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Economic and Environmental Energy Scheduling of Smart Hybrid Micro Grid Based on Demand Response

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Abstract

Micro grids have gained significant recognition as crucial components of distribution networks, responsible for generating electrical energy at a local level. These self-contained systems are capable of operating independently or in conjunction with the main power grid, providing numerous advantages for both consumers and utilities. One of the key advantages of microgrids is their effortless management. Unlike traditional centralized power grids, microgrids can be easily controlled and monitored due to their smaller size and localized nature. This allows for more efficient energy management, as operators can closely monitor and adjust the generation, distribution, and consumption of electricity within the microgrid. By having a clear understanding of the energy demand and supply within the system, operators can optimize the use of resources and ensure a more reliable and stable power supply. The proposed model in this research focuses on optimizing economic and emission factors in relation to the main grid mode, utilizing a short-term operational approach with optimal units and real-time pricing (RTP) strategy. The study incorporates a multi-objective function for operating costs and emissions using the augmented ε-constraint method, along with fuzzy decision-making techniques to achieve the best solution. Furthermore, the microgrid includes interruptible and shiftable loads that can engage in demand response initiatives, leading to an evaluation of the results based on various demand response programs.

1. Introduction

1.1 Aims and Motivations

Recently, microgrids have been integrating energy systems to meet growing energy needs and to lower greenhouse gas emissions. Energy systems are now being integrated into microgrids as a solution to rising energy demands and the necessity to cut down on greenhouse gas emissions [1]. These systems utilize different energy sources such as electricity, heat, and gas in a coordinated and efficient manner [2]. The uptick in energy usage has significantly contributed to the rise in sustainable energy production. With the global population continuously expanding, the demand for energy to power, businesses, and industries has also grown [3].

Nomenclature

i	Time period	P_L	Total Load
s	CHP Unit index	C_{LR}	Load reduction cost
n	DG Unit index	C_{CHP}	CHP unit operational cost
k	Heat only Unit index	C_{DG}	DG unit operational cost
j	Thermal Unit index	C_H	Heat only unit operational cost
l	Load demand index	C_{TH}	Thermal unit operational cost
S	Number of CHP Units	C_{ES}	Energy storage unit operational cost
N	Number of DG Units	$C^B{}_G, C^S{}_G$	Purchased power cost and sold power cost with main grid
K	Number of Heat only Units	α, β, λ	Cost factors of units
J	Number of Thermal Units	ϕ, π, ρ	Cost factors of boiler
Υ_{LR}	Price quantity offer for load reduction	σ, τ, γ	Emission factors of Units and main grid
ΔP_{LR}	Power quantity offer for load reduction	$\mu^B{}_G, \mu^S{}_G$	Cost of purchased and sold power factors
$P_L{}^{IN,max}$	Maximum power of interruptible load	P_{CHP}	Power generated of CHP units
$P_L{}^{SH,max}$	Maximum power of shiftable load	P_{DG}	Power generated of DG units
$P_L{}^{SH}$	Power of shiftable load	H_H	Heat generated of Heat only units
ψ	Load shift factor	P_{TH}	Power generated of Thermal units
$P_{L,A}{}^{SH}$	Power load of shiftable load after shift	H_{CHP}	Heat generated of CHP units
$P_{L,B}{}^{SH}$	Power load of shiftable load before shift	$C^{ES}{}_{CA}$	Capital cost of energy storage unit
L_{dis}	Lifetime of energy storage unit in discharge state	$C^{ES}{}_{O\&M}$	Operation and maintenance cost of energy storage unit
L_{ch}	Lifetime of energy storage unit in charge state	P_{dis}	Power of energy storage unit in discharge state
P_{ch}	Power of energy storage unit in charge state	L_{dis}	Lifetime of energy storage unit in discharge state

The increase in energy demand has strained conventional fossil fuel resources, leading to a quest for renewable and eco-friendly energy alternatives [4]. To meet this escalating load for energy while minimizing the environmental impact, the integration of multi energies has become essential. Microgrids, specifically, are considered ideal for incorporating these systems because of their high energy usage and opportunity for improving energy efficiency [5]. Integrating multiple energy carriers in microgrids offers numerous benefits. It boosts energy supply diversity and resilience, reducing the risk of shortages or interruptions. Moreover, it improves energy efficiency by optimizing energy carrier usage cost-effectively. This can lead to significant energy savings and lower expenses for residents. Embracing these methods makes it possible to enhance the reliability and effectiveness of energy systems [7]. In addition, multi-carrier energy systems have the potential to seamlessly integrate with smart grid technology, offering opportunities such as optimizing energy demand and storing energy through the use of energy management strategies in smart homes [8][9]. These multi energy systems can be referred to as the integration of multiple energy sources in smart grids [9][10]. It is crucial to address uncertainties by implementing proactive measures to effectively manage them. Analyzing the impacts of uncertainties is essential for making informed decisions in energy operations [10]. One common uncertainty is the fluctuation of energy prices, particularly in global markets [11]. Strategies such as demand-side engagement and energy storage systems can help mitigate the effects of uncertain energy prices [12]-[15]. Demand-side engagement allows consumers to adjust their energy usage during peak periods, while energy storage systems ensure energy demand is met when needed [16][17]. Various types of energy storage systems are available to meet specific performance requirements [18]. The loads in energy systems are usually random variables, but they can be regulated by offering economic incentives, it considerably affects the stability of energy systems [18][19].

1.2 Related Researches and Contributions

This part discusses previous research conducted on energy systems in different environments. In [20], the scientists examine the modeling of an energy hub in an integrated energy system for infrastructures. The research focuses on addressing efficiency issues using an engineering equation solver. The goal is to achieve cost-effective and environmentally friendly performance in the generation aspect. In [21], the lexicographic technique is used to address the energy optimization strategy of multi-energy systems, with an emphasis on economic and environmental indicators. The objective of this method is to enhance customer contentment by integrating demand management strategies. In citation [22], the aim of cutting down operational costs is achieved by utilizing peer-to-peer power flow and integrating with electric vehicles (EVs) in the midst of varying electricity prices and diverse driving patterns of EVs. On the other hand, the scholars in reference [23] concentrated on a tactic employing fuzzy logic to effectively address optimal energy management. In reference [24], the primary target is to decrease operational costs and emissions by incorporating solar-powered compressed air energy storage with Quasi-optimization. The optimization considers uncertainties related to solar irradiance and energy demand. In contrast, reference [25] suggests utilizing non-dominant genetic for energy operation without load management.

This approach aims to enhance appliance performance by reducing costs and improving efficiency. Reference [26] concentrates on running the energy hub through compressed air storage and electric vehicles to address electricity price uncertainties in robust optimization. Conversely, authors in references [27] and [28] introduce robust optimization methods to model power scheduling for minimizing energy expenses. Additionally, there are various research gaps that can be filled by addressing the following points:

1) Many research projects aim to meet energy system needs at minimal operational expenses, but often neglect demand management. The models proposed in these studies are usually tailored to meet the system's technical constraints, resulting in a lack of suitable models to improve adaptability to fluctuations in gas and electricity prices.
2) The demand management in existing literature are typically modeled according to energy market prices. In contrast, our study focuses on modeling these strategies based on bidding prices and load shifting for the day-ahead market.

This paper delves into the exploration of energy management and demand response as strategic methods for day-ahead scheduling. The microgrid's current loads are supported by a variety of generation units including CHP, DG, thermal unit, heat only unit, ES unit, and the main grid to fulfill their electricity and heat power needs. Our research centers on the effects of demand response on objective functions through the analysis of load reduction and load shift. By efficiently handling generation and demand, microgrids can minimize operational costs and emissions. To enhance this, we apply a multi-objective function that takes into account operating costs and emissions using the augmented ε-constraint method. Furthermore, we incorporate a fuzzy decision-making process to determine the optimal solution. The novelties of this work can be summarized as follows:

1) Recognizing the importance of energy management and demand response in day-ahead scheduling.
2) Investigating the effects of demand response on load reduction and load shift.
3) Implementing a multi-objective function with the augmented ε-constraint method for operating cost and emission.
4) Utilizing a fuzzy process to determine the optimal solution.

2. Modeling of Demand Response

Three types of loads are classified according to their consumption characteristics per hour: interruptible load, non-interruptible load, and shiftable load. Demand response is relevant for interruptible and shiftable loads. Interruptible loads can be decreased by considering the offer price per kilowatt, as shown in equation (1) for the cost of reduction load in interruptible load [29].

$$C_{LR} = \Delta P_{LR}(t) \times \Upsilon_{LR} \tag{1}$$

$$0 \le \Delta P_{LR}(t) \le P_{L}^{IN,\max} \tag{2}$$

Shiftable loads have the ability to be transferred from peak to off-peak loads. The process of load shifting involves decreasing the amount of electricity purchased from the main grid during peak load periods, as indicated by constraint (3), which sets the limit for shiftable loads during operation. Equations (4) and (5) illustrate the loads after the shift and the range of shiftable loads [30].

$$0 \le P_{L}^{SH}(t) \le P_{L}^{SH,\max} \tag{3}$$

$$P_{L,A}^{SH}(t) = \left(\psi(t).P_{L,B}^{SH}(t), t\right) \tag{4}$$

$$\psi^{\min} \le \psi(t) \le \psi^{\max} \tag{5}$$

$$\sum_{i=1}^{t}\left\{P_{L,A}^{SH}(t)+P_{L,B}^{SH}(t)\right\}=P_{L}^{SH,\max} \tag{6}$$

Constraint (6) illustrates the load balance constraint both prior to and following the load shift. The utilization of the load balance constraint is necessary as it ensures that shiftable loads are not disregarded, but rather transferred from one time period to another [31].

3. Modeling Objectives

The objectives considered in this study are as follows:

3.1 Operational Cost Modeling

The operation cost modeling is as follow [32]:

$$\begin{aligned} F_1 = \sum_{i=1}^{t}\Bigg(& \sum_{s=1}^{S} C_{CHP}^{t,s} + \sum_{n=1}^{N} C_{DG}^{t,n} + \\ & \sum_{k=1}^{K} C_{H}^{t,k} + \sum_{j=1}^{J} C_{TH}^{t,j} + \\ & C_{ES} + \sum_{i=1}^{t} C_{G}^{B} - C_{G}^{S} + \sum_{l=1}^{L} C_{LR}^{t,l} \Bigg) \end{aligned} \tag{7}$$

Where:

$$\begin{aligned} C_{CHP}^{t,s} &= \alpha_{t,s} + \beta_{t,s} P_{CHP}(t,s) + \lambda_{t,s} P_{CHP}(t,s)^2 \\ &+ \phi_{t,s} + \pi_{t,s} H_{CHP}(t,s) + \rho_{t,s} H_{CHP}(t,s)^2 \end{aligned} \tag{8}$$

$$C_{DG}^{t,n} = \alpha_{t,n} + \beta_{t,n} P_{DG}(t,n) + \lambda_{t,n} P_{DG}(t,n)^2 \tag{9}$$

$$C_{H}^{t,k} = \alpha_{t,k} + \beta_{t,k} H_{H}(t,k) + \lambda_{t,k} H_{H}(t,k)^2 \tag{10}$$

$$C_{TH}^{t,j} = \alpha_{t,j} + \beta_{t,j} P_{TH}(t,j) + \lambda_{t,j} P_{TH}(t,j)^2 \tag{11}$$

$$C_{ES} = \begin{cases} \dfrac{C_{CA}^{ES} / L_{ch} + C_{O\&M}^{ES}}{\eta_{ch}\eta_{dis}} \\ C_{CA}^{ES} / L_{dis} + C_{O\&M}^{ES} \end{cases} \tag{12}$$

$$L_{ch} = \frac{N_B V_B Q_B N_C}{P_{ch}(t)} \tag{13}$$

$$L_{dis} = \frac{N_B V_B Q_B N_C}{P_{dis}(t).\eta_{dis}} \tag{14}$$

$$C_{G}^{B} = \mu_{G}^{B}(t).P_{G}^{B}(t) \tag{15}$$

$$C_{G}^{S} = \mu_{G}^{S}(t).P_{G}^{S}(t) \tag{16}$$

Here cost of CHPs, DGs, heat only resources, thermal resources and ES resources are modeled by Eqs (8)-(12), respectively. Eqs (13) and (14) are ES life span in charge and discharge, respectively. The cost of main grid is modeled by (15) and (16).

3.2 Emission Modeling

The emission objective is modeled as follow:

$$F_2 = \sum_{i=1}^{t}\left(\sum_{s=1}^{S} E_{CHP}^{t,s} + \sum_{n=1}^{N} E_{DG}^{t,n} \right. \\ \left. + \sum_{k=1}^{K} E_{H}^{t,k} + \sum_{j=1}^{J} E_{TH}^{t,j} + \sum_{i=1}^{t} E_{G}^{B}\right) \tag{17}$$

$$E_{CHP}^{t,s} = \sigma_{t,s} + \tau_{t,s} P_{CHP}(t,s) + \gamma_{t,s} P_{CHP}(t,s)^2 \tag{18}$$

The emission modeling of CHP is modeled by (18). The emission objective of the resources is same with CHP modeling.

4. Modeling Constraints

The constraints like energy balance for electrical and heat energies are formulated by (19) and (20), respectively. The constraints (21) and (22) are ES discharge and charge modeling, respectively. The energy limit constraints of units are modeled by Eqs (23)-(29). The ramp up and down and up and down time of CHPs are formulated by (30)-(33), respectively. The constraints (34) and (35) stat of charge (SOC) and limit of SOC in ES resources, respectively [32][33].

$$\sum_{i=1}^{t}\begin{Bmatrix} P_L(t) + \Delta P_{LR} \\ +P_G^S(t).x_G^S \\ +P_{ch}(t).x_{ch} \end{Bmatrix} = \sum_{i=1}^{t}\begin{Bmatrix} P_{CHP}(t,s).x_{CHP(t,s)} \\ +P_{DG}(t,n).x_{DG(t,n)} + P_{TH}(t,j).x_{TH(t,j)} \\ +P_{dis}(t).x_{dis} + P_G^B(t).x_G^B \end{Bmatrix} \tag{19}$$

$$\sum_{i=1}^{t}\{H_L(t)\} = \sum_{i=1}^{t}\{H_{CHP}(t,s).x_{CHP(t,s)} + H_H(t,k).x_{H(t,k)}\} \tag{20}$$

$$x_{dis} + x_{ch} \le 1 \tag{21}$$

$$x_G^S + x_G^B \le 1 \tag{22}$$

$$P_{CHP}^{\min} \le P_{CHP}(t,s) \le P_{CHP}^{\max} \tag{23}$$

$$P_{DG}^{\min} \le P_{DG}(t,n) \le P_{DG}^{\max} \tag{24}$$

$$H_{CHP}^{\min} \le H_{CHP}(t,s) \le H_{CHP}^{\max} \tag{25}$$

$$H_H^{\min} \le H_H(t,k) \le H_H^{\max} \tag{26}$$

$$P_{TH}^{\min} \le P_{TH}(t,j) \le P_{TH}^{\max} \tag{27}$$

$$0 \le P_{dis}(t) \le P_{dis}^{\max} \tag{28}$$

$$0 \le P_{ch}(t) \le P_{ch}^{\max} \tag{29}$$

$$\sum_{i=1}^{t} P_{CHP}(t,s) - \sum_{i=1}^{t} P_{CHP}(t-1,s) \le R^u \tag{30}$$

$$\sum_{i=1}^{t} P_{CHP}(t-1,s)-\sum_{i=1}^{t} P_{CHP}(t,s)\le R^{d} \tag{31}$$

$$\sum_{i=1}^{t} x_{CHP(t,s)}(t+1,s)\ge MUT \tag{32}$$

$$\sum_{i=1}^{t} 1-x_{CHP(t,s)}(t+1,s)\ge MDT \tag{33}$$

$$SOC^{\min}\le SOC(t)\le \%100 \tag{34}$$

$$SOC(t)=SOC(t-\Delta t)-\frac{(P_{dis}(t)/\eta_{dis})+(P_{ch}(t)\eta_{ch})}{N_B V_B Q_B} \tag{35}$$

5. Methodology

The augmented ε-constraint method is implemented by formulating a mathematical model representing the multi-criteria problem, including objective functions and constraints. This method introduces small positive numbers called epsilon values, acting as thresholds on the problem. The goal is to find solutions that minimize or maximize the objective functions while satisfying the augmented ε-constraint method. During optimization, candidate solutions that satisfy the epsilon constraints are generated and evaluated based on their objective function values and feasibility. The Pareto frontier represents solutions that cannot be improved in one objective without sacrificing performance in another, embodying compromises between various objectives. The augmented ε-constraint method follows a sequence of steps to obtain solutions on the Pareto frontier. [34]-[36]:

$$\min_{x\in X} f_j(x) \tag{36}$$

S.T:

$$f_z(x)\le \varepsilon_z \qquad z=1,2,\ldots,Z \qquad z\ne j \tag{37}$$

Choosing the best Pareto solution from the set of Pareto optimal solutions is crucial in order to achieve the most favorable outcome in terms of operational cost and emissions. To determine the optimal solution, a fuzzy decision-making process will be employed, which takes into account the uncertainty and imprecision associated with these factors.In this process, a membership function will be defined for both operational cost and emissions. The membership function represents the degree to which a particular solution satisfies the desired criteria. It assigns a value between 0 and 1, where 0 indicates no satisfaction and 1 indicates complete satisfaction.The fuzzy decision-making process involves evaluating each Pareto solution based on its membership values for operational cost and emissions. The solutions with higher membership values will be considered more favorable, as they better align with the desired criteria. By employing this fuzzy decision-making process, the best Pareto solution can be identified. This solution will have the highest membership values for both operational cost and emissions, indicating that it offers the best trade-off between these two factors. Selecting the best Pareto solution is important as it allows decision-makers to make informed choices that balance the trade-off between operational cost and emissions. By considering the membership values, decision-makers can prioritize solutions that minimize operational cost while also minimizing emissions, or vice versa, depending on the specific goals and priorities of the decision-making process. Overall, the fuzzy decision-making process enables a comprehensive evaluation of the Pareto optimal solutions, taking into account the uncertainty and imprecision associated with operational cost and emissions. By selecting the best Pareto solution based on the defined membership function, decision-makers can make well-informed decisions that optimize both cost and emissions [37][38].

$$f_\xi^k = \begin{cases} 1 & F_\xi^k \le F_\xi^{\min} \\ \dfrac{F_\xi^{\max} - F_\xi^k}{F_\xi^{\max} - F_\xi^{\min}} & F_\xi^{\min} \le F_\xi^k \le F_\xi^{\max} \\ 0 & F_\xi^k \ge F_\xi^{\max} \end{cases} \tag{38}$$

$$f^k = \frac{\sum_{\xi=1}^{P} w_\xi . f_\xi^k}{\sum_{k=1}^{K} \sum_{\xi=1}^{P} w_\xi . f_\xi^k} \tag{39}$$

The weight factor of the ξth objective function, denoted as w_ξ, will be determined based on the economic and environmental conditions. In this particular study, the weight factors assigned to each objective are all equal to 0.5 [39].

6. Case Studies

The approach recommended in this section is executed through numerical simulation and a case study, with the case study being centered around demand response programs. The case studies are listed in Table.1.

Table 1 *Case studies in microgrid*

Case	Load shifting	Load reduction
Case 1	-	✓
Case 2	✓	-
Case 3	✓	✓

Fig. 1 shows the utilization of a 21-bus network for implementing the aforementioned cases. The emission and economic data of resources like CHPs, thermal units, DGs, ES and heat only units are extracted from references [40]-[43]. Figs. 2 and 3, shown energy demand of microgrid and electrical price of main grid in energy market considering price traffics. In Fig. 4, factor of load shifting with value 20% is shown.

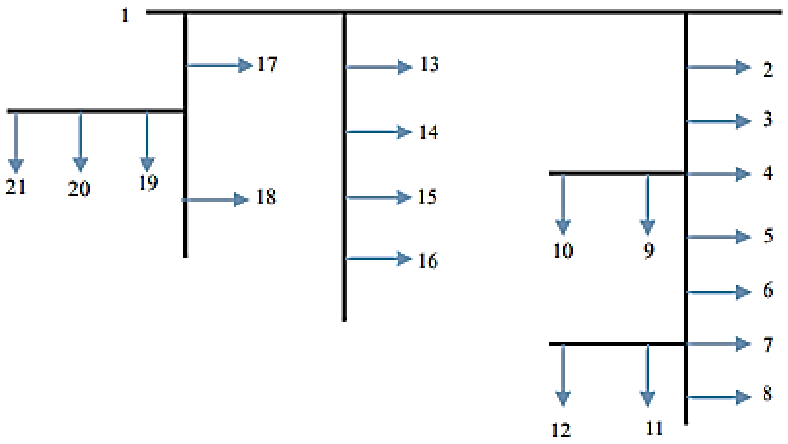


Fig. 1 *Microgrid system*

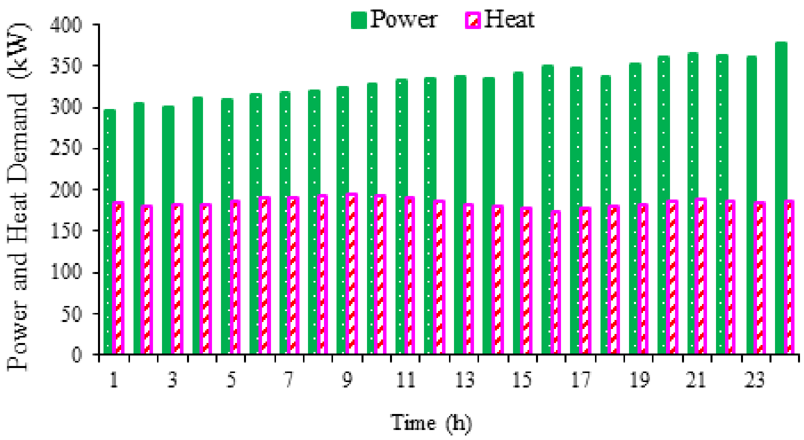


Fig. 2 *Energy demand*

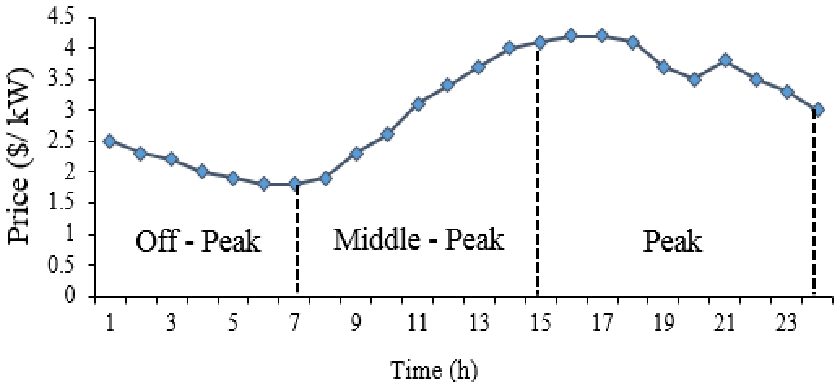


Fig. 3 *Electrical price in main grid*

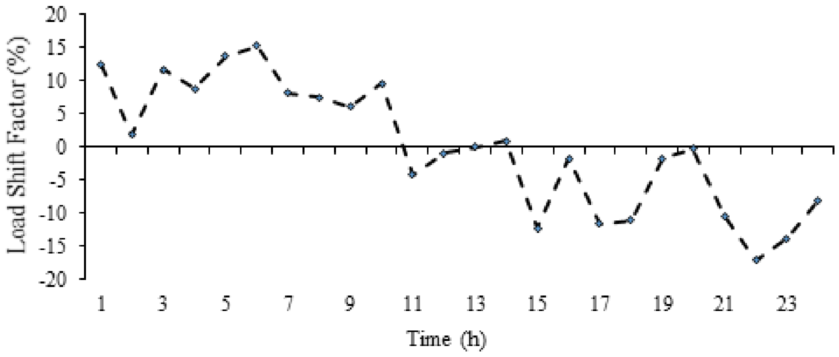


Fig. 4 *Factor for load shifting model*

Table 2 *Data of load reduction model*

Data				
Value (kW)	1-50	51-80	81-90	91-105
Cost ($)	1	5	15	25

6.1 Results

In this subsection, results of cases are analyzed as follow:

6.1.1 Case 1

The economic scheduling in this case is simulated using the load reduction method. Fig.5 (a) displays the Pareto optimal solution after 15 iterations. In Fig.6 (a), the 6th solution is identified as the best compromise solution in the fuzzy decision-making process. The fuzzy decision-making process further enhances the efficiency of the system by identifying the best compromise solution that balances cost, energy consumption, and emissions. By avoiding power purchases during high energy price hours, the system is able to significantly reduce costs and emissions. Notably, power purchase from the main grid is avoided between 14-21 due to high energy prices during those hours. The demand during this period is met by resources. A visible reduction in load occurs from 14-24, with a total reduction of 431 kW, primarily driven by the high energy prices during the middle peak and peak hours. Meanwhile, Fig.7 (a) illustrates the heat generated by the CHP unit and the heat-only unit. The total operational cost in this case amounts to $37,069, with the highest costs attributed to purchased power from the main grid and the heat-only unit. Additionally, the total emissions stand at 9.8848 tons.

6.1.2 Case 2

The study delves into the effects of incorporating shiftable loads into economic scheduling strategies. Shiftable loads refer to the practice of moving energy consumption from periods of high electricity prices to times when prices are lower. The fifth solution derived from the fuzzy decision-making process, as depicted in Fig.5 (b), is identified as the optimal compromise solution. The power generation units responsible for supplying electricity in this solution are detailed in Fig 6 (b). During the hours of 1- 9, when energy prices are at their lowest, the main grid is utilized to meet demand. As a result, resources are predominantly active during mid-peak and peak times to fulfill energy requirements, thereby reducing emissions from the main grid. Fig.7 (b) showcases the heat output from CHP and heat-only units, with the heat-only unit playing a significant role in meeting heat demand. The resources are associated with the highest costs and emissions, amounting to $42,682 and 8.8953 tons, respectively.

6.1.3 Case 3

The examination of the impact of reduced load and shift load techniques on economic scheduling in this scenario has revealed that the 8th option, depicted in Fig.5(c), stands out as the most optimal compromise in the fuzzy decision-making process. In Fig. 6(c), it is evident that the load reduction has decreased to 335 kW compared to the initial case. Furthermore, Fig.7(c) showcases the heat produced by the units, which remains consistent with the initial case. This assessment underscores the significance of incorporating reduced load and shift load methods in economic scheduling to enhance cost-effectiveness and overall efficiency in energy management systems.

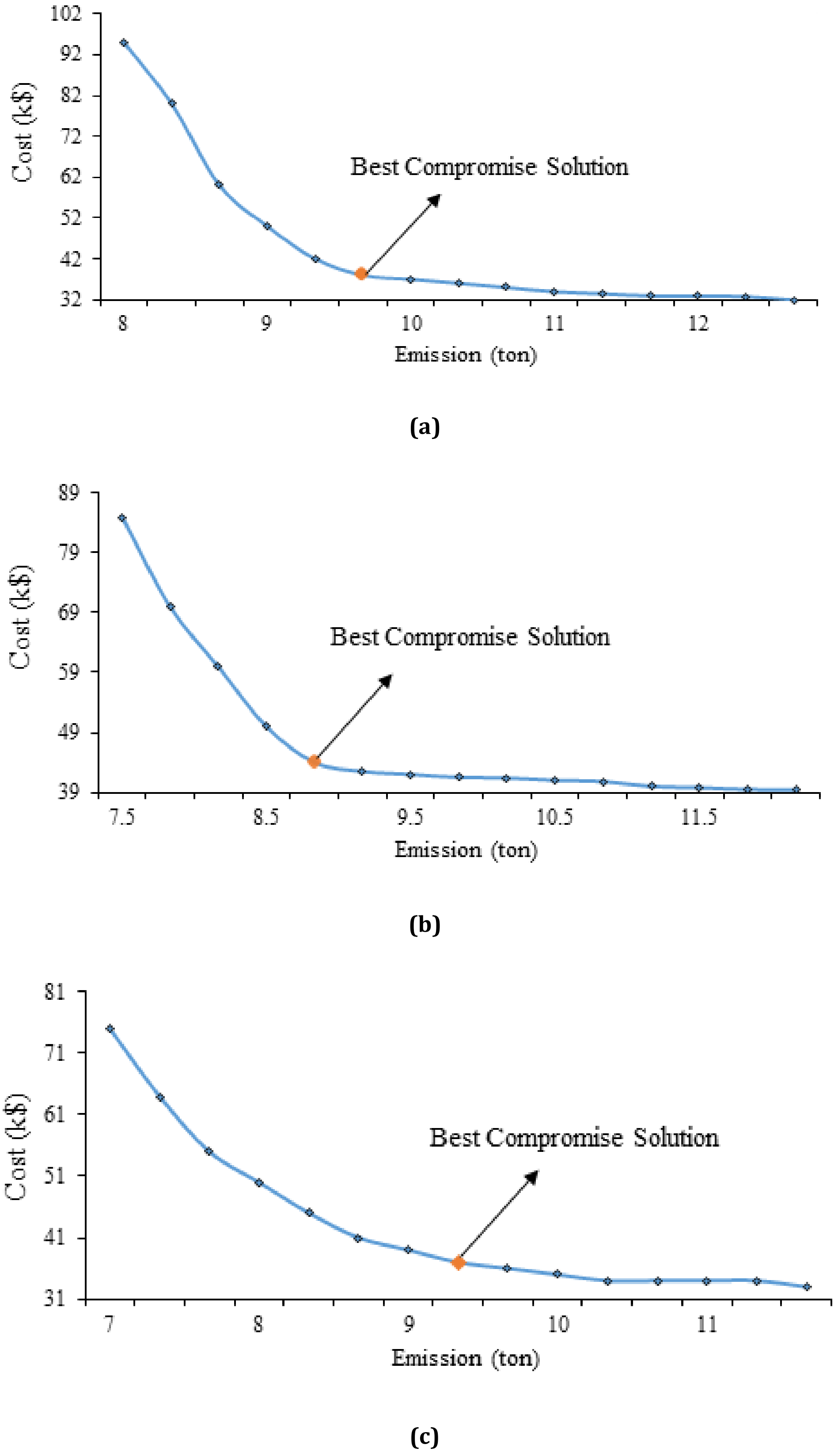
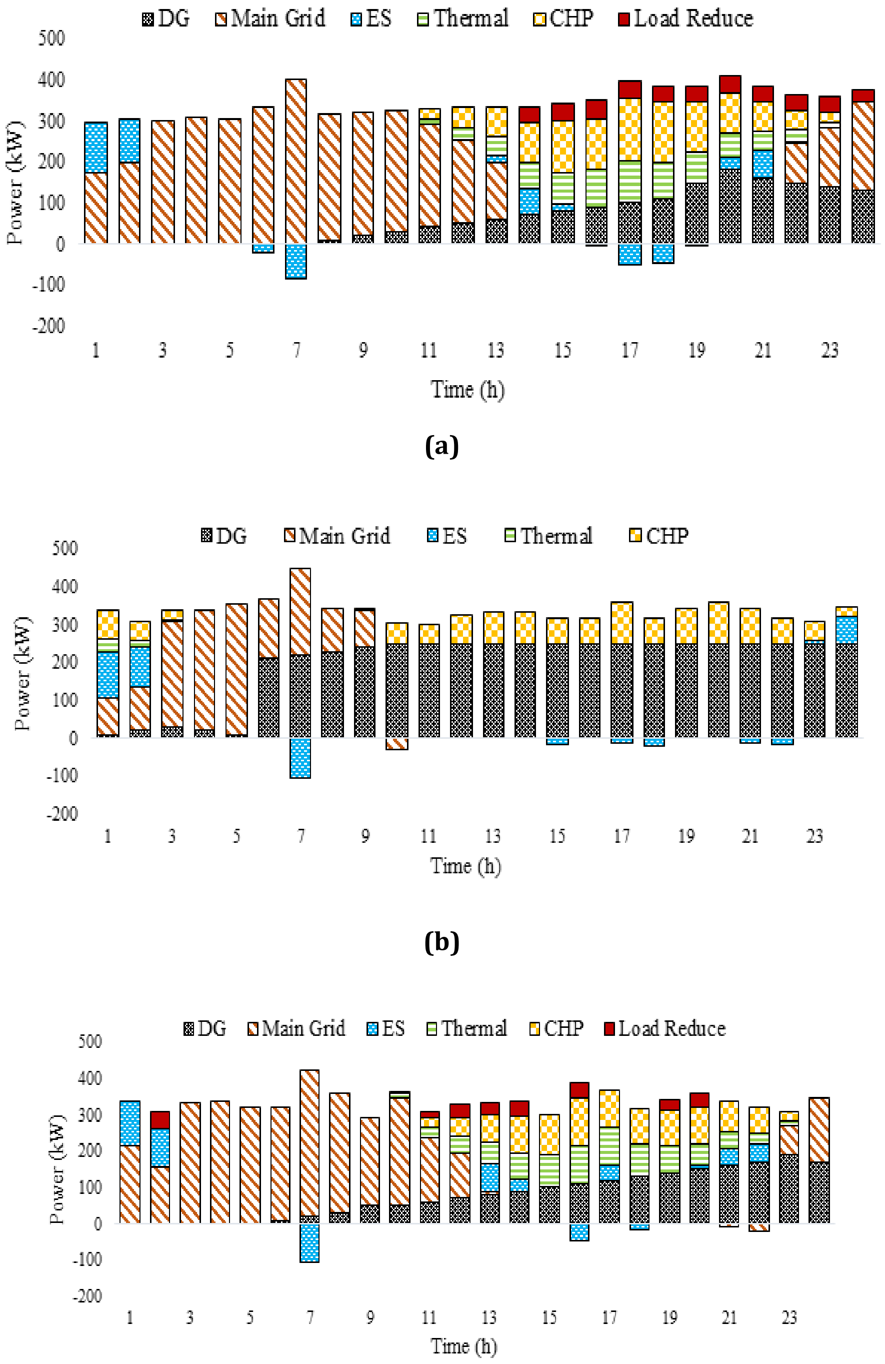


Fig. 5 *Pareto front of case studies. (a) Case1; (b) Case 2; and (c) Case 3*

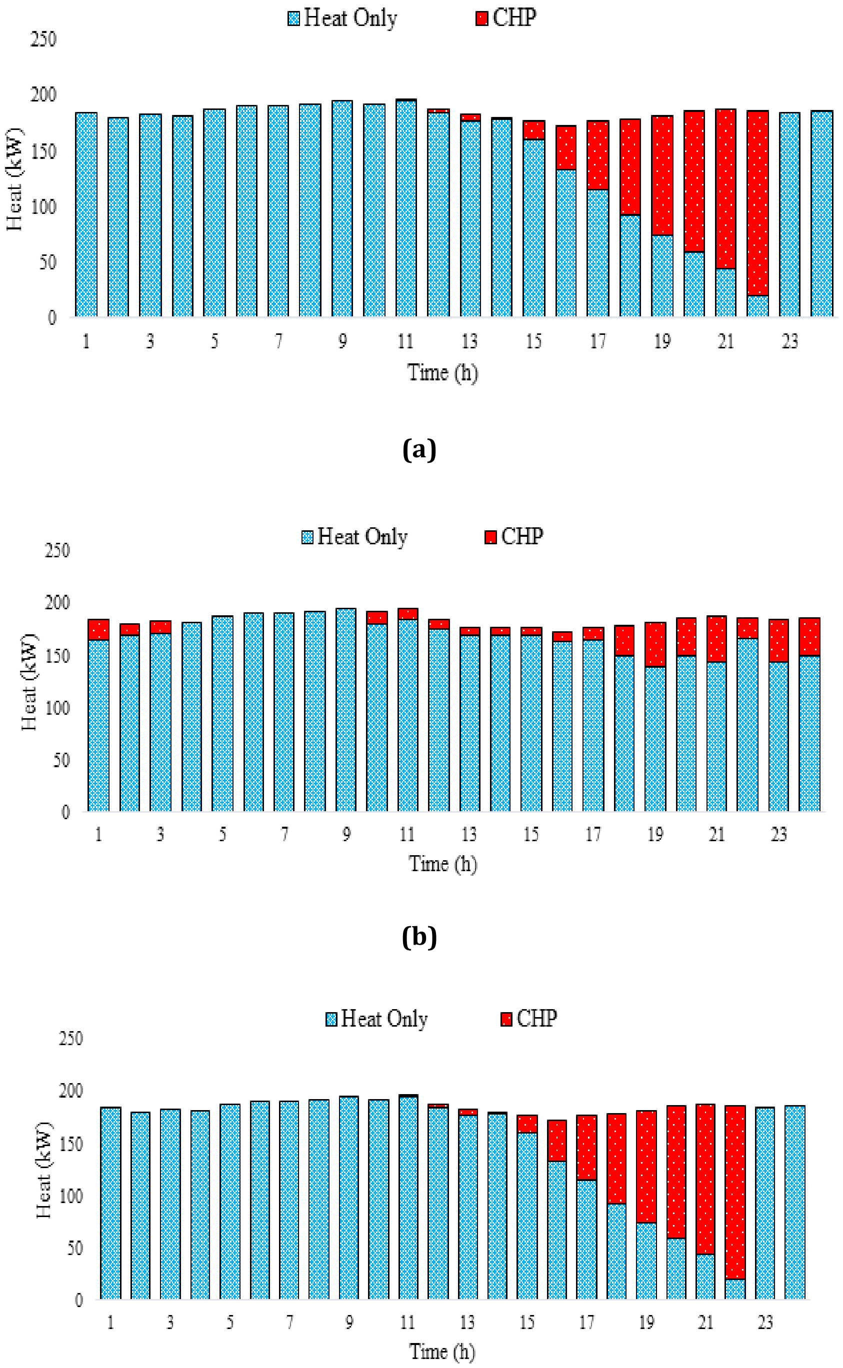


(a)

(b)

(c)

Fig. 6 *Power dispatched in case studies. (a) Case1; (b) Case 2; and (c) Case 3*



(a)

(b)

(c)

Fig. 7 *Heat dispatched in case studies. (a) Case 1; (b) Case 2; and (c) Case 3*

7. Conclusion

In this study, a method is introduced for the efficient modeling of an smart microgrid with multiple goals in the day ahead. These goals consist of minimizing emission and costs on the generation side, considering demand response programs such as load shifting and load reduction method. The proposed method employs the augmented ε-constraint method to obtain non-dominated Pareto solutions for the goals. Finally, several case studies are conducted to validate the proposed method. The participation of the demand shifting and load reduction leads to reduce emission, costs and loss of energy supply probability than non-participation. The results in some case studies are validated as follow:

- Electrical load management by load reduction leads to peak load shaving, whereby emission and cost in microgrid are reduced.
- Optimal dispatch of units considering load management by load shifting leads to decrease power generation from main grid with high emission and pricing.

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Conflict of Interest

The authors declare that they have no known competing interests.

Author Contribution

Harikumar Pallathadka, Shavan Askar, Ankur Kulshreshta, M. K. Sharma, Sabir Widatalla, I.S. Mude have equal contributions reviewing and editing the writing, formal analysis, software development and conceptualization.

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