Operations Research Forum (2024) 5:4
https://doi.org/10.1007/s43069-023-00289-2

RESEARCH

Modeling Uncertainty Energy Price Based on Interval Optimization and Energy Management in the Electrical Grid

Julio César Machaca Mamani[1] · Freddy Carrasco-Choque[2] · Edith Fernanda Paredes-Calatayud[3] · Helfer Cusilayme-Barrantes[3] · Rocío Cahuana-Lipa[4]

Received: 31 October 2023 / Accepted: 18 December 2023 / Published online: 30 December 2023

Abstract
Energy providers are faced with the challenge of effectively managing electrical energy systems amidst uncertainties. This study focuses on the management and dispatch of energy demand in the electricity microgrid, employing an interval optimization strategy to address electricity price uncertainties. The demand response program (DRP) incentive modeling is utilized to implement demand dispatch. To mitigate the impact of electricity price uncertainties, an incentive modeling approach based on offering reduced electricity demand during peak periods is proposed. The interval optimization approach is employed to minimize operational costs, with the epsilon constraint-based fuzzy method utilized to solve and address the problem. The effectiveness of the proposed modeling approach under conditions of uncertainty is demonstrated through the use of the microgrid in various case studies and numeric simulations. The participation of the DRP leads to minimizing the average and deviation costs by 9.5% and 6.5% in comparison with non-participation.

Keywords Electricity microgrid · Interval optimization strategy · Electricity price uncertainties · Epsilon constraint method

---

This article is part of the Topical Collection on *Mathematical Models and Optimization for Environmental Engineering and Sustainable Technologies*

✉ Julio César Machaca Mamani
julio.mamani.pr@gmail.com

[1] Academic Department of Business Studies, National University José María Arguedas, Andahuaylas-Apurímac, Peru

[2] Department of Basic Sciences, Frontera National University of Sullana, Sullana, Peru

[3] Department of Ecotourism, National Amazonian University of Madre de Dios, Puerto Maldonado, Peru

[4] Ciencias de la Salud, Universidad Tecnológica de los Andes, Andahuaylas, Perú

Nomenclature

t, T	Time (hour)
m, M	Micro turbine (MT) index (–)
NC	Consumers' number
D_{eq}, D_{RE}	Consumers' demand and demand reduced by DRP (kW)
Ψ_{RE}	Offer price for DRP ($)
C_{RE}	DRP price ($)
A, B, C	MT fuel cost ($)
P_m, P_{PM}	MT power and PM power (kW)
c_{PM}	Price of electricity in PM ($)
Θ_{RE}	Binary variable of the DRP
τ_{RE}, κ_{RE}	Binary variable for before and after DRP

1 Introduction

1.1 Aims

Currently, electrical networks are developing by using modern and new technologies like smart grids with communication and computing infrastructures, offering great opportunities for automation and management [1–3]. With smart grids, the task of consumers in relation to energy grids has shifted to that of user participants and is no longer a passive consumer [4–6]. As a result, consumers are more actively participating in energy exchange strategies. For this purpose, a power or energy control system can be taken into account as a modern tool to intelligently manage power demand on the consumers' side [6, 7]. Regarding data and information such as electricity prices in energy markets and peak power demand, energy optimization on the consumers' side is used to adjust the power consumption modeling of users as part of a demand response program (DRP) [8]. In addition, in view of the growing environmental and economic problems in many countries, the use of smart grids and different approaches to optimal energy scheduling is increasing. In recent decades, fossil fuels have been the main resource of energy production, especially energy electricity [9–12]. Therefore, the use of diverse solutions is required to address all the mentioned challenges and problems. Thus, smart grids and communication links between energy companies and consumers have been deployed to improve economic and technical indicators [12–14]. In addition, consumers can participate in energy savings based on electricity price signals by integrating smart grids into electricity networks [14]. The consumer can be assumed as a backup resource in power grids to reduce power production during peak demand [15]. By using this solution, the role of the generator is taken over by the consumers, and the power in the energy plans is limited to the peak demand [16].

1.2 Related Works, Research Gaps and Contributions

Energy management in power grids has been studied in recent years by researchers; a number of these studies are presented. In [17] used the power dispatch of the electrical grids through the classification of devices and on minimizing the cost of power consumption. In [18] discusses energy optimization with regard to emissions and power production costs in power grids. The optimal joint of electrical microgrids with the optimal energy design of renewable resources is reported in [19]. The optimal power management in power grids considering the uncertainty of plug electric vehicles (PEV) was studied in [20]. In [21], onsite power production and consumer load management are implemented to reduce costs and maximize reliability. Authors in [22] the self-planning of power resources considering risk control under conditions of load uncertainty is examined in order to maximize power savings. The hybrid modeling of the optimization is introduced in [23] to manage the demand in power grids during emergency hours. In [24] economic modeling of power grids with optimal participation of renewable energy sources and load planning is examined. The evaluation of electrical grids with a view to maximizing energy efficiency by modeling the optimal configuration has been proposed in [25]. The minimization of the total annualized cost and lifecycle emissions of the residential building by data-driven demand modeling is presented in [26]. In this reference, the optimal joint of the energy system with demand is modeled via a mobility model and robust approach based on electricity price. In [27] Mixed Integer Linear Programming approach is implemented to optimize the operation of the heating and cooling energy system at Parma University to improve thermal comfort using heat pumps. In Table 1, a summary of the mentioned papers in the literature is compared with this paper. Although appropriate studies are investigated in the literature on the optimal energy management of microgrids and energy grids, there are several research gaps which should be addressed as follows:

1. The aim of most studies is to meet the demand for energy systems with the minimum cost without considering DRP modeling. The proposed models are solved

Table 1 Survey of mentioned studies with this work

Ref	**Uncertainty parameter** Electricity Price	**Uncertainty approach** Interval approach	**Optimization method** Epsilon-constraint	**DRP model** Incentive
[17]	✓	X	X	X
[18]	X	X	X	X
[19]	X	X	X	X
[20]	X	X	X	X
[21]	X	X	X	X
[22]	X	X	X	X
[23]	✓	X	X	X
[24]	✓	X	X	X
[25]	X	X	X	X
[26]	✓	X	X	X
[27]	X	X	X	X
Our study	✓	✓	✓	✓

regarding the technical constraints of the system. Therefore, in these studies, there are no appropriate models to increase the flexibility of the system.

2. The incentive strategy is taken into account as the DRP for consumers in the optimal energy management in the microgrid. However, participation in the incentive strategy is not considered in the literature.

To address these gaps, this work proposed the optimal performance of electrical microgrids under severe uncertainty of power market price and under DRP through an interval-based optimization model which is not investigated in the previous works. The interval approach converts a single objective problem into a bi-objective model in which the average and deviation costs of the electrical microgrid should be minimized. To solve such a bi-objective problem, epsilon constraint and fuzzy methods are used. Also, DRP is implemented to help the electrical microgrid reduce its operation costs through the reduction of load in peak times. The DRP is implemented through incentive modeling. As a solution, incentive modeling based on the bid price to reduce electricity demand is proposed as a reserve strategy. However, innovations in this work can be highlighted as follows:

(A) An incentive strategy is considered as demand-side reserve to peak demand reduction.
(B) The interval approach is proposed to solve electricity price uncertainty.
(C) The epsilon constraint and fuzzy methods are employed to solve the bi-objective model with average and deviation costs as new functions.

2 DRP Modeling

In this section, the incentive strategy based on the power microgrid is modeled through consumer participation in energy saving. The DRP will be implemented on the condition that consumers are offered prices that allow them to control and reduce their self-consumption. The DRP mathematics is formulated as follows:

$$C_{RE} = \sum_{t=1}^{T} \psi_{RE} \times D_{RE}\,(t) \times \theta_{RE}\,(t) \quad \forall t \tag{1}$$

$$\tau_{RE}\,(t) - \kappa_{RE}\,(t) = \theta_{RE}\,(t) - \theta_{RE}\,(t-1) \quad \forall t \tag{2}$$

Equation (1) is the operating cost of DRP, and the DRP time for demand reduction is formulated by Eq. (2). The starting and ending time of DRP for each consumer at time t is modeled by Eq. (2).

3 Electricity Price Modeling

The electricity price model is proposed under conditions of uncertainty in the power market. The log-normal function is employed to model the electricity price, the uncertainty price modeling is as follows [28]:

$$G(p_E, \mu, \sigma) = \frac{1}{p_E \sigma \sqrt{2\pi}} e^{\left(-\frac{(Ln(p_E)-\mu)^2}{2\sigma^2}\right)} \tag{3}$$

where Θ, μ, and σ are the distribution function parameter, standard deviation and mean value, and respectively. The parameter of the distribution function (electricity price) is produced as a random variable according to the Monte Carlo method at bounds [$p_E{}^{\min}$, $p_E{}^{\max}$]:

$$p_E^{\min} \leq p_E\ (t) \leq p_E^{\max} \tag{4}$$

The Monte Carlo method is used for random generation of the electricity price and prevents data creation in the optimization process.

4 Objective Function

A scheme of the power microgrid is shown in Fig. 1. The generation side is the micro-turbine (MT) and the power market (PM). MTs run on fossil fuels to generate electricity. PM electricity production has various prices at any hour of the day.

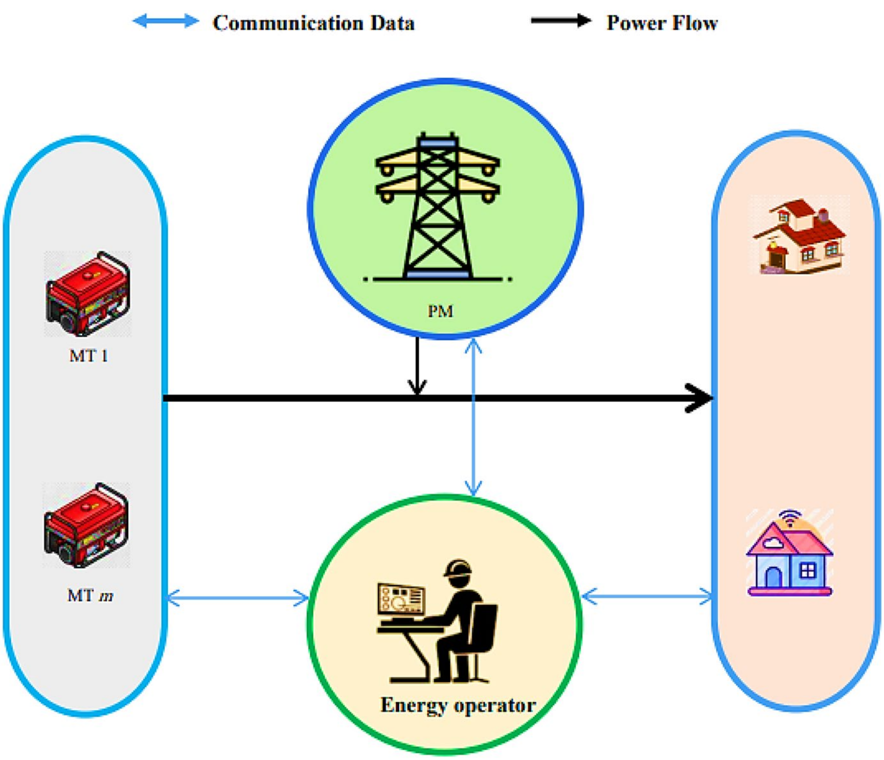


Fig. 1 Microgrid overview

The operator acts as a coordinator between the MTs and PM with the demand side through data communication in the grid. Consumers can receive an optimal share of power consumption by using the price of the offer to reduce demand and the data transmitted by the operator. Thus, the objective function is formulated in the power microgrid, provided that the fuel costs MTs, PM costs, and DRP costs are minimized by Eq. (5):

$$\begin{aligned}\min f = & \sum_{t=1}^{T}\left[\sum_{m=1}^{M}\left\{AP_m^2(t,m) + BP_m(t,m) + C\right\}\right] + \\ & \sum_{t=1}^{T}\left[P_{PM}\,(t) \times c_{PM}\,(t)\right] + \sum_{t}^{T}\left[C_{RE}\right]\end{aligned} \tag{5}$$

Here, the costs of the MTs, PM, and DRP are formulated in the objective function Eq. (5). The first, second, and third terms of the objective function Eq. (5) are the cost of MT, PM, and DRP, respectively.

4.1 Demand Supply Modeling

The energy requirement must always be covered by the generators. In these constraints, energy generation on the generation side should be equal to energy demand at each time. This constraint yields an energy supply to demand as follows:

$$\begin{aligned} & P_{PM}\,(t) + \sum_{m=1}^{M} P_m\,(t,m) = \\ & D_{eq}\,(t) - D_{RE}\,(t)\end{aligned} \tag{6}$$

4.2 DGs Capacity Constraint

The power generation by MTs has a minimum and maximum limit. Hence, limited power generation by MTs is formulated as follows:

$$P_m^{\min} \le P_m(m,t) \le P_m^{\max} \tag{7}$$

5 Modeling Uncertainty of the Objective Function

The interval modeling for solving the objective Eq. (5) with price uncertainty in the power market is formulated. In this method, the lower and upper intervals of the objective function Eq. (5) are formulated considering uncertain parameters (electricity price) [29].

$$\max f\,(x) = f^{\max}(x) \tag{8}$$

$$\min f\ (x) = f^{\min}(x) \tag{9}$$

In the following, the upper and lower of the objective function are formulated by deviation and average amounts by bi-objective function as follows:

$$f^{d}\ (x) = \frac{f^{\max}(x) + f^{\min}(x)}{2} \tag{10}$$

$$f^{a}\ (x) = \frac{f^{\max}(x) - f^{\min}(x)}{2} \tag{11}$$

Finally, the objective function should be formulated by new modeling via average and deviation amounts as follows:

$$\min \left[f^{d}\ (x), f^{d}\ (x)\right] \tag{12}$$

6 Optimization Method

The bi-objective functions are obtained by the interval method that has a conflict nature with solutions of the Pareto front. Hence, the epsilon constraints method is implemented to generate the solutions of the Pareto front of the average and deviation amounts. The epsilon constraint method can be modeled as follows [30]:

$$\min_{x \in X} f_j\ (x) \tag{13}$$

Subject to:

$$f_z\ (x) \le \varepsilon_z \quad z = 1, 2, ..., Z \quad z \ne j \tag{14}$$

where z, j, and x are objectives, main objective function, and variables, respectively.

6.1 Decision-Making Method

Since, average and deviation amounts are optimized in this study, simultaneously. The frontier solutions will be obtained. The energy operator must determine the optimal solution for objectives in the frontier solutions as a decision maker. Hence, the max–min fuzzy method is proposed for a determined optimal solution as follows [31, 32]:

$$\Gamma\left(f_z(\vartheta)\right) = \begin{cases} 0 & otherwise \\ \frac{f_z^{\max} - f_z\ (\vartheta)}{f_z^{\max} - f_z^{\min}} & f_z^{\min} \le f_z\ (\vartheta) \le f_z^{\max} \\ 1 & f_z^{\min} \ge f_z\ (\vartheta) \end{cases} \tag{15}$$

Here, $\Gamma\ (f_z\ (\vartheta))$ and $f_z(\vartheta)$ are membership functions or solutions in the *zth* objective and value of objective at ϑth frontier solutions, respectively. Also, to determine the optimal solution in frontier solutions maximum and minimum procedure is presented in Eq. (16). In Eq. (16), a high rate of minimum solution is introduced as the optimal solution.

$$\max\left\{\min\Gamma\left(f_z(\vartheta)\right)\right\} \tag{16}$$

7 Simulation and Numerical Results

Modeling the proposed microgrid based on energy management and uncertainty of the electricity price in the energy market is implemented by numerical simulation in this section. Hence, two case studies were performed to numerically simulate the power management. The cases are the following:

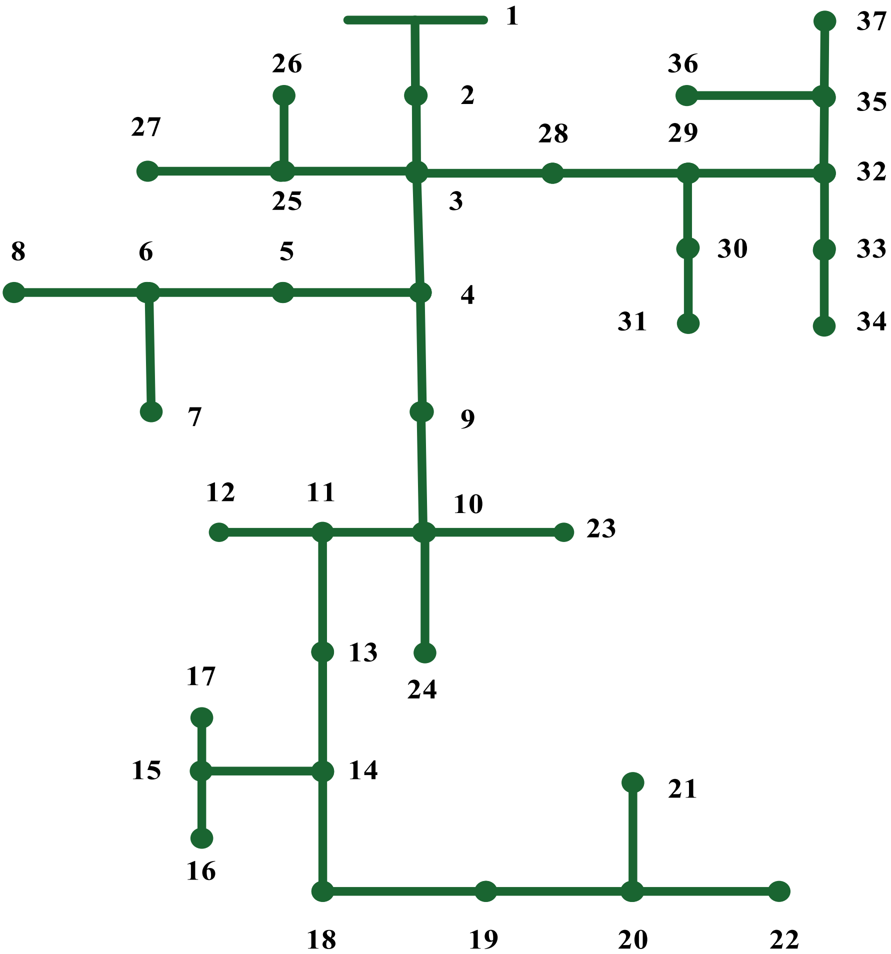


Fig. 2 Microgrid test system

- Case 1) Energy management of the microgrid without DRP.
- Case 2) Energy management of the microgrid with DRP.

The case studies considering non-participation (Case 1) and participation (Case 2) of consumers in the demand reduction approach as a reserve strategy for demand management in peak time are introduced. The 37-bus test grid as a microgrid is depicted in Fig. 2 [33]. The bid price for DRP implementation and demand curve are provided in Fig. 3 and Table 2, respectively. The MT data based on fuel costs is listed in Table 3. The price of electricity in PM considering uncertainty is shown in Fig. 4. It should be mentioned that the value of the uncertainty is considered by 15% than the expected value. In this figure, the lower, upper, and expected electricity price is considered. The DICOPT solver and MINLP program are used in GAMS software for obtaining results of the numerical simulation.

7.1 Results Analysis

The validation of the energy management in microgrids for case studies 1 and 2 is analyzed through a discussion of the results. The analysis includes the examination of power demand with and without the DRP setup, as shown in Fig. 5. It is evident that consumer involvement in the DRP strategy reduces power requirements during peak times. The DRP strategy is not limited to hours 14:00 and 15:00; instead, the maximum DRP for demand reduction is scheduled between

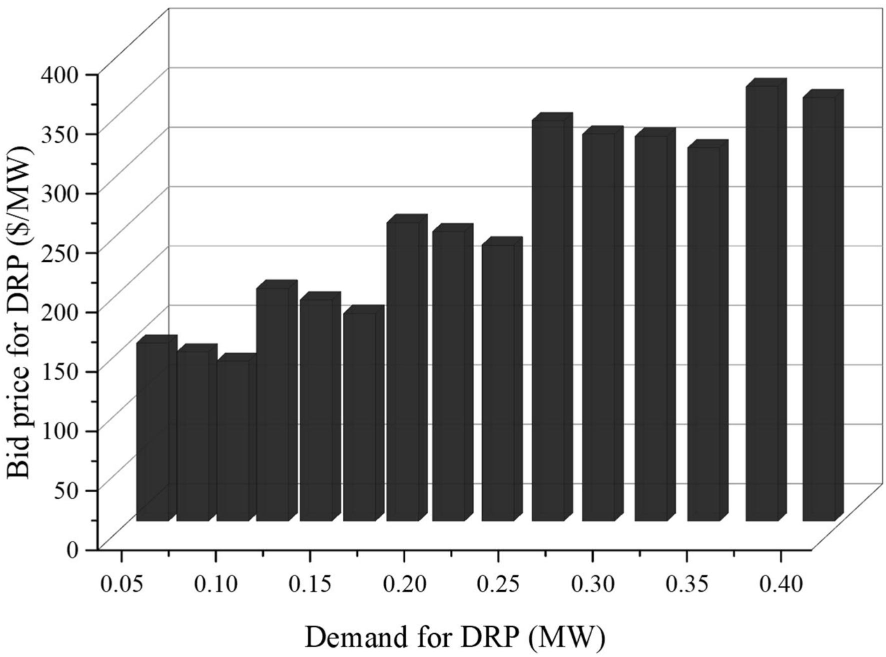


Fig.3 Offer price for DRP

Table 2 Electrical demand in microgrid

Hour	Electrical demand (MW)	Hour	Electrical demand (MW)
1	2.1	13	2.95
2	1.8	14	2
3	1.7	15	2
4	1.6	16	2.5
5	1.78	17	2.6
6	2	18	2.55
7	2.4	19	2.4
8	2.45	20	2.5
9	2.7	21	2.6
10	2.9	22	2.6
11	3	23	2.3
12	3.2	24	2.3

5:00 and 13:00. Overall, the DRP strategy successfully reduces the total power demand by 1.33 MW across all hours. This indicates that the DRP strategy is strategically scheduled during high PM prices, and the implementation cost of the DRP amounts to $386.4. Figure 6 shows the solutions of the Pareto front of average and deviation amounts for cases 1 and 2. The solutions are extracted by the epsilon constraint method and by fuzzy approach; the best solution was selected (optimal solution marked in red). In Case Study 1, the average and deviation amounts of the costs in the optimal solution are equal to $3685.3 and $153.2, respectively. The value of the optimal solution by the fuzzy method in Case 1 is 0.53. On the other side, amounts of the average and deviation with DRP in Case 2 and the optimal solution are equal to $3333.3 and $143.2, respectively. The optimal solution has a value of 0.51, which is obtained by the fuzzy method. It is visible that the amounts of the average and deviation with participation of the DRP are minimized by 9.5% and 6.5% according to Case 1, respectively. Also, the fuel costs of the MTs and PM in Case 2 are reduced by 2.6% and 3.4% in comparison with Case 1, respectively. It can be concluded that thanks to the implementation of the DRP strategy, the operation of the electricity microgrid is reliable and stable in conditions of electricity price uncertainty. Figures 7 and 8 present the power generation data for the MTs and PM in the Case studies. It is observed that the power generation by the MTs and PM in Case 2 is lower by 5.21% and 14.3%, respectively, compared to Case A. Figure 9 provides a comparison between the results of Cases 1 and 2. The implementation

Table 3 MT data

MT	A ($/MW^2)	B($/MW)	C($)	P^{min} (MW)	P^{max} (MW)
1	31.5	14.5	53.3	0	1.1
2	38.2	15.6	54.2	0	1.2
3	33.3	15.3	56.3	0	1.2

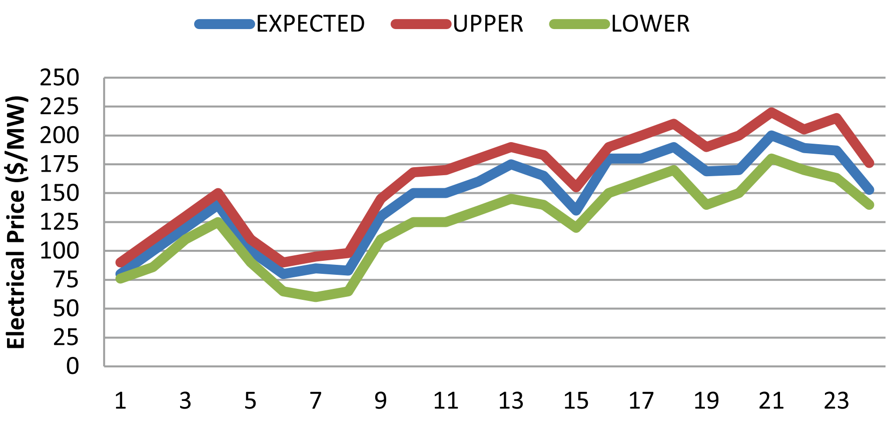


Fig. 4 Power price in PM

of the DRP in Case 2 effectively reduces deviation and average costs, demonstrating a robust approach to mitigating the impact of power price uncertainty in the energy market.

7.2 Verifying Optimization Method

In this section, the proposed optimization method is verified than the weight sum method for solving objective functions under changing uncertainty rates of the electricity prices for both case studies. Also, confirmation of the proposed optimization method than weight sum method is analyzed by the maximum spread (MS) approach. The MS approach is modeled based on the convergence metric of objective functions than each other. The MS approach is calculated as follows [34]:

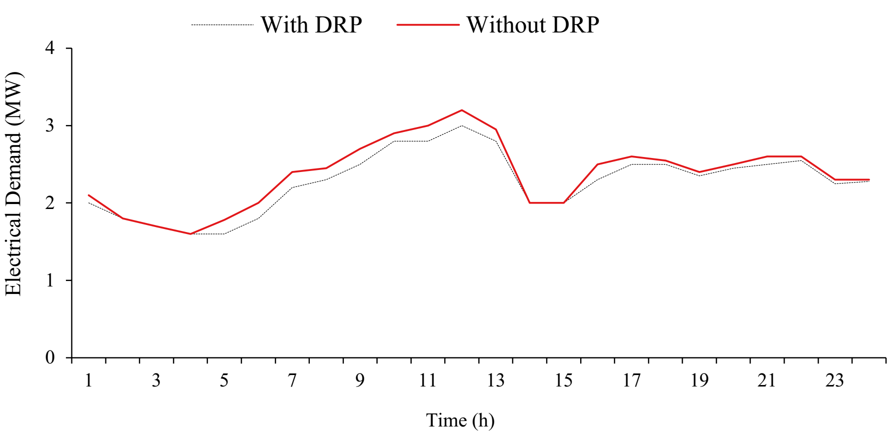
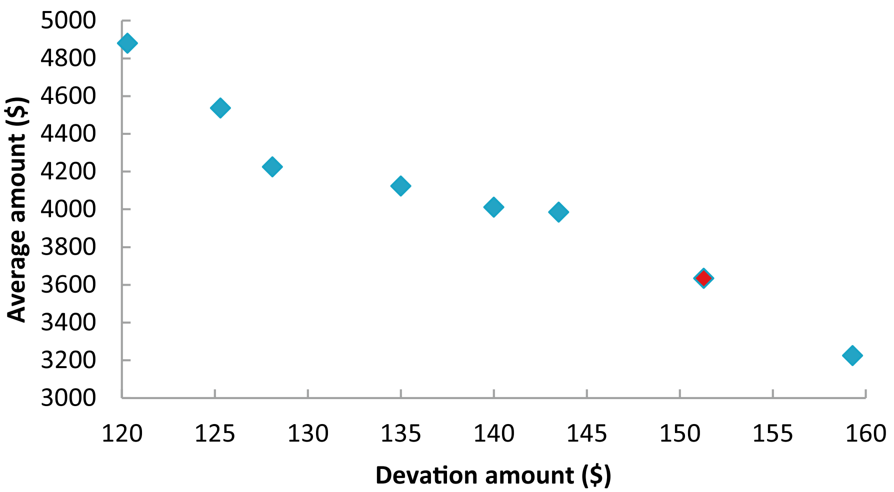
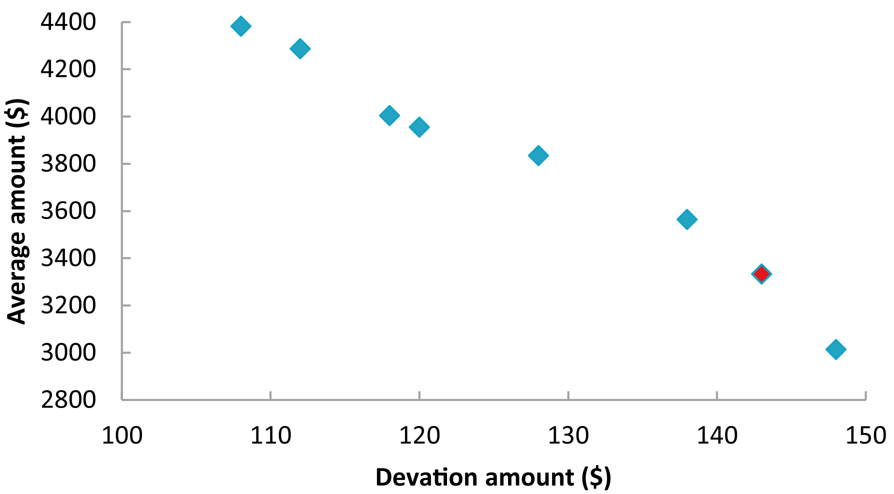


Fig. 5 Powerdemand with DRP



(a)



(b)

Fig. 6 Solutions of the Pareto front. **a** Case 1. **b** Case 2

$$MS = \sqrt{\sum_{j=1}^{n} \max\left[d\left(f_j^{\max}, f_j^{\min}\right)\right]} \tag{17}$$

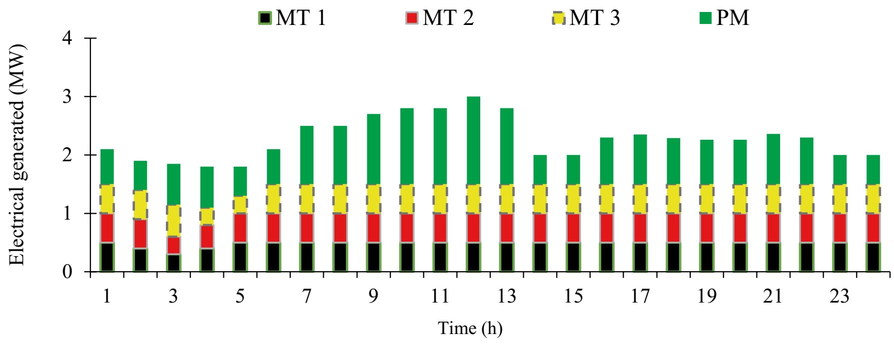


Fig. 7 Power generation in Case 1

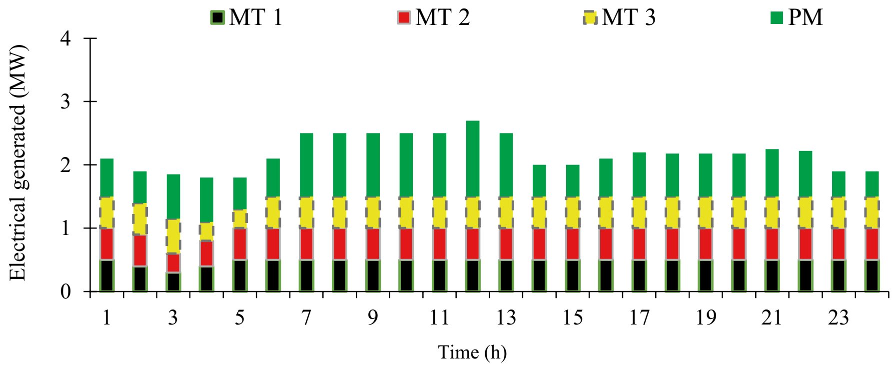


Fig. 8 Power generation in Case 2

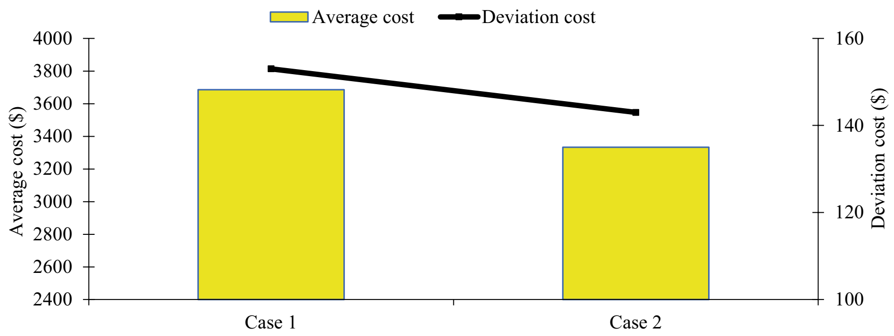


Fig. 9 Results of the Case studies

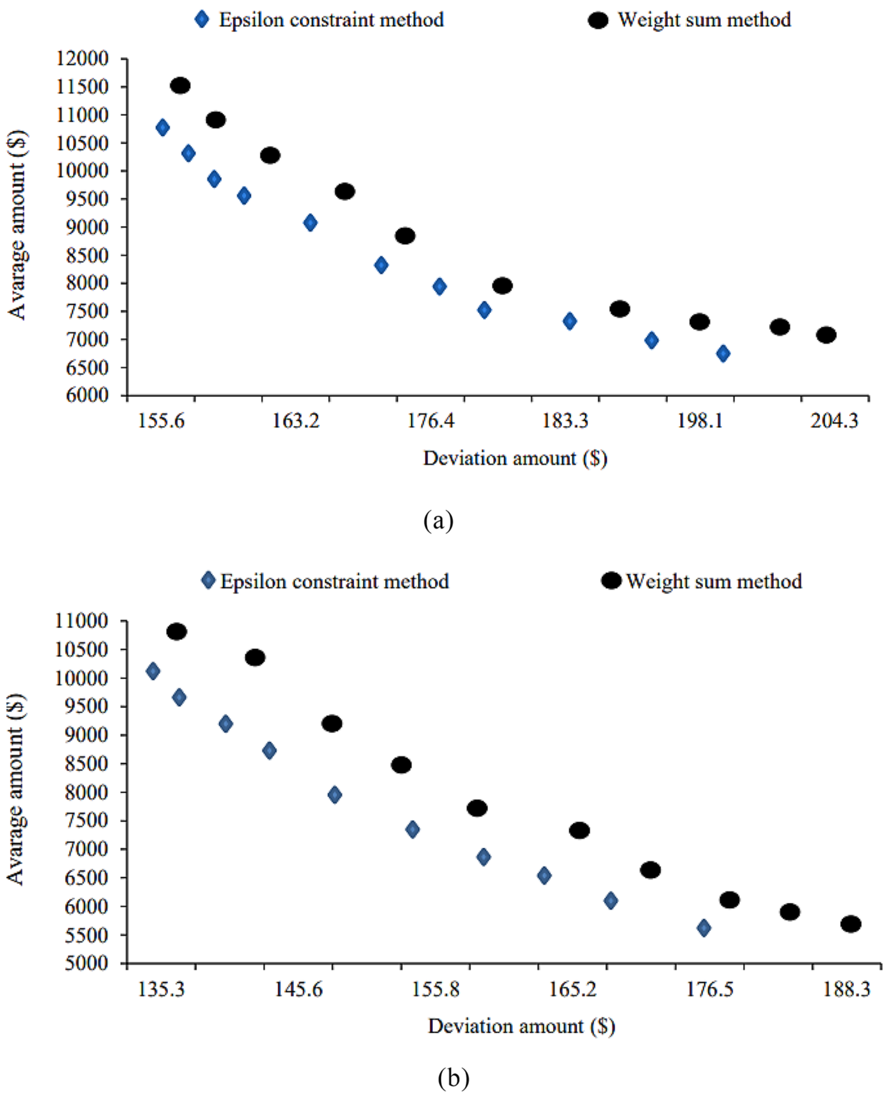


Fig. 10 Comparison of objective functions by epsilon constraint and weight sum methods. **a** Case 1. **b** Case 2

where $f_j^{\max}$ and $f_j^{\min}$, *d()* are the maximum and minimum values of the *jth* objective function and Euclidean distance, respectively. In this section, the value of the electricity price uncertainty is taken by 30% for Cases 1 and 2. Also, solving objective functions such as average and deviation costs is done by epsilon constraint and weight sum methods. It should be mentioned that the steps of the weights for the weight sum method are equal to 0.1 for each objective. Hence, ten Pareto front solutions are obtained for objectives by epsilon constraint and weight sum methods. In Fig. 10, a comparison of the objective functions by utilization of the epsilon constraint and

Table 4 MS value for objective functions

Cases	MS value			
	Methods			
	Epsilon constraint method		Weight sum method	
	Average amount ($)	Deviation amount ($)	Average amount ($)	Deviation amount ($)
Case 1	28.3	5.3	31.6	5.8
Case 2	26.8	5.1	29.3	5.4

weight sum methods for Cases 1 and 2 is shown. It is clear that the obtained Pareto front solutions by the epsilon constraint method have more optimal values than the weight sum method. In Table 4, the values of the MS approach for analyzing the convergence of epsilon constraint and weight sum methods are listed. As shown, the epsilon constraint method has more convergence than the weight sum method.

8 Conclusion

An interval modeling is employed in this paper to represent the modeling uncertainty of price-based in the microgrid. In order to account for the uncertainty of electricity prices, the deviation and average values are proposed as bi-criteria functions. Furthermore, the demand side employed the DRP strategy to effectively regulate power usage during periods of high demand. To generate Pareto frontal solutions and determine the most suitable option from these solutions, the epsilon constraints and fuzzy methods were utilized. The study includes two separate case studies that involve numerical simulations and the analysis of results obtained for optimal energy management. In Case 1, the implementation of DRP was not taken into account. Conversely, in Case 2, DRP was integrated into the energy management system. The outcomes of Case 2 demonstrate the achievement of optimal energy cost despite the uncertainties associated with electricity prices. The participation of the DRP in Case 2 leads to minimizing the average and deviation costs by 9.5% and 6.5% in comparison with Case 1.

Author Contribution All authors have equal contributions including conceptualization, methodology, software, data curation, formal analysis, writing—review and editing, and writing—original draft.

Availability of Data and Materials The data that support the findings of this study are available from the corresponding author upon reasonable request.

Declarations

Ethics Approval and Consent to Participate There are no human subjects in this manuscript and informed consent is not applicable.

Competing Interests The authors declare no competing interests.

References

1. Han L, Yu HH (2023) An empirical study from Chinese energy firms on the relationship between executive compensation and corporate performance. Nurture 17(3):378–393. https://doi.org/10.55951/nurture.v17i3.356
2. Rehan R (2022) Investigating the capital structure determinants of energy firms. Edelweiss Appl Sci Technol 6(1):1–14. https://doi.org/10.55214/25768484.v6i1.301
3. Tolmachev Y, Starodubceva SV (2022) Flow batteries with solid energy boosters. J Electrochem Sci Eng 12(4):731–766. https://doi.org/10.5599/jese.1363
4. Norouzi N, Bozorgian A (2023) Energy and exergy analysis and optimization of a pentageneration (cooling, heating, power, water and hydrogen). Iran J Chem Chem Eng. https://doi.org/10.30492/ijcce.2023.560423.5529
5. Aalami H, Moghaddam M, Yousefi G (2010) Demand response modeling considering interruptible/curtailable loads and capacity market programs. Appl Energy 87(1):243–250
6. Chamandoust H et al (2022) Optimal hybrid participation of customers in a smart micro grid based on day ahead electrical market. Artif Intell Rev 55:5891–5915. https://doi.org/10.1007/s10462-022-10154-z
7. Aikhuele D (2023) Development of a statistical reliability-based model for the estimation and optimization of a spur gear system. J Comput Cogn Eng 2(2):168–174. https://doi.org/10.47852/bonviewJCCE2202153
8. Chugo D, Muramatsu S, Yokota S, She JH, Hashimoto H (2022) Stand-up assistive devices allowing patients to perform voluntary movements within the safety movement tolerance. J Artif Intell Technol 2(4):164–173
9. Siano P (2014) Demand response and smart grids-a survey. Renew Sustain Energy Rev 30:461–478
10. Chen H, Wu H, Kan T, Zhang J, Li H (2023) Low-carbon economic dispatch of integrated energy system containing electric hydrogen production based on VMD-GRU short-term wind power prediction. Int J Electr Power Energy Syst 154:109420. https://doi.org/10.1016/j.ijepes.2023.109420
11. Qi H et al (2021) Optimisation of a smart energy hub with integration of combined heat and power, demand side response and energy storage. Energy 234:121268
12. Bakis R, Koc C, Bayazit Y, Cabuk SN (2020) Application of geographic information system to select dam location for hydropower. Int J Sustain Energy Environ Res 9(1):56–72
13. Ajam M, Mohammadiun H, Dibaee Bonab MH, Mohammadiun M (2022) Energy, exergy, and economic analyses of a combined heat and power generation system with a gas turbine and a horizontal axis wind turbine. Iran J Chem Chem Eng 41(6):2100–2120
14. Lak Kamari M, Isvand H, Alhuyi Nazari M (2020) Applications of multi-criteria decision-making (MCDM) methods in renewable energy development: a review. Renew Energy Res Appl 1(1):47–54
15. Zhang L, Sun C, Cai G, Koh LH (2023) Charging and discharging optimization strategy for electric vehicles considering elasticity demand response. eTransportation 18:100262. https://doi.org/10.1016/j.etran.2023.100262
16. Morales-España G, Martínez-Gordón R, Sijm J (2022) Classifying and modelling demand response in power systems. Energy 242:122544. https://doi.org/10.1016/j.energy.2021.122544
17. Shen L, Li Z, Sun Y (2016) Performance evaluation of conventional demand response at building-group-level under different electricity pricings. Energy Build 128:143–154. https://doi.org/10.1016/j.enbuild.2016.06.082
18. Nezhadkian M et al (2023) A model for new product development in business companies based on grounded theory approach and fuzzy method. J Comput Cogn Eng 2(2):124–132. https://doi.org/10.47852/bonviewJCCE2202260
19. Jiang J, Zhang L, Wen X, Valipour E, Nojavan S (2022) Risk-based performance of power-to-gas storage technology integrated with energy hub system regarding downside risk constrained approach. Int J Hydrogen Energy 47(93):39429–39442. https://doi.org/10.1016/j.ijhydene.2022.09.115
20. Okampo EJ, Nwulu N (2021) Techno-economic evaluation of reverse osmosis desalination system considering emission cost and demand response. Sustain Energy Technol Assess 46:101252. https://doi.org/10.1016/j.seta.2021.101252
21. Chen L, Tang H, Wu J, Li C, Wang Y (2022) A robust optimization framework for energy management of CCHP users with integrated demand response in electricity market. Int J Electr Power Energy Syst 141:108181. https://doi.org/10.1016/j.ijepes.2022.108181

22. Torriti J, Hassan MG, Leach M (2010) Demand response experience in Europe: policies, programmes and implementation. Energy 35:1575–1583. https://doi.org/10.1016/j.energy.2009.05.021
23. Nawaz A, Zhou M, Wu J, Long C (2022) A comprehensive review on energy management, demand response, and coordination schemes utilization in multi-microgrids network. Appl Energy 323:119596. https://doi.org/10.1016/j.apenergy.2022.119596
24. O′Connell N, Pinson P, Madsen H, O′Malley M (2014) Benefits and challenges of electrical demand response: a critical review. Renew Sustain Energy Rev 39:686–699. https://doi.org/10.1016/j.rser.2014.07.098
25. Mittelviefhaus M et al (2021) Optimal investment and scheduling of residential multi-energy systems including electric mobility: a cost-effective approach to climate change mitigation. Appl Energy 301:117445
26. Ghilardi LM et al (2021) Co-optimization of multi-energy system operation, district heating/cooling network and thermal comfort management for buildings. Appl Energy 302:117480
27. Gholinejad HR et al (2020) A hierarchical energy management system for multiple home energy hubs in neighborhood grids. J Build Eng 28:101028
28. Bai L, Li F, Cui H, Jiang T, Sun H, Zhu J (2016) Interval optimization based operating strategy for gas-electricity integrated energy systems considering demand response and wind uncertainty. Appl Energy 167:270–279
29. Chamandoust H et al (2020) Multi-objective operation of smart stand-alone microgrid with the optimal performance of customers to improve economic and technical indices. J Energy Storage 31:101738
30. Cao B, Dong W, Lv Z, Gu Y, Singh S, Kumar P (2020) Hybrid microgrid many-objective sizing optimization with fuzzy decision. IEEE Trans Fuzzy Syst 28(11):2702–2710. https://doi.org/10.1109/TFUZZ.2020.3026140
31. Chamandoust H et al (2021) Energy management of a smart autonomous electrical grid with a hydrogen storage system. Int J Hydrogen Energy 46(34):17608–17626
32. https://cmte.ieee.org/pes-testfeeders/resources/
33. Mirjalili S, Lewis A (2015) Novel performance metrics for robust multi-objective optimization algorithms. Swarm Evol Comput 21:1–23
34. Chamandoust H et al (2017) Optimal hybrid system design based on renewable energy resources. Proceedings of the IEEE Smart Grid Conference (SGC). https://doi.org/10.1109/SGC.2017.8308878