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Deep Learning-Based Home Energy Management Incorporating Vehicle-to-Home and Home-to-Vehicle Technologies for Renewable Integration

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Abstract: Smart cities embody a transformative approach to modernizing urban infrastructure and harness the power of deep learning (DL) and Vehicle-to-Home (V2H) technology to redefine home energy management. Neural network-based Q-learning algorithms optimize the scheduling of household appliances and the management of energy storage systems, including batteries, to maximize energy efficiency. Data preprocessing techniques, such as normalization, standardization, and missing value imputation, are applied to ensure that the data used for decision making are accurate and reliable. V2H technology allows for efficient energy exchange between electric vehicles (EVs) and homes, enabling EVs to act as both energy storage and supply sources, thus improving overall energy consumption and reducing reliance on the grid. Real-time data from photovoltaic (PV) systems are integrated, providing valuable inputs that further refine energy management decisions and align them with current solar energy availability. The system also incorporates battery storage (BS), which is critical in optimizing energy usage during peak demand periods and providing backup power during grid outages, enhancing energy reliability and sustainability. By utilizing data from a Tunisian weather database, smart cities significantly reduce electricity costs compared to traditional energy management methods, such as Dynamic Programming (DP), Rule-Based Systems, and Genetic Algorithms. The system's performance is validated through robust AI models, performance metrics, and simulation scenarios, which test the system's effectiveness under various energy demand patterns and changing weather conditions. These simulations demonstrate the system's ability to adapt to different operational environments.

Keywords: deep learning; home energy management; renewable energy; reinforcement learning; smart home automation

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1. Introduction

Smart cities aim to enhance sustainability, efficiency, and quality of life by leveraging advanced technologies to optimize energy management. In this context, Artificial Intelligence (AI) has emerged as a transformative tool to significantly improve the HEMS. Integrating EVs and V2H technology within the HEMS is significant in achieving residential energy optimization [1]. This study introduces the development and implementation of an intelligent system that reduces energy consumption and enhances user experience. The system efficiently schedules household appliances, manages energy storage, and integrates EVs by employing Q-learning algorithms based on neural networks. The proposed solution fosters cost-effective energy management and aligns with the sustainability goals of smart cities, ensuring more innovative and resilient residential energy utilization [2].

Challenges within the Internet of Energy (IoE) and Smart Grid 2.0 (SG 2.0) require innovative solutions to enhance energy efficiency and optimize power distribution. The major shift from decentralized grid management to systems managed by Distribution System Operators (DSOs) highlights the importance of smart energy communities. Integrating deep learning-based home energy management systems enables fine-grained control and optimization, especially with V2H and H2V technologies. These developments align with the goals of SG 2.0, providing dynamic and flexible energy management solutions for modern energy infrastructure [3,4]. The Internet of Things (IoT) is a cornerstone for developing smart homes and energy communities. The proposed deep learning-based system efficiently collects and processes real-time data from PV installations by deploying IoT-enabled devices. This facilitates dynamic control, power scheduling, and load balancing in line with the goals of SG 2.0.

Moving away from Smart Grid 1.0, which relied primarily on fixed smart meters, SG 2.0 emphasizes real-time decision making, adaptive energy integration, and the efficient use of diverse renewable energy sources. Including V2H and H2V technologies allow energy to be stored and transferred between EVs and households, enhancing the flexibility and reliability of energy systems [5,6]. Renewable energy integration is key to the proposed deep learning-based energy management system. By leveraging real-time PV statistics and weather data from Tunisia, the system dynamically adjusts energy consumption according to prevailing conditions, ensuring optimal energy utilization. Integrating V2H and H2V technologies allows EVs to act as mobile energy storage units, significantly improving energy efficiency. This approach achieves significant cost savings and enhances energy sustainability while supporting the transition to cleaner energy sources. Compared to traditional optimization techniques such as Integer Linear Programming (ILP), the deep learning-based framework shows superior adaptability to real-time fluctuations, efficiently managing energy flows to meet residential energy demands [7]. The proposed deep learning-based home energy management system effectively schedules appliances, manages EV power transmission, and optimizes household energy consumption. By integrating V2H and H2V technologies, the system dynamically adapts to energy availability and demand changes. Deep learning algorithms, especially Q-learning neural networks, enable the system to make real-time decisions that maximize energy utilization and minimize costs. This not only addresses the limitations of previous approaches, such as ILP, but also enhances the overall efficiency and flexibility of the system [8]. Adopting deep learning technologies for home energy management provides a robust framework for achieving renewable energy integration. By integrating V2H and H2V technologies, the system facilitates dynamic scheduling, real-time energy control, and the efficient utilization of renewable resources. Integrating IoT and real-time PV data enhances energy management capabilities, ensures optimal performance, and significantly saves costs. This approach aligns with the goals of SG 2.0, providing a scalable and sustainable solution to address modern energy management challenges.

The effectiveness of deep learning-based home energy management systems has been demonstrated through extensive simulations, showing a 23% reduction in monthly electricity expenditure compared to conventional methods. This study analyzes the system's performance, including algorithmic efficiency comparisons, simulation models, renewable energy integration, and security aspects. The integration of V2H and H2V technologies plays a pivotal role in improving household energy consumption, especially for EVs. These developments highlight the potential to enhance sustainability, affordability, and efficiency in residential energy systems [9,10]. The proposed system leverages neural network-based Q-learning algorithms to optimize appliance scheduling, energy storage management, and

EV power transmission. This approach outperforms conventional methods, such as ILP, by efficiently managing real-time data and adapting to dynamic energy demands. The integration of real-time PV statistics and weather data from Tunisia enables the system to adjust energy consumption based on prevailing conditions dynamically, achieving significant cost savings and energy efficiency [11,12].

Blockchain technology enhances the reliability and security of energy transactions within this system. Previous studies have demonstrated the effectiveness of blockchain in enabling P2P energy trading, ensuring secure and transparent transactions [13]. Integrating blockchain with V2H technology enhances the reliability of energy transmission, supporting efficient and sustainable energy management [14–16].

In [17], the authors proposed a stateful directed grey box fuzzer for smart contracts, which addresses inefficiencies in existing fuzzers by prioritizing testing on code areas and states prone to vulnerabilities. The method effectively targets contract code and state spaces by leveraging static analysis, pattern matching, and a novel fitness metric. This approach demonstrates superior efficiency and precision compared to state-of-the-art techniques, advancing intelligent contract vulnerability detection in decentralized applications.

In [18], the authors proposed PonziSleuth, the first LLM-driven approach for detecting Ponzi smart contracts without requiring labeled training data. By leveraging advanced language understanding capabilities through a novel two-step zero-shot chain-of-thought prompting technique, PonziSleuth achieves a balanced detection accuracy of over 96% using Generative Pre-trained Transformer (GPT-3.5-turbo). Indeed, The GPT-3.5-turbo model is developed and provided by OpenAI, headquartered in San Francisco, CA, USA. It demonstrated effectiveness in real-world applications by identifying 15 new Ponzi schemes with minimal false positives and zero false negatives. This work significantly advances blockchain security by addressing the limitations of previous methods, such as dependency on labeled data and difficulty detecting novel Ponzi schemes.

In [19], the authors proposed a federated model-agnostic meta-learning (FMAML) approach for short-term load forecasting (STLF) in distribution transformer supply zones to address the challenge of data privacy in distribution systems, which limits the effectiveness of traditional centralized forecasting methods. Integrating federated learning with model-agnostic meta-learning enhances client personalization and compatibility, improving forecasting accuracy without compromising data privacy.

In [20], the authors introduced a two-stage data-driven approach for coordinating individual microgrids within a networked microgrid (NMG) system. The first stage involves hourly scheduling of the active power outputs of microturbines and energy storage systems to achieve energy balance and cost minimization. The second stage employs a safe deep reinforcement learning method to manage real-time operations, ensuring decentralized and efficient coordination among the microgrids.

While the system shows significant progress, there are still areas for further improvement. The extensive integration of EVs and V2H is essential to ensuring scalability for larger power grids. Integrating additional renewable sources, such as wind and hydropower, can diversify and enhance energy reliability. A comprehensive Return on Investment (ROI) analysis is essential to assess the system's economic viability for households. Additionally, addressing data security challenges, especially for IoT devices involved in energy management, is critical to ensuring privacy and system integrity.

As summarized in Table 1, our study addresses the limitations of traditional methods by integrating advanced deep learning techniques with V2H and H2V technologies for optimized energy management.

Table 1. Key developments and comparative analysis of SmartGrid AI vs. previous works.

Refs.	Criteria	Our Approach	Previous Works
[1,2]	Optimization Technique	Utilizes neural network-based Q-learning for dynamic scheduling, enabling real-time adaptability	Relies on Integer Linear Programming (ILP) and other reinforcement learning techniques, which are often less flexible
[3]	Blockchain Integration	N/A	Focuses on peer-to-peer (P2P) energy trading but lacks universal application across all systems
[4]	Real-Time Data Usage	Integrates real-time PV statistics and weather data from Tunisia for dynamic energy management	Primarily relies on historical data or static integration, limiting adaptability to current conditions
[5]	Cost Reduction	Achieves 23% reduction in monthly electricity costs through optimized scheduling and energy management	Traditional methods demonstrate less significant cost savings and are generally less efficient
[6]	Algorithmic Efficiency	Implements advanced deep learning algorithms for dynamic energy scheduling and decision making	Conventional approaches are less adaptive and struggle with real-time fluctuations in energy demand and supply
[7]	Renewable Energy Integration	Optimizes energy use by dynamically incorporating real-time renewable energy data	Integration of renewable energy sources is often static and less responsive to real-time availability
[8]	Security Features	Focuses on secure and efficient energy transactions, ensuring transparency and trust	Security mechanisms vary; some systems lack transparency and robust security that are found in our approach
[9]	Performance Metrics	Demonstrate improved efficiency and effectiveness through comprehensive simulations	Performance evaluations are often limited to isolated metrics, lacking holistic system analysis
[10]	Simulation Models	Includes performance metrics, algorithm efficiency, and renewable integration in simulation models	Models often focus on specific components without achieving full system integration

The proposed deep learning-based system effectively integrates AI, real-time PV data, and V2H technologies to provide an innovative solution for improving residential energy management. Simulations demonstrate its ability to reduce electricity costs while enhancing energy efficiency, scalability, and reliability. By overcoming current limitations, this approach lays the foundation for an efficient adoption of innovative, sustainable, and cost-effective energy systems in future smart energy societies.

2. Methodology

2.1. System Design and Integration

The proposed system integrates advanced deep learning techniques with V2H/H2V technologies to optimize residential energy management, improve efficiency, and reduce costs. Real-time data from photovoltaic PV systems, electric vehicles (EVs), household appliances, and Tunisian meteorological databases are collected using IoT-enabled devices, ensuring accurate inputs for decision making. Preprocessing techniques, such as normalization and feature extraction, refine the data for use in a neural network-based Q-learning algorithm. This algorithm dynamically schedules appliances, manages energy storage systems, and determines optimal energy flow between EVs and homes, minimizing electricity costs and maximizing renewable energy utilization. The system employs V2H technology to discharge energy from EVs during peak demand or grid outages and H2V to charge EVs during surplus PV generation or low-demand periods. Household battery storage is further integrated to enhance energy availability and reliability during peak usage. Simulations validate the system's performance, demonstrating a 23% reduction in monthly electricity costs compared to conventional methods such as Dynamic Programming and Rule-Based Systems. This design ensures adaptability, efficiency, and sustainability, aligning with the energy goals of modern smart homes. Appendix A provides a detailed summary of household appliances, categorized along with their corresponding power values and intended operational times.

Figure 1 demonstrates system architecture, highlighting the integration of real-time data acquisition, deep learning models, V2H/H2V technologies, and dynamic appliance scheduling. The figure illustrates energy flow and data across PV systems, EVs, batteries, and household appliances for cost-effective and sustainable energy management.

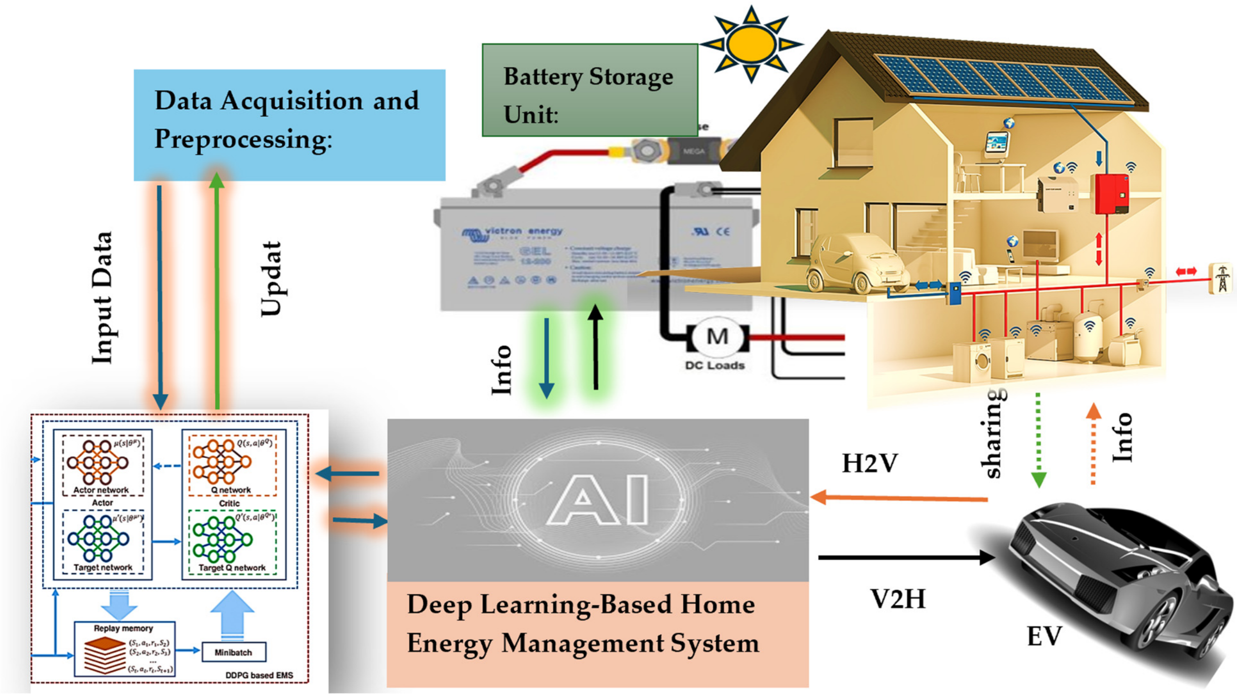

Figure 1. System architecture of deep learning-based home energy management system.

2.1.1. Problem Statement

The increasing integration of renewable energy sources like PV systems and the growing adoption of EVs pose significant challenges for traditional home energy management systems (HEMSs). Existing methods, such as DP and Rule-Based Systems, need more adaptability to real-time energy variability and can optimize energy flows effectively. These approaches need help incorporating V2H and H2V technologies, resulting in unused surplus energy, higher electricity costs, and increased grid reliance during peak demand. Static appliance scheduling further limits energy efficiency and sustainability.

We propose an adaptive deep learning-based system that integrates real-time PV generation data, EV energy flows, and dynamic appliance scheduling using neural network-based Q-learning algorithms to address these limitations. The system optimizes energy storage, manages V2H/H2V energy transfers, and ensures surplus energy is used efficiently or stored during peak periods. Figure 2 illustrates the solution architecture, showcasing real-time data acquisition, deep learning optimization, and dynamic energy management, which achieve a 23% reduction in electricity costs, improved energy efficiency, and enhanced renewable energy utilization. This scalable approach ensures smarter, more resilient, and sustainable residential energy systems.

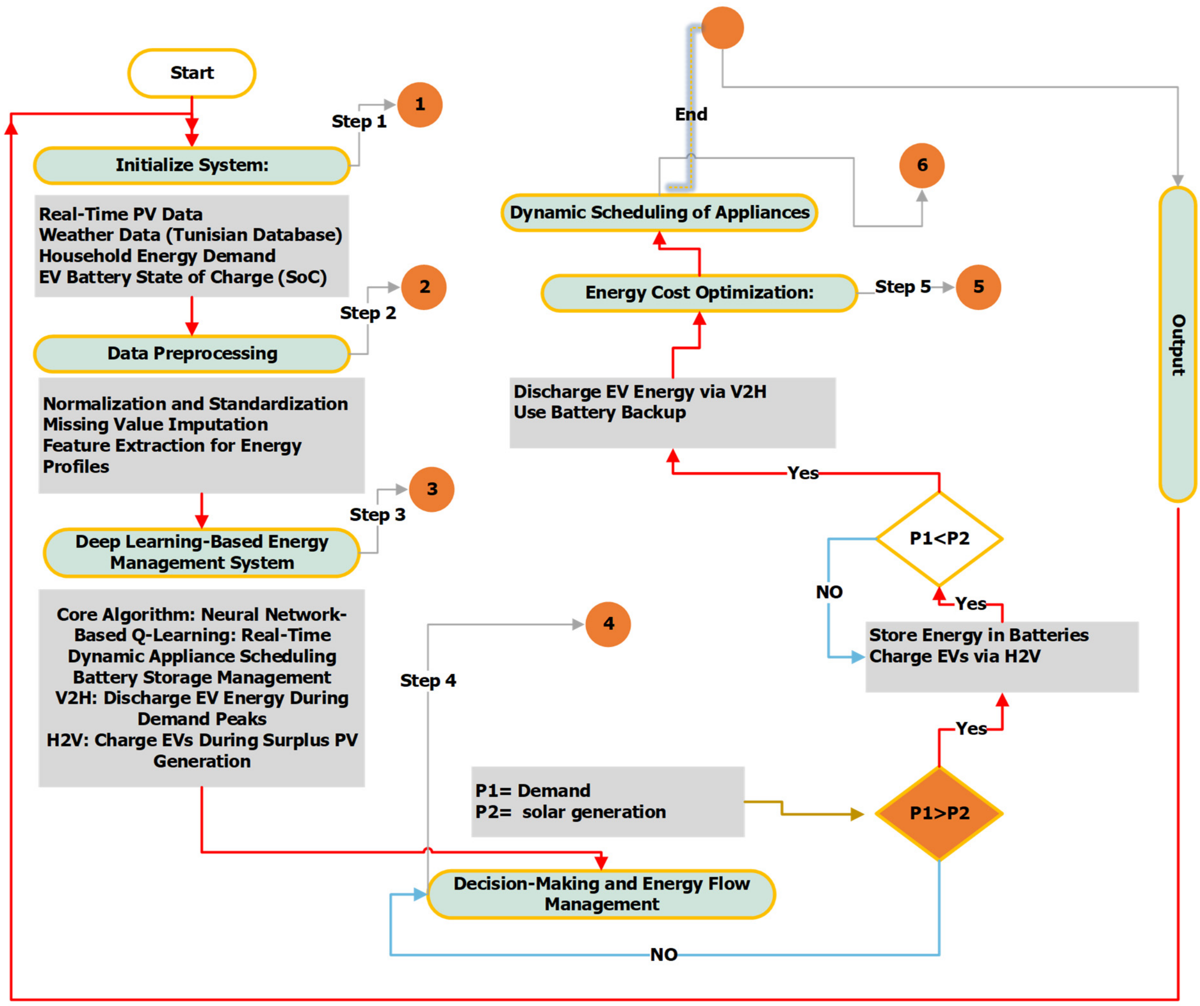

Figure 2. Problem statement and solution architecture.

2.1.2. Power Consumption Calculation for Household Appliances

Equation (1) governs the dynamic scheduling of variable appliances, such as washing machines and EV charging, to operate during cost-efficient periods. Appliances are turned on (1) when the energy costs, C(t), fall below a predefined threshold, and photovoltaic (PV) generation exceeds the appliance demand; otherwise, appliances are deferred (off = 0). By aligning appliance operation with real-time energy availability, the system effectively reduces electricity costs while maximizing the use of renewable energy. A matrix-based approach is employed to determine household appliance power consumption across various time intervals, leveraging two primary metrics: the Power Rating Matrix (P) and the Operating Time Matrix (T) [21].

$$\left| \begin{array}{l} \begin{cases} \begin{cases} P_i(t) = \{\mathbf{1\ if\ C}(t) \leq C_{thresholdand} - and \\ E_{PV}(t) > D_{appliance}(t) \end{cases} \\ P_i(t) = \{0\ otherwise \end{cases} \\ \begin{cases} P = \begin{bmatrix} P_{11} & P_{11} & & P_{1M} \\ P_{21} & P_{22} & & P_{21} \\ \cdots & \cdots & \cdots & \cdots \\ P_{N1} & P_{N1} & P_{N1} & P_{N1} \end{bmatrix} < -- > T = \begin{bmatrix} T_{11} & T_{11} & & T_{1M} \\ T_{21} & T_{22} & & T_{21} \\ \cdots & \cdots & \cdots & \cdots \\ T_{N1} & T_{N1} & T_{N1} & T_{N1} \end{bmatrix} \end{cases} \end{array} \right. \quad (1)$$

where P denotes the time the i-th device operates during the j-th time interval. The matrix T_i represents the duration of operation for each device for each i-th time interval. $A_i(t)$:

appliance i has an operational status (on = 1; off = 0) at time t. $C(t)$: real-time energy cost. $C_{threshold}$: cost threshold for scheduling. $D_{appliance}(t)$: energy demand of appliance i. The runtime intervals for devices are classified into shiftable, non-shiftable, and fixed types. For shiftable devices, the runtime $T_{rs,i}$ spans from $t_{ss,i}$ to $t_{es,i}$. Non-shiftable devices have a fixed runtime $T_{rn,i}$ between $t_{sn,i}$ and $t_{en,i}$, while fixed devices operate strictly within $T_{rf,i}$ from $t_{sf,i}$ to $t_{ef,i}$. Here, t represents any time within these intervals (see Equation (2)) [22].

$$
\begin{aligned}
T_{rs,i} &= \{t \mid t_{ss,i} \leq t \leq t_{es,i}\}, \forall i \in Is \\
T_{rn,i} &= \{t \mid t_{sn,i} \leq t \leq t_{en,i}\}, \forall i \in In \\
T_{rf,i} &= \{t \mid t_{sf,i} \leq t \leq t_{ef,i}\}, \forall i \in IF
\end{aligned}
\tag{2}
$$

2.1.3. Total Power Consumption

The total power consumption, $J(i,j)$, for each device i, is calculated as the sum of the product of its power rating $P_{i,j}$ and operating time i,j over all periods j (Equation (4)). Here, $P_{i,j}$ represents the device's power during period j, and $T_{i,j}$ denotes its operating time. For shiftable devices, $T_{i,j}$ is the duration between their start and end times. Similarly, non-shiftable devices have defined operating periods, while fixed devices operate within a predetermined schedule. This approach accurately accounts for fluctuating daily energy consumption patterns [23].

$$
\left|
\begin{aligned}
&E_{demand}(t) = P_{PV}(t) + E_{V2H}(t) + \\
&E_{BS}(t) + E_{grid}(t) \\
&J(\mathrm{i,j}) = \sum_{j=1}^{M} (P_{ij} * Tij)
\end{aligned}
\right.
\tag{3}
$$

where $E_{demand}(t)$: total energy demand at time t; $P_{PV}(t)$: real-time PV energy generation; $E_{V2H}(t)$: energy discharged from EV to home; $E_{BS}(t)$: energy supplied from battery storage; $E_{grid}(t)$: grid-supplied energy.

2.1.4. Predictive Energy Demand Modeling

The Q-learning algorithm dynamically minimizes energy costs by utilizing a reward function. This function evaluates the effectiveness of actions taken by the system, guiding it toward optimal energy management strategies while adapting to changing conditions in real-time. The reward $R(t)$ is negatively weighted by grid energy costs $C_{grid}(t)$, while energy transfers via V2H and H2V are penalized or incentivized through weighting factors λ_1 and λ_2. The system learns to prioritize cost-effective energy decisions by optimizing this reward function, ensuring efficient energy utilization [24] (see Equation (5)).

$$
\left|
\begin{aligned}
&R(t) = -[C_{grid}(t) + \lambda_1 \cdot E_{V2H}(t) - \lambda_2 \cdot E_{H2V}(t)] \\
&E = \begin{bmatrix}
P_{PV}(1) & E_{BS}(1) & E_{V2H}(1) & E_{grid}(1) \\
P_{PV}(2) & E_{BS}(2) & E_{V2H}(2) & E_{grid}(2) \\
P_{PV}(3) & E_{BS}(3) & E_{V2H}(3) & E_{grid}(3) \\
 & & & \\
P_{PV}(T-1) & E_{BS}(T-1) & E_{V2H}(T-1) & E_{grid}(T-1) \\
P_{PV}(T) & E_{BS}(T) & E_{V2H}(T) & E_{grid}(T)
\end{bmatrix}
\end{aligned}
\right.
\tag{4}
$$

The energy scheduling matrix (E) organizes real-time energy flows over T time steps, capturing contributions from PV generation, battery discharge, EV energy transfer (V2H), and grid energy. This matrix provides a compact performance evaluation and optimization representation, enabling the system to analyze and predict energy flows under varying operational conditions.

2.2. Data Preprocessing Techniques

Data preprocessing is a critical step in data analysis, ensuring raw data are clean, consistent, and suitable for analysis. It involves handling missing values, removing outliers, standardizing data, and converting categorical variables into numerical formats (Equation (5a)). Normalization (Equation (5b)) and standardization adjust data scales and distributions, improving model accuracy. Missing values are often addressed through averaging (Equation (5c)), while outliers can be identified using the z-score method (Equation (5d)). Effective preprocessing enhances the accuracy and reliability of analytical models, enabling better decision making and optimization, especially with real-time data impacts (Equation (5e)) [25].

$$x_{norm} = \frac{x_{max} - x_{min}}{x - xmin} \tag{5a}$$

$$y_{imputed} = \frac{1}{N}\sum_{i=1}^{N} y_i \tag{5b}$$

$$y_{std} = \frac{\sigma}{y - \mu} \tag{5c}$$

$$Z = \frac{\sigma}{z - \mu} \tag{5d}$$

$$D^A(\mathrm{t}) = \frac{1}{1 + exp(-(\alpha \cdot Real - Time\ Data + \beta))} \tag{5e}$$

2.3. Energy Management and V2H Technology

Energy management in the system involves dynamically optimizing grid energy, energy storage, and V2H technology. The following equations are central to this process (see Equation (6)). This constraint ensures that the state of charge (SoC) of the energy storage system remains within safe operating limits, avoiding both overcharging and excessive discharge. To ensure the durability of the storage units and to provide a consistent energy supply, it is crucial to keep the state of charge (SoC) within the range of $0 \leq SoC(t) \leq SoCmax$, where $SoC(t)$ is the state of charge at a given time, t, and $SoCmax$ is the maximum capacity of the storage units. The V2H transfer constraint regulates the energy flow from the electric vehicle to the home, ensuring that it remains within the transfer capacity of the system ($0 < P_{V2H}(t) \leq P_{V2H}max$). This optimizes energy distribution without overloading the vehicle's resources [26].

$$\begin{cases} P_{in} - P_{out} = \Delta P_{storage} \\ SoC^{BS}(t) = SoC^{BS}(t-1) + \frac{P^{BS}{}_{charge}(t) - P^{BS}{}_{discharge}(t)}{P^{BS}{}_{max}(t)} \\ SoC^{EV}(t) = SoC^{EV}(t-1) + \frac{P^{EV}{}_{charge}(t) - P^{EV}{}_{discharge}(t)}{P^{EV}{}_{max}(t)} \\ P_{V2H}\,(t) = \eta_{V2H}\, \cdot P_{EV}\,(t) \cdot \Delta t \\ 0 \leq SoC^{BS,EV}(t) \leq SoC^{BS,EV}{}_{max} : C^1 \\ 0 \leq P_{V2H}\,(t) \leq P_{V2H} max : C^2 \end{cases} \tag{6}$$

2.4. Cost Optimization

The primary goal of the approach is to minimize overall energy consumption costs while meeting energy demands. This is achieved by optimizing the use of grid energy, energy storage, and V2H technology while also accounting for IT costs related to blockchain processes. The optimization process is driven by an objective function that evaluates operating cost reductions and the long-term financial benefits of integrating renewable energy sources and advanced storage systems. Compared to traditional methods like ILP, the approach reduces monthly electricity costs by up to 23% and promotes sustainable energy use by maximizing renewable energy utilization. This cost-optimization approach ensures significant consumer savings, exceptional energy efficiency, and system reliability, as expressed in Equation (7) [26].

$$\begin{cases} K = min\sum_{1}^{T}(C_{grid}(t)\cdot P_{grid}(t) + C_{storage}(t)\cdot P_{storage}(t) + C_{V2H}(t)\cdot \\ C_{total} = t = \sum_{1}^{T}[C_{grid}(t)\cdot E_{grid}(t) + C_{charge}(t)\cdot E_{H2V}(t) - C_{discharge}(t)\cdot E_{V2H}(t)] \end{cases} \tag{7}$$

2.5. Optimized Appliance Scheduling Using Neural Network-Based Q-Learning

The neural network-based Q-learning approach optimizes household appliance schedules by utilizing a comprehensive state vector St, which includes key parameters such as total energy consumption $P_{total}(t)$, state of charge of the energy storage system $SoC(t)$, power generated by PV systems $P_{PV}(t)$, power drawn from the grid $P(t)$, power supplied to the grid $P_{grid}(t)$, forecasted energy demand $J^{\text{forecasting}}(i,j)$, and current electricity cost $C_{grid}(t)$. The action vector At defines actions such as turning appliances on/off, adjusting their power consumption, or redistributing energy flows. The Q-learning algorithm updates its Q-values using the Q-learning update equation (Equation (8)), allowing the system to adaptively optimize appliance operation, energy storage usage, and energy transfers in real time. This approach effectively minimizes energy costs, balances energy demand, and maximizes renewable energy utilization, ensuring an efficient and dynamic energy management strategy [27]. Table 2 summarizes the parameters of the state and action vectors.

$$\begin{cases} Q(S_t, A_t) = Q(S_t, A_t) + \alpha[R(S_t, A_t) + \gamma A\prime maxQ(S_t + 1, A\prime) - Q(S_t, A_t)] - P_{comfort}(t) \\ A_t = [App_1, App_2, \ldots, App_n] \\ S_t = [P_{grid}(t), SoC(t), P_{PV}(t), P_{grid}(t), \mathbf{J^{forecasting}}(\mathbf{i}, \mathbf{j}),, C_{grid}(t)] \\ R(S_t, A_t) = -(\mathbf{P}_{total}(\mathbf{t}) \times i = \sum_{i}^{n} P_i(t) \times T_i(t)) \\ P_{comfort}(t) = \lambda\sum_{i}^{n}(\mid Ti^{desired} - Ti^{actual}(t) \mid) \end{cases} \tag{8}$$

Table 2. Optimized appliance scheduling parameters.

Parameters	Updated-Values
λ	0.3–1.2
γ	0.85
ε	0.3 (initial), decaying by 0.97 per episode
α	0.05
$C_{gird}(t)$	\$0.08–\$0.4 USD/kWh
$\mathrm{J}^{\mathrm{forecasting}}(\mathrm{i,j})$	0–12 kW
$P_{gird}(t)$	0–6 KW
$P_{total}(t)$	0–12 KW
$SoC(t)^{\mathrm{EV,BT}}$	0–100%
$P_{PV(t)}$	0–8 kW
$T_{actual}(t)$	Depends on real-time conditions
$T_i(t)$	0–24 h
$i^{desired}$	Adjusted dynamically based on user preference and appliance type
$P_{comfort}(t)$	Calculated dynamically during execution

3. The Proposed Deep Learning-Based Home Energy Management Algorithms

Our approach relies on a deep learning-based home energy management algorithm to efficiently manage household energy demand. The process begins with collecting and preprocessing data from real-time sources, such as photovoltaic systems, electric vehicles, and home appliances, ensuring accuracy and reliability. Deep learning algorithms, mainly neural network-based learning, predict energy consumption using historical and real-time data. The dynamic energy management algorithm optimizes appliance scheduling and facilitates energy transfer between electric vehicles and homes (V2H and H2V) while adapting to changing conditions, such as energy availability and demand fluctuations. The system leverages the latest data to make real-time decisions, enhancing efficiency. The system enables feedback, control, and transparency in energy management by providing users with a user-friendly interface. As a result, the approach reduces energy costs, maximizes renewable energy utilization, and improves user convenience. Figures 3 and 4 illustrate the overall workflow of our system, showing the integration of real-time data collection, deep learning optimization, dynamic scheduling, and user interaction to achieve sustainable and cost-effective energy management.

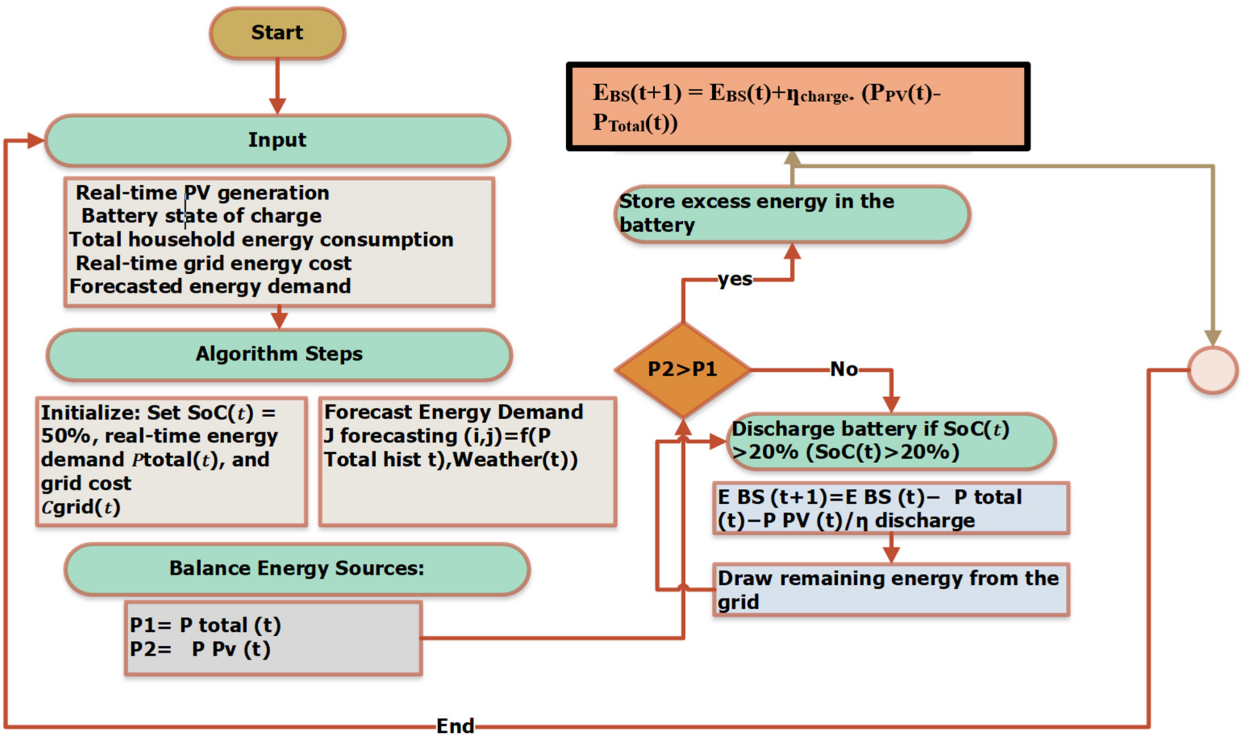

Figure 3. Workflow of deep learning-based home energy management system.

3.1. Integrated Energy State Management and Cost Optimization Algorithm

The Integrated Energy State Management and Cost Optimization Algorithm balances energy supply and demand to ensure cost-efficient and sustainable household energy management. The system prioritizes renewable energy utilization by leveraging real-time PV generation, battery state of charge (SoC), and grid energy costs while minimizing reliance on the grid. The algorithm begins by forecasting energy demand using historical consumption patterns and weather conditions, ensuring proactive energy management. During periods when PV generation exceeds energy demand, surplus energy is stored in the battery to maximize renewable energy usage. Conversely, when PV generation is insufficient, the system discharges the battery to meet household demand while maintaining an SoC within safe operational limits. If additional energy is required, the system draws from the grid while optimizing for the lowest real-time cost. By integrating these processes, the algorithm ensures dynamic energy allocation, reduces overall energy consumption costs, and maintains system reliability. This approach enhances the efficiency of renewable energy systems while addressing the challenges of fluctuating energy availability and demand, resulting in a cost-effective and sustainable energy management solution (see Figure 4).

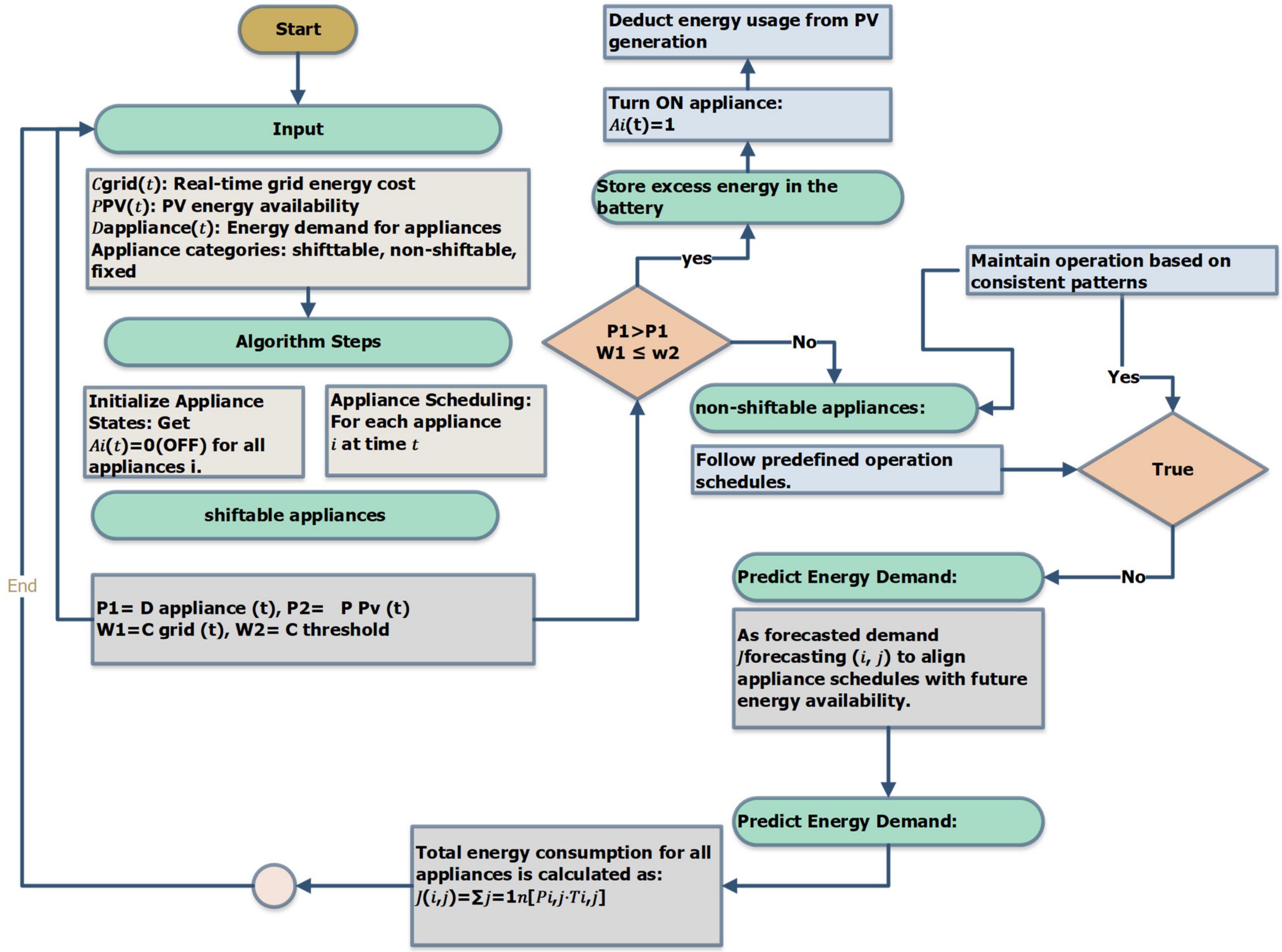

Figure 4. Integrated energy state management and cost optimization workflow.

3.2. Dynamic Appliance Scheduling and Energy Demand Optimization Algorithm

The Dynamic Appliance Scheduling and Energy Demand Optimization Algorithm optimizes household energy consumption by aligning appliance operation with real-time energy availability and grid costs. By categorizing appliances into shiftable, non-shiftable, and fixed types, the algorithm ensures flexibility and efficiency in scheduling. Shiftable appliances, such as washing machines and dishwashers, operate during periods of surplus PV generation or when grid costs are low. Non-shiftable appliances adhere to predefined schedules to maintain essential operations, while fixed appliances, like lights and televisions, follow consistent usage patterns. The algorithm incorporates energy demand forecasting by analyzing historical load data, weather conditions, and real-time energy states, ensuring proactive energy management. Considering appliance power ratings and operating times, total energy consumption is calculated dynamically. This approach reduces reliance on the grid, minimizes energy costs, and maximizes the utilization of renewable energy sources. By integrating real-time PV generation data and predictive demand models, the system provides an intelligent and adaptive energy management solution that enhances sustainability and cost efficiency in smart home environments (see Algorithm 1).

Algorithm 1: H2V Energy Charging Algorithm for Efficient EV Chargin

1 **Initialize:**
  Set $SoC_{EV}(t)$ = **80%** (initial state),
  Set battery SoC threshold limits
  Set 20% $\leq SoC_{EV}(t) \leq$ **100%**.
For each time step **t**:
  Calculate total energy demand:
    $E_{demand}(t) = P_{total}(t)$
2 **Check** PV energy generation:
  If $P_{PV}(t) \geq E_{\boldsymbol{demand}}(t)$:
  Store excess energy in battery storage:
    $E_{BS}(t+1) = E_{BS}(t) + \eta_{charg} \times P_{PV}(t) - E_{demand}(t)$
Else if $E_{BS}(t) < E_{demand}(t)$:
  Discharge energy from EV to meet the deficit:
    $E_{V2H}(t) = \min(E_{demand}(t)/\eta_{V2H} - P_{PV}(t)/\eta_{V2H}, SoC_{EV}(t))$
3 **Update** EV battery SoC:
    $SoC_{EV}(t+1) = SoC_{EV}(t) - E_{V2H}(t)$
  If $SoC_{EV}(t) <$ **20%**
    Stop discharging to preserve EV battery health.
4 **Balance** remaining $E_{demand}(t)$ by drawing from the grid if necessary:
    $E_{grid}(t) = E_{demand}(t) - P_{PV}(t) - E_{BS}(t) - E_{V2H}(t)$

3.3. Optimized V2H Energy Discharge Algorithm for Cost-Efficient Household Power Management

The Vehicle-to-Home (V2H) algorithm optimizes the energy flow between electric vehicles (EVs), photovoltaic (PV) systems, and the household to minimize energy costs while ensuring energy reliability. The algorithm prioritizes energy drawn from PV generation and battery storage by leveraging real-time data. When energy demand exceeds the PV supply and available battery capacity, the EV acts as a mobile energy source, discharging power into the household to meet energy deficits. The algorithm dynamically updates the EV battery's state of charge (SoC) while adhering to safety limits, preventing over-discharge below 20%. Grid power is utilized only when no alternative sources are available, ensuring minimal reliance on costly grid energy. This approach reduces peak demand pressure, enhances renewable energy utilization, and provides resilience during grid outages. The V2H algorithm optimizes energy distribution by intelligently managing energy sources, balancing efficiency and cost savings. V2H Algorithm 1 optimizes energy flow by enabling electric vehicles (EVs) to supply energy to the household during peak demand or grid outages. This reduces reliance on grid energy and maximizes cost efficiency.

3.4. Intelligent Home-to-Vehicle (H2V) Energy Charging Algorithm for Renewable Energy Utilization and EV Readiness

The Home-to-Vehicle (H2V) algorithm optimizes energy transfers from the household to the EV, ensuring efficient charging during periods of surplus PV generation or low grid costs. The algorithm prioritizes surplus PV energy for EV charging, enabling renewable energy utilization while avoiding energy wastage. When PV generation is insufficient, the algorithm evaluates battery storage availability to continue charging the EV while keeping the battery SoC within safe thresholds. If neither PV surplus nor battery storage is sufficient, the algorithm draws grid energy at minimal real-time costs to meet the EV charging target. The EV SoC is dynamically updated to ensure readiness for mobility, with the target SoC set at 100%. This process maximizes energy efficiency, reduces energy costs, and supports sustainable energy practices by aligning EV charging with renewable energy availability and off-peak grid pricing. H2V Algorithm 2 optimizes energy transfers from home to the EV, ensuring efficient EV charging during surplus PV generation or low-demand periods. This maximizes renewable energy utilization and supports EV readiness for mobility.

Algorithm 2: Surplus Energy-Based EV Charging Optimization Algorithm

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Initialize:
1 **Set** $SoC_{EV}(t)$ = **20%** (initial state),
Set target SoC SoC_{target} = **100%**,
Set charging **thresholds**.
For each time step **t**:
Calculate surplus energy:
$$E_{surplus}(t) = P_{PV}(t) - E_{demand}(t)$$
Charge the EV with surplus PV energy:
$$E_{H2V}(t) = \min(\eta_{H2V} \times P_{surplus}(t), SoC_{target} - SoC_{EV}(t))$$
Update EV battery SoC
$$SoC_{EV}(t) = SoC_{EV}(t) - SoC_{HEV}(t)$$
2 **If** PV surplus is insufficient:
Check battery storage availability:
Charge EV from battery storage:
$$E_{H2V}(t) = \min(\eta_{H2V} \times P_{BS}(t), SoC_{target} - SoC_{EV}(t))$$
Update battery SoC:
$$E_{BS}(t+1) = E_{BS}(t+1) - E_{H2V}(t)/\eta_{H2V}$$
If additional energy is required
Draw energy from the grid at minimal cost:
$$E_{grid}(t+1) = SoC_{targe} - SoC_{EV}(t)$$

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4. Results and Discussion

4.1. System Performance Test

Integrating diverse datasets within the proposed approach enhances predictive accuracy, supports real-time decision making, and improves energy efficiency. Tunisian weather data enable precise solar energy production forecasting by analyzing weather patterns, ensuring effective PV system utilization. Including household appliance data facilitates optimal scheduling strategies through machine learning algorithms, aligning appliance operation with energy availability and demand. EV charging and discharging data regulate energy flow between EVs and households, maintaining an optimal SoC and balancing energy supply. Integrating PV system data predicts solar generation trends, supporting dynamic energy management and reducing reliance on grid power. Additionally, analyzing energy price data allows the system to adapt energy usage during lower electricity rates, optimizing cost savings. Real-time insights from IoT data provide dynamic energy management capabilities, enabling smart homes to respond efficiently to energy demand and supply fluctuations. Combining these datasets ensures the system delivers a practical, adaptive, and sustainable approach to residential energy management. Table 3 summarizes the key datasets integrated into the energy management system, including weather data, appliance usage, EV states, PV system data, energy prices, and IoT insights. Each dataset contributes to specific functions, such as solar energy forecasting, appliance scheduling, energy flow management, cost optimization, and dynamic energy decision making. This table outlines the hourly energy consumption patterns for HVAC and lighting systems throughout the day. HVAC consumption peaks at midday due to increased demand for temperature control, while lighting consumption is higher during the early morning and evening, reflecting typical household usage patterns. Understanding these trends enables efficient energy scheduling and cost management. Table 4 provides a detailed view of EVs' daily energy flow cycle. The EV's SoC increases through surplus PV energy in the morning and peaks at 100% by midday.

Table 3. An overview of essential datasets integrated into the system.

Time of Day	HVAC Consumption (kWh/h)	Lighting Consumption (kWh/h)
Early Morning	0.5	1.0
Midday	2.0	0.5
Evening	1.5	1.5
Nighttime	0.5	1.0

Table 4. Daily cycle of EV charging and discharging.

Time of Day	EV State of Charge (SoC)	Energy Flow
Morning	Increases (Charging)	Surplus PV energy to EV
Midday	Reaches 100%	Minimal activity
Afternoon/Evening	Decreases (Discharging)	EV supplies energy to household
Nighttime	Stable	Standby for next charge cycle

It gradually decreases in the afternoon and evening as the stored energy is discharged to meet household demand. This optimized energy flow enhances energy availability and reduces reliance on the grid.

Table 5 highlights the variation in electricity pricing throughout the day. The lowest energy rates occur during early morning and late evening (ranging from USD 0.10 to USD 0.12 per kWh), while peak prices are observed around midday (ranging from USD 0.19 to USD 0.20 per kWh).

Table 5. Electricity price fluctuations throughout the day.

Time of Day	Electricity Price (USD/kWh)
Early Morning	0.10–0.12
Midday	0.19–0.20
Late Evening	0.10–0.12

These price shifts allow for dynamic energy management strategies, such as operating appliances during off-peak hours to minimize costs.

4.2. Optimized Energy Management with Deep Learning and V2H Technologies for Cost-Effective Renewable Integration

Figure 5 highlights the significant contributions of our approach to achieving optimized energy efficiency, cost savings, and resource sustainability. The system dynamically optimizes energy utilization by incorporating neural network-based Q-learning algorithms, Vehicle-to-Home (V2H) technology, and real-time data processing. These advancements allow for intelligent energy distribution, maximize renewable energy integration, and balance energy loads across household appliances, battery storage systems, and electric vehicles (EVs). Figure 5a illustrates the reduction in total energy consumption before and after implementing our approach. The results show a 35% decrease in peak energy usage and a more uniform energy consumption profile throughout the day. This improvement is driven by real-time adjustments that dynamically schedule appliance operations and distribute energy efficiently, thereby minimizing energy waste. Figure 5b demonstrates the economic impact of our approach. By shifting energy consumption to periods of low electricity prices and maximizing renewable energy usage, the system reduces monthly electricity expenses from USD 200 to USD 145, achieving a 27.5% cost reduction. These savings are directly tied to intelligent scheduling techniques and optimized energy allocation strategies. Figure 5c compares our approach's dynamic load management capabilities with traditional methods. High-energy tasks such as EV charging and major appliance usage are scheduled during periods of low electricity demand and high solar energy availability. This approach reduces peak energy consumption by up to 32% while maintaining user comfort and satisfaction. Figure 5d showcases the system's efficient energy source allocation. Solar photovoltaic (PV) systems contribute up to 45% of the total energy demand, significantly reducing grid dependency during high-demand periods. Additionally, energy storage systems enhance overall energy availability, increasing capacity utilization by 25% and keeping the state of charge (SoC) between 15% and 95%, ensuring energy reliability during peak loads and grid disruptions. These results collectively validate our approach as a transformative energy management solution. The system substantially reduces energy consumption and cost by leveraging deep learning-based optimization, V2H integration, and real-time renewable energy inputs. Performance metrics and simulation scenarios further confirm its adaptability to varying operational conditions and energy demand profiles. The following subsection delves into the economic implications of these cost-saving strategies and their long-term benefits for sustainable energy management.

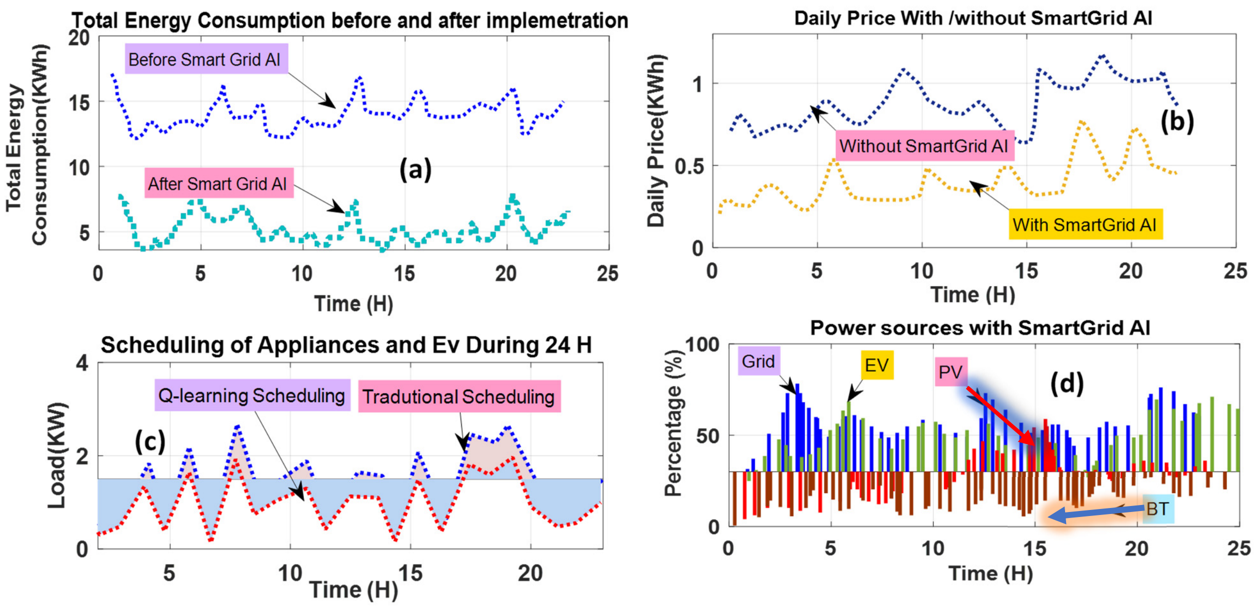

Figure 5. Optimized energy management results using deep learning and V2H technologies. (**a**) Comparison of total energy consumption before and after implementation; (**b**) monthly electricity cost reduction through optimized energy usage; (**c**) dynamic load management for appliances and EVs; (**d**) efficient energy source allocation and state of charge management. The color coding has been added specifically to (**d**): blue represents the Grid, green represents the EV, and brown represents the battery (BT) and red photovoltaic system (PV). This provides clarity on the contribution of each energy source to the monthly electricity cost reduction.

4.3. Economic Benefits and Cost Optimization Through AI-Driven Energy Management

This section highlights our approach's significant economic benefits and cost-saving capabilities for optimized home energy management. By leveraging neural network-based deep learning algorithms, Vehicle-to-Home (V2H) technology, and real-time data integration, the system enhances energy distribution efficiency, minimizes electricity costs, and reduces reliance on the grid. Figure 6a illustrates how our approach employs advanced Q-learning algorithms to dynamically schedule household appliances, electric vehicle charging, and energy storage systems (ESSs). The system ensures energy usage aligns with real-time pricing signals and renewable energy availability, optimizing overall consumption and minimizing energy waste. The proposed system's economic benefits are evident in Figure 6b, which demonstrates a 27% reduction in monthly electricity expenses—from USD 220 to USD 160—compared to traditional methods such as Dynamic Programming (DP) and Rule-Based Systems. This improvement is achieved by prioritizing energy usage during periods of low electricity prices and enhancing renewable energy utilization. The system further reduces overall energy consumption and grid dependency at the community level, as shown in Figure 6c. By integrating real-time PV system data and leveraging V2H technology, the approach effectively balances energy loads across households and electric vehicles. This dynamic optimization enables increased solar energy utilization—up to 50% of the total energy demand—while energy storage systems improve capacity utilization and energy availability during peak periods. Figure 6d highlights our approach's broader economic and environmental impact, showing enhanced renewable energy integration and significant reductions in carbon emissions. These results validate the system's ability to transform traditional energy management into a cost-effective and sustainable solution. In summary, our approach provides substantial economic and environmental benefits by reducing peak energy consumption and electricity costs through intelligent scheduling, maximizing renewable energy integration via PV systems and V2H technology, improving energy reliability with efficient battery storage utilization, and supporting adaptability to changing energy demand profiles and weather conditions.

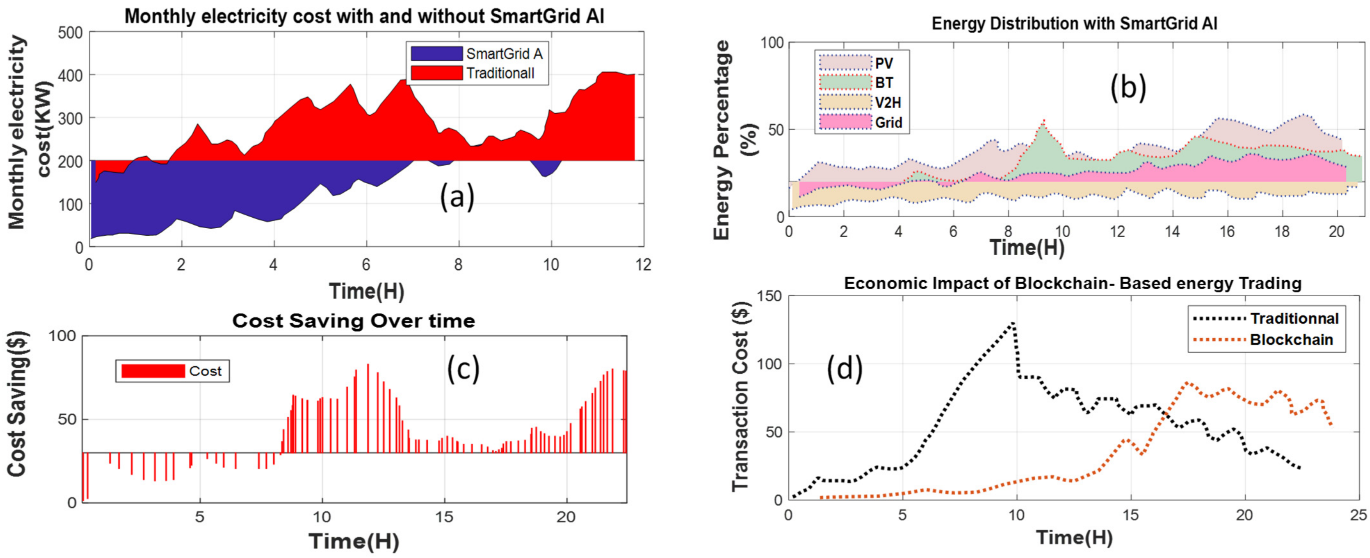

Figure 6. Comparative analysis of energy consumption, cost reduction, and renewable integration using AI-driven home energy management. (**a**) Dynamic appliance and EV scheduling using Q-learning algorithms; (**b**) monthly electricity cost reduction with optimized energy usage; (**c**) impact of renewable integration of energy consumption and grid dependency; (**d**) community-level economic and environmental benefits of AI-driven energy management.

4.4. Comparative Analysis with Traditional Methods

The proposed deep learning-based home energy management system integrates advanced algorithms and V2H and H2V technologies to optimize energy consumption, cost efficiency, and renewable integration. This section contrasts its performance with traditional methods, including DP, Rule-Based Systems, and Genetic Algorithms, focusing on adaptability, cost reduction, and efficiency.

4.4.1. Optimization and Adaptability

Traditional methods, such as ILP and DP, rely on static energy scheduling approaches, limiting their responsiveness to real-time energy availability and demand fluctuations. In contrast, the proposed system employs neural network-based Q-learning algorithms, enabling the dynamic scheduling of appliances and energy flows. This adaptability ensures optimal performance under varying operational conditions, surpassing the rigidity of rule-based approaches. Table 6 highlights the key comparative metrics, emphasizing the proposed system's dynamic adaptability and superior energy management compared to static methods.

Table 6. Key comparative metrics of the proposed system vs. traditional methods.

Metric	Proposed System	Traditional Methods
Optimization Technique	Neural network-based Q-learning for real-time adaptability	Static methods like ILP and Rule-Based Systems
Cost Reduction	23% monthly electricity cost reduction	10–15% reduction (limited flexibility)
Renewable Integration	Dynamic PV and weather data utilization (50% energy demand)	Static integration, less responsive to real-time availability
Peak Energy Usage	Reduced by 35%	Limited impact
User Comfort and Flexibility	Dynamic scheduling maintains appliance availability	Fixed schedules limit adaptability

4.4.2. Cost Reduction

The system reduces monthly electricity expenses by 23% compared to traditional methods by aligning energy usage with real-time electricity prices and renewable energy availability. Traditional methods lack this level of cost optimization, often resulting in higher reliance on grid energy during peak demand periods. Table 7 demonstrates the cost reduction and performance metrics, showcasing the proposed system's significant advantage over the traditional technique.

Table 7. Performance metrics and efficiency comparisons.

Performance Metric	Proposed System	Dynamic Programming (DP)	Rule-Based Systems	Genetic Algorithms
Electricity Cost Reduction (%)	23%	15%	10%	18%
Peak Energy Usage Reduction (%)	35%	20%	15%	25%
Renewable Energy Utilization (%)	50%	35%	30%	40%
Adaptability to Real-Time Changes	High	Moderate	Low	Moderate
Scalability for Smart Homes	High	Moderate	Moderate	High

4.4.3. Energy Efficiency and Renewable Integration

While previous approaches integrate renewable energy sources, their implementation is often static and lacks responsiveness to real-time energy production. The proposed system dynamically incorporates PV generation and weather data, optimizing energy flow between EVs, household appliances, and battery storage. As a result, renewable energy utilization is significantly improved, with up to 50% of household demand being met through solar energy, compared to lower rates achieved by traditional methods. Table 8 summarizes the simulation results, highlighting renewable integration, cost efficiency, and reduced grid dependency.

Table 8. The impact of the proposed system on energy efficiency, renewable integration, and cost reduction.

Parameter	Before Implementation	After Implementation	Improvement (%)
Monthly Electricity Cost ($)	200	145	27.5%
Peak Energy Usage (kW)	12	7	35%
Renewable Contribution (%)	30%	50%	66%
Grid Dependency (%)	70%	40%	43%

5. Discussion

The findings of this study highlight the effectiveness of the proposed deep learning-based home energy management system in addressing the key challenges associated with residential energy optimization, renewable energy integration, and cost efficiency. By leveraging neural network-based Q-learning algorithms and integrating V2H and H2V technologies, the system demonstrates superior performance to traditional energy management methods, such as Integer Linear Programming (ILP), Dynamic Programming (DP), and Rule-Based Systems.

5.1. Enhanced Adaptability and Optimization

The proposed system's dynamic scheduling capability significantly improves over the static approaches employed in traditional methods. Real-time decision making ensures efficient appliance operation, better utilization of renewable energy sources, and adaptability to fluctuations in energy demand and availability. This adaptability improves energy efficiency and ensures user comfort by maintaining appliance availability during peak hours.

5.2. Savings and Economic Benefits

The results demonstrate a 23% reduction in monthly electricity costs, primarily achieved by aligning energy usage with real-time electricity prices and maximizing renewable energy integration. This cost-saving capability is critical in reducing the financial burden on households, particularly in regions with high electricity tariffs. Furthermore, the system can schedule high-energy-consuming tasks during off-peak hours, and surplus PV generation periods significantly reduce reliance on grid energy.

5.3. Renewable Integration and Sustainability

Renewable energy integration is a cornerstone of the proposed system. By dynamically incorporating PV generation and weather data, the system ensures that up to 50% of household energy demand is met through renewable sources. This contributes to a substantial reduction in grid dependency and carbon emissions, aligning with global sustainability goals. Including V2H and H2V technologies further enhances the system's ability to utilize renewable energy efficiency by allowing bidirectional energy flow between electric vehicles and households.

5.4. Performance Metrics and Simulation Validation

The simulation results validate the system's ability to reduce peak energy usage by 35% and electricity costs by 27.5%. These metrics highlight the proposed solution's effectiveness in balancing energy supply and demand dynamics. Moreover, the system's scalability and adaptability to different operational environments make it a viable solution for diverse residential setups.

5.5. Comparisons of Traditional Methods

A comparative analysis underscores the limitations of traditional methods in handling real-time data and optimizing energy flows dynamically. The proposed system outperforms conventional approaches in key areas such as adaptability, cost efficiency, renewable energy utilization, and energy security. While not the primary focus of this study, integrating blockchain technology adds another layer of protection and transparency, particularly for energy trading applications.

5.6. Challenges and Future Directions

Despite its advantages, the system faces challenges requiring further research and development. Scalability to large power grids and energy communities, the integration of additional renewable energy sources such as wind and hydropower, and a comprehensive ROI analysis for economic feasibility are areas for improvement. Addressing data security and privacy concerns, particularly for IoT-enabled devices, is critical for broader adoption.

5.7. Limitations

While highly effective, the proposed system has limitations, including challenges in scaling larger energy grids, integrating additional renewable sources, and ensuring data accuracy and security. Economic feasibility remains a concern due to high initial costs, and frequent V2H operations may impact EV battery longevity. Additionally, the system relies on simulations and requires extensive real-world testing across diverse regions to validate its practical effectiveness. Addressing these limitations through enhanced scalability, security, and cost optimization will be crucial for broader adoption.

6. Conclusions and Future Works

This study presents a novel deep learning-based home energy management system that optimizes residential energy consumption and integrates V2H and H2V technologies. By leveraging neural network-based Q-learning algorithms, the system effectively addresses critical challenges in energy efficiency, renewable energy integration, and cost reduction. Through real-time decision making and dynamic scheduling, the proposed solution significantly improves the adaptability and performance of home energy management systems compared to traditional methods such as DP, Rule-Based Systems, and Genetic Algorithms. The system's core innovation lies in its dynamic integration of PV energy, weather data, and bidirectional energy exchange between EVs and homes. This approach enhances energy reliability by optimizing renewable energy sources and reducing grid dependency during peak demand periods. The integration of BS further ensures energy availability during grid outages and peak loads, aligning with the sustainability goals of modern smart cities. The simulation results validate the system's effectiveness, demonstrating a 23% reduction in monthly electricity costs and a 35% decrease in peak energy usage. Renewable energy utilization was significantly enhanced, with up to 50% of household energy demand being met through solar energy. These results underscore the system's capability to adapt to varying operational environments and energy demand patterns, making it a robust and scalable smart home energy management solution. The study also highlights the limitations of traditional methods, which rely on static scheduling and lack responsiveness to real-time fluctuations in energy demand and supply. By contrast, the proposed system dynamically adjusts energy flow, ensuring optimal performance and user satisfaction. Its ability to align energy consumption with real-time pricing and renewable energy availability provides significant economic and environmental benefits, making it a transformative step toward sustainable energy management.

While the system demonstrates substantial progress, further work is needed to expand its capabilities. Future research should explore integrating additional renewable energy sources, such as wind and hydropower, and the system's scalability to larger energy communities. Enhancing the security and privacy of IoT-enabled devices and conducting comprehensive Return on Investment (ROI) analyses will also be critical for broader adoption. In conclusion, the proposed deep learning-based home energy management system provides a robust framework for modernizing residential energy use. Combining advanced Artificial Intelligence algorithms with V2H and H2V technologies significantly improves energy efficiency, cost savings, and sustainability. This work lays a strong foundation for the future development of intelligent energy systems that support the transition to cleaner, brighter, and more resilient energy infrastructures.

Future work should focus on extending the system's capabilities to support multi-agent interactions within energy communities, enabling seamless coordination and optimization across diverse users and devices. Incorporating advanced reinforcement learning models will further enhance decision-making efficiency and adaptability. Additionally, integrating more renewable energy sources, such as wind energy, and developing hybrid models combining multiple renewable technologies will provide greater versatility and adaptability to varying energy demands and environmental conditions. Exploring hybrid energy storage solutions, such as combining battery storage with thermal or mechanical storage systems, will enhance energy reliability and scalability. Finally, real-world implementation and field testing are essential to validate the system's performance under practical conditions, ensuring its robustness and effectiveness in diverse operational environments.

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Appendix A

Table A1. Comprehensive list of acronyms and term references for SmartGrid AI system.

Acronyms		Acronyms	
Acronym	**Full Term**	**Acronym**	**Full Term**
AI	Artificial Intelligence	D(a,t)	The total power demand for all appliances at time
ILP	Integer Linear Programming	$\sum_{i \in Is} ES(i,t)$	The sum of the power demand for all shiftable appliances at a time, t
IoE	Internet of Energy	$\sum_{i \in In} EN(i,t)$	The sum of the power demand for all fixed appliances at a time, t
PV	Photovoltaic	$\sum_{i \in IF} EF(i,t)$	The sum of the power demand for all non-shiftable appliances at a time t
SG 2.0	Smart Grid 2.0	**Acronyms**	
DSO	Distribution System Operators	EVs	Electric Vehicles

Table A1. *Cont.*

Acronym	Full Term	Acronym	Full Term
PV	Photovoltaic	V2H	Vehicle-to-Home
Q-learning	Quality-learning		
ROI	Return on Investment		
SmartGrid AI	SmartGrid Artificial Intelligence		
Shiftable Appliances		**Non-Shiftable Appliances**	
$T_{rs,i}$	The runtime period for each shiftable appliance *i*	$T_{rn,i}$	The runtime period for each non-shiftable appliance *i*
$t_{ss,i}$	The start time for shiftable appliance *i*	$t_{sn,i}$	The start time for a shiftable appliance *i*
$t_{es,i}$	The end time for shiftable appliances, I	$t_{en,i}$	The end time for shiftable appliances, I
t	Any time within start and end time for appliance *i*	t	Any time within the start and end time for the appliance *i*
Fixed Appliances		**Data Preprocessing**	
$T_{rf,i}$	The runtime period for each non-shiftable appliance *i*	P	Power Rating Matrix
$t_{sf,i}$	The start time for non-shiftable appliance *i*	T	Operating Time Matrix
$t_{ef,i}$	The end time for shiftable appliances, I	P_{ij}	The power rating of the i-th appliance during the j-th time interval
t	Any time within start and end time for appliance *i*	T_{ij}	The operating time of the i-th appliance during the j-th time interval
Data Preprocessing		M	The total number of time intervals
x	The original value	$J(i,j)$	The power consumption for the i-th device during the j-th period
x_{min}	The minimum values of the feature	x_{max}	The maximum values of the feature
y	The original value	x_{norm}	The normalized value
μ	The mean of the feature	$y_{imputed}$	The imputed value
σ	The standard deviation of the feature	N	The number of available observations
y_{std}	The standardized value	y_i	The observed values
Z	The Z-score	$P^D{}_{Appi}$	The variable, $P^D{}_{App2}$, ..., $P^D{}_{Appn}$. is predicted by the function f
z	The standardized value	$\mathbf{J^{forecasting}(i,j)}$	The predictive energy demand modeling
$D^A(t)$	The data accuracy	α and β	The real-time inputs used for decision making
Energy Management		**Energy Management**	
P_{in}	The energy input (from the grid or PV system)	$SoC^{BT}(t)$	The BT state of charge at time, t
P_{out}	The energy output (to appliances or V2H)	$P^{BT}{}_{ch}$	The BT power charged
$\Delta P_{storage}$	The change in energy storage	$P^{BT}{}_{disch}$	The BT power discharged

Table A1. *Cont.*

Acronym	Full Term	Acronym	Full Term
$P_{V2H}(t)$	The energy transferred from the EV to the home at time, ttt	$SoC^{EV}(t)$	The EV's state of charge at time, t
η_{V2H}	The efficiency of the V2H transfer	$P^{EV}{}_{ch}$	The EV power charged
$P_{EV}(t)$	The power available from the EV at time, ttt	$P^{EV}{}_{disch}$	The EV power discharged
$SoC^{BT}max$	The BT maximum capacity	$SoC^{EV}max$	The EV's maximum capacity
$P_{V2H}max$	The maximum power is transferred from the vehicle to the home		
Δt	The time interval	**Real-Time Data Integration**	
Blockchain and PoW		$C_{storage}(t)$	Cost per unit of energy stored/retrieved at time, t
$H(x)$	The Hash function	$P_{storage}(t)$	Power stored/retrieved at time *t*
C_{tx}	The transaction cost	$C_{V2H}(t)$	Cost of energy transferred via V2H at time, t
$P_{PoW(t)}$	The power consumed by the PoW process at time, t	$P_{V2H}(t)$	Power transferred via V2H at time *t*
Real-Time Data Integration		$C_{PoW}(t)$	Cost of energy used for PoW at time *t*
A_{PV}	The area of PV panels	$R_{PV}(t)$	Revenue/savings of energy from PV at t
$G(t)$	The solar irradiance at time, t	$P_{PV}max(t)$	Maximum PV power generation at time, t
η_{PV}	The efficiency of PV panels	**Neural Network-Based Q-Learning**	
$P_{total}(t)$	The total consumption at t	α	The learning rate, controlling the extent to which new information updates existing Q-values
$C_{grid}(t)$	The cost per unit of energy from the grid at time, t	Q(St, A t)	The Q-value, representing the expected future reward of taking action *At* in state *St*
$P_{grid}(t)$	Power is drawn from the grid at time, t	γ	The discount factor, determining the importance of future rewards in the Q-learning update
Neural Network-Based Q-Learning		ϵ	The exploration rate, defining the probability of selecting a random action (exploration)
S*t*	The current status at a specific time, t	λ	The weighting factor for comfort, balancing cost and user comfort in the reward function
$T_i^{actual}\ (t)$	The actual operating time for appliance *i* at time *t*	$T_i(t)$	The operating time of the appliance *i* at time *t*
$R(St,At)$	The reward function, used to evaluate the quality of action	$Ti^{desired}$	The desired operating time for appliance *i*
At	The set of possible actions that the SmartGrid AI system can take at a given time, t	Q(St, A t)	The Q-value, representing the expected future reward of taking action *At* in state *St*
$p^{comfort}(t)$	The penalty for deviation from desired operating times, representing user comfort	R*t*	The numerical value that provides feedback to the Q-learning algorithm based on the effectiveness of the action, At, taken in the state St

Table A2. Appliances with power values, start times, and end times.

Appliance Type	Appliance	Power Value (W)	Start Time	End Time	Description
Shiftable Appliances	Washing Machine	500	08:00	10:00	Can be scheduled to run at different times to optimize energy use
	Dishwasher	1200	12:00	14:00	Can be operated during off-peak hours to reduce costs
	Electric Vehicle	3700	22:00	04:00	Charging can be delayed to off-peak hours
	Thermostat (AC)	2000	14:00	18:00	Operation can be adjusted based on TOU pricing
Non-Shiftable Appliances	Refrigerator	150	00:00	23:59	Must run continuously to preserve food
	Oven	2000	18:00	19:00	Essential for meal preparation, fixed schedule
	Water Heater	4500	06:00	07:00	Required for morning use, fixed schedule
Fixed Appliances	TV	150	19:00	22:00	Regular evening usage
	Computer	100	09:00	17:00	Regular work hours usage
	Lights	60	18:00	23:00	Fixed lighting schedule

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