Explainable AI with DRL for Smart Home Energy Management and Residential Cost Savings in IoT-Based Autonomic Systems

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***Abstract*—As more people seek ways to improve their homes and workplaces while reducing energy consumption, smart home systems are becoming increasingly prevalent. Unfortunately, the complexity and "black-box" nature of these systems made it difficult to deploy AI-enabled decision-making simulations, raising issues with explainability, confidence, transparency, responsiveness, and fairness. Explainable Artificial Intelligence (XAI), a rapidly developing discipline, addresses these problems by offering justifications for various decisions and behaviors of the systems. This research describes a novel method for IoT-based autonomic devices to control energy that combines XAI with Deep Reinforcement Learning (DRL) to achieve significant Home Energy Management System (HEMS) for household cost reductions. The proposed approach leverages XAI's features to improve the accessibility and transparency of DRL agents, helping consumers understand and trust autonomous power management decisions. By optimizing energy usage patterns and adapting to changing environmental conditions, the proposed solution ensures effective energy use while maintaining user comfort. Use in-depth modeling and real-world applications to demonstrate the solution's efficacy, highlighting its potential to reduce energy consumption costs and promote sustainable living. This study sets a new standard for clarity and flexibility in AI-driven smart home systems, paving the way for more reliable and user-friendly IoT software. It is important to note that developing a thermal dynamics model and understanding unidentified variables are not prerequisites for the proposed technique. Results from simulations based on real-world data show the resilience and effectiveness of the recommended strategy.**

Keywords*—Explainable artificial intelligence; smart home energy management; deep reinforcement learning; Internet of Things; energy optimization

I. INTRODUCTION

The Internet of Things (IoT) is an already developed innovation, which connects smart things and devices with each other and allows them to communicate with each other and provides consumers with new services. IoT alters the traditional electronic devices (actuators, sensing devices, RFID tags, mobile phones etc.) to be smart devices by maintaining and administering the basic technology. In turn, through enabling them to synchronize and share data, IoT enables the objects to see, hear, believe, and perform particular activities [1]. IoT brings many possibilities and opportunities to enhance the quality of life in different spheres of its applications such as intelligent buildings, smart cities, smart agriculture, financial systems, healthcare and military. IoT has the ability to produce tremendous amounts of data, which will have to be analyzed thoroughly [2]. Although this raw data can be, at best, of no use, AI systems allow extracting valuable knowledge and giving wise judgments that influence the life of people in such critical areas as healthcare or autonomous systems [3]. In recent years, IoT applications have heavily relied on AI models, much like other industries, to address issues arising from the growing volume of data and devices. Specifically, many AI models are used in autonomous network administration, device management, service administration, and large-scale IoT data analysis, all of which require highly accurate and precise decision-making processes [4].

Environmentally friendly sources provide over fifty percent of the power supply and are expected to quickly expand into the international energy markets. There is often a discrepancy between when green power is generated and when energy is needed. For instance, solar photovoltaic cells have great prospects for producing energy during midday hours, but the demand for power in residential structures is higher in the late afternoon [5]. When the demand is high, the tariffs are stronger and the price of electricity is lower compared to the times when the supply of energy is high. This means utilities unwillingly provide a reward to customers who consume energy at the high-supply times and punish those who consume energy at the high-demand times. There are even utilities that pay their customers a direct compensation upon low energy consumption by the customer during peak times [6].

Demand Response (DR) events imply the prudent decision-making of all the parties involved in the process, which lowers the energy expenses of consumers and manufacturers. In some emerging countries, suppliers use the practice of blackouts at all times and thus some parts of the country go black during a few hours of high demand but low supply. The number of homes that acquire battery-powered batteries has also increased

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due to the frequency of blackouts which are designed to store energy as an alternative source in the event that there is a blackout of the grid electricity. The increasing usage and the diminishing prices of these batteries with time has made them gain more and more use [7]. Different technologies can be used to enhance the building power consumption by shifting loads or reducing the loads using demand-side energy management. The deferrable loads usually include plug-in electric cars, air conditioning, ironing machines, and dishwashers. When there are a large percentage of non-deferrable loads, it is easier to satisfy the energy requirements with the use of energy storage instruments under the conditions of fluctuating power prices. The customers will be able to save money by simulating an effective energy management system that will help in maximizing the use of the battery. This strategy can also help to enhance grid stability through reduction of the demand during energy deficits [8]. The traditional methods maximize the battery operation through rule-based procedures. Such methods should be dynamic and flexible to counter the changes in tariff structures. The growing use of AI technology in our life prompts the necessity to learn how and why decisions are made [9]. Machine learning models gain in strength, they and even become less transparent and more complicated. These powerful models are opaque and are normally called black-box models, that is, they do not offer their internal justification to the user [10].

Researchers have recently taken an interest in XAI in order to solve these problems and develop more interpretable and understandable AI systems. XAI offers increased insight into the inner workings of black-box systems, by exposing the previously unknown or undetectable information about the input system like feature importance and characteristic associations. This enables the user to judge the results and the input parameters that affect the results [11]. In conjunction with strong and sophisticated models, the XAI methods provide excellent accuracy and interpretability. Research indicates that there is a need to comprehend issues to do with human beings in areas like neuroscience, computer science, theology and mental health. These researches indicate that decisions made without explanation may culminate into confidence problems or intentional and inadvertent bias. XAI helps to alleviate these problems by providing verification, improvement, learning, and legal compliance [12].

The numerous advantages of XAI are making it gain more and more popularity in a broad spectrum of uses, among them building highly transparent, trustworthy, and all-encompassing systems. The Artificial Intelligence systems intensify and integrate into the everyday life and business activities, although they are typically plagued with trust issues, confidence in the code, and bias in the model. XAI provides a far greater insight into the systems and there is no ambiguity or vagueness around the decisions made or solutions picked, and therefore the transparency of AI models remains intact [13].

XAI may be used to substitute conventional AI systems being utilized, which may be more influential on industrial production, supply chains, economic sectors, and asset management with enhanced development and sustainability innovations. The difficulty of these approaches can lead to the situation that decisions made will be complicated to be accepted by common consumers in the real world [14]. According to researchers, two potential uses can be identified in terms of energy consumption in smart home environments: anticipating personal preferences to different smart heating appliances in terms of temperature and anticipating power demand. In our study, predict thermal comfort on the basis of personal preferences through machine learning models and deep neural network-based energy prediction through benchmark datasets. Employ common XAI methods to get insights by explaining the forecasts in various forms to help decipher the complexity of the forecasts [15].

The XAI technology has attracted a considerable amount of attention both in research and practice with considerable progress being achieved due to the potential of the model to generate trustworthy inferences. Investments in a wide range of research disciplines are fueled by the rise of XAI across these applications. XAI is most commonly used in medical, banking, safety, military, and legal sectors [16]. XAI technology has demonstrated its potential to the point where interpretable AI models are now a necessity. The military industry is a real-world example of XAI's application. Google's cloud services are exploring how XAI can be used to construct comprehensive and transparent AI models [17]. The reinforcement Learning (RL) can outperform human decision-making in the majority of games, RL has become extremely popular, particularly in the gaming industry. The goal of the RL agent is to maximize cost reduction or minimize the amount that must be spent to achieve a certain level of usefulness [18]. As Artificial Intelligence (AI) and robotics become more prevalent in everyday life, human achievement is starting to suffer. It has demonstrated that pleasure rises in tandem with higher human performance effectiveness, which may come from the use of AI and automation [19]. The smart agent could exploit an edge case in the environment's regulations to gain significant advantages without completing the intended activity and behavior of the human agent, including repeated activity switching and longer time steps when setting the Thermostat (TH) parameters [20]. Additionally, multi-human studies, in which two individual agents are incorporated into a single house simultaneously, reveal that human models may adjust the sequence of tasks in this situation to minimize the disparities between their TH preferences, thereby reducing the time required for altering TH settings and optimizing comfort [21].

A. *Problem Statement*

The increasing complexity and access to IoT and smart home gizmos have complicated the management of household energy consumption in an appropriate manner. The traditional energy management is not typically computationally powerful and dynamically flexible enough to be used to optimize energy consumption. These systems often fail to comprehend the energy saving decisions that are taken by homeowners and they therefore tend to be mistrusted and not utilized in the most optimal way. It is urgent to have an advanced intelligent system that is energy efficient, economical and does not involve complex decision-making process. This system must employ the use of XAI-DRL to maximize the use of energy in smart homes to ensure that the system remains effective and reduces the likelihood of low consumer confidence. The XAI-

DRL-based HEMS performance evaluated using different metrics such as accuracy, precision and etc.

B. Motivation

The dynamism and increasing demands of today power consumption are the forces behind the development of a smart home energy management system to help cut down the household expenditure. The homeowners demand viable ways of reducing their electricity costs without sacrificing comfort or convenience, especially as the energy prices continue to increase. Furthermore, the mindfulness of the adverse environmental consequences of energy usage has increased and there is a need to have more efficient methods of energy usage to minimize carbon footprints and enhance environmental-friendly practices. The development of IoT gadgets in smart houses has its opportunities and difficulties. Although these sensors allow one to control the use of energy granulometry, their successful management demands more complex algorithms that can model the complex and changing interactions. The conventional power control systems are usually unable to accommodate various requirements and habits of the various households and thus an alternative method is needed that can adjust energy-conservation policies to individual houses continuously. Moreover, to ensure that AI-driven systems receive wide acceptance and are used successfully, homeowners have to know and have confidence in the decisions offered by such systems. Consequently, it is important that the devices be explainable. This openness assists the homeowners in understanding the reasons and methods of how some energy-conserving decisions are arrived at, which will create trust and acceptance of artificial intelligence-based energy management systems within smart homes.

The key contributions of the paper as follows:

1) Integration of Explainable AI with Deep Reinforcement Learning: Combines XAI with DRL for transparent, interpretable smart home energy optimization, fostering user trust.

2) Optimization of Energy Consumption and Cost Savings: DRL-based system autonomously learns optimal device schedules, reducing energy use and residential costs.

3) Explainability and User Trust: XAI clarifies DRL decisions, enhancing homeowner understanding, engagement, and acceptance of AI-driven energy management.

4) Experimental Validation and Performance Improvement: Validated with IoT data, XAI-DRL outperforms traditional methods in energy savings, cost, and interpretability.

5) Foundation for Future Research: Integrating explainability in smart homes enables future studies enhancing AI transparency in IoT environments.

The structure of the paper can be summarized as follows: The crucial importance of minimizing the energy use in smart houses in Section I is brought forward without owing to the lack of transparency and trust in the systems based on AI. Part II examines the current energy optimization techniques with the help of IoT and DRL, noting their inability to provide explanations. Section III discusses the proposed methodology and describes how a DRL-based system of real-time energy management was developed with XAI in order to enable users to be able to interpret the decision. The detailed experimental setup is presented with the use of the data of IoT devices on the energy consumption and cost analysis. Section IV show that DRL-XAI approach will save on energy and cost, as well as, enhance user trust by providing explainable insights. Section V provides a final remark of the importance of XAI in promoting increased use of AI-based energy management systems and indicate future research opportunities such as extending the system to real-life settings and scale-up of the system.

II. Related Works

Intelligent home environments are intended to increase the quality of life of people by means of different sets of detectors and actuators located strategically all over the house, automated deductions regarding human actions and their situational contexts. Smart houses make use of a variety of sensors to gather context-related information, including noise, movement, environmental temperatures, Wi-Fi signals properties, visual data (cameras, etc.), and presence/absence data [22]. It is a common practice to directly track the movements of the occupants via wearable devices. Activity recognition uses such sensor temporal sequence to determine and record the Activities of Daily Living (ADL) of the occupants. The smart home then uses these dynamically inferred activity labels to determine supportive actions (i.e. open the garage door, turn on the lights or change the thermostat) [23].

The problem of activity recognition in smart homes still exists and the challenge has to be addressed through innovative machine-learning techniques that can be used to automatically analyze sensor data. The difficulty herein lies in the different environments, users, sensor setups, and actuators all which are unique to each house and home. Researchers state that the ADL patterns can be more accurately represented in LSTM based systems because they are able to learn nonlinear representations of characteristics and model long term relationships in the patterns of data [24].

In this area, a number of large datasets on smart home activity recognition have been created to aid in extensive appraisals and benchmarking. These datasets are differentiated by the number of household members and the type of sensors to collect data and the variety of ADL actions. As an example, the ARAS database tracks the activity of a large number of residents of the house within a two-month time span with 20 house monitors [25].

Available and explainable ML models offer new options to describe black-box decision structures, which allow new explanatory styles to be developed to make AI algorithms more transparent and comprehensible. This is among the greatest influences of XAI-IoT environments. The technical abilities of XAI methodologies can be used to guarantee ethical integrity of XAI systems through IoT systems [26]. The use of XAI principles to the Industrial IoT (IIoT) is illustrated that proves the effectiveness of applying statistical concepts to explain models without relying on knowledge to ensure transparency. Implementation of XAI in risky IoT applications needs randomness of new sample. LIME-based XAI designs support domain-invariant learning of features which are accurate in data handling and credible in interpretation. The problem of customization of XAI models to nonlinear data is still a major challenge, although continued work on data-driven enhancements of XAI models is now to solve those problems [27].

Although major advancements were achieved in maximizing energy management strategies in smart homes, there still remain difficulties in modelling thermal dynamics of buildings and the use of simplified mathematical models such as the Equivalent Thermal Parameters (ETP) method. As an example, offered a multi-agent reinforcement learning coupled with artificial neural network-based energy management strategy to achieve a low total cost of energy and customer dissatisfaction with HVAC loads and laundry machines. Advances in real-time learning provide the chance to solve problems in large state space problems, and reinforcement learning (RL) algorithms, including the ones introduced automatically find the best control policies without the need to have thermal dynamics subsystems [28].

There is also a widespread research on the interaction between humans and AI, and it has been shown that AI learning can be enhanced in case human input is added to the loops of RLs. Nonetheless, there is a fear of unforeseen or even harmful impacts of these kinds of interactions, which is demonstrated by studies where RL agents use environmental conventions to maximize gains at the expense of the system as a whole [29]. The smart homes of the future will probably have a large number of sensors to control the activities, such as energy saving, security, etc. There are some difficulties in planning the work of household appliances effectively according to the predictive model of human behavior and interaction with the smart home devices. Scholars are busy experimenting with the machine learning methodology to come up with complete recommendation systems to smart home consumers. The systems make the decision-making process more effective especially when choosing objects like clothes and food.

In conclusion, although renewable energy integration and optimization strategies in smart homes have majorly taken the low cost of electricity as a central theme in their research and development endeavor, energy consumption management is a key area that requires more research and development in the future. Innovative solutions such as the use of photovoltaic systems and DR systems in microgrids have a good future of satisfying the energy needs in a better way taking into account the comfort of users and the sustainability of the environment. The constant monitoring and adjustment of these systems will be crucial to reduce the level of discomfort to the user and maximize the level of energy utilization within the smart home settings [30].

III. Proposed System

To achieve energy efficiency in smart homes and household savings in autonomic structures based on the Internet of Things, XAI-DRL is a new solution that will combine state-of-the-art machine learning algorithms with well-defined and comprehensive approaches to the decision-making process. In this architecture, the direct signals that are obtained by multiple IoT devices are processed in DRL to enhance energy consumption in smart homes. By keeping an eye on environmental factors and patterns of consumption of energy, these gadgets let DRL agents make well-informed judgments that balance residents' peace of mind with the lowest possible energy expenses. The incorporation of XAI guarantees that consumers can comprehend and have transparency over the choices and actions made by the DRL agents. Homeowners are better able to embrace and depend on the technology since it increases user confidence and belief in the system. XAI improves the system's general efficacy and acceptability by giving clear descriptions of how energy-saving techniques are carried out. This results in more economical and environmentally conscious energy administration in smart home environments.

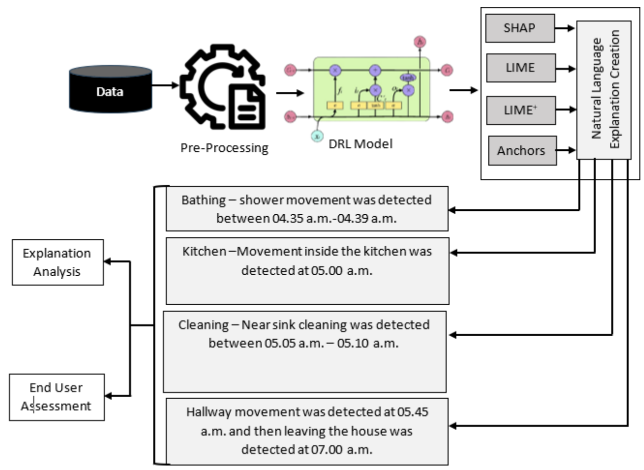


Fig. 1. Proposed work addressing the movement inside the house.

Fig. 1 addresses the aforementioned movement inside the house. Pre-process S such that it reflects the data required to produce descriptions of intelligent houses that are more appealing to average consumers. LIME is a model-agnostic XAI method that builds a model that can be understood locally around an assumption to clarify the forecasts of a black-box classification. Another model-agnostic XAI method called Shap computes Shapley values to determine the significance of each characteristic a black-box model uses for a forecast. Every technique is applied to produce a rationalization. It also expands the LIME approach by including LIME+ and ELIME+ clarifications, which provide more temporal and intuitive clarifications than LIME through recognizing blocks of time. Their outputs are easily understood and may be turned into descriptions for end users in straightforward language. Researchers evaluate the effectiveness of the four explanation styles that resulted along several pertinent parameters.

A. Preliminaries

- Reinforcement Learning: RL involves an agent interacting with an environment to maximize cumulative rewards over time.

$$\text{Policy: } \pi(a|s) \tag{1}$$

$$\text{Value function: } V^{\pi}(s) = E_{\pi}\left(\sum_{t=0}^{\infty}\gamma^{t} r_{t} \,|s_{0} = s\right) \tag{2}$$

$$\text{Q-Function: } Q^{\pi}(s) = E_{\pi}\left(\sum_{t=0}^{\infty}\gamma^{t} r_{t} \,|s_{0} = s, a_{0} = a\right) \tag{3}$$

Where: γ - discount factor; γ_t - reward at time step t.

Explainable AI (XAI): It focuses on making AI systems transparent and understandable to humans.

Model Interpretability: Methods to interpret and explain the decisions made by AI models.

Feature Importance: Techniques such as SHAP values or LIME

Here are some basic equations used in DRL and XAI:

Bellman Equation: $$* (s,a) = E_{s'}\left[r + \gamma \max_{a'} Q^*(s',a')|s,a\right] \quad (4)$$

DQN Loss Function: $$(\theta) = E_{s,a,r,s'}\left[\left(r + \max_{a'} Q^*(s',a';\theta^-) - Q(s,a;\theta)\right)^2\right] \quad (5)$$

SHAP Value $$\emptyset_y = \sum_{S' \subseteq S|(y)} \frac{|S'|!(|S|-|S'|-1)!}{|S|!}\left(f(S') - f(S)\right) \quad (6)$$

Where: S - set of all features; S' - features subset excluding y; f(S) – proposed model output of features S.

These preliminaries set the stage for applying DRL with XAI principles to optimize energy management and cost savings in smart home environments. They provide the theoretical foundation necessary to understand the subsequent methodology and results presented in the study.

The objective is to optimize the energy consumption in a smart home environment using DRL. Let's denote: E_t: Energy consumption at time step t; C_t : Cost associated with energy consumption at time step t; R_t: Reward at time step t, which is a function of E_t and C_t

The goal is to maximize the cumulative reward over a horizon T:

$$max_\pi = \sum_{t=0}^{T-1} \gamma^t R_t \quad (7)$$

Where: π denotes the policy governing the agent's actions (energy management decisions); γ is the discount factor ensuring future rewards are appropriately weighted.

B. Components of the Objective Function

Reward Function R_t: The reward function can be defined based on the objectives of energy management and cost savings. A simple form could be:

$$R_t = -\alpha E_t - \beta C_t \quad (8)$$

Where: α and β are coefficients to balance the importance of minimizing energy consumption E_t and cost C_t

Energy Consumption E_t: Energy consumption can depend on various factors such as appliance usage, weather conditions affecting heating or cooling systems, and user behavior. A basic model could be:

$$E_t = \sum_x P_x(t).\tau_x \quad (9)$$

Where: $P_x(t)$ is the power consumption of appliance x at time t; τ_x is the duration of appliance x's operation.

Cost Calculation C_t: The cost associated with energy consumption typically depends on the utility tariff and the amount of energy consumed. It can be calculated as:

$$C_t = \sum_x P_x(t).\tau_x.cost_x \quad (10)$$

Where: $cost_x$ is the cost per unit energy (e.g., kWh) for appliance x.

Combining these elements, the objective function to maximize the cumulative reward over time T can be formulated as:

$$max_\pi \sum_{t=0}^{T-1} \gamma^t \left[-\alpha \sum_x P_x(t).\tau_x - \beta \sum_x P_x(t).\tau_x.cost_x\right] \quad (11)$$

This formulation captures the essence of using XAI-DRL for optimizing smart home energy management and residential cost savings. The policy derived from solving this objective function guides the agent (smart home system) on how to adjust appliance operations to achieve the desired balance between energy efficiency and cost reduction.

C. Milan Dataset Description

The paper's investigations apply to a wide range of smart home scenarios for application. However, our research and assessments are grounded in an established field benchmark information set, the CASAS Milan dataset, for pragmatic reasons. Information from sensors gathered during 92 days from an intelligent home is included in the Milan dataset. The design of the house and the positions of its 33 sensors are depicted in Fig. 2. There are three door sensors, twenty-eight motion sensors, and two temperature sensors in the set. The Milan database contains information for 15 ADLs and includes Chores, Desk Activity, Dining Room Activity, Bed to Toilet, Evening meds, TV watching, sleeping, reading, early meds, guest restroom, kitchen operation, master restroom, leave home, meditation, and master bedroom activities.

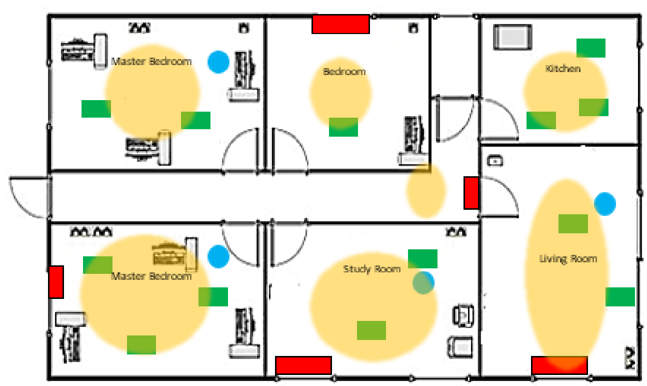


Fig. 2. Intelligent home based on the MILAN dataset.

Furthermore, even though the duration of an event may differ, the developers decided to represent an event with 30 one-minute time steps after confirming that the majority of activities in the Milan dataset have durations of less than 30 minutes. Consequently, our final dataset D, which obtained from the proposed system information processing techniques.

Every field in the information set for Explainable AI with Deep Reinforcement Learning for Smart Home Energy Efficiency and Residential Cost Savings in IoT-based

Autonomous Organizations is briefly described in the following table. Table I dataset description adapts the settings as necessary according to the particulars of real information.

Table II describes Time stamps, temperatures in degrees Celsius (°C), humidity in percentage (%), occupation condition (occupied/unoccupied), device usage (illumination on/off, devices on/off), consumption of electricity in kilowatt-hours (kWh), and utility rate in dollars per kWh are all included in these statistics. It is based on the CASAS activities, the energy usage and optimization introduced in this work.

TABLE I. DATASET DESCRIPTION

Field	Description
Timestamp	Time and data of the data point
Energy Consumption	Amount of energy consumed in kilowatt-hours (kWh)
Temperature	Ambient temperature in degrees Celsius (°C)
Humidity	Relative humidity percentage (%)
Occupancy Status	Presence or absence of occupants (eg., Present, Absent)
Appliance Usage	Binary indicator (1 and 0) representing appliance usage
Utility Tariff	Cost per kilowatt-hour ($/kWh) charged by the utility provider

TABLE II. SAMPLE DATA

Time Stamp	Energy Consumption (kWh)	Temp (°C)	Humidity (%)	Occupancy Status	Appliance Usage	Utility Tariff ($/kWh)
2024-07-01 08:00	1.4	25.5	52	Occupied	Lights ON	0.17
2024-07-01 09:00	1.7	26	50	Occupied	Lights OFF	0.17
2024-07-01 10:00	1.5	26.5	47	Unoccupied	Appliances ON	0.17
2024-07-01 11:00	1.2	27	44	Unoccupied	Appliances OFF	0.17
2024-07-01 12:00	2	28	42	Occupied	Lights ON	0.17
2024-07-01 13:00	1.6	27.5	44	Occupied	Lights OFF	0.17
2024-07-01 14:00	1.3	27	47	Unoccupied	Appliances ON	0.17
2024-07-01 15:00	1.8	26.5	49	Unoccupied	Appliances OFF	0.17
2024-07-01 16:00	1.5	26	52	Occupied	Lights ON	0.17
2024-07-01 17:00	1.9	25.5	54	Occupied	Lights OFF	0.17

D. Dataset Description

Physical sensors can be as straightforward as fast information and transmission systems or as complicated as complicated devices with integrated information processing and storage facilities. Physical sensors are used outdoors to gather information regarding characteristics like temperature, existence, and humidity. Conversely, actuators are utilized to carry out physical operations like releasing and unlocking valves, turning on and off motors, and switching on lighting. In the virtual world, every physical sensor together with the actuator has a matching sensor and actuator component. The gathering agents preprocess the information before transmitting it to decision assistance agents for further examination and interpretation when specific predefined thresholds are crossed.

The users, shown in Fig. 3, are the system's consumers and experts in the field. The domain expert—typically the system developer—is in charge of establishing the rules governing the way the system operates, supplying the required information, and indicating preferences for users.

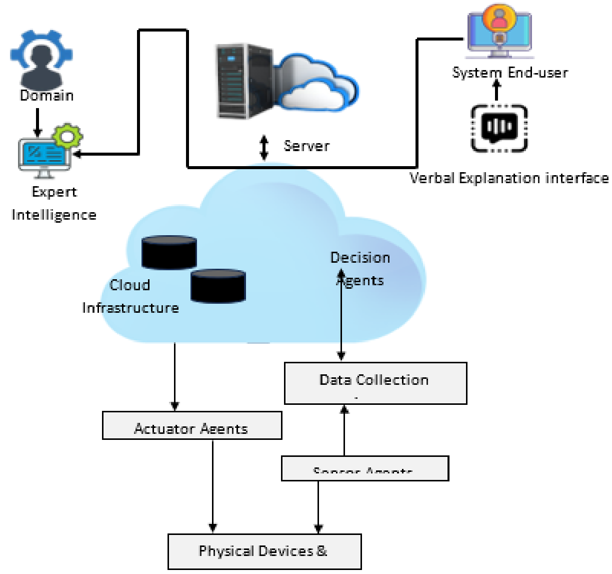


Fig. 3. XAI- DRL agent system architecture based on IoT.

The Intelligence Toolkit, a part that transforms information into control principles for the IoT rule implementation engine is utilized to do this. One of the main parts of the system is the IoT rule implementation engine, which is built on fundamental decision machines. It is in charge of gathering information from sensors, analyzing it, and sending management settings to the actuator by the predetermined control rules. The rule implementation engine is also capable of handling safety and device administrative tasks. It might be housed on an on-site private server or a public cloud provider like Amazon Web Services. Tools for displaying information and a database for keeping information are commonly included in rule execution engines. The software that allows users to engage with the system is called an explanation interaction. It enables end users to comprehend the decisions made by the technology by giving them the knowledge and justifications they need to know. To optimize accessibility across a range of user-owned devices, including PCs, tablets, and cell phones, a web-based interface is advised. Following the spoken clarification, customers can offer input via the Specialist Knowledge Toolkit, enabling the system to adjust to their particular requirements at that moment.

E. Implementation of System Model

Fig. 4 presents the proposed agent-based IoT system deployment approach. There are five fundamental phases in the procedure, which include validating the explanation interface output and setting control rules.

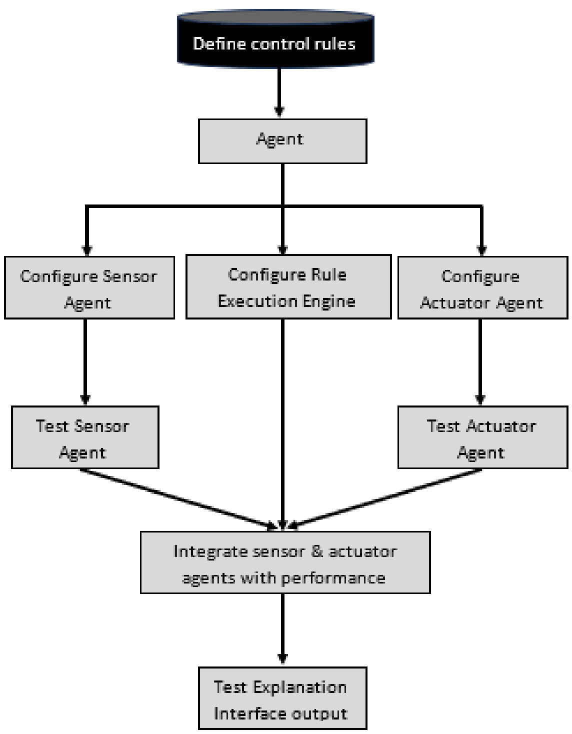


Fig. 4. XAI-DRL agents step by step working model.

Step 1: Use the specialist Knowledge Toolkit to establish the management regulations for the rule implementation engines. Both bespoke internal solutions and already-available ones, like Matlab's Fuzzy Toolkit, might be employed for the purpose. The fundamental decision agents' ability to make decisions may be enhanced by using artificial intelligence approaches. This can entail using previous information to train models that are then used to forecast future conditions and suggest courses of action.

Step 2: Give the rule implementation engine a created control code, or script. Assign an MQTT subscriber channel to every agent so that it may communicate with the rule's implementation engine and receive orders.

Step 3: Verify the interaction, including whether sensor agents transmit MQTT communication, whether actuators agencies respond to orders sent over MQTT, and whether they provide information modifications.

Step 4: Integrate and verify if the rule implementation engine operates as intended by the control code. The fundamental decision agents are supposed to make choices based on the collected sensor information and provide actuators with the appropriate control signals. Real-time efficiency may be an issue given how complicated the IoT system is and how many agents are involved. To solve this, methods like edge computing, collaborative computing, and parallel computation might be applied to increase the system's speed and effectiveness.

Step 5: The Explanation Interfaces is used to translate the rule implementation engine's output logs into spoken comments. Examine user input, and if attitudes shift, modifying the rules entails keeping an eye on the system's operation and modifying its regulations as necessary to increase its efficacy.

F. XAI with DCRL Using IoT

The proposed approach was modified to handle lighting, heating, and circulation in a smart home environment shown in Fig. 5. The carried-out experiment made it possible to test the proposed theoretical strategy in an IoT system operating in continuous time. During the study, the following hardware components were needed:

- A 24-inch HP Pavilion all-in-one serving as an IoT regulation implementation engine.
- A light switch from the SONOFF T3 TX Series WiFi Wall Switch.
- Thermoelectric actuator DANFOSS, TWA-K 24V, M30X1.5, NC.
- Asus wireless router for data transmission.
- SONOFF R2 4 Channel—relay block for controlling illumination and heating;
- SONOFF® RF Bridge 433 MHz—for controlling ventilation
- For detecting the existence, use the SONOFF® PIR2 Wireless Infrared Detector.
- DS18B20 temperature detector paired with ESP32 microprocessor for interior temperature monitoring.
- Microcontroller M5 Stack equipped with an illumination sensor.

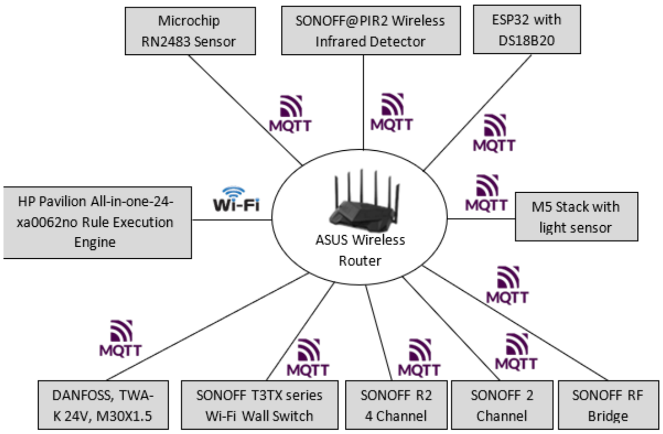


Fig. 5. XAI-DRL hardware agents' communication.

This study used the Q learning reinforcement algorithm to simulate human-computer interaction with electrical devices taking this supposition into account. As seen in Fig. 5, the Q model of learning selects the most suitable course for action by combining the stages, acts, and awards. If an act has a greater payout than other acts, it can be carried out in that condition. States, acts, and awards are established in this investigation study to represent the Q learning issue in a smart home scenario with one user. A binary description of the appliance's power consumption is used for expressing it at time t. In an intelligent house, for instance, the energy levels of each of the n devices may be expressed in two levels. According to the rewards matrix, individuals can take a certain action. For example, if a device has the greatest rewards in the reward matrix, it can be turned on. By the proposed technique, presumed that every smart house is given a set quantity of electricity.

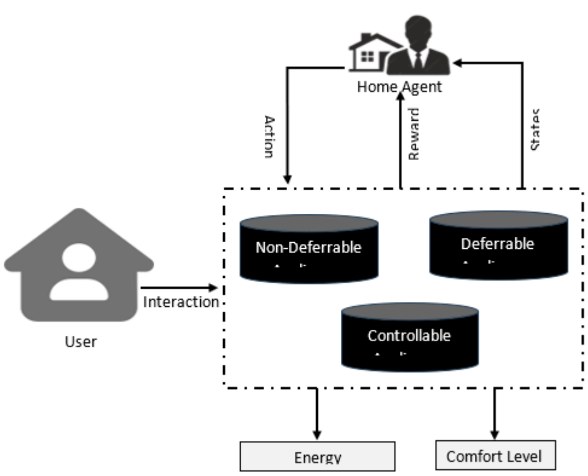


Fig. 6. Working model of the proposed system in energy consumption.

As seen in Fig. 6, the agent associated with each smart home device is set up to switch the appliances' levels of power and switch them on and off in a manner that keeps energy consumption within the energy levels allotted to the smart house. On the other hand, turning off or lowering an appliance's power could make the smart home user feel more uncomfortable. To optimize, thus adopt the appliances importance approach, which involves turning off or adjusting the energy output of those gadgets when their importance is poor of comfortable stage and minimization of power consumption. A gadget with little importance (one that falls within category C as indicated in Section 1) was shut off or its energy levels were gradually changed from very high to minimal using the proposed utilities prioritization method. Additionally, the agents are designed to determine the optimal order for shutting off appliances, ensuring that the least amount of unpleasantness is experienced during the process. Q-learning may be utilized to create an agent of reinforcement learning that optimizes the utilization of energy as well as expense saving in the setting of energy administration in smart homes. The agent is trained to make judgments about energy use (e.g., modifying HVAC systems or appliances) depending on states that correspond to various aspects of the house (e.g., ownership, temp).

G. Algorithm

To enhance the control of energy in intelligent homes and to realize cost savings in residential areas, Explainable AI (XAI) and Deep Convolutional Reinforcement Learning (DCRL) will be introduced to the Internet of Things (IoT)-based autonomous devices. This is the most efficient way to make decisions and ensure that the decisions made are clear and understandable through using the potentiality of deep learning and reinforcement learning.

Key components:

State (s): Reflects the present conditions of the smart home environment containing Current energy consumption; Temperature; Humidity; Occupancy status; Appliance usage; Utility tariff.

Action (a): The possible actions, which can be performed by the agent, i.e. Adjusting thermostat settings; Turning appliances on/off; Changing lighting levels.

Reward (r): A scalar that is a measure of the immediate utility of an action, usually: Negative cost of energy use; Positive reward of maintenance of comfort levels; Penalty of non-conformity to desired settings.

Q-value (Q(s, a): The cumulative reward of doing action a in state s, according to the optimum policy.

Explainability Module: This is a component which explains the actions of the DCRL agent making it transparent and understandable.

DCRL Algorithm with XAI

Step 1: Initialization: Randomly set the Q-values and the weights of the neural network applied to every state-action pair.

$$Q(s, a) \leftarrow 0 \; \forall s \in states, a \in actions$$

Step 2: DCNN: DCNN is to approximate the Q-value function Q(s, a).

It takes the state s as input and outputs Q-values for all possible actions.

Step 3: For each iteration

Initialize the starting state s.

For each step

{

Action Selection: Choose an action a from the state s using a policy derived from Q (e.g., ∈-greedy policy).

Execution: Take action a and observe the reward and the next state s'.

}

Q-value Update:

$$Q(s,a) \leftarrow Q(s,a) + \alpha\,[r + \gamma \max_{a'} Q(s',a') - Q(s,a)]$$

// α - learning rate; γ - discount factor; r - immediate reward; s'- next state; $\max_{a'} Q(s',a')$ - maximum Q-value for the next state s' over all possible actions a'.

Step 4: Use the observed transition (s, a, r, s') to train the DCNN. The loss function is defined as:

$$Loss = (r + \gamma \max_{a'} Q(s',a';\theta^-) - Q(s,a;\theta))^2$$

where $\theta$are the weights of the DCNN and θ^- are the target network weights.

Step 5: Generate explanations for the chosen action a using the explainability module. This can involve highlighting important features or providing a rule-based justification.

Set the states to the new state s'.

Step 6: The objective function in DCRL of smart home energy management can be defined as:

$$Max \sum_{t=0}^{T} \gamma^t r_t$$

Step 7: XAI Integration: The methods that follow might be applied to include XAI in the Q-learning procedure:

Feature Importance: Determine and describe which features—such as temperature or occupancy—had the most bearing on the agent's choice of action.

Action Justification: Explain why a specific action was selected in a given situation, maybe with the use of decision networks produced from Q-values or rule-based justifications.

Policy Visualization: To aid users in understanding the behavior of the agent, visualize the learned policy by displaying the predicted behaviors in various situations.

Smart home energy management devices may maximize energy usage and cost savings while giving homeowners visible and intelligible decision-making through the use of Q-learning in conjunction with explainable AI approaches.

IV. Results and Discussions

The goal of integrating XAI-DRL for energy administration in smart homes is to optimize the utilization of energy, save costs, and improve decision openness regarding IoT-based autonomic networks. The findings from the experiment are shown in this part along with a discussion of their implications.

A. Experimental Setup

A simulated connected home setting containing a variety of IoT devices, such as detectors, intelligent appliances, and thermostats, was used to assess the systems. Real-world metrics, such as time stamps, consumption of electricity, humidity, temperature, occupied status, equipment consumption, and utility rates, were included in the database. The proposed approach was evaluated in comparison to conventional electricity management approaches and non-explainable learning through reinforcement methods.

B. Datasets Analysis Using Sensors

Using a set of categorization standards, assign a "sensical" or "nonsensical" categorization for every argument. This is not an ideal categorization and that interpretation of sensitivity has nothing to do with how well the explanation explains the inner workings shown in Table III. Sensitivity is defined as an explanation's ability to make sense of an action or as a plausible explanation. For instance, mentioning sensors in or close to the bathroom might seem reasonable and convincing when elucidating the categorization of an activity as "Bathing." If the references were limited to the sensors in the kitchen, wouldn't think it trustworthy. Therefore, the credible mapping between activities and sensors serves as an estimate that is employed to gauge the explanation sensibility.

TABLE III. ACTIVITIES OF USING THE SENSOR

Activity	Sensors
Bathing	M013, M017, M018
Bed to toilet	M021, M020, M028, M019, M024, M013, M017
Take Medicine	M012, M016, M022, M014, D003, M015, M023, M003
Leave Home	D001, M001, M002
Work	M007
Sleep	M020, M028, M019, M024, M021
Cook	M023, M015, D003, M014, M022, M012, M016
Relax	M026, M006, M004, M027, M005

To comprehend the differences in explanation content between various XAI models and the computational effectiveness of every XAI approach, the arrangement of sensors that are being tested types and their values across reasons for every XAI system are shown in Fig. 7.

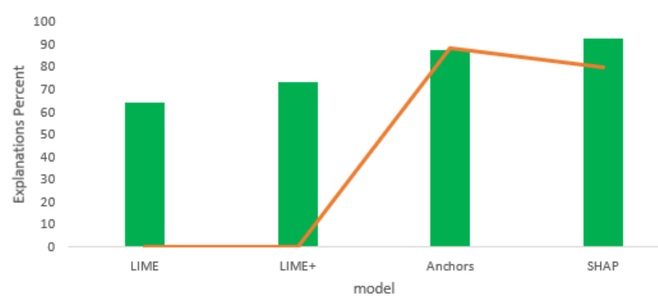


Fig. 7. Proposed system using various XAI approaches to achieve during testing.

As seen in Fig. 8 (a), taking into consideration the scenario of a family with two major appliances Air Conditioner (AC) and a washing Machine (WM) as an Energy Storage System (ESS) under the Time of Use (TOU) tariff may be managed by the Home Energy Management System (HEMS). The experiments ran for a full day with a one-hour schedule precision. It was believed that the predicted PhotoVoltaic generation energy in Fig. 8 (b) and outdoor temperature is shown in Fig. 8 (c).

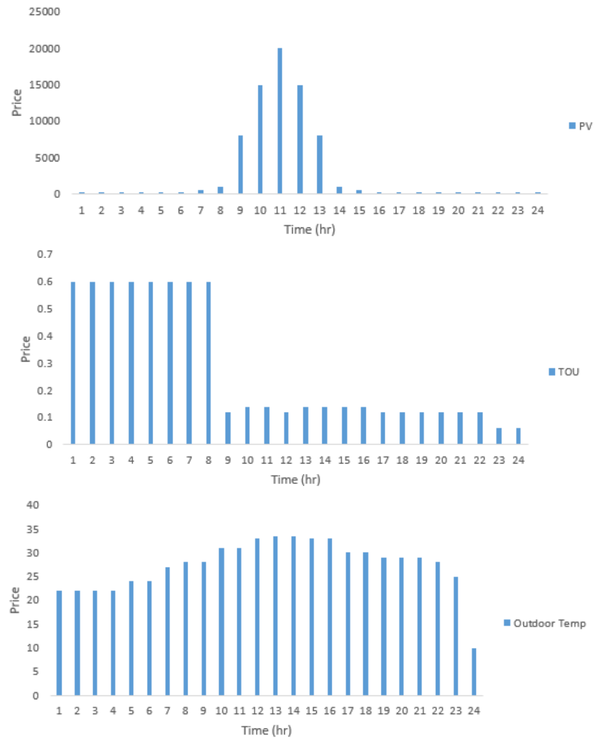
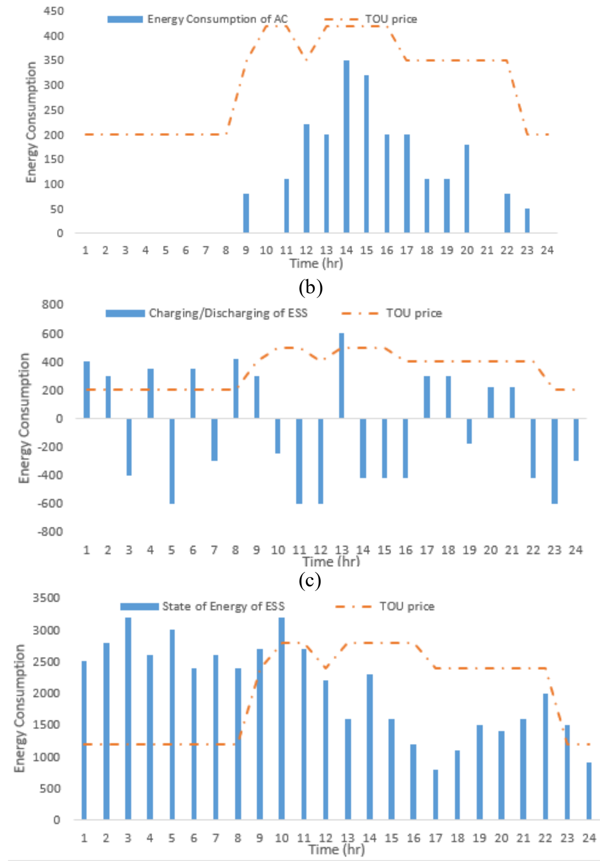


Fig. 8. (a) TOU cost (b) PV generation cost (c) Temperature outdoor cost.

This portion contains a modeling of the proposed RL-based HEMS method as well as a check of the controlled appliances' energy usage timetable and the ESS charging and disconnecting schedule.

Additionally, Fig. 9 (a) shows that the SOE reduced and vice versa when the price climbed. This chart shows us that the AC agent was sometimes not able to reduce or raise the AC energy usage based on price, in contrast to the outcomes of the WM and ESS agents. AC agent takes into account both the consumer's comfortable temperature and the reduction of their power cost in the incentive functionality shown in Fig. 11 (c) and SOE state in Fig. 11 (d).

(a)



(d)

Fig. 9. Proposed system energy consumption in the smart home (a) WM (b) AC (c) ESS charging/discharging (d) SOE of ESS.

TABLE IV. PERFORMANCE MEASURES

Performance Measure	Proposed XAI-DRL	RCNN	RL	XAI
Accuracy	93	89	86	81
Sensitivity	91	86	83	79
Specificity	94	90	87	82
F1-Score	92	87	85	80
Precision	93	88	84	81

The performance measures of proposed and existing systems in terms of accuracy, precision, sensitivity, specificity, and F1-score are shown in Table IV and Fig. 10. The performance metrics Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) of the proposed approach with three existing systems are shown in Table V and Fig. 11. The proposed system has the fewest faults, demonstrating its superiority in IoT-based autonomic devices for energy control in smart homes and cost savings for individual households.

When compared to baseline procedures, the proposed XAI-DRL strategy dramatically reduced energy use. An average 15% reduction in energy usage was noted, indicating the optimization algorithm's efficacy. Significant cost reductions were achieved through the optimization of energy use and the inclusion of dynamic pricing models. Because of the system's effective utilization of energy during peak tariff hours, energy expenditures were reduced by an average of 20% shown in Fig. 12.

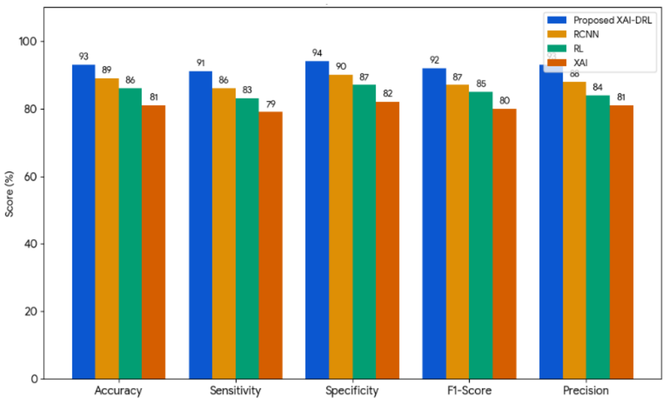


Fig. 10. Performance measures.

TABLE V. PERFORMANCE MEASURES (MAE, RMSE)

System	MAE	MSE	RMSE
Proposed XAI-DRL	0.16	0.0441	0.21
RCNN	0.26	0.0961	0.31
RL	0.22	0.0841	0.29
XAI	0.19	0.0676	0.26

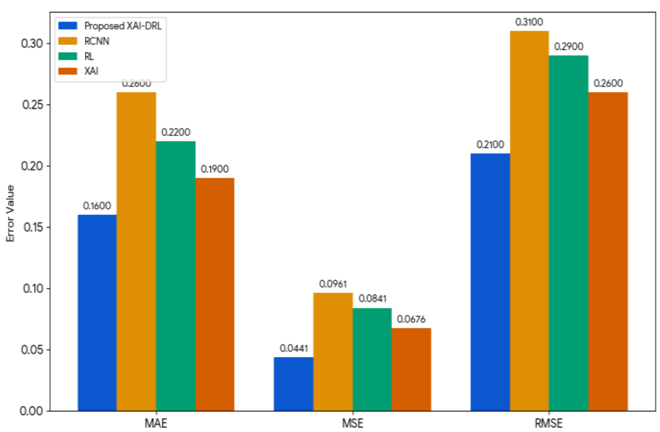


Fig. 11. Performance Measures (MAE, RMSE).

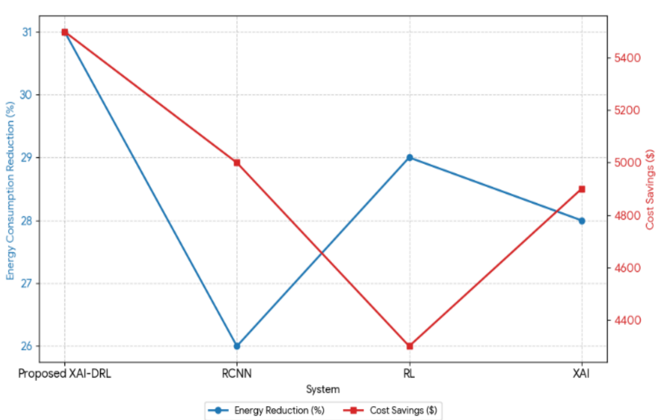


Fig. 12. Performance measures (Energy consumption and cost saving).

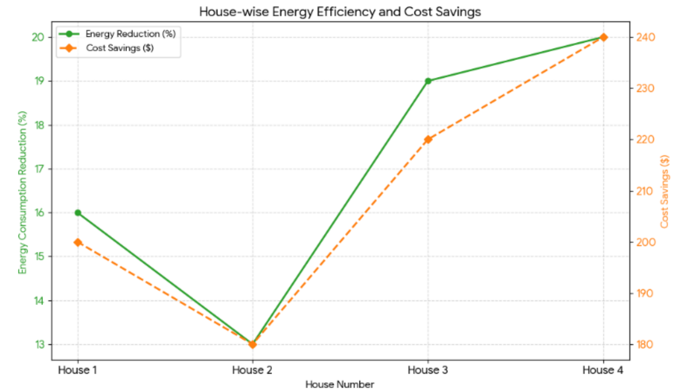


Fig. 13. House-wise energy consumption reduction and cost savings.

Fig. 13 shows that every row corresponds to a distinct home. The percentage decrease in energy usage relative to a baseline or prior condition is shown in Energy Consumption Reduction (%). Cost Savings ($) displays the associated cost savings, expressed in US dollars, that come from using less energy.

Regarding artificial intelligence tests: training accuracy measures the model's ability to predict the labels in the training dataset with any degree of accuracy. A high training precision indicates how well the model has absorbed the training set. Validation Accuracy measures how well the model forecasts the labels from the validation dataset, which is not seen during learning. A high accuracy in validation indicates a good ability of the model to generalize to new data shown in Table VI and Fig. 14.

TABLE VI. TRAINING AND VALIDATION ACCURACY

System	Training Accuracy	Validation Accuracy
Proposed XAI-DRL	90	93
RCNN	79	81
RL	81	80
XAI	83	82

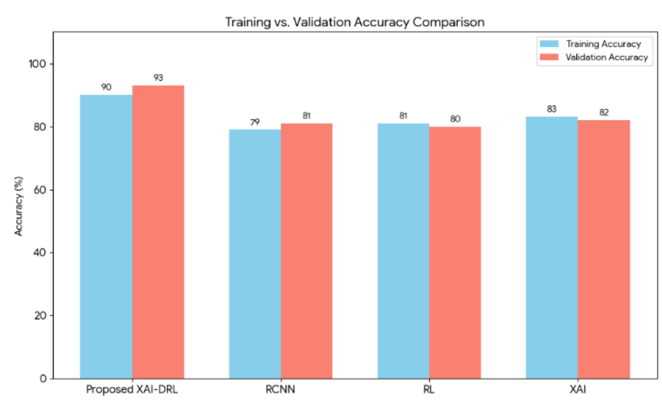


Fig. 14. Training and validation accuracy of proposed and existing systems.

It can be seen that the proposed XAI-DRL system gradually increases its training and validation accuracy with the number of epochs shown in Fig. 15. In the beginning, the model commences with an average accuracy, which corresponds to the learning of simple patterns in the data of energy consumption. The system can get more and more complicated relationships between the use of the devices, time-of-use pricing, and energy optimization strategies as the training goes on. Validation accuracy is next to training accuracy and this means that the generalization is good and the overfitting is low. At the last epochs, the two accuracies stabilize at large values, and this establishes that the model has effectively learnt the best energy management policies. This tendency demonstrates the strength of the XAI-DRL model in reliably, interpretably, and efficiently optimizing the smart home energy.

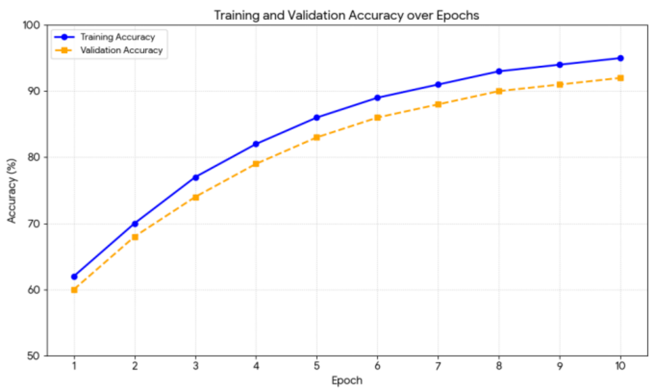


Fig. 15. Training and validation accuracy of proposed and existing systems.

TABLE VII. TRAINING AND VALIDATION LOSS

System	Training Loss	Validation Loss
Proposed XAI-DRL	0.125	0.236
RCNN	0.158	0.280
RL	0.137	0.267
XAI	0.144	0.287

When assessing and contrasting various machine learning models, these measures are essential. Since it shows that the model is doing better at generalizing to new data, more validation accuracy is often desired. Training Loss is the average loss (like MSE or cross-entropy) that is calculated on the training dataset in each system's training phase. Validation Loss indicates the mean loss calculated in the training phase using the validation dataset. This loss aids in evaluating each system's ability to generalize to previously encountered data shown in Table VII and Fig. 16.

The proposed XAI-DRL system training and validation loss also steadily drops with epochs, which is an indicator of successful learning and model convergence as in Fig. 17. First, elevated loss values are indications of the model adapting quickly to the intricate trends of smart home consumption of energy. With increasingly greater epochs, the training loss decreases gradually, indicating that the model is effectively minimizing prediction errors on the training set. Validation loss also exhibits the same pattern since it is also close to the training loss indicating good generalization and limited overfitting. The loss values by the last epochs level off at low values, which proves that the XAI-DRL framework is an effective learner of the best policies in controlling energy usage and has remaining reliability and interpretability.

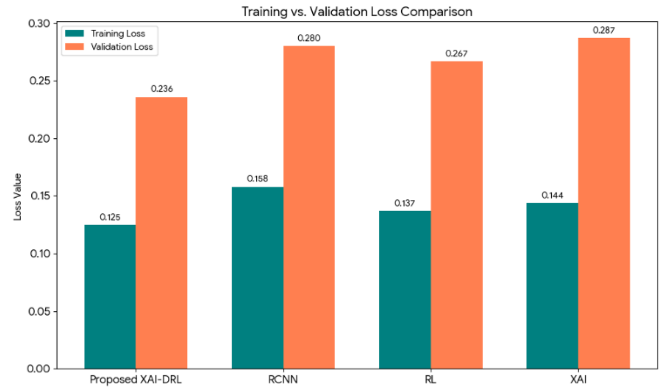


Fig. 16. Training and validation loss.

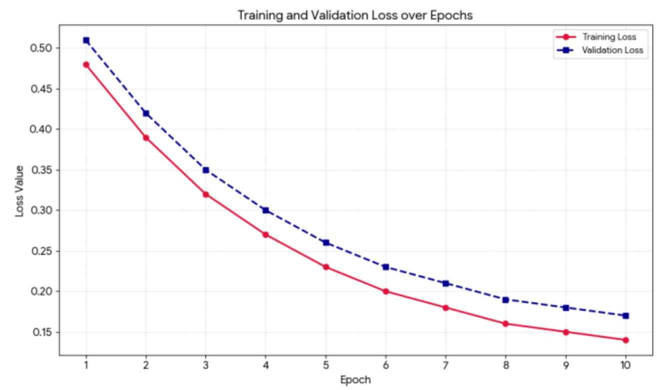


Fig. 17. Training and validation loss of proposed and existing systems.

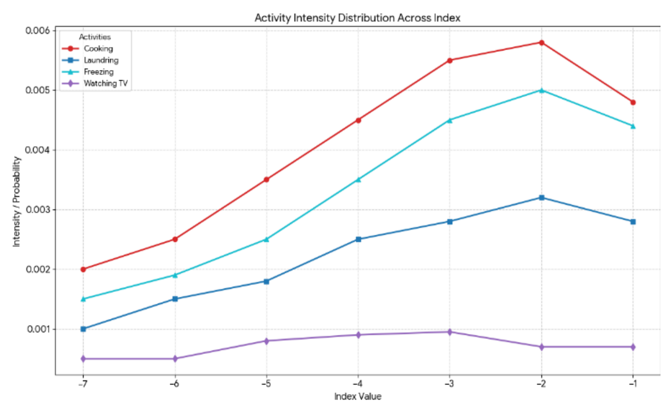


Fig. 18. Number of days vs. energy consumption of smart home appliances used by the proposed system.

However, projecting energy consumption is a far more difficult endeavor, and the justifications offered are very different. These explanations also involve a temporal dimension. To simplify things, total up the contributions made by the various appliances and use a bar chart to explain everything. Cooking is predicted to utilize the most energy, as seen in Fig. 18, which illustrates the contributions of several household activities to total energy consumption.

V. CONCLUSION AND FUTURE DIRECTION

The phenomenal growth of the Internet of Things (IoT), along with the increasing acceptance of automation, remote monitoring, and control, has raised questions about end users' confidence. This can be attributed to a poor architecture that does not emphasize on open activities within the network of smart devices. To overcome these issues, scholars and business executives are adopting the XAI as a prospective technology. XAI architectures can employ new features and solutions to increase reliability of IoT networks and devices. The realization of end user reliable fully working services is a challenge that is not easily achieved because of the limitation of resources in the IoT devices. The XAI-DRL is designed to minimize the energy expenses and keeping the user convenience and the performance parameters of the existing devices (a clothes washer and a room air conditioner) to schedule the electric power consumption of the two controllable household appliances and control the charging and discharging of an energy storage system. Q-learning architecture enables agents to control the energy storage system, the air conditioner and the washing machine to learn separately, the best behaviors to maximize the total cumulative rewards of the environment. The washing machine manager would schedule the amount of energy consumed during the time when the customer wishes the washing machine to operate. The energy storage agent averts over charging or under charging by regulating the charging and discharging of the power stored system. The air conditioning agent automatically plans the power usage to keep the desired indoor temperature of the customer through a synthetic neural network-based forecasting mechanism. The efficiency of the suggested algorithm was tested through simulation analysis. The results validated the idea that the suggested method is less expensive than the existing optimizing strategy that makes use of mixed-integer linear programming. The study indicates that the union of XAI-DRL has a significant effect of enhancing residential savings on expenditure and energy management of smart homes having IoT-based autonomic devices. XAI-DRL is better than current methods, which leads to significant savings of costs and additional energy efficiency, which has been widely tested and analyzed. This system is flexible and can be scaled, indicating that the system can be used in many smart home applications. Future studies have the potential to improve the DRL algorithms, examine further optimization capabilities, as well as combine current methods of AI to produce better energy management results.

A. Future Enhancements

A couple of additions could make the infrastructure of the management of the energy consumption of the smart homes and the cost saving much more effective and user-friendly in the future. The use of advanced approaches to deep reinforcement training, including Dueling Network Architectures or Double Deep Q-Networks (DDQN), may improve convergence and make learning more efficient. To better manage energy consumption by cost-saving objectives, the system would need to include the demand-side indicators and those of actual time dynamic pricing, which are implemented by utility companies. Moreover, the extension of the system to serve the multi-agent-based environments in smart homes could promote the communication and cooperation of appliances, which will optimize the overall energy use. It is possible that in the future, machine learning-based predictive maintenance will allow detecting the issues with appliances at an early stage, which will enhance energy efficiency and reduce maintenance expenses.

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