

**SMART HOME ENERGY MANAGEMENT SYSTEM USING REINFORCEMENT LEARNING**

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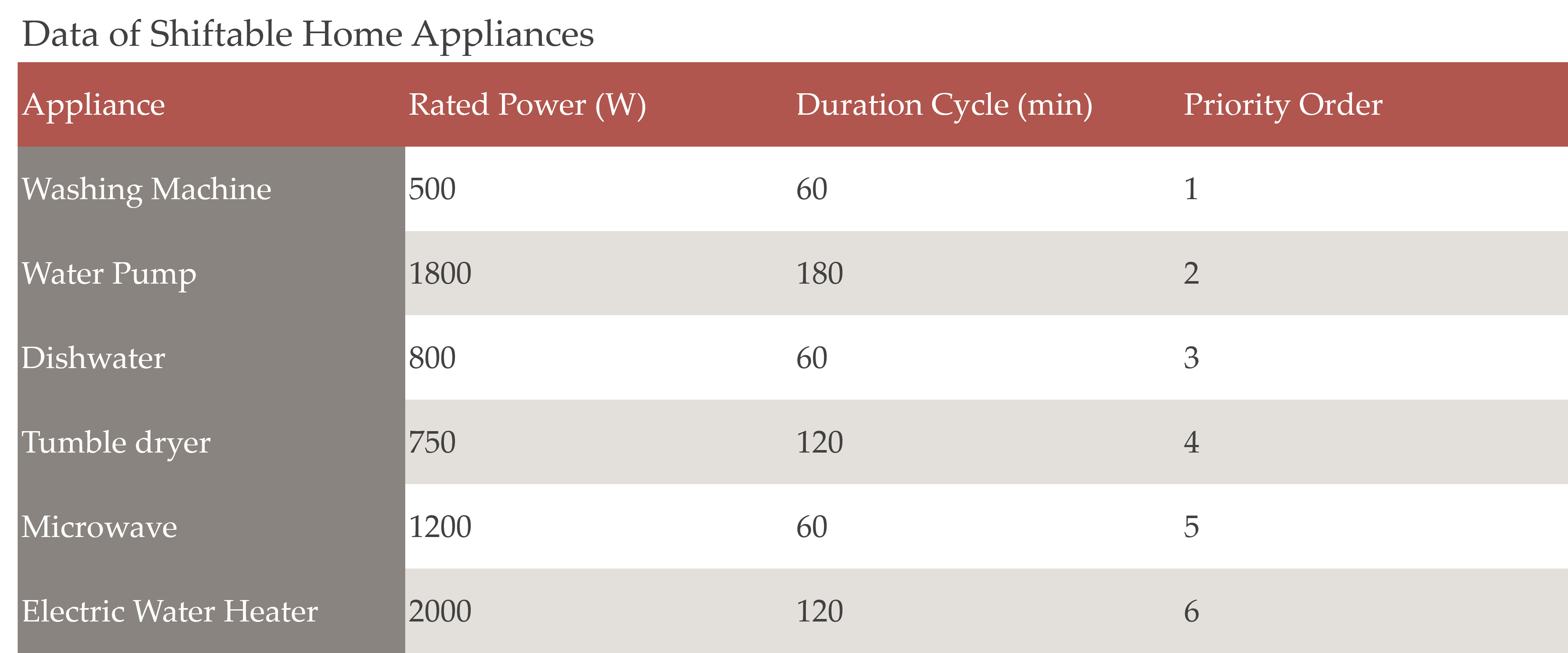
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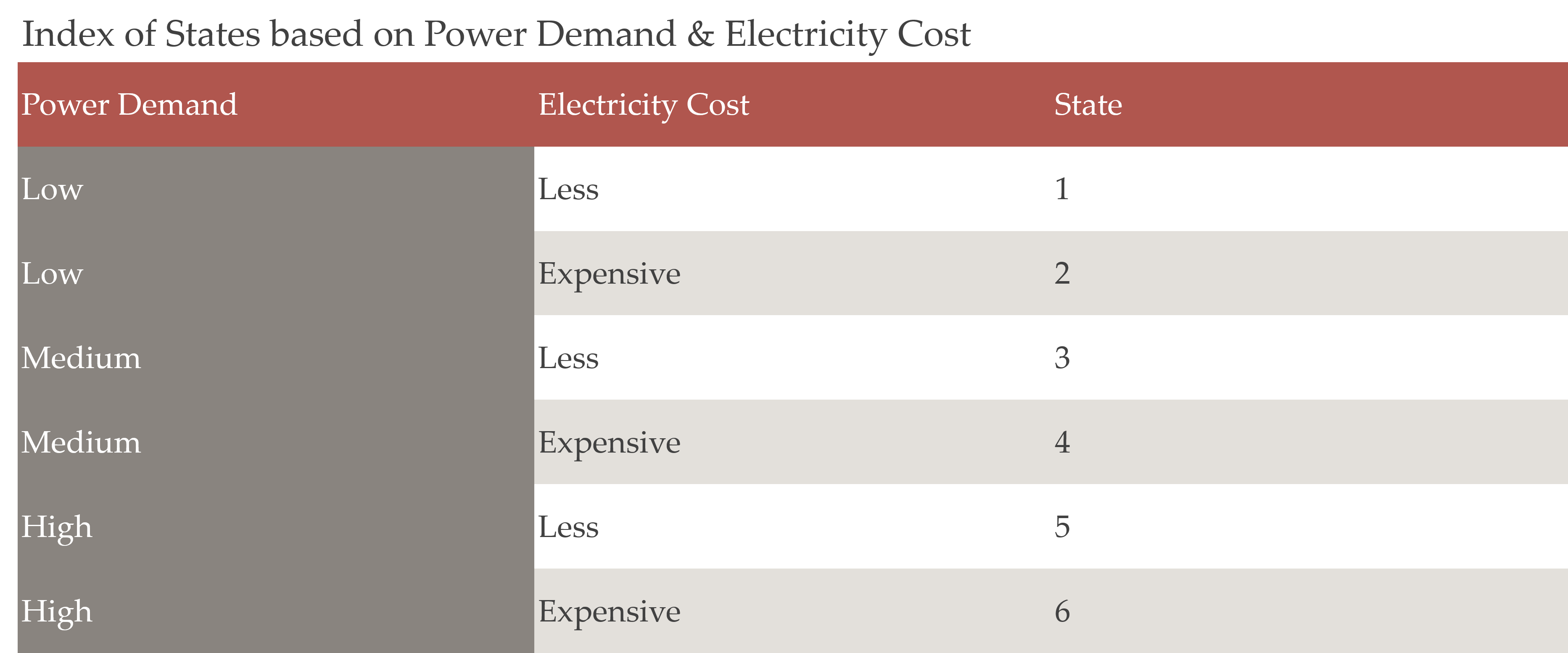
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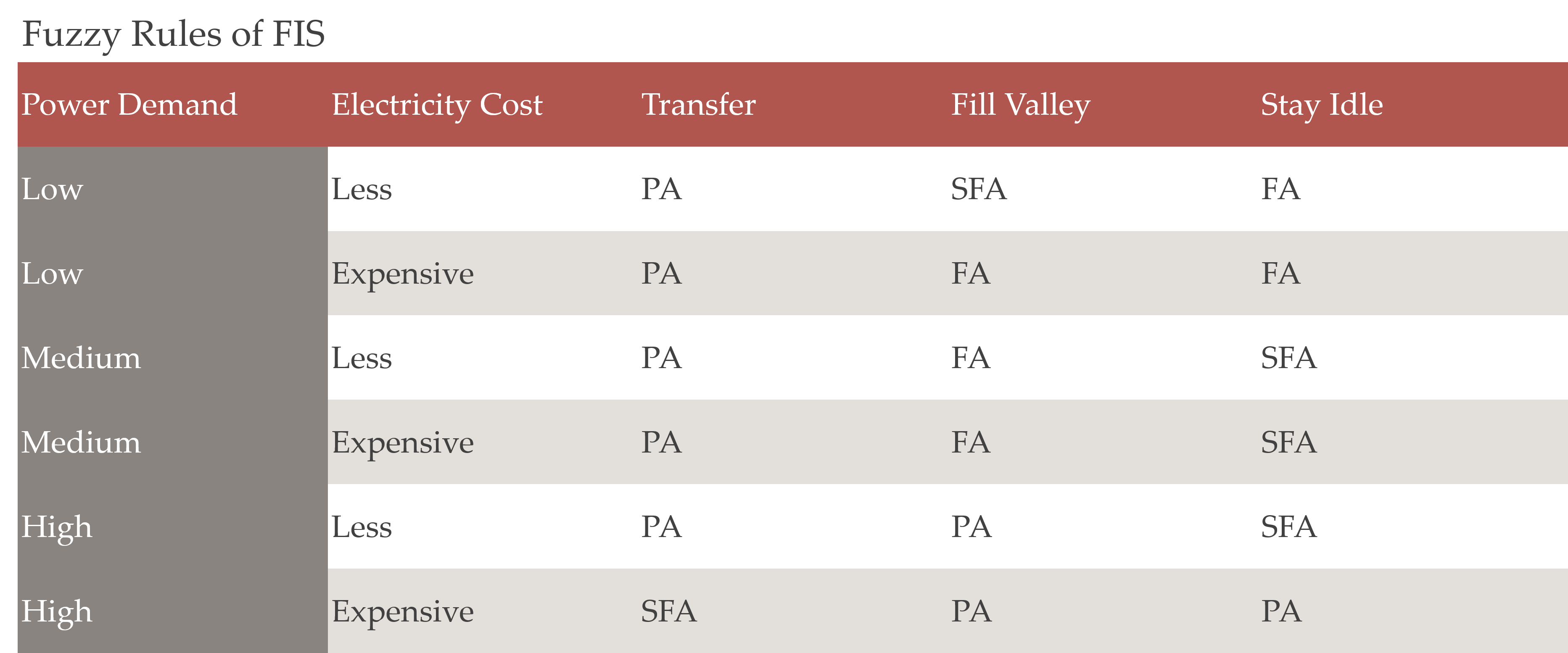
**1. ABSTRACT**

Integrating machine learning techniques into smart home energy management has emerged as a promising approach to optimize energy consumption while improving user comfort. This paper investigates the application of deep reinforcement learning (DRL) algorithms for indoor and domestic hot water temperature control to utilize photovoltaic (PV) power generation for energy saving. In addition, a dynamic indoor temperature setpoint method is offered to ensure flexibility and maximize savings. The results show that the DRL algorithm with dynamic set point adjustment achieves an average energy saving of 8% compared to rule-based algorithms, with maximum savings of up to 16% during the summer season. In addition, user comfort remains uncompromised as the algorithm maintains temperature values ​​within 1% of set values. The analysis suggests that even greater savings are possible by changing comfort thresholds. In addition, the DRL approach demonstrates the effectiveness of demand-side control by achieving more than 10% load shift to optimize solar self-consumption. In particular, the consumption of renewable energy in the DRL-based model is 9.5% higher compared to the rule-based approaches, indicating a reduced dependence on grid energy. This study highlights the potential of DRL algorithms in smart home energy management, as they enable significant energy savings by ensuring user comfort and efficient use of renewable energy sources.

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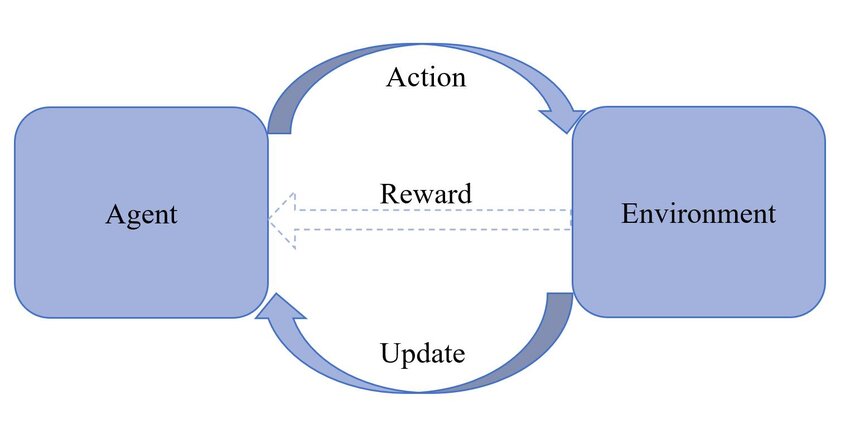
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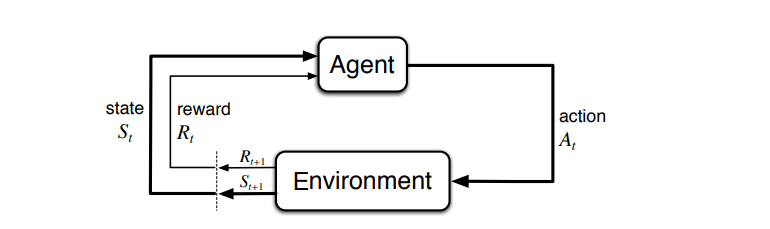


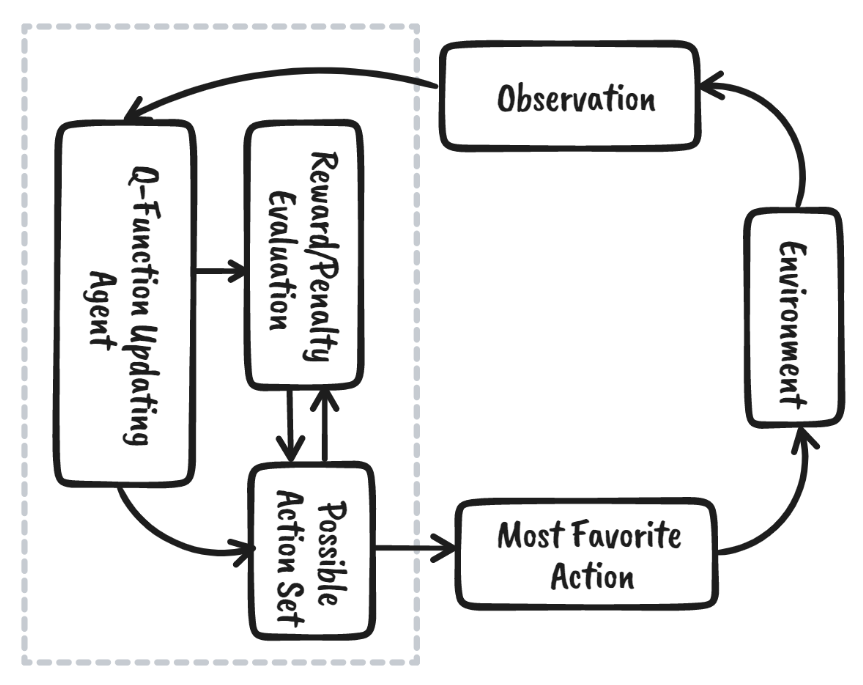


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**LIST OF ABBREVIATIONS**

DRL - Deep Reinforcement Learning

HVAC - Heating, Ventilation, and Air Conditioning

IoT - Internet of Things

MDP - Markov Decision Process

ESS - Energy Storage Systems

SHEMS - Smart Home Energy Management Systems

Q-learning - Quality Learning

DQL - Deep Q Learning

**2. INTRODUCTION**

The transition towards smart grids, characterized by advanced information and communication technologies such as the Internet of Things (IoT), presents significant opportunities for enhancing energy efficiency in smart homes. With the integration of internal networks, intelligent controls, and home automations, smart homes are poised to leverage dynamic electricity pricing and optimize energy usage, particularly concerning Heating, Ventilation, and Air Conditioning (HVAC) systems, which account for a substantial portion of household energy consumption. Despite advancements, optimizing energy costs while maintaining thermal comfort in smart homes remains challenging due to uncertainties in building thermal dynamics, fluctuating parameters (e.g., renewable energy output, electricity prices), and interrelated operational constraints.

This paper addresses the energy optimization challenge in smart homes equipped with renewable energy sources, Energy Storage Systems (ESS), HVAC systems, and non-shiftable loads, without relying on detailed building thermal dynamics models. Our objective is to minimize energy costs over a defined time horizon while ensuring indoor temperature comfort. However, traditional optimization approaches face complexities in accurately modelling indoor temperature dynamics and handling uncertain parameters. Moreover, temporally-coupled operational constraints further complicate decision-making.

To overcome these challenges, we propose a Deep Deterministic Policy Gradients (DDPG) based energy management algorithm. Unlike conventional methods, DDPG does not necessitate prior knowledge of uncertain parameters or detailed building models. Our contributions include formulating the energy cost minimization problem as a Markov Decision Process (MDP) and designing an energy management algorithm that schedules ESS and HVAC systems based on current environmental observations.

Simulation results, based on real-world data, demonstrate that our proposed algorithm achieves energy cost savings ranging from 8.10% to 15.21% compared to baseline strategies, without compromising thermal comfort. Furthermore, robustness testing indicates the algorithm's potential in balancing comfort and cost efficiency, outperforming even "optimal" strategies.

**2.1 OBJECTIVE OF THE PROJECT**

A Smart Home Energy Management System (SHEMS) is designed to optimize energy consumption within residential spaces through the integration of advanced technologies and intelligent control mechanisms. The primary objective of a SHEMS is to enhance energy efficiency, reduce utility costs, and promote sustainability while maintaining comfort and convenience for homeowners.

The acronym SMART stands for Specific, Measurable, Achievable, Relevant, and Time-bound, and these principles guide the goals and functionality of a SHEMS:

1. Energy Efficiency: The core aim of a SHEMS is to maximize energy efficiency by monitoring and controlling the usage of electrical appliances, lighting, heating, and cooling systems. It achieves this by analysing real-time energy consumption patterns and implementing automated adjustments to minimize wastage.

2. Cost Reduction: By optimizing energy consumption, a SHEMS helps homeowners to reduce their electricity bills significantly. Through features like demand response, peak shaving, and load balancing, it ensures that energy is used when it's most cost-effective, thereby lowering overall utility expenses.

3. User Comfort and Convenience: While prioritizing energy savings, a SHEMS ensures that the comfort and convenience of occupants are not compromised. Smart thermostats, lighting controls, and automated schedules enable users to customize their preferences while still maintaining energy efficiency.

4. Integration of Renewable Energy Sources: SHEMS can integrate renewable energy sources such as solar panels or wind turbines into the home energy system. It manages the generation, storage, and consumption of renewable energy efficiently, further reducing reliance on traditional grid power and promoting sustainability.

5. Remote Monitoring and Control: With the advent of IoT (Internet of Things) technology, SHEMS enables remote monitoring and control of home energy systems via smartphones or computers. This allows homeowners to track energy usage, receive alerts about abnormalities, and adjust settings even when they are away from home.

6. Environmental Sustainability: By reducing energy consumption and promoting the use of renewable energy sources, SHEMS contributes to environmental sustainability by lowering carbon emissions and minimizing the ecological footprint associated with residential energy usage.

The objective of a Smart Home Energy Management System is to optimize energy consumption, reduce costs, enhance user comfort, integrate renewable energy sources, enable remote monitoring and control, and promote environmental sustainability, all while adhering to SMART principles to ensure effectiveness and efficiency.

**2.2 PROBLEM STATEMENT**

The current energy consumption dynamics within residential settings lack efficient optimization, resulting in excessive energy wastage, higher utility costs, and increased environmental impact. There is a critical need for a pioneering solution to revolutionize energy management within homes, addressing these pressing issues effectively.

Existing Smart Home Energy Management Systems (SHEMS) often lack the sophistication and integration necessary to fully harness the potential synergy between the electricity grid supply and various home appliances. The absence of intelligent algorithms and automation limits homeowners' ability to achieve optimal energy efficiency and cost savings.

Therefore, the core problem addressed by this research endeavour is the absence of a cutting-edge SHEMS capable of ingeniously optimizing energy utilization within residential settings. The lack of such a system leads to inefficiencies in energy consumption, resulting in higher utility bills for homeowners and increased environmental impact due to unnecessary energy wastage.

Furthermore, the complexity of residential energy consumption patterns requires a solution that goes beyond basic automation and incorporates advanced algorithms to adapt to changing usage patterns and preferences.

In summary, the primary problem statement is to develop a sophisticated SHEMS that leverages advanced algorithms and intelligent automation to optimize energy utilization within residential settings, thereby enabling unprecedented levels of energy efficiency, cost savings for homeowners, and a significant reduction in environmental impact.

**2.3 SCOPE AND MOTIVATION**

The objective of this research project is the design and implementation of Dynamic Response (DR) mechanisms inside Smart Home Energy Management Systems (SHEMS) to successfully balance electricity supply and demand, particularly during peak usage periods. This entails incorporating Reinforcement Learning (RL) models, which are known for their expert decision-making abilities, into the SHEMS framework. The goal is to optimize energy use without relying on prior information of the environment, hence increasing adaptability and reactivity.

Furthermore, the study stresses SHEMS' substantial contribution to environmental sustainability by reducing carbon footprints. SHEMS implements DR techniques to assure effective energy utilization while also reducing the environmental impact of residential energy usage.

Furthermore, the impetus for this research stems from the various benefits provided to users. Homeowners can save significantly on their electricity bills by implementing DR-enabled Electricity Bill Optimization. Furthermore, the emphasis on user comfort and satisfaction in disaster recovery plans guarantees that energy management measures do not jeopardize occupant comfort and convenience. This comprehensive strategy seeks to improve the user experience while encouraging energy efficiency and sustainability.

In summary, this study aims to improve SHEMS capabilities by including DR processes powered by RL models. The ultimate goal is to optimize energy consumption dynamics, reduce carbon footprint, provide cost savings to consumers, and emphasize user comfort and satisfaction in residential environments.

**3. LITERATURE SURVEY**

Smart Home Energy Management Systems: Previous research has extensively explored various approaches to optimize energy consumption in smart homes. Studies have investigated the integration of renewable energy sources, such as solar power, and the utilization of advanced control strategies to improve energy efficiency while maintaining user comfort.

Deep Reinforcement Learning (DRL) in Energy Management: The application of DRL algorithms in energy management systems has gained traction due to their ability to adapt to dynamic environments and learn optimal control policies. Research has demonstrated the effectiveness of DRL in optimizing energy consumption, particularly in the context of smart homes with diverse energy sources and fluctuating demand.

Photovoltaic Integration: With the increasing adoption of photovoltaic systems in residential settings, research has focused on maximizing the utilization of solar energy through intelligent control algorithms. Techniques such as predictive modeling and optimization algorithms have been employed to enhance the performance of PV systems and reduce reliance on grid electricity.

Indoor Temperature Control: Maintaining indoor comfort while minimizing energy consumption is a critical aspect of smart home energy management. Studies have investigated advanced control strategies, including model predictive control and reinforcement learning, to dynamically adjust indoor temperature settings based on user preferences, occupancy patterns, and external factors.

Domestic Hot Water Management: Efficient management of domestic hot water systems is essential for reducing energy waste in residential buildings. Research has explored methods for optimizing hot water production and distribution, including scheduling algorithms, thermal storage strategies, and integration with renewable energy sources.

Energy Savings and User Comfort: Balancing energy savings with user comfort is a key challenge in smart home energy management. Previous studies have evaluated the impact of different control strategies on energy consumption, user satisfaction, and comfort levels, highlighting the importance of adaptive and personalized approaches.

Renewable Energy Utilization: The integration of renewable energy sources, such as solar power and wind energy, presents opportunities for reducing greenhouse gas emissions and promoting sustainability. Research has investigated methods for maximizing the utilization of renewable energy in smart homes through intelligent control and optimization techniques.

Demand-Side Management: Demand-side management strategies aim to modify energy consumption patterns to reduce peak demand and improve grid stability. Studies have examined the effectiveness of demand response programs, load shifting techniques, and incentive-based schemes in incentivizing consumers to adjust their energy usage behavior.

Grid Energy Optimization: Optimizing grid energy usage is crucial for reducing overall energy costs and enhancing the reliability of electricity supply. Research has explored various approaches, including demand forecasting, real-time pricing, and distributed energy storage, to optimize grid energy consumption in residential areas.

Sustainability in Residential Settings: Promoting sustainability in residential buildings involves not only reducing energy consumption but also minimizing environmental impact and promoting resource efficiency. Research has addressed various aspects of sustainable residential design, including energy-efficient building materials, passive design strategies, and smart home technologies.

This literature survey provides an overview of key research areas relevant to smart home energy management, highlighting the potential of deep reinforcement learning algorithms and other advanced techniques to optimize energy consumption, enhance user comfort, and promote sustainability in residential settings.

**4. PRECEDING WORK AND DRAWBACKS**

**Preceding Work:**

1. Technology Integration: In the last decade, tremendous progress has been achieved in integrating numerous technologies within SHEMS. IoT devices, such as smart thermostats, lighting controls, and energy meters, allow for real-time monitoring and control of energy consumption. Furthermore, advances in wireless communication protocols and sensor technologies have enabled seamless integration and interoperability of many devices in the home energy ecosystem.

2. Data Analytics and Machine Learning: Preceding work has focused on leveraging data analytics and machine learning algorithms to analyse energy consumption patterns and predict future usage trends. By analysing historical data and user behaviour, SHEMS can proactively adjust energy settings to optimize efficiency and reduce waste. Machine learning algorithms, such as regression analysis, clustering, and neural networks, have been employed to develop predictive models for energy demand forecasting and anomaly detection.

3. Demand Response Programs: Many utility companies have implemented demand response programs in collaboration with SHEMS providers to incentivize homeowners to reduce energy consumption during peak demand periods. These programs offer financial incentives or rebates to homeowners who participate in load-shifting activities or allow their SHEMS to automatically adjust energy usage based on grid signals. Preceding work has focused on developing algorithms and protocols for seamless integration between SHEMS and demand response programs.

4. Renewable Energy Integration: With the increasing adoption of renewable energy sources such as solar panels and wind turbines, SHEMS have been developed to intelligently integrate and manage these decentralized energy resources. Preceding work has focused on optimizing the utilization of renewable energy based on factors such as weather conditions, energy generation capacity, and household energy demand. Additionally, grid-interactive capabilities enable SHEMS to sell excess energy back to the grid or store it in battery systems for future use.

5. User Interface and Experience: Preceding work has emphasized the importance of user-friendly interfaces and personalized experiences in SHEMS design. Intuitive mobile applications and web interfaces allow homeowners to easily monitor energy consumption, adjust settings, and receive personalized recommendations for energy savings. Customizable preferences and scheduling options enable users to tailor SHEMS settings according to their lifestyle and preferences.

**Drawbacks:**

1. Complexity and Installation Challenges: One of the major drawbacks of SHEMS is the complexity of installation and setup, which can be daunting for homeowners without technical expertise. Integrating multiple devices, configuring communication protocols, and troubleshooting compatibility issues can pose significant challenges, leading to delays and frustration during deployment.

2. Cost and Affordability: The initial cost of purchasing and installing SHEMS components, including smart devices, sensors, and controllers, can be prohibitive for many homeowners. While long-term cost savings may justify the investment, the upfront expenses often act as a barrier to adoption, especially for low-income households.

3. Reliability and Performance: SHEMS rely heavily on interconnected devices and communication networks to function effectively. Any disruptions or failures in the system, such as network outages, device malfunctions, or software glitches, can compromise the reliability and performance of the system, leading to suboptimal energy management and user dissatisfaction.

4. Privacy and Security Concerns: The collection and storage of sensitive energy consumption data by SHEMS raise privacy and security concerns among homeowners. Unauthorized access to personal information, data breaches, and cyber-attacks pose significant risks, undermining user trust and confidence in the system.

5. Limited Compatibility and Interoperability: The lack of standardization and interoperability among different SHEMS components and protocols hinders seamless integration and compatibility. Homeowners may face compatibility issues when attempting to connect devices from different manufacturers or using proprietary communication protocols, limiting the scalability and flexibility of the system.

6. User Engagement and Behaviour Change: Despite the availability of sophisticated energy management features, many homeowners struggle to actively engage with SHEMS and adopt energy-saving behaviours. Lack of awareness, motivation, and feedback mechanisms may contribute to passive usage patterns and minimal energy savings, undermining the overall effectiveness of the system.

Conclusion:

While Smart Home Energy Management Systems offer numerous benefits in terms of energy efficiency, cost savings, and environmental sustainability, they also face several challenges and drawbacks. Addressing these issues, such as complexity, cost, reliability, privacy, compatibility, and user engagement, is crucial to realizing the full potential of SHEMS and promoting widespread adoption among homeowners. Continued research, innovation, and collaboration among stakeholders, including manufacturers, policymakers, utility companies, and consumers, are essential to overcome these challenges and create more accessible, reliable, and user-friendly SHEMS solutions for residential energy management.

**5. TENTATIVE PROPOSED METHOD**

Q-learning is a fundamental concept in the field of reinforcement learning (RL). It is a model-free, off-policy RL algorithm used for learning optimal action-selection policies in Markov decision processes (MDPs). The objective of Q-learning is to learn a policy that maximizes the cumulative reward over time.

Here's a brief overview of how Q-learning works:

1.State-Action Values (Q-Values): In Q-learning, we maintain a table (or function approximation) of state-action values, denoted as Q-values. The Q-value represents the expected cumulative reward of taking a particular action in a specific state and following an optimal policy thereafter.

2.Initialization: Initially, the Q-values are typically initialized randomly or to some arbitrary values.

3.Exploration and Exploitation: During learning, the agent explores the environment by selecting actions based on a policy. This policy could either be exploratory (choosing actions randomly) or greedy (choosing actions that maximize the current estimate of Q-values). Q-learning employs an ε-greedy policy, where the agent chooses a random action with probability ε and chooses the action with the highest Q-value with probability 1-ε.

4.Learning Update Rule: After taking an action and observing the resulting state and reward, the Q-value for the chosen action in the current state is updated using the Bellman equation:

Q(s, a) = Q(s, a) + α \* [r + γ \* max(Q(s', a')) - Q(s, a)]

Where:

- Q(s, a) is the Q-value of state-action pair (s, a).

- α (alpha) is the learning rate, determining the weight of new information compared to existing knowledge.

- r is the reward received after taking action a in state s.

- γ (gamma) is the discount factor, indicating the importance of future rewards.

- s' is the next state after taking action a.

- a' is the next action chosen in the next state.

5.Convergence: Through repeated interactions with the environment and updates to Q-values, Q-learning aims to converge to the optimal Q-values for each state-action pair.

6.Policy Extraction: Once the Q-values have converged, the agent can extract an optimal policy by selecting the action with the highest Q-value in each state.

Q-learning is a foundational algorithm in reinforcement learning and has been widely used in various applications, including game playing, robotics, and optimization problems. It forms the basis for more advanced RL techniques and algorithms.

Q-learning is a reinforcement learning technique that can be applied to Smart Home Energy Management Systems (SHEMS) to optimize energy consumption. In Q-learning, an agent learns to make decisions by interacting with its environment and receiving rewards or penalties based on its actions. Here's how Q-learning can be implemented in SHEMS:

1.State Representation: The first step in applying Q-learning to SHEMS is to define the state space. This involves identifying relevant factors that influence energy consumption, such as occupancy patterns, weather conditions, appliance usage, and electricity prices. The state space should capture the current state of the home environment, allowing the agent to make informed decisions.

2.Action Selection: Next, the agent needs to select actions based on the current state. In the context of SHEMS, actions could include adjusting thermostat settings, scheduling appliance usage, or activating energy-saving modes on smart devices. The agent explores different actions and evaluates their impact on energy consumption and user comfort.

3.Reward Design: The agent receives rewards or penalties based on its actions and their consequences. In SHEMS, rewards could be based on factors such as energy savings, cost reduction, or user satisfaction. For example, the agent might receive a positive reward for reducing energy consumption during peak hours or a negative reward for exceeding a predefined energy budget.

4.Q-Value Update: The Q-value represents the expected cumulative reward for taking a specific action in a given state. The agent updates its Q-values based on the rewards received and the transition to the next state. The Q-value update equation is given by:

Q(s, a) = Q(s, a) + α \* [r + γ \* max(Q(s', a')) - Q(s, a)]

Where:

- Q(s, a) is the Q-value of state-action pair (s, a).

- α (alpha) is the learning rate, determining the weight of new information compared to existing knowledge.

- r is the reward received after taking action a in state s.

- γ (gamma) is the discount factor, indicating the importance of future rewards.

- s' is the next state after taking action a.

- a' is the next action chosen in the next state.

5.Exploration vs. Exploitation: Q-learning involves a trade-off between exploration (trying new actions to learn their effects) and exploitation (choosing actions based on current knowledge to maximize rewards). To balance exploration and exploitation, the agent can use techniques such as ε-greedy exploration, where it chooses a random action with probability ε and the action with the highest Q-value with probability 1-ε.

6.Policy Improvement: As the agent learns through interactions with the environment, it gradually improves its policy (strategy for selecting actions) to maximize long-term rewards. The agent converges to an optimal policy that achieves the highest possible cumulative reward over time.

By applying Q-learning methodology to SHEMS, homeowners can benefit from optimized energy consumption, reduced utility costs, and enhanced user comfort and satisfaction. Additionally, Q-learning enables SHEMS to adapt to changing environmental conditions and user preferences, making them more versatile and effective in real-world applications.

Inputs:

Power Demand: Reflects the current energy requirements of the home.

Electricity Cost: Represents the cost of electricity consumption.

Objective:

Optimise energy usage while minimising electricity costs.

Q-Learning Approach:

Define states based on power demand and electricity cost.

Determine actions to adjust energy usage accordingly.

Develop a reward function to incentivise cost-efficient energy management.

Learning Process:

Explore different actions initially to learn their impact.

Exploit learned knowledge to make optimal decisions over time.

Implementation:

Update Q-values based on observed rewards and states.

Use learned Q-values to guide energy management decisions.

By employing Q-learning in Smart Home Energy Management, we enable dynamic optimisation of energy usage to minimise costs while meeting household demands.

**6. PROJECT FLOW/ FRAMEWORK OF THE PROPOSED SYSTEM**

To propose a framework for a Smart Home Energy Management System (SHEMS) based on Q-learning methodology, we can outline the following components:

1. Data Collection and Monitoring Module:

- Sensors and smart meters collect real-time data on energy consumption, weather conditions, occupancy patterns, and appliance usage.

- Data is transmitted to the central control unit for processing and analysis.

2. State Representation and Feature Extraction:

- The system preprocesses the raw data to extract relevant features that characterize the current state of the home environment.

- Features may include temperature, humidity, occupancy status, appliance power consumption, time of day, and electricity prices.

3. Q-learning Agent:

- The Q-learning agent is responsible for making decisions to optimize energy consumption based on the current state of the home environment.

- It maintains a Q-table or neural network that stores Q-values for state-action pairs.

- The agent selects actions to maximize long-term rewards while balancing exploration and exploitation.

4. Action Selection and Control Module:

- Based on the Q-values, the agent selects actions to adjust thermostat settings, schedule appliance usage, or activate energy-saving modes on smart devices.

- Actions are executed through actuators and smart controllers connected to appliances and HVAC systems.

5. Reward Mechanism:

- The system defines a reward function that provides feedback to the agent based on the consequences of its actions.

- Rewards may be based on factors such as energy savings, cost reduction, user comfort, and environmental impact.

- The agent updates its Q-values using the reward received and the transition to the next state.

6. Exploration and Exploitation Strategy:

- The system employs an exploration-exploitation strategy to balance the agent's learning process.

- Techniques such as ε-greedy exploration or softmax action selection are used to encourage exploration while leveraging the agent's current knowledge.

7. User Interface and Feedback Mechanism:

- The system provides a user interface that allows homeowners to monitor energy consumption, adjust preferences, and receive feedback on energy-saving strategies.

- Feedback mechanisms inform users about the system's actions, energy savings achieved, and potential adjustments to improve performance.

8. Integration with External Factors:

- The system integrates with external factors such as electricity prices, grid demand, and weather forecasts to optimize energy consumption further.

- Demand response mechanisms allow the system to respond to grid signals and adjust energy usage during peak periods or when renewable energy generation is high.

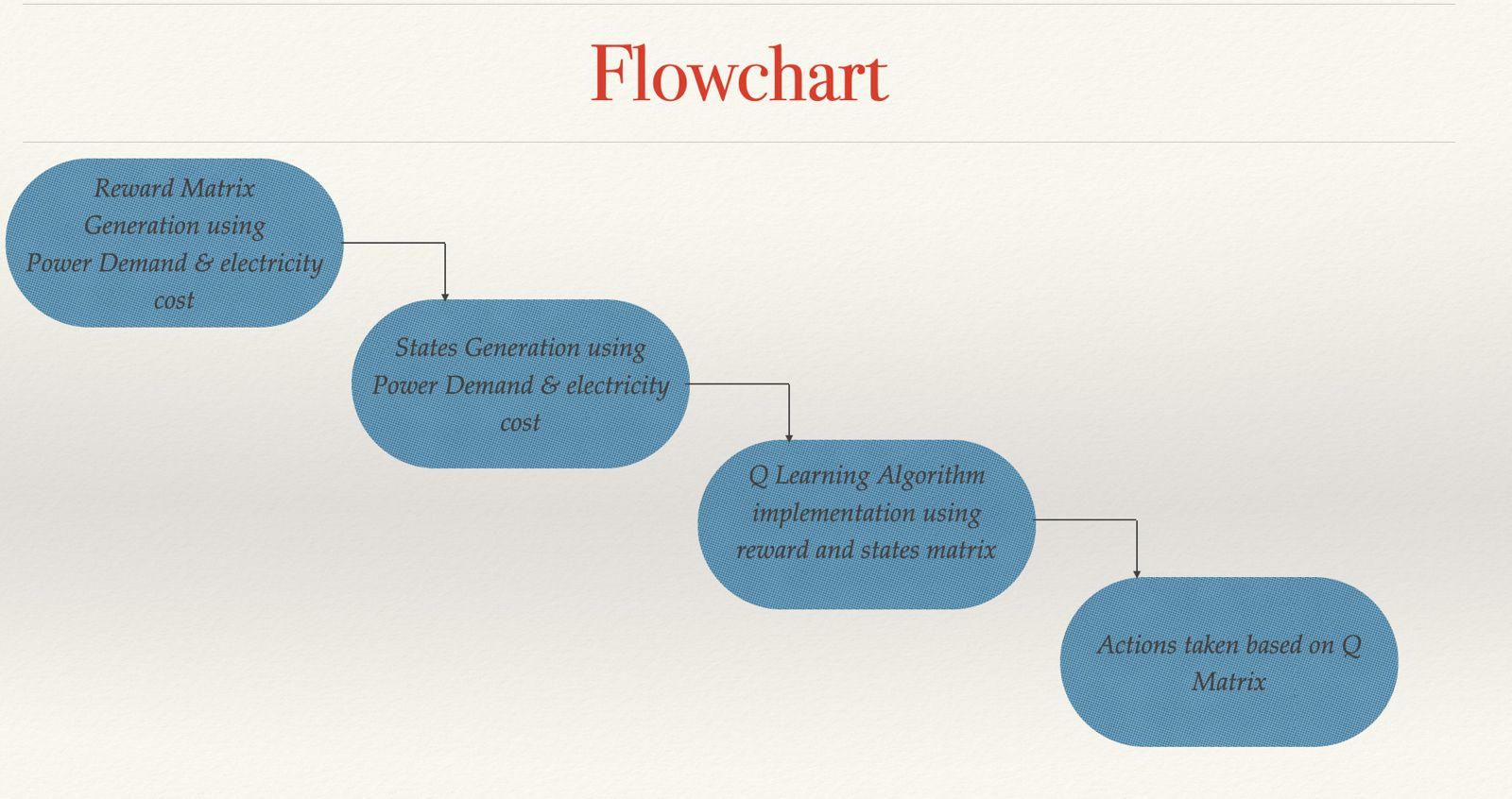
9. Continuous Learning and Adaptation:

- The system continuously learns and adapts to changing environmental conditions, user behaviour, and energy requirements.

- Regular updates and refinements to the Q-learning algorithm ensure that the system remains effective and responsive over time.

By implementing this framework, homeowners can benefit from a robust and adaptive Smart Home Energy Management System that optimizes energy consumption, reduces utility costs, and enhances user comfort and satisfaction while promoting environmental sustainability.

**FLOWCHART:**



**7. HARDWARE AND SOFTWARE REQUIREMENTS**

Hardware and software requirements for implementing the proposed Smart Home Energy Management System (SHEMS) based on Q-learning methodology may include:

**Hardware Requirements:**

1. Sensors and Smart Meters:

- Temperature sensors

- Humidity sensors

- Occupancy sensors

- Smart meters for electricity consumption monitoring

2. Actuators and Smart Controllers:

- Thermostats for HVAC systems

- Smart plugs or switches for controlling appliances

- Smart lighting controls

3. Central Control Unit:

- Microcontroller or single-board computer (e.g., Raspberry Pi) to serve as the central control unit

- Sufficient processing power and memory to handle data processing and analysis tasks

4. Communication Network:

- Wi-Fi or Ethernet connectivity for communication between sensors, actuators, and the central control unit

- Zigbee, Z-Wave, or other wireless protocols for interoperability with smart devices

5. User Interface:

- Display screen (e.g., touchscreen panel or computer monitor) for visualizing energy consumption data and system status

- Input devices (e.g., keyboard, touchpad, or touchscreen) for user interaction

**Software Requirements:**

1. Operating System:

- Linux-based operating system (e.g., Raspbian for Raspberry Pi) for the central control unit

2. Programming Languages:

- Python for developing the SHEMS software components

- JavaScript/HTML/CSS for developing the user interface (if applicable)

3. Machine Learning Libraries:

- TensorFlow, PyTorch, or Scikit-learn for implementing Q-learning algorithm

- NumPy and Pandas for data manipulation and analysis

4. IoT Middleware:

- MQTT or CoAP for communication between IoT devices and the central control unit

- MQTT broker software (e.g., Mosquitto) for managing message communication

5. Database Management:

- SQLite or MongoDB for storing historical data on energy consumption, state-action pairs, and Q-values

6. Data Visualization:

- Matplotlib or Seaborn for generating plots and visualizing energy consumption trends

- Dashboard frameworks (e.g., Flask or Django) for developing interactive user interfaces

7. Development Tools:

- Integrated development environment (IDE) such as Visual Studio Code or PyCharm for software development

- Git for version control and collaboration

8. Security Software:

- Firewalls and encryption protocols to secure communication and protect user data privacy

9. External Integration Tools:

- APIs or SDKs for integrating with external services such as weather forecasts, electricity price data, or demand response signals

By meeting these hardware and software requirements, it is possible to develop and deploy a functional Smart Home Energy Management System (SHEMS) based on Q-learning methodology, providing homeowners with energy-saving benefits and enhanced control over their home environment.

**8. Proposed System**

## 8.1 Reinforcement Learning

Reinforcement Learning (RL) stands at the forefront of innovation within Smart Home Energy Management Systems (SHEMS), revolutionizing the way energy resources are managed and optimized in residential environments. At its core, RL empowers an agent to actively engage with the home environment, making decisions aimed at maximizing cumulative rewards. These decisions encompass a wide array of tasks, ranging from fine-tuning thermostat settings to orchestrating the usage of various appliances and optimizing energy sources. The agent's decision-making process hinges upon the system's states, which encapsulate critical parameters such as current energy consumption levels, room temperatures, and occupancy status. Through the feedback loop of rewards or penalties, the agent continuously evaluates the efficacy of its actions, facilitating iterative learning and improvement over time.

Within the intricate landscape of SHEMS, fundamental objectives revolve around optimizing energy usage, managing costs based on fluctuating time-of-use tariffs, ensuring optimal user comfort, and championing sustainable energy practices. RL methodologies serve as the cornerstone in achieving these objectives by endowing the agent with adaptive decision-making capabilities. Techniques such as Q-learning and Deep Q-Networks (DQN) stand as stalwarts in this domain, facilitating the agent's ability to navigate complex decision spaces and refine its strategies for energy management.

However, the integration of RL techniques in SHEMS is not without its challenges. Modeling uncertainties, navigating intricate state-action spaces, and striking the delicate balance between exploration and exploitation pose formidable obstacles. Yet, despite these challenges, the marriage of RL techniques with SHEMS has yielded transformative applications across various facets of energy management within smart homes. From dynamic HVAC control and intelligent lighting systems to optimized appliance scheduling and demand-side management strategies, the impact of RL in SHEMS is profound.

The tangible benefits of RL in SHEMS are undeniable. Energy savings, reduced environmental footprint, and heightened user satisfaction stand as hallmarks of its success. By harnessing RL algorithms and methodologies, SHEMS can continuously adapt and refine their decision-making processes, ultimately paving the way for more sustainable and efficient energy management practices. As we look to the future, the role of RL in SHEMS promises to be pivotal, driving innovation and shaping the landscape of smart home energy management for years to come.

## 8.2 Markov Decision Process

Smart Home Energy Management Systems (SHEMS) stand as pivotal solutions in the quest for efficient, sustainable, and user-centric energy management within residential settings. At the heart of SHEMS lies the Markov Decision Process (MDP), a foundational framework that provides a structured methodology for decision-making in uncertain environments. By encapsulating essential components such as states, actions, transition probabilities, and rewards in a Markovian fashion, MDP simplifies the complex task of energy management within smart homes.

In the realm of SHEMS, states serve as the cornerstone, representing critical parameters such as energy consumption levels, room temperatures, and occupancy status. Actions, on the other hand, encompass a diverse spectrum of tasks ranging from adjusting thermostat settings to orchestrating the usage of various appliances and optimizing energy sources. Transition probabilities quantify the likelihood of transitioning between states based on chosen actions, while rewards offer valuable feedback on the desirability of state-action pairs, facilitating policy optimization.

The primary objectives of employing MDP in SHEMS are multifaceted, spanning from optimizing energy utilization and managing costs based on time-of-use tariffs to ensuring user comfort and promoting sustainable energy practices. Through the utilization of MDP algorithms such as value iteration or policy iteration, SHEMS can derive optimal policies that strike a delicate balance between energy efficiency and user satisfaction.

However, the integration of MDP techniques in SHEMS is not without its challenges. Modeling uncertainties, handling large state-action spaces, and addressing dynamic environmental factors pose formidable obstacles. Yet, despite these challenges, the integration of MDP techniques has led to significant advancements in SHEMS applications. From dynamic HVAC control and intelligent lighting systems to optimized appliance scheduling and demand-side management strategies, MDP has revolutionized energy management within smart homes.

Central to the efficacy of MDP is the Markov Property, which asserts that future outcomes are solely determined by the current state, encapsulating all necessary information from the past. This property simplifies the decision-making process by allowing MDPs to utilize only the current state to determine future actions, without any reliance on prior states or actions, thereby streamlining decision-making in uncertain environments.

In essence, MDP serves as a cornerstone framework in the development of Smart Home Energy Management Systems, enabling efficient, sustainable, and user-centric energy management practices. By leveraging MDP techniques, SHEMS can navigate complex decision landscapes, adapt to dynamic environmental conditions, and optimize energy utilization in real-time, ultimately fostering smarter, more efficient, and eco-friendly home environments.

## **8.3** Q Learning

Q-learning stands as a cornerstone reinforcement learning technique that has garnered considerable attention in the development of Smart Home Energy Management Systems (SHEMS). At its core, Q-learning enables an agent to make optimal decisions by estimating the value, known as the Q-value, associated with each state-action pair in the environment. This iterative learning process unfolds through trial and error, as the agent explores different actions, receives feedback in the form of rewards or penalties, and updates its Q-values accordingly.

In the intricate landscape of SHEMS, states encapsulate critical variables such as energy consumption levels, room temperatures, and occupancy status, while actions encompass a diverse array of tasks including adjusting thermostat settings, managing appliance usage, and optimizing energy sources. The primary objectives of integrating Q-learning in SHEMS revolve around optimizing energy usage, managing costs based on time-of-use tariffs, ensuring user comfort, and promoting sustainable energy practices.

Q-learning algorithms, often coupled with exploration-exploitation strategies like epsilon-greedy or softmax, empower the agent to learn optimal policies for energy management over time. Despite facing challenges such as handling uncertainties, addressing complex state-action spaces, and adapting to dynamic environmental conditions, the application of Q-learning in SHEMS has led to significant advancements.

Practical implementations of Q-learning in SHEMS span various aspects such as HVAC control, smart lighting, appliance scheduling, and demand-side management. The benefits accrued from these implementations are tangible, including energy savings, reduced environmental impact, and enhanced user satisfaction.

The Q-learning algorithm updates Q-values based on a formula that guides the agent's learning process. This formula includes several key components:

- Q(s, a): Current Q-value for the state-action pair (s, a).

- α: Learning rate, controlling the impact of new information on Q-values.

- R: Reward received for taking action 'a' in state 's'.

- γ: Discount factor, determining the importance of future rewards.

- max\_{a'} Q(s', a'): Maximum Q-value for the next state 's' after taking action 'a'.

This formula serves as the cornerstone of the agent's learning process, facilitating the updating of Q-values based on observed rewards and estimated future rewards. Through iterative updates of Q-values, the agent gradually enhances its decision-making capabilities, ultimately leading to more efficient and effective energy management strategies within SHEMS.

In conclusion, Q-learning stands as a fundamental technique in the arsenal of tools for developing Smart Home Energy Management Systems. Its application enables intelligent decision-making, fosters energy efficiency, and enhances user experience, ultimately contributing to the creation of smarter, more sustainable, and more efficient home environments.

## **8.4** Deep Q Learning

Deep Q-learning (DQL) stands as a significant advancement of traditional Q-learning, harnessing the power of deep neural networks to revolutionize decision-making in Smart Home Energy Management Systems (SHEMS). By employing deep neural networks to approximate the Q-values associated with various state-action pairs, DQL enables agents to develop intricate and nuanced strategies for energy management. This approach is particularly valuable in SHEMS, where input data is often high-dimensional and includes sensor readings, historical energy consumption patterns, and environmental variables.

Within the context of SHEMS, DQL empowers agents to optimize energy usage, navigate dynamic tariffs, maintain user comfort, and promote sustainable energy practices. Through an iterative process of exploration and exploitation, guided by feedback from the environment in the form of rewards or penalties, the deep neural network learns to predict Q-values. Exploration strategies such as epsilon-greedy or softmax play a crucial role in balancing the exploration of new actions with the exploitation of known effective actions.

Despite facing challenges such as managing non-linear relationships in data, addressing model complexity, and ensuring training convergence, DQL has demonstrated remarkable promise in SHEMS applications. Implementations of DQL in SHEMS encompass a diverse array of areas including HVAC control, smart lighting, appliance scheduling, and demand-side management.

The adoption of DQL techniques yields tangible benefits for SHEMS, including heightened energy efficiency, cost reduction, enhanced user experience, and the fostering of a more sustainable energy ecosystem. By leveraging deep neural networks, SHEMS can navigate intricate decision landscapes, adapt to evolving environmental conditions, and optimize energy utilization in real-time, ultimately contributing to the creation of smarter, more efficient, and eco-friendly home environments.

In conclusion, DQL represents a significant leap forward in the realm of Smart Home Energy Management Systems, enabling agents to make intelligent decisions that drive energy efficiency, cost savings, and user satisfaction. With further advancements and refinements, DQL holds the potential to transform the way energy is managed and utilized in residential settings, paving the way for a more sustainable and efficient future.

**9. MODULES**

Here are the key modules/components of the Smart Home Energy Management System (SHEMS) based on Q-learning methodology:

1. Data Collection and Preprocessing Module:

- Responsible for collecting real-time data on energy consumption, weather conditions, occupancy patterns, and appliance usage.

- Preprocesses raw data to extract relevant features and prepare it for analysis.

2. State Representation Module:

- Defines the state space by identifying relevant factors that influence energy consumption (e.g., temperature, occupancy, electricity prices).

- Represents the current state of the home environment to enable informed decision-making by the Q-learning agent.

3. Q-learning Agent Module:

- Implements the Q-learning algorithm to optimize energy consumption based on the current state of the home environment.

- Maintains a Q-table or neural network to store Q-values for state-action pairs.

- Selects actions to maximize long-term rewards while balancing exploration and exploitation.

4. Action Selection and Control Module:

- Selects actions based on the Q-values provided by the Q-learning agent and executes them through actuators and smart controllers.

- Adjusts thermostat settings, schedules appliance usage, or activates energy-saving modes on smart devices to optimize energy consumption.

5. Reward Mechanism Module:

- Defines a reward function to provide feedback to the Q-learning agent based on the consequences of its actions.

- Calculates rewards based on factors such as energy savings, cost reduction, user comfort, and environmental impact.

6. Exploration and Exploitation Strategy Module:

- Implements an exploration-exploitation strategy to balance the agent's learning process.

- Utilizes techniques such as ε-greedy exploration or softmax action selection to encourage exploration while leveraging the agent's current knowledge.

7. User Interface Module:

- Provides a user interface for homeowners to monitor energy consumption, adjust preferences, and receive feedback on energy-saving strategies.

- Displays system status, energy consumption trends, and potential adjustments to improve performance.

8. External Integration Module:

- Integrates with external factors such as electricity prices, grid demand, and weather forecasts to optimize energy consumption further.

- Receives signals for demand response and adjusts energy usage accordingly to contribute to grid stability.

9. Continuous Learning and Adaptation Module:

- Enables the system to continuously learn and adapt to changing environmental conditions, user behaviour, and energy requirements.

- Updates the Q-learning algorithm and system parameters to ensure optimal performance over time.

These modules work together to form a cohesive Smart Home Energy Management System (SHEMS) based on Q-learning methodology, providing homeowners with optimized energy consumption, reduced utility costs, and enhanced control over their home environment.

**10. REFERNCES**

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**APPENDIX**

**Source Code:**

% Define parameters

num\_states = 6; % Total number of states (3 states in your case)

num\_actions = 3; % Total number of actions (e.g., Transfer, Fill Valley,

Stay Idle)

time\_steps = 24; % Time steps (e.g., 24-hour period)

% Initialize Q-table

Q = rand(num\_states, num\_actions); % Placeholder Q matrix for demonstration

% Note: You should use a trained Q matrix instead of random values

% Define rewards matrix (ensure it has num\_states rows and num\_actions

columns)

rewards = rand(num\_states, num\_actions); % Use appropriate values instead of

random for demonstration

% Define hyperparameters for Q-learning

alpha = 0.1; % Learning rate

gamma = 0.9; % Discount factor

epsilon = 0.1; % Exploration rate

% Number of episodes for training

num\_episodes = 1000;

function [next\_state, reward] = execute\_action(current\_state, action)

% Define the next state and reward based on the current state and chosen

action

switch current\_state

case 1 % State 1

if action == 1 % Transfer

next\_state = 2; % Transition to State 2

reward = -1; % Example reward for Transfer action in State 1

elseif action == 2 % Fill Valley

next\_state = 3; % Transition to State 3

reward = 2; % Example reward for Fill Valley action in State

1

elseif action == 3 % Stay Idle

next\_state = current\_state; % Stay in State 1

reward = 0; % Example reward for Stay Idle action in State 1

end

case 2 % State 2

if action == 1 % Transfer

next\_state = 4; % Transition to State 4

reward = 1; % Example reward for Transfer action in State 2

elseif action == 2 % Fill Valley

next\_state = 5; % Transition to State 5

reward = -1; % Example reward for Fill Valley action in

State 2

elseif action == 3 % Stay Idle

next\_state = current\_state; % Stay in State 2

reward = 0; % Example reward for Stay Idle action in State 2

end

case 3 % State 3

if action == 1 % Transfer

next\_state = 6; % Transition to State 6

reward = -1; % Example reward for Transfer action in State 3

elseif action == 2 % Fill Valley

next\_state = 1; % Transition to State 1

reward = 1; % Example reward for Fill Valley action in State

3

elseif action == 3 % Stay Idle

next\_state = current\_state; % Stay in State 3

reward = 0; % Example reward for Stay Idle action in State 3

end

case 4 % State 4

if action == 1 % Transfer

next\_state = 5; % Transition to State 5

reward = 0; % Example reward for Transfer action in State 4

elseif action == 2 % Fill Valley

next\_state = 6; % Transition to State 6

reward = 1; % Example reward for Fill Valley action in State

4

elseif action == 3 % Stay Idle

next\_state = current\_state; % Stay in State 4

reward = 0; % Example reward for Stay Idle action in State 4

end

case 5 % State 5

if action == 1 % Transfer

next\_state = 6; % Transition to State 6

reward = -1; % Example reward for Transfer action in State 5

elseif action == 2 % Fill Valley

next\_state = 1; % Transition to State 1

reward = 2; % Example reward for Fill Valley action in State

5

elseif action == 3 % Stay Idle

next\_state = current\_state; % Stay in State 5

reward = 0; % Example reward for Stay Idle action in State 5

end

case 6 % State 6

if action == 1 % Transfer

next\_state = 1; % Transition to State 1

reward = 0; % Example reward for Transfer action in State 6

elseif action == 2 % Fill Valley

next\_state = 2; % Transition to State 2

reward = 1; % Example reward for Fill Valley action in State

6

elseif action == 3 % Stay Idle

next\_state = current\_state; % Stay in State 6

reward = 0; % Example reward for Stay Idle action in State 6

end

end

end

% Q-learning process

for episode = 1:num\_episodes

% Choose a random initial state for each episode

state = randi(num\_states);

% Simulate a 24-hour period (or adjust as needed)

for hour = 1:time\_steps

% Choose action based on epsilon-greedy strategy

if rand < epsilon

% Explore: Choose a random action

action = randi(num\_actions);

else

% Exploit: Choose the action with the highest Q-value for the

current state

[~, action] = max(Q(state, :));

end

% Execute the selected action and observe the next state and reward

[next\_state, reward] = execute\_action(state, action);

% Determine the maximum Q-value for the next state

max\_Q\_next = max(Q(next\_state, :));

% Update the Q-value for the current state and action using the

Q-learning update rule

Q(state, action) = Q(state, action) + alpha \* (reward + gamma \*

max\_Q\_next - Q(state, action));

% Set the next state as the current state

state = next\_state;

end

end

% Create a table from the Q matrix

q\_table = array2table(Q, 'VariableNames', {'Transfer', 'Fill Valley', 'Stay

Idle'});

q\_table.State = (1:num\_states)'; % Add state numbers as a column

% Move the 'State' column to the first position in the table

q\_table = movevars(q\_table, 'State', 'Before', 'Transfer');

% Display the Q matrix as a table

disp('Q matrix after training:');

Q matrix after training:

disp(q\_table);

**State Transfer Fill Valley Stay Idle**

**\_\_\_\_\_ \_\_\_\_\_\_\_\_ \_\_\_\_\_\_\_\_\_\_\_ \_\_\_\_\_\_\_\_\_**

1 10.724 15.263 13.737

2 13.027 12.801 10.573

3 11.363 14.737 13.263

4 12.709 13.363 11.157

5 5.4874 15.737 8.8704

6 13.737 12.594 12.196

% Create a table from the rewards matrix

rewards\_table = array2table(rewards, 'VariableNames', {'Transfer', 'Fill

Valley', 'Stay Idle'});

rewards\_table.State = (1:num\_states)'; % Add state numbers as a column

% Move the 'State' column to the first position in the table

rewards\_table = movevars(rewards\_table, 'State', 'Before', 'Transfer');

% Display the rewards matrix as a table

disp('Rewards matrix after Q-learning training:');

Rewards matrix after Q-learning training:

disp(rewards\_table);

**State Transfer Fill Valley Stay Idle**

**\_\_\_\_\_ \_\_\_\_\_\_\_\_ \_\_\_\_\_\_\_\_\_\_\_ \_\_\_\_\_\_\_\_\_**

1 0.73789 0.41926 0.64471

2 0.91495 0.51566 0.1923

3 0.7573 0.0040475 0.29297

4 0.79608 0.34786 0.49946

5 0.46648 0.24077 0.90546

6 0.1777 0.47646 0.50768

% Determine optimal actions based on Q-values

optimal\_actions = zeros(num\_states, time\_steps);

% For each state and time step, determine the action with the highest Q-value

for hour = 1:time\_steps

for state = 1:num\_states

[~, optimal\_action] = max(Q(state, :));

optimal\_actions(state, hour) = optimal\_action;

end

end

% Assuming `optimal\_actions` matrix is already defined and processed to find

optimal actions for each state and time step.

% Separate actions based on the optimal\_actions matrix

transfer\_actions = double(optimal\_actions == 1); % Transfer action

fill\_valley\_actions = double(optimal\_actions == 2); % Fill Valley action

stay\_idle\_actions = double(optimal\_actions == 3); % Stay Idle action

% Check the shape of the data matrices

assert(size(transfer\_actions, 1) == num\_states, 'Transfer actions matrix:

number of rows should match num\_states');

assert(size(transfer\_actions, 2) == time\_steps, 'Transfer actions matrix:

number of columns should match time\_steps');

assert(size(fill\_valley\_actions, 1) == num\_states, 'Fill Valley actions

matrix: number of rows should match num\_states');

assert(size(fill\_valley\_actions, 2) == time\_steps, 'Fill Valley actions

matrix: number of columns should match time\_steps');

assert(size(stay\_idle\_actions, 1) == num\_states, 'Stay Idle actions matrix:

number of rows should match num\_states');

assert(size(stay\_idle\_actions, 2) == time\_steps, 'Stay Idle actions matrix:

number of columns should match time\_steps');

% Define time array (1 to 24)

time\_array = 1:time\_steps; % Make sure this has length = time\_steps

% Plot heatmap for Transfer actions

figure;

heatmap(transfer\_actions, 'XData', time\_array, 'YData', 1:num\_states, ...

'Colormap', [1, 1, 1; 0, 0, 1]); % White for other, blue for Transfer

xlabel('Time (hours)');

ylabel('Mode');

title('Transfer Actions Over Time and Mode');

% Plot heatmap for Fill Valley actions

figure;

heatmap(fill\_valley\_actions, 'XData', time\_array, 'YData', 1:num\_states, ...

'Colormap', [1, 1, 1; 0, 1, 0]); % White for other, green for Fill

Valley

xlabel('Time (hours)');

ylabel('Mode');

title('Fill Valley Actions Over Time and Mode');

% Plot heatmap for Stay Idle actions

figure;

heatmap(stay\_idle\_actions, 'XData', time\_array, 'YData', 1:num\_states, ...

'Colormap', [1, 1, 1; 1, 0, 0]); % White for other, red for Stay Idle

xlabel('Time (hours)');

ylabel('Mode');

title('Stay Idle Actions Over Time and Mode');

disp('Displaying separate heatmaps for each action: Transfer, Fill Valley,

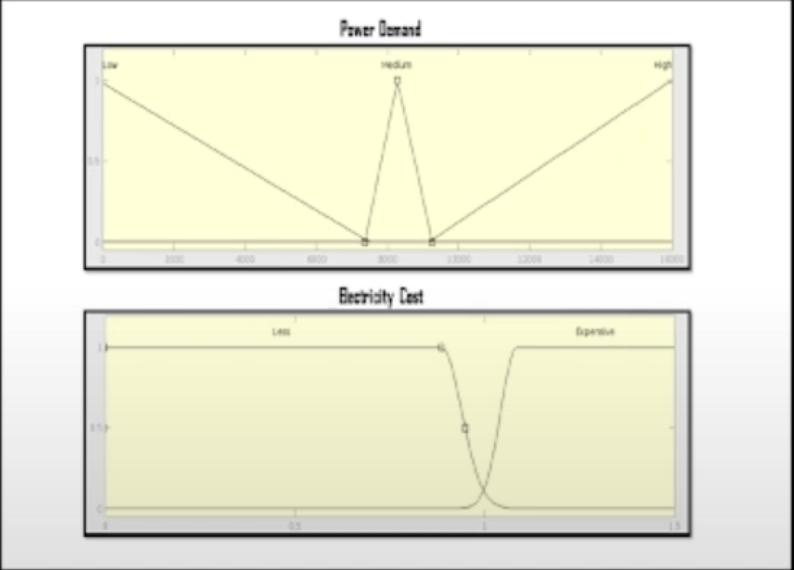
and Stay Idle.');

Displaying separate heatmaps for each action: Transfer, Fill Valley, and Stay Idle.

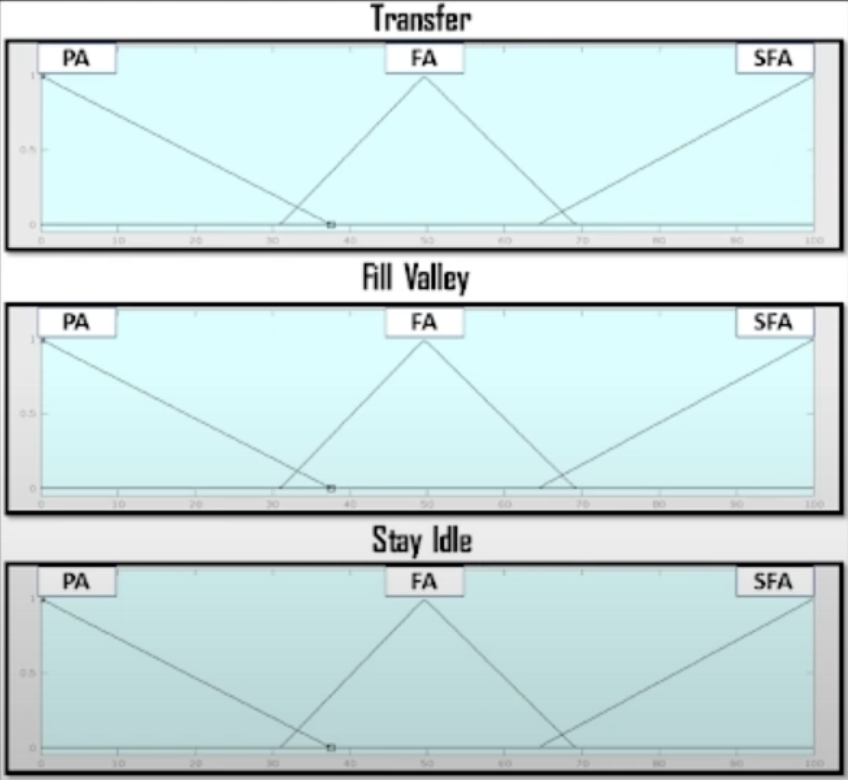
**Screenshots:**

**Results: Reward Matrix Output**

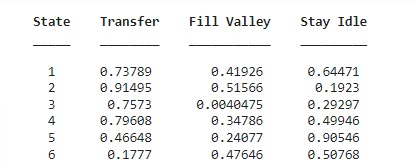
Inputs



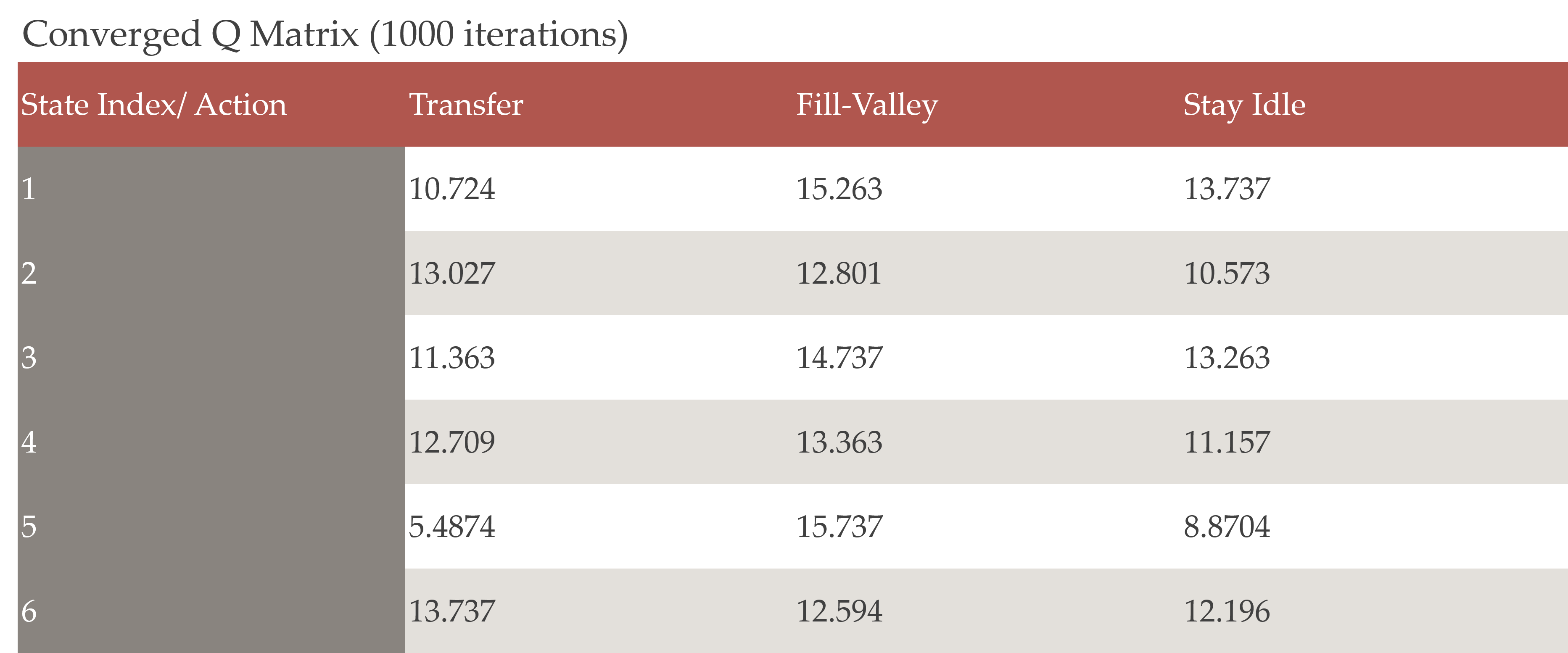
Actions



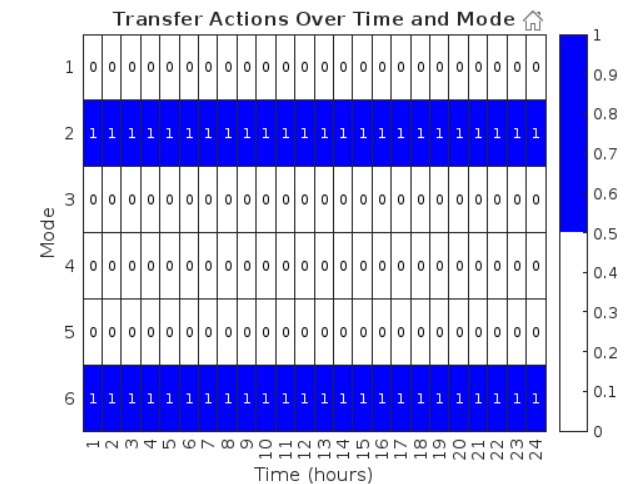
Reward Matrix

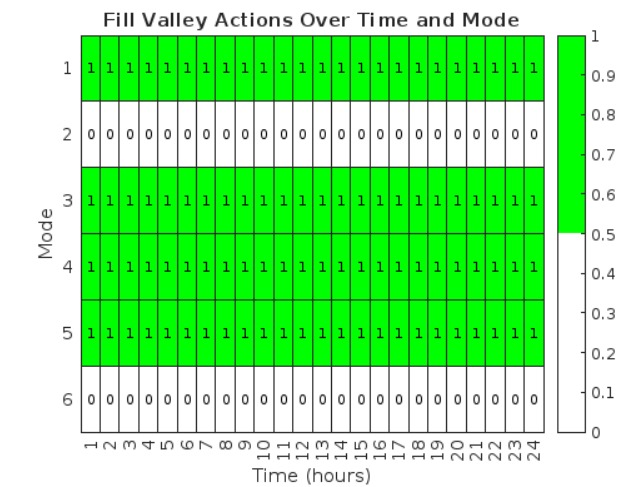


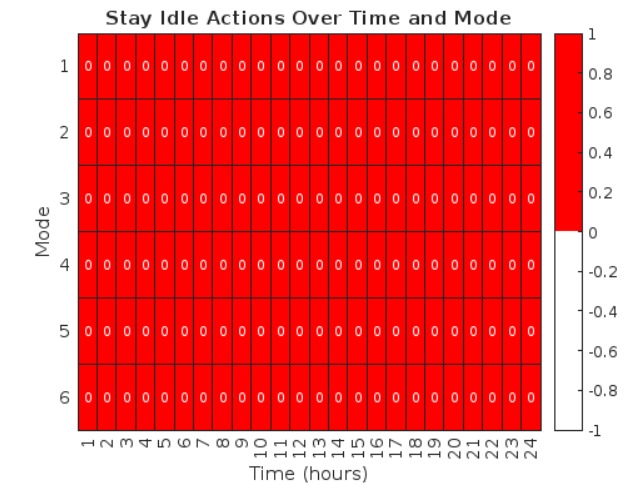
**Results: Converged Q Matrix**



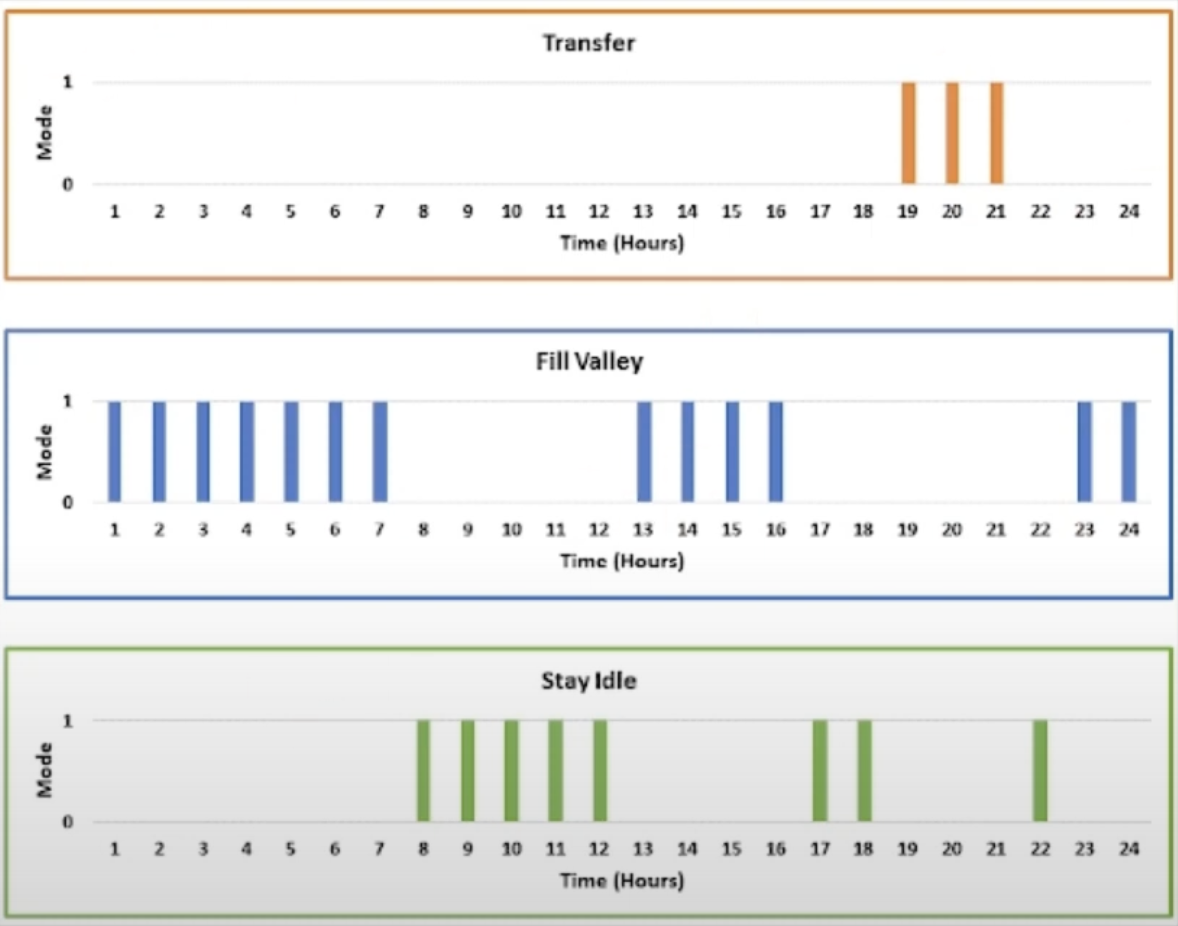
**Results: Actions Over Time & Mode**







**Results: Actions taken based on Q-Matrix**



**Results: Power Consumptions Profile After Optimisation**

