW while concurrently decreasing operational costs for EDCS amounting to \$43234.3.



In Figure 5, we can see the representation of the Pareto frontier and the best solution reached in scenario B. The best solution encompasses various objectives such as cost, emission, and consumer comfort. It is worth noting that the cost amounts to \$426133.6, while emissions reach 5888.101kg and consumers' comfort stands at a high percentage of 78.9%. Additionally, the maximum membership value for this optimal solution demonstrates a strong score of 0.438. Comparing this scenario with scenario A reveals notable improvements in certain areas. Specifically, operation costs decreased by 1.63%, and an impressive margin of 5.35% reduced emissions. As a result, both financial burdens and pollution levels have been successfully minimized in comparison to the previous situation. However, it is essential to highlight that even amidst these positive changes, consumers' comfort experienced considerable enhancement as it increased by an impressive rate of 2.6%. Furthermore, within this contextually rich environment found in scenario B where optimization efforts are undertaken through ECDS and OGS methods; not only has power generation seen significant reduction but also emissions from EC sources have been considerably diminished.

The energy scheduling of scenario B is listed in Table.5. In scenario B, electrical and heat generation by DGs are similar to the previous scenario. The discharging power of the ESS at hours 10 and 20 with high electrical prices and peak demand is scheduled. Regarding the contribution of OGS and EDCS in the energy hub system, the costs and the emission pollution related to the EC are reduced.



Fig. 5 - Pareto frontier and the best solution in scenario B

Hour	Electrical generated (kW)				Heat generated (kW)				
	CHP 1	CHP 2	EC	Battery	Boiler	Boiler 2	CHP 1	CHP 2	
					1				
1	125	120	185.9	-30	100	120	0	110	
2	125	120	290.1	0	90	120	0	110	
3	125	120	222.1	0	0	120	0	80	
4	125	120	181.1	0	0	120	70.7	110	
5	125	120	0	0	45.4	120	100	110	
6	125	120	228.7	0	0	120	100	80	
7	125	120	116.3	0	100	120	0	110	
8	125	120	80.7	0	100	120	0	100	
9	120	110	335.4	0	100	120	100	21	
10	120	115	328.1	27.1	0	120	100	82	
11	125	120	336.5	0	0	120	100	64	
12	125	120	325.1	0	100	120	10	55	
13	125	120	325.4	0	32.9	120	6	110	
14	125	120	262.1	-30	0	120	100	17	
15	125	120	93.8	0	0	120	100	6	
16	125	120	91.6	0	0	120	100	60	
17	125	120	109.8	5	23	120	80	76	
18	125	120	523.4	0	100	120	10	90	
19	115	120	391.4	0	90	120	90	25	
20	115	120	305.7	22.5	60	120	90	110	
21	125	120	246.1	0	90	120	90	25	
22	125	120	196.1	0	50	120	0	30	
23	125	120	204.2	0	50	120	50	50	
24	125	120	193.3	0	100	120	20	110	

Table 5 - Energy scheduling in scenario B

### 6. Conclusion

This paper delves into the investigation of day-ahead energy scheduling for a smart EH system from a multiobjective optimization perspective. The proposed strategies, namely EDCS and OGS, are examined as means to achieve optimal energy scheduling. By utilizing fuzzy methods, the study seeks to solve multiple objective functions such as minimizing operation costs and emissions while maximizing consumers' comfort. Through numerical simulations conducted based on two scenarios, it is observed that both EDCS and OGS present significant opportunities for consumers in terms of demand management during periods of high energy prices. Furthermore, these strategies optimize energy generation from utilities. Specifically, when implemented in scenario B, the EDCS and OGS successfully minimize operation costs and emission pollution while ensuring an optimal level of energy consumption for enhanced consumer comfort compared to scenario A. Overall, the objectives are found to be better achieved in scenario B as compared to scenario A.

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