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Theme

AN INTELLIGENT SYSTEM FOR ENERGY MANAGEMENT IN SMART HOMES BASED ON MULTI-AGENT ARCHITECTURE AND FUZZY LOGIC

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Abstract

The increasing demand for energy efficiency and sustainability in smart home environments has spurred the development of advanced energy management systems (EMS). This thesis proposes a novel approach integrating multi-agent reinforcement learning (MARL) with fuzzy logic for efficient energy management in smart homes. The system employs a distributed architecture where autonomous agents interact with various smart devices to optimize energy consumption while considering user preferences and comfort levels.

The use of MARL enables the system to adapt and learn from dynamic environments, allowing for real-time decision-making and optimization of energy usage. Each agent operates independently, yet collaboratively, to achieve the overarching goal of minimizing energy consumption and costs while maintaining user comfort. Fuzzy logic is incorporated to handle uncertainties and imprecise data inherent in smart home environments, providing robustness and flexibility to the decision-making process.

The proposed system demonstrates significant improvements in energy efficiency compared to traditional approaches. Furthermore, the integration of fuzzy logic enhances the system's ability to handle complex and uncertain environments, resulting in more reliable and adaptive energy management solutions for smart homes. This research contributes to advancing the field of smart home automation by offering a scalable and intelligent energy management system capable of optimizing energy usage while ensuring user satisfaction and comfort.

Key Words: Smart homes, Energy management system, Reinforcement learning, Q-learning, Fuzzy logic.

Resumé

La demande croissante d'efficacité énergétique et de durabilité dans les environnements de maison intelligente a stimulé le développement de systèmes avancés de gestion de l'énergie (EMS). Ce memoire propose une nouvelle approche intégrant l'apprentissage par renforcement multi-agents (MARL) avec une logique floue pour une gestion efficace de l'énergie dans les maisons intelligentes. Le système utilise une architecture distribuée dans laquelle des agents autonomes interagissent avec divers appareils intelligents pour optimiser la consommation d'énergie tout en tenant compte des préférences des utilisateurs et des niveaux de confort.

L'utilisation de MARL permet au système de s'adapter et d'apprendre des environnements dynamiques, permettant une prise de décision en temps réel et une optimisation de la consommation d'énergie. Chaque agent fonctionne de manière indépendante, mais en collaboration, pour atteindre l'objectif primordial de minimiser la consommation d'énergie et les coûts tout en maintenant le confort des utilisateurs. La logique floue est incorporée pour gérer les incertitudes et les données imprécises inhérentes aux environnements de maison intelligente, offrant ainsi robustesse et flexibilité au processus de prise de décision.

Le système proposé démontre des améliorations significatives en termes d'efficacité énergétique par rapport aux approches traditionnelles. De plus, l'intégration de la logique floue améliore la capacité du système à gérer des environnements complexes et incertains, ce qui donne lieu à des solutions de gestion de l'énergie plus fiables et adaptatives pour les maisons intelligentes. Cette recherche contribue à faire progresser le domaine de la domotique intelligente en proposant un système de gestion de l'énergie évolutif et intelligent capable d'optimiser la consommation d'énergie tout en garantissant la satisfaction et le confort des utilisateurs.

Mots clés : **Maisons intelligentes, Système de gestion de l'énergie, Apprentissage par renforcement, Q-Learning, Logique floue.**

ملخص

أدى الطلب المتزايد على كفاءة الطاقة واستدامتها في البيئات المنزلية الذكية إلى تحفيز تطوير أنظمة إدارة الطاقة المتقدمة .(EMS) تقترح هذه الأطروحة نهجًا جديدًا يدمج التعلم المعزز متعدد العوامل (MARL)مع المنطق الغامض لإدارة الطاقة بكفاءة في المنازل الذكية. يستخدم النظام بنية موزعة حيث يتفاعل الوكلاء المستقلون مع العديد من الأجهزة الذكية لتحسين استهلاك الطاقة مع مراعاة تفضيلات المستخدم ومستويات الراحة.

يمكّن استخدام MARL النظام من التكيف والتعلم من البيئات الديناميكية، مما يسمح باتخاذ القرار في الوقت الفعلي وتحسين استخدام الطاقة. يعمل كل وكيل بشكل مستقل، ولكن بشكل تعاوني، لتحقيق الهدف الشامل المتمثل في تقليل استهلاك الطاقة والتكاليف مع الحفاظ على راحة المستخدم. تم دمج المنطق الغامض للتعامل مع حالات عدم اليقين والبيانات غير الدقيقة المتأصلة في بيئات المنزل الذكي، مما يوفر القوة والمرونة لعملية صنع القرار.

يوضح النظام المقترح تحسينات كبيرة في كفاءة استخدام الطاقة مقارنة بالطرق التقليدية. علاوة على ذلك، فإن تكامل المنطق الغامض يعزز قدرة النظام على التعامل مع البيئات المعقدة وغير المؤكدة، مما يؤدي إلى حلول أكثر موثوقية وتكيفًا لإدارة الطاقة للمنازل الذكية. يساهم هذا البحث في تطوير مجال أتمتة المنزل الذكي من خلال تقديم نظام ذكي وقابل للتطوير لإدارة الطاقة قادر على تحسين استخدام الطاقة مع ضمان رضا المستخدم وراحته.

<u>الكلمات المفتاحية:</u> المنازل الذكية، نظام إدارة الطاقة، التعلم المعزز، التعلم-Q ، المنطق الضبابي

Acknowledgement

I hereby declare that this thesis, is the result of our own original work, and has not been submitted previously, in whole or in part, for any degree or other qualification at any other institution.

All sources of information and data that have been utilized in this research have been properly acknowledged, and references to the work of others have been clearly indicated. We have adhered to the academic standards and integrity required for this research, ensuring that all contributions from other researchers and sources are appropriately cited.

We certify that this thesis has been composed entirely by ourselves and that any assistance received in writing this thesis, as well as all sources used, have been duly acknowledged.

Dedication

We would like to express our deepest gratitude to all those who have supported me throughout the course of our thesis journey.

First and foremost, we would like to thank our advisor, DR.Ali Wided, for their invaluable guidance, continuous support, and encouragement. Their expertise, patience, and insights have been instrumental in shaping this research and bringing it to fruition. We are truly grateful for the opportunity to work under their mentorship.

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Our deepest appreciation goes to our family for their unwavering love, patience, and encouragement. Their belief in us has been a source of motivation and strength throughout our academic journey.

Lastly, we wish to thank all the individuals whose contributions, whether directly or indirectly, have enriched this research and made this thesis possible. Your support and encouragement have been invaluable, and we deeply grateful to each one of you.

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Table of Abbreviations

EMS	Energy management system
HEMS	Home energy management system
IoT	Internet of things
HIHREM	hybridized intelligent home renewable energy management
SHEMS	Smart home energy management system
DR	Demand response
FR	Fuzzy reasoning
RL	Reinforcement learning
MARL	Multi-agent reinforcement learning
FMDP	Finite Markov decision process
NN	Neural networks
PV	Solar photovoltaic
ELM	Extreme learning machine
HVAC	Heating, ventilation and air conditioning
MAQL	Multi-agent Q-learning
MARL	Multi-agent reinforcement learning
FQL	Fuzzy Q-learning

General Introduction

Context:

The contemporary world is witnessing a significant transformation in the way energy is consumed and managed, driven by the advent of smart technologies and the urgent need for sustainable practices. Smart homes, equipped with advanced sensors, smart devices, and interconnected systems, present a unique opportunity to optimize energy consumption, reduce costs, and enhance user comfort. However, the inherent complexity and dynamic nature of residential environments pose considerable challenges for effective energy management.

Traditional energy management systems (EMS) often rely on centralized control mechanisms or simplistic heuristic approaches, which may not be sufficiently adaptive to the fluctuating demands and diverse preferences of smart home inhabitants. To address these limitations, there has been growing interest in leveraging artificial intelligence (AI) techniques, particularly multi-agent reinforcement learning (MARL), to create more flexible and responsive EMS. MARL provides a decentralized framework where multiple autonomous agents interact with the environment and each other, learning to make optimal decisions through continuous feedback and adaptation.

Problem Statement

Traditional energy management systems typically operate on fixed schedules, meaning they follow predetermined plans for energy usage without considering real-time changes in factors like demand, pricing, or the availability of renewable energy sources. This lack of adaptability can lead to various problems:

1. **Without adjusting to actual energy needs, these systems may waste energy or use it less effectively than possible, leading to inefficiencies.**
2. **Inefficient energy usage often translates to higher costs for users, as they may need to purchase more expensive energy during peak demand periods or rely on less efficient sources.**

3. **When demand for electricity surpasses the capacity of the grid to deliver it, the system experiences strain. This can lead to issues like power outages or voltage fluctuations, impacting reliability and stability**
4. **Traditional systems may prioritize energy savings over user comfort, leading to situations where users of appliances experience discomfort due to inflexible optimization strategies.**
5. **Traditional systems have difficulty adjusting to dynamic factors like fluctuating energy prices, variable renewable energy generation, or unpredictable user behavior. This lack of adaptability hinders their ability to optimize energy usage effectively.**

The shortcomings of traditional energy management systems underscore the need for more flexible, adaptive, and data-driven approaches to better address the complexities of modern energy consumption and production.

Objectives

The primary objective of this thesis is to develop a system that enhances comfort and energy efficiency in buildings, aligning with consumer trends emphasizing energy conservation and improved home comfort.

Research Focus, Objectives & Contributions

The proposed system in this thesis focuses on enhancing comfort, reducing costs, and saving energy within a smart home environment. It aligns with current consumer trends where energy conservation and improved home comfort are the primary motivations for adopting smart home technology. The main objective of this thesis is to assist users in enhancing both comfort and energy efficiency in their buildings while ensuring usability. To achieve this goal, the system is designed to meet the following specific objectives:

1. **Implement a reinforcement learning framework using a multi-agent Q-learning algorithm**
2. **Employ a demand response mechanism to reduce or schedule power-shiftable or time-shiftable loads to off-peak periods.**
3. **Utilize an ELM-based Neural Network to effectively handle unpredictable factors, unlike traditional methods that assume perfect predictions.**

4. **Enable each agent (representing different loads) to independently learn and make decisions, leading to an efficient and adaptive energy management system in a smart home.**
5. **Use the dissatisfaction coefficient to measure user comfort.**
6. **Integrate fuzzy logic with MARL to handle uncertainties and imprecise data inherent in smart home environments.**

The proposed approach will be evaluated through a series of simulation experiments and real-world implementations, assessing its performance in terms of energy savings, user comfort, and system reliability. By demonstrating the effectiveness of this integrated approach, this thesis aims to contribute to the advancement of smart home technologies, offering innovative solutions for achieving sustainable and energy-efficient living spaces.

Organization

We organized this thesis into three chapters:

- **Chapter 1:** In this chapter, we present a general overview on smart homes and energy management systems.
- **Chapter 2:** In this chapter, we present a data-driven approach for energy management in smart homes using multi-agent reinforcement learning.
- **Chapter 3:** In this chapter, we extend the module to include a fuzzy Q learning approach for multi-agent energy management in smart homes.

Chapter 1

State of the art

1 Introduction

In recent years, the concept of smart homes has evolved from a futuristic fantasy to a tangible reality, revolutionizing the way we interact with our living spaces. At the heart of this revolution lies the integration of cutting-edge technology into everyday household functions, creating environments that are not only more convenient and efficient but also environmentally sustainable. Smart homes are equipped with interconnected devices and systems that enable homeowners to remotely monitor and control various aspects of their homes, from temperature and lighting to security and entertainment, using smartphones or other devices.

One of the key components driving the advancement of smart homes is energy management systems (EMS). These systems utilize sophisticated algorithms and sensors to optimize energy usage within the home, resulting in reduced consumption, lower utility bills, and minimized environmental impact. By intelligently managing heating, cooling, lighting, and other energy-intensive processes, EMS empowers homeowners to make informed decisions about their energy usage and adopt more sustainable practices without sacrificing comfort or convenience.

In this chapter, we'll explore the fundamental principles of smart homes and energy management systems, delve into the technologies that make them possible, and examine the benefits they offer to homeowners. From increased efficiency and cost savings to enhanced comfort and environmental stewardship, the potential of smart homes and EMS to reshape the way we live and interact with our surroundings is boundless.

2 Smart homes

Smart homes are becoming increasingly popular as advancements in technology allow for automation and improved control over various aspects of household activities [1]. From controlling appliances to enhancing security measures, smart home systems provide convenience, efficiency, and enhanced living experiences for residents.[2]

2.1 Definition:

B. K. Sovacool and D. D. Furszyfer [3] define smart homes as "technologies refer to devices that provide some degree of digitally connected or enhanced services to occupants", which is now a big concept in discussion and innovation.

These days, this idea serves as a platform for combining amenities and gadgets for daily lives by utilizing a variety of methods, of which are networks, controllers, media and security systems to create intelligent and effective residential buildings.[4]

Rasha El-Azab [5] defines smart homes as "any residential buildings using different communication schemes and optimization algorithms to predict, analyze, optimize and control its energy-consumption patterns according to preset users' preferences to maximize home-economic benefits while preserving predefined conditions of a comfortable lifestyle".

This term has been widely used to refer to homes with regulated energy systems. Compared to typical unautomated homes, this automation technique validates easier lifestyles for homeowners, particularly for the elderly or disabled.it has recently expanded to encompass a variety of technological uses in one location[5].

2.2 Motivations for smart homes adoption

In a systematic review conducted by li et al.[4] they figured that smart homes can provide a set of services to give motivation for smart home adoption :

- efficient energy management by having transparent usage on energy and flexibility, also reduce consumption and be considerable on environmental impact.
- better financial spending through lowering energy consumption and so expenses.
- better living quality with its control abilities, enhanced security and provide fun and comfortable experiences.
- better health care with the improvements on the quality of life and home care and security.

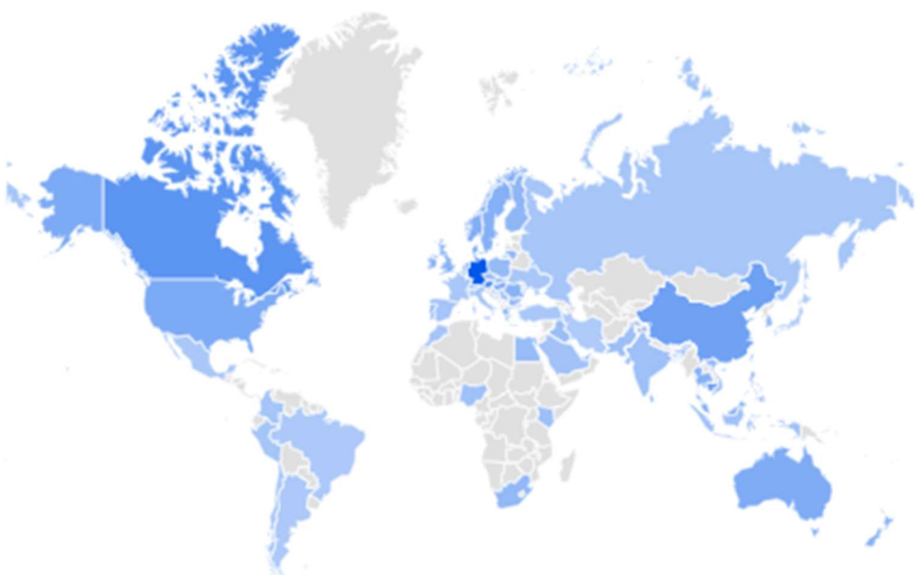

Figure 1 A map showing different countries interest in smart homes (taken from trends.google.com)

2.3 Barriers and challenges for smart homes adoption

While the concept of smart homes promises increased convenience and automation, there are potential drawbacks and concerns associated with this technology. One of the main concerns is the issue of privacy and security. With the integration of various smart devices and sensors, there is an increased risk of potential security breaches and data privacy infringements. Hackers could potentially gain access to personal data and exploit vulnerabilities in the smart home systems, leading to significant privacy concerns for the residents.[6]

In another review by Balta-Ozkan et al.[7] which was conducted on smart homes considers the potential drawbacks and concerns associated with this technology, such as privacy and security risks, environmental impact, and potential loss of traditional skills.

- Resistance to changing lifestyles consumers and homeowners are less likely to be drawn to technology that deviates from established norms, surroundings, or knowledge and may even give them a sense of being "out of control." The house is a representation of who you are.

- Users' information may be collected by smart homes; thus, it is important to properly protect personal data and ensure that control over critical network systems is well managed and hard top penetrate by hackers.
- High upfront costs, complexity in installation and setup, compatibility issues with existing devices, and the learning curve for users to understand and navigate the features and functionalities of smart home systems.
- The reliance on technology in smart homes could lead to a loss of traditional skills and knowledge related to household maintenance and management. As users become more dependent on automated systems, they may become less proficient in manual household tasks and repairs, potentially leading to a decreased sense of self-sufficiency.

Moreover, there is a growing concern about the environmental impact of smart home technology. The production and disposal of electronic devices and smart home components contribute to electronic waste, which poses environmental challenges. Additionally, the constant connectivity and power usage of smart devices may lead to increased energy consumption, contradicting the goal of sustainability and energy conservation.[8]

2.4 Potentials and benefits:

Despite these concerns and challenges, the potential benefits of smart homes cannot be ignored. They have the potential to greatly enhance convenience, comfort, energy efficiency, and safety in our daily lives.[9]

Residents of smart houses enjoy cozy, completely managed, and safe lifestyles. In addition, smart homes have the potential to generate revenue by selling clean, renewable energy to the grid, saving both energy and money. On the other hand, several governments are encouraged to develop potential smart-home technologies due to the likely decline in overall residential energy loads. To promote the integration of smart homes, several nations have already passed numerous laws, regulations, and subsidy programs. One such program encourages the heating system to be optimized.[5]

Sovacool & Furszyfer[3] ushered a review that estimated a 7% of global household being smart with a $44 billion in revenue and 22 billion of that revenue placed in Europe. And overseeing a 30% growth of smart homes, mainly in western Europe.[5]and powering it with sufficient green energy will pose a significant improvement on climate change and global warming.[10]

Moving forward, further research and development are necessary to address the identified concerns and challenges. Future studies should focus on enhancing smart home security, minimizing environmental impact, and exploring the social and ethical implications of smart homes. By critically evaluating the implications of smart home technology and considering the trade-offs between convenience and associated risks, the future development of smart homes can be aligned with the broader goals of sustainability, security, and user well-being.[11]

2.5 Practical Applications of Smart Homes

Smart home technology has a wide range of practical applications that can significantly improve the way we live. One of the most popular applications is in the realm of energy management. Smart homes allow for the efficient control of lighting, heating, cooling, and other energy-consuming devices, resulting in reduced energy consumption and lower utility bills. By integrating smart thermostats, automated lighting systems, and energy-efficient appliances, homeowners can optimize their energy usage and contribute to a more sustainable living environment.[12]

Another practical application of smart homes is in enhancing home security. With the use of smart surveillance cameras, motion sensors, and smart locks, homeowners can remotely monitor and secure their properties. They receive real-time alerts and can even take immediate action to address any potential security threats, providing peace of mind whether they are at home or away.[13]

Smart homes also offer practical solutions for aging in place and independent living. By incorporating smart home technology such as automated medication reminders, fall detection sensors, and emergency response systems, elderly individuals can maintain their independence while receiving necessary support and assistance. This enables them to live comfortably and safely in their own homes for as long as possible.[14]

In the realm of entertainment and lifestyle, smart homes provide practical applications for seamless connectivity and convenience. Integrating smart entertainment systems, voice assistants, and smart appliances allows for effortless control and management of home entertainment and daily tasks. From streaming music and videos to setting reminders and managing schedules, smart homes enhance the overall quality of life for occupants.[15]

Furthermore, smart homes offer practical applications in health and wellness. By incorporating smart health monitoring devices and sensors, individuals can track their health metrics and receive personalized insights for maintaining a healthy lifestyle. This proactive approach to health management can lead to improved well-being and early detection of health issues.[16]

As smart home technology continues to advance, the practical applications of smart homes will expand even further, offering innovative solutions for various aspects of daily living. With the increasing integration of artificial intelligence and machine learning capabilities, smart homes will be able to anticipate and adapt to the needs and preferences of occupants, further enhancing the practicality and efficiency of home management.[17]

3 Smart homes energy management systems (SHEMS)

Many countries are facing the problem of managing their energy supply while taking into account the ecological and environmental effects of increased energy output.[18]

Recent advancements in EMS for smart homes leverage AI algorithms to analyze energy consumption patterns and optimize energy usage in real-time. IoT-enabled devices, such as smart meters, sensors, and actuators, facilitate seamless communication and coordination among various appliances and energy sources within the home. Machine learning techniques enable EMS to learn from historical data and adapt to changing preferences and external factors, thus enhancing energy efficiency.[19] [20]

The future of EMS in smart homes holds promising opportunities for innovation and improvement. Integration with renewable energy sources, such as solar panels and wind turbines, can further enhance sustainability and reduce dependence on traditional energy grids.[21] Additionally, advancements in AI and machine learning algorithms will enable EMS to provide more personalized and adaptive energy management solutions, tailored to individual user preferences and lifestyle patterns.[20]

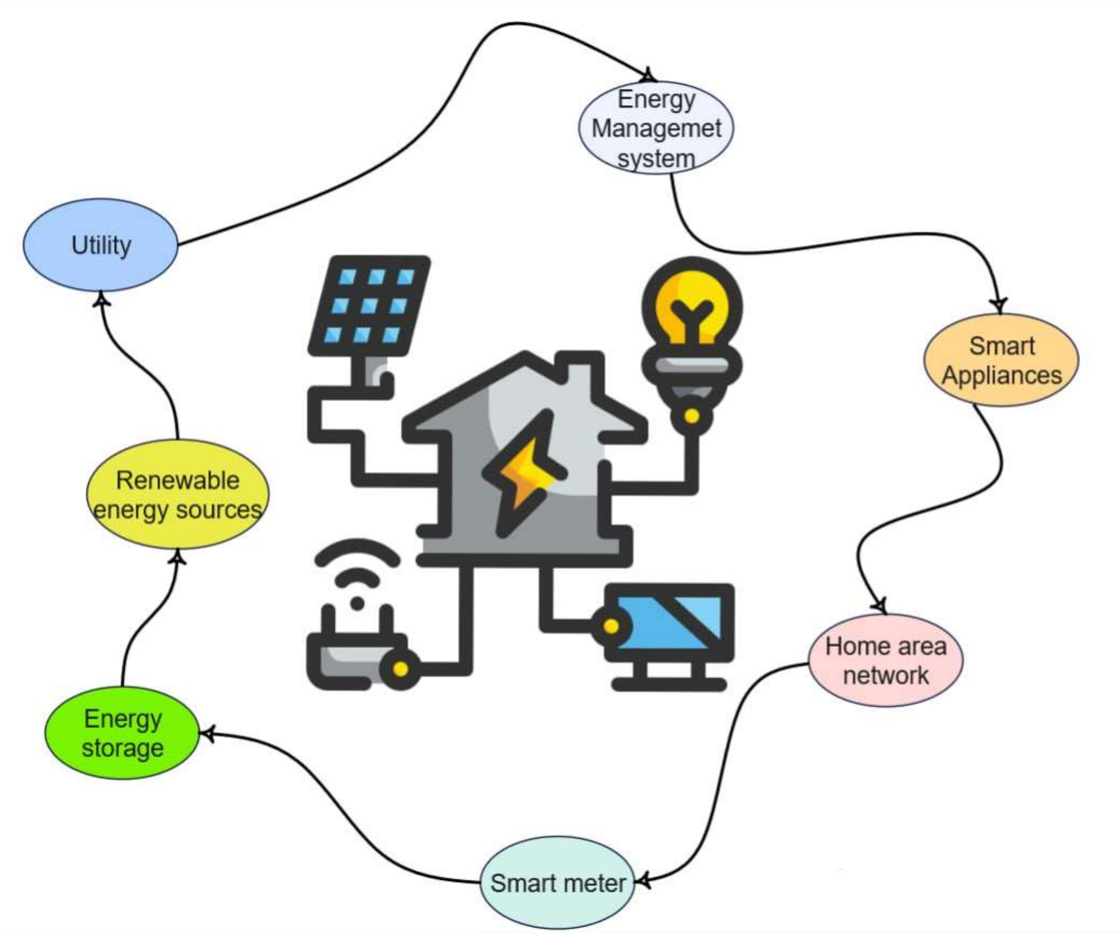

Figure 2 Home energy management systems

3.1 Hybridized intelligent home renewable energy management (HIHREM)

As smart home technology continues to advance, the concept of Hybridized Intelligent Home Renewable Energy Management emerges as a cutting-edge solution for optimizing energy usage and promoting sustainability within residential environments. HIHREM integrates advanced HEMS with renewable energy sources and intelligent algorithms to create a comprehensive and efficient energy management system.[22]

To seamlessly incorporate renewable energy sources, such as solar panels, wind turbines, and energy storage systems, into the overall energy management strategy of a smart home. By leveraging renewable energy, homeowners can significantly reduce their reliance on traditional grid power and contribute to a cleaner and more sustainable environment.[23]

Moreover, HIHREM utilizes intelligent algorithms and machine learning capabilities to autonomously manage energy usage based on user behavior, environmental factors, and energy production from renewable sources. This proactive approach not only ensures optimal energy efficiency but also maximizes the utilization of clean energy, further reducing the carbon footprint of the home. HIHREM also incorporates real-time monitoring and control features, allowing homeowners to access detailed insights into energy consumption and production. Through connected platforms and smart devices, occupants can remotely adjust energy settings, monitor renewable energy generation, and receive personalized recommendations for optimizing energy usage.[24] [25]

HIHREM is designed to facilitate seamless integration with smart grid technologies and demand response capabilities. This enables the system to automatically adjust energy usage based on peak demand periods, pricing fluctuations, and grid conditions, further enhancing energy efficiency and cost savings.[26]

3.2 HEMS in relation to smart homes and IoT

In the context of smart homes, the concept of the Internet of Things plays a significant role in enabling seamless connectivity and interoperability among various devices and systems. IoT technology facilitates the integration of diverse smart home devices, such as thermostats, lighting systems, security cameras, and appliances, into a unified network that can be centrally controlled and managed. This interconnected ecosystem of smart devices, enabled by IoT, provides homeowners with a comprehensive and cohesive platform for monitoring and controlling various aspects of their home environment.[27]

IoT technology in smart homes goes beyond simple connectivity, as it enables devices to communicate and interact with each other autonomously. For example, a smart thermostat can communicate with smart lighting systems and motion sensors to adjust temperature and lighting based on occupancy patterns, thereby optimizing energy usage and enhancing user comfort. This level of automation and intelligence, driven by IoT, enhances the overall efficiency and convenience of smart home systems.[28]

The integration of HEMS into the IoT framework further enhances the capabilities of smart homes by providing real-time energy consumption data and facilitating automated energy management. With HEMS leveraging IoT technology, homeowners gain the ability to remotely monitor and control energy usage through a unified interface, allowing for precise adjustments and optimizations based on energy consumption patterns and user preferences. The integration of HEMS into the IoT framework further enhances the capabilities of smart homes by providing real-time energy consumption data and facilitating automated energy management. With HEMS leveraging IoT technology, homeowners gain the ability to remotely monitor and control energy usage through a unified interface, allowing for precise adjustments and optimizations based on energy consumption patterns and user preferences. As IoT technology continues to advance, the potential for smart homes to adapt and evolve based on dynamic environmental and user-specific factors becomes even more pronounced. The integration of IoT and HEMS lays the foundation for a future where smart homes intelligently respond to changes in energy demand, external conditions, and user behavior, ultimately leading to greater energy savings and enhanced sustainability.[27] [29] [30]

The integration of IoT with smart home energy management systems not only fosters seamless connectivity and intelligent automation but also enables data-driven decision-making, ultimately contributing to the efficient and sustainable management of energy within residential environments. As smart home technology and IoT continue to converge, the potential for innovative and interconnected solutions in energy management and sustainability remains promising.[31]

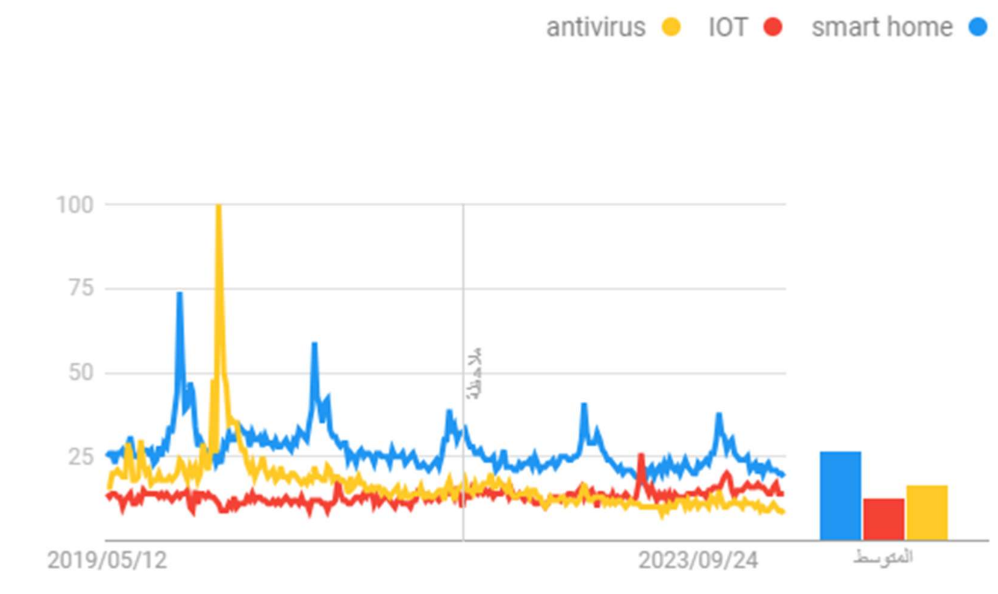

Figure 3 Worldwide shopping interest of "smart homes" "IoT" "Antiviruses" (taken from trends.google.com)

3.3 Energy benefits of smart home technologies

The integration of smart home technologies, particularly Home Energy Management Systems and the Internet of Things, brings significant benefits to energy management within residential environments. These smart technologies offer multiple advantages that contribute to energy efficiency, reduced energy costs, and enhanced sustainability for homeowners and occupants.[32]

Optimizing Energy Usage: Smart homes energy management systems, such as HEMS, enable homeowners to optimize their energy usage effectively. By providing real-time energy consumption data and remote access to energy-consuming devices, HEMS allows for precise control and adjustments to minimize wastage. This capability not only leads to lower utility bills but also promotes more sustainable energy practices within the home environment.[33]

Integrating Renewable Energy Sources: such as solar panels or wind turbines, into the overall energy management strategy. Smart home systems can effectively harness and maximize the use of clean energy while reducing reliance on traditional grid power, thereby promoting a more sustainable and eco-friendly energy consumption model.[34]

Data-Driven Decision-Making: The combination of IoT-enabled sensors and HEMS facilitates comprehensive data collection and analysis, leading to actionable insights for improving energy efficiency and sustainability. These insights empower homeowners to make informed decisions regarding energy usage and conservation, ultimately contributing to more effective energy management within the smart home environment.[32]

Achieving Greater Energy Savings: Ultimately, the integration of smart home technologies results in greater energy savings for homeowners. By leveraging advanced features such as demand response capabilities and personalized recommendations for energy optimization, smart homes ensure that energy resources are utilized efficiently, leading to significant cost savings and reduced environmental impact.[35]

3.4 Infrastructure of HEMS

A home energy management system consists of several interconnected components designed to monitor, control, and optimize energy usage within the home. These components work together to collect data, analyze consumption patterns, and implement energy-saving strategies.[36]

Central controller: a device or component that serves as the central point of control and coordination for various connected devices and systems within the home. It acts as the brain of the smart home ecosystem, facilitating communication, data processing, and decision-making to optimize energy usage and enhance overall home automation.[37] It communicates with all connected devices, sensors, and appliances within the smart home ecosystem. This communication can be facilitated through wired or wireless protocols such as Wi-Fi, Zigbee, Z-Wave, or Bluetooth.[38]

Figure 4 An example of a central controller for HEMS (taken from www.smart4energy.com)

IoT devices & appliances: Internet of Things (IoT) devices, such as smart thermostats, smart lighting systems, and smart appliances, are integrated into the home's infrastructure. These devices can communicate with the EMS, enabling remote control and automation of energy-consuming devices based on predefined rules and user preferences.[37]

Equipped with connectivity features, enabling them to communicate, interact, and be controlled remotely via a network, typically the internet. These appliances integrate advanced technologies such as sensors, microprocessors, and wireless communication protocols to offer enhanced functionality, automation, and convenience for homeowners.[39]

Figure 5 An example of different IoT devices (taken from www.wnbfinancial.com/IoT)

Sensors & Smart Meters: Sensors are deployed throughout the home to collect real-time data on energy consumption, environmental conditions, and occupancy patterns. Smart meters provide detailed information on electricity usage, allowing for accurate monitoring and analysis. Unlike traditional analog meters, smart meters are equipped with digital technology and communication capabilities, enabling them to transmit energy usage data remotely to utility companies in near real-time.[40]

Energy Sources and Grid: In advanced EMS setups, integration with renewable energy sources (e.g., solar panels, wind turbines, battery storage) and utility grid interfaces enables dynamic energy management strategies, such as demand response and peak shaving. These integrations enable homeowners to optimize energy usage, reduce costs, and contribute to a more sustainable energy ecosystem.[41] Energy storage devices plays a crucial role in balancing supply and demand, stabilizing the grid, and enabling the integration of intermittent renewable energy sources.[36]

User Interface: A user-friendly interface, such as a mobile app or web portal, allows homeowners to interact with the EMS, monitor energy usage in real-time, and adjust settings remotely. The interface may also provide energy consumption insights, personalized recommendations, and energy-saving tips to encourage behavior change and promote energy efficiency.[40]

Communication Network: A network that can be wired or wireless, depending on the specific requirements of the home. Wi-Fi, Zigbee, Z-Wave, and Bluetooth are common communication protocols used in smart home environments. effective communication is essential for the seamless operation and optimization of a smart home EMS, enabling efficient energy management, enhanced user experience, and integration with external systems for a more sustainable and resilient energy ecosystem.[36] [38]

Computational embedded controllers, local-area network communication middleware, and transmission control protocol/internet protocol (TCP/IP) communication for wide-area integration with the utility company using wide-area network communication are the three main components needed for home energy management systems.[5]

- **PLC:** refers to the use of Power Line Communication (PLC) technology to transmit data and commands over existing electrical power lines within a home's wiring infrastructure. PLC allows devices and systems to communicate with each other without the need for dedicated communication cables or wireless networks, leveraging the electrical wiring already present in the building.[5]
- **Zigbee:** is a wireless communication protocol commonly used in smart home environments to enable devices to communicate with each other. It operates on the IEEE 802.15.4 standard and is designed for low-power, short-range wireless communication between devices.[42]
  Zigbee technology provides a reliable, low-power, and interoperable wireless communication solution for smart home environments, enabling seamless connectivity and control of devices and systems within the home. Its mesh networking capabilities, low power consumption, and standardized approach make it a popular choice for building robust and scalable smart home ecosystems.[38] [43]

- **Wi-Fi:** is a widely used wireless communication technology that follows the IEEE 802.11 standard that enables devices to connect to the internet and local networks wirelessly. In the context of smart homes, Wi-Fi plays a significant role in enabling connectivity, control, and communication among various devices and systems.[38]

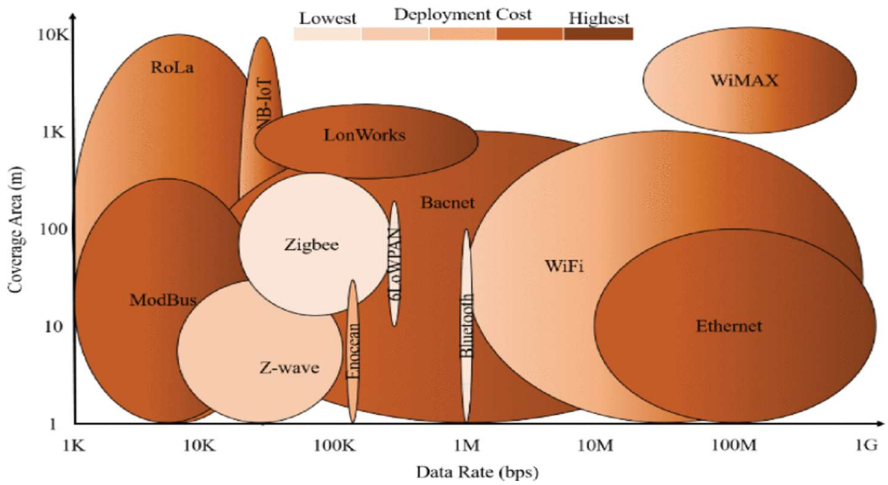

Figure 6 Communication Technologies of HEMS [36]

A smart home load: refers to the total electrical load or energy demand of all devices and appliances within a smart home environment. This includes any electrical equipment, such as lighting, heating, cooling, entertainment systems, kitchen appliances, and other electronic devices, that consume electricity.[18] and it can be classified based on its nature of operation schedulable and nonschedulable.[5]

- **Schedulable Loads:** devices or appliances that can be programmed or scheduled to operate at specific times or under certain conditions. These loads typically have adjustable settings or programmable features that allow users to set timers, schedules, or automation rules for their operation, such as washing machines, dish washers and lighting systems.[5]
- **Nonschedulable Loads:** devices or appliances that operate independently of user schedules or are not easily adjustable in terms of timing or operation. These loads typically have fixed or unpredictable usage patterns and cannot be easily controlled or scheduled for specific times, such as refrigerators and servers.[5] Nonschedulable loads may still benefit from energy management strategies such as load prioritization, demand response, or adaptive control algorithms to optimize their operation and minimize energy waste without compromising their essential functions.[39]

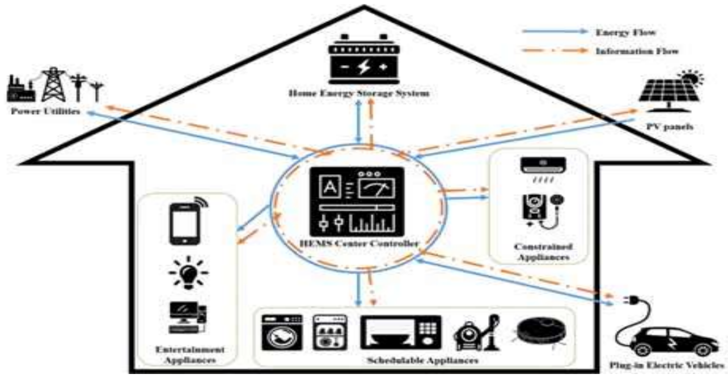

Figure 7 Typical architecture of a representative HEMS[36]

3.5 Challenges with SHEMS

Smart homes energy management systems face several challenges in their quest to optimize energy consumption. One major challenge is the complexity of the residential energy ecosystem, which includes a wide range of interconnected devices and appliances with varying energy requirements. Coordinating and optimizing the operation of these diverse components in real time requires sophisticated algorithms and decision-making processes.[44]

The unpredictable nature of human behavior and occupancy patterns poses a significant challenge for smart homes energy management systems. It is essential for these systems to accurately predict and adapt to the changing energy needs of occupants to avoid any discomfort while still maximizing energy efficiency.[45]

Integrating renewable energy sources, such as solar panels or wind turbines, into the energy management system presents technical challenges. These systems must effectively balance the intermittent availability of renewable energy with the fluctuating energy demands of the household.[46]

Cybersecurity is another critical challenge As these systems rely on interconnected devices and data collection, protecting against potential cyber threats and ensuring data privacy is crucial.[47]

3.6 Demand response (DR)

Demand response programs allow utilities to manage energy consumption during peak hours by incentivizing consumers to reduce their electricity usage or shift it to off-peak times. This is achieved through automated signals from the utility company to the smart home energy management system, which then adjusts energy usage based on preset preferences and optimization algorithms. By participating in demand response programs, smart homes can contribute to grid stability and reliability while potentially benefiting from financial incentives or reduced electricity costs. Reinforcement learning algorithms[19] [48]

3.7 Challenges with DR

One of the primary challenges faced by demand response systems is the variability and unpredictability of energy demand. Occupants' behavior, as well as their energy usage patterns, can fluctuate significantly, making it challenging for smart homes to accurately anticipate and respond to demand response signals in a timely and efficient manner. Moreover, the integration of renewable energy sources presents technical hurdles for demand response systems. The intermittent nature of renewable energy generation, such as solar and wind power, requires sophisticated algorithms and predictive models to balance energy supply and demand effectively, especially during peak demand periods. Furthermore, the security and privacy of data processed and communicated within demand response systems are paramount. As these systems rely on communication between smart devices and utility providers, robust cybersecurity measures must be in place to safeguard against potential cyber threats and ensure the integrity and confidentiality of sensitive energy consumption data.[49]

3.8 Economic values

One of the key considerations in implementing smart home energy management systems is ensuring a financial return for the customer's investment. Smart home energy management systems offer a variety of ways to achieve a financial return on investment. Through the optimization of energy usage, these systems can lead to significant savings on electricity bills over time.[50] Additionally, some utility companies offer incentives and rebates for customers who implement energy-saving technologies, further improving the financial outlook for smart home energy management systems. To make smart home energy management systems more accessible to a wider range of customers, it is important for the regulatory market to limit the current prices of smart home devices, making them more affordable for consumers.[51]

The integration of smart home energy management systems with renewable energy sources, such as solar panels or battery storage, can lead to even greater financial returns by reducing reliance on the traditional grid and potentially generating income through excess energy production.[23]

Emphasizing the financial benefits of smart home energy management systems is crucial for encouraging widespread adoption and ensuring a positive impact on both household budgets and overall energy conservation efforts. By focusing on and promoting the economic benefits of smart home energy management systems, it becomes more likely that consumers will be willing to invest in and adopt these systems, leading to a more sustainable and energy-efficient future.[52]

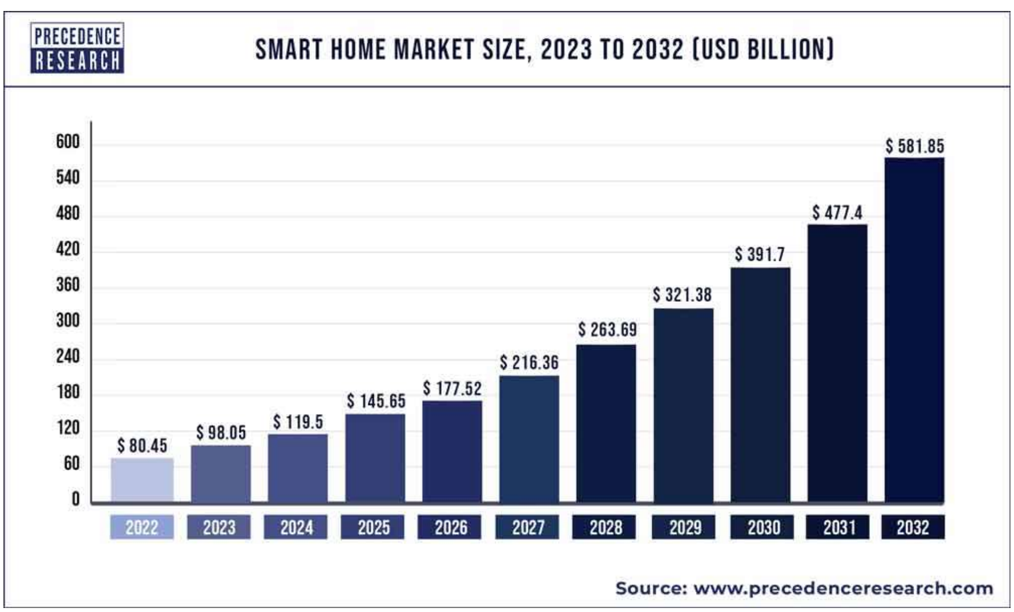

Figure 8 smart homes expected market growth for 2032(taken from www.precedenceresearch.com)

3.9 Related works

A Home Energy Management System With Renewable Energy and Energy Storage Utilizing Main Grid and Electricity Selling[53]	Contributions	- Proposed a novel Home Energy Management System (HEMS) architecture integrating Renewable Energy Sources (RES), Energy Storage Systems (ESS). - Utilized particle swarm optimization (PSO) and binary particle swarm optimization (BPSO) algorithms to optimize the energy cost and PAR.
	Objective Functions	- Minimization of Daily Energy Cost. - Reduction of Peak-to-Average Ratio (PAR)
	Advantage	-The integration of Renewable Energy Sources (RES) and Energy Storage Systems (ESS) into the HEMS provides a comprehensive solution for managing energy in households.
	Limitations	- Model assumptions may not fully capture real-world complexities. - Data accuracy and availability are crucial, and inaccurate data could lead to suboptimal outcomes
Low-cost fuzzy logic-controlled home energy management system[54]	Contributions	- Cost-effective real-time energy management for residences. - Utilization of fuzzy logic inference engines for intelligent decision-making. - Integration of multiple sensors for precise control.
	Objective Functions	-Minimization of Energy Consumption -Optimize Energy Distribution.
	Advantage	-Flexibility with Fuzzy Logic Controller - Improved Energy Utilization -Cost Savings -Flexibility and Adaptability
	Limitations	- Sensor Accuracy and Reliability - Complexity and Maintenance - Data Privacy and Security - Limited Adaptability
Demand Response Strategy Based on Reinforcement Learning and Fuzzy Reasoning for Home Energy Management [55]	Contributions	- Integrating Reinforcement Learning (RL) and Fuzzy Reasoning (FR) techniques. - Utilizes Q-learning to schedule smart home appliances, shifting electricity usage from peak to off-peak hours while maintaining user preferences.
	Objective Functions	- Minimize electricity costs by shifting consumption to off-peak periods. - Optimize battery energy storage usage for cost and efficiency.
	Advantage	- Effective control in complex systems. - Learning and adaptation capabilities. - Shifts appliance usage from peak to off-peak hours, reducing electricity costs.
	Limitations	- Learning Time: RL algorithms require significant training time, impacting quick decision-making. - User Cooperation: Success depends on user cooperation and reliable feedback, which may not always be guaranteed. - Complexity in rule design.

Table 1 A comparative analysis of different contributions or approaches to home energy management systems (HEMS)

Application of Predictive Control in Scheduling of Domestic Appliances[56]	Contributions	- Development of an appliance scheduling algorithm for reducing energy costs and peak-power consumption. - Utilized a Model Predictive Control (MPC) strategy for real-time operation of appliances within the HEMS. - Formulation of appliance dynamics into a Mixed-Integer Linear Programming (MILP) problem.
	Objective Functions	. Minimize Total Electricity Cost . Minimize Peak Power Consumption . Dynamic Appliance Scheduling . Adaptation to Real-time Market Conditions . Balance Load Distribution
	Advantage	- The Model Predictive Control (MPC) strategy enables real-time decision-making for efficient appliance management. - Reduced energy costs by optimizing appliance scheduling based on real-time electricity market conditions.
	Limitations	- The computational complexity of the mixed-integer linear programming optimization used in real-time scheduling may limit scalability. - Possible impact on user comfort and convenience. - Potential scalability issues with larger and more complex household setups
Demand Response in HEMSs Using DRL and the Impact of Its Various Configurations and Environmental Changes[57]	Contributions	- Development of an appliance scheduling algorithm for reducing energy costs and peak-power consumption. - Utilized a Model Predictive Control (MPC) strategy for real-time operation of appliances within the HEMS. - Formulation of appliance dynamics into a Mixed-Integer Linear Programming (MILP) problem.
	Objective Functions	. Minimize Total Electricity Cost . Minimize Peak Power Consumption . Dynamic Appliance Scheduling . Adaptation to Real-time Market Conditions . Balance Load Distribution
	Advantage	- The Model Predictive Control (MPC) strategy enables real-time decision-making for efficient appliance management. - Reduced energy costs by optimizing appliance scheduling based on real-time electricity market conditions.
	Limitations	- The computational complexity of the mixed-integer linear programming optimization used in real-time scheduling may limit scalability. - Possible impact on user comfort and convenience. - Potential scalability issues with larger and more complex household setups

Table 2 A comparative analysis of different contributions or approaches to home energy management systems (HEMS) (continues)

In[53]**:** Integration of Renewable Energy Sources (RES) and Energy Storage Systems (ESS) provides a comprehensive solution for managing energy in households. However, model assumptions may not fully capture real-world complexities, and inaccurate data could lead to suboptimal outcomes.

In[54]**:** Cost-effective real-time energy management leads to potential cost savings. The utilization of fuzzy logic inference engines enables precise control. However, dependence on sensors may pose accuracy and reliability challenges, and fuzzy logic systems might be complex to maintain and manage.

In[55]**:** Integration of Reinforcement Learning (RL) and Fuzzy Reasoning (FR) offers effective control in complex systems, and adaptation capabilities allow systems to adjust to user preferences and environmental changes. However, RL algorithms may require significant training time, and success depends on consistent user cooperation and feedback.

In[56]**:** Model Predictive Control (MPC) enables quick responses to changing conditions, and optimization based on real-time market conditions reduces energy costs. However, mixed-integer linear programming (MILP) may limit scalability, and optimization might prioritize cost over user comfort.

In[57]**:** Deep Reinforcement Learning (DRL) offers real-time optimization for demand response, and DRL systems provide scalable and adaptable solutions. However, large amounts of data are needed for effective training of DRL models, and DRL models may struggle to adapt quickly to new conditions not encountered during training.

After reviewing the findings from the related works, we have decided to utilize Reinforcement Learning (RL) and fuzzy reasoning in our approach. These techniques have consistently proven to be optimal solutions for addressing the complexities of home energy management systems, as highlighted in the literature. Their effectiveness in providing effective control in complex systems, adapting to user preferences and environmental changes, and offering scalable solutions aligns well with our project objectives.

4 Conclusion

As we conclude from this chapter, it becomes clear that these innovations are not just about convenience or efficiency; they represent a fundamental shift in the way we think about and interact with our living spaces. By harnessing the power of technology to automate and optimize energy usage, smart homes offer a glimpse into a future where sustainability and comfort go hand in hand.

The potential of smart homes and EMS to revolutionize the way we live is vast. From reducing our carbon footprint and easing the strain on our planet's resources to enhancing our quality of life and saving money on utility bills, the benefits are undeniable. However, realizing this potential requires not only technological advancements but also widespread adoption and awareness among homeowners, businesses, and policymakers.

In the next chapter we’ll look at intelligent approaches.

Chapter 2

A data-driven approach for energy management in smart homes using multi-agent reinforcement learning

1 Introduction

Smart homes equipped with an array of interconnected devices and sensors, offer a promising avenue for optimizing energy consumption. However, harnessing the full potential of these technologies requires sophisticated approaches that go beyond simple automation. Enter multi-agent reinforcement learning (MARL), a data-driven methodology that leverages artificial intelligence to orchestrate energy usage across diverse smart home environments.

In order to achieve effective home-based demand response (DR), this chapter suggests a revolutionary reinforcement learning-based paradigm for home energy management (HEM). The hourly energy consumption scheduling problem at hand is appropriately expressed as a discrete time step with finite Markov decision process (FMDP). In order to address this issue, a data-driven approach built on neural networks (NN) and the Q-learning algorithm is created, which produces better results on budget-friendly scheduling for the HEM system. In particular, actual energy pricing and solar photovoltaic (PV) generation data are analyzed in real time for extreme learning machine (ELM) uncertainty prediction in rolling time windows. The test findings show that the suggested data-driven based HEM framework is effective.

2 Contribution statement

The system proposed in this chapter does not aim to address all the issues within a smart home environment. Instead, its primary focus lies on enhancing comfort, reducing costs, and saving energy. This emphasis is based on the current consumer trends where the primary motivation for adopting smart home technology is energy conservation and improved home comfort. Consequently, the main objective of this thesis is to assist users in enhancing both the comfort and energy efficiency of their buildings while ensuring usability. To achieve this overarching goal, the system is designed to accomplish the following specific objectives:

- Provide an approach that utilizes a reinforcement learning framework based on a multi-agent Q-learning algorithm to make decisions regarding energy consumption one hour ahead.
- Use a demand response mechanism to reduce or schedule power-shiftable or time-shiftable loads to off-peak periods.
- The proposed model utilizes an Extreme Learning Machine (ELM) based Neural Network (NN) to effectively handle unpredictable factors, unlike traditional methods that assume perfect predictions. It incorporates Q-learning to continuously improve decision-making, enabling optimal Demand Response (DR) decisions and ensuring efficient energy management despite uncertainties. This combination of ELM and Q-learning allows for more accurate and reliable energy consumption strategies in smart homes.
- In the proposed system, each agent (representing different loads) can independently learn and make decisions, leading to an efficient and adaptive energy management system in a smart home.
- Use the dissatisfaction coefficient to measure user comfort. This coefficient varies based on an individual's reliance on a specific device. If someone heavily relies on a particular appliance and prefers it to start quickly, the dissatisfaction coefficient for that appliance will be higher. Conversely, if they can tolerate waiting longer without much inconvenience, the coefficient will be lower.

3 Multi-Agent Reinforcement Learning

3.1 The Reinforcement Learning Framework

Reinforcement learning have emerged as promising solutions for optimizing energy consumption in residential buildings. These systems leverage reinforcement learning algorithms to learn and adapt to the energy needs and usage patterns of occupants, ultimately maximizing energy efficiency while maintaining user comfort. By continuously monitoring and analyzing factors such as weather conditions, occupancy patterns, and energy consumption data, these systems can make intelligent decisions regarding the operation of home appliances, HVAC systems, and energy storage devices.[58] Through the use of reinforcement learning, these systems can learn optimal strategies for scheduling energy usage, such as when to charge electric vehicles, when to run appliances, and when to use renewable energy sources.[59] By using real-time data, these systems can also take advantage of dynamic pricing models and energy demand response programs to further optimize energy consumption.[60] Overall, smart homes energy optimization systems using reinforcement learning are designed to strike a balance between energy cost and user comfort by making data-driven decisions and adapting to changing circumstances. They offer significant potential for reducing energy consumption, lowering costs, and promoting sustainability in residential buildings.[59]

The state of the art in smart homes energy optimization systems using reinforcement learning is constantly evolving with advancements in machine learning and data analytics. One recent development is the integration of deep reinforcement learning, which allows for more complex decision-making processes and improved energy optimization outcomes. This approach has shown promising results in adapting to dynamic and unpredictable environments, further enhancing energy efficiency and user comfort.[59]

There has been a growing focus on the use of multi-agent reinforcement learning, it enables coordination and collaboration between different devices and appliances within a smart home, leading to more holistic and integrated energy management strategies.[61] The use of multi-agent reinforcement learning has the potential to optimize energy consumption at a broader scale and address interconnected energy needs within a household. Additionally, advancements in AI-driven smart home technology have paved the way for enhanced user comfort and energy efficiency. These systems can learn user preferences and adapt energy usage patterns based on individual needs, schedules, and comfort levels.[62]

One of the key advantages of MARL is its ability to facilitate cooperation and communication between different agents, allowing them to work together towards common energy management goals. For example, agents can learn to schedule the operation of appliances in a way that minimizes peak energy demand and takes advantage of off-peak pricing, leading to cost savings for the household.[63]

MARL can adapt to changing conditions and user preferences by continuously learning and updating its strategies. For instance, if a new energy-efficient appliance is added to the smart home, the MARL system can learn to integrate it into the overall energy management framework, maximizing its benefits while minimizing its impact on energy costs.[63]

MARL can address the challenge of distributed energy resources, such as solar panels or energy storage systems, by optimizing their utilization in conjunction with other energy-consuming devices. This holistic approach to energy management ensures that the smart home operates as an integrated system, leveraging both energy-efficient technologies and intelligent decision-making to achieve optimal energy consumption patterns.[64]

The integration of multi-agent reinforcement learning in smart homes energy optimization systems represents a significant advancement in the pursuit of sustainable and efficient residential energy usage. As research in this field continues to progress, the potential for MARL to revolutionize energy management in smart homes is increasingly evident, offering scalable and adaptive solutions for diverse energy optimization challenges.[65]

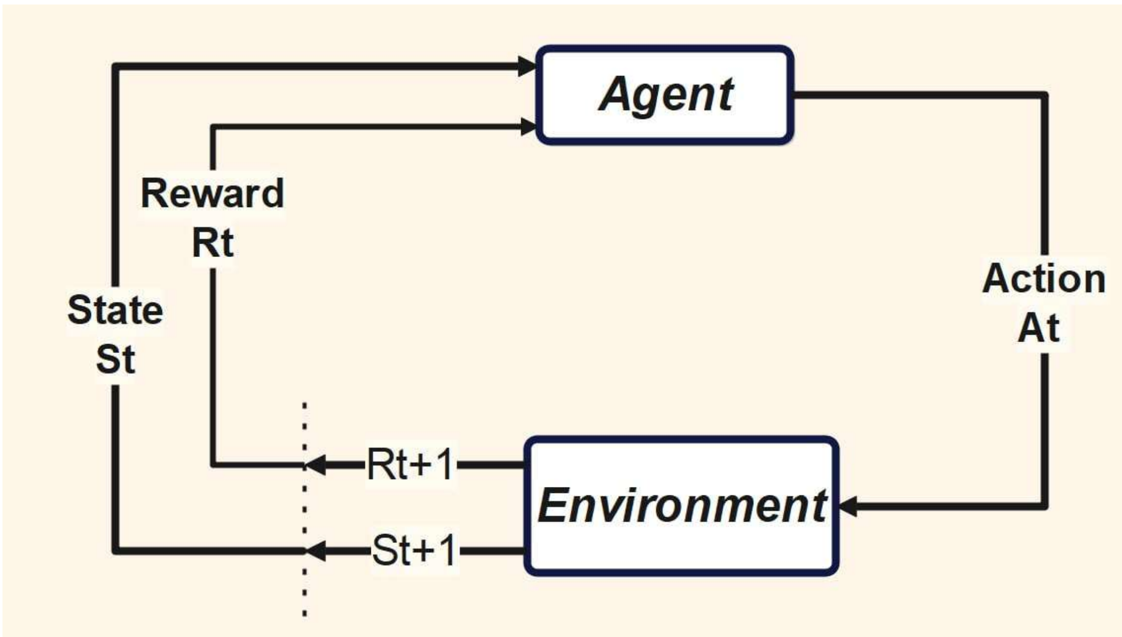

Figure 9 A recursive representation of the Agent-Environment interface.

Cooperative multi-agent systems with partial observability offer a promising approach to addressing the challenges of smart homes energy management. In the context of energy optimization, the concept of partial observability refers to the limited visibility agents have into the state of the environment, which is common in real-world scenarios. This limitation necessitates collaborative decision-making among agents to effectively manage energy consumption and promote sustainability within a smart home environment.[66]

It can be designed to enable communication and collaboration among different devices and appliances. By leveraging partial observability, these systems can adapt to the dynamic and uncertain nature of energy usage patterns, human behavior, and the availability of renewable energy sources. With interconnected agents, each responsible for controlling specific components, cooperative multi-agent systems have the potential to optimize overall energy consumption while considering user comfort, cost-effectiveness, and sustainability.[67]

We may create a comprehensive method to optimize energy consumption in smart homes by utilizing data-driven approaches and Multi-Agent Reinforcement Learning (MARL). We can suggest such a procedure as follows:

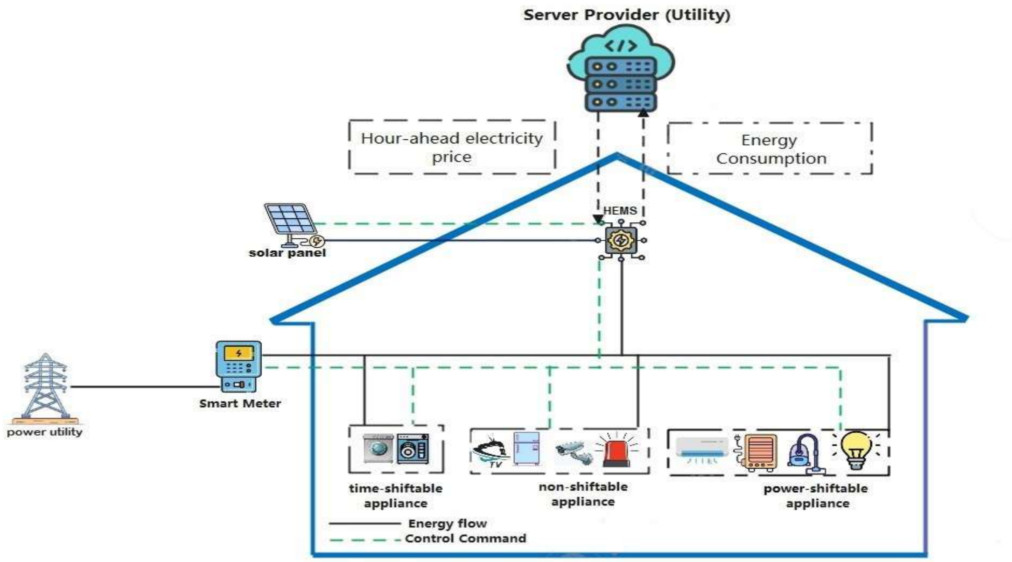

Figure 10 Our proposed architecture of a home energy management system

As depicted in **Figure 10,** this study addresses a HEMS comprising three agents, representing non-shiftable appliance load, power-shiftable appliance load, time-shiftable appliance load, respectively. The envisioned HEMS in this thesis incorporates multiple agents, each responsible for controlling various types of smart home appliances in a decentralized manner.

It's important to note that smart meters are presumed to be installed on smart home appliances to monitor their usage and receive control commands from the agents. Within each time slot, we establish hour-ahead energy consumption actions for home appliances

4 Proposed Multi-agent Q-learning method for Decision-making

Multi-agent Q-learning (MAQL) is a reinforcement learning technique that enables multiple agents to learn optimal policies for decision-making in cooperative or competitive environments. In MAQL, agents interact with the environment, observe the outcomes of their actions, and update their Q-values based on the observed rewards and state transitions. Here's how we can propose a MAQL method for decision-making:

Sophisticated reinforcement learning techniques are utilized by MARL agents to maneuver over the intricate terrain of energy management. These agents are encouraged to conduct behaviors that result in energy conservation while lowering expenses and preserving occupant comfort by specifying suitable reward functions. To ensure efficient energy usage without compromising comfort, a smart thermostat agent might be trained to modify temperature settings in response to occupancy patterns and outside temperature forecasts.

Within the data-driven framework, we introduce a unique and flexible HEM technique that does not rely on a specific model. This method is based on the combination of the extreme learning machine (ELM) and the Q-learning algorithm. The test findings demonstrate that the proposed HEM approach is capable of achieving favorable performance in terms of reducing power costs for householders, as well as enhancing computational efficiency. The traditional HEM methods rely on optimization algorithms assuming accurate prediction of uncertainty.

Nevertheless, this assumption is impractical and illogical given that the inaccuracies in predictions cannot be avoided. In contrast, our proposed model-free data-driven HEM technique can effectively address future uncertainties by utilizing the ELM based NN and determine the optimal DR decisions through the learning capabilities of the Q-learning algorithm. To address the issue of managing numerous loads in a residential dwelling, such as non-shiftable loads, power-shiftable loads, time-shiftable loads, a multi-agent Q-learning algorithm based on reinforcement learning (RL) is created. This technique aims to solve the Home Energy Management (HEM) problem associated with these loads. By using a fully decentralized approach, it is possible to acquire optimal scheduling decisions for different home appliances and electric vehicle charging, ensuring efficient energy consumption.

ITEM	STATE	ACTION 1=ON/0=OFF	REWARD EQUATION
REF	$\{(P_t^G, P_{t+1}^G, \ldots, P_T^G), (\lambda_t^{PV}, \lambda_{t+1}^{PV}, \ldots, \lambda_T^{PV})\}$	1	(1)
AS	$\{(P_t^G, P_{t+1}^G, \ldots, P_T^G), (\lambda_t^{PV}, \lambda_{t+1}^{PV}, \ldots, \lambda_T^{PV})\}$	1	(1)
AC1	$\{(P_t^G, P_{t+1}^G, \ldots, P_T^G), (\lambda_t^{PV}, \lambda_{t+1}^{PV}, \ldots, \lambda_T^{PV})\}$	{0.7, 0.8, …, 1.4}	(2)
AC2	$\{(P_t^G, P_{t+1}^G, \ldots, P_T^G), (\lambda_t^{PV}, \lambda_{t+1}^{PV}, \ldots, \lambda_T^{PV})\}$	{0.7, 0.8, …, 1.4}	(2)
HTR	$\{(P_t^G, P_{t+1}^G, \ldots, P_T^G), (\lambda_t^{PV}, \lambda_{t+1}^{PV}, \ldots, \lambda_T^{PV})\}$	{0.5, 0.6, …, 1.5}	(2)
L1	$\{(P_t^G, P_{t+1}^G, \ldots, P_T^G), (\lambda_t^{PV}, \lambda_{t+1}^{PV}, \ldots, \lambda_T^{PV})\}$	{0.2, 0.3, …, 0.6}	(2)
L2	$\{(P_t^G, P_{t+1}^G, \ldots, P_T^G), (\lambda_t^{PV}, \lambda_{t+1}^{PV}, \ldots, \lambda_T^{PV})\}$	{0.2, 0.3, …, 0.6}	(2)
WM	$\{(P_t^G, P_{t+1}^G, \ldots, P_T^G), (\lambda_t^{PV}, \lambda_{t+1}^{PV}, \ldots, \lambda_T^{PV})\}$	0/1	(3)
DW	$\{(P_t^G, P_{t+1}^G, \ldots, P_T^G), (\lambda_t^{PV}, \lambda_{t+1}^{PV}, \ldots, \lambda_T^{PV})\}$	0/1	(3)

Table 3 Table representing state/action/reward of each agent

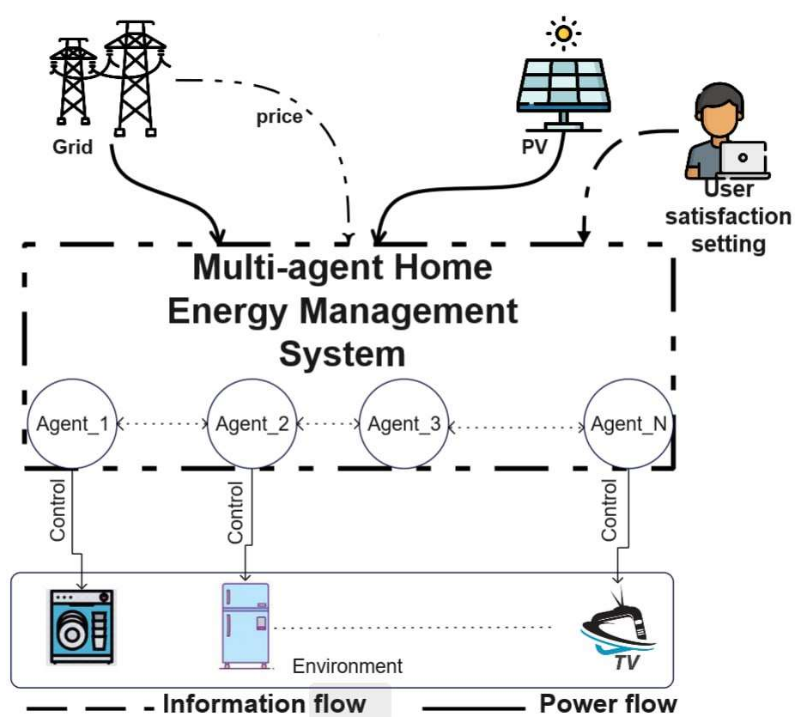

Figure 11 multi-agent home energy management system

4.1 PROBLEM MODELLING

a. Agent Representation: Each appliance or energy-consuming device in the smart home is represented as an agent within the MARL framework. Agents interact with the environment by adjusting their operational settings, such as temperature, power consumption levels, or scheduling.

- $Ƥ_t$: Electricity prices in time slot t.
- $ƛ_t^{PV}$: Solar generation in time slot t.
- $r_{it}^{NS}/r_{jt}^{PS}/r_{mt}^{TS}$: Reward of non-shiftable appliances/Power shiftable appliances/Time shiftable appliances.
- $E_{jt}^{NS}/E_{jt}^{PS}/E_{jt}^{TS}$: Energy consumption of non-shiftable appliances/Power shiftable appliances /Time shiftable appliances.
- $i \in \Omega^{NS}$ the index of non-shiftable appliances.
- $j \in \Omega^{PS}$ the index of power shiftable appliances.
- $m \in \Omega^{TS}$ the index of time shiftable appliances.

b. State Representation: The state (s_t) in a time slot t of the environment encompasses various factors, including current energy consumption levels, external weather conditions, occupancy patterns, and energy prices. Data from sensors installed throughout the home provide real-time information about these variables, forming the basis for state representation, which consists of two vectors.

$$s_t = \{(Ƥ_t^G, Ƥ_{t+1}^G, \dots, Ƥ_T^G), (ƛ_t^{PV}, ƛ_{t+1}^{PV}, \dots, ƛ_T^{PV})\}$$

- $(Ƥ_t, Ƥ_{t+1}, \dots, Ƥ_T)$ current electricity price.
- $(ƛ_t^{PV}, ƛ_{t+1}^{PV}, \dots, ƛ_T^{PV})$ current solar panel output (solar generation).

c. Action Space: Agents have a discrete action space corresponding to the available actions they can take, such as adjusting thermostat settings, turning appliances on/off, or scheduling energy-intensive tasks during off-peak hours. The action space can also include cooperation actions, such as coordinating usage to minimize peak demand.

- **Action set for non-shiftable appliance agent:** like refrigerator and alarm systems high dependability is necessary to guarantee everyday ease and security, so their needs must be met immediately and cannot be planned. Therefore, the non-shiftable appliance agent can only do one action: turning it "on".
- **Action set for power-shiftable appliance agent:** like heating and light it can function with flexibility by using energy within a set range. Therefore, discrete actions, denoted by 1, 2, 3..., which represent the power ratings at various levels, can be selected by power-shiftable agents.
- **Action set for time-shiftable appliance agent:** To lower electricity costs and prevent peak energy consumption, time-shiftable loads can be scheduled from peak to off-peak times. Time-shiftable appliances feature two modes of operation: "on" and "off," such as the dishwasher and washing machine.

d. Reward Design: The reward function incentivizes energy-efficient behavior while considering user comfort and cost savings. Rewards can be based on factors such as reducing overall energy consumption, avoiding peak demand periods, adhering to user preferences, and minimizing deviations from optimal energy usage patterns.

- **The reward of non-shiftable appliance agent:**

$$r_{it}^{NS} = -\text{Ƥ}_t\left[E_{it}^{NS} - \lambda_{it}^{PVs}\right]^{+} i \in \Omega^{NS} \; t = \{1,2,\ldots,T\} \tag{1}$$

Since non-shiftable loads are immutable, the non-shiftable appliance agent's reward solely relates to power costs.

- **The reward of power-shiftable appliance agent**

$$r_{jt}^{PS} = -\text{Ƥ}_t\left[E_{jt}^{PS} - \lambda_{jt}^{PVs}\right]^{+} - \alpha_j^{PS}(E_{j,max}^{PS} - E_{jt}^{PS})^2 \; j \in \Omega^{PS} \; t = \{1,2,\ldots,T\} \tag{2}$$

Where the cost of electricity is shown in the first term and the cost of unhappiness resulting from power-shiftable appliances' lower power ratings is shown in the second. A quadratic function with an application-dependent coefficient[68], $\alpha j \; PS$, defines this dissatisfaction cost. It can be modified to create a trade-off between the cost of power and the degree of satisfaction.

- **The reward of time-shiftable appliance agent**

$$r_{mt}^{TS} = -\text{Ƥ}_t[u_{mt}E_{mt}^{TS} - \lambda_{mt}^{PVs}]^{+} - \alpha_m^{TS}(t_m^s - t_m^{ini})^2 \; m \in \Omega^{TS} \; t = [t_m^{ini}, t_m^{end}] \tag{3}$$

Where $\boldsymbol{u_{mt}}$ is the binary variable that denotes the time-shiftable appliance m's operating position in time slot t, $\boldsymbol{u_{mt}}$ **= 1 (on) or** $\boldsymbol{u_{mt}}$ **= 0 (off).** The waiting period for time-shiftable loads to begin would increase homeowner discontent costs when they are scheduled. Thus, while using time-shiftable equipment, the electricity expense (first term) and the discontent cost (second term) should be considered concurrently. The dissatisfaction coefficient, or $\boldsymbol{\alpha_m^{TS}}$, is based on an individual's dependence on devices and describes the tolerance of waiting time for the appliance. Therefore, a larger $\boldsymbol{\alpha_m^{TS}}$ indicates a higher likelihood of discontent when waiting for the appliance to start. Keep in mind that the time-shiftable appliance m should begin operating during its regular operating hours $[\boldsymbol{t_m^{ini}}, \boldsymbol{t_m^{end}}]$**.**

- **Total Reward of HEM System**
The total reward R can be obtained by giving the rewards (see Eqs. (1 – 3)) of each agent in the suggested HEM system.

$$\mathbf{R} = -\sum_{i \in T} \left\{ \begin{array}{c} \text{Ƥ}_t\left(\left[E_{it}^{NS} - \lambda_{it}^{PVs}\right]^{+} - \left[E_{jt}^{PS} - \lambda_{jt}^{PVs}\right]^{+} - \left[u_{mt}E_{mt}^{TS} - \lambda_{mt}^{PVs}\right]^{+}\right) \\ -\left(\alpha_j^{PS}\left(E_{j,max}^{PS} - E_{jt}^{PS}\right)^2 - \alpha_m^{TS}\left(t_m^s - t_m^{ini}\right)^2\right) \end{array} \right\} \tag{4}$$

- **Action-value Function**
The predicted sum of future rewards for the horizon of K time steps can be used to assess the quality of action $\boldsymbol{a_t}$ under state $\boldsymbol{s_t}$, or energy consumption scheduling in time slot $\boldsymbol{t}$.

$$Ϙ_{\pi}(s,a) = ƛ_{\pi}\left[\sum_{k=0}^{k} \gamma^{k} . r_{t+1} \mid s_t = s, a_t = a\right] \quad (5)$$

Where $\boldsymbol{\pi}$ is the policy mapping from a system state to an energy consumption schedule, and $\boldsymbol{Ϙ_{\pi}(s,a)}$ is the action-value function. The discount rate, represented by $\boldsymbol{\mu} \in$ **[0,1],** indicates the proportional significance of present rewards in relation to future ones. When $\boldsymbol{\gamma} = \mathbf{0}$, the agent appears to be myopic since it is solely concerned with the reward that is being offered now, but $\boldsymbol{\gamma} = \mathbf{1}$ shows that the agent is foresighted and takes future rewards into account. A fraction in the range **[0,1]** for γ is recommended in order to balance the trade-off between the present reward and the future reward.

Finding the ideal policy $\boldsymbol{\pi}$, or a series of ideal operating actions for each household appliance, is the goal of the energy consumption scheduling issue in order to maximize the action-value function.

e. Decentralized Decision-Making: Agents make decisions autonomously based on their local observations and interactions with the environment. Decentralized MARL algorithms, such as Q-learning, Deep Q-Networks (DQN), or Policy Gradient methods, enable agents to learn optimal policies independently while coordinating their actions to achieve collective goals.

f. Learning from Data: Data-driven techniques play a crucial role in initializing agent policies, learning from historical data, and updating models over time. Machine learning algorithms, such as supervised learning or reinforcement learning, can be used to train initial policies or improve agent performance based on feedback from the environment.

g. Adaptation to Dynamic Environments: The MARL framework enables agents to adapt to changes in the environment, such as fluctuations in occupancy patterns, weather conditions, or energy prices. Agents continuously learn from new data and adjust their policies accordingly, ensuring robust performance in dynamic scenarios.

h. Evaluation and Optimization: The performance of the MARL-based energy management system is evaluated based on metrics such as energy efficiency, cost savings, and user comfort.

4.2 The Markov decision process (MDP)

A paradigm for making decisions sequentially is the Markov Decision Process (MDP).

MDP M = (S, A, T, γ, R) typically consists of the following:

- **S:** is the state space.
- **A:** is the action space.
- **T:** S × A × S → [0, 1] is the transition probability model.
- **γ:** is the discount factor.
- **R:** S × A × S → R is the reward function.
- a policy is a set of functions π (a|s): S → A.

The aim of MDP is to find a policy that maximizes $\boldsymbol{\sum_{t=0}^{\infty} E[\gamma^{t} R(s_t, a_t, s_{t+1})]}$. The Markov property is satisfied by the state transition since just the previous state and the current action are needed for the future state to occur. States are not always observable in the real world. For instance, the position of the PV panel and the weather have an impact on PV generation. The condition that is hidden from us is made up of this latent data. What we see is that the Markov property does not hold for the PV generating value in the past.[69] This research presents an innovative approach to data-driven HEM (Home Energy Management) using multi-agent reinforcement learning. The challenge of scheduling household energy usage one hour in advance is defined as a finite Markov decision process (FMDP) with discrete time intervals.

4.3 The ELM based feedforward neural networks for uncertainty prediction

ELM based feedforward neural networks offer an alternative approach for uncertainty prediction in the context of multi-agent energy optimization. ELM is a type of neural network that is particularly suited for real-time learning and prediction tasks.[70]

In the context of renewable energy management, ELM-based feedforward neural networks can be utilized to predict uncertainty associated with energy generation and consumption patterns. By leveraging historical data on renewable energy production, weather fluctuations, and user behavior, these networks can forecast uncertain scenarios and variability in energy supply and demand. This predictive capability can aid agents in making informed decisions to optimize energy dispatch and storage strategies, thereby mitigating the impact of uncertainty on smart home energy management.[71]

4.3.1 Advantages of ELM-Based Feedforward Neural Networks

ELM-based neural networks offer fast learning capabilities, making them suitable for processing large volumes of data in real-time. This aspect is particularly beneficial for applications in smart home environments where rapid adaptation to changing conditions is essential.[72] Additionally, it requires minimal tuning of parameters, reducing the complexity associated with traditional neural networks and enhancing their efficiency in uncertainty prediction tasks.it also excel in their ability to handle non-linear problems and high-dimensional data. This makes them well-suited for capturing the complex and dynamic nature of energy optimization tasks within smart home environments. The network's feedforward architecture enables efficient and straightforward information flow, resulting in expedited prediction and decision-making processes.[73] And it exhibits robust generalization performance, allowing them to effectively adapt to diverse and evolving patterns in energy consumption and production. This robustness is instrumental in ensuring reliable uncertainty predictions and facilitating adaptive energy management strategies that align with changing environmental and user dynamics.[74] Furthermore, the simplicity of ELM-based networks contributes to their computational efficiency, reducing the computational burden associated with uncertainty prediction tasks. This efficiency is particularly advantageous in scenarios where real-time responsiveness and low-latency decision-making are essential for effective energy optimization and smart home management.[75]

4.3.2 Integration of ELM-Based Networks with data-driven solution

Since the input weights and biases of the hidden layer are randomly generated and free to be modified further when employing ELM algorithm, various special features can be acquired, e.g., fast learning speed and strong generalization. To deal with the uncertainties of energy pricing and solar generations, we present an ELM based feedforward NN to dynamically anticipate future trends of these two uncertainties. Specifically, at each hour, the inputs of the trained feedforward NN are past 24-hour energy price data and solar generation data, and its outputs are the anticipated future 24-hour trends of electricity prices and solar generations. This expected information will be supplied into the decision-making process of energy consumption scheduling, as explained in the following subsection.

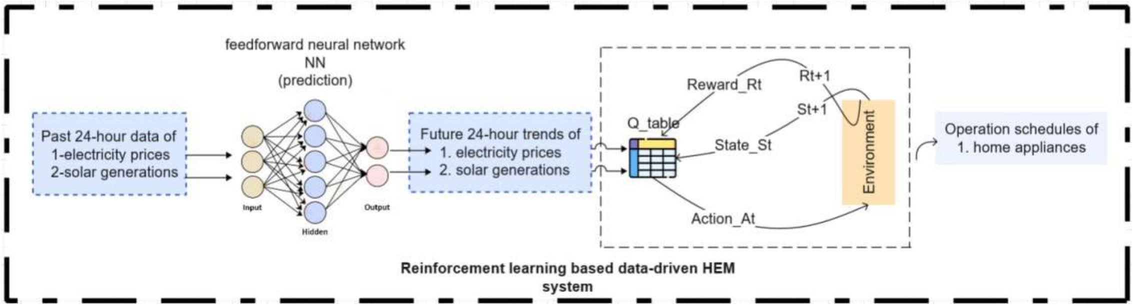

Figure 12 ELM-Based Networks with data-driven solution

The diagram in figure 12 illustrates a reinforcement learning (RL) based data-driven Home Energy Management (HEM) system.

- The system collects historical data on electricity prices and solar generation over the past 24 hours. This data is used as input for the predictive model.
- A feedforward neural network is employed to predict future trends based on the past data. The input layer takes in the past 24-hour data, processes it through hidden layers, and produces output representing the future 24-hour trends of electricity prices and solar generation.
- The predicted future trends are fed into the Q-learning module. The Q-learning algorithm maintains a Q-table, which stores the expected rewards for state-action pairs.
- he environment is updated based on the actions taken by the RL agent. This interaction continuously informs the Q-learning algorithm, allowing it to learn and optimize the scheduling of home appliances to reduce costs and improve efficiency.

In summary, the system uses past data to predict future trends with a neural network, which then informs an RL-based decision-making process to optimize the operation schedules of home appliances. This integration aims to enhance energy management by making informed, cost-effective decisions.

4.4 Reinforcement Learning (RL Algorithms)

The proposed reinforcement learning-based data-driven method consists of two main components an ELM-based feedforward neural network trained to predict future trends of electricity prices and solar generations, and a multi-agent Q-learning algorithm used to make hour-ahead energy consumption decisions.

Algorithm 1: Demonstrates the proposed data-driven solution approach for energy management in a smart home. The algorithm starts by setting up parameters and then proceeds to cycle through time slots. During each iteration, it runs the home energy management system, gathers data on future electricity prices and solar generation, and guides agents' actions according to their dissatisfaction coefficients.

Algorithm 1: Proposed Data-driven Solution Approach
1. **Initialization:** Begin by setting up initial parameters like power rating, time considerations, dissatisfaction coefficient α, discount factor γ, and learning rate θ. 2. **Loop over time slots**: Iterate over each time slot t from 1 to T. 3. **HEMS execution**: For the HEMS, execute **Algorithm 2.** 4. **Receive information**: Obtain extracted information about future electricity prices and solar generations. 5. **Agent processing:** For each agent, perform the following steps: o Sort agents in descending order based on dissatisfaction coefficient α. o Execute **Algorithm 3.** 6. **End loop**: End the loop over time slots.

Algorithm 2: Involves updating the input data for past electricity prices and solar generation, then using a feedforward neural network to predict future electricity prices and solar generation trends. The initial weights and biases of the network, along with past data, are used as inputs to forecast future values, which are then presented as the output.

Algorithm 2: Feedforward neural network (NN) used for feature extraction
1. Update Data: o Update the input data for electricity prices $\{\mathrm{P}_{t-23} \dots \dots \mathrm{P}_t\}$ and solar generation $\{\lambda_{t-23}^{SP} \dots \dots . \lambda_t^{SP}\}$. **2. Input:** o Initial weights and biases of the network o Past electricity price data $\{\mathrm{P}_{t-23} \dots \dots \mathrm{P}_t\}$. o Past solar generation data $\{\lambda_{t-23}^{SP} \dots \dots . \lambda_t^{SP}\}$. **3. Extract Future Trends:** o For electricity prices: o Predict future electricity prices $\{\mathrm{P}_{t+1}\ \mathrm{P}_{t+2}\ \mathrm{P}_{t+3} \dots\ \mathrm{P}_T\}$ using the neural network with input features $\{\mathrm{P}_{t-23} \dots \dots \mathrm{P}_t\}$ o For solar generations: o Predict future solar generations $\{\lambda_{t+1}^{SP}\ \lambda_{t+2}^{SP}\ \lambda_{t+3}^{SP} \dots\ \lambda_T^{SP}\}$using the neural network with input features $\{\lambda_{t-23}^{SP} \dots \dots . \lambda_t^{SP}\}$.. **4. Output Extracted Information:** o Present the forecasted future trends of electricity prices and solar generations as the output.

Algorithm 3: Initialize parameters and Q-values, then iterate through episodes by selecting actions based on a greedy policy, observing rewards and next states, and updating Q-values until convergence is achieved, ultimately outputting the optimal policy for energy management.

Algorithm 3: Optimizing HEM with Q-Learning Algorithm

1. **Initialization:**
   Set $\boldsymbol{\gamma}$, $\boldsymbol{\alpha}$ parameters and environment rewards in matrix.
   Initialise $Q(\boldsymbol{s_t}, \boldsymbol{a_t}), \forall \boldsymbol{s} \in \boldsymbol{S}, \forall \boldsymbol{a} \in \boldsymbol{A}$
2. **Repeat for each episode σ:**
   Initialize the starting state $\boldsymbol{s}$
3. **Repeat:**
   - Choose the action at: Based on the current state st, the agent selects an action at using **Ɛ-greedy policy**
   - Observe the current reward $\boldsymbol{r_t}(\boldsymbol{s_t}, \boldsymbol{a_t})$, and the next state $\boldsymbol{s_{t+1}}$: Interact with the environment by taking the chosen action $\boldsymbol{a_t}$ and observe the resulting reward and the next state
   - Update the Q-value $Q(\boldsymbol{s_t}, \boldsymbol{a_t})$, based on Eq. (8)
4. **Until $\boldsymbol{s_{t+1}}$ is terminal:** Continue the loop until reaching a terminal state, where the episode ends
5. **If** $|\, Q^{(\sigma)} - Q^{(\sigma-1)} | \leq \tau$ then $\boldsymbol{\sigma} = \boldsymbol{\sigma} + \mathbf{1}$.
6. **Else Exit loop.**
7. **Output the best policy** $\boldsymbol{\pi}^*$ $\boldsymbol{i.e.}, \{\boldsymbol{a_t^*}, \boldsymbol{a_{t+1}^*}, \boldsymbol{a_{t+2}^*}, \boldsymbol{a_{t+3}^*}, \boldsymbol{a_T^*}\}$.
8. **Implement the optimal action** $\boldsymbol{a_t^*}$ for the current time slot **t**.

5 Experimental results

5.1 Data Set

In this study, we used actual data to train our proposed feedforward neural network. Specifically, we collected hourly data on electricity prices and solar generation over a period of two years, from May 1, 2024, to May 4, 2024. This data, covering 4 days, was obtained from PJM, an organization that operates a regional transmission organization in the United States.[76] The use of this real-world data ensures that our model is trained on accurate and relevant information, which improves its ability to predict future trends and make reliable decisions.

5.2 Experimental environment

Python: Is a high-level, interpreted programming language known for its readability, simplicity, and versatility. It is a Programming language having properties like it is interpreted, object-oriented and it is high-level too. created in 1980s by Guido van Rossum during his research at the National Research Institute for Mathematics and Computer Science in the Netherlands and first released in 1991. It is widely used in machine learning due to its extensive libraries and frameworks, such as TensorFlow, Keras, and scikit-learn, which provide powerful tools for building and deploying machine learning models efficiently.[77]

Figure 13 Python's logo (taken from www.freebiesupply.com)

Google colab: short for Google Colaboratory, is a free, cloud-based platform provided by Google that allows users to write and execute Python code in a Jupyter Notebook environment. It is particularly popular for machine learning, data analysis, and education due to its ease of use and accessibility.[78]
We use google colab to train our program and test our data with the help of , processing all this data can require powerful hardware, which is where Google's cloud comes in.

Figure 14 Google Colab's logo (taken from www.stickpng.com)

TensorFlow: is an open-source machine learning framework developed by the Google Brain team. It is widely used for building and deploying machine learning and deep learning models. TensorFlow assists with all stages of the process, from data preparation all the way through to running the models.[79]

We use it to build our models and train the data-intense neural networks.

Figure 15 TensorFlow's logo (taken from albertfattal.com)

Pandas: is an open-source data manipulation and analysis library for the Python programming language. It provides data structures and functions needed to work with structured data seamlessly and efficiently. It simplifies the process of data manipulation and analysis, making it an essential library for anyone working with data in Python.[80]

Figure 16 Pandas's logo (taken from www.freecodecamp.org)

NumPy (Numerical Python): is a fundamental library for numerical computing in Python. It provides support for large, multi-dimensional arrays and matrices, along with a collection of mathematical functions to operate on these arrays.[81]

Figure 17 NumPy's logo (taken from branditechture.agency)

Matplotlib: is a comprehensive library for creating static, animated, and interactive visualizations in Python. It is widely used in data science, machine learning, and scientific research for its ability to generate a wide variety of plots and graphs.[82]

Figure 18 matplotlib's logo (taken from seeklogo.com)

PyTorch: is an open-source machine learning library developed by Facebook's AI Research lab (FAIR). It is widely used for deep learning applications due to its flexibility, ease of use, and dynamic computational graph capabilities.[83]

Figure 19 PyTorch's logo (taken from http://softscients.com)

5.3 Experimental parameters

In experimental setups, both cost evaluation and the dissatisfaction coefficient are key parameters that need to be defined and adjusted to evaluate the performance of the MARL-based SHEMS:

5.3.1 Cost evaluation

Cost evaluation is a critical aspect of SHEMS as it directly relates to the financial impact of energy consumption and the effectiveness of the energy management strategies implemented by the system. The primary cost component, representing the total monetary expense incurred by consuming electricity.

Energy consumption cost is calculated as the product of the amount of electricity consumed (measured in kilowatt-hours, kWh) and the electricity price (cents per kWh). when the electricity price varies with time (e.g., peak vs. off-peak rates), the cost calculation needs to consider these fluctuations.

The reward function in MARL incorporates cost-related metrics to guide the learning process. A typical reward function might be:

$R = -(\text{Energy Consumption Cost} + \text{Peak Demand Charges}) - \alpha \cdot \text{User Dissatisfaction}$

5.3.2 User comfort

The dissatisfaction coefficient α: This coefficient essentially quantifies the level of user dissatisfaction resulting from deviations from their preferred comfort settings, such as temperature or appliance usage schedules.

α represents a numerical value that quantifies the discomfort or dissatisfaction experienced by users when the system's actions do not align with their preferences.

It is used in the reward function to penalize the system for actions that lead to user discomfort, thereby encouraging the system to find a balance between optimizing energy consumption and maintaining user comfort.

Incorporation in Reward Function: In a typical MARL setup for SHEMS, the reward function is designed to reflect both the energy consumption and the level of user satisfaction. A common form of the reward function R might include terms for both energy savings E and user satisfaction S: $R=-E-\alpha \cdot S$

Here, E represents the energy consumed (or cost associated with it), and S represents the dissatisfaction or deviation from user preferences. The coefficient **α** scales the dissatisfaction term, effectively controlling its impact on the overall reward.

Impact on System Behavior: A higher value of α increases the penalty for user dissatisfaction, making the system more conservative in making energy-saving decisions that would significantly affect user comfort. Conversely, a lower value of α reduces the emphasis on user satisfaction, allowing the system to prioritize energy savings more aggressively, even at the cost of some user discomfort.

The dissatisfaction coefficient α in SHEMS with MARL is a critical parameter that helps balance the trade-off between energy efficiency and user comfort. By appropriately tuning α, the system can ensure that energy-saving measures do not excessively compromise user satisfaction, thereby achieving a more optimal and user-friendly home energy management solution.

5.4 Results and discussion

5.4.1 Case Study setup

Name	*Diss. Coeff*	*Type*	*Power Rating (kWh)*	*Time Slot*
REF	100	NS	0.5	[1, 8]
AS	100	NS	0.1	[1, 8]
AC1	0.05	PS	[0.7, 1.4, 0.1]	[1, 8]
AC2	50	PS	[0.7, 1.4, 0.1]	[1, 8]
HTR	0.12	PS	[0.5, 1.5, 0.1]	[1, 8]
L1	20	PS	[0.2, 0.6, 0.1]	[5, 7]
L2	0.03	PS	[0.2, 0.6, 0.1]	[5, 7]
WM	0.10	TS	0.7	[6, 8]
DW	0.06	TS	0.3	[6, 8]

Table 4 Parameters of each house appliances

This chapter involves conducting simulations using a total of nine appliances, including two solar panels, two non-shiftable appliances (REF and AS), five power-shiftable appliances (AC1, AC2, HTR, L1, L2), and two time-shiftable appliances (WM, DW). The specifications of these household appliances are shown in Table 4. In addition, our proposed HEMS approach is applicable to Buildings that have a greater number of home appliances and renewable resources. Python is utilized to implement all simulations in Google Colab, and graphs are drawn with PyTorch.

5.4.2 Feedforward NN performance

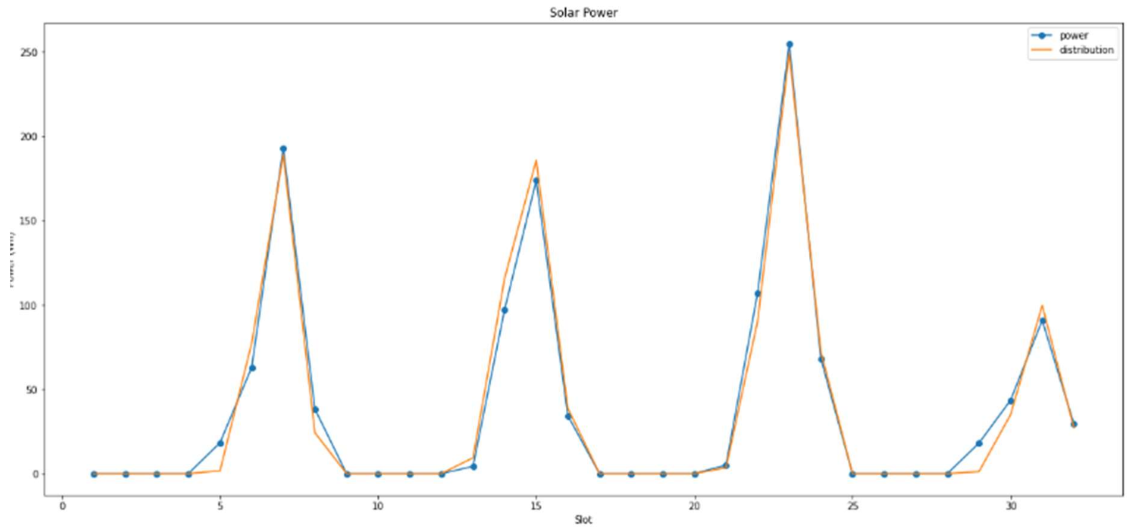

Figure 20 Comparison of the electricity price and the actual electricity price

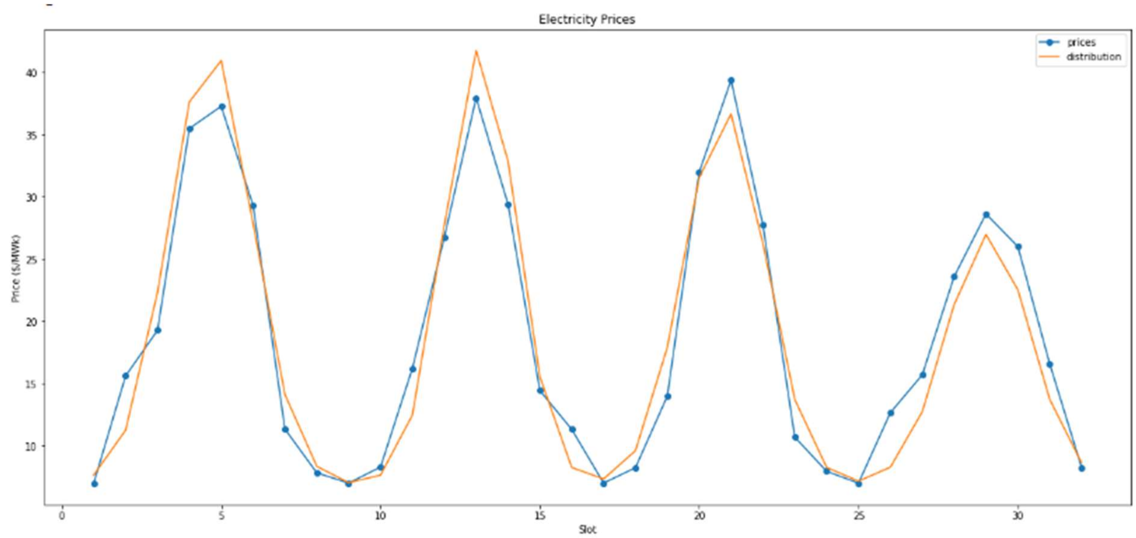

Figure 21 Comparison of the predicted solar generation and the actual solar generation

Figure 22 , and 23 demonstrate the efficacy of the proposed feedforward neural network in extracting features from energy prices and solar generations. The blue line in both of these figures reflects the projected future values, whereas the orange line represents the actual numbers. It is evident that the extracted trends of power prices and solar generations closely resemble the actual trends, although there may be slight discrepancies in some cases.

5.4.3 Q-learning algorithm performance

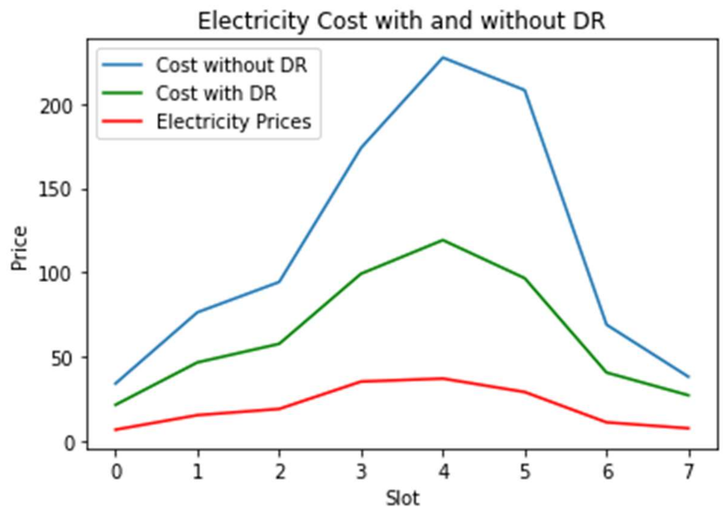

Figure 22 Electricity cost with and without DR

Figure 22 provides the daily electricity cost of individual household appliances under two scenarios: with and without demand response (DR).The analysis of electricity expenses in these two scenarios demonstrates that the implementation of Demand Response (DR) can lead to a substantial reduction in electricity expenditures.

6 Conclusion

In conclusion, a data-driven approach to energy management in smart homes using multi-agent reinforcement learning holds tremendous potential for maximizing efficiency, reducing costs, and promoting sustainability. By harnessing the power of artificial intelligence and leveraging vast amounts of data, MARL empowers smart home ecosystems to adapt, learn, and evolve in pursuit of optimal energy usage. As we strive towards a more energy-efficient future, MARL stands as a beacon of innovation and progress in the realm of smart home technology.

Chapter 3

A fuzzy Q learning approach for multi-agent energy management in smart homes

1 Introduction

MARL offers a decentralized framework where autonomous agents interact with the environment and each other to learn optimal energy usage strategies. This distributed nature enables scalability and adaptability, crucial for handling the diversity of devices and user preferences in smart homes.

Fuzzy logic, on the other hand, provides a mechanism for dealing with uncertainties and imprecise data—a common characteristic of residential environments. By capturing and reasoning with vague or ambiguous information, fuzzy logic enhances the robustness and flexibility of decision-making processes in energy management systems.

In this chapter, we explore the synergies between MARL and fuzzy logic, aiming to develop a comprehensive approach for intelligent home energy management. By integrating these two techniques, we seek to harness the collective intelligence of autonomous agents while leveraging the nuanced reasoning capabilities of fuzzy logic. This integration promises to overcome the limitations of traditional methods and unlock new opportunities for optimizing energy usage in smart homes.

Through theoretical analysis, simulation studies, and real-world experiments, we aim to demonstrate the effectiveness of our proposed approach. We anticipate that our research will contribute to advancing the state-of-the-art in smart home automation, offering scalable, adaptive, and intelligent solutions for energy management. Ultimately, our goal is to pave the way towards sustainable and energy-efficient living environments that prioritize both environmental conservation and user comfort.

2 Contribution statement

Fuzzy logic contributes significantly to the efficiency, robustness, and adaptability of a multi-agent reinforcement learning (MARL) home energy management system (HEMS). Its integration addresses several key challenges and enhances the overall performance of the system.

- We'll integrate fuzzy logic with MARL to handle uncertainties and imprecise data inherent in smart home environments. Fuzzy logic provided a robust mechanism for making nuanced decisions under uncertainty, enhancing the agents' ability to manage energy effectively.
- Fuzzy logic incorporates human-like reasoning through a set of fuzzy rules that map inputs to outputs in a way that is intuitive and interpretable. These rules help agents make better decisions in complex, uncertain environments.
- Fuzzy membership functions can be dynamically adjusted based on real-time data, enabling our system to adapt to changing conditions and user preferences.

3 Fuzzy Reinforcement Learning

In recent years, the adoption of fuzzy reinforcement learning in multi-agent systems has garnered significant attention in the field of smart homes energy optimization. It offers a unique approach to decision-making under uncertainty, allowing agents to navigate complex and dynamic environments with imprecise information.[84]

One of the key advantages of fuzzy reinforcement learning is its capability to handle partial observability and uncertain data, which is particularly relevant in the context of smart homes energy management. By incorporating fuzzy sets and fuzzy logic, agents can effectively deal with vague or indeterminate information, enabling them to make robust decisions in scenarios where traditional crisp modeling may fall short.[85] It can enhance the adaptability of multi-agent systems in smart homes by enabling agents to learn from imprecise feedback and progressively improve their decision-making processes. This adaptive learning mechanism is essential in addressing the dynamic nature of energy usage patterns and accommodating user preferences, thereby contributing to more personalized and efficient energy management solutions.[86]

With its integration in multi-agent systems, it extends to the optimization of distributed energy resources within smart homes. By leveraging fuzzy logic-based control mechanisms, agents can dynamically adjust the utilization of energy-producing devices, such as solar panels, based on varying environmental conditions and user requirements. This flexibility in decision-making contributes to maximizing the overall energy efficiency and resilience of the smart home ecosystem.[87]

The application of fuzzy reinforcement learning in multi-agent systems aligns with the overarching goal of achieving sustainable and efficient residential energy usage. By enabling agents to reason and act in uncertain and ambiguous environments, fuzzy reinforcement learning contributes to the development of robust and adaptive energy optimization strategies that can effectively balance comfort, cost-effectiveness, and environmental impact.[88]

As research and development in the field of smart homes energy optimization progress, the integration of fuzzy reinforcement learning in multi-agent systems is poised to play a pivotal role in addressing the inherent uncertainties and complexities associated with energy management. The combination of fuzzy logic principles and reinforcement learning techniques offers a promising avenue for creating intelligent, adaptable, and user-centric energy optimization solutions within smart home environments.[89] [90]

3.1 Fuzzy sets and Fuzzy systems

Fuzzy sets and fuzzy systems are mathematical frameworks used to represent and reason with uncertain or vague information in decision-making processes. Developed by Lotfi A. Zadeh in the 1960s as an extension of classical set theory and logic, fuzzy logic provides a means of capturing and processing imprecise or qualitative information, which is prevalent in many real-world applications.[91]

3.1.1 Fuzzy Sets

- **Extension of Classical Sets:** In classical set theory, an element either belongs to a set or does not. Fuzzy set theory relaxes this crisp boundary by allowing elements to belong to a set to varying degrees, represented by membership grades between 0 and 1.
- **Membership Functions:** A fuzzy set is defined by a membership function that assigns a degree of membership to each element of the universe of discourse. This membership function can take various forms, such as triangular, trapezoidal, or Gaussian, depending on the characteristics of the fuzzy set.
- **Representation of Uncertainty:** Fuzzy sets provide a flexible and intuitive way to model uncertainty, ambiguity, or imprecision in data or knowledge representation. They are particularly useful in domains where quantitative measurements may be subjective or qualitative in nature.[92] [93]
- Fuzzy sets provide a mathematical framework for representing and reasoning with vague or ambiguous information, allowing for a more expressive and flexible modeling of energy optimization variables and objectives.[94]

3.1.2 Fuzzy Systems

- **Fuzzy Logic:** Fuzzy logic is a formalism for reasoning under uncertainty, where linguistic variables and fuzzy rules are used to express knowledge and make decisions. Fuzzy logic extends classical Boolean logic by allowing intermediate truth values between true and false.
- **Fuzzy Inference:** Fuzzy inference is the process of deriving fuzzy conclusions from fuzzy premises using fuzzy rules and fuzzy reasoning mechanisms. It involves fuzzification (converting crisp inputs into fuzzy sets), rule evaluation (applying fuzzy rules), and defuzzification (converting fuzzy outputs into crisp values).
- **Applications:** Fuzzy systems find applications in a wide range of fields, including control systems, pattern recognition, decision support systems, expert systems, artificial intelligence, and robotics. They are particularly well-suited for tasks involving uncertainty, approximation, and human-like reasoning.
- **Type-1 Fuzzy Systems:** In Type-1 fuzzy systems, each fuzzy set has a crisp membership function that maps elements of the universe of discourse to degrees of membership. Type-1 fuzzy logic operates on single-valued fuzzy sets and is relatively straightforward to implement and interpret.
- **Type-2 Fuzzy Systems:** Type-2 fuzzy systems generalize Type-1 fuzzy logic by allowing the membership function of a fuzzy set to itself be fuzzy. This introduces a higher level of uncertainty and complexity but can provide more expressive power and better handling of uncertainty in certain applications.[95] [96]

4 Proposed fuzzy Q learning (FQL)

We utilize the Q-learning technique to leverage the knowledge we have obtained about the expected future pricing of power and the outputs from solar panels to identify the best policy, and we integrate fuzzy logic into the Q-learning framework by incorporating fuzzy evaluations into the reward function. This enhancement enables the system to account for the uncertainties and imprecision inherent in the environment, leading to more nuanced and effective energy management decisions. Specifically, fuzzy logic is used to evaluate the rewards associated with the operation of various appliances, balancing energy efficiency, cost, and user comfort.

4.1 Fuzzy Logic Control approach

Fuzzy logic (FL) is founded on the notion that many ideas and variables in the physical world cannot be accurately specified using precise numerical values. In our case this phenomenon occurs because some phrases, such as "hot," might have varying interpretations and may not be directly linked to a specific temperature that represents the concept of "hot." Consequently, FL offers us a more flexible and sophisticated approach in describing these notions by assigning degrees of membership to values that encapsulate them.

Fuzzy logic (FL) has found applications in diverse fields including control systems, decision-making, pattern recognition, and data modeling. In our systems, fuzzy logic can be employed to modify the system's output by considering various input variables, such as temperature and humidity, and their levels of membership in fuzzy sets. we can utilize it to assess the ambiguity in decision-making. and the lack of accuracy in the data, leading to decisions being made using vague guidelines.

FL operates with approximations rather than precise values. A Fuzzy Inference System (FIS) facilitates the transformation of inputs into outputs by utilizing a collection of fuzzy rules and their corresponding fuzzy Membership Functions (MFs). Figure 23 shows a diagram of FL controller.[97]

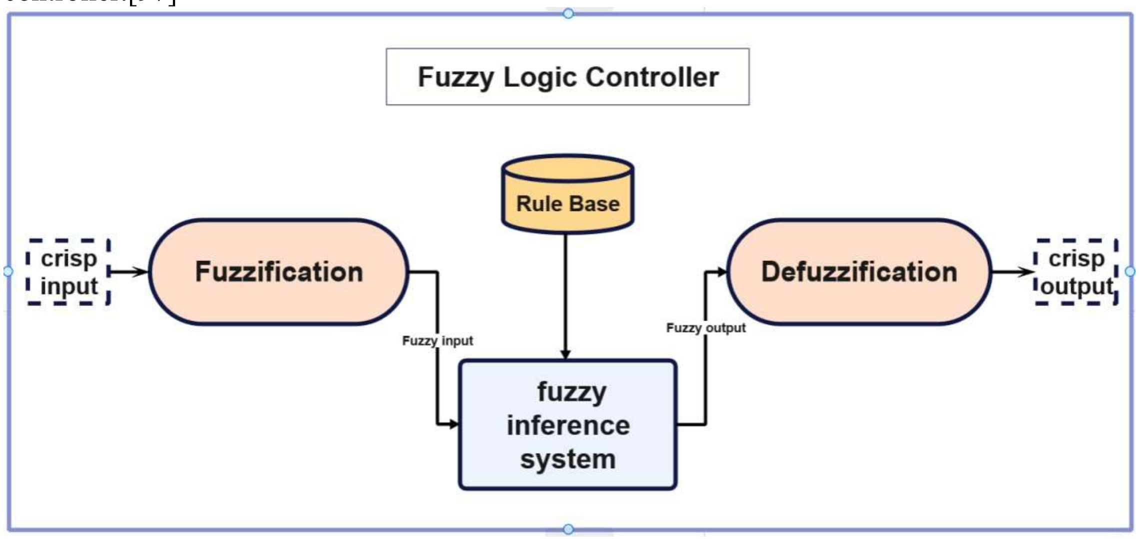

Figure 23 Fuzzy logic control (FLC)

- We Define the variable for the input and the output of the system.
- Determine the fuzzy sets with their membership function (Membership bell function and triangular membership function) for each input and output variable.
- We'll define the rules that'll produce the outputs of the system.
- Fuzzification entails assessing the level of membership of each input variable to each fuzzy set.
- Fuzzy inference involves utilizing the rules to assess the degree of membership of each output variable to each fuzzy set based on the fuzzified input variables.
- Finally, the defuzzification process entails evaluating the level of membership of each output variable to each fuzzy set and consolidating them to derive a singular crisp value for each output variable.

4.1.1 Inputs and outputs of the system

Input variables: Input fuzzy variables are variables that take input values in the fuzzy inference system. These variables are typically characterized by membership functions that describe how each input value belongs to different fuzzy sets.

In our system, the input fuzzy variables represent the electricity_Price, solar_Generation and power_Demand:

a. Electricity price: In figure 24 he generalized bell membership function (gbellmf) is used to define cheap and expensive fuzzy sets for the Electricity price with a universe discourse of [0 100] (DA/kWh).

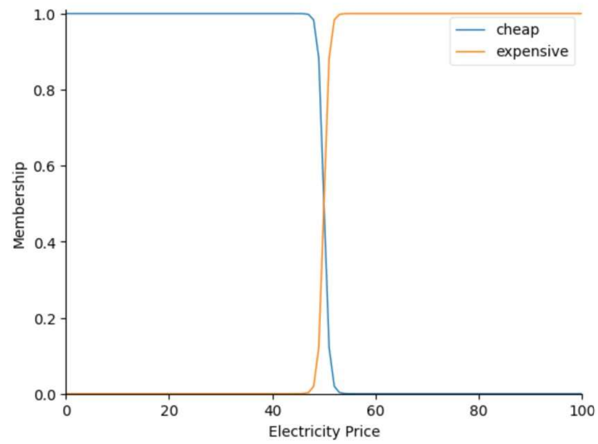

Figure 24 Electricity price

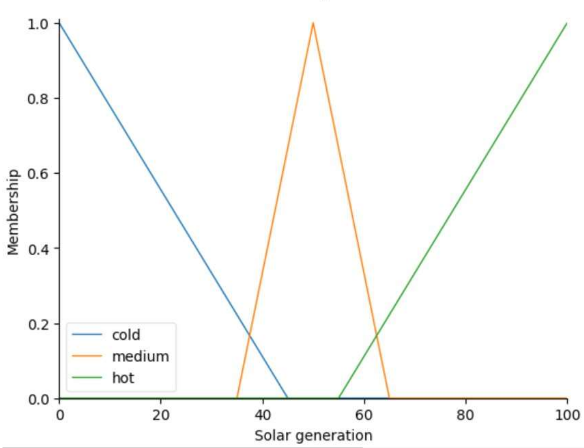

Figure 25 Solar Power generation

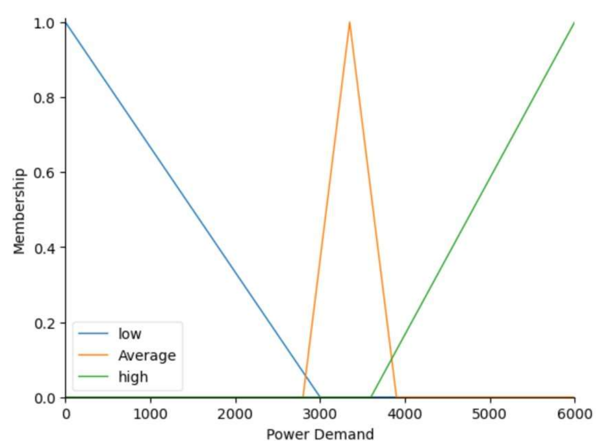

Figure 26 Power Demand

b. Solar generation: In figure 25 the triangular membership function (trimf) is used to define cold, medium and hot fuzzy sets for the Solar generation with a universe discourse of [0 100] (DA/kWh).

c. Power demand: In figure 26 the triangular membership function (trimf) is used to define low, average and high for the fuzzy sets of the power demand with a universe discourse of [0 6000] (watt).

Output variables: These output rewards guide the decision-making process within our HEMS, helping users or the automated systems make choices that align with energy efficiency goals, cost savings, or other predefined criteria. The specific actions associated with each reward level can be customized based on the context and objectives of the HEMS implementation.

Evaluating the degree to which the action made at is appropriate for a certain state is the goal of this reward. This is an example of fuzzy logic in action evaluation in a given state.

The system's outputs, which are shown in figures 27, 28, and 29, are an assessment of the random action that was specified in Q-learning. The fuzzy sets are classified as Very Good Action (VGA), Good Action (GA), and Bad Action (BA) for each action performed (output). With a triangular membership function (trimf) and a universal discourse of [0 100], which uses values out of 100 to assess every action that is conceivable.

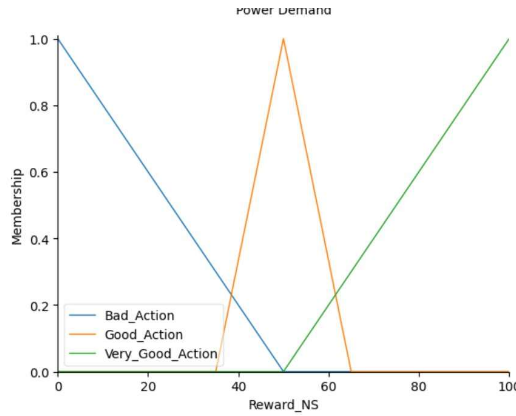

Figure 27 Reward of Non-shiftable appliances

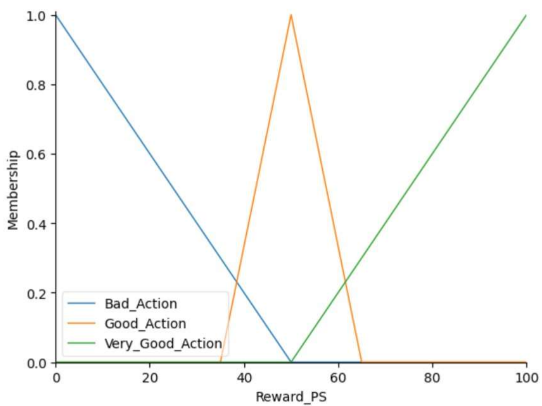

Figure 28 Reward of Power-shiftable appliances

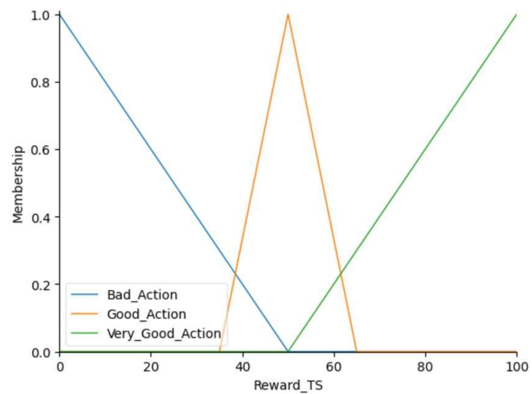

Figure 29 Reward of Time-shiftable appliances

4.1.2 Membership functions

The generalized Bell Membership Function: is a type of membership function used in fuzzy logic to define fuzzy sets, it has a bell-shaped curve and is characterized by three parameters that control its shape and position. And it's defined by the following formula[98]:

$$gbellmf(z;a,b,c) = \frac{1}{1+\left(\frac{|x-c|}{a}\right)^{2b}}$$

- **x:** is the input value.
- **a:** is the width parameter (control the width of the bell curve).
- **b:** is the slope parameter (control the slope of the curve).
- **c:** is the center parameter (defines the center of the bell curve).

The triangular membership function: is commonly used in fuzzy logic systems to represent the degree of membership of a variable to a fuzzy set, it's defined by three parameters: the left endpoint a, the peek b and the right endpoint c. The function increases linearly from a to band decreases linearly from b to c (in the shape of a triangle). Mathematically, the triangular membership function is given by[98] :

$$\mu(x;\ a,b,c) = \begin{cases} 0 & if \quad x \le a \\ \frac{x-a}{b-a} & if\ a < x < b \\ \frac{c-x}{c-b} & if\ b < x < c \\ 0 & if \quad x \ge c \end{cases}$$

Certainly! In the fuzzy logic system, the trimf function is used to create triangular membership functions for the output variables **Reward_NS**, **Reward_PS**, and **Reward_TS**. Triangular membership functions are a common choice in fuzzy logic because they are simple yet effective in modeling fuzzy sets with a clear peak and linear decrease on both sides.

Here's how the trimf function is used to define the triangular membership functions for each output variable:

Reward of NS appliances:

a. **Bad Action:** fuzz.trimf (Reward_NS.universe, [0, 0, 50]) creates a triangular membership function with a peak at 0 and a base ranging from 0 to 50 on the x-axis. This represents a low reward or negative outcome for non-shiftable appliances.
b. **Good Action:** fuzz.trimf (Reward_NS.universe, [35, 50, 65]) creates a triangular membership function with a peak at 50 and a base ranging from 35 to 65 on the x-axis. This represents a moderate reward or positive outcome for non-shiftable appliances.
c. **Very Good Action:** fuzz.trimf (Reward_NS.universe, [50, 100, 100]) creates a triangular membership function with a peak at 100 and a base ranging from 50 to 100 on the x-axis. This represents a high reward or very positive outcome for non-shiftable appliances.

Reward of PS appliances:

a. **Bad Action:** fuzz.trimf (Reward_PS.universe, [0, 0, 50]) creates a triangular membership function with a peak at 0 and a base ranging from 0 to 50 on the x-axis, similar to Reward_NS. This represents a low reward or negative outcome for power-shiftable appliances.
b. **Good Action:** fuzz.trimf (Reward_PS.universe, [35, 50, 65]) creates a triangular membership function with a peak at 50 and a base ranging from 35 to 65 on the x-axis, similar to Reward_NS. This represents a moderate reward or positive outcome for power-shiftable appliances.
c. **Very Good Action:** fuzz.trimf (Reward_PS.universe, [50, 100, 100]) creates a triangular membership function with a peak at 100 and a base ranging from 50 to 100 on the x-axis, similar to Reward_NS. This represents a high reward or very positive outcome for power-shiftable appliances.

Reward of TS appliances:

a. **Bad Action:** fuzz.trimf (Reward_TS.universe, [0, 0, 50]) creates a triangular membership function with a peak at 0 and a base ranging from 0 to 50 on the x-axis, similar to Reward_NS and Reward_PS. This represents a low reward or negative outcome for time-shiftable appliances.

b. **Good Action:** fuzz.trimf(Reward_TS.universe, [35, 50, 65]) creates a triangular membership function with a peak at 50 and a base ranging from 35 to 65 on the x-axis, similar to Reward_NS and Reward_PS. This represents a moderate reward or positive outcome for time-shiftable appliances.

c. **Very Good Action:** fuzz.trimf(Reward_TS.universe, [50, 100, 100]) creates a triangular membership function with a peak at 100 and a base ranging from 50 to 100 on the x-axis, similar to Reward_NS and Reward_PS. This represents a high reward or very positive outcome for time-shiftable appliances.

4.1.3 Fuzzy rules

Power demand	Electricity price	Solar generation	NS	PS	TS
Low	Cheap	Cold	GA	GA	GA
Low	Expensive	Cold	BA	GA	GA
Average	Cheap	Cold	BA	GA	GA
Average	Expensive	Cold	BA	BA	GA
High	Cheap	Cold	BA	BA	BA
High	Expensive	Cold	BA	BA	BA
Low	Cheap	Moderate	VGA	VGA	VGA
Low	Expensive	Moderate	GA	VGA	VGA
Average	Cheap	Moderate	GA	VGA	VGA
Average	Expensive	Moderate	GA	GA	VGA
High	Cheap	Moderate	BA	GA	GA
High	Expensive	Moderate	BA	GA	GA
Low	Cheap	Hot	VGA	VGA	VGA
Low	Expensive	Hot	VGA	VGA	VGA
Average	Cheap	Hot	VGA	VGA	VGA
Average	Expensive	Hot	GA	VGA	VGA
High	Cheap	Hot	GA	GA	VGA
High	Expensive	Hot	GA	GA	GA

Table 5 Fuzzy rules table, BA=Bad Action, GA=Good action, VGA=Very good action

Rules define the behavior of the fuzzy logic system based on combinations of input conditions, leading to specific outputs in terms of reward levels for different actions or decisions. Each rule captures a different scenario or combination of factors that influence the system's response.

4.2 Fuzzy Q learning method

The flow chart in figure 30 illustrates the systematic integration of fuzzy logic with a Q-learning algorithm within a home energy management system. It highlights the sequence of processing, fuzzy logic application, reinforcement learning and decision making, demonstrating how these components interact to achieve optimized energy management in smart homes.

Fuzzy Logic Implementation to obtain a current reward:
The mapping of inputs (Electricity price, Solar generation and Power demand) to outputs (Reward of NS appliances, PS appliances and TS appliances) is provided by a fuzzy inference system (FIS), which is based on a collection of fuzzy rules and related fuzzy membership functions (MFs).

Q-learning implementation to make an optimal decision:

- Initialize the Q-learning agent responsible for controlling smart home devices.
- The agent selects actions based on the current state, Q-values, and ε-greedy strategy.
- Define reward functions to evaluate the performance of actions in terms of the outputs provided by the FIS.
- Update the Q-values using the Q-learning algorithm based on the observed reward and the maximum future reward
- The ideal Q-values will be discovered, upon the Q-matrix achieving convergence.
- Execute the selected actions to adjust the operation of smart home devices (e.g., turning off lights, adjusting thermostat settings).

Assess the system's performance using metrics such as energy consumption, cost savings, and user comfort levels.

Refine the fuzzy logic rules, Q-learning parameters, and system configurations to improve overall performance.

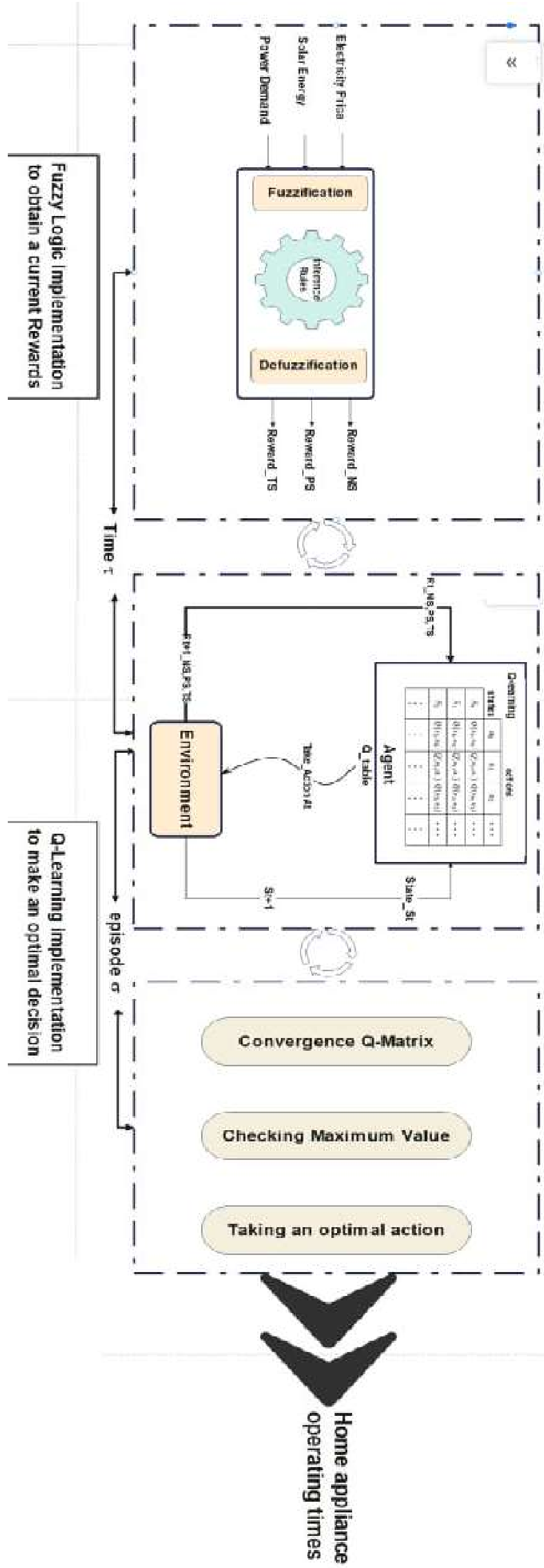

Figure 30 Implementation of fuzzy logic and Q-learning in the system's operation

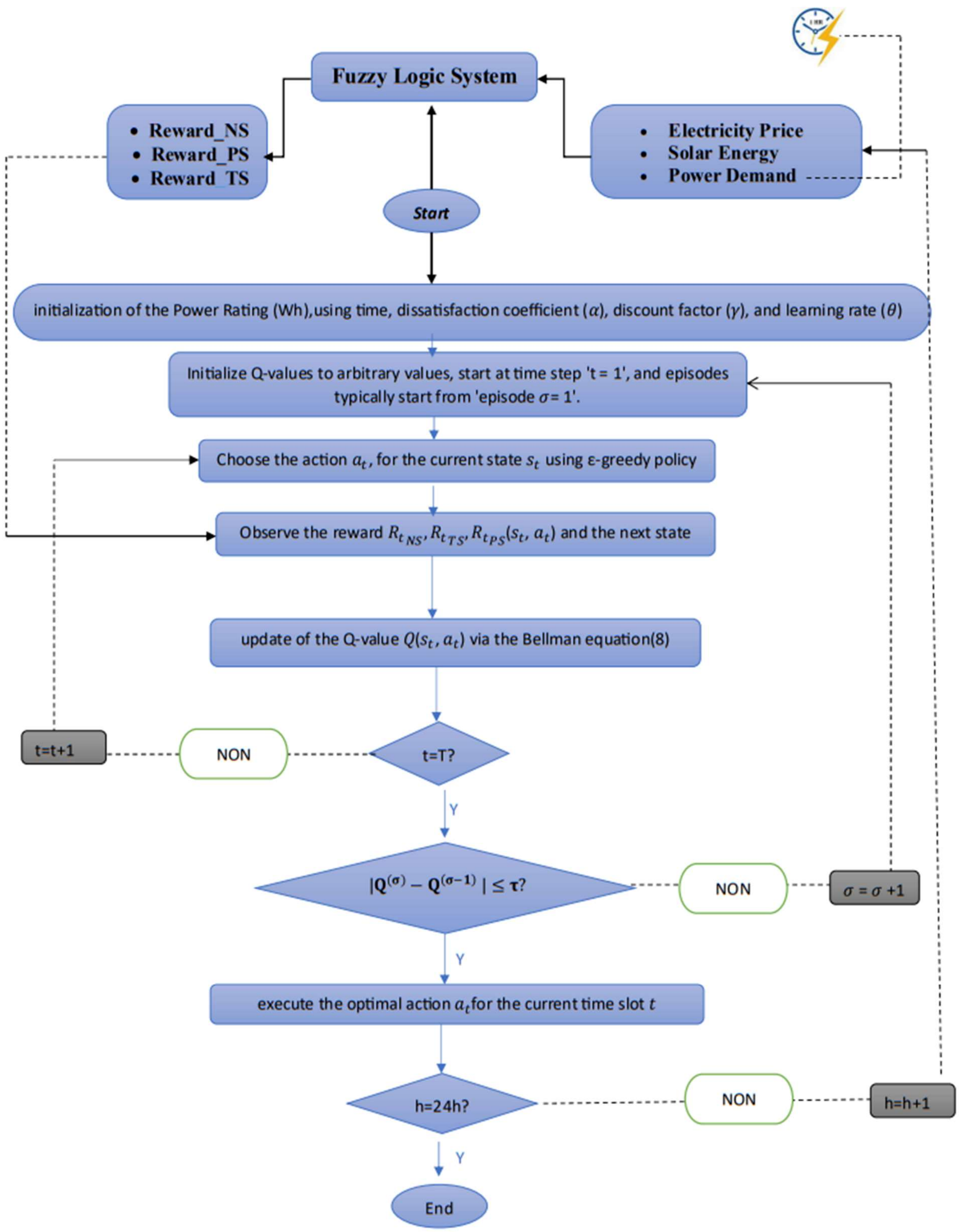

Figure 31 flow chart of FQL algorithm

Detailed Steps of FQL algorithm:

Step 1: Initialize the fuzzy logic system along with other parameters.

Step 2: For each time step t :

- Use the fuzzy logic system to determine rewards based on current inputs (Electricity Price, Solar Energy, and Power Demand).
- Choose an action a_t for the current state s_t using the ϵ-greedy policy.
- Observe the rewards R_{tNS} , R_{tTS} , and R_{tPS} from the fuzzy logic system.
- Update the Q-values (s_t,a_t) using the observed rewards and the Bellman equation.

Step 3: Check for convergence and repeat the process until optimal policies are learned.

Step 4: Execute the optimal actions over each hour, ensuring efficient power management.

5 Experimental results

5.1 Experimental environment

In addition to the experimental environment of the previous chapter we'll also use :

SciKit fuzzy: (often abbreviated as sklearn) which is an open-source machine learning library for Python. It is built on top of other popular Python libraries like NumPy, SciPy, and matplotlib, providing simple and efficient tools for data analysis and modeling.
Scikit-learn is widely used for both academic research and practical machine learning applications.[99]

Figure 32 Scikit's logo (logosdownload.com)

5.2 Experimental parameter

Cost evaluation: It involves assessing the financial implications of energy consumption and management strategies to ensure that the system not only optimizes energy usage and maintains user comfort but also minimizes energy costs considering some key Elements:

- Analyze usage patterns to identify peak consumption periods and high-energy devices.
- Calculate the total cost of energy consumed over a specific period.
- Use fuzzy logic to manage uncertainties in energy prices and consumption patterns. Fuzzy rules can help adjust the energy consumption dynamically based on the fuzzy input variables.
- Convert precise cost-related inputs into fuzzy values to account for imprecise and uncertain factors affecting energy costs.

Dissatisfaction coefficient: often denoted as α, is a parameter used in optimization problems to quantify the level of dissatisfaction or penalty associated with certain decisions or actions. It is particularly useful in applications like Home Energy Management Systems (HEMS) where multiple objectives must be balanced, such as minimizing energy cost while ensuring user comfort and appliance scheduling preferences. In the context of our system, the dissatisfaction coefficient **α** could be used for:

- **Optimize Energy Usage:** Balance between minimizing energy costs and maintaining user comfort. A higher $\boldsymbol{\alpha}$ might indicate a higher priority on user comfort over cost savings, while a lower $\boldsymbol{\alpha}$ might prioritize cost savings even if it slightly affects user comfort.
- **Appliance Scheduling:** It can penalize schedules that are inconvenient for users, even if they are energy-efficient.
- **Penalty Factor:** Act as a penalty factor in an optimization problem. If the energy usage deviates from a preferred pattern or exceeds certain limits, α can be used to penalize these deviations.
- **Quantify User Comfort:** Reflect how much a user is dissatisfied with the operation of their appliances. For example, turning off or delaying the operation of certain appliances to save energy may increase user dissatisfaction...

Objective Function: This objective function is used in optimization problems related to energy management, where the goal is to find a schedule or strategy that minimizes both the direct energy costs (related to energy consumption) and the indirect costs associated with user dissatisfaction (related to the timing or pattern of energy usage). Adjusting the dissatisfaction coefficient $\boldsymbol{\alpha}$ allows balancing between cost optimization and user satisfaction, as a higher $\boldsymbol{\alpha}$ value implies a higher penalty for user dissatisfaction in the optimization process.

$$\text{Minimize} \sum_{t=1}^{T} (C_t \cdot P_t + \alpha \cdot D_t)$$

where:

- $\boldsymbol{C_t}$: is the cost of energy at time t.
- $\boldsymbol{P_t}$: is the power consumption at time t.
- $\boldsymbol{D_t}$: is the dissatisfaction level at time t.
- **α:** is the dissatisfaction coefficient.
- **T:** is the total time period.

The dissatisfaction cost refers to the monetary value associated with user dissatisfaction in a given system or scenario. It is calculated by multiplying the dissatisfaction level by a coefficient that represents its importance relative to other factors, such as energy cost. This dissatisfaction cost is then combined with other costs, such as energy usage, to determine the overall cost or expense incurred.
Here's a step-by-step explanation of how to calculate the dissatisfaction cost:

1. Define the dissatisfaction coefficient; it determines the weight of dissatisfaction in the total cost calculation
2. Generate dissatisfaction levels
3. Calculate the dissatisfaction cost.

Modelling of the dissatisfaction levels on non-shiftable Appliances

Dissatisfaction levels are generated randomly for each of the 24 time slots using two methods: Controlled and Non-Controlled Dissatisfaction Level.

1. **Non-Controlled Dissatisfaction Level(D1)**
   Uses non-shiftable agent. Q_Table to determine the upper limit for dissatisfaction levels, focusing on the power consumption without considering energy cost.
2. **Controlled Dissatisfaction Level (D2)**
   Uses Q_Table cost to determine the upper limit for dissatisfaction levels, incorporating energy costs into the calculation, which reflects a controlled scenario.

Modelling of the dissatisfaction levels on time-shiftable Appliances

Dissatisfaction levels are generated randomly for each of the 24 time slots using two methods: Controlled and Non-Controlled Dissatisfaction Level.

1. **Non-Controlled Dissatisfaction Level (D1):**
   generates dissatisfaction levels based on power consumption values from time-shiftable agent. Q_Table, ignoring energy costs. This represents a scenario without control measures.
2. **Controlled Dissatisfaction Level (D2):**
   generates dissatisfaction levels based on energy costs from Q_Table cost, incorporating energy costs into the calculation, which represents a controlled scenario.

Modelling of the dissatisfaction levels on power-shiftable Appliances

Dissatisfaction levels are generated randomly for each of the 24 time slots using two methods: Controlled and Non-Controlled Dissatisfaction Level.

3. **Non-Controlled Dissatisfaction Level (D1):**
   generates dissatisfaction levels based on Energy consumption (WH) values from power-shiftable agent. Q_Table, ignoring energy costs. This represents a scenario without control measures.
4. **Controlled Dissatisfaction Level (D2):**
   generates dissatisfaction levels based on Electricity Price (Centime/Wh) from Q_Table cost, incorporating energy costs into the calculation, which represents a controlled scenario.

6 Results and discussion

6.1.1 Case Study setup

APPLIANCES	TYPE	DISSATISFACTION COEFFICIENT	POWER(WH)	TIME SLOT
REF	NS	0.03	500	[1, 24]
AS	NS	0.02	100	[1, 24]
AC1	PS	0.05	[700, 1400, 100]	[1, 24]
AC2	PS	0.06	[700, 1400, 100]	[1, 24]
HTR	PS	0.12	[500, 1500, 100]	[1, 24]
L1	PS	0.5	[200, 600, 100]	[1, 24]
L2	PS	0.03	[200, 600, 100]	[1, 24]
WM	TS	0.1	700	[6, 8]
DW	TS	0.06	300	[6, 8]

Table 6 Parameters of each house appliances

Chapter 3 - A fuzzy Q learning approach for multi-agent energy management in smart homes

This chapter involves conducting simulations using a total of nine appliances also, with a main difference in the number of time slots. The specifications of these household appliances are shown in Table 6.

6.2 Energy consumption and electricity price

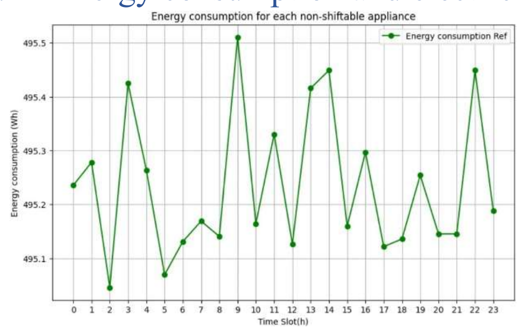

Figure 33 Energy consumption of REF throughout the day

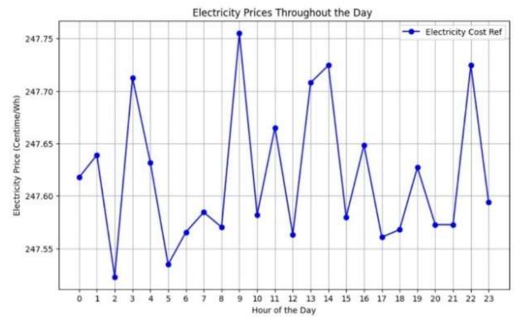

Figure 37 Electricity cost for the REF throughout the day

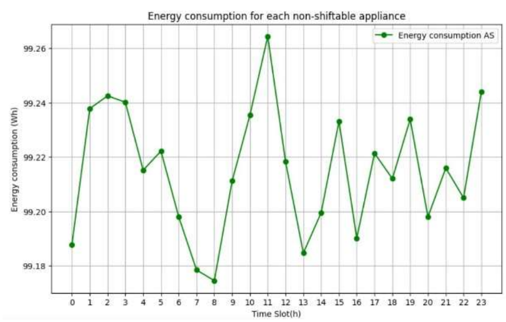

Figure 34 Energy consumption of AS throughout the day

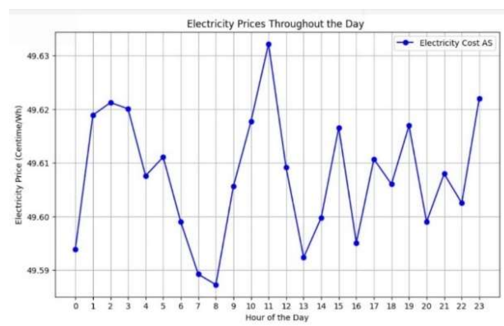

Figure 38 Electricity cost for the AS throughout the day

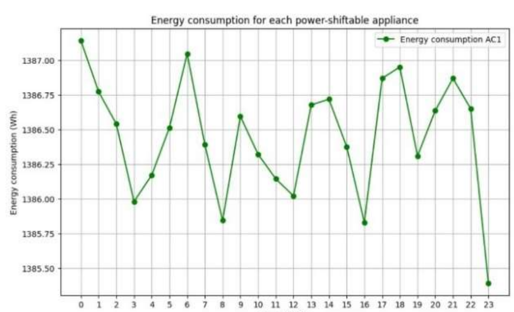

Figure 35 Energy consumption of AC1 throughout the day

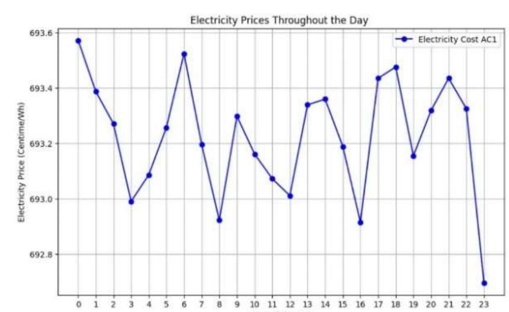

Figure 39 Electricity cost for the AC1 throughout the day

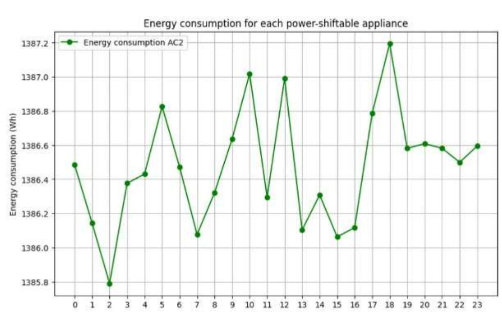

Figure 36 Energy consumption of AC2 throughout the day

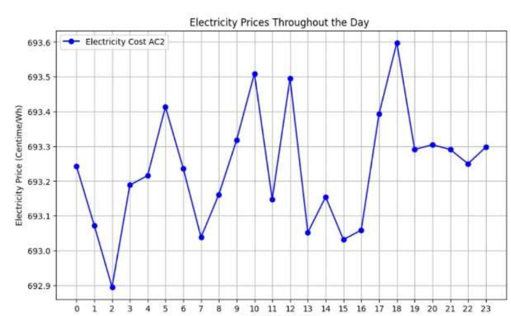

Figure 40 Electricity cost for the AC2 throughout the day

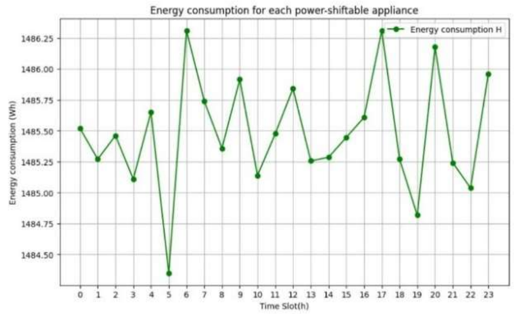

Figure 41 Energy consumption of HTR throughout the day

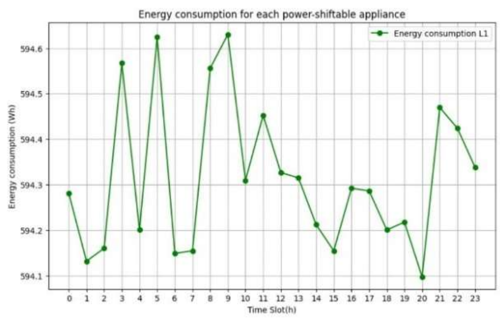

Figure 42 Energy consumption of L1 throughout the day

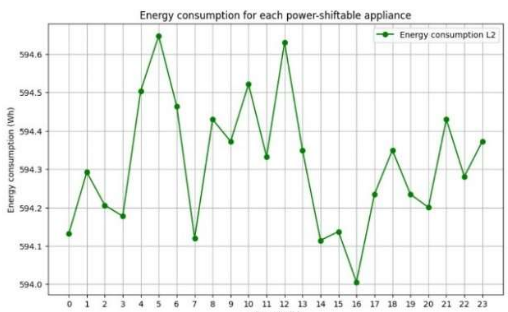

Figure 43 Energy consumption of L2 throughout the day

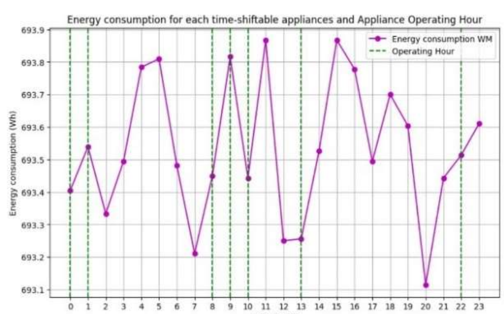

Figure 44 Energy consumption of WM throughout the day

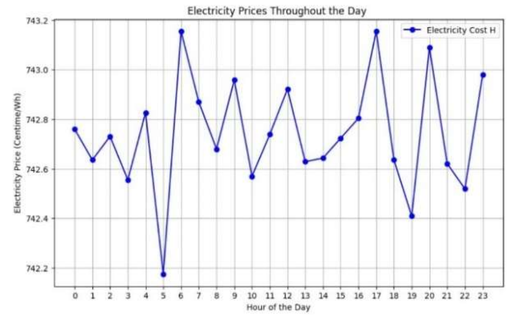

Figure 46 Electricity cost for the HTR throughout the day

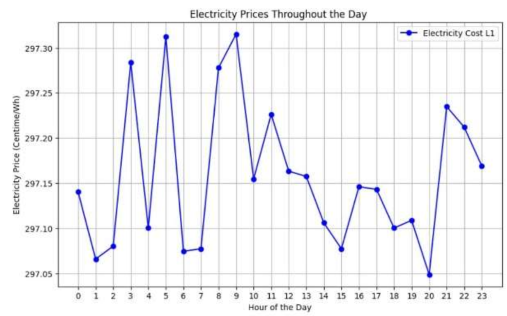

Figure 47 Electricity cost for the L1 throughout the day

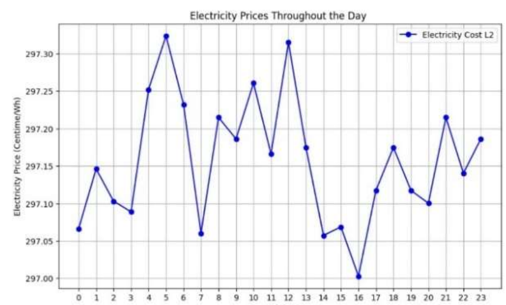

Figure 48 Electricity cost for the L2 throughout the day

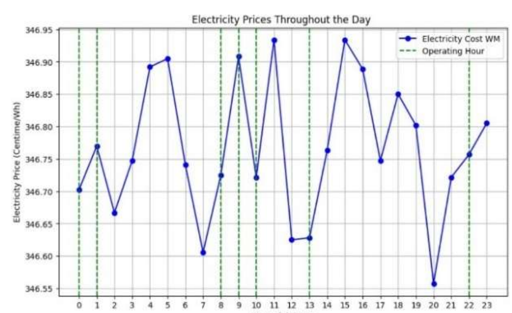

Figure 49 Electricity cost for the WM throughout the day

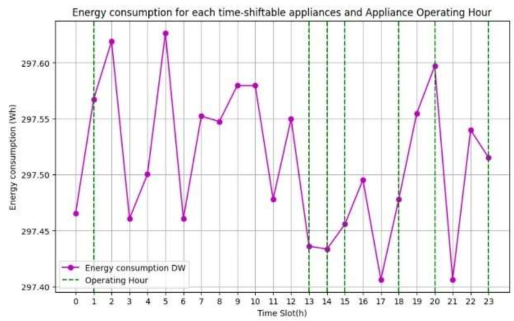

Figure 45 Energy consumption of DW throughout the day

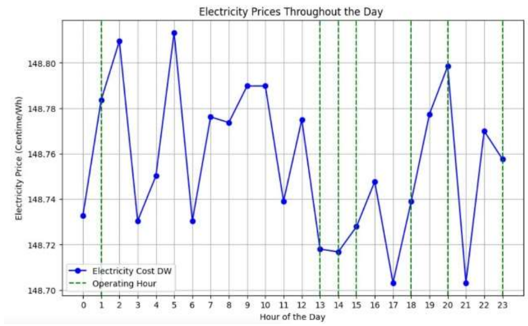

Figure 50 Electricity cost for the DW throughout the day

6.3 User comfort

The following figures provide a comprehensive view of how energy and dissatisfaction costs vary over a 24-hour period for non-shiftable, power-shiftable, and time-shiftable appliances.

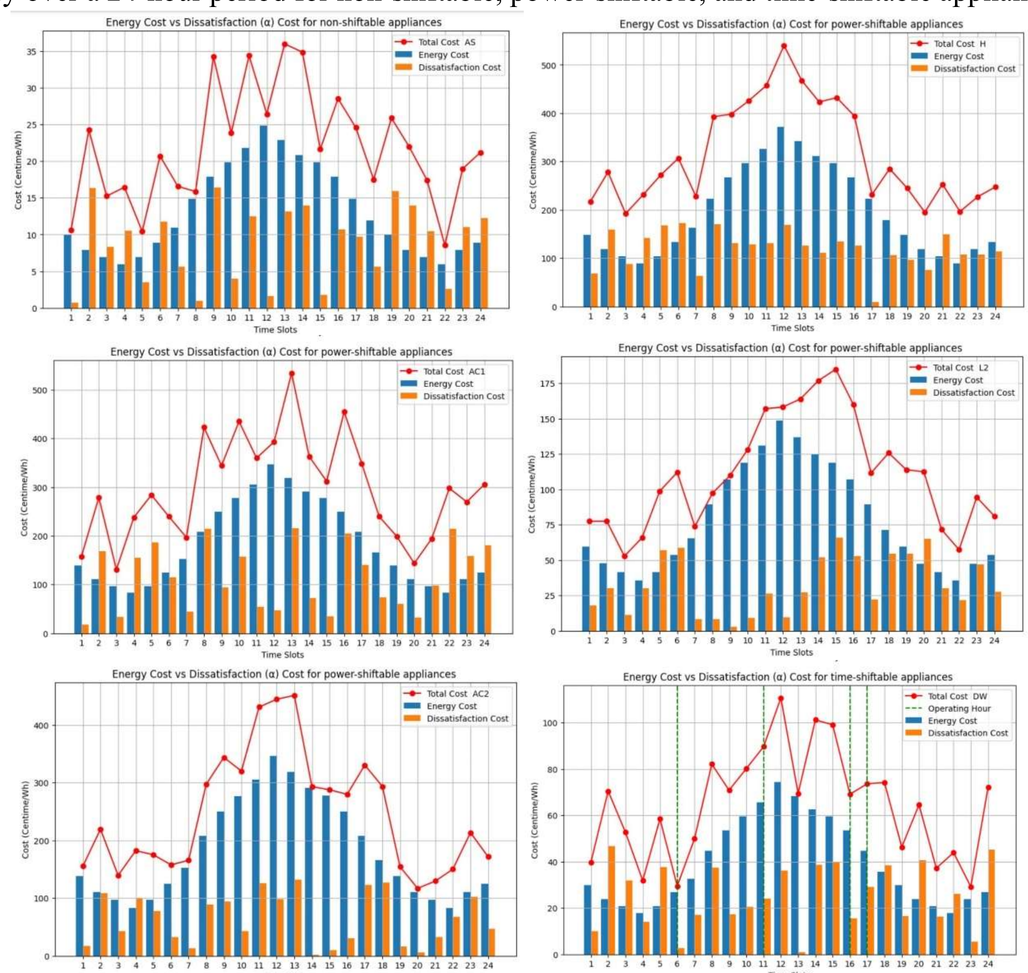

Figure 51 cost and user comfort of all appliances throughout the day

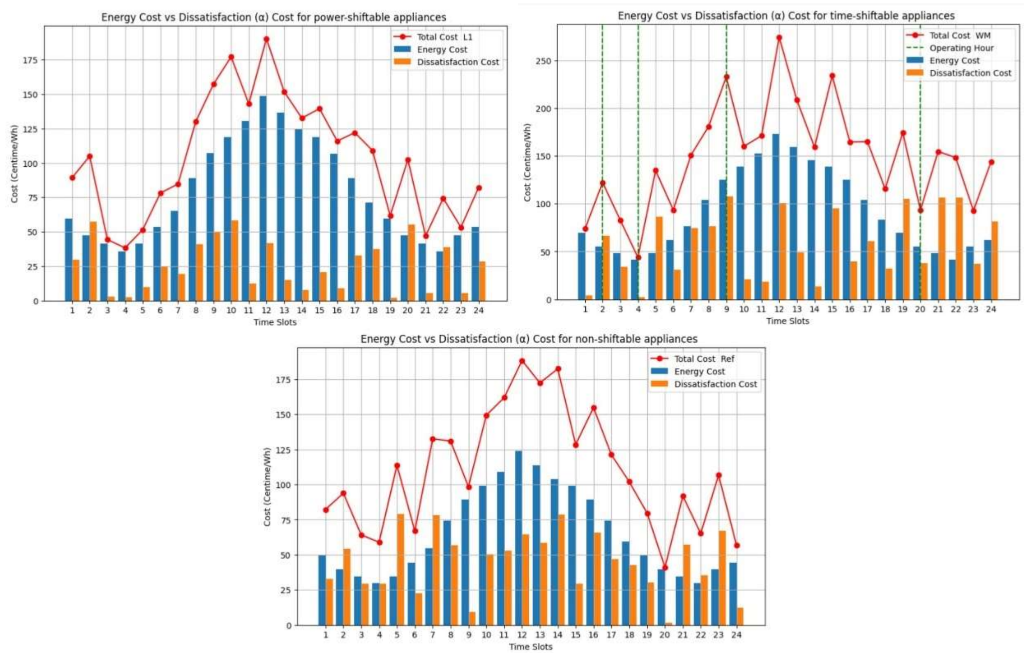

Figure 52 cost and user comfort of all appliances throughout the day (continues)

The total cost is particularly high during certain time slots, likely due to the combined effect of high energy and dissatisfaction costs

The Total Cost in energy management considers both energy costs and dissatisfaction costs, aiming for an optimal balance to minimize overall expenses while maintaining consumer satisfaction.

Adjusting the value of α allows for tuning the trade-off between cost optimization and user satisfaction according to specific preferences or constraints.

6.4 Comparison between the FQL approach and the MAQL approach

The figures show that with MAQL approach, the total cost (red line) exhibits sharp peaks and valleys, indicating more rigid decision boundaries and higher sensitivity to small changes. In contrast, with FQL approach, the smoother variations suggest that costs are averaged out over time, reducing the impact of extreme values and making the system more robust.

With MAQL approach, dissatisfaction costs (orange bars) are lower with clear, distinct values, whereas in with FQL approach the higher overall dissatisfaction costs indicate a more nuanced understanding of user preferences and dissatisfaction levels, resulting in a better-balanced cost structure.

The integration of fuzzy logic in FQL approach produces smoother, more realistic, and adaptive representations of costs and operating hours. This approach minimizes abrupt changes and effectively manages uncertainty, leading to a more robust and practical decision-making framework. Consequently, it aligns more closely with real-world scenarios where data is frequently imprecise and decisions must accommodate varying degrees of uncertainty.

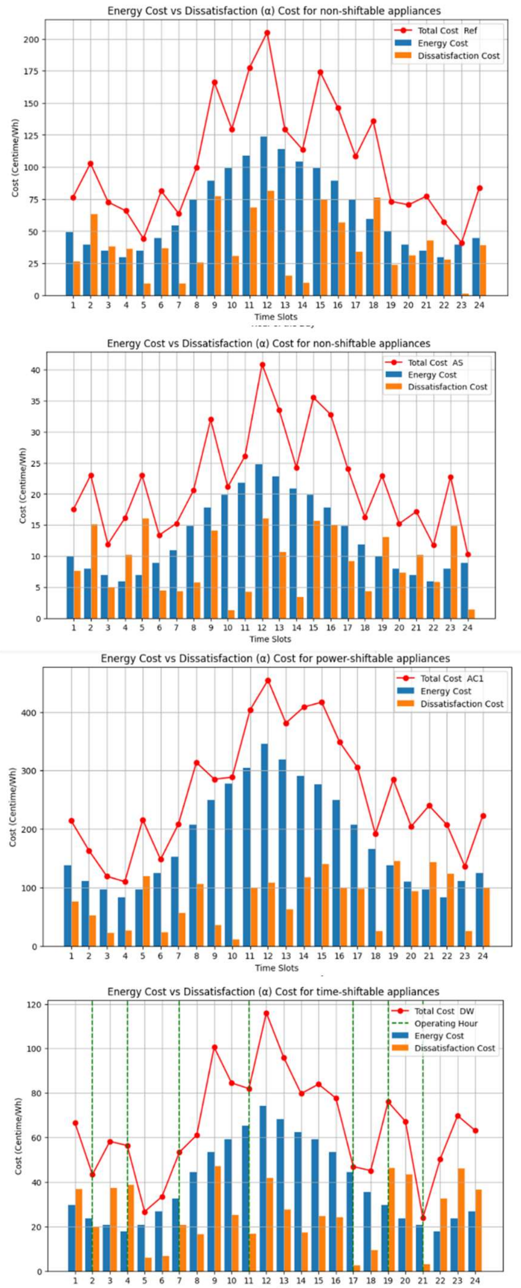

Figure 53 the cost and user comfort of some appliances in the MAQL approach

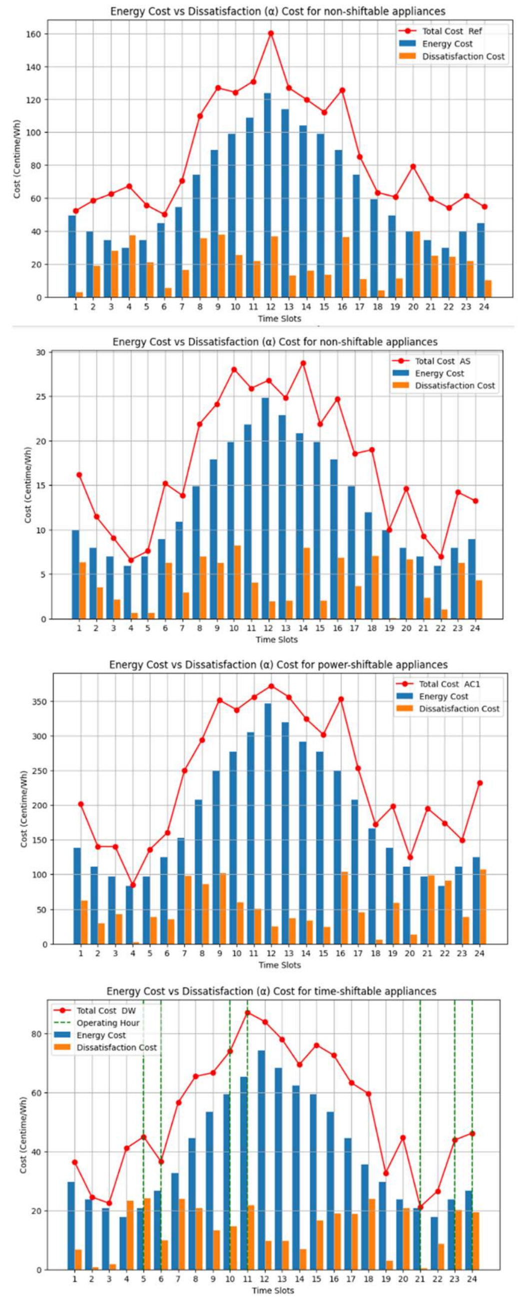

Figure 54 the cost and user comfort of some appliances in the FQL approach

7 Conclusion

Despite the promising potential of MARL, it faces significant challenges in handling the uncertainties and imprecise data typical of real-world scenarios. This is where fuzzy logic, an approach designed to model and reason with vagueness and ambiguity, becomes valuable. By incorporating fuzzy logic into MARL, we can enhance the decision-making capabilities of autonomous agents, enabling them to process imprecise information and make more robust and nuanced energy management decisions.

General Conclusion

The integration of fuzzy logic into a multi-agent reinforcement learning framework for home energy management has proven to be a powerful approach for optimizing energy consumption in smart homes. By combining the strengths of both techniques, we have developed a system that is not only efficient and adaptive but also capable of handling the complexities and uncertainties of real-world environments. This research contributes to the advancement of smart home technologies, offering innovative solutions that promote sustainable and energy-efficient living while prioritizing user comfort and satisfaction.

By employing Q-learning within the MARL framework, our system demonstrated the capability to learn optimal energy management policies through continuous interaction with the environment. This enabled real-time adaptation to changing energy demands and dynamic pricing models.

The incorporation of user preferences and comfort levels into the decision-making process ensured that the energy management strategies were aligned with the occupants' needs. The system balanced energy efficiency with user satisfaction, leading to practical and acceptable solutions for smart home residents.

Through extensive simulations, we demonstrated that our integrated fuzzy logic and MARL-based HEMS significantly outperformed traditional energy management systems. The system achieved notable improvements in energy savings, cost reduction, and user comfort, validating the effectiveness of our approach.

While this thesis has laid a solid foundation for intelligent energy management in smart homes, several avenues for future research remain, like explore advanced reinforcement learning algorithms, such as deep reinforcement learning, to enhance learning efficiency and decision-making capabilities, thereby enabling the system to handle more complex and high-dimensional state spaces. Incorporate direct user feedback mechanisms to continually refine and tailor energy management strategies to evolving user needs and preferences, potentially developing user-friendly interfaces for real-time feedback and adjustments. Develop strategies to improve the system's scalability for application in larger buildings, commercial complexes, and multi-unit residential areas, possibly through hierarchical or distributed control mechanisms. Explore user-centric adaptations that account for diverse behaviors and preferences, including personalized energy management plans and adaptive learning algorithms tailored to individual user profiles.

References

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