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ORIGINAL RESEARCH

Enhanced demand side management for solar-based isolated microgrid system: Load prioritisation and energy optimisation

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Abstract

A novel control mechanism is presented for rural microgrids, standing out in the current literature with its advanced approach to load prioritisation and energy allocation. The system's main goal is to maximise energy supply to essential loads while effectively managing available resources. Distinct from traditional methods, this mechanism dynamically classifies loads according to user-defined priorities, adjustable based on the control system's computational power and complexity. A critical feature is the utilisation of the Particle Swarm Optimisation (PSO) algorithm to optimise demand side management (DSM). This innovative approach leverages day-ahead load and generation forecasts to ensure optimal energy distribution across load levels, maintaining continuous power supply to high-priority loads and reducing blackout risks due to generation and load fluctuations. Analyses under stochastic scenarios demonstrate the robustness of the control action, with percentile-based day-ahead forecasting allowing for adaptation to significant variations in renewable energy generation patterns. The implementation results are significant, maintaining 100% supply continuity to essential loads throughout the day, even with generation fluctuations up to -20%. This marks a considerable improvement in load satisfaction, increasing it from 83% to 96%. A significant advancement in microgrid control is contributed, providing an adaptive, user-centric approach that enhances load management and energy distribution, and facilitates more resilient and efficient microgrid systems in the face of highly variable renewable energy sources (RESs).

KEYWORDS

distributed energy resources, particle swarm optimization, renewable energy resources, rural electrification, stochasticity

1 | INTRODUCTION

Access to modern power is regarded as a crucial component of sustainable development. However, 2.8% of urban residents and 17.5% of rural residents worldwide still lack access to electricity, making up more than 9.5% of the population [1]. Due to the uneven geographic layout, grid development in rural areas faces a number of difficulties that have slowed the rate of electrification. Even with grid extension as a possibility, these isolated areas have a smaller population and inadequate infrastructure, which leads to fewer prospects for institutional investment and a low rate of return on investment [2, 3]. Among several options, renewable energy sources (RESs) have been essential in electrifying rural areas in developing nations [4]. Isolated renewable options for expanding access to electricity in rural areas include independent microgrids powered by micro-hydro, solar PV, and wind [5, 6]. By creating independent microgrids, local users can produce electricity from renewable sources to power their homes and even a few small businesses [7, 8]. By 2016, 133 million people had access to lighting and other services thanks to isolated renewable energy, of which 100 million used solar lights, 24 million had solar home systems, and at least 9 million relied on microgrids [5].

Due to a huge reduction in the cost of renewable energy, consumers, municipalities, and utilities have begun to use distributed energy resources (DERs) to produce their own electricity. Solar PV module costs have decreased by more than 80% since 2009, while PV power costs have decreased by 73% [5]. This is due to a sharp decline in the cost of the most crucial isolated system components, which has further decreased prices and enhanced affordability, together with a quick increase in the efficiency of modern appliances. Communities can create microgrid systems to generate electricity by employing the idea of leveraging DER. This infrastructure enables more flexible power delivery with the help of DER assets located closer to the load demand [9, 10]. It is a grid line concept that works with both isolated and parallel connections to the grid, as well as having a backup supply of its own. The microgrid can be used to offer the necessary reactive power to the line to increase the voltage supply when they are linked to the utility grid in parallel. Additionally, they can be disconnected from the grid in isolated case scenarios (sometimes referred to as grid failures during parallel connection) to supply power to the customers and, if possible, meet load demands. However, the unpredictability of RESs like solar and wind raises concerns about the system's ability to ensure a steady supply. Increases in demand or decreases in a generation will change the system's ability to handle its load, which could lead to a blackout. There is always a cap on how much energy the system can supply, even with the best generation-side architecture.

For example, the electrification of Nepal's rural areas has been made possible in large part by isolated RESs (i.e., microgrids) [11]. However, the unpredictable nature of the sources and inadequate infrastructure for resource management are the main problems with renewable energy, which raises concerns about the system's reliability and security [12]. Table 1 presents the availability and reliability of five microgrid systems in Nepal, where the supply deficit has occurred in most of them. In addition, the availability of solar-based microgrids is observed to be very low. One of the major reasons behind this deficit supply is that the installed generation in Nepal's isolated microgrid is constrained in how much energy it can produce. The capacity to ensure continuous supply is constrained, particularly for storage-based microgrids because of the expense of installing the necessary number of generating, controlling, and storage components.

Considering the behaviours of user the domestic electric load profile are usually cyclical in nature with typically a morning and evening peak and lower based demand during the night period [14, 15]. Various research has been conducted to understand the consumption pattern of load for better implementation of demand response programs. With the technology available to manage the load on the appliance level shifting and shedding might help maintain stability in the system. Yet the untimely shedding and shifting of load can result in to decrease in user satisfaction. Multiple pieces of research tend to classify the load to improve user satisfaction for the implemented demand response. Researchers tend to perform classification of the load based on user preference, energy demand, and their use in flexibility [13, 16]. A study [17], classifies the load based on their dependency on time, it discussed two different classes considering static and dynamic behaviours to time. It implemented user satisfaction levels based on time and devices to achieve maximum user comfort based on the defined user budget limit. Also, evolutionary placement algorithm (EPA) based genetic algorithm has been implemented to generate energy allocation patterns to yield maximum user conform to the defined budget limit. Shedd-able and unshed-able classifications are as simple as they sound such that the loads are shed if they fall into that category [18]. Through the implementation of shedd-able and unshed-able loads, the paper demonstrated how the prediction of total future demand can be used to maintain the target peak at an optimal level [16]. Similarly, Ref. [19] classified home appliances into three different categories appliances with real-time energy consumption modes, an appliance with periodic nonreal-time energy consumption modes, and an appliance with non-periodic nonreal-time consumption modes and presented two different algorithms dynamic priority allocation and scheduling algorithms. This paper discusses the implementation of scheduling appliances to improve the period to increase the utilisation of renewable energy. A study [20], discusses a 2-level classification of appliances for 3-bedroom residences in the city of Ibadan. The author classifies the appliances in the household based on their flexibility to use. Such load demand requires continuous and instantaneous power with flexibility is addressed as critical load and appliances with somewhat controllable and schedulable

TABLE 1 Availability and reliability of isolated microgrid of Nepal [13].

Indicators	Solar-wind-battery microgrid, Bhorleni	Solar-battery microgrid, Dubung	Solar-diesel-battery microgrid, Harkapur	Microhydro microgrid, Dhading	Haluwa Khola Minihydro microgrid, Ramechhap
Availability (hours per 24)	<8	>23	8–15	16–22	>23
Reliability (interruptions/week)	4–14	3	4–14	3	3
Adequacy of the electricity to meet uses	Supply deficit	Spare power	Supply deficit	Supply deficit	Supply deficit

appliances as uncritical load, which further uses priority arbitration allowing room for discrimination in the satisfaction within the load class. The papers show the effectiveness in power distribution through improvement in the percentage of user satisfaction on both classes of load for a standalone PV-Battery system. Results show that the load satisfaction for the critical and uncritical loads can be increased from 49.8% and 23.7% to 93.8%, 74.2%.

As the grid system is transforming towards a smart grid, various technologies have been developed and are being improved in order to achieve smart grid objectives [21, 22]. With microcontroller-based technology, more flexibility on the load can be achieved with a decentralised control of the grid energy [23] such that individual households are employed with remote control technology to handle the consumption. Each household smart meter is coupled with an energy management system (EMS) or designed with an inbuilt EMS known as advanced metering infrastructure (AMI) [24]. These controllers are integrated with data acquisition system (sensors), computation and control technology (microcontroller/processor, programable logic circuit) [25, 26], and communication technology (Zigbee, WIFI, LoWAN, Bluetooth) [23, 26–28], which enable the controller to communicate with the local smart meter, remote user controller, or/and central controller (i.e. utilities). On the other hand, utilities or distribution system operators (DSOs) are able to obtain accurate data on the consumption pattern, enabling them to manage and better plan their future management and investments in networks [29]. Recent research on smart gird technology show that implementation optimisation algorithm in combination with smart technology to control load on the appliance level can reduce peak load by 5.21%–7.35% [30].

With the available information in hand, a predictive model-based approach such as daily, hourly forecasting of load, and generation can be implemented to predict the level variation in load of the system that can occur. Many of the concepts for DSM used in today's context rely on the predicted data of load such as day ahead or hourly forecasted data [31]. In Ref. [32], the research considers forecasting of load data and shifts the load to suitable times to reduce the gap between the peak load and average load by optimising the value of peak to average ratio. Whereas, the method proposed by Hoffman, A. [16] first predicts the load using the ARX (Auto Regression) model and calculates the required kVA to be shed to keep the demand below the current target peak. Ref. [33] proposes a stochastic approximated framework, based on the probability density function for the wind speed forecast and employs a control index that takes into account the generation condition instability. Similarly, the model predictive control method in Ref. [34] considers the stochasticity of demand and generation to reduce peak load and balance the load to supply and maintain the SoC of the battery. However, a question on what basis the control action must be performed should be answered, for example, various strategies are implemented such as to reduce the cost of energy for individual consumers [35], to perform peak shaving or load shifting [36–38], or to minimise carbon emission [39] and to optimise the size of the storage unit, to maintain battery life [40, 41] etc. DSM strategies with optimisation processes such as Heuristic Optimization (HO) [30, 42], Genetic Algorithm Optimization (GAO) [43], Hybrid Bacterial Foraging (HBF) [44], Whale Optimization (WO) [45], Particle Swarm Optimization (PSO) [46, 47], and Fuzzy Logics [48] are implemented to find the optimal point for timely control action to maintain user satisfaction at the same time.

Dynamic control of the electric load is now possible thanks to technological advancements such as the smart meter, smart grid, multiagent control, home energy management system, building energy management system, and smart appliances [48–52]. This creates possibilities for load management at the appliance level. The residential sector is a major consumer of energy in the case of Nepal as per the economic survey of 2019/20 at 43.3%, and the country followed by the industrial sector at 36.3% [53]. Whereas in the case of an isolated microgrid, 70% of the total energy used is from residential loads. The majority of household load consumption occurs during dawn and dusk when electricity generation is at its lowest, which indicates that storage provides 70% of the energy used. If the energy in the store runs out, the system will be forced into a total blackout. A continuous supply of anything vital or of higher priority can be maintained by reducing the consumption of superfluous or low-priority items. To ensure customer satisfaction and prevent a total blackout, load classification can be used to save energy for higher-priority loads [54]. As some loads or equipment have a greater impact on people's daily lives than others, users can maintain a continuous supply of the appliance they require during crucial generation hours in exchange for the unneeded load using the DSM technique to classify loads on different levels of priority. This paper focuses on the DSM technique to increase the distribution efficiency of an isolated microgrid system as an alternative to adding more generation, which increases the system's capacity to maintain dependable supply. DSM can be used to extend the boundaries of isolated microgrids a little further, thanks to cutting-edge technology like smart metering and remote communication control capability. As a result, this research offers a DSM technique to manage the load in order to increase the isolated microgrid's maximum capacity. The main area of this paper is the implementation of priority on the appliance level of the load in the residential microgrid sector. The paper showed a way to control demand for home load by placing appliances in order of importance considering the household load as the biggest consumer in rural areas.

However, even with the implementation of a forecasting method to manage the load through DSM, stochasticity in the load and generation pose a major drawback to efficiently manage the load. Variations in the load and generation affect the optimal control of load which can degrade the satisfaction of control implemented based on forecasting [55]. To capture the stochastic nature of the load, this paper presents a mechanism for implementing priority-based DSM considering the random nature of load and generation. This paper encapsulates the stochastic nature of through forecasting using a time series model, and random variation of generation up to 20% variation using the probability density function, and control index is framed in different percentile levels of the forecasted data. As we know, fluctuations in load and generation can reduce the efficiency of energy distribution with limited supply, especially in rural isolated microgrids. Here, this paper proposes the priority-based shedding of load by encapsulating the nature of load in each priority level through an optimally distributed energy to maintain user satisfaction through optimisation using particle swarm optimisation which helps to maintain supply to higher priority load set by user and utility.

This paper contributes in three main areas to implement direct load control-based DSM in isolated microgrid systems:

a. Innovative load management through DSM: This paper introduces a simple and practical approach for load management in isolated microgrid systems, particularly in rural areas. This involves classifying electrical loads based on user-defined priorities and managing them dynamically to optimise energy usage. It emphasises the use of advanced DSM techniques that leverage smart metering and remote communication technologies. This allows for a more efficient allocation of limited energy resources, especially in scenarios where RESs are the primary supply.
b. Stochastic forecasting and optimisation for energy management: A significant scientific contribution of the paper is the implementation of stochastic forecasting models. These models predict day-ahead load and generation patterns, considering the inherent unpredictability of RESs like solar and wind. This paper employs advanced optimisation algorithms, such as Particle Swarm Optimization (PSO), to distribute energy effectively across different load levels. This strategy is crucial in maintaining supply continuity to high-priority loads, even during significant fluctuations in energy generation.
c. Integrating RESs in rural electrification: This paper contributes to the field of rural electrification by demonstrating how isolated microgrids, powered by RESs, can be effectively utilised to extend electricity access to underserved areas. It provides a comprehensive analysis of the economic and technological viability of renewable energy solutions in rural settings. The paper's insights into cost reduction trends and the efficiency of renewable energy components are particularly valuable for policymakers and stakeholders in the energy sector.

The presented paper is organised with the following structure. It begins by providing an overview of the issues that have surfaced in rural microgrids and/or rural electrification systems. The adopted approaches, architecture, and methodology are described in Section 2. In Section 3, the results of the investigation are discussed. Finally, the conclusions have been discussed in Section 4.

2 | METHODOLOGY

The cost of adopting or updating a new or advanced metring system might be high for developing nations. A complex control system might not be appropriate for the area, given the limited resources in the rural areas, since the costs might outweigh the advantages of adopted management strategies for control. A straightforward metering control system could satisfy the management requirements of emerging nations with rural microgrids that have lower demand. By integrating coloured indications to show grid health and forbidding the usage of major appliances during peak hours, Gridshare's pilot project in Bhutan eliminates brownout problems [56]. Similarly, different low-cost metres have been created by businesses like Sparkmeter and power colonies, which offer features like time of use tariffs, current limitations, prepayment metering, maximum daily energy limits, and also enable simple control from power plants [57]. These metres are used in many developing countries, including Nepal, where they are mostly found in small, isolated microgrids. Retrofitting, which enables remote control over the user load at a cheap cost, is an alternative to modernising the metering infrastructure [58]. In this paper, we consider the use of smart metres with the microgrid system based on their technological features for better distribution of energy. It is based on the concept of direct load control (DLC) and features AMI. The term “AMI" refers to a metring technology that has been integrated with several other technologies, including home area networks, advanced sensors, control systems, standardised software interfaces, and information management systems. AMI is also capable of bi-direction communication, allowing the gathering and dissemination of information between the user-end and utilities. The real-time data or level of details within a data depends on the sampling time defined in the system or the uplink transmission capacity of the AMI systems typically use a communication interval of 15 min to once per hour [59]. With the implementation of AMI metering utilities will be in continual communication with customers, allowing utilities to transmit real-time control signals to prevent excessive energy demand during a crucial moment. A detailed description of the proposed architecture and the controlling methods are given in the following sub-sections:

2.1 | System architecture

This paper considers a smart metre-based home automation system that enables communication between the utility and users for the implementation of DLC. Figure 1 depicts an architecture that allows a DLC-based system on various tiers while considering the limitations of the current technology available with Nepal's microgrid. The proposed DSM technique relies on darkening superfluous appliances at various priority levels in exchange for maintaining power supply continuity to critical appliances. The proposed DSM system employs appliance shedding-based control to load at critical times, such as lower generation or higher demand periods and measures the energy required throughout the day to maintain supply. The system considers controlling appliances via the smart metre, with multi-level control acting as a remote controller inside each household, allowing a direct control link for the utility to manage the consumption of specific sets of appliances. The control can be accomplished utilising a home

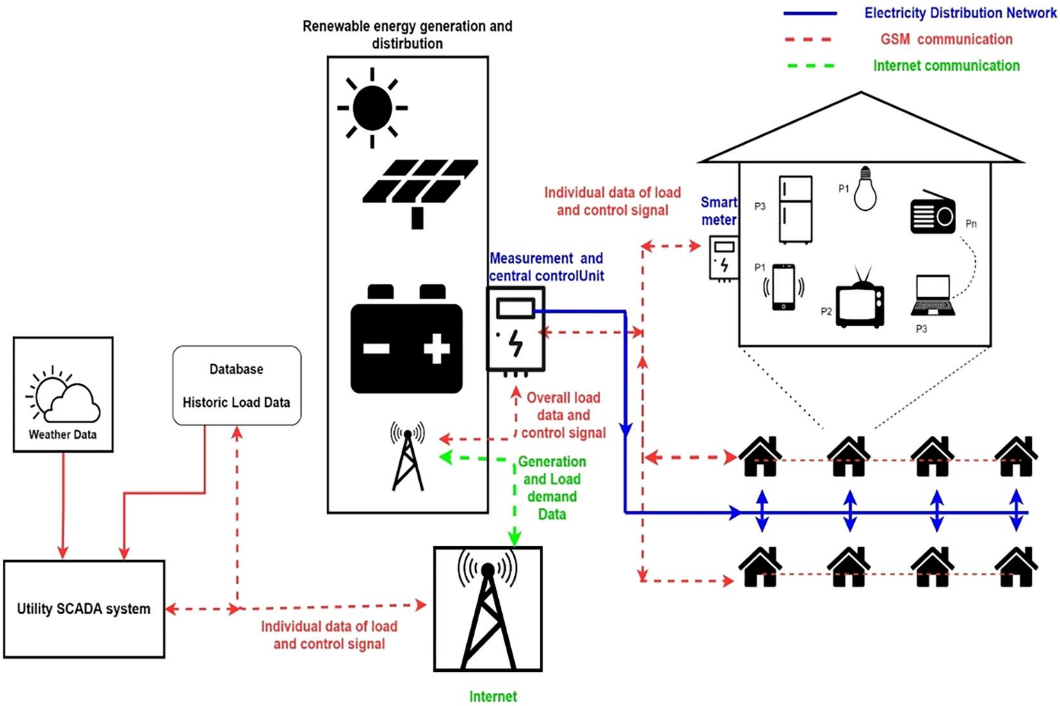


FIGURE 1 Proposed architecture for the implementation of DSM strategy.

energy management system (HEMS) through IoT-based control or other cutting-edge load observation and control technology, depending on the communication technology accessible at the site and location. The smart metre and AMI-based metering protocols both support Internet and GSM-based connectivity for the transmission of real-time data and control signals. It is considered that every home is required to have an AMI-connected smart metre that can communicate with both appliances and the nearest communication centre.

Similarly, Figure 2 shows the working architecture of the proposed DSM strategy. Through the use of a smart metre, the control system coordinates two controllers (a central and a real-time remote controller). Based on the microgrid system's generation and day-ahead predictions, the central controller uses an optimisation algorithm to determine the best course of action. The energy-based model was developed to do a 24-h computation of energy consumption based on potential demand and generation for the day ahead. It is difficult to accurately pinpoint the accurate generation throughout the day together with the demand because generations that rely on RESs are stochastic in nature. Therefore, the energy-based model created allows utility companies to estimate the consumption, creation, and availability of energy in the storage on an hourly, half-hourly, or quarterly basis based on which control action can be run. The algorithm determines the total amount of energy that may be served to each set of appliances and the minimal amount of energy needed to maintain a continuous supply to the essential appliances based on the anticipated data of generation and consumption. For isolated microgrids, continual cloudy days can drain the battery to its lowest level, causing supply deficit problems that can result in a total blackout even though the system is optimally constructed with multiple days of autonomy. When the minimum amount of demand energy is recognised, it can be stored in battery backups by taking the appropriate control measures, including

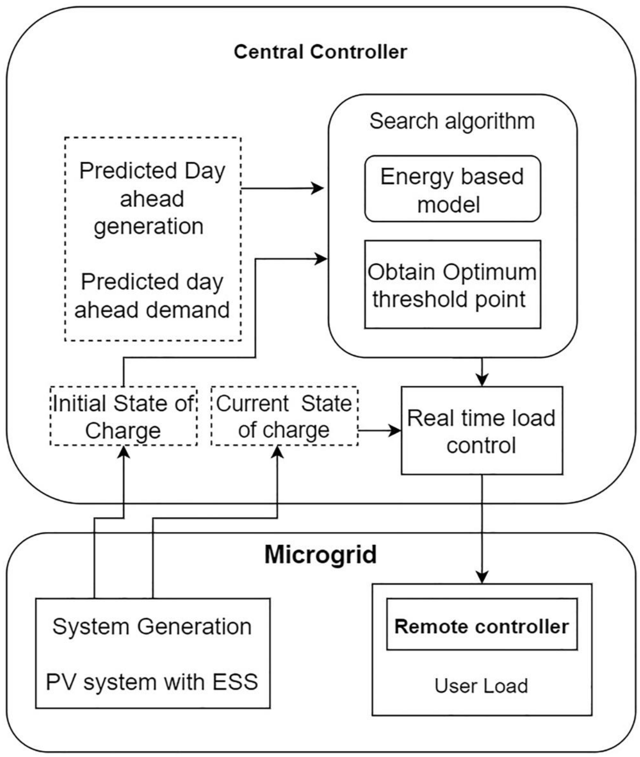


FIGURE 2 Work architecture of proposed DSM strategy.

cutting back on needless electric load. The model and predicted data are combined to create an optimisation problem that assigns a minimal threshold point in the battery's state of charge (SoC) that signifies the shifting or shedding of load. The central control monitors the battery capacity in real-time based on the optimal load-shedding point, and when it crosses the lower bound of any priority level, it sends a signal to the remote-control unit, which is the implemented AMI technology, to reduce or shift superfluous appliance energy usage. Figure 3 depicts how a remote control operates on various appliance sets. Each appliance set has a remote control or individual control option. Considering the priority set and level of control required metering technology allows remote control of individual or set of appliances for optimal control of electric load in the residential sector.

2.2 | System modelling

An energy-based microgrid model has been considered from the previous study, performed to examine the possible implementation of priority-based shedding in isolated [60]. This study examines the effectiveness of load control for a standalone photovoltaic system using battery energy storage technology (BESS). The PV solar cell, batteries, user loads, and power electronic converters (PEC) are thus the system's main

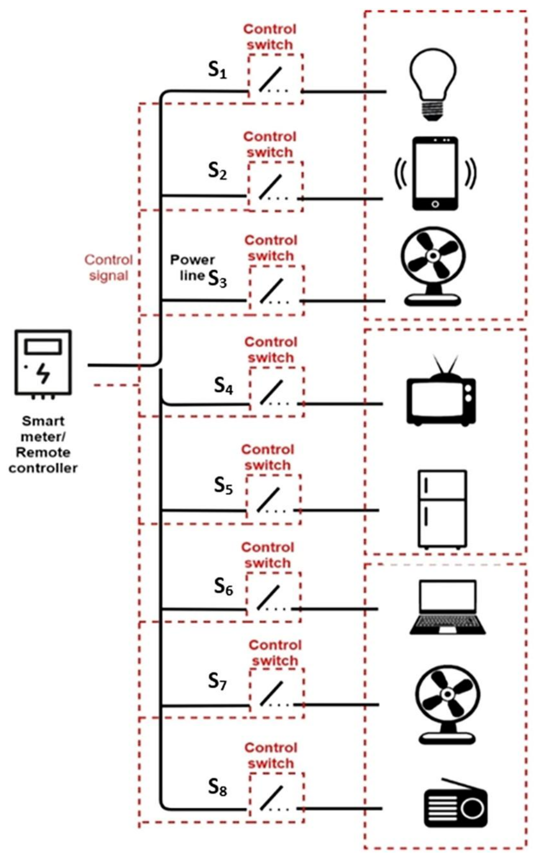


FIGURE 3 Remote control architecture.

components. The relationship can be stated as Equations (1) and (2) in the condition of a stable energy system.

$$P_{load} + P_{Loss} = P_{supply} \tag{1}$$

$$P_{supply} = P_{Generation} + P_{storage} \tag{2}$$

The effectiveness of PECs and the operated appliances determines the system's actual demand. Whereas it increases the complicity in taking each appliance's efficiency into account. As a result, the model simply takes PEC efficiency into account. Equation (3) provides the power demand of various appliances considered at the current moment "t". Here, $E_{demand}(t)$ is the energy demand, $PowerAppliance(i)$ is the power demand of ith appliance and n defines the number of appliances. The capacity of the inverter determines the upper limit of energy consumption. The energy flow through at a time interval of t can be computed using Equation (4), which is the maximum power that can flow through the inverter during t time. Similarly, the boundary condition of energy used at interval time Δt is shown in Equation (5). Demand and generation determine the system's charging and discharging for this system, where E_{PV} (t) is the energy produced by PV during the time range t, and $\eta_{Inverter}$ defined the energy efficiency of the inverter as shown in Equation (6).

$$E_{demand}(t) = \sum_{i=1}^{n} Power_{Appliance}(i) \times \Delta t \tag{3}$$

$$E^{max}_{inveter} = P^{max}_{inverter} \times \Delta t \tag{4}$$

$$E_{demand}(t) = \left\{ \begin{array}{c} \Delta E^{max}_{inveter} \; if \, E_{demand}(t) \geq E^{max}_{inveter} \\ E_{demand} \; if \; E_{demand} < E^{max}_{inveter} \end{array} \right\} \tag{5}$$

$$\Delta E(t) = E_{PV}(t) - \frac{E_{demand}(t)}{\eta_{Inverter}} \tag{6}$$

Similarly, Equation (7) defines the battery system's limitation, where the SoC stands for the battery's state of charge. The modelled battery's SoC should fall within the maximum and minimum limits. However, if the discharging or charging energy is particularly strong, the battery's SoC can reach its limit in a matter of hours or even minutes. The inverter capacity and charger controller capacity are considered by the system to restrict the amount of energy passing through the battery. Equations (8-11) can be used to compute the energy charging and discharging rate. Where depending on the system's location, $\Delta E^{max}_{Charging}(t)$) is the maximum charging energy, $BESS_{size}$ is the battery size, and TSH is the total number of hours of sunlight. Similar to that, t designates the time frame during which the energy calculation is made. Sometimes when charger capacity is mentioned, the TSH can be an ambiguous phrase. The inverter's capacity also determines the battery's maximum power flow when it is in the discharging mode.

$$SoC_{max} \geq SoC \geq SoC_{min} \tag{7}$$

$$\Delta E^{max}_{Charging}(t) = \frac{BESS_{size}}{TSH}.\Delta t \tag{8}$$

$$TSH = \frac{BESS_{size}}{\Delta E^{max}_{Charging}(t)} \times \Delta t \tag{9}$$

$$E^{max}_{Charging}(t) = P^{max}_{charger} \times \Delta t \tag{10}$$

$$\Delta E = \left\{ \begin{array}{c} \Delta E^{max}_{Charging}(t)\ if\ \Delta E \geq E^{max}_{Charging}(t) \\ \Delta E(t)\ if\ \Delta E \leq \Delta E^{max}_{Charging}(t) \end{array} \right\} \tag{11}$$

The battery powers the entire system at night and/or on overcast days, therefore Equation 12 takes this into account by regulating demand. Additionally, the charge controller directs the flow of energy based on the battery's capacity for storage. As a result, it is essential to prevent the battery system from overcharging and over-discharging. The charge controller sets a time restriction on how much energy can be stored because the battery SoC cannot be charged beyond 200% of its maximum capacity. The energy that is on hand and kept in the battery system is denoted by $\Delta AE(t)$. The SoC_{max} may change over a longer period, but because the simulation is run for a shorter period, the SoC_{max} is treated as constant. Similar to the previous situation, the battery is safeguarded by the circumstances as specified by Equations (14) and (15) when the ΔE is negative (i.e., in the discharging mode).

$$\Delta AE(t) = SoC_{max} - SoC\ (t) \tag{12}$$

$$\Delta E = \left\{ \begin{array}{c} \Delta E(t)\ if\ \Delta E(t) \leq \Delta AE(t) \\ \Delta AE(t)\ if\ \Delta E(t) > \Delta AE(t) \end{array} \right\} \tag{13}$$

$$\Delta AE(t) = SoC(t) - SoC_{min} \tag{14}$$

$$\Delta E(t) = \left\{ \begin{array}{c} \Delta AE(t)\ if\ \Delta E(t) \geq \Delta AE(t) \\ \Delta E(t)\ if\ \Delta E(t) < \Delta AE(t) \end{array} \right\} \tag{15}$$

2.3 | Load prioritisation

Nepalese microgrids lack hourly appliance demand data. Bottom-up load modelling can generate hourly load patterns based on survey data. Based on an on-site survey, the model uses the power consumption pattern of each microgrid appliance to determine the daily load pattern. The model generates a percentage-based hourly appliance load demand. Each item or collection of appliances might have a different priority level. In our scenario, the bottom-top load model is employed to detect daily appliance or priority load penetration. Based on the survey data, the algorithm identifies each appliance's total energy use. Equation (16) can be used to figure out how much power each set of appliances needs.

$$P_{Load}(t) = P_1(t) + P_2(t) + \ldots P_n(t) \tag{16}$$

Where, $P_1(t)$ is to sum the power demand of each appliance for n number of appliances in each priority set. Each priority set can contain one appliance or set of appliance controls implemented on each appliance based on their priority. $P_1(t)$ can be calculated using Equation (17).

$$P_1(t) = \sum_{i=1}^{N} PowerAppliance_i(t) \tag{17}$$

Similar to this, the energy demand for the T period can be estimated as follows, where T is the sample period and 1 for intervals of 60 min, and T/60 for other rates of measurement $T = 15/60$, for example, stands for 15 min, and $T = 30/60$, a 30-min interval. Equation (18) can be used to determine the amount of energy used by each appliance or group of appliances. The sum of the total energy demand for T time can be used to compute the total energy consumed, as shown in Equation (19).

$$E_{Pn} = P_n(t) \times T \tag{18}$$

$$E_{total,t} = \sum_{i=i}^{n} P_n(t) \times T \tag{19}$$

In this paper, an appliance-level remote survey was used to build a load profile based on energy penetration. The survey collected data on appliances' power usage, quantities, and 24-h consumption schedules. The load model was developed to identify the percentage use of each appliance throughout the day. Based on the survey data, the probability of use of each appliance at each hour is developed. Ten residential families, 15 business loads, and two industrial users were surveyed out of 225 (i.e. 202 households, and 23 business and industrial consumers) in the Sugarkhal microgrid. Sugarkhal microgrid is a solar-powered isolated microgrid with BESS, which is located in the Mid-western region of the country (GPS: 28.6306; 81.9388). The detailed specification of the Sugarkhal microgrid is given in Table 2. Figure 4 depicts sector-wise microgrid energy utilisation based on the survey perform. Data collected indicate that the majority of microgrid consumers are residential covering 64% of the load, followed by commercial covering 19% followed by industrial load at 17% of total energy consumed in the system. Residential and commercial loads are the microgrid's main consumers, so this study mainly focuses on residential loads.

TABLE 2 Technical details of Sugerkhal microgrid.

Generation type	Solar PV
Generation capacity	75 kW
Storage type	BESS
Battery capacity	425 kWh
Grid type	Isolated
Location	Sugerkhal, Karnali
Supply household	202

Based on the collected data from the Sugrekhal microgrid, an analysis has been done on the system capacity that maintains supply to the load. To perform the analysis and forecasting, data are converted into hourly energy demand. The data faces various null points which are caused due to load shedding in the system. It is observed that fluctuation in a generation has a huge impact on system reliability as a lower generation means a lower availability of the energy to be served. During these days the capacity of the system to server energy becomes lower even with a battery as backup. Figure 5 shows the hours of blackout faced by the system each day from January till August. We can observe that the lower generation days result in lower SoC at the end of the day resulting in multiple hours of blackout. We can observe that the system faces up to 13 h of load shedding, from the figure we can see the daily generation of the system such that starting from mid-June system faces multiple lower generation days, which indicates the start of cloudy and rainy days in Nepal. Similar to Figure 5(b), we can observe that during the lower generation period, most of the day faces lower SoC resulting in multiple hours of blackouts. As compared to the daily generation capacity of the system generation, the generation can decrease by 70% percentage of the maximum generation capacity per day.

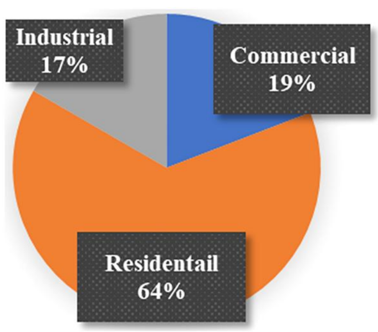


FIGURE 4 Sector-wise energy demand of Sugerkhal solar microgrid.

Table 3 shows the proposed priority categories for the residential loads, which are suggested based on user preference to trade off comfort and energy efficiency [60]. By limiting customer usage, the utility is able to save energy. For example, in the case of Sugrekhal microgrid, the grid can save 29.15% of the total energy used throughout the day by cutting back on 50% of the energy used by cooling appliances. A general overview of the appliance set based on prioritising three levels is given.

2.4 | Load forecasting model

A critical first step in implementing DSM in any area of the electrical market is comprehending the nature of demand. Compared to industrial sector usage, residential customers account for the majority of the demand in the Nepalese microgrid [4, 61]. According to research [1], home consumers' demand varies more than that of other industries. Similarly, the demand variation is rather typical for a system where residential loads predominate. Hence, the utility can manage distribution in isolated microgrids efficiently based on the amount of energy that is available by looking at past data to estimate future load. The suggested DSM uses demand forecasting data for the day ahead to assign the best energy based on the appliance and prevent system blackouts. The system distributes energy to each appliance or group of appliances using day-ahead forecasting. We see stochastic short-term load forecasting as one approach to solve the load fluctuation problem [62]. Utility companies rely on short-term forecasting to maintain generation balance while keeping costs low and preventing system instability [42]. Here, the concept of using predicted data is based on historical load data. It is impossible to estimate the load on each priority level or appliance level

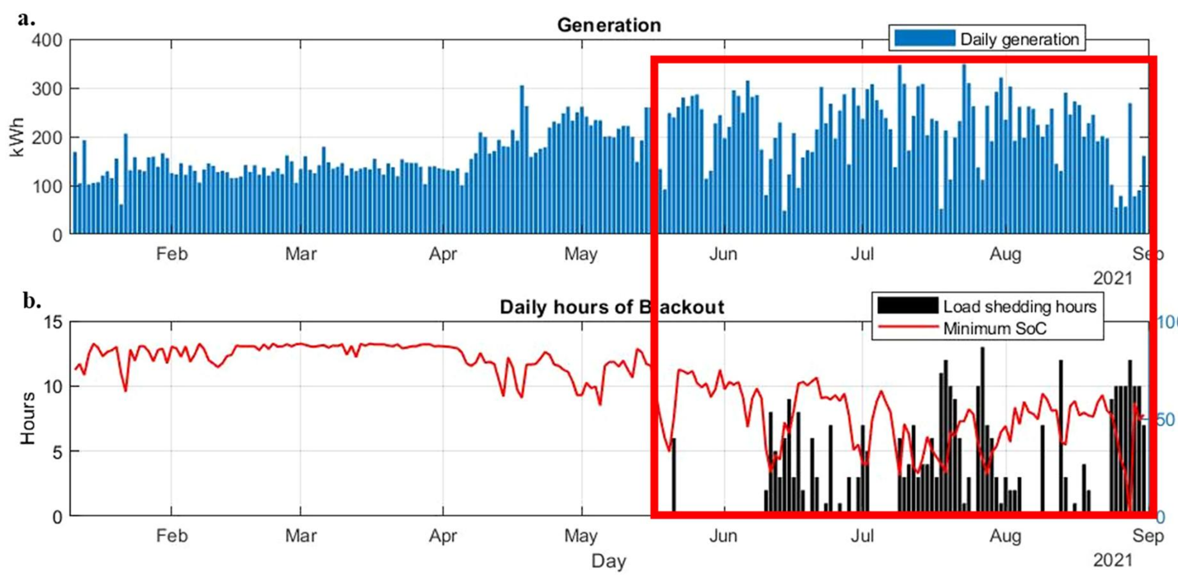


FIGURE 5 (a) Generation of Sugerkhal microgrid (b) Minimum SoC and hours of blackout faced by the system.

since historical data on how each appliance has been used is not always accessible. As a result, the proposal is to anticipate the hourly load on each priority level for utilities using survey data on appliance-level demand and historical data on overall load. The forecasting that has been put into practice includes hybrid top-bottom and bottom-top approaches to demand forecasting. The overall flow of hourly demand predictions for each appliance or priority is depicted in Figure 6. Both a bottom-up strategy based on appliance-based load analysis [63] and a top-down strategy based on time series forecasting [64, 65] is used to look at the energy demand penetration of load for the proposed hourly forecasting of load on the appliance level. Where, the bottom top approach method helps determine the penetration level of each appliance within the total energy demand of any household [63, 66], allowing them to capture the behaviours of electric demand based on seasonal and random behaviours of used appliances. With regard to the classification of load, as discussed in the literature, a survey-based study on the application of rural microgrid along with their classification and demand penetration of each appliance is shown in Table 3.

In more detail, the Auto-Regressive Integrated Moving Average (ARIMA) model is used to forecast short-term values in a stochastic manner. In the ARIMA model formula, the three main terms, p, d, and q, represent the autoregressive term, the number of differences required to make the time series stationary, and the moving average term, respectively [67, 68]. Figure 7 illustrates the steps taken to determine the values for p, d, and q in order to identify the ideal ARIMA model [65]. Due to a lack of information on the numerous variables and characteristics that affect the load, a time series forecasting method is used. The forecasting is carried out using historical data on the microgrid's electric load consumption. Since forecasting is done on an hourly basis, a total of 24-h data are generated from 24 different models. To forecast the electricity demand, 24 individual equations have been used for the training. It can be mathematically represented by Equations (20–23).

$$Y'_t = c + \phi_1 \times Y'_{t-1} \tag{20}$$

$$Y'_t = Y^f_t - Y_{t-1} \tag{21}$$

$$Y'_t = Y_{t-1} - Y_{t-2} \tag{22}$$

TABLE 3 Priority-based energy penetration.

Priority level	Appliance	Power demand (Watts)	Average per HHs/220	H/day	Penetration rate	Priority based penetration
Priority 1 (highest)	Lighting load	5	5.64	4	7.4%	37.96%
	Fan	55	2.68	3	29.15%	
	Mobile	10	2.04	1	1.3%	
Priority 2 (medium)	Refrigerator	180	0.32	6	22.8%	25.97%
	TV	50	0.24	4	3.2%	
Priority 3 (lowest)	Iron	500	0.04	1	1.3%	36.07%
	Fan	55	2.68	3	29.15%	
	Printer	400	0.08	1	2.1%	
	Photocopy	115	0.04	1	0.3%	
	Computer	200	0.12	2	3.2%	

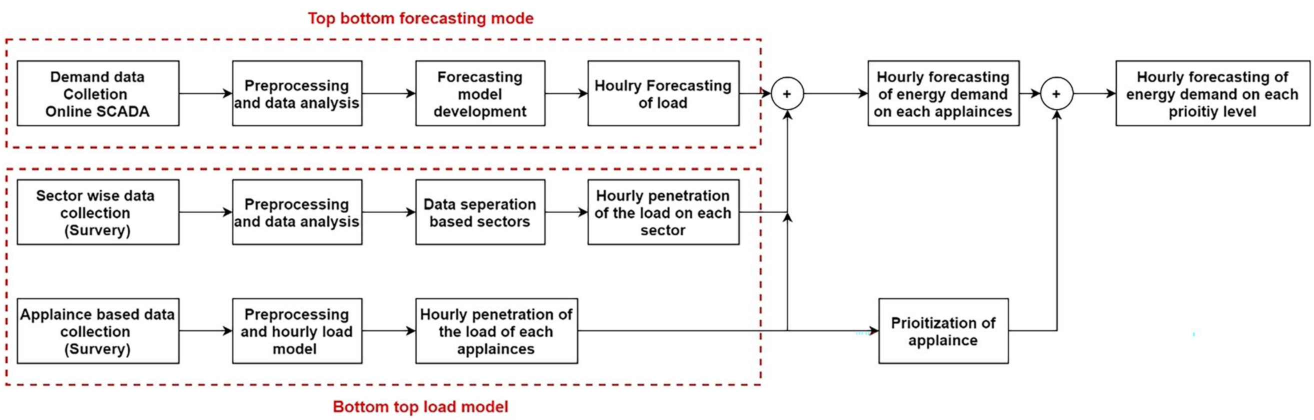


FIGURE 6 Priority-based load forecasting flow.

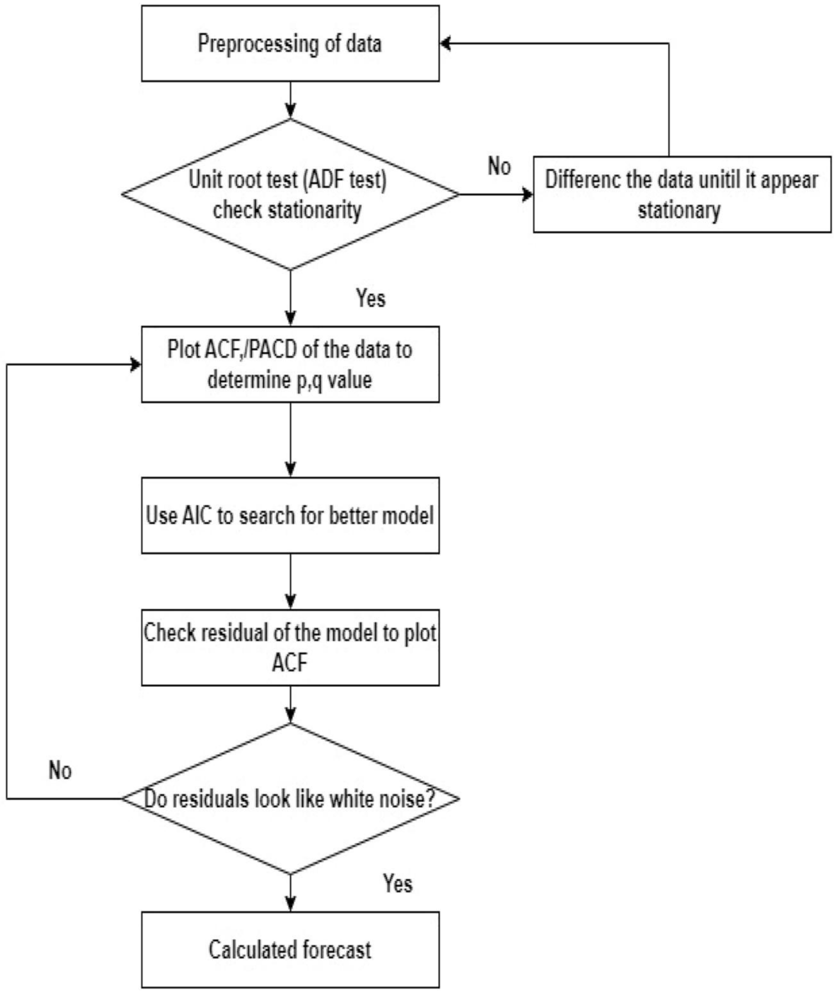


FIGURE 7 ARIMA forecasting model development.

$$Y_t^f = Y_{t-1} + \mu + \phi_1 \left(Y_{t-1} - Y_{t-2}\right) \tag{23}$$

This is an ARIMA (1,1,0) model, which is a first-order autoregressive model with one order of non-seasonal difference and a constant term. Here, $Y_t^{f'}$ refers to the first-order differencing performed to achieve stationary in the data, ϕ_1 is the coefficient, and c is the constant term. Similarly, Y_t^f refers to the predicted data for the same hour and the days earlier (i.e., Y_{t-1} and Y_{t-2}). We create 48 different prediction equations to build a model that can estimate the daily electricity load with a half-hour interval. Due to the lack of seasonality in the ARIMA model, only the tendency component of the data is considered. A years worth of data is needed to create a forecasting model, but because there are not any available in Nepal's microgrid, the model is created using only 7 months' worth of data, with the remaining weeks' worth of data utilised for comparison and analysis.

The difference between the observed value and the matching fitted value is what is left over after a model has been fitted, and this is known as the residual. It is possible to model the residual from the training data set using the normal distribution. The model leverages the residual distribution from the training model's potential forecast using Monte Carlo simulation to get a prediction interval. Equation (24) is utilised to calculate the error in forecasted values. In time series analysis, residuals can be used to assess a model's ability to detect trends in the data. A successful forecasting model will produce residuals with a constant variance, zero mean, and no correlation between them. It displays the residual histogram that was derived from the fitted model. Equation (25) can be used to express the residual's normal distribution function. Here in Equation (25), μ indicates the mean of the residual and σ is the standard deviation.

$$e_t = Y_t' - Y_t \tag{24}$$

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2} \tag{25}$$

2.5 | Optimisation model

The goal is to allocate optimal energy to higher-priority loads to preserve supply continuity for higher-priority loads followed by lower-priority loads. During low-generation periods, the system uses the battery, depleting its energy. To maximise appliance service hours, a battery restriction point can be set below which unneeded loads can be set to conserve wasteful conversion. Maximising the hours of energy served on each priority level is the goal of this optimisation issue. Model-based simulation can determine appliance and priority-set energy hours. The shedding-based DSM optimisation method can discover the optimum shedding point that maximises energy served to the highest priority load. Figure 8 shows the optimisation flow. The model simulation uses anticipated load, generation, and battery SoC. As per the predicted interval, forecasted data is generated from the higher percentile, and optimisation updates the SOC level based on priority. The algorithm removes load from different levels of storage based on the SoC, the amount of power expected to be made, and how much power is used. The optimisation technique employed in this paper is the PSO, which searches through hyperspace for a specific solution using the particles specified in the issue. PSO provides better flexibility in the addition and reduction of objective points in a single hyperspace. Multiple objective points can be identified by adding an axis to the existing space for optimising a single variable. The vector graphic in Figure 9 can be used to explain how a particle moves within this optimisation technique.

Here in Figure 9, $X_i(t)$ represent the position of ith particle at time step t, similarly, $G(t)$ represent the global best and $P_i t)$ represents the personal best of ith particle at time step t. V_i(t)

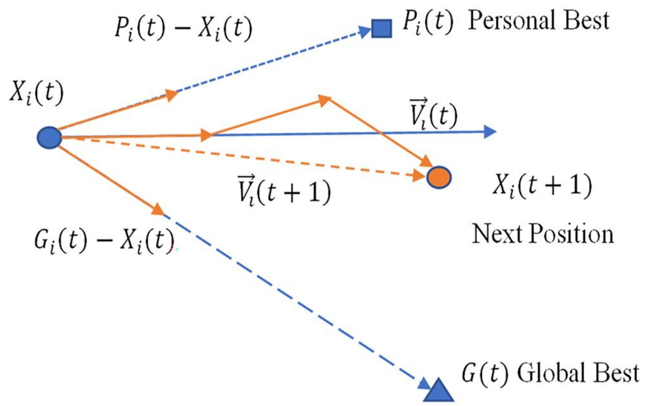
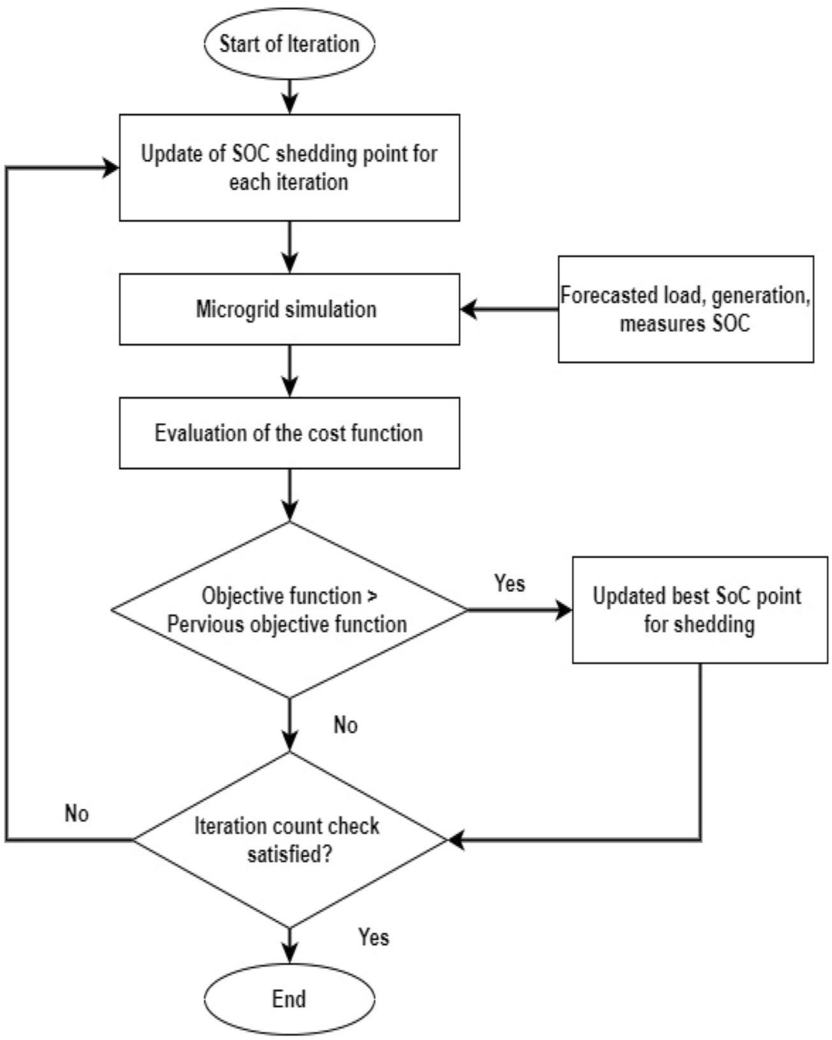


FIGURE 9 Vector representation of Particle motion to identify a new position.

FIGURE 8 Optimisation flow.



defined the velocity of the particle during the time step t. The new position of the particle can be calculated using two model Equations as given by Equations (26) and (27).

$$V_i(t+1) = w \times V_i(t) + r_1 \times c_1 \times (P_i(t) - X_i(t)) + r_2 \times c_2 \times (G(t) - X_i(t)) \quad (26)$$

$$\vec{X_i}(t+1) = \vec{X_i} + \vec{V_i}(t+1) \quad (27)$$

Here, $V_i(t+1)$ is the resultant velocity towards the new position, w is the inertia coefficient, and r_1 and r_2 are random values from 0 to 1. Using Equation (26), the velocity towards the new position is calculated, the second term defines the velocity towards the personal best position (the cognitive component), and the third represents the velocity towards the global best position (social component). Acceleration coefficients c_1 and c_2 are positive constants. The number of variables depends on the number of optimum points.

2.6 | Objective function

DSM maximises energy use for the highest-priority appliance. The system calculates the objective function based on each appliance's hours of service. The user or utility sets priority level and appliance weight based on field, condition, and customer agreement. Higher priorities are given more time, followed by lesser priorities in order. Equation (28) calculates the hourly service ratio, where PW_N represents the appliance weight/priority level for N controls, and S_N represents the hour of service to the N priority level. N is the number of control priority levels, increasing the level of priority increases computing complexity. Since the electricity supply must be maximised for all appliances, load priority may vary from user to user. Equation (28) calculates the objective function for N appliances with weights PW_1,PW_2,PW_3, …,PW_N and hourly consumption t_1, t_2, and t_3.

$$PW_1 \times S_1 + PW_2 \times S_2 + PW_3 \times S_3 + \ldots + PW_N \times S_N = objective\,fucntion \text{ (user satisfaction)} \quad (28)$$

$$S_1 = \frac{t1}{t_{SR}}, S_2 = \frac{t2}{t_{SR}}, \ldots\ldots\ldots\; S_n = \frac{tn}{t_{SR}} \quad (29)$$

Here in Equation (28), S can be calculated using Equation (29), t_1 is the hours of load served and t_{SR} is hours of service required for one day, if the model simulation is performed for 2 days it will be 48. Likewise, considering lower simulation or period of served required on each appliance say 15 min than considering a 1-day simulation $t_{SR} = 96$.

Similarly, the weight on each priority level is set by the user or utility, to maximise the weight set with the following constraints, $PW_1 > PW_2 > PW_3 > \ldots > PW_N$, and $PW_1 + PW_2 + P_{W3} + \ldots + PW_N = 1$, (i.e., $Objectivefucntion \leq 1$). The optimisation is done to maximise the objective function, which is achieved when S_1,S_2,S_3,…,$S_n = 1$; that is, the ratio of total hours of load served to total hours of required served is 1 for each priority level. To test the working of optimisation simulation is performed in a scenario considering three levels of priority control. Here, the objective function is termed user satisfaction and is addressed as so in further sections. The simulation of the overall model has been done in MATLAB, along with optimisation, forecasting, and analysis of the results obtained.

3 | RESULTS AND DISCUSSION

3.1 | A stochastic variation in demand

With the model mentioned in the previous section, a day-ahead stochastic model-based demand management for the Sugerkhal microgrid system is simulated and optimised. When using a day-ahead demand management plan, prediction errors can lead to incorrect judgements and decreased customer satisfaction. The stochastic load forecasting model implements a day-ahead forecasting-based DSM that compares user preference-based satisfaction on load distribution on different priority levels. We simulate a day with less storage and lower generation on the Sugerkhal system. Forecasting is done using an ARIMA (1,1,0) model and a Monte Carlo simulation to get a bootstrapped residual-based prediction interval. Figure 10 compares hourly load forecasts to actual load on different percentiles considered within the prediction interval. Here, MAPE ranges from 8.55% at the 50th percentile to 41.23% at the 90th percentile. Comparing hourly load forecasts with median spike variation shows a substantial demand variation from hours 13 to 17. A rapid rise in energy consumption for an hour or longer can reduce availability for the rest of the day. As daily energy consumption is 207.03 kWh, the median projection forecasts 14.08 kWh of excess demand. The simulation takes into account all nine forecasting percentiles to avoid scenarios with high energy demand that is not balanced.

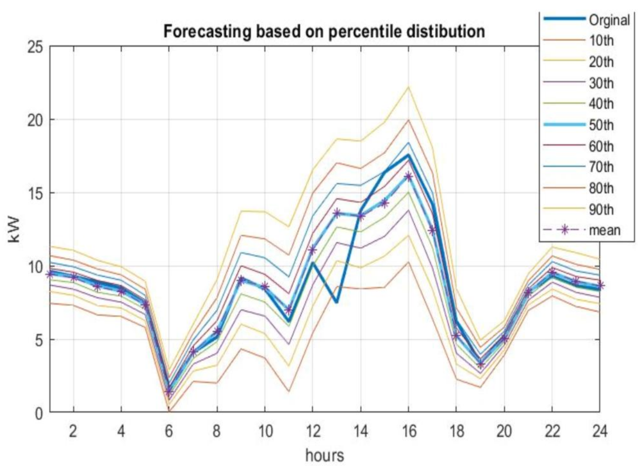


FIGURE 10 Percentile forecasting of load consumption in Sugarkhal microgrid.

The system calculates the objective function based on each appliance's hours of service, that is, to maximise the hours of service on the appliance with higher priority. The user or utility sets priority level and appliance weight based on field, condition, and customer agreement. Higher priorities have higher service time, followed by lesser priorities in order. The objective function is maximised when the ratio of total hours of load served to total hours of necessary served is 1, as discussed in section 2.6. Simulating three levels of priority control is used to evaluate optimisation, where the system complexity determines the priority level. In this paper, the simulation is done using the penetration level of each priority. In three different cases, load penetration is analysed to prove the algorithm's effectiveness. The simulation is run for the different penetration percentages of each priority in the daily load, which are taken into consideration in Table 4. Here, the case represents the daily energy penetration level of each priority, considering cases where energy penetration of higher priority load is higher compared to lower priority load (i.e. Priority 3) in case 1 and equal penetration level in case 2 to lower penetration of higher priority load in case 3.

In Section 2.4 of the manuscript, the forecasted load model incorporates a two-tier priority control system, specifically managing loads classified as P1 and P2. Table 4 details the allocation of priority weights, assigning a value of 0.6 to P1 and 0.1 to P3, the lowest priority category. These weights, whose sum equals 1 as explained in Section 2.6, were established through an iterative hit-and-trial method. This process adhered to the constraint (PW1 > PW2 > PW3) and was aimed at enhancing the overall efficacy of the method. In scenarios where the system requires varying or dynamic priority weights, specialised optimisation algorithms can be applied to further refine and maximise the method's efficiency. For the evaluation of the optimisation model, data from the Sugerkhal microgrid simulating a day with a maximum generation of 46% (i.e., 35kW peak generation) were used. It was observed that on days with lower generation, achieving a value of 1 for the objective function (i.e., user satisfaction) established challenging. The data indicate that DSM through priority-based load shedding is more likely to maintain supply when higher priority loads constitute a smaller proportion of the daily demand. This is illustrated in Table 5, which shows the optimised shedding points for each of the three control scenario levels, as derived from the optimisation process. Compared to scenarios without DSM, there is a noticeable enhancement in achieving the objective function, indicative of an improvement in the supply to higher-priority loads.

Figure 11 illustrates how optimisation works as well as the improvements made to the objective function. Two levels of flexibility in regulating the load level of shedding could improve the user experience. We can see that in all cases, priority 1 (P1) and priority 2 (P2) are completely served, which is achieved by shedding priority 3 (P3), and the figure on the right shows the total energy served at each priority level. The optimisation converter is set to the value that provides the maximum hours of service on a higher priority load; the figures on the left show the maximisation of the objective function concerning two levels of shedding. Even if the system's penetration of higher priority loads is greater than that of lower priority loads, it is nevertheless able to achieve higher levels of user satisfaction by providing higher hours of energy service to higher priority loads despite the load's different levels of penetration.

To find the optimum point for shedding the load, the optimisation is performed using PSO techniques as discussed in section 2.5. The optimisation is performed with the forecasted value of generation and demand, and the initial state of charge. The optimum point of shedding is obtained for 10th to 90th percentile-based forecasting of load. Table 6 shows the optimum points that have been identified.

For each percentile-based forecasting, the simulation presents an expected user satisfaction or objective function obtained using optimisation. Table 7 shows the expected user satisfaction with each percentile of the forecasted load obtained through simulation. The system with DSM implemented is expected to achieve maximum user satisfaction till the actual load is close to or lower than the 40th percentile of the forecasted demand condition with zero deviations in a generation. Likewise, considering the deviation in the forecasted value it can be seen that the best percentile forecasting is the 50th percentile of the forecasting model here the model expects to obtain 0.99 user satisfaction for the considered forecasted generation. In case the demand increases above the expected 50th percentile of the forecasted load, user satisfaction decreases which shows lower energy demand served for a higher percentile for the forecasted load. As in a higher percentile of load, the demand on higher priority load is comparatively more, as the optimisation algorithm sheds the lower priority to achieve maximum hours of load served to higher priority loads.

3.2 | Stochastic variation on generation

On the other hand, forecasting errors may affect the proposed system's capacity to achieve user satisfaction against expected

TABLE 4 Energy penetration of each priority set.

	Daily energy penetration			
Priority level	Case 1	Case 2	Case3	Priority weights (PWn)
Priority 1	50%	33.3%	15%	0.6
Priority 2	35%	33.3%	35%	0.3
Priority 3	15%	33.3%	50%	0.1

TABLE 5 Optimised SoC and objective function.

case	Objective function	1st level	2nd level
No DSM	0.8685	20.00	20.00
1	0.9583	43.33	20.00
2	0.9636	28.11	20.00
3	0.9726	24.45	20.00

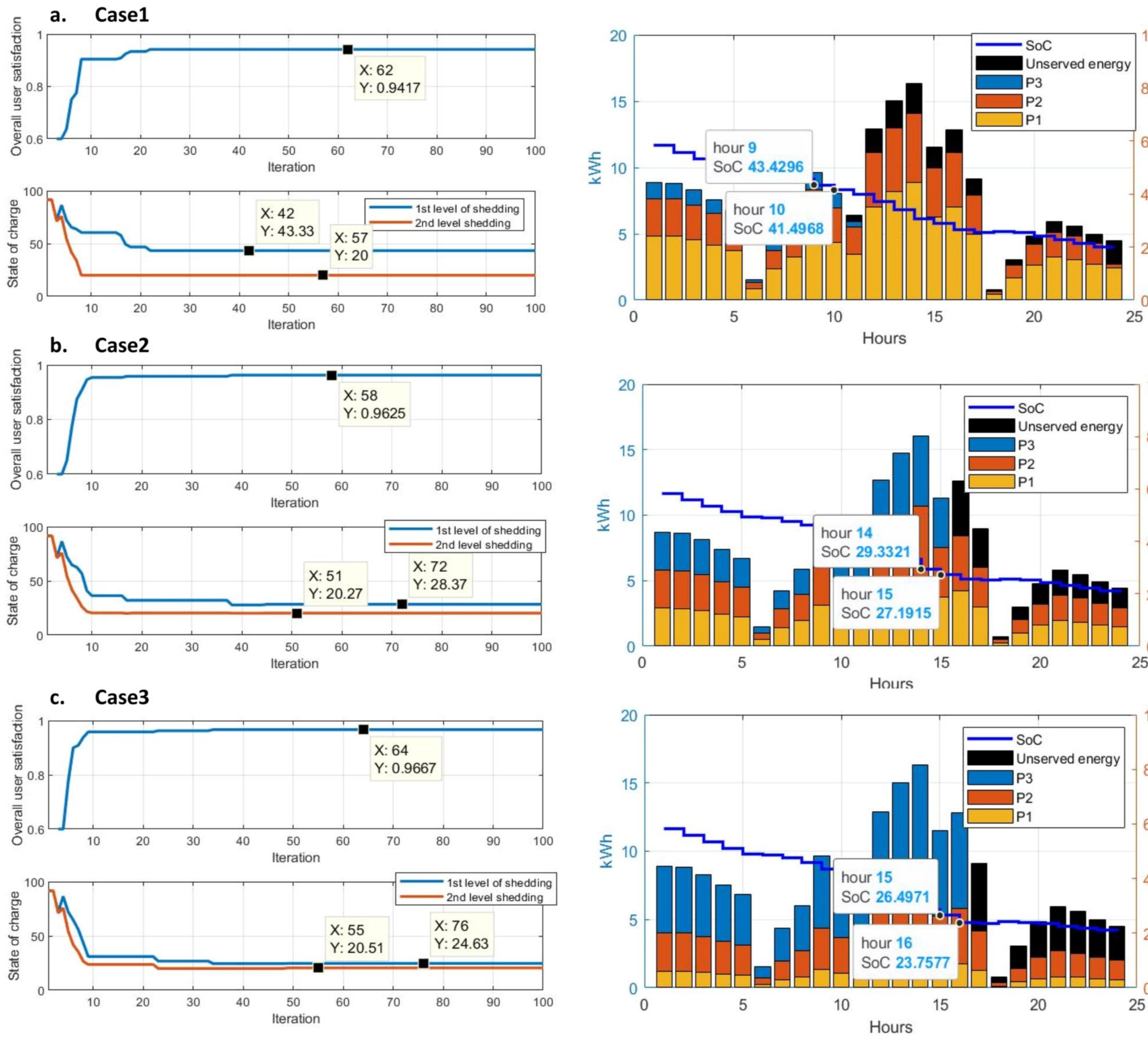


FIGURE 11 Optimisation and optimised hourly energy served for, (a) case 1, (b) case 2, and (c) case 3.

TABLE 6 Optimum Shedding point from 10th to 90th percentile.

	10th	20th	30th	40th	50th	60th	70th	80th	90th
Level 1%	34.21	28.12	25.39	20.46	25.45	29.65	32.84	33.76	35.36
Level 2%	30.68	24.71	22.32	20.00	20.00	20.00	20.00	20.00	20.00

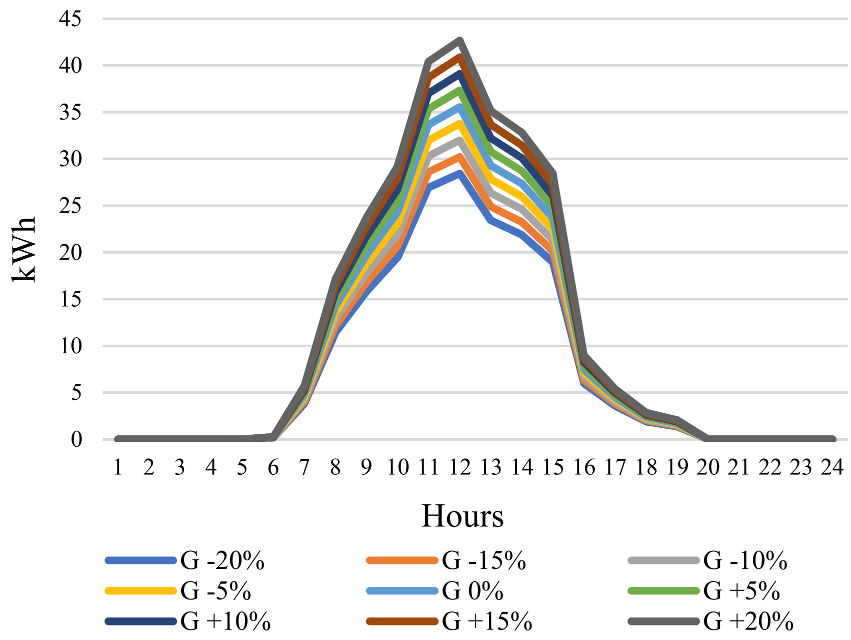
TABLE 7 Expected user satisfaction for the different percentile of forecasted load.

Expected user satisfaction (objective function)									
	10th	20th	30th	40th	50th	60th	70th	80th	90th
User satisfaction	1.00	1.00	1.00	1.00	0.99	0.97	0.95	0.93	0.92

user satisfaction. In the case of reduced generation, the predicted generation decreases total energy availability when shedding points are reached early. Since generation forecasting is not part of the research, yet is a factor that affects the system, we consider up to 20% generation fluctuation in the forecasting of real generation data. Figure 12 illustrates the considered solar generation based on predictions. All nine generation situations are simulated. The microgrid model is optimised with an initial battery SoC charge of 44%. The lower SoC replicates the lower generation days till day 2. During the sensitivity analysis, simulated errors of −20%, −15%, −10%, −5%, 0%, +5%, +10%, +15%, and +20% are taken into account. The total priority load provided throughout the day shows the working or optimisation in priority-based DSM.

In our scenario, the lowest potential generation is considered to be 20% lower than the predicted hourly load served. The actual load demand percentage is calculated for different percentile control settings. Figure 13 displays the energy supplied by the system while taking into account a 20 percent decrease in a generation. Even though all of the priorities are met during the early hours, the system will still experience a complete blackout for 4 hours if the priority-based shedding

FIGURE 12 Percentile forecasting of generation in Sugarkhal microgrid.



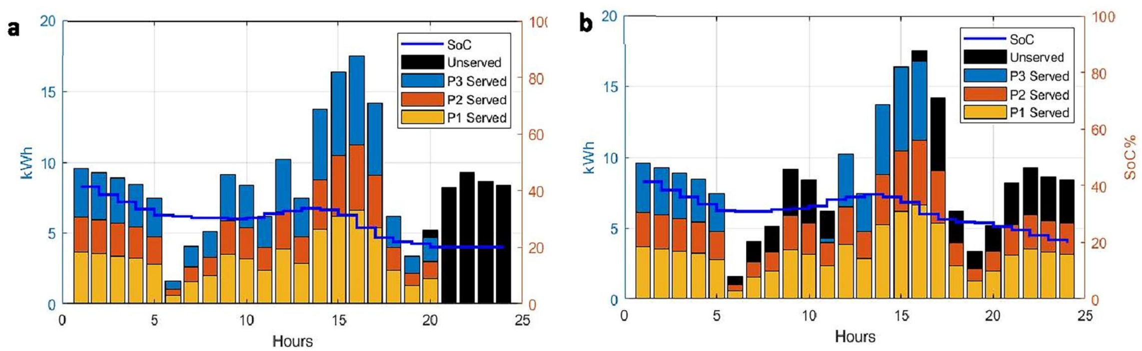


FIGURE 13 (a) Load served without DSM (b) Load served with DSM, for 20% lower generation.

strategy is not implemented, as shown in Figure 13a. However, with the introduction of priority-based DSM, the system is now able to continue supplying priority 1 (P1) and priority 2 (P2) throughout the day without interruption by offloading lower priority loads. As part of the implementation of priority-based load shedding, the system is compelled to consume less energy, which frees up resources that may be put toward sustaining the provision of power to loads with a higher priority over an extended period of time. Additionally, the system will experience partial shedding during the fifth hour, trading the use of lower priority demand and increasing the availability of storage.

In a similar manner, the scheduling pattern of the microgrid system has been evaluated for DSM, with many variations of generations as indicated (for example, −15%, −10%, −5%, 0%, +5%, +10%, +15%, and +20% of simulation errors). Figure 14 presents the findings obtained from conducting this sensitivity analysis. As can be seen in Figure 14 (a–h), the availability of the supply to all of the loads improves as the generation capacity of the system grows. P1 and P2 appear to be supplied in all of the situations, but P3 appears to be turned off for the beginning cases when there is a minimum amount of generation. The point of shedding the system is determined based on optimisation and the shedding point implemented can be seen in Table 8 for different generation conditions. When a simulation error of −15% is applied, the P3 is turned off for 13 h, as illustrated in Figure 14 (a–h). Similarly, when the generation is less than 10 percent of the base case, P3 is cut off for 8 hours, 7 hours when it is five percent lower generation, 4 hours when it is the base case, 3 hours when it is five percent, and only 1 hour when it has 10 percent higher generation. However, when the generation is greater than 15 percent, all loads are supplied throughout the day. It implies that when the generation is more than +15%, the system can achieve maximum user satisfaction by supplying the entire energy by serving the total. This is because the system is able to supply the total amount of energy. Table 8 shows the percentage of energy served on each priority while analysing the sensitivity of the generation. In cases of 10% and 20% higher generation, the complete load is served, resulting in maximum user satisfaction achieved. As generation decreases user satisfaction decreases as the shedding of lower priority load comes into play.

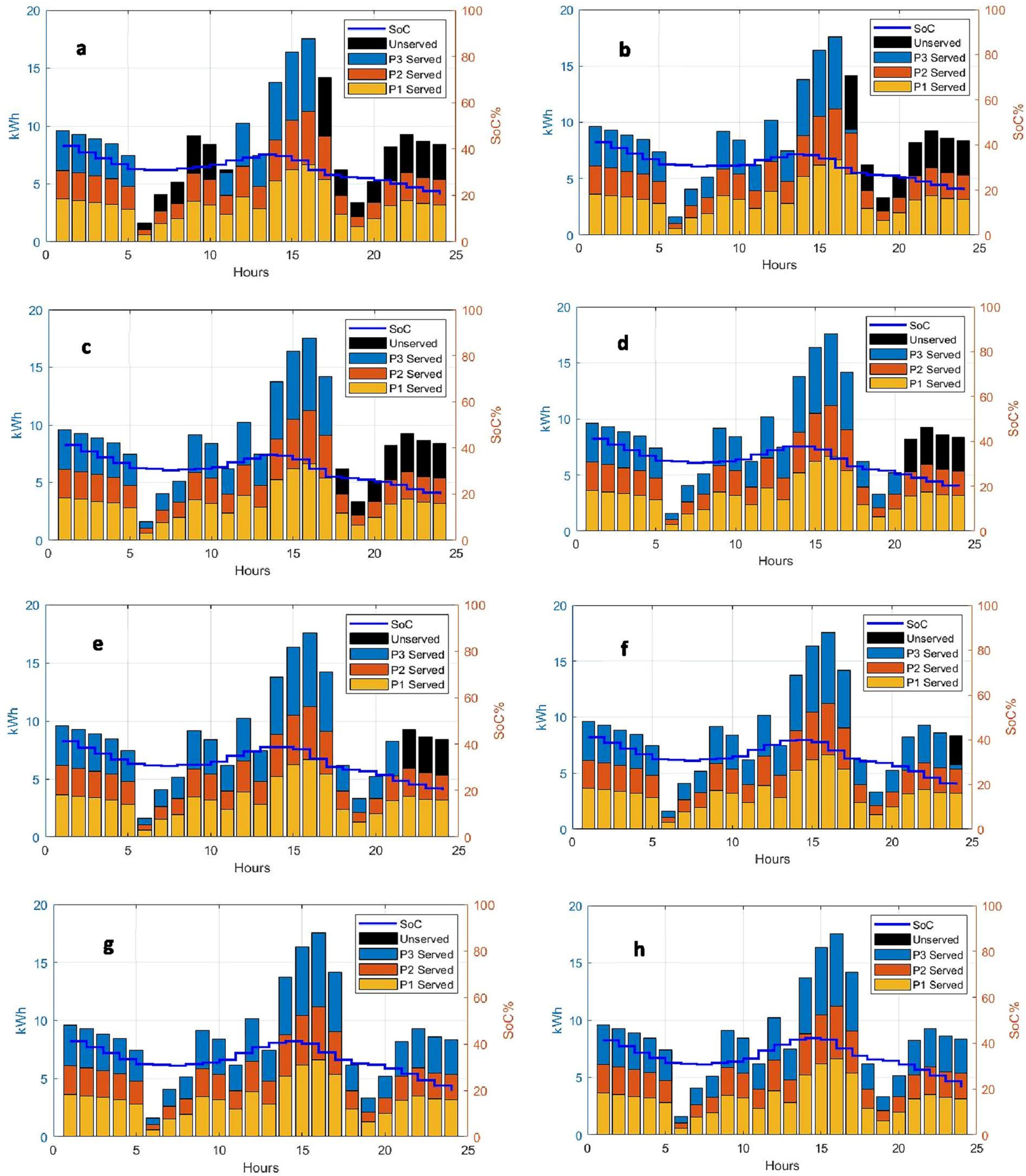


FIGURE 14 Change in generation by percentage as: (a) - 15%, (b) −10%, (c) −5%, (d) 0%, (e) +5%, (f) +10%, (g) +15%, (h) +20%.

TABLE 8 Comparison of the hours of served maintained by the proposed DSM under different generation conditions.

	With DSM									
Priority	+20%	+15%	+10%	+5%	0%	−5%	−10%	−15%	−20%	Without DSM at −20%
P1	100%	100%	100%	100%	100%	100%	100%	100%	100%	83.07%
P2	100%	100%	100%	100%	100%	100%	100%	100%	100%	83.07%
P3	100%	100%	96%	87%	83%	76%	56%	55%	52%	83.07%

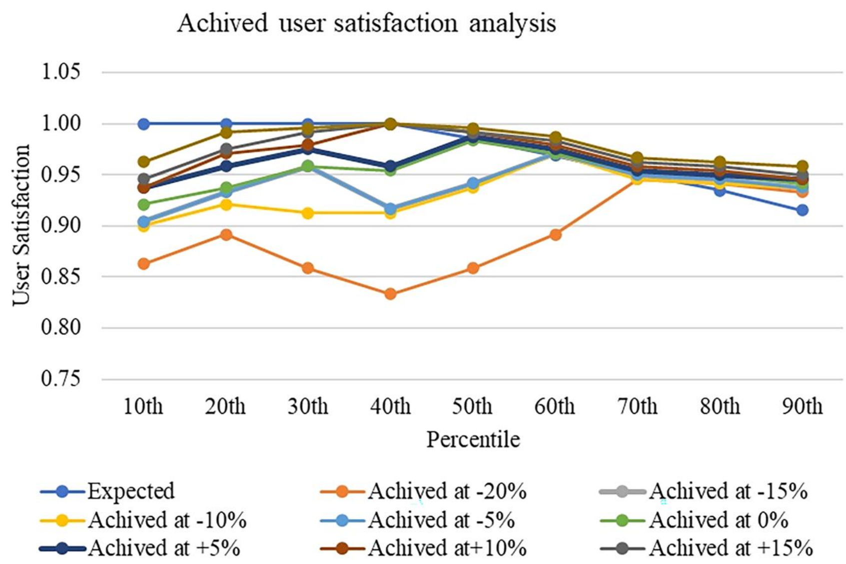


FIGURE 15 User satisfaction analysis under different percentile of generation.

In light of the fact that the data for Figure 15 has been plotted, we are able to see that when the generation variation is +10% or higher than the expected generation, taking the control point from 40th percentile-based forecasting into consideration in our case, shedding load at 20.46% and 20.00% of the load can obtain higher levels of user satisfaction. If the system acquires a greater generation, it is preferable to set the point of shedding at a minimum SoC because this will ensure that the system does not experience any shedding that is not necessary. On the other hand, if the fluctuation of generation is between +5% and 0%, applying the control point acquired from the 50th or median forecast demonstrates superior user satisfaction, which in our example is 0.98 and 0.99 for 0% and +5%, respectively. Also, for variations between −15% and −20%, the 70th percentile shows a better achievement of user satisfaction compared to implementing another percentile. In the same vein, for higher percentile-based forecasting, the system is able to obtain higher user satisfaction for variations up to −10%, and in our particular instance, this is accomplished by using a control point obtained from the 60th percentile forecast. Since the system isn't producing as much energy as expected, it's better to use higher percentile forecasting to make users experience better energy services through the DLC strategy of DSM, which will keep the supply going for higher priority loads. In all conditions, the optimisation is able to maintain user satisfaction above 90% by trading the supply in lower priority.

4 | DISCUSSION AND CONCLUSIONS

Supply deficit challenges will occur in isolated microgrid systems because of the rising demand trend and fixed generation rating. The communities connected to rural microgrid systems are forced to face blackouts during lower-generation days and critical periods. Such microgrids in developing or/and underdeveloped nations may require additional investments to add new resources, which may be unable to be made at that time. This paper proposes a DSM-based technique for extending available resources and ensuring continued supply to critical load types in order to address the concerns about system supply shortfalls and blackouts. The direct control of load through AMI technology is a key component of the proposed DSM strategy, allowing the utility to maintain the supply of the user-preferred load by trading load consumption of lower priority loads. The system used a smart metering system to control the load and incorporated shedding-based control into the remote controller. This system is based on stochastic day-ahead load forecasting algorithms. The optimisation method optimised the energy consumption for each appliance or combination of appliances by locating an optimal shedding point in the SoC of the battery, taking into account the isolated microgrid based on BESS. The system recognises shedding for three degrees of priority using the PSO algorithm, where the degree of control can be extended as per the user or utility requirements. Lower energy availability for lower priority loads during a crucial period is caused by increasing penetration of loads with higher priority.

Results show that the application of the proposed algorithm to maintain a continuous supply of load through prioritisation improves user satisfaction by maintaining continuity in supply for higher priority load. The simulation is tested for stochastic load and generation conditions. Here, analysis through simulation shows that even during under-forecasting conditions, improved user satisfaction or higher service hours to higher priority load can be achieved through optimising control action by incorporating percentile-based forecasted load data. In the presented conditions even in the worst case when generation fluctuation is −20% lower than expected the system can still archive 100% supply to both second and higher priority loads. For under forecasting conditions, variation up to −10% obtains better user satisfaction with control signal obtained from the 60th percentile, likewise, for variation in a generation move upstream with higher generation lower percentile is more suited. With variation between −15% and −20% 70th percentile shows better user satisfaction. For stochastic forecasting of day-ahead load and generation, the research for implementing demand control through energy allocation for isolated microgrid systems with battery storage. The system can maintain user satisfaction higher than 0.9 by supplying electricity to the load with the highest priority even with higher demand in the respective load category during major fluctuations in the generation of the renewable energy system.

The implementation of prioritisation-based load-shedding methods has been shown to be highly effective in managing energy distribution during periods of reduced power generation, ensuring a consistent and satisfactory power supply for high-priority users. Future developments aim to enhance this strategy by introducing additional layers of optimisation. This includes developing specific energy models for individual appliances to better understand their consumption patterns, analysing appliance storability characteristics to improve user satisfaction, and incorporating the stochastic nature of energy generation for more refined load control. Additionally, refining forecasting models by integrating environmental factors is planned to improve the accuracy of microgrid system control. Furthermore, the strategy involves setting up microgrids in laboratory environments, integrating energy management testbed equipment, and communication technologies, both wired and wireless sensor networks, to assess the effectiveness of the proposed architecture in DSM.

It is essential to acknowledge the open challenges and future outlooks in this field. Despite the progress made in enhancing microgrid systems and implementing efficient DSM strategies, several challenges remain. These include the need for further optimisation of energy storage technologies to handle the intermittent nature of RESs more effectively, and the integration of more advanced predictive analytics for load and generation forecasting. Additionally, there is a pressing need to address the scalability and adaptability of these systems in diverse geographical and socio-economic settings. Looking forward, the focus should also be on the development of more robust regulatory frameworks and policy support to facilitate wider adoption and integration of these systems. The future of microgrid systems and DSM lies in harnessing emerging technologies such as artificial intelligence and the Internet of Things (iot) to create smarter, more responsive, and user-centric energy networks. This will not only improve energy efficiency and reliability but also play a crucial role in advancing global sustainable energy goals.

AUTHOR CONTRIBUTIONS

Yaju Rajbhandari: Conceptualization; Data curation; Formal analysis; Investigation; Methodology; Visualization; Writing – original draft; Writing – review & editing. **Anup Marahatta:** Conceptualization; Investigation; Validation; Visualization; Writing – original draft; Writing – review & editing. **Ashish Shrestha:** Conceptualization; Funding acquisition; Investigation; Methodology; Supervision; Validation; Visualization; Writing – original draft; Writing – review & editing. **Anand Gachhadar:** Resources; Software; Supervision; Validation; Writing – review & editing. **Anup Thapa:** Funding acquisition; Project administration; Resources; Software; Supervision; Validation; Writing – review & editing. **Francisco Gonzalez Longatt:** Supervision; Validation; Writing – review & editing. **Petr Korba:** Supervision; Validation; Visualization; Writing – review & editing.

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CONFLICT OF INTEREST STATEMENT

None.

DATA AVAILABILITY STATEMENT

Data are Available on request.

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