Renewable Energy 91 (2016) 293–301

Contents lists available at ScienceDirect

Renewable Energy

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

Achieving an optimal trade-off between revenue and energy peak within a smart grid environment☆

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ARTICLE INFO

Article history:
Received 2 April 2015
Received in revised form
13 January 2016
Accepted 18 January 2016
Available online 1 February 2016

Keywords:
Demand response
Smart grid
Day-ahead pricing
Demand side management
Bilevel programming
Peak minimization

ABSTRACT

In this paper, we consider an energy provider whose goal is to simultaneously set revenue-maximizing prices and meet a peak load constraint. The problem is cast within a bilevel setting where the provider acts as a leader (upper level) that takes into account a smart grid (lower level) that minimizes the sum of users' disutilities. The latter bases its actions on the hourly prices set by the leader, as well as the preference schedules set by the users for each task. We consider both the monopolistic and competitive situations, and validate numerically the potential of this approach to achieve an 'optimal' trade-off between three conflicting objectives: revenue, user cost and peak demand.

1. Introduction

Despite technological advancements that have allowed an increase in energy production, both traditional and green, together with a decrease of consumption in the residential and transportation markets, demand for energy is due to grow at a fast pace in the near future, putting at stress the production and distribution system, as well as the supply-demand balance. Instabilities, that trigger a chain of adverse effects for all energy users, can be mitigated by either investing to maintain a large capacity, at a high cost, or by implementing *demand side management* (DSM) programs that, through controls at the customer level, make the best use of the current capacity [1,2]. In short, DSM can be characterized by a set of tools for shaping the load curve, through peak clipping, valley filling, load shifting, strategic conservation, strategic load growth and flexible load shape [3]. In order to achieve these objectives, several programs have been put in place, such as conservation and energy efficiency programs, fuel substitution, demand response, and residential or commercial load management [1,4,5]. In particular, the problem that consists of adjusting the load curve by taking explicitly into account customer reaction to prices has been addressed in several articles, such as in Ref. [6], where residential load control through real-time pricing has been considered. Actually, real-time pricing is frequently referred to by economists as the most direct and efficient demand response program [7–9]. For a thorough literature review concerning dynamic pricing, as well as analyses of real cases, the interested reader is referred to [10].

In the present paper, we focus on peak load minimization through *load shifting*. The importance of the issue can be illustrated by the example of the United Kingdom, where the minimum load during summer nights is around 30% of the winter peak, while the average load is around 55% of the installed generation capacity [11], emphasizing large fluctuations in the load curve, with close to half the generation capacity being idle for long periods of time. One foresees that the importance of load shifting will become even more apparent when the market share of plug-in cars (fully electric or hybrid) becomes significant. On average, PHEVs (plug-in electric vehicle) can be driven for 5 miles per kWh [12] and hence, their

☆ This paper was intended as part of the special issue entitled "Optimization Methods in Renewable Energy Systems Design" Volume 87, Part 2, Pages 835–1030 (March 2016). However, the article was accepted after the deadline for acceptance for this issue and we were unable to delay compilation of the issue. We apologize for any inconvenience this may cause.

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http://dx.doi.org/10.1016/j.renene.2016.01.055

intensive use may double the average residential electric load [13], thus putting the network at risk.

In many countries, base load is produced by coal or nuclear power plants whereas peak load is provided by natural gas, hydro or renewable power. For this reason, electricity production during peak periods is more costly than in the off-peak. Besides, installed production capacity has to be larger than peak load in order to ensure power supply. Since a reduction in peak load induces a decrease of production and capacity cost, it deserves to be analyzed properly.

The specific issue that this paper addresses is Energy Peak Minimization (EPMP). It involves two decision levels: an energy provider and its customers. These two levels have conflicting objectives. The energy provider is interested in maximizing its revenue, whereas customers try to minimize their total disutility. While many articles have formulated the problem as a Nash game [13–17], the relationship between a company and its customers better fits the leader-follower framework. More precisely, our aim is to integrate demand response explicitly into the decision making process of the energy provider. To this end, we propose a bilevel programming approach. In this setting, the *leader* integrates within its decision process the reaction of the *follower*. Once the leader sets his variables, the follower solves an optimization problem, taking the leader's decisions as given. Bilevel programming has been used to tackle several problems including, but not limited to, toll pricing [18,19], freight tariff setting [20,21], network design and pricing [22–25], electric utility planning [26,27]. One should keep in mind that bilevel programs are intrinsically difficult (NP-hard) [28,29]. Besides their nonconvex and combinatorial nature, the feasible region of the leader is generally nonconvex, and can be disconnected or empty [30]. In the context of EPMP, bilevel programming allows to integrate DSM techniques and demand response within the optimization process of an energy provider.

The contribution of this paper is twofold. First, we develop a bilevel model for peak minimization of an energy provider, with the aim to achieve an optimal trade-off between revenue and peak power consumption without delaying demand for electricity arbitrarily. The model uses day-ahead real-time pricing and is solved for a global optimum. We also propose a variant of the model that involves competing providers. Next, we analyze the relationship between the energy provider and its customers, where the latter are inter-connected via smart metering devices (automatic energy consumption scheduler [13]). In this environment, the customers not only share an energy source, but also communicate with each other via the network of smart meters which forms the smart grid. A detailed survey of smart grid and the associated enabling technologies are provided in Ref. [31]. In the absence of such technology, it would be difficult for customers to keep track of hourly prices and shift their demand accordingly, as well as for the provider to observe the actual demand response to its pricing strategy. Smart meters enable two-way information flow and constitute an important feature of the system, allowing the application of DSM techniques. While it can be argued that metering is more expensive and may be difficult to manage for residential customers, yet it significantly decreases meter reading costs, besides assisting different pricing strategies, and improved technology provides ever easier meter management [32]. Moreover, the smart grid system allows aggregation of residential customers with similar needs and different preferences. Since customers can act as a large client aiming at system optimum, their bargaining power is vastly increased. A survey on demand response and smart grids can be found in Ref. [33].

The paper is organized as follows. The next section presents the modeling framework. It is followed by experimental results involving different parameters and instances, and a conclusion that points out challenges related to this field of research.

2. The bilevel models

Let us consider a power sharing system involving a set of customers denoted by N, each one equipped with a smart metering device. Each customer n operates a set A_n of electric residential appliances, such as air conditioners, radiators, washers, driers, refrigerators, freezers, pool heaters, etc. The appliances can be turned on and off at any time, and their power can be adjusted at any desired level. In the United States, 45% of household appliance consumption belongs to that category of preemptive devices (see Fig. 1), and it follows that their intelligent control may yield a significant decrease in peak consumption.

For the sake of this study, we adopt a 24-h planning horizon H. Each customer n is characterized by its daily demands $E_{n,a}$, as well as time windows $T_{n,a}$ transmitted to the smart meter, one per appliance $a \in A_n$. The set of such devices retrieves and transmits data, and thus forms the smart grid (Fig. 2). The grid is connected to a power source and receives hourly prices from the electricity supplier, 24 h in advance. It allows customers to benefit from cooperation. While users are expected to have similar needs with respect to power consumption and task scheduling, some of them might yet be more reluctant to postpone their loads, whereas others are willing to switch to cheaper time slots. Such behavior differences enter the model and are taken into account by the energy provider. Precisely, the population heterogeneity with respect to price perception is captured by an *inconvenience factor* specific to each customer.

We emphasize the importance of the smart grid as a middle agent that takes charge of scheduling, since one may not expect the customers to monitor prices in real time, and to optimally schedule their appliances accordingly.

In our *day-ahead pricing* model, the leader applies DSM to control and smooth out the load curve. To tackle EPMP, two scenarios are considered: monopolistic and competitive pricing, and these will be detailed in the next two subsections. Both of them fit the bilevel paradigm, which is ideally suited at modeling game-

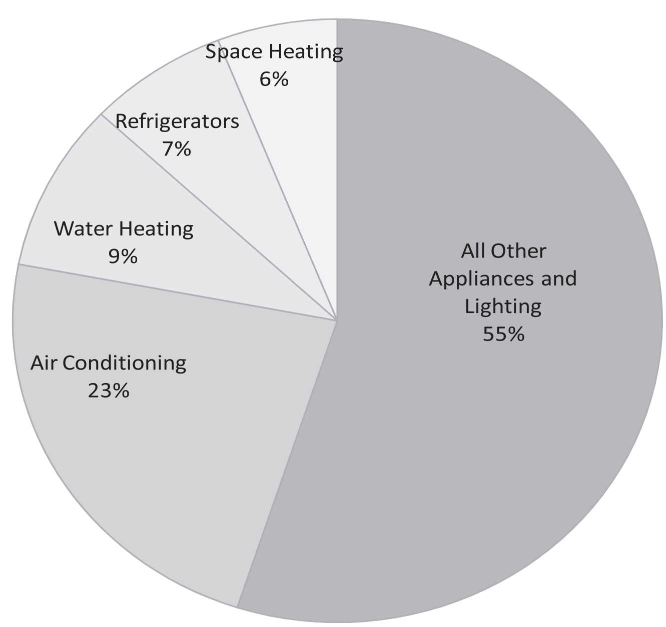

Fig. 1. Residential electricity use in the USA, 2011 [34].