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A Belief-desire-intention Agent Model for Modeling End-user Decision-Making under Demand Response#

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ABSTRACT

Accurate modeling of end-users' decision-making behavior is crucial for validating demand response (DR) policies. However, existing models usually represent the decision-making behavior as an optimization problem, neglecting the impact of human psychology on decisions. In this paper, we propose a Belief-Desire-Intention (BDI) agent model to model end-users' decision-making under DR. This model has the ability to perceive environmental information, generate different power scheduling plans, and make decisions that align with its own interests. The key modeling capabilities of the proposed model have been validated in a household end-user with flexible loads.

Keywords: demand response, decision-making model, BDI agent, household power scheduling

NONMENCLATURE

Abbreviations	
BDI	Belied-desire-intention
DR	Demand Response
HEMS	Home Energy Management System
MCDM	Multi-criteria Decision Making
AC	Air Conditioner
EWH	Electric Water Heater
WM	Washing Machine
DW	Dishwasher

1. INTRODUCTION

Demand response (DR) is recognized as an efficient technology to reduce peak electricity loads [1]. The basic idea of DR is that household end-users can reduce their electricity consumption during peak hours in response to the incentive price from utility grids [2]. The reaction of end-users is crucial for the success of DR [3]. Hence, the accurate modeling of end-users' decision-making is important for evaluating the effectiveness of DR policies.

Currently, the decision-making problem for end-users under DR is typically formulated as an optimization problem [4]. The optimal power scheduling plan is derived by solving an optimization model under DR signals [5]. Various optimization models have been employed to address the decision-making problem, including linear programming [6] and nonlinear programming [7]. These optimization models have different objective functions and constraints. Regarding optimization objectives, the most common objective is the minimization of operation cost. Additionally, end-user discomfort resulting from adjusting set-points of temperature-controlled loads and altering the operation times of shiftable loads, are also considered. In terms of constraints, the focus is primarily on decision variable constraints, ensuring that the optimized decision variables remain within allowable ranges. For example, the optimal temperature for temperature-controlled loads should be maintained within the comfortable temperature range.

However, the actual decision-making process for end-users is not a simple optimization process. Just like humans make decisions, end-users should select what they consider the most appropriate power scheduling plan from a set of possible plans based on the DR signals. Firstly, end-users can adjust their acceptable temperature tolerance range based on their perception of the incentive electricity price, which depends on the knowledge they possess. Secondly, when faced with multiple options, end-users typically make decisions based on relative values rather than the absolute values of economic cost or comfort. Unfortunately, existing optimization models often fail to incorporate these considerations. It can lead to a misunderstanding of end-user decision-making behavior.

A cognitive agent model, namely belief-desire-intention (BDI), has been widely used to model the human decision-making process in social science [8]. It is

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based on three mental modules: beliefs (agent's perceptions about environment and own states), desires (goals), and intentions (plans or actions) [9]. The performance of the BDI agent model has been validated in many fields, such as evacuation simulations [10], cropping plan decisions [11], land changes [12] and traffic simulations [13].

Inspired by this idea, this paper proposes a BDI agent model to simulate end-users' decision-making processes under DR. Three mental modules are specifically developed to represent the end-user's perception, reasoning and decision-making processes under demand response.

2. METHODOLOGY

2.1 Overview of the proposed model

The architecture of the proposed end-user decision-making agent model, based on the BDI paradigm, is illustrated in Fig. 1. It is composed of three modules: belief module, desire module, and intention module. The specific functions of each module can be described as: 1) Belief updating. The end-user updates its beliefs by continuously observing the environment (e.g., DR signals from the utility grids) through the perceptual processor. Day-ahead alternative power scheduling plans from the household's HEMS are also collected. The beliefs are classified into three categories based on their source: itself, environment, and power scheduling plans. 2) Desire updating. Based on these new beliefs, the end-user's DR goals are identified through a cognitive processor and transformed into desires. The desires are hierarchical, encompassing the most basic temperature set-point requirements and further extending to cost and comfort needs. 3) Intention generation. Based on the beliefs and desires, the planner in the intention module generates alternative power scheduling plans through a multi-objective optimization model (implemented via HEMS). The generated plans are stored in the intention set and are transformed into the beliefs. A power scheduling plan is defined as the temperature and start time settings for various flexible household appliances (e.g., ACs, EWHs, WMs, DWs) to achieve the end-user's goals. The decision-maker uses a multi-criteria decision making model to compare the plans. An optimal or satisfactory plan is selected from these plans and executed through the HEMS.

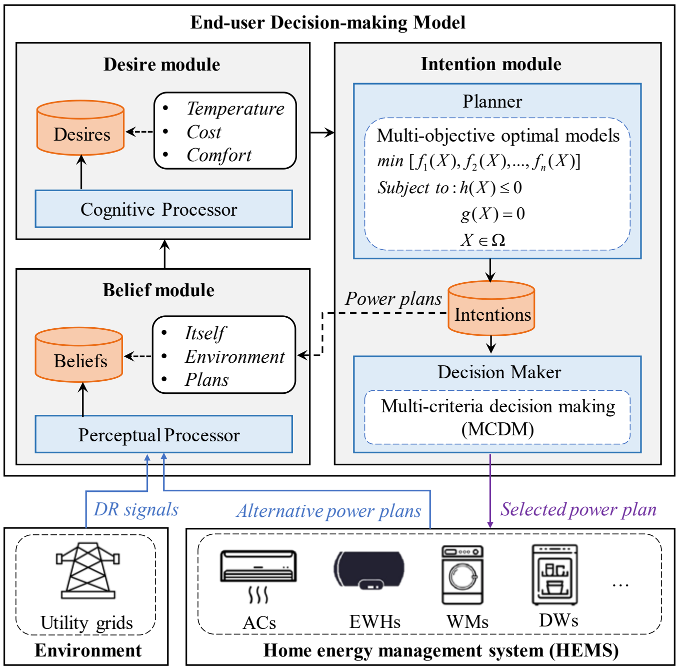

Fig. 1 Overview of the proposed BDI model

2.2 Belief module

The beliefs of an end-user model are formed by the information from the environment and its own internal characteristics. The beliefs can be represented by a hierarchical structure. It consists of three classes: *Itself*, *Environment* and *Plans*. An example of the hierarchical structure for an end-user's beliefs is shown in Fig. 2. Each class contains several sub-classes to represent more specific concepts. For example, *cost-oriented* and *comfort-oriented* represent end-users' personal attitudes towards participation in DR. *DR signals* represent the DR environmental information received by end-users. The *original power plan* represents end-users' household scheduling plans before DR. The *advanced power plans* represent the optimal scheduling plans recommended by HEMS under the DR price signals.

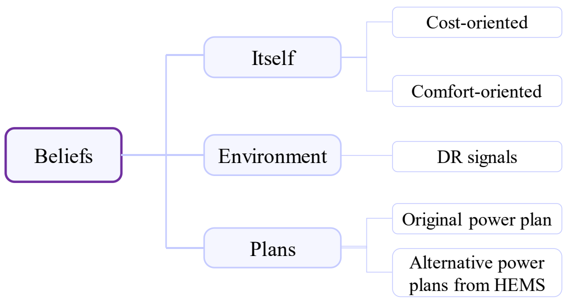

Fig. 2 The hierarchical structure for end-users' beliefs

2.3 Desire module

A desire library stores the collection of an end-user's desires, which are formed based on the existing beliefs. In the context of DR, desires can be divided into different levels. The most basic level is, for example, end-users determining their acceptable temperature adjustment range based on perceived price signals. The advanced level is, for example, end-users aiming to ensure comfort while obtaining more economic benefits when participating in DR.

2.3.1 Temperature adjustment range

The temperature adjustment range acceptable to end-users is related to their perceived DR signals. Generally, the higher the incentive electricity price, the stronger the end-users' willingness to adjust their temperature range, as shown in Figure 3.

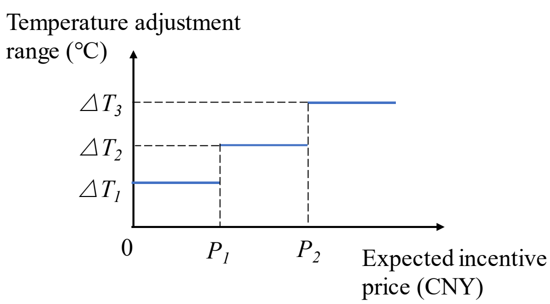

Fig. 3 The relationship between incentive electricity price signals and the temperature adjustment range

2.3.2 Cost and comfort indicators

Cost and comfort indicators represent typical evaluation criteria for different power scheduling plans when end-users participate in DR, as detailed below:

a) Cost indicator

The cost indicator represents the economic benefits the end-user gains from participating in DR.

$$F_{benifit} = max(\sum_{t=1}^{T} EP(t) \cdot \sum_{j \in N} \Delta P_j(t) \cdot \Delta t + W_{DR} * IP)$$

Where T is the number of time intervals of a day (t = 1, …, T); Δt is the time interval [h]; $EP(t)$ is the electricity price at time t [CNY/kWh]; $\triangle P_j(t)$ is the change in power consumption of flexible load j at time t before and after DR [kW]; N is the types of flexible loads including the AC, EWH, WM and DW; W_{DR} is the response electricity amount during the DR period; IP is the incentive price.

b) Comfort indicator

The comfort indicator represents the operating time shift deviation φ_{shift} of shiftable loads and the set-point temperature deviation φ_{tcl} of thermostatically controlled loads.

$$F_{comfort} = min(\omega_1 \cdot \varphi_{shift} + \omega_2 \cdot \varphi_{tcl})$$

$$\varphi_{shift} = \sum_{s \in N(s)} | T_{start,s}^{DR} - T_{start,s}^{ori} |$$

$$\varphi_{tcl} = T_{change} \cdot \sum_{m \in N(m)} | T_{set,m}^{DR} - T_{set,m}^{ori} |$$

Where ω_1 and ω_2 are the weights; $N(s)$ is the types of shiftable loads including the WM and DW; $T_{start,s}^{DR}$ is the starting time of shiftable appliance s after DR [h]; $T_{start,s}^{ori}$ is the original starting time of shiftable appliance s before DR [h]; $N(m)$ is the types of thermostatically controlled loads including the AC and EWH; $T_{set,m}^{DR}$ is the set-point temperature of thermostatically controlled appliance m after DR [℃]; $T_{set,m}^{ori}$ is the original set-point temperature of thermostatically controlled appliance m before DR [℃]; T_{change} is the duration of the temperature adjustment [h].

2.4 Intention module

In the planner, end-users set their acceptable temperature adjustment range under the corresponding DR incentive price and generate a series of power scheduling plans that can achieve their desired goals. These plans are stored in an intention set for decision-making. In this work, we use a multi-objective optimization model to generate these plans, which are implemented by HEMS. For details on the multi-objective optimization model, refer to the work in [4], which will not be elaborated here.

After obtaining these alternative power scheduling plans, the multi-criterion decision model (MCDM) is used to represent the selection process of plans. The utility function of each plan can be calculated as follows:

$$UF = \alpha * \Delta F_{benifit} + \beta * \Delta F_{comfort}$$

Where, α is the weight of cost indicator; β is the weight of comfort indicator.

Finally, the agent selects the plan with the largest utility function to commit.

3. CASE STUDY

To demonstrate the key modeling capabilities of the proposed BDI decision-making model, a household end-user was selected as the research subject. The flexible loads of this household include a room air conditioners (AC), an electric water heater (EWH), a washing machine (WM), and a dishwasher (DW). The mathematical models for each appliance were established with reference to the literature [14,15]. The model parameters are listed in Table 1.

Table 1. Model parameters of flexible loads

Load Type	Parameters	Value
AC	Power (W)	1200
	Efficiency	3.3
	Dead-band (℃)	1
	Original temperature setting (℃)	26
EWH	Power (W)	2500
	Efficiency	80%
	Dead-band (℃)	10
	Original temperature setting (℃)	65
WM	Power (W)	150
	Switch-on time	19:00
	Operation duration (min)	60
DW	Power (W)	200
	Switch-on time	18:00
	Operation duration (min)	90

The daily fixed electricity price for end-users is 1 CNY/kWh. The utility grids issue DR signals one day in advance, including the DR period and the incentive price. In this paper, the DR period is set from 17:00 to 20:00. To compare the effects of different incentive prices, the incentive prices are set at 1.5 CNY/kWh and 2.5 CNY/kWh. After perceiving electricity price signals, the acceptable temperature adjustment ranges for end-users are shown in Table 2.

Table 2. Acceptable temperature adjustment ranges under different incentive prices

Incentive Price	Temperature settings	
	AC	EWH
1.5 CNY/kWh	[25, 27 ℃]	[60, 70 ℃]
2.5 CNY/kWh	[23, 29 ℃]	[55, 75 ℃]

4. RESULTS

4.1 Alternative power scheduling plans under different incentive electricity prices

The alternative household power scheduling plans under different incentive electricity prices were obtained through a multi-objective optimization model. Several important plans were selected and were presented in Table 3 and Table 4.

Using the plans ID 1 from Table 1 as an example, it represents adjusting the temperature set-point of the adjustable load AC to 27 ℃ during the DR period (an increase of one degree compared to the original temperature setting) for one hour. The economic benefit indicator for this plan is 0.1 CNY, the temperature deviation indicator is 1 ℃*h, and the time deviation indicator is 0 (no adjustment of time-shiftable loads). Plans ID 2 represents adjusting the AC set-point temperature to 27 ℃ for the entire DR period, lasting three hours. The indicators for this plan are as follows: the economic benefit indicator is 0.7 CNY, the temperature deviation indicator is 3 ℃*h, and the time deviation indicator is 0. The same principle applies to other plans IDs, and will not be reiterated here. It should be noted that the plans displayed in Table 1 only represent the indicators for adjusting a single adjustable load. Higher economic benefits can be achieved through different combinations of load adjustments, such as both changing the temperature set-point of temperature-controlled loads and adjusting the start time of shiftable loads, as detailed in Section 4.2. End-users can select acceptable power scheduling plans based on the above cost and comfort indicators.

Table 3. Power scheduling plans under 1.5 CNY/kWh incentive electricity price

Plans ID	Types of adjusted loads	Economic Benefit Indicator (CNY)	Temperature Deviation Indicator (℃*h)	Time Deviation Indicator (h)
1	AC	0.10	1	0
2	AC	0.70	3	0
3	EWH	0.73	5	0
4	EWH	0.94	15	0
5	WM	0.23	0	1
6	DW	0.30	0	1
7	DW	0.60	0	2

In Table 4, plans ID 1 and ID 2 represent adjusting the AC set-point temperature to 27 ℃ for 1 hour and 3 hours respectively (the same as in Table 3). The economic benefits achieved are higher due to the increased incentive electricity prices. Plans ID 3 represents the end-user making a more aggressive adjustment to the temperature set-point, setting it to 29 ℃ under an incentive electricity price of 2.5 CNY/kWh. Compared to Plans ID 2, this plan results in greater economic benefits but also a larger temperature deviation.

Table 4. Power scheduling plans under 2.5 CNY/kWh incentive electricity price

Plans ID	Types of adjusted loads	Financial Benefits Indicator (CNY)	Temperature Deviation Indicator (℃*h)	Time Deviation Indicator (h)
1	AC	0.14	1	0
2	AC	0.98	3	0
3	AC	2.17	9	0
4	EWH	1.02	5	0
5	EWH	1.31	15	0
6	EWH	1.88	30	0
7	WM	0.38	0	1
8	DW	0.50	0	1
9	DW	1.00	0	2

4.2 Power plans selection based on multi-criteria decision making model

Taking the incentive electricity price of 2.5 CNY/kWh as an example, end-users compared and selected different alternative power scheduling plans based on a multi-criteria decision model. They ultimately determined the plan that satisfied their preferences: adjusting the AC temperature set-point to 27 ℃ for 3 hours; adjusting the EWH temperature set-point to 60 ℃ for 1 hour; adjusting the WM start time to 20:00; and adjusting the DW start time to 20:00, as shown in Figure 4.

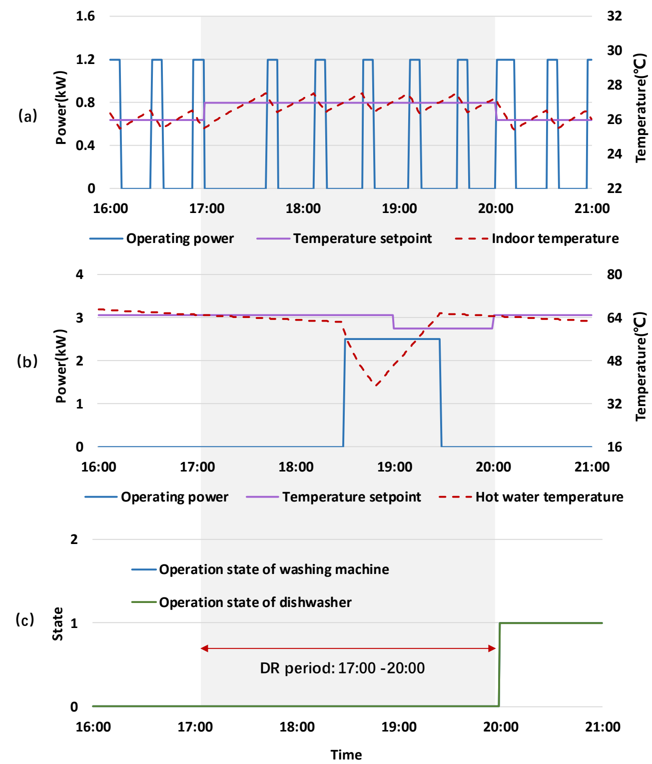

Fig. 4 Selected power scheduling plan of flexible loads: (a) AC; (b) EWH; (c) WM and DW

5. CONCLUSIONS

Accurate modeling of end-users' decision-making behavior is important for evaluating demand response policies. Based on paradigms of human decision models in the field of social science, this paper proposes a belief-desire-intention (BDI) agent model to simulate end-users' decisions in DR programs. The belief, desire, and intention mental modules in the model are concretely designed through multi-objective optimization models and multi-criteria decision models. This model can express the end-user's perception, reasoning, and decision-making process. A household end-user with various flexible loads such as AC, EWH, WM, and DW is modeled to analyze their decision-making process under different electricity price signals. The results show that the end-user can analyze different household power scheduling plans and select the appropriate plan for implementation.

This paper merely proposes a basic framework for a human-like decision-making model. In the future, more elements can be added to this framework, such as the theory of bounded rationality and analysis of end-users' characteristics through social surveys.

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