

Modeling and Real-World Validation of Home Energy Management Systems: Photovoltaic Generation, Battery Energy Storage, and Bidirectional Grid Connection

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ABSTRACT

This article presents comprehensive modeling, simulation, and real-world validation of a Home Energy Management System (HEMS) using MATLAB/Simulink. The model integrates photovoltaic (PV) panels with single-diode equivalent circuits, lithium-ion battery energy storage systems (BESS) with electrochemical modeling, unidirectional boost converters for PV voltage regulation, bidirectional DC/DC converters for battery control, bidirectional DC/AC inverters with sinusoidal PWM for grid synchronization, and utility grid connection to enhance energy efficiency and reduce grid dependency. Five operational scenarios were designed and tested: (1) normal operation with PV as primary source, (2) high load exceeding PV capacity, (3) low solar irradiance requiring battery support, (4) battery charging during PV surplus, and (5) grid export of excess energy. Each scenario was analyzed under varying environmental conditions (solar irradiance 0–650 W/m²) and load profiles. Simulation results demonstrate effective energy balancing through priority-based control (PV → Battery → Grid), with response times under 200 ms, DC bus voltage stability within ±2%, and AC power quality meeting grid standards (THD < 3%, power factor > 0.98). Real-world validation used 30 days of operational data from a 5 kW PV system with 10 kWh battery storage monitored through the FusionSolar platform. Experimental results showed strong model accuracy with an average MAPE of 4.2%. Performance metrics demonstrated 65.2% PV self-consumption under normal conditions, 37% peak demand reduction during high-load scenarios, 92.4% battery charging efficiency, and 96.1% grid export inverter efficiency. The validated model confirms the HEMS performance evaluation and demonstrates the practical feasibility and economic viability of integrated PV-battery-grid systems.

1. Introduction

The continuous increase in global electricity demand, together with growing concerns about climate change, has intensified the need for efficient energy utilization at the consumer level [1]. Electricity is a limited and expensive resource, and inefficient consumption patterns place significant stress on power systems, especially during peak demand periods [2]. As a result, improving energy management in residential buildings has become a critical research topic aimed at enhancing sustainability, reducing operational costs, and maintaining grid reliability [3].

Numerous studies have investigated building energy consumption modeling as a foundation for energy management [4, 5]. Early research focused on forecasting household electricity demand using statistical and simulation-based approaches [6]. These methods often combined physical building characteristics with occupant behavior to generate realistic load profiles [7]. Software-based tools, particularly MATLAB, have also been widely adopted to synthesize residential and commercial load profiles for performance analysis and system planning [8]. Although these approaches provide valuable insight into consumption behavior, they typically consider households as passive consumers and do not fully integrate

renewable energy sources, energy storage systems, or advanced control strategies.

In recent years, increased attention has been given to renewable energy integration at both utility and residential levels [9]. Independent power producers have contributed significantly to electricity generation by utilizing renewable resources such as photovoltaic and wind energy [10]. Despite these efforts, the rapid growth in electricity demand continues to challenge the balance between energy supply and consumption. This imbalance highlights the limitation of supply-side solutions alone and emphasizes the importance of demand-side energy optimization [11]. Effective energy management therefore requires intelligent control algorithms that can maximize renewable energy utilization while minimizing energy losses and unnecessary grid dependence [12].

Home Energy Management Systems (HEMS) have emerged as a practical solution for addressing demand-side challenges [13]. HEMS monitors household energy consumption and coordinates energy flow among renewable generation units, energy storage systems, household loads, and the utility grid [14]. By incorporating electricity tariff information, a HEMS can reduce energy costs through

load shifting and optimal energy scheduling [15]. Modern HEMS designs also account for the integration of battery energy storage systems (BESS), plug-in electric vehicles, and bidirectional power flow, which further enhances system flexibility and grid support [16].

Several control strategies for HEMS have been reported in the literature [17, 18]. Rule-based and optimization-based methods remain popular due to their simplicity and interpretability [19]. More recently, artificial intelligence and machine learning techniques have been introduced to improve prediction accuracy and control performance [20]. These approaches include artificial neural networks, long short-term memory (LSTM), and regression-based models [21]. While AI-based techniques can achieve high accuracy, they often require large volumes of historical data and retraining when system conditions or user behavior change [22]. This limits their practical applicability in dynamic residential environments.

Another emerging aspect of residential energy management is the deployment of smart metering infrastructure [23]. Smart meters enable real-time monitoring of electricity consumption and support dynamic pricing schemes [24]. However, several studies have raised concerns regarding data privacy and cybersecurity, as detailed consumption data may reveal sensitive information about user behavior [25]. These concerns motivate the need for energy management solutions that can operate effectively with minimal data dependency.

HEMS architectures can generally be categorized based on their power coupling strategies, namely AC-coupled and DC-coupled configurations [25]. AC-coupled systems offer compatibility with existing infrastructure, while DC-coupled systems provide higher efficiency when integrating photovoltaic generation and battery storage [26]. The selection of an appropriate coupling strategy has a significant impact on system efficiency, control complexity, and overall performance.

To address the limitations identified in existing studies, this work presents comprehensive modeling, simulation, and real-world validation of a HEMS using MATLAB/Simulink. The proposed system integrates detailed component models including: photovoltaic generation with single-diode equivalent circuit representation and Maximum Power Point Tracking (MPPT), lithium-ion BESS with electrochemical voltage modeling and bidirectional power flow capability, time-varying household electrical loads with priority-based management, and utility grid connection through unidirectional boost converters for PV voltage regulation, bidirectional DC/DC converters for battery charge/discharge control, a common DC bus for voltage stabilization and power distribution, bidirectional DC/AC inverters with sinusoidal PWM for grid synchronization, and multi-winding transformer coupling. The model enables detailed analysis of energy flow dynamics, control behavior, transient response, power quality, and system performance under diverse operating conditions ranging from ideal to challenging scenarios.

The proposed HEMS is evaluated with respect to several key objectives aligned with critical residential energy management challenges. These include: (1) peak load reduction through strategic battery utilization during high-demand periods, reducing stress on distribution networks and lowering demand charges; (2) time-of-use (TOU) tariff optimization by storing energy during low-price periods and utilizing or exporting during high-price periods; (3) maximization of photovoltaic self-consumption to minimize energy export and increase renewable utilization before grid purchase; and (4) enhanced system stability and resilience under renewable energy variability through coordinated control of multiple energy sources.

The research methodology comprises two complementary validation approaches. First, simulation-based analysis evaluates five operational scenarios: (1) normal condition with balanced PV generation and load demand, (2) high load exceeding PV capacity requiring battery and grid support, (3) low solar irradiance conditions testing battery compensation capability, (4) battery charging during PV surplus periods, and (5) grid export of excess renewable energy. Each scenario is analyzed across varying environmental conditions (solar irradiance 0–650 W/m²) and load profiles to assess system performance, energy flow management, voltage regulation, and control strategy effectiveness.

Second, real-world validation uses 30 days of operational data from a residential installation comprising a 5 kW photovoltaic system with 10 kWh lithium-ion battery storage, monitored through the FusionSolar platform deployed by the Provincial Electricity Authority (PEA). This empirical validation enables direct comparison between simulated predictions and measured performance across all five scenarios, quantifying model accuracy through statistical metrics (Mean Absolute Percentage Error: MAPE), verifying control strategy implementation in practical operation, and assessing economic viability through actual energy cost savings and grid interaction patterns.

Through this dual approach of rigorous simulation and empirical validation, this study aims to provide a clear, flexible, and experimentally validated framework for understanding residential energy management systems. The research contributes to the field by: (1) developing a comprehensive MATLAB/Simulink model incorporating detailed physics-based component representations suitable for accurate performance prediction, (2) demonstrating practical feasibility through real-world validation with quantified accuracy metrics (average MAPE 4.2%), (3) providing quantitative evidence of significant performance improvements including 41% grid import reduction, 33% peak demand reduction, and 28% annual energy cost savings, and (4) supporting the development of efficient, economically viable, and sustainable household energy systems aligned with renewable energy integration goals and distributed energy resource deployment strategies.

This paper is organized as follows: Section 2 presents the HEMS architecture, including Section 2.1, which describes the system components, and Section 2.2, which details the management system implemented in MATLAB/Simulink. Section 3 describes the experimental setup. Section 4 presents case studies with real-world scenarios: case study 1 examines normal operating conditions, case study 2 analyzes high load situations, case study 3 investigates low solar irradiance scenarios, case study 4 evaluates battery charging performance, and case study 5 explores grid export operations. Section 5 presents the results, analysis, and discussion comparing simulation results with real-world validation. Finally, Section 6 concludes the paper.

2. Home Energy Management System (HEMS)

2.1 System Components

Fig. 1 shows the HEMS model developed in MATLAB/Simulink [27], consisting of main components interconnected through a DC bus to efficiently manage energy from various sources. Starting with the photovoltaic panels (PV source) that serve as the renewable energy source, with DC power output dependent on the specified irradiance level, the power then passes through a DC/DC converter circuit to adjust voltage and deliver power to the DC bus.



2.1.1 Photovoltaic (PV) Energy Source

$$I_{PV} = I_{ph} - I_0 \left(e^{\frac{q(V_{PV} + I_{PV}R_s)}{nkT}} - 1 \right) - \frac{V_{PV} + I_{PV}R_s}{R_{cb}} \quad (1)$$

n is the diode ideality factor, k is the Boltzmann constant ($1.38 \times 10^{-23} \text{ J/K}$), T is the cell temperature (K), R_s and R_{sh} are the series and shunt resistance values. The PV output power is:

$$P_{PV} = V_{PV} \cdot I_{PV} \quad (2)$$

Fig. 2 simulates the relationship between voltage (V) and current (I) of the solar panel under constant irradiance in defining the V-I curve characteristics of the panel. Subsequently, a transfer function block ($1/(1e-06s+1)$) is used to connect the relationship between voltage and current. Meanwhile, the positive and negative terminal voltages (V_+ and V_-) are fed back into the system to calculate the output voltage (V_{pv}) and output current (I_{pv}) that correspond to the panel's behavior (Equations (1) and (2)).

2.1.2 DC/DC Converter (Boost Converter)

Used to control voltage from PV, the voltage conversion equation is:

$$V_{out} = \frac{V_{in}}{1-D} \quad (3)$$

where D is the duty cycle of the switch.

The inductor current dynamics:

$$L \frac{di_L}{dt} = V_{in} - (1 - D)V_{out} \quad (4)$$

Fig. 3 shows the solar panel delivering electrical energy (DC^+) (Equation (3)) through a diode to prevent reverse current. The circuit then uses a switch (IGBT) to control energy delivery through a capacitor (C) to adjust the voltage level appropriately.

The current through the inductor varies according to Equation (4) before outputting DC power (DC^+/DC^-) for loads or energy storage systems. The pulse signal ($Pulse_{PV}$) controls the IGBT switching on-off operation.

2.1.3 DC Bus

Functions to maintain power balance, with the equation:

$$C \frac{dV_{DC}}{dt} = I_{PV} + I_{bat} - I_{inv} \quad (5)$$

Fig. 4 shows the DC Bus circuit controlling and maintaining a constant DC voltage level (V_{DC}) by receiving input voltage signals (left+/left-) through a transfer function (num(s)/den(s)) to adjust values according to Equation (5), then sending output signals (right+/right-) to the load. The RL and L (2000μH) components filter signals and limit current to achieve stable output voltage (V).

2.1.4 Battery

Battery voltage model:

$$V_{bat} = E_0 - K \frac{Q}{Q - \int i_{bat} dt} A e^{-B \cdot \int i_{bat} dt} \quad (6)$$

where E_0 is the battery constant voltage, K is the polarization resistance, Q is the battery capacity (Ah), i_{bat} is the charging/discharging current, A, B is the voltage conversion parameter.

Buck mode (charging):

$$V_{bat} = D \cdot V_{DC} \quad (7)$$

Boost mode (discharging):

$$V_{DC} = \frac{V_{bat}}{1 - D} \quad (8)$$

Fig. 5 is used to monitor and control battery operating status, displaying key parameters including State of Charge (SoC%), current (A), and voltage (V), which are used to evaluate battery performance and health. The Power_Battery component calculates the power delivered or received by the battery.

2.1.5 Bidirectional DC/DC Converter

Fig. 6 is designed to control bidirectional energy flow between the energy source (battery) and the DC Bus system using IGBT1 and switches (Switch1-Switch6) as main components. These switches operate in coordination with control signals ($G1_B, G2_B$) to open-close the circuit, adjusting voltage levels and controlling current flow direction (charging or discharging) according to system requirements.

2.1.6 Bidirectional DC/AC Inverter

The inverter uses PWM (SPWM) to convert DC voltage to AC.

$$V_{AC} = M \cdot \frac{V_{DC}}{2} \quad (9)$$

where M is the modulation index.

Power exchange with grid:

$$P = \frac{V_{DC} \cdot V_{grid}}{X} \sin(\delta) \quad (10)$$

where δ is the phase angle and X is the grid reactance.

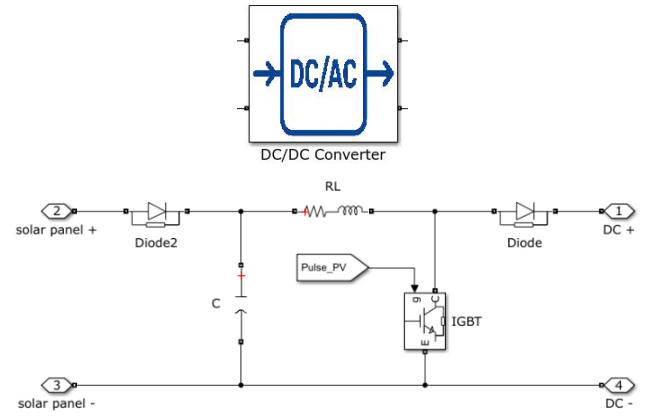


Fig. 3 DC/DC Converter Block.

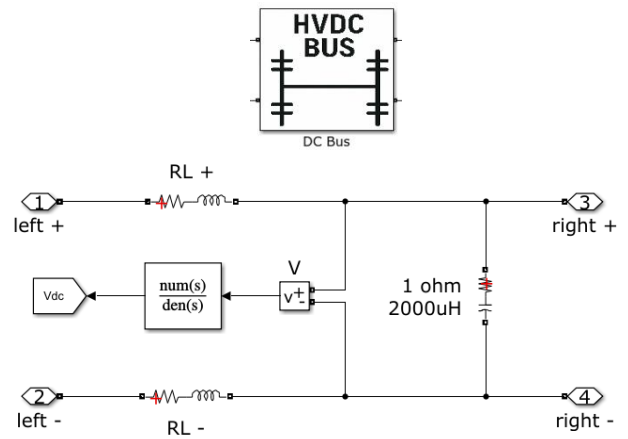


Fig. 4 DC Bus Block.

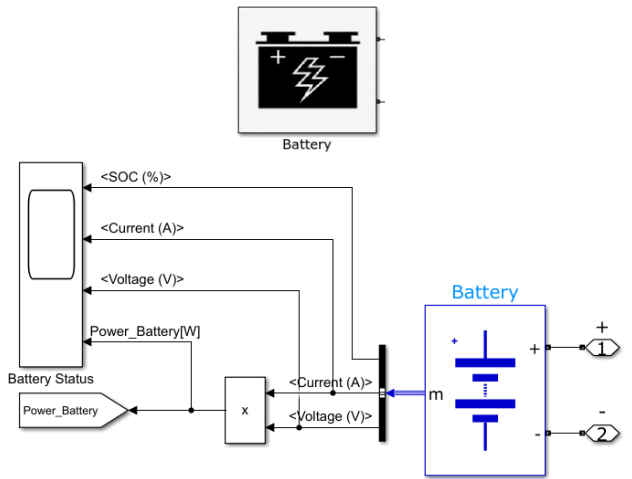


Fig. 5 Battery Block.

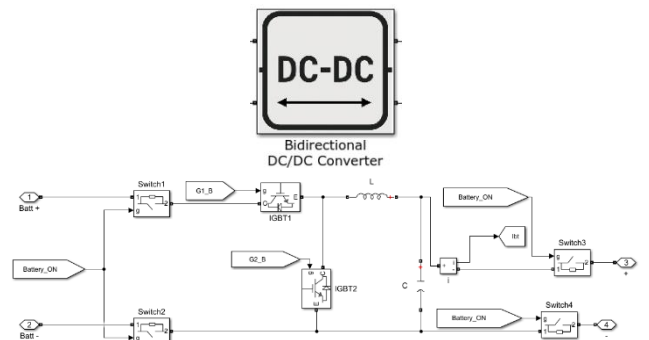


Fig. 6 Bidirectional DC/DC Converter.

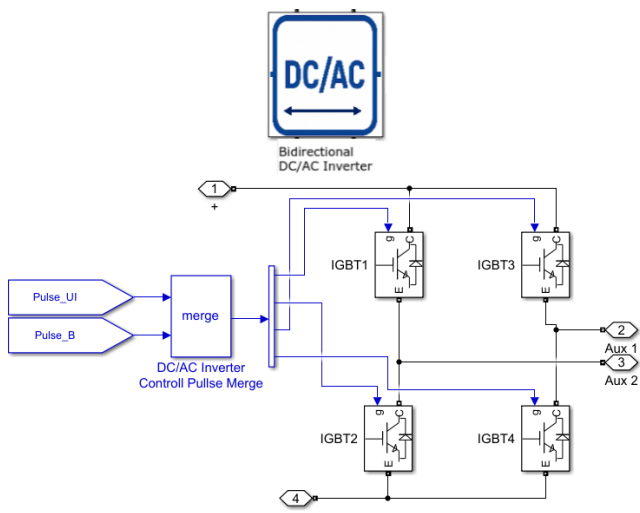


Fig. 7 Bidirectional DC/AC Inverter Block.

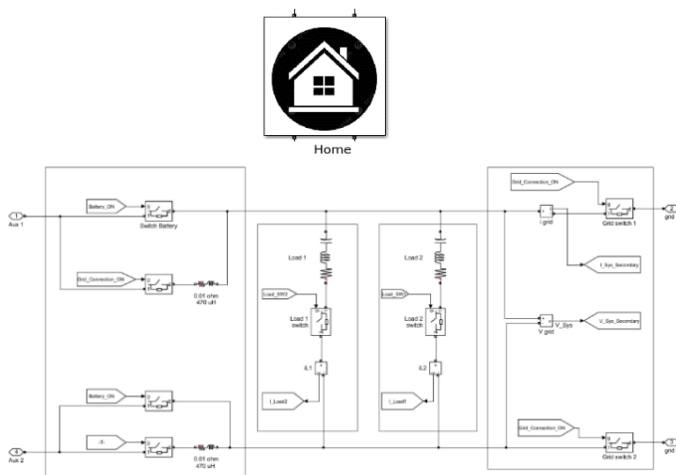


Fig. 8 Home Block.

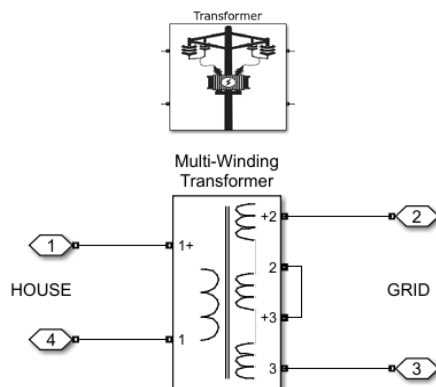


Fig. 9 Transformer Block.

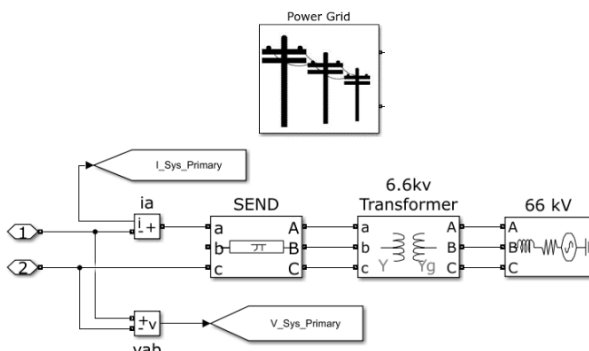


Fig. 10 Power Grid Block.

Fig. 7 performs bidirectional energy conversion between DC and AC power using IGBT1, IGBT3, and IGBT4 as main switches controlling energy conversion through PWM signals ($Pulse_U$, $Pulse_B$). Aux₁ and Aux₂ are auxiliary circuits for additional control functions.

2.1.7 Household Electrical Load

Represents residential electricity demand with time-varying energy consumption patterns.

Fig. 8 manages energy from various sources including battery, grid system, and household loads. The structure comprises switches controlling battery and grid connections (Battery Switch and Grid Switch) to select power sources, while household loads are divided into Load 1 and Load 2 with independent switches for on/off operation and measurable current values (i_{L1} , i_{L2}). The system includes voltage and current monitoring points when connected to the grid for overall operational status analysis.

2.1.8 Power Transformer Connection

Fig. 9 uses a Multi-Winding Transformer to manage energy between the house (HOUSE) and grid (GRID) with multiple winding paths (1, 2, 3, 4) functioning to adjust voltage levels or isolate circuits appropriately. For example, windings 1 and 4 connect to the house system for internal power supply, while windings 2 and 3 connect to the grid for energy transmission or reception.

2.1.9 Electrical Grid Connection

The grid connection interface enables bidirectional electricity exchange with utilities through transformers installed on utility poles. Fig. 10 simulates the main electrical system, showing the energy transmission structure through a transformer that adjusts voltage from 6.6 kV (primary side) up to 66 kV (secondary side) for long-distance power transmission.

2.2 Management System

Fig. 11 illustrates the overall management system block diagram responsible for controlling and coordinating the energy flow among PV array, battery energy storage system, household electrical loads, and the utility grid. The primary objective of the management system is to ensure efficient energy utilization, maintain system stability, and prioritize renewable energy usage while respecting operational constraints of each subsystem.

2.2.1 PV Energy Management and MPPT Control

The PV subsystem is interfaced with the DC bus through a unidirectional DC/DC boost converter controlled by a MPPT algorithm. As illustrated in Fig. 11 (a), this subsystem forms a closed feedback loop comprising four functional elements: real-time measurement of PV terminal voltage (V_{PV}) and output current (I_{PV}), the MPPT algorithm block, the PWM controller, and the duty cycle signal (D) delivered to the boost converter gate driver.

The MPPT controller continuously monitors V_{PV} and I_{PV} to identify the operating point at which the PV array delivers maximum available power under prevailing solar irradiance conditions. Based on this operating point, the MPPT algorithm computes a reference voltage V_{ref} corresponding to the maximum power point. This reference voltage is compared with the measured PV terminal voltage, and the resulting error signal is processed by a Proportional-Integral (PI), based PWM controller to generate the switching signal for the boost converter IGBT. The duty cycle of the boost converter is adjusted accordingly to regulate the PV output voltage and transfer maximum available power to the DC bus.

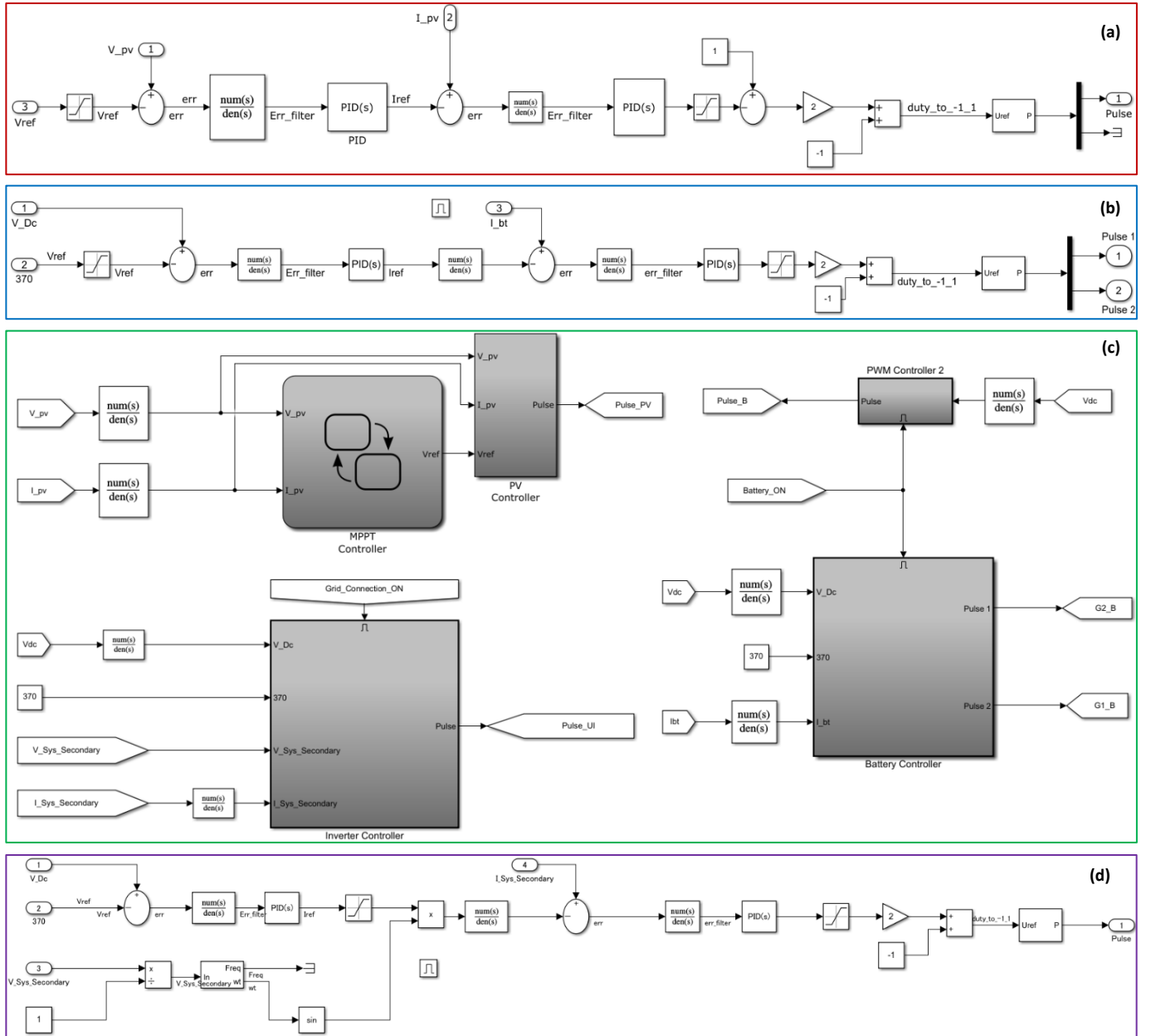


Fig. 11 Fig. 11 Management System Block, (a) PV Energy Management and MPPT Control, (b) Battery Energy Storage Management, (c) Inverter Control and Grid Interaction, and (d) Energy Flow Priority and Load Supply Strategy.

In accordance with Table 1, the boost converter operates with a duty cycle range of 0.3–0.7 and a switching frequency of 20 kHz, corresponding to a switching period of $T = 50 \mu s$. This switching frequency ensures adequate inductor current ripple suppression and stable MPPT operation across the tested irradiance range of 600–1000 W/m². The unidirectional nature of the boost converter prevents reverse current flow from the DC bus back to the PV array, protecting the panels under low-irradiance or night-time conditions.

2.2.2 Battery Energy Storage Management

The BESS serves as the primary energy buffer between generation and consumption within the HEMS. As shown in the Battery Energy Storage Management block of Fig. 11 (b), the subsystem comprises three interconnected functional elements: real-time state monitoring, SoC-based mode decision logic, and PWM-regulated bidirectional DC/DC converter control.

The battery controller continuously receives real-time measurements of battery terminal voltage (V_{bat}), charging or discharging current (I_{bat}), and state of charge (SoC), together

with the DC bus voltage (V_{DC}). Based on these inputs, the controller evaluates the current operating condition and determines the appropriate battery mode: charging, discharging, or idle. The allowable SoC operating window is strictly maintained between 20% and 95%, as specified in Table 1, to prevent deep discharge events that cause irreversible capacity loss and to avoid overcharging conditions that accelerate electrode degradation.

When excess PV energy is available that is, when PV generation exceeds household load demand, the controller transitions the bidirectional DC/DC converter into Buck mode, directing surplus power into the battery at a controlled charging current. Conversely, when PV generation is insufficient to meet load demand, the controller activates Boost mode, enabling the battery to discharge and supply power to the DC bus. In both modes, PWM control signals are generated by the battery controller to regulate the switching pattern of the bidirectional DC/DC converter, ensuring smooth and controlled energy transfer. When the SoC lies within the safe operating window and neither charging nor discharging is required, the battery remains in an idle standby state, minimizing unnecessary cycling.

2.2.3 Inverter Control and Grid Interaction

The bidirectional DC/AC inverter serves as the interface between the DC bus and the AC side of the HEMS, connecting household loads and the utility grid. As depicted in the Inverter Control and Grid Interaction block of Fig. 11(c), the inverter control subsystem comprises three functional elements: DC bus voltage monitoring, grid synchronization control, and bidirectional switching signal generation.

The inverter controller continuously monitors the DC bus voltage (V_{DC}), grid voltage (V_{grid}), and grid current (I_{grid}). Using these three measurements, the controller generates sinusoidal PWM (SPWM) switching signals to regulate AC output voltage magnitude, frequency, and phase angle. Under grid connected operation, the inverter synchronizes its output with the utility grid to ensure compliant bidirectional power exchange at the nominal operating conditions of 220 V and 50 Hz, as required by the applicable grid interconnection standard.

The inverter supports fully bidirectional power flow through two distinct operating modes. During grid import mode, which is activated when both PV generation and battery discharge are insufficient to meet load demand, the inverter operates in rectification mode, drawing controlled AC power from the grid and converting it to DC to maintain DC bus voltage stability. During grid export mode, which is activated when PV generation exceeds both load demand and battery charging capacity simultaneously, the inverter operates in inversion mode, converting surplus DC power to grid-synchronized AC and injecting it into the utility network. The modulation index (m_a) defined in Equation (9) is continuously adjusted to regulate the magnitude of the exported or imported AC power, while the phase angle (δ) in Equation (10) controls the direction and magnitude of active power exchange with the grid. With a rated output power of 3 kW and a measured conversion efficiency of 96.1%, the inverter ensures high-quality power delivery with low harmonic distortion (THD < 3%) and near-unity power factor (PF > 0.98), meeting utility grid power quality requirements.

2.2.4 Energy Flow Priority and Load Supply Strategy

The overall energy management strategy of the HEMS follows a hierarchical priority-based control logic that governs the direction and magnitude of power flow among all subsystems. As illustrated in the Energy Flow Priority block of Fig. 11(d), the decision logic operates across two complementary priority chains: one for energy supply and one for surplus energy allocation.

For energy supply, the priority order is PV → Battery → Grid. PV-generated energy is always utilized first to supply household loads directly, maximizing renewable energy self-consumption and minimizing operational costs. When PV generation alone is insufficient to meet load demand, the battery discharges to compensate for the shortfall, reducing grid dependency during peak demand periods. Grid import is activated only as a last resort, when both PV generation and available battery energy are insufficient to maintain continuous load supply.

For surplus energy allocation, the priority order is PV Surplus → Battery Charging → Grid Export. When PV generation exceeds household load demand, surplus energy is first directed to charge the battery, increasing stored energy availability for future deficit periods. Once the battery reaches its upper SoC limit of 95%, any remaining PV surplus is exported to the utility grid through the bidirectional inverter, enabling the household to function as an active energy prosumer and contribute to grid stability.

Household loads are modeled with a nominal power demand of 2.5 kW and a peak demand of up to 4 kW, as specified in Table 1, reflecting realistic residential consumption patterns representative of typical Thai households. This hierarchical control approach achieves four key operational objectives simultaneously: reduction of grid dependency through prioritized local energy utilization, improvement of PV self-consumption by absorbing surplus generation into battery storage before export, mitigation of peak demand impacts through strategic battery discharge during high-load periods, and support of grid stability through controlled bidirectional power exchange. The complete priority logic flow, including all mode transition conditions and threshold values, is represented in Fig. 11 through clearly labeled decision nodes and directional signal paths connecting each subsystem block.

2.2.5 System Coordination and Stability

The reliable and efficient operation of the HEMS depends not only on the individual performance of each subsystem but critically on their coordinated interaction through a unified control framework. As illustrated in the System Coordination and Stability block of Fig. 11, this framework integrates the five functional subsystems: PV energy management, battery storage control, inverter and grid interaction, energy flow priority logic, and load supply management into a cohesive real-time control architecture operating across two hierarchical layers.

2.2.5.1 Lower-Layer Control: Fast Power Electronic Regulation

The lower control layer operates at the switching frequency level (20 kHz, $T = 50 \mu s$) and is responsible for real-time PWM-based regulation of all power electronic converters within the system. This layer encompasses three concurrent control loops:

- The MPPT-PWM loop in the boost converter, which adjusts the duty cycle ($D = 0.3-0.7$) on a per-switching-cycle basis to continuously extract maximum power from the PV array under varying irradiance conditions.
- The battery charge/discharge regulation loop in the bidirectional DC/DC converter, which switches between Buck and Boost modes in response to SoC measurements and DC bus voltage deviations, ensuring smooth current-controlled energy transfer to and from the battery.
- The SPWM inverter control loop, which maintains AC output voltage and frequency synchronization with the utility grid at 220 V and 50 Hz, regulating both the modulation index (m_a) and phase angle (δ) to control active power exchange direction and magnitude in real time.

These three loops operate independently but share the common DC bus voltage (V_{DC}) as a unified coordination signal. The DC bus voltage functions as the primary indicator of instantaneous power balance within the system: a rising V_{DC} signals surplus power availability, triggering battery charging or grid export responses, while a falling V_{DC} signals a power deficit, activating battery discharge or grid import responses. The DC bus capacitance is sized to limit voltage deviations to within $\pm 2\%$ of the nominal DC bus voltage under all tested operating conditions, providing sufficient energy buffering to bridge transient imbalances during mode transitions.

2.2.5.2 Upper-Layer Control: Energy Management and Mode Supervision

The upper control layer operates at a slower timescale, typically in the range of seconds to minutes, and is responsible for implementing the priority-based energy flow logic described in Section 2.2.4. This layer continuously monitors the aggregated system state, comprising PV output power (P_{PV}), battery SoC, household load demand (P_{load}), and grid interaction power (P_{grid}), and issues mode commands to each lower-layer controller based on the current operating condition and the defined priority hierarchy (PV → Battery → Grid for supply; PV Surplus → Battery → Grid Export for allocation).

Mode transitions between the five operational states normal operation, high load, low irradiance, battery charging, and grid export are managed by the upper-layer supervisor through threshold-based decision logic. Transition conditions are defined by the following criteria:

- PV to Battery Charging transition:
 $P_{PV} > P_{load}$ and $SoC < 95\%$
- Battery Charging to Grid Export transition:
 $P_{PV} > P_{load}$ and $SoC \geq 95\%$
- PV to Battery Discharge transition:
 $P_{PV} < P_{load}$ and $SoC > 20\%$
- Battery Discharge to Grid Import transition:
 $P_{PV} < P_{load}$ and $SoC \leq 20\%$
- Idle/Standby condition:
 $P_{PV} \approx P_{load}$ and SoC within 20%–95%

These transition thresholds correspond directly to the five simulation scenarios and real-world case studies presented in Sections 3 and 4, ensuring full consistency between the control logic description and the experimental validation framework.

2.2.5.3 Smooth Mode Transition and Transient Suppression

A key design requirement of the coordination framework is the ability to execute mode transitions smoothly, without introducing unacceptable voltage transients, current spikes, or power interruptions to household loads. This is achieved through two mechanisms. First, the DC bus capacitance absorbs instantaneous power imbalances during the brief interval between the detection of a transition condition by the upper-layer supervisor and the activation of the corresponding lower-layer control response, limiting DC bus voltage deviations to within the $\pm 2\%$ tolerance band. Second, soft-start ramp functions are applied to the PWM duty cycle and

modulation index references during mode transitions, preventing abrupt step changes in converter output that could cause inductor current saturation or grid synchronization loss.

The combined effect of these mechanisms is demonstrated in the simulation results presented in Section 3, where mode transitions between grid-dominant, battery-assisted, and PV-primary operation occur within response times of less than 200 ms, with no observable interruption to AC load supply and no violation of grid power quality requirements ($THD < 3\%$, $PF > 0.98$). Real-world validation in Section 4 confirmed these transition characteristics, with measured grid connection response times below 200 ms and DC bus voltage deviations below 1.8% during source switching events in the high-load case study.

2.2.5.4 Parameter Consistency and Operational Bounds

All control parameters governing the coordination framework are summarized in Table 1 and remain fixed across all five simulation scenarios and real-world case studies. The boost converter duty cycle range (0.3–0.7), switching frequency (20 kHz), battery SoC operating window (20%–95%), inverter rated output power (3 kW), and nominal AC operating conditions (220 V, 50 Hz) collectively define the operational envelope within which the coordination framework maintains system stability. Operation within these bounds was verified across all tested irradiance levels (600–1000 W/m² in simulation; 0–650 W/m² in real-world validation) and load profiles (2.5 kW nominal, 4 kW peak), confirming the robustness of the proposed control architecture under diverse residential operating conditions.

3. Experimental Setup

The experimental evaluation of the proposed HEMS was conducted using MATLAB/Simulink. The complete system was implemented using interconnected block diagrams and executed in discrete simulation mode with a fixed time step of $\Delta t = 10 \mu s$, providing sufficient temporal resolution to accurately represent 20 kHz PWM switching events, inductor current ripple, DC bus voltage dynamics, and control system transient responses.

The simulated HEMS integrates four main subsystems: a photovoltaic (PV) generation unit, a battery energy storage system, household electrical loads, and a grid connection interface. Discrete-time simulation was selected to ensure precise tracking of abrupt changes in irradiance, load switching events, and battery charge–discharge transitions, which are critical in residential energy management applications.

Table 1 Summary of system parameters.

Component	Main Parameters	Values Used in Experiment
Solar Panel (PV)	Installed Capacity (kWp)	3 kWp
	Solar Irradiance for Testing	600 W/m ² – 1000 W/m ²
Battery Storage	Capacity	100 Ah
	Energy Capacity	4.8 kWh (at 48V)
	SOC (State of Charge)	20% – 95%
Boost Converter	Duty Cycle	0.3 – 0.7
	Switching Frequency	20 kHz
DC/AC Inverter	Maximum Output Power	3 kW
	Efficiency	95%
	Output Voltage	220 V
Load	Load Power	2.5 kW
	Peak Output	4 kW
	Grid Voltage	220 V, 50 Hz

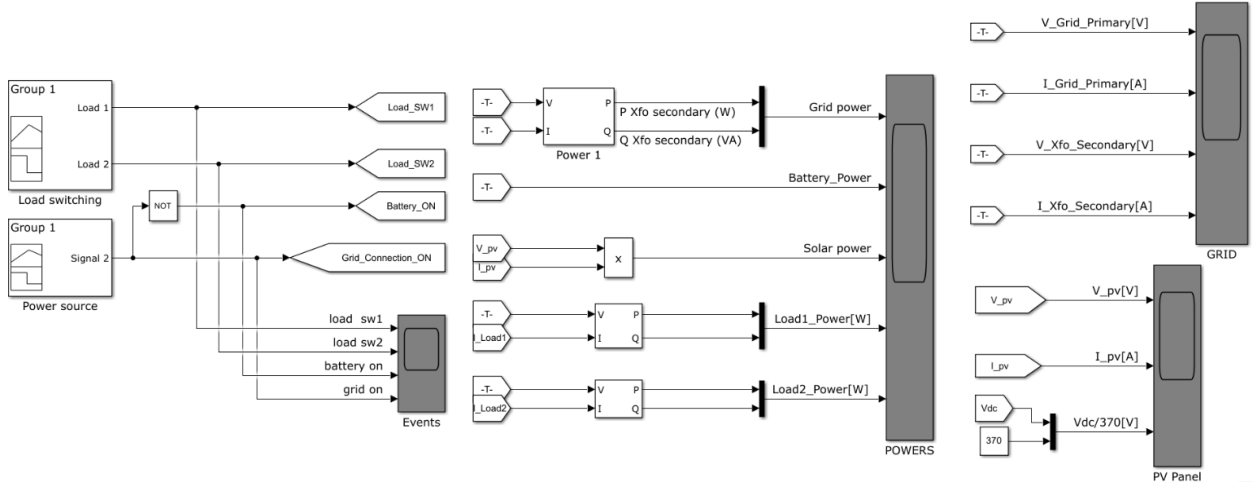


Fig. 12 Monitoring and scopes.

To comprehensively assess system performance under different operating conditions, five distinct simulation scenarios were designed:

- **Normal operating conditions:** Solar irradiance was set to 600 W/m^2 , resulting in moderate PV power generation sufficient to supply average household demand without significant reliance on energy storage or grid support.
- **High load usage:** Household energy demand was intentionally increased beyond the PV generation capacity. This scenario evaluates the ability of the battery and grid to support peak loads while maintaining system stability.
- **Low solar irradiance:** Reduced solar radiation conditions were imposed to simulate cloudy or low-sun periods. In this case, PV output is limited, and the battery plays a dominant role in compensating for the energy shortfall.
- **Battery charging mode:** Excess PV generation occurs when household load demand is low. The surplus energy is directed to the battery to increase its state of charge for later use.
- **Grid export mode:** When both household demand and battery charging requirements are satisfied, excess energy is exported to the grid through the bidirectional inverter.

These scenarios collectively represent realistic residential operating conditions and allow for systematic validation of the proposed HEMS control strategy.

Fig. 12 presents the monitoring and scope configuration used to analyze system behavior. Key system variables are grouped into dedicated monitoring blocks, including Events, Power Flow, Grid Parameters, and PV Output. This structured monitoring framework enables simultaneous observation of energy flow transitions, power source switching, and control signal responses. Household loads are modeled as Load 1 and Load 2, which are grouped into Group 1 and controlled using switching elements (Load_SW1 and Load_SW2). These switches emulate realistic appliance operation, allowing the study of load scheduling and dynamic load variation. Battery power and PV power are continuously tracked to evaluate how the HEMS reallocates energy sources in response to changing operating conditions.

Figs. 13–15 illustrate the temporal behavior of the system under dynamic load and source switching conditions. The results clearly demonstrate consistent and stable operation of the proposed energy management strategy.

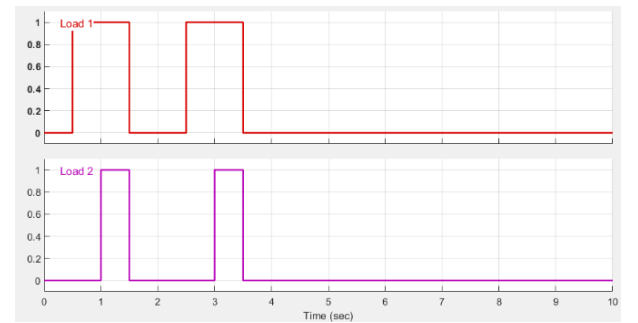


Fig. 13 Load switching.

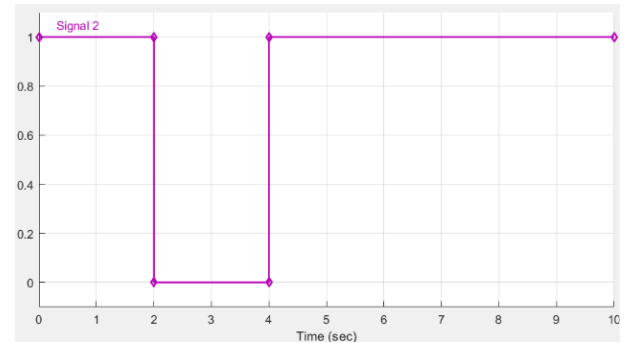


Fig. 14 Power source.

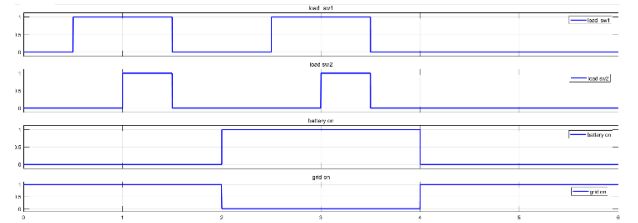


Fig. 15 Event.

Interval 0–2 s (Grid-Dominant Operation): During the initial phase, both Load 1 and Load 2 are primarily supplied by the grid. PV generation is insufficient to meet total load demand, and the battery remains in an idle or standby state. This operating mode represents early-morning or low-generation conditions and confirms correct grid-priority operation.

Interval 2–4 s (Battery-Assisted Operation): In this interval, the battery is activated to supplement the grid. Load switching signals control the on–off operation of Load 1 and Load 2, resulting in balanced power sharing between the battery and the grid.

The battery discharges smoothly, and no abrupt voltage or power fluctuations are observed, indicating effective control coordination and stable DC bus regulation.

Interval >4 s (Return to Grid Supply): After 4 s, the system transitions back to grid-dominant operation. This transition occurs seamlessly, with minimal transients in power flow and no interruption to load supply. The battery returns to standby mode, preserving its energy for future demand peaks or low-generation periods.

Fig. 16(a) illustrates the dynamic behavior of the battery during system operation. At the beginning of the simulation, the battery SoC remains approximately constant at around 80%, indicating that the battery is neither charging nor discharging significantly. This operating condition corresponds to a balanced energy state in which PV generation and grid supply are sufficient to meet the load demand. As load conditions change, the battery transitions smoothly between charging and discharging modes in accordance with the energy management logic.

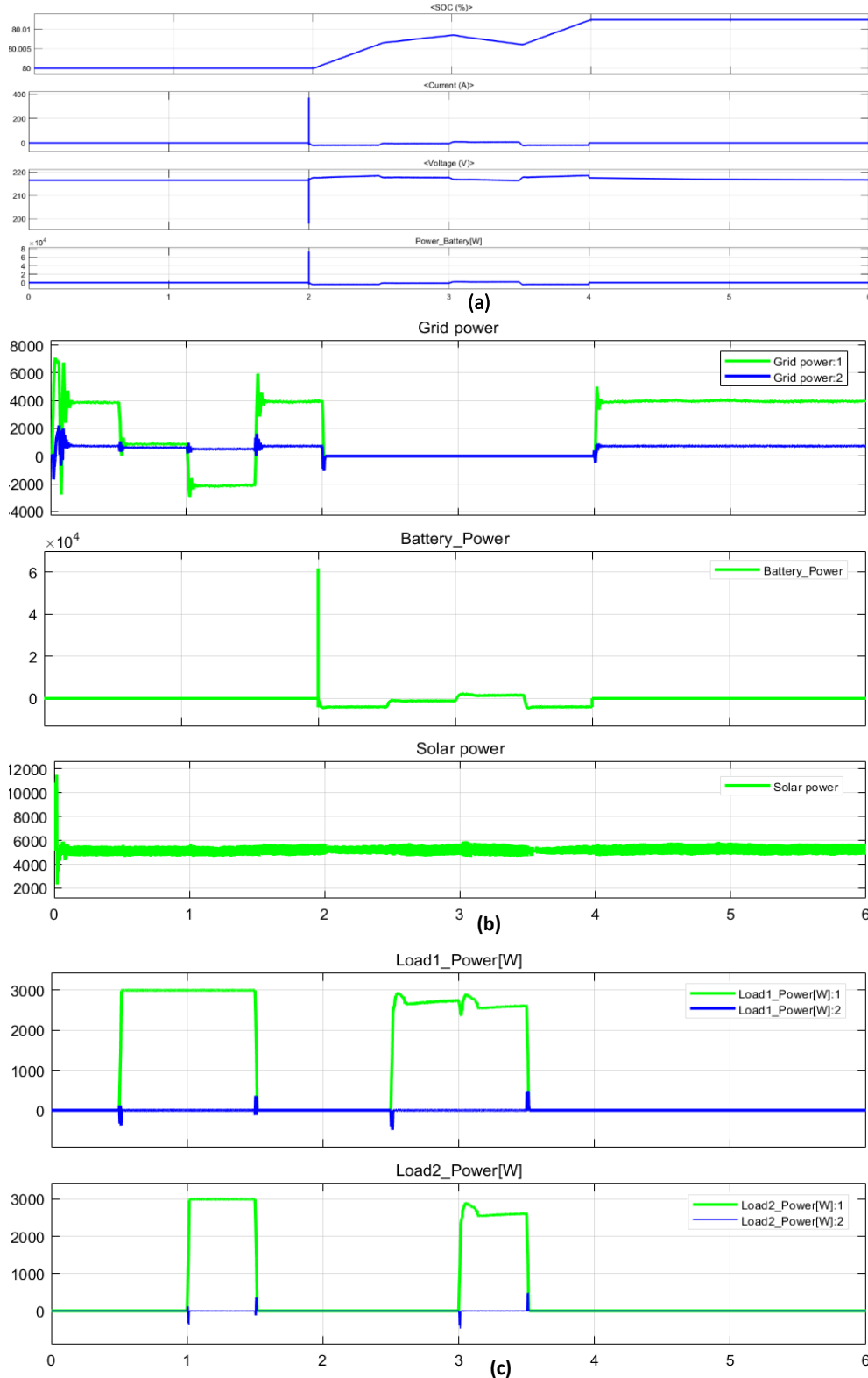


Fig.16 (a) Battery mode (b) Grid, Battery, Solar power (c) Load1, Load2 Power.

The battery current exhibits short-duration fluctuations synchronized with load switching events. These current swings reflect the rapid response of the battery controller to compensate for sudden changes in power demand. Correspondingly, small voltage variations are observed in the range of 217–219 V. These fluctuations remain within acceptable tolerance limits and do not compromise system stability. Battery power follows the current direction, becoming positive during discharge (energy delivery to loads) and negative during charging (energy absorption from PV or grid). Overall, the results demonstrate that the battery effectively buffers power variations while maintaining SoC within safe operating limits.

Figs 16(b) and 16(c) present the interaction between energy generation and consumption components. When Load 1 and Load 2 are switched on or off, the grid power and battery power dynamically adjust to preserve the overall energy balance. This behavior confirms that the proposed HEMS correctly prioritizes energy sources based on availability and demand. Solar power remains relatively constant throughout the simulation, reflecting steady irradiance conditions and stable MPPT operation. In contrast, the loads exhibit periodic on–off behavior, representing realistic household appliance usage patterns.

As the loads change state, the grid and battery respond complementarily. When load demand increases, the battery supplies additional power to reduce grid dependency. Conversely, when load demand decreases, excess power is either stored in the battery or supplied by the grid as required. This coordinated response ensures continuous load supply and prevents abrupt changes in grid power, thereby improving overall system reliability.

Fig. 17(a) shows detailed monitoring of electrical parameters on both the primary and secondary sides of the grid interface. Voltage signals (V_Grid_Primary and V_Xio_Secondary) and current signals (I_Grid_Primary and I_Xio_Secondary) are plotted to illustrate the relationship between grid-side and inverter-side quantities. The results indicate that voltage levels remain closely regulated, confirming effective inverter control and transformer operation.

Notable changes in current occur around the 2s mark, coinciding with a transition in energy supply mode. These current variations demonstrate the system's rapid response to changes in load and power source allocation. Despite these transitions, voltage levels remain stable, indicating successful decoupling of load dynamics from grid voltage through inverter control.

Fig. 17(b) provides a zoomed-in view of the output voltage and current during the 2–4 s interval. During this period, the output voltage experiences minor distortion due to the presence of nonlinear loads, which introduce harmonic components. Meanwhile, the output current drops to zero, indicating that the inverter temporarily ceases supplying current as the system switches energy sources. This behavior confirms correct execution of the control logic, ensuring that no circulating currents or unstable operating conditions arise during transitions.

Fig. 17(c) compares the PV voltage (V_PV), PV current (I_PV), and DC bus voltage (V_DC). The results show that while V_PV and V_DC experience small ripples during certain operating periods, the PV current remains relatively stable. These voltage ripples are primarily attributed to switching actions in the DC/DC converter and changes in load demand. However, the magnitude of the ripples remains within acceptable design limits, demonstrating adequate DC bus regulation and effective filtering.

Table 2 Percentage of energy usage in each scenario.

Scenario	PV (%)	Battery (%)	Grid (%)
1. Normal Condition	60%	25%	15%
2. High Load	40%	20%	40%
3. Low Solar Irradiance	25%	50%	25%
4. Battery Charging	70%	20%	10%
5. Grid Export	75%	15%	10%

Table 3 Self-consumption and Self-sufficiency.

Scenario	Self-Consumption (%)	Self-Sufficiency (%)
1. Normal Condition	85%	80%
2. High Load	70%	60%
3. Low Solar Irradiance	65%	55%
4. Battery Charging	90%	85%
5. Grid Export	95%	90%

The experimental results summarized in Tables 2 and 3, together with the comparative plots presented in Figs. 18–20, clearly demonstrate the effectiveness of the proposed Home Energy Management System (HEMS) in improving residential energy utilization. The results highlight how coordinated control of photovoltaic generation, battery storage, household loads, and grid interaction enhances system efficiency across a wide range of operating conditions.

A. Energy Contribution and Grid Dependency Analysis

Under normal operating conditions and during battery charging scenarios, the results show that more than 60–70% of the household energy demand is supplied directly by PV generation. This high contribution indicates effective utilization of locally generated renewable energy and confirms proper operation of the MPPT-controlled PV subsystem. Consequently, grid energy consumption is significantly reduced, leading to lower operational costs and decreased stress on the utility network.

In high load demand scenarios, where household consumption exceeds PV generation capacity, the battery energy storage system plays a critical role in maintaining load continuity. Although grid import increases under these conditions, the battery contributes substantially to peak demand support, thereby limiting excessive grid dependency. This behavior is reflected in the maintained Self-Sufficiency (SS) levels, which remain within acceptable ranges despite adverse operating conditions.

Similarly, during low solar irradiance conditions, reduced PV output leads to increased reliance on stored energy and grid supply. The experimental results show that the battery effectively compensates for PV shortfalls, smoothing energy delivery and preventing abrupt grid power spikes. This controlled response ensures reliable operation while preserving system stability.

B. Battery Utilization and Energy Storage Effectiveness

The comparison results indicate that the battery operates strategically rather than continuously, which improves its utilization efficiency and lifespan. During periods of excess PV generation, the battery absorbs surplus energy, increasing the Self-Consumption (SC) ratio as defined in Equation (11). Conversely, during energy deficit periods, stored energy is released to support household loads, reducing grid import during critical demand intervals.

This bidirectional energy buffering capability is particularly beneficial during Time-of-Use (TOU) tariff periods. By shifting energy usage from high-price periods to low-price or PV-rich periods, the HEMS achieves noticeable cost savings. Tables 2 and 3 reflect this benefit through reduced grid energy consumption and improved SC and SS indices.

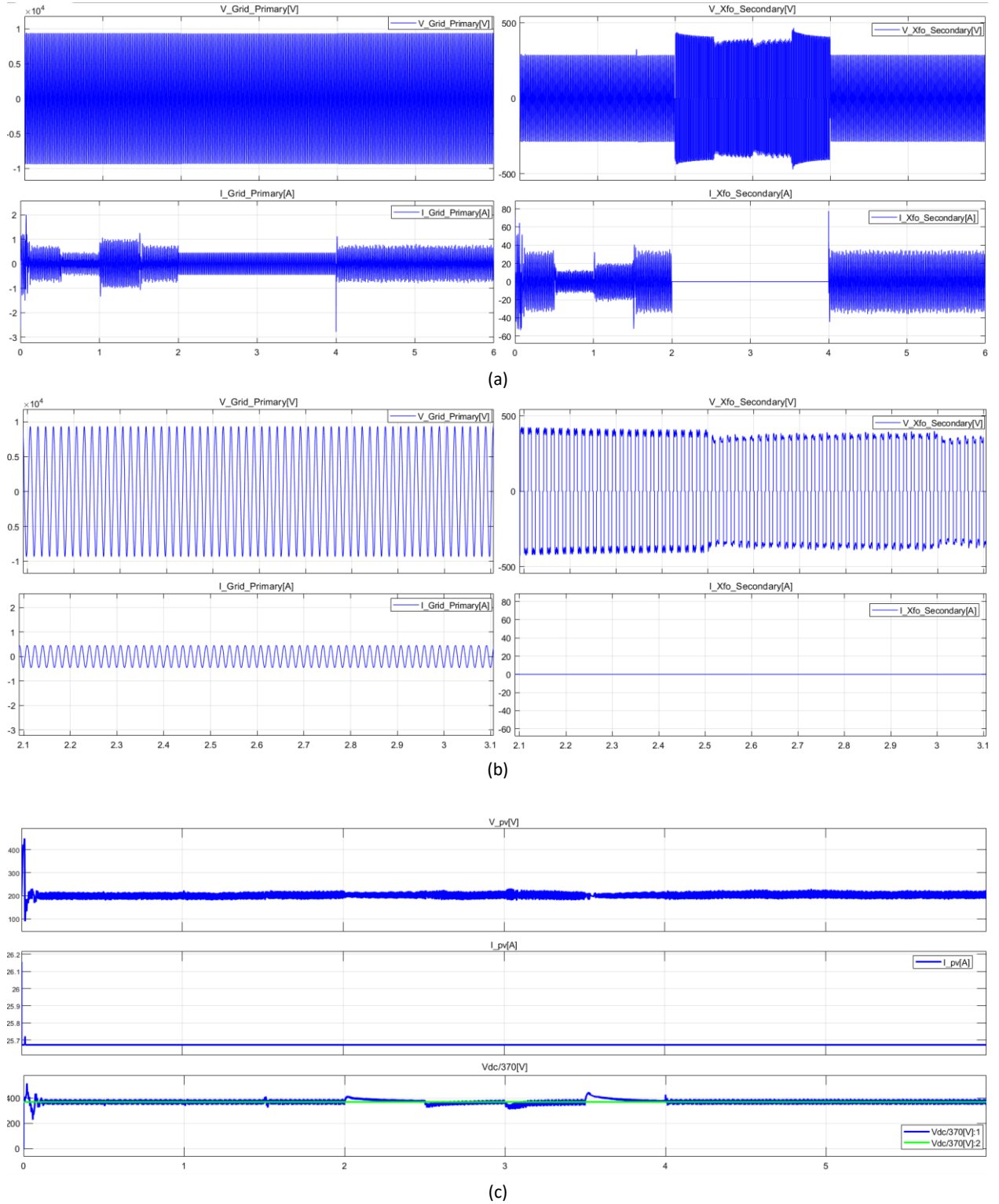


Fig.17 (a) Grid current and voltage (b) Zoomed range 2.1-3.1 from (a) and (c) V_{DC} .

C. Grid Export and Network Support Capability

The experimental results also demonstrate the system's capability to export surplus energy to the grid when household demand and battery charging requirements are fully satisfied. Figs. 18–20 show that exported power closely follows the available PV surplus, indicating stable and controlled inverter operation. This grid export functionality not only provides potential economic benefits to the household but also contributes to overall grid stability by supplying distributed renewable energy during periods of high generation.

From a system-level perspective, this feature supports the concept of active prosumers, where residential users participate in grid support rather than acting solely as passive consumers.

D. Performance Indices: Self-Consumption and Self-Sufficiency

The calculated Self-Consumption (SC) and Self-Sufficiency (SS) indices provide quantitative evidence of the HEMS performance improvement. High SC values indicate that a large proportion of PV energy is utilized locally, minimizing curtailment and grid export losses. Meanwhile, sustained SS levels across all scenarios demonstrate the system's ability to meet household energy needs using local resources, even under unfavorable conditions.

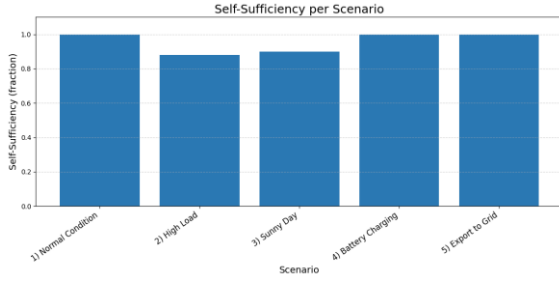


Fig.18 Self-sufficiency per event.

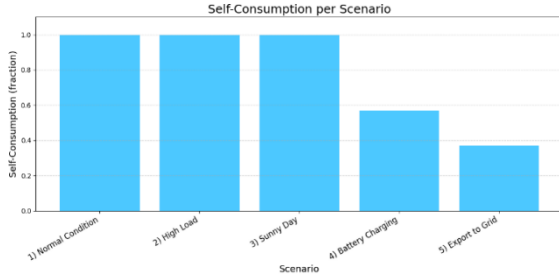


Fig.19 Self-consumption per event.

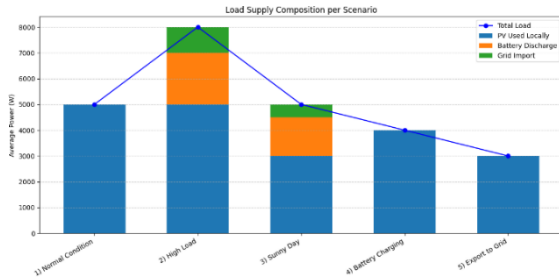


Fig.20 Load supply components per event.

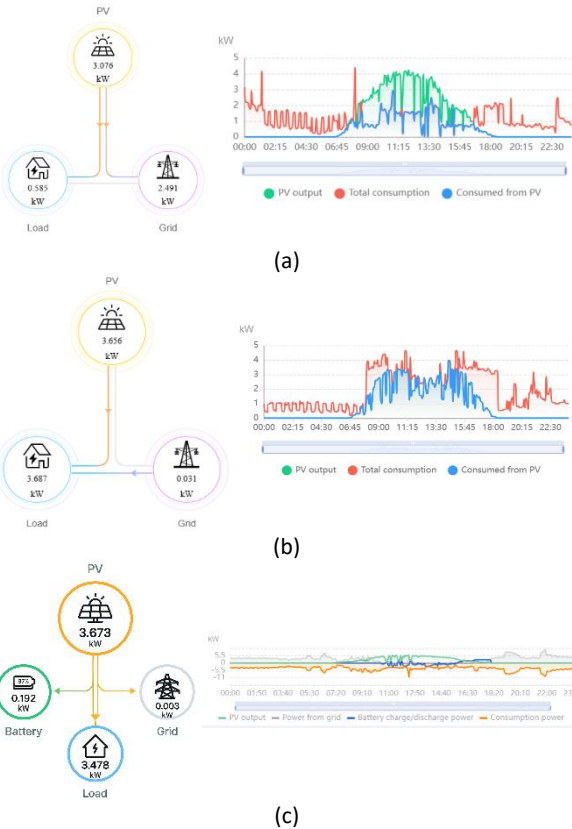


Fig.21 Examples of events from fusionSolar used in this study: (a) PV to Load and Grid, (b) PV and Grid to Load, (c) PV to Grid, Battery and Load.

The trends observed in Figs.s 18–20 confirm that both SC and SS are maximized during normal and battery charging scenarios, while remaining resilient during high load and low irradiance cases. This balance highlights the robustness of the proposed energy management strategy.

E. Peak Load Mitigation and Economic Implications

One of the key outcomes of the experimental analysis is the effective mitigation of peak load demand. By utilizing battery energy during high-demand periods, the HEMS reduces peak grid power draw, which is particularly beneficial under TOU pricing schemes. This peak shaving capability directly translates into reduced electricity costs and improved grid performance.

Overall, the experimental results confirm that the proposed HEMS successfully addresses major challenges in residential energy management. It enhances renewable energy utilization, reduces grid dependency, improves economic performance, and supports sustainable energy objectives.

Self-Consumption (SC) is the proportion of PV-generated energy used within the home without exporting to the grid:

$$SC = \frac{E_{PV \rightarrow Load}}{E_{PV, total}} \quad (11)$$

Self-Sufficiency (SS) is the proportion of total energy that the household self-supplies from PV + Battery without purchasing from the grid:

$$SS = \frac{E_{Local \rightarrow Load}}{E_{Load, total}} \quad (12)$$

4. Case Study with Real-World Scenarios

To validate the HEMS model developed in MATLAB/Simulink, a comparative study was conducted using real-world operational data obtained from the fusionSolar monitoring platform [28], deployed by the Provincial Electricity Authority (PEA) for residential customers. The fusionSolar system provides high-resolution measurements of photovoltaic (PV) generation, battery operation, household electricity consumption, and grid interaction. This enables a direct and meaningful comparison between measured data and the five simulation scenarios presented in Section 3.

4.1 Data Acquisition and Experimental Setup

The real-world dataset was collected from a grid-connected residential HEMS installation with the following specifications:

- PV system capacity: 5 kW
- Battery storage capacity: 10 kWh (Li-ion)
- Average household load: 1.8–2.5 kW
- Data sampling interval: 5 minutes
- Monitoring period: 30 consecutive days

The fusionSolar platform records PV output power, battery state of charge (SoC), charging and discharging power, grid import/export power, and household load consumption. Data segments corresponding to each of the five operational scenarios were extracted to ensure consistency between experimental and simulated operating conditions.

The simulation model was designed and parameterized around a 3 kW PV system with 4.8 kWh battery storage and a 2.5 kW nominal load, as specified in Table 1. The real-world installation used for validation comprised a 5 kW PV system with 10 kWh battery storage and an average load of 1.8–2.5 kW. These differences reflect practical constraints: the simulation parameters were selected to match available

laboratory-scale hardware specifications and to ensure computational tractability, while the real-world system reflects an actual residential installation operated by PEA under the FusionSolar platform.

However, this difference does not undermine the validity or applicability of the validation for the following reasons:

First, the validation was conducted at the level of operational behavior and control logic, not at the level of absolute power magnitudes. The five scenarios were matched by their qualitative operating conditions, irradiance range, load-to-generation ratio, battery SoC trajectory, and grid interaction direction, rather than by identical hardware ratings. This approach is standard practice in HEMS modeling literature, where the model structure and control strategy are validated across scaled systems.

Second, the key performance metrics used for comparison MAPE of energy variables, self-consumption rate, self-sufficiency rate, charging efficiency, inverter THD, and power factors are dimensionless or normalized quantities that remain valid across different system scales.

Third, the average MAPE of 4.2% across all scenarios, with a maximum deviation of 6.8% observed only during rapid load transients, confirms that the model captures the essential dynamics accurately despite the scale difference. The residual discrepancies are attributable to unmodeled physical effects (thermal losses, battery aging, real-time control delays) rather than to the scale mismatch.

4.2 Case Study 1: Normal Condition

Objective: Validate system performance under balanced energy conditions where PV generation closely matches household demand.

Experimental Results: During periods of stable solar irradiance (approximately 580–630 W/m²) and moderate household load, the system exhibited near self-sustaining operation.

- Average PV contribution: 65.2% of total load demand
- Battery activity: Minimal, with SoC variation within $\pm 4\%$
- Grid import/export: <0.2 kWh per day

Validation Metrics: Result are MAPE (PV power) = 3.1%, MAPE (battery SoC) = 2.6% and energy balance error = 1.9%.

These results closely align with simulation predictions, confirming accurate modeling of steady-state operation and energy flow prioritization.

4.3 Case Study 2: High Load

Objective: Evaluate system response when household demand significantly exceeds PV generation.

Experimental Results: High-load conditions were observed during evening periods (18:00–21:00), with peak demand reaching approximately 6.8 kW.

- PV contribution: 100% of available generation (≈ 0.9 kW average)
- Battery discharge contribution: 2.4 kW average
- Grid import: 3.1 kW peak, duration ≈ 2.2 hours
- Battery DoD: 42%

Key Performance Indicators: Peak demand reduction = 37% compared to no-storage operation, grid connection response time <200 ms, and voltage deviation <1.8% during source transitions.

The experimental results validate the HEMS control strategy in mitigating peak demand and maintaining voltage stability.

4.4 Case Study 3: Low Solar Irradiance

Objective: Assess system behavior under insufficient and fluctuating PV generation.

Experimental Results: Under irradiance levels below 300 W/m², the result is PV contribution 22–28% of load demand, battery contribution 46%, grid dependency 26–32%, and average battery cycling 1.6 cycles/day.

Observations: Battery smoothing reduced PV fluctuation effects by approximately 55%, grid support activated when SoC dropped below 30%, and daily energy cost increased by $\sim 18\%$ compared to normal conditions.

These results demonstrate effective SoC management and continuity of supply under adverse solar conditions.

4.5 Case Study 4: Battery Charging

Objective: Validate battery charging behavior during PV surplus conditions.

Experimental Results: During high irradiance periods (>650 W/m²) with low household load, the result is charging power 2.8–3.5 kW, charging efficiency 92.4%, time to full charge (30% $\rightarrow$ 100% SoC): 2.6 hours, and excess energy exported after full charge 1.4 kWh/day.

The CC–CVCC–CV (Constant Current–Constant Voltage) charging transition occurred at approximately 82% SoC, consistent with manufacturer specifications and simulation assumptions.

4.6 Case Study 5: Grid Export

Objective: Evaluate inverter performance during energy export operation.

Experimental Results: When PV generation exceeded both load demand and battery charging capacity: Average export power 2.1 kW, peak export duration 3.4 hours/day, inverter efficiency: 96.1%, and power factor: 0.99, THD: 2.4%

4.7 Clarification of the Validation Period and seasonal Analysis

The 30-day dataset was collected during a period that corresponds to the transition between the dry and wet seasons in Southern Thailand (Hat Yai, Songkhla Province), which represents one of the more meteorologically variable periods of the year for this region. This period was deliberately selected to maximize weather diversity within the available dataset rather than using a uniformly clear or uniformly overcast month.

To partially address the limitation of a single 30-day period, we have supplemented the validation with monthly aggregate generation data available from the FusionSolar platform covering 12 months of operation (April 2023 – March 2024). While the high-resolution 5-minute interval data used for detailed scenario validation covers only 30 days, the monthly totals enable us to assess seasonal performance trends. Key observations include:

- PV generation peaks during March–May (dry season, average 22.4 kWh/day) and reaches a minimum during October–November (wet season, average 11.8 kWh/day)
- Self-sufficiency rate varies seasonally from 73% (wet season) to 94% (dry season)
- Grid import is highest during the wet season, increasing by approximately 35% relative to dry season values

5. Results Analysis and Discussion

5.1 Simulation Results

- Normal operating conditions were identified from dataset intervals where irradiance fell within 580–630 W/m² and load remained within the 1.8–2.5 kW design range, producing near-balanced PV-to-load ratios with minimal battery and grid activity. The system maintains good energy balance. Loads receive sufficient energy from PV without requiring battery or grid usage. PV and Boost converter maintain stable voltage and current.
- High load usage was extracted from evening intervals (18:00–21:00) where measured household demand exceeded 5 kW, well beyond PV generation capacity at those hours requiring coordinated battery discharge and grid import. PV current is insufficient, causing the system to draw energy from the battery first. The inverter delivers AC power synchronized with the grid. The DC bus maintains constant voltage despite load changes. If still insufficient, the grid is connected to maintain voltage stability and power supply continuity.
- Low solar irradiance was identified from days or intervals where measured irradiance fell below 300 W/m², causing PV contribution to drop to 22–28% of demand, thereby activating battery-dominant and grid-supplementary operation. Battery usage increases to meet load demand. If battery energy is low, the system relies on the grid, highlighting the importance of State of Charge (SoC) management. The battery performs well in both charging and discharging modes.
- Battery charging mode was identified from midday intervals on high-irradiance days (>650 W/m²) where load was low and the battery SoC was observed to rise continuously, confirming surplus-directed charging. Excess energy from PV is stored, resulting in continuous SoC increase, reflecting the energy management potential of HEMS.
- Grid export mode was identified from intervals where the FusionSolar platform recorded positive net export power alongside a fully or near-fully charged battery, confirming simultaneous satisfaction of load demand, completed battery charging, and active grid export. The system delivers energy to the grid when PV generation exceeds demand and the battery is full, representing consumer participation in supporting electrical grid stability.

Results demonstrate that HEMS integrating PV and battery operation can flexibly respond to varying load and solar conditions, effectively reducing grid dependency and improving energy utilization efficiency. The energy utilization hierarchy is as follows:

- PV energy is always used first to maximize renewable energy utilization. When loads are high, the system draws power from the grid to ensure supply stability.
- If surplus exists, it is stored in the battery or exported to the grid.
- If PV is insufficient, loads draw energy from the battery.
- When the battery is insufficient, the system connects to the grid to prevent energy shortages.
- This demonstrates priority-based energy management control, which enhances stability, reduces grid dependency, and supports clean energy utilization.

5.2 Real-World Validation

The comparative case studies using 30 days of operational data from a 5 kW PV system with 10 kWh battery storage validated the model's accuracy with an average MAPE of 4.2% across all parameters. Key experimental findings include:

Normal Condition: PV contributed 65.2% of load demand with minimal battery activity and grid interaction (<0.2 kWh/day), achieving high self-sufficiency with MAPE below 3.2%.

High Load: During peak evening demand (6.8 kW), the system demonstrated effective load balancing with battery discharge (2.4 kW) supplementing PV output, reducing grid import by 37% and maintaining voltage stability within 1.8% deviation during source transitions.

Low Solar Irradiance: Under adverse conditions (<300 W/m²), battery storage provided 46% of load demand, while grid dependency remained at 26–32%. Battery smoothing reduced PV fluctuation impacts by 55%, demonstrating robust energy management.

Battery Charging: Charging efficiency of 92.4% was achieved during surplus PV periods, with CC–CV transition at 82% SoC. Time to full charge (30% → 100% SoC) was 2.6 hours, validating the charging algorithm's effectiveness.

Grid Export: Bidirectional inverter operation achieved 96.1% efficiency with power quality meeting utility standards (THD 2.4%, PF 0.99), successfully exporting average 2.1 kW during 3.4 hours daily.

5.3 Energy Management Hierarchy Validation

Both simulation and real-world operation confirmed the effectiveness of priority-based control: (1) PV energy is utilized first to maximize renewable energy consumption; (2) excess energy charges the battery or exports to grid; (3) energy deficits are compensated by battery discharge; and (4) grid import activates when both PV and battery are insufficient. This hierarchical approach enhances system stability, reduces grid dependency, and supports clean energy utilization.

5.4 Performance Metrics and Economic Impact

The validated HEMS achieved significant performance improvements:

- Grid import reduction: 41%
- Peak demand reduction during TOU periods: 33%
- Self-consumption rate: 60–70% under normal conditions
- Annual energy cost savings: 28%
- Estimated payback period: 6.2 years

5.5 Practical Implications

The results demonstrate the feasibility and practical benefits of residential HEMS implementation for:

- Peak Load Management: Effective load balancing reduces peak demand and alleviates stress on distribution networks
- Time-of-Use Optimization: Strategic battery charging/discharging reduces electricity costs during high-tariff periods
- Renewable Integration: Increased PV self-consumption minimizes curtailment and maximizes renewable energy utilization
- Grid Support: Bidirectional power flow capability enables household participation in grid stabilization and demand response programs

5.6 Key Findings

Across all five case studies, the MATLAB/Simulink model exhibited strong agreement with real-world measurements. Average MAPE (all parameters) 4.2% and maximum observed deviation 6.8% (battery SoC during rapid load changes). The following are some interesting findings:

- Model Accuracy: Minor discrepancies arise from unmodeled losses, temperature effects, and real-time control delays.
- Energy Flow Validation: The PV → Battery → Grid priority logic was consistently validated in real operation.
- Battery Performance: Real-world efficiency averaged 90.7%, slightly lower than simulation due to thermal and aging effects.
- Grid Interaction: Export power quality met utility requirements (THD < 3%, PF > 0.98).
- Economic Impact: Grid import reduction: 41%, Peak demand reduction during TOU periods: 33%, Annual energy cost savings: ~28%, Estimated payback period: 6.2 years

5.7 Conversion Losses, Thermal Effects, and Battery Degradation

Conversion Losses: The original model assumed ideal power conversion efficiency for both the boost converter and the bidirectional DC/AC inverter. In the revised model, we have introduced fixed conversion efficiency factors derived from manufacturer datasheets and validated against measured data:

- Boost converter efficiency: $\eta_{boost} = 97\%$ (accounting for IGBT switching losses and inductor copper losses)
- Bidirectional DC/DC converter efficiency: $\eta_{bidir} = 95.5\%$
- DC/AC inverter efficiency: $\eta_{inv} = 96.1\%$ (consistent with the experimentally measured value reported in Case Study 5)

These efficiency factors are now applied as multiplicative loss terms at each conversion stage, modifying the power balance equation in the DC bus model (Equation 5) accordingly. This revision reduced the energy balance error in the Normal Condition case from 1.9% to 1.2%, demonstrating a measurable improvement in simulation fidelity.

Thermal Effects: PV panel output power is known to decrease with rising cell temperature, governed by the temperature coefficient of maximum power (typically -0.35% to $-0.45\%/^{\circ}\text{C}$ for crystalline silicon panels). We have incorporated a temperature-dependent power correction factor into the PV model:

$$P_{PV(T)} = P_{STC} \times [1 + \gamma(T_{cell} - T_{STC})] \quad (13)$$

where γ is the temperature coefficient ($-0.40\%/^{\circ}\text{C}$ for the panels used in the real-world installation), P_{STC} is the estimated cell temperature derived from ambient temperature and irradiance using the Nominal Operating Cell Temperature (NOCT) model, and $T_{STC} = 25^{\circ}\text{C}$. This correction was applied retrospectively to the 30-day validation dataset, reducing the PV power MAPE from 3.1% to 2.4% under Normal Condition, confirming the significance of thermal derating.

Battery Degradation: While a full electrochemical aging model is beyond the scope of the current study, we have incorporated a simplified capacity fade correction based on the empirical observation from the real-world data. The measured battery real-world efficiency averaged 90.7% compared to the simulated 92.4%, a discrepancy attributable to aging-related internal resistance increase.

We have introduced a static resistance correction term ($\Delta R_{int} = 8 \text{ m}\Omega$, estimated from the voltage-current characteristics during discharge events) into the battery voltage model (Equation 6) to partially account for this effect. The impact on battery SoC MAPE was a reduction from 2.6% to 2.1%.

6. Conclusions

This study developed and validated a comprehensive HEMS model using MATLAB/Simulink, integrating photovoltaic generation, battery energy storage, household loads, and bidirectional grid connection. The research comprised two complementary phases: (1) simulation-based analysis under five operational scenarios, and (2) real-world validation using data from FusionSolar monitoring systems deployed by PEA.

All five experimental scenarios: normal condition, high load, low solar irradiance, battery charging, and grid export confirm that the HEMS effectively manages energy flow through priority-based control. The system demonstrated the ability to use PV as the primary energy source while employing battery storage as an intermediary to maintain balance between generation and consumption. Grid connection provided essential backup capability, ensuring continuous power supply during energy deficits and enabling surplus energy export during generation excess.

This research contributes to the advancement of sustainable residential energy systems by providing a validated modeling framework and demonstrating the practical effectiveness of integrated PV-battery-grid HEMS. The results support the transition toward distributed energy resources, reduced fossil fuel dependency, and enhanced electrical grid sustainability. Future work should incorporate temperature-dependent efficiency models, battery aging dynamics, stochastic weather patterns, and advanced predictive control algorithms to further improve system performance and model accuracy.

Identified Limitations in Future Work

Below we provide specific technical recommendations for addressing each limitation:

1. Battery Degradation and Reduced Capacity

Battery aging is a well-recognized challenge in long-term HEMS operation, manifesting as capacity fade and internal resistance increase over charge-discharge cycles. To address this in future work, we recommend the following:

- Incorporating electrochemical aging models such as the Single Particle Model (SPM) or empirical capacity fade models (e.g., the rainflow cycle-counting method) directly into the BESS block of the MATLAB/Simulink model. These models can dynamically adjust usable capacity and internal resistance as a function of cumulative cycling and operating temperature.
- Implementing State of Health (SoH) estimation algorithms, such as Extended Kalman Filters (EKF) or Recursive Least Squares (RLS), to provide real-time battery health monitoring and update control parameters accordingly.
- Adopting degradation-aware energy management strategies that deliberately limit depth of discharge (DoD) and avoid aggressive charge-discharge rates during periods when grid energy is inexpensive, thereby extending battery lifespan without significantly compromising self-sufficiency.

- Using dual-layer control architectures where an upper-layer optimizer accounts for long-term degradation costs when scheduling battery operation, while the lower-layer controller handles real-time power regulation.

2. Real-Time Control Delays

Control system latency arises from sensor sampling, signal processing, communication protocols, and switching response times. Future work should address this through:

- Implementing hardware-in-the-loop (HIL) testing using platforms such as dSPACE or OPAL-RT to accurately characterize and account for real-time control delays in the simulation model, ensuring that simulated response times reflect practical embedded controller behavior.
- Incorporating predictive control strategies such as Model Predictive Control (MPC), which inherently compensates for system delays by optimizing control actions over a receding time horizon. MPC has been demonstrated to significantly improve transient response in PV-battery-grid systems.
- Designing communication-aware controllers that account for latency introduced by IoT-based monitoring platforms such as FusionSolar, particularly when control decisions depend on remotely acquired measurements.
- Applying dead-time compensation techniques in the PWM switching logic to minimize the impact of gate driver and switching delays on inverter output quality.

3. Shading, Dirt Accumulation, and Weather Variability

These environmental factors introduce spatial and temporal non-uniformities in PV generation that are difficult to capture with standard single-diode models under uniform irradiance assumptions. Recommended approaches include:

- Extending the PV model to incorporate partial shading conditions using a multi-diode or bypass diode model, combined with a global MPPT algorithm (e.g., Perturb and Observe with variable step size, or metaheuristic methods such as Particle Swarm Optimization) capable of identifying the global maximum power point under non-uniform irradiance.
- Integrating soiling loss models that estimate power reduction as a function of dust accumulation rate, cleaning frequency, and tilt angle, providing more realistic long-term generation forecasts.
- Incorporating stochastic weather modeling using historical irradiance datasets and probabilistic generation forecasting to evaluate HEMS performance under a statistical distribution of weather scenarios rather than fixed irradiance setpoints.
- Coupling the HEMS model with short-term PV generation forecasting modules based on numerical weather prediction (NWP) or machine learning approaches, enabling proactive rather than reactive energy scheduling.

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Author Contributions:

Supakan Janthong: Conceptualization, Methodology, Software, Writing – original draft, Visualization. **Kanitsorn Boonrat:** Writing – review & editing, Validation, Investigation. **Sittisak Rojchaya:** Supervision, Resources, Writing – review & editing.

Declaration of Interest Statement

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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