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Home energy management strategy to schedule multiple types of loads and energy storage device with consideration of user comfort: a deep reinforcement learning based approach

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With the increase in the integration of renewable sources, the home energy management system (HEMS) has become a promising approach to improve grid energy efficiency and relieve network stress. In this context, this paper proposes an optimization dispatching strategy for HEMS to reduce total cost with full consideration of uncertainties, while ensuring the users' comfort. Firstly, a HEMS dispatching model is constructed to reasonably schedule the start/stop time of the dispatchable appliances and energy storage system to minimize the total cost for home users. Besides, this dispatching strategy also controls the switching time of temperature-controlled load such as air conditioning to reduce the energy consumption while maintaining the indoor temperature in a comfortable level. Then, the optimal dispatching problem of HEMS is modeled as a Markov decision process (MDP) and solved by a deep reinforcement learning algorithm called deep deterministic policy gradient. The example results verify the effectiveness and superiority of the proposed method. The energy cost can be effectively reduced by 21.9% at least compared with other benchmarks and the indoor temperature can be well maintained.

KEYWORDS

home energy management system, dispatchable load, optimal dispatching strategy, users' comfort, deep reinforcement learning

1 Introduction

1.1 Background

The rapid increase in population growth and energy consumption has brought about many environmental problems such as global warming (Weil et al., 2023) and energy crisis (Hafeez et al., 2020a). Among all energy consumption, household energy consumption is an important component (Zhang et al., 2023). To optimize the energy structure of households and reduce energy consumption, energy consuming equipment such as rooftop photovoltaics (PV), heat pumps, electric vehicle (EV), and batteries have been widely promoted. With the rapid increase in the number of distributed PV (Li et al., 2024) and EVs

(Yin and Qin, 2022), home energy system management (HEMS) has become the most important aspect of achieving demand-side energy management in smart grids (Hafeez et al., 2021; Huy et al., 2023). The HEMS can make decisions for demand response based on current electricity prices, predicted photovoltaic output, user preferences, and device characteristics, achieving intelligent scheduling of home equipment and reducing electricity costs (Kikusato et al., 2019; Gomes et al., 2023). The HEMS is a key component in achieving zero-energy homes and has the potential for widespread application in residential distribution systems. The scheduling strategies used in HEMS mainly include real-time energy allocation, day ahead scheduling, and closed-loop energy management. Among them, day ahead scheduling can reduce computational complexity and improve computational efficiency, which is widely accepted and applied (Ren et al., 2024).

1.2 Related works

There are lots of related work have been conducted based on HEMS. Liu et al. in (Liu et al., 2022) proposes a HEMS for residential users that incorporates the uncertainty of data-driven results to achieve the best trade-off between electricity cost and the preference level. Tostada-Veliz et al. in (Tostado-Véliz et al., 2022) develops a HEMS that includes three novel demand response routines focused on peak clipping and demand flattening strategies. Chakir et al. in (Chakir et al., 2022) propose a management system for a future household equipped with controllable electric loads and an electric vehicle equipped with a PV-Wind-Battery hybrid renewable system connected to the national grid. However, these studies only consider the dispatch strategy of single type of load, which may not in line with real usage scenarios. In the real home energy system, there are multi-types of loads, such as dispatchable load and non-dispatchable load, all these types loads should be considered in the constructed system. To this end, Rehman et al. in (ur Rehman et al., 2022) proposed a holistic method to optimize the use of different types of home appliances according to the prosumers preferences and defined schedule. Dorahaki et al. in (Dorahaki et al., 2022) presents develop a behavioral home energy management model based on time-driven prospect theory incorporating energy storage devices, distributed energy resources, and smart flexible home appliances, which considers the dispatch of different types of appliances. Nezhad et al. in (Esmael Nezhad et al., 2021) proposes a new model for the self-scheduling problem using a home energy management system (HEMS), considering the presence of different types of loads, such as an air conditioner and EV. When temperature-controlled load such as air conditioner contained in the HEMS, the users' comfort should be considered in the dispatch strategy. Song et al. in (Song et al., 2022) presents an intelligent HEMS with three adjustable strategies to maximize economic benefits and consumers' comfort. Youssef et al. in (Youssef et al., 2024) proposes strategies that are evaluated in terms of consumer comfort, and cost, with waiting time used to assess user comfort. Once the users' comfort is taken into account, the single objective optimization will change into a multi-objective optimization. It is difficult and important to balance performance of different objectives to obtain the optimal dispatch strategy in the multi-objective optimization. To this end, several studies (Ullah

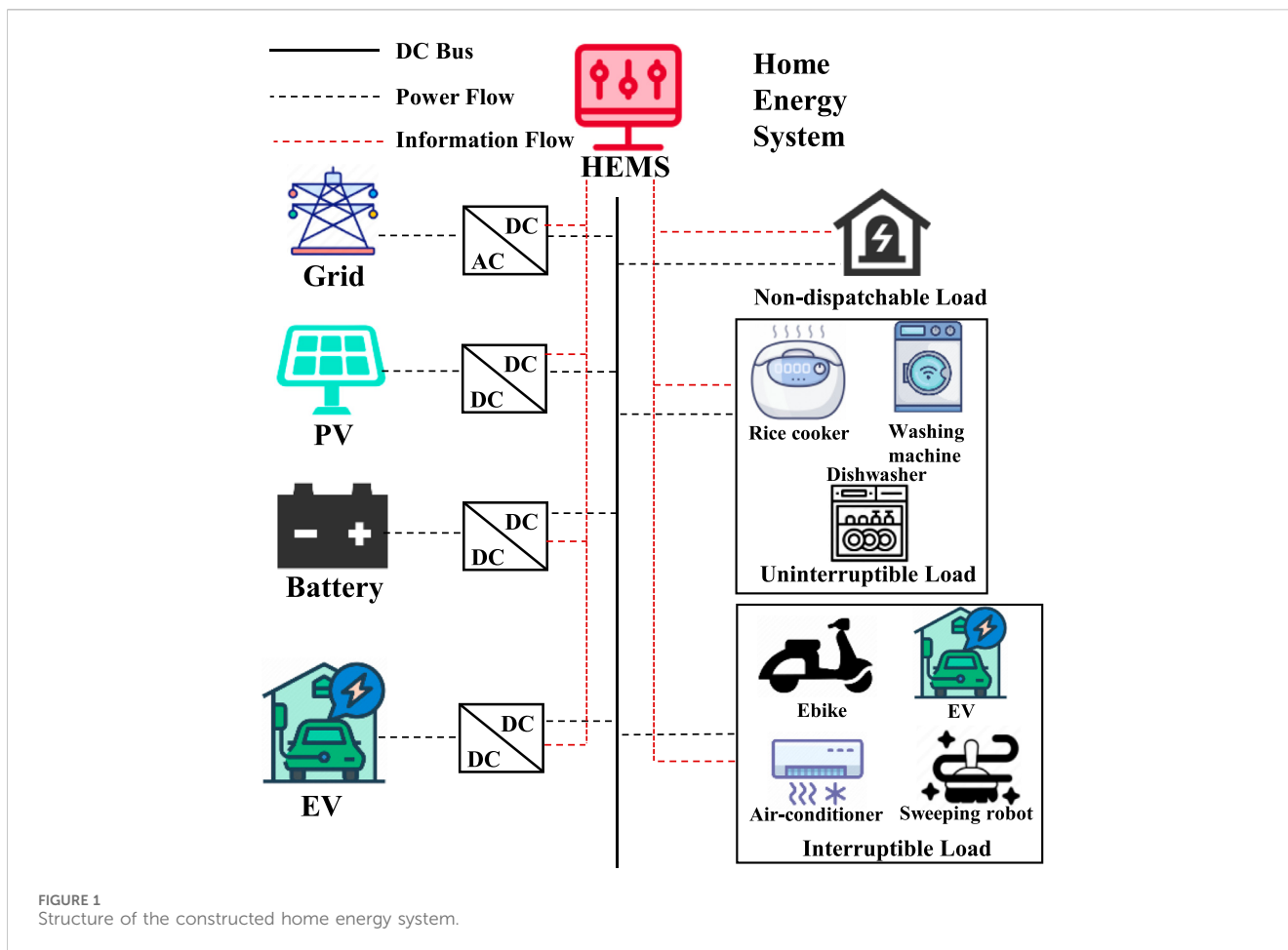
et al., 2021; Alzahrani et al., 2023) are proposed for tackling this problem.

Then, how to obtain the optimal dispatch strategy of the HEMS is a crucial problem (Xiong et al., 2024). Normally, the optimization-based methods such as stochastic programming method (SP) (Hussain et al., 2023) and robust optimization method (RO) (Wang et al., 2024) are utilized to solve the optimization problem of HEMS. Tostado et al. in (Tostado-Véliz et al., 2023a) develops a novel SP-based home energy management model considering negawatt trading. Kim et al. in (Kim et al., 2023) proposes an SP-based algorithm to reduce computation time while preserving the stochastic properties of generated scenarios based on the Wasserstein-1 distance. Nevertheless, the SP-based method requires both vast computational ability and accurate distribution of random variables that may not be realized in practice (Xiong et al., 2023a). In this context, the RO-based methods are widely applied. Tostado et al. in (Tostado-Véliz et al., 2023b) proposes a fully robust home energy management model, which accounts for all the inherent uncertainties that may arise in domestic installations. Wang et al. in (Wang et al., 2024) proposes a multi-objective two-stage robust optimization to address the inherent uncertainty of DES, aiming to concurrently realize energy savings, carbon emission reduction, and load smoothing. However, the optimization results calculated by RO method are usually conservative and utilize only one dispatch solution to deal with all uncertainties of whole dispatch period. To this end, the learning-based methods have been utilized to solve this problem (Hafeez et al., 2020b; Ben Slama and Mahmoud, 2023; Ren et al., 2024).

To bridge these gaps, this paper proposes an optimized scheduling model for home energy management to minimize the electricity cost with consideration of users' comfort. Then, a novel deep reinforcement learning (DRL) based algorithm is utilized to deal with the uncertainties. The main contributions of this paper are summarized as follows:

- 1) This paper develops an optimized scheduling model for home energy management to schedule both interruptible load and uninterruptible load, which takes consideration of time-of-use price and users' comfort. Different from the Refs. (Chakir et al., 2022; Tostado-Véliz et al., 2022), The optimized strategy for scheduling multi types of loads based on the time-of-use electricity price and real-time energy storage system charging status, which can reduce user electricity costs while ensuring users' comfort.
- 2) The optimization problem of the HEMS is modeled as a Markov decision process (MDP) and then solved by deep deterministic policy gradient (DDPG) algorithm. Moreover, compared with the optimization-based methods in Refs. (Hussain et al., 2023; Wang et al., 2024; Xiong et al., 2024), the applied DDPG method can achieve fast decision making since the learned policy can be generalized to other situations without resolving the optimization model after the agent is trained.

The following sections are organized: The proposed system is described in detail in Section 2. The mathematical modeling



and optimization algorithm are discussed in Section 3. Section 4 presents and analyzes the simulation results obtained for the proposed system. The paper concludes in Section 5.

2 System model

The modelled HEMS architecture is shown in Figure 1. It can be obtained that the constructed system includes HEMS, PV, energy storage and different types of loads. Note that the load can be divided into dispatchable load and non-dispatchable load. Besides, the dispatchable can be further divided into interruptible load and uninterruptible load, which are specifically shown in the Figure 1. The HEMS updates electricity prices, weather, and other information in real time. The HEMS controller is the core component of the entire system, which collects information from upper-level suppliers such as daily electricity prices and household load usage preferences, and calculates the most economical scheduling strategy based on various constraints. In this paper, the HEMS is modelled as a DRL agent for improving the control efficiency.

TABLE 1 Parameters of PV model.

Parameter	Value	Parameter	Value
G_{STC}	1,000 W/m ²	k	0.005
T_r	25°C	$P_{PV, rated}$	5.2 kW

2.1 PV model

To construct the model of PV, temperature and light radiation intensity are the key factors for determining the output of PV (Xiong et al., 2023b). These factors can be represented in the following model:

$$P_{PV,t} = P_{PV, rated} \frac{G}{G_{STC}} (1 - k(T_c - T_r)) \tag{1}$$

where $P_{PV, rated}$ is the rated output of PV in the normal operating condition; T_r is the rated temperature under normal test conditions. G , k and T_c are the light radiation intensity, power temperature coefficient, and atmospheric temperature, respectively. The details of parameters of the PV model are shown in the Table 1.

2.2 Load model

The household electricity load can be divided into dispatchable load, non-dispatchable load, and temperature-controlled load based on the degree of controllability (Hafeez et al., 2020c).

2.2.1 Non-dispatchable load

The non-dispatchable load refers to a load does not adjust operating power or operating time, such as lighting fixtures, televisions, etc. Thus, the non-dispatchable load does not participate in scheduling, but is directly incorporated into the total energy consumption as an important load.

2.2.2 Dispatchable load

Dispatchable load refers to the load with certain elasticity time, which can participate in system dispatching, such as sweeping robots, dryers and other equipment. Dispatchable load can only be started and stopped within the specified operation time, and all other times are closed. The specific constraints are as follows:

$$\begin{cases} S_{A,t} = \{0, 1\}, t \in [t_{start}, t_{stop}] \\ S_{A,t} = 0, t \notin [t_{start}, t_{stop}] \\ 1 \leq t_{start} \leq H - t_a + 1 \\ t_a \leq t_{stop} \leq H \end{cases} \quad (2)$$

where $S_{A,t}$ is the auxiliary variable of the dispatchable load equipment. When $S_{A,t}$ is 1, the equipment is turned on, and when $S_{A,t}$ is 0, the equipment is turned off; t_{start}, t_{stop} represent the starting and ending times of the operating range of dispatchable load equipment; t_a is the rated working time of the dispatchable load; H is the number of sub time periods with equal time length. In this article, a day is divided into 24 parts, that is, H is 24, per unit time period $\Delta t = 1$.

Furthermore, the dispatchable load can be divided into interruptible load and uninterruptible load. The interruptible load can be modelled as:

$$E_{in,i} = \sum_{t=t_{start,i}}^{t_{stop,i}} P_{in,i} S_{in,i,t} \quad (3)$$

where the subscript *in* represents interruptible flexible loads; $E_{in,i}$ is the total rated energy consumption of device i ; $P_{in,i}$ is the unit time power of device i .

The mathematical model for uninterruptible flexible loads is:

$$\sum_{t=\tau+1}^{\tau+t_{un,i}} S_{un,i,t} \geq t_{un,i} [S_{un,i,\tau+1} - S_{un,i,\tau}], \tau \in [t_{start,i} - 1, t_{stop,i} - t_{un,i}] \quad (4)$$

where the subscript *un* represents uninterruptible loads; τ is the time node. Eq. 4 indicates that if device i starts working at time $\tau+1$, it must continue working for at least $t_{un,i}$ periods.

2.2.3 Temperature-controlled load

Temperature-controlled load refers to household equipment with indirect energy storage characteristics, such as air conditioning. The comfort index for residents in this paper is indoor temperature, so the following constraints need to be met (Dongdong, 2020):

$$T_{\min} \leq T_{i,t} \leq T_{\max} \quad (5)$$

TABLE 2 Parameters of battery model.

Parameter	Value	Parameter	Value
η_c	0.9	η_d	0.9
$SOC_{B,\min}$	0.2	$SOC_{B,\max}$	0.9
cap	3 kWh		

where $T_{i,t}$ is the indoor temperature; T_{\min} and T_{\max} are the minimum and maximum indoor temperatures allowed, respectively.

Due to changes in outdoor temperature, it is not possible to directly set the rated operating time of the air conditioner. Its thermo-dynamic model and working time model can be expressed as:

$$T_{i,t+1} = \left(1 - e^{-\frac{\Delta t}{RC}}\right) [T_{o,t} - RP_C S_{C,t} \Delta t] + e^{-\frac{\Delta t}{RC}} T_{i,t} \quad (6)$$

$$t_C = \sum_{t=t_{start,air}}^{t_{stop,air}} S_{C,t} \quad (7)$$

where $T_{o,t}$ is the outdoor temperature; C is the equivalent thermal capacitance; R is the equivalent thermal resistance; P_C is the rated operating power of the air conditioner; $S_{C,t}$ is the operating status of the air conditioner throughout the entire working range, with the air conditioner on as 1 and the air conditioner off as 0; $t_{start,air}$ and $t_{stop,air}$ represents the start and end times of the air conditioning operation interval; t_C is the working time, determined by specific working conditions.

2.3 Battery model

Energy storage devices participate in scheduling through charging and discharging, balancing power fluctuations and improving system flexibility. This article reflects the remaining capacity of energy storage devices through the State of Charge (SOC), which can be expressed as:

$$SOC_{B,t} = SOC_{B,t-1} + (P_{c,t} \eta_c / cap - P_{d,t} / (cap \cdot \eta_d)) \Delta t \quad (8)$$

$$\begin{aligned} 0 &\leq P_{c,t} \leq P_{c,\max} \\ 0 &\leq P_{d,t} \leq P_{d,\max} \end{aligned} \quad (9)$$

$$SOC_{B,\min} \leq SOC_{B,t} \leq SOC_{B,\max} \quad (10)$$

where $SOC_{B,t}$ represents the SOC of the battery at the time-step t ; $P_{c,t}$ and $P_{d,t}$ are the charge and discharge power of the battery at the time-step t ; η_c and η_d are the charge and discharge efficiency at the time-step t ; $SOC_{B,\min}$ and $SOC_{B,\max}$ are the minimum and maximum of the state of charge; cap is the rated power of the battery. The details of parameters of the battery model are shown in the Table 2.

2.4 Problem formulation

To meet the power balance needs of household residents and the demand for excess photovoltaic power grid, HEMS needs to interact with the power grid for energy exchange, which can be expressed as:

$$P_{L,t} = P_{M,t} + P_{CSC,t} + \sum_{i=1}^{m+n} P_{A,i} S_{A,t} \quad (11)$$

$$P_{G,t} = P_{L,t} - P_{P,t} - P_{B,t} S_{B,t} - P_{E,t} S_{E,t} \quad (12)$$

where $P_{L,t}$ is the total power of the load; $P_{A,t}$, and $P_{M,t}$ represent the power of dispatchable loads and non-dispatchable loads, respectively; $P_{G,t}$ is the interaction energy with the power grid; $S_{E,t}$ is the EV switch state.

This paper aims to minimize the total cost with consideration of comfort, so the optimization objective can be formulated as:

$$\min C_G - \beta C_{com} \quad (13)$$

$$\begin{cases} C_{G,t} = P_{G,t} R_{b,t}, P_{G,t} \geq 0 \\ C_{G,t} = |P_{G,t}| C_{P,t}, P_{G,t} < 0 \end{cases} \quad (14)$$

$$C_{com} = 1 - \frac{(t_{si} - T_{si})}{\Delta T_i} \quad (15)$$

Where $C_{G,t}$ is the cost generated by the interaction energy between the system and the power grid; $R_{b,t}$ is the real-time electricity price prediction information (RTP) for the day ahead; $C_{P,t}$ is the electricity price for photovoltaic surplus electricity; β is a weight coefficient, which aims to balance the energy cost saving and maintenance of user's comfort during the optimization process. C_{com} is the index of comfort; t_{si} represents the actual starting time of the electrical appliance; T_{si} represents the desired starting time; ΔT is the allowed working time.

3 Applied deep reinforcement learning algorithm

In this paper, a novel DRL algorithm called deep deterministic policy gradient (DDPG) is applied to solve the optimization problem for improving the solving efficiency (Shi et al., 2023).

3.1 Formulate the optimization problem as an MDP

When applying the DRL algorithm, the optimization problem should first be modeled as a Markov Decision Process (MDP), which can be expressed as follows:

State set S : the state set is composed of the state of agent at each time-step t , which can be represents $S = (s_1, s_2, \dots, s_t)$. The state of agent at each time-step t can be denotes as:

$$s_t = (P_{PV,t}, P_{fix,t}, P_{in,t}, P_{um,t}, SOC_{B,t}, SOC_{EV,t}, T_{i,t}, R_{b,t}, C_{P,t}) \quad (16)$$

where $P_{fix,t}$ is the non-dispatchable load at time-step t .

Action set A : the action set is composed of the action of agent at each time-step t , which can be represents $A = (a_1, a_2, \dots, a_t)$.

$$a(t) = (\alpha_{in,t}, \alpha_{um,t}, \alpha_{air,t}, P_{SOC,t}, P_{EV,t}) \quad (17)$$

where $\alpha_{in,t}$, $\alpha_{um,t}$, $\alpha_{air,t}$ are the switching variables of interruptible load, uninterruptible load and air conditioning, respectively; $P_{SOC,t}$ is the action of battery at the time-step; $P_{EV,t}$ is the action of battery at the time-step.

Reward function R : The reward at time t $r(t)$ represents an immediate reward, which is obtained when the agent executes action

$a(t)$ based on state information $s(t)$. The real-time reward can be formulated as:

$$r(t) = -(C_G - \beta C_{com}) \quad (18)$$

Transition Probability P : once the current information (such as $a(t), s(t)$) is determined, the probability of transitioning to the next state $s(t+1)$ is fixed.

3.2 Applied the DDPG algorithm to solve the MDP

Then, the modeled MDP can be solved by proposed DDPG algorithm to obtain the optimal dispatch strategy, which is illustrated in Figure 2. The DDPG algorithm, as an advanced deep reinforcement learning algorithm, is very suitable for solving complex multidimensional optimization problems in continuous action spaces (Zheng et al., 2023). In the DDPG algorithm, the policy function maps the state to the expected output, while the critical function maps the state and action to the expected maximum output R_t , which maximizes the action value function $Q^\pi(s_t, a_t)$. The calculation formula for the action value function $Q^\pi(s_t, a_t)$ is as follows:

$$Q^\pi(s_t, a_t) = \mathbb{E}_\pi [G(s_t, a_t) + \gamma \mathbb{E}_{a_{t+1} \sim \pi} [Q^\pi(s_{t+1}, a_{t+1})]] \quad (19)$$

The DDPG algorithm is based on the actor critic framework, which consists of two main parts (actor network and critic network), with each part containing two networks (i.e., the main network and the target network). The actor network adjusts the value of the parameters θ^μ in the policy function $\mu(s|\theta^\mu)$ by fitting the current state to the corresponding actions. The critic network is used to adjust the value of the parameters θ^Q in the action-value function $Q(s, a|\theta^Q)$.

The parameters θ^Q in the critic network are updated by minimizing the value of the loss function $\mathcal{J}(\theta^Q)$, which is expressed as follows:

$$E_{(s,a)} \left[\left(Q(s_t, a_t|\theta^Q) - y_t \right)^2 \right] \quad (20)$$

where $y_t = r_t(s_t, a_t) + \gamma Q(s_{t+1}, \mu(s_t|\theta^\mu)|\theta^Q)$.

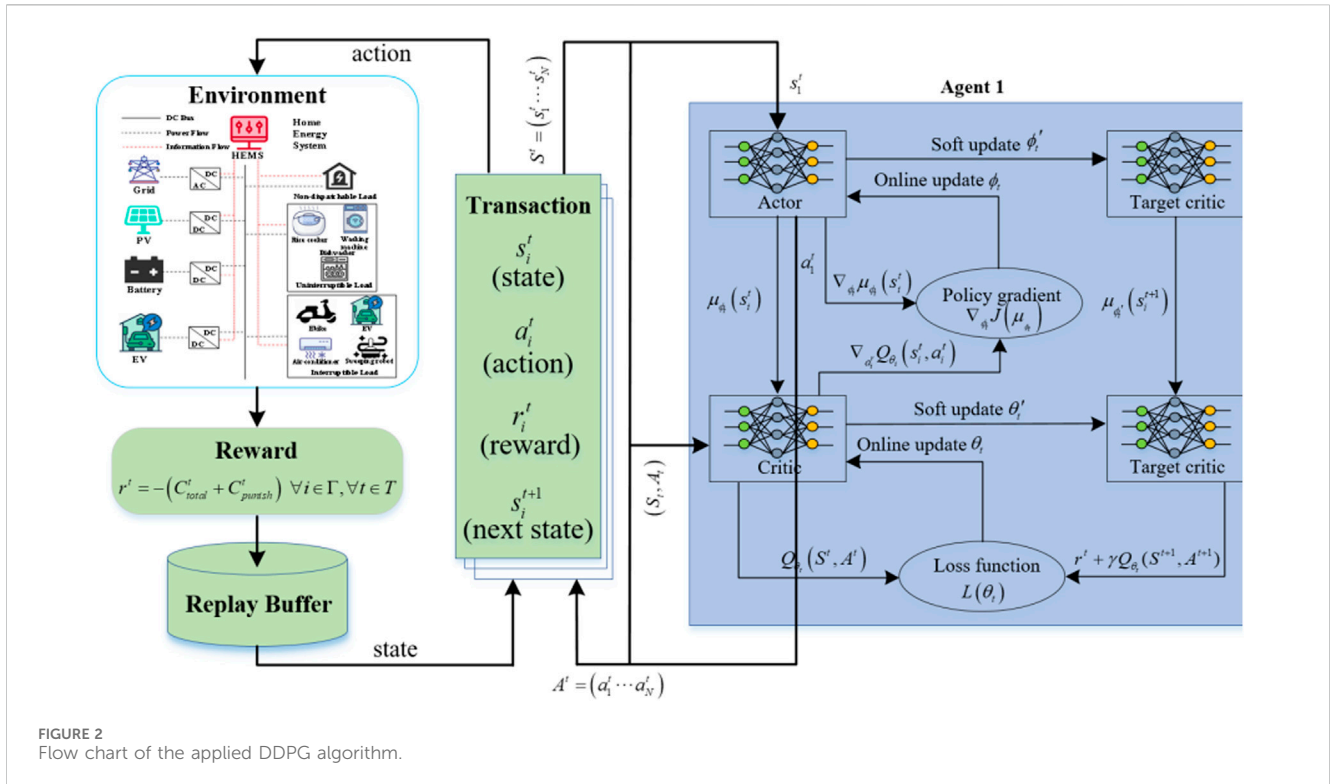
In the actor network, the parameters θ^μ are updated through the policy gradient function as follows:

$$\begin{aligned} \nabla_{\theta^\mu} J^{\theta^\mu} &\approx \mathbb{E}_{s_t \sim \rho} \left[\nabla_{\theta^\mu} Q(s, a|\theta^Q) \Big|_{a=\mu(s|\theta^\mu)} \nabla_{\theta^\mu} \mu(s|\theta^\mu) \right] \\ &= \mathbb{E}_{s_t \sim \rho} \left[\nabla_a Q(s, a|\theta^Q) \Big|_{a=\mu^\theta(s)} \nabla_{\theta^\mu} \mu(s|\theta^\mu) \right] \end{aligned} \quad (21)$$

where ρ represents the discount factor; β represents the specific strategy corresponding to the current policy π .

In order to improve the stability and reliability of the learning process of the DDPG algorithm, two different target networks are added to the actor network and the critic network, respectively. They are the target actor network $\mu'(s|\theta^{\mu'})$ and the target critic network $Q'(s, a|\theta^{Q'})$. In each iteration, the weight factors ($\theta^{\mu'}$ and $\theta^{Q'}$) will be soft updated according to the following formulas:

$$\text{Soft update} \begin{cases} \theta^{Q'} \leftarrow \tau \theta^{Q'} + (1 - \tau) \theta^Q \\ \theta^{\mu'} \leftarrow \tau \theta^{\mu'} + (1 - \tau) \theta^\mu \end{cases} \quad (22)$$



where τ represents the soft update coefficient, and $\tau \ll 1$.

The specific training process of the proposed algorithm is described in Algorithm 1, which is shown as below:

- 1: **Input:** states of agent s_t .
- 2: **Output:** action of agent a_t .
- 3: **Initialize:** the weights of actor and critic networks θ^a and θ^c ; the weights of target networks θ^a , θ^c .
- 4: **for** episode = 1 **to** max episode **do**
- 5: Initialize **Environment**
- 6: **for** time step = 1 **to** max step **do**
- 7: Select action $a(t)$ based on $Q^\pi(\cdot|s(t))$.
- 8: Execute the actions and obtain the reward $r(t)$, observe the set of next state $s(t+1)$.
- 9: Store the transition pair $(s(t), a(t), r(t), s(t+1))$ in the replay buffer.
- 10: **end for**
- 11: **If** time step \geq update step **do**
- 12: Sample a mini-batch transition from the replay buffer.
- 13: Minimize the loss function to update the weights of critic network θ^c as Eq. 20 shows.
- 14: Update the weights of actor network θ^a by computed the policy gradient based on Eq. 21.
- 15: Update the weights of target networks based on Eq. 22.
- 16: **end if**
- 17: **end for**

Algorithm 1. Training procedures of proposed DDPG method.

4 Cased study

4.1 Case setting

To verify the effectiveness of the proposed method, a smart home energy system is constructed. The simulation period is set as 1 day with 24 h from 00:00–24:00. There are six dispatchable devices in the home, which are shown in the Table 3. Note that the superscript “*” in the first column of Table 1 indicates the household appliance is an uninterrupted load. The PV generation and non-dispatchable load are shown in the Figure 3. The capacity of battery is 3 kWh, while the charging/discharging efficiency is 0.95. The minimum and maximum of the state of charge SOC_{min} and SOC_{max} are 0.2 and 0.9. To meet comfort constraints, the indoor temperature must be limited between 25°C and 27°C when the air-conditioning is running. The simulation model is constructed in MATLAB 2018b and the training procedure of DRL method is conducted in Python based on a workstation computer with 32 GB RAM and Intel Core i9-10920X CPU.

4.2 Optimization results obtained by the applied DDPG method

To obtain the optimal dispatch strategy of HEMS, the DDPG algorithm is applied. The hyper-parameters of the agent are set as the Table 4 shown. The total training episodes is 8,000 for ensuring convergence of agent. Besides, the learning rate of actor and critic network are set as 0.002 and 0.001 for ensuring the exploring ability and decision-making ability, respectively. The soft update coefficient and batch size are set as 0.001 and 256 to stable the training process.

TABLE 3 Parameters of dispatchable load (WU et al., 2019).

Household appliances	Power/kW	Working interval	Required working hours/h	Minimum continuous working hours/h
Washing machine*	1	14:00–21:00	2	2
Rice cooker*	0.8	06:00–12:00	1	1
Dishwasher*	0.73	18:00–24:00	1	1
Electric vehicle	2.5	00:00–08:00	5	1
Electric bicycle	0.9	00:00–08:00	3	1
Sweeping robot	0.35	10:00–18:00	2	1
Air-conditioning	2.1	00:00–07:00	-	1
		18:00–24:00		

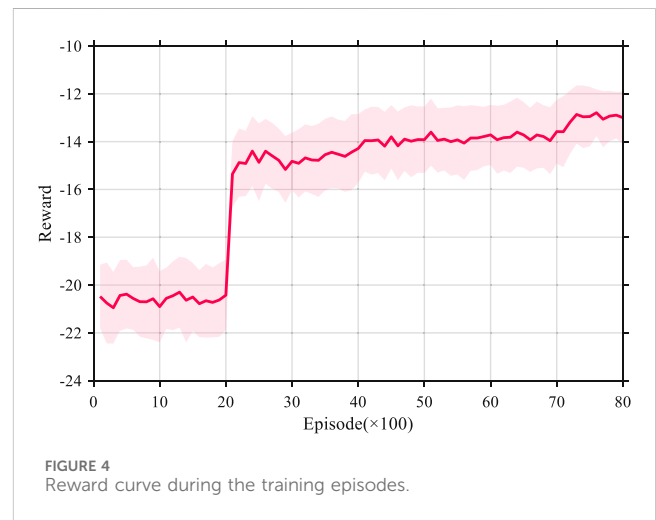
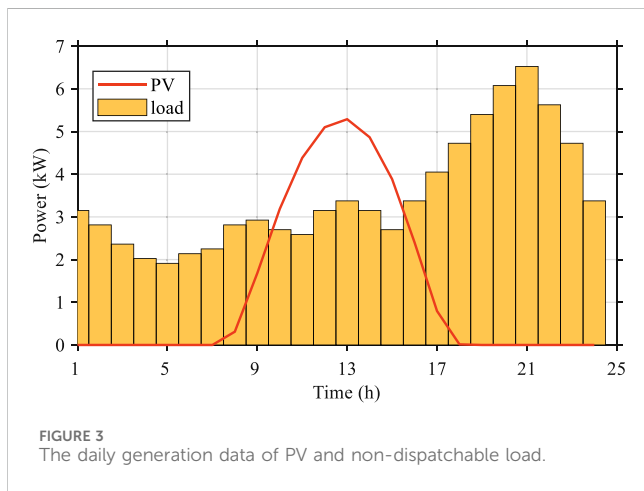


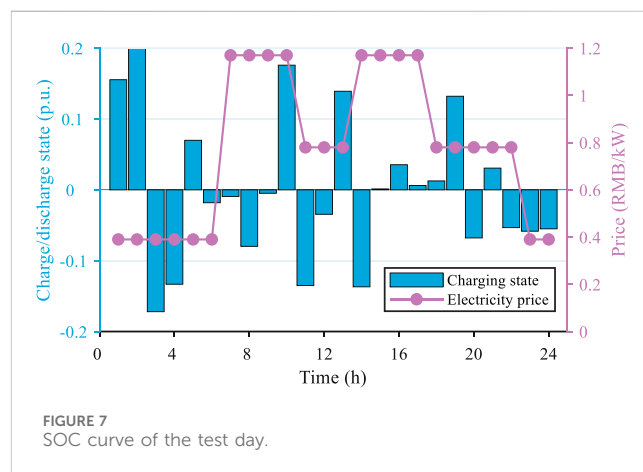
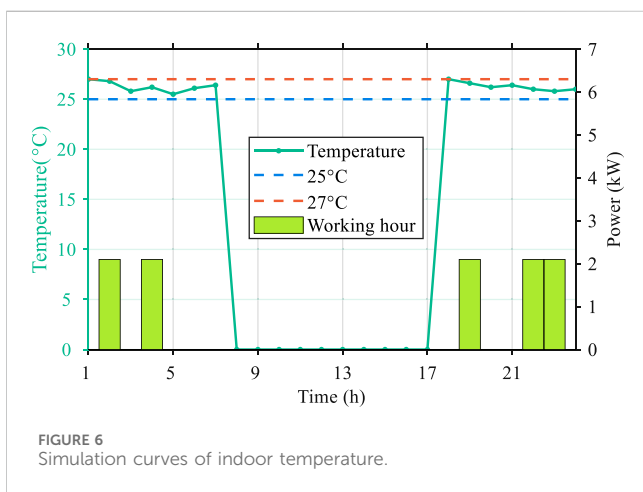
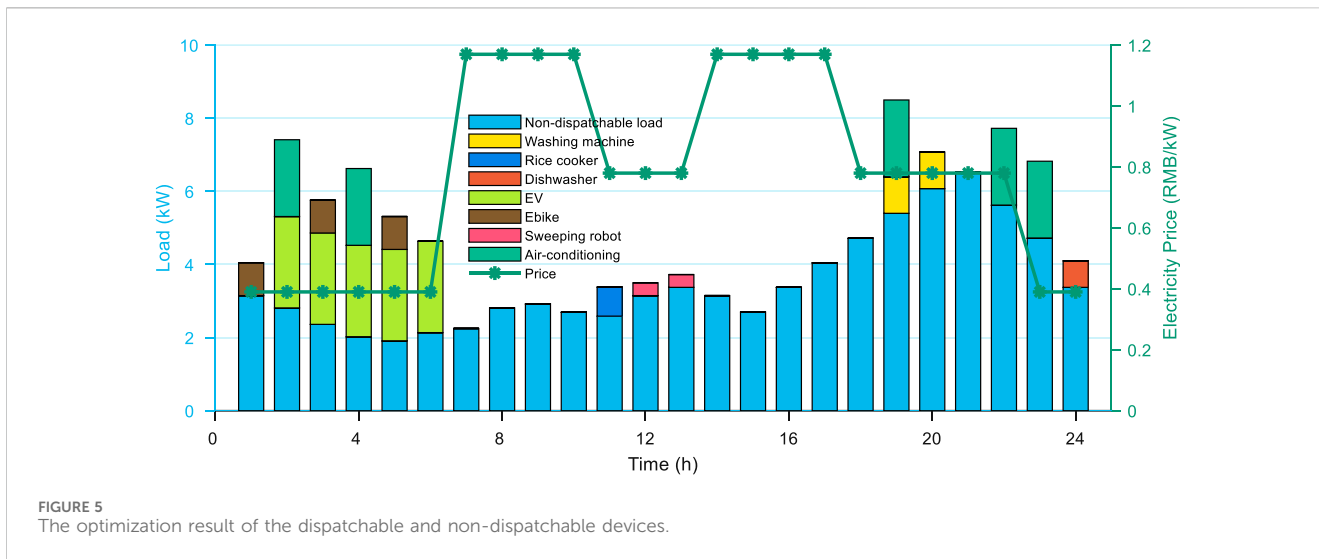
TABLE 4 Hyper-parameters settings of the applied DRL model.

Parameter	Value
Train episodes	8,000
Learning rate of actor network	0.002
Learning rate of critic network	0.001
Soft update coefficient	0.001
Batch size	256

At each episode, the agent gets current state from the constructed home energy system, and then give the decided action back. The changes of reward of the applied DRL method during the whole training episodes is illustrated in the Figure 4. It can be obtained that the reward stays in a low range with an average value -21 in the first 2000 episodes, which indicates that the agent cannot finds the optimal policy for HMS dispatching. Then, the reward rises gradually to -14 and then converges to -13 after the ceaseless interaction between agents and environment, which means the agent can obtain better strategy for dispatching the system.

After the agent is well-trained, the optimal energy management strategy for HES can be obtained. The results of the dispatch optimization for devices are presented in Figure 5. The needs of non-dispatchable devices are satisfied first. Then, the dispatchable devices should be dispatch with consideration of the real-time electricity price and permitted working interval of each device. It can be observed that all the uninterruptible devices are scheduled at a relatively low price point for saving the total cost. For example, the work time-point of washing machine is scheduled at 19:00 and 20:00 caused by the low price. Thus, the dispatch strategy of the uninterruptible devices is quite reasonable.

Furthermore, the interruptible devices can be dispatchable at discontinuous time-point, whose dispatch strategy can be more flexible. When dispatching the interruptible devices, the system cost should be the first and only consider factor. It can be obtained that the EV and Ebike are scheduled to charge during the 00:00–06:00 cause the lower electricity price. Therefore, both the interruptible and uninterruptible devices can be reasonably scheduled after the agent is well-trained, which means that the proposed method can effectively realize the HEM optimal operation.



When dispatching the air-conditioning device, the comfort factor should be taken into account. The indoor temperature changes like a non-linear process when the air-conditioning working. Thus, the air-conditioning does not need to working continuous with consideration of cost saving. The dispatching result of air-conditioning and the indoor temperature are shown in Figure 6. Note that the comfort constraint only set between 00:00–07:00 and 18:00–24:00. It can be obtained that the air-conditioning is scheduled to work at 5 hours for keep the indoor temperature between 25°C–27°C. As the temperature curve shows, the indoor temperature always stays between 25°C and 27°C, which indicates the comfort constraint can be well limited.

Generally, the energy storage device can store electricity during lower electricity price periods and release it during higher prices to reduce system costs. Thus, an energy storage device is equipped in the paper. The SOC curve of the applied energy storage device is illustrated in Figure 7. It can be found that the energy storage device charging when electricity price is low and discharging when the price is high, which can effectively reduce the system cost. Hence, the results effectively demonstrate that the proposed approach can

efficiently schedule the energy storage device in real-time to reduce the operating cost after the agent is well-trained.

4.3 Comparison results with other benchmarks

The above results have verified the effectiveness of the proposed method. To further verify the effectiveness and progressiveness of the proposed method, the proposed method is separately compared with the optimization method based on stochastic programming (SP) and the optimization method based on deterministic optimization (DO) (Alzahrani et al., 2023). The difference between SP and DO is that DO only consider optimization problems in deterministic scenarios, which does not consider uncertainties of PV and loads.

The optimization results of the three algorithms are shown in Table 5. Compared to traditional optimization methods, the proposed method can better cope with the uncertainty of PV output and load demand to achieve better optimization results. It can be obtained that the proposed method can achieve the lowest total cost compared with other two method, which the total

TABLE 5 Comparison results of different methods.

Method	Total cost/RMB	Cost of purchasing electricity/RMB	Revenue from selling electricity/RMB	Average comfort
SP	34.73	50.21	15.48	0.79
DO	32.78	45.63	12.85	0.86
Proposed	26.89	40.60	13.71	0.89

operation cost can be reduced by 21.9% at least. The proposed method can reasonably schedule the different types of appliances for reducing the cost of purchasing electricity and improving revenue from selling electricity. Besides, the proposed can maintain the highest comfort for the home users by reasonably dispatching the switching time of air-conditioning. The DO method solves the modelled optimization problem under deterministic conditions, and the final cancelled optimization effect is not significantly different from the optimization effect of the proposed method. This also fully demonstrates the effectiveness of the proposed method. However, the DO method cannot address the issue of output uncertainty and is not applicable to actual operating conditions. Therefore, the proposed method is more suitable for optimizing the operation of the HES in uncertain environments.

5 Conclusion

This paper proposes an optimized scheduling model for home energy management to minimize costs of household users with consideration of comfort of user. To enhance solution efficiency, a novel DRL-based algorithm call DDPG is applied to solve the optimization problem. Firstly, the results show that the proposed method can effectively dispatch both interruptible and uninterruptible loads, so the total cost of household user is obviously reduced while maintain high comfort. The optimal dispatch problem of HEMS is modeled as a MDP and solved by DDPG algorithm. The agent has converged after 8,000 episodes training, which means that the proposed DRL method can obtain the optimal policy for dispatching the HEMS. In the future work, the multi-agent deep reinforcement learning algorithm will be used to improve the efficiency of model training and decision making.

Data availability statement

The raw data supporting the conclusion of this article will be made available by the authors, without undue reservation.

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TP: Conceptualization, Software, Writing–original draft. ZZ: Conceptualization, Data curation, Formal Analysis, Writing–review and editing. HL: Conceptualization, Investigation, Methodology, Software, Writing–original draft. CL: Investigation, Methodology, Project administration, Resources, Writing–original draft. XJ: Conceptualization, Methodology, Writing–review and editing. ZM: Conceptualization, Methodology, Supervision, Writing–review and editing. XC: Conceptualization, Investigation, Writing–review and editing.

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Conflict of interest

Authors TP, HL, and XJ were employed by Southern Power Grid Research Institute Co., Ltd. Authors ZZ, CL, ZM, and XC were employed by Power Dispatch Control Center of Guangdong Power Grid Co., Ltd.

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