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Modeling and analysis of residential flexibility: Timing of white good usage

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HIGHLIGHTS

- Two methodologies for modeling individual customer flexibility behavior are proposed.
- Models and analysis use real-world data from a field trial with smart appliances.
- Customer flexibility behavior is best modeled with finite mixture models.
- Presented models can be used for data generation in simulations.

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ABSTRACT

Challenges that smart grids aim to address include the increasing fraction of supply by renewable energy sources, as well as plain rise of demand, e.g., by increased electrification of transportation. Part of the solution to these challenges lies in exploiting the opportunity to steer residential electricity consumption (e.g., for flattening the peak load or balancing the supply and demand in presence of the renewable energy production). To optimally exploit this opportunity, it is crucial to have insights on how flexible the residential demand is. Load flexibility is characterized by the amount of power, time of availability and duration of deferrable consumption. Residential flexibility however, is challenging to exploit due to the variation in types of customer loads and differences in appliance usage habits from one household to the other. Existing analyses of individual customer flexibility behavior in terms of timing are often based on inferences from surveys or customer load patterns (e.g., as observed through smart meter data): there is a high level of uncertainty about customer habits in offering the flexibility. Even though some of these studies rely on real world data, only few of them have quantitative data on actual flexible appliance usage, and none of them characterizes individual user behavior. In this paper, we address this gap and contribute with: (1) a new quantitative specification of flexibility, (2) two systematic methodologies for modeling individual customer behavior, (3) evaluation of the proposed models in terms of how accurately the data they generate corresponds with real world customer behavior, and (4) a basic analysis of factors influencing the flexibility behavior based on statistical tests. Experimental results for (2)–(4) are based on a unique data set from a real-life field trial.

1. Introduction

The rapid integration of renewable energy sources into the power grid and their intermittent nature has created a need for flexibility in energy demand. Flexibility is generally regarded as the amount of load that is shiftable over various time scales and is quantized by 3 parameters [1]: (1) the *amount* of deferrable energy (i.e., the amount of energy that can be delayed without jeopardizing customer convenience or quality of the task to be fulfilled by a smart device), (2) the *time* of availability (i.e., the time at which a customer offers the device flexibility for exploitation), and (3) the *deadline* to exploit the offered flexibility (i.e., the maximum allowable delay for the energy consumption). Once flexibility is known and thus adequately characterized, it can be utilized by demand response (DR) algorithms to coordinate the demand-supply balance in the network. Various DR algorithms have already

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been proposed to exploit such flexibility: for an overview, we refer to [2,3]. Hence, proposing a new DR algorithm is not our focus.

Our main objective is to characterize and model the flexibility as DR's main asset, to improve the efficiency of DR assessment. One of the main challenges in the widespread deployment of DR algorithms (especially in the residential sector) is the uncertainty surrounding their impact [4,5]. A poor understanding of flexibility characteristics as DR's main asset leads to inefficient DR assessment and uncertain conclusions (i.e., accurate evaluation of DR algorithms is impossible without in-depth analysis of the flexibility parameters). The outcome of our flexibility modeling and characterization (which is based on a unique dataset from a real-life field trial) can foster more realistic assessment of the potential impact of DR algorithms and pave the way to their realization in smart grid.

Flexibility of large industrial customers has already been extensively assessed and exploited by long standing programs (e.g., [6–10]). Since the inception of the smart grid, that industrial flexibility has increasingly been complemented by residential flexibility since the inception of the smart grid. Residential customers form a promising source of flexibility due to their widespread distribution and substantial share of electricity market and hence are the focus of our study here.

Residential flexibility however, is challenging to characterize due to the large variety of appliances and their diverse consumption patterns, as well as the uncertainty associated with appliance usage due to different usage habits among various households. A substantial amount of research has analyzed the flexibility potential of residential customers from various perspectives. A brief overview is presented in the next section.

1.1. State of the art in residential flexibility assessment

Methods to assess residential flexibility potential in literature can be categorized into two main streams, according to the objective they pursue: *DR-based* and *DR-independent* methods. The *DR-based* methods are often tailored to the underlying DR scheme (i.e., price-based or incentive-based DR) and their main objective is to model the responsiveness of customers to price signals or incentive programs. In price-based DR schemes, an elasticity matrix models customer flexibility as changes in aggregated demand in response to price changes [11–14]. However, an elasticity matrix can only measure the aggregated flexibility potential and not the appliance specific flexibility. Price-demand models based on mixed integer linear programming (e.g., [15]) or probabilistic models (e.g., [11,16]) are proposed to predict the customer consumption patterns from the appliance level perspective in response to dynamic prices. For incentive-based DR schemes, Hu et al. [17] propose a stochastic model to assess the probability distribution of residential demand in response to certain incentives. The proposed residential responsive demand model is formulated with consideration of the customer portfolio and household characteristics obtained from time-of-use surveys, rather than actual measurement of real behavior.

One of the limitations of DR-based approaches is that any quantization and assessment of flexibility potential is inevitably influenced by the underlying DR algorithm. Additionally, the impact of the underlying DR algorithm on the flexibility is not measurable. In other words, customers might exhibit different flexibility behavior when assessed with other DR-based methods. Hence, the outcome of the analysis of a particular DR-based method cannot be employed to reliably assess the impact of the other DR algorithms. Instead, DR-independent methods (including the modeling approaches in this paper), offer an unbiased analysis where the customer flexibility behavior is not influenced by the specifics of any DR algorithm.

In *DR-independent* methods, the main objective is to model customer flexibility potential (independent of the underlying DR scheme) and subsequently use the model to assess the potential impact of DR algorithms on peak load reduction or demand-supply balancing. Some of these methods are derived merely based on appliance energy usage patterns that are either obtained from sub-metering of household appliances [18] or assumed by studying the characteristics of the various appliances [19]. Analyzing the flexibility potential based on appliance energy usage patterns provides insights about the potential amount of deferrable energy of each appliance. However, it does not completely characterize the flexibility potential because customer behavior affecting the time of availability and deadline to exploit the offered flexibility is not accounted for. One of the popular means to take into account customer appliance usage habits in the flexibility model is collecting time-of-use surveys. Laicane et al. [20] performed a time-of-use survey on a four-person household to determine its appliance usage behaviors, particularly for washing machine and dishwasher, to quantify the flexibility potential. The model was then used to shift appliance usage accordingly for peak load reduction. Safdarian et al. [21] used a similar approach on 1600 Finnish households to assess the benefits of demand response on the operation of distribution networks. However, time-of-use surveys may be inaccurate in modeling the customer appliance usage habits because they indicate the self-reported behavior of the customer, which may differ from the real behavior.

Another approach taken by DR-independent methods is to obtain a time series estimate of flexibility of residential customers based on the clustering of their load profiles. Kouzelis et al. [22] proposed a methodology for analyzing the flexibility potential of residential heat pumps in a probabilistic way from the aggregated load profile of the customers. The proposed methodology compares the load profile of the flexible customer with electrically similar non-flexible customers by means of clustering the customer load profiles and then statistically infers the flexibility potential thereof. Labeeuw et al. [23] also used clustering of customer load profiles to derive a time series estimation of load curves and determine demand reduction potential of wet appliances in terms of amount of deferrable load only (without assessing the flexibility duration). They additionally incorporated attitude measurements based on questionnaires in their studies to account for customers willingness to participate in DR based on survey data. Despite valuable contributions of these approaches in terms of amount of deferrable energy and time of availability, they do not give any assessment of the deadline to exploit the flexibility due to limitations in their measurements.

In both of the aforementioned DR-based and DR-independent categories, modeling of customer responsiveness to participate in DR algorithms is not based on real-word scenarios where households are provided with smart appliances and required to configure their appliances flexibly. Hence, the uncertainty about limitations of DR algorithms due to the differences in customers' real-life (power consumption) habits remains largely unresolved. To address this gap, Kobus et al. [24] conducted a longitudinal study for one year over 77 Dutch households. Each household was given a smart washing machine, and an energy management system that received daily dynamic prices. The customers' behavioral changes with respect to a reference group was then studied for a full year to explore the potential role of smart appliances in shifting real electricity demand of smart washing machines in response to dynamic tariffs. Still, a limitation of this valuable work is that the analysis is tailored specifically to the underlying DR scheme.

D'Hulst et al. [25] also have based their analysis on a real world scenario where customers are provided with a platform to operate their smart devices and offer their flexibility for DR exploitation.