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AI-Based Energy Guardianship for Vulnerable Households in Renewable Energy Communities

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Abstract

The increasing diffusion of Renewable Energy Communities offers new opportunities to support vulnerable households through locally generated renewable energy. However, current Home Energy Management Systems mainly optimize energy efficiency and cost reduction, while providing limited support for protecting critical household loads under constrained energy availability. This paper proposes an AI-based Energy Guardianship framework that combines a commissioning phase, in which a Local Appliance Atlas is created from the electrical signatures of the appliances actually installed in a specific dwelling, with an online phase that identifies operating appliances from aggregated measurements and dynamically allocates available energy according to appliance priority. Appliance identification is performed using rich electrical signatures including transient behavior, dynamic V-I trajectories, harmonic information, power profiles, and conventional electrical features extracted from aggregate voltage and current measurements. Unlike conventional home energy management systems, where appliance identification is mainly used to optimize energy consumption, the proposed framework exploits NILM information to support socially aware decisions that preserve critical services while delaying or limiting non-essential loads. A low-cost monitoring architecture is developed to recognize household appliances through electrical signatures and classify loads according to their criticality. When power thresholds are approached, the system recommends demand-side actions, postpones non-essential consumption, and protects critical devices. Preliminary simulation scenarios demonstrate the feasibility of the proposed framework in protecting vulnerable users under limited energy availability while simultaneously improving photovoltaic self-consumption and reducing dependence on grid energy. Although optimization is not the primary objective, the framework naturally supports renewable-aware energy scheduling and future interaction with energy service providers.

Keywords: NILM; AI; energy poverty; smart energy management; photovoltaic scheduling; human-centric approach; renewable energy communities

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1. Introduction

The increasing electrification of modern society has significantly improved living standards, technological accessibility, and the diffusion of electrically powered services within residential environments. However, a growing number of households are experiencing conditions of energy poverty, characterized by limited access to affordable and reliable electricity. This phenomenon particularly affects vulnerable users, including elderly people, low-income families, and individuals relying on electrically powered medical or essential domestic appliances. In these situations, limited contractual power, intermittent renewable energy availability, or economic constraints may prevent the simultaneous operation of all household loads, making intelligent energy allocation a critical requirement rather than a simple optimization problem. Ensuring the continuity of supply for critical appliances therefore becomes a fundamental objective for future residential energy management systems.

Unlike conventional residential energy management, the challenge addressed in this work is not simply to reduce energy consumption or electricity costs, but to determine which appliances should continue operating when the available energy is insufficient to satisfy all household demands.

At the same time, the widespread deployment of smart meters, low-cost sensing technologies, residential photovoltaic systems, and battery storage has accelerated the development of advanced Home Energy Management Systems (HEMS). Modern HEMS increasingly exploit Artificial Intelligence (AI) to optimize energy consumption, reduce electricity costs, maximize photovoltaic self-consumption, and support demand response strategies. While these approaches have demonstrated remarkable effectiveness in improving residential energy efficiency, their primary objective remains the optimization of energy flows and economic performance.

However, situations of energy scarcity require a fundamentally different decision criterion. When the available energy is insufficient to satisfy all household demands, the central question is no longer how to optimize energy consumption, but which appliances should continue operating to protect user well-being. Current HEMS generally treat electrical loads according to economic or operational criteria and rarely incorporate appliance criticality, health relevance, or user vulnerability into the supervisory decision process. Consequently, the protection of vulnerable users remains largely outside the scope of conventional residential energy management systems.

To enable this transition from energy optimization to human-centered energy management, reliable identification of the operating household appliances becomes a fundamental prerequisite. This requirement naturally motivates the adoption of Non-Intrusive Load Monitoring (NILM) techniques as the sensing layer of the proposed Energy Guardianship framework.

Non-Intrusive Load Monitoring has become one of the most effective techniques for identifying household appliances from aggregate electrical measurements acquired at a single monitoring point [1,2]. Recent advances in machine learning and deep learning have considerably improved appliance recognition accuracy by exploiting steady-state electrical parameters, transient characteristics, harmonic content, and Voltage-Ccurrent (V-I) signatures [3–5]. Consequently, NILM has become a key enabling technology for smart homes, demand response, and residential energy management.

However, the objective of the proposed framework differs substantially from conventional NILM applications, focusing on energy optimization [6–9]. Rather than performing universal appliance recognition, the proposed Energy Guardianship framework adopts a house-specific commissioning strategy. During an initial commissioning phase, only the appliances actually installed within the monitored dwelling are individually characterized through a comprehensive set of electrical descriptors—including dynamic V-I trajectories, transient behavior, harmonic features, and conventional electrical measurements—and stored in a Local Appliance Atlas. During normal operation, the aggregated household signal is continuously compared exclusively with this local atlas, enabling reliable identification of the active appliance within a limited and previously known classification space.

This strategy considerably reduces the complexity of the identification problem while reflecting the practical deployment of residential energy management systems, where the set of installed appliances changes infrequently and can be characterized during installation or subsequent maintenance operations. More importantly, within the proposed framework appliance identification is not an end, but the enabling stage for socially aware supervisory decisions aimed at protecting vulnerable users during periods of constrained energy availability.

This paper proposes a human-centric AI-assisted energy management framework specifically designed for residential users affected by energy poverty conditions [10,11]. The proposed system integrates NILM techniques, electrical load signature analysis, and intelligent decision-making algorithms to dynamically manage household appliances according to available energy resources, photovoltaic generation, battery availability, and user-defined priority levels. Unlike conventional NILM applications aimed at universal appliance recognition, the proposed framework adopts a house-specific commissioning strategy. During installation, the electrical signatures of the appliances present in the dwelling are acquired and stored in a local appliance atlas. During normal operation, appliance identification is therefore performed by comparing the aggregated electrical measurements only with these previously commissioned signatures, significantly reducing the complexity of the recognition task while improving its reliability. The framework continuously monitors the aggregate electrical demand, identifies the active loads, and evaluates whether the requested appliance should be allowed, delayed, limited, or denied.

A key contribution of the proposed methodology is the introduction of an ethical load prioritization mechanism capable of distinguishing critical appliances from flexible or non-essential loads. In this way, the system aims to guarantee the operation of health-related and essential devices while optimizing the allocation of limited energy resources and improving photovoltaic self-consumption or energy communities [12]. The proposed approach is intended for applications in low-income households, weak-grid or off-grid systems, emergency residential conditions, and energy-constrained smart homes.

The main contributions of this paper can be summarized as follows:

1. A human-centric AI-based architecture for residential energy management under energy poverty conditions [13];
2. The integration of NILM techniques with intelligent load orchestration and ethical energy allocation;
3. A load prioritization strategy based on appliance criticality, flexibility, and user vulnerability;
4. An adaptive decision-making framework capable of dynamically allowing, postponing, limiting, or denying appliance activation according to available energy resources [14–20];
5. Preliminary simulation scenarios demonstrating the feasibility of the proposed approach in residential photovoltaic systems with constrained power availability.

The remainder of the paper is organized as follows. Section 2 describes Renewable energies communities and the energy poverty problem. Section 3 presents the proposed system architecture and the NILM-based monitoring framework. Section 4 describes the mathematical formulation of the ethical energy allocation problem and the AI-based decision engine. Section 5 presents simulation scenarios and preliminary results. In Section 6 a brief discussion on the policy clusters emerging from the literature. Finally, Section 7 concludes the paper and discusses possible future developments.

2. Renewable Energy Communities, Energy Poverty and Vulnerable Users

Renewable Energy Communities (RECs) have emerged as one of the most promising instruments for supporting the European energy transition, enabling the active participation of citizens, local authorities, small enterprises, and other stakeholders in decentralized renewable energy production and consumption. Their legal foundation was established through the European Clean Energy for All Europeans Package, particularly Directive (EU) 2018/2001 on the promotion of renewable energy sources (RED II) and Directive (EU) 2019/944 on common rules for the internal electricity market. These directives introduced the concepts of Renewable Energy Communities and Citizen Energy Communities, recognizing their role in fostering renewable energy deployment, increasing energy efficiency, strengthening local energy resilience, and delivering environmental, economic, and social benefits to community members [21–23].

The implementation of energy communities has expanded rapidly across Europe, although significant differences remain among Member States due to variations in regulatory frameworks, market structures, and incentive mechanisms. Recent studies have highlighted both the opportunities and challenges associated with energy communities, including governance models, citizen engagement, regulatory barriers, economic sustainability, and the integration of distributed energy resources into local energy systems [24–31]. Mapping activities conducted at the European level indicate a continuous growth in the number of operational communities, confirming their relevance as a key pillar of a decentralized and participatory energy system [32–35].

In Italy, Renewable Energy Communities were initially introduced through the provisions of Decree-Law No. 162/2019 ("Milleproroghe"), which anticipated some of the measures contained in RED II and enabled the first pilot initiatives of collective self-consumption and shared renewable generation [26]. A comprehensive legal framework was subsequently established through Legislative Decree No. 199/2021, which formally transposed RED II into the Italian regulatory system and defined the organizational, technical, and economic requirements for Renewable Energy Communities [27–29]. More recently, Ministerial Decree No. 414/2023 established the operational incentive scheme for energy sharing, introducing a dedicated tariff mechanism and financial support measures aimed at accelerating the deployment of community-based renewable generation throughout the country [30].

The Italian experience is particularly relevant because it combines environmental objectives with social and territorial development goals. Several studies have emphasized the strategic role that local administrations, public institutions, and community organizations can play in facilitating the creation and long-term sustainability of Renewable Energy Communities [35–37]. Furthermore, Italian research has demonstrated that energy communities can contribute not only to increasing renewable energy penetration and reducing electricity costs but also to promoting social cohesion and local participation in energy governance processes [33,38,39]. In this context, Renewable Energy Communities can represent an effective instrument for addressing energy poverty and supporting vulnerable consumers, particularly when combined with advanced digital technologies capable of improving energy management and demand-side flexibility.

Although Renewable Energy Communities promote the sharing of locally generated renewable energy, they do not inherently define how limited energy resources should be allocated among participating households during periods of energy scarcity. Existing frameworks mainly regulate energy sharing from technical and economic perspectives, whereas the protection of vulnerable users and the prioritization of critical electrical services remain largely unexplored. This gap motivates the need for supervisory Energy Guardianship strategies capable of supporting socially aware energy allocation.

Despite the growing body of literature on Renewable Energy Communities, relatively limited attention has been devoted to the specific challenges faced by vulnerable households operating under contractual power limitations, economic constraints, or dependence on critical electrical appliances. This gap becomes particularly relevant in the context of energy poverty, where access to affordable and reliable electricity remains a major concern. Consequently, the integration of Artificial Intelligence techniques and Non-Intrusive Load Monitoring systems within Renewable Energy Communities may provide new opportunities for developing user-centered energy governance frameworks capable of identifying household loads, prioritizing essential services, supporting informed energy decisions, and enhancing the social inclusiveness of the energy transition.

Despite the significant opportunities offered by Renewable Energy Communities, a substantial portion of European citizens continues to experience difficulties in accessing affordable and reliable energy services. Energy poverty has emerged as a major socio-economic challenge within the European Union and has become increasingly relevant in the context of the ongoing energy transition. According to the European Commission, energy poverty refers to a situation in which households are unable to access essential energy services necessary to guarantee an adequate standard of living, including heating, cooling, lighting, domestic hot water, and the operation of electrical appliances [40,41]. The phenomenon is multidimensional and results from the interaction of low household income, poor energy efficiency of buildings, rising energy prices, and limited access to renewable energy technologies [42].

Recent energy crises and fluctuations in electricity and gas prices have further highlighted the vulnerability of millions of European citizens. Studies indicate that energy poverty is not limited to economically disadvantaged households but also affects elderly people, individuals with chronic health conditions, persons with disabilities, and families living in inefficient dwellings [43–45]. Consequently, energy poverty is increasingly recognized not only as an economic issue but also as a matter of public health, social equity, and energy justice. Long-term exposure to inadequate indoor temperatures and restricted energy use has been associated with adverse health outcomes, reduced quality of life, and social exclusion [44,46].

The concept of vulnerable energy users has therefore gained increasing attention in European energy policies. Vulnerable consumers are generally characterized by a reduced capacity to cope with energy-related risks and may depend on electricity for critical services essential to their well-being and safety. Examples include households relying on medical devices such as oxygen concentrators, refrigerated medicines, mobility support systems, for example Continuous Positive Airway Pressure (CPAP) equipment. In such situations, involuntary power interruptions or excessive restrictions in electricity consumption may have consequences that extend beyond economic hardship and directly affect health and personal safety [40,42].

Renewable Energy Communities have recently been identified as a promising mechanism for mitigating energy poverty by facilitating access to locally generated renewable electricity and promoting a more equitable distribution of energy benefits among participants [47,48]. However, most existing approaches focus primarily on maximizing self-consumption, optimizing economic returns, and improving community-level energy efficiency. Comparatively less attention has been devoted to the development of intelligent mechanisms specifically designed to identify, support, and protect vulnerable users under conditions of limited energy availability or contractual power constraints [49].

The proposed Energy Guardianship framework is therefore conceived as a supervisory layer that complements, rather than replaces, conventional Home Energy Management Systems. While HEMS primarily optimize energy consumption, costs, and renewable

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energy utilization, Energy Guardianship introduces socially aware decision criteria to ensure that limited energy resources are preferentially allocated to appliances supporting vulnerable users and essential household services.

3. Proposed System Architecture

The proposed framework is designed as an intelligent residential energy management architecture capable of assisting vulnerable users operating under conditions of limited energy availability, contractual power constraints, or fluctuating renewable energy generation. The system integrates Non-Intrusive Load Monitoring, electrical load signature analysis, photovoltaic-aware energy management, and AI-based decision-making mechanisms to dynamically coordinate household electrical loads according to both technical and social constraints.

Unlike conventional Home Energy Management Systems, the proposed framework operates through two complementary phases. During an initial commissioning phase, the electrical signatures of the appliances installed in the monitored dwelling are individually acquired and organized into a local appliance atlas. During normal operation, the aggregated electrical signal is continuously analyzed and compared exclusively with these previously commissioned signatures. Consequently, appliance identification is performed within a known residential environment rather than through universal appliance classification. This strategy significantly improves robustness while reducing the complexity of the recognition problem. Figure 1 illustrates the overall workflow of the proposed commissioning and online operation phases.

As illustrated in Figure 1, the framework is organized into two complementary phases: Commissioning (Offline) and Online Operation (Real-Time).

During the Commissioning Phase, each appliance installed in the dwelling is measured individually under controlled operating conditions. For every appliance, voltage and current waveforms are acquired and a comprehensive set of electrical descriptors is extracted (V_{rms}, I_{rms}, active, reactive and apparent power, power factor, peak values, crest factors), transient characteristics associated with switching events, harmonic components, and particularly the dynamic V-I trajectory, which represents the temporal evolution of the appliance electrical behavior. The extracted information is stored in a Local Appliance Atlas, representing the electrical fingerprint of all appliances installed in that specific house.

The proposed approach therefore creates a house-dependent electrical atlas, rather than relying on a universal appliance database. This reflects the practical commissioning procedure that can be performed once during installation and updated whenever appliances are replaced or new devices are introduced.

During the Online Operation Phase, only the aggregated voltage and current measured at the household supply point are available. The same set of electrical features is extracted in real time from the aggregated signal and compared with the signatures stored in the local appliance atlas. The appliance exhibiting the highest similarity is identified as the active load. Since the comparison is limited to the appliances present in the home, the identification task becomes significantly more reliable than general-purpose appliance classification.

Once the operating appliance has been identified, the supervisory Energy Guardianship algorithm evaluates its assigned priority together with the currently available energy resources (photovoltaic production, battery state-of-charge, and grid availability). According to this assessment, the system determines whether the appliance should be supplied without restriction, temporarily delayed, power-limited, or disconnected. Consequently, appliance identification is not an end in itself but constitutes the enabling stage for intelligent and socially oriented energy allocation decisions.

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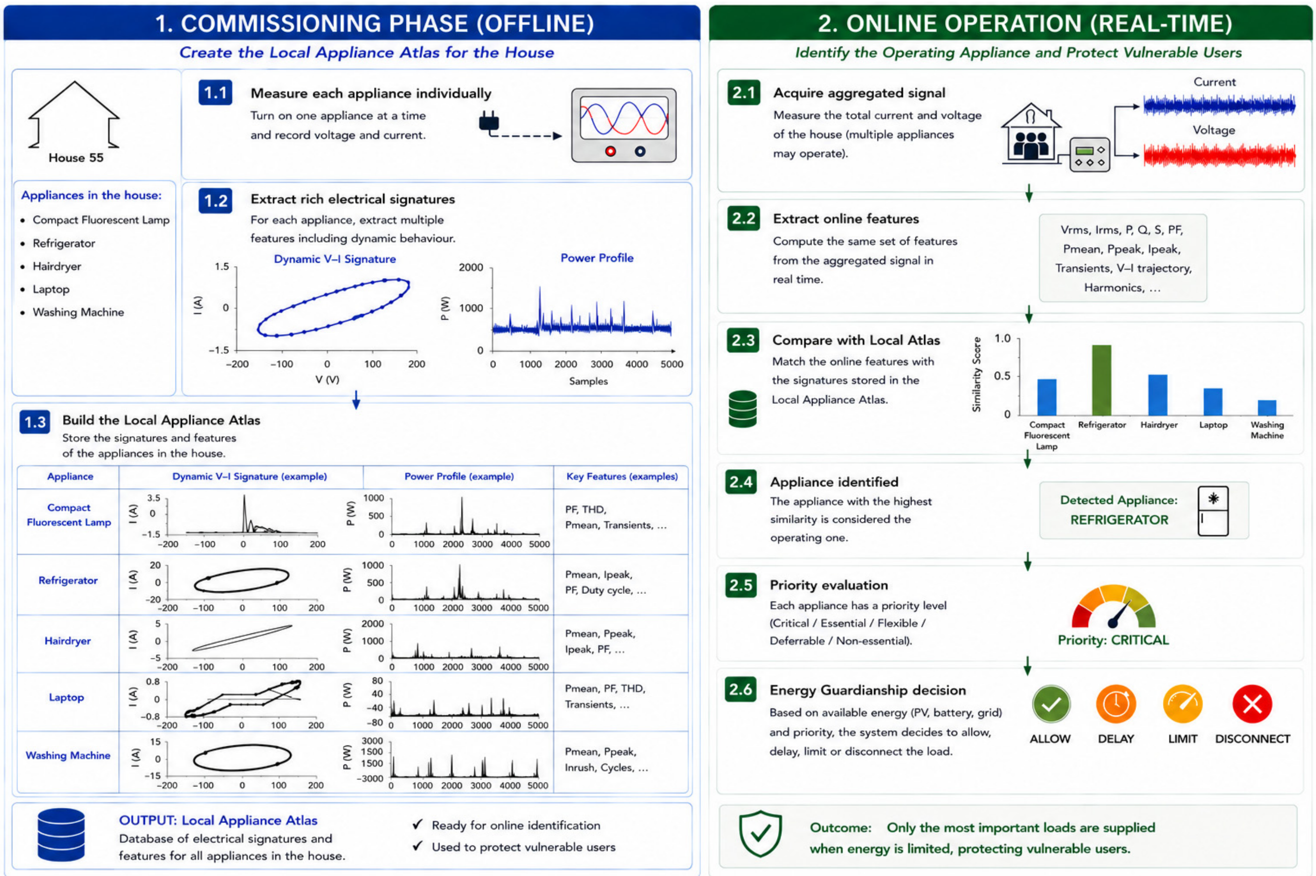

Figure 1. Proposed two-phase Energy Guardianship framework. (**1**) Commissioning phase (offline): a Local Appliance Atlas is created by measuring each appliance individually (**1.1**), extracting electrical signatures and features (**1.2**), and storing representative dynamic V–I signatures together with the associated electrical descriptors (**1.3**). (**2**) Online operation (real-time): the aggregated household signal is acquired (**2.1**), electrical features are extracted (**2.2**), compared with the Local Appliance Atlas (**2.3**), and used to identify the operating appliance (**2.4**). The identified load is then assigned a priority level (**2.5**), enabling the Energy Guardianship system to decide whether the load should be allowed, delayed, limited, or disconnected according to the available energy resources (**2.6**).

This two-stage architecture clearly separates the creation of the appliance knowledge base from the real-time supervisory control process, allowing the proposed framework to combine reliable appliance identification with ethical energy management for vulnerable households.

Furthermore, the proposed framework can be integrated within Renewable Energy Communities, where the availability of locally generated renewable electricity varies throughout the day according to photovoltaic production profiles and community consumption patterns. In this context, AI-based decision support can contribute to improving the allocation of shared renewable energy resources, maximizing the benefits delivered to vulnerable users while maintaining the overall efficiency of the community. Such an approach extends the traditional concept of demand-side management toward a broader vision of socially aware energy governance.

The overall architecture of the proposed system is composed of six main layers: 1 Electrical Data Acquisition Layer (hardware); 2 Event Detection Layer; 3 Load Identification Layer; 4 Energy Constraint Assessment Layer; 5 AI-Based Decision Layer; 6 Load Actuation and User Feedback Layer.

A. Electrical Data Acquisition Layer

The first layer of the proposed architecture is responsible for acquiring and preprocessing the electrical information required by the subsequent NILM and AI-based decision-making modules. Since the framework is intended for large-scale deployment in residential environments and for vulnerable households characterized by limited economic resources, the monitoring infrastructure has been deliberately designed according to a non-intrusive philosophy. Unlike conventional appliance-level monitoring systems, which require dedicated sensors for each load, the proposed solution relies on a single measurement point installed at the entrance of the residential electrical system. This approach significantly reduces installation costs, minimizes user intervention, and facilitates integration into existing homes and Renewable Energy Communities.

The acquired electrical quantities provide a comprehensive representation of the instantaneous operating condition of the household and constitute the primary input for load identification and energy management algorithms. The monitored variables include

$$V(t), I(t), P(t), Q(t), PF(t)$$

where $V(t)$ is the measured voltage, $I(t)$ is the aggregate current absorbed by the household, $P(t)$ is the active power, $Q(t)$ is the reactive power, and $PF(t)$ represents the power factor. These measurements constitute the raw information used both during the commissioning phase to generate the Local Appliance Atlas and during online operation to identify active appliances from aggregated measurements.

In addition to conventional electrical measurements, the framework also considers information related to distributed energy resources and local renewable generation. The increasing diffusion of photovoltaic systems and residential energy storage devices requires the energy management algorithm to continuously evaluate the availability of local energy resources. Therefore, the following variables are acquired:

$$P_{PV}(t),\ SOC(t), E_{budget}(t)$$

where $P_{PV}(t)$ denotes the instantaneous photovoltaic power generation, $SOC(t)$ represents the battery State of Charge, and $E_{budget}(t)$ indicates the available energy budget allocated to the user over a predefined time horizon.

The integration of these variables enables the framework to evaluate not only current consumption patterns but also the expected availability of renewable energy resources. Such information is particularly important when supporting vulnerable users operating under contractual power limitations or during periods of reduced photovoltaic production.

Figure 2 illustrates the overall conceptual architecture of the proposed AI-based Energy Guardianship framework. The figure highlights the interaction between electrical measurements, NILM-based appliance identification, renewable energy monitoring, and the intelligent decision-making module responsible for supporting vulnerable users through adaptive load management strategies.

B. NILM Event Detection Layer

The second layer of the framework is responsible for identifying significant variations in aggregate electrical demand associated with appliance activation or deactivation. Since only global household measurements are available, event detection represents a critical step in the overall NILM process. The objective is to identify the precise moments at which changes occur in the electrical load profile and to isolate the corresponding electrical signatures for subsequent classification.

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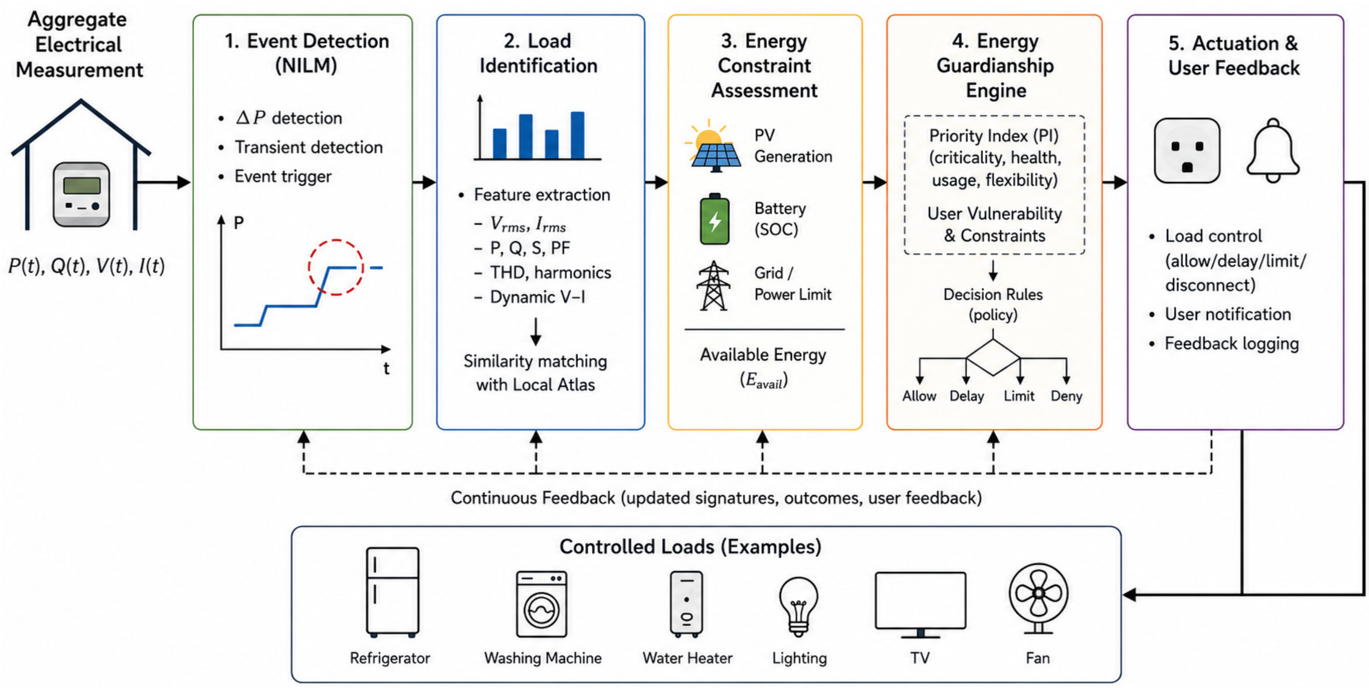


Figure 2. Proposed workflow of the Energy Guardianship framework. The process starts from the acquisition of aggregated electrical measurements after a variation on requested power (red circle), from which load activation events are detected using NILM techniques. Electrical features are then extracted and compared with the Local Appliance Atlas to identify the operating appliance. The identified load is evaluated according to the available energy resources (photovoltaic generation, battery state of charge, and grid power limit). The Energy Guardianship Engine combines the available energy with the appliance Priority Index (PI) and user-related constraints to determine the most appropriate action (allow, delay, limit, or disconnect). Finally, the selected control action is applied to the appliance, user feedback is provided, and the monitoring process continues in a closed loop, enabling continuous adaptation of the system while protecting vulnerable users and maximizing the utilization of available energy.

An event can be mathematically represented as follows:

$$e_k = \{t_k, \Delta P_k, \Delta Q_k\} \tag{1}$$

where t_k is the event occurrence time; ΔP_k is the active power variation; and ΔQ_k is the reactive power variation.

The proposed framework can employ conventional NILM event detection techniques [1] such as threshold-based detection; CUSUM algorithms; Generalized Likelihood Ratio (GLR); and the Sequential Probability Ratio Test (SPRT).

The event detection stage identifies significant power transitions satisfying

$$\mid \Delta P(t) \mid > \gamma \tag{2}$$

where γ represents a predefined detection threshold selected to distinguish genuine appliance events from measurement noise and background fluctuations.

Figure 3 presents a representative example of the event detection process. The figure illustrates how sudden variations in aggregate power consumption are identified and transformed into candidate NILM events. These detected transitions constitute the input for the subsequent load identification stage, where appliance signatures are extracted and classified.

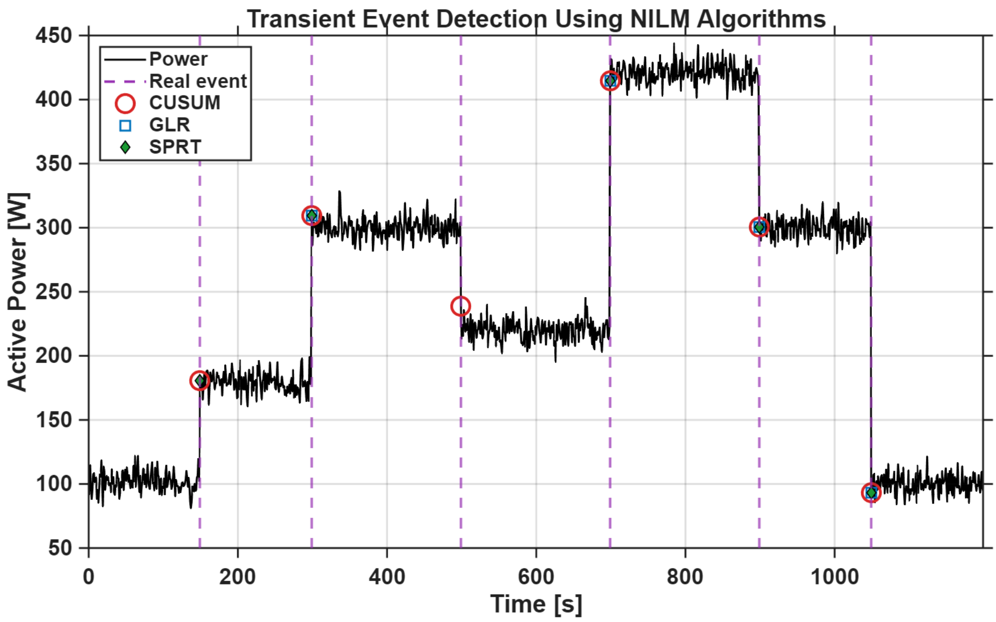


Figure 3. Example of NILM event detection based on aggregate household power measurements. Significant variations in active power exceeding the detection threshold are identified as candidate appliance switching events and forwarded to the load identification module.

C. Load Identification Layer

Following event detection, the framework proceeds with appliance identification through the extraction and analysis of electrical load signatures. The purpose of this stage is to determine which appliance generated the detected event and to estimate its operational characteristics. Accurate appliance identification is essential for implementing priority-based energy management strategies and for distinguishing critical loads from non-essential ones.

For each detected event, a feature vector is generated according to

$$\mathbf{f}_k = [\Delta P, \Delta Q, PF, THD, H_3, H_5, H_7, \tau] \tag{3}$$

where THD represents the Total Harmonic Distortion, H_3, H_5, and H_7 correspond to harmonic components of the current waveform, and τ denotes the transient duration associated with the switching event.

The resulting feature vector contains both steady-state and transient information, enabling the characterization of a wide range of residential appliances. Resistive devices typically exhibit limited harmonic distortion and nearly unity power factor, whereas inductive and nonlinear loads generate distinctive harmonic patterns and phase relationships that can be exploited for classification purposes.

The appliance classification process can be expressed as

$$\hat{L}_k = f(\mathbf{f}_k) \tag{4}$$

where $\mathbf{f_k}$ is the extracted feature vector and $\hat{L}_k$ denotes the estimated appliance class.

Among the various NILM feature extraction techniques proposed in the literature, Voltage–Current (V-I) trajectories have attracted considerable attention due to their capability to visually represent the electrical behavior of appliances [1,5,6], and they can be useful to illustrate the identified firms of different loads (see Figure 1), the V-I trajectories are obtained by plotting instantaneous current as a function of voltage over one or more electrical cycles. Different appliance categories generate distinctive geometric patterns reflecting their electrical characteristics, phase displacement, nonlinearities, and harmonic content.

Figure 4 compares representative V-I trajectories associated with resistive, inductive, and nonlinear residential loads, like Lissajous figures. Resistive appliances typically generate narrow linear patterns, while inductive loads exhibit elliptical trajectories caused by phase displacement between voltage and current. Nonlinear electronic devices produce more complex trajectories characterized by distortions and asymmetries resulting from harmonic generation.

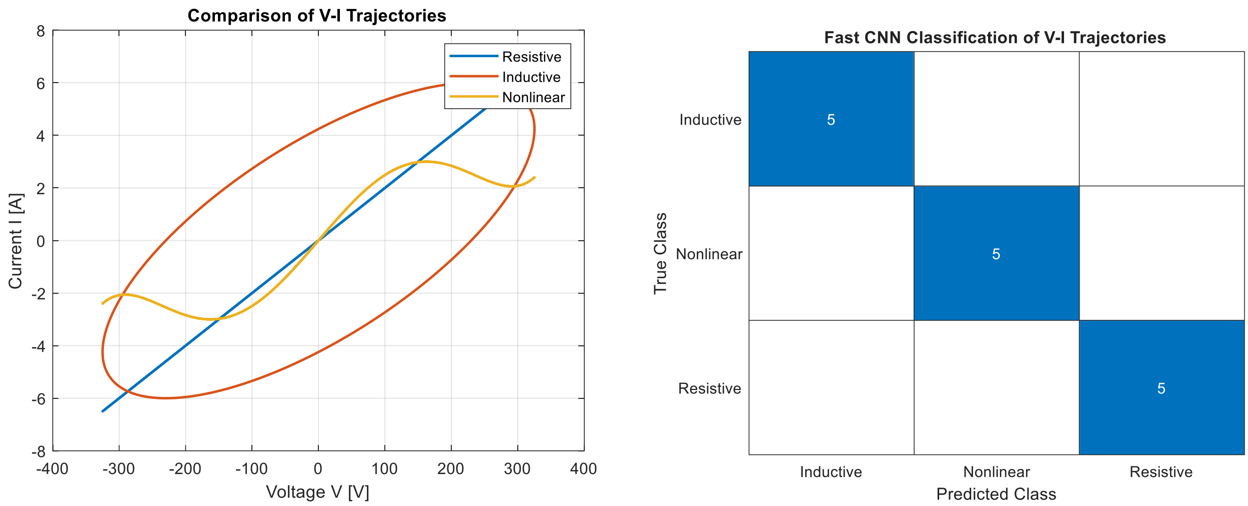


Figure 4. Representative Voltage-Current (V-I) trajectories for resistive, inductive, and nonlinear residential appliances. The distinctive geometric patterns can be exploited by NILM algorithms and CNN-based classifiers for appliance recognition and electrical load characterization Convolutional Neural Networks (CNN) can be introduced to obtain information on loads [6,7].

These graphical representations can be further processed using image-based machine learning techniques. Convolutional Neural Networks (CNNs) have demonstrated remarkable performance in appliance recognition tasks by automatically extracting relevant features from V-I trajectory images [6,7]. Such approaches eliminate the need for extensive manual feature engineering and provide improved classification accuracy under varying operating conditions.

It should be emphasized that appliance identification is not the final objective of the proposed framework. Instead, the recognized appliance represents the input information required by the Energy Guardianship supervisory layer, which determines the most appropriate management action according to appliance priority and available energy resources.

D. Energy Constraint Assessment Layer

Following appliance identification, the framework evaluates the current energy availability and verifies whether the detected load can be safely accommodated within the existing operational constraints. This stage represents the interface between appliance recognition and intelligent decision-making, transforming electrical measurements into actionable information regarding the current energy state of the household.

Unlike traditional energy management systems that assume unlimited grid availability, the proposed architecture is specifically designed to operate under constrained energy conditions. Such conditions may arise from contractual power limitations, reduced photovoltaic generation, limited battery storage availability, participation in Renewable Energy Communities, or energy-budget restrictions associated with vulnerable households.

The total available power is defined as

$$P_{avail}(t) = P_{grid}(t) + P_{PV}(t) + P_{battery}(t) \tag{5}$$

where ($P_{grid}(t)$) represents the power available from the electrical grid, ($P_{PV}(t)$) is the instantaneous photovoltaic generation, and ($P_{battery}(t)$) denotes the power supplied by the local energy storage system.

The system continuously verifies the following constraint:

$$\sum_i P_i(t) \leq P_{avail}(t) \tag{6}$$

where ($P_i(t)$) represents the power demand associated with the active household appliances.

When this condition is violated or predicted to be violated in the near future, the system enters a constrained operating mode and activates the AI-based decision engine. This predictive approach enables preventive actions before overload conditions or involuntary service interruptions occur.

In addition to instantaneous power availability, the framework evaluates several complementary constraints that influence energy allocation decisions. These include contractual power limits imposed by the electricity provider, minimum battery State-of-Charge preservation thresholds, available daily energy budgets, forecast uncertainty associated with photovoltaic generation, and user-specific operational requirements. Such constraints are particularly relevant in the case of vulnerable users, whose access to electricity may depend on limited economic resources or on the availability of community-shared renewable energy.

The Energy Constraint Assessment Layer therefore provides a dynamic representation of the household energy status. Rather than considering energy solely as an electrical quantity, this layer introduces contextual information that allows the system to evaluate whether future appliance activations are technically feasible and socially desirable. Consequently, energy management decisions are no longer based exclusively on electrical optimization criteria but also on the preservation of user well-being and service continuity.

Figure 5 illustrates the proposed energy constraint evaluation process. The figure shows how grid power, photovoltaic generation, battery availability, and contractual limits are combined to determine the instantaneous energy margin available for residential loads. The resulting information is subsequently transferred to the AI-Based Decision Layer.

E. AI-Based Decision Layer

The AI-Based Decision Layer constitutes the core intelligence of the proposed Energy Guardianship framework. While conventional Home Energy Management Systems typically aim to minimize electricity costs or maximize self-consumption, the proposed architecture introduces a broader decision-making paradigm in which technical objectives are balanced with social, ethical, and health-related considerations.

The primary objective of this layer is to determine the most appropriate operating strategy for each identified appliance while ensuring that vulnerable users maintain access to essential energy services. To achieve this goal, every appliance is assigned a priority level reflecting its functional importance, flexibility, and potential impact on user well-being.

The framework categorizes residential loads into five priority classes:

- Critical Loads: Medical and life-support devices whose operation must be guaranteed whenever possible.
- Essential Loads: Appliances required for safety, communication, food preservation, or basic living conditions.

- Flexible Loads: Appliances whose operation can be temporarily modified without significant user discomfort.
- Deferrable Loads: Appliances that can be shifted in time to periods characterized by higher renewable energy availability.
- Non-Essential Loads: Discretionary loads that may be postponed, limited, or denied during constrained operating conditions.

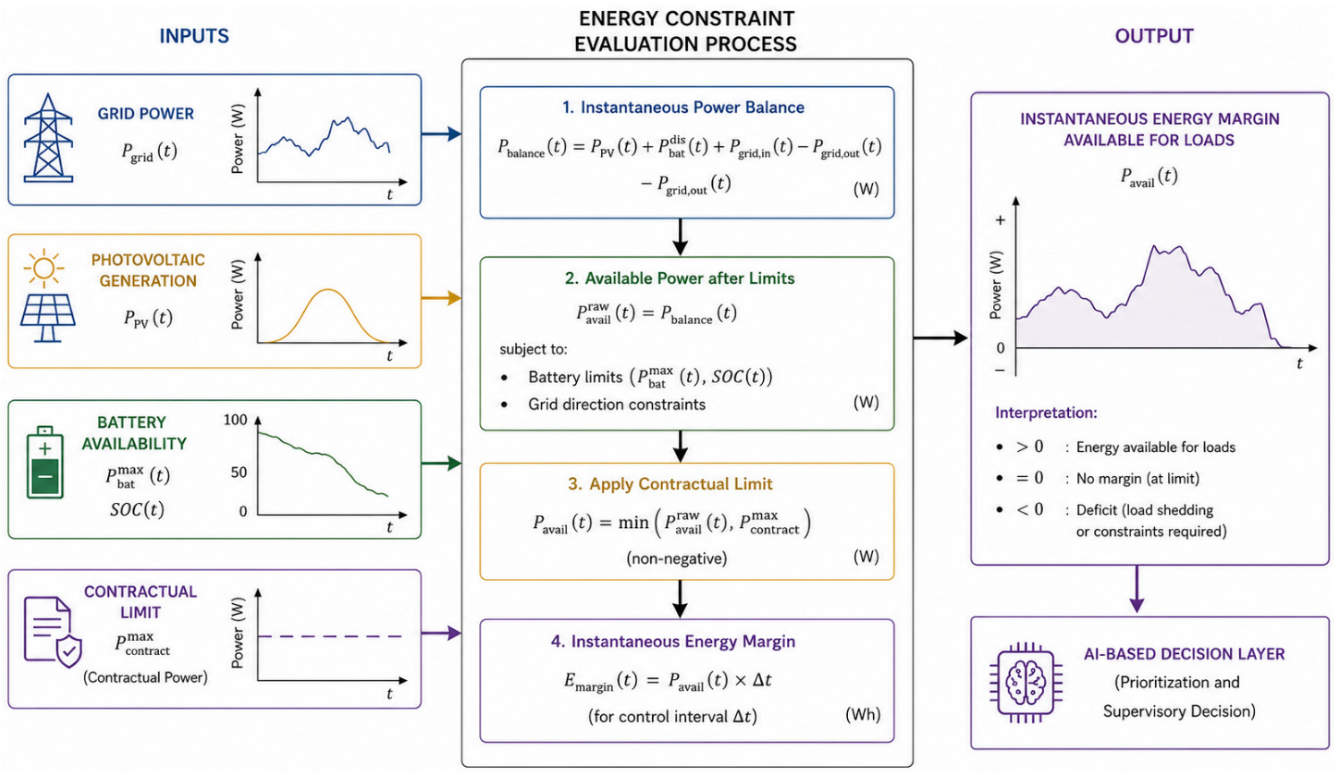


Figure 5. Energy constraint evaluation process adopted by the proposed Energy Guardianship framework. The available energy is computed by combining four inputs: grid power, photovoltaic generation, battery availability, and contractual power limits. The evaluation process consists of four sequential steps: (**1**) instantaneous power balance, (**2**) estimation of the available power considering battery and grid constraints, (**3**) application of the contractual power limit, and (**4**) computation of the instantaneous energy margin. The resulting available energy margin is then supplied to the Energy Guardianship decision layer, where it is combined with appliance priority information to determine the appropriate control action.

To quantify the relative importance of each appliance, a Priority Index (PI) is introduced:

$$PI_i = w_1 C_i + w_2 H_i + w_3 U_i - w_4 F_i \tag{7}$$

where C_i represents the technical criticality of the load, H_i denotes its health relevance, U_i expresses its utility from the user's perspective, and F_i quantifies its operational flexibility. The weighting coefficients w_1, w_2, w_3 and w_4 can be adapted according to household characteristics, community policies, or specific user requirements.

In the present implementation, the weighting coefficients are initially set to $w_1 = 0.30$, $w_2 = 0.35$, $w_3 = 0.20$, and $w_4 = 0.15$. The health-relevance coefficient is assigned the highest value because the primary objective of the proposed framework is the continuity of electrical services that may affect user health and safety. Technical criticality is assigned second-highest weight, while user utility and operational flexibility have lower weights. These values represent an initial expert-based calibration and are not intended to be universally optimal. They can be modified according to household characteristics, healthcare recommendations, user preferences, or Renewable Energy Community policies. Future implementations may calibrate the coefficients through user surveys, multi-criteria optimization, or learning-based procedures.

The parameters C, H, U, and F are assigned integer values between 0 and 5, representing the appliance's criticality, health relevance, user utility, and operational flexibility, respectively. Higher values of C, H, and U increase the priority index, whereas higher values of F indicate greater scheduling flexibility and therefore reduce the appliance priority.

This formulation enables the framework to combine electrical and social dimensions into a unified decision variable. Consequently, two appliances with similar power ratings may receive completely different management actions depending on their functional role and their contribution to user well-being.

Based on the available energy resources, the identified appliance class, and the computed Priority Index, the AI engine generates one of four possible actions:

$$a_i(t) \in allow, delay, deny, limit$$

where

- Allow authorizes normal operation;
- Delay postpones appliance activation to a more favorable energy period;
- Deny prevents activation when energy resources are insufficient;
- Limit reduces operating conditions or power consumption.

The decision-making process can also exploit photovoltaic forecasts, battery availability, and Renewable Energy Community participation. For example, a washing machine may be automatically delayed until periods of high photovoltaic production, whereas a medical respiratory support device would be immediately authorized regardless of the current energy condition.

The proposed framework therefore extends traditional demand-side management approaches by introducing the concept of ethical energy allocation. Rather than maximizing purely economic indicators, the system explicitly prioritizes user safety, health, and quality of life. This human-centric perspective is particularly relevant for vulnerable households affected by energy poverty, contractual power limitations, or dependence on critical electrical equipment.

To illustrate this concept, Figures 6 and 7 compare the electrical signatures of two representative appliances characterized by significantly different social relevance. The first example corresponds to a Continuous Positive Airway Pressure (CPAP) device used for respiratory support, while the second represents a typical residential entertainment load. Although both appliances consume electrical energy, their impact on user well-being differs substantially. The ability of NILM algorithms to recognize these appliances enables the framework to implement differentiated energy management policies during periods of constrained energy availability.

The CPAP signature is characterized by a slightly elliptical and moderately distorted V-I trajectory resulting from the combined contribution of the internal blower motor and the electronic switching converter responsible for airflow regulation. The observed phase displacement between voltage and current indicates the presence of an electromechanical load, while the limited trajectory distortion suggests a relatively stable operating condition with moderate harmonic content. Such characteristics are consistent with low-power medical respiratory assistance devices designed for continuous overnight operation. Unlike many domestic appliances that exhibit highly variable operating profiles, CPAP systems typically operate under quasi-steady-state conditions, generating predictable electrical signatures that can be reliably identified through NILM techniques. This property is particularly important within the proposed Energy Guardianship framework, as it enables the recognition of medically relevant equipment whose uninterrupted operation directly affects user health and well-being.

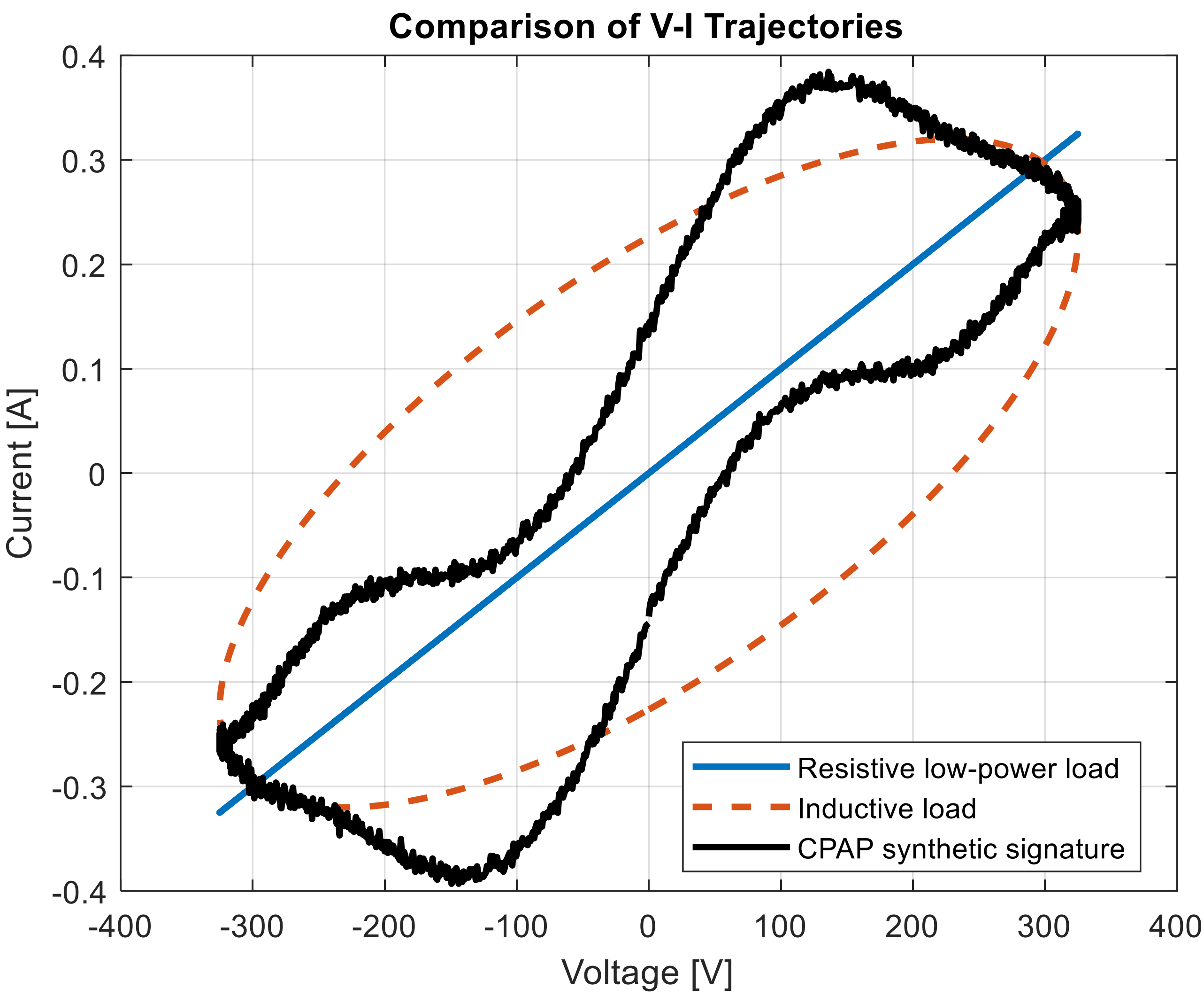


Figure 6. Synthetic Voltage–Current (V-I) trajectory associated with a CPAP respiratory support device. The identified electrical signature is classified as a critical load and assigned the highest priority level within the Energy Guardianship framework.

Equation (7) becomes

$$PI_{CPAP} = 0.30(5) + 0.35(5) + 0.20(5) - 0.15(0) = 4.25.$$

Figure 7 presents the V-I trajectory associated with a representative non-critical residential entertainment device. Although its average power consumption may be comparable to that of the CPAP system, its electrical signature reveals substantially different operating characteristics. The trajectory exhibits a strongly nonlinear shape with pronounced distortions caused by the switching power supply typically employed in modern consumer electronics. The resulting harmonic content produces irregular current patterns and asymmetric trajectory regions that clearly distinguish the device from medically critical equipment.

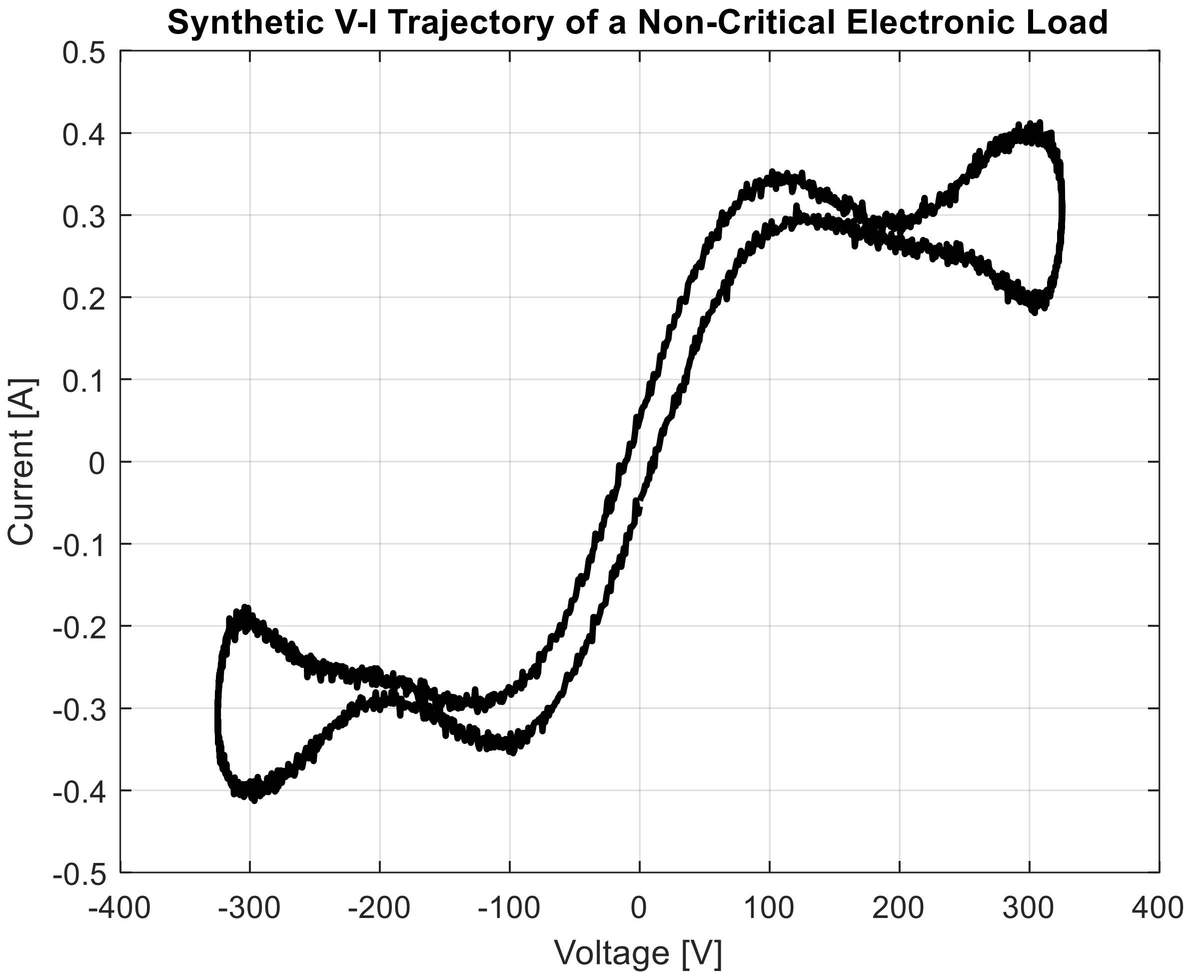


Figure 7. Representative V-I trajectory associated with a non-essential residential entertainment load. The identified appliance can be delayed or temporarily restricted during energy-constrained operating conditions without compromising user health or safety.

Equation (7) becomes

$$\mathrm{PI}_{\mathrm{TV}} = 0.30(1) + 0.35(0) + 0.20(2) - 0.15(5) = -0.05$$

The comparison between Figures 6 and 7 highlights a fundamental concept underlying the proposed framework: appliances with similar electrical power ratings may have profoundly different implications for user welfare. While both devices contribute to the overall household energy demand, their social relevance and operational priority differ significantly. The entertainment load primarily provides discretionary services and can therefore be postponed, limited, or temporarily denied without affecting essential household functions. Conversely, interruption of a CPAP system may directly compromise the user's health condition. By exploiting NILM-based appliance recognition, the framework can therefore perform energy allocation decisions based not only on electrical consumption but also on the functional importance of the identified appliance.

Based on the computed Priority Index (PI), appliances are classified into five operational categories. Loads with $PI \geq 3.5$ are classified as Critical, since they support essential medical or safety-related functions and should always be supplied whenever technically feasible. Appliances with $2.5 \leq PI < 3.5$ are considered Essential, as they perform important household functions whose interruption should be minimized. Loads with $1.5 \leq PI < 2.5$ are classified as Flexible and may be temporarily rescheduled without significantly affecting user well-being. Appliances with $0.5 \le PI < 1.5$ are considered Deferrable, meaning that their operation can be postponed until sufficient energy becomes available. Finally, loads with $PI < 0.5$ are regarded as Non-essential and may be temporarily denied under constrained energy conditions. These threshold values represent an initial expert-based configuration adopted for the present study and can be refined during the commissioning phase according to household characteristics, user requirements, healthcare recommendations, or future optimization procedures.

NILM techniques are increasingly being integrated into smart-home and smart-grid environments to improve energy monitoring, appliance identification, demand response, and distributed energy resource management [8,14,16]. Most existing residential energy management systems, however, are primarily designed to optimize energy efficiency, reduce electricity costs, or maximize self-consumption. Comparatively less attention has been devoted to the protection of vulnerable users and the preservation of essential energy services under constrained operating conditions [8,10]. In addition, only a limited number of studies explicitly consider the interaction between NILM-based load identification, energy poverty mitigation strategies, and Renewable Energy Communities capable of providing shared photovoltaic resources to support vulnerable households [11]. The proposed framework addresses this gap by combining appliance recognition, human-centric prioritization, and adaptive energy allocation policies within a unified Energy Guardianship architecture.

Although the current supervisory layer adopts a deterministic rule-based strategy, the proposed architecture has been conceived to progressively incorporate adaptive Artificial Intelligence techniques. The commissioning phase naturally enables continuous learning from multiple residential installations by collecting anonymous operational data, user interactions and supervisory outcomes. This information can be exploited to automatically calibrate the weighting coefficients of the Priority Index, adapting the Energy Guardianship strategy to different household characteristics, medical conditions and user preferences without modifying the overall decision framework.

Similarly, appliance electrical signatures cannot be considered static throughout the appliance lifetime. Aging effects, maintenance operations, supply voltage variations and changes in operating conditions progressively modify the electrical behavior of household appliances. For this reason, the proposed framework relies on a local appliance atlas that can be continuously updated during normal operation. AI-assisted learning algorithms may periodically refine the stored signatures by incorporating newly acquired measurements, thereby improving appliance recognition robustness while preserving the house-specific nature of the commissioning process.

Future developments will investigate reinforcement learning, adaptive optimization and online learning algorithms capable of simultaneously updating appliance signatures, calibrating priority coefficients and learning user-specific energy management preferences from long-term residential operations.

F. Load Actuation and User Feedback Layer

The final layer of the proposed architecture is responsible for implementing the decisions generated by the AI engine and communicating the resulting actions to the end user. This layer transforms high-level energy management decisions into physical control actions capable of modifying appliance operation while maintaining transparency and user involvement. Unlike fully autonomous control systems, the proposed framework adopts a cooperative approach in which automated actions are complemented by informative feedback and decision support recommendations.

The actuation process can be implemented through several commercially available technologies, including smart plugs, remotely controllable relays, home energy management systems, smart appliances, and inverter control interfaces. These devices enable the framework to execute the actions generated by the decision layer, including load activation, postponement, limitation, or temporary denial. Depending on the available infrastructure, the control strategy may be implemented either directly through automatic switching actions or indirectly through user recommendations requiring manual intervention.

A key characteristic of the proposed architecture is the integration of user-centered feedback mechanisms. Rather than simply disconnecting appliances when energy constraints occur, the system explains the reason for each decision and proposes alternative operating strategies. Examples include postponing flexible appliances to periods characterized by photovoltaic surplus generation, selecting lower-energy operating modes, reducing simultaneous appliance operation, or exploiting available energy resources within a Renewable Energy Community.

An example of system feedback is as follows:

"The washing machine activation has been postponed due to limited available energy. Suggested activation time: 12:00 PM during expected photovoltaic surplus conditions."

Such recommendations provide users with a clear understanding of the energy management process while preserving their autonomy and decision-making capabilities. This aspect is particularly important for vulnerable households, where trust, transparency, and ease of use are essential requirements for technology acceptance.

From a broader perspective, the load actuation and user feedback layer represents the interface between artificial intelligence and human behavior. By combining automated control actions with educational and informative recommendations, the framework promotes greater energy awareness while simultaneously protecting critical household services. This approach supports the transition from conventional energy management systems toward socially aware Energy Guardianship solutions capable of balancing technical efficiency, renewable energy integration, and user well-being.

Figure 8 summarizes the processes introduced in Section 3 and illustrates the interactions among the Technical, Power and Economic, and Guardianship layers composing the proposed Energy Guardianship framework that will be described in Section 4.

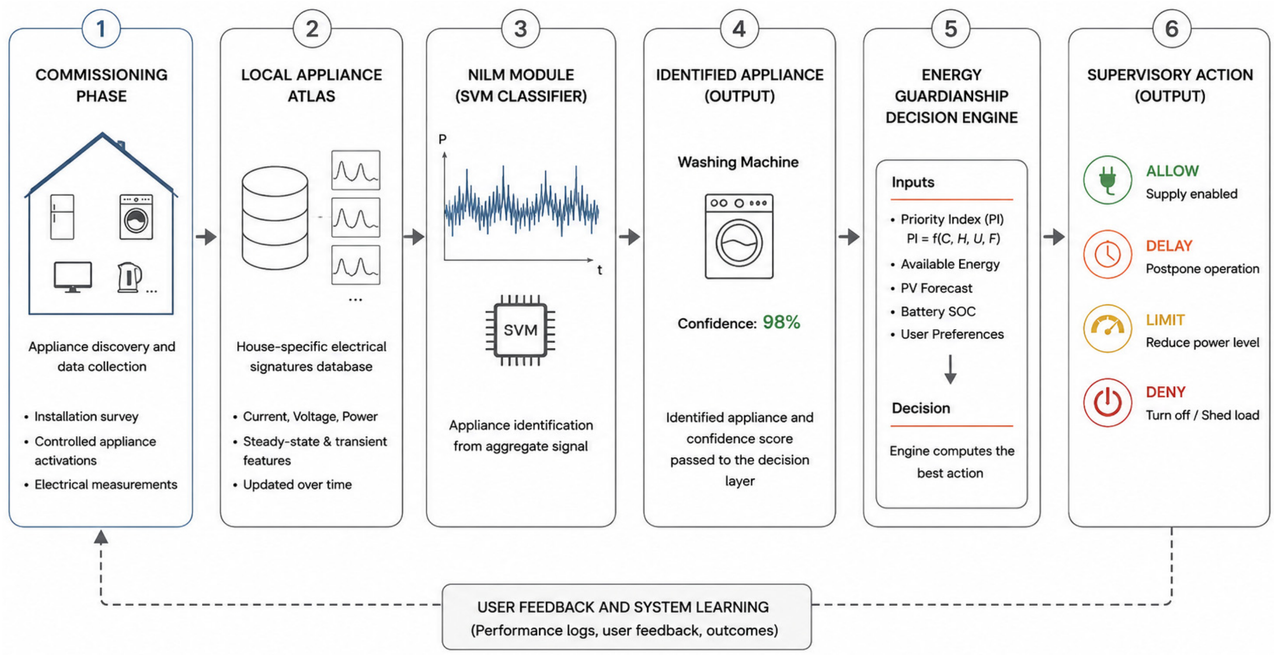


Figure 8. Overall workflow of the proposed Energy Guardianship framework. (**1**) During the commissioning phase, the household appliances are individually measured to build a house-specific

database. (**2**) The resulting Local Appliance Atlas stores representative electrical signatures and features for each appliance. (**3**) During online operation, the NILM module identifies the active appliance from the aggregated electrical signal. (**4**) The identified appliance and its confidence score are forwarded to the decision layer. (**5**) The Energy Guardianship Decision Engine combines the appliance Priority Index (PI), available energy resources, battery state of charge, photovoltaic generation, and user preferences to determine the appropriate action. (**6**) The supervisory controller executes the selected action (allow, delay, limit, or deny). A continuous feedback loop updates the Local Appliance Atlas and supports the adaptation of the proposed framework over time based on system performance and user feedback.

4. Mathematical Formulation of the Proposed Energy Guardianship Framework

This section presents the mathematical formulation of the proposed AI-based Energy Guardianship framework. The objective of the system is to dynamically allocate limited electrical energy resources while preserving the operation of critical household appliances, supporting vulnerable users, and maximizing the effective utilization of locally available renewable energy resources [8,14,16]. Unlike conventional Home Energy Management Systems, which primarily focus on cost reduction and energy efficiency, the proposed framework introduces a human-centric decision paradigm in which technical optimization is combined with health, social, and user-priority considerations.

The mathematical formulation reflects the two-stage architecture introduced in the previous section. During the commissioning phase, the local appliance atlas is generated from individually measured appliance signatures. During online operation, the identified appliance, together with the available energy resources, provides the information required by the supervisory decision process described in the following subsections. Consequently, the mathematical model does not address universal appliance classification, but rather the real-time allocation of limited energy resources among previously commissioned household appliances.

The mathematical model integrates three main components: (i) aggregate load monitoring and NILM-based appliance identification (the technical overview), (ii) energy availability assessment under constrained operating conditions (power and economic frame), and (iii) AI-assisted decision-making based on appliance criticality and user vulnerability (guardianship frame).

The technical frame works on voltage and current acquisition; it hosts (A) aggregate load monitoring and NILM-based appliance identification, (B) event detection formulation, (C) electrical load signature.

The economic frame hosts (D) available energy assessment under constrained operating conditions and (E) integration of a battery model for the renewable community.

The Guardianship frame hosts (F) the ethical load priority model, (G) AI-based decision formulation, (H) human-centric operational constraints, (I) renewable-aware load scheduling.

The resulting formulation enables adaptive energy allocation strategies capable of responding to changes in household demand, photovoltaic generation, battery availability, and user requirements.

The mathematical formulation is organized into three complementary frames: the Technical Frame, responsible for appliance monitoring and identification; the Power and Economic Frame, which evaluates the available energy under operational constraints; and the Guardianship Frame, where AI-assisted supervisory decisions are taken according to appliance priority and user vulnerability. The overall architecture is illustrated in Figure 9.

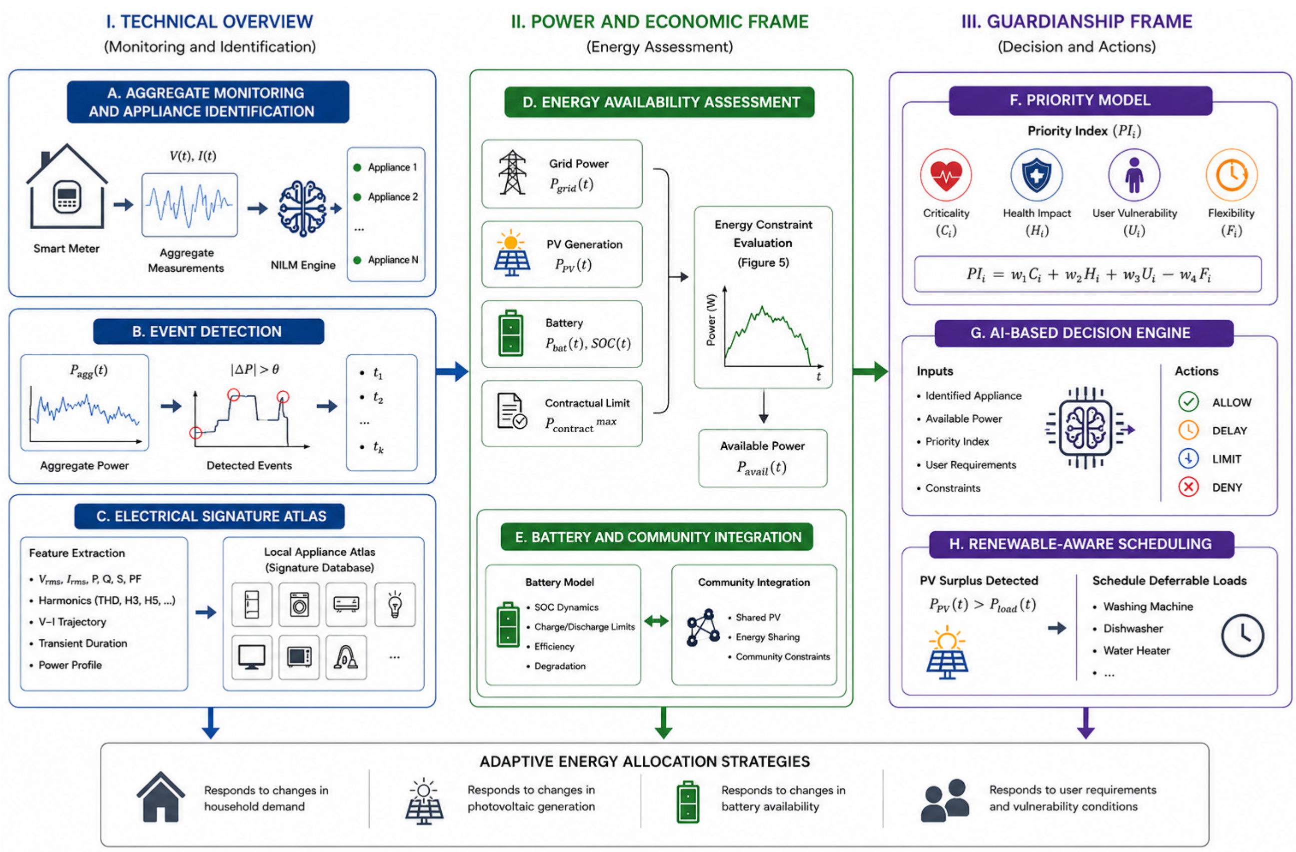


Figure 9. Mathematical architecture of the proposed Energy Guardianship framework. The formulation is organized into three complementary conceptual layers. The technical overview describes the electrical monitoring process, including aggregate load acquisition, NILM-based appliance identification, event detection, and the extraction of multidimensional electrical signatures used to construct the Local Appliance Atlas. The power and economic frame evaluates the instantaneous energy availability by combining grid power, photovoltaic generation, battery operation, and contractual power constraints, providing the available energy margin for supervisory control (external inputs). Finally, the Guardianship frame integrates ethical load prioritization, AI-assisted decision-making, human-centric operational constraints, and renewable-aware scheduling to determine the appropriate management action for each appliance. The interaction among these three layers enables adaptive energy allocation strategies capable of responding to variations in household demand, renewable generation, battery availability, contractual limitations, and user vulnerability, ensuring that critical electrical services are preferentially maintained under constrained energy conditions.

A. Aggregate Load Model

The aggregate residential electrical demand measured at the smart meter can be represented as the superposition of the contributions generated by all active appliances connected to the household electrical installation. Since the proposed architecture relies on a single measurement point, the aggregate demand constitutes the only directly observable electrical quantity available to the NILM subsystem.

The aggregate power demand is expressed as

$$P_{agg}(t) = \sum_{i=1}^{N} s_i(t) P_i(t) + n(t) \tag{8}$$

where

- N is the total number of appliances connected to the residential installation;
- $s_i(t)$ in {0, 1} represents the operating state of the i-th appliance;

- $P_i(t)$ is the instantaneous power absorbed by the i-th appliance;
- $n(t)$ represents measurement noise, unmodeled disturbances, and unknown load contributions.

The primary objective of the NILM subsystem is to estimate the hidden appliance states

$$\hat{s}_i(t)$$

using only aggregate measurements acquired at the household service entrance. This estimation process transforms a single aggregated electrical signal into appliance-level information that can subsequently be used for energy management purposes.

In the proposed framework, the estimation of the appliance states is constrained to the appliances previously characterized during the commissioning phase. This assumption considerably reduces the dimensionality of the identification problem while improving robustness under practical residential operating conditions.

In the context of the proposed framework, appliance identification is not performed solely for monitoring purposes. Instead, the estimated appliance states constitute the foundation for implementing priority-aware energy allocation strategies. Once a load is identified, the framework can associate technical and social attributes with the corresponding appliance, allowing differentiated treatment during constrained operating conditions.

B. Event Detection Formulation

The first stage of the NILM process consists of detecting appliance switching events. These events correspond to transitions between different operating states and are generally associated with significant variations in aggregate active and reactive power.

A switching event is identified whenever the variation in aggregate power exceeds a predefined detection threshold:

$$\mid \Delta P(t) \mid = \mid P(t) - P(t-1) \mid = \gamma \tag{9}$$

with γ represents the event detection threshold.

The threshold must be selected carefully to balance detection sensitivity and robustness against measurement noise. Excessively low thresholds may generate false alarms, whereas excessively high thresholds may cause small appliance activations to remain undetected.

For each detected event, the framework generates an event descriptor, by referring to Equation (1):

$$e_k = \{t_k, \Delta P_k, \Delta Q_k\}$$

where

- t_k is the event occurrence time;
- ΔP_k is the variation in active power;
- ΔQ_k is the variation in reactive power.

The event descriptor provides a compact representation of the observed transition and constitutes the input to the feature extraction module. In practical implementations, several event detection approaches can be adopted, including threshold-based techniques, Cumulative Sum (CUSUM) algorithms, Generalized Likelihood Ratio (GLR) methods, and Sequential Probability Ratio Tests (SPRT). These techniques enable reliable identification of appliance activation and deactivation events under realistic residential operating conditions.

Accurate event detection is particularly important within the proposed Energy Guardianship framework because the quality of appliance identification directly affects subsequent prioritization and energy allocation decisions.

C. Electrical Load Signature Representation

Following event detection, the framework extracts a set of electrical features that characterize the detected appliance. These features collectively define the electrical signature of the load and provide the information required for appliance classification.

The load signature vector is defined in Equation (3), by considering different periods, as

$$\mathbf{f}_k(i) = [\Delta P(i), \Delta Q(i), PF(i), THD(i), H_3(i), H_5(i), H_7(i), \tau(i)] \quad (10)$$

where $PF(i)$ is the power factor of i-period, and the same for the quantities defined in (3). It is necessary to collect multiple temporal signatures for each appliance, capturing its behavior under different operating conditions. This allows the artificial intelligence model to learn the intrinsic variability of electrical signatures, recognizing that appliance patterns are not fixed but change over time due to operating conditions, aging, and usage characteristics.

The selected features combine steady-state and transient information. Active and reactive power variations provide information regarding appliance size and operating characteristics, while harmonic components capture nonlinear behavior generated by electronic converters and switching devices. The transient duration provides additional information regarding motor-driven appliances and dynamic loads.

These features are particularly useful because appliances characterized by similar power consumption may still exhibit significantly different electrical signatures. Consequently, NILM techniques can distinguish between appliances that consume comparable electrical power but have very different functional roles within the household.

The appliance classification problem of Equation (4) can therefore be formulated as

$$\hat{L}_k = f(\mathbf{f}_k(i)) \quad (11)$$

where

- $f_k(i)$ is the extracted feature vector;
- $\hat{L}_k$ is the identified appliance class.

The classification function may be implemented using machine learning algorithms, decision trees, support vector machines, random forests, or deep learning approaches such as Convolutional Neural Networks (CNNs). In the proposed framework, appliance recognition is subsequently integrated with user-priority information, enabling the AI engine to associate each identified load with a specific energy management policy.

This capability represents a fundamental step toward the realization of Energy Guardianship strategies. For example, a CPAP respiratory support device and a television set may exhibit comparable power ratings but generate different electrical signatures. Through NILM-based identification, the framework can recognize the medical device and assign it a higher operational priority, thereby ensuring continuity of service during periods of limited energy availability.

D. Available Energy Model

After appliance identification, the proposed framework continuously evaluates the instantaneous availability of electrical energy resources to determine whether new load requests can be safely accommodated. Unlike traditional residential energy management systems that assume unlimited grid availability, the proposed architecture explicitly considers the variability of renewable energy generation, battery storage limitations, and contractual power constraints. This capability is particularly relevant for vulnerable households, where limited energy resources may directly affect the availability of essential services.

As defined in Equations (5) and (6), the available power is defined as the sum of all energy sources currently accessible to the residential system:

$$P_{avail}(t) = P_{grid}(t) + P_{PV}(t) + P_{battery}(t)$$

where

- $P_{grid}(t)$ is the maximum power available from the electrical grid;
- $P_{PV}(t)$ represents the instantaneous photovoltaic generation;
- $P_{battery}(t)$ denotes the power supplied by the battery storage system.

The framework continuously verifies the fundamental operating condition

$$\sum_{i=1}^{N} P_i(t) \leq P_{avail}(t) \tag{12}$$

which guarantees that the aggregate household demand remains compatible with the available energy resources. Violation of this condition may result in overload situations, excessive battery depletion, or contractual power exceedance. Therefore, whenever the predicted demand approaches the available energy limit, the system activates the AI-based decision module and evaluates alternative load management actions.

A distinctive aspect of the proposed approach is that energy availability is not interpreted solely as a technical constraint but also as a resource that must be allocated according to user needs and appliance criticality. Consequently, the Available Energy Model constitutes the quantitative basis upon which the Energy Guardianship strategy is implemented. Figure 5 summarizes the proposed energy constraint evaluation process adopted by the supervisory layer.

E. Battery State-of-Charge Constraint

When battery storage is available, the framework introduces an additional layer of protection based on the battery State of Charge (SOC). Battery resources can significantly increase energy resilience, particularly in households equipped with photovoltaic systems or participating in Renewable Energy Communities. However, excessive battery depletion may compromise the availability of energy during future critical situations.

The battery State of Charge is defined as

$$SOC(t) = \frac{E_{battery}(t)}{E_{battery,max}} \tag{13}$$

where

- $E_{battery}(t)$ is the energy currently stored in the battery;
- $E_{battery,max}$ is the maximum storage capacity.

To preserve emergency energy reserves, the following safety constraint is imposed:

$$SOC(t) \geq SOC_{min} \tag{14}$$

where SOC_{min} represents a minimum reserve threshold defined according to household requirements.

The introduction of a minimum SOC constraint enables the framework to reserve part of the stored energy for future operation of critical appliances. For example, in households containing respiratory support devices or medical refrigeration systems, battery reserves may be preserved to ensure continuity of service during periods characterized by low photovoltaic production or temporary grid outages. This approach transforms the battery from a simple energy storage device into a strategic resource supporting vulnerable-user protection.

F. Ethical Load Priority Model

One of the most innovative contributions of the proposed framework is the introduction of an Ethical Load Priority Model capable of combining electrical, functional, and social information into a unified decision-making process.

Conventional energy management systems generally prioritize appliances according to economic criteria or electrical efficiency metrics. In contrast, the proposed Energy Guardianship framework explicitly incorporates user well-being, health relevance, and appliance criticality into the prioritization process.

Each appliance is assigned a Priority Index (*PI*) defined as (7)

$$PI_i = w_1 C_i + w_2 H_i + w_3 U_i - w_4 F_i$$

where

- C_i represents appliance criticality;
- H_i quantifies health relevance;
- U_i expresses user utility;
- F_i denotes load flexibility;
- w_1, w_2, w_3, w_4 are weighting coefficients.

Higher values of PI_i indicate appliances that should receive preferential access to available energy resources.

Based on this index, appliances are grouped into five priority classes, as in Table 1.

Table 1. Priority classes.

Class	Description
Critical	Medical and safety devices (e.g., CPAP systems, oxygen concentrators)
Essential	Refrigeration systems, communications, basic lighting
Comfort	Ventilation systems, low-power heating and cooling
Deferrable	Washing machines, dishwashers, water heaters
Non-Essential	Entertainment devices and discretionary loads

This classification allows the framework to distinguish between appliances with similar electrical characteristics but substantially different impacts on user well-being. The Energy Guardianship framework faces different management strategies during energy-constrained conditions for two similar power loads, a CPAP respiratory support device and a television.

To facilitate the practical implementation of the proposed Priority Index, each component can be evaluated on a normalized scale ranging from 0 to 5. In particular, the technical criticality score (C) quantifies the consequences associated with the interruption of the appliance, the health relevance score (H) reflects its impact on user health and safety, the utility score (U) represents the perceived benefit provided to the user, and the flexibility score (F) describes the possibility of postponing or modifying the appliance operation without significant discomfort. This simple scoring approach enables the framework to translate technical, social, and health-related considerations into a unified decision metric. A CPAP respiratory support device can be characterized by C = 5, H = 5, U = 5, and F = 0, reflecting its critical role and limited operational flexibility. Conversely, a residential television may be assigned C = 1, H = 0, U = 2, and F = 5, indicating low criticality and high flexibility. Such a representation allows the proposed Energy Guardianship framework to distinguish between appliances with similar electrical consumption but substantially different implications for user well-being, thereby supporting socially aware energy allocation decisions.

G. AI-Based Decision Formulation

The AI-based decision engine represents the central intelligence of the proposed framework. Its role is to determine the most appropriate management action for each appliance request while simultaneously satisfying electrical constraints and protecting vulnerable users.

For each appliance, the system generates one of four possible actions:

$$a_i(t) \in \{allow, delay, limit, deny\}$$

where

- Allow authorizes normal operation;
- Delay postpones activation to a later time;
- Limit reduces power consumption or operating conditions;
- Deny rejects activation.

The decision process is formulated as an optimization problem:

$$J = \lambda_1 E_{viol} + \lambda_2 C_{cost} + \lambda_3 D_{comfort} + \lambda_4 R_{risk} \tag{15}$$

where

- E_{viol} represents violations of electrical constraints;
- C_{cost} is the economic cost of energy consumption;
- $D_{comfort}$ quantifies user discomfort;
- R_{risk} measures social and health-related risks.

The weighting coefficients λ_i regulate the trade-off between energy efficiency and vulnerable-user protection.

Unlike conventional optimization frameworks, the proposed objective function explicitly incorporates social risk. This allows the system to prioritize user well-being and critical service continuity even when such decisions are not optimal from a purely economic perspective.

H. Human-Centric Operational Constraints

To guarantee adequate protection of vulnerable users, the framework introduces additional operational constraints reflecting ethical and social requirements.

The most important constraint concerns the operation of critical appliances:

$$D_{critical} = 0 \tag{16}$$

which states that critical appliances should never be denied under normal operating conditions.

This constraint fundamentally differentiates the proposed Energy Guardianship framework from conventional Home Energy Management Systems. Whereas traditional approaches primarily seek to optimize efficiency and cost, the proposed system prioritizes continuity of service for medically relevant and safety-related equipment.

Consequently, even under severe energy limitations, the AI engine is required to explore alternative actions affecting lower-priority loads before considering restrictions on critical appliances.

This human-centric constraint represents the defining characteristic of the proposed Energy Guardianship framework and clearly differentiates it from conventional residential energy management systems, where economic optimization generally remains the primary objective.

I. Renewable-Aware Load Scheduling

The final component of the mathematical formulation concerns photovoltaic-aware scheduling strategies. The increasing diffusion of distributed renewable generation creates opportunities for shifting flexible loads toward periods characterized by abundant local energy production.

Flexible appliances can therefore be scheduled according to the condition

$$P_{PV}(t) > P_{load}(t) \tag{17}$$

which indicates the presence of photovoltaic surplus generation.

When this condition occurs, the framework may recommend or automatically initiate the operation of deferrable appliances such as washing machines, dishwashers, or water heaters. This strategy increases renewable self-consumption, reduces electricity purchases from the grid, and improves the overall sustainability of household energy management.

In the context of Renewable Energy Communities, photovoltaic-aware scheduling can be further extended to exploit shared renewable resources available at the community level. Consequently, vulnerable households may benefit not only from locally generated photovoltaic energy but also from coordinated energy sharing mechanisms that enhance resilience and reduce exposure to energy poverty. Such integration between NILM, AI-based decision-making, and renewable-aware scheduling represents a key step toward socially inclusive and human-centric energy governance systems.

Although photovoltaic-aware scheduling contributes to increasing renewable self-consumption and reducing grid dependence, these improvements should be regarded as secondary outcomes of the proposed framework. The primary objective remains the protection of vulnerable users through the continuity of critical household services whenever available energy becomes limited.

5. Results

This section presents a set of preliminary simulation scenarios developed to evaluate the behavior of the proposed AI-Based Energy Guardianship framework under constrained residential energy conditions. The simulations aim to demonstrate the feasibility of combining Non-Intrusive Load Monitoring, appliance prioritization, Renewable Energy Community support, and AI-assisted decision-making to protect vulnerable users while improving the utilization of available energy resources.

The objective of the analysis is not to provide a fully optimized implementation or a complete techno-economic assessment, but rather to illustrate the operational principles of the proposed architecture and highlight its potential benefits in situations characterized by limited energy availability. Attention is devoted to scenarios representative of energy poverty conditions, where households may experience temporary or persistent restrictions in electricity access and where intelligent energy allocation mechanisms become essential for preserving critical services.

The simulation environment reproduces a residential user equipped with a smart meter, access to community-shared photovoltaic generation, and limited contractual power availability. The proposed framework continuously identifies active appliances through NILM techniques, evaluates available energy resources, computes appliance priority levels, and generates adaptive control actions according to both technical and social constraints.

5.1. Simulation Setup

The proposed Energy Guardianship framework was evaluated using the Plug Load Appliance Identification Dataset (PLAID), considering both the PLAID 2014 and PLAID 2018 datasets [20]. As illustrated in Figure 1, the evaluation follows the same two-stage architecture adopted by the proposed framework: an offline commissioning phase followed by online real-time operation.

During the commissioning phase (left side of Figure 1), a residential dwelling is selected from the PLAID database. Since the dataset provides the list of appliances available in each monitored house, every appliance belonging to the selected dwelling is individually analyzed. Aggregate voltage and current measurements are used to extract a multidimensional electrical signature, including dynamic V-I trajectories, power profiles, transient behavior, harmonic information and conventional electrical features. These signatures are then stored in a local appliance atlas, which represents the electrical fingerprint of the appliances actually installed in that specific house.

During the online operation phase (right side of Figure 1), one or more appliances are randomly activated among those available in the commissioned dwelling, reproducing realistic residential operating conditions. The aggregate voltage and current signals are continuously monitored, and the same feature extraction procedure is applied. The online feature vector is then compared with the signatures stored in the local appliance atlas, allowing the operating appliance to be identified through the highest similarity score.

Once the appliance has been identified, the Energy Guardianship supervisory layer evaluates its priority together with the instantaneous availability of electrical energy—considering grid supply, photovoltaic generation and battery availability—and determines the appropriate management action (Allow, Delay, Limit or Deny) according to the mathematical formulation presented in Section 4.

Unlike conventional NILM benchmark studies, where the objective is universal appliance recognition across heterogeneous datasets, the proposed evaluation reproduces the expected deployment of a real residential installation. The classification problem is therefore restricted to the appliances previously commissioned within the monitored dwelling, providing a realistic assessment of the Energy Guardianship framework operating under practical residential conditions.

5.2. Evaluation Scenarios

To assess the effectiveness of the proposed Energy Guardianship framework, a set of representative operating scenarios was developed to reproduce realistic residential conditions under limited energy availability. Rather than evaluating isolated components, the proposed cases progressively validate the complete supervisory architecture, from appliance identification to the final AI-assisted decision-making process.

The scenarios were selected to investigate the principal operating conditions expected in a residential Renewable Energy Community. They include situations involving power constraints, protection of critical appliances for vulnerable users, renewable-aware scheduling based on photovoltaic availability, and adaptive management of available energy resources. Together, these cases demonstrate how the proposed framework combines appliance identification, energy availability assessment, and human-centric supervisory decisions within a unified Energy Guardianship strategy.

It is worth emphasizing that the objective of these case studies is not to optimize photovoltaic production or battery operation, but to demonstrate the capability of the proposed supervisory framework to allocate limited energy resources according to appliance criticality and user vulnerability. Improvements in renewable energy utilization and reductions in grid energy consumption should therefore be regarded as secondary outcomes naturally arising from the Energy Guardianship decision process.

The following subsections describe each operating scenario and discuss the corresponding supervisory actions performed by the proposed framework.

5.3. Simulated Energy Poverty Residential Scenario

Energy poverty is commonly associated with difficulties in maintaining adequate energy services due to economic, technical, or infrastructural limitations. While conventional residential energy management studies typically assume stable access to electricity and nominal contractual power levels, many vulnerable households operate under substantially different conditions. In practice, economically fragile users may face temporary power restrictions, reduced contractual availability, weak-grid conditions, emergency situations, or energy rationing policies that significantly limit the simultaneous use of domestic appliances.

To reproduce such conditions, the proposed simulations consider a vulnerable residential user whose nominal contractual power availability may be reduced below standard residential values. Under these circumstances, the operation of household appliances becomes highly dependent on intelligent scheduling and prioritization mechanisms. Without adequate energy management strategies, simultaneous activation of multiple appliances may rapidly exceed the available energy budget, leading to overload conditions or forced service interruptions.

The considered user is assumed to be a member of a Renewable Energy Community equipped with shared photovoltaic generation and distributed battery storage systems. This assumption reflects the growing role of Renewable Energy Communities as instruments for combating energy poverty and supporting socially inclusive energy transitions. Through the community infrastructure, vulnerable households can partially benefit from locally generated renewable energy even when their individual resources are limited.

Unlike conventional Home Energy Management Systems that primarily aim to reduce electricity costs or maximize self-consumption, the proposed framework introduces a human-centric prioritization strategy capable of determining which appliances should receive energy during constrained operating conditions.

An important characteristic of the proposed approach is the strategic use of battery resources. Instead of treating battery storage as a generic backup system, the framework reserves a portion of the available energy to guarantee the operation of medically critical and socially essential appliances. Consequently, during periods of limited energy availability, the AI engine evaluates appliance criticality before authorizing energy allocation. Critical devices such as medical refrigerators, CPAP respiratory support systems, communication devices, and basic lighting services receive the highest operational priority, whereas discretionary appliances may be postponed or temporarily denied.

This approach extends traditional demand-side management concepts toward a broader Energy Guardianship paradigm in which electrical energy is not allocated solely according to efficiency criteria but also according to vulnerability, health relevance, and user welfare. Such a framework may be particularly valuable in vulnerable residential districts, Renewable Energy Communities, emergency shelters, weak-grid environments, and future resilience-oriented smart-grid infrastructures.

Scenario 1—Power Overload

This first scenario evaluates the behavior of the proposed Energy Guardianship framework under constrained power availability. The objective is to verify that the supervisory algorithm correctly identifies the operating appliance and applies priority-based management actions whenever the instantaneous energy demand exceeds the available resources. This scenario can initially be addressed as a HELM problem.

The residential appliances considered in the simulations are summarized in Table 2.

Table 2. Residential loads considered in the simulation.

Appliance	Rated Power	Priority Class
Medical Refrigerator	150 W	Critical
Refrigerator	200 W	Essential
Lighting	120 W	Essential
Fan	80 W	Comfort
Washing Machine	1800 W	Deferrable
Water Heater	2000 W	Deferrable
Television	100 W	Non-Essential

The selected appliance portfolio intentionally combines loads characterized by different power levels and social relevance. While the medical refrigerator and household refrigerator are required to remain operational throughout the day, other appliances exhibit varying degrees of flexibility and can therefore be shifted according to renewable energy availability and system constraints.

The simulations assume the presence of a vulnerable user requiring uninterrupted operation of refrigeration-related services. Such an assumption reflects realistic residential scenarios involving medicine preservation, food storage, and health-related needs. Consequently, these appliances are treated as protected loads throughout the entire simulation horizon.

The aggregate residential demand was evaluated over a 24 h period using a temporal resolution of five minutes. This sampling interval allows the representation of realistic residential consumption patterns while maintaining manageable computational complexity.

Figure 10 presents the baseline residential demand profile obtained without AI-assisted energy management. In this scenario, appliance activation follows user requests without any coordination mechanism. As a result, several high-power appliances operate simultaneously during evening hours, producing demand peaks that exceed the available contractual power limit. The figure clearly illustrates the occurrence of overload conditions generated by the concurrent operation of the washing machine and water heater.

Furthermore, the baseline scenario highlights the inefficient utilization of renewable energy resources. Most photovoltaic production occurs during daytime hours, whereas a significant portion of flexible loads remain concentrated in the evening. Consequently, available photovoltaic energy is only partially exploited, increasing dependence on the electrical grid and reducing the potential benefits associated with Renewable Energy Community participation.

5.4. Technical Overview

Considering the framework explained in Figure 8, the first part is the technical overview. The aggregate residential power signal used in the simulations was generated by combining the operating profiles of the residential appliances listed in Table 2 together with Gaussian measurement noise intended to emulate realistic smart-meter acquisition conditions. The resulting signal reproduces the typical behavior of a residential installation in which multiple appliances operate simultaneously and where individual electrical contributions are not directly observable.

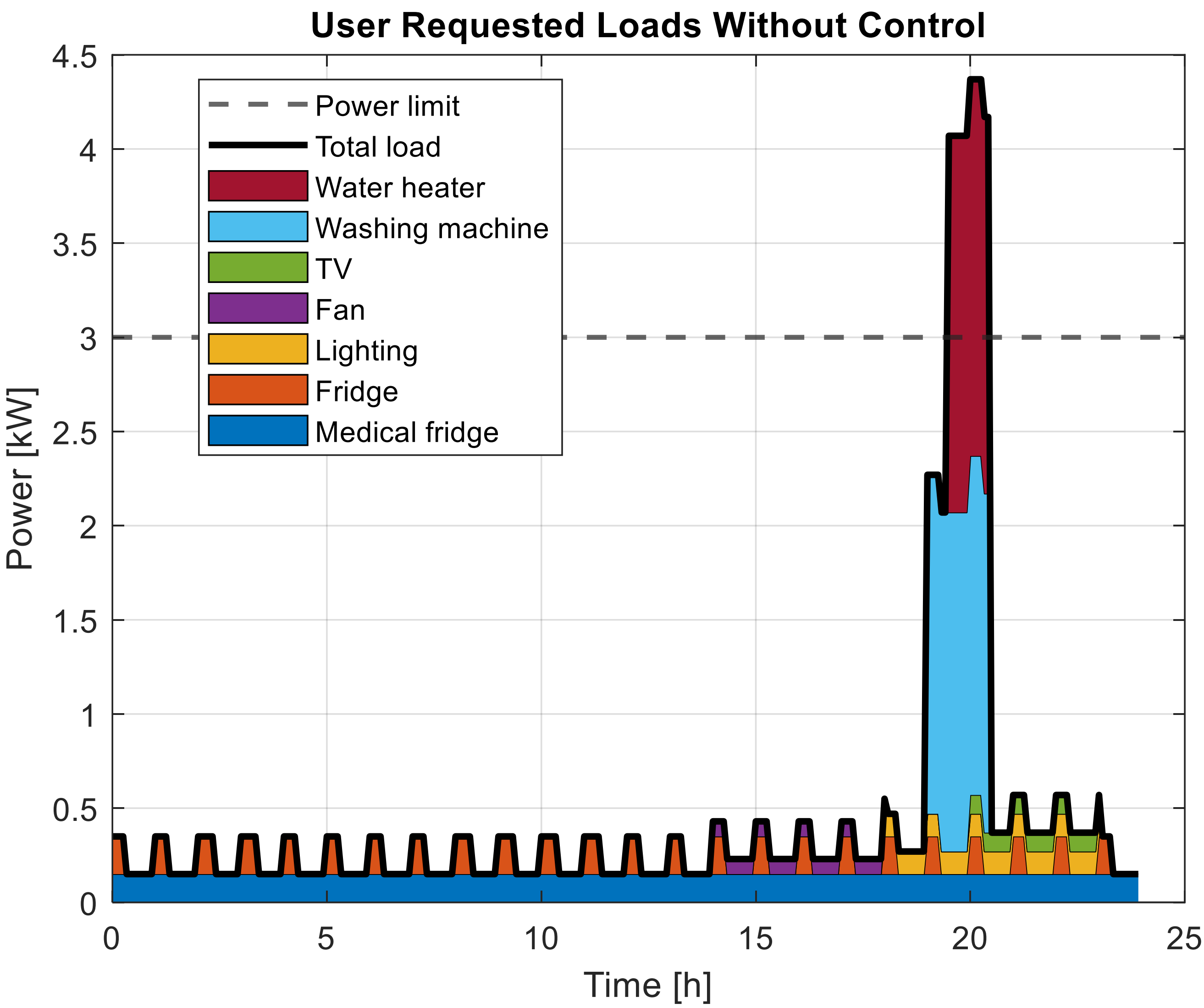


Figure 10. Composition of the residential electrical demand in the baseline scenario without AI-assisted management. The simultaneous operation of high-power appliances generates overload conditions and poor synchronization with photovoltaic generation, resulting in reduced renewable energy utilization and increased stress on limited energy resources.

The NILM subsystem continuously monitored the aggregate electrical demand $P_{agg}(t)$ and performed event detection using a threshold-based transient detection strategy derived from conventional NILM methodologies. The objective of this stage was to identify significant changes in power consumption associated with appliance activation or deactivation events. Although more sophisticated approaches such as CUSUM, GLR, and SPRT algorithms could be employed, a threshold-based implementation was considered sufficient for demonstrating the feasibility of the proposed framework.

An event was detected whenever $|\Delta P(t)| > \gamma$, $\gamma = 50$ W

The selected threshold provides a compromise between sensitivity and robustness against measurement noise. Small fluctuations caused by normal signal variability are ignored, while significant appliance switching events are successfully detected and forwarded to the load identification module.

Following event detection, the framework extracted simplified electrical signatures composed of active power variation ΔP, reactive power variation ΔQ, and transient duration τ.

Although the simulations adopted a simplified feature set, the proposed architecture can easily be extended to include additional NILM descriptors such as harmonic content, Total Harmonic Distortion (THD), current waveform characteristics, and Voltage–Current (V-I) trajectory features.

Since the effectiveness of the proposed Energy Guardianship framework strongly depends on the reliability of appliance identification, a preliminary validation of the NILM classification stage was performed using the publicly available PLAID [20]. The objective of this analysis is not to optimize the classification architecture itself, but rather to verify that the selected electrical features provide sufficient information to distinguish among common residential appliances.

A Support Vector Machine (SVM) classifier was trained using electrical signature features extracted from the appliance measurements. The considered appliance categories include both low-power electronic devices and high-power domestic loads typically encountered in residential environments. Accurate identification of these appliances is essential because the subsequent AI-based decision engine relies on appliance recognition to assign operational priorities and determine energy allocation policies.

Figure 11 reports the confusion matrix obtained during the classification process by working on the whole PLAID database. Most appliance categories exhibit a high concentration of correctly classified samples along the main diagonal, indicating satisfactory recognition performance. Misclassification events are primarily associated with appliances characterized by similar electrical operating characteristics, such as nonlinear electronic loads supplied through switching power converters. However, when the proposed approach operates on the local load atlas generated for a specific household during the commissioning phase, the confusion matrix becomes almost entirely diagonal, with classification accuracies approaching 100%. This improvement is due to the reduced variability of appliance signatures within the same installation, allowing the AI-based classifier to distinguish loads with significantly higher reliability.

The obtained results confirm that NILM-based appliance recognition can provide sufficiently accurate appliance-level information for the implementation of the proposed Energy Guardianship framework. In particular, the ability to distinguish critical appliances from non-essential loads represents a fundamental prerequisite for enabling human-centric energy allocation strategies under constrained energy conditions.

5.5. Power and Economic Frame

Following appliance identification, the proposed framework continuously evaluates the instantaneous availability of electrical energy resources and determines the most appropriate operating strategy for each appliance request. This stage integrates energy constraint assessment with AI-based decision-making, allowing the system to dynamically allocate limited energy resources while preserving the operation of critical loads.

The available residential power is calculated according to Equations (12) and (13), considering the combined contribution of grid supply, photovoltaic generation, and battery storage resources. The framework continuously verifies whether the requested aggregate demand can be safely accommodated within the available energy budget: $P_{avail}(t) < P_{requested}(t)$ where $\mathrm{P}_{\mathrm{requested}}(\mathrm{t})$ represents the total power associated with currently active and newly requested appliances.

Unlike conventional residential energy management systems that assume stable energy availability, the proposed framework explicitly incorporates the variability of renewable generation and battery storage resources. Consequently, the available energy becomes a time-dependent quantity that changes continuously throughout the day according to weather conditions, user behavior, and storage system status.

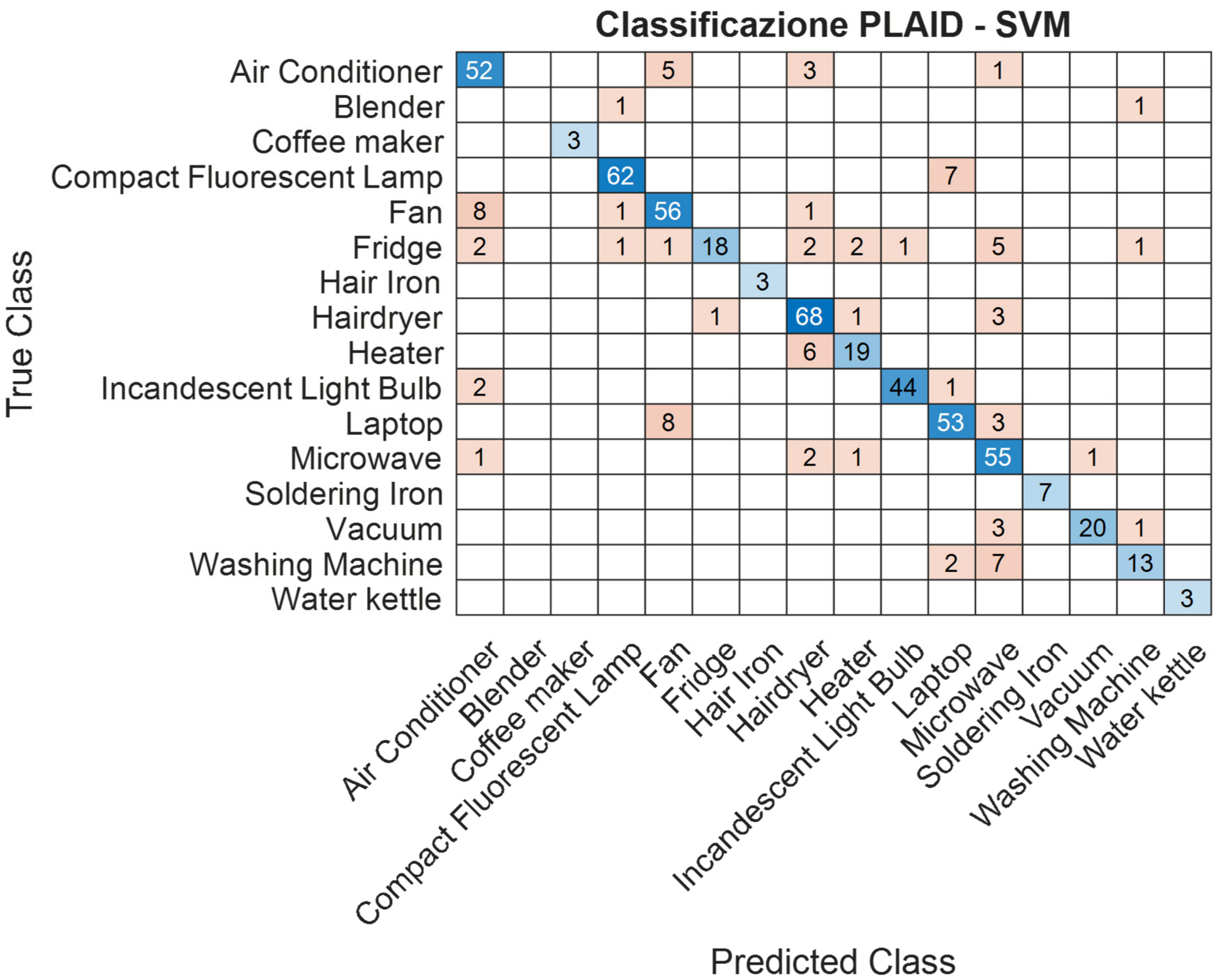


Figure 11. Confusion matrix of the SVM-based appliance classification model evaluated on the PLAID [20]. Rows represent the true appliance classes, while columns correspond to the predicted classes. The high concentration of samples along the main diagonal indicates satisfactory classification performance for most appliance categories. Misclassifications primarily occur among appliances exhibiting similar electrical characteristics and operating behaviors, highlighting the challenges associated with distinguishing loads with comparable power consumption and waveform features. These results confirm the effectiveness of NILM-based load identification as a prerequisite for the proposed AI-Based Energy Guardianship framework. A color scale has been introduced, where blue denotes correct and highly confident classifications, gradually transitioning to pink, which highlights misclassifications and increasing interpretation errors.

Simulation results revealed that energy availability strongly depends on the combined effects of photovoltaic production and battery State of Charge. During daytime periods characterized by high solar irradiation, photovoltaic generation substantially increased the available energy budget, allowing the activation of most residential appliances without violating power constraints. Conversely, during evening hours photovoltaic production decreased while battery reserves progressively declined, creating operating conditions characterized by reduced energy availability.

Under these circumstances, simultaneous operation of high-power appliances such as washing machines and water heaters frequently generated potential overload conditions. Without intelligent coordination mechanisms, these situations would lead to contractual power violations, excessive battery depletion, or involuntary interruption of essential services.

To address this problem, the proposed AI-Based Energy Guardianship engine continuously evaluates appliance requests according to the following criteria:

- Instantaneous available electrical power;
- Battery availability and reserve requirements;
- Photovoltaic generation conditions;
- Appliance priority class;
- User vulnerability considerations.

Based on these factors, the decision engine dynamically generates one of four possible actions:

$$a_i(t) \in \{allow, delay, limit, deny\}$$

where the selected action aims to simultaneously satisfy technical constraints and human-centric protection objectives.

5.6. Guardianship Frame

Once the load has been identified and the power constraint has been evaluated, the Guardianship AI-based framework starts (load is not a critical factor). Figure 12 shows that due to the limited available power, decisions have to be made. If PV and battery power are not present, $P_{avail}(t) = P_{grid}(t)$.

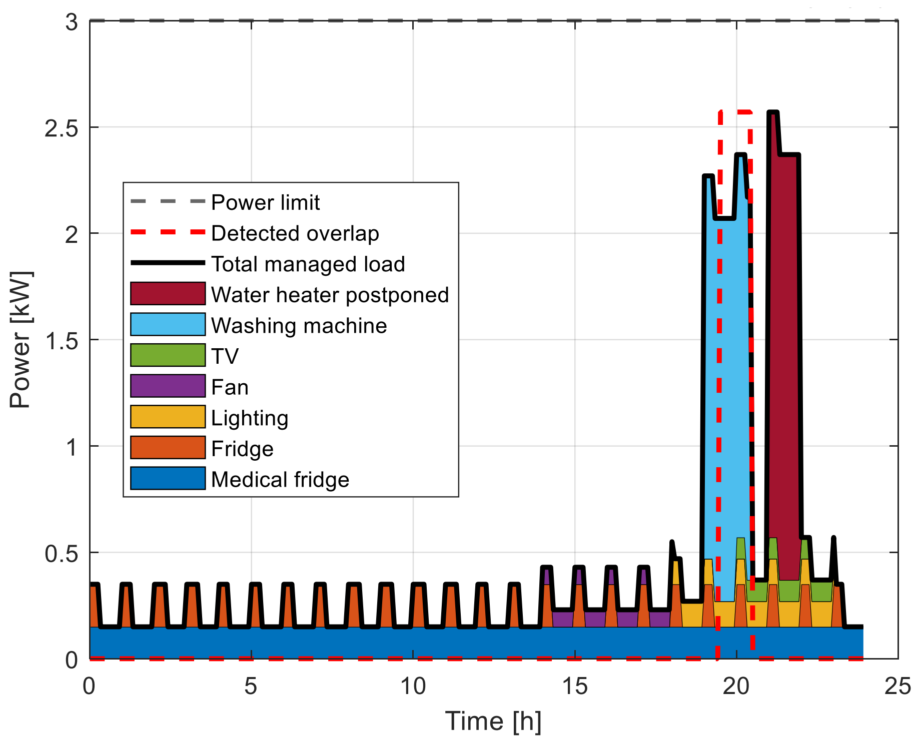


Figure 12. Comparison between aggregate residential demand and available energy resources during the simulated day. The water heater has been postponed.

A particularly significant result concerns the management of medically relevant and essential appliances. Throughout all simulated scenarios, critical refrigeration-related loads remained continuously operational, even during severe energy shortages. This behavior reflects the human-centric design philosophy of the proposed framework, where continuity of essential services takes precedence over purely economic or efficiency-oriented objectives.

In contrast, flexible and non-essential appliances exhibit adaptive operating schedules. The washing machine and water heater are frequently shifted toward periods characterized by more power availability.

Scenario 2—Protection of Critical Appliances

The second simulation scenario evaluates the capability of the proposed Energy Guardianship framework to protect medically relevant and critical household appliances during periods of temporary energy scarcity. Unlike conventional residential energy management systems, which typically prioritize loads according to power consumption or economic criteria, the proposed framework explicitly incorporates appliance criticality and user vulnerability into the decision-making process.

To reproduce a realistic constrained operating condition, a temporary overload situation was generated through the simultaneous activation of multiple household appliances. Under these circumstances, the total requested power exceeded the available energy resources derived from the grid, photovoltaic generation, and battery storage. Consequently, the AI engine was required to determine which appliances should continue operating and which loads could be temporarily restricted without compromising essential household services.

The decision process was based on the Ethical Load Priority Model introduced in Section 4. Each identified appliance was assigned a Priority Index reflecting its technical importance, health relevance, user utility, and operational flexibility. Medically relevant devices, such as CPAP respiratory support systems or medical refrigeration units used for medicine preservation, received the highest priority level and were therefore protected from service interruption.

As a result, the medical refrigerator (or CPAP system) remained continuously operational

$$a_{MR}(t) = allow$$

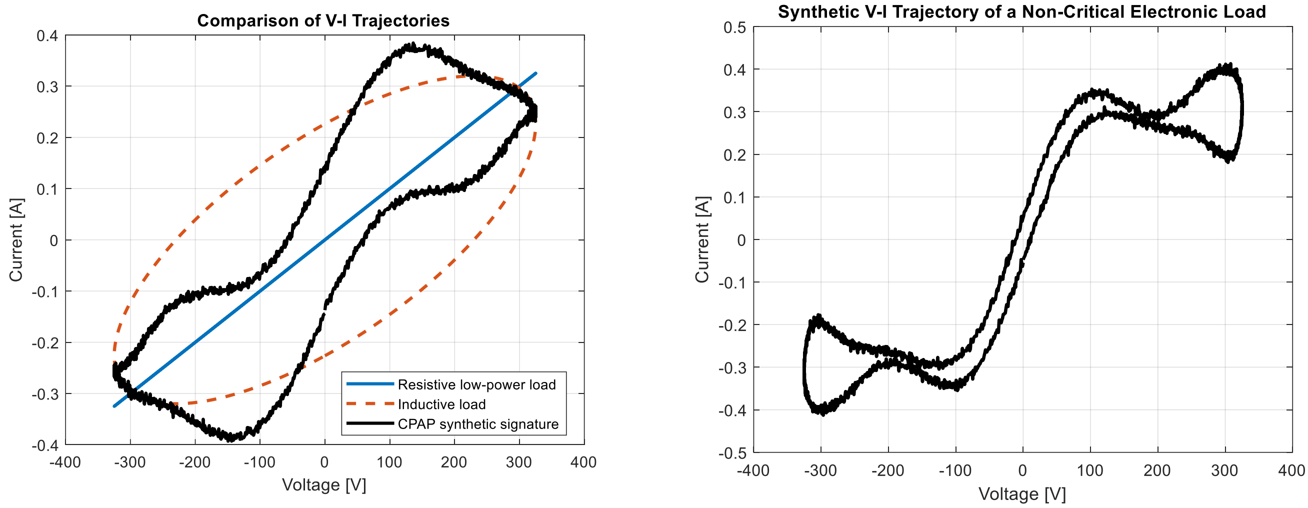
while the television load was denied

$$a_{TV}(t) = deny$$

This behavior illustrates one of the fundamental principles of the proposed Energy Guardianship framework. Although the television and the medical device may exhibit comparable power consumption levels, their impact on user well-being differs substantially. Consequently, the decision process is not driven exclusively by electrical demand but also by the functional role of the appliance within the household.

Figure 13 provides a conceptual representation of this decision-making process. The figure compares the electrical signatures (V-I trajectories, not all features) associated with a medically critical appliance and a non-essential entertainment load (added to the PLAID database). Through NILM-based load identification, the framework recognizes the appliance category and associates it with the corresponding priority class before generating the final management action.

The example demonstrates how electrical signature recognition can be transformed into socially aware energy management decisions. Once the appliance has been identified, the AI engine evaluates the current energy constraints and determines whether the requested load should be authorized, postponed, limited, or denied. In the considered scenario, the medical refrigerator (or CPAP device) receives priority access to the available energy resources, whereas the television is temporarily disconnected to preserve energy availability for critical services.



allowed ***denied***

Figure 13. Conceptual example of critical-load protection during an energy-constrained operating condition. The NILM subsystem identifies the electrical signatures of a medically relevant appliance (medical refrigerator or CPAP device) and a non-essential entertainment load. Based on the assigned priority levels, the AI engine authorizes the operation of the critical appliance while temporarily denying the lower-priority television load to preserve essential energy services.

The obtained results highlight an important limitation of traditional demand-side management approaches. Conventional optimization strategies would typically treat both appliances as electrical loads characterized only by their power demand. In contrast, the proposed framework introduces an additional semantic layer that links appliance recognition with user vulnerability and health-related requirements. This capability enables the implementation of ethical energy allocation policies specifically designed to support vulnerable users operating under constrained energy conditions.

From a practical perspective, this scenario is representative of several real-world situations, including energy-poverty households, emergency shelters, weak-grid residential areas, and Renewable Energy Communities supporting medically fragile users. In all these cases, preserving the operation of essential appliances becomes more important than maximizing purely economic performance indicators.

Overall, the results demonstrate that NILM-based appliance identification combined with AI-driven prioritization can effectively support human-centric energy management strategies. By ensuring uninterrupted operation of medically relevant devices while selectively restricting non-essential loads, the proposed Energy Guardianship framework contributes to improving residential energy resilience and protecting vulnerable users during periods of limited energy availability.

When a user requests the activation of an appliance that cannot be safely supplied under the current operating conditions, the AI-based Energy Guardianship System does not immediately disconnect the load. Instead, it first issues a visual and/or audible warning informing the user that the requested appliance is not compatible with the available power or energy budget and indicating the reason for the restriction. A short grace period is then provided, allowing the user to voluntarily switch off lower-priority appliances or cancel the request. If the operating conditions remain unchanged after this predefined interval, the system automatically disconnects the requested appliance or the whole system, thereby preserving the operation of critical loads and preventing overload conditions. This two-stage strategy combines user awareness with automated protection, improving both system reliability and user acceptance while ensuring uninterrupted supply to high-priority appliances.

Scenario 3–PV-Aware Scheduling

This scenario investigates the interaction between Energy Guardianship and renewable energy availability. The objective is to verify that flexible appliances can be automatically scheduled when surplus photovoltaic energy becomes available, without compromising the supply of critical household services.

The considered residential user belongs to a Renewable Energy Community characterized by shared photovoltaic generation resources. During daylight hours, photovoltaic production follows the typical bell-shaped profile shown in Figure 13, reaching its maximum value around midday. The AI-based management system continuously monitors the available photovoltaic power and evaluates whether flexible appliances can be shifted toward periods characterized by renewable energy surplus.

Unlike the previous scenarios, where appliance requests were evaluated only according to available power and priority constraints, the proposed strategy also incorporates a renewable-awareness criterion. Deferrable appliances such as washing machines and water heaters are therefore scheduled according to the condition $P_{PV}(t) > P_{load}(t)$.

When this condition is satisfied, the framework recommends or automatically authorizes the activation of flexible appliances. Conversely, when photovoltaic generation is insufficient, non-urgent appliance requests may be postponed to periods characterized by higher renewable energy availability.

Figure 14 illustrates the photovoltaic generation profile considered in the simulations together with the operating periods selected for flexible loads. The results show that the washing machine and water heater are automatically shifted from evening hours toward midday periods characterized by abundant solar generation.

This scheduling strategy produces several benefits. First, it increases photovoltaic self-consumption by directly utilizing locally generated renewable energy. Second, it reduces dependence on the electrical grid during peak demand periods. Third, it preserves battery storage resources for future operation of critical appliances. Finally, it decreases the probability of overload conditions and improves the overall resilience of the residential energy system.

The AI engine generated the following representative actions:

- Washing machine request at 7:00 PM → postponed to 12:15 PM.
- Water heater request at 8:00 PM → postponed to 1:00 PM.
- Television request during photovoltaic surplus → allowed without restrictions.
- Medical refrigerator operation → continuously maintained regardless of photovoltaic conditions.

The comparison with the baseline scenario demonstrates that photovoltaic-aware scheduling significantly improves the utilization of renewable energy resources while maintaining user comfort and protecting vulnerable users. Critical and essential loads remain continuously supplied, whereas flexible loads are automatically coordinated with renewable energy availability.

These results confirm that the integration of NILM-based appliance identification, Energy Guardianship principles, and photovoltaic-aware scheduling can provide an effective strategy for supporting vulnerable households participating in Renewable Energy Communities. By combining technical optimization with human-centric priorities, the proposed framework contributes to both renewable energy integration and socially inclusive energy management. Figure 15 illustrates the PV-aware scheduling strategy, shifting flexible loads toward periods of higher photovoltaic generation while preserving critical-load operation.

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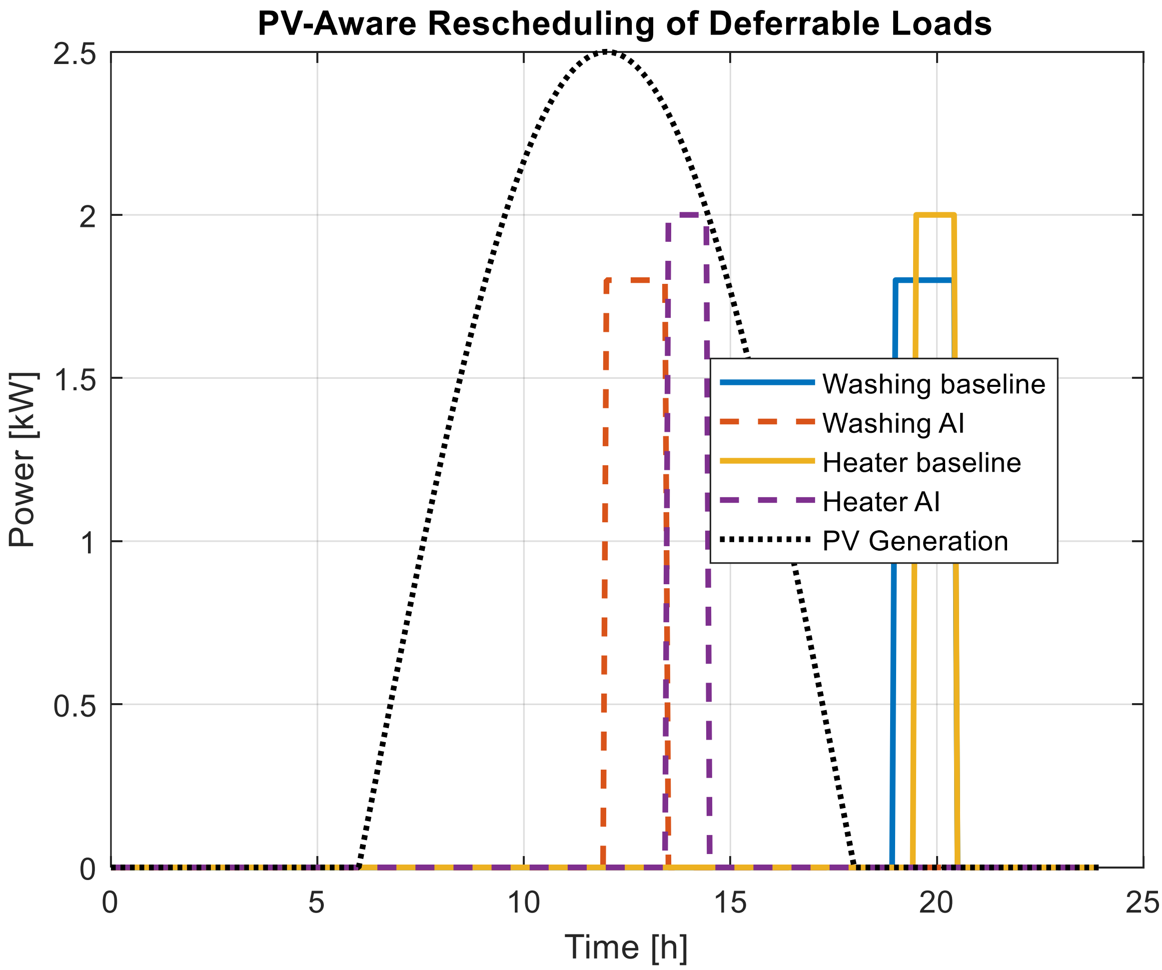

Figure 14. The proposed Energy Guardianship framework shifts flexible loads from evening hours to periods of high photovoltaic generation, increasing renewable energy utilization and reducing dependence on grid-supplied electricity.

The performance obtained with the proposed AI-assisted photovoltaic-aware scheduling strategy compared with the baseline scenario. The results show a significant improvement in the utilization of renewable energy resources. Photovoltaic self-consumption increases from 42% to 71%, considering the load profile in Figure 11, demonstrating the effectiveness of shifting flexible loads toward periods characterized by high solar generation. The improved synchronization between appliance operation and photovoltaic production also reduces the amount of energy purchased from the electrical grid, decreasing daily grid consumption from 8.3 kWh to 5.1 kWh. This reduction is particularly relevant for vulnerable households, as it contributes to lowering electricity costs and increasing energy autonomy. The increase in photovoltaic self-consumption should be interpreted as a consequence of the supervisory decision process rather than as the primary optimization objective. The framework continues to prioritize user protection while naturally improving renewable energy utilization.

It should be emphasized that this advanced functionality requires a comprehensive knowledge of the household's deferrable loads, including their operating constraints, flexibility windows, and user preferences. Furthermore, effective scheduling depends on a reliable forecast of the renewable energy generation expected for the following day, together with an estimation of the share of available energy that will be allocated to the vulnerable user within the Renewable Energy Community. These additional inputs enable the AI-based decision-making system to optimize appliance scheduling while ensuring both energy availability for critical loads and efficient utilization of locally generated renewable energy.

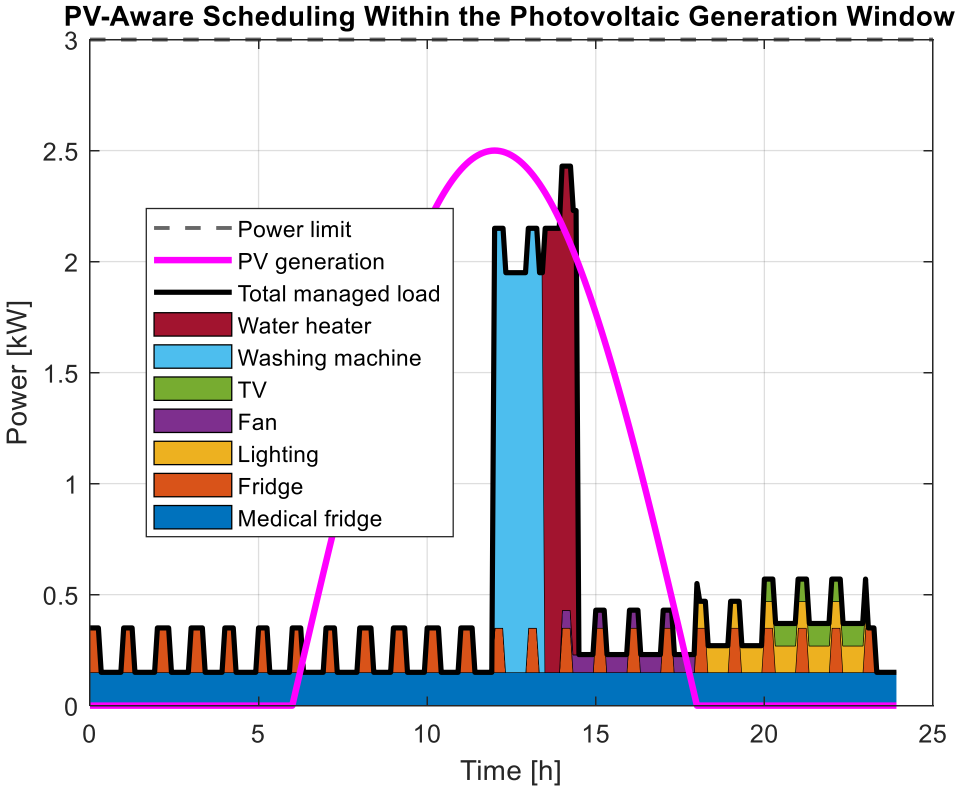

Figure 15. Photovoltaic-aware scheduling scenario. Flexible appliances are automatically shifted toward periods characterized by high photovoltaic generation, increasing renewable self-consumption while preserving battery reserves and ensuring the operation of critical loads.

Scenario 4–Guaranteed Flat-Power Service Through Community Battery Support

The fourth scenario explores a future extension of the proposed Energy Guardianship framework in which distributed battery storage resources available within a Renewable Energy Community are strategically used to support vulnerable users experiencing severe economic hardship. In this case, the objective is no longer limited to optimizing energy consumption or preventing temporary overload conditions. Instead, the framework is employed as a social energy protection mechanism capable of guaranteeing a minimum level of electrical service even for households that would otherwise face disconnection from the electrical grid due to payment arrears or other socio-economic vulnerabilities.

Under the current paradigm, users affected by prolonged financial difficulties may experience service interruptions that completely eliminate access to electricity. Such situations can have serious consequences, particularly for households relying on medically relevant devices, refrigeration of medicines, communication systems, or basic domestic services. The proposed Energy Guardianship approach introduces an alternative model in which a minimum electrical power allocation, referred to as a flat-power service, is maintained through the coordinated use of community battery resources and locally available renewable generation.

In this configuration, the framework continuously evaluates the minimum power required to support appliances classified as Critical and Essential. Rather than supplying all household loads, the available energy is reserved for a restricted set of services necessary to guarantee health, safety, and basic living conditions. Typical supported appliances include medical refrigerators, CPAP systems, medicine storage equipment, communication devices, basic lighting, and domestic refrigeration.

The guaranteed power allocation can be expressed as

$$P_{flat}(t) = \sum_{i \in \mathcal{C}} P_i(t) + \sum_{j \in \mathcal{E}} P_j(t)$$

where P_i and P_j denote the sets of critical and essential appliances, respectively, whose protection constitutes the core objective of the proposed Energy Guardianship framework.

Whenever community battery resources are available, the framework prioritizes the satisfaction of this minimum energy demand before allocating resources to lower-priority loads. Consequently, non-essential and deferrable appliances may remain unavailable, while vulnerable users continue to receive a guaranteed level of electricity sufficient to preserve fundamental energy services.

This approach introduces a significant conceptual shift in the role of energy management systems. Rather than acting exclusively as optimization tools, AI-based energy management platforms become instruments of social protection and energy inclusion. The objective evolves from maximizing efficiency toward guaranteeing a minimum right to energy access, consistent with emerging concepts of energy justice and socially inclusive energy transitions.

From the perspective of Renewable Energy Communities, the proposed mechanism can be interpreted as a form of collective solidarity. Community-shared batteries and renewable resources are not only used to improve economic performance but also to provide resilience services for the most vulnerable members of the community. Such a model could contribute to mitigating the effects of energy poverty, reducing involuntary service disconnections, and ensuring continuity of critical energy services during periods of economic or technical hardship.

The proposed scenario therefore extends the Energy Guardianship paradigm beyond conventional demand-side management. By combining AI-based load identification, ethical prioritization policies, and community energy resources, the framework enables the implementation of a guaranteed minimum-energy service capable of protecting vulnerable users while preserving the sustainability of the overall energy system.

The obtained results confirm that battery storage further increases the resilience of the Energy Guardianship framework, extending the operating time of critical appliances without modifying the underlying priority-based decision process.

Figure 16 illustrates the guaranteed power allocation strategy for vulnerable users under different operating conditions. The figure highlights how the proposed Energy Guardianship framework prioritizes the continuous supply of critical and essential appliances, ensuring a minimum guaranteed power level even when the available energy is limited due to grid constraints or reduced renewable generation. This behavior represents one of the key distinguishing features of the proposed approach, shifting the objective from conventional energy optimization toward the protection of vulnerable households.

Overall, the presented scenarios demonstrate that the proposed framework consistently integrates commissioning-assisted appliance identification, energy availability assessment and AI-based supervisory decision-making. The results confirm that Energy Guardianship is capable of dynamically allocating limited energy resources according to appliance criticality and user vulnerability, while improvements in renewable energy utilization emerge as a beneficial secondary effect rather than the primary objective of the proposed methodology.

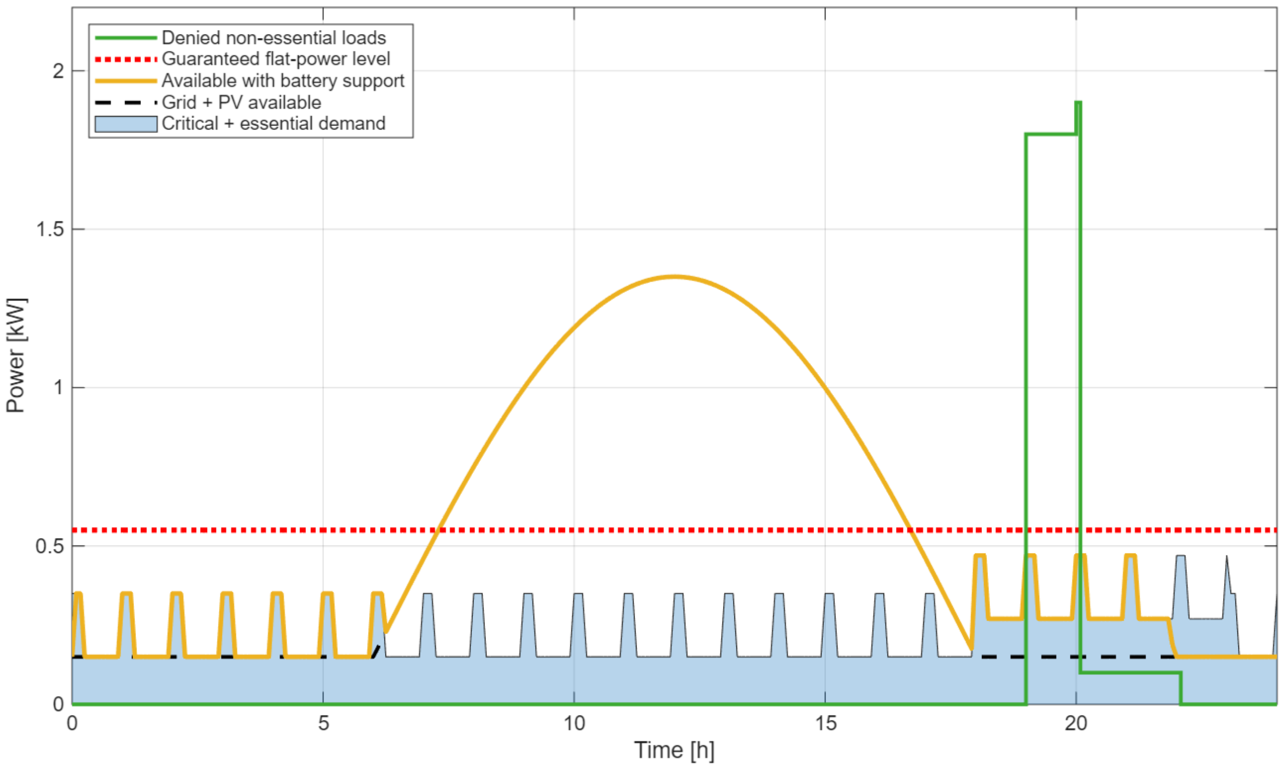

Figure 16. Operation of the proposed flat-power service concept for vulnerable users. The Energy Guardianship framework guarantees a minimum power allocation dedicated to critical and essential loads by combining residual grid power, community photovoltaic generation, and battery storage support. Non-essential loads are selectively denied during constrained operating conditions, ensuring continuity of medically relevant and basic residential services. The proposed approach transforms community energy storage from a conventional optimization resource into a resilience and social inclusion instrument capable of mitigating the effects of energy poverty.

6. Discussion: Thematic Clustering of Energy Poverty Mitigation Policies

To better position the proposed framework within the broader scientific discourse on energy poverty, a detailed analysis of the literature was conducted with particular attention to the systematic review identified as reference [50]. This study represents one of the most comprehensive recent investigations of the relationship between community energy initiatives, energy poverty alleviation, and social inclusion. By examining more than 200 scientific contributions, the review provides a valuable overview of the strategies currently adopted worldwide to improve energy accessibility for vulnerable households and to strengthen social participation within the energy transition process.

The proposed Energy Guardianship framework complements these policy-oriented approaches by introducing a technical supervisory layer capable of translating social protection principles into real-time operational decisions. Through the integration of commissioning-assisted appliance identification, energy availability assessment and AI-based decision-making, the framework provides a practical mechanism for prioritizing essential electrical services under constrained energy conditions.

Starting from the evidence collected in [50] and from the wider body of literature analyzed in this work, a thematic clustering of energy poverty mitigation policies was developed. The objective was not to perform a statistical clustering of publications, but rather to identify recurring intervention patterns, common objectives, and shared operational mechanisms emerging across different geographical contexts and regulatory frameworks. This process allowed the identification of five major policy clusters that collectively describe the evolution of current approaches to energy poverty mitigation.

The first cluster comprises economic support policies, including social tariffs, direct subsidies, financial assistance schemes, energy vouchers, and debt-relief mechanisms. These interventions primarily target the affordability dimension of energy poverty by reducing the economic burden associated with electricity and heating services. Although such measures often provide immediate relief to vulnerable households, their effectiveness is frequently dependent on the continuity of public funding, and they rarely address the structural causes of energy deprivation.

The second cluster includes energy efficiency policies, which focus on reducing energy demand through improvements in building performance and appliance efficiency. Typical measures involve thermal insulation, building retrofits, efficient heating and cooling systems, smart energy management technologies, and appliance replacement programs. Unlike economic support mechanisms, these interventions seek to generate long-term benefits by permanently reducing energy consumption and associated costs.

The third cluster encompasses energy literacy and participation policies, which aim to increase consumer awareness and promote informed energy-related behaviors. Educational campaigns, personalized energy advice, training programs, and community engagement initiatives belong to this category. The literature highlights that improved energy literacy can significantly enhance the effectiveness of both financial and technological interventions by enabling households to make better use of available resources.

The fourth cluster corresponds to community energy initiatives, which constitute the central focus of the review presented in [50]. These approaches include renewable energy communities, citizen energy cooperatives, collective self-consumption schemes, and shared generation projects. Beyond their economic benefits, community energy models contribute to social inclusion by encouraging citizen participation, local governance, collective ownership, and a more democratic management of energy resources. Several studies reviewed in [50] identify these initiatives as promising instruments for simultaneously addressing affordability, sustainability, and social cohesion.

The fifth cluster includes energy inclusion and protection policies, which specifically target vulnerable consumers exposed to energy insecurity or potential service disconnection. This category encompasses minimum service guarantees, protection from disconnection, identification of vulnerable users, emergency support mechanisms, and priority access to essential energy services. These measures recognize energy as a fundamental enabler of health, well-being, and social participation, and therefore seek to ensure continuity of supply even under adverse economic conditions. Figure 17 illustrates the clusters.

While the reviewed literature mainly focuses on regulatory measures, financial support, governance models and community participation, comparatively limited attention has been devoted to operational AI-based supervisory systems capable of implementing these policies at the household level. The proposed Energy Guardianship framework addresses this gap by combining appliance identification, ethical prioritization and adaptive energy allocation within a unified decision-making architecture. At first glance, the proposed Energy Guardianship approach may appear to overlap with the objectives of conventional HEMS. However, the two paradigms differ substantially. While HEMS optimize energy flows according to technical and economic criteria, Energy Guardianship places vulnerable people at the center of the decision-making process, ensuring that available energy is allocated according to human needs, appliance criticality, and social priorities rather than efficiency alone. Figure 18 summarizes this conceptual transition from energy management to energy protection.

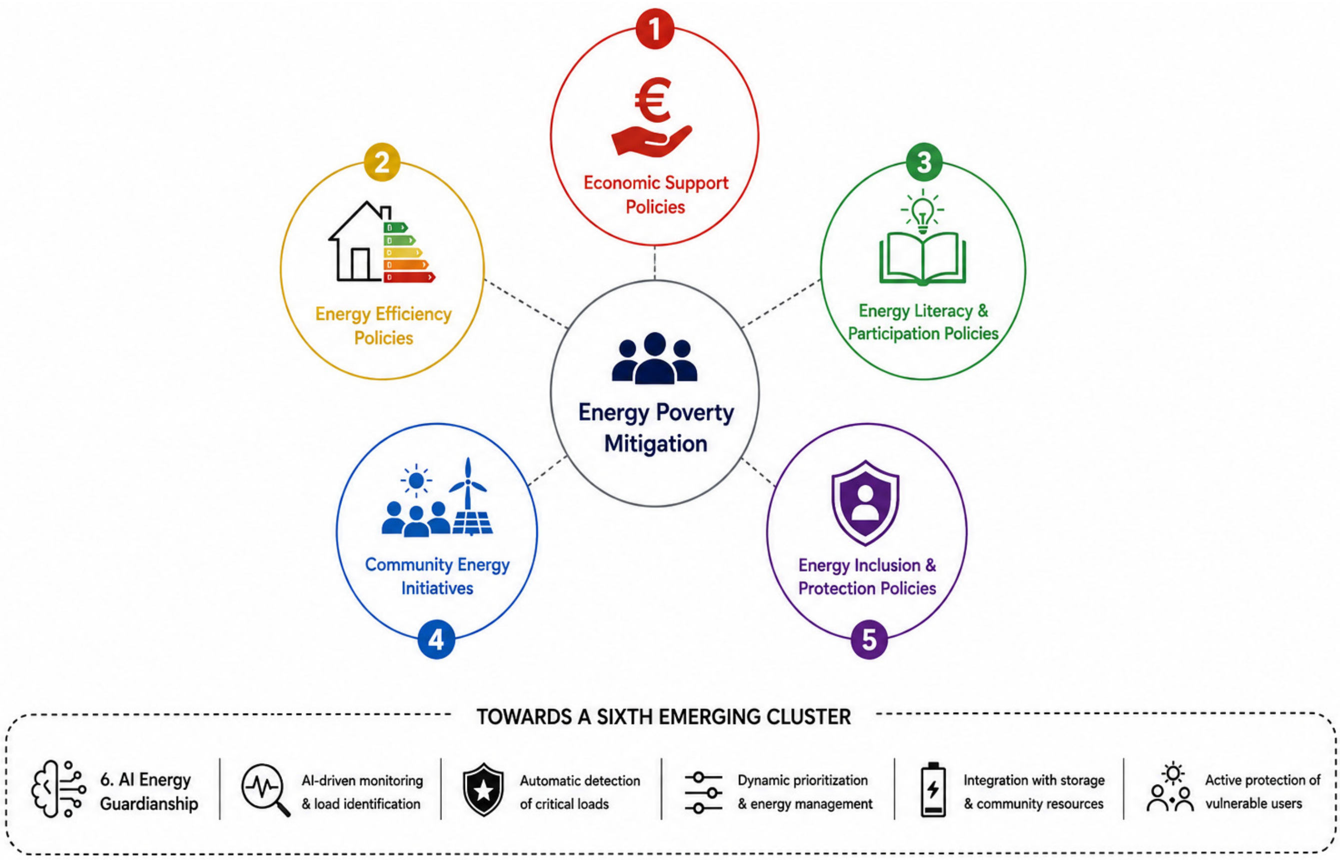

Figure 17. Literature-based clustering of energy poverty mitigation policies. The first five clusters summarize the principal policy approaches emerging from the analysis of more than 200 studies reviewed in [50]. Building upon these established categories, this work proposes a sixth cluster, AI Energy Guardianship, which integrates AI-based appliance identification, adaptive prioritization, and energy-aware decision-making to provide proactive protection for vulnerable energy users under constrained energy availability.

While the above five clusters effectively capture the dominant approaches currently discussed in the literature, the results obtained in this work suggest the emergence of a further policy dimension that is not yet fully represented in existing classifications. This sixth cluster can be described as AI Energy Guardianship. Unlike previous approaches, which have primarily focused on affordability, efficiency, education, participation, or protection, AI energy guardianship introduces intelligent and adaptive decision-making capabilities into the management of vulnerable consumers.

Within this paradigm, artificial intelligence techniques, non-intrusive load monitoring systems, predictive algorithms, and priority-aware energy management strategies can be combined to actively protect users rather than simply assist them. Critical appliances such as medical devices, refrigeration systems for medicines, communication equipment, and other essential loads may be automatically identified and prioritized during periods of limited energy availability. At the same time, non-essential loads can be postponed, curtailed, or rescheduled according to predefined protection policies.

The introduction of distributed energy resources, battery storage systems, and renewable energy communities further enhances the relevance of this emerging cluster. In such scenarios, energy management systems may evolve from passive monitoring tools into active guardians capable of dynamically allocating available resources to preserve essential energy services. Consequently, the concept of energy inclusion is extended beyond guaranteed access to electricity, embracing the broader objective of ensuring the continuous operation of services that are critical for health, safety, and social participation.

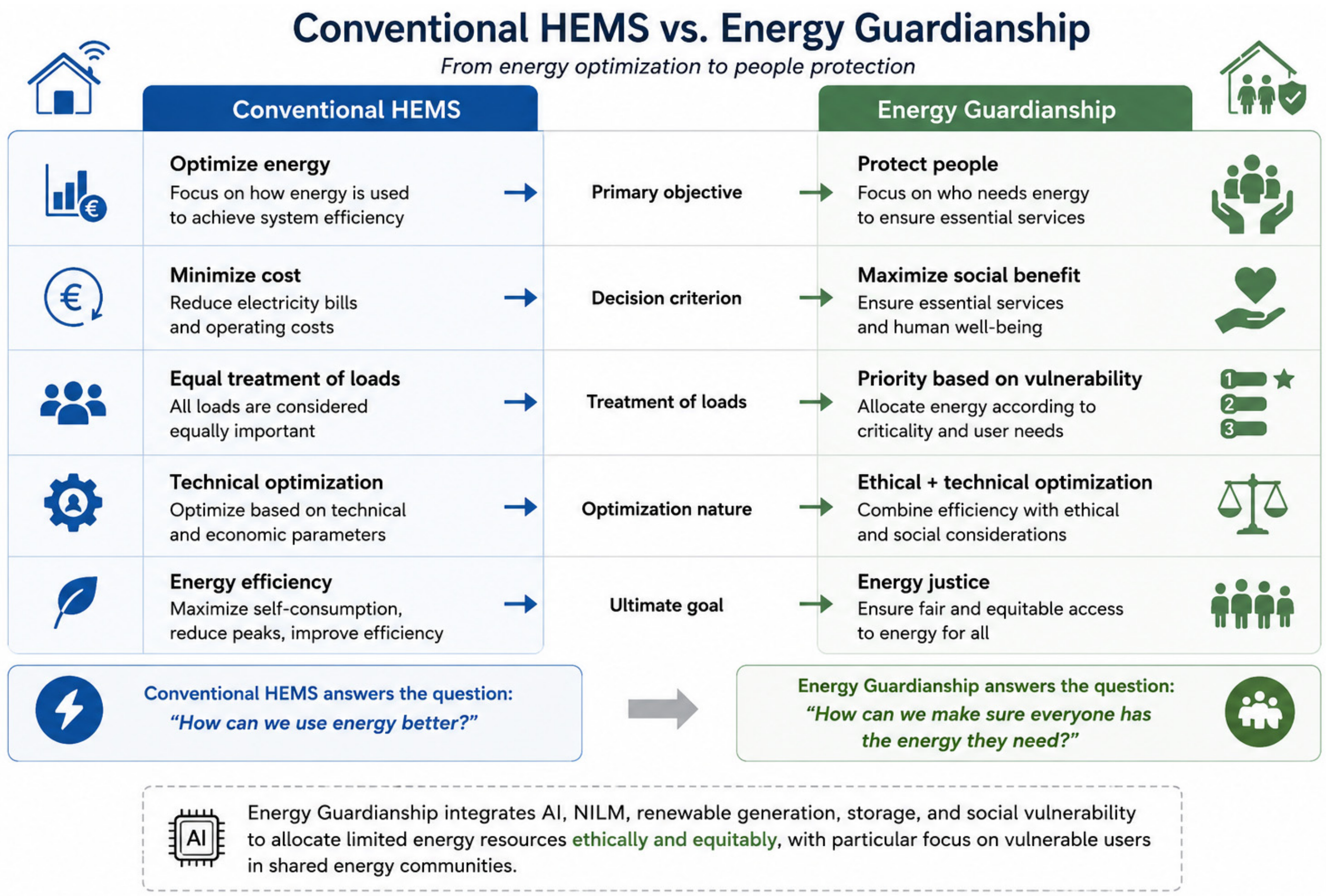

Figure 18. Comparison between conventional HEMS and the proposed Energy Guardianship approach. Unlike traditional HEMS, which focus on energy efficiency and cost optimization, Energy Guardianship prioritizes vulnerable users, combining AI-based energy management with technical, ethical, and social decision criteria to ensure equitable access to essential energy services.

Furthermore, the proposed AI energy guardianship paradigm may also contribute to a more profound transformation of current energy poverty mitigation strategies. Traditional protection mechanisms are generally based on power limitation schemes, where vulnerable users are guaranteed access to a restricted level of instantaneous power. However, in the presence of distributed energy resources, renewable energy communities, and battery energy storage systems, surplus renewable energy can be accumulated and subsequently allocated to vulnerable consumers according to social and technical priorities. Under these conditions, the protection paradigm could evolve from a power-based limitation approach toward an energy-based allocation framework. Rather than restricting users to a predefined maximum power level, vulnerable households could be guaranteed a minimum daily energy budget, dynamically supplied through stored renewable energy resources. Such an approach would provide greater operational flexibility while ensuring the continuity of essential services and promoting a more equitable utilization of locally available renewable energy. This shift may represent a significant step from energy protection toward genuine energy inclusion, where the objective is no longer merely to limit consumption, but to guarantee access to a sufficient quantity of energy required for daily living activities.

From this perspective, AI energy guardianship may represent the next evolutionary step in energy poverty mitigation policies, complementing existing approaches while offering new opportunities for the protection of vulnerable consumers within increasingly digitalized and decentralized energy systems.

Unlike conventional Home Energy Management Systems, whose primary objective is energy optimization, the proposed framework employs appliance identification as an enabling technology for protecting vulnerable users. Improvements in photovoltaic self-consumption and renewable energy utilization therefore emerge as complementary outcomes of the supervisory strategy rather than its principal objective. This distinction represents the defining characteristic of the proposed Energy Guardianship paradigm, Figure 19.

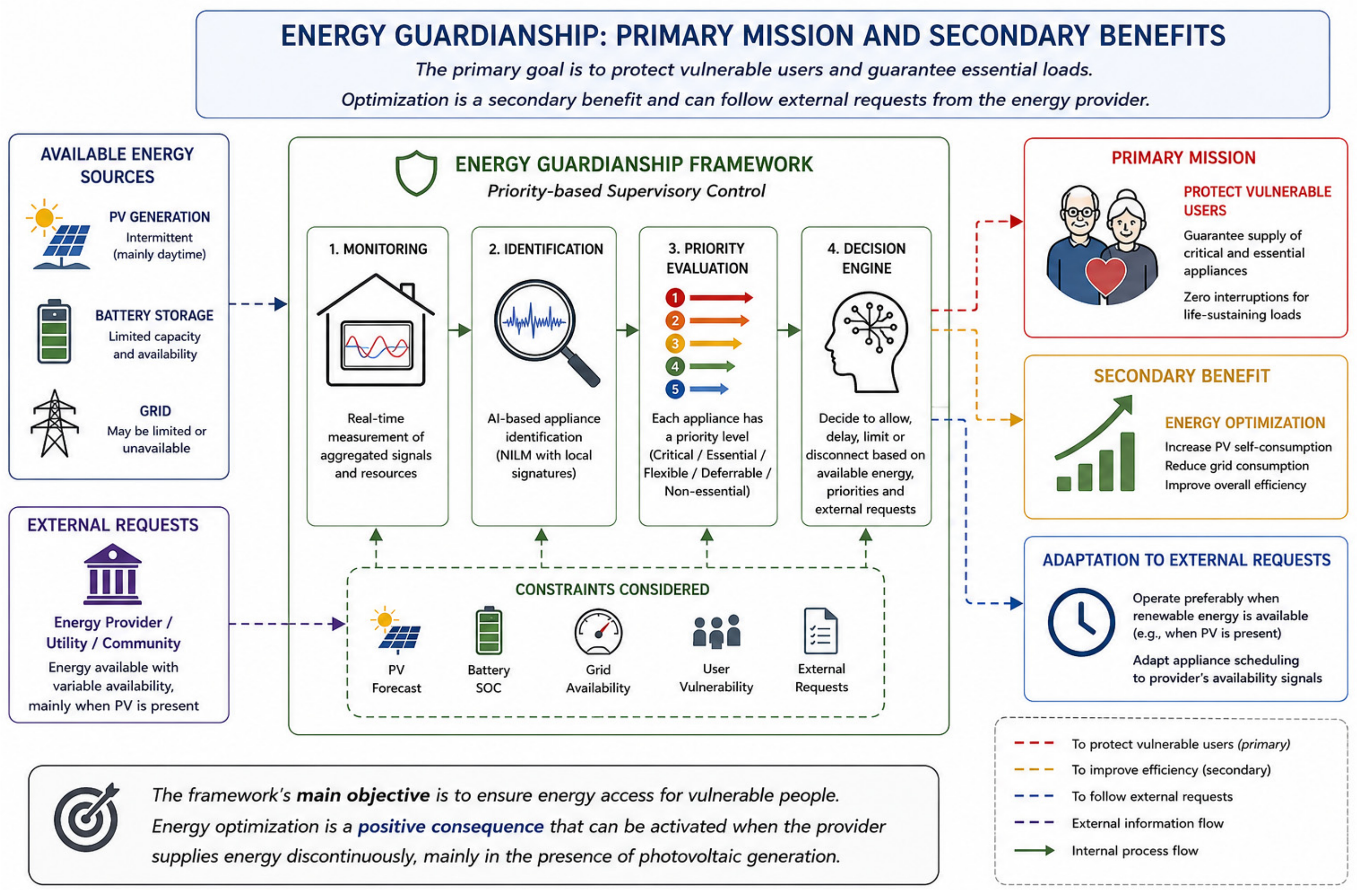

Figure 19. Conceptual architecture illustrating the primary objective and secondary benefits of the proposed Energy Guardianship framework. The supervisory system continuously evaluates locally available energy resources (photovoltaic generation, battery storage and grid availability), appliance priorities and external availability signals to ensure the uninterrupted supply of critical loads serving vulnerable users. While the protection of vulnerable households represents the primary mission of the framework, the same decision-making process can also improve renewable energy utilization and photovoltaic self-consumption whenever surplus energy is available or supplied according to external service-provider requests. Therefore, energy optimization emerges as a complementary outcome of the priority-based supervisory strategy rather than its principal objective.

Despite the encouraging results obtained from the proposed simulation scenarios, several challenges remain before large-scale deployment. Future implementations should investigate user acceptance, privacy-preserving management of appliance data, interoperability with existing smart-home platforms, and compliance with evolving regulatory frameworks governing Renewable Energy Communities. Moreover, large-scale experimental validation and hardware implementation will be necessary to further assess the robustness and practical applicability of the proposed Energy Guardianship framework under real operating conditions.

Beyond the current implementation, Artificial Intelligence is expected to play an increasingly important role in the evolution of the proposed Energy Guardianship framework. Rather than being limited to the final supervisory decision, AI transforms conventional electrical sensing into an intelligent appliance identification system capable of continuously learning from residential operation. The commissioning-assisted Local Appliance Atlas provides the initial knowledge base, while future AI algorithms may progressively update appliance signatures to compensate for aging effects, changes in operating conditions, supply voltage variations and the presence of electrically similar appliances. At the same time, distributed learning strategies can exploit knowledge collected from multiple households to refine priority coefficients and improve identification robustness, while preserving user privacy through local processing and privacy-preserving learning mechanisms. Artificial Intelligence may also adapt the priority model according to long-term user behavior and explicit user feedback. For example, if a medical device is permanently dismissed because it is no longer required or has become defective, the AI can progressively reduce its operational priority, allowing the available energy to be allocated to other appliances with lower Priority Index values that better reflect the user's current needs.

In this perspective, Artificial Intelligence becomes the enabling technology that continuously improves both appliance recognition and supervisory decision-making, making Energy Guardianship increasingly adaptive, resilient and suitable for large-scale deployment within Renewable Energy Communities.

7. Conclusions

This paper has presented an AI-based Energy Guardianship framework designed to support vulnerable households operating under constrained energy availability within Residential Renewable Energy Communities. Unlike conventional Home Energy Management Systems, whose primary objective is the optimization of energy consumption and economic performance, the proposed framework introduces a human-centered supervisory paradigm in which appliance criticality and user vulnerability become the principal decision criteria.

The proposed methodology is based on a two-stage architecture consisting of an offline commissioning phase and an online operational phase. During commissioning, the appliances installed in a dwelling are individually characterized to generate a Local Appliance Atlas containing multidimensional electrical signatures. During real-time operation, aggregate voltage and current measurements are analyzed through NILM techniques, allowing appliance identification within the commissioned residential environment and providing the information required by the AI-based supervisory decision engine. This house-specific approach simplifies the appliance identification problem while reflecting the practical deployment of residential energy management systems.

The presented simulation scenarios demonstrate the capability of the proposed framework to combine appliance identification, energy availability assessment and priority-based supervisory control. The results show that the framework successfully preserves the operation of critical appliances, manages power constraints through adaptive load scheduling and supports the integration of photovoltaic generation and battery storage under representative residential operating conditions.

Although the proposed supervisory strategy naturally increases renewable energy utilization and photovoltaic self-consumption, these improvements should be regarded as complementary outcomes rather than the primary objective of the framework. The central purpose of Energy Guardianship remains the protection of vulnerable users through the continuity of essential household services whenever the available energy becomes insufficient to satisfy all electrical demands.

Future research will focus on extending the proposed framework by integrating predictive renewable generation models, battery aging models, dynamic electricity pricing and real-time interaction with energy service providers. These developments will enable Energy Guardianship to support coordinated energy allocation within Renewable Energy Communities while preserving its fundamental mission of ensuring equitable, resilient and socially aware access to electrical energy.

On the other hand, a future development of the proposed Energy Guardianship framework is the introduction of adaptive learning mechanisms capable of continuously refining appliance priorities according to long-term user behavior and explicit user feedback. This would allow the supervisory system to progressively adapt to changes in household needs, such as the installation of new appliances, the dismissal of medical devices, or variations in user habits, while preserving the overall priority-based decision strategy. Such adaptive capabilities would further improve the flexibility, personalization, and long-term effectiveness of the proposed framework.

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