Markov model in home energy management system

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Abstract. An intelligent home energy management system was proposed. Reinforcement learning and a markov prediction model were used to help the system make decisions. The Markov model predicted the future state of users or the weather, and the intelligent decision-making support system sent signals to local controllers to control furniture. This work benefits energy management because if the system knows the user’s next state, it can control a specific appliance to save energy. Meanwhile, if the system can predict the weather, the house can use green energy rationally. The proposed energy management system could be applied in an intelligent house, city energy management systems, and building energy management. The state prediction helped the decision-making system make accurate and rational decisions.

1. Introduction
The development of computer technology, network technology, control technology, and artificial intelligence has promoted the application of smart homes. A smart home is defined as an efficient, comfortable, safe, convenient, and environmentally friendly living environment integrating system, structure, service, and management [1, 2]. For example, a home monitoring system on a Wi-Fi network can monitor the work of each module in the network; the system can not only include the wireless control of lamps and curtains, but also detect the indoor environmental temperature, humidity, and air composition [3]. Edge computing technology has been used to relieve the pressure of the cloud computing center and improve the efficiency of data processing.

However, these architectures do not have ability to analyze data and predict the next state. Reinforcement learning is a machine learning approach focused on goal-directed learning from interaction [4, 5]. Due to the development of smart sensors, communication, and control methods in electric systems, reinforcement learning is expected to be applied in intelligent home systems. Electronic control-based systems have been applied in intelligent houses; for example, a building automation system manages the energy consumption under the home energy management system [6]. As a computer-aided tool, the home energy management system is used to monitor the energy and water consumption of the home, control the operation mode of household appliances, fans, lighting, and water pumps, and reset the room temperature to optimize energy consumption [6].

The home energy management system is expected to be more advanced when combined with reinforcement learning. Moreover, it is supposed to be autonomous. Since energy consumption is not constant across time and households, decision-making by the home energy management system is complicated. Thus, a reinforcement learning-based decision-making support system was proposed [7-10]. This idea helped each user find their optimal approach to managing their home’s energy.

In this paper, the application of reinforcement learning and the Markov decision process in home energy management are discussed with detailed examples. The main problems facing such application
are disclosed, and the development trends home energy management systems are presented.

2. Markov Model of Home Energy Management System

2.1 Home Energy Management System

A large amount of pollution is produced in the process of power generation, how to effectively manage energy is an important question at present [11].

Each smart home has a master controller. The master controllers separate the house into different parts. Each part has a local controller that can access the master controller’s orders. The main controller and the local controller are distributed in the way of star topological method (Figure 1), and the communication network manages the exchange of information. Sensors in the house collect information about the environment and users’ behaviors, and send this data to controllers through the communication network. The controllers analyze this data and control the furniture accordingly.

![Figure 1. The star topological method](image)

2.2 Intelligent decision-making support system

The intelligent decision-making support system can make rational decisions as humans do. It has the ability to deal with complicated situations, diagnose problems, and propose solutions to help users in an effective way [12, 13]. The home energy management system will apply intelligent decision-making support systems to make objective and accurate decisions. The intelligent decision-making support systems can analyze the user’s behavior mode and environmental changes so as to predict the trend of power consumption and make plans in advance on how to control this power consumption; hence, effective management of household energy consumption can be realized.

The home energy management system must be able to accurately detect massive amounts of information regarding users and the environment. For example, it can use cameras to detect the user’s identity, pyroelectric sensors to detect the user’s location, and contact switch sensors to detect the state of electrical appliances. Moreover, the system requires a set of complex sensors to determine the user’s location and states, along with light sensors, wind sensors, and thermometers to determine the weather outside. After getting this information, intelligent decision-making support systems can make decisions for the power supply. For example, it can turn off televisions or lights in vacant rooms; set the refrigerator’s temperature according to the room’s temperature; and use solar energy to heat water instead of electricity.

All of the actions mentioned above are taken with known user behavior and weather conditions. If the intelligent decision-making support systems can establish a household energy consumption prediction model according to the characteristics of household electricity consumption and members' electricity consumption habits, the system will reduce energy waste. It is possible to achieve this by using the Markov model to predict the user’s behavior.
2.3 Reinforcement learning

Reinforcement learning is a machine learning approach focused on goal-directed learning from interaction. This means that the reinforcement learning system obtains information from the environment and responds to it [12, 13].

The working process of reinforcement learning can be described as shown in Figure 2 [14].

![Figure 2. The working process of reinforcement learning [14]](image)

In each time step T, the agent receives a certain representation of the environment state and selects an action based on it. After each time step, the agent receives a digital reward for their action.

A reinforcement learning task can be modeled as a Markov decision process. The state of the environment only depends on the current state and the selected action, and thus existing information can be used to predict the future state and the expected return of the state. At this time, the reward value function only depends on the current state and action, and has nothing to do with other historical states and actions.

MDP can be generally expressed as a four tuple \((S, A, T, R)\), where \(S\) represents the state space composed of all environment states, \(S\) can be composed of multiple variables. \(A\) represents the set of all actions that can be executed by the learner (agent), and \(T\) is a function of state transfer possibility \(S*A*S\rightarrow[0,1]\). \(T(S, A, S_1)\) represents the possibility of agent \(A\) transferring from \(S\) to \(S_1\). \(R\) is the reward function \(R:S*A*S\rightarrow R\).

Then, we formulate a policy to manage the behavior of agents. The policy is a mapping of the current state and the future state. The goal of reinforcement learning is to find the optimal policy that will result in the largest reward.

2.4 Markov prediction model

The Markov prediction model is employed to predict the probability of events. It is based on the Markov chain, and predicts the future of each time step or period of change according to the current situation. If we can assume that each state transition of the user is only related to the state of the previous moment, we can use the Markov prediction model to predict the user’s next state; then, the home energy management system can send commands earlier so that more energy can be saved [15, 16].

In the Markov prediction model, the state is a condition of an event in a certain period. The possibility of the next state is called the state transferring probability. Each state has the probability to transfer to another state, and thus we can build a transfer probability matrix following equation.

\[
P = \begin{bmatrix}
P_{11} & P_{12} & \cdots & P_{1n} \\
P_{21} & P_{22} & \cdots & P_{2n} \\
\vdots & \vdots & \ddots & \vdots \\
P_{n1} & P_{n2} & \cdots & P_{nn}
\end{bmatrix}
\]  

(1)

Where \(P_{11}\) is the probability of state 1 transferring to state 1. Here is an example. A driver selects a parking space before arriving at their destination. The status of the parking space, 0 or 1, indicates whether the parking space is empty (0 indicates that the parking space is empty, and 1 indicates that it is not empty). The probability of emptiness is \(p\) and the probability of non-emptiness is \(1 - p\). If the current parking distance is \(x\), the parking cost is \(x\). If the driver has not found a parking space at the
destination, they can only park at the paid parking space. The parking cost is $c$.

Suppose that $f(x, i)$ is the minimum parking cost, where $x$ is the distance, and $i$ is the parking space status.

$$f(x, i) = \begin{cases} \min(x, c) & i = 0 \\ c & i = 1 \end{cases}$$

(2)

For the convenience of calculation, an auxiliary function $F(x)$ is introduced ($F(0)=c$):

$$F(x) = pf(x, 0) + (1 - p)f(x, 1).$$

(3)

Then, we can obtain

$$f(x, i) = \begin{cases} \min[x, F(x - 1)] & i = 0 \\ F(x - 1) & i = 1 \end{cases}.$$  

(4)

In order to obtain minimum value of the $f(x,i)$ we need to use a new function $g(x)=F(x-1)-x$. It can be proved that $g(x)$ is a decreasing function. Thus, there is an $S$ such that $g(S)>0$ and $g(S+1)<0$.

Supposing that $v(x,S)$ means the lowest cost, we can obtain

$$v(x, S) = \begin{cases} c & x = 0 \\ px + (1 - p)v(x - 1, S) & 0 < x \leq S \\ v(S, S) & x > S \\ S - q(1 - qS)/p + qSc. & \end{cases}$$

(5)

With this function, we can obtain an optimal solution of $S$, and thus find the lowest value of $v(x,S)$. This is a Markov chain.

### 2.5 Methods

In order to predict the user’s behavior, the system must obtain enough data to calculate the probability (Tables 1 and 2). The intelligent house has a complex sensors system. The system obtains information useful for the prediction, and transmit it to a receiver. Data acquisition is carried out periodically, and for each period of time the receiver stores the data in a specific node.

| Title                   | Value                                                                 |
|-------------------------|----------------------------------------------------------------------|
| Time (a period)         | $x$: xx, $y$: yy                                                      |
| Location sensor 1       | 1 means there are people detected; 0 means there are not             |
| Location sensor 2       | Camera 1                                                             |
|                         | Camera 2                                                             |
|                         | Users ID                                                             |

| Title                   | Value                                                                 |
|-------------------------|----------------------------------------------------------------------|
| Switch sensor 1         | 1 means the furniture is working; 0 means it is not                  |
| Switch sensor 2         |                                                                      |
| Switch sensor 3         |                                                                      |

The advantage of this data structure is that it allows us to confirm the user’s state immediately. For example, as shown in Tables 1 and 2, if location sensor 1’s value is 1, camera 1’s value is 1, and switch sensor 1’s value is 1, the system can confirm that user 1 is turning on the furniture 1 in room 1. This can be called state 1. Through different permutations and combinations, we can obtain the different states of a user.

The system needs to preprocess the collected data. Yan et al suggest to use a basic near sorting algorithm to deal with duplicate data. This approach enables the system to delete duplicate data. The specific steps are as follows:

- Step 1: Sort the data. Keep the states with the similar in the adjacent regions.
Step 2: Move a window with the same step on the sorted dataset. While moving the window, each new record in the dataset is compared with all previous records to detect duplicate records. Then, the data first entering the dataset leaves the window, and the next data enters the window. The window moves all the way to the end of the data.

After processing the data, the system can calculate the probability of transfer. We note that the user’s behavior could differ between weekends and workdays. In order to make predictions more accurate, the system needs to consider this and prevent the model from overfitting. During data analysis, the system should consider that there may be differences in user behavior on different days of the week, and hence it is necessary to distinguish the data of each day of the week. When users are on vacation, their behaviors will also be different from those on typical weekdays. The system should be able to identify the time window length of the current behavior. For example, the similarity between Monday of week n and Monday of week n-1 is calculated, as shown in Table 3. If the similarity is greater than a certain threshold, the user has a new lifestyle or schedule in week n.

When we finish considering all of these complex situations, the system can begin to calculate the state transfer probability. We then obtain this state transfer probability matrix.

|     | P1   | P2   | ... | Pn   |
|-----|------|------|-----|------|
| P1  | P11  | P12  | ... | P1n  |
| P2  | P21  | P22  | ... | P2n  |
| ... | ...  | ...  | ... | ...  |
| Pn  | Pn1  | Pn2  | ... | PNN  |

The system thinks that the events with the highest probability will occur.

If the system needs to calculate the probability of being in a certain state after several state transitions, it will use another variable called state probability $\pi_j(k)$. This variable means the probability of an event in the initial state transfer k times and transfer into state j. Then, we have

$$\pi_j(k) = \sum_{i=1}^{n} \pi_{i}(k-1)p_{ij} (j = 1,2,3,...n).$$

In other words, when the state at moment 0 is known, the probabilities of various states after K state transitions can be obtained.

Through the prediction of user behavior, the system can not only improve users’ comfort but also better and more objectively manage energy consumption. When users have a low probability of using a specific piece of furniture, the system can turn it off automatically. If users have a high probability to use the piece of furniture again, the system will set the furniture in standby mode and it will turn on faster.

For example, if the users leave a room with the air conditioner working. The system could judge whether the user will return to this room. If not, the air conditioner will be turned off; if the user will return, the air conditioner will instead work in low-power mode. In such a case, the smart home system can save energy while ensuring the comfort of users.

The system can also be used to predict the weather. If the water heating system can predict sunny days, it can stop the electric water heater and use the solar water heater. If it can predict a windy day, the electric water heater will start to work early and make sure that there is hot water available for when users arrive home.

3. Limitations and future plans

This article proposes a Markov prediction model to predict users’ behavior. However, it still has some limitations.

This article faces a problem in calculating the threshold variable to help the system determine the similarity between two Mondays. It is significant to judge if a future day is a holiday or a work day.
because this will influence users’ living habits profoundly. We also failed to find a way to determine the state transfer similarity between two days. If the criteria for determining whether they are similar are too high or too low will both have an impact on the prediction model.

Furthermore, this article only proposes an approach to build a mathematical model. It does not build a complete system that can be directly applied in an intelligent house.

Moreover, in some cases, the situation considered in this article is too idealistic. Sometimes users’ complex behavior is difficult for sensors to detect. We may need to use more complex detectors to determine the state. Additionally, sometimes the system makes reasonable predictions but users do something else. If the autonomy of the system is too high, it will occasionally bring trouble to users.

The most important problem people will meet when using this system would be security. The majority of people are worried if their privacy is well protected. The system has significant information about users’ behavior in the house. Such data seems uncontrolled when the system is connected to the internet, and thus some people may refuse to use the system.

In the future, we can think about how to make better use of the model prediction and how can the system save energy when predicting the next state. Many households and cities would benefit from continued research on this system.

4. Conclusions
An intelligent home energy management system is proposed. It employs reinforcement learning and a Markov prediction model to make decisions. The Markov prediction model is able to predict the future state of users or the weather, and the intelligent decision-making support system sends signals local controllers to control furniture.

This work—benefits the energy management. If the energy management system knows the user’s next state, it can better control appliances to save energy. Furthermore, if the system can predict changes in the weather, the house can use green energy rationally.

This research can not only be applied in an intelligent house, but also in city energy management systems and building energy management systems. Ultimately, state prediction helps the decision-making system make accurate and rational decisions.

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