國立臺灣大學電機資訊學院資訊工程研究所

碩士論文

Department of Computer Science and Information Engineering
College of Electrical Engineering and Computer Science
National Taiwan University

Master Thesis

結合使用者自我節能意識於多人智能家庭的需量電力管理系統

Demand Side Management System with Self-Awareness of Energy Saving for Multi-User Smart Home

洪正皇

Jheng-Huang Hong

指導教授：傅立成 博士

Advisor: Li-Chen Fu, Ph.D.

中華民國 110 年 1 月

January 2021

doi:10.6342/NTU202100623

國立臺灣大學碩士學位論文

口試委員會審定書

結合使用者自我節能意識於多人智能家庭的需量電力管理系統

Demand-Side Management System with Self-Awareness of Energy Saving for Multi-User Smart Home

本論文係洪正皇君（學號 R07922050）在國立臺灣大學資訊工程學系完成之碩士學位論文，於民國 110 年 1 月 29 日承下列考試委員審查通過及口試及格，特此證明

口試委員：

傅立成

（指導教授）

許永真　　于天立

蔣宗哲　　廖世偉

系 主 任　洪士灝

誌謝

充實的碩士生活已經接近尾聲，回首兩年半以來的求學過程，有許多開心的時候、偶爾也有徬徨的時候，都使得這段經歷無可替代，而其中我也受過許多人的幫助，不論是在學術上作為我的良師益友，亦或是在學術外作為我的生活調劑，他們的陪伴都是協助我完成本篇著作的重要因素。

首先，感謝我的家人，對於我做的決定都會無條件的支持，而在有需要的時候，也往往都能得到他們的幫助，感謝爸爸媽媽給予我追求夢想的自由，又隨時在身後做我堅強的後盾。

再來感謝我的指導教授傅立成教授，他在學術上有著豐富的經驗，也十分耐心的對所有學生進行多次一對一的指導。從論文的方向探索到最後的完成，教授與我分享了許多他的見解以及建議，有了他的指導，我才能站在巨人的肩膀上開始做研究，也少走了很多彎路。

最後，感謝實驗室的學長姊與學弟妹、以及這段時間一起奮鬥的所有夥伴們，很開心身邊有一群能夠一起成長的好友，在幾次我想放棄學術研究的時候，他們都是使我繼續前進的動力，儘管未來各奔東西，期望大家能也能互相鼓勵進步。

洪正皇　謹誌於

國立臺灣大學資訊工程研究所

智慧型機器人與自動化實驗室

2021 年 1 月

doi:10.6342/NTU202100623

中文摘要

隨著全球能源消耗上升，如何有效的使用能源變成一個重要的議題，需求端管理系統是一項能用來解決此議題的技術。對於每一間建築，一天中會有用電的高峰時段，這些用電高峰會導致電源供應方的負擔，在時間電價機制的鼓勵下，需求端管理系統可以協助使用者將非立即需要的用電轉移至離峰時段。另外，隨著物聯網技術的發展，家中可連網的裝置能夠形成一個家庭區域網路，使得管理系統能夠監控家中的整個狀況，並協助使用者控制電器節省能源。

在這篇論文中，我們著重在住宅型房屋，實現了能夠應用在多使用者智能家居中的需量管理系統，其中包含了個人化、自動化以及節能動機三大概念，首先識別正在使用裝置的使用者身分，所有服務都將根據使用者個人習慣運行。在自動化的部分，透過多個深度強化學習代理們，分別管理不同的電器、能源儲存系統及再生能源，識別使用者的當前行為以更準確的控制所有電器。除此之外，我們使用最大似然估計來估計電器的使用時間分佈，並計算各項電器的彈性度以量化使用者使用電器的規律程度。為了進一步節省能源，節能模組會提供使用者節能建議，節能建議的時機及內容會根據個人節能分數和電器彈性度決定，並且考慮到多使用者家庭的情況。同時，個人化的能源使用情況也會經由視覺化界面提供給使用者，這些能源反饋資訊能夠提高使用者的自我節能意識。

在實驗結果中，當提供能源反饋後，使用者會願意主動執行更多節能行為，進而降低更多能源花費。此外，根據使用者體驗調查結果，所提出的系統在實用性及易用性上都取得使用者的認同。

關鍵字：需量管理系統、家庭區域網路、強化學習、深度 Q-網絡、電器可控性、用戶行為、節能動機、智慧電網

doi:10.6342/NTU202100623

ABSTRACT

As global energy consumption keeps increasing, the energy efficiency has become an important issue. Demand side management (DSM) system is a technology that can be used to solve this issue. In many houses, there are some time periods in a day when consumers have high electricity demands, and these peak demands will cause a burden on the smart grid. In order to solve energy efficiency problem, the demand side management system can help users to postpone non-urgent demands to off-peak hour subject to the mechanism of real-time pricing policy. In addition, due to great advancement of Internet of Things (IoT) technology, the devices which have internet module can all be connected into a home area network, enabling DSM to monitor the entire state of house and to control appliances.

In this thesis, we focus on a residential house and implement a demand side management system that can be applied to multi-user smart home, which includes three important elements: personalization, automation, and energy saving motivation. First, the system will recognize the identity of all users, which facilitates personalized services to be provided in a multi-user smart home. In automation part, multiple reinforcement learning agents are developed to separately manage different appliances from different categories, energy storage system, and renewable energy resource so that all devices are under accurate control. Moreover, we use maximum likelihood estimation to estimate the usage time distribution of various appliances, and also evaluate their flexibility in order to quantify the regularity of appliance usage of every user. According to appliance flexibility, the energy saving module will suggest users to undertake more energy saving actions. The timing and content of these suggestions will be determined by our proposed energy saving suggestion decision (ESSD) algorithm.

doi:10.6342/NTU202100623

Meanwhile, the information of the personalized energy usage will also be provided to users through a visual interface. Such energy feedback information can improve the users' self-awareness of energy saving.

In the experimental results, DSM that integrates automation and energy feedback helps users decrease energy costs more than DSM with only automatic smart control. Throughout the experiment, we notice that energy feedback dose let users be more aware of need for energy saving and hence reduce more energy saving behaviors. Lastly, according to user experience survey, users agree that the design of the proposed system is practical and easy to use, with an average satisfaction score being 4.4 out of 5.

Keywords – Demand side management, home area network, reinforcement learning, Deep Q-Network, appliance flexibility, user behavior, self-awareness of energy saving, smart grid.

doi:10.6342/NTU202100623

CONTENTS

doi:10.6342/NTU202100623

doi:10.6342/NTU202100623

LIST OF FIGURES

doi:10.6342/NTU202100623

doi:10.6342/NTU202100623

LIST OF TABLES

doi:10.6342/NTU202100623

Chapter 1

Introduction

1.1 Background

The global population is continually increasing, and the resources demanded by human also continue to grow. According to the IEA Global Energy Report [1], the renewable energy resources, such as solar power and wind power generation, are unreliable ones which can hardly satisfy the human needs. Nowadays, most countries still rely on non-renewable resources for power supply. In 2018, the total electricity consumption increased by 2.3% as compared with that in 2017, and almost doubled the average growth rate since 2010. In fact, there is about 75.3% of energy consumption comes from non-renewable energy resources, such as thermal power generation and nuclear power generation, and 27% of energy consumption is from residential demand [2]. Moreover, carbon emissions in 2018 have increased by 1.7% as compared to that in 2017. Therefore, efficient use of energy has become a major issue worthy to be studied. In order to improve the energy efficiency, demand side management (DSM) system [3] is a common technology which can be deployed in a smart home.

Usually, a day can be divided into two time periods, namely peak time period and off-peak time period, referring to the curve of daily energy demand. The peak time period represents the duration of a day for higher electricity demand, usually from

doi:10.6342/NTU202100623

daytime to midnight. Normally, in the daytime, there is a large amount of commercial electricity demand, whereas at night the commercial electricity demand will decrease while the residential electricity demand will increase. The off-peak time period refers to the duration of a day over which the electricity demand is relatively low. For the power supplier, the electricity demand from users should be satisfied at any time, and therefore the power supplier should provide sufficient power supply capacity during the peak hours, which adversely leads to an increase in the cost of producing electricity. The DSM system can schedule the usage of appliances that are not necessarily used during the peak hours. A possible solution is to advance or to postpone the timing of using these appliances so that the resulting electricity consumption curve won't experience peaks nor cause a burden on the power supplier.

When designing a system, how to encourage residents to adopt DSM technology needs to be considered [8]. If a system often overrides the decisions made by residents, then the residents will prefer not to use the system. In other words, the system not only needs to save energy, but it should also consider the comfort as preference of residents. Balancing the energy saving and the comfort level of residents is a challenge since the appliance usage preference of a resident may change over time. Therefore, the DSM system should track the residents' living habits, and try to update estimates of them over time. In this thesis, through knowing the locations of the residents in the house and the states of appliances, the context recognition engine can discover the global context in the smart home, and infer the preference of appliance usage of the residents [34]. In machine learning field, the reinforcement learning technology can learn and execute the appropriate actions based on the current states of house to obtain the maximum long-term expected reward [20]. The reinforcement learning can be updated according to the changes of residents' living habits, and meet the needs of residents at any time.

doi:10.6342/NTU202100623

Taking residential house as an example, a residential smart home usually includes an energy storage system, a small scale photovoltaics, and various types of appliances with different characteristics. In order to monitor the demands from residents, the hardware devices such as smart meter and smart plugs are needed. To manage the complex smart home environment, the multi-agent technology can be applied. An agent represents an autonomous entity [5] and will decide what actions to perform to achieve its designated goals. For example, an energy storage agent will determine whether to charge, discharge or do nothing to achieve the goal of reducing the electricity cost for residents. A multi-agent system is composed of multiple agents, where each agent has its behavior and goal, and interacts with each other through the network. In this thesis, a multi-agent system consisting of four agents is implemented to manage three clusters of home appliances, energy storage system (ESS) and renewable energy resource (RES) without disturbing the comfort level of residents. Each agent chooses the best action to achieve the purpose of DSM by using deep Q-network technology.

DSM is an important function in the smart home field, which is a technology that is applied to the consumer’s side to improve the efficiency of energy usage. In a sense, DSM is the center of smart home to exchange information and manage the electric entities through home area network, including sensors, controllers, smart appliances, RES and ESS and the rest. After formulating the state and the objective function of the smart home, DSM can optimize the decision to achieve its purpose particularly like saving user's energy cost. Moreover, DSM will adjust the duration of appliances usage according to the electricity price mechanism from the underlying utility company to make the curve of demands complies with what the company anticipates while saving user's energy costs. In some literature [4], they instead use home energy management system (HEMS) technology to manage the energy usage of a smart home, which adopt

doi:10.6342/NTU202100623

the identical approach and achieves just like DSM.

In general, residents tend to save as much energy as possible to minimize their electricity cost, but they hardly know the attributes of every appliance in the home, which causes an obstacle to residents to perform some energy saving actions. To remove this obstacle, a smart home system with display media can show the information about the household energy consumption to residents. Therefore, in addition to design a powerful DSM system, how to increase the motives of residents to save energy also has considerable potential to facilitate energy saving [6]. Moreover, different residents should receive energy feedback with different contents so that each of them can accurately recognize the information related to him/her [7]. Thus, the residents can be aware of the electricity cost of each appliance, and try to alleviate the energy wasting behavior to save more energy.

In this thesis, we divide energy saving into passive saving and active saving. The former represents that the energy management system manages appliances and saves energy for users on the premise of maintaining user's comfort, which has been widely studied so far. However, for users who are used to spending a lot of energy, passive saving may not achieve a good result, because the system needs to spend too many efforts to cater to the user's habits while keeping their comfort. On the other hand, the latter refers to the case where users actively change their energy usage habits to save more energy consumption. In fact, active saving can be achieved by enhancing users' self-awareness of energy saving.

doi:10.6342/NTU202100623

1.2 Challenges

Although the field of DSM has been studied for a long time, there are still many challenges waiting to be solved, especially after considering energy saving motives of users. In this thesis, we try to solve three challenges. First, the DSM system needs to have the ability to be applied to multi-user smart homes, and provide tailored services for each user. Second, it is difficult to ensure that the smart control of DSM will not decrease user's comfort. We introduce appliance flexibility into the proposed system to measure the regularity of usage of every appliance. Finally, in order to improve the user's self-awareness of energy saving, the proposed system will determine the timing and content of energy feedback to the users.

1.2.1 Challenges of Multi-User Smart Home

In a residential home, there is a high probability of having more than one resident, and there are two situations that would not happen in a single-user household. The first is that two or more users may stay at home at the same time. Under that circumstance, it is necessary to know the location of each user at home and the state of appliances in order to analyze the context of each user through the help from the context recognition engine, allowing DSM to make a control policy for every single user. The second situation is that different users stay at home alone at different times. A system that only considers a single user situation cannot get good results, because users have different living habits. A DSM system designed for single user is not sufficient for multiple users.

Since the Internet of Things (IoT) technology has been developed for many years, the motion sensor is a basic device. Through common motion sensors, it is likely a management system can predict the number of people at home, but it cannot know the

doi:10.6342/NTU202100623

identity of the user. As a result, the management system cannot make the tailored services for every user. The proposed system will recognize the users' identity through the augmented reality (AR) device. In addition to customizing the control policy based on the user's identity, we also use this information to improve the user's self-awareness of energy saving. After the smart plugs collect the data of appliance usage, the system will convert the raw data into meaningful information. According to the location and activity of users, the data which are relevant to them will be displayed back to them through a visual interface to improve the user's self-awareness of saving energy, but not dumping huge amount of raw data to the users.

1.2.2 Challenges of Balancing User's Comfort and Smart Control

Generally, automatic smart control of appliances can bring convenience to users. However, if the smart control is too dominant, it might cause a problem and may conflict with the user's preference. In this thesis, we try to solve this issue through estimating the regularity of usage time of every appliance, despite that each usage time regularity can be different amount appliances, and even over different users. For those appliances whose usage time is relatively fixed, it means that the user highly needs to use these appliances at certain specific times. Under this circumstance, the user may not be willing to change the appliance's usage time, but it is easier for the DSM system to perform smart control due to the regularity of the appliance usage time. In addition, for appliances with irregular usage time, it is difficult to predict whether the user will turn on the appliance due to the uncertainty of user's behavior. In other words, even if the user performs an activity that has been performed before, the user still has a high

doi:10.6342/NTU202100623

probability of using different appliances at this time. Therefore, smart control of these irregular appliances not only cannot improve the convenience of the user, but also can be defying user's preferable behavior.

After we evaluate the regularity of usage time of every appliance, the flexibility of that appliance will be estimated. Appliance flexibility represents the degree to which an appliance can participate in demand response. In other words, electrical appliances with irregular usage time will have greater flexibility since these appliances can be used earlier or later, or with even reduced usage time. However, the comfort of the user also needs to be considered. The DSM system cannot turn off too many appliances for energy saving. In addition, the usage time of a low flexibility appliance is relatively regular. In general, the history living habits of a user can be used to infer his/her preferences of appliances. Since the uncertainty of the user behavior for these appliances is negligible, the DSM system can help users automatically control these appliances according to their preferences to improve convenience. Although DSM provides the control policy, the user decisions should still be regarded as the most important reference to follow. Then, the control of highly flexible appliances will be designed to respect user's preference and not to affect their daily activities.

1.2.3 Challenges of Self-Awareness of Energy Saving

The more and more electrical products have been used in the home, making the human's life more convenient, but also causing an increase in energy demands. Moreover, complicated electrical appliances make it difficult for users to understand the detailed information about the status of each appliance. The users often use more energy consumption than just necessary to enjoy the higher quality of life. In order to avoid the waste of energy, the system can provide energy information back to users. It

doi:10.6342/NTU202100623

thus becomes a challenge how to enhance user's self-awareness of energy saving through energy feedback, which will be addressed in this thesis. First of all, the amount of data collected through sensors are huge and disorderly. These raw data are not appropriate to be directly displayed to the user. Therefore, the proposed system will analyze the raw sensor data and transform them into meaningful information before presenting it to the user.

In order to further improve the user's self-awareness of energy saving, giving users energy saving suggestion is a way to induce them to be willing to save energy. Similar to the way how we gather energy information, besides the collected data about the state of the appliances, we also need to collect the location data of the user before we can analyze the right energy information and make the right energy saving suggestion. Note that the timing and content of the energy saving suggestions are two important factors. Choosing a suitable time to issue energy saving suggestions can prevent the system from overly disturbing users and make users willing to continue using the system. In addition, choosing appropriate content for the energy saving suggestion will help users more likely accept the suggestion. On the other hand, if the suggestion is rejected frequently, then that suggestion will be ignored almost directly by users and hence become redundant. Therefore, we focus on optimizing the timing and content of energy saving suggestion, and motivate users to volunteer to save energy as much as possible rather than to treat it as a burden.

doi:10.6342/NTU202100623

1.3 Related Work

The concept of DSM has been proposed since 1979 [9], and many research studies in this field have been proposed [10] [11]. Since the performance of hardware equipment is getting better and better, the energy management system can accomplish complex data analysis and appliance control. It can also integrate the renewable energy, energy storage system and devices that have network ability to form an IoT network. Through load shifting and reducing of the usage time of unnecessary appliances, DSM can improve energy efficiency and save electricity cost for users. In addition, incorporating renewable energy resource (RES) and energy storage system (ESS) into the management system can also improve the performance of DSM and reduce the burden on the energy supplier at peak times of electricity demand.

In the existing literatures, there are many approaches to implement a DSM system, including mixed-integer linear programming [12], game theory [13], heuristic algorithms [14] [15] and machine learning (ML) model [16] [17]. These approaches aim to find the optimal control policy to help users manage the appliances. In work [18], the authors proposed a novel electricity price model based on game theory. Even there is no exchange of information between households, game theory can still adjust its own optimal control policy and correspond to the control policies of other households [3]. The authors implement a two-step centralized game with one energy supplier and multiple consumers. In environment setting, each house is equipped with smart plugs that can monitor and control various electrical appliances, and consumers can also communicate with suppliers in two-ways connection. The supplier will update the electricity price based on the electricity load, and the consumers will determine the schedule of appliance usage in order to meet lowest electricity cost. However, ML technology has just been applied to the DSM field in recent years, mainly using the

doi:10.6342/NTU202100623

reinforcement learning (RL) method. In work [19], RL technology is used to replace the complex thermodynamic model. The authors aim to improve the energy efficiency of water heater by scheduling the timing of heating. Although the temperature sensor in the existing water heater has some errors, the RL approach can learn this uncertainty of heater in different houses, but the traditional thermodynamic model cannot learn adaptively. Our previous work [20] used RL as the main technology for determining control policies. In addition, the multiple RL agents are updated once a day to adaptively learn the user habits and to better manage various appliances. It saves energy while also ensuring user comfort.

After studying the literatures about smart homes, we can discover that the way to save energy is not limited to managing electrical appliances through DSM. The energy feedback technology has also achieved good results in energy saving [7] [21]. Energy feedback generally uses in-home displays to show energy consumption information. If the content of these information is critical enough, users can be motivated to perform more energy saving behaviors. In work [22], the author proposed a smart home system integrating energy efficiency features, which aims to improve the energy consumption awareness of each house. The system collects energy consumption information at the appliance level rather than the household level. There is a visual interface for users to view and compare the energy consumption of these appliances through their mobile phones. The system also contains interaction techniques, which allow users to send selected information to other larger screens in the home through their mobile phones to display them. Furthermore, a room-context aware HEMS is proposed in work [23]. The system has three major functions: eco-feedback, eco-control and eco-automation. Eco-feedback enables the system to display the room context related energy consumption information to the user through some screens. Then, eco-control allows the user to

doi:10.6342/NTU202100623

Table 1-1 Comparison among different approaches of smart home system

	Distinguishing the multiple users' ID	**Considering user habits**	**Energy feedback**	**Energy saving suggestion**	**Control pattern**
Li *et al.*[24]					**automatic**
Wen *et al.*[25]		✓			**automatic**
Brülisauer *et al.*[26]			✓		**manual**
Raza *et al.*[27]		✓	✓	✓	**manual**
Proposed Method	✓	✓	✓	✓	**hybrid**

directly operate their electrical appliances through the smartphone interface. Finally, the eco-automation provides a setting function for user to design the simple rules to automatically control appliances. This system makes good use of room-context information and a good combination of energy feedback and appliance control.

According to our understanding, there is no literature that focuses on combining the advantages of DSM and energy feedback to develop a system that is more suitable for users. We organize the smart home energy management system that is related to demand response [24] [25] and energy feedback [26] [27], as shown in Table 1-1. For DSM system, it is the current trend to make it applicable to multiple user house. However, most research studies did not consider the identity of users. Therefore, the system's strategy for multi-user situations is similar to the situation where a single user uses a large number of appliances at the same time. Thus, the multi-user issue is only regarded as a single super user issue, which cannot completely solve the problem. In addition, the studies that focus on energy feedback usually only analyze the energy usage and submit the consumption reports to users. Since these reports may not be real-time, the instant energy saving opportunities will be lost. These studies also failed to

doi:10.6342/NTU202100623

take advantage of the home area network to enhance the convenience of appliances control for user. In summary, it can be seen that the multi-user DSM system that integrates the concept of user's self-awareness of energy saving has great potential for the underlying research.

1.4 Objective

After brief review of the related literatures, we found that DSM still has many challenges that need to be solved. This thesis presents a DSM system with user's self-awareness of energy saving, which attempts to achieve three objectives. The first objective of our research is to deal with multi-user home issues, which not only touch upon appliance usage conflicts among users at home, but also on different living habits of users. The second objective is to evaluate the usage time regularity of electrical appliances. The appliance flexibility is formulated and used to quantify each appliance regularity. The third objective is to introduce the concept of user's self-awareness of energy saving into the DSM system. Since DSM automatically manages appliances based on user habits, increasing the user's self-awareness of energy saving can induce them to adjust their living habits and thus save more energy.

1.4.1 Multi-user Demand Side Management System

If the system wants to provide personalized services to users, only knowing the number of people at home is not enough to achieve this goal. The system also needs to know the user's identity and their location. With this user information, the system can recognize the users who are using the appliances and infer their contexts as well as

doi:10.6342/NTU202100623

analyze their living habits. However, there may exist conflicts in the use of electrical appliances among different users. In order to resolve this conflict, we have customized a scale based on the energy saving amount of different users to evaluate the users' priority in using the appliance. Thus, when the system provides the energy saving suggestions to users, it will refer to this scale so that the users who tend to use less energy as habits will have higher appliance usage priority.

1.4.2 Appliance Flexibility Analysis

An energy management system should not disturb the living habits of users while seeking energy saving. The system needs to evaluate whether the appliances should be controlled automatically or controlled by users. Therefore, we introduce the appliance flexibility into the philosophy of our work. The flexibility of an appliance represents the degree to which an appliance can participate the demand response. The higher the flexibility of an appliance is, the higher the possibility that the user is willing to adjust the usage time of this appliance. Conversely, for appliances with lower flexibility, users are less willing to adjust their usage time. Then, the system can assist the user with automated energy management based on the user's usage habits of the appliance.

1.4.3 User's Self-Awareness of Energy Saving

Although automated home energy management systems have been developed for decades, few studies have incorporated into the system the willingness of user to control home appliances for the sake of saving energy. The previous section proposed the appliance flexibility to evaluate the timing of applying automatic control or user control. In some cases, the system will ask users if they need to use some appliances. With the

doi:10.6342/NTU202100623

reduction of automatic control appliances, some energy-saving possibilities are left. As the automatic control of electrical appliances is reduced, the energy saving performance of the system will be relatively deteriorated, but the user's right to control electrical appliances can be preserved. This thesis aims to integrate self-awareness of energy saving into DSM, motivating users to save energy when they have control of appliances. The system uses the modified context recognition engine [20] to derive the user's potential activities from the sensor network, and determines energy saving suggestion based on the activities. The involved decision here includes the timing and content of the suggestion. This suggestion and related energy consumption information will be displayed to the user, so that the user can understand the cost made by his/her current behavior, as well as the direction of behavior change to achieve energy saving. Through energy feedback and energy saving suggestions, users' self-awareness of energy saving can be greatly enhanced.

doi:10.6342/NTU202100623

1.5 Thesis Organization

The remainder of this thesis is organized as follows. Preliminary materials are introduced in Chapter 2. Next, Multi-User Home Energy Management System is presented in Chapter 3, which is followed by system evaluation in Chapter 4. Finally, conclusion is made in Chapter 5.

In Chapter 2, we introduce the preliminary materials in this thesis. For example, the concept of Demand Side Management (DSM), which is a core idea in the field of energy saving and smart grid, aims at managing the energy usage to reduce the risk of damage to the power system due to unbalanced energy flow, moreover, the Context Recognition Engine (CRE) in the previous research [34], which is an unsupervised analytics framework, tries to discover the potential daily contexts that will be integrated into this thesis.

In Chapter 3, we detail the proposed DSM system which integrates the self-awareness of energy saving and the automated control agents into multi-user smart home environment. First, we deal with the automated user preference inference system by the integration of CRE. Second, the energy feedback and energy saving suggestions are provided to enhance the user's self-awareness of energy saving. Finally, we develop the multiple deep Q-network agents to realize the precise control in the DSM problem.

In Chapter 4, we first show the details of the experiment environment, and then conduct several experiments to demonstrate the performance of the proposed system and also make some comparison between different scenarios.

In Chapter 5, we give an overall conclusion of this thesis, followed by some discussions on our future work.

doi:10.6342/NTU202100623

Chapter 2

Preliminaries

2.1 Demand Side Management

Demand side management (DSM) is a mechanism for adjusting the energy consumption patterns on consumer side. DSM reshapes the demand curve and improves the stability of the grid by reducing the energy demand during peak periods [3]. The energy suppliers usually use some financial incentives to prompt consumers to adjust their demand curve. The suppliers will formulate the electricity price mechanism such as Time of Use (TOU) pricing, real time pricing (RTP) tariffs and so on [28] [29]. TOU is a rate used to decide the electricity price. TOU pricing is a static mechanism that does not change with the date after the price is set in advance. The electricity price announced by the energy supplier changes with the time of the day, and even changes in weekends or seasons. On the other hand, RTP is a dynamic electricity price mechanism. The electricity price will be recalculated at regular intervals. The dynamic price mechanism can more accurately reflect the real time energy consumption in the electricity price, but it is more difficult to apply to demand response because the system cannot know whether the price will increase or decrease in the next period.

Based on different energy prices, DSM has several methods to reshape the demand curve [30], including peak clipping, valley filling, load shifting, strategic conservation,

doi:10.6342/NTU202100623

strategic growth, and flexible load shape. As shown in Figure 1-1, peak clipping is a direct load control technique, which can reduce the amount of energy usage during peak hours. On the other hand, valley filling establishes user's energy demand at off-peak hours, thereby making the energy demand more stable. With peak clipping and valley filling, the difference between peaks and troughs will be reduced and the grid burden of peak energy consumption will also be eased. Next, load shifting has been widely used in many DSM studies. With the TOU mechanism, load shifting directly shifts the electricity demand from peak to off-peak hours by scheduling the usage time of time-independent appliances. For strategic conservation and strategic growth, these two methods are dominated by the planning of energy market and the operation of the energy supplier. When there is a shortage of energy, DSM needs to cooperate with the energy supplier to complete strategic conservation. On the other hand, strategic growth is used to deal with the unexpected increase in user demand. Finally, flexible load shape refers to the flexibility of energy demand. Through flexible load, DSM can coordinate the energy consumption habits of different consumers and also can cooperate with the financial incentives of energy supplier to complete demand response.

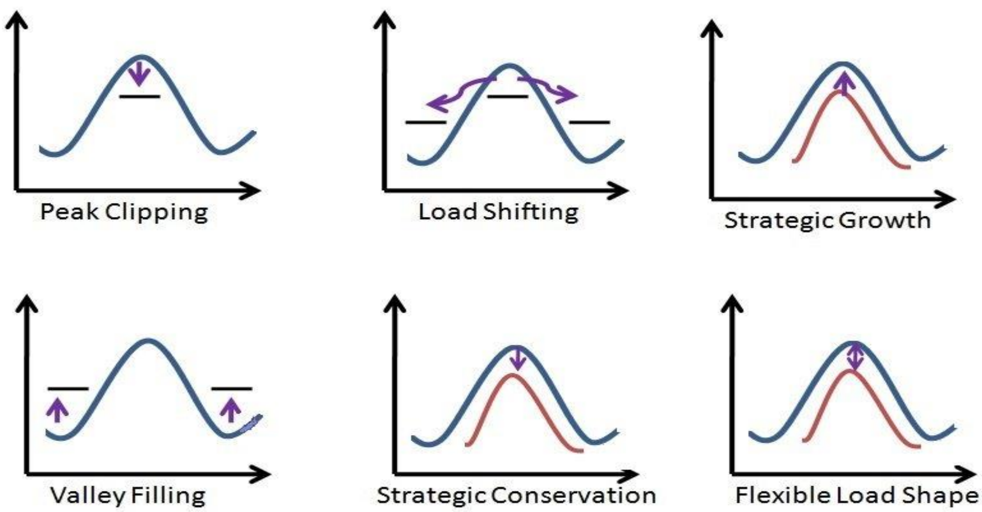


Figure 2-1 Demand side management techniques

doi:10.6342/NTU202100623

2.2 Simultaneous Localization and Mapping

Simultaneous Localization and Mapping (SLAM) was first proposed in the field of robotics. This technology allows the robot to start from an unknown location, record environmental information and locate its own position during the movement. After exploring for a period of time, the robot can construct a map of its area to achieve the purpose of simultaneously drawing the map and positioning itself. SLAM has always been a hot research topic of more than 30 years since it is indispensable for autonomous robots [31]. SLAM technology has made great progress and has derived many practical applications [32] [33].

Nowadays, SLAM is a fundamental technique in augmented reality (AR), which provides the function of recognizing the unknown areas and positioning. Since the camera is mainly used as a sensor, visual SLAM has become the mainstream SLAM technology in AR. The term visual SLAM comprises all SLAM approaches that take image-like data as input. Generally speaking, visual SLAM is composed of tracking, mapping, global optimization and relocalization. Tracking the frames that collected by the camera can maintain the local camera trajectory. Mapping process uses tracked sensor data to construct a map. Because some drift may have happened in tracking phase, the global optimization is needed to correct these errors. When the system has the map Information but no camera pose, relocalization can compare the current frame with the map and re-estimate the camera pose.

doi:10.6342/NTU202100623

2.3 Context Recognition Engine

The context recognition engine is an unsupervised analytics framework to discover potential daily contexts for real smart living environments [34]. The heterogeneous sensors in the home are integrated and a snapshot of the value of a group of sensors is regarded as a home context. Context recognition engine (CRE) can discover and record the new contexts, which can be used to recognize the current context of a home. After the current context is recognized, the user behavior and their appliance preferences can be inferred. Therefore, context information is an important factor when DSM decides the control strategy. CRE consists of context discovery, context recognition and context adaptation to analyze the living habit of consumer and recognize the current context.

The number of combinations of sensor values grows exponentially based on the number of sensors. Among the large number of combinations, some of them describe the same activity, such as that different sensor data will be obtained when watching TV with or without a fan. Thus, some combinations can be clustered together. In context discovery stage, a hierarchical clustering algorithm is used to integrate these heterogeneous sensor data. The hierarchical structure including location-based layer and feature-based layer. The data in different locations and sensor types will be processed independently. The same type sensors in the same location will be clustered first and the clustering results between heterogeneous sensors will be fused to find the context within one location. Finally, the context of every location will be integrated together to form a global context.

doi:10.6342/NTU202100623

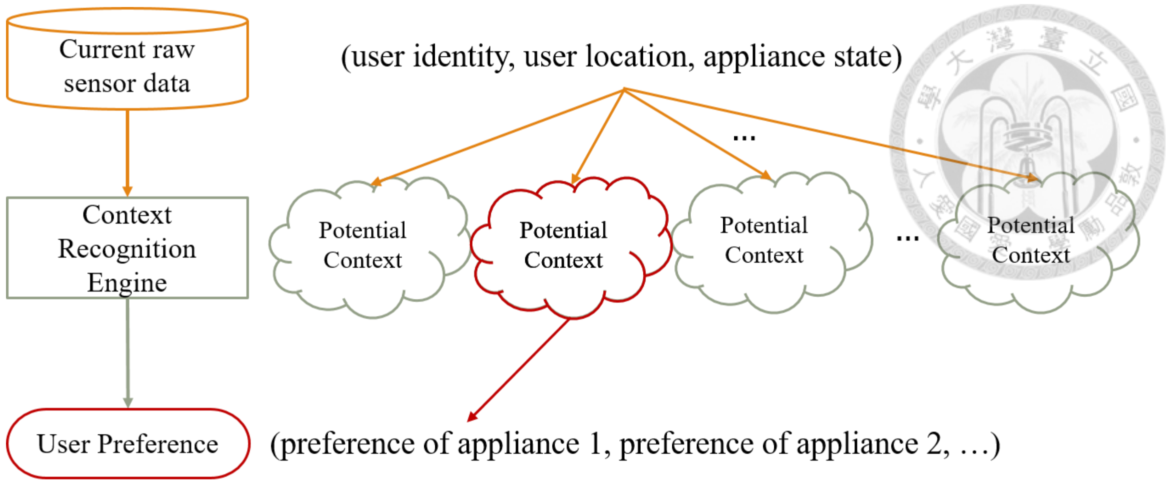


Figure 2-2 The overview of context recognition procedure

Figure 2-2 shows the context recognition procedure. When the new sensor data are collected, this procedure will be activated. CRE will recognize the current context by estimating probability that the sensor data belongs to each context cluster. After the context of new collected data has been recognized, the appliance usage preference of consumer can be inferred from the cluster head, which is the major point of the cluster. If the new collected data is far away from the existing context clusters, the context adaptation mechanism will create a new cluster and add it to the existing clusters.

2.4 Appliance Flexibility

Flexibility load refers to the energy load that can be changed variable in the DSM field, which comes from the energy demand that users are willing to reduce or reschedule. As the proportion of power generation from renewable energy resource is increasing year by year, and the stability of renewable energy resource is lower than traditional way of power generation, maintaining the balance of supply and demand in the energy market has become more challenging. Therefore, not only the utility

doi:10.6342/NTU202100623

company has the responsibility to provide sufficient energy, but the demand side can also provide flexibility loads to increase the stability of the grid. In some studies, only the overall flexibility of the house is estimated. Work [36] estimated the flexibility of houses based on the population in the house and the time of day; work [37] estimated the flexibility of houses based on the factors such as type of house and season. The overall flexibility of the house allows the grid to give priority to the houses that need energy immediately when distributing energy. The utility company usually gives some benefits to houses with higher flexibility. However, the DSM system needs the flexibility of each electrical appliance to manage the usage time of them. The system can require users to provide an acceptable range of electrical appliance usage time, or predict the usage time based on user habits. With the range of appliance usage time, the flexibility of the appliance can be estimated.

In this thesis, the appliance flexibility is estimated. First, the system can obtain the appliance usage habits of users from the recorded historical appliance data. Next, we use a statistical model to fit the probability distribution of appliance usage time. The appliances with more dispersed usage time represent higher flexibility. However, many studies directly take high-flexibility appliances to participate in demand response and determine the usage time of the appliances for the user. This may cause discomfort to the users because their habits may be changed over time. We regard the flexibility value as an indicator, which indicates whether the usage time of the appliance is regular or messy.

doi:10.6342/NTU202100623

2.5 Reinforcement Learning

Reinforcement learning (RL) is a technology in the field of machine learning. The core concept of RL is trial and error. What RL does is to determine an action after observing the environment. The software or hardware that uses RL to determine and execute an action can be called an agent. After executing an action, the environment will give the agent a reward, and the agent can adjust the RL model based on the reward. Basic reinforcement learning includes the following five elements:

- S: a set of the environment states, where the elements are observations of the environment.
- A: a set of actions that the agent can perform.
- P: the transition probability between states.
- R: the reward that can be obtained by performing a specific action in a given state.
- M: an environment model that interacts with agents, simulates the state of the environment, and provides reward.

An agent will interact with the environment in discrete time steps. The process of one interaction includes multiple steps. First, the agent will observe the environment to obtain the current state. Second, the agent estimates the value of all executable actions in the current state through its RL model. Third, the agent needs to select an action and execute it in the environment. According to the designed selection strategy, the agent can directly select the most valuable action to expect the greatest reward, or select other actions to explore whether it can find better results than expected. Fourth, after the agent makes an action, the environment model will calculate a reward value to the agent from the environment state changed by the action. Finally, the agent learns the quality of an

doi:10.6342/NTU202100623

action from the reward and updates its RL model to evaluate the value of each action more accurately.

Q-learning [38] [39] one of the techniques in reinforcement learning, its main approach is to build a Q-table. The Q-table maintains the value of performing an action in the given state. When the agent needs to select an action, it will refer to the value in the Q-table. In addition, the Q-function is an function used to estimate the expected value of an action. The return value can be regarded as an assessment of the quality of an action. The Q-function is defined in (2-1)

$$Q^{new}(s_t, a_t) \leftarrow (1 - \alpha) \cdot Q(s_t, a_t) + \alpha \cdot \left(r_t + \gamma \cdot Q(s_{t+1}, a_{t+1})\right) \quad (2\text{-}1)$$

where $Q^{new}(s_t, a_t)$ is the updated Q value, while $Q(s_t, a_t)$ is the old Q value, α is the learning rate, γ is the discount factor and r_t is the reward received when moving from s_t to s_{t+1}. The discount factor γ represents the degree of importance of the expected reward in the future. When γ is close to 1, the expected reward after several time steps will still affect the current Q value; on the contrary, when γ is close to 0, it means that short-term rewards are more important.

At the beginning of learning, the value in the Q-table can be initialized to zero or some random floating point numbers. At each time step t, according to the current state s_t, the agent will determine an action a_t. After that, the environment will give the agent a reward value according to the change of state. With the reward from environment, the agent can use the Q-function to update the Q value of $(s_t,\ a_t)$ in the Q-table. After long-term training, the agent can select the most suitable action in every given state.

The size of the Q-table is the number of elements in the state space multiplied by the number of elements in the action space. This is an important complexity issue. When the number of elements in the state space and the action space increases, the size of the Q-table will rise rapidly, resulting in the maintenance of the Q-table will be quite time-

doi:10.6342/NTU202100623

consuming. In the DSM field, the number of elements in the state space grows exponentially with the number of appliances, the number of users, and time. The number of elements in the action space is also dominated by the number of appliances. Therefore, the Q-table is not good enough.

In order to solve the problem of the rapid growth of the Q-table, Deep Q-Network [39] had been proposed, which uses a neural network to replace the entire Q-table. The neural network needs to feed many input-output pairs to approximate a function that $f(\text{input}) = \text{output}$. The input of the Q-network is the current state, and its output is the Q value of each action. In addition, the Q network can also be designed into different architectures to address different problems. Figure 2-3 shows the difference between Q-learning and DQN. Q-learning uses a look-up table to find the Q value for each state-action pair; DQN uses a neural network to estimate the Q value of all actions for the current state.

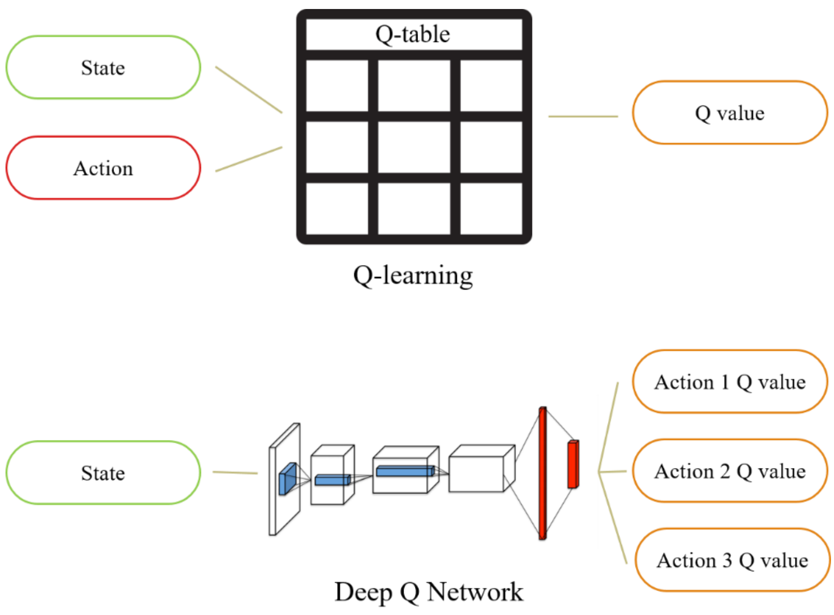


Figure 2-3 The concept of Q-learning and Deep Q-Network

doi:10.6342/NTU202100623

Chapter 3

Multi-User Home Energy Management System

Since cost saving and convenient life are some goals to be pursued by most people, home energy management systems which can achieve these pursuits become more and more popular worldwide. In a smart home environment, many ambient devices with communication function and an aggregator can establish a home area network, which forms the basis of home energy management system. With the support of these hardware devices, there are many approaches to implement an energy management system. The key to affect the quality of a management system lies in the optimization of control policies. After reviewing the research studies and the achievements of the smart home field, we propose a novel DSM that integrates the concept of users of energy saving into a multi-user smart home environment.

doi:10.6342/NTU202100623

3.1 Smart Environment

In this section, the configuration of a smart home environment will be introduced. As shown in Figure 3-1, a smart home is usually equipped with home appliances, smart plugs with measurement function, and an aggregator that can communicate between energy supplier and consumer. Smart plugs have the ability to turn on or off the power of electrical appliances and measure their energy consumptions at the same time. The system can receive and integrate device data through the aggregator and get the time-of-use (TOU) pricing information provided by the utility company. Normally, a home IoT system will enable the DSM to monitor and manage electrical appliances in the home environment.

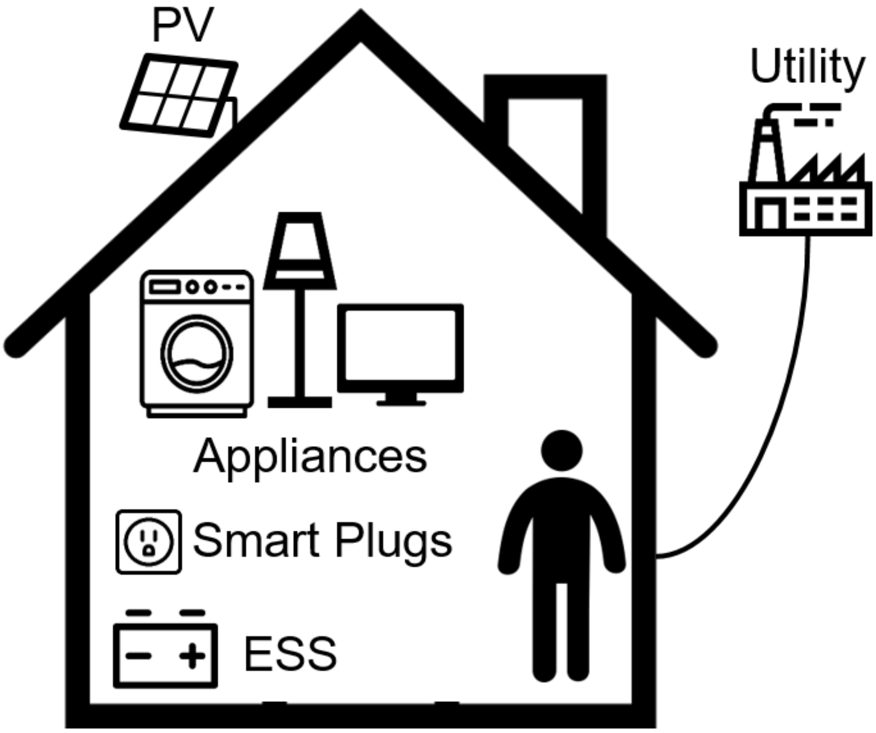


Figure 3-1 Grid-Hybrid system configuration in smart home

doi:10.6342/NTU202100623

Furthermore, photovoltaics (PV) is the most popular renewable energy resource for home users. The advantage of PV is that the size of the solar panels is mild and will not be restricted by the terrain. As long as there is sunlight, it is suitable for installing PV systems. The energy generated by PV will be stored in the energy storage system (ESS) and used to meet the electricity demands. DSM can determine the timing of charging and discharging of ESS to reduce the amount of energy purchased from the utility company in peak hour, saving the consumer's costs. Our proposed system, including PV and ESS, will determine the control policy of appliances based on the TOU pricing mechanism, which is one of price mechanisms of a utility company in Taiwan.

In this thesis, we also incorporate the augmented reality (AR) technology into our system, where an AR device with camera and visual interface is equipped. Through use of the camera, SLAM technology from Chapter 2 can build a map of the home environment and help the system obtain user location information. Note that the AR device is used to serve as a user visual interface, which displays energy consumption information and energy saving suggestions as shown in Figure 3-2. With user location and appliance status collected from smart plugs, DSM can analyze user behavior and home contexts to formulate the control policies.

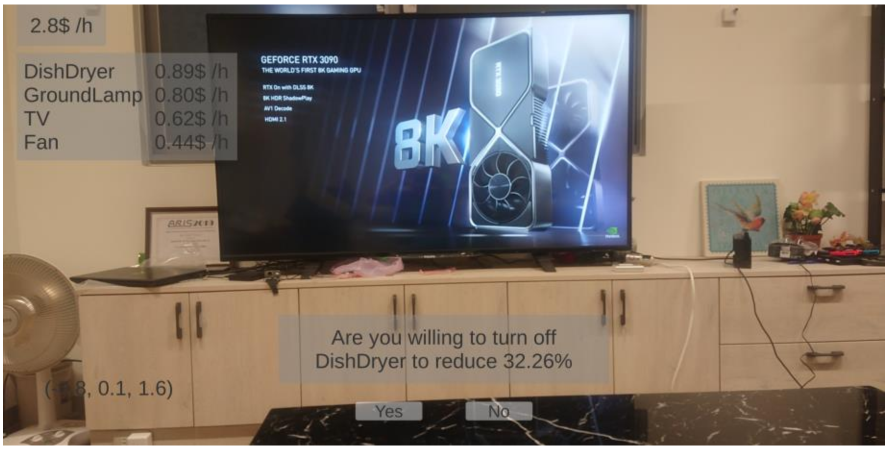


Figure 3-2 User view on AR device

doi:10.6342/NTU202100623

3.2 System Architecture

Different from the existing general DSM literatures, we hope that the DSM system no longer just exercises fully automated management, which might lead to excessive energy saving and affect user comfort, or to excessive emphasis on user comfort which limiting the ability of DSM. It turns out that our proposed system determines the optimal timing of controlling or not controlling electrical appliances and incorporates the concept of self-awareness of energy saving. The system is divided into three layers according to its functions: data layer, process layer, and energy saving layer, as shown in Figure 3-3. We will first briefly overview the entire architecture of the proposed system, where the details of each module will be introduced in the following sections.

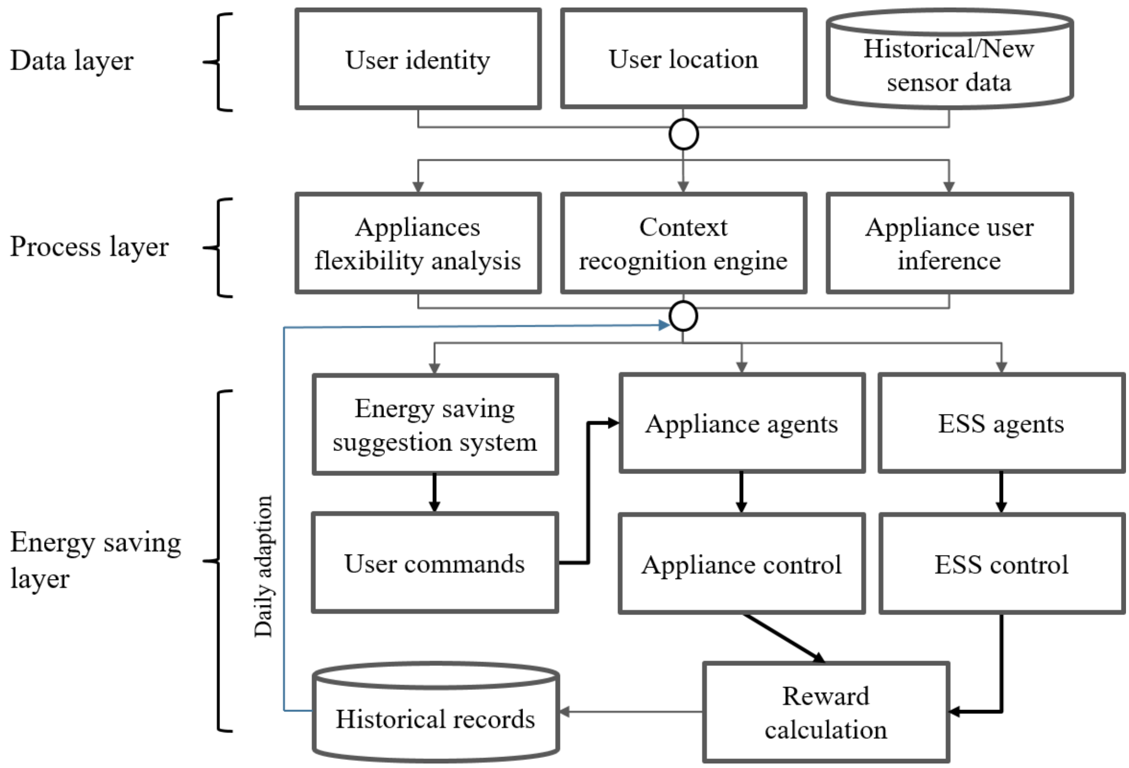


Figure 3-3 System overview of the proposed system

doi:10.6342/NTU202100623

In the data layer, each appliance is equipped with a smart plug to measure the energy consumption. Besides that the users can manually control these plugs, a DSM system can also automatically control the state of these plugs. As for users, we assume that each of them is equipped with an AR device, and a simple login system as well as SLAM technology are implemented on such device. Here, our system can track the identity of each user and his/her indoor location in real time. These data related to users and electrical appliances will be further analyzed by the process layer described below.

In the process layer, both appliance flexibility and context information are evaluated from historical data and will be updated adaptively. Appliance flexibility is used to indicate the degree of regularity in the usage time of electrical appliances. In our research, the flexibility of each appliance will be assessed, unlike the assessment of the flexibility load of the entire house. Those appliances that have regular usage time can be automatically managed by appliance agents. In addition, a CRE [34] is used to recognize the user context, where the context information represents the current behavior of the user and the state of the environment. In particular, there is one cluster head of each context cluster, where the cluster head is simply the context that takes place the most frequently. In other words, the cluster head can reasonably represent the user's appliance usage habit at that moment. Therefore, the user’s usage preference of the appliance is defined by the cluster head, and the preference will be updated if the user manually turns on or off the electrical appliance. The last module in process layer is to identify the appliance user. In a multi-user smart home, the behaviors and habits of different users are different. If a DSM system only considers the environment at the house level, it may misjudge the activities of the users, such as confusing the activities of two users. Therefore, the system also needs the information about the user who is using which appliances to identify the correct behaviors and habits of every user.

doi:10.6342/NTU202100623

In the energy saving layer, an automated energy management system composed of four agents is one of our major part responsible for energy saving energy saving. Similar to our previous work [20], all the electrical appliances are classified into three kinds, namely, heavy conflict (HC) appliances, possible conflict (PC) appliances, and less conflict(LC) appliances. The factors for the classification of appliances include the relationship between the location of user and the state of the appliance, the switching frequency of appliances, and whether the usage time of the appliances can be postponed. These factors are selected to define different management strategies for each type of appliances. The details of these three types of appliances are shown in Table 3-1.

Table 3-1 Classification of electrical appliances

Appliance classification	Heavy Conflict (HC)	Possible Conflict (PC)	Less Conflict (LC)
Association with user presence	Strong	Medium	Less
Tolerance for frequent switching	Yes	No	No
Deferrable	No	No	Yes
Example	Lights, fan	TV, computer	Washing machine, dish dryer

In order to manage the classified appliances, there are four agents deployed in the automated management system as shown in Figure 3-4. The appliances of each type are managed by a correspondingly designed agent, which account for three agents, and the fourth agent is designed to manage ESS and PV. Note that the agent will estimate the value of each control decision based on the state of the current environmental and select the best action from the candidate set. To meet these purposes, these agents use deep Q-network (DQN) model to calculate the Q value. An action with a higher Q value means that the action is more valuable. The objective function and detailed design of DQN will be introduced in Section 3.5.

doi:10.6342/NTU202100623

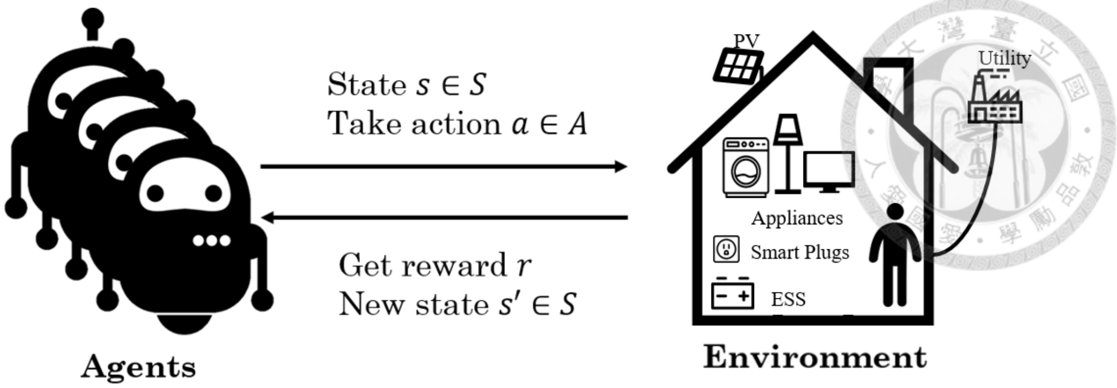


Figure 3-4 The operation between agent and environment

In the smart home field, the current mainstream energy management system is still the automatic control of some or all electrical appliances to save energy. However, when the system helps users save energy, it is often restricted by the user's habits in his/her daily life since the control policy of appliances must not compromise the user comfort. Therefore, the habits of users will affect the performance of an energy management system. The proposed system provides energy feedback and energy saving suggestion (EFES) to increase the users' self-awareness of energy saving. Taking the impact of user factors on energy saving into account, energy feedback may lower user's reluctance to accept the energy saving measure which usually various from ignorance of energy consumption of the involved activity. In addition, the system will also analyze the appliances usage habits of a user to find out which appliances may be turned off or the usage time may be pushed back more likely by the users, and then give that user energy saving suggestions when his/her personal energy consumption exceeds a predefined threshold. Under this circumstances, the automatic control system and EFES develop the energy saving policies respectively from the system side and the user side. These two modules cooperate and complement each other. According to the flexibility of the appliances and the current time, the system will decide to adopt automatic control or feed back to the users with some suggestions facilitating energy saving.

doi:10.6342/NTU202100623

3.3 Appliance Flexibility Analysis

The proposed system includes an automatic control system and EFES. One challenge is to ensure that these two modules will not conflict each other during cooperation. The most important step is to analyze the flexibility of electrical appliances. The flexibility of electrical appliances quantifies the degree of regularity concerning the usage time of the appliances. Since the usage time of a high-flexibility appliance is not fixed, the system needs to ask the user's current intention about how to use the electrical appliance through EFES instead of guessing whether the user needs the appliance. Conversely, the appliances with low flexibility can be managed by the automatic control system after knowing the user's habits of appliance usage. In other words, appliance flexibility is an important index that can help us coordinate the timing of management between the automatic control system and EFES.

Users usually have different requirements for using different appliances. Specifically, the function of appliances affects the turn-on timing, operating duration, and user's preference of appliances. For example, the usage timing of lights is related to the location of the user, the operating duration of the washing machine is fixed, and the usage preference for entertainment appliances may generally be higher. We propose a general approach to estimate the flexibility of each appliance by discovering the distribution of the usage time of appliances. Since the appliances belonging to the LC type mentioned in Section 3.2 are schedulable appliances, and these appliances only need to be executed within an acceptable time range to the user, it does not matter whether the execution of these appliances is at a fixed time or not. Therefore, only the flexibility of electrical appliances other than LC appliances will be analyzed.

doi:10.6342/NTU202100623

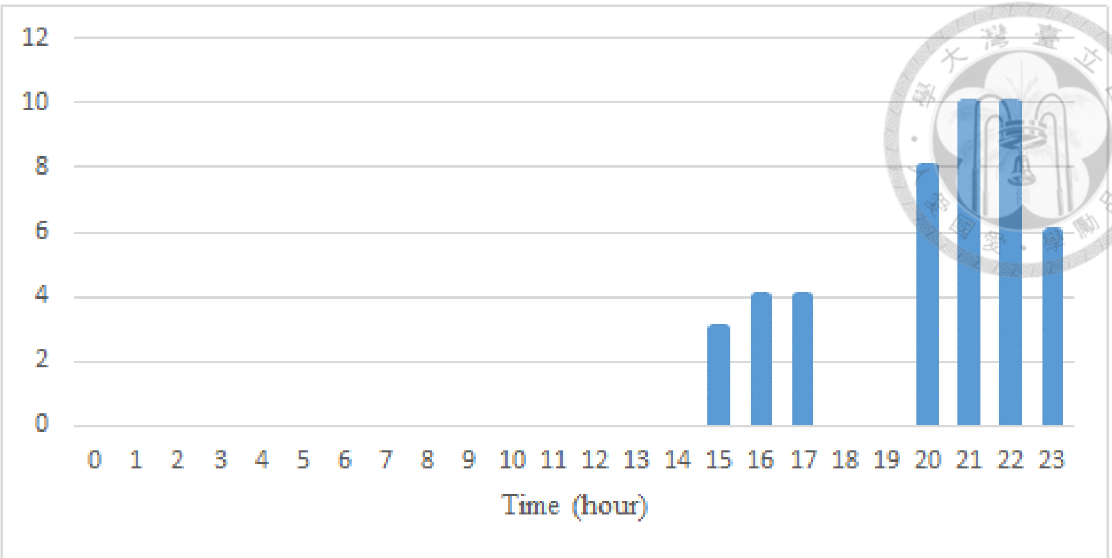


Figure 3-5 The example of the number of times an appliance was used in 10 days

In order to analyze the flexibility of electrical appliances, the probability of electrical appliances being used at a certain time needs to be estimated. We use one minute as a time interval and record the number of times the user has used the appliance in this time interval. As shown in Figure 3-5, this appliance is mostly used at night, and sometimes will be used in the afternoon. If this appliance is used at night every day, the probability of this appliance operating at night is 1. On the contrary, the probability of this appliance operating during the day is 0. Equation (3-1) shows the usage probability of an electrical appliance a at a specific time t:

$$Prob_a(t) = \frac{\sum_{i=1}^{N} x_{t,i}}{N} \tag{3-1}$$

where N is the number of days of historical data, $x_{t,i}$ represents whether this appliance is being used at time t on day i. Here, $x_{t,i}$ is 1 when this appliance was used at that moment; otherwise, $x_{t,i}$ is 0.

doi:10.6342/NTU202100623

We can intuitively find that when the user has a probability of using an electrical appliance at a certain time being 0.5, which means that this usage habit is irregular. A method is needed to measure the degree of dispersion of appliance usage. In information theory, entropy is a concept used to measure the amount of information. When the uncertainty of the measured target is higher, the more information will be measured by entropy. Therefore, we calculate the entropy of the appliance usage probability distribution during every hour, say, h, to obtain the uncertainty of its usage time in that particular hour, which is defined as the flexibility of the appliance of hour h in this thesis and is shown in (3-2).

$$flexibility_{a,h} = -\sum_{t=60h}^{60h+59} Prob_a(t)\, log_e\, Prob_a(t) \tag{3-2}$$

where $Prob_a(\cdot)$ represents the probability about the appliance a operating at a given minute (1440 minutes in a day). Therefore, according to (3-2) the flexibility of one hour is the sum of 60 minute discrete entropy.

Figure 3-6 Energy consumption information on AR interface

doi:10.6342/NTU202100623

3.1 Self-Awareness of Energy Saving

Energy feedback is a method that can enhance user's self-awareness of energy saving. A common way is to provide users with sorted household energy consumption data through email or web pages for viewing [26] [27], which requires users to spend extra effort to receive this information and it is hard to be real-time. In this thesis, an AR energy feedback application is implemented. As shown in Figure 3-6, the real-time energy consumption will be displayed in the corner of the screen of an AR headset in semi-transparent form. It will not block the view of user, but also allows the user to know the energy consumption information at any time. In addition, the user can choose to show or hide the detailed information block that contains consumption of each appliance. If the user chooses to display the detailed information block, only the appliance that is related to the user will be displayed. These designs keep the user interface clean most of the time.

In order to determine the user context and provide appropriate energy feedback, the proposed system needs to maintain the information of the electrical appliances that the user is using. Some appliances can be shared by multiple users. We call them multi-user appliances, such as TV and light. However, some appliances can only be used by

Table 3-2 The classification of single-user appliance and multi-user appliance

Appliance type	Appliance name	Use distance (m)	Unused distance (m)
Single-user appliance	computer	1	5
	water heater	0.5	inf
	dish dryer	0.5	inf
Multi-user appliance	night lamp	3	3
	ground lamp	6	6
	fan	2	2
	TV	2	5

doi:10.6342/NTU202100623

one person, which are called single-user appliances in our work, such as hair dryer and computer. The distance between the user and the appliance determines the relationship between them. We define the using distance and unusing distance for each appliance.

If the user wants to operate an appliance, it needs to enter the using distance of that appliance. On the contrary, when the user is too far away from the appliance, the system will consider that the user no longer uses this appliance. Table 3-2 shows the classification of electrical appliances in this chapter.

Figure 3-7 shows a flowchart of how to infer the user of the appliance. For a multi-user appliance, all users within the use distance will be considered to be using the appliance until the location of user exceeds the unused distance or the appliance is turned off. In addition, the analysis of a single-user appliance is more complicated. Even

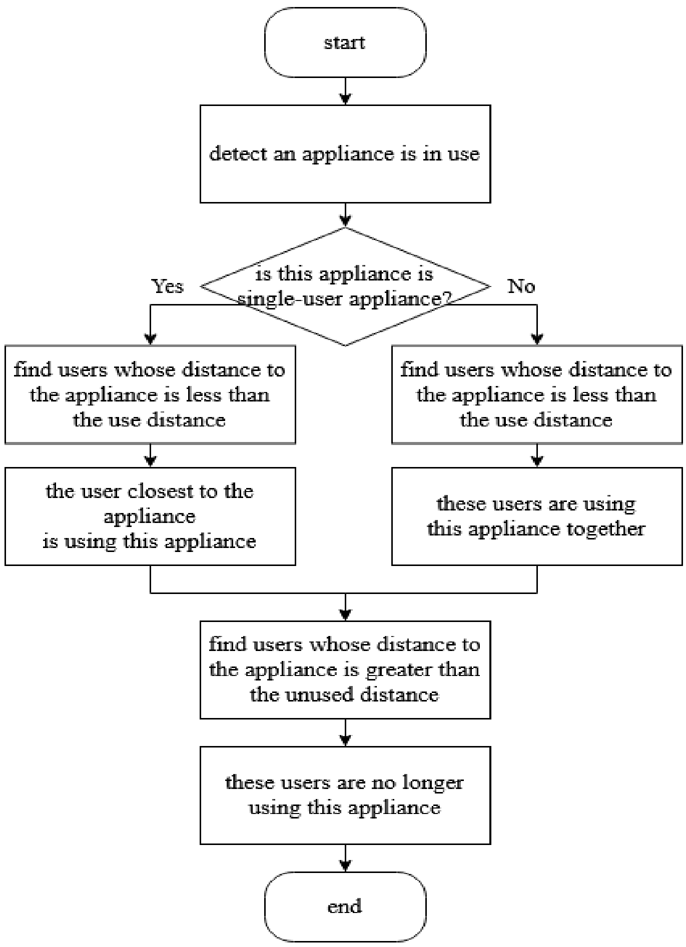


Figure 3-7 Flowchart of appliance user inference

doi:10.6342/NTU202100623

Algorithm 1 Appliance User Inference

```
  global variable: UsingList
for each appliance a in use do
    MinDis ← inf
    User ← None
    for each resident r do
        if a ∈ multi-user appliance and Dis(a, r) < UseDis(a) then
            Add a into UsingList[r]
        else if a ∈ single-user appliance and Dis(a, r) < min{MinDis, UseDis(a)} then
            MinDis ← Dis(a, r)
            User ← r
        end if
    end for
    if User ≠ None then
        Remove a from UsingList[r'], ∀r' ≠ User
        Add a into UsingList[User]
    end if

    for each resident r that a in UsingList[r] do
        if Dis(a, r) > UnusedDis(a) then
            Remove a from UsingList[r]
        end if
    end for
end for
```

Figure 3-8 Algorithm 1: An algorithm to guess who is the user of the appliance

if there are multiple users within the using distance of the single-user appliance, only one person is using the appliance. Therefore, the system will consider the closest one to be the appliance user. As shown in Figure 3-8, the proposed Algorithm 1 is used to maintain a list of all users and the appliances they are using.

The purpose of Algorithm 1 is to maintain the appliance user list, which is UsingList. Algorithm 1 is divided into two parts. The first part finds out the appliances that are using by the user and adds it to the list. The second part removes the appliances that are no longer used from the list. $\text{Dis}(a, r)$ returns the distance between the user r and the appliance a. The values of $\text{UseDis}(a)$ and $\text{UnusedDis}(a)$ are listed in Table 3-2 above. This algorithm is executed every five seconds to maintain the relationship between the user and the appliance in real time. Therefore, the personal energy consumption information can be displayed on the AR interface.

doi:10.6342/NTU202100623

3.2 Multiple Deep Q-Network Agents

There are many types of electrical appliances. According to appliance characteristics, they will be suitable for different demand response strategies. For example, the lights can be turned on or off according to the user's demand, rather than being scheduled to off-peak hours by the system. Therefore, we classify electrical appliances and design different control policies for them. In this thesis, there are four Deep Q-Network (DQN) agents, three of them manage the three types of electrical appliances mentioned in Section 3.2, namely HC, PC, and LC. The remaining one agent manages the energy storage system (ESS) system. These agents are called HC agent, PC agent, LC agent and ESS agent, respectively.

Before starting to construct the neural network (NN) model of DQN, there are three parts that we need to define first, which are state space, action space and reward function. State is the input of NN, and the output is an estimate of the Q value of each action. After the agent takes the action, the reward function is used to evaluate the quality of the action.

3.2.1 State Space

Before starting to construct the neural network (NN) model of DQN, there are three parts that we need to define first, which are state space, action space and reward function. State is the input of NN, and the output is an estimate of the Q value of each action. After the agent takes the action, the reward function is used to evaluate the quality of the action.

State space is defined as the observation of the environment, including the information that will affect the decision-making of agents. The state of a smart home is

doi:10.6342/NTU202100623

composed of electrical appliances state, user information, Photovoltaic (PV) and ESS state of charge (SOC). Since the agents have different control policies, their state space should only contain the information related to the policy. We define the state space of each agent based on the information observed from the environment.

- **Heavy Conflict (HC) state**

The HC state consists of the user location, HC appliances state, user preference, and time information, as shown below.

$$S_{HC} = \left(L, app_{i,0}^{h}, \ldots, app_{i,j}^{h}, app_{i+1,0}^{h}, \ldots, w_{i,j}^{h}, \ldots, Time\right) \tag{3-3}$$

In HC state, the appliance will be subscripted according to the room where it is located. The notation L is the current location of the user. When the user appears in space i, the value of L will be set to i; $app_{i,j}^{h}$ is the state of the j-th HC appliance in space i, where 0 is off and 1 is on. Immediately after the appliance state, $w_{i,j}^{h}$ is user preference for $app_{i,j}^{h}$ comes from CRE, $w_{i,j}^{h}$ is set to 1 to indicate that the user wants to use this appliance, 0 to indicate that the user does not want to. Finally, the format of $Time$ is the hour of the day.

- **Possible Conflict (PC) state**

The PC state is familiar with HC which consists of the user location, PC appliances state, user preference, and the time information as shown below.

$$S_{PC} = \left(L, app_{i,0}^{p}, \ldots, app_{i,j}^{p}, app_{i+1,0}^{p}, \ldots, w_{i,j}^{p}, \ldots, Time\right) \tag{3-4}$$

In PC state, the notation L is the current position of the user, and its value is the index number of the space; $app_{i,j}^{p}$ is the state of the j-th PC appliance in the space i,

doi:10.6342/NTU202100623

where 0 is off and 1 is on. Next, $w_{i,j}^{p}$ is user preference for $app_{i,j}^{p}$ from CRE; the value of $Time$ is the hour of the day. PC state and HC state have many similar designs. These designs are based on the control policies of agents. Although the control policies of HC agent and PC agent are different, the state space they need to achieve their goals is still similar. The control of these two clusters of electrical appliances is related to the user location and user preferences, which makes the two agents similar; however, PC appliances cannot be switched on and off frequently while HC appliances can tolerate frequent state switching, which results in the two clusters of electrical appliances cannot being managed by the same agent.

- **Less Conflict (LC) state**

The LC state consists of the state of LC appliances, time information, and the energy usage information of past 24 hours that shown as below.

$$S_{LC} = \left(app_0^l, \dots, app_j^l, Time, EU_0, EU_1, \dots, EU_{23}\right) \tag{3-5}$$

In the LC state, the app_j^l is the state of the j-th LC appliance in the house. Note that LC appliances are not distinguished by space because this cluster of appliances is relatively irrelevant to the location of the user. LC appliances are schedulable appliances that do not require users to operate when it is working, such as washing machines. The range of value of app_j^l is a discrete integer from -2 to 23, where -2 means that the user does not need to use this appliance; -1 means this appliance is waiting to be scheduled; 0 to 23 means that this appliance has been scheduled by the agent and this value is the appliance start time. Next, $Time$ is the current hour of the day, and EU_t is the total energy consumption (kWh) from t-th hour to $(t+1)$-th hour. The LC state does not include user preferences because LC appliances are

doi:10.6342/NTU202100623

appliances that need to be scheduled, and the user preferences are consistent with the state of the appliance. For example, when the user turns on the dish dryer, the agent should schedule it to a suitable start time for users, and there is no need to analysis the user preference of the dish dryer. In addition, in order to determine the suitable start time, the LC state includes the past energy consumption EU_t.

- **ESS state**

The ESS state consists of the time information, ESS state of charge (SOC), PV production amount and the past 24 hours' energy usage information as mention below.

$$S_{ESS} = (Time, SOC, PV, EU_0, EU_1, \dots, EU_{23}) \tag{3-6}$$

In the ESS state, $Time$ is the current hour of the day. Since this agent manages ESS and PV instead of electrical appliances, there is no appliance state information, but the ESS and PV information needs to be included in the ESS state. SOC represents the state of charge of ESS, and PV represents the electricity generated by solar power. The ESS state also includes the energy consumption EU_t in the past 24 hours, making the ESS agent capable of long-term planning. In addition, the agent cannot make the SOC exceed the maximum capacity of the ESS and needs to comply with the charge-discharge rate limits, which are shown in (3-7) and (3-8).

$$ESS_{min} \leq PV + SOC \leq ESS_{max} \tag{3-7}$$

$$-P_{ESS} \cdot \Delta t \quad \leq E_{ESS,\Delta t} \leq P_{ESS} \cdot \Delta t \tag{3-8}$$

In (3-7), ESS_{max} is the maximum capacity of ESS, ESS_{min} is a minimum capacity limit we set to protect the equipment from over-discharge. The value of ESS_{min} is set to 15% of ESS_{max}. Since energy generation from PV will be stored in the ESS before distribution, $PV + SOC$ needs to be less than the upper limit of the

doi:10.6342/NTU202100623

ESS capacity and greater than the minimum limit. In (3-8), P_{ESS} is the rate of charging and discharging, $E_{ESS,\Delta t}$ is the amount of charging or discharging in a period Δt. When P_{ESS} is greater than 0, it means charging. On the contrary, if P_{ESS} is less than 0, it means discharging. When the agent breaks these limits, the environment will give the agent a negative reward, and the agent should update its DQN model.

3.2.2 Action Space & Reward Function

These agents are designed to manage electrical appliances and ESS. Each agent is given an action space, which includes all actions that the agent can perform. After the agent selects an action based on the current state, the reward function is used to estimate the value of this action performed in the environment. The agent updates the DQN model through rewards and learns control policies that maximize rewards for the future. Due to the different characteristics of each cluster of appliances, the agents have their own action space and reward function and are independent of each other, which are described below.

- **Heavy Conflict (HC) reward & action**

The action space of the HC agent is composed of the actions to turn on or off HC appliances. The agent can choose to control a HC appliance at each time step. In addition, a special action that not controlling any appliances is also included in the action space. When the current state is good enough and changing the state of any appliance may become worse, the agent can choose not to control any appliance.

The characteristic of HC appliances is that the state of such appliances is usually related to the user location, such as lights and fans. When the user leaves the room, the

doi:10.6342/NTU202100623

HC appliances in the room can be temporarily turned off until the user returns. The reward function of the HC agent is designed based on this characteristic and shown in (3-9).

$$r_{HC} = \begin{cases} -\sum_i \sum_j L_i \oplus app_{i,j}^h, & if\ w_{i,j}^h = 1 \\ -\sum_i \sum_j app_{i,j}^h, & else \end{cases} \tag{3-9}$$

The HC reward equation is divided into two formulas based on user preferences. When the user wants to use the j-th appliance in space i, that is, $w_{i,j}^h = 1$, the agent will manage the state of the appliance based on the user's location. When there is a user in space i, the symbol L_i is equal to 1, otherwise L_i is equal to 0, and $\oplus$ is a exclusive-or symbol. Thus, the control policy of the upper formula in (3-9) is that if the user is in space i, all HC appliances in space i that the user wants to use need to be turned on, and HC appliances in other spaces can be temporarily turned off; for the control policy of the lower formula in (3-9), if the user does not want to use this appliance, it should be turned off no matter which space the user stays in.

- **Possible Conflict (PC) reward & action**

The action space of the PC agent is similar to that of the HC agent. It is composed of the actions of turning on or off the PC appliances, and the action that not controlling any appliances is also included in the PC action space. Unlike the HC agent, although the state of PC appliances is related to the user location, it is not suitable for temporarily turning off when the user leaves, such as a computer. The reward function of PC agent only considers user preferences and is shown in (3-10).

doi:10.6342/NTU202100623

$$r_{PC} = \begin{cases} \sum_i \sum_j app_{i,j}^p , & if\ w_{i,j}^p = 1 \\ -\sum_i \sum_j app_{i,j}^p , & else \end{cases} \tag{3-10}$$

The control policy of the PC agent is that if $w_{i,j}^p$ is set to 1, it means that the user wants to use the j-th PC appliance in the space i, and the agent needs to keep this appliance on for the user. On the contrary, for appliances that the user does not want to use, the agent can turn them off. In other words, the user context and user preferences inferred from CRE dominate the control policy of PC agent. In order to make the agent to take following the user behavior as the top priority, when user changes activity or manually turns on/off the appliances, the agent will not change the state of these appliances within 10 minutes. This 10 minutes allows CRE to infer the user's new activity and preferences of appliances to avoid wrong user context inference affects the user comfort.

- **Less Conflict reward & action**

The characteristic of LC appliances is that the usage time of such appliances can be deferred. Therefore, the action space of the LC agent includes the actions that scheduling the appliances to each hour. When the user does not have LC appliances that need to be used, the agent can choose the action that not to schedule any appliances. In order to reduce the user's cost and to maintain the stability of the smart grid, the reward function of the LC agent is shown in (3-11).

$$r_{LC} = -\alpha \times \sum_t EU_t \times TOU_t - \beta \times PEAK_{EU} - \gamma \times PAR \tag{3-11}$$

where EU_t is the total energy consumption in the t-th hour, TOU_t is the energy price in the t-th hour, $PEAK_{EU}$ is the maximum value of the energy usage curve in a day, and PAR is the peak to average radio value, which is defined in (3-12) and (3-13).

doi:10.6342/NTU202100623

The reward function of the LC agent contains three factors. The first factor is the cost of users. This cost is the sum of the energy price per hour multiplied by the energy consumption per hour in 24 hours. The higher the cost, the worse reward the agent will get. The second factor is the peak value of the energy usage curve. Peak demand will cause a burden on the energy supplier and affect the stability of the smart grid. A higher peak value will result in a worse reward. The third factor is the peak-to-average radio (PAR) value of the energy usage curve. An energy usage curve may have a large peak demand, but the difference between the peak and off-peak values is not significant. This kind of energy usage curve is less likely to occur the unexpected energy demand, which will lead to unstable of energy supply. Therefore, the agent should consider both the peak demand and the PAR value at the same time. When the PAR value is greater, the agent will receive the worse reward. In order to balance the impact of these three factors on rewards, α, β, and γ are normalization parameters that make the weights of these three factors are similar.

$$PAR = \frac{PEAK_{EU}}{RMS_{EU}} \tag{3-12}$$

$$RMS_{EU} = \sqrt{\left(\sum_{t=0}^{23} {EU_t}^2\right)/24} \tag{3-13}$$

- **ESS reward & action**

The ESS agent manages the ESS and energy generation from PV. ESS is an energy buffer that can store energy for use by appliances during peak demand. The energy generation from PV will also be stored in the ESS and managed by the agent. There are only three actions in the action space of the ESS agent, discharging the ESS, charging the ESS, and doing nothing. Note that the charging instructions of the ESS agent refer to buying energy from the smart grid and storing it in the ESS. Moreover, the purchased energy plus the PV generation in a time period will not exceed the charging rate limit

doi:10.6342/NTU202100623

of the ESS. The control policy of the ESS agent is to achieve load shifting by adjusting the timing of charging/discharging. The reward function of the ESS agent is shown in (3-14).

$$r_{ESS} = -\alpha \times \sum_{t} EU_t \times TOU_t - \beta \times PEAK_{EU} - \gamma \times PAR \tag{3-14}$$

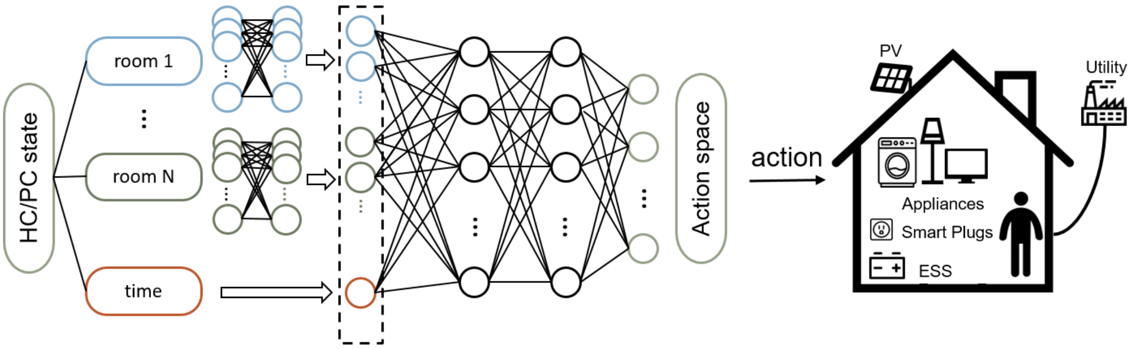
Similar to the LC agent, the ESS agent can also transfer the time to purchase energy from the grid. Therefore, its control policy is also to reduce the user's cost, the peak value of the energy usage curve, and the PAR value of the energy usage curve. The reward function is composed of these three factors multiplied by their respective normalization parameters.

These four agents select an action from their own action space every five seconds to realize the real-time management system. However, in some special cases, the flexibility of one or more appliances will be higher than usual. Since the usage time of highly flexibility appliances is irregular, we think it is unreasonable to let agents manage these appliances at this moment. Therefore, agents will temporarily not actively change the state of the appliance when the flexibility of the appliance is greater than a threshold, and the user can adjust this threshold according to their preferences.

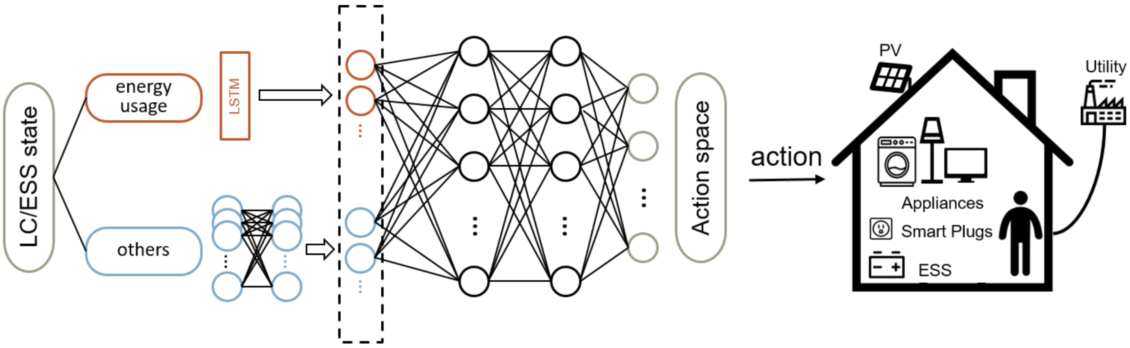
doi:10.6342/NTU202100623

3.2.3 Neural Network Architecture

After introducing the design of state space, action space and reward function, we construct the neural network (NN) as the decision DQN model of the agent, which calculates the Q value of each action. Different from our previous work [20], in this thesis, we first group the states, and then design the corresponding neural network architecture to strengthen the room-based information. The proposed model is shown in Figure 3-9. Since the definition of the state space of each agent is different, there are corresponding adjustments in the model architecture.



(a)



(b)

Figure 3-9 (a) Model architecture of HC/PC agents (b) Model architecture of LC/ESS agents

doi:10.6342/NTU202100623

In the HC and PC agents, all the state related to the location will be grouped first, including appliances, user preferences, and presence states. In order to extract the relationship between the appliances and the users, the states belonging to the same room are distributed into a group. Each group will pass through two layers of fully connected NN to extract room-based features. These two NN layers extract the high-level features that based on the room. The time information and characteristics and of these different rooms will be concatenated together. Next, another three layers of fully connected NN are designed to evaluate the value of each action in the action space. The number of neural of the last network layer is the same as the total number of actions. Each output of the neural corresponds to the Q value of an action in the given state.

On the other hand, the LC and ESS state contains the energy consumption of the past 24 hours. The model of LC and ESS agents contains a Long Short-Term Memory (LSTM) layer which is used to analyze this time-series energy usage information and explore its trends. The output of the LSTM layer is concatenated with the rest of the state except for energy usage. Similar to the model of HC/PC agents, after concatenating the extracted features and the rest states, the Q value of each action is calculated through the three layers fully connected NN. The number of neural of the last network layer should be the same as the number of actions.

3.3 Multi-user Demand Side Management

There are more than one resident living in a house is a common situation in realistic. The existing literatures lack research to distinguishing users. The system may apply the same control policy to users with different living habits, which cannot meet the expectations of users. Therefore, we want to design a multi-user DSM and provide

doi:10.6342/NTU202100623

services based on the user identity. The functions of the proposed system including assisting users to automatically manage the electrical appliances and providing the personalized energy feedback and energy saving suggestion (EFES).

3.3.1 User Energy Saving Score

In a multi-user residential house, the appliances usage habits of users are different. Some usage habits may cause some energy waste. In order to quantify the energy saving degree of user, we estimate the energy saving score for each user. When the system provides the user with energy saving suggestions, the user can choose to accept or not. Function (3-15) is the basic for calculating user energy saving score.

$$S(sign \times \log_{10} E) \tag{3-15}$$

$$S(x) = \frac{x}{\sqrt{1 + x^2}} \tag{3-16}$$

In (3-15), E is the amount of energy consumption that suggest to save, $sign$ is used to represent the user saves energy or not. If the user accepts the energy saving suggestion, it is set to 1, otherwise it is set to -1, S is one kind of the function that having a characteristic S-shaped curve and defined in (3-16). Since the energy saving score is related to the amount of energy saved after turn off an appliance, it is necessary to avoid the score being determined by a few electrical appliances that have large energy consumption. We take the logarithm of the amount of saved energy. In this way, the higher the energy saved still can earn the higher the score. At the same time, it also ensures that the low energy consumption appliances can get some score. Figure 3-10 shows the orthogonal coordinate system of function (3-16). When the user accepts the energy saving suggestion, the user will get a positive score, otherwise, the user will get a negative score.

doi:10.6342/NTU202100623

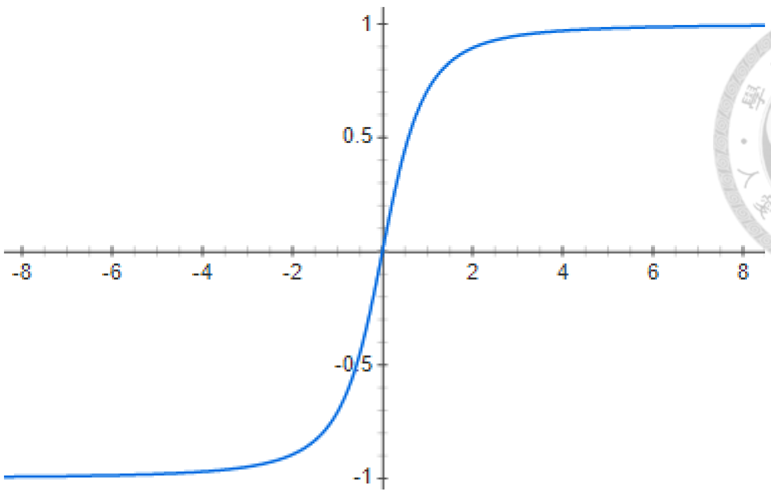


Figure 3-10 The orthogonal coordinate graph of function $S(x) = \frac{x}{\sqrt{1+x^2}}$

When a user performs multiple energy saving behaviors in succession, this needs to be encouraged. We use a memory cell to record the cumulative value of the energy saving score. When the system receives the user's response to the energy saving suggestion, the value of the memory cell will be updated through Equation (3-17).

$$Memory_{r,\,new} = S(sign \times log_{10} E) + \lambda_m \times Memory_{r,\,old} \tag{3-17}$$

where $Memory_{r,\,new}$ is the new value of memory cell of user r, λ_m is a discount factor used to avoid unlimited accumulation of energy saving score and preserve a part of the old value of memory cell. However, when the signs of $Memory_{r,\,old}$ and the output of S are different, the memory cell will be reset to 0 before updating. Since the memory cell is used to store the bonus for repeating the energy saving behaviors, it should be reset when the behavior changed. In addition, Equation (3-17) can also give the penalty score to energy waste users.

doi:10.6342/NTU202100623

The user energy saving score is defined in (3-18), the initial value of the score of all users are set to 0, while the positive value means energy saving and the negative value means energy waste. This score will be updated immediately after the value of memory cell is updated.

$$Score_{r,\,new} = \lambda_s \times Score_{r,\,old} + Memory_{r,\,new} \tag{3-18}$$

where $Score_{r,\,new}$ is the new energy saving score after user r accepts or refuses the suggestion, λ_s is a discount factor that preserve some energy saving habits of the user, $Memory_{r,\,new}$ is the bonus for performing the energy saving behaviors multiple times in succession. Therefore, there are two factors that related to the user energy saving score, including whether the user is a long-term energy saving person and whether the energy saving behavior is continuous.

3.3.2 Energy Saving Suggestion Decision

When users live in a house, they will need a certain amount of energy consumption to meet their daily needs. We call it basic energy consumption. Due to the habit of appliances usage and the lack of understanding of appliances consumption, the actual energy consumption will be greater than the basic energy consumption. The purpose of the DSM system is to reduce energy waste and make the actual energy consumption close to the basic energy consumption. However, a general DSM system will consider the user comfort, even if the user habit will waste some energy, which forms a bottleneck in energy saving. Therefore, DSM system still has undeveloped energy saving potential in improving user habits. After analyzing the appliances usage habits of users, the proposed system will provide users with energy saving suggestion when the power consumption is higher than the threshold. The suggestion has played a

doi:10.6342/NTU202100623

function of reminding and enhancing energy saving habits of users.

First, CRE will identify the user context. At the same time, the system will calculate the current user's energy consumption and compare it with the past electricity consumption. In the same user context, if the current power consumption is greater than the historical power consumption, it means that the user may be able to complete the same activity with less energy consumption. At this time, the system can suggest the user to turn off some unnecessary electrical appliances. The next step is to decide which appliance the user may be willing to turn off and put it in the suggestion. From the flexibility value mentioned in Section 3.3, we can know the regularity of electrical appliances. We think that high-flexibility appliances are more suitable to be included in energy saving suggestions because users will not insist on using these appliances at a fixed time. On the contrary, low-flexibility appliances are not suitable for energy saving suggestions since usage time of these appliances usually does not change. However, in order to avoid the system suggesting a user to turn off an appliance that is important to other users, the system will only make energy saving suggestions based on the appliances that used by the suggestion receiver.

In addition, there may have some conflicts of appliance usage between users in a multi-user household. Such as that one user wants to turn on an appliance and another user does not. The system should not make the decisions that will sacrifice the comfort of any user. We want to design the energy saving suggestion that allow the energy saving user to guide other users. Assuming that users have high energy saving score, they seldom leave the unnecessary appliances operating. When the system decides a highly flexible appliance that is suggested to be turned off for a user, it will avoid suggesting that the user turn off the appliances which is using by the users with higher energy saving score. This reflects two things. The first thing is that if a user accepts the

doi:10.6342/NTU202100623

energy saving suggestion, his energy consumption pattern will be closer to the user with high energy saving score. The second thing is that users with a high energy saving score will have additional benefits. The appliances they used will not appear in energy saving suggestions from users with lower score. In other words, their rights to use appliances are less likely to conflict with other users. We take the energy saving score as a priority to improve the conflict problem of appliances. As shown in Figure 3-11, Algorithm 2 is the proposed energy saving suggestion decision algorithm.

Algorithm 2 Energy Saving Suggestion Decision

for each resident r in the house **do**
    $\text{context}_r \leftarrow \text{CRE}(r)$
    if $\text{EC}_{now} >$ average EC_{his} of context_r **then**
        $\text{F} \leftarrow \varnothing$
        for each a in UsingList[r] **do**
            $\text{F} \leftarrow \text{F} \cup (a, \text{flexibility}(a))$
        end for
        sort F by second key in decreasing order
        for each a in F **do**
            if a not in use by any other resident k that $\text{Score}_k > \text{Score}_r$ **then**
                SuggestTurnOff(r, a)
                break
            end if
        end for
    end if
end for

Figure 3-11 Algorithm 2: An algorithm for determining the energy saving suggestions

doi:10.6342/NTU202100623

Figure 3-12 shows the flowchart of Algorithm 2. The proposed system will provide energy saving suggestion for the user whose power consumption exceeds the threshold. The threshold is defined as the average of the historical power consumption in the same user context. When the current power consumption of the user is greater than the threshold, the appliances that user is using by this user will be sorted according to the appliance flexibility value. Next, the system checks which appliances are also being used by other users with higher energy saving score and excludes them. Among the remaining appliances, the one with the highest flexibility will be included in the energy saving suggestion.

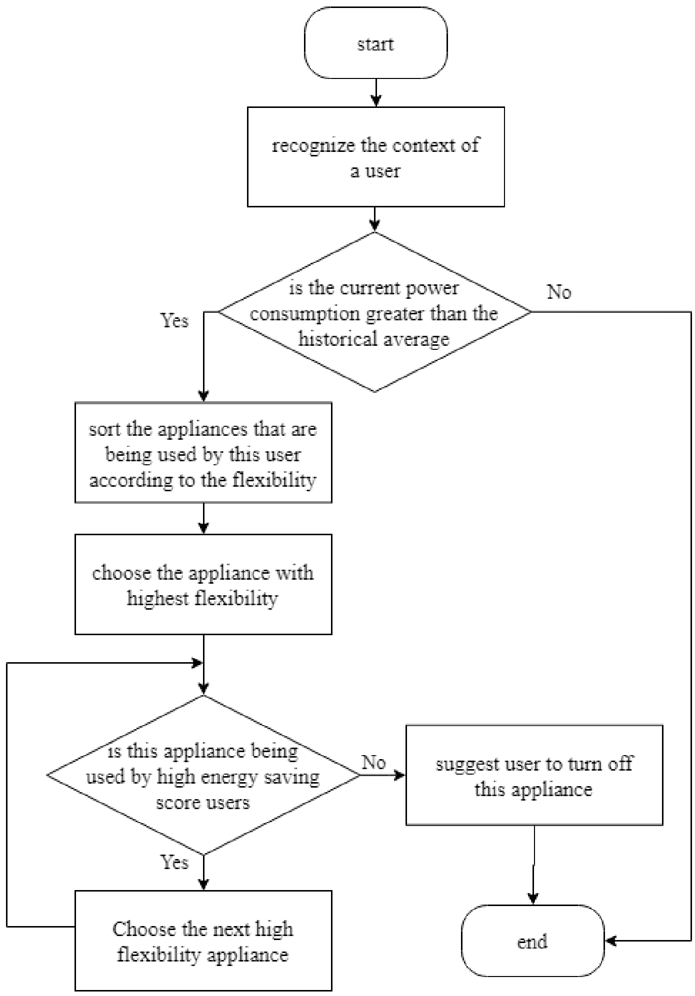


Figure 3-12 Flowchart of providing energy saving suggestions

doi:10.6342/NTU202100623

3.3.3 AR Localization and Interface

We assume that every user is equipped with an AR device at home. As shown in Figure 3-13, an application is designed to collect user information and provide an interface for user to communicate with DSM. Figure 3-14 shows the flowchart of the application. First, a login system is designed to obtain the user identity and his past data. With the login system, the device does not have to be bound to the same user. When some users are not at home, the AR device at home can be shared by switching logged-in user. Through SLAM technology and the camera on the AR device, the system can construct a map of the home environment and maintain the coordinates of the camera in the real world. Each active device will transmit its coordinates to the DSM system every five seconds. Assuming that every user at home is wearing the AR device, the device location can represent the location of users.

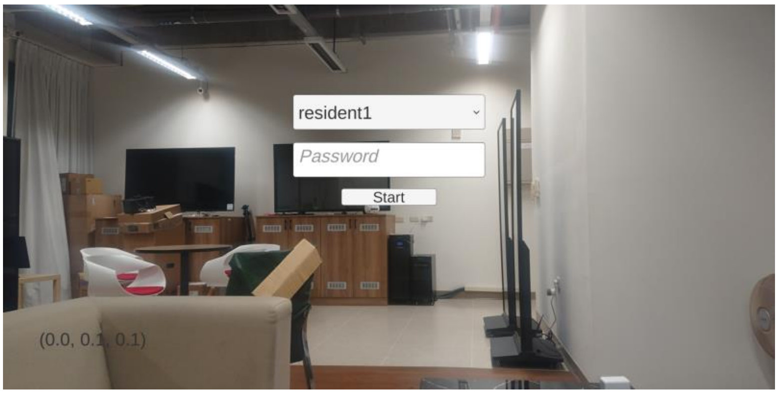


Figure 3-13 The AR application used to provide energy information

doi:10.6342/NTU202100623

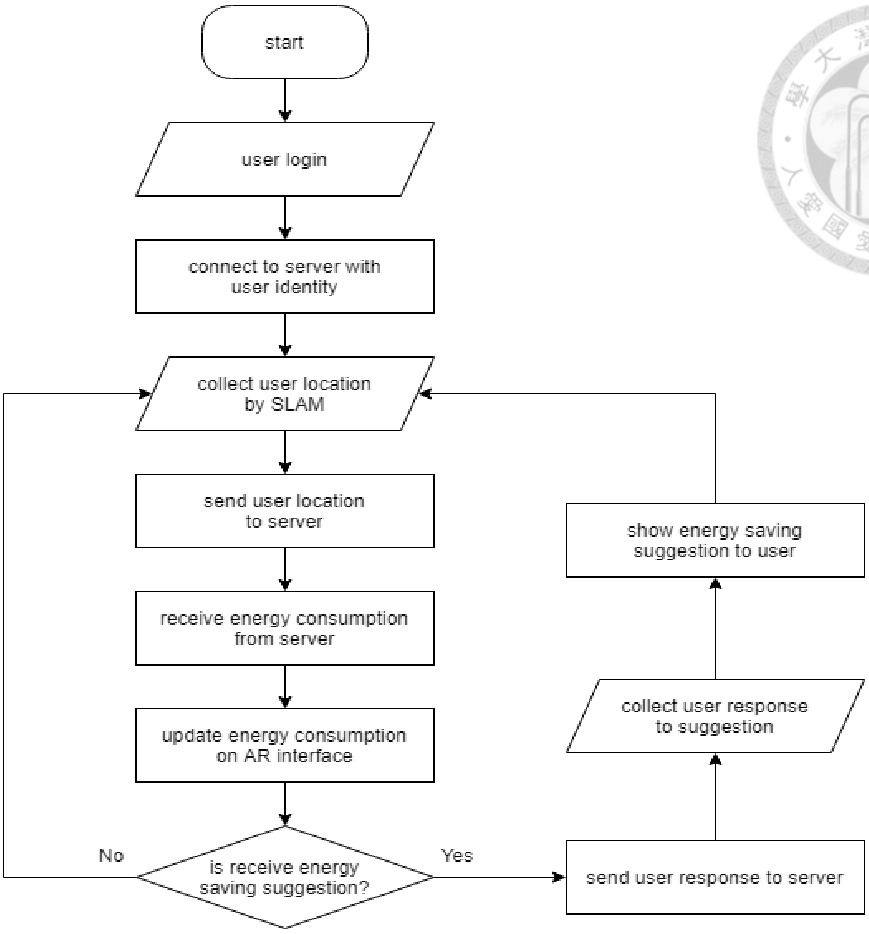


Figure 3-14 Flowchart of AR application

This application can receive two kinds of messages at any time, one is the energy consumption of electrical appliances and the other is energy saving suggestions. However, the energy consumption information may be too abstract for the users. We convert the energy consumption into cost before displaying it to user. The DSM system uses Algorithm 1 in Section 3.4 to determine the list of appliances that each user is using. Therefore, the application will only receive the energy consumption information related to the logged-in user and display the current electricity cost in the corner of the screen. The user can quickly display or hide the cost details of each appliance with a simple click. For the second type of message that the application will receive, energy saving suggestion message, this message contains the appliance suggested to the user to turn off, which is determined by Algorithm 2. After receiving a suggestion, the

doi:10.6342/NTU202100623

application will calculate the cost saved by turning off the appliance. The suggestion and benefits are provided to the user at the same time. The user can simply click to agree or disagree with this suggestion. A reply message will be sent to the DSM system and execute the control command if user agree this suggestion.

We implemented this application on Magic Leap [35] and Android smartphone. These devices can be connected to our system server at the same time to maintain the information of multiple users in a smart home. The summary of communication between AR device and DSM system is shown in Figure 3-15. By exchanging the information of energy consumption, energy saving suggestions and user control commands, the connection between the user and the electrical appliances can be established. When the AR technology becomes more mature, this application can also be implemented on the other lighter AR device, which improves user acceptance of AR device without affecting the performance of the proposed system.

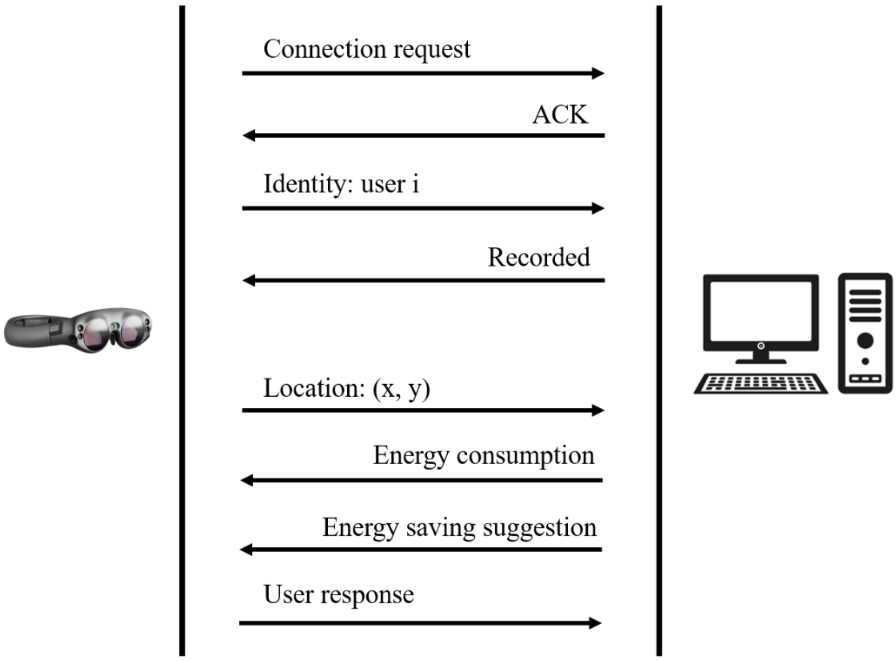


Figure 3-15 Communication between the AR device and the system server

doi:10.6342/NTU202100623

Chapter 4

System Evaluation

In order to evaluate the DSM system, the current data format of the public datasets is usually the energy consumption of appliances recorded in a few days to several weeks. Some datasets even only contain the household energy consumption rather than appliance level information. However, the proposed system includes agents to automatically manage electrical appliances and also includes energy feedback and energy saving suggestions (EFES) to enhance users' self-awareness of energy saving. In order to evaluate the proposed system, the data needs to include appliance and EFES information. We set up a smart home environment and implemented the DSM system on the computer and the AR application on Magic Leap and Android smartphone. Several users are invited to our smart home to stay for hours. The environment state when the users stay at home is recorded. With these recorded data, the system evaluation includes the evaluation of appliance flexibility, energy saving suggestions, DQN agents and multi-user smart home.

doi:10.6342/NTU202100623

4.1 Data Collection

With our smart home environment, there are seven electrical appliances placed in this environment. These electrical appliances are powered by sockets, so that we can collect and record appliance-level information. SmartThings Smart Plug is used in this thesis, each electrical appliance is connected to a smart plug to measure energy consumption and control the power connection. The location of these appliances and the environment space are shown in Figure 4-1. Due to the design of the building, this space does not have an indoor bathroom. We divide this space into bedroom, living room and kitchen. Users will randomly perform some activities in these places. For every user at home, they are required to wear an AR device, which can collect the identity and location of user. The user information and appliance information collected by the smart plug will be sent back to the DSM server and recorded every five seconds.

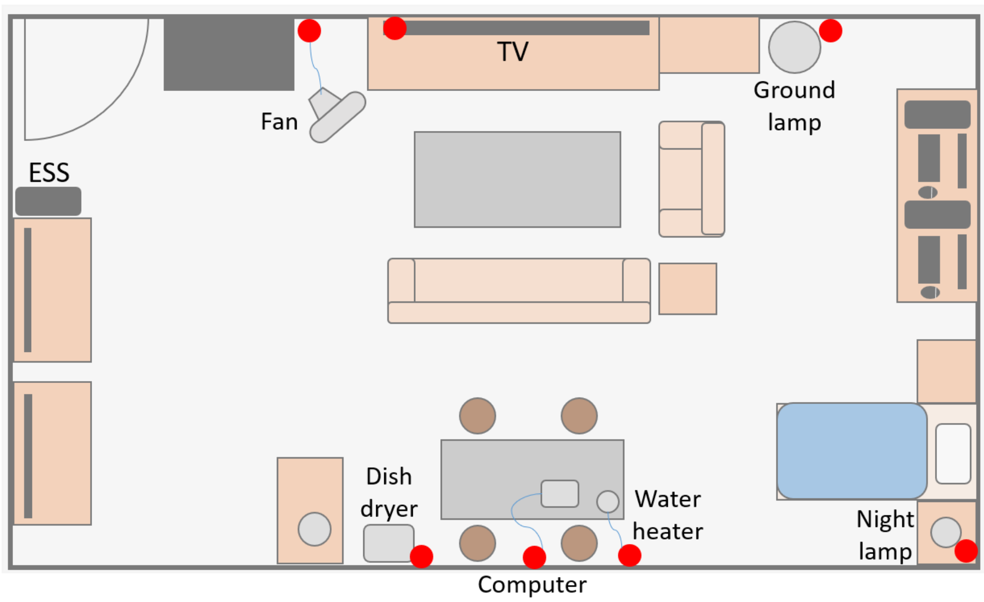


Figure 4-1 Electrical appliances configuration

doi:10.6342/NTU202100623

Table 4-1 Specification of energy storage system

Manufacturers	Capacity	Charge		Discharge
		Voltage	Current	Voltage
Flight Tech.	6 kWh	220 Vdc	1-4 A	220/110 Vac, 60Hz

The proposed system includes ESS and PV. A programmable energy storage device is installed in this experiment environment. Table 4-1 shows the specifications of this energy storage device. However, we set a limit that the ESS state of charge must be greater than 0.9 kWh to avoid damage to the battery due to low power. The value of 0.9 is determined from 15% of the maximum capacity of this energy storage device. Regarding the PV system, since we do not have solar panels, a PV module is used to record and predict solar power generation through the autoregressive moving average model, which was also used in our previous work [20].

Table 4-2 User activity list

index	1	2	3	4	5	6	7
activity	watch TV	use computer	sleep	wash dish	eat food	study	boil water

Based on the electrical appliances in our smart home environment, we designed seven activities and listed them in Table 4-2. Eight users were invited to this environment to perform activities in three scenarios. For each scenario, the user needs to perform twelve activities, which are randomly selected from the activities in Table 4-2. Some activities may be performed more than once at different times. For each activity, the user needs to perform the activity for about an hour and then change to the next activity. In order to have a whole day data to evaluate the proposed system, we assume that the rest of the day is sleep time and night light is used. To compare the

doi:10.6342/NTU202100623

performance of the system in different scenarios, the user will perform the same twelve random activities in each scenario, and the error value of the experiment results caused by the random activities can be reduced. In other words, the user needs to repeat the same twelve random activities three times. The random activities performed by each user are shown in Table 4-3, where the numbers correspond to the index in Table 4-2.

Table 4-3 Twelve indexed activities for eight users

User	#1~#6 activities	#7~#12 activities
#1	2, 4, 3, 3, 5, 3	7, 4, 4, 7, 5, 1
#2	5, 7, 6, 1, 1, 2	3, 5, 3, 4, 2, 6
#3	3, 6, 6, 2, 7, 4	1, 4, 1, 3, 5, 6
#4	1, 6, 2, 5, 7, 3	1, 2, 1, 7, 2, 3
#5	7, 1, 5, 3, 7, 6	3, 3, 2, 5, 4, 7
#6	7, 1, 2, 2, 5, 6	6, 1, 6, 5, 3, 3
#7	5, 1, 5, 3, 4, 1	2, 7, 5, 7, 4, 1
#8	5, 2, 3, 1, 3, 3	7, 7, 4, 1, 4, 5

The first scenario is used as a control group. The system only records the location of user and the state of the appliances. The agents and EFES modules in the energy saving layer will not be activated. The second scenario is used to evaluate the performance of EFES. The system will provide the energy feedback and energy saving suggestions. As in the first scenario, the location of user and the state of the appliances will be recorded. The third scenario is a multi-user home. Two users perform their activities in the smart home environment at the same time. They may share some appliances to perform the same activities, or they may perform independent activities separately. In this scenario, the system will also provide energy feedback and energy saving suggestions. The location of users and the state of the appliances will be recorded. In addition, the multi-user home scenario also needs a control group for comparison.

doi:10.6342/NTU202100623

According to the identity of the users in the same group in third scenario, we merge the data collected by them in the first scenario two by two. The merged result represents a scenario that the system does not provide EFES in a multi-user home.

After collecting the data of each user in the three scenarios, we use three criteria to evaluate our system, namely the peak of the energy usage curve, peak-to-average ratio (PAR) and the cost of energy consumption in a day. These three criteria are often used to evaluate a DSM system.

The peak value of the energy usage curve is the maximum energy consumption in a day. Since the energy supplier needs to meet the energy demand of users at any time, the large peak demand will cause the cost of the utility company to increase. The second criterion, PAR is a value related to the curve waveform, which is defined in Equation (3-12). If there are more users living in a house, the total amount of energy consumption may be higher, resulting in higher peak demand. However, this peak demand is acceptable if the energy consumption curve is a flat waveform. As shown in Figure 4-2, the peak demand of the energy consumption curve on the left image is much higher than the demand at other hours, which causes problems when the utility company determines the amount of energy generation. However, although the peak demand in the right image is higher than the left image, the curve of right image is smoother, which

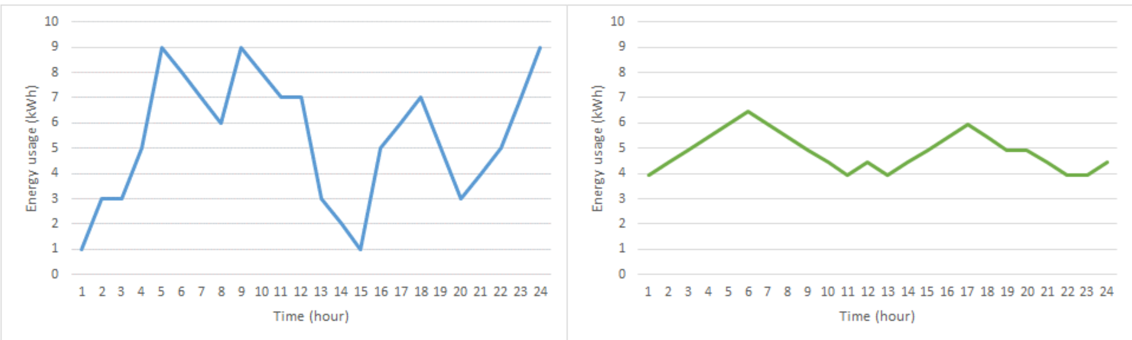


Figure 4-2 Non-smooth curve (left) and smooth curve (right)

doi:10.6342/NTU202100623

is less likely to make the utility company to generate insufficient or surplus energy. Generally speaking, the PAR value of the energy curve similar to the right image is smaller than the PAR value of the left image. Therefore, PAR is an important criterion and needs to be minimized.

The third criterion is the cost of energy consumption as defined in (4-1), which is the value that users want to reduce. The cost is sum of the energy usage multiplied by the energy pricing of 24 hours.

$$cost = \sum_t EU_t \times TOU_t \tag{4-1}$$

where t is the hour, EU_t is the energy usage at hour t, TOU_t is the time-of-use energy pricing. In Taiwan, the time-of-use (TOU) pricing model of the utility company includes two prices, peak price and off-peak price. The peak hour of the day is from 7 am to 10 pm and the corresponding electricity price is 4.44 (NTD/kWh), the rest of the day is off-peak time, and the corresponding electricity price is 1.8 (NTD/kWh). The TOU electricity price for a whole day is shown in Figure 4-3.

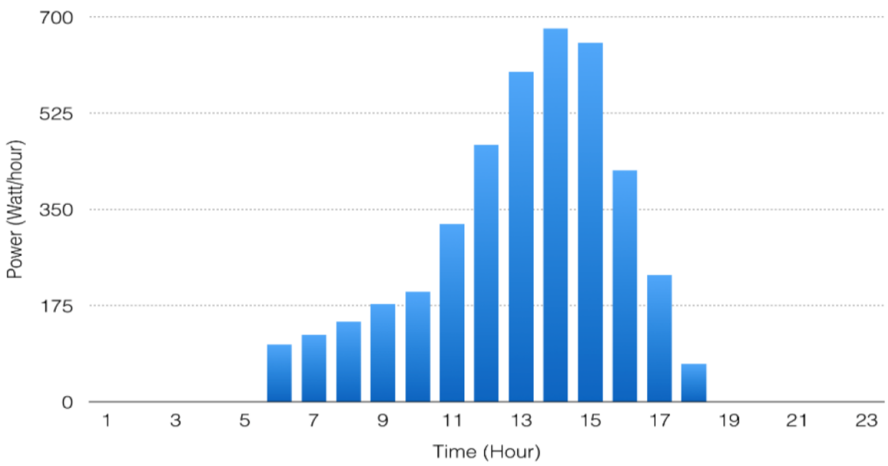


Figure 4-3 Solar power production in one day

doi:10.6342/NTU202100623

The self-defined parameters in some equations and their default values are described as following:

Table 4-4 Self-defined parameters

Parameter	Description	Value
ESS_{max}	maximum capacity of ESS	6 (kWh)
ESS_{min}	minimum capacity limit we set to protect the equipment from over-discharge	0.9 (kWh)
α	normalization parameter of cost in the reward function of LC/ESS agent	0.04
β	normalization parameter of peak in the reward function of LC/ESS agent	1
γ	normalization parameter of PAR in the reward function of LC/ESS agent	3
λ_m	discount factor of value of memory cell	0.8
λ_s	discount factor of energy saving score	0.8

4.2 Evaluation of Appliances Flexibility

Appliance flexibility based on the definition of Equation (3-2) is used to represent the regularity of appliance usage time. There is no optimal value for the flexibility of an appliance, only the suitable flexibility value for describing an appliance. Flexibility is a required value to provide customized services for different users. As shown in Figure 4-4, the x axis represents hour, and the y axis is the flexibility value. There are appliance flexibilities of computer, TV and water heater of three users, where the flexibility of the same user is displayed in the same row; the flexibility of the same appliance is displayed in the same column. Each line chart is one appliance flexibility for a user in a day. As we can see, the flexibility value will vary according to the user, the type of appliance, and the time of day. Thus, appliance flexibility is a necessary value for the system to determine corresponding policies for different users.

doi:10.6342/NTU202100623

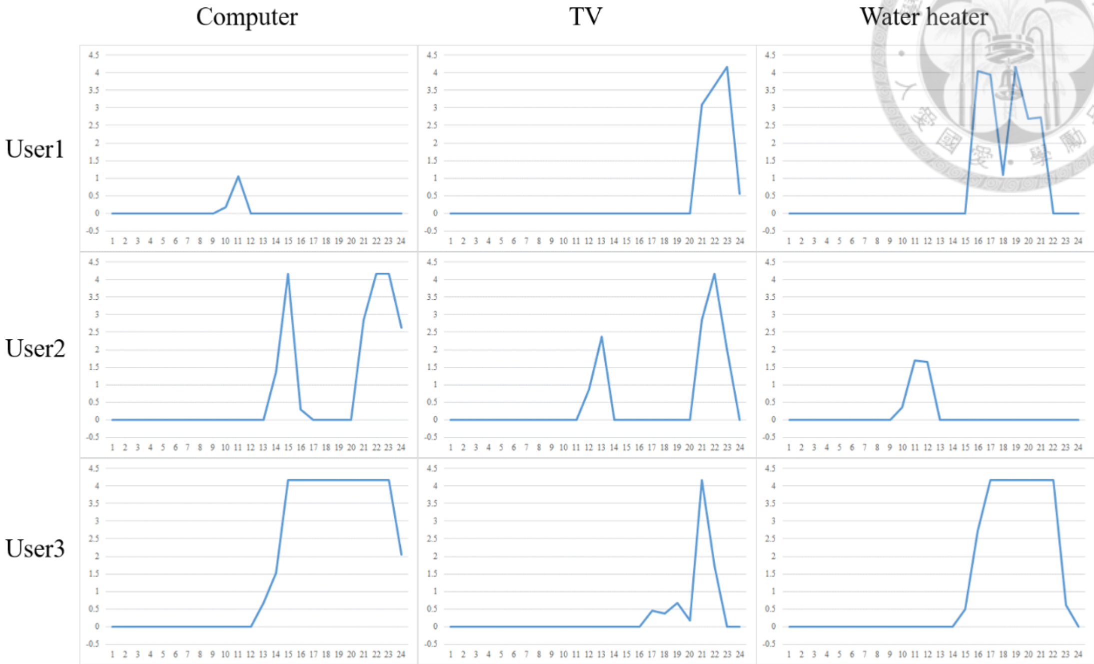


Figure 4-4 Three appliance flexibility of three users

In this thesis, the value of flexibility is used for comparison. When the system is deciding on energy saving suggestions, a comparison of flexibility will occur among appliances, and the appliances with higher flexibility are selected. Since the usage time of these appliances is variable, users may be willing to reduce or change the usage time of these appliances. In addition, flexibility comparison will also occur when the system decides whether to automatically manage some appliances. A threshold value is used to compare with the flexibility of the appliance. If the flexibility is greater than the threshold, it means that the usage habit of appliances is unstable. The system should not guess the user preference and turn the appliance on or off.

doi:10.6342/NTU202100623

4.3 Evaluation of Energy Saving Suggestion

Energy feedback and energy saving suggestions (EFES) are part of the functions of the proposed system. Its purpose is to enhance users' self-awareness of energy saving and enable them to perform energy saving behaviors. Table 4-5 shows the user's daily cost in scenario 1 and scenario 2. In these two scenarios, the system will not automatically change the state of any appliances. Furthermore, the user will receive the EFES provided by the system in scenario 2, but not in scenario 1.

Table 4-5 User daily cost in scenario 1 and scenario 2

User	Scenario 1	Scenario 2	Difference	
	Cost	Cost	Cost reduction	Acceptance rate of suggestions
#1	48.37	47.23	-2.36%	33%
#2	75.47	78.99	4.67%	50%
#3	79.50	48.89	-38.50%	60%
#4	93.97	79.85	-15.02%	67%
#5	65.80	55.51	-15.64%	67%
#6	105.79	73.90	-30.15%	50%
#7	60.59	54.30	-10.39%	67%
#8	56.99	57.37	0.67%	50%
		AVG :	**-13.34%**	**56%**

For users 1, 2, 8 in the Table 4-5, their cost has not changed much with or without EFES provide by the system. We observed their appliance usage and did some analysis. Since users 2 and 8 used more appliances in scenario 2, even if they accepted the energy saving suggestions and reduced the usage time of some appliances, the cost would still increase slightly. However, user 1 is less willing to reduce the usage time of appliances to save costs, resulting in a small cost reduction. In addition, for the other five users,

doi:10.6342/NTU202100623

EFES serves as a reminder, allowing users to think about whether they do not need to use some electrical appliances. Then, the users will reduce the use of these appliances to save costs.

4.4 Evaluation of Deep-Q Network Agents

There are four DQN agents in the proposed system, namely HC, PC, LC and ESS agent, as described in Section 3.5. These agents will adjust the control policies according to their reward function. Table 4-6 shows the energy consumption of the second scenario that with EFES and additional apply the DQN agents, and compared it with scenario 1. After applying the proposed system, the reduction of peak value, PAR and energy cost are calculated. Reducing the peak value of the energy consumption curve and reducing the energy cost is the intuitive goal of smart grid. Reducing PAR is also equivalent to reducing the peak energy demand, while avoiding the large fluctuations in the energy consumption curve.

Table 4-6 Detail of cost, peak and PAR reduction with or without the agents

User	w/ suggestion only			w/ suggestion & agents			Difference		
	Cost	Peak	PAR	Cost	Peak	PAR	Cost	Peak	PAR
#1	47.23	1.37	2.21	37.55	0.94	1.55	-31.57%	-29.77%	-20.48%
#2	78.99	2.05	1.87	53.88	1.23	1.57	-40.15%	-15.75%	-31.79%
#3	48.89	1.08	1.72	41.38	0.86	1.44	-19.61%	-16.43%	-15.36%
#4	79.85	1.83	1.79	44.37	0.86	1.43	-53.22%	-20.19%	-44.44%
#5	55.51	1.77	2.36	37.76	1.01	1.71	-42.71%	-27.79%	-31.97%
#6	73.90	1.68	1.79	67.25	1.51	1.75	-10.44%	-2.15%	-9.00%
#7	54.30	1.59	2.24	44.38	1.10	1.71	-31.09%	-23.68%	-18.27%
#8	57.37	1.30	1.77	44.52	0.95	1.49	-27.16%	-15.55%	-22.40%
						AVG :	-31.99%	-18.91%	-24.21%

doi:10.6342/NTU202100623

Due to the different living habits of each user, the proposed system has different performances for different users. After applying the proposed system, the user cost, peak value and PAR value can be reduced. For users 3 and 6, they have saved at least 30% of their costs through energy saving suggestions, and the cost that the agent can save is limited. Figure 4-5 shows the energy usage of user 6. The blue line is the energy usage curve when the system only provides energy feedback and energy saving suggestions (EFES); the red line is the energy usage curve when both EFES and the agents are applied. There are two obvious intersections between the blue line and the red line. They are between 9 a.m. to 10 a.m. in the morning and 9 p.m. to 10 p.m. in the evening. After 10 a.m., it is usually the peak hour for electricity demands. The proposed system can manage ESS and schedulable appliances to transfer some energy to the off-peak hours at night. This load shifting can not only reduce the user cost, but also reduce the peak value and PAR value of the energy usage curve. In addition, the agent will also assist users to turn off some unnecessary electrical appliances to save more energy. In the result, the agents reduced the 31.99% of cost, 18.91% of the peak value, and 24.21% of the PAR value in average.

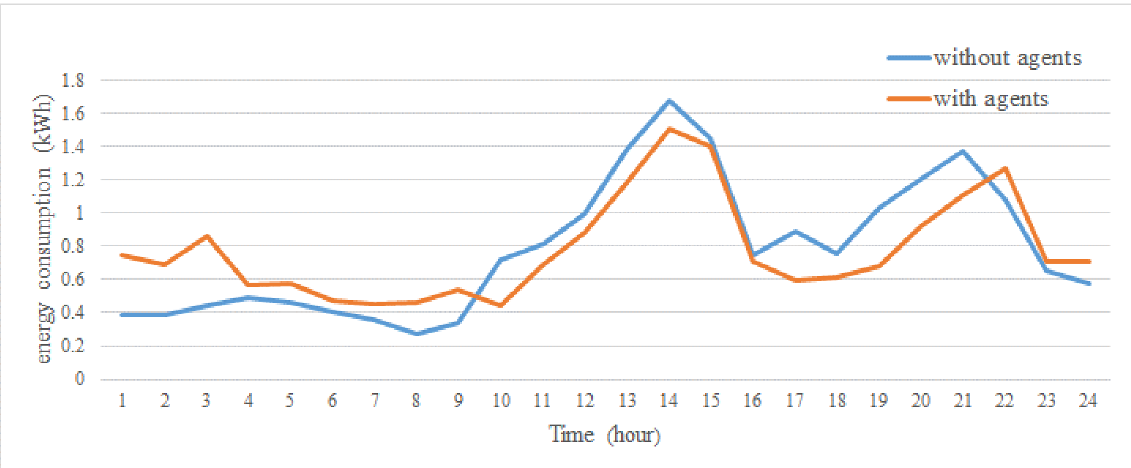


Figure 4-5 Energy usage of user 6 in one day

doi:10.6342/NTU202100623

4.5 Evaluation of Multi-User Smart Home

In the third scenario of our data collection, two users stay in the smart home environment to perform their activities at the same time. The system will give the two users their own energy feedback and energy saving suggestions. However, according to the Algorithm 2, the electrical appliances used by higher energy saving score user are less likely to be suggested to be turned off. After applying the control policy of the agents to the collected data, the performance of the proposed system in the multi-user smart home is shown in Table 4-7.

Table 4-7 Performance of the proposed system in multi-user smart home

User	w/o suggestion & agent			w/ suggestion & agents			Difference		
	Cost	Peak	PAR	Cost	Peak	PAR	Cost	Peak	PAR
#1 & #3	90.18	2.07	1.78	55.80	1.13	1.49	-38.12%	-45.47 %	-16.21%
#2 & #4	100.95	2.25	1.75	52.47	1.30	1.72	-48.02%	-42.43%	-1.68%
#5 & #6	109.36	2.21	1.58	57.45	1.19	1.56	-47.46%	-45.96%	-0.93%
#7 & #8	69.84	1.48	1.64	56.54	1.39	1.72	-19.04%	-6.27%	4.71%
						AVG :	**-38.16%**	**-35.03%**	**-3.53%**

In the multi-user scenario, the proposed system can help users reduce cost, peak and PAR value at most of the time. However, in the group of users 7 and 8, their PAR value increased instead. According to the definition of PAR in Equation (3-12), its value is related to the peak value and energy usage during the day. This increase in PAR value is due to the decrease in cost at uneven hours. The group of users 7 and 8 are more economical than other groups in the situation without the proposed system. Since the cost and peak value of this group are the least, the performance of the DSM system will be limited. The proposed system can still achieve the 19.04% cost reduction and the

doi:10.6342/NTU202100623

6.27% peak reduction in this group. Therefore, we think this slightly increase in PAR value is acceptable. In general, the proposed system can achieve average reductions of 38.16%, 35.03%, and 3.53% in cost, peak value, and PAR value in multi-user smart home evaluation, respectively.

Another evaluation is to compare the difference between the multi-user situation and the single-user situation. In Algorithm 2, the proposed system maintains the electrical appliances used by users with high energy saving score through suggestions, and expects other users to learn the usage habits of them. Table 4-8 shows the user cost of the single-user scenario and the multi-user scenario. In the table, every two users are grouped together and displayed in the same row. Group 1 includes users 1 and 3, group 2 includes users 2 and 4, and so on. When multiple users live together, there will be more electrical appliances that must be used than a single-user house. Electrical appliances that one user does not need to use may be needed by another user, and the cost saved in a multi-user house will be less than the sum of cost that can be saved when each user lives alone. In addition, Table 4-9 shows the energy saving scores of each

Table 4-8 Cost comparison between the single-user house and multi-user house

User	**Single-user cost**			**Group**	**Multi-user cost**		
	Original	Proposed	**Difference**		Original	Proposed	**Difference**
#1	48.37	37.55	**-10.82**	#1	90.18	55.80	**-15.06**
#3	79.50	41.38	**-38.12**				**-19.31**
#2	75.47	53.88	**-21.59**	#2	10 0.95	52.47	**-23.33**
#4	93.97	44.37	**-49.60**				**-25.15**
#5	65.80	37.76	**-28.04**	#3	109.36	57.45	**-29.31**
#6	105.79	67.25	**-38.54**				**-22.59**
#7	60.59	44.38	**-16.21**	#4	69.84	56.54	**-7.26**
#8	56.99	44.52	**-12.47**				**-6.04**

doi:10.6342/NTU202100623

user in the single-user scenario and a multi-user scenario, when the proposed system is applied to user 3 alone, user 3 accepts more energy saving suggestions and saves more cost than user 1, so user 3 has higher Energy saving score; however, when two users live in a smart home environment at the same time, the energy saved by user 1 and user 3 are closer than the scenario they live separately, and the similar results also occurred in the group of user 7 and 8. The proposed Algorithm 2 allows users to learn the habits of energy saving users, and lets the amount of saved energy by users live in the same house are similar.

Table 4-9 Comparison of energy saving score between single user and multi-user

User	Energy saving score	
	Single-user scenario	Multi-user scenario
#1	-1.65	-0.30
#3	2.50	2.53
#2	0.34	0.23
#4	2.03	2.37
#5	0.83	0.72
#6	0.68	0.47
#7	2.42	2.71
#8	-1.53	-0.93

4.6 Evaluation of User Satisfaction

User satisfaction is mainly to investigate whether users are satisfied with the implemented AR interface and the energy feedback and energy saving suggestions provided by the system. We asked eight users to fill out an online satisfaction survey after experiencing the proposed system. This survey contains five questions. For each

doi:10.6342/NTU202100623

question, users can choose an integer score from 0 to 5. Table 4-10 shows the content of the questions and the average score get from the eight users. When designing the energy feedback and energy suggestions, we hope to design an easy-to-use and useful interface. The survey questions are also designed for these goals to find out the direction for future improvements. According to the results, users mostly agree that the proposed system has the following advantages:

- The proposed system is easy-to-use.
- The proposed system that integrates energy saving suggestions and automatic management system is satisfactory.
- The proposed system will not disturb the user's daily life.

However, there still has the potential for improvement in the content of energy saving suggestions. As shown in Table 4-5 in Section 4.3, the average acceptance rate of users for energy saving suggestions is 56%, but the acceptance rate between different users is various. We think that the proposed system should be adjusted according to the user's acceptance rate of suggestions. For users who often refuse or ignore the energy saving suggestions, the system should reduce the frequency of providing energy saving suggestions to avoid disturbing the users.

Table 4-10 Survey of user satisfaction

Questions about the satisfaction of the proposed system	Average score (0~5)
1) This system is easy-to-use for the first time users.	4.750
2) Are you satisfied that this system integrates energy saving suggestion and automatic management instead of letting the system controlling all appliances?	4.500
3) Are you satisfied with the content of energy saving suggestions?	3.875
4) This system will not affect your living habit.	4.375
5) Assuming that AR technology is popular, are you willing to use this system in your home?	4.500

doi:10.6342/NTU202100623

Chapter 5

Conclusions

5.1 Summary

The problem addressed in this thesis is the energy efficiency of multi-user residential houses. A multi-user demand-side management system that integrates users' self-awareness of energy saving and automated control agents is proposed. We think that appliances with irregular usage time are not suitable for automatic management by the system since it is difficult for the system to accurately guess the thoughts of users. In this thesis, the usage time distribution of appliance is estimated through MLE, and the flexibility of the appliance is defined as the entropy of the usage time distribution. The more irregular the usage time of the appliance, the greater the flexibility. Therefore, unlike common fully automated control systems, the proposed system saves energy from two aspects. The first aspect aims to improve the users' self-awareness of energy saving to save energy. The system will provide each user with energy feedback and energy saving suggestions. Energy feedback will provide the energy consumption of appliances to users so that they can know the cost of each appliance and each activity; besides, the proposed algorithm, energy saving suggestion decision, which discovers the appliance that has energy saving potential and asks users whether they are willing to reduce the usage time of this appliance. The second aspect is to use agents to

doi:10.6342/NTU202100623

automatically manage electrical appliances and ESS to save energy. There are four agents to manage three types of appliances and one ESS. These agents can not only help users to automatically turn on or off some electrical appliances to improve the convenience of users' life. It can also arrange the execution time of the schedulable appliances and determine the timing of ESS to charging or discharging to achieve load shifting. In order to know which appliances the user wants to use, CRE is used to identify the current user context, and the appliances preferences of user can be further inferred.

Furthermore, an AR application that can be executed on Magic Leap and android smartphone is implemented to provide a human-computer interaction interface between the user and the system. This application helps the proposed system collect user identity and user location information. The user identity is collected by a login system. After the user logs into the system, the visual SLAM technology is used to construct a map of the environment and locate the user's location in real time. This application returns the identity and real-time location of user to the system server through the internet, and receives energy feedback and energy saving suggestion from the server and displays them through the AR interface.

In the results of the system evaluation, the flexibility evaluation of appliances shows that the flexibility will be changed according to user habits, types of appliances and time. Due to irregular usage time of high flexibility electrical appliances, an energy management system should not automatically change the state these of these appliances to avoid violating the user's appliance preferences. Therefore, the flexibility of appliances is an important indicator for maintaining the user comfort. In terms of performance, the proposed system was evaluated in multiple scenarios. First, in the evaluation of energy feedback and energy saving suggestions (EFES), although the cost

doi:10.6342/NTU202100623

reduction of EFES is uneven among different users, the system can still achieve an 13.34% of average cost reduction among eight users. Second, in the evaluation of DQN agents, in addition to considering user cost, these agents also have the important goals to reduce the peak value and the PAR value of the energy usage curve. Based on the results of EFES evaluation, the proposed system can still achieve the additional 31.99% of cost reduction, 18.91% of peak reduction and 24.21% of PAR reduction. Finally, in the evaluation of multi-user house, the proposed system can achieve 38.16%, 35.03% and 3.53% of cost reduction, peak reduction and PAR reduction, respectively. Since multiple users need to use more electrical appliances, the cost reduction per person is likely to be less than the cost reduction for a single user. However, the proposed system provides the energy saving suggestions so that the users can learn the appliances usage habits of high energy saving score users.

5.2 Future Work

In future work, the frequency of energy saving suggestions can be adjusted according to the user's energy saving score, and the probability of the user accepting each energy saving suggestion can be estimated. For users who are less willing to save energy, the system can only provide suggestions that have a higher probability of being accepted. In addition, in order to enhance the self-awareness of energy saving, the system can sort out each user's energy consumption habits and allow all users to compare with each other, thereby improving their energy consumption habits.

doi:10.6342/NTU202100623

REFERENCE

[1] IEA (2019), "Global Energy & CO2 Status Report 2019", IEA, Paris https://www.iea.org/reports/global-energy-co2-status-report-2019

[2] IEA (2019), "Electricity Information 2019", IEA, Paris https://www.iea.org/reports/electricity-information-2019

[3] B. P. Esther and K. S. Kumar, "A survey on residential Demand Side Management architecture, approaches, optimization models and methods", Renewable and Sustainable Energy Reviews, pp. 342-351, 2016.

[4] B. Mahapatra and A. Nayyar, "Home energy management system (HEMS): concept, architecture, infrastructure, challenges and energy management schemes", Energy Systems, pp. 1-27, 2019

[5] P. G. Balaji and D. Srinivasan, "An Introduction to Multi-Agent Systems", Innovations in Multi-Agent Systems and Applications - 1, Springer, Berlin, Heidelberg.

[6] K. Buchanan, R. Russo, and B. Anderson, "Feeding back about eco-feedback: How do consumers use and respond to energy monitors?", Energy Policy, pp. 138-146, 2014.

[7] P. Petkov, S. Goswami, F. Köbler, and H. Krcmar, "Personalised eco-feedback as a design technique for motivating energy saving behaviour at home", Proceedings of the 7th Nordic Conference on Human-Computer Interaction: Making Sense Through Design, pp. 587-596, 2012.

[8] D. Marikyan, S. Papagiannidis, E. Alamanos, "A systematic review of the smart home literature: A user perspective", Technological Forecasting and Social Change, pp. 139-154, 2019.

[9] H. Shareef, M. S. Ahmed, A. Mohamed, and E. Al Hassan, "Review on Home

doi:10.6342/NTU202100623

Energy Management System Considering Demand Responses, Smart Technologies, and Intelligent Controllers," IEEE Access, pp. 24498-24509, 2018.

[10] J. LaMarche, K. Cheney, K. Roth, O. Sachs ,and Marco Pritoni, "Home Energy Management: Products & Trends", ACEEE, 2017

[11] B. Zhou, W. Li, K. Chan, Y. Cao, Y. Kuang, X. Liu, X. Wang, "Smart home energy management systems: Concept, configurations, and scheduling strategies", Renewable and Sustainable Energy Reviews, pp. 30-40, 2016.

[12] N. Baumgärtner, R. Delorme, M. Hennen, and A. Bardow, "Design of low-carbon utility systems: Exploiting time-dependent grid emissions for climate-friendly demand-side management", Applied Energy, pp. 755-765, 2019.

[13] C. Li, X. Yu, W. Yu, G. Chen, and J. Wang, "Efficient Computation for Sparse Load Shifting in Demand Side Management", IEEE Transactions on Smart Grid, pp. 250-261, 2017.

[14] S. Kazmi, N. Javaid, M. J. Mughal, M. Akbar, S. H. Ahmed and N. Alrajeh, "Towards Optimization of Metaheuristic Algorithms for IoT Enabled Smart Homes Targeting Balanced Demand and Supply of Energy", IEEE Access, pp. 24267-24281, 2019

[15] T. Molla, B. Khan, B. Moges, H. H. Alhelou, R. Zamani and P. Siano, "Integrated optimization of smart home appliances with cost-effective energy management system", CSEE Journal of Power and Energy Systems, pp. 249-258, June 2019

[16] X. Xu, Y. Jia, Y. Xu, Z. Xu, S. Chai and C. S. Lai, "A Multi-Agent Reinforcement Learning-Based Data-Driven Method for Home Energy Management", IEEE Transactions on Smart Grid, pp. 3201-3211, July 2020

doi:10.6342/NTU202100623

[17] B. Wang, Y. Li, W. Ming and S. Wang, "Deep Reinforcement Learning Method for Demand Response Management of Interruptible Load", IEEE Transactions on Smart Grid, pp. 3146-3155, July 2020

[18] Z. M. Fadlullah, D. M. Quan, N. Kato, and I. Stojmenovic, "GTES: An Optimized Game-Theoretic Demand-Side Management Scheme for Smart Grid", IEEE Systems Journal, pp. 588-597, 2014.

[19] H. Kazmi, F. Mehmood, S. Lodeweyckx, J. Driesen, "Gigawatt-hour scale savings on a budget of zero: Deep reinforcement learning based optimal control of hot water systems", Energy, pp. 159-168, 2018.

[20] C. Tai, J. Hong and L. Fu, "A Real-time Demand-side Management System Considering User Behavior Using Deep Q-Learning in Home Area Network," IEEE International Conference on Systems, Man and Cybernetics (SMC), Bari, Italy, pp. 4050-4055, 2019

[21] Yolande A.A. Strengers, "Designing eco-feedback systems for everyday life", Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, pp. 2135–2144, 2011.

[22] M. Jahn, M. Jentsch, C. R. Prause, F. Pramudianto, A. Al-Akkad, and R. Reiners, "The Energy Aware Smart Home", 2010 5th international conference on future information technology, pp. 1-8, 2010.

[23] N. Castelli, G. Stevens, T. Jakobi, and N. Schönau, "Beyond eco-feedback: Using room as a context to design new eco-support features at home", Advances and New Trends in Environmental and Energy Informatics, pp. 177-195, 2016.

[24] C. Li, X. Yu, W. Yu, G. Chen and J. Wang, "Efficient Computation for Sparse Load Shifting in Demand Side Management", IEEE Transactions on Smart Grid, pp. 250-261, 2017.

doi:10.6342/NTU202100623

[25] Z. Wen, D. O'Neill and H. Maei, "Optimal Demand Response Using Device-Based Reinforcement Learning", IEEE Transactions on Smart Grid, pp. 2312-2324, 2015.

[26] M. Brülisauer, L. Goette, Z. Jiang, J. Schmitz, and R. Schubert, "Appliance-specific feedback and social comparisons: Evidence from a field experiment on energy conservation", Energy Policy, 2020.

[27] R. Raza and N. U. Hassan, "Quantifying the Impact of Customized Feedback on User Energy Consumption Behavior with Low-cost IoT Setup", 2020 International Conference on UK-China Emerging Technologies (UCET), pp. 1-4, 2020

[28] F. Pallonetto, S. Oxizidis, F. Milano, and D. Finn,"The effect of time-of-use tariffs on the demand response flexibility of an all-electric smart-grid-ready dwelling", Energy and Buildings, pp. 56-67, 2016.

[29] A. Mohsenian-Rad and A. Leon-Garcia, "Optimal Residential Load Control With Price Prediction in Real-Time Electricity Pricing Environments", IEEE Transactions on Smart Grid, pp. 120-133, 2010.

[30] T. Logenthiran, D. Srinivasan, and T. Z. Shun, "Demand Side Management in Smart Grid Using Heuristic Optimization", IEEE Transactions on Smart Grid, pp. 1244-1252, 2012.

[31] C. Cadena et al., "Past, Present, and Future of Simultaneous Localization and Mapping: Toward the Robust-Perception age", IEEE Transactions on Robotics, pp. 1309-1332, 2016

[32] A. R. Khairuddin, M. S. Talib, and H. Haron, "Review on Simultaneous Localization and Mapping", 2015 IEEE International Conference on Control System, Computing and Engineering (ICCSCE), pp. 85-90, 2015.

doi:10.6342/NTU202100623

[33] C. Yu et al., "DS-SLAM: A Semantic Visual SLAM towards Dynamic Environments", 2018 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), pp. 1168-1174, 2018.

[34] C. Wu, Y. Xie, S. K. Pradhan, L. Fu, and Y. Zeng, "Unsupervised context discovery based on hierarchical fusion of heterogeneous features in real smart living environments", 2016 IEEE International Conference on Automation Science and Engineering (CASE), pp. 1106-1111, 2016.

[35] Magic Leap, a wearable spatial computer that brings the physical and digital worlds together, https://www.magicleap.com/en-us

[36] J. Torriti, "Household electricity demand, the intrinsic flexibility index and UK wholesale electricity market prices", Environmental Economics and Policy Studies, pp. 1-21, 2020.

[37] L. Söder et al., "A review of demand side flexibility potential in Northern Europe", Renewable and Sustainable Energy Reviews, pp. 654-664, 2018.

[38] H. Van Hasselt, A. Guez, and D. Silver, "Deep reinforcement learning with double q-learning", AAAI, 2016.

[39] V. Mnih et al., "Human-level control through deep reinforcement learning", Nature, pp. 529, 2015.

doi:10.6342/NTU202100623