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Adaptive Dynamic Programming for Residential Energy Scheduling with Solar Energy

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Abstract— **Residential energy scheduling on demand side is a hot research area for saving energy and balancing loads. In this paper, an adaptive dynamic programming method is proposed for residential energy scheduling to reduce cost between two adjacent housing units. Two sets of storage batteries and solar stations make energy scheduling problems quite complicated while using traditional methods. The scheduling algorithm is designed based on action dependent heuristic dynamic programming. In the utility function, the weighting function is given to adjust the remaining capacities of batteries. Furthermore, the temperature becomes an input of neural networks to stay close to reality. Simulation results show the effectiveness of saving cost and balancing loads.**

I. INTRODUCTION

ENERGY crisis becomes more and more severe on this planet since 1970s. Traditional fossil fuels have limited reserves and arise serious environmental concerns. With the decreasing of fossil fuel resources, saving energy and applying renewable resources become a efficient solution to us. Thus, smart gird is widely studied all over the world. Many efforts have been made to energy generators and energy transmission to end users [1]–[3]. With the applications of renewable energy genaration, solar energy, wind energy and storage systems appear in the residential area, which makes the residential energy scheduling problem complicated. Along with the development of smart grid, intelligent optimization is needed to solve the residential energy scheduling problem [4]–[6].

With the characteristics of self-learning and evolution, the adaptive dynamic programming (ADP) was proposed by Werbos [7], [8] to achieve optimal control policy by solving the Hamilton-Jacobi-Bellman (HJB) equation [9]–[18]. ADP solves the HJB equation forward-in-time [19], [20]. Thereafter, other researchers studied further and acquired many achievements, such as the adaptive critic designs [21]. Jiang et al. developed robust adaptive dynamic programming for the design of robust optimal controllers for linear and nonlinear systems [22]. Wang et al. proposed an intelligent-optimal control scheme for unknown nonaffine nonlinear discrete-time systems in [23].

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The combination of intelligent algorithms and residential energy scheduling has been studied by many scientists. ADHDP was used for the design of a static compensator by Mohagheghi [24]. Fuselli et al. achieved home energy management with the ADP method [25]. A demand response strategy was proposed to charge EVs on residential distribution networks by Niyato [26]. Huang and Liu developed a self learning scheme to achieve residential energy management and control [27].

The rest of the paper is organized as follows: Section II describes the residential energy scheduling problem and the related preparatory work. Section III introduces the simulation algorithm and control strategies of the batteries. The simulation results are shown in section IV. Finally, the paper concludes in section V.

II. RESIDENTIAL ENERGY SCHEDULING

A. Problem Descriptions

The residential energy-related components include two household loads, two storage batteries, two solar power stations and the utility grid. They are all connected via the power management unit (PMU), which controls the energy transmission. All the above components are located in two housing units separately except the public utility grid and the PMU. The energy transmission problem arises under the circumstance of the residential real-time pricing, It is hard to determine the energy transmission directions and the amount of energy at the appropriate time, which makes it a residential energy scheduling problem in time and space.

Fig. 1 shows the structure and the power flow directions of the residential energy scheduling. It is obvious that load 1, solar 1 and battery 1 locate in their corresponding housing unit 1. Therefore, the loads, solar powers and batteries are primarily responsible for the energy usage on its own side. Therefore, the aim of energy scheduling is to manage the power flows between all energy-related components in Fig. 1 under the circumstance of RRTP. As a result, the cost can be saved for the residents and the load balancing can be improved for the utility gird .

B. Scheduling Preparation

In order to manage and schedule the energy transmission, the preparation work needs to be done beforehand. There are many preset rules to follow in order to improve the authenticity of the application simulation.

Residential real-time pricing is an important idea in the efficient electricity market, which can promote the optimal allocation of electric power resources. The heavy load of

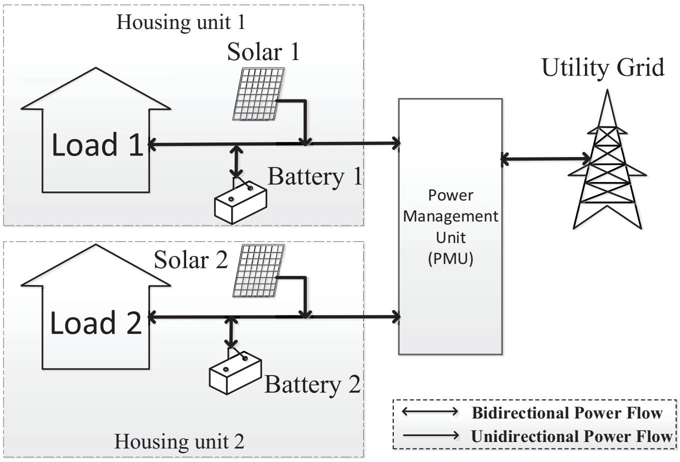

Fig. 1. Power flows of the residential energy scheduling

the utility grid is the main factor to the residential real-time price. Big electric demand usually causes high real-time price. Driven by high electricity price, the users will adjust their electricity loads to save total costs. Therefore, the load balance of the utility grid can be improved. One residential load and the residential real-time price (RRTP) are depicted in Fig. 2. Spikes appear during the daytime because humans are basically diurnal. Besides, there is a positive correlation between the residential household load and RRTP.

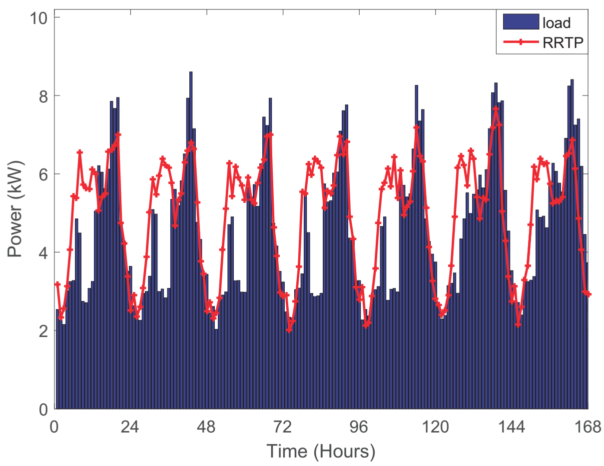

Fig. 2. One residential load and the residential real-time price

The storage batteries are set with the capacities of 50 kW·h. The maximum charge and minimum discharge rates are 5kW. In order to extend the batteries' lifespan, the minimum remaining capacities are also 5kW. The charge and discharge cycles can affect battery life. Therefore, the batteries are supposed to have a charge and discharge cycle once a day. When batteries discharge, the priority orders of energy receivers are the load on its own side and the load on the other side. No other batteries energy receivers are allowed in order to reduce energy loss during transmissions.

Solar energy is a widely distributed renewable energy. The solar energy materials capture the sunlight and transfer electron from its oxidation state to the conduction band of anode to generate electricity energy. The amount of solar generation is affected by the solar radiation intensity. However, the temperature has a strong relationship with the radiation intensity [28]. Thus, the real temperature is incorporated as one of the ADP-based inputs. In Fig. 3, one solar power output is shown within a week. All the solar data comes from the PV system in Braedstrup city of Denmark [29]. When solar power stations generate energy, the priority orders of energy receivers are the load on its own side, the load on the other side, the battery on its own side, the battery on the other side and the utility grid.

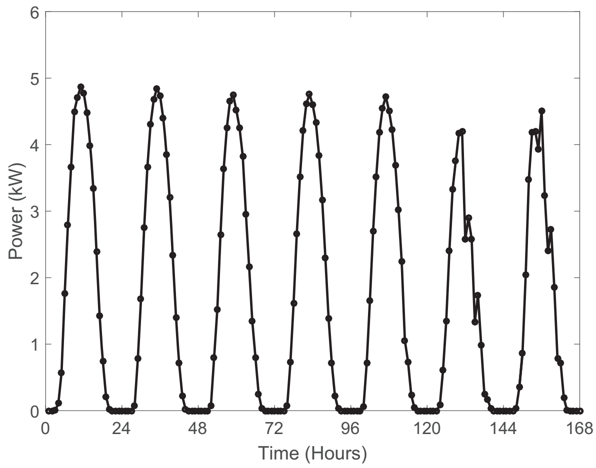

Fig. 3. Solar power of Braedstrup in one week (July 2006)

Temperature, as a weather forecast target, can be predicted with a very small error. Due to its relationship with sunlight intensity and solar power generation, the temperature can be used to help to schedule the energy transmission. Fig. 4 shows the temperature change of Braedstrup in one week in July 2006.

The PMU is the vital energy conversion hub which controls all the energy transmission (including the directions and amounts of energy). Inside this residential area, each energy consumer can be powered by one or more energy providers at the same time. Every component operates by their corresponding priority to avoid any conflict.

III. Simulation Algorithm

A. *Adaptive Dynamic Programming*

The residential energy scheduling is designed based on adaptive dynamic programming. ADP is a very useful tool in solving optimal control problems by employing the Bellman principle of optimality [30]. By minimizing the utility function, two neural networks, the action network and the critic network can be used to achieve the optimization process. Action dependent heuristic dynamic programming is a type of ADP. It is well suited to tackle the residential energy

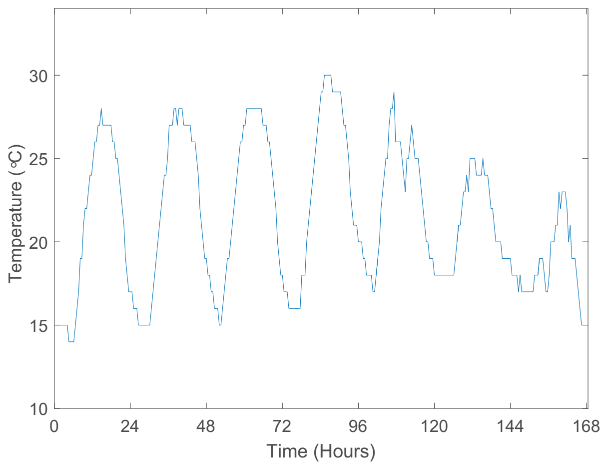

Fig. 4. Temperature of Braedstrup in one week (July 2006)

scheduling problem. During the training and optimization, the critic network plays an important role in the training and optimization process. The associated performance index function is defined as follows:

$$J(t) = \sum_{i=0}^{\infty} \gamma^i U(t+i), \tag{1}$$

where $\gamma \in [0, 1)$ is the discount factor and $U(t+i)$ is the utility function.

The utility function is assumed as:

$$\begin{aligned} U(t) =& C(t)P(t) + C_s(t)P_{\text{sell}}(t) \\ &+ \lambda(t)C_{\text{bp}}(t)[C_{\text{Ab1}}(t) + C_{\text{Ab2}}(t)] \end{aligned} \tag{2}$$

where $C(t)$, $C_s(t)$, $C_{\text{bp}}(t)$ are the RRTP, the feed-in tariff and the penalty price. Besides, $P_{\text{sell}}(t)$, $C_{\text{Ab1}}(t)$ and $C_{\text{Ab2}}(t)$ means the power selling back to the utility grid, the absent power of battery 1 and the absent power of battery 2. It is important to note the variable weighting function $\lambda(t)$, which shows that different weather conditions have different influence on weighting parameters. When the day is sunny, the batteries should store more energy with a high value; while in cloudy days, the weighting function should be small to have batteries to discharge more energy. The critic network's training and improvement are based on the mapping $Q(t-1) \longleftarrow \gamma Q(t) + U(t)$. $Q(t)$ and $U(t)$ are the the output of critic network and utility function at time t. $Q^*(t-1) = \gamma Q(t) + U(t)$ can be used to acquire the ideal output of critic network at time $t-1$. Thus the ideal training target $Q^*(t-1)$ can be used to train critic network at time $t-1$.

B. Batteries Control

The storage batteries are controlled with the five kinds states with five specific numbers $(u_1, u_2 = 1, 0, -1, -2, -3)$. The five states are charging state $(u_1, u_2 = 1)$, idle state $(u_1, u_2 = 0)$, discharging state A $(u_1, u_2 = -1)$, discharging state B $(u_1, u_2 = -2)$ and discharging state C $(u_1, u_2 = -3)$. Discharging state A means the batteries discharge to the household loads on its own side, while discharging state B means the batteries discharge to the household loads on the other side. In discharging state C, batteries will discharge to household loads on both sides. Each battery has five states. Therefore, there are 25 kinds of control scheme (or control matches).

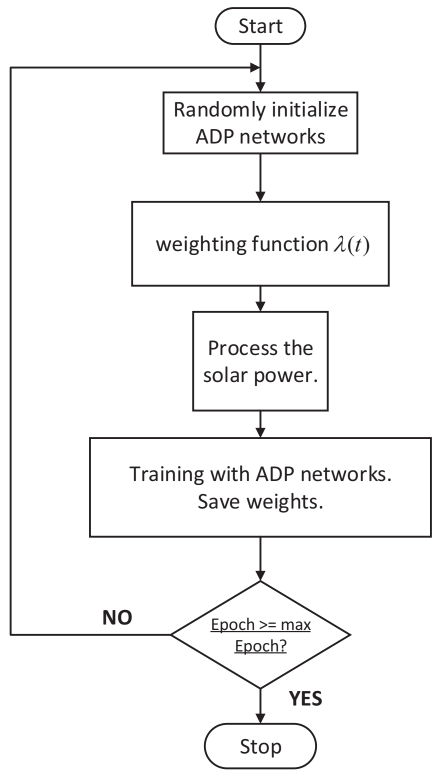

Fig. 5. The residential energy scheduling algorithm

C. Algorithm

The detailed adaptive dynamic programming algorithm for residential energy scheduling is shown in Fig. 5. As it can be seen, the prepared data is summarized and processed before the training of adaptive dynamic programming for residential energy scheduling neural networks (ADP networks). The training process is summarized as follows (**Algorithm 1**):

First, initialize the ADP networks. Collect and pre-process the related data. The data includes the RRTP, the penalty price, the weather types and the solar power. Besides, the maximum epochs need to be determined and the loops begin.

Second, the weather weighting function $\lambda(t)$ should be determined. Then the solar energy will be handled first according to the energy receivers' priorities.

Third, randomly select control strategies for battery 1 and battery 2. Train the corresponding ADP network within a specified day by [31] and find the best control strategy. Afterwards, save and pass the best weights to the next training.

Thereafter, the trained algorithm have the ability to guide

Algorithm 1 Adaptive dynamic programming for residential energy scheduling

Part I: Initialization

1: Initialize the ADP network.

2: Give the basic parameters for the adaptive dynamic programming for residential energy scheduling such as the training function, the number of layers and the number of neurons of each layer (the input layer, the hidden layer and the output layer).

3: Collect and pre-process data which include the RRTP, the penalty price, the weather types and the solar power.

4: Give the computation precision $\varepsilon > 0$ and the number of loops.

Part II: Iteration

1: Begin the loop and determine the weather weighting function $\lambda(t)$.

2: Process the solar energy with their priorities.

3: Select control strategies for batteries 1 and battery 2 randomly. Train the corresponding ADP network within a specified day and try to find the best control strategy. Afterwards, save and pass the best weights to the next training.

4: Decide whether it is the maximum epoch. If so, go to the next step. Otherwise, go to Part I and repeat the process.

5: Pick the best ADP networks and calculate the cost.

6: Evolve in applications.

the residential energy scheduling and evolve during applications.

The adaptive dynamic programming for residential energy scheduling is designed to solve energy transmission problems between two housing units and the utility grid. It is a complicated problem for the multiple energy transmission directions. Inside housing unit 1, the solar power 1 gives energy; the household load 1 absorbs energy; battery 1 is a local energy buffer device. Moreover, energy can be transferred between devices of two housing units and the utility grid. All the energy transmissions are via the PMU.

IV. Simulation

In the simulation scenario, the critic network structure is 10-20-1. The 10 inputs are the RRTP, the temperature, two batteries' energy status, two household loads, two solar energy status and two control actions (u_1,u_2). Their hidden layer has 20 neurons, and the aim of the output layer is to minimize the total cost. Each day the ADP network is trained to acquire the states' features and optimize the total cost accordingly. The simulation is done in the environment of the MathWorks Matlab R2015b on a DELL computer with Intel Core i5 CPU @3.2GHz and 8GB ram.

Fig. 6 shows the remaining capacities of battery 1 and battery 2. It is obvious that the batteries have a charge and discharge cycle each day. With the help of the penalty cost in the utility function, the batteries try to absorb energy during the morning and night when the RRTP is low while they output electricity energy to the household loads during the daytime when the RRTP is high. Furthermore, the solar energy makes the situation a little more complicated. During the noon time, when the RRTP is high, the solar energy flows in the direction of loads and batteries. However, it can not be ignored that the loads take precedence over the batteries. Therefore, battery 1 and battery 2 are fully discharged at that time.

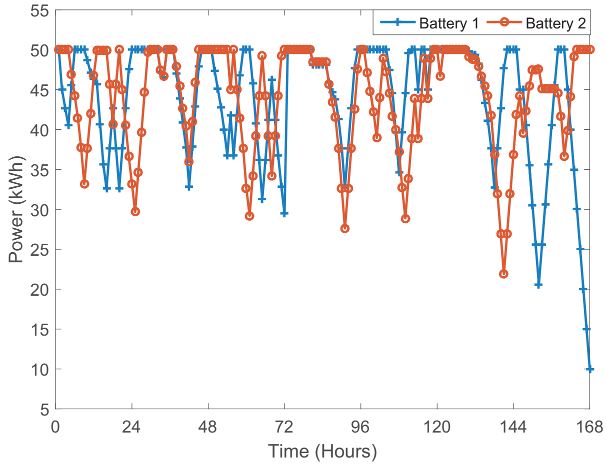

Fig. 6. Remaining capacities of battery 1 and battery 2 in one week

In Fig. 7, battery 1, solar 1 and load 1 are put together to explain the energy changes. Each day battery 1 are usually fully charged during the night and the noon time. The RRTP is low at the night time so battery tries to get energy from the utility grid. When the solar energy generates electricity energy with a peak value, the excess energy goes to the battery to make it fully charged. That is how the energy changes in batteries. At most of the time solar 1 doesn't have enough energy to meet load 1 precisely. In addition, battery 1's energy changes are affected by solar 1 and solar 2 together.

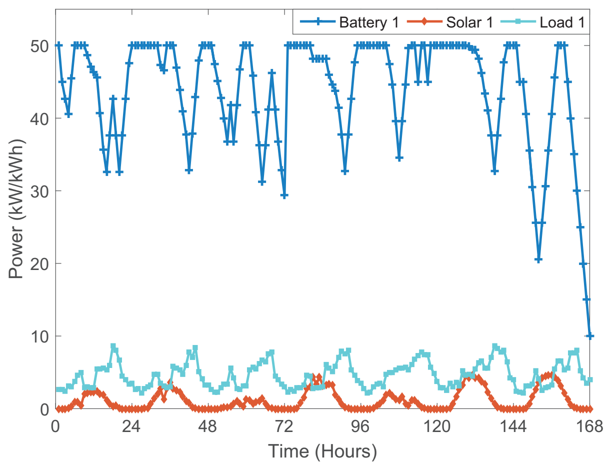

Fig. 7. Energy changes of battery 1, solar 1 and load 1 in one week

The household loads are met by the solar energy, the battery energy and the utility grid energy in order of priority. Even solar 1 and solar 2 also have different priorities. Fig. 8 depicts the energy parts of household load 1 which includes the solar energy, the battery energy and the grid energy. The solar energy is processed first so that the red solar energy outputs to load 1 during the daytime especially at the noon time. Furthermore, the batteries and the utility supply energy to meet the rest load. The blue battery energy usually outputs during the daytime when the RRTP is high, while the green utility grid energy provides additional energy to load 1.

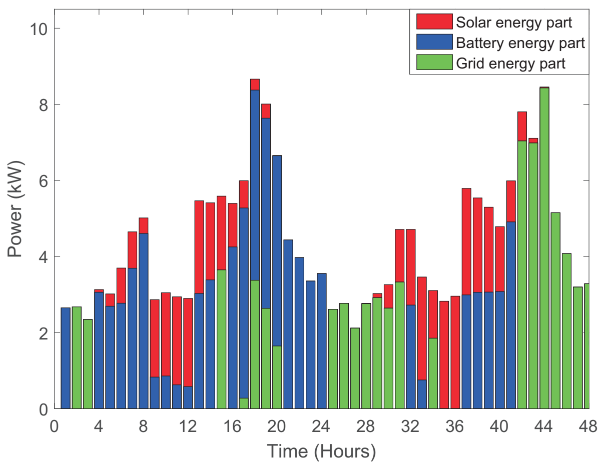

Fig. 8. Energy components of load 1 in two days

During the one-week simulation, the cost of buying energy from the utility grid is 3436.9 cents and the income of selling energy to the utility grid is 11.8435 cents. Without the solar stations and the batteries, the original cost will be 8205.9 cents. 58.3% of the original cost can be saved for users after employing adaptive dynamic programming for residential energy scheduling. The users can benefit from the adaptive dynamic programming-controlled residential energy scheduling.

V. Conclusions

This paper presents an adaptive dynamic programming-controlled residential energy scheduling algorithm to solve the energy transmission inside the micro smart grid area. Two adjacent housing units are equipped with the solar station and the storage battery. Therefore, between the two houses, the energy transmission is complicated. ADP has the ability to solve dynamic programming problems. The variable weighting function is proposed to control the batteries energy status. Furthermore, the temperature has been incorporated into the neural networks' inputs to acquire the characteristics of the solar energy. The simulation results show that the presented residential energy scheduling algorithm saves cost for users by adjusting the electricity load in time and space.

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