Engineering Applications of Artificial Intelligence 71 (2018) 166–174

Contents lists available at ScienceDirect

Engineering Applications of Artificial Intelligence

journal homepage: www.elsevier.com/locate/engappai

Multi-time slots real-time pricing strategy with power fluctuation caused by operating continuity of smart home appliances

Hongbo Zhu[a,b], Yan Gao[a,*], Yong Hou[c,d], Li Tao[a,b]

[a] School of Management, University of Shanghai for Science and Technology, Shanghai 200093, China
[b] Faculty of Mathematics and Physics, Huaiyin Institute of Technology, Huai'an 223003, China
[c] Institute for Energy Studies, University of North Dakota, Grand Forks, ND 58202, USA
[d] Clean Republic LLC, Grand Forks, ND 58203, USA

ARTICLE INFO

Keywords:
Smart grid
Smart home appliance
Real-time pricing
Social welfare maximization
Demand response

ABSTRACT

Demand side management aims to match power demand to supply through cutting the peak and filling the valley, is one of the most important factors in smart grid. The real-time pricing (RTP) mechanism is an ideal method to adjust power balance between supply and demand. Its implementation has a profound impact on users' behavior, and on operation and management of the power grid. In this research, we propose an expectation social welfare maximization model, considering the classification of the smart home appliances (SHA) and the correlation of power consumption of multi-time slots. Users can arrange their appliances more profitable and more closely to reality with the advantage of multi-time slots RTP strategy. The constraint in the model reflects the fluctuation (uncertainty) of power consumption caused by operating continuity of the SHA. By introducing probabilistic constraints, the uncertainty optimization model is transformed into a convex optimization problem. The existence and uniqueness of the optimal solution are shown, and its properties are further analyzed. Considering the convex optimization problem is separable in dual domain, this study proposes a decentralized online RTP algorithm to determine each user's demand and energy supplier's supply simultaneously. By utilizing Armijo line search to instead of fixed step size of the dual subgradient method, the decentralized online RTP algorithm proposed in this research can overcome the defects of slow convergence and even no convergence from the original dual subgradient method. Finally, the simulation validates the rationality and feasibility of optimization model by the decentralized online RTP algorithm.

1. Introduction

In today's electric power grid, excessive demand for electricity during rush hour is one of the major factors which leading to power outage. To mitigate this phenomenon, nations must invest huge extra capital to meet the rising peak load demand. For example, in the United States, peak demand sums up to only 100 h per year, but it accounts for 10%–20% of the electricity cost in the whole electric power industry annually. In the national electricity market of Australia, 20%–30% of electricity network capacity or $60 billion cost is spent on meeting, no more than 90 h, peak demand in a year (Zhang et al., 2017). It indicates that the most important cost for the electricity industry should be determined by how to meet peak power demand. The most effective way of solving this problem is cutting the peak and filling the valley, which is also the objective that research on demand side management (DSM) in smart grid should be achieved (Chrysopoulos et al., 2014; Liu et al., 2017a, b; Chakraborty et al., 2015; Tan et al., 2014).

DSM mechanisms based on real-time pricing (RTP) can effectively promote electric consumers adjusting their inherent mode of using electricity (Mandal et al., 2015). For example, the individual customer may reset his/her air conditioner temperature or reprogram the charging process of his/her electric car (Liu et al., 2017a, b). These changes may help us to achieve the objective of cutting the peak load in demand side. Some smart home appliances (SHA) have the characteristics of delay and operating continuity, such as electric bowl and washer. Their working time is elastic but uninterrupted. This requires energy supplier (ES) to take into account the continuous dependence among slots in the formulation of RTP optimal problem. Thus, a more accurate and sustainable power supply strategy can be obtained. The electricity price determined by ES becomes the decision variable to control the whole interaction process, which influences not only on the user's power consumption behavior, but also on the power supply plan.

* Corresponding author.
E-mail addresses: zhb8151@hyit.edu.cn (H.B. Zhu), gaoyan@usst.edu.cn (Y. Gao), yong.hou.3@und.edu (Y. Hou), 11080038@hyit.edu.cn (L. Tao).

https://doi.org/10.1016/j.engappai.2018.02.010
Received 16 September 2017; Received in revised form 27 January 2018; Accepted 17 February 2018

Aiming at maximizing the social welfare, Mohsenian-Rad et al. adopted the pricing principle and proposed multiple innovative RTP models (Mohsenian-Rad et al., 2010; Samadi et al., 2012, 2010). These models have been paid much attention and been improved by a lot of researchers in the past several years. Based on these models, many extended ones have been presented with regard to different situations (Chen et al., 2013; Qian et al., 2013; Li and Lin, 2015; Longe et al., 2017; Scur and Barbosa, 2017; Tan et al., 2017; Tsui and Chan, 2012; Wang et al., 2017; Zhao et al., 2011), for instance, adding household appliances' classification in models, a two-stage optimization problem was proposed (Tsui and Chan, 2012). It showed that each user reacts to the price and maximizes its payoff while the retailer designs the RTP in response to the forecasted user reactions to maximize its profit. Consider a single household scenario given the price information, a versatile convex programming framework for the load management of various household appliances for supporting demand response in a smart home was proposed (Tsui and Chan, 2012). In view of the uncertainties in household appliance operation time and energy consumption and energy generated from renewable resources, Chen et al. (2013) designed a stochastic scheduling algorithm.

The existing social welfare maximization models are usually discrete as a single slot problem. This ignores the operating continuity of SHA. From multi-time slots perspective, Qian et al. (2013) proposed a household scenario, it fully reflected the characteristics of household appliances, but they do not consider the correlation between time slots.

In this paper, aiming to provide a more comprehensive view at the DSM within the contexts of the classification of SHA and the uncertainty caused by operating continuity of appliances, we propose an expectation social welfare maximization model with multi-time slots uncertainty. A novel RTP scheme for future smart grid is given based on this model. With this scheme, the price is determined at the beginning of energy scheduling horizon. The contributions can be summarized as follows:

• Formulates an expectation social welfare maximum model, considering the correlation between multi-time slots, the uncertainty caused by operating continuity of home appliances, and the classification of SHA, which makes the RTP optimization model has more practical significance.

• Transforms the uncertainty optimization into a convex optimization problem by introducing probabilistic constraints, and discusses its existence, uniqueness and other properties of the global optimal solution.

• Proposes a decentralized online RTP algorithm through utilizing Armijo line search to instead of the fixed step size of the dual subgradient method. The proposed algorithm inherits the advantage of dual subgradient method protecting user's privacy. Therefore, privacy is guaranteed because no entity needs to reveal or exchange private information. Furthermore, the algorithm this research proposed overcomes the defects of slow convergence and even no convergence from the dual subgradient algorithm.

The remainder of the paper is organized as follows. The classification of appliances and problem statement is introduced in Section 2. In Section 3, we develop the expectation maximization social welfare model to describe the problems with elaborate mathematical analysis. To provide the convenience for solving the model, we transform the uncertainty optimization into a convex optimization problem through introducing probabilistic constraints. The existence and uniqueness of the solution are proved, and its properties are further analyzed. In Section 4, we use the decentralized online RTP algorithm proposed in Section 3 to evaluate the performance of the model. The paper is concluded in Section 5.

2. Classification of appliances and problem statement

We consider a micro-grid with one ES and several residential users. The ES and all users have been connected with each other through an information communication infrastructure. Assume that each user is equipped with a smart meter which has an energy consumption scheduling (ECS) unit capable of controlling the home energy. Consider the optimization in a smart home, where smart appliances are networked together and are controlled by home ECS. Each appliance is scheduled to consume electricity or remain idle in each time interval (e.g., an hour) during the day. A whole cycle is considered as $\mathbb{K} = \{t, t+1, \dots, K\}$.

2.1. Classification of appliances

Denote that $\{I = 1, 2, \dots, N\}$ represents the set of all residential users, each user $i \in I$ has three types of appliances, denote as A_i, B_i and C_i. The first type A_i includes must-run appliances, which consumes a fixed amount of energy during a fixed period of time. There is no flexibility to redistribute the energy consumption across time due to this type of appliances are inelastic. Examples of such appliances include lighting appliance, television and refrigerator. To ensure that user's utility is not substantially affected, such appliance's operation schedule cannot be interrupted by the ECS unit. The second type B_i includes elastic appliances such as air-conditioner. The use of this type of appliances is affected by electricity price directly. Power consumption drops while electricity price is high, and vice versa. Users obtain higher satisfaction for more power consumption. The last type C_i includes semi-elastic appliances, for instance, washer, dryer and dish washer, etc. Their operation time can be changed with the price similar to the type B_i, but their total amount of electricity is fixed. Furthermore, users may obtain a higher satisfaction to finish the work during a certain time than in other time durations. To summarize, effective adjustment of flexible appliances B_i and C_i is the key to peak shaving and valley filling.

Based on two-way communications, smart meter could gather information of user's electricity usage patterns and provide automatic control to household appliances B_i and C_i, which forms the home energy management system (Angelis et al., 2013). As illustrated in Fig. 1, the role of ECS embedded in smart meter at each household is to control the ON–OFF switch and operating mode of B_i and C_i appliances. The information of ES's electricity price and the user's energy demand can be exchanged via home area network. Thus, the smart meter automatically coordinates all appliances to satisfy the user's need by demand response.

2.1.1. Must-run appliances

Denotes a_u^i as the appliance of user i, we express its energy consumption over the scheduling horizon $\mathbb{K}$ by a scheduling vector $\vec{x}_{a_u^i} = (x_{a_u^i,t}, x_{a_u^i,t+1}, \dots, x_{a_u^i,K})$. As a must-run appliance, each $a_u^i \in A_i$ operates in a working period $\mathbb{K}_{a_u^i} \subseteq \mathbb{K}$, during which it consumes $r_{a_u^i,k}$ energy per time slot. This is mathematically described as

$$x_{a_u^i,k} = \begin{cases} r_{a_u^i,k}, & k \in \mathbb{K}_{a_u^i}, \\ 0, & \text{otherwise}. \end{cases} \tag{1}$$

It should be noticed that the time slots in $\mathbb{K}_{a_u^i}$ being allowed to be intermittent. Let M_{A_i} denote the number of must-run appliances. At every time slot in operation interval $\mathbb{K}_{a_u^i}$, the aggregate power consumption $E_{a_u^i} = \sum_{u=1}^{M_{A_i}} x_{a_u^i,k}$ of must-run appliances is known.

2.1.2. Elastic appliances

For each appliance $a_u^i \in B_i$, the energy consumption per time slot is subject to

$$0 \le x_{a_u^i,k} \le r_{a_u^i,k}^{\max},\ \forall k \in \mathbb{K}, \tag{2}$$

where $r_{a_u^i,k}^{\max}$ is the maximum energy that can be consumed in the time slot when appliance a_u^i is working. Suppose user i equipped with M_{B_i} elastic appliances, and $R_{a_u^i,k}^{\max} = \sum_{u=1}^{M_{B_i}} r_{a_u^i,k}^{\max}$ denotes the maximum total power consumption in time slot k. This type of appliance is more flexible, so the mode of operation is not unique. We will give the reference aggregate power consumption $\sum_{u=1}^{M_{B_i}} x_{a_u^i,k}$ for users to develop their own unique