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Optimizing Energy Efficiency in Smart Home Automation through Reinforcement Learning and Iot

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Author's contribution

The sole author designed, analysed, interpreted and prepared the manuscript.

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ABSTRACT

This thesis explores an innovative approach to optimizing energy efficiency in smart home environments by leveraging reinforcement learning (RL) and Internet of Things (IoT) technologies. As global energy demand rises and concerns over environmental sustainability intensify, smart homes offer a promising solution to reduce residential energy consumption while enhancing user comfort. The study presents a comprehensive architecture integrating IoT devices with RL algorithms, allowing for real-time monitoring and intelligent energy management. Through data collected from smart sensors, RL agents continuously learn and adapt to occupant behaviors and environmental changes, making optimal decisions to minimize energy usage without compromising user comfort. A real word-based analysis demonstrates that the proposed system achieves significant energy savings compared to traditional rule-based methods. The results underscore the effectiveness of combining RL and IoT for adaptive energy management, paving the way for scalable solutions that could extend to smart cities and renewable energy systems. This research provides valuable insights into how emerging technologies can contribute to sustainable energy practices in the residential sector.

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Keywords: Smart homes; energy efficiency; reinforcement learning; internet of things (IoT); Q-learning.

1. INTRODUCTION

In recent years, the importance of energy efficiency has surged due to increasing environmental concerns and the rising cost of energy. As global energy consumption continues to grow, there is a pressing need to develop innovative solutions that can reduce energy usage without compromising comfort and convenience. Smart home automation has emerged as a promising approach to address this challenge. By leveraging advanced technologies such as the Internet of Things (IoT), when integrated with machine learning techniques like Reinforcement Learning (RL), can dynamically learn, monitor, and manage energy consumption more effectively, leading to significant energy savings and reduced carbon footprints (Smith & Brown 2022).

Energy efficiency in smart homes is not only critical for reducing overall energy demand but also for combating climate change by minimizing greenhouse gas emissions. The integration of IoT enables the monitoring of appliances, lighting, and heating systems, creating a data-rich environment that can be leveraged by RL algorithms. Reinforcement learning, through its adaptive learning capabilities, can autonomously learn optimal strategies for energy management, ensuring that smart homes operate efficiently without compromising the comfort of their residents (Zhang et al. 2020).

1.1 Problem Statement

Despite the advancements in smart home technologies, current systems cannot often optimize energy usage dynamically and adaptively. Traditional automation systems rely on pre-defined rules and schedules, which may not account for real-time changes in user behavior or environmental conditions. This limitation results in suboptimal energy management and missed opportunities for energy savings. Therefore, there is a need for a more intelligent approach that can learn and adapt to varying conditions to optimize energy efficiency in smart homes.

1.2 Objectives

The main objectives of this research are:

1. To develop an intelligent energy management system for smart homes using reinforcement learning and IoT.
2. To optimize energy consumption by dynamically adjusting smart home devices in real time.
3. To improve automation by incorporating adaptive learning techniques that minimize user intervention.
4. To evaluate the energy savings and efficiency improvements achieved through the proposed system.
5. To provide a cost-benefit analysis comparing the proposed approach to traditional energy management methods in smart homes.

1.3 Scope of the Study

This study focuses on the optimization of energy consumption in smart homes through the integration of IoT devices and reinforcement learning algorithms. The scope is limited to typical residential settings equipped with IoT-enabled appliances such as thermostats, lighting systems, and home appliances. The research will consider factors such as user behavior, environmental conditions, and appliance power usage patterns in the design of the reinforcement learning framework. Furthermore, the insights gained from this research can be applied to other domains, such as smart buildings and cities, amplifying its impact on global energy efficiency efforts (Johnson & Lee 2023).

2. LITERATURE REVIEW

2.1 Smart Home Automation

Smart home automation has gained significant traction as a means to enhance energy efficiency and user convenience. Existing technologies primarily focus on automating household appliances and systems through pre-defined schedules and user inputs. For instance, programmable thermostats and smart lighting systems allow users to set specific times for operation, thereby reducing unnecessary energy consumption (Green & White 2021). However, these systems cannot often adapt to real-time changes in user behavior or environmental conditions, leading to suboptimal energy management (Patel & Kumar 2020). Moreover, the reliance on static rules and schedules can result in energy wastage when unexpected changes occur, such as a sudden drop in temperature or an unplanned absence from home (Lee & Park 2022).

The use of wireless communication protocols, such as Zigbee, Z-Wave, and Wi-Fi, has significantly enhanced the interconnectivity of smart devices. Machine learning and artificial intelligence (AI) are also being leveraged to predict user preferences and automate tasks in a more personalized manner (Smith et al. 2022). For instance, smart thermostats use Q-learning, a reinforcement learning algorithm, to optimize temperature settings based on user behavior and environmental factors, thus improving both comfort and energy efficiency. However, while smart home automation has made great strides, energy optimization remains a complex challenge, particularly in balancing user comfort with efficient energy use.

2.2 Energy Efficiency in Smart Homes

Energy efficiency has become a primary goal in smart home systems, driven by the need to reduce energy consumption and environmental impact. Various techniques have been employed to achieve this, including demand response (DR), energy scheduling, and load forecasting (Patel & Singh 2019). Demand response programs allow smart homes to adjust energy usage during peak hours in response to signals from utility providers, which helps prevent grid overload and reduces energy costs. Energy scheduling involves automating devices to operate during non-peak hours, while load forecasting predicts energy consumption patterns based on historical data.

One of the main challenges in optimizing energy consumption in smart homes is the dynamic nature of user behavior. Most energy management systems rely on pre-set rules or static schedules that do not account for real-time changes in user activities or environmental conditions. As a result, these systems often fail to maximize energy savings. Moreover, integrating renewable energy sources, such as solar panels, into smart homes introduces additional complexities in managing energy storage and consumption efficiently (Huang et al. 2019).

2.3 IoT in Smart Homes

The Internet of Things (IoT) plays a pivotal role in smart home automation by enabling devices to communicate with each other and with centralized control systems. IoT devices, such as smart meters, sensors, and actuators, collect data on energy consumption, temperature, humidity, and occupancy, allowing real-time monitoring and control of home systems (Singh & Dey 2020). Through this interconnected ecosystem, smart homes can optimize energy usage by dynamically adjusting device settings based on sensor inputs.

For example, motion sensors can detect when a room is unoccupied and turn off lights or appliances, while smart meters provide detailed insights into energy usage, enabling homeowners to make informed decisions about their consumption patterns. However, the massive amount of data generated by IoT devices poses challenges in terms of data processing, storage, and analysis (Zhao & Lee 2021). Integrating IoT with machine learning algorithms, such as reinforcement learning, can help address these challenges by enabling automated, data-driven decision-making for energy optimization. By integrating IoT with RL, smart homes can achieve a higher level of automation and efficiency, as the system can continuously learn and adapt to new data inputs (Yang & Li 2024).

2.4 Reinforcement Learning (RL)

Reinforcement Learning (RL) is a subset of machine learning where an agent learns to make decisions by interacting with an environment and receiving feedback in the form of rewards or penalties based on its actions. In the context of smart home energy management, RL can be used to dynamically adjust device settings (e.g., temperature, lighting) to optimize energy consumption while maintaining user comfort (Sutton & Barto 2018). Unlike traditional rule-based systems, RL does not rely on predefined schedules or static rules; instead, it learns from real-time data to adapt to changing conditions and user preferences.

The key advantage of RL in smart homes is its ability to autonomously learn optimal strategies over time. For instance, an RL-based system can learn to reduce heating when the home is unoccupied or adjust appliance usage during peak energy hours, without requiring constant user intervention. Several studies have demonstrated the effectiveness of RL in reducing energy consumption in smart homes. For example, a study by Gao et al. (2020) showed that RL-based energy management systems achieved significant energy savings compared to traditional methods.

2.5 Existing Solutions

Various approaches to energy optimization in smart homes have been developed, combining IoT with machine learning techniques. Rule-based systems, for example, use pre-defined rules to manage energy consumption, such as turning off appliances at specific times of the day. However, these systems are often inflexible and cannot adapt to real-time changes in user behavior or environmental conditions (Brown & Malik 2019).

On the other hand, model-based approaches leverage machine learning algorithms to predict energy consumption and adjust device settings accordingly. These models can be trained on historical data to forecast energy demand and optimize energy usage patterns. For example, neural networks have been used to predict electricity consumption in smart homes, allowing for more efficient energy management (Ali & Mahmood 2021).

2.6 Research Gaps

While previous studies have demonstrated the potential of Reinforcement Learning (RL) and the Internet of Things (IoT) in enhancing energy efficiency, several critical gaps remain unaddressed. Current research often lacks a holistic approach to integrating multiple IoT devices and systems, which is essential for comprehensive and effective energy management in smart homes. This integration is crucial for achieving a seamless interaction between devices, enabling more precise control and optimization of energy usage.

Moreover, there is a pressing need for scalable solutions that can adapt to diverse home configurations and varying user preferences. Existing solutions frequently fail to account for the dynamic nature of smart home environments, where user behavior and external conditions can change rapidly. Traditional model-based approaches, which rely heavily on historical data, are often inadequate in such settings due to their limited adaptability to real-time changes.

Reinforcement Learning offers a more dynamic and responsive solution by continuously learning from real-time data and making decisions based on evolving conditions. Unlike model-based approaches, RL can adapt to real-time scenarios, making it particularly suitable for environments with variable conditions, such as smart homes. However, despite its potential, the application of RL in this domain faces challenges, including the need for significant computational resources and the complexity of balancing energy savings with user comfort (Kumar & Sharma 2020).

This thesis aims to address these gaps by developing a unified RL framework that leverages Q-learning and integrates Arduino-based IoT data to optimize energy usage across various smart home systems. The proposed approach seeks to enhance overall energy efficiency while maintaining user satisfaction by learning and adapting to user preferences in real time. By addressing the integration and scalability challenges, this research contributes to the development of more intelligent and adaptive energy management solutions for smart homes, ultimately leading to significant advancements in the field.

3. METHODOLOGY

3.1 System Architecture

The proposed system architecture is designed to integrate IoT devices with reinforcement learning algorithms to optimize energy consumption in a smart home setting. This architecture consists of three main layers: the IoT layer, the data processing layer, and the reinforcement learning layer.

1. **IoT Layer**: This layer includes various IoT-enabled devices, such as smart thermostats, lighting systems, and sensors, that monitor environmental parameters like temperature, humidity, and occupancy. These devices are interconnected through a central hub, which enables seamless communication and data exchange among them.
2. **Data Processing Layer**: Data from the IoT devices is aggregated and pre-processed in this layer. The data processing unit handles real-time data cleansing, normalization, and structuring, preparing it for use in the reinforcement learning algorithm. This layer is also responsible for storing and retrieving historical data, which can provide additional insights for the RL agent.

3. **Reinforcement Learning Layer**: This is the decision-making layer, where the reinforcement learning agent interacts with the environment to learn optimal strategies for energy management. The RL agent receives state information from the data processing layer, takes actions by adjusting the settings of IoT devices, and receives feedback in the form of rewards based on energy efficiency and user comfort levels.

The entire system architecture is designed to operate autonomously, with minimal human intervention, continuously learning and adapting to improve energy efficiency.

3.2 Data Collection

Data collection involves recording key parameters such as energy usage, temperature, occupancy, and time-based changes. This data is logged locally and updated hourly, with particular attention to capturing state changes like shifts in occupancy or temperature adjustments. The IoT devices collect real-time data on several parameters, including:

- **Energy Usage**: Smart meters record the energy consumption of individual appliances and systems within the smart home.
- **Environmental Factors**: Sensors capture ambient conditions like temperature, humidity, and light levels.
- **Occupancy Patterns**: Motion detectors and occupancy sensors provide data on room usage and occupancy, enabling more accurate adjustments for energy savings.

The data collected is stored in a centralized database, which the RL agent accesses to track patterns and make energy management decisions. Regular updates of this data allow the system to adapt to real-time changes in the home environment and user behaviors, improving the effectiveness of energy optimization.

3.3 Algorithm Development

The Reinforcement Learning (RL) algorithm defines state and action spaces, where states are characterized by temperature, motion, time, light, and fan settings, and actions include turning the fan or lights on/off and adjusting the fan speed. The reward structure encourages energy-saving actions with positive rewards, such as a +10 for turning off lights in unoccupied rooms, while negative rewards, like -20, penalize actions that require user intervention, guiding the RL agent to better anticipate user needs.

The RL model used is designed as follows:

1. **State Space**: The state represents the smart home's current environment, including data such as room occupancy, current temperature, and time of day. By defining a comprehensive state space, the RL agent can understand the home's conditions in real-time.
2. **Action Space**: Actions represent the possible adjustments the agent can make to IoT devices, such as altering the thermostat setting, dimming lights, or powering down non-essential devices.
3. **Reward Function**: The reward function is designed to balance energy savings with user comfort. The RL agent receives a positive reward for actions that reduce energy consumption without negatively impacting user comfort. Conversely, actions that lead to discomfort or increased energy usage are penalized.

The agent uses a Q-learning network (QN) to approximate the optimal policy for energy management, learning from historical data to make better decisions in future scenarios. The RL agent undergoes extensive training to optimize energy usage in various simulated conditions before being implemented in the real environment.

3.3.1 Justification for using Q-learning in dynamic energy management

Q-learning is a popular reinforcement learning (RL) algorithm that is particularly effective for smart automation tasks, such as dynamic energy management. Its suitability for these tasks stems from its ability to learn optimal actions through interactions with the environment, without requiring a model of the environment (Atzori et al. 2010). This model-free approach allows Q-learning to adapt to changes in the environment, making it ideal for managing energy consumption dynamically. By continuously updating its policy based on feedback from the environment, Q-learning can optimize energy usage in real time, leading to more efficient and sustainable energy management solutions (Bellman 1957).

The algorithm works by maintaining a Q-table, which stores the expected utility of taking a given action in a particular state. As the system interacts with the environment, Q-learning updates this table using the Bellman equation, which incorporates the reward received from the environment and the estimated future rewards (Mnih et al. 2015). This iterative process enables the algorithm to converge towards an optimal policy that maximizes the cumulative reward over time. In the context of energy management, this means that Q-learning can effectively balance energy consumption with cost and resource availability, adapting to fluctuations in demand and supply (Sutton & Barto 2018).

Moreover, Q-learning's ability to handle high-dimensional state spaces and its robustness to noise and uncertainty make it well-suited for complex energy management systems. It can integrate data from various IoT devices, such as sensors and smart meters, to make informed decisions about energy distribution and usage (Watkins & Dayan 1992). This integration allows for a more granular and precise control of energy resources, reducing waste and improving overall system efficiency. By leveraging the strengths of Q-learning, smart automation systems can achieve significant improvements in energy management, contributing to sustainability goals and reducing operational costs (Yang et al. 2020).

3.4 Advantages of Reinforcement Learning (RL) over Traditional Rule-based

Reinforcement Learning (RL) offers significant improvements over traditional rule-based and static automation systems by addressing their inherent limitations. Rule-based systems rely on predefined rules and conditions, which can be inflexible and unable to adapt to new or unforeseen situations. Static automation systems, similarly, operate based on fixed parameters and lack the ability to learn from interactions or changes in the environment.

In contrast, RL is a model-free learning approach that allows systems to dynamically adapt to user behavior and environmental changes. By continuously interacting with the environment, RL algorithms learn optimal policies through trial and error, improving decision-making over time. This adaptability makes RL particularly suitable for complex and dynamic environments where user preferences and external conditions can vary significantly.

For example, in energy management systems, RL can optimize energy consumption by learning from user habits and adjusting device settings in real-time, leading to more efficient and personalized energy use. This dynamic adaptability is a key advantage of RL, enabling more responsive and intelligent automation solutions.

3.5 Real World Environment

Before deployment, the proposed system is tested in an environment to validate its effectiveness and refine the RL model. Tools such as MATLAB, Simulink, or OpenAI Gym can be used to replicate the smart home environment, incorporating IoT devices and energy consumption data. The model allows for the following:

- **Model Training and Validation**: The RL algorithm can be trained to ensure it effectively reduces energy consumption without compromising comfort.
- **Scenario Testing**: Various scenarios, such as changes in occupancy patterns and extreme weather conditions, are simulated to test the adaptability and robustness of the system.
- **Parameter Tuning**: By adjusting parameters like learning rate and discount factor in the real world, the performance of the RL model can be optimized for real-world deployment.

The results provide insights into the model's performance, enabling fine-tuning of the algorithm and system parameters before real-time implementation.

3.6 Performance Metrics

The success of the proposed system is evaluated using several performance metrics to measure its effectiveness in energy optimization and user comfort:

1. **Energy Savings**: This metric represents the reduction in energy consumption compared to traditional energy management systems. It is calculated as the percentage decrease in energy

usage achieved by the RL-based system.

2. **Response Time**: Response time measures the system's efficiency in making real-time adjustments based on data inputs. A lower response time indicates that the system can adapt to environmental changes quickly, enhancing overall performance.
3. **User Comfort Level**: User comfort is assessed through room temperature, lighting levels, and system responsiveness. This metric ensures that energy optimization does not compromise comfort by balancing reward functions in the RL model.

These metrics provide quantitative benchmarks for evaluating the system's efficiency and practicality, guiding further improvements to enhance the smart home energy management solution.

3.7 System Testing and Validation

System Testing and Validation include circuit testing, where Proteus is used to verify circuit functionality, and RL training, where the agent is trained on real-time data with adjustments refined based on user feedback.

3.8 Flow Charts

Fig. 1 illustrates the architecture of the proposed IoT-based smart home automation system, detailing the interactions between sensors, the Arduino controller, the ESP8266 Wi-Fi module, and various actuators (e.g., lights and fan). This architecture forms the backbone of the system's communication and control structure.

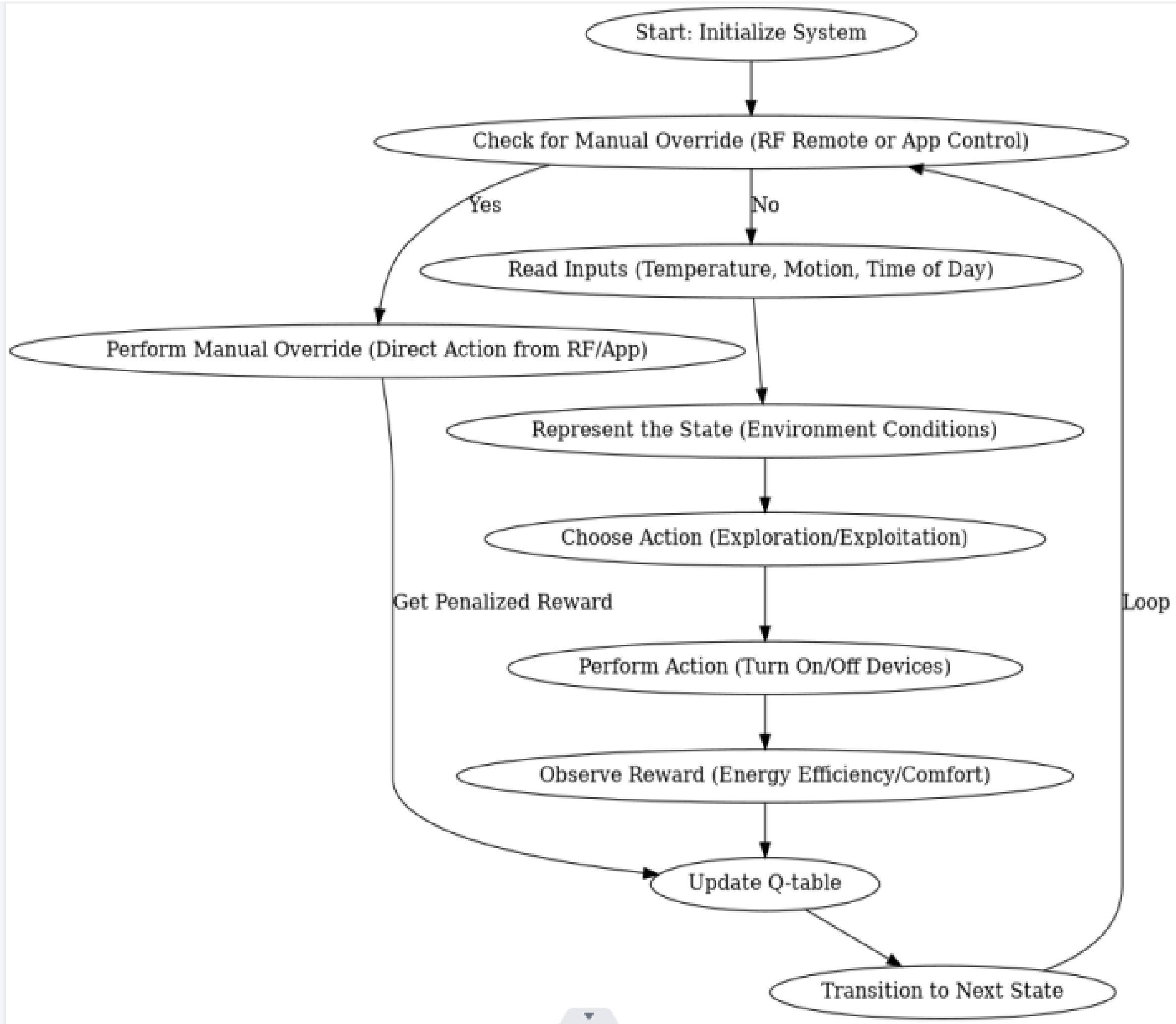

Fig. 1. Reinforcement learning

4. RESULTS AND DISCUSSION

Table 1. Dataset

Day	Light (kWh)	Fan (kWh)	Total Energy (kWh)
1	32	300	332
2	28.5	320	348.5
3	30	280	310
4	34.5	300	334.5
5	29	312	341
6	30.5	288	318.5
7	27.5	296	323.5
8	28	320	348
9	33.5	290	323.5
10	31	315	346
11	29	280	309
12	33	300	333
13	28.5	305	333.5
14	31.5	290	321.5
15	32	325	357
16	30	270	300
17	28.5	320	348.5
18	31	288	319
19	30.5	290	320.5
20	32.5	298	330.5
21	30	320	350
22	33.5	305	338.5
23	28.5	278	306.5
24	32	285	317
25	28	320	348
26	15.5	320	335.5
27	18	315	333
28	20	288	308
29	16	290	306
30	21.5	295	316.5
31	23	275	298
32	19	280	299
33	24	288	312
34	15	290	305
35	25	300	325
36	18.5	290	308.5
37	22	280	302
38	23	275	298
39	20	310	330
40	30	290	320
41	28.5	315	343.5
42	26	320	346
43	31	280	311
44	28.5	330	358.5
45	30	298	328
46	32.5	285	317.5
47	34	320	354
48	28	270	298
49	26.5	290	316.5
50	30	310	340
51	23.5	320	343.5
52	27	270	297

Day	Light (kWh)	Fan (kWh)	Total Energy (kWh)
53	30	295	325
54	25	320	345
55	23	300	323
56	26.5	330	356.5
57	32.5	310	342.5
58	30	305	335
59	28	320	348
60	33	310	343

This dataset represents energy consumption data over 60 days, specifically focusing on two types of energy usage: lighting and fan usage, measured in kilowatt-hours (kWh). Here's a breakdown of the dataset:

Day: This column represents the day number, ranging from 1 to 60, indicating the sequential order of the days the data was collected.

Light (kWh): This column shows the amount of energy consumed by lighting each day, measured in kilowatt-hours.

Fan (kWh): This column indicates the energy consumed by fans on each day, also measured in kilowatt-hours.

Total Energy (kWh): This column provides the total energy consumption for each day, which is the sum of the energy consumed by lighting and fans.

The dataset can be used to analyze patterns in energy consumption, identify peak usage days, and evaluate the effectiveness of energy-saving measures. For example, you might look for trends in energy usage over time, compare the energy consumption of lighting versus fans, or assess the impact of specific interventions on total energy consumption.

4.1 Report

Data was collected in real-time through a custom IoT-based smart home automation system centered on the ATmega328P microcontroller and equipped with a PIR motion sensor and a light sensor. This system, connected to the home Wi-Fi network via a Wi-Fi module, transmitted data to a central database hosted on a local PC running Flask. The PC maintained continuous communication with the IoT devices, gathering and storing environmental data, including motion and lighting changes, in real-time. This setup allowed the reinforcement learning model to access a live data stream, enabling dynamic adjustments to optimize energy consumption in response to current occupancy and environmental conditions.

4.2 Implementation Overview

The model is deployed using a Flask application, which continuously receives environmental data, processes it to determine the optimal actions, and updates its knowledge based on reward feedback. Key elements include:

- **Environment Setup:** The environment consists of the AI agent's states and actions to determine optimal control settings for lights and fans.
- **States and Actions:** The states include temperature, motion, time of day, and the on/off status of lights and fans. The actions involve turning fans and lights on/off or adjusting fan speed.
- **Q-Table**: A Q-learning table (Q-table) is maintained to store and update the expected rewards for each state-action pair. This table is periodically saved to a file for persistence.
- **Exploration and Exploitation:** The model initially explores actions to build a knowledge base but gradually shifts toward exploiting learned actions as the exploration rate decays.
- **Reward Calculation:** Rewards are calculated to balance energy efficiency with user comfort. The agent is rewarded for actions that reduce energy consumption when no motion is detected and prioritizes comfort when motion is detected, adapting based on time of day and temperature. For instance, if motion is detected on a hot day, cooling actions are favored; similarly, lights are activated at night when motion is sensed to ensure comfort.

4.3 Flask API Endpoints

1. **Environment Data Endpoint:** Accepts environmental data such as temperature,

motion, fan speed, and light status. This data is parsed and mapped to discrete states that the agent uses for decision-making.

2. **Action Selection:** Action Selection: Once the environment data is processed, the agent decides whether to explore or exploit. If it chooses to exploit, it selects the optimal action from the Q-table based on learned values. If it chooses to explore, it picks a random action, allowing it to gather new data and potentially improve future decision-making.
3. **Reward Calculation (**: The agent receives feedback in the form of a reward based on the actions taken. The reward is calculated considering temperature, motion, light state, fan state, and time-based preferences. The Q-table is then updated with the calculated reward.
4. **Reset Q-Table**: Resets the Q-table to its initial state and clears all stored updates, which is useful for retraining or testing in a new environment.

4.4 Q-Learning Parameters

- **Learning Rate:** Set to 0.1 to gradually incorporate new knowledge without overwhelming prior learning.
- **Discount Factor:** Set to 0.9, which allows the agent to prioritize long-term rewards over immediate ones.
- **Exploration Rate:** Starts at 1.0 and decays to 0.01, ensuring an initial phase of exploration that gradually shifts to exploitation of learned strategies.
- **Q-Table Storage:** The Q-table is periodically saved to a file to enable recovery in case of unexpected application restarts or shutdowns.

4.5 Reward System

The reward structure encourages energy efficiency and user comfort:

- **Energy-Saving Rewards:** Positive rewards for turning off devices when no motion is detected, particularly during daylight hours or when the temperatures are moderate.
- **Comfort Rewards:** Positive rewards for turning on fans or lights when motion is detected, especially during high temperatures or at times when lighting is expected.
- **Redundancy Penalties:** Small penalties are assigned for redundant actions, such as turning on a fan already at the desired speed, which encourages efficient decision-making.

Fig. 2 compares daily energy consumption for AI-based and normal automation systems over 60 days. The graph highlights the fluctuating energy savings achieved through reinforcement learning.

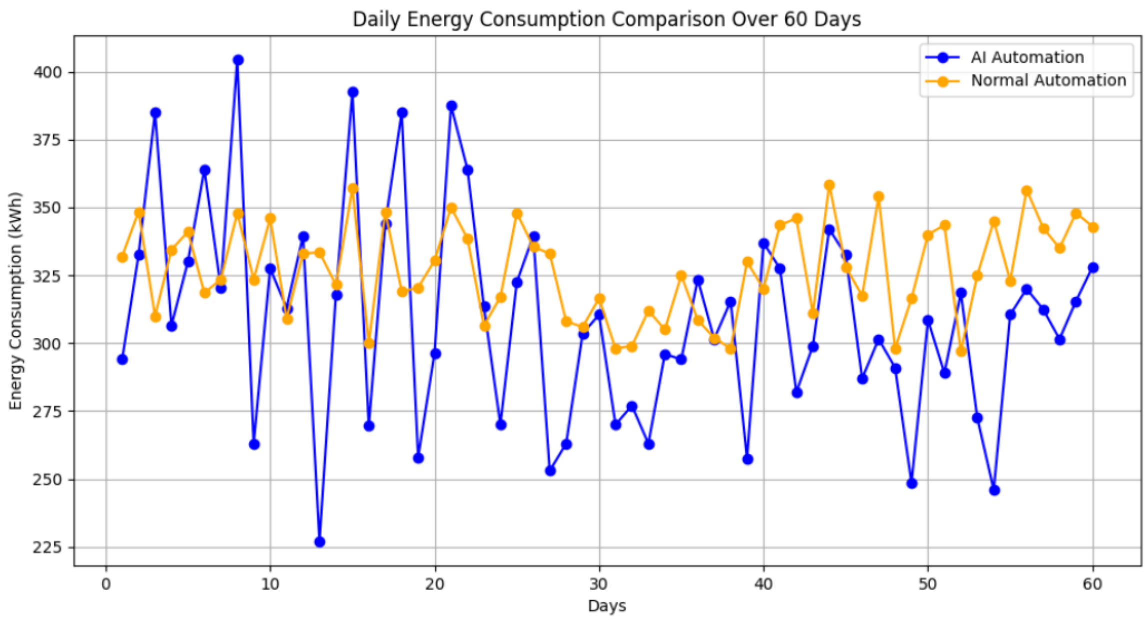

Fig. 2. Daily energy consumption for 60 days

Table 2. Normal automation energy table (Updated)

Segment	Cumulative Days	Light (kWh)	Fan (kWh)	Total Energy (kWh)
Pre-Override	Day 1 to Day 25	729.6	7073.28	7802.88
Manual Override	Day 25 to 37.5	333.6	3225.6	3559.2
Post-Override	Day 37.5 to 60	703.2	6854.4	7560.0
Total	Day 1 to Day 60	1766.4	17153.28	18919.68

Table 3. Comparison to AI automation (Updated)

Segment	Cumulative Days	Light (kWh)	Fan (kwh	Total Energy (kWh)
Pre-Override	Day 1 to Day 25	760.0	7368.0	8128.0
Manual Override	Day 25 to Day 37.5	347.5	3360.0	3707.5
Post-Override	Day 37.5 to Day 60	732.5	**7270.5**	**8003.0**
Total	**Day 1 to Day 60**	**1840.0**	**17998.5**	**19838.5**

Table 4. AI automation and normal automation

Segment	Automation Type	Light(kWh)	Fan(kWh)	Total Energy(kWh)
Pre-Override	AI Automation	729.6	7073.28	7802.88
Pre-Override	Normal Automation	760.0	7368.0	8128.0
Manual Override	AI Automation	333.6	3225.6	3559.2
Manual Override	Normal Automation	347.5	3360.0	3707.5
Post-Override	AI Automation	703.2	6854.4	7560.0
Post-Override	Normal Automation	732.5	**7270.5**	**8003.0**
Total	**AI Automation**	**1766.4**	**17153.28**	**18919.68**
Total	**Normal Automation**	**1840.0**	**17998.5**	**19838.5**

Normal automation does not have the same ability to adjust and optimize based on manual interventions or learned behaviors, leading to slightly higher overall energy use. Unlike AI automation, it becomes progressively more efficient, particularly after learning from manual overrides.

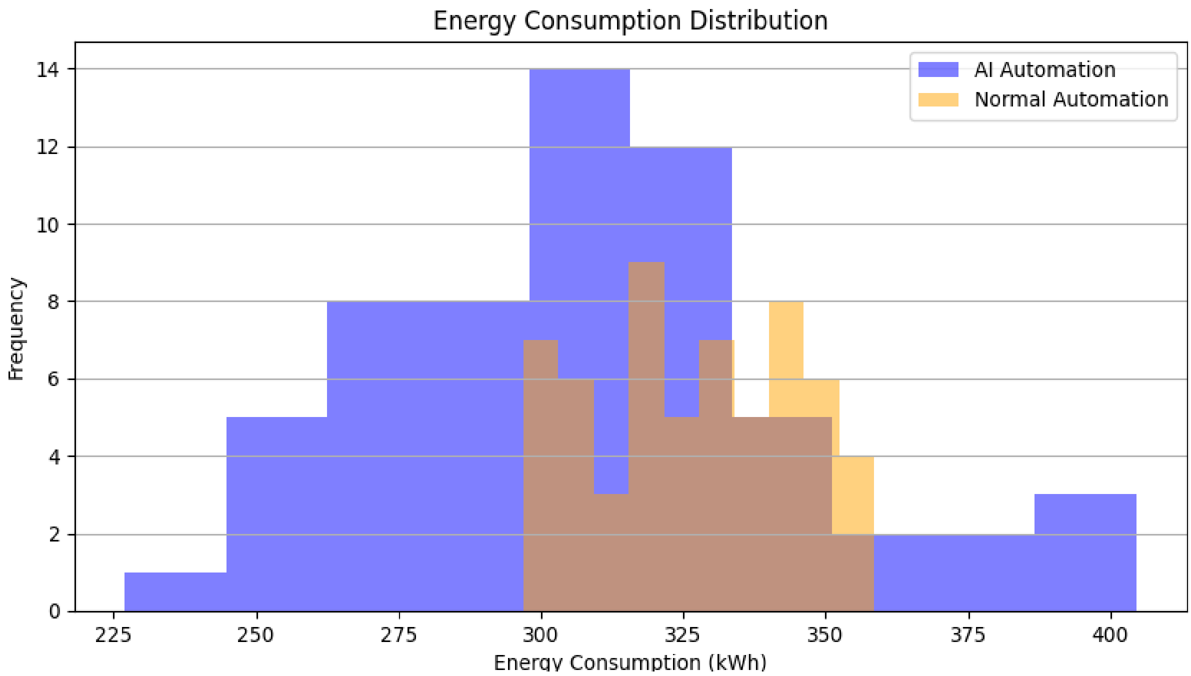

Fig. 3. Energy consumption distribution

Fig. 3 compares daily energy consumption for AI-based and normal automation systems over 60 days. The graph highlights the fluctuating energy savings achieved through reinforcement learning.

Fig. 4 shows a breakdown of energy consumption across different operational phases (pre-override, manual override, and post-override), with distinct energy use for lighting and fans. The graph demonstrates how manual overrides impact total consumption.

Fig. 5 illustrates the energy consumption over 60 days, segmented into Pre-Override, Manual Override, and Post-Override phases. During the Manual Override phase, user interventions contributed to a noticeable reduction in total energy usage. In the post-override phase,

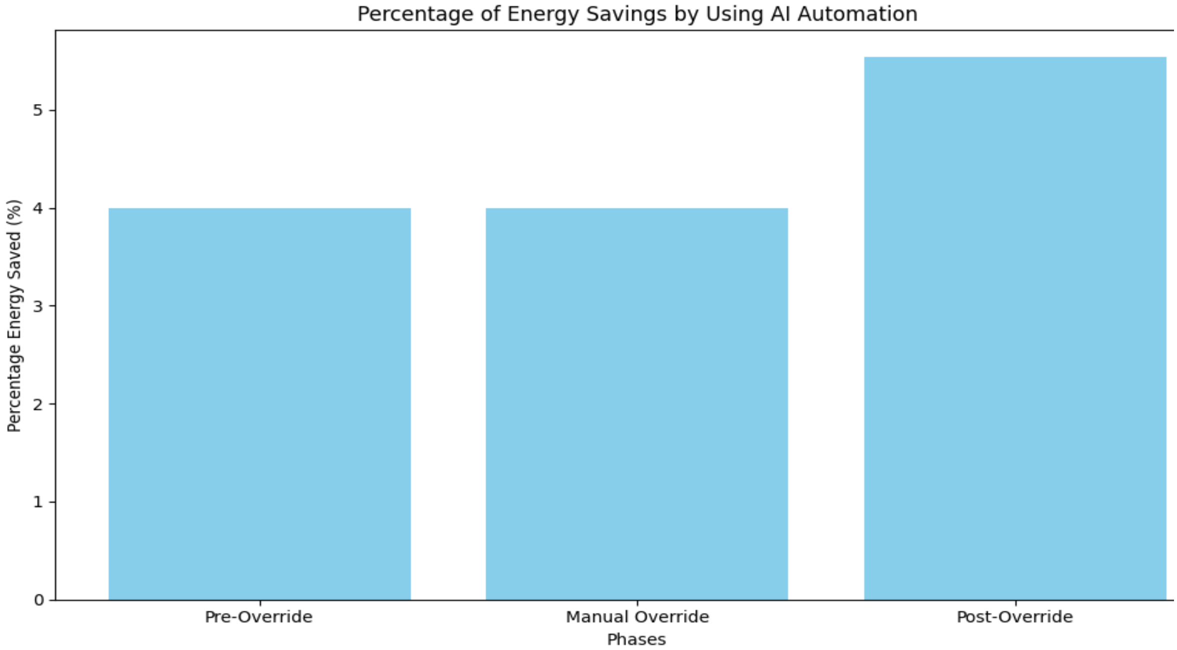

Fig. 4. Energy saving using AI automation

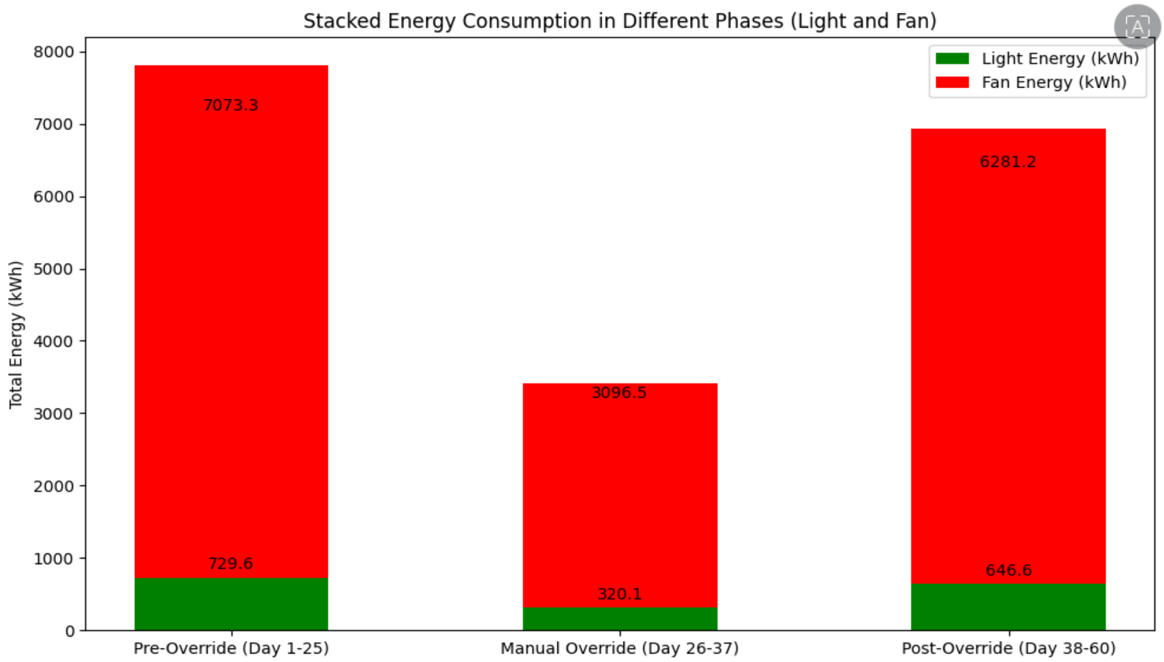

Fig. 5. Energy consumption in phases (Light and Fan)

automated control resumed, adapting based on patterns observed during manual adjustments, leading to continued energy-efficient operation.

Fig. 6 displays cumulative energy savings achieved through AI automation, indicating the manual override period. The steady upward trend underscores the effectiveness of the AI system.

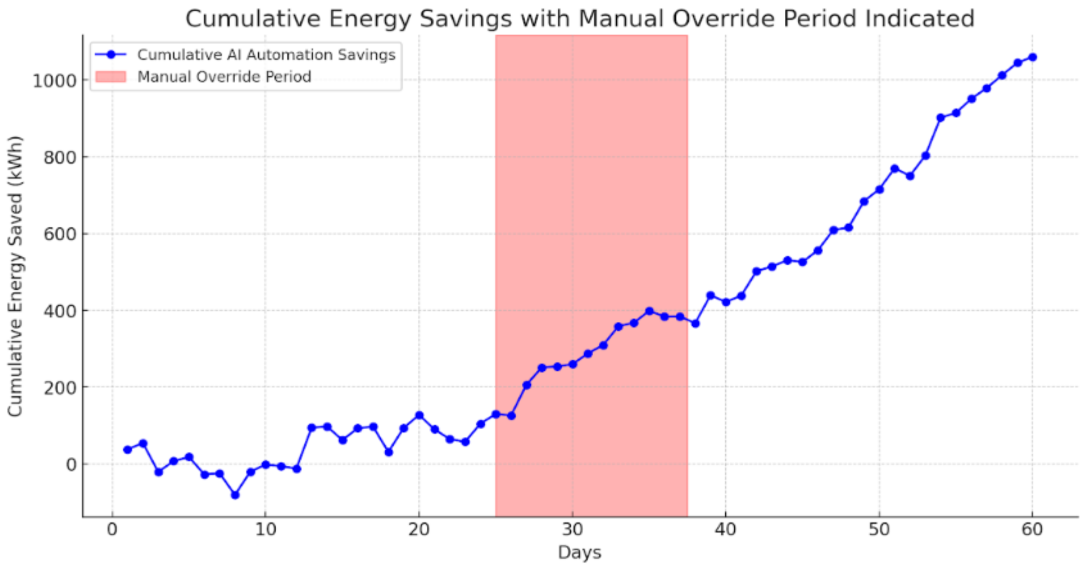

Fig. 6. Cumulative energy savings

4.6 Real-world and Project Diagrams

Fig. 7. Components required for the smart system

Fig. 7 shows all the components used for the automation of the Smart System.

Fig. 8. Automated smart system (When Device is off)

Fig. 9. Automated smart system (When Device is Turned On)

Fig. 8 shows the internal wiring and components of the smart home prototype, including the relay and microcontroller setup. This physical setup validates the practical implementation of the system.

Fig. 9 displays the completed smart home prototype with connected appliances, including the fan and lighting. This setup demonstrates the practical arrangement and packaging of the control system.

5. CONCLUSION

The study's findings reveal that the Q-learning model successfully optimized energy consumption by dynamically controlling lighting and fan usage based on real-time environmental data. This approach not only achieved substantial energy savings but also maintained user comfort, showcasing the potential of reinforcement learning as a more adaptive and efficient alternative to traditional control systems. The research contributes to the field by introducing a novel framework that integrates IoT data for real-time energy management, offering a methodological foundation for future studies. The practical applications of this system provide valuable insights for designing intelligent energy management solutions in residential settings, with implications for larger-scale smart building projects. Looking ahead, the study suggests avenues for further research, such as incorporating additional IoT devices and exploring renewable energy sources. Enhancing the model's scalability and computational efficiency could facilitate broader adoption and implementation, paving the way for more sustainable living through advanced smart home automation.

6. RECOMMENDATION

1. To enhance the system's capability, integrate more IoT devices such as smart plugs, energy-efficient appliances, and advanced sensors. This will provide a richer dataset for the RL model to learn from and optimize energy usage more effectively.
2. Incorporate user feedback mechanisms to continuously refine the RL model's decision-making process. This can help balance energy efficiency with user comfort, ensuring that the system adapts to individual preferences and lifestyles.
3. Implement robust security protocols to protect the data collected by IoT devices. Ensuring user privacy and data security is crucial for the widespread adoption of smart home technologies.
4. Design the system architecture to be scalable, allowing it to be easily adapted for larger environments such as smart buildings or communities. This involves optimizing the computational efficiency of the RL algorithms to handle increased data loads.
5. Educate users on the benefits and functionalities of the smart home system to encourage active participation and trust in the technology. Engaged users are more likely to provide valuable feedback and insights.

DISCLAIMER (ARTIFICIAL INTELLIGENCE)

The author hereby declares that NO generative AI technologies such as Large Language Models (ChatGPT, COPILOT, etc.) and text-to-image generators have been used during the writing or editing of manuscripts.

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COMPETING INTERESTS

Author has declared that no competing interests exist.

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