Networked Hybrid AC-DC Microgrids: Leveraging Fog Computing and Linear Solver for Efficient Energy Management

Vikas Ranveer Singh Mahala[1,3], Anshul Yadav[2], D. Saxena[1], Rajesh Kumar[1]
[1]Department of Electrical Engineering, Malaviya National Institute of Technology, Jaipur, India.
[2]Central Electronics Engineering Research Institute, Council of Scientific & Industrial Research, Pilani, India.
[3]Department of Electrical Engineering, Swami Keshvanand Institute of Technology, Management & Gramothan, Jaipur, India.

***Abstract*—The global electricity landscape is undergoing a profound transformation, with an increasing demand for resilient and sustainable energy infrastructure. In this context, microgrids (MGs) have emerged as a promising solution, offering localized, decentralized energy generation and distribution. This research paper proposes a distributed energy management system for grid-connected hybrid AC-DC MGs, interconnected through a DC link. The work proposes a three-layer cloud fog-enabled energy management system of networked MGs which aims to minimize the energy cost by facilitating optimal energy utilization within each MG as well as among the connected MGs. The paper presents a fog-enabled comprehensive mathematical model of networked MGs to ensure fast data transmission and real-time decision-making within the system. K-mean clustering is used to segregate the load into three categories residential, commercial, and industrial each of which is primarily supplied by an individual MG. Python 3.10.12 programming has been employed for simulating the model, ensuring a realistic and adaptable approach to assess the suggested energy management system's efficacy and performance within the context of networked MGs. Simulation results demonstrate that the proposed model of networked MGs integrating fog computing and MILP optimization, enhances optimal energy allocation and utilization within and among MGs along with minimizing the operating cost of networked MGs effectively.**

***Index Terms*—Networked Hybrid Microgrid, Energy Management, Fog Computing, MILP.**

I. Introduction

The global electricity landscape is witnessing a massive transformation pushed through increasing strength call for, issues over weather alternate, and the preference for a more sustainable and resilient electricity infrastructure. In this context, microgrids (MGs) have emerged as a promising technique to address those demanding situations by way of enabling localized, decentralized strength technology, distribution and intake [1] . Moreover, the concept of networked MGs [2], included with modern technology like fog computing and machine learning techniques, has garnered good sized attention as a method to decorate the overall performance and effectiveness of power control within those small-scale energy structures.

MGs offer a number of benefits to various sectors, along with residential groups, commercial complexes, and isolated locations. They constitute a paradigm change from traditional centralised electricity grids. Distributed energy resources (DERs), such as solar photovoltaics (PV), wind turbines, batteries, and small scale generators, are a part of a MG [3], [4]. By effectively integrating these diverse energy sources, microgrids can function both connected to and disconnected from the main utility grid, providing improved energy resilience, reducing transmission losses, and facilitating the integration of renewable energy [5].

The concept of networked MGs takes the advantages of standalone MGs a step further by interconnecting multiple MG systems. Through this interconnected approach, excess energy generated in one MG can be shared and utilized by others, enabling a more efficient utilization of resources and improved overall grid stability [2], [6]. Additionally, networked MGs enable collaboration among neighboring communities and institutions, fostering a sense of energy self-sufficiency and mutual support.

To optimize the energy management within networked MGs, fog computing techniques have emerged as a transformative technology [7]. Fog computing, an expansion of edge computing, disperses computing resources and data processing capacities, moving them in proximity to the network edge where data originates. By reducing latency and bandwidth requirements, fog computing enables real-time data analysis and decision-making, critical for the dynamic and distributed nature of MG operations. Fog computing enables networked MGs to collect data from numerous interconnected components such as smart metres, sensors, and energy storage devices. This data may then be analysed in real time to alter energy distribution, forecast demand patterns, and respond effectively to fluctuations in renewable energy output [8] - [10]. The use of fog computing in networked MGs supports energy managers to make informed decisions more quickly, resulting in enhanced energy efficiency, cost savings, and grid stability [6], [11].

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Addressing the intricate challenge of optimizing energy allocation and utilization within networked MGs requires advanced optimization techniques. One such powerful approach is the Mixed-Integer Linear Programming (MILP) solver, which plays a pivotal role in enhancing energy management efficiency [12] - [14]. MILP formulates the energy management problem as a linear optimization model, considering various constraints and discrete decision variables, such as energy storage and load allocation. By leveraging MILP, energy managers can efficiently allocate resources, plan energy schedules, and ensure the optimal operation of the entire networked MG system. This mathematical framework enables them to make informed decisions on which MG to draw power from for a particular MG and determine the appropriate amount to meet demand while minimizing costs. By using MILP, energy managers can strike an optimal balance between energy generation, consumption, and storage, thus maximizing the overall efficiency and sustainability of networked MGs [15].

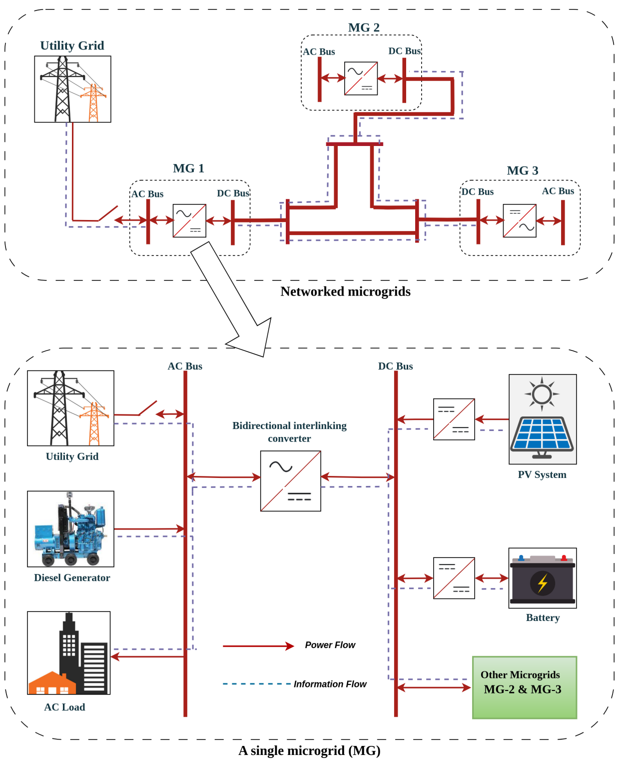

Fig. 1: The framework of networked hybrid AC-DC microgrids.

Several studies have investigated the benefits and challenges of networked MGs in enhancing energy management and grid stability. Researchers have demonstrated the advantages of interconnected MG systems in sharing excess energy and optimizing resource utilization, leading to improved overall efficiency and sustainability [16] - [19]. Additionally, fog computing has garnered significant attention for its role in decentralizing data processing and enabling real-time analysis at the boundary of the network. Studies have highlighted the potential of fog computing in enhancing the performance of MG operations by reducing latency, enabling faster decision-making, and facilitating efficient energy distribution. Moreover, some researchers have explored the integration of machine learning techniques with fog computing to optimize MG operations, predict energy demand patterns, and enhance load forecasting accuracy [20] - [22]. These combined approaches have shown promise in achieving higher energy efficiency, better demand response, and improved grid management. However, despite the growing interest in both networked MGs and fog computing, it is evident that there is still a dearth of research specifically focused on the integration of these two technologies. Not much work has been done in the area of networked MGs with fog computing model, which represents a crucial research gap. Further investigation and empirical studies are needed to explore the potential synergies, challenges, and practical implementation of this integrated model to realize its full benefits in the realm of sustainable and resilient energy systems.

This research introduces a novel distributed energy management system for grid-connected hybrid AC-DC MGs, which are interconnected through a DC link. The main objective of this study is to enhance energy efficiency and cost-effectiveness by integrating fog computing and MILP optimization techniques. The key contributions of this paper are as follows:

- Three-layer cloud-fog computing: The adoption of a three-layer cloud-fog computing system ensures rapid data transmission within the networked MG system, facilitating real-time analysis and decision-making for efficient energy management.
- MILP optimization: To reduce costs and optimise the use of energy resources, the study proposes MILP optimization strategies inside individual MGs and between MGs . This improves overall energy efficiency.
- K-mean clustering for load segregation: By utilizing K-mean clustering, the load data is effectively segregated into the three networked MG as residential, commercial and industrial MGs, allowing for tailored energy management strategies based on customer types.
- Mathematical model development: A mathematical model of the grid-connected networked MGs is presented, offering a solid framework for understanding and optimizing the energy management system.

The subsequent sections of the paper are structured as follows. Section II presents the framework of Networked hybrid AC-DC MGs components, along with the mathematical modeling. In Section III, we propose the fog-enabled optimization model for the networked hybrid MG. Subsequently, Section IV provides simulation results and in-depth discussions. Finally, Section V concludes this paper, summarizing the key findings and contributions of our research on efficient energy management in grid-connected hybrid AC-DC MGs through the integration of fog computing and optimization techniques.

II. Networked hybrid AC-DC microgrid

Networked hybrid AC-DC MG is a sophisticated energy system that connects multiple MG systems through DC communication. This design provides energy sharing and seamless operation between different MGs, resulting in resource efficiency and grid stability. The hybrid nature of the system, integrating both alternating current (AC) and direct current (DC) technologies, enhances flexibility and accommodates diverse energy sources, including renewable and energy storage devices.

As illustrated in Fig. 1, the configuration of the envisaged networked hybrid AC-DC MGs is presented. Each discrete hybrid AC-DC MG is comprised of diverse energy sources and loads, meticulously linked to AC and DC sub-grids. Within the AC sub-grid, a shared AC bus connects diesel generators (DGs) and AC loads, whereas the DC sub-grid interconnects photovoltaics (PV), energy storage systems (Battery), and the DC link for other MG to a communal DC bus. Bidirectional interlinking converters (BICs) facilitate the seamless connection between the AC and DC sub-grids. Moreover, the AC bus is linked to the utility grid (UG) to offer backup power and facilitate surplus energy exchange. Through the interconnection of multiple MGs via a DC network at their individual DC buses, a comprehensive networked MG system is established. The DC network's flexibility allows for modifications based on the interconnection relationships of multiple MGs, making it adaptable for large-scale system applications. The proposed networked MG system employs two-way communication links to ensure effective and efficient energy operations among its interconnected components. Energy exchange between neighboring entities within the community MG is facilitated through BIC's. Smart meters at both ends of power lines monitor energy consumption, generation, and distribution throughout the network, including the main grid. The MG energy management system, operating in individual fog layers, oversees energy operations within each MG, while a central energy management system in the cloud coordinates the excess and shortage of power information from all MGs. Acting as prosumers in the energy trading process, MGs can buy or sell energy based on their power surplus or deficit. In case of insufficient local power generation, MGs can purchase power from other MGs within the community, and if needed, from the main grid. The MILP method is employed to optimize the net available power of each MG, ensuring efficient energy utilization and seamless grid operations.

The proposed architecture of the networked hybrid AC-DC MG is driven by several compelling reasons. Firstly, hybrid AC/DC MGs capitalize on the inherent benefits of both AC and DC MGs, streamlining the integration of diverse energy sources and loads by reducing multiple power conversion stages. Additionally, these hybrid systems are seamlessly compatible with the conventional utility grid [23] - [25]. Secondly, the inclusion of a DC network in the MG facilitates easier power merging and simplifies system analysis, eliminating concerns related to reactive power sharing and frequency synchronization that are common in traditional AC-based networks [26]. Overall, the development of this architecture represents a significant step towards enhancing energy efficiency and grid stability in modern MG applications.

III. Proposed Fog-enabled optimization model

Fig. 2 depicts the architecture of the proposed fog-enabled optimisation model, which seeks to improve energy management inside the networked MG system by leveraging advanced fog computing and MILP optimisation techniques. This section presents the key components of the model, as follows:

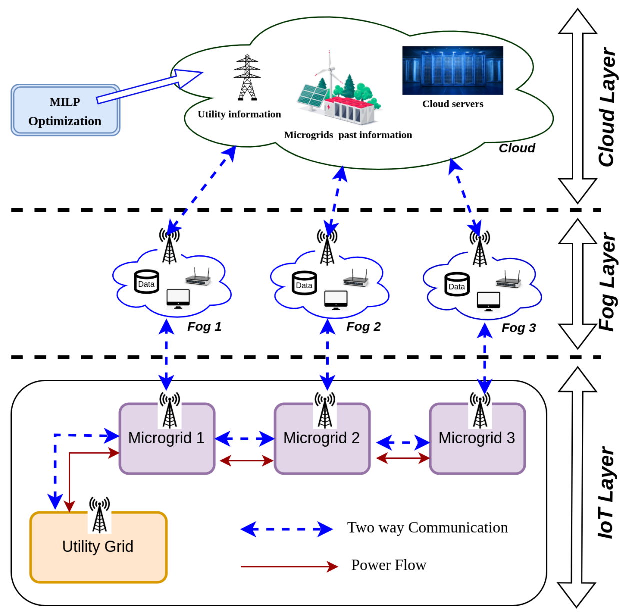

Fig. 2: Proposed three-layer cloud-fog model.

A. Three-layer Cloud-Fog Computing

The proposed fog-enabled optimization model encompasses a three-layered architecture, each playing a pivotal role in revolutionizing energy management within the networked MG system. At the topmost layer is the cloud layer, representing an extensive storage space with substantial computational capabilities. It provides various services to consumers, categorized into Infrastructure as a Service (IaaS), Platform as a Service (PaaS), and Software as a Service (SaaS) [27]. The cloud layer acts as the central hub, connecting service providers, utilities and past MG information. Data summaries from the fog layer are stored in the cloud's significant storage for long-term records. Additionally, the cloud layer regulates policies and executes punitive measures for malicious units.

Crucially, it is within the cloud layer that the optimization (MILP) algorithm is implemented.

The fog layer acts as an intermediary between the cloud and consumer layers, reducing communication delays and bringing services in close proximity to the network's edge [28]. It temporarily stores data before sending it to the cloud for permanent storage. Inside the fog layer, data from all networked MGs and consumers, along with their energy consumption specifics, are centralized. This layer incorporates network equipment with distributed computational capabilities and local servers, effectively bringing cloud computing closer to devices, enabling immediate analysis and temporary data retention. For this proposed model, three fog nodes are established, each assigned to manage one of the three MGs. These fog nodes store all individual information pertaining to their respective MGs, enabling efficient and localized energy management.

Lastly, the device layer encompasses the tangible elements of MGs, including renewable sources, sensors, meters, energy storage systems, and AC-DC loads. These constituents function according to data sourced from the fog layer and engage with their virtual counterparts, thus promoting a harmonized and cooperative energy management procedure. This paper's focus revolves around three MGs and a utility grid, all interconnected to internet of things (IoT) devices that effectively store and transmit data to the fog layer [29]. The proposed fog-enabled optimization model harnesses the strengths of fog computing, enabling real-time monitoring, rapid data analysis and localized energy management. This distributed architecture empowers the networked MG system to optimize energy utilization efficiently and achieve improved grid performance.

The utilization of the proposed three-layer cloud-fog computing technique offers distinct advantages over traditional cloud computing. Firstly, it establishes a real-time monitoring framework that can promptly track load changes at any time, accommodating abrupt unit entries and exits within the networked MG system. Secondly, the fog computing layer facilitates fast and accurate optimization for energy management in Networked MGs. This distributed architecture ensures swift data transactions by gathering data readings in a decentralized manner through fog computing. In contrast to cloud computing, which mandates centralized data collection and analysis, cloud-fog computing dispenses with this necessity by empowering the fog layer to act as a decentralized data aggregator and logger. Drawing inspiration from the natural world, where fog resides closer to the ground compared to clouds, the cloud-fog concept situates the fog layer beneath the cloud layer, facilitating rapid data collection and transmission. This paradigm eradicates the primary constraint of cloud computing, mitigating latency by obviating the reliance on a centralized data transmission and recording framework. The fog computing approach proves to be advantageous in providing real-time insights and quick decision-making in energy management for networked MGs.

B. Microgrid components

The MG proposed in this paper incorporates several essential components, each playing a vital role in ensuring the MGs efficiency and reliability. The photovoltaic (PV) module serves as a renewable energy source, harnessing solar energy and converting it into electricity to promote environmental sustainability. The diesel generator(DG) acts as a backup power source, ensuring uninterrupted electricity supply during low solar generation or high demand periods. The energy storage system, typically in the form of batteries, balances energy by storing excess power and supplying it during peak periods or insufficient renewable energy availability. The Bidirectional Interlinking Converter (BIC) facilitates seamless energy exchange between AC and DC sub-grids, contributing to grid stability and optimal energy utilization. AC loads represent electrical devices within the MG that consume energy, catering to various users needs. The utility grid (UG) interfaces with the MG, enabling external power exchange and offering supplementary support during emergencies or peak demands. Together, these integrated components form an efficient and resilient MG system that optimizes energy usage, fosters sustainability and supports modern energy requirements.

C. MILP Optimization

To minimize costs and optimize energy resource utilization in the networked MG system, Mixed-Integer Linear Programming (MILP) optimization strategies are proposed. MILP is chosen as the optimization model due to its ability to handle discrete decision variables, which are essential in representing binary decisions related to the operation of various components within the MG. By formulating the energy management problem as a linear optimization model with constraints and discrete decision variables, MILP allows for identifying optimal energy allocation strategies while considering practical limitations and operating conditions. This optimization framework not only enhances overall energy efficiency by reducing wastage but also promotes sustainable energy practices within the MG, ensuring the optimal use of resources and contributing to the long-term viability of the energy system.

D. K-mean Clustering

K-means clustering is a popular unsupervised machine learning algorithm used for data segmentation and pattern recognition. It aims to partition data points into K clusters, where each data point belongs to the cluster with the nearest mean. The algorithm iteratively assigns data points to the nearest cluster center (centroid) and updates the centroids based on the average of the data points in each cluster. This process continues until convergence, where the centroids stabilize and no further changes occur [30]. In the context of the networked MG system, K-means clustering is applied to the load data to group customers into three categories: residential, commercial, and industrial MGs. This segmentation enables tailored energy management strategies based on different customer types, facilitating efficient resource allocation and optimized energy usage specific to the requirements of each MG category, ultimately enhancing customer satisfaction and MG performance.

E. Objective Function

The energy trading method in this research study is meant to minimise costs inside a networked MG model comprised of three MGs and a utility grid. When a particular MGs energy demand exceeds the supply from its PV, Battery, and DG components, it can trade energy with the other two MGs ("a" and "b") that have surplus energy, or it can source energy from the utility grid(referred to as grid "c"), all while minimising costs. The Cost function is formulated as follows:

$$\begin{aligned} Cost = prc.MG_a[t] * A + prc.MG_b[t] * B \\ + prc.UG_c[t] * C \end{aligned} \tag{1}$$

- Power balance

$$\begin{aligned} P_{UG}, i(t) + P_{DG}, i(t) + \eta_{DC-AC} P_{DC-AC}, i(t) \\ = P_{Load}, i(t) + P_{AC-DC}, i(t) \end{aligned} \tag{2}$$

$$\begin{aligned} P_{Batt,C}, i(t) - P_{Batt,D}, i(t) + \eta_{AC-DC} P_{AC-DC}, i(t) \\ + P_{PV}, i(t) = P_{MG}, i(t) + P_{DC-AC}, i(t) \end{aligned} \tag{3}$$

- Constraints

$$SOC_{min} \leq SOC(t) \leq SOC_{max} \tag{4}$$

$$P_{DG,min} \leq P_{DG}(t) \leq P_{DG,max} \tag{5}$$

$$0 \leq P_{UG}(t) \leq P_{UG,max} \tag{6}$$

where $prc.MG_a[t]$, $prc.MG_b[t]$, and $prc.UG_c[t]$ represent the price rates per unit of energy for microgrid "a", microgrid "b", and the utility grid "c", respectively, at a given time interval t. A, B and C are the energy traded from microgrid "a" , microgid "b" and utility grid "c", at a given time interval t. $P_{UG},i(t)$, $P_{DG},i(t)$,$P_{Batt,C},i(t)$, $P_{Batt,D},i(t)$,$P_{MG},i(t)$ are real power outputs in kW of UG, DG, battery charge,battery discharge and power transfer between i^{th} MG and network during time slot t , respectively. The terms $P_{DC-AC},i(t)$ and $P_{AC-DC},i(t)$ represent the power transferred from the DC bus to the AC bus and from the AC bus to the DC bus through a BIC with efficiencies η_{DC-AC} and η_{AC-DC} in the i^{th} MG during the time slot t, respectively. Additionally, $P_{PV},i(t)$ denotes the PV output, and $P_{Load},i(t)$ signifies the actual AC load within the i^{th} MG during the same time slot t.

Eq.(1) presents the system's objective function, encapsulating the overarching optimization goal. Eq. (2) and (3) delineate the power equilibrium at the AC and DC buses within the i-th MG, respectively, ensuring energy balance within the MG configuration. To preserve battery health and enhance its longevity, State of Charge (SOC) limitations, as depicted in Eq.(4), impose crucial constraints on the maximum and minimum SOC values. These constraints prevent overcharging or deep discharging, which could jeopardize battery performance and lifespan. Ensuring safe and efficient operation, Eq. (5) define the essential maximum and minimum constraints for diesel generators, preventing equipment damage and energy wastage. Utility grid constraints are vital for grid stability and reliability. Eq.(6) establishes maximum constraints for the utility grid, contributing to balanced electricity distribution, averting overload situations, and safeguarding against power outages and equipment impairment.

The main goal of the cost function is to determine the optimal arrangement for energy exchange between the MGs and the utility grid, taking into account the varying cost rates associated with each energy source. The core aim of cost minimization is realized through the determination of optimal values for A, B and C, which when harmonized, result in the comprehensive reduction of energy procurement costs for the deficient MG.

The implementation of the mathematical model, encompassing the three-layer cloud-fog computing architecture and the MILP optimization algorithm, is executed through the utilization of the Python programming language. The pseudocode of the model is outlined in Algorithm 1, wherein N signifies the number of MGs, t stands for the timestamp, P_{Net} denotes the net power, S_t represents the snapshot capturing real-time networked grid data stored within the fog layers, and P_{Req} designates the power requirement or the deficit power specific to each MG. This implementation enables real-time computation and decision-making, thereby facilitating efficient energy management across the networked MG system.

IV. Simulation Results and Discussions

The result and discussion section of the proposed model present a comprehensive analysis based on real-world data obtained from the Australian grid. The load data and PV data [31] from 300 customers have been collected to simulate a networked hybrid AC-DC MG model. Through the application of K-mean clustering, the load data is effectively segregated into residential (MG1), commercial(MG2) and industrial(MG3) MGs, facilitating tailored energy management strategies to suit the specific needs of each customer category. Additionally, price data from the Australian Energy Market Operator (AEMO) [32] has been integrated into the model. The simulation encompasses 24-hour data, captured at half-hour intervals, allowing for a detailed assessment of the MGs performance and energy distribution. The simulation is conducted using Python 3.10.12, ensuring a realistic and adaptable approach to assess the suggested energy management

Algorithm 1 Pseudocode of Problem Solution

```
Initialize the networked microgrid environment.
Initialize the networked fog-cloud environment.
for t = 1 to 47 do :
    for N = 1 to 3 do :
        Get Cumulative P_Load, P_PV data from respective cluster group.
        P_Net ← P_Load − P_PV
        if P_Net > 0 then
            P_Net ← Min(P_Net, P_Batt)
        end if
        if P_Net > 0 then
            P_Net ← Min(P_Net, P_DG)
        end if
        Fog layer prepare snapshot S_t of relevant information.
        Send S_t to Cloud layer.
    end for
    From S_t, determine P_Req
    if P_Req > 0 then:
        Optimizer needed.
        Use MILP to Minimize network fitness function.
    else
        No Optimizer needed.
    end if
end for
Exit Environment.
```

system's efficacy and performance within the context of networked MGs.

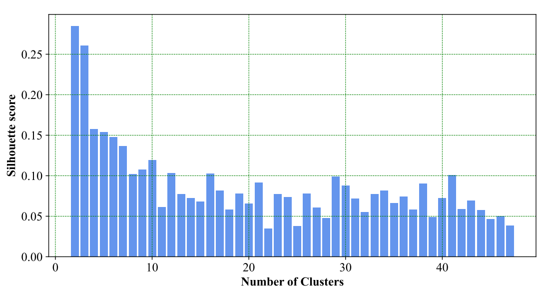

Fig. 3: K-mean clustering sillhoute score.

The subsequent analysis delves into the outcomes of the simulation, critically examining the energy efficiency of the MG, its adeptness in managing loads, and the efficacy of the employed strategies in optimizing the utilization of energy resources, all while maintaining dependable and sustainable power provision across different customer segments. To enhance clarity, this section focuses on presenting the simulation outcomes for MG2. Additionally, a comprehensive overview of power exchange interactions among all three MGs and the utility grid is presented, offering a comprehensive

TABLE I: Networked Microgrids Information

Microgrid	Maximum Load	Number of customers
Residential(MG1)	100 kW	179
Commercial (MG2)	120 kW	32
Industrial(MG3)	40 kW	89

TABLE II: Networked Microgrid System Parameters

Parameters	MG1	MG2	MG3
$P_{UG,max}(kW)$	300	300	300
$P_{Batt,max}(kW)$	121	210	55
$P_{DG,max}, P_{DG,min}(kW)$	85,0	147,0	39,0
SOC_{max}, SOC_{min}	1,0	1,0	1,0
$\eta_{DC-AC}, \eta_{AC-DC}$	0.92,0.92	0.92,0.92	0.92,0.92

insight into the energy dynamics and resource optimization achieved through the model's implementation.

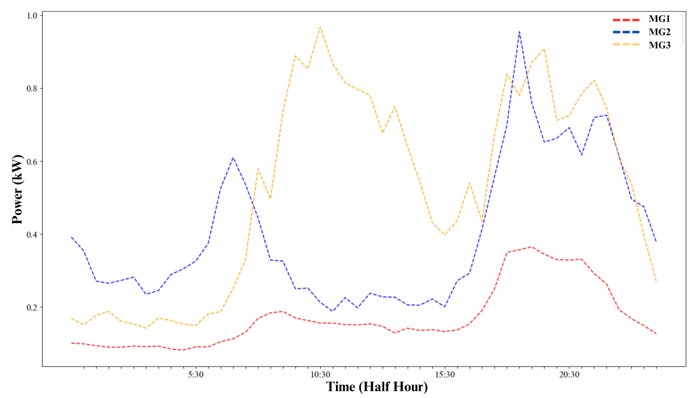

Fig. 4: Load distribution by K-mean clustering.

Fig. 3 illustrates the silhouette score, a vital metric in k-means clustering, which determines the effectiveness of load data categorization, forming the basis for dividing the load into three distinct categories as guided by the model. This silhouette score serves as a gauge for evaluating cluster quality, quantifying the separation between clusters on a scale from -1 to 1. A higher silhouette score signifies well-defined clusters, where data points exhibit proximity to their respective clusters and distance from neighboring ones, culminating in more precise and reliable clustering outcomes. Concurrently, Table I provides insights into the demographic distribution, revealing the number of customers and their peak load demands across the three interconnected MGs. Results from Table I have been used to get the optimal system parameters presented in Table II. Furthermore, Fig. 4 visualizes the load distribution achieved through K-means clustering, offering a graphical representation of how the load is optimally distributed among the three MGs, as coordinated by the clustering technique.

The load dynamics of MG2 are vividly portrayed in Fig. 5, describing its demand profile alongside available PV energy

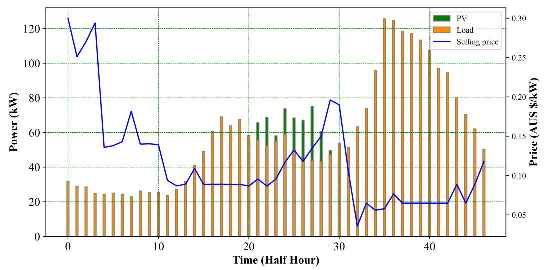

Fig. 5: Power and price data of MG 2(Commercial).

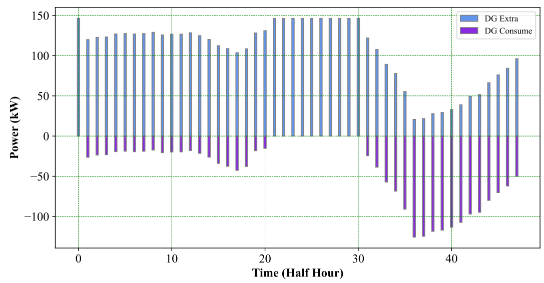

Fig. 6: Diesel usage of MG 2(Commercial).

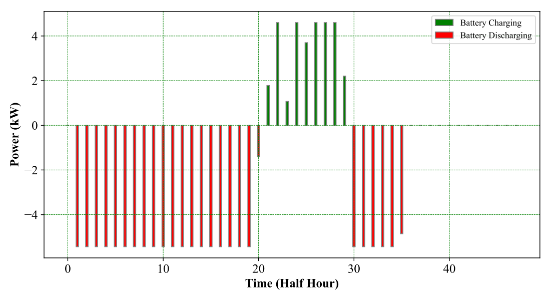

Fig. 7: Battery usage of MG 2(Commercial).

and prevailing electricity prices. Fig. 6 offers an insight into MG2's DG, showcasing its accessible power and the extent of power contribution to the MG2 Load. Furthermore, Fig. 7 presents the battery profile of MG2, capturing its charging and discharging patterns. Upon closer examination of Fig. 5, 6, and 7, a recognizable trend emerges: during the time slot ranging from 20 to 30, PV power(P_{PV}) surpasses the load demand (P_{Load}) , prompting the battery to undergo charging ($P_{Batt,C}$) . Notably, the DG (P_{DG}) exhibits zero consumption during this interval. Beyond this timeframe, the load is predominantly satisfied through a sequential hierarchy, starting with PV energy, followed by battery utilization($P_{Batt,D}$), and subsequently by DG intervention if needed. In instances where the load demand remains unmet, the system seamlessly taps into the resources of the other two microgrids(P_{MG}) and utility grid(P_{UG}) to ensure continuous and efficient power supply.

Table III gives the additional energy requirements of individual MGs (MG1, MG2, MG3) at different time slots (t),

TABLE III: Networked Microgrid Energy Interactions

Time Slot (t)	Additional Energy Requirement of MG (kWh)		Energy Met by MG
36	MG1	05.450	MG2
37	MG1	06.408	MG2
38	MG1	12.381	MG2
39	MG1	07.761	MG2
40	MG1	01.071	MG2
41	MG3	02.618	MG1
42	MG3	01.375	MG1
43	MG3	00.008	MG3

TABLE IV: Networked Microgrid Profit Analysis

Time Slot (t)	Optimized Cost (AUS $/kWh)	Unoptimized Cost (AUS $/kWh)	Profit %
36	0.315	0.540	41.67
37	0.490	0.588	16.67
38	0.804	1.176	31.63
39	0.504	0.795	36.60
40	0.0696	0.093	25.16
41	0.170	0.490	65.31
42	0.089	0.149	40.27
43	0.0005	0.000612	18.30

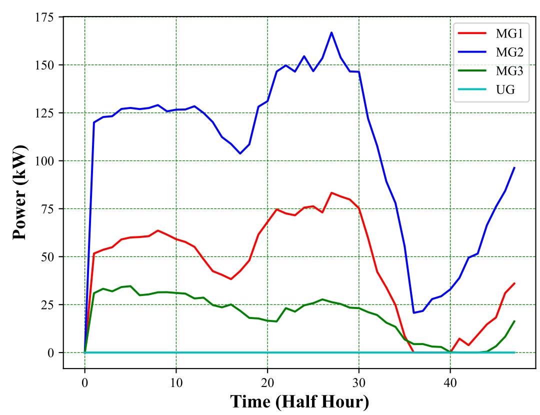

Fig. 8: Energy exchange among networked microgrid.

which are met by other networked MGs in a way to minimize the operating cost of the networked MGs. Table IV compares the cost of meeting the additional energy requirement of a MG optimally from the networked resources with the cost if the additional energy requirement is met directly by the UG. The calculated profit signifies the advantageous outcome of transferring power from optimized cost sources, i.e., other networked MGs, instead of procuring energy directly from the UG. The findings highlight MGs pivotal role in effective energy management, ensuring minimal costs within and among MGs. This underscores the potential for cost-efficient energy utilization by strategically leveraging interconnected MGs. Fig.

8 vividly illustrates the intricate dynamics of power exchange within the networked MG model. Evidently, all three MGs adeptly meet their energy demands by seamlessly drawing from their individual sources such as PV, DG, and Battery, or by orchestrating power exchange among themselves. Notably, this effective energy-sharing mechanism obviates the need for importing energy from the utility grid, highlighting the model's self-sufficiency and resilience. This seamless and efficient power sharing is underpinned by the three-layer cloud-fog computing system's implementation, which expedites real-time data transmission within the MG network. This, in turn, supports precise real-time analysis and decision-making processes, thereby optimizing energy management strategies and enhancing overall operational efficiency.

V. Conclusion

In conclusion, the study on Networked Hybrid AC-DC MGs, synergistically leveraging Fog Computing and Linear Solver, has presented a robust and innovative approach for enhancing energy management efficiency in modern power systems. The integration of fog computing at different layers of the MG architecture has demonstrated its effectiveness in enabling real-time data analysis, faster decision-making, and efficient energy distribution. This, in turn, addresses the dynamic and distributed nature of MG operations, resulting in improved overall performance and grid stability. The utilization of MILP optimization further enhances energy allocation and utilization within and between MGs, effectively minimizing costs and maximizing energy efficiency.

In the future, this research could extend its investigation to explore the impact of battery charging and discharging dynamics within the networked MG model, accounting for potential non-linearities. Additionally, further studies could delve into the intricate interactions between different MGs, considering various load profiles and renewable energy outputs from the latest dataset, to develop even more sophisticated optimization strategies for enhanced energy management and grid stability.

References

[1] S. Ahmad, M. Shafiullah, C. B. Ahmed and M. Alowaifeer, "A Review of Microgrid Energy Management and Control Strategies," in IEEE Access, vol. 11, pp. 21729-21757, 2023, doi: 10.1109/ACCESS.2023.3248511.

[2] Q. Xu, T. Zhao, Y. Xu, Z. Xu, P. Wang and F. Blaabjerg, "A Distributed and Robust Energy Management System for Networked Hybrid AC/DC Microgrids," in IEEE Transactions on Smart Grid, vol. 11, no. 4, pp. 3496-3508, July 2020, doi: 10.1109/TSG.2019.2961737.

[3] S.Parhizi, H.Lotfi, A.Khodaei, and S.Bahramirad, "State of the Art in Research on Microgrids: A Review," *IEEE Access*, vol. 3, pp. 890-925, 2015.

[4] W. Su, J. Wang, and J. Roh, "Stochastic energy scheduling in microgrids with intermittent renewable energy resources," IEEE Trans. Smart Grid, vol. 5, no. 4, pp. 1876–1883, July 2014.

[5] S. K. Rathor and D. Saxena, "Decentralized Energy Management System for LV Microgrid Using Stochastic Dynamic Programming With Game Theory Approach Under Stochastic Environment," in IEEE Transactions on Industry Applications, vol. 57, no. 4, pp. 3990-4000, July-Aug. 2021, doi: 10.1109/TIA.2021.3069840.

[6] M. Dabbaghjamanesh, A. Kavousi-Fard and Z. Y. Dong, "A Novel Distributed Cloud-Fog Based Framework for Energy Management of Networked Microgrids," in IEEE Transactions on Power Systems, vol. 35, no. 4, pp. 2847-2862, July 2020, doi: 10.1109/TPWRS.2019.2957704.

[7] S. A., R. Kumar and R. C. Bansal, "Multiagent-Based Autonomous Energy Management System With Self-Healing Capabilities for a Microgrid," in IEEE Transactions on Industrial Informatics, vol. 15, no. 12, pp. 6280-6290, Dec. 2019, doi: 10.1109/TII.2018.2889692.

[8] C. Mouradian, D. Naboulsi, S. Yangui, R. H. Glitho, M. J. Morrow and P. A. Polakos, "A Comprehensive Survey on Fog Computing: State-of-the-Art and Research Challenges," in IEEE Communications Surveys & Tutorials, vol. 20, no. 1, pp. 416-464, Firstquarter 2018, doi: 10.1109/COMST.2017.2771153.

[9] S. Chouikhi, M. Esseghir and L. Merghem-Boulahia, "Energy Consumption Scheduling as a Fog Computing Service in Smart Grid," in IEEE Transactions on Services Computing, vol. 16, no. 2, pp. 1144-1157, 1 March-April 2023, doi: 10.1109/TSC.2022.3174698.

[10] O. R. Merad-Boudia and S. M. Senouci, "An Efficient and Secure Multidimensional Data Aggregation for Fog-Computing-Based Smart Grid," in IEEE Internet of Things Journal, vol. 8, no. 8, pp. 6143-6153, 15 April15, 2021, doi: 10.1109/JIOT.2020.3040982.

[11] K. Monteiro, M. Marot and H. Ibn-khedher, "Review on microgrid communications solutions: a named data networking – fog approach," 2017 16th Annual Mediterranean Ad Hoc Networking Workshop (Med-Hoc-Net), Budva, Montenegro, 2017, pp. 1-8, doi: 10.1109/MedHocNet.2017.8001656.

[12] X. Wu, W. Zhao, X. Wang and H. Li, "An MILP-Based Planning Model of a Photovoltaic/Diesel/Battery Stand-Alone Microgrid Considering the Reliability," in IEEE Transactions on Smart Grid, vol. 12, no. 5, pp. 3809-3818, Sept. 2021, doi: 10.1109/TSG.2021.3084935.

[13] M. Ott, M. AlMuhaini and M. Khalid, "A MILP-Based Restoration Technique for Multi-Microgrid Distribution Systems," in IEEE Access, vol. 7, pp. 136801-136811, 2019, doi: 10.1109/ACCESS.2019.2942633.

[14] A. A. Badr, A. Safari, and S. N. Ravadanegh, 'Power system islanding considering effect of microgrid by MILP formulation', Electric Power Systems Research, vol. 216, p. 109093, 2023.

[15] A. C. Luna, N. L. Diaz, M. Graells, J. C. Vasquez and J. M. Guerrero, "Mixed-Integer-Linear-Programming-Based Energy Management System for Hybrid PV-Wind-Battery Microgrids: Modeling, Design, and Experimental Verification," in IEEE Transactions on Power Electronics, vol. 32, no. 4, pp. 2769-2783, April 2017, doi: 10.1109/TPEL.2016.2581021.

[16] B. Chen, J. Wang, X. Lu, C. Chen and S. Zhao, "Networked Microgrids for Grid Resilience, Robustness, and Efficiency: A Review," in IEEE Transactions on Smart Grid, vol. 12, no. 1, pp. 18-32, Jan. 2021, doi: 10.1109/TSG.2020.3010570.

[17] M. N. Alam, S. Chakrabarti and A. Ghosh, "Networked Microgrids: State-of-the-Art and Future Perspectives," in IEEE Transactions on Industrial Informatics, vol. 15, no. 3, pp. 1238-1250, March 2019, doi: 10.1109/TII.2018.2881540.

[18] G. Cui, Q. -S. Jia and X. Guan, "Energy Management of Networked Microgrids with Real-Time Pricing by Reinforcement Learning," in IEEE Transactions on Smart Grid, doi: 10.1109/TSG.2023.3281935.

[19] Qi Hong Lai; Chun Sing Lai; Loi Lei Lai, "Networked Microgrids Energy Management Under High Renewable Penetration," in Smart Energy for Transportation and Health in a Smart City , IEEE, 2023, pp.211-232, doi: 10.1002/9781119790402.ch8.

[20] Z. A. Khan et al., "Energy Management in Smart Sectors Using Fog Based Environment and Meta-Heuristic Algorithms," in IEEE Access, vol. 7, pp. 157254-157267, 2019, doi: 10.1109/ACCESS.2019.2949863.

[21] D. A. Chekired, L. Khoukhi and H. T. Mouftah, "Fog-Computing-Based Energy Storage in Smart Grid: A Cut-Off Priority Queuing Model for Plug-In Electrified Vehicle Charging," in IEEE Transactions on Industrial Informatics, vol. 16, no. 5, pp. 3470-3482, May 2020, doi: 10.1109/TII.2019.2940410.

[22] S. Z. Tajalli, A. Kavousi-Fard, M. Mardaneh, A. Khosravi and R. Razavi-Far, "Uncertainty-Aware Management of Smart Grids Using Cloud-Based LSTM-Prediction Interval," in IEEE Transactions on Cybernetics, vol. 52, no. 10, pp. 9964-9977, Oct. 2022, doi: 10.1109/TCYB.2021.3089634.

[23] A. Gupta, S. Doolla, and K. Chatterjee, "Hybrid AC-DC microgrid:

Systematic evaluation of control strategies," IEEE Trans. Smart Grid, vol. 9, no. 4, pp. 3830-3843, Jul. 2018.
[24] N. Eghtedarpour and E. Farjah, "Power control and management in a hybrid AC/DC microgrid," IEEE Trans. Smart Grid, vol. 5, no. 3, pp. 1494-1505, May 2014.
[25] Q. Xu, J. Xiao, P. Wang, and C. Wen, "A decentralized control strategy for economic operation of autonomous AC, DC, and hybrid AC/DC microgrids," IEEE Trans. Energy Convers, vol. 32, no. 4, pp. 1345-1355, Dec. 2017.
[26] L. Cost, Levelized Cost and Levelized Avoided Cost of'New Generation: Resources in the Annual Energy Outlook 2019, U.S. Energy Inf. Admin., 2019.
[27] B. Wickremasinghe and B. Rajkumar, "CloudAnalyst: A CloudSim-based tool for modelling and analysis of large scale cloud computing environments," School Comput. Inf. Syst., Univ. Melbourne, Melbourne, VIC, Australia, MEDC Project Rep. 22, 2009, pp. 433–659, no. 6.
[28] M. H. Y. Moghaddam and A. Leon-Garcia, "A fog-based Internet of energy architecture for transactive energy management systems," IEEE Internet Things J., vol. 5, no. 2, pp. 1055–1069, Apr. 2018
[29] Y. Boloorchi and S. Azizi, "An IoT-Fog-Cloud Framework for Demand Side Management in Smart Grid," 2021 5th International Conference on Internet of Things and Applications (IoT), Isfahan, Iran, 2021, pp. 1-6, doi: 10.1109/IoT52625.2021.9469712.
[30] S. Na, L. Xumin and G. Yong, "Research on k-means Clustering Algorithm: An Improved k-means Clustering Algorithm," 2010 Third International Symposium on Intelligent Information Technology and Security Informatics, Jian, China, 2010, pp. 63-67, doi: 10.1109/IITSI.2010.74.
[31] Solar Home Electricity Data. Retrieved from https://www.ausgrid.com.au/Industry/Our-Research/Data-to-share/Solar-home-electricity-data.
[32] Nem Data Dashboard.https://aemo.com.au/en/energy-systems/electricity/national-electricity-market nem/data-nem/data-dashboard-nem