International Journal of Computational and Experimental Science and ENgineering
(IJCESEN)
Vol. 11-No.1 (2025) pp. 1004-1011
http://www.ijcesen.com
ISSN: 2149-9144

Research Article

Optimal Energy Management in Microgrids: A Demand Response Approach with Monte Carlo Scenario Synthesis and K-Means Clustering

K. Neelashetty[1]*, Sonali Goel[2], Farooqhusain Inamdar[3], Yeswanth Dintakurthy[4], L. N. Sastry Varanasi[5], V. B. Murali Krishna[6]

[1] Department of Electrical and Electronics Engineering, Guru Nanak Dev Engineering College, Bidar 585 403, Karnataka, India.
*** Corresponding Author Email:** neelshettyk@gmail.com – **ORCID:** 0000-0003-2822-8747

[2] Department of Electrical Engineering, ITER, Siksha 'O' Anusandhan Deemed to be University, Bhubaneswar, India.
Email: sonali19881@gmail.com – **ORCID:** 0000-0002-5085-9417

[3] Department of Mathematics, Maulana Azad National Urdu University, Hyderabad, India.
Email: farooqhusain2690@gmail.com – **ORCID:** 0000-0001-5744-1542

[4] MS from Department of Computer Science, University of North Texas, Denton, USA.
Email: yeswanthd.96@gmail.com – **ORCID:** 0009-0002-7517-4040

[5] Department of Electrical Engineering, National Institute of Technology Andhra Pradesh, Tadepalligudem 534 101, India.
Email: sastry.ramyasri@gmail.com - **ORCID:** 0000-0002-2060-7868

[6] Department of Electrical Engineering, National Institute of Technology Andhra Pradesh, Tadepalligudem 534 101, India.
Email: muralikrishna.cuk@gmail.com - **ORCID:** 0000-0003-0643-8217

Article Info:

DOI: 10.22399/ijcesen.1023
Received : 05 December 2024
Accepted : 10 February 2025

Keywords :

Renewable energy systems,
Microgrid,
Photovoltaic system,
Wind energy system,
Energy management.

Abstract:

With the increasing integration of renewable energy sources and growing energy demands, microgrids have emerged as a viable solution for enhancing sustainability, efficiency, and resilience in power systems. Effective energy management is crucial to achieving these objectives while maintaining grid stability and minimizing operational costs. This study proposes an advanced energy management strategy for microgrids based on demand response, leveraging Monte Carlo simulations and K-means clustering for scenario-based decision-making. Due to the stochastic nature of photovoltaic (PV) and wind power generation, Monte Carlo simulation is employed to generate multiple potential scenarios that capture the uncertainties associated with renewable energy production. To mitigate computational complexity, K-means clustering is applied for scenario reduction, grouping similar scenarios while preserving the dataset's representativeness. This approach effectively reduces the microgrid's operational cost from 14,033 Rs. to 13,785 Rs. without compromising system reliability. Furthermore, the proposed response mechanism actively engages consumers in adjusting their electricity consumption patterns based on real-time pricing signals and system constraints. By dynamically aligning energy demand with supply fluctuations, the microgrid effectively reduces peak loads and enhances cost-efficiency. The results demonstrate that the proposed methodology not only optimizes economic performance but also strengthens the resilience of microgrid operations in the face of renewable energy variability.

1. Introduction

Power generation from renewable energy sources (RES) heavily depends on climatic conditions, making the produced energy intermittent [1] and uncontrollable, particularly in microgrids (MGs) incorporating photovoltaic (PV) and wind turbine (WT) systems [2]. Additionally, integrating RES into MGs creates a disparity between net power demand and actual load patterns, leading to non-uniform energy distribution [3].
To address peak load demands, source-side management techniques—such as committing and

scheduling conventional (often inefficient) peaking generators [4] and utilizing battery energy storage systems (BESS)can enhance generation capacity [5]. However, these approaches contribute to increased end-user tariffs [6]. While BESS deployment improves reserve capacity and frequency stability in MGs, it also raises initial costs and electricity prices [7]. Consequently, implementing an effective energy management system is crucial for peak load shifting, demand stabilization, and optimizing energy distribution with dedicated units [8].

MGs frequently operate in coordination with the main grid, purchasing or selling electricity based on supply-demand dynamics [9]. By optimizing operational costs, MGs can minimize electricity purchases during peak hours when prices are high, leading to significant cost savings and improved profitability [10]. For MGs relying on conventional generators (such as diesel or gas), fuel costs represent a major operational expense [11]. Optimizing generator scheduling helps reduce fuel consumption and overall MG operating costs.

Demand response (DR) programs encourage consumers to adjust their energy usage in response to grid conditions or price signals. Implementing DR strategies allows MGs to shift loads away from peak periods, reducing reliance on expensive energy imports and alleviating stress on the grid infrastructure. Additionally, MGs can participate in wholesale electricity markets by selling surplus energy or providing ancillary services such as frequency regulation and voltage control. Strategic market participation enables MGs to maximize revenue from energy sales while minimizing purchase costs [12].

For MGs, particularly those involving substantial investments in renewable energy systems, storage solutions, and advanced control mechanisms, operational cost optimization is critical for ensuring a favorable return on investment (ROI). Lower operational costs lead to shorter payback periods and greater long-term savings, reinforcing the economic viability of these energy systems.

Microgrids (MGs), characterized by their ability to operate both in isolation and in conjunction with the main grid, present a promising solution for enhancing energy efficiency, reliability, and sustainability. Demand Response (DR) programs have emerged as an effective strategy for optimizing load consumption patterns by incentivizing consumers to adjust their energy usage based on price signals or grid conditions. By shifting or reducing loads during peak hours, DR helps alleviate grid stress, reduce dependence on costly peak power generation units, and increase the utilization of renewable energy sources (RES), thereby minimizing overall operational costs.

Researchers proposed an optimal scheduling and consumer incentive mechanism using K-means clustering for resource aggregation [13]. The compensation was distributed equally among all resources within a cluster. Their case study, which included 548 distributed generators (DGs) and 20,310 consumers, utilized active power (as an electrical signature) to determine centroids based on squared Euclidean distance. Resources were categorized as small if their centroid was close to 1 kW and medium if it ranged between 3 kW and 30 kW. The K-means clustering algorithm was designed to optimize intra-cluster similarity while maximizing inter-cluster differences. During clustering, consumer profiles dynamically shifted between clusters to minimize intra-cluster distances. Since K-means requires a predefined number of clusters and centroids, each data point in the dataset is assigned to its nearest cluster and remains fixed, classifying K-means as a hard-clustering method. The optimal number of clusters was determined using the elbow method.

The authors proposed a method to minimize DR costs by shifting load from peak demand hours to periods of high PV generation, thereby reducing global emissions [14]. Their approach formulated the objective function as a linear, convex optimization problem. DR events were executed in steps to systematically reduce load to baseline levels. Further, a model was developed to minimize DR incentive costs by increasing on-site power self-consumption through the deployment of distributed energy resources (DERs) [15]. A parallel-based approach was employed to reduce convergence time, ensuring robustness even as residential load participation increased. The objective function was structured to lower consumer tariffs and the costs associated with DR curtailment.

Additionally, it was introduced an optimization-based methodology for virtual power plant resource scheduling, integrating K-means clustering for resource aggregation and compensation allocation [16]. Compensation was either equally distributed among similar resource types participating in the DR program or allocated based on individual contributions.

Buildings account for nearly 40% of electricity consumption, with heating, ventilation, and air conditioning (HVAC) systems offering the highest demand flexibility among building appliances. Effective energy management requires accurate load monitoring and classification. A hybrid approach combining K-nearest neighbors (KNN) and K-means clustering was utilized to identify small DC loads from datasets, enhancing load categorization and management efficiency [17].

The signatures of current waveform are employed to train the KNN model to discover the DC load and the K-means clustering is employed for discovering whether the system is in steady state or not. Therefore, this technique overcomes the disadvantage of K-means where, it requires complete details of dataset prior. The prosumer joined in wholesale market for energy trade will get more rewards when aggregated instead as a single entity. From the literature, the resource flexibility available at both ends i.e., supply side and demand side. Those are PV, WT, loads such as HVAC and storage system like BESS [18-20]. Static pricing does not employ flexibility in resources from the demand side. Therefore, there is no decrease of peak load, no shift of peak load, no modification in carbon emissions and no decrease in consumer's tariff. The customers are unavailable at home all day to accomplish their loads in harmony with the price signals. Figure 1 indicates the components of the MG.

In the context of MG's, DR-based energy management systems (EMS) play a pivotal role in ensuring that both supply-side and demand-side resources are optimally managed. By integrating real-time data from RES generation, load demand, and market prices, EMS can dynamically adjust the dispatch of energy resources, schedule storage systems, and manage the interaction with the main grid. This paper proposes a DR-based energy management framework for MG's, focusing on reducing operational costs while ensuring reliability. The proposed approach utilizes advanced optimization techniques to align energy consumption with renewable generation, thus enhancing the economic and environmental performance of the MG.

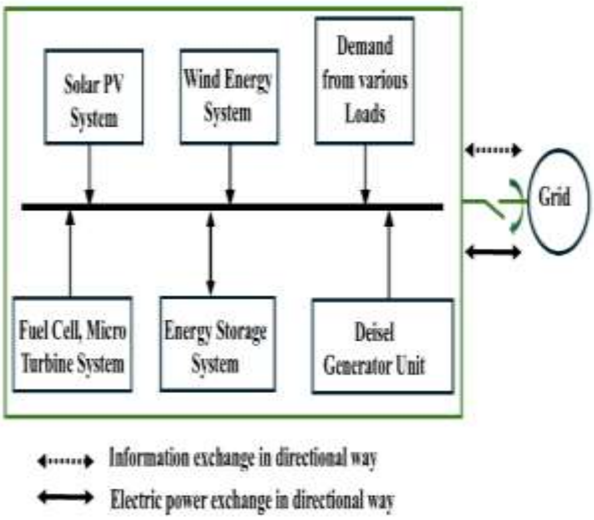

Figure 1. *Microgrid components for energy management.*

2. Modeling of Microgrid

The MG is connected to the utility grid, allowing for the exchange of energy. In this mode, the MG can import energy from the grid when local generation is deficient or export excess energy when local generation surpasses local demand. During autonomous mode, the microgrid functions self-reliantly from the main grid. This can happen intentionally, during intentional islanding, or automatically, during grid outages or faults. The microgrid depends exclusively on its local generation and storage resources to meet its demand.

2.1 Load demand

MG's load demand varies during the day because of various factors, including meteorological conditions, economic activity, and consumer behavior. The load demand might exhibit either stochastic or predictable variations based on many parameters such as seasonality, day of the week, and time of day. Probability distribution of normal distribution of load demand is specified as follows (1).

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma^2}} \quad (1)$$

A. Wind turbine

The primary objective of wind turbines is to harness the kinetic energy of the wind. The turbine's blades are designed to collect as much wind energy as feasible. Since wind power generation doesn't release greenhouse gases or other pollutants related to the burning of fossil fuels, it is regarded as a clean and renewable energy source.

$$PDF(v) = \frac{q}{c}\left(\frac{v}{c}\right)^{q-1} exp\left(-\left(\frac{v}{c}\right)^{q}\right) \quad (2)$$

$$q = \left(\frac{\delta}{\mu}\right)^{-1.086} \quad (3)$$

$$c = \frac{\mu}{\gamma\left(1+\frac{1}{h}\right)} \quad (4)$$

In (2)-(3), q is the shape parameter, c is the scale value and v is the random variable. The Weibull distribution's skewness and kurtosis are determined by its shape parameter, which also defines the distribution's characteristics. Because of this, it can effectively convey the erratic and intermittent nature of wind resources. A distribution with rising wind speed at higher values is specified when k > 1, which is suitable for locations with frequent, high-speed winds. It represents a distribution with decreasing wind speed at increasing values for $0 < k < 1$.

B. PV generation

Since the beta distribution is confined between 0 and 1, which closely matches the properties of PV output, it is frequently used to describe PV generation. The variability of solar photovoltaic (PV) generation is caused by various factors, including the weather, cloud cover, intensity of sunlight, and time of day.

C. Diesel generator

$G_{1,DA}^{t}$ are the power generation and operational cost of generator 1 respectively, T is the total number of scheduling hours, LD_{avg} is the average load demand of the system, LD_t is the load demand at time 't'. The amount of energy exchange with the grid is the difference of modified load demand after application of demand response and total generation day-ahead. Eq. (5) indicates the total day-ahead operational cost of the MG, $P_{dch,t}^{BESS}$ and $P_{ch,t}^{BESS}$ are the discharge and charge powers at time 't', a_0, a_1 and a_2 are the generator cost co-efficient.

$$OC_{G1,DA}^{t} = a_o\left(G_{1,DA}^{t}\right)^2 + a_1 G_{1,DA}^{t} + a_2 \tag{5}$$

$$LD_{avg} = \sum_{t=1}^{24} \frac{LD_t}{T} \tag{6}$$

$$SoC_{t+1}^{MG} = SoC_t^{MG} + \Delta T\left(\eta_{ch}^{BESS} P_{ch,t}^{BESS} - \frac{P_{dch,t}^{BESS}}{\eta_{dch}^{BESS}}\right) \tag{7}$$

$$SoC_{min}^{MG} \le SoC_t^{MG} \le SoC_{max}^{MG} \tag{8}$$

$$0 \le P_{ch,t}^{MG} \le X_{t,ch}^{MG} P_{ch}^{MG} \tag{9}$$

$$0 \le P_{dch,t}^{MG} \le X_{t.dch}^{MG} P_{dch}^{MG} \tag{10}$$

$$X_{t,ch}^{MG} + X_{t.dch}^{MG} \le 1 \tag{11}$$

$$V_i^{lb} \le V_i \le V_i^{ub} \tag{12}$$

$$P_{gi}^{lb} \le P_{gi} \le P_{gi}^{ub} \tag{13}$$

$$Q_{gi}^{lb} \le Q_{gi} \le Q_{gi}^{ub} \tag{14}$$

$$P_{ij}^{lb} \le P_{ij} \le P_{ij}^{ub} \tag{15}$$

$$\sum_{t=1}^{24} \sum_{i=1}^{33} P_{dg,i}^{t} - P_{l,i}^{t} + P_{RES,i}^{t} \pm P_{BESS,i}^{t} = 0 \tag{16}$$

Eq. (8), Eq. (9) and Eq. (10) indicate the limits on state of charge of the battery and state of charge in the current hour respectively. The functions of BESS in the discharging status when the output power of the RES's units is less than the discharging threshold. When considering the ESS's maximum charging and discharging power, its operational strategy is defined as follows: BESS serves as vital elements of isolated MG's that keep energy balance and voltage profiles intact. Eq. (12-16) indicates the power flow equations. Eq. (17) indicates the cost for energy exchange between the grid and the MG. Eq. (18) indicates the total cost of the MG.

$$CE_{Exch}^{t} = E_{Exch}^{t} * EP_{Grid}^{t} \tag{17}$$

$$TC = C_{DS}^{t} \pm CE_{Exch}^{t} \tag{18}$$

3. Proposed Methodology

These sections describe the proposed methodology with supporting flowcharts and explanation of the same. The following points explain the proposed methodology step-by-step. The limitations of the coefficients and cost limitations are given in Table 1.

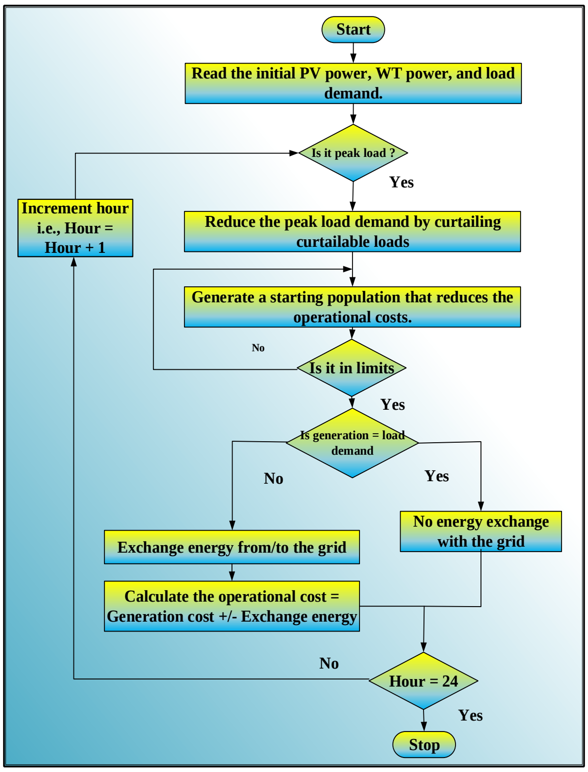

Figure 2. *Proposed methodology of energy management.*

- Collect necessary details such as previous patterns in energy consumption, meteorological data for estimates of PV and wind power generation, electricity costs, and operational limitations.
- Examine the data collected to identify trends, patterns, and unknowns related to the production and use of energy.
- To create scenarios for unpredictable features, such forecasts for PV and wind power generation, use Monte Carlo simulation.
- To generate a variety of scenarios that represent various potential outcomes for the generation of renewable energy, sample from probability distributions.
- Utilize K-means clustering to combine related scenarios according to their shared attributes, such the amount of wind and solar power generated as shown in Figure 2.

- To mitigate the computational burden while maintaining the diversity of scenarios, choose hypothetical situations from each cluster.
- Create a first population of candidate solutions that reflect various energy resource configurations, demand response strategies, and storage utilization.
- To find the day-ahead operational cost for any potential solution, use the cost valuation function.
- Consider how variables, including fluctuations in the production of renewable energy and the efficiency of demand response, may affect operating costs.

Table 1. *Coefficients and cost limitations.*

Type	Gr. parameters				
	Lower limit	***Upper limit***	a_0	a_2	a_1
Gr. 1	0	150	0.01	2	10
Gr. 2	0	120	0.02	3	8
Gr. 3	0	100	0.015	1	12
Wind	0	270	-	-	-
PV	0	250	-	-	-

4. Results and Discussions:

The test system consists of IEEE-33 bus system with 3 diesel generators, one PV and one WT. The maximum peak load on the system is 830.3 kW and the minimum load demand on the system is 144.4 kW. Table I. indicates the cost co-efficient and limits on generation. Figure 3 collectively prove the process and significance of scenario generation and reduction in EMS. In such systems, managing the inherent uncertainty in the power generation from RES's and load demand is critical for cost-effective and reliable operation. Initially, the system produces many highly variable scenarios, reflecting the unpredictability in renewable energy generation and demand. However, as scenario reduction techniques are applied, the complexity is diminished, and clearer, more manageable patterns emerge.

This reduction in complexity is vital for day-ahead and real-time energy management strategies, as it permits grid operators and decision-makers to propose a range of potential outcomes while evading overwhelming computational demands. By dropping the number of scenarios without forfeiting critical information, energy systems can better integrate RES's, optimize costs, and ensure grid stability, even in the face of uncertainty. Figure 4 indicates the load demand before the application of DR program and Figure 5 specifies the load demand after the application of DR. Figure 6 indicates the power generation from PV and wind turbine for 24-hour scheduling.

Figure 7 indicates the dispatch schedule of the diesel generators. From Figure 7, the power generation from generator 3 is less when compared with the other generator set. Since the incremental fuel cost of this generator is the highest. Figure 8 represents the total operational cost after application of DR over a 24-hour period.

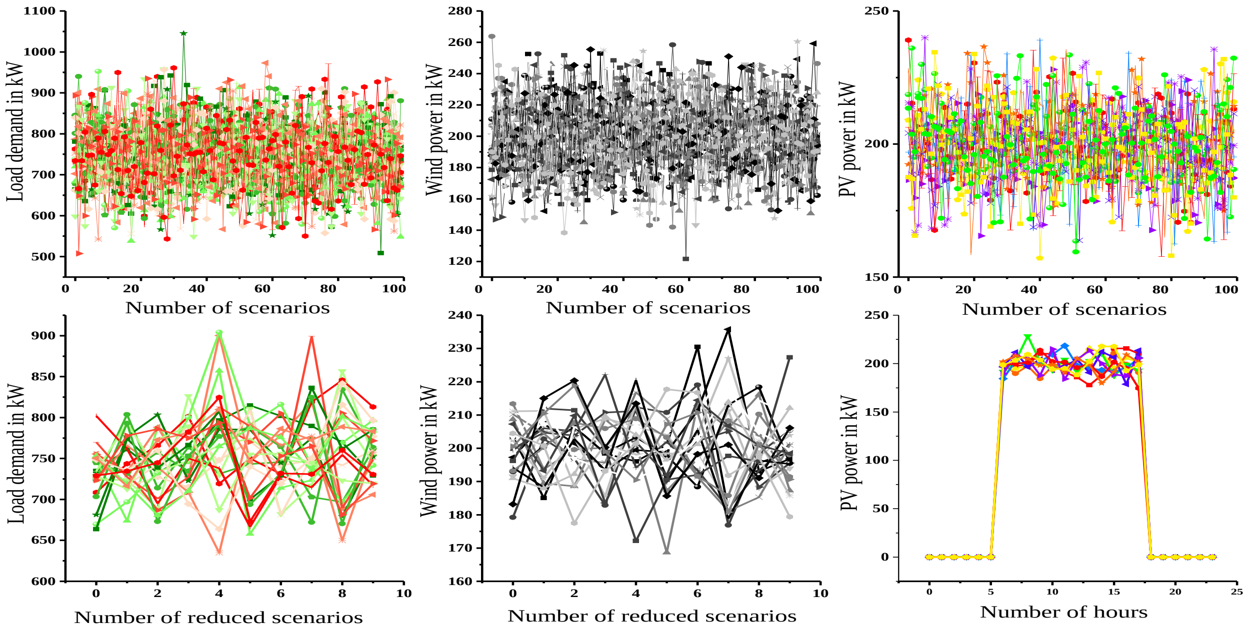

Figure 3. *Scenario generation and reduction using MCS and K-means clustering respectively.*

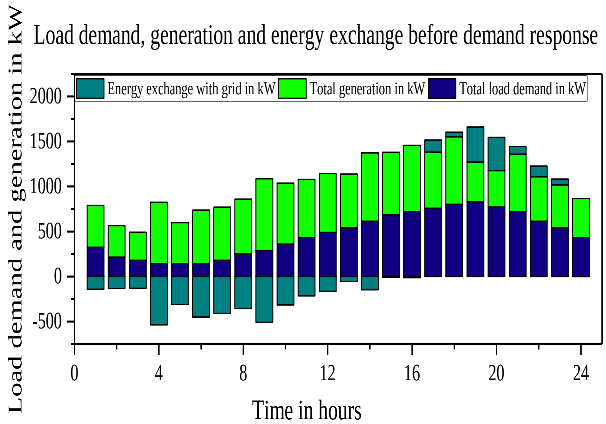

Figure 4. *Load demand before application of demand response program.*

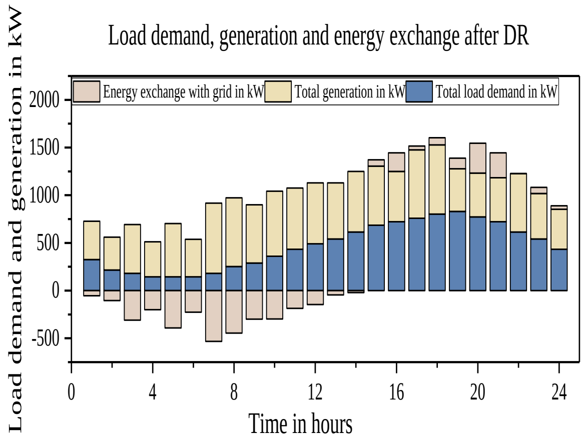

Figure 5. *Load demand after application of demand response program.*

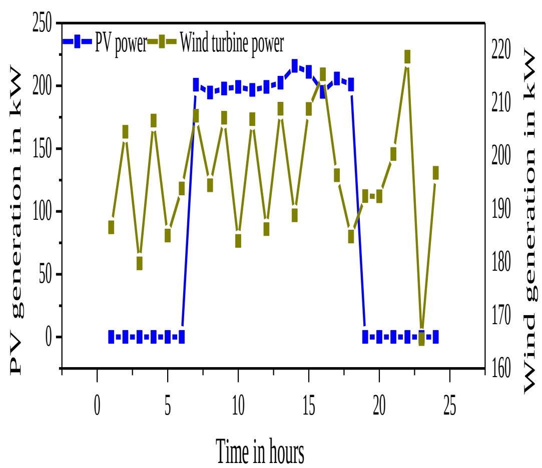

Figure 6. *Power generation by uncertain sources.*

The operational cost replicates the cost associated with running generator units and managing internal power systems within the MG. The energy exchange cost shows the cost associated with importing or exporting power from/to the grid, which is inclined by market conditions, grid tariffs, and energy demand. During the initial hours (0-5 hours), the total cost is negative, representing a period of net

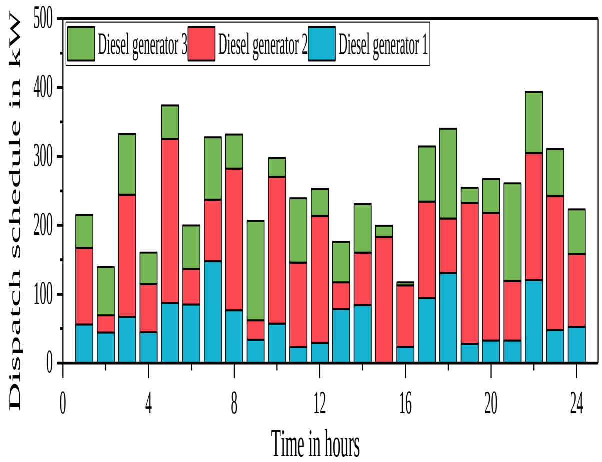

Figure 7. *Dispatch schedule of controllable sources.*

savings or profit, likely due to power being pumped to the grid. This scenario is imitated by negative operational and energy exchange costs. The MG is generating excess renewable energy, which is sold back to the grid, leading to a reduction in costs. Between hours 5 and 15, the operational cost remains relatively stable, while the energy exchange cost varies. This period might reflect a balance between grid imports and internal power generation, with limited cost variation. After hour 15, both the operational cost and energy exchange cost increased significantly, peaking at around hour 20. This increase could be due to higher energy demand, reduced availability of renewable energy, or reliance on more expensive energy imports from the grid.

The varying costs suggest that the DR mechanism has been employed to minimize operational costs during peak demand periods. The DR shifts load to lower-cost periods, reflected in the stable cost periods around 10-15 hours. Nevertheless, during certain periods, especially post-hour 15, the DR strategy might be less effective due to higher grid dependency or reduced renewable generation, leading to higher operational and energy exchange costs.

The overall trend reveals that integrating DR mechanisms can effectively reduce costs during specific time periods (0-10 hours). However, the system encounters challenges in upholding low costs when renewable energy is scarce, and grid dependency increases during peak hours (15-23 hours). The graph suggests a well-balanced EMS for an important portion of the day, though potential improvements could be made to further decrease costs during high-demand periods, possibly by enhancing storage systems or enhancing the responsiveness to real-time market prices.

Figure 9 indicates the total cost and the cost of energy exchange between the grid and the MG.

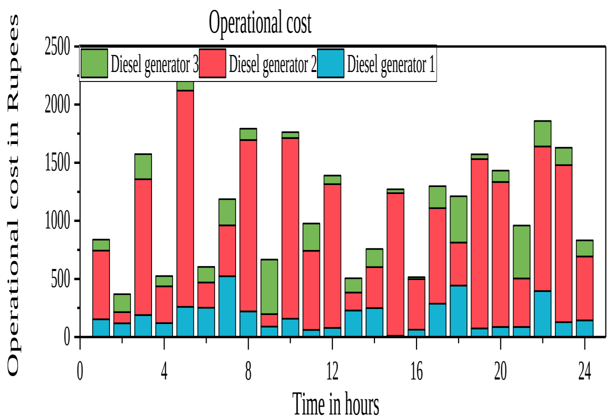

Figure 8. *Total operational cost of controllable sources.*

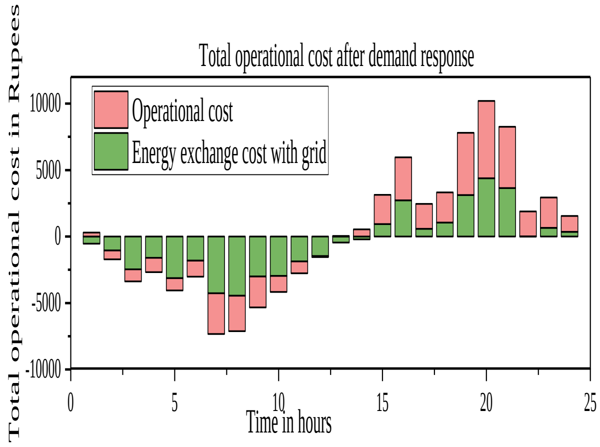

Figure 9. *Total cost i.e., sum of energy exchange and total operational cost.*

Table 2. *Comparison of proposed study*

Parameter	**Ref [6]**	**Proposed**
Total operational cost	12122	12016
Total cost	14033	13785

Table 2 indicates the comparison of proposed methodology with the available methodology interms of total operational cost and total cost in the MG. Similar works has been done and reported in the literature [21-24].

4. Conclusion

This study explored the application of demand response (DR) techniques in a microgrid (MG) environment to reduce operational expenses, particularly in the presence of intermittent renewable energy sources such as wind and solar power. By integrating Monte Carlo simulation with K-means clustering, we addressed the challenges posed by the fluctuating and unpredictable nature of these renewable resources. Our findings demonstrate that demand response, when combined with advanced scenario generation and reduction techniques, significantly enhances the sustainability and economic feasibility of MG operations. The total operational cost was reduced by 0.88%, while the overall MG cost decreased by 1.79% compared to existing literature. By dynamically adjusting energy consumption in response to variations in renewable generation, MG operators can effectively mitigate uncertainty and reduce dependence on costly conventional energy sources. Monte Carlo simulation enabled the generation of diverse scenarios that captured the inherent variability of solar and wind power generation. The subsequent application of K-means clustering facilitated the identification of representative scenario clusters, reducing computational complexity without sacrificing accuracy. This approach provides a robust framework for optimizing MG operations, improving cost efficiency, and enhancing grid reliability.

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
- **Conflict of interest:** The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper
- **Acknowledgement:** The authors declare that they have nobody or no-company to acknowledge.
- **Author contributions:** The authors declare that they have equal right on this paper.
- **Funding information:** The authors declare that there is no funding to be acknowledged.
- **Data availability statement:** The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

References

[1]. Zhang, Y., & Su, Y. (2024). Towards a Sustainable Future: Exploring Innovative Financing Models for Renewable Energy. *MEDAAD*, 34-40. DOI: 10.70470/MEDAAD/2024/006

[2]. Rao, C. U. M., Babu, A. S., Krishna, B. M., & Sudheer, P. (2019). Performance Validation of PV Cell Configurations. *Journal of Advanced Research in Dynamical and Control Systems*, *11*(6), 1943023X. DOI:

[3]. Pagidela, Y., & Visali, N. (2024). A Short review on Optimal Allocation of Microgrid. *Journal of Modern Technology*, 132-140.

[4]. G. V. Mrudul, Rohit. G, Harshavardhan. G, Dhanush. K, & Anudeep. B. (2024). Efficient Energy

Management: Practical Tips for Household Electricity Conservation. *Journal of Modern Technology*, *1*(1), `1~8.

[5]. Uddin, M., Romlie, M. F., Abdullah, M. F., Abd Halim, S., & Kwang, T. C. (2018). A review on peak load shaving strategies. *Renewable and Sustainable Energy Reviews*, *82*, 3323-3332. DOI: https://doi.org/10.1016/j.rser.2017.10.056.

[6]. Conejo, A. J., Morales, J. M., & Baringo, L. (2010). Real-time demand response model. *IEEE Transactions on Smart Grid*, *1*(3), 236-242. DOI: 10.1109/TSG.2010.2078843

[7]. Pourmousavi, S. A., & Nehrir, M. H. (2014). Introducing dynamic demand response in the LFC model. *IEEE Transactions on Power Systems*, *29*(4), 1562-1572. DOI: 10.1109/TPWRS.2013.2296696

[8]. Medina, J., Muller, N., & Roytelman, I. (2010). Demand response and distribution grid operations: Opportunities and challenges. *IEEE Transactions on Smart Grid*, *1*(2), 193-198. DOI: 10.1109/TSG.2010.2050156

[9]. Parvania, M., & Fotuhi-Firuzabad, M. (2010). Demand response scheduling by stochastic SCUC. *IEEE Transactions on smart grid*, *1*(1), 89-98. DOI: 10.1109/TSG.2010.2046430

[10]. Deng, R., Yang, Z., Chow, M. Y., & Chen, J. (2015). A survey on demand response in smart grids: Mathematical models and approaches. *IEEE Transactions on Industrial Informatics*, *11*(3), 570-582. DOI: 10.1109/TII.2015.2414719

[11]. Bakare, M. S., Abdulkarim, A., Zeeshan, M., & Shuaibu, A. N. (2023). A comprehensive overview on demand side energy management towards smart grids: challenges, solutions, and future direction. *Energy Informatics*, *6*(1), 4. DOI: https://doi.org/10.1186/s42162-023-00262-7

[12]. Mathieu, J. L., Price, P. N., Kiliccote, S., & Piette, M. A. (2011). Quantifying changes in building electricity use, with application to demand response. *IEEE Transactions on Smart Grid*, *2*(3), 507-518. DOI: 10.1109/TSG.2011.2145010

[13]. Abrishambaf, O., Faria, P., & Vale, Z. (2020). Ramping of demand response event with deploying distinct programs by an aggregator. *Energies*, *13*(6), 1389. DOI: https://doi.org/10.3390/en13061389

[14]. Lezama, Fernando, Ricardo Faia, Pedro Faria, and Zita Vale. "Demand response of residential houses equipped with PV-battery systems: An application study using evolutionary algorithms." *Energies* 13, no. 10 (2020): 2466. DOI: https://doi.org/10.3390/en13102466

[15]. Faria, P., Spínola, J., & Vale, Z. (2018). Distributed Energy Resources Scheduling and Aggregation in the Context of Demand Response Programs. *Energies*, *11*(8), 1987. https://doi.org/10.3390/en11081987

[16]. Y. T. Quek, W. L. Woo and T. Logenthiran. (2016) "DC equipment identification using K-means clustering and kNN classification techniques," *2016 IEEE Region 10 Conference (TENCON)*, Singapore, 2016: 777-780. DOI: 10.1109/TENCON.2016.7848109.

[17]. Chen, Y., Xu, P., Gu, J., Schmidt, F., & Li, W. (2018). Measures to improve energy demand flexibility in buildings for demand response (DR): A review. *Energy and buildings*, *177*, 125-139. DOI: https://doi.org/10.1016/j.enbuild.2018.08.003

[18]. Sheela, M. S., Gopalakrishnan, S., Begum, I. P., Hephzipah, J. J., Gopianand, M., & Harika, D. (2024). Enhancing Energy Efficiency With Smart Building Energy Management System Using Machine Learning and IOT. *Babylonian Journal of Machine Learning*, *2024*, 80-88. DOI: https://doi.org/10.58496/BJML/2024/008

[19]. Goel, S., Jena, B., & Sharma, R. (2024). A Case Study on Optimal Tilt Angle and Spacing for Rooftop Solar Photovoltaic System at Bhubaneswar. *Journal of Modern Technology*, *1*(2), 121-131.

[20]. Yan, X., Ozturk, Y., Hu, Z., & Song, Y. (2018). A review on price-driven residential demand response. *Renewable and Sustainable Energy Reviews*, *96*, 411-419. DOI: https://doi.org/10.1016/j.rser.2018.08.003

[21]. S, D., C, venkatesh, M, M., S.Archana Devi, & T, J. (2024). Optimal Speed Control of Hybrid Stepper Motors through Integrating PID Tuning with LFD-NM Algorithm. *International Journal of Computational and Experimental Science and Engineering*, 10(4). https://doi.org/10.22399/ijcesen.489

[22]. Çağlan, A., & Dirican, B. (2024). Evaluation of Dosimetric and Radiobiological Parameters for Different TPS Dose Calculation Algorithms and Plans for Lung Cancer Radiotherapy. *International Journal of Computational and Experimental Science and Engineering*, 10(2). https://doi.org/10.22399/ijcesen.335

[23]. Machireddy, C., & Chella, S. (2024). Reconfigurable Acceleration of Neural Networks: A Comprehensive Study of FPGA-based Systems. *International Journal of Computational and Experimental Science and Engineering*, 10(4). https://doi.org/10.22399/ijcesen.559

[24]. Radhi, M., & Tahseen, I. (2024). An Enhancement for Wireless Body Area Network Using Adaptive Algorithms. *International Journal of Computational and Experimental Science and Engineering*, 10(3). https://doi.org/10.22399/ijcesen.409