

MICROCONTROLLER-BASED RESIDENTIAL MICROGRID POWER MANAGEMENT WITH IOT INTEGRATION

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ABSTRACT

Microgrids combine battery energy storage devices and renewable resources with the utility grid. An intelligent energy switching approach between solar, battery and grid ensures continuous supply of power by dynamically adjusting to resource availability and load requirements. In this paper, a novel microcontroller-based energy management scheme (MCU-based EMS) is proposed by combining both on-grid and off-grid power management systems allowing microgrids to function smoothly in both grid-connected and islanded modes. In the off-grid management, a Maximum Power Point Tracking (MPPT) algorithm is used for maximizing the extraction of available PV power. Further, a DC-DC boost converter is employed for boosting the voltage to match the battery's charging need and loads. In on-grid management, an H-inverter along with a synchronizer circuit is used to supply loads during peak shaving hours. Besides, a bidirectional buck-boost converter ensures battery charging and discharging. The microcontroller intelligently controls the transition between operating modes by continuously assessing power demand and availability to identify the best source. A key component of the system is the Adaptive Spatio-Temporal Graph Convolutional Learning (ASTGCL) model, which enables proactive and dynamic energy management by forecasting the best power dispatch based on environmental data, resource availability, and load demand. Real-time monitoring, performance tracking, and remote control for increased efficiency are made possible with IoT integration. Real-time hardware implementation and simulation studies are used to validate the proposed model. The simulation results show that the proposed technique outperforms conventional models in terms of achieving quick, seamless switching, guaranteeing a continuous supply and maximizing the usage of renewable energy. With a mode-switching time of only 24 ms, the proposed MCU-based EMS significantly outperforms other conventional methods like MGIB (120 ms), NILM (95 ms), M-GRU-based NILM (110 ms) and FF-SHMS (105 ms).



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I. INTRODUCTION

Fossil fuel depletion globally has started to shift our interests towards the utilization of renewable energy resources. Presently, microgrids (MGs) are gaining attention since they have the ability to enhance the controllability and reliability of power systems [1]. Microgrid is an integrated source of power from utility grid, energy storage devices and renewable sources that can operate either in standalone or in grid-tied mode [2]. However, this integration poses new challenges for managing and controlling power to meet demand needs and supply the load. Energy management and control strategies are divided into upper and lower-level controls. The primary control (lower-level control) is responsible for frequency and voltage stabilization.

The Energy Management System (EMS), that is upper-level control is responsible for predicting the availability of load demand and renewable power resources. It is also responsible for scheduling available load demand and energy production within a MG [3]. Photovoltaic (PV) power producers which can operate in off-grid mode are attractive sources of power in mountainous or remote places, where the installation of grid supply is not possible. A common configuration for isolated PV system consists of three converters namely a buck and boost converter for PV charging and discharging and one for regulating loads [4], [5]. Normally, electric meters measure the energy consumption at each house and billing is produced at the end of each month which inhibits remote tracking of energy usage.

With the help of IoT, the remote monitoring of house current consumption on web application is made possible [6]. The integration of IoT in EMS helps the individuals, companies and industries to control their devices based on the energy consumption ensuring optimal use of power. Many techniques developed for managing energy is limited in handling highly dynamic AC loads and grid disturbances [7]. In this paper, a novel MCU-based EMS is proposed for managing power flow between different power sources ensuring an uninterrupted power supply to loads and also reducing harmonics in grid. The main contributions of this paper are,

- An off-grid power management system is developed using PV panels to prioritize solar energy during maximum solar power generation with MPPT and switch to battery during low generation, where bidirectional buck-boost converters are used for effective battery charging and discharging.
- An on-grid power management system is proposed for intelligently switching between solar, grid, and battery power, wherein a bidirectional converter is used for effective grid-based battery charging and synchronizer circuit for continuous AC load operation.
- Real-time performance tracking, remote monitoring, and user-driven modifications based on usage patterns are all made possible by IoT.
- IoT is used for monitoring the system remotely to gain real-time performance insights and user-driven modifications.
- The proposed method reduced consumption costs, increased energy efficiency, decreased grid dependency and ensured a more sustainable power supply while maximizing the use of solar power.

This research paper's contents are classified into the following sections: A survey of various literatures on energy management in microgrids is discussed in section 2; section 3 deals with the working of the proposed methodology in detail; the hardware and simulation results are presented in section 4 and section 5 talks about the conclusion of this paper.

II. LITERATURE REVIEW

In this section, various literatures on energy management in residential settings is discussed. The purpose, methods, advantages and disadvantages of different literatures is mentioned below. In [8] developed an efficient energy management plan to satisfy energy requirements and provide a steady supply of electricity under various load scenarios. A smart communication system based on IoT is created for a hybrid microgrid that combines Vanadium Redox Flow Battery (VRFB) storage, PV and a biogas plant. The microgrid operation is monitored and controlled in real time through Raspberry Pi while the system circuits for the hybrid microgrid electrical interface is realized through a PSCAD simulation research. In [9] presented a Fuzzy logic-based Framework for Smart Home Monitoring Systems (FF-SHMS) that uses IoT to improve energy efficiency. In order to manage resource-constrained loads and promote sustainability, the presented fuzzy architecture optimizes the design of intelligent microgrids with integrated storage. Additionally, the framework optimizes the microgrid's economic benefits by enhancing electricity and storage utilization of renewable energy sources.

By effectively assessing various criteria the suggested framework undergone simulation to obtain superior performance. In [10] utilized a Non-Intrusive Load Monitoring (NILM) technology for managing energy in home microgrids integrated with PV and battery storage with the help of IoT. The usage of energy in each home is monitored by Artificial Neural Network (ANN) optimized with Particle Swarm Optimization (PSO). Then the monitored energy is sent through ThingSpeak IoT to the customers. The NILM technique eliminates the smart meter setup thereby reducing the cost for installation. In [11] implemented a Multi-task Gated Recurrent Unit (M-GRU)-based NILM model for handling energy in residential microgrid. M-GRU-based NILM is used for extracting individual customer's energy consumption from smart meters. Then, the extracted information is given to the microgrid for managing energy consumption. The operating cost of the model is reduced by 45% while user satisfaction is increased by 65%. In [12] developed a hierarchical IoT-based renewable energy self-consumption approach for Microgrid-Enabled Intelligent Buildings (MGIBs) aiming to automate and digitalize energy supply and consumption.

Initially, a 2D fusion layered architecture is implemented for the microgrids to interact with the loads. Then, a state transition strategy is employed for maintaining the operating states of consumers and suppliers based on event and temporal triggers. Finally, self-regulated coordination between power generation and demand is achieved by power balance control approach. Monitoring consumption, generation and supply data is handled by the FIWARE framework. In [13] designed a smart Home Energy Management System (HEMS) for prosumers to handle energy efficiently. K-means clustering combined with ANN is utilized for load forecasting to predict energy needs. Energy usage is scheduled using Teaching-Learning-Based Optimization (TLBO), which aims to minimize energy drawn from the grid and lower overall costs by identifying the best times to charge or discharge batteries and when to shift or reduce energy consumption. In [14] formulated an intelligent demand response approach for uninterrupted supply of energy from batteries, renewables and grids. Only lights and AC are currently controlled according to the SoC value of battery. The model maximized the use of renewables thereby reducing electricity cost, peak demand and carbon emissions. According to the existing literatures, the use of real-time MPPT at the hardware conversion step is not highlighted. The proposed system uses MPPT-based DC-DC converters, which allow for the best possible solar energy extraction in a range of irradiance levels. This efficiently guarantees the optimal use of the PV electricity that is available.

III. PROPOSED METHODOLOGY

The working mechanism of the proposed MCU-based EMS is discussed in this section and the block diagram of the proposed technique is illustrated in Figure 1(a). Inputs such as weather characteristics (irradiance, temperature, etc.), historical PV output, battery SoC data, grid data and load demand are collected at each time step of the historical time window of previous observations.

These inputs are used by the ASTGCL framework, which predicts the optimal power contribution from each source for the next day. The microcontroller or smartphone then receives the predicted power dispatch and uses it to carry out the suggested actions by alternating between power sources and choosing the proper operating mode (off-grid or on-grid) as needed. The off-grid or island mode is where the solar panels or battery storage devices supply power to the loads without the use of grid power. With the availability of solar power, the loads are supplied with solar energy. The excess solar power not used by the loads is used to charge the batteries without violating their battery SoC.

When solar power is not available, the batteries supply power to the loads. In on-grid mode, the solar panels, batteries and grid operate together for supplying power to loads. When solar power is available, the loads are supplied energy from solar panels and excess solar is stored in batteries. When solar is not available, battery supplies power. If both become outage, grid supplies power to AC loads. When the grid demand is low, the batteries are charged from them and during grid outage periods, this stored energy will be supplied to the loads. Ultimately, IoT is integrated into the system for monitoring real-time energy consumption updates, grid status, battery State of Charge (SoC) and grid condition.

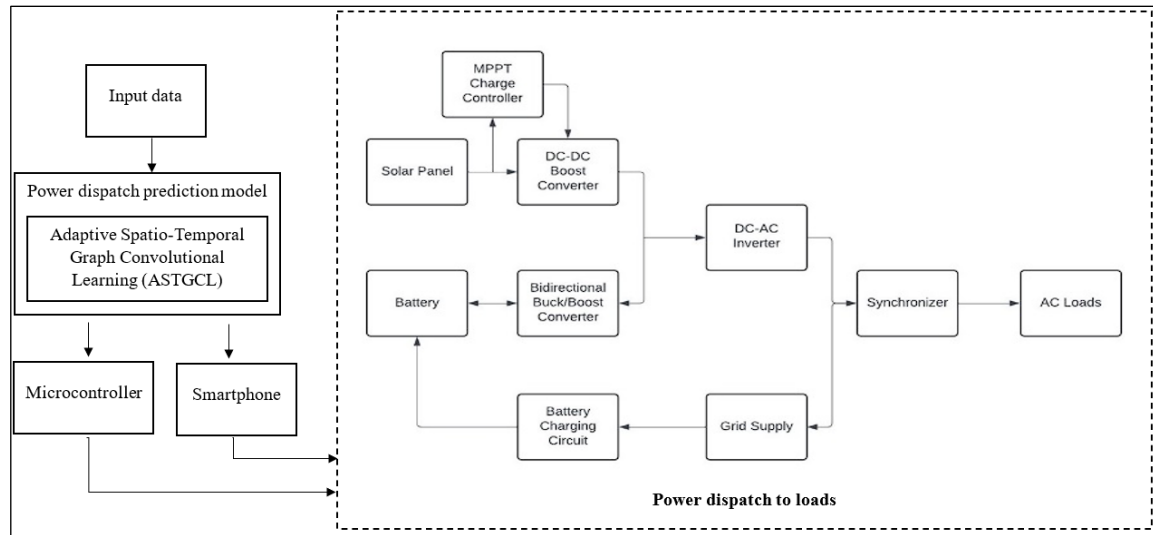


Figure 1(a): Block diagram of the proposed MCU-based SEM.

Source: Authors, (2026).

III.1 ADAPTIVE SPATIO-TEMPORAL GRAPH CONVOLUTIONAL LEARNING (ASTGCL)

The proposed system uses a dynamic selection process amongst three potential sources—solar panels, battery storage, and the utility grid—to guarantee a continuous supply of electricity to the demand. Environmental sensors track sun irradiance to ascertain the availability of solar electricity, while a microprocessor uses relay control to manage the switching mechanism. Power flow is anticipated and planned in advance using an optimization method since switching between sources may cause brief periods of disruption in energy dispatch. In particular, depending on the previous records, the ASTGCL model is utilized to anticipate the ideal share of power to be pulled from each source at every time step. Reliability and efficiency are achieved in hybrid energy management by combining real-time relay-based switching with predictive dispatch planning. The block diagram of the ASTGCL architecture is provided in Figure 1(b).

III.1.1 Feature Data Augmentation

When gathering input data, problems such as noise, sensor faults, communication errors and missing values often arise. The presence of these irregularities can decrease the precision of power dispatch forecasting in the microgrid system. In order to surmount this obstacle and enhance the forecasting model's resilience against absent or corrupted solar data, three strategies for feature-level data masking are developed: short-term, long-term and regional data masking.

Short-Term Data Masking: Short-term data masking is used to mimic transient disturbances in input data like temperature, PV output or irradiance. Even with the presence of actual input data, the masking system selectively masks them to imitate transient environmental disturbances. The robustness of power dispatch forecasting by each source is increased by training the model under these circumstances, which helps it maintain accuracy even in the face of abrupt changes or missing data. In order to handle the short-term missing data, the following formula is used to mask each input data.

$$\hat{I}_f^t = \begin{cases} I_f^t, & \text{if } E_f^t \geq T_{short} \\ -1, & \text{otherwise} \end{cases} \quad (1)$$

Here, $\hat{f}_f^t$ is the masked data of each input feature f at time t , I_f^t is the original input data f at time t , E_f^t is a randomly generated masking indicator and T_{short} is the masking threshold for simulating brief missing or corrupted data.

Long-Term Data Masking: Long-term data masking simulates situations in which sensor malfunctions or maintenance outages may render irradiance or temperature to be completely inaccessible for prolonged periods of time. For example, the temperature probe may be unavailable for days or the irradiance sensor may malfunction for a few hours.

The model learns to rely on the remaining features and maintain accurate predictions during extended data loss by being trained with such long-term masked inputs. The following equation is adopted to model long term data masking for each input feature like irradiance, temperature, etc.

$$\hat{I}_f = \begin{cases} I_f, & \text{if } E_f \geq T_{long} \\ -1, & \text{otherwise} \end{cases} \quad (2)$$

Here, T_{long} is the masking threshold for simulating extended loss in data caused by sensor malfunctions.

Regional Data Masking: Multiple input feature failures at the same time are represented by regional data masking. Extreme weather events like storms, grid outages, inverter tripping or communication system malfunctions that impact multiple sensors at once might cause this. For instance, because the monitoring system goes offline during a strong rainstorm, readings for temperature, panel voltage and irradiance may all be absent for a while. The forecasting model learns to maintain stability and continue prediction even when multiple critical inputs are lost at the same time by simulating such multi-feature outages during training.

$$\hat{I}^t = \begin{cases} I^t, & \text{if } E^t \geq T_{region} \\ -1, & \text{otherwise} \end{cases} \quad (3)$$

Here, $\hat{I}^t$ is the masked multi-feature input, E^t is a random masking indicator that determines whether the multi-feature data is available or missing at time t and T_{region} is the probability of missing or corrupted data.

III.1.2 Topology Data Augmentation

In the proposed model, the loads are provided with electricity by one or more sources, such as the grid, solar panels or batteries, depending on the grid status, battery SoC and solar energy availability at the time. The model employs two matrices to dynamically manage this power allocation: a fixed adjacency matrix F_A that depicts the potential connection between the sources and loads and a real-time optimized matrix O_A that modifies the strength of these connections in real-time based on available data. The system can determine the strength of each link at any given time by using this dynamic matrix. For instance, during times of high solar generation, the load-to-solar panel connection is strengthened, the grid connection is decreased and battery-to-solar panel connection is enhanced.

By combining the matrices using Hadamard product and addition operations, the microcontroller may intelligently switch power sources by determining the effective power flow between various sources and loads at any given time. The addition operation adds the fixed and optimized matrices connection strengths to capture local features—such as direct and immediate power flows like solar panels providing electricity to a nearby load or charging a connected battery. The product operation highlights global aspects, which reflects greater system-wide interactions such as coordinated power balancing between the grid, solar panels and batteries during periods of high demand. The local L_A and global G_A adjacency matrices are given by Equations, respectively.

$$L_A = F_A \oplus O_A; F_A, O_A \in R^{S \times S} \quad (4)$$

$$G_A = F_A \otimes O_A; F_A, O_A \in R^{S \times S} \quad (5)$$

Here, R is a set of real numbers and S denotes the power sources and loads connected to microgrid.

Both L_A and G_A are given to graph neural modules for producing learned feature representations both locally GNN_l and GNN_g globally to capture power flow behaviours within the system.

III.1.3 Spatio-Temporal Contrastive Learning

Spatial Contrastive Learning

The system effectively learns and distinguishes between local GNN_l and global GNN_g representations with the aid of spatial contrastive learning. The microgrid system is trained by the model to identify and align patterns that appear in both global and local representations. It helps the system acquire relevant energy flow behaviours by increasing the similarity between related local and global patterns while differentiating unrelated patterns with the help of loss function, which is mathematically modeled by the Equation (6).

$$L_{spatial} = -\frac{1}{N} \sum_{j=1}^N \log \frac{\exp(\cos(GNN_l^j, GNN_g^j)/\tau)}{\sum_{k=1}^N \exp(\cos(GNN_l^j, GNN_g^k)/\tau)} \quad (6)$$

where, batch size is denoted by N , local and global representations for the j -th sample are represented by GNN_l^j and GNN_g^j , respectively, cosine similarity is indicated by $\cos(\cdot)$ and the τ parameter controls the concentration of the distribution. The similarity between related local-global pairings is captured by numerator, while the denominator accounts for all pairs including unrelated pairs.

Temporal Contrastive Learning

Temporal contrastive learning aims to differentiate between similar and dissimilar time steps in order to improve the model's capacity to learn intrinsic temporal dynamics. It creates GNN_t by concatenating two representations, GNN_l and GNN_g , at each time step t . The model chooses the least (negative sample GNN_t^-) and most similar (positive sample GNN_t^+) time steps from other intervals for each time step and the temporal loss function is given as:

$$L_{temp} = -\frac{1}{T} \sum_{t=1}^T \log \frac{\exp(\cos(GNN_t, GNN_t^+)/\tau)}{\exp(\cos(GNN_t, GNN_t^-)/\tau)} \quad (7)$$

Here, T is the total number of time steps and t is the current time step.

III.1.4 Joint Learning

The joint representation GNN_R is formed by GNN_l and GNN_g representations, which is then fed into power dispatch prediction module for determining the optimal power allocation of solar, battery or grid sources to loads. The model is optimized to minimize a dispatch loss function $L_{dispatch}$ that concurrently takes into account the supply side and the demand side of the microgrid operation in order to provide precise energy dispatch. To avoid scheduling resources in an impractical manner, the supply-side term assesses the difference between the actual supply capacity at each time step and the expected power contribution from the available sources (grid, solar, and wind). However, in order to guarantee that consumption needs are sufficiently satisfied, the demand-side term records the discrepancy between the actual demand and the anticipated power delivered to the load. According to formal definitions, the dispatch loss is:

$$L_{dispatch} = 0.5 * |\hat{P}_{T+1}^{supply} - P_{T+1}^{supply}| + 0.5 * |\hat{P}_{T+1}^{load} - P_{T+1}^{load}| \quad (8)$$

$$\text{Where: } P_{T+1}^{supply} = P_{T+1}^{solar} + P_{T+1}^{battery} + P_{T+1}^{grid}.$$

The joint learning is facilitated by integrating auxiliary loss functions $L_{spatial}$ and L_{temp} and the total loss function is modeled as follows:

$$L = L_{dispatch} + 0.5 * L_{spatial} + 0.5 * L_{temp} \quad (9)$$

The proposed model predicts the dispatch ahead of time and sends it to the microcontroller and smartphone, in contrast to traditional sense-then-act systems, which have the microcontroller wait for real-time measurements before making a decision. By drastically cutting down on response time, this proactive prediction allows for quicker control actions, smooth energy management, and increased microgrid system stability.

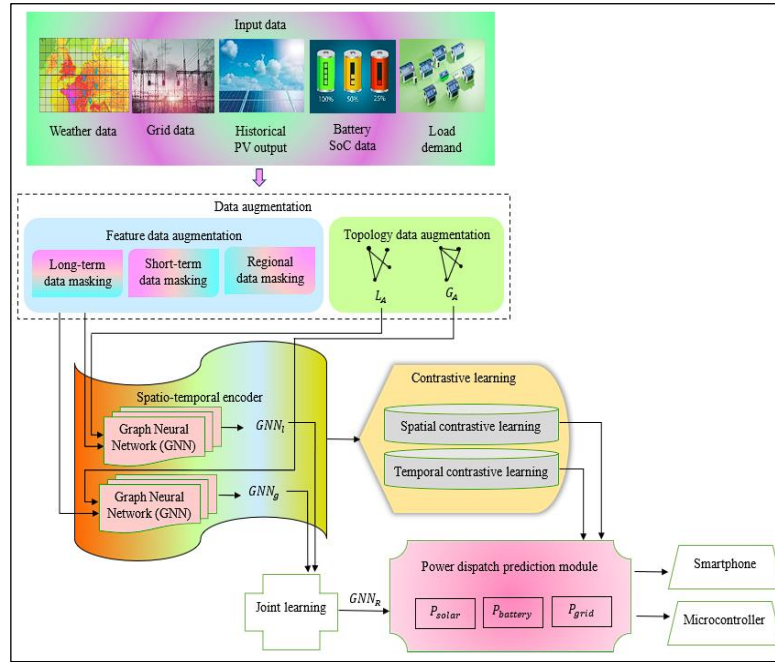


Figure 1(b): Architecture of Adaptive Spatio-Temporal Graph Convolutional Learning (ASTGCL).
Source: Authors, (2026).

III.2 COMPONENTS

A brief explanation of each of the components used in the proposed model is provided below.

III.2.1 MPPT Controller

The power produced by solar panels varies throughout the day due to the varying solar irradiance. In order to extract maximum amount of power from the solar panels, MPPT controller is used. The role of MPPT is to continuously monitor the current and voltage of the solar panels and adjusts the operating point to track the maximum power point at which the current and voltage is maximum. The MPPT controller then signals the boost converter to change its duty cycle for making the solar panels operate at its maximum power point.

III.2.2 DC-DC Boost Converter

The boost converter steps up the voltage coming from the solar panels to match the battery requirements or DC bus voltage. Besides, the converter adjusts the voltage and current of the solar panels for producing maximum solar power under varying sunlight based on the signal from MPPT. The working of MPPT controller along with boost converter ensures better energy harvesting.

III.2.3 Bidirectional Buck-Boost Converter

The bidirectional buck-boost converter allows bidirectional flow of power from grid or solar panels to batteries and from batteries to loads. The flow of power from grid or solar panels to batteries is known as charging and the power flow from batteries to loads is known as discharging. During charging, the converter acts in boost mode if the voltage coming from solar panels or grid is lower than the battery voltage. It also acts in buck mode to lower the input voltage if it is higher than the battery voltage. During discharging, the converter acts only in boost mode to step up the voltage to match the higher voltage of loads. This mode changing behavior ensures safe charging and discharging of batteries protecting battery lifetime.

III.2.4 DC-AC Inverter

The DC-AC inverter converts the stepped DC voltage coming from the boost converter or bidirectional buck-boost converter into AC voltage that can be efficiently supplied to the AC loads without any issues. A single-phase H-bridge inverter topology is utilized in the proposed model for converting DC to AC voltage. In the H-bridge inverter network, the four switches S_1 , S_2 , S_3 and S_4 are connected in a bridge configuration across the DC source and the switches are turned ON and OFF in a specific sequence for producing AC voltage across the load. In order to produce an approximate sine wave, Pulse Width Modulation (PWM) is used for rapid switching. Then, a filter made up of inductor and capacitor, LC filter converts the approximate waveform into a clean AC sine wave by the removal of high-frequency switching components thereby ensuring efficient and safe operation. The circuit diagram of the H-bridge inverter is shown in Figure 2 and the connection of bidirectional buck-boost and MPPT-based boost converter to the H-bridge inverter is displayed in Figure 3.

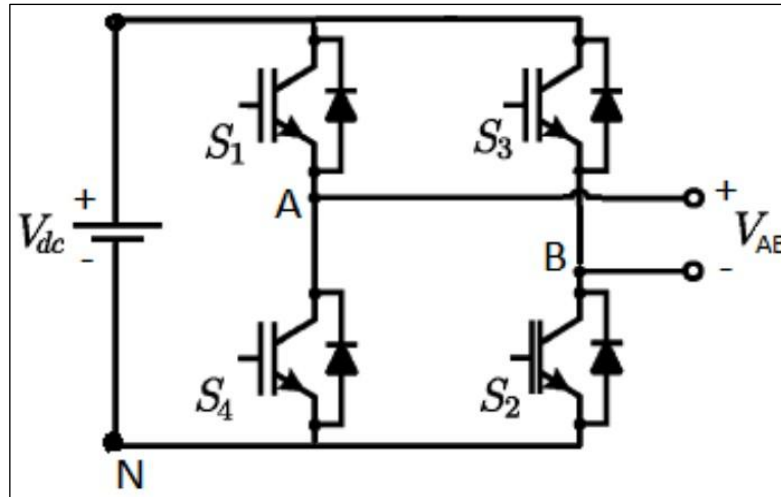


Figure 2: Circuit diagram of a single-phase H-bridge inverter.
Source: Authors, (2026).

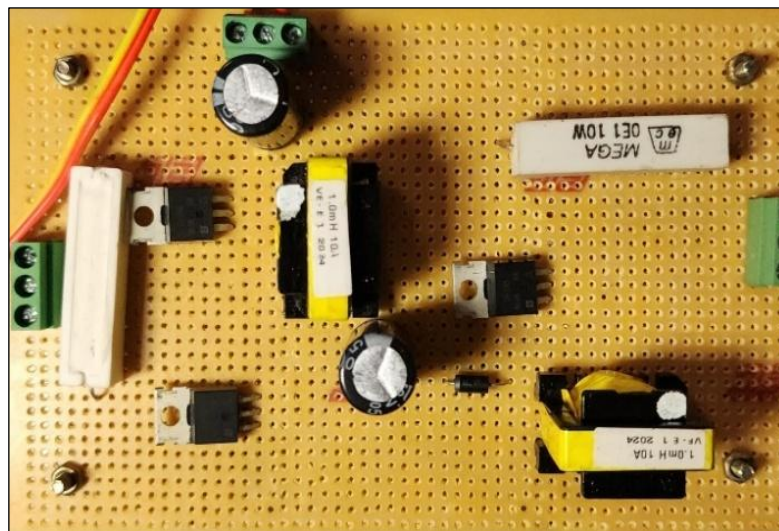


Figure 3: Bidirectional buck-boost converter and MPPT-based boost converter connected to H-bridge inverter.
Source: Authors, (2026).

III.2.5 Synchronizer Circuit

The AC signal produced by the H-bridge inverter must be in sync with the grid signal for preventing voltage surges and large circulating currents. In order to match the voltage, phase and frequency of inverter's output signal with the grid signal's voltage, phase and frequency, synchronizer circuit is used. The zero-crossing detector outputs a signal to the synchronizer circuit whenever the grid voltage crosses zero thereby providing phase reference of the grid. Then, the synchronizer circuit makes the voltage given by batteries to match the grid voltage in amplitude, frequency and phase. The incorporation of zero-crossing detector in the circuit is shown in Figure 4.

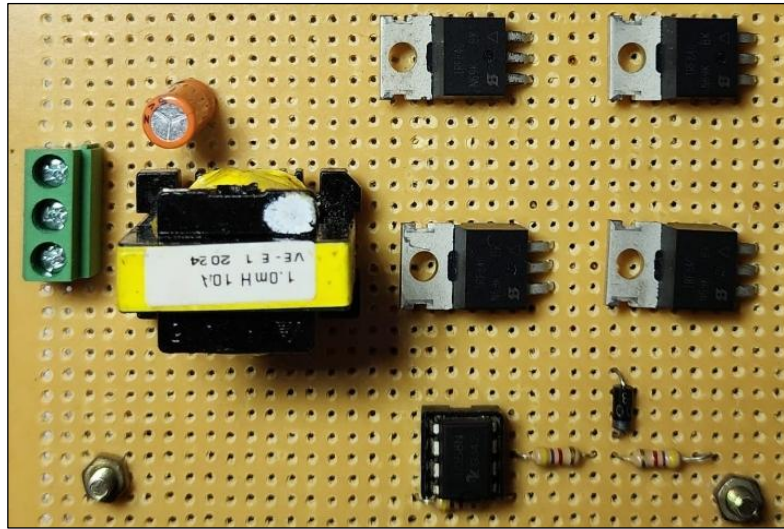


Figure 4: H-bridge inverter with LC Filter, alongside a zero-crossing detector circuit.
Source: Authors, (2026).

III.2.6 ESP8266 Microcontroller

The hardware setup of microcontroller-based mode switching hardware is depicted in Figure 5. In the figure, an ESP8266 microcontroller is used to manage relays that turn an inverter's output on or off. The blue coloured components in Figure 5 are known as relays that connects to the load by switching on the inverter and disconnects from the load by turning off the switch. This switching can be controlled manually or remotely via the IoT with the help of ESP8266's built-in Wi-Fi.

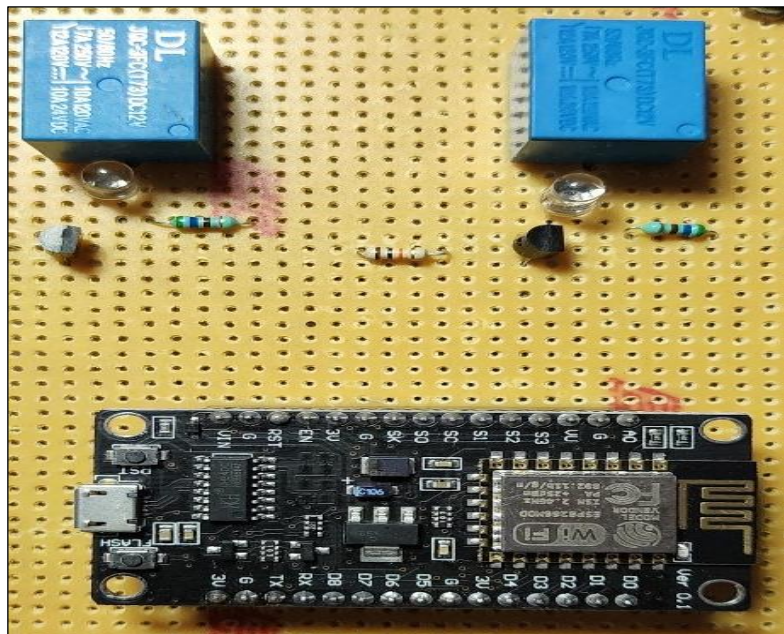


Figure 5: ESP8266 microcontroller for mode switching.
Source: Authors, (2026).

III.2.7 IoT Integration

A specialized mobile application called Blynk is developed for monitoring the real-time power system updates like grid status, load conditions, battery level and power flow remotely. The mode switching is also enabled by the consumers using the Blynk user interface. The developed IoT hardware setup worked efficiently within the Wi-Fi range of the test environment. The connection of the Blynk app with the proposed MCU-based EMS is displayed in Figure 6.



Figure 6: Proposed MCU-based EMS managed with the Blynk app.
Source: Authors, (2026).

IV. RESULTS

In this section, the hardware and simulation results of the proposed MCU-based EMS is discussed. To obtain the hardware results, the proposed system is implemented using MPPT, DC-DC boost converter, bidirectional buck-boost converter, H-bridge inverter, synchronizer circuit and IoT and validated in real-world. The system is validated against power efficiency, control stability and remote operability and the results obtained through validation are discussed below.

In the context of the H-bridge inverter, power efficiency is the ratio of AC power output provided to the household AC loads to the DC input power given by the batteries or PV panels. The system's overall energy conversion performance is indicated by this metric, which tells how well the inverter transforms DC power into suitable AC power. Usually, power efficiency is expressed in percentage and it is calculated using the formula given below.

$$P_{\eta} = \frac{P_{AC,OUT}}{P_{DC,IN}} \quad (10)$$

Here, efficiency is denoted by P_{η} , output power produced by inverter is represented as $P_{AC,OUT}$ and power supplied by the panels or batteries is given by $P_{DC,IN}$.

Table 1: Power efficiency of H-bridge inverter.

MODE	RMS OF AC OUTPUT VOLTAGE	RMS OF AC OUTPUT CURRENT	DC INPUT VOLTAGE	DC INPUT CURRENT	EFFICIENCY (P_{η})
Off-grid	230	4.98	48	23	92.3
On-grid	230	5.39	48	26	94.7

Source: Authors, (2026).

The power efficiency of H-bridge inverter under grid-tied and standalone modes is displayed in Table 1. In off-grid condition, an output voltage of 230 V and output current of 5 A is supplied to the loads. The input voltage and current supplied from the panels or batteries are 48 V and 23 A. Now, we calculate the efficiency for off-grid condition as,

$$P_{\eta} = \frac{230 \times 4.98 \times 0.89}{48 \times 23} \times 100\% = 92.3\%$$

The efficiency for on-grid mode is estimated as,

$$P_{\eta} = \frac{230 \times 5.39 \times 0.953}{48 \times 26} \times 100\% = 94.7\%$$

Here, 0.89 and 0.953 are known as power factors denoting a portion of current that is reactive. In standalone mode, there is no reference signal for converting DC into AC, therefore the power factor is large denoting the wastage of power (reactive power).

However, in grid-tied conditions, there is a reference signal from the grid for DC to AC converter, therefore the production of reactive power is less denoting lower power factor of 0.953 compared to off-grid mode. In standalone microgrid and on-grid operation, P_{η} is obtained as 92.3% and 94.7% respectively. The reason for the increased efficiency in on-grid mode is that the inverter synchronizes with the grid's AC signal, which offers a reliable reference for output power generation. Off-grid mode, on the other hand, requires the inverter to independently generate the AC waveform without the aid of an external reference, which leads to a modest decrease in efficiency and a rise in power losses. The inverter's performance is demonstrated by the close alignment of these values with those of commercially available hybrid inverters. Even with different load demand, the produced AC current is stable thereby eliminates load damage. The utilization of LC filter in the H-bridge inverter topology reduces the distortion present in the generated AC wave by the inverter. The reduction of harmonics with the employment of LC filter is illustrated in Table 2 and THD is calculated by the following equation.

$$THD (\%) = \frac{\sqrt{V_2^2 + V_3^2 + V_4^2 + \dots + V_n^2}}{V_1} \times 100 \quad (11)$$

Table 2: Comparison of THD present in the inverter generated output in the presence and absence of LC filter.

FILTER	FUNDAMENTAL V1 (V_RMS)	V3 HARMONIC (V_RMS)	V5 HARMONIC (V_RMS)	V7 HARMONIC (V_RMS)	THD (%)
Without filter	230	18	12	8	10
With LC filter	230	8	4	2	3,98

Source: Authors, (2026).

By substituting the table values in Equation 2, the THD is obtained as,

$$THD (\%) = \frac{\sqrt{V_3^2 + V_5^2 + V_7^2}}{V_1} \times 100 = 10 \% \text{ (Without filter)}$$

$$THD (\%) = \frac{\sqrt{8^2 + 4^2 + 2^2}}{230} \times 100 = 3.98 \% \text{ (With filter)}$$

Since the harmonics is reduced by LC filter, the generated voltage is suitable for integrating with grid connection. The process by which a power management system smoothly switches between different operating modes is known as mode switching. The smooth switching is measured using the time taken by the system to switch from grid-tied mode to off-grid mode or vice versa. Mode switching time is normally measured in milliseconds (ms). Despite the existence of several approaches, it is commonly calculated by,

$$t_{switch} = t_{mStart} - t_{mEnd}$$

where, t_{switch} is the mode switching time, t_{mStart} denotes the starting time of the switching operation and t_{mEnd} indicates the time when the switching operation ends. There was no noticeable voltage sag or load supply disruption during the mode-switching time, which was recorded at about 24 ms. This demonstrates that the system can continue to supply electricity even in the event of grid instability or solar unavailability. The MPPT algorithm efficiently tracked the maximum power point in solar irradiance, successfully extracting maximum power under diverse environmental conditions. The bidirectional buck-boost converter functioned reliably in both charging and discharging modes, facilitating smooth transitions based on the load demand and battery SoC. Its current-limiting and voltage-regulating capabilities protected the battery from under-voltage and overcurrent conditions, contributing to longer battery life and safer operation. The H-bridge inverter with an LC filter, driven using Sinusoidal Pulse Width Modulation (SPWM), produced a stable and smooth AC output waveform. The LC filter effectively reduced switching harmonics and delivered a clean sinusoidal voltage suitable for domestic loads. The inverter maintained consistent output voltage and frequency even under varying load conditions, reflecting its robustness and reliable dynamic response. Overall, the hardware results validate the practical feasibility of the proposed system, highlighting its suitability for efficient and sustainable domestic energy management with minimal grid dependency.

The software results obtained through MATLAB/Simulink simulation are discussed in detail below. One of the important parameters that denotes the successful system design is the supply of power to loads without any interruption. The continuous supply of power to household loads is portrayed in Figure 7. The energy requirement fluctuates throughout the day in the test configuration, peaking at nine in the morning. The demand continuously increases at a steady pace from 1 AM to 9 AM and then progressively declines from 10 AM to 3 PM. It rises once more between 4 and 6 PM, then starts to fall after 7 PM. The load demand is met by solar power between 7 AM and 5 PM, with any extra energy being stored in the battery. Before sunrise, the battery and grid supply the load in turn, and after sunset, the grid is used after the battery has discharged to its full capacity. According to the simulation results, the grid, solar, and battery contributions at each time step precisely match the load requirement, guaranteeing constant power availability for the full twenty-four hours. By ensuring an uninterrupted supply, this integrated use of solar, battery, and grid resources improves consumer satisfaction. Cost optimization is not included in the model, despite the fact that this guarantees continuous power. By taking cost into account, battery charging might be moved from the early morning low-demand hours (1–5 AM) to times of higher demand, such the morning peak.

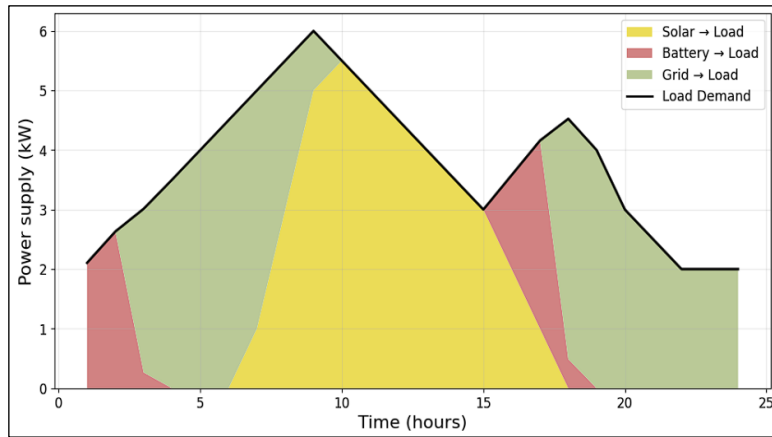


Figure 7: Continuous power supply to load.

Source: Authors, (2026).

The utilization of solar for household appliances by various techniques is shown in Figure 8. Regarding solar use, the following conclusions are from the figure. At about 57.5%, NILM has the lowest utilization, followed by FF-SHMS at 59.1%. MGIB achieves 62%, while M-GRU-based NILM comes in third with 60.2%. With the highest solar utilization of 78.6%, the proposed MCU-based EMS performs better than any other methods. The highest PV power utilization is achieved by using MPPT, which continuously modifies the PV operating point to extract maximum power under variable weather circumstances.

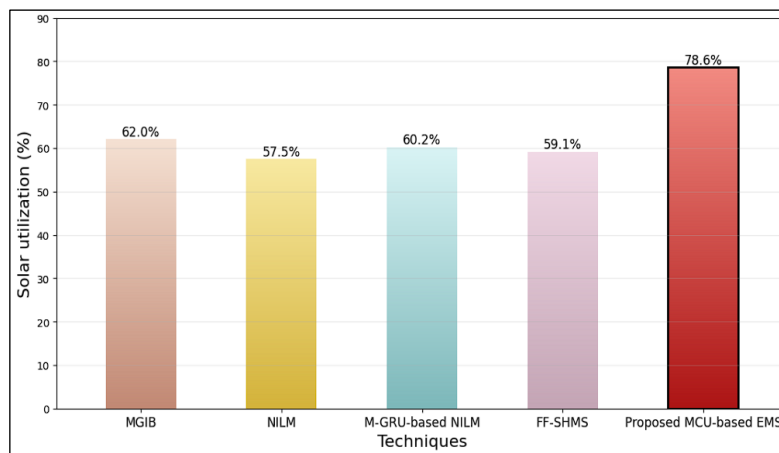


Figure 8: Comparison of solar utilization by different techniques.

Source: Authors, (2026).

Figure 9 depicts the mode-switching times of various energy management models including MGIB, NILM, M-GRU-based NILM, FF-SHMS and the proposed MCU-based EMS. The switching periods for the conventional systems are higher, ranging from 95 to 120 ms; MGIB is 120 ms, NILM is 95 ms, M-GRU-based NILM is 110 ms, and FF-SHMS is 105 ms. On the other hand, a much faster switching time of 24 ms is attained using the proposed MCU-based EMS. By enabling fast switching between on-grid and off-grid modes, the proposed framework eliminates the delays associated with traditional techniques and guarantees a continuous power supply while making the best use of renewable energy.

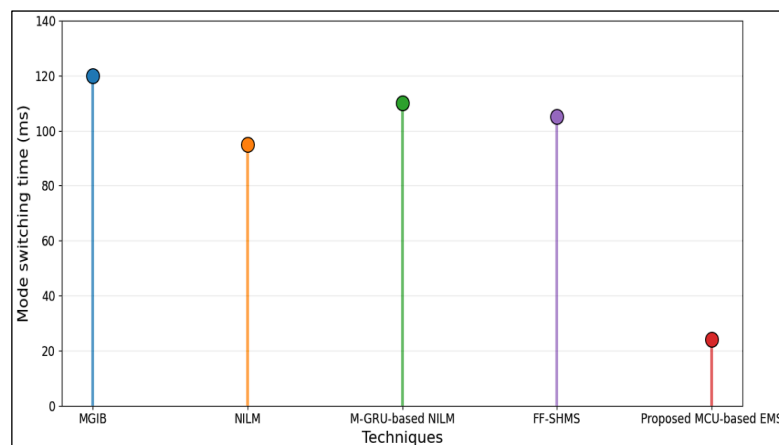


Figure 9: Mode switching times of different techniques.

Source: Authors, (2026).

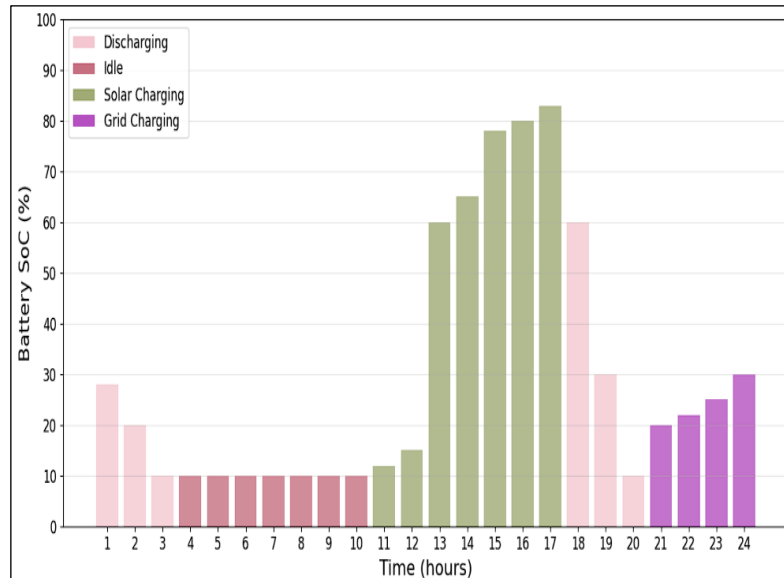


Figure 10: Controlled battery charging and discharging based on SoC.
Source: Authors, (2026).

The battery's controlled charging and discharging behavior during a 24-hour period is depicted in Figure 10, where the SoC is kept within safe bounds to avoid overcharging and deep draining. The SoC of the battery should be in the range between 10% and 90%. If the battery SoC reaches above 90%, then it is known as overcharging and if the SoC reaches below 10%, then it is known as undercharging. So, during charging, the battery must not go above 90% and during discharging, the battery should not go below 10%. This ensures the safety of battery and prolongs battery life. From the graph, it is inferred that the SoC is maintained by the proposed methodology. At the start of the day, the battery has 30% SoC and till 3 AM, it is draining energy. Since the SoC reaches 10% at the end of 3 AM, the battery is not discharging and it is idle until 10 AM. At 11 AM, there is excess solar power, the battery starts charging and at 17 PM, the SoC reaches 82%. Then, again it starts discharging until the SoC becomes 10%. Since the grid has low demand during late night hours, the battery starts to charge again by maintaining SoC.

V. CONCLUSION

In this paper, continuous power supply to home loads is achieved using the proposed MCU-based EMS. An intelligent microcontroller supplies the power continuously by switching between the power sources efficiently by checking the availability of power sources and demand needs. The model runs in two modes: grid-tied mode, which uses the grid and battery and isolated mode, which uses solar and battery power. The proposed model is constructed using various devices like synchronizer circuit, bidirectional buck-boost converter, DC-DC boost converter and MPPT algorithm. The model is also integrated with IoT using Blynk user interface for real-time energy consumption and generation monitoring.

The proposed strategy is evaluated both in hardware and software using power efficiency, mode switching time and maximum solar utilization. According to experimental results, the power efficiencies of 92.3% and 94.7% is achieved in standalone and grid-tied mode respectively. Seamless mode-switching is accomplished in less than 24 ms with no voltage sag. Under various load scenarios, the system achieved an average solar utilization of 78.6% higher than traditional methods. The system can be improved by integrating Artificial Intelligence (AI) and Machine Learning (ML) techniques which can estimate load demand, predict solar irradiance, and optimize battery charging and discharging. This efficiently distributes energy, reduces reliance on the grid and prolongs battery life. Besides, the model experiences slight delay in synchronizing the battery signal with grid electricity.

VI. AUTHOR'S CONTRIBUTION

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Approval of the final text: Venkatakrishnan GR, Sai Kanna R and Raymond Jude J.

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