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Shifting Boundary for price-based residential demand response and applications

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HIGHLIGHTS

- A unique model on appliance level for PBP demand response behavior analysis is proposed.
- Shifting Boundary is introduced for PBP effect estimation in the model.
- Typical residential daily load curve under specific TOU and RTP can be estimated by Shifting Boundary within the model.
- TOU optimization can be processed by Shifting Boundary analysis.
- Effect of smart meter implementation can be estimated by Shifting Boundary analysis reversely.

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ABSTRACT

Demand Response (DR) is one of the typical methods for optimizing load characteristics in power systems. Utilities offer DR schemes to generate incentives toward consumers' power consumption behavior for load optimization. In tariff planning, power consumption variation is an important issue which is difficult to be analyzed quantifiably. This paper develops a boundary model for analyzing consumers' power consumption behaviors, with a particular focus on residential home appliances. Candidate tariffs are analyzed in this model for their load variation potentials. Using three case studies, this paper reflects the potential for practical applications of the model on pricing and smart meter deployment.

1. Introduction

Demand Response (DR) in power systems is a concept defined as "changes in electric usage by end-use customers from their normal consumption patterns in response to changes in the price of electricity over time, or to incentive payments designed to induce lower electricity use at times of high wholesale market prices when system reliability is jeopardized" [1]. DR entails "all intentional modifications to consumption patterns of electricity of end-use customers that are intended to alter the timing, level of instantaneous demand, or the total electricity consumption" [2]. Based on the behavior-driven mechanism, different DR programmes have been divided into two types: Incentive-Based Programmes (IBP) and Price-Based Programmes (PBP) [2]. IBPs rely on the operation mechanism that programme sponsors (i.e. electricity companies) pay participating electric users to reduce their electricity loads at requested times, usually triggered by either grid reliability issues or high electricity prices [3]. IBPs are usually adopted by electricity companies to change the electricity consumption patterns of large electric users (e.g. industrial and commercial organization users). IBPs, as suggested by Albadi in [2], include classical IBP (e.g. Direct Control) and market-based IBP (e.g. Emergency Demand Response Programmes). PBPs rely on the operation mechanism that electric users are economically rational, tending to use less electricity at times when electricity prices are high, given the time-varying rates which can reflect the value and cost of electricity at different times are enabled by electricity companies via different tariffs [3]. PBPs are usually adopted by electricity companies to change the behavior of small and price-sensitive electric users (e.g. small commercial and domestic electric users). PBPs include Time of Use (TOU), Critical Peak Pricing (CPP), Extreme Day CPP (ED-CPP), Extreme Day Pricing (EDP), and Real-Time Pricing (RTP). Refs. [2,3] provide a comprehensive account of the operations on these IBPs and PBPs.

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Demand response attracts researchers as one important research domain in power systems. Effect of DR can be analyzed statistically by various measured data, which is introduced by Ueno in [4]. The impact of DR on power system operation level is also focused by multiple studies, such as the voltage control approach mentioned by Alireza in [5]. These studies focus on static DR modeling for quantifying DR effect. Most of DR effect estimation is to find out the load variation under different DR schemes. A popular method is price-elasticity-style modeling, which emphasizes on establishing a price–load elasticity matrix as the bridge between tariff and load of customer group. Some researchers use a direct proportional coefficient between price and demand to represent the relationship. Joung, Moghaddam, Ferreira, Kwag and Venkatesan have indicated their price elasticity models separately in [6–10]. The elasticity matrices in these models are summarized by large set of historical data and contain the advantages of using practical cases whose load patterns are similar to the selected historical data set. But for other cases, e.g. effect analysis of an unimplemented tariff format in tariff planning, this method will lose robustness. Unlike the static price-elasticity-style modeling, another research attention is paid to customer consuming behaviors at appliance level. Load is decoupled by different appliances and the behavior toward each appliance is modeled. The logic chain is Behavior Incentive → Behavior Change on Appliances → Load Change on Appliances → Total Load Change. This method is targeting on behavior variation incentives and has more stable result than elasticity matrix as the primary cause of load variation (Behavior Incentives) is modeled as well. Various methods are implemented in relevant load model or DR analysis. Shao, Pipattanasomporn and Rahman proposed a residential load model in [11]. This model decouples the load into 4 types of appliances: Space Cooling/Heating, Water Heating, Clothes Dryer and Electric Vehicle. But for demand response research on a large group of residential customers, this model lacks a consideration of a complete set of appliances and their penetration, as well as the behavior variation. In Ghorbani's study [12], a load model was introduced with emphasis on operational level of appliances, which is more suitable for customers' power quality analysis than demand response. Electric Power Research Institute (EPRI) in the US has also developed a demand response model framework in [13]. The load modeling in this framework includes the analysis of both appliances and general residential life-style behaviors. However this framework lacks the details of model construction, thus can only be used as a guide for future model research. Models proposed by Walker, Capasso and Dickert in [14–16] appear to contain more suitability than the previous cases. In these studies, appliance usage is considered with home activities and penetration levels. They have high resolution of time steps, i.e. less than one hour. But these models are established at an individual consumer level so that they do not consider behavior tropism and uncertainty of a consumer population. Moreover, the behavior variation triggered by price change is not considered in these studies. Meng and Mohsenian-Rad have provided DR models with consideration of load decoupling and behavior pattern variation in [17,18]. But these two models do not cover the constraint of behavior variation, such as appliance switch-on limitation from leaving home or time limitation for dining.

In this paper, a unique model for residential DR analysis was introduced. This model constructs load based on behaviors of different appliances on a multi-agent system. Behavior tropism and uncertainty of large consumer group are achieved by probabilistic modeling of consumers' behavior. A new concept, 'Shifting Boundary', was implemented in this model to measure the largest load shifting potential of several Price-Based Demand Response tariffs. With 'Shifting Boundary', estimation of consumers' behavior change, load variation is no longer limited by historical data set. Effects of new tariffs can be estimated by this model even without historical data. Also, behavior alternation calculation with the constraints from life-style has been considered. Three case studies on load variation estimation, tariff optimization and smart meter deployment effect estimation were selected to reveal the practical application potential of the model.

A model framework of individual consumer behavior and group power consumption is introduced in Section 2. Based on this framework, Section 3 describes the model for behavior shifting using Shifting Boundary. With Shifting Boundary, quantification of behavior transformation is achievable. To reveal the effect of Shifting Boundary, Section 4 provides a case study on the whole model. Sections 5 and 6 provide another two case studies to indicate that different PBPs (or different smart meter installation scale) can be evaluated by using Shifting Boundary.

2. Residential customer behavior modeling

2.1. Multi-agent system modeling

Agent based model or multi-agent system is a simulation system for reproducing the interaction between environment and a group of individuals. In this system, agent is an individual unit with intelligence and independent ability for action and decision making. Agents receive information from environment and then generate their own actions toward environments. On the other hand, environment changes its status by actions from agents and then generate new information to agents [19].

Price-Based Demand Response possesses a loop interaction structure as shown in Fig. 1. Price generator creates price information by power consumption information collected from consumers.

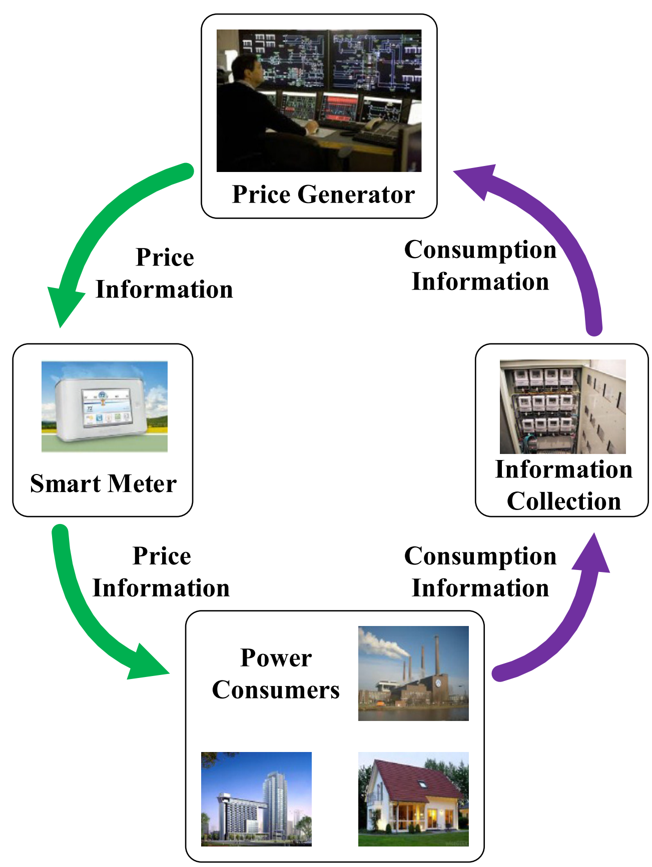

Fig. 1. Loop interaction structure of PBPs.