



Original research article

Rethinking the privacy of the smart grid: What your smart meter data can reveal about your household in Ireland

Rouzbeh Razavi^{a,*}, Amin Gharipour^b^a Department of Management & Information Systems, Kent State University, OH, USA^b School of Information and Communication Technology, Griffith University, Australia

ARTICLE INFO

Keywords:

Smart meter analytics
Socio-demographic classification
Customer segmentation
Demand side management

ABSTRACT

The global market for smart electricity meters has grown rapidly in recent years and is anticipated to sustain its solid increase in the near future. By analyzing half-hourly meter data from over 4000 Irish households, this study seeks to examine the relationship between households' attributes and their electricity demand through the following questions: (1) knowing a given set of household attributes, can we accurately classify households according to their demand volume and daily demand pattern and (2) can we infer some of the key households' characteristics from their meter data. The attributes considered include the size, presence of kids, social class, employment status and the annual income of the households. A range of machine learning methods including tree-based algorithms, support vector machines and neural networks are deployed to answer these questions. The results suggest the potential for reasonably accurate segmentation of consumers according to their demand volume while the classification based on daily demand patterns were shown to be more challenging. For predicting household attributes, higher accuracy values are reported when predicting the household size, social class, and employment status. On the contrary, inferring the household income category and the presence of children in the household were shown to be more difficult.

1. Introduction

Electricity smart meters are electronic devices that are deployed by utilities to measure the electricity consumption of consumers at frequent intervals. They also provide a two-way communication link for transmitting meter readings to the utility provider and receiving control and configuration commands. The introduction and deployment of such meters have prominently transformed the utility market for both electricity providers and consumers. In the United States (U.S.) alone, electric providers had installed 65 million smart meters, as of 2015, which accounts for more than half of the U.S. households. The deployment is expected to exceed 90 million units by 2020 [1].

These smart meters generate massive volumes of data on a daily basis, and the industry has witnessed many commercial offerings for storage and analysis of such data during recent years. According to a study, the utility data analytics market is currently in excess of a billion dollars in total annual spending and is forecasted to grow to \$3.8 billion by 2020 [2]. If properly analyzed, smart meter data can help better understanding residential households and their electricity demand behavior which in turn can open up new revenue opportunities. In fact, the return on investment on the grid analytics is estimated to be more

than 500% for utility providers over a nine-year period [2].

This research utilizes a quantitative methodology to examine the possibility of classifying households, based on their demand volume and daily demand shape, by using a set of their attributes. The study additionally seeks to investigate the potential of smart meter data in predicting those household attributes. Household characteristics considered in this study include the size and composition of households, as well as socio-economic factors such as employment status, social class, and income. Attendant questions addressed by this paper are as follow.

1. By knowing a given set of household attributes, can we accurately classify households according to their demand volume and daily demand patterns? This also includes identification of key households characteristics that determine the volume and daily pattern of the electricity consumption.
2. Can we infer household attributes from their high-resolution electricity meter data?

The following section discusses how utility companies and public sector policy-makers may benefit from this research.

* Corresponding author.

E-mail address: rrazavi@kent.edu (R. Razavi).

1.1. Research motivations and benefits

This section describes how utility companies and public sector policy-makers benefit from the enhanced understanding of the relationships between household attributes and the electricity consumption volume and patterns. For utility companies, smart meter analytics comes with numerous advantages that can be classified into two categories. The first category is related to grid optimization and operational intelligence where the utility company relies on near real-time meter data to enhance grid performance. This includes use cases such as fault detection [3], improving the break-to-fix time, detection of energy theft events [4,5] and demand forecasting [6]. The second category is consumers' analytics, which includes insights into customers' electricity consumption behaviors and habits, household characteristics and demand-side management programs in light of such insights [7]. This latter category is also where this research is focused.

By appropriate segmentation of consumers based on their demand volume and daily patterns, utilities can identify and target households with high Customer Lifetime Value (CLV). In addition, there are strong incentives for both energy providers and energy policy-makers to encourage modification of demand behavior of consumers. For example, utility providers are eager to identify consumers who are likely to have high daily peak consumptions to target them for their demand management programs. With modified customer behavior, utilities can better manage demand and also improve their environmental credentials by reducing harmful emissions. The price elasticity of residential electricity demand is low in most markets [8,9]. As a result, simple time-varying pricing strategies are unlikely to be adequate on their own to ensure successful demand management programs. Therefore, it becomes essential to understand the underlying determinants and key household attributes that have the highest influence on the volume and daily patterns of demand.

Furthermore, it is vital for energy providers to be able to get to know their consumers in an agile and cost-efficient fashion [10]. With this perspective, the second research question of this study aims at investigating the possibility of inferring household's socio-demographic characteristics from their meter data. More specifically, for energy providers, the enhanced understanding of the demographics of their customers can improve many aspects of their decision support platforms and business intelligence functions. This includes demand-side management programs [11], consumer communications, marketing initiatives and collection strategies [12]. Also, understanding of household characteristics in local areas is of great importance for policy-makers and public authorities, beyond only the energy sector. Currently, census data serves as a primary source for many social and economic studies by policy-makers. A unique value of census data for decision makers is that it enables enhanced understanding of the combinations of characteristics of households such as education, socio-economic and employment status at the local level [13]. Despite these values, there are some challenges associated with census data including the increased cost of collecting data, difficulties of enumeration and the usual long delays between enumeration and publication of local level statistics [14]. The second question of this research attempts to investigate the potential of smart meter data to infer household attributes, which can be used to enrich and supplement census data.

1.2. Literature review

Numerous past research studies have focused on the issue of energy consumption, mostly from economics and engineering perspectives. A large body of econometric investigations is concerned with electricity demand behavior of consumers in response to different pricing strategies, including various time-varying and non-linear pricing schemes [15]. Because of the unavailability of sub-hourly electricity consumption data at scale in the past, the area of energy analytics has not been widely explored until recent years where more studies began to appear

[16,17].

Non-Intrusive Load Monitoring (NILM), is a process for energy disaggregation of households and can be used for deducing the type of appliances that are used in the house [15]. NILM can provide detailed information about consumers' activities and their behaviors [18]. However, currently, the meter reading frequency reported to the energy provider is probably insufficient for many of the NILM applications [19]. For example, in most deployments, the frequency of relaying a meter reading varies from every hour to every five minutes, which is very far from a sampling rate of 1–1.2 kHz needed for most NILM applications [19].

Similar to this study, consumer segmentation has been considered a crucial element for enabling various smart meter analytics [20]. The authors in [21,22] provided a survey of consumer segmentation in the electricity markets and discussed how it could be used for establishing successful demand-side management programs. Similar customer clustering frameworks are introduced in [23,24] for defining optimal tariff strategies. Segmentation methodologies such as Self-Organizing Maps (SOM) and K-means clustering are deployed to identify load patterns in [25] and to present a consumer characterization framework in [26].

The study in [27] deploys a hidden Markov model framework for segmentation of consumers that can be used for enrolling consumers in demand management programs. The population sample in the study, however, consists of nearly 1000 Google employees, which is unlikely to be an appropriate representative of the national population. Similarly, the authors in [28] deployed a hierarchical clustering approach to define segments of customers for energy programs. The result of the study suggests that customer segments exhibit consistent behavior. However, the result was presented based on the survey of 85 households, and the statistical properties of presented results should be validated through a more extensive study.

The study in [29] introduces a density-based algorithm for time-series segmentation of smart meter consumers using data from the Pecan Street Project [30]. The Pecan Street project provides high-resolution demand data from nearly 1300 houses and apartments in Austin, Texas [30]. Using the same dataset, authors in [31] deployed a neural network based optimization for residential demand forecasting. A number of unsupervised learning methods for segmentation of consumers are benchmarked in [32] using the Pecan Street data.

The effect of lifestyle factors and household demographics in responding to energy conservation programs is examined in [33,34]. The work in [35] presented a slightly different customers' segmentation framework based on the psychographic attributes including the way consumers feel, think, and act in regards to their electricity usage. However, the study is based on survey data from consumers and their attitude and perspective towards electricity consumption without processing of any consumption data. The same limitation applies to similar studies in [36,37,34].

In regards to the socio-demographic attributes, household size has been shown to have a substantial impact on the total demand, although the size of the impact varies with geography and other factors [17,38,39]. For example, authors in [40] have reported an 8% jump in the overall usage for every additional household member in China, while this quantity was reported to be as high as 21% for Dutch households [39]. Furthermore, the research in [41] reported that the presence of kids in the household results in a relatively significant increase in the electricity consumption of Irish families. Similar results are published for U.S. households [42], but only when kids are three years or older. Considering a group of Dutch families, authors in [39] also investigated the effect of the presence of kids in the family and concluded that households with children consume almost 20% more electricity.

The effects of household social class and employment on electricity consumption have been investigated in [43,44]. The analysis in [44] suggests that households of the highest social class (e.g., high managerial and professional) consume 36% more electricity compared to

Download English Version:

<https://daneshyari.com/en/article/6557179>

Download Persian Version:

<https://daneshyari.com/article/6557179>

[Daneshyari.com](https://daneshyari.com)