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Bottom-up modeling of small-scale energy consumers for effective Demand Response Applications

A. Chrysopoulos [a,b,*], C. Diou [a,b], A.L. Symeonidis [a,b], P.A. Mitkas [a,b]

[a] ECE Department, Aristotle University of Thessalonki, Thessalonki, Greece
[b] Information Technologies Institute, CERTH, Thessalonki, Greece

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ABSTRACT

In contemporary power systems, small-scale consumers account for up to 50% of a country's total electrical energy consumption. Nevertheless, not much has been achieved towards eliminating the problems caused by their inelastic consumption habits, namely the peaks in their daily power demand and the inability of energy suppliers to perform short-term forecasting and/or long-term portfolio management. Typical approaches applied in large-scale consumers, like providing targeted incentives for behavioral change, cannot be employed in this case due to the lack of models for everyday habits, activities and consumption patterns, as well as the inability to model consumer response based on personal comfort. Current work aspires to tackle these issues; it introduces a set of small-scale consumer models that provide statistical descriptions of electrical consumption patterns, parameterized from the analysis of real-life consumption measurements. These models allow (i) bottom-up aggregation of appliance use up to the overall installation load, (ii) simulation of various energy efficiency scenarios that involve changes at appliance and/or activity level and (iii) the assessment of change in consumer habits, and therefore the power consumption, as a result of applying different pricing policies. Furthermore, an autonomous agent architecture is introduced that adopts the proposed consumer models to perform simulation and result analysis. The conducted experiments indicate that (i) the proposed approach leads to accurate prediction of small-scale consumption (in terms of energy consumption and consumption activities) and (ii) small shifts in appliance usage times are sufficient to achieve significant peak power reduction.

1. Introduction

Optimal operation of the electrical power grid requires efficient balancing between supply and demand in real time. Given this requirement, utilities, energy retailers and Distribution System Operators (DSOs) need to estimate and schedule their aggregate energy portfolio (consumption/production) for an extended time horizon. Typically, slight increases or decreases in demand are dealt in Day-Ahead or Real-Time Energy Stock Markets, where additional supplies' procurement or surplus energy sale is possible (Holmberg and Newbery, 2010). All in all, contemporary power systems can roughly forecast expected power demand and predict some of the power peaks, based on historical data, thus ensuring the proper operation of the power grid. However, the grid's quality of service is far from optimal, since it does not lead to major energy savings and grid stability. Were one able to perform small-scale consumer modeling and power peak smoothing, numerous problems related to grid stability can be dealt with Symeonidis et al. (2011). To do so, one has to understand the end-use habits of the inelastic consumers, such as households or small businesses.

The residential sector accounts for a major portion of the overall energy consumption worldwide (Eia, 2011); still, it remains as an uncharted and unattended "region". First of all, real-time monitoring and control systems are mainly applied to the generation and transmission phases of the electrical grid, or to large commercial/industrial consumers and not small-scale consumers. Additionally, there is little margin for demand control (and, thus, profit) over individual small-scale consumers and it can only be applied if the respective infrastructure is installed (smart meters, smart appliances). Practically, changes in small-scale consumption can only be achieved via changes in everyday consumer habits and activities triggered by personalized pricing incentives (e.g. Time-of-Use

* Corresponding author at: ECE Department, Aristotle University of Thessalonki, Thessalonki, Greece. Tel.: +30 2310996349; fax: +30 2310996398.
E-mail addresses: achryso@issel.ee.auth.gr (A. Chrysopoulos), diou@iti.gr (C. Diou), asymeon@issel.ee.auth.gr (A.L. Symeonidis), mitkas@auth.gr (P.A. Mitkas).

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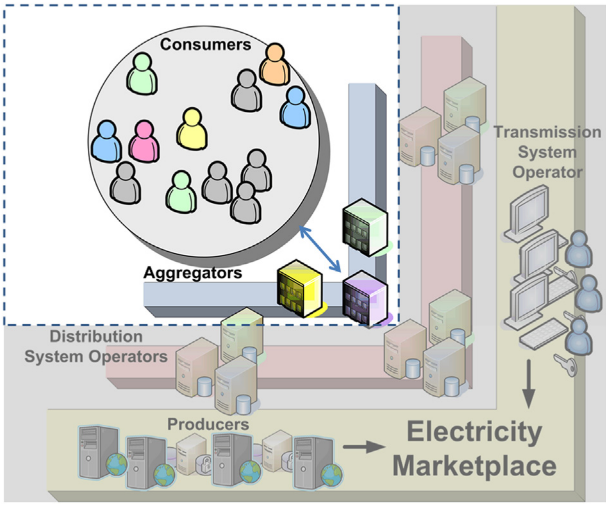

Fig. 1. This figure presents the current power system status. In this work, only the interactions between small-scale consumers and the aggregators are examined (highlighted part).

pricing schemes, Albadi and Elsaadany, 2008). Such incentives should suggest limited alterations, otherwise they will significantly affect consumers' *comfort* and may not be accepted.

On the other hand, should one succeed in modeling small-scale consumers in an activity- and a comfort-based context, the gains would be substantial. Small modifications in each individual consumption can have a major impact on the aggregate power demand. For example, a utility may succeed in high acceptance rates via the appropriate *Demand Response* (DR) programs, where end-use customers deviate from their normal consumption patterns, in response to electricity price changes over time or load (The et al., 2006). Thus, by modeling the interaction between the small-scale consumers and the energy suppliers/aggregators (Fig. 1) one could predict the resulting impact or savings, make decisions to stabilize energy supply or provide incentives for installation retrofitting and electrical appliance upgrade.

Current work introduces a modeling approach for small-scale consumers based on electrical consumption measurements that can aggregate their appliance and/or activity end-use. An event detection algorithm has been developed to analyze installation consumption data and train appliance consumption and consumer activity models. These models can then be used to simulate small-scale consumption at different aggregation levels, starting from a single appliance up to an entire installation. Furthermore, a consumer response model has been designed comprising a set of load shifting operations that are specific to pricing incentives.

An Autonomous Household Agent (AHA) architecture, that integrates the proposed consumption and activity models, is also presented. Fig. 2 illustrates how the proposed agent implements the interaction with the environment in the context of the power system. Each AHA interacts only with the household appliances and the aggregator (or energy supplier). Note that, since electricity consumers act independently in real-life, no communication between individual AHAs is performed. The proposed agent architecture and associated models allow not only the estimation and simulation of aggregated expected power consumption, but also the evaluation of the impact of appliance usage habits changes on the aggregated load curve. In the context of this paper, experiments were carried out using real electrical measurements collected from the EU-funded DEHEMS project.[1] Results indicate that (i) the proposed modeling approach leads to accurate load prediction, and (ii) small changes in appliance usage patterns are sufficient to significantly increase demand side control and, thus, increase the power network stability.

The rest of the paper is organized as follows. Section 2 provides a focused overview of the state-of-the-art on small-scale consumer modeling, including agent-based approaches. Section 3 discusses the agent architecture and the embodied modules and defines the consumer modeling elements (consumption models, activity models etc.). Section 4 presents the experimental evaluation of the proposed approach while Section 5 summarizes work performed, probes on directions for further research, and concludes the paper.

2. State of the art

In order to evaluate Demand Response potential, as well as the impact of new technologies in individual installations (such as smart appliances and renewable production capabilities), small-scale consumers must be modeled with respect to their end-use behavior and the appliances within the installations. This fine grained and tuning-enabling modeling methodology used for (mostly) residential sector energy consumption is *Bottom-up* (as opposed to the *Top-down* approaches that treat the residential sector as an energy sink and regress or apply factors that affect consumption to determine trends, relying on statistical data and economic theory, Swan and Ugursal, 2009). In principle, bottom-up modeling approaches use individual household models and aggregate the results. Aggregation is achieved by extrapolating models to group households, neighborhoods, cities and so on, by combining measurements with demographic data. Bottom-up modeling methods can be classified into two main categories: *Statistical* and *Engineering* (Swan and Ugursal, 2009).

Statistical methods model the aggregated household consumption without mapping the load curve to consumer end-uses. Thus, they cannot be used for modeling consumer behavior and designing effective DR programs. On the other hand, *Engineering methods* (EM) rely on more detailed information, but the models are built on assumptions made by human experts and demographic data and do not rely on historical values, although historical data can be used for calibration.

White-box Power Models: An interesting subset of EM that allows for some parametrization is denoted in the bibliography as *White-box Power Models* (WBM) (Paatero and Lund, 2006). They are able to calculate use over time for each appliance and aggregate to determine total demand. These models enable consumption micro-management and retrofit (e.g. smart appliance purchases and micro-generation), since changes in household demand can be attributed to individual loads, as well as impact assessment of various pricing policies (Gottwalt et al., 2011).

The first work in this direction was made by Walker and Pokoski (1985). They define models based on an "availability" function, that statistically estimates the number of residents of an installation that can use an available appliance, and on a "proclivity" function, which defines the probability that an individual will use a specific appliance at any given time of day. The most well known WBM approach, though, is presented in the work of Capasso et al. (1994), who employed distributions based on demographic surveys over appliance ownership, family types and lifestyle to create appliance use profiles of the Italian residential sector and compare them against existing load recordings.

On the other hand, Paatero and Lund (2006) presented a simplified but efficient bottom-up model, used to generate realistic residential electricity consumption data on an hourly basis from a few up to thousands of households. The model exploits input data available in public reports and statistics. The conducted analysis

[1] http://www.dehems.eu