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ORIGINAL RESEARCH

A novel automated demand response control using fuzzy logic for islanded battery-operated rural microgrids

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Abstract
Islanded rural microgrid require continuous resource monitoring. Demand response schemes have been phenomenal in managing loads. However, urban demand response schemes are well equipped with market prices and peak time penalties to control deferrable loads. In rural microrids, regular loads such as fans, lights and water pumps are normally used that do not fall under category of deferrable loads. In addition, full liberty of utilizing regular load at any time, lack of awareness and no information of storage reserves make task of load management more complex. In this research fully automated two layered demand response scheme is designed for regular operating loads. The first layer control is load mode control. The mode of operation is decided on the state of charge (SoC) of battery. In second layer, fuzzy controller is designed on the consumer's routines, SoC and ambient temperature as membership function. Results are assessed in terms of consumers comfort and availablity of SoC. The load operation in automated demand response remained indentical to actual rutine operation as per consumer's desire with 5 to 7% deviation. In all modes of operation SoC levels remained 15% higher and heavy load operated 13.5% more compare to relevant study.

1 | INTRODUCTION

Microgrid systems with distributed generation have been successful in electrifying far-flung areas [1, 2]. The operation of low-voltage microgrids is critical as it has a massive impact on the performance due to limited power backup and abrupt variation in the overall load [2, 3]. This impact is interpreted in terms of the stability of such islanded microgrids which is at stake due to the utilization of intermittent distributed generation sources. This in turn requires the application of battery storage systems for voltage and frequency stability, under varying load conditions [3, 4]. In general, there is a direct relation between the load profile and the social activities of the consumers. In other words, social factors are heavily associated with variations in the load [4]. Thus, there is a need to match the load with the social characteristics of the community to efficiently utilize the limited available assets such as battery storage. Factors such as lack of education and awareness about renewable energy systems, utilization of inefficient devices, and theft and damage of the renewable energy systems are common consequences, which may subsequently lead to microgrid failure, especially in rural communities [5]. Recent research trends lack the social factors incorporation in developing demand response programs.

In the literature, there are several approaches applied for the performance improvement of demand response (DR) and demand side management (DSM)programs where most of the research works uses the pricing mechanism. In [1] the dynamic electricity pricing mechanism is proposed using the particle swarm optimization algorithm. A hybrid demand response scheme is introduced in [3] for the optimal operation of the microgrid in terms of cost where maximize the microgrid operator benefit and reduce the overall operation cost.

In [4], the coupon-based demand pricing scheme is proposed using the unit commitment optimization model. In [6], blockchain technology has been used to support real-time price-based DR programs' uncertain environment with customer satisfaction, as an integral part of the algorithm. Market price has been taken as a factor for developing a demand response program. A two-way framework is presented in [7] to reduce market power using mixed-integer quadratic programming (MIQCP). However, the demand response programs do not cover the dynamic behaviour of consumers in terms of scheduling the loads. A dynamic pricing economic model is proposed in [8] to implement a demand response program with renewable power generation.

The authors in [9] presented a heat load demand response model that takes care of the heating load and consumer comfort. The overall consumers' comfort including the cooling and other responsive loads is, however, not considered in this research work [9]. A stepwise cost-based demand response program has been developed in [10] and price-based tariff for a home energy management system is simulated in [11] and price based two-stage coordination approach is implemented in [12]. An emergency demand response program is implemented in [13] where the consumers must inform about the load utilization plan a few hours earlier to adjust the participation cost. The technique uses an economic optimization algorithm to reduce the overall production. The strategy is effective in urban areas still, the less educated areas in the developing world may face problems in achieving the goals of the proposed strategy. In [14], a preference-based demand response (DR) multi-objective optimization model is proposed that optimizes the Energy Management Cost based on the multiple factors, including the inconvenient operating hours and thermal discomfort, that are recorded in the consumers' load profiles.

The proposed strategy is good for grid-connected areas. An AC Optimal Power Flow (OPF) framework is designed by authors in [15], for online scheduling of loads based on the present and past provided information of the consumers, whereas the research work in [16] used the incentive-based demand response program in which the consumers are considered as investors. Many microgrid systems presented in literature have considered the utility grid, as a backup in case of insufficient supply from renewable resources. Such proposed microgrid systems lack controllability and flexibility of utility involvement. Multi-option power transfer hybrid generation system is presented in [17]. The proposed system utilized supervisory control to manage successful power transfer from wind/PV systems to grid-connected loads. Supervisory control with three modes of operation, including, (i) normal operation, (ii) dispatch operation, and (iii) averaging operation, provide flexible power transfer and management of supply/demand [17]. The proposed system contains hysteresis-controlled battery storage to provide backup and smoothing of power injected to the grid via a low pass filter strategy of averaging operation.

However, the central supervisory control suffers from complications in energy management in case of a configuration change (connection of a new device). An energy management system based on a multi-agent system (MAS) for a hybrid generation system was presented in [18]. This system highlights the aspects of the connection of backup sources, such as fuel cells and diesel engines with the main system. A hybrid system utilizing MAS tackles the abrupt configurational changes to retain the supply of power to various loads. However, frequent charging and discharging of the storage has adverse effects on the battery life. To resolve this issue, a model of predictive supervisory control for optimal management and operation of a hybrid system was presented by authors in [19]. The proposed strategy primarily focuses on finding the optimal operating point (power references) of wind and PV systems to meet the load demand. It also incorporated optimization of peak values of surge current. The authors presented a steady-state analysis of a practical implemented hybrid generation system in [20]. The study reported the performance of a 4 kW grid-connected hybrid wind/PV system with battery storage.

In [21], a hybrid off-grid system comprising solar PV and wind systems is presented. Similarly, in [22], a PQ droop control technique is developed with the objective of active and reactive power sharing whereas in [23], a control strategy for the hybrid power system using MPPT technique is evaluated. However, the defined loads were taken in all the generation-based control schemes. Installation of an islanded microgrid in rural communities shows the great potential of electrification for areas remote from the national grid and the effective utilization of local resource generation. Microgrids have raised the living standards of isolated rural areas while providing immense opportunities for their development and improvement of their economic situation. However, due to a lack of awareness among the masses of rural areas, efficient utilization of limited electric power is often not considered which results in potential blackouts or brownouts. Therefore, an effective energy management system is required to manage the energy utilization in microgrids. The proposed energy management system by authors in [24] consists of supervisory control based on fuzzy logic to control the battery State of Charge (SoC) and the hydrogen level. This energy management system is composed of a control system that minimizes the utilization cost of the hybrid system [24].

In [25], day ahead scheduling model is developed for prosumers based on stochastic approach to address the uncertainties in the energy generation systems. In [26], a simultaneous management of different markets such as electricity, heat and hydrogen is developed using hierarchical decentralized framework whereas a two stage optimal scheduling framework for energy communities has been designed by authors in [27]. An interesting algorithm has been designed in [28] where 100% renewable energy communities having individual load controls with small generators. The uncertainties are addressed using the stochastic formulation that shows improved results. In [29], the resilience of DC microgrids is addressed using 3 stage hierarchical approach whereas in [30] the a two-stage stochastic model is used to address the severe uncertainties of distributed generations and their impact on the overall system. In [31], a multi objective model is developed for the energy hub for converters' variable efficiency, equipment deprivation yearly expansion of the load and energy prices. In [32], a bi-level bidding system to manage energy transfer in the interconnected small grids for the conventional consumers is developed, in which the conditional value at risk (CVaR) method is employed to manage uncertainties whereas in [33], a dynamic model to is developed to for better resilience of the distribution network during unexpected contingent events.

It is evident from the literature review that the most common loads in rural communities are fans, lights, motor pumps for irrigation etc. Normally, the demand response schemes provide liberty to participate in the demand response programs or to schedule the loads as per the market prices. In some cases, consumers are forced to use certain devices in a given period to reduce the stress on the available resources. In both cases, consumers are aware of the loads, market prices, and provided incentives. In the case of the developing world, where the level of education and knowledge among consumers is relatively lower, such demand response schemes cannot be applied widely. Furthermore, there is no pricing mechanism available to incentivize the consumers, especially in the case of islanded rural microgrids. In such instances, loads are used randomly without taking care of available resources which leads to potential blackouts.

This article proposes a comprehensive automated demand response scheme for the regular loads of the rural community whose operational significance varies with the time of the day and temperature factors. Section 1 discusses the contribution of this article whereas Section 2 defines the assessment of resident routines and load operation in coordination with the resident social activities. Section 3 elaborates on the control technique implemented followed by the results and discussion section.

1.1 | Shortcomings in the existing demand response schemes in rural microgrids perspective

To the best of the author's knowledge, most of the recent research works focus on optimization techniques and market-driven prices for isolated microgrids. There is a need to develop a flexible, automated dynamic demand response scheme that addresses the consumer's regular load utilization. The below points summarize the types and models of currently implemented demand response schemes. Though researchers have validated the enormous utilization of these demand response schemes utility of current demand response schemes is limited in the perspective of rural areas of developing countries.

1. Demand response schemes inclusive of the monetary parameters such as market prices and penalties for peak time load utilization are meant for effective load consumption of responsive flexible loads, such as washing machines, microwave ovens, dishwashers, air conditioners, or heating loads.
2. Usually, in urban areas, consumers have the option to defer the operation of flexible loads to off-peak hours as they have updated knowledge of market prices and the status of generation sources.
3. Significant research works are not available for incorporation of the social factors for designing demand management or demand response schemes. On the other hand, if social factors are considered, then consumer understanding of load management and scheduling is assumed to be at a higher level.

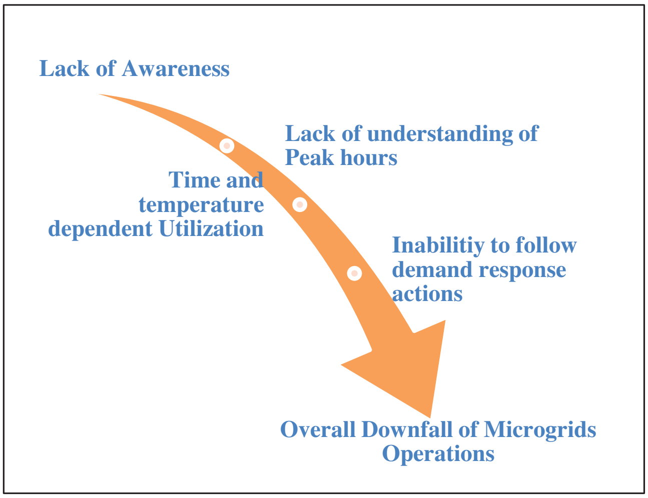


FIGURE 1 Cause and effect diagram of the rural microgrids highlighting the major factors affecting the microgrid instability.

1.2 | Problem statement and contribution

The consumers of rural communities in the developing world possess only a limited set of loads such as fans, lights, and motors whose operation cannot be deferred, as it may significantly impact the consumers' comfort and critical economic operations. The operation of these loads is time and weather-dependent and cannot be treated as deferable loads. The load criticality varies with the variation in the daily routines and ambient temperature.

The residents have full control of the load operation based on their needs and comfort which barely takes care of islanded microgrid power availability constraints. Moreover, lack of awareness, education, and other social factors, as shown in Figure 1 result in an overall lack of understanding of effective load management. Therefore, the task of managing the limited reserves in an islanded microgrid becomes even more complex.

This work proposes a dynamic demand response scheme for regular operating loads, whose operation cannot be deferred instantly. The main contributions of the paper are:

- A novel demand response scheme that intelligently controls the load operation based on dynamic resident routine, whose

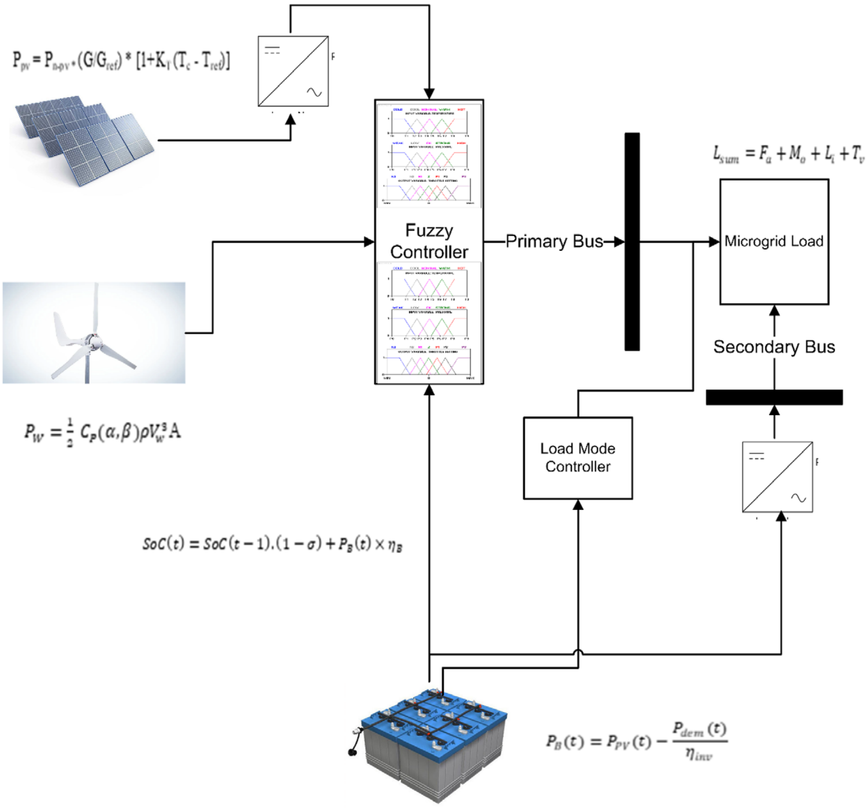


FIGURE 2 Proposed control architecture.

operational cruciality varies with the time of the day and weather changes

- A simple controller design with the flexibility of easy inclusion and exclusion of design parameters such as Time of day, state of charge, and weather as per the need of the community and to reduce human intervention to conserve energy.
- An integrated intelligent bi-level controlling architecture with enhanced operational flexibility to control the user load dynamics varying with time and weather.

The proposed methodology is based on a two-tier system as shown the block diagram of Figure 2, which includes the development of a demand response scheme following the social parameters in terms of power reliability and consumer comfort using Fuzzy Logic. To develop the demand response scheme based on the social parameters, interviews were taken to identify load operation concerning social routines and temperature variations. The following section describes the loads' operational characteristics for the development of the control strategy.

2 | INTERVIEW-BASED LOAD CHARACTERIZATION AND ASSESSMENT

A rural area of Pakistan is selected for the study. The significant social factors to be included in the design of a rural isolated microgrid controller are analyzed in detail. To incorporate the social factors in the control scheme, the time and associated load consumption are needed. This is because the type of load varies

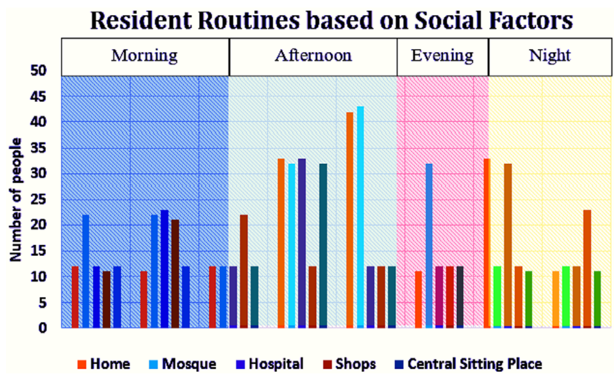


FIGURE 3 Consumers' routine based on the interview.

with the location and its consumption depends on the number of people in that location at various instants of time and weather profile.

To understand the load consumption trends of the community, their preferable loads at various instants of times and temperatures were recorded. Interviews with some of the residents were conducted to estimate the consumers' routines, and the preferable electric load they utilize for different periods and at variable room temperatures. Apart from interviews, authors had a chance to spend days in the village which gives an even more clear idea of resident routines. Figure 3 shows the estimated number of people in various locations at different instants of time. Table 1 clearly shows that the assumed four-time spans have different loads that operate in the associated time. The information from the interview helped in developing

TABLE 1 Interview-based routine of the consumers.

Activity time	11 AM to 3:00 PM Late morning to late afternoon	3:00 PM to 5:00 PM Late afternoon to early evening	5:00 PM to 7:00 AM Early evening to late evening	7:00 PM to 9:00 PM Early late evening to an early night
Operational load during summers	Fans, motor	Fans, motor	Fans, TVs, lights	Light, fan, TVs
Operational load during winters	Motors	Motors	TVs, light	TVs, light

consumer-related load profiles and provided a basic understanding of priority loads, location, and time of use of the priority loads. Based on the consumers' routine, the early night load in summer is highest, while during winter, the overall consumption does not include heavy loads other than motors. Therefore, the observed social routine indicates that load variations are following the consumers' routine that is time of the day, and the other factor is temperature impact.

Briefly, considering the time of the day represents the daily routine of the consumers and can be added as a social factor that may be used in the control scheme to prioritize the load and satisfy the load utilization as per the settled routines. Another factor is the temperature which is related to the comfort level.

To integrate the social factors with the availability of the reserves, the SoC is taken as a third factor to be incorporated in the demand response scheme. Based on these three factors, fuzzy membership functions and load mode controller is designed in Sections 3 and 4 respectively. The priority loads shall be automatically turned on and off while taking care of the comfort level and available reserves. Since most of the loads are operational from the late morning till afternoon and then at night, for simplicity and validation of the algorithm, simulation is performed for the busiest hours of the day, during which the majority of the loads are running. Eight hours are considered for simulation, starting from the late morning till early night hours.

3 | FUZZY LOGIC-BASED DEMAND RESPONSE

Based on the social factors assessed on routines and interviews, three major membership functions were developed. The time of the Day, temperature, and SoC of the storage is taken as the membership functions. Fuzzy triangular membership functions have been used in this research as it is based on extensive research on various membership functions, triangular and gaussian membership functions are found to be performing well over other membership functions [23]. The rules are defined based on the developed membership functions. Here, we describe the mathematical representation of the summer and winter load of the residential microgrid. The fans are considered as 120 Watt each, lights are 18–30 watts, TV wattage is 150 watt each and motors/water pumps are 100 kW each, which is the highest load.

$$\mathbf{L}_{\mathbf{sum}} = \mathbf{F}_{\mathbf{a}} + \mathbf{M}_{\mathbf{o}} + \mathbf{L}_{\mathbf{i}} + \mathbf{T}_{\mathbf{v}} \tag{1}$$

$$\mathbf{L}_{\mathbf{win}} = \mathbf{M}_{\mathbf{o}} + \mathbf{L}_{\mathbf{i}} + \mathbf{T}_{\mathbf{v}} \tag{2}$$

where $\mathbf{L}_{\mathbf{sum}}$ represents summer load, $\mathbf{L}_{\mathbf{win}}$ is the winter load, $\mathbf{F}_{\mathbf{a}}$ is the fan load, $\mathbf{M}_{\mathbf{o}}$ is the Motor load, $\mathbf{L}_{\mathbf{i}}$is the lighting load and $\mathbf{T}_{\mathbf{v}}$ is the Television load. The total power consumption of these loads in summer and winter can be expressed as [24],

$$\mathbf{P}_{\mathbf{summer}} = \sum_{1}^{\mathbf{K}} \mathbf{P}_{\mathbf{ck}} \tag{3}$$

$$\mathbf{P}_{\mathbf{winter}} = \sum_{1}^{\mathbf{K}} \mathbf{P}_{\mathbf{ck}} \tag{4}$$

where $\mathbf{P}_{\mathbf{summer}}$ represents overall consumption of the summer load and $\mathbf{P}_{\mathbf{ck}}$ represents the load of summer where K varies from 1 to K. Similarly, $\mathbf{P}_{\mathbf{winter}}$ represents the winter load and $\mathbf{P}_{\mathbf{ck}}$ represents the load of winter where **k** varies from 1 to **K**. The power consumption patterns are required for the estimation of energy consumed by each load which can be calculated and expressed as [34].

$$E_{\text{daily}} = \frac{3600 \times W_{\text{standby}} + \sum_{n=1}^{n_{\text{app}}} f \times W_{\text{cycle,n}} \times t_{\text{cycle,n}}}{} \text{Kwh/day} \tag{5}$$

where E_{daily} is the energy consumption per day (kWh), W_{standby} is standby power consumption in watts, $W_{\text{cycle, n}}$ is nominal power consumption in watts, f is the mean starting frequency of each appliance, $t_{\text{cycle,n}}$ is the average cycle length for an appliance and N_{app} is the total number of appliances

The values of the other two membership functions are based on the comfort and discomfort level of the consumers which can be formulated as Equation (6) [36].

$$\boldsymbol{\mu}_1 \left[1 - \left(\frac{\mathbf{e}_\tau}{\boldsymbol{\tau}_{\mathbf{set}}}\right)\right]^2 + \boldsymbol{\mu}_2 \left[1 - \left(\frac{\mathbf{e}_{\mathrm{L}}}{\mathbf{L}_{\mathbf{set}}}\right)\right]^2 + \boldsymbol{\mu}_3 \boldsymbol{\mu}_2 \left[1 - \left(\frac{\mathbf{e}_\alpha}{\mathbf{A}_{\mathbf{set}}}\right)\right]^2 \tag{6}$$

where, $\boldsymbol{\tau}_{\mathbf{set}}, \mathbf{L}_{\mathbf{set}}, \mathbf{A}_{\mathbf{set}}$are temperature, illumination, and air quality, respectively. $\boldsymbol{\mu}_1$, $\boldsymbol{\mu}_2, \boldsymbol{\mu}_3$ are weight factors that are user-defined values and, it is assumed that cumulative weights factors with the defined variables equal to 1.

The fuzzy membership functions are based on the following equations [37]. We consider **E** as a set having a real number. A fuzzy subset is a set of ordered pairs:

$$\mathbf{ToD} = \left\{ \frac{\mathbf{X}, {}^{-}{}_{\text{morning}}(\mathbf{X})}{\mathbf{x}}, \frac{\mathbf{X}, {}^{-}{}_{\text{noon}}(\mathbf{X})}{\mathbf{x}}, \frac{\mathbf{X}, {}^{-}{}_{\text{evening}}(\mathbf{X})}{\mathbf{x}} \in \mathbf{E} \right\} \tag{7}$$

$$\mathbf{SoC} = \left\{ \left\{ \frac{\mathbf{X}, {}^{-}{}_{\text{low}}(\mathbf{X})}{\mathbf{x}}, \frac{\mathbf{X}, {}^{-}{}_{\text{Mid}}(\mathbf{X})}{\mathbf{x}}, \frac{\mathbf{X}, {}^{-}{}_{\text{high}}(\mathbf{X})}{\mathbf{x}} \in \mathbf{E} \right\} \right\} \tag{8}$$

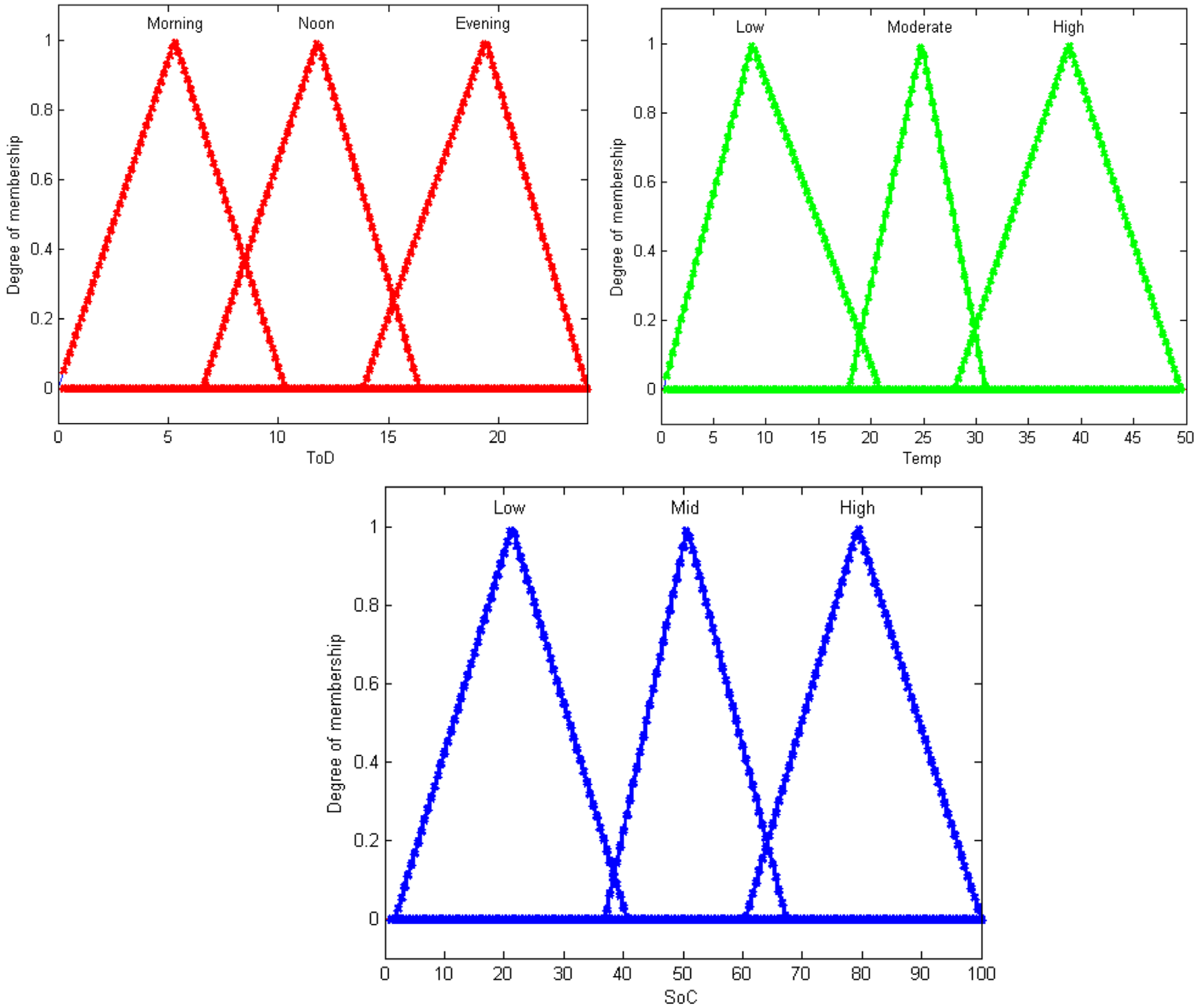


FIGURE 4 Designed fuzzy logic-based membership functions based on the routine of the consumers.

$$\mathbf{Temp} = \left\{ \left\{ \left\{ \frac{\mathbf{X}, \boldsymbol{\mu}_{\text{low}}\ (\mathbf{X})}{\mathbf{x}}, \frac{\mathbf{X}, \boldsymbol{\mu}_{\text{Moderate}}\ (\mathbf{X})}{\mathbf{x}}, \frac{\mathbf{X}, \boldsymbol{\mu}_{\text{high}}\ (\mathbf{X})}{\mathbf{x}} \in \mathbf{E} \right\} \right\} \right\} \tag{9}$$

where $\tilde{\boldsymbol{\mu}}$ is a function $:\boldsymbol{\mu}\ :\ \mathbf{E} \rightarrow [0,\ 1]$.

This system is modelled in MATLAB Simulink and tested for various scenarios and conditions of SoC of storage using load mode control. This control scheme is preferred due to its simplicity in terms of implementation, its high reliability, and because of its high efficiency. The membership functions (Figure 4) and fuzzy rules were designed based on the operational routines of the consumers.

4 | MICROGRID MODE SELECTION CONTROLLER

A load mode controller decides the microgrid operational mode. There are three modes of operation, namely, Normal mode, Energy Conservation mode, and Emergency mode. The controller decides on one of the operational modes based on the battery SoC. A simulated model of a controller is developed in MATLAB/Simulink for the mode selection. Based on the mode of the controller, the fuzzy logic controller decides for the loads to be operated in that mode. The decision for selection and operation of the loads is based on the time of the day, state of charge of storage, and ambient temperature of the area. The load mode selection and associated fuzzy-based demand response scheme work centrally and thus can be called a centralized controlling scheme. The available solar power, wind power, and state of charge values can be computed using the mathematical model proposed in [35, 38, 40]. The mechanical power proposed in [29] for the wind turbines is computed using, an Equation (10).

$$P_W = \frac{1}{2} C_p(\alpha, \beta) \rho V_w^3 A \tag{10}$$

where P_W the mechanical power of the wind turbine that is dependent on the speed of the wind that blows here 'ρ' is the air density (kg/m^3), V_w is the wind velocity, A is swept the area, C_p is the power coefficient. The PID controller takes P_W

value of the wind turbine generator as one of the variables for decision-making. Here C_p is defined as [39]:

$$C_p \quad (\alpha, \beta) = 0.22\left(\frac{116}{\gamma}\right) - 5 - 0.4\beta)\exp^{\frac{-125}{\gamma}} \tag{11}$$

$$\gamma = \left[\frac{1}{\lambda + 0.08\beta} - \frac{0.035}{1+\beta^3}\right]^{-1} \tag{12}$$

$$\lambda = \frac{R_W}{V_W} \tag{13}$$

where R_W is the blade radius (m), V_W is the wind speed (m/s), and C_p is the power coefficient, C_p –λ curves for different blade pitch angles. the function of the tip speed ratio λ, blade pitch angle β, and where ωB is the blade angular velocity (rad/s).

For the proposed MATLAB simulations, the change in solar PV power is taken as proportional to the change in solar irradiation. The first order transfer function solar PV model is expressed here as [40]:

$$TF_{PV} = \frac{\Delta P_{PV}}{\Delta P_{\varphi}} = \frac{1}{1 + sT_{PV}} \tag{14}$$

where TF_{PV} is the first-order transfer function of Solar PV systems, ΔP_{PV} is change is solar PV power and ΔP_{φ} is the change in irradiation of solar PV power. The state of the charge of the battery is represented as:

The power from PV can be defined as [32].

$$P_{pv} = P_{n-pv*}\left(G/G_{ref}\right) * \left[1 + K_T\left(T_c - T_{ref}\right)\right] \tag{15}$$

$$T_c = T_{amb} + (0.0256 * G) \tag{16}$$

Where, T_c= Cell temperature (°C), T_{amb}= Ambient temperature (°C), G = solar radiation (W/m^2), P_{pv} = Output power from PV cell (W), $P_{n\text{-}PV}$ = Nominal power from PV cell at reference conditions (W), G_{ref} = solar radiation at reference condition (1000 W/m^2), K_T = Temperature coefficient at maximum power (3.7 × 10^{-3} (1/°C)), K_{ref} = PV cell temperature at reference conditions (25°C) [41].

The battery power can be calculated as given in Equation (17) [43].

$$P_B(t) = P_{PV} \quad (t) - \frac{P_{dem}(t)}{\eta_{inv}} \tag{17}$$

where $P_{PV}(t)$ is the total power produced by the PV system and $\frac{P_{dem}(t)}{\eta_{inv}}$ the total power demand by the loads at time t η_{inv} is the inverter efficiency.

$$SoC \quad (t) = SoC\,(t-1)\,.\,(1-\sigma) + P_{pv}(t) - \frac{P_{dem}(t)}{\eta_{inv}} \times \eta_B \tag{18}$$

where $SoC(t)$ is the state of the charge of the battery at any instant of time t, that is, the charge quantity available in the battery during the normal, emergency and energy conservation modes of operation. T and $SoC(t-1)$ is the state of the charge of the previous time step and $P_{dem}(t)$ is power demanded at times t and η_B is the storage efficiency. Substituting Equation (17) in (19), Equation (18) can be re-written as:

$$SoC \quad (t) = SoC\,(t-1)\,.\,(1-\sigma) + P_B(t) \times \eta_B \tag{19}$$

where $\mathbf{P_B(t)}$ and η_{inv}, η_B and σ are the inverter efficiency, storage efficiency, and hourly self-discharge respectively and the subtraction sign indicates the discharging of the storage, $SoC(t-1)$.

In total, three cases were simulated to validate the performance of the fuzzy load controller as shown in Figure 5. The input parameters discussed above were changed concerning each scenario. The three cases along with the variations in input parameters are shown in the Table 2. The first case scenario is Normal mode, followed by Energy conservation and emergency mode. To analyze the controller performance, abrupt variations in the input values of solar and wind power were given in a pattern that solar was higher that decreased later in the simulation whereas wind power was taken as lower initially that increased in the end. Constant variations in the SoC of the storage were performed in each stage to analyze the variations in the load.

5 | SIMULATIONS RESULTS AND DISCUSSIONS

The extensive simulation results of the proposed hybrid AC islanded microgrid system are presented in this section, for all three modes of operation, that is, Normal, Energy Conservation, and Emergency modes. The power curves, percentage SoC of battery, DC link voltage, and DC link current are studied in response to the change in load consumption. As shown in Figure 3, the highest load is during the late morning until early night, which is 9 h of operation. That is why simulation is only performed for 9 h of operation when demand response schemes are implemented. In the proposed dynamic demand response, the controller will either allow or not allow the operation of different loads based on the decision parameter values. It is possible that user may not operate the load even when the controller has allowed the free operation of the load. The results for the operation of loads shown are based on the controller decision for the load operation. 1 means load can be operated while 0 means load must be turned off.

5.1 | Normal mode operation (70% initial SoC of battery)

With 70% of the battery, the load mode controller is assumed to be in normal operation. Under normal operation, the load remains constant for the entire simulation as shown in Figure 6a. The load is not reduced as ample solar power is available which is enough to feed the load. During the 4th hour, the solar power is reduced, and the battery fulfils the power difference. At the same time, wind power production starts, which reduces the power supply to the load from battery storage. It can be seen

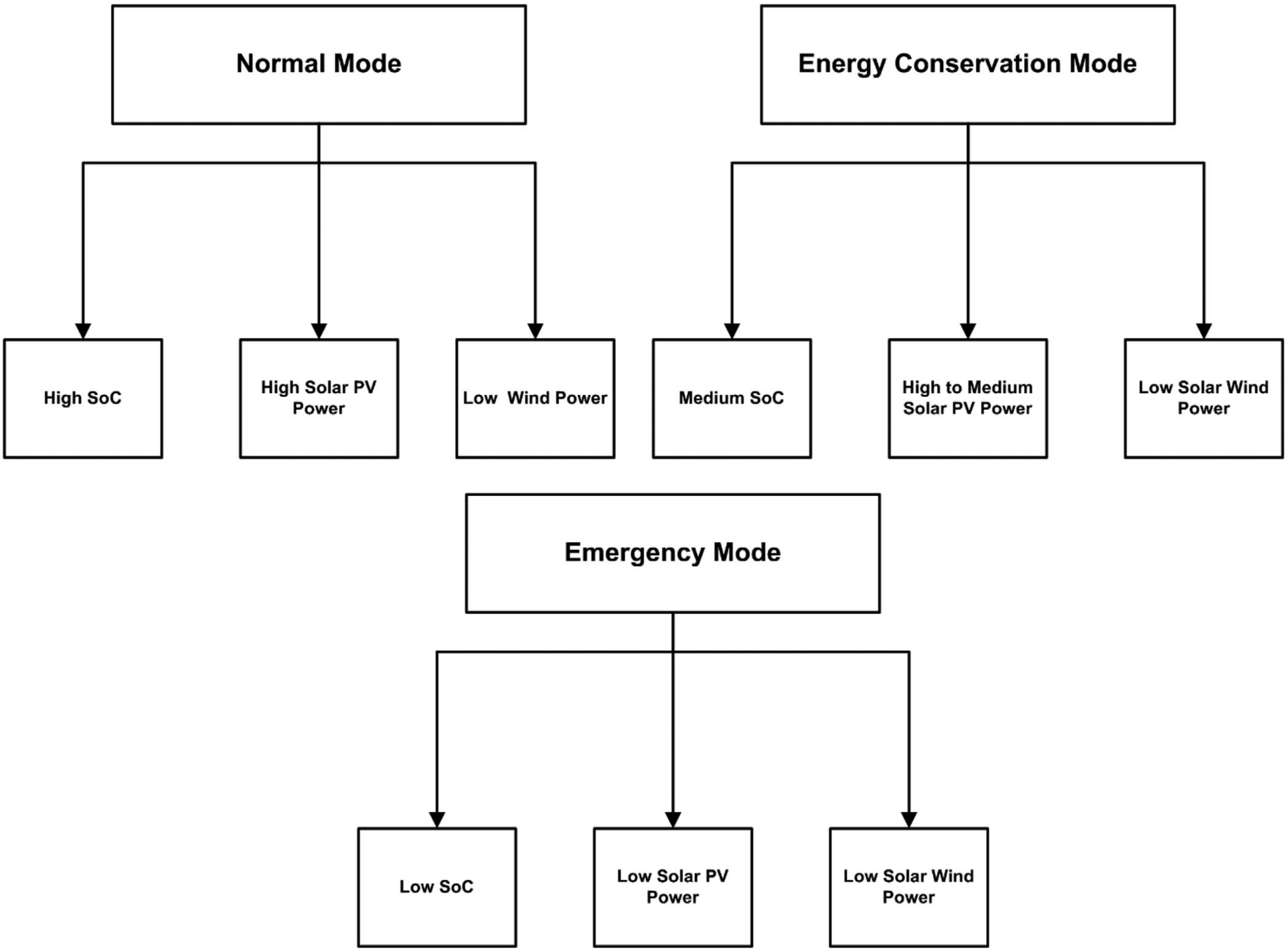


FIGURE 5 Case study topology for different modes of operation.

TABLE 2 Details of case studies simulated along with the input and out parameters.

Scenarios	Input parameters			Output parameter
	SoC	**Solar power (1.5 MW)**	**Wind power (3 MW)**	**Load power (3 MW)**
Normal mode	>70%	Ample solar power of in the initial state and gradually reduces	Low wind power initially increases gradually	Remains constant
Energy conservation mode	>50% SoC < 60%	Ample solar is available in the initial state and reduces gradually	Low wind power initially increases gradually	Higher load initially
Emergency mode	SoC < 50%	Ample solar is available in the initial state and reduces gradually	Low wind power initially increases gradually	Higher load initially

in Figure 6b, the SoC remains well within the available limits and the load mode controller keeps all the load operational during the entire scenario. The DC link current and voltage remains stable throughout the load operation as shown in Figure 6c.

The operational loads under the normal mode and their percentage of operation can be seen in Figure 7. The recorded temperature was low initially that gradually increases during the daytime, due to which the fan remained unoperated initially and started operation as temperature rises. The 10–15 min operation breakup of fans can be observed in between 5 and 6 h. On the other hand, the heavy load of the motor remained operational entire day with some minor 10–15 min operational breaks. Since the operation of the heavy load is critical during the daytime, that is why its operation remains active most of the time. It is worth mentioning here that the load criticality changes with time. Due to the evening, and higher temperatures, the two loads that are considered critical, are fans and lights, which remained turned on. The TV load was also operational under the given scenario, as it has a very limited consumption compared to the other loads.

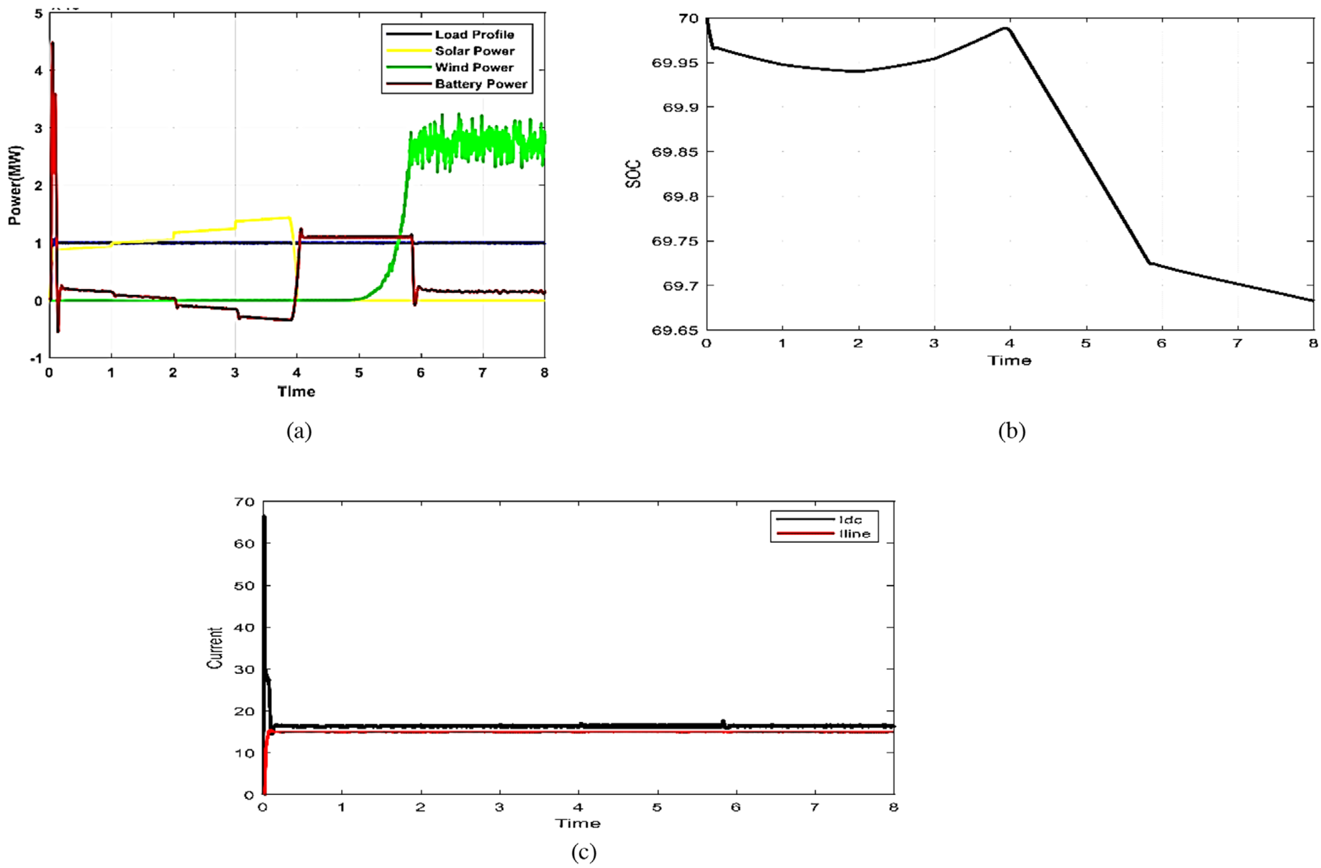


FIGURE 6 (a) Generation, storage, and load profile trends during the normal mode. (b) SoC of battery storage during the normal mode. (c) Load and DC link currents of microgrid for the normal mode.

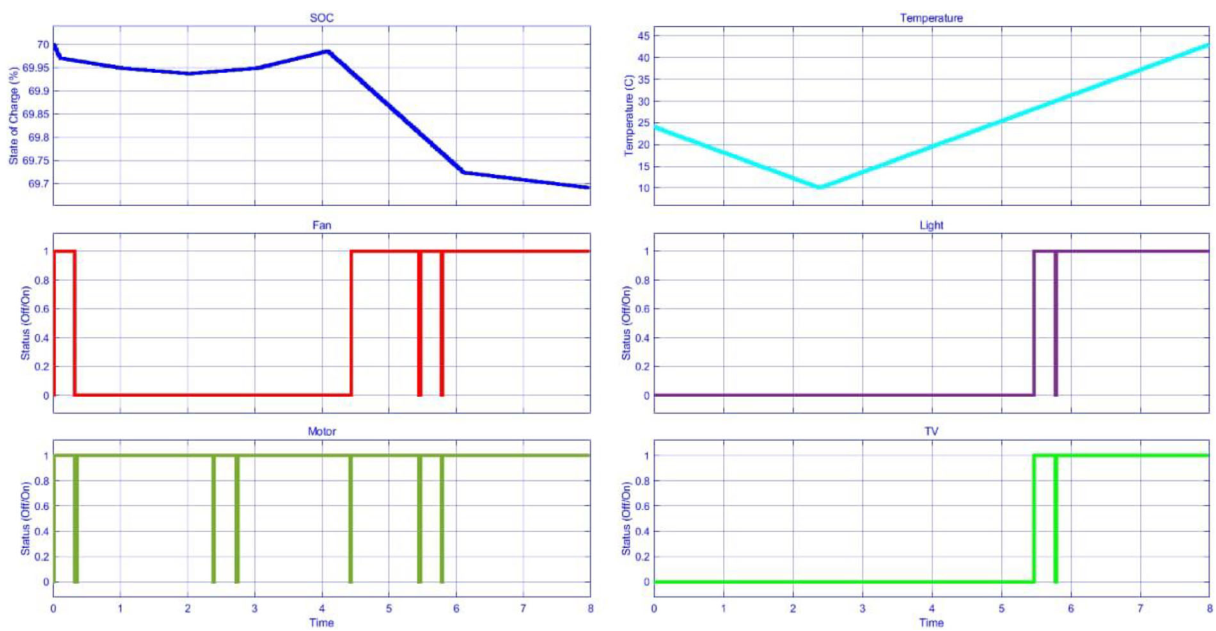


FIGURE 7 Behaviour of loads under dynamic demand response scheme under the normal model.

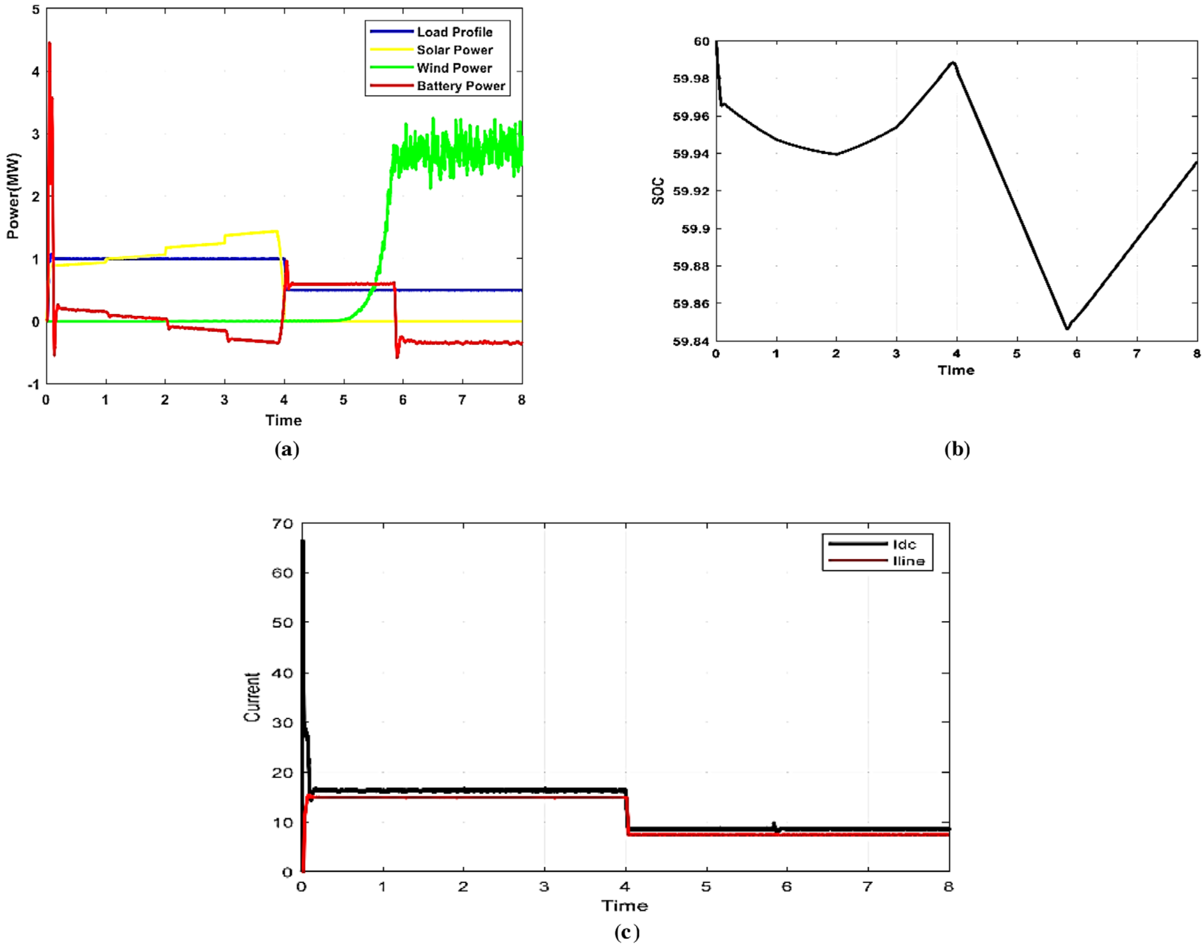


FIGURE 8 (a) Generation, storage, and load profile. (b) SoC of the microgrid during the energy conservation mode. (c) DC Link current and load of the microgrid during the energy conservation mode.

5.2 | Energy conservation mode (60% initial SoC of battery)

For the 60% initial SoC of the battery, power curves for wind, solar, battery, and load are shown in Figure 8a. The graph shows that only solar power is available for the first 4 h of the simulation time, while SoC is above 58%. Therefore, the Energy Conservation mode does not activate, and all the load demand is satisfactorily met. However, after the duration of first 4 h, power generation from both sources depletes. Hence, the load mode controller establishes the Energy Conservation mode and sends a signal to the fuzzy controller to reduce the most appropriate load. The load is compensated through the battery which drops the SoC below 58 %. As soon as wind power is available after 6 h, which charges the battery and SoC starts to recover, as shown in Figure 8b. However, SoC is less than 60% and the energy conservation mode remains activated. The current is shown in Figure 8c, which remains stabilized.

The demand response scheme in the energy conservation mode can be seen in Figure 9. The temperature remained low initially and increases gradually during the daytime, due to which the electric load of fans remained during the second half of the day. On the other hand, heavy loads remained off during the evening time and remained operational for 2.5 h only, due to the limited storage availability. Lighting load remained on during the night-time in the energy conservation mode of operation. However, the TV load was allowed operation only for 0.5 h compared. As observed from the simulation results, the load mode controller opts for a certain percentage of the total load to be operated, following the demand response scheme based on social factors. The decision to run the most appropriate load is made on the consumer's comfort, as a priority. Due to the integration of the two controllers, the systems do not enter in the blackout stage and due to the energy conservation mode's intelligent and proactive operation, the charging of storage is initiated as well, thus providing better reliability.

5.3 | Emergency mode (50% initial SoC of battery)

In this scenario, the initial SoC of the battery is set at 50%. As illustrated in Figure 10a, solar energy provides power only for the first 4 h of the total duration. The wind turbine initiates

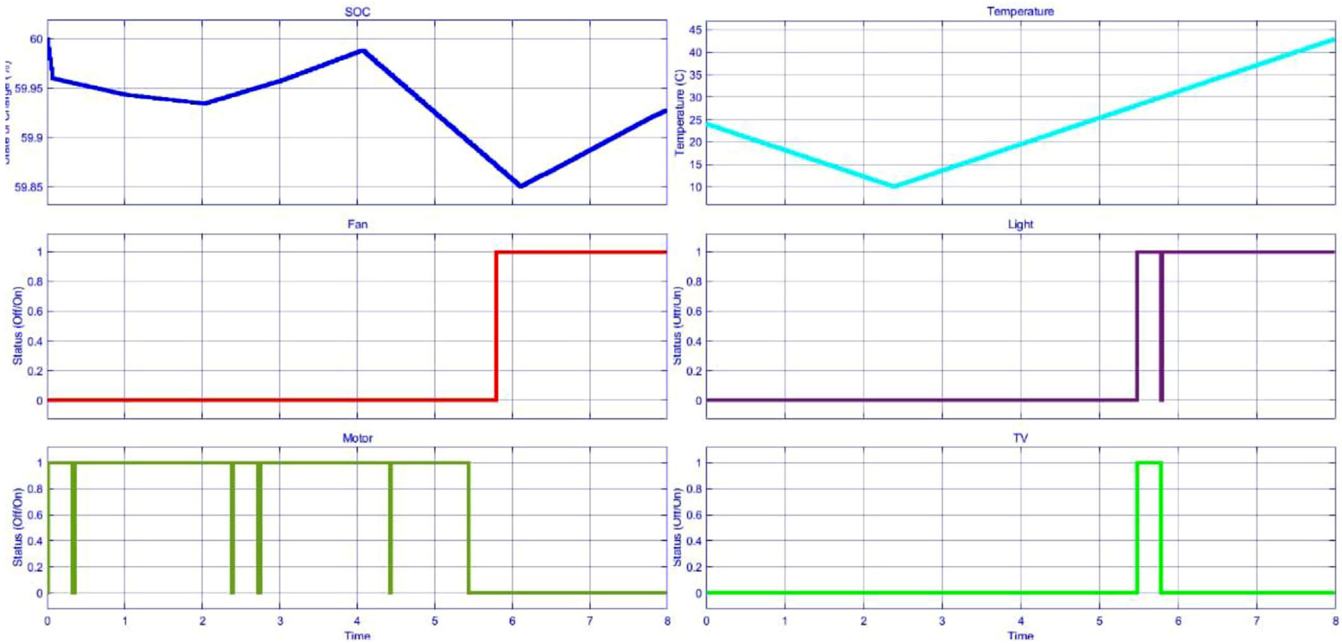
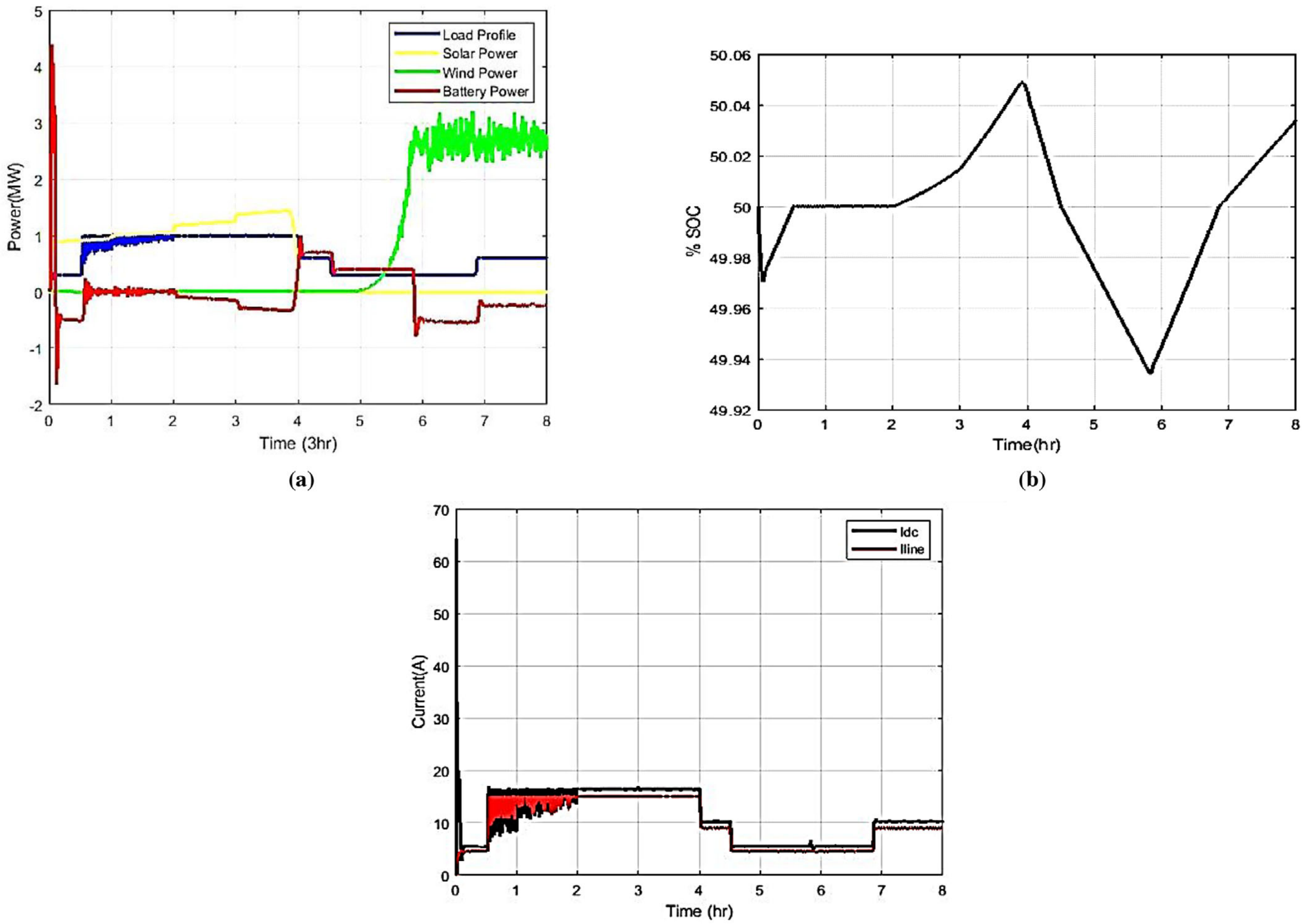


FIGURE 9 Behaviour of loads under dynamic demand response scheme under the energy conservation mode.



(a) (b) (c)

FIGURE 10 (a) SoC of the microgrid during the emergency mode. (b) Generation, storage, and load profile trends. (c) DC Link current and load of the microgrid during the emergency mode.

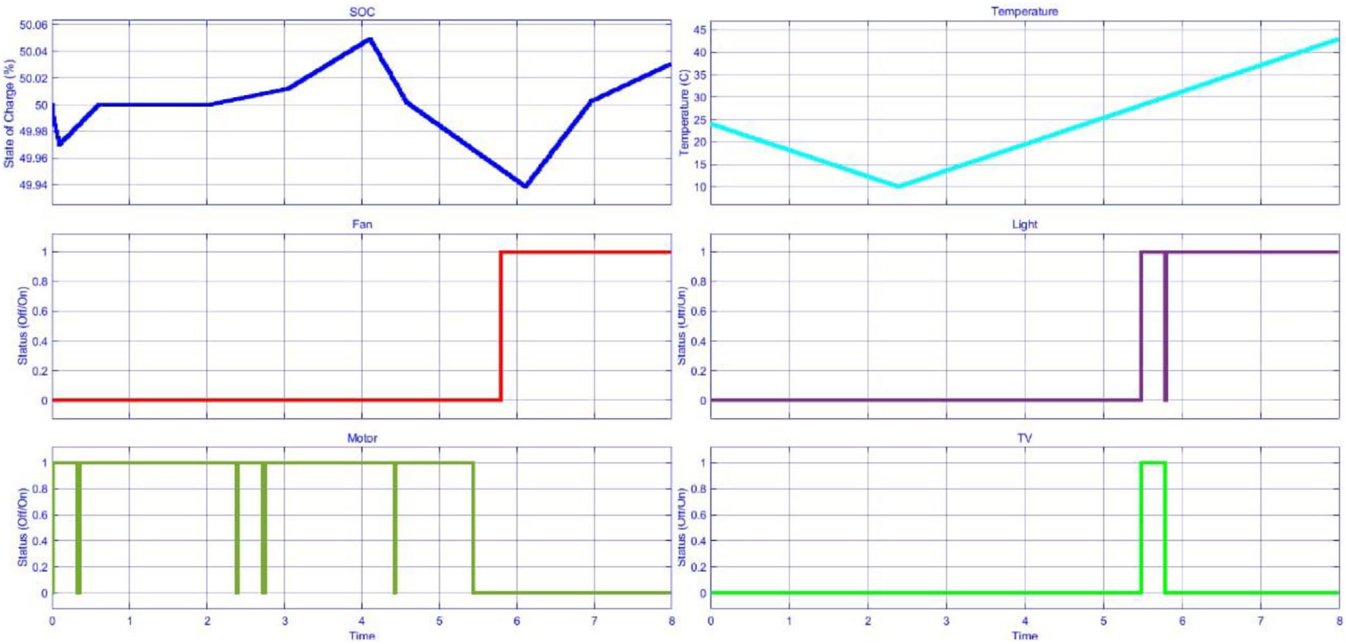


FIGURE 11 Behaviour of loads under dynamic demand response scheme for the emergency mode.

generation after 6 h. At the start, SoC falls below 50%, as shown in Figure 10b and only the solar source is available. Consequently, the energy conservation mode is activated for 1.5 h, while at 1.5 h, SoC recovers to 50%, thus the energy conservation mode is deactivated. At 4 h, the unavailability of solar and wind causes activation of the energy conservation mode again, as SoC drops down to 50%.

At 4.5 h, SoC drops even below 50% due to which the Emergency mode is activated, thus providing power to the most critical loads for that time. At 7 h, SoC recovers to a value greater than 50%, as shown in Figure 10c. As the wind power production starts, the emergency mode is deactivated. For the rest of the time, the energy conservation mode operates as SoC remains less than 60%. There is a slight disturbance in the current as shown in Figure 10c that stabilizes after the load operation of the dynamic demand response occurs.

The emergency mode of operation is exhibited in Figure 11. This is the worst-case scenario as the SoC is under 50%, in addition to the high temperatures. During this situation, the fans were forced to remain off during day the usual operational time for almost 2.5 h. The loads relevant to the lights, electric motor, and TV behaved in the same manner, as in the energy conservation mode. During emergency mode, the SoC improved, when fans were off-state. The overall system remained reliable, and consumer comfort was also addressed.

The results of the automated demand response schemes were compared with the scheduled loads of interviews in Table 1, which shows that consumers' requirements were well addressed in the automated demand response scheme with a very minor deviation.

Figure 12 compares the actual load operation (interview-based schedule) on an hourly basis with the automated demand response for all the modes of operation. It is observed that there is a close resemblance between the load operational hours and the actual schedules of operation. However, during the energy conservation and emergency modes, there is a slight deviation in the operational hours of the heavy loads due to SoC constraints to avoid blackouts. As a priority, the fans remained operational in all the modes of operation, followed by the lighting load with minor unmet durations. However, the motor load was reduced in the energy conservation and emergency modes due to SoC constraints. It can be seen that unmet hours for motors in energy conservation and emergency mode reaches about 3.5 h. Furthermore, during the late-night operation, the lights and TV are turned off, thus enhancing the performance of SoC with minimal disturbance to the consumers' comfort.

There is as minimum as ±5–7% deviation in the loads' operation in all modes compared to the actual routine due to the fact the in simulations, the controller decides based on the temperature, SoC and time of the day whereas the consumers are more focused on time of the day and temperature without consideration of SoC.

5.4 | Performance comparison

The current research is compared with the system designed by the authors in [42]. Table 3 summarizes the comparison between the prior and proposed research. In [42], the distinctive load was controlled using the fuzzy logic controller with multiple inputs, such as Solar PV power, SoC, and ambient temperature. The prime objective was to control the load with better SoC availability during the night hours. However, the prior work has not considered the social factor parameter, such as the time of the day and temperature.

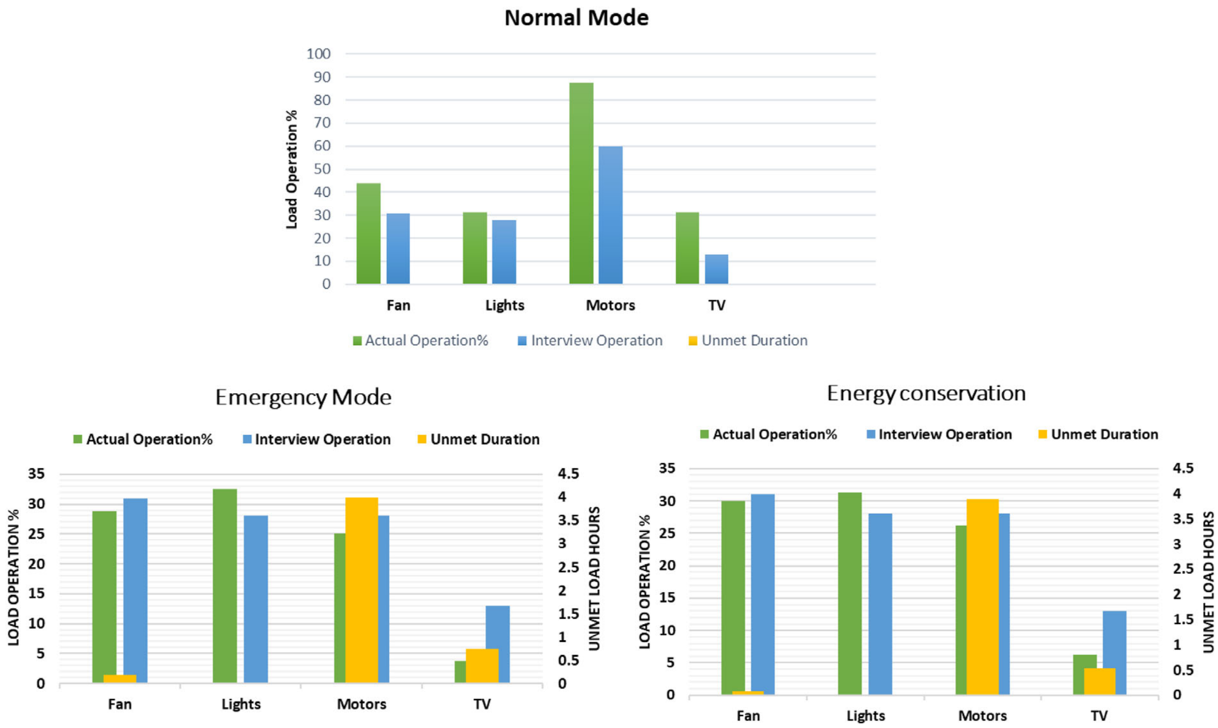


FIGURE 12 Comparison of load operation with actual routine and fuzzy controller under demand response time.

TABLE 3 Comparison of the proposed technique with the distinctive load control technique.

Controller	Membership function	%Operation of loads of water pump	%Operation of loads of lights	%Operation of loads of fans	%Operation of loads of extra load	SoC%
Distinctive fuzzy controller	Solar irradiations, state of the charge, temperature	12.5%	37.5	50%	10.41%	25%
Mode adjustment controller integrated with fuzzy dynamic demand response controller	State of the charge, temperature and time of the day	26%	31.25%	30.5%	6.25%	40%

The comparison is made on the operational timing of the load while introducing a social factor parameter of the time of the day. The social factors and load mode control provided a relatively smooth and continued power supply during the operational hours compared to the distinctive load model controller. This is because the proposed controller is fed by two sources that are wind and solar, which remained operational simultaneously, though in [42], these were tested with only one source. The distinctive load controller performs well in the case of lighting, since the lights remained on for the entire night, in the case of the proposed scheme the lights were turned off after a certain time as per the interviews taken from the consumers and based on their routine patterns. Due to addition of social parameters, the operational percentages between the proposed technique and the distinctive load controller differs a lot.

The operation of pumps is critical for any agricultural area and thus it was considered as critical during the day times. The operation of heavy load such as pumps was 13.5% higher compared to the operation of pumps in [42]. However, the operation of lights and fans differs from that of distinctive load controller due to addition of temperature and time of day parameters which better utilizes the load operation while keeping the user comfort in consideration. The overall SoC remained 15% higher than the distinctive load controller due to addition of more parameters in the fuzzy controller that reduces the operation of the loads as per the requirements of the customers.

6 | CONCLUSION

This research work assesses the inclusion of social factors, as an additional control parameter in the Fuzzy Logic Controller to enhance the consumers comfort with an isolated microgrid in rural areas. The results have been compared with a prior study conducted for load control. The load operation in automated demand response remained identical to the actual routine operation, as per the consumers' desire with ±5–7% deviation. In all modes of operation of the microgrid, the SoC levels remained 15% higher and heavy load operated 13.5% more compared to the relevant study.

It is concluded that with the incorporation of social factors in the control scheme for the automation of the demand response, there is further enhancement of the consumers' comfort level. Moreover, the automation reduces user intrusion, thus minimizing blackout risks. Since regular loads, such as fans, lights, and TV sets are mostly used simultaneously by the consumers in a rural microgrid, these have the greatest impact on the battery SoC and thus, may contribute to a worst-case scenario leading to blackouts. Therefore, it is concluded that the social factor integration in the microgrid controllers can reduce the misuse of the loads, eventually resulting in an enhanced rate of islanded microgrids successful projects.

In future work, real-time information on weather and consumer activities relevant to a particular microgrid installation site can be acquired. On the other hand, proper sizing of the power sources and their economic assessment in the proposed dynamic demand response scheme can be done in future. This can further substantiate this research work's conclusions and help in the optimal utilization of the available green energy resources in a rural community, thus lowering the number of blackouts in relation to social factors and weather conditions.

AUTHOR CONTRIBUTIONS

Fawad Azeem: Conceptualization, Data curation, Formal analysis, Software, Zulfiqar Ali Memon: Methodology, Project administration, Validation, Sobia Baig: Investigation, Supervision, Tareq Manzoor: Investigation, Software, Writing - original draft, Faisal Abbas: Investigation, Visualization, Writing - original draft, Mohd Asif Shah: Resources, Writing - original draft.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

DATA AVAILABILITY STATEMENT

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

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