Energy and Buildings 84 (2014) 537–547

Contents lists available at ScienceDirect

Energy and Buildings

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

Robust scheduling of smart appliances with uncertain electricity prices in a heterogeneous population

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ARTICLE INFO

Article history:
Received 24 February 2014
Received in revised form 21 August 2014
Accepted 21 August 2014
Available online 29 August 2014

Keywords:
Demand response
Heterogeneous population
Optimal scheduling
Robust optimization
Smart grids
Smart homes
Uncertain prices

ABSTRACT

Majority of the research conducted in the field of optimal scheduling of smart appliances does not consider the inherent uncertainties in this problem. Besides, the ones that count for the uncertainty usually assume full knowledge about the exact form of the probability distribution of the uncertain parameters. This assumption is hardly fulfilled in reality. In this paper, we seek to find solutions that are robust with respect to the probability distribution of the uncertain parameters while making no explicit assumptions about their exact forms. Accordingly, we define a chance-constrained model to find the optimal schedule and use robust optimization to characterize its solution and the associated uncertain parameters.

We also consider the effect of heterogeneous populations on the optimal solution while simultaneously determining the most appropriate classification for accurate predictions. In the process, we investigate the effect of delays in information sharing on computed optimal conditions and we develop a new classification for in-house appliances. We explore features of our model using price data from the "Olympic Peninsula" project. We anticipate that by pursuing optimal options, a typical customer can save up to 33% in her electricity bills while sacrificing 19% of her comfort level. Moreover, in a heterogeneous population, while the results suggest no direct dependency between savings and income level, a meaningful correlation is detected between savings and employment status.

1. Introduction

Smart-Grid emerged as an opportune response for challenges to reliable decision-making in increasingly complex power networks. The confluence of information technology and advanced measurements (synchrophasors, smart meters, etc.) enables the conceptualization of power network on a granularity where both generation stations and individual appliances are simultaneously visible. These resources to "think fast and big" provide Smart grid with the capacity to engage load as a resource to manage intermittency in power supply and demand, and to find the most optimal solutions in real time for operation efficiency and resilience to disturbances. This has heralded Smart Grid as the enabler for energy-related challenges such as energy sustainability, fossil fuel emissions into the environment, demand growth, aging asset bases and increased complexity in the power grid [1]. Various approaches have been proposed among various stakeholders of the power network system to envision and categorize features of smart grids. Accordingly, smart grids are characterized as power grids with five major features: reliability, renewable resources, demand response, electric storage and electric transportation [1].

Currently, 20% of power generation capacity is latently available just to meet peak demand, incurring high operational costs on the power network [2]. As peak demand occurs about 5% of the time significant savings can be achieved by "peak curtailment" or "peak leveling", i.e., using demand-side management (DSM) or demand response techniques to manage and shape consumption profiles at the consumer side in order to achieve smoother usage trends [3]. One type of demand response uses automated two-way communication between power utilities and consumers so that consumers can respond and coordinate their behaviors according to conditions imposed by the power grid. Electricity prices serve as an efficient and practical incentive for customers to change their consumption behaviors. For instance, with proper incentives, customers could likely shift their deferrable energy usage from high price peak periods to lower price off-peak periods.

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http://dx.doi.org/10.1016/j.enbuild.2014.08.035
0378-7788/

A reasonable assumption that could underlie predictive models of demand response is that consumers will optimize their respective consumptions in response to dynamic electricity prices. To do so, they each need to solve an optimization problem to find a schedule for appliances that is optimal to her preferences. In practice, these algorithms can be solved by energy consumption scheduling (ECS) units which are embedded in the smart meter of every house. Although the real consumer behavior will deviate from the optimal scheme, this approach provides an appropriate benchmark for decision making purposes, both for individual customers at household level and for power system operators in managing generation and power delivery systems (e.g., projecting electricity prices and amount of demand response based on the optimal scheme with consideration of deviations, and preparing resources accordingly). Finding the optimal schedule of operation for appliances in a household subject to real-time and uncertain prices remains a challenge in the smart grid context, and constitutes the main contribution of the present paper.

A challenge in addressing this problem consists of accounting for the various uncertainties in characterizing the underlying model. Clearly, properly incorporating these uncertainties into the model-based predictions can significantly increase the effectiveness of ensuing decisions. The major source of uncertainty in the present context is the price of electricity. The ECS scheduler requires some estimate about the future electricity price, say for the next 24 h, to be able to find the optimal decision at the current point in time.

In the present study, we propose a model to find the optimal schedule of operation for smart appliances in a household on one typical day, taking into account uncertainty in future electricity prices. We define a chance-constrained optimization problem and use robust optimization techniques to tackle it. Robust optimization is a rather new technique in modeling uncertainty, which is most suitable for situations in which no exact probability distribution of the uncertain parameter is available [4]. Instead, we require the solution to be feasible for all the instances of the uncertain parameter which lie in an uncertainty set. This yields an optimal solution that is robust with respect to the probability distribution of future electricity prices. As part of our model, we propose a new categorization scheme for appliances in a given house. This detailed appliance model aims to more realistically capture the properties of the devices in a house.

Given the above model, we will discuss finding the most appropriate uncertainty set associated with our specific problem. We then solve this task for a single customer as the first step. Investigating the model performance in a sample heterogeneous population is another challenging and relevant topic that we address in this study. From the utility company's perspective it is crucial to have an estimate of the aggregate consumption behavior in a region assuming that all customers are behaving optimally. This can be a useful benchmark for decision making purposes. To conduct this analysis, we initially perform sensitivity analyses to find the most crucial parameters of the model that can trigger different behaviors among different people. Based on a sensitivity analysis, we categorize people according to their socio-economic characteristics. We discover much more significant dependence of consumption patterns on employment status rather than on income level of customers.

Generally speaking, various time scales can be used for measurement, aggregation and decision-making phases of a problem. In this work, we seek to know whether the aggregation time scale can change the outcomes of the optimal scheduling problem or not. We will use multiple time scales to answer this question. Answering this problem, helps the utility companies to find appropriate time intervals to communicate with the customers in terms of sending price signals. It will also help customers to understand the required frequency for updating their behaviors. We use real electricity price data from Pacific Northwest National Laboratory (PNNL) pilot project called "Olympic Peninsula" to conduct our simulations [5].

The remainder of the paper is organized as follows: Section 2 reviews the literature on intelligent scheduling in smart homes. Robust optimization method and robust counterpart approximation for chance-constraints are briefly discussed in Section 3. Our proposed model to find the optimal load schedule is presented in Section 4 followed by the subsequent simulation results and discussions in Section 5. Then, the problem is extended to the case of a heterogeneous population in Section 6. Section 7 discusses the significance of aggregation time scale in the model outcomes. Finally, Section 8 concludes the paper.

2. Related work

Smart scheduling is traditionally formulated as an optimization problem in which the consumers wish to minimize their electricity costs [6–10] or maximize a weighted sum of their utility function (i.e., level of satisfaction) minus the cost [11–14]. This objective is combined with some constraints on the operation condition of appliances, reflecting customer preferences [6,11]. In some cases, the authors introduce a so-called "inconvenience term" or "waiting cost" into their objective functions to account for the discomfort caused by the delay in satisfying customers' electricity needs [15].

We categorize technical contributions to this problem into two general classes. The first class consists of those which formulate a deterministic scheduling problem [3,7–12,16–18], whereas the papers falling into the second category integrate some kind of uncertainty into their models [14,19–22].

In [7,9], the energy consumption of appliances is optimally scheduled based on a time varying curve of electricity price and available power. A three phase strategy including prediction, scheduling and real-time control of appliances within a building is studied by Kang et al. in [8]. Mohsenian-Rad et al. [3] find the optimal schedule for one customer and then extend it for a group of customers borrowing concepts from game theory. In [17], the authors combine the problem of finding the optimal consumption schedule with future price prediction in a real-time pricing environment. They use a weighted average price prediction filter to estimate the unknown future prices. A similar work by Samadi et al. [12], simultaneously solves the scheduling problem on the consumer side with the pricing problem on the power supplier side. Caprino et al. [16] propose an automatic coordination system to schedule major household appliances in order to achieve peak reduction. The authors in Ha et al. [18], use a mixed integer linear program to concurrently control the electrical energy consumption and production in a single dwelling.

In an attempt to model the appliances in more detail for energy management purposes, the authors in [10] incorporate constraints to count for the uninterruptible and sequential modes of operation in a mixed-integer linear programming framework. On the same thread to detail the appliance model, Li et al. [11] introduce four general types of appliances, each with a particular utility function.

All the previously mentioned papers include no source of uncertainty into their models. However, it is undeniable that uncertainty is dramatically intertwined with this particular problem and ignoring it is likely to yield sub-optimal results. The subsequent parts examine the literature accounting for uncertainty in power scheduling problems. One of the earliest works to consider price uncertainty was put forward by Conejo et al. in [19]. The authors develop an ARIMA model to predict confidence intervals for future energy prices; based on that they formulate a robust schedule optimization problem. Kishore et al. [15] propose a dynamic programming algorithm in which a transition matrix models the evolution of appliance modes over time.