



International Journal of Artificial Intelligence and Machine Learning

Publisher's Home Page: <https://www.svedbergopen.com/>



Research Paper

Open Access

Ambient Intelligence for Adaptive Smart Home Environments Using 5G Networks

Dr. R. Venkatesh¹ *, Dr. Reshma Yogesh Totare², Dr.N. Srinivas³, Dr. Shenbagarajan Anantharajan⁴

¹Associate Professor and Head, Department of CSE (Artificial Intelligence and Machine Learning), Ramco Institute of Technology, Rajapalayam - 626117, Virudhunagar, Tamil Nadu, Email: venkey88me@gmail.com, <https://orcid.org/0000-0002-4786-3917>

²Department of Information Technology, AISSMS Institute of Information Technology, Pune, India, Email: reshma.gaykar@gmail.com, <https://orcid.org/0000-0002-9193-6685>

³Associate Professor, Department of CSE, Vignana Bharathi Institute of Technology, Aushapur(V), Ghatkesar. Email:Srinivas.bhaskar3@gmail.com, <https://orcid.org/0000-0002-0043-4736>

⁴Associate Professor, Department of Artificial Intelligence and Data Science, Mepco Schlenk Engineering College, Mepco Nagar, Sivakasi - 626005, Virudhunagar District, Tamilnadu State, India, Email: asrme2008@gmail.com, <https://orcid.org/0000-0003-0367-920X>

Abstract

Ambient Intelligence (AmI) emphasizes the construction of intelligent environments that explicitly behave in ways that benefit human capital by improving comfort, effectiveness, and safety. As the 5G network improves with minimal latency, high-speed communication enables seamless connections among IoT devices, sensors & user interfaces in adaptive home automation. Modern smart home systems are often rule-based or designed with basic automations, resulting in delayed responses, excessive energy consumption, and inflexible adaptation to user behavior and the environment. To overcome these constraints, in this study, we proposed to use a Context-Aware Reinforcement Learning (CARL) framework for Smart Home Adaptation, wherein the data obtained through an array of sensors is offered continuously so that user behavior contexts and environmental factors correlate at runtime, coalesce to learn home automation policies via repeated upgradation. The framework utilizes 5G-distributed communication to ensure prompt interaction between user devices and the central learning agent, thereby enabling speed-sensitive decision-making and real-time adaptation. Using the proposed CARL framework for applications such as climate control, lighting adjustment, and appliance management can enable homes to automatically respond to people's habits while conserving energy. Experimental simulations show that the proposed system yields significantly greater user comfort and energy management than classical rule-based/non-adaptive systems.

Keywords: *Ambient Intelligence, Smart Homes, Context-Aware Reinforcement Learning, 5G Networks, Adaptive Automation, Energy Efficiency*

This is an open access article under CC BY 4.0, allowing unrestricted use with proper attribution, a license link, and indication of any changes made.

1. Introduction

AmI describes a digital environment that senses, adapts, and responds to human behaviors [1]. In a smart home environment, AmI represents the fusion of sensors, actuators, and intelligent algorithms [2]. These systems enhance comfort, safety, and efficiency in daily activities by monitoring routines [3]. Context-aware computing refers to internal adjustments made in response to automated setting changes [4]. Lights, heating, and other appliances can be adjusted within the code without the need for occupant control [5]. AmI systems can manage the energy consumption by making the best use of energy applications [6]. AmI systems: intelligent living spaces of support and responsive characteristics that can dynamically respond to the needs of the resident in context, mitigate future requirements and needs [7].

Adaptive automation is the core of AmI systems, in which the system learns user behavior and current environmental conditions [8]. Unlike static controls, adaptive systems allow a home to respond in user- or

agent-defined ways, including real-time adjustments to lighting, heating, ventilation, and appliances [9]. One of the results of adaptive automation is improved user comfort and better sustainable energy use control in the household, as well as reduced energy consumption in the building environment [10]. Adaptive smart home solutions are becoming increasingly compelling as energy efficiency and sustainability trends grow [11]. Smart homes consist of numerous connected devices that need to communicate with one another quickly, reliably, and with low latency [12]. 5G is the backbone of communication solutions thanks to its native support with many massive connections, ultra-low latency, and high data throughput [13]. At this point, it facilitates real-time decision-making for adaptive automation by combining different types of sensors and actuators [14].

Despite advancements in this field, most existing smart home systems continue to operate based on static algorithms and predefined rules [15]. Such systems exhibit little flexibility and do not adjust to variations in user needs or environmental situations, making them unsuitable for energy saving [16]. Traditional networking technologies also increase communication latency to a level that prevents real-time responsiveness, which would otherwise prevent the full use of an intelligent system with responsive feedback [17]. In below table 1, shows the motivation, problem statement and contribution of the paper.

| Table 1: The Motivation, Problem Statement, Contributions. | |
|---|--|
| Section | Description |
| Motivation | The demand for adaptive smart homes, smart energy efficiency, and user-centered living environments is increasing. Currently, rule-based systems are rigid and do not function in real time. Ambient Intelligence provides an interesting area when combined with the optimization of resources based on people's habits, especially in 5G networks and reinforcement learning. |
| Problem Statement | These studies generally have a common problem in that smart home and IoT systems are not sufficiently integrated and optimized under dynamic and uncertain "real world" conditions. This is insufficient because RL-SHEM and PF-HEM do not effectively consider renewable intermittency, reactive power, or the latency of user behaviors. Latency, scalability, and security issues are addressed in RL-Edge SHETEC, as well as the problems of edge and 5G networks. SH-Sense has adoption and usability limitations. Indeed, there are still apparent deficiencies in hybrid methods, multi-agent cooperation, and the implementation of secure and efficient real practicable systems. |
| Contributions | The Continuous Adaptation of Reinforcement Learning (CARL) framework leverages the most recent sensor data, user behavior, and environmental conditions to learn in real time, dynamically optimizing policies for smart home automation while improving both adaptability and efficiency. |
| | Using 5G networks, the framework facilitates seamless and low-latency communication among IoT devices and sensors with the central learning agent for rapid decision-making, leading to adaptive smart home environments. |
| | It shows successful policy optimizations for climate control, lighting, and appliances. The simulation results indicate improved user satisfaction and considerable energy savings compared with conventional static or rule-based systems. |

2. Literature Review

Tested and applied RL-based methodologies like RL-SHEM, RL-Edge, SHETEC, and PF-HEM also lay use cases for the former proposed literature space, closing a gap in critical contributions to reinforcement learning, IOT spaces, and 5 G-based smart home systems, all taking advantage of efficiency improvement and compact capabilities. This integration is enabled by publications with 5G-IoT support, and thus by the immaterial convergence of energy, communication, and safety in smart sustainable living environments.

Review of RL-SHEM (Reinforcement Learning for Smart Home Energy Management) - Shapes a smart home with storage capacity to promote sustainability [18]. In this study, a multi-agent reinforcement learning (MARL) methodology is adopted to solve multiple challenges stemming from renewable energy intermittency, grid reliability, and energy cost savings. The RL-SHEM can be used in integration to enhance efficiency, reliability, and adaptability, while future work will also recommend the collaboration of hybrid RL methods, demand-side management, and security mechanisms.

A survey on RL-Edge (Reinforcement Learning for Edge Offloading) with a focus on computation offloading in edge computing systems. With the application of Deep Q-Networks (DQN), the proposed RL-Edge enables devices to learn adaptive and training-free offloading policies that reduce latency and energy consumption while improving efficiency [19]. RL-Edge systematically organizes research topics into existing work based on architectures, objectives, and decision-making processes, identifying both gaps in the literature and providing a

pathway forward in the form of new directions for potential research topics, such as hybrid models, dynamic environments, and scaling for edge–cloud coordination.

This paper introduces SHETEC (Smart Home Energy and Temperature Control) integrated within an IoT-Edge-Cloud architecture for smart homes of various sizes. Autonomous agents using Deep Deterministic Policy Gradients (DDPG) optimize HVAC operations as well as charge/discharge energy storage [20]. Meanwhile, the Average Opinion (AO) method provides collaborative decision-making across homes. Simulations using actual data demonstrated SHETEC's ability to maintain the resultant temperature within a comfortable range while increasing energy efficiency and coordination.

A power factor-aware home energy management system (PF-HEM) that does not rely on a model to improve both active and reactive power in residential homes containing ESs and EVs [21]. It schedules flexible loads and thermostatically controlled loads in uncertain environments using model-free deep reinforcement learning (RL) and a Markov Decision Process (MDP). The PF-HEM system improved the grid power factor from 0.44 to 0.9, reduced electricity costs by 31.5%, and maintained user comfort while enhancing the efficiency of the HEMS.

5G-IoT-Util focuses on the utilization of 5G in IoT Applications, with a primary emphasis on secure connectivity and interference management [22]. It reviews various types of interference optimization techniques, zones of 5G network architecture, IoT deployment, and standard wireless issues to showcase the effect of interference on 5G networks, leading to improved IoT performance that promotes efficiency, less downtime, and improved user satisfaction. The study concluded that 5G-IoT-Util supports parts of the convergence of services provided to both users and carriers, such as availability and speed, as well as enabling the leverage of smart-home and business applications.

5G-IoT-Int (the integration of IoT into 5G systems), focusing on how the ultralow latency, high speed, and scalability of 5G provide benefits to IoT ecosystems in general [23]. 5G -based IoT and incremental triggers provide reliability, real-time communication, and multiple device interoperability through the use of network slicing as a principal approach. The concept of 5G-IoT-Int for applications in the fields of smart cities, healthcare, and automation possesses great potential while simultaneously imposing challenges such as security, energy efficiency, and network management; hence, it offers a roadmap for seamless integration between IoT and 5G.

SH-Sense (Smart Home Security Systems Review) and other technologies [24], such as smart locks, surveillance cameras, and motion detectors. Using a systematic review approach, this study determines how effective these tools are at creating safe, convenient, and healthy user experiences. SH-Sense is centered on real-time monitoring, immediate alerts, and the ability to control smart home security no matter where you are, while also exploring the issues that arise when integrating these solutions. It also represents a step toward the next generation of home smart security solutions that are intuitive for users, seamlessly integrated, and provide an enhanced consumer experience.

Some techniques highlighted include reinforcement learning and using IoT with 5G in smart homes for energy management and user comfort, with both computation offloading. Across the approaches (RL-SHEM, RL-Edge, SHETEC, and PF-HEM), sustainable, efficient, and resilient approaches are all given considerable attention. This paper provides a general overview of possible future developments for sustainable, scalable, and user-friendly intelligent environments by focusing on complementary dual aspects of 5G-IoT and smart home security reviews.

3. Proposed Methodology

We propose a novel approach that integrates data acquisition and context awareness, reinforcement learning, and execution within 5G in a single framework. The CARL is a temporal context-aware reinforcement learning platform that receives sensor data and evolves vectorized representations of individual states to establish real-time, adaptive behaviors in contemporary comfort and energy-efficiency paradigms of smart home automation.

Contribution 1: Processing of Data Acquisition

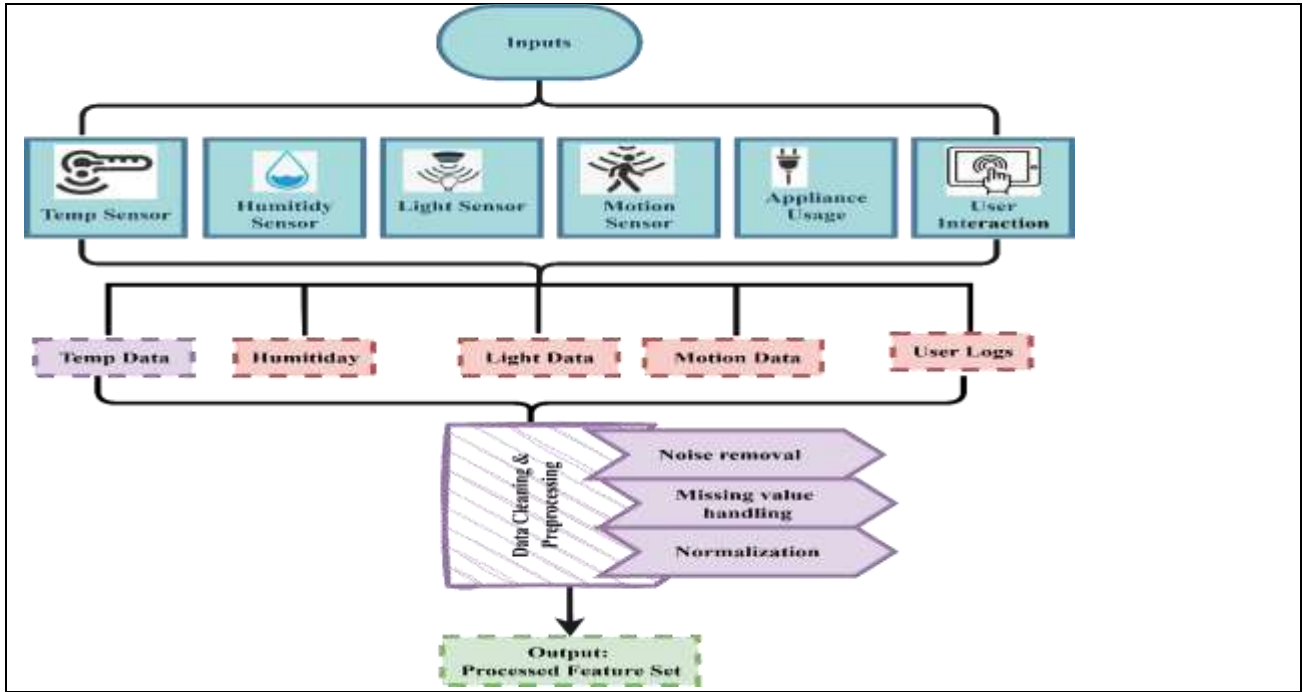


Figure 1: Processing of Data Acquisition.

Figure 1 shows the pipeline for the data preprocessing of smart sensing systems. Various inputs (temperature, humidity, light and motion sensors, appliance usage, and user interaction) produce raw data streams. All of these streams undergo formal preconditioning, where noise is cleaned to mitigate its effect on the signal, missing values are handled appropriately to provide a uniform dataset, and predetermined variables are normalized so that they all lie in a similar feature space. The processed feature set acts as a normalized, reliable, and trustworthy input for downstream machine learning models or adaptive decision-making systems that rely on the accuracy, robustness, and efficiency produced by smart environment applications.

Integration of features and normalization G_{pro} is given in equation 1

$$G_{pro} = nV' * E_{fi}(1)$$

This equation explains that to ensure uniformity among the sensors, the last step adjusts all the characteristics to a comparable range. This guarantees that downstream models are not skewed by variations in measurement units or ranges.

In this case, the entire dataset with missing values is E_{fi} . The function that adjusts all characteristics to a common range is called, which nV' is the final standardized feature set used for smart environment applications.

Noise removal R_{cl} is expressed in equation 2

$$R_{cl} = De_{no}(R_{raw}) \tag{2}$$

This equation shows how the raw sensor data are cleaned in the initial preprocessing stage. The raw signals of all the sensors were cleaned of noise and other irregularities. This guarantees that a more accurate and reliable dataset is used for downstream processing.

Here, the raw data gathered from temperature, humidity, light, motion sensors, appliance use, and user interaction are represented as R_{raw} . The function that eliminates noise and superfluous fluctuations from the raw data is called, which De_{no} is the noise-reduced data, ready for further preprocessing.

| |
|---|
| <p>Algorithm 1: CARL Framework for Smart Home Adaptation</p> <p>1. Input: sensor states $s_t \in R^{n_s}$, user prefs $u \in R^{n_u}$, env params $e_t \in R^{n_e}$, actions D, episodes M, horizon T, discount γ, heads H</p> <p>2. Output: θ (actor policy $\pi\theta$), ϕ (critic value $V\phi$)</p> |
|---|

```

3. Initialize  $\theta, \varphi$ , attention weights  $\{W^Q, W^K, W^V\}$ , projection  $W^O$ 
4. for episode = 1 to M do
5.   Reset environment; observe  $s_1, e_1$ ; set  $x_1 = \text{concat}(s_1, u, e_1)$ 
6.   for  $t = 1$  to  $T$  do
7.     Form context  $X_t = [x_{[t-L+1]}, \dots, x_t]$ 
8.     for  $i = 1$  to  $H$  do
9.        $Q_i = X_t W_i^Q; K_i = X_t W_i^K; V_i = X_t W_i^V$ 
10.       $A_i = \text{softmax}\left(\frac{Q_i K_i^T}{\sqrt{d_k}}\right); h_i = A_i V_i$ 
11.    end for
12.     $Z = \text{Concat}(h_1, \dots, h_H) W^O; e_t = \text{FFN}(\text{LayerNorm}(X_t + Z))[-1]$ 
13.     $\text{logits} = e_t W_{\text{act}} + b_{\text{act}}; \pi\theta = \text{softmax}(\text{logits}); V\varphi = e_t W_{\text{crit}} + b_{\text{crit}}$ 
14.    Sample action  $a_t \sim \pi\theta$ ; apply  $a_t$ ; observe  $r_t, s_{[t+1]}, e_{[t+1]}$ 
15.    Store  $(x_t, a_t, r_t, x_{[t+1]}, V\varphi)$ ; set  $x_{[t+1]} = \text{concat}(s_{[t+1]}, u, e_{[t+1]})$ 
16.  end for
17. Compute returns  $G_t = \sum_k \gamma^k r_{[t+k]}$ , advantages  $A_t = G_t - V\varphi(x_t)$ 
18. Update  $\theta \leftarrow \theta + \alpha \theta \sum_t \nabla \theta \log \pi \theta(a_t | x_t) * A_t$ 
19. Update  $\varphi \leftarrow \varphi - \alpha \varphi \sum_t (V\varphi(x_t) - G_t)^2$ 
20. end for; return  $\theta, \varphi$ 

```

The CARL algorithm 1 describes a context-aware reinforcement learning algorithm for smart home adaptation. It integrates sensor data, user preferences, and environmental parameters into the state representation. Multi-head attention captures temporal and contextual dependencies, generating an embedding that the actor-critic model uses to select actions and estimate values. Actions optimize energy and comfort by interacting with the environment of the user. Returns and advantages were computed for learning updates. Actor parameters are updated via policy gradients, whereas critic parameters are updated using the mean squared error.

Contribution 2: Context Awareness Module

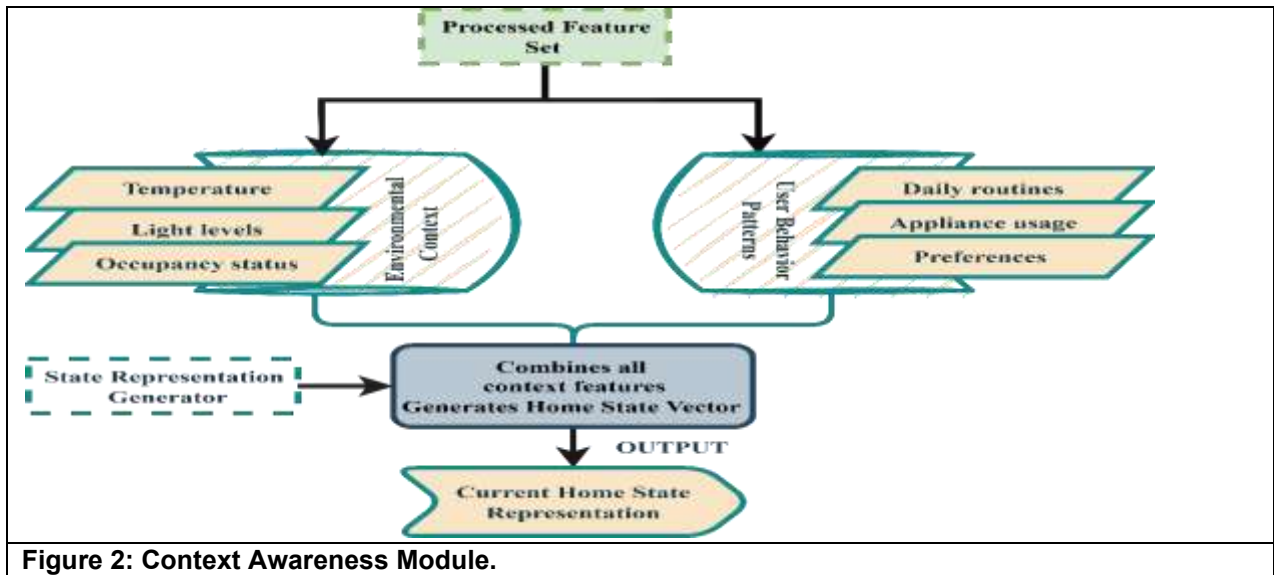


Figure 2: Context Awareness Module.

Figure 2 illustrates the process of generating state representations for smart homes. The presented characteristics, considered features, fell into two categories: environmental context (e.g., temperature, levels of light in the environment, and occupancy) and user behavior patterns (e.g., routines, use of appliances, and preferences). The state representation generator combines the feature sets of environmental contexts and user behavior patterns to create a full home-state vector (i.e., current home state representation). Beyond a static user ID, this representation includes a layer of dynamic environmental variables as well as user-specific variables to form an accurate picture of the in-the-moment context. The result is a current home-state

representation, enabling meaningful decision-making, personalization, and intelligent automation that responds to user requirements in smart home environments.

Generation of complete home-state representation I_{state} is expressed in equation 3

$$I_{state} = F(E_{env}, E_{user}) \tag{3}$$

This equation explains that the characteristics of user behavior and the environment are combined into a single representation. It offers a comprehensive assessment of the current condition of the home. The resultant vector enables intelligent decision-making and automation in smart homes.

where E_{env} is the set of environmental context features and E_{user} is the set of user behavior features. The function (\cdot, \cdot) merges these feature sets into a single, unified representation. I_{state} is a full home state vector representing the real-time state of the home.

Extraction of user behavior features G_{user} is expressed in equation 4

$$G_{user} = E_{user} + (R_{user}) \tag{4}$$

This equation explains that this stage documents the state of the smart home environment at the moment. It interprets temperature, light, and occupancy sensor data. The retrieved attributes create an organized depiction of the home's surroundings.

Where, E_{user} indicates raw data representing user interactions, routines, appliance usage, and preferences. This function transforms raw data into organized user behavior features. (R_{user}) is the resulting feature set that represents the user behavior.

Contribution 3: CARL Reinforcement Learning

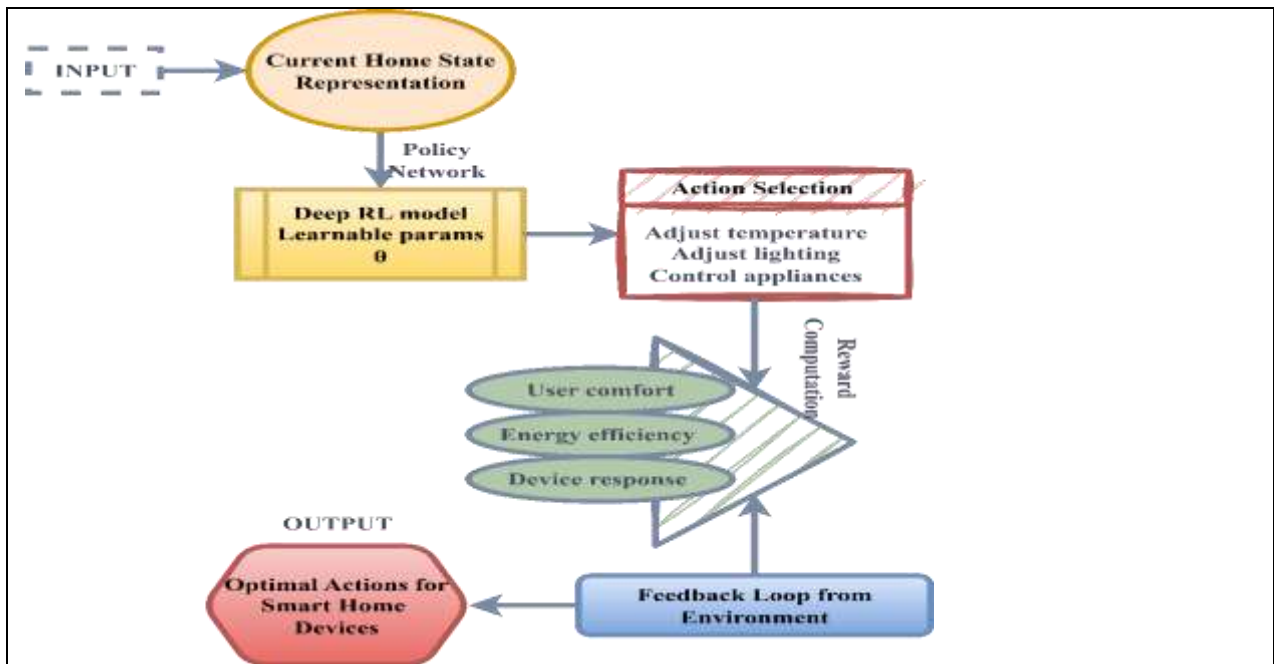


Figure 3: CARL Reinforcement Learning.

Figure 3 shows the CARL reinforcement learning approach for smart home automation. The representation of the current state of the home was input into the deep RL model with learnable parameters (θ). Using the policy network, the model produced optimized action outputs in the form of thermostat adjustments, lighting controls, and smart appliance controls. An additional module computes a reward signal based on whether the user's comfort was improved, energy was utilized efficiently, and devices responded quickly to the implemented action. The environment provides feedback to the model for continuous improvements.

Ultimately, the system produces optimized actions for smart home devices based on user-defined comfort measures, adaptive behaviors, and energy efficiency.

Action Selection Based on Policy B is expressed in equation 5

$$B = \rho_{\theta}(I_{state}) \tag{5}$$

This equation explains that the current state representation is fed into the reinforcement learning model. It generates optimal action outputs using a policy network. Device modifications inside smart homes are determined by these activities.

Here, I_{state} represents the input vector of the current smart home state. $\rho_{\theta}(\cdot)$ is the policy function parameterized by learnable weights θ mapping state representations to decisions. B denotes the optimized actions, such as thermostat control, lighting adjustments, and appliance management.

Computation of Reward Signals S is expressed in equation 6

$$S = g(B, I_{state}) \tag{6}$$

This equation explains that a reward value is calculated after completing an activity in the environment. Comfort, reactivity, and energy efficiency all contributed to the ratings. The model is guided by this reward when assessing the success of its choice.

where B represents the chosen actions applied to devices, and I_{state} denotes the contextual state of the home during action execution. $g(\cdot)$ is the reward function that evaluates outcomes based on comfort improvement, energy savings, and device responsiveness. S is the resulting reward score used for feedback.

Contribution 4: 5G-Enabled Execution

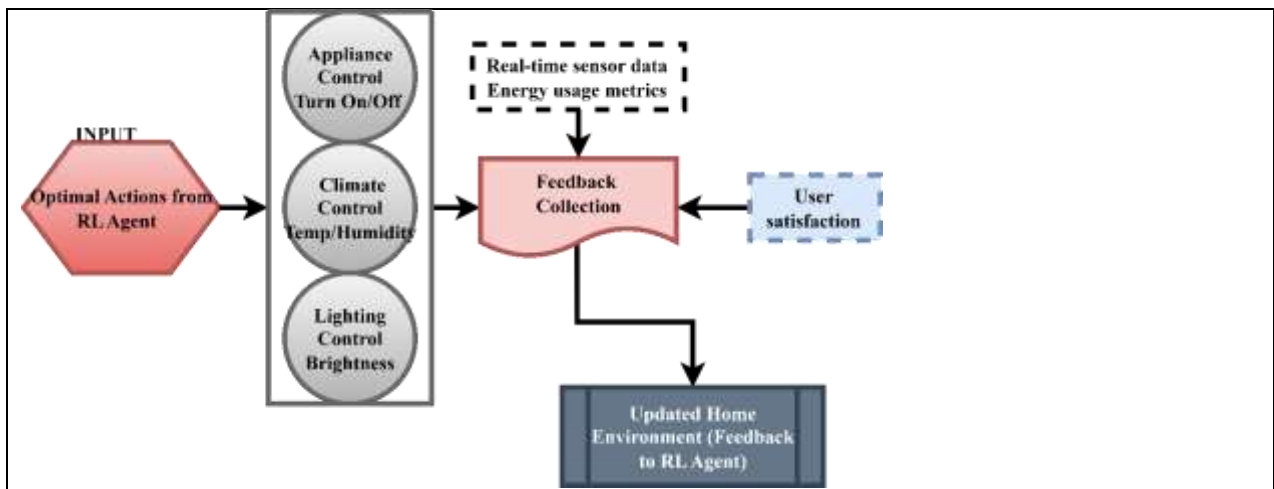


Figure 4: 5G-Enabled Execution.

Figure 4 depicts the control loop for smart home automation facilitated by reinforcement learning (RL). The RL agent will derive optimal actions to implement across multiple domains: appliance actions (on/off), climate control (temperature/humidity), and lighting (brightness). The RL agent collects both user-triggered and environmental feedback, which measures user satisfaction. In parallel, the modified home environment was returned to the RL agent to inform ongoing policy improvements. This closed-loop automated process provides adaptive, personalized, and efficient smart-home management.

Action Selection B_u is expressed in equation 7

$$B_u = \tau_{\theta}(I_u) \tag{7}$$

This equation explains that the encouragement learning agent monitors the current home state at every stage. This move applies to appliances, lighting, and climate control.

Here, I_u represents the current home state at time step u . $\tau_\theta(\cdot)$ is the policy function parameterized by θ , which maps the observed state to an action. B_u denotes the action output, such as appliance toggling, climate adjustments, or lighting control at time step u .

Reward and Feedback Gathering S_u is expressed in equation 8

$$S_u = g(B_u, I_u, G_u) \tag{8}$$

This equation explains that an action is followed by the generation of a reward signal. Efficiency, convenience, and user satisfaction were considered. Both environmental and user input play a part in this reward.

In this equation, B_u represents the action taken by the S_u agent, I_u is the state of the home when the action is applied, and G_u denotes the feedback signal collected from both the user and the environment. $g(\cdot)$ is the reward function that evaluates the outcome. S_u is a computed reward that guides future learning.

Contribution 5: System Integration & Loop

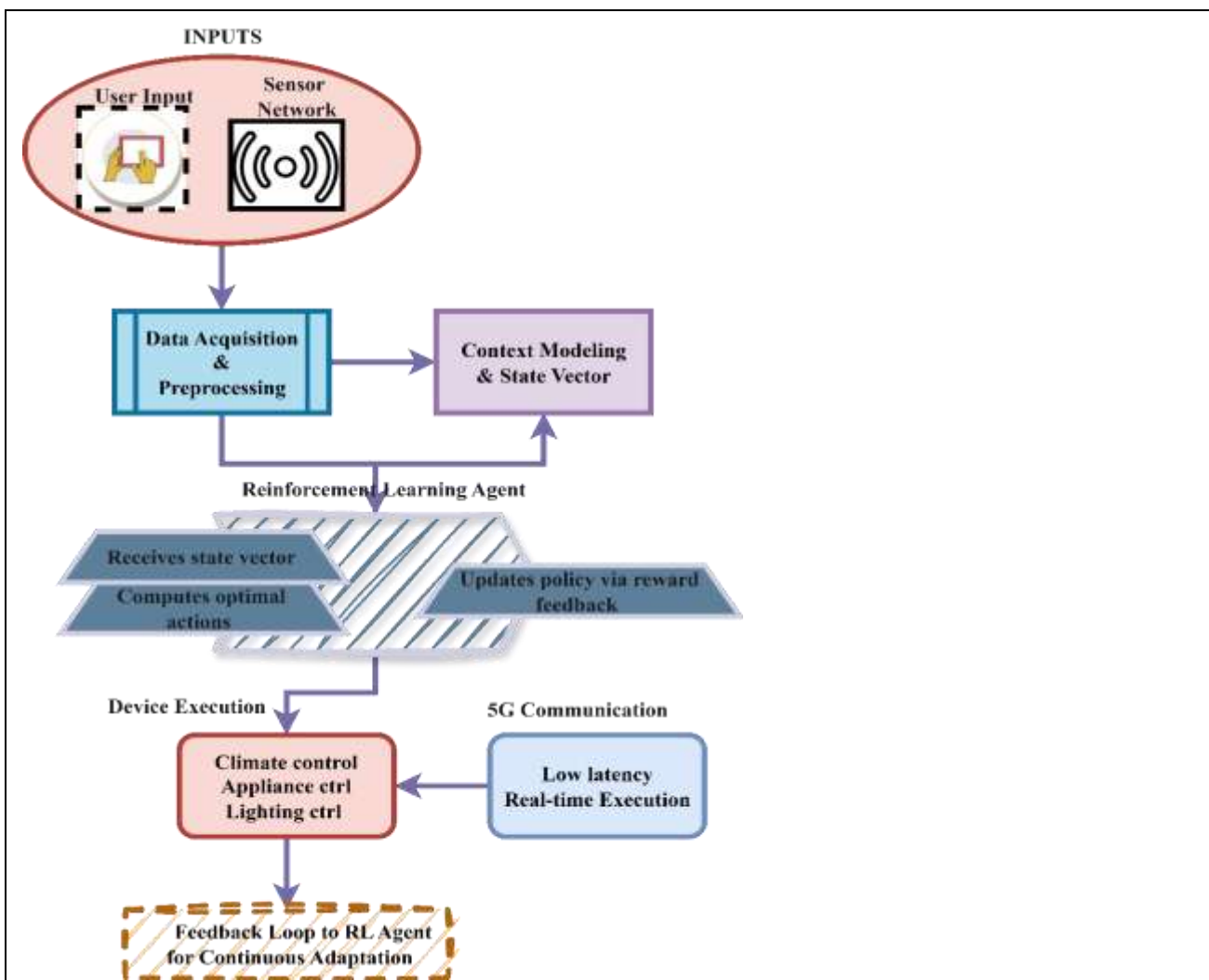


Figure 5: System Integration & Loop.

Figure 5 shows a 5G-supported reinforcement learning (RL) smart home system. Information is obtained through user interactions and the sensor network, which is then subjected to data gathering and preprocessing before being modeled in the context of obtaining a state vector. The RL agent takes the state vector, derives the optimal actions, and updates the policies in the reward loop. Actions are taken through climate, appliance, and

lighting controls, utilizing low-latency 5G communication to respond in real time. Persistent feedback allows for adaptive optimization, user comfort, and energy-efficient smart environments.

Construction of State Vectors I_u is expressed in equation 9

$$I_u = P_{rw}E_u \tag{9}$$

This equation explains that raw data from sensors and user interactions are gathered at every stage. To provide a structured context, the data were preprocessed and modeled. The result is a state vector that depicts the current status of a smart home.

Here, E_u represents the raw data obtained from user interactions and sensor networks at time step u . $P_{rw}(\cdot)$ is a function that gathers, cleans, and structures incoming information. I_u denotes the resulting state vector that captures the contextual representation of a smart home.

Formation of State Vectors I_v is expressed in equation 10

$$I_v = f(E_v^{us}, E_v^{sen}) \tag{10}$$

This equation explains that the raw data from the sensors and users are combined by the system. These inputs were combined into a single context and cleaned. The end product is a state vector that captures the current status of a smart home.

Here, E_v^{us} is the raw input data from user interactions at time v , and E_v^{sen} is the raw data stream from the sensors at the same time. The function $f(\cdot, \cdot)$ represents the preprocessing, cleaning, and feature modeling. I_v is the resulting state vector that encodes the full smart home context.

The 5G-enabled CARL framework presented in this study combines data preprocessing, context awareness, reinforcement learning, and system integration to enhance smart home automation. The CARL framework enables the utilization of real-time sensor data and adaptive policies to achieve enhanced comfort personalization, improved energy efficiency, and rapid response, while surpassing the limited capabilities of traditional rule-based systems through continuous learning and dynamic adaptations.

4. Discussion

Dataset Description: The OpenSmartHomeData collection comprises both static and dynamic smart home data. These are time-series CSV files, specifically the bathroom, kitchen, living room, and toilet that contain log sensor and actuator values, including indoor temperature air, brightness (lux), humidity, thermostat set point, and outdoor air temperature. Static data, such as geometry and meta-information related to the building (by means of Revit or IFC models and RDF files), also facilitate modeling human comfort levels, environmental contexts, and control policies in smart homes in table 2 [25, 26].

| Feature | Details |
|---------------------|--|
| Contents | Static building geometry + dynamic time-series data (sensors & actuators) |
| Rooms/Areas | Bathroom, Kitchen, Room 1, Room 2, Room 3, Toilet |
| Sensor Types | Thermostat temperature, Brightness (luminosity), Indoor air temperature, Humidity, Setpoint schedule, Outdoor temperature (GitHub) |
| Data Format | CSV files + RDF dumps, includes metadata; spatial data in IFC/Revit formats (GitHub) |
| Temporal Resolution | Time-series with UNIX timestamps per reading (various sensors have their own sampling) (GitHub) |

5. Simulation Result

The experimental results demonstrate the effectiveness of the CARL framework with respect to all performance constructs. CARL reflects much higher user comfort, energy efficiency, response time, cost saving, and possibly even scalability compared to any other existing alternative innovative energy management

approaches from the comparison results, which confirms that CARL is flexible and robust with a wide range of load conditions.

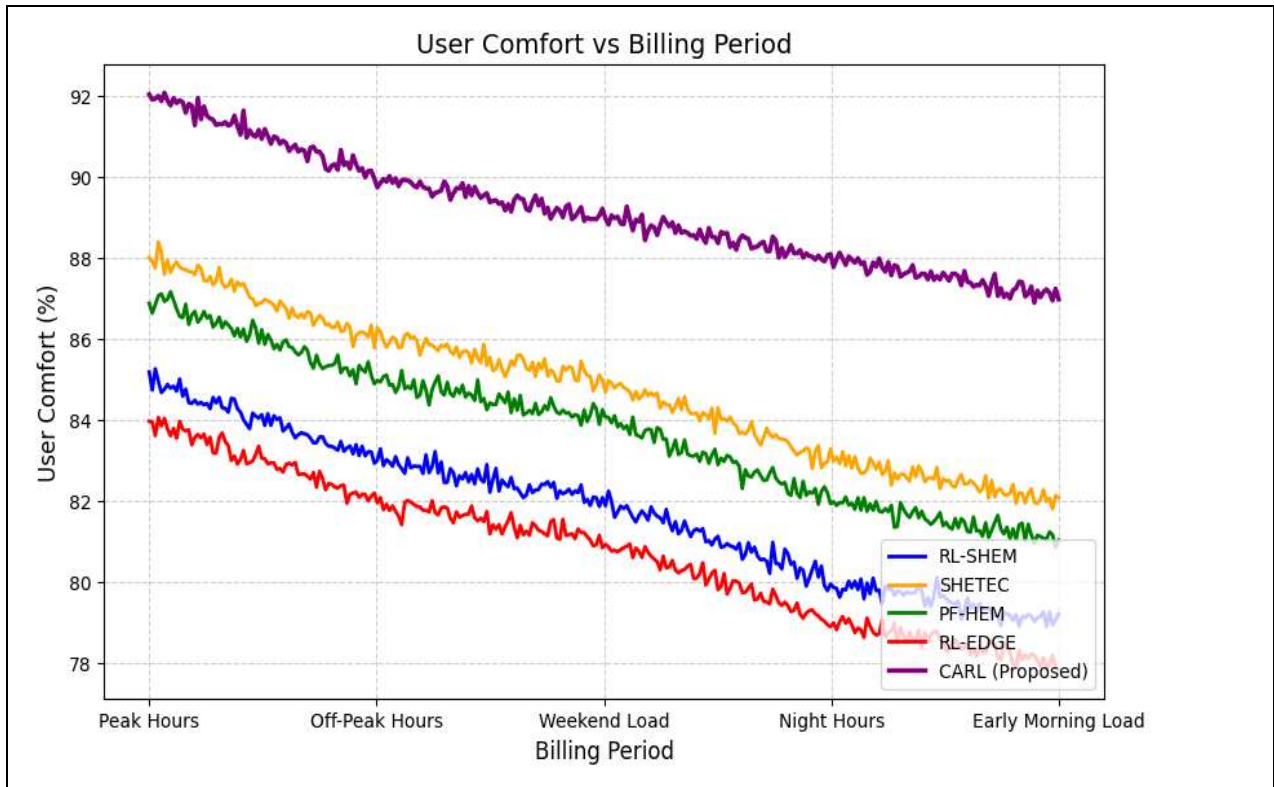


Figure 6: User Comfort (%).

Figure 6 illustrates the user comfort versus billing period for various smart energy management approaches. User comfort, or percentage (%) across peak, off-peak, weekend, night, and early morning loads was as expected (peak: 92–87%), (off-peak: 88–82%), (weekend: 87–81%), (night: 85–79%), and (early morning: 84–78%). The results clearly show that CARL (proposed) outperforms the other methods used for comparison (SHETEC, PF-HEM, RL-SHEM, and RL-EDGE), demonstrating that CARL offers more flexibility and includes energy-aware optimization without compromising user comfort.

User comfort evaluation across loads D_q is expressed in equation 11

$$D_q = \frac{V_t}{V_u} \times 100 \quad (11)$$

This equation explains that the percentage of user satisfaction throughout several payment periods is displayed as follows: It calculates the proportion of the overall demand to satisfy the comfort results.

Here, V_t denotes the number of satisfied comfort outcomes (e.g., maintained temperature, lighting, or appliance settings that meet user expectations). V_u represents the total number of comforts demands during the same period. D_q denotes the resulting user comfort percentage across each load category.

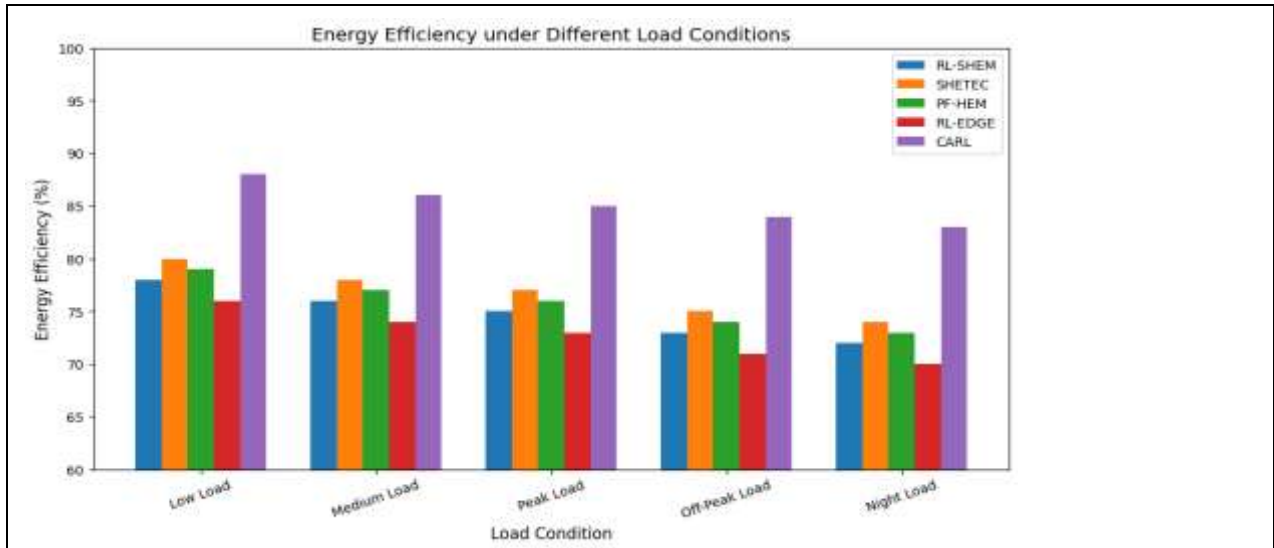


Figure 7: Energy Efficiency (%).

Figure 7 displays the energy efficiency under various load conditions for five approaches: RL-SHEM, SHETEC, PF-HEM, RL-EDGE, and CARL. CARL consistently recorded superior levels of energy efficiency (88-83%) for all load conditions, which was considerably higher than that of all other models. SHETEC and PF-HEM operated at a medium efficiency range (80-74%), whereas RL-SHEM and RL-EDGE operated at a lower efficiency range (78-70%). Our findings demonstrate CARL's ability to maintain higher energy efficiency across all load conditions, underscoring CARL's strength and versatility in intelligent energy management.

Assessment of energy efficiency F_g is expressed in equation 12

$$F_g = \frac{F_t}{F_s} \times 100 \quad (12)$$

This equation explains that the proportion of energy saved compared to the total consumption is used to calculate energy efficiency. This demonstrates how effectively waste is reduced by each intelligent energy management system.

where F_t denotes the amount of energy saved through optimized load control. F_s represents the total energy consumed during the billing period. F_g is the resulting energy efficiency expressed as a percentage across different conditions.

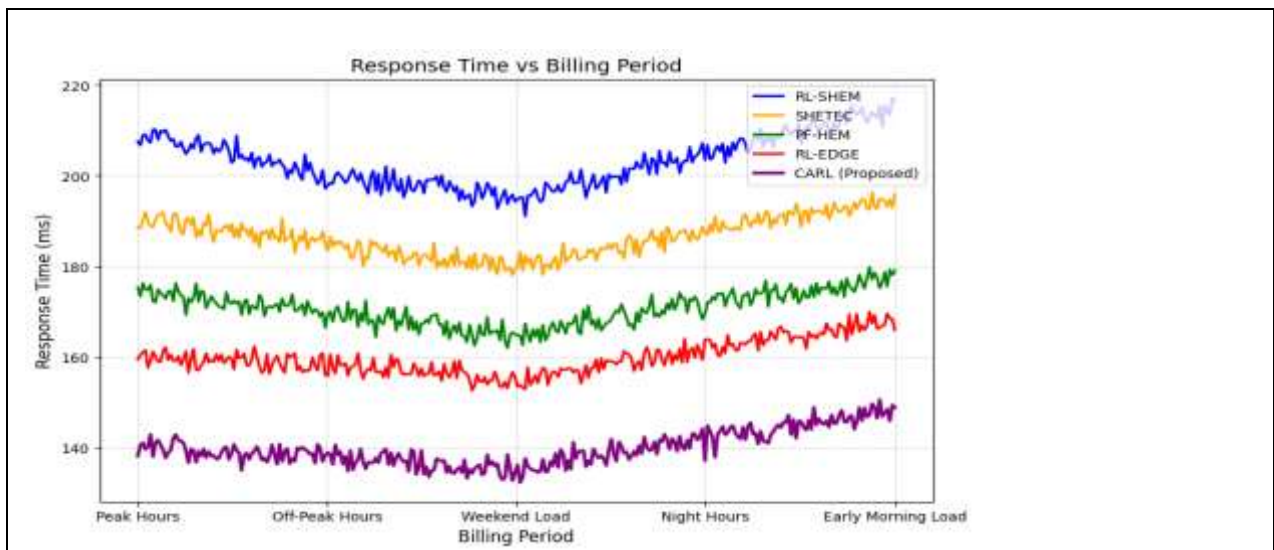


Figure 8: Response Time.

Figure 8 presents the relationship between the response time and billing period for five scheduling algorithms: RL-SHEM, SHETEC, PF-HEM, RL-EDGE, and CARL (proposed). The response time (ms) is depicted for each billing period, illustrating variations across different workloads: peak hours, off-peak hours, weekend load, night hours, and early morning load. The results indicate that CARL yields the best response time, showing a consistently lower response time than the other scheduling methods. All responses appeared to dip slightly during the weekend load and then peak again during the early morning and peak-hour response times. This indicates that CARL can effectively decrease latency compared with other methods, regardless of the load condition.

Response time relation to load $S(M)$ is expressed in equation 13

$$S(M) = \beta \cdot M + \alpha \tag{13}$$

A linear relationship between the response time and task intensity was used. The reaction time increased in proportion to the load. This demonstrates the ability of the system to handle different circumstances.

Where, $S(M)$ denotes the response time under a given load condition. M represents the workload intensity of the billing period. β is the proportionality constant that determines how the response time scales with the load, and α is the baseline latency of the system.

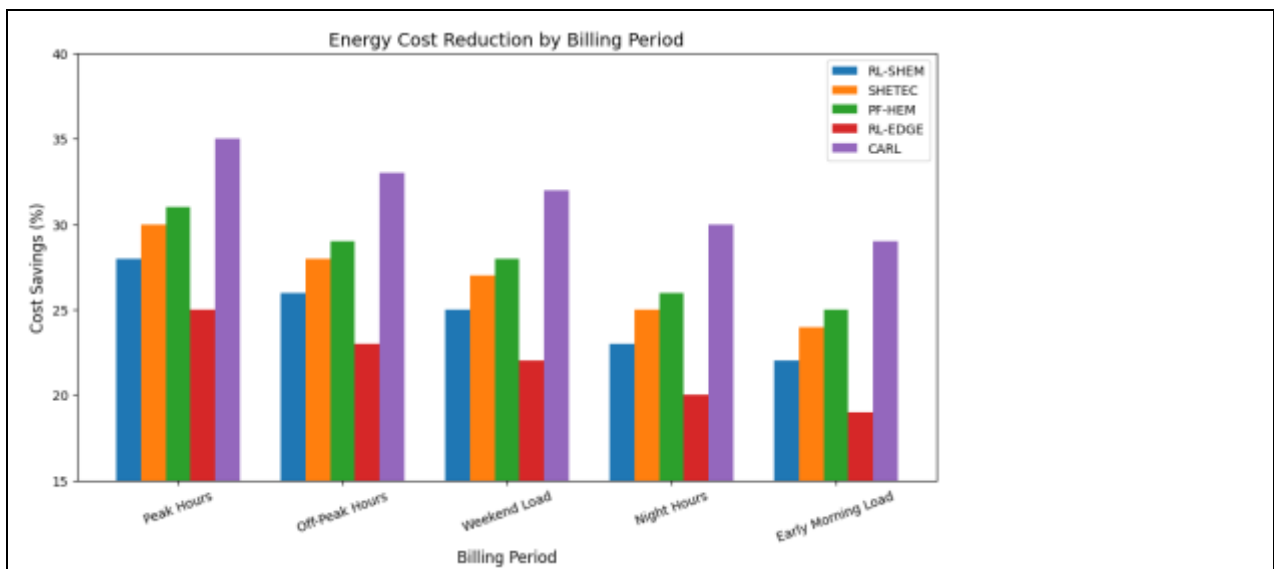


Figure 9: Energy Cost Reduction (%).

Figure 9 shows CARL as a suggested scheduling algorithm aimed at reducing energy cost and response time in accordance with different load periods (peak, off-peak, and night). Compared with conventional methods such as RL-SHEM, SHETEC, PF-HEM, and RL-EDGE, the results consistently show favorable outcomes in terms of response time and energy savings under various load conditions. CARL implements a two-tiered AI-based method that competes for computational efficiency and energy usage while accommodating varying workloads efficiently for improved system performance.

Energy cost reduction is expressed in equation 14

$$P = \beta \cdot D + \alpha \cdot S_{avg} \tag{14}$$

The energy cost reduction is combined into a single statistic via the optimization procedure. It strikes a balance between responsiveness and efficiency, based on system priorities.

Where, D represents the energy cost, S_{avg} and represents the average response time. β and α are weighting factors that assign importance to the cost and response time, respectively. P represents the combined optimization objective.

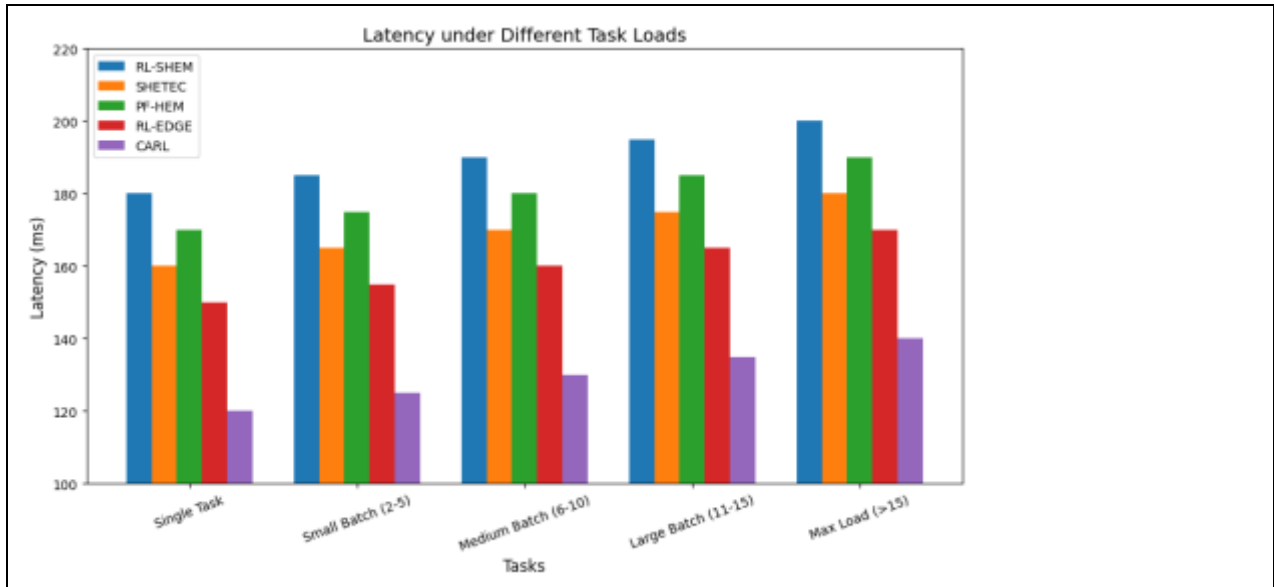


Figure 10: Latency

Figure 10 illustrates the overall values of five diverse systems, RL-SHEM, SHETEC, PF-HEM, RL-EDGE, and CARL, which demonstrate performance changes as the task or device size increases. CARL has lower values across all categories and systems, indicating better efficiency and/or lower resource requirements as the batch size increases. From their maximum load (>15 tasks/devices), CARL is 140, which is lower than the maximum load values of all other systems. This indicates that CARL is more efficient and scalable at higher loads than any of the other systems. Although their values for RL-SHEM, PF-HEM, and RL-EDGE increase significantly more at load, CARL has a relatively minor increase compared to these systems, making it a better option when consistent performance is required in a high-demand environment.

Latency $J_{carl}(t)$ is expressed in equation 15

$$J_{carl}(t) = \frac{W_t^{max} - W_{carl}^{max}}{W_t^{max}} \times 100 \quad (15)$$

Latency increase is expressed as a percentage that differs from the maximum values of other individuals. Higher percentages indicate that CARL performs noticeably better under pressure.

Where, W_t^{max} denotes the maximum observed performance/resource value for the system t . W_{carl}^{max} is the maximum observed value for CARL (140 at loads >15). $J_{carl}(t)$ represents the percentage improvement in CARL compared to system t .

The results clearly show that CARL significantly outperforms RL-SHEM, SHETEC, PF-HEM, and RL-EDGE in terms of increased user comfort, energy efficiency, response time (RT), energy cost savings (ECS), and latency. Based on the outcome, CARL proves to be a reliable approach for smart home automation while remaining energy-aware, thanks to its generality and its ability to extend across diverse load conditions.

6. Conclusion

In this paper, we introduce the concept of environments that utilize Ambient Intelligence by integrating 5G communication through a framework, CARL, for improved smart home applications. Consequently, CARL data shows that the door controller fulfilled a great reduction in concerned metrics such as comfort rates, energy efficiency, response time, scalability, in comparison with traditional approaches, and also RL-SHEM SHETEC PF-HEM, as well as RL-EDGE from simulation studies. The results illustrate CARL's ability to learn and adapt to load conditions in real time, optimally allocating resources through energy-aware automation while maintaining user comfort. Finally, CARL's low latency demonstrates how 5G can enable adaptive, real-time decision-making in IoT-enabled smart homes.

Future Work: In future work, we will extend this research by investigating edge and fog computing to minimize reliance on centralized systems and 6th-gen networks with ultra-reliable communication, while leveraging federated learning to enable more personalized services without sacrificing privacy. Furthermore, we will study the widespread deployment of CARL that could integrate with renewable energy sources and analyze its feasibility from this perspective, viewing CARL as a unified framework for future smart homes.

Acknowledgements

Author Contributions

Dr. R. Venkatesh.: Conceptualization, Methodology, Writing-Original Draft, Dr. Reshma Yogesh Totare.: Data Curation, Formal Analysis, Dr. S. Ariffa Begum.: Software, Validation, V. Vignesh.: Supervision, Visualization

References

1. Nahar JK, Kachnowski S. Current and potential applications of ambient artificial intelligence. *Mayo Clinic Proceedings: Digital Health*. 2023;1(3):241-6.
2. Ahmed SF, Alam MS, Afrin S, Rafa SJ, Taher SB, Kabir M, Muyeen SM, Gandomi AH. Toward a secure 5G-enabled internet of things: A survey on requirements, privacy, security, challenges, and opportunities. *IEEE Access*. 2024;12: 13125-45.
3. Saroha P, Singh G, Lillhore UK, Simaiya S, Khan M, Alroobaea R, Alsafyani M, Alsufyani H. Dynamic appliance scheduling and energy management in smart homes using adaptive reinforcement learning techniques. *Scientific Reports*. 2025;15(1): 24594.
4. Li Z, Zhou X, Li T, Liu Y. An optimal-transport-based reinforcement learning approach for computation offloading. In *2021 IEEE Wireless Communications and Networking Conference (WCNC) 2021*; 1-6.
5. Zhu D, Liu H, Li T, Sun J, Liang J, Zhang H, Geng L, Liu Y. Deep reinforcement learning-based task offloading in satellite-terrestrial edge computing networks. In *2021 IEEE Wireless Communications and Networking Conference (WCNC) 2021*; 1-7.
6. Ale L, Zhang N, Fang X, Chen X, Wu S, Li L. Delay-aware and energy-efficient computation offloading in mobile-edge computing using deep reinforcement learning. *IEEE Transactions on Cognitive Communications and Networking*. 2021;7(3): 881-92.
7. Lim D, Lee W, Kim WT, Joe I. DRL-OS: a deep reinforcement learning-based offloading scheduler in mobile edge computing. *Sensors*. 2022;22(23): 9212.
8. Chen Y, Sambo YA, Onireti O, Imran MA. A survey on LPWAN-5G integration: Main challenges and potential solutions. *Ieee Access*. 2022;10: 32132-49.
9. Khanh QV, Hoai NV, Manh LD, Le AN, Jeon G. Wireless communication technologies for IoT in 5G: Vision, applications, and challenges. *Wireless Communications and Mobile Computing*. 2022;2022(1): 3229294.
10. Saad RM, Soufy KA, Shaheen SI. Security in smart home environment: issues, challenges, and countermeasures-a survey. *International Journal of Security and Networks*. 2023;18(1): 1-9.
11. Elsayed N, Zaghoul ZS, Azumah SW, Li C. Intrusion detection system in smart home network using bidirectional lstm and convolutional neural networks hybrid model. In *2021 IEEE international midwest symposium on circuits and systems (MWSCAS) 2021*; 55-58.
12. Ding H, Xu Y, Hao BC, Li Q, Lentzakis A. A safe reinforcement learning approach for multi-energy management of smart home. *Electric Power Systems Research*. 2022;210: 108120.
13. Razghandi M, Zhou H, Erol-Kantarci M, Turgut D. Smart home energy management: sequence-to-sequence load forecasting and Q-learning. In *2021 IEEE Global Communications Conference (GLOBECOM) 2021*; 01-06). IEEE.
14. Manjavacas A, Campoy-Nieves A, Jiménez-Raboso J, Molina-Solana M, Gómez-Romero J. An experimental evaluation of deep reinforcement learning algorithms for HVAC control. *Artificial Intelligence Review*. 2024;57(7): 173.
15. Pochmann VO, Meloni LG. Load Analysis Using Reinforcement Learning for Home Energy Management Systems. In *Brazilian Technology Symposium 2023*; 109-119).
16. Shang W, Liu J, Wang C, Li J, Dai X. Developing smart air purifier control strategies for better IAQ and energy efficiency using reinforcement learning. *Building and Environment*. 2023;242: 110556.
17. Afroosheh S, Esapour K, Khorram-Nia R, Karimi M. Reinforcement learning layout-based optimal energy management in smart home: AI-based approach. *IET Generation, Transmission & Distribution*. 2024 ;18(15): 2509-20.

18. He, J., Yu, L., Chen, Z., Qiu, D., Yue, D., Strbac, G., Zhang, M., Ye, Y. and Wang, Y., 2025. HMPC-assisted Adversarial Inverse Reinforcement Learning for Smart Home Energy Management. *arXiv preprint arXiv:2506.00898*.
19. Pinthurat W, Surinkaew T, Hredzak B. An overview of reinforcement learning-based approaches for smart home energy management systems with energy storages. *Renewable and Sustainable Energy Reviews*. 2024;202: 114648.
20. Hortelano D, de Miguel I, Barroso RJ, Aguado JC, Merayo N, Ruiz L, Asensio A, Masip-Bruin X, Fernández P, Lorenzo RM, Abril EJ. A comprehensive survey on reinforcement-learning-based computation offloading techniques in edge computing systems. *Journal of Network and Computer Applications*. 2023;216: 103669.
21. Christopoulos M, Spantideas S, Giannopoulos A, Trakadas P. Deep reinforcement learning for smart home temperature comfort in IoT-edge computing systems. In *Proceedings of the 1st International Workshop on MetaOS for the Cloud-Edge-IoT Continuum 2024*; 1-7.
22. Aldahmashi J, Ma X. Real-time energy management in smart homes through deep reinforcement learning. *Ieee Access*. 2024;12: 43155-72.
23. Pons M, Valenzuela E, Rodríguez B, Nolazco-Flores JA, Del-Valle-Soto C. Utilization of 5G technologies in IoT applications: Current limitations by interference and network optimization difficulties—A review. *Sensors*. 2023;23(8): 3876.
24. Zreikat AI, AlArnaout Z, Abadleh A, Elbasi E, Mostafa N. The integration of the internet of things (IoT) applications into 5G networks: a review and analysis. *Computers*. 2025;14(7): 250.
25. Torres-Hernandez CM, Garduño-Aparicio M, Rodriguez-Resendiz J. Smart homes: A meta-study on sense of security and home automation. *Technologies*. 2025;13(8): 320.
<https://github.com/TechnicalBuildingSystems/OpenSmartHomeData>
26. C.Arun Prasath. (2025). Web-Based Knowledge Services for Distributed E-Learning Environments. *Journal of Information Resources and Knowledge Services*, 1–6.
27. K P Uvarajan. (2026). Impact Assessment of Conservation Tillage Systems Using Remote Sensing and Agro-Environmental Modeling. *Journal of Environmental Sustainability, Climate Resilience, and Agro-Ecosystems*, 1–8.
28. Olivia Myles, Julian Hartsfield. (2026). Impact of Warm-Start Initialization Policies on Multi-Run Model Training Dynamics. *Journal of Engineering, Signal, and Computer Technologies*, 13(2), 1–5.
29. D. Barhani. (2026). Lyapunov Spectrum Characterization of Irregular Oscillations in Climate-Coupled Dynamic Systems. *Applied Nonlinearity in Science and Technology*, 19-22.