Agent-based small-scale energy consumer models for energy portfolio management

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Abstract—In contemporary power systems, residential consumers may account for up to 50% of a country’s total electrical energy consumption. Even though they constitute a significant portion of the energy market, not much has been achieved towards eliminating the inability for energy suppliers to perform long-term portfolio management, thus maximizing their revenue. The root cause of these problems is the difficulty in modeling consumers’ behavior, based on their everyday activities and personal comfort. If one were able to provide targeted incentives based on consumer profiles, the expected impact and market benefits would be significant. This paper introduces a formal residential consumer modeling methodology, that allows (i) the decomposition of the observed electrical load curves into consumer activities and, (ii) the evaluation of the impact of behavioral changes on the household’s aggregate load curve. Analyzing electrical consumption measurements from DEHEMS research project enabled the model extraction of real-life consumers. Experiments indicate that the proposed methodology produces accurate small-scale consumer models and verify that small shifts in appliance usage times are sufficient to achieve significant peak power reduction.

I. INTRODUCTION

Energy trading is a relatively new, complex and volatile market as electricity is a flow commodity, which means that demand must always equal supply in real time, and extremely expensive to store in large amounts. Another reason is that the quality of transmitted power must remain in acceptable levels to achieve reliable and safe operation. Moreover, electricity value is highly driven by weather conditions and market operations for the relevant raw materials used to produce it.

Given this complexity, a market participant (such as Energy Services Companies (ESCOs) and Distribution System Operators (DSOs) faces high levels of uncertainty in both prices (price risk) and quantities (volumetric risk) traded. The former is linked to the volatility in spot prices due to uncertainty because of its competitor and counterpart strategies, whereas the latter refers to the uncertainty due to customer power consumption variation.

One of the main problems of current electricity markets is the lack of customer price elasticity of demand, as customers are only able to communicate with their suppliers, paying at a fixed price no matter what is the underlying cost for the utility and hence are isolated from the wholesale market, although there is an abundance of evidence suggesting that they would otherwise respond to its dynamics.

This paper presents the detailed implementation of a bottom-up consumer modeling methodology, for producing residential consumer behavior models fitting to electrical consumption measurements. Such models are useful to formulate demand response or policy programs regarding the residential sector, taking into consideration the existing customers, as well as the future market opportunities. Demand Response (DR) can be characterized any action taken to reduce electricity demand in response to price, monetary incentives, or utility directives so as to maintain reliable electric service or avoid high electricity prices. In other words, DR is any price-based effort to increase customers’ price elasticity of demand.

To apply the proposed methodology, we use a set of electrical appliances and probabilistic activity models encapsulated in an autonomous household agent. This approach allows not only estimation and simulation of the aggregated expected power consumption, but also evaluation of the impact of behavioral changes on the household’s aggregate load curve. Experiments were carried out using real electrical measurements collected from the DEHEMS European research program. The results indicate that (i) the proposed models achieve accurate load prediction and (ii) small changes in appliance usage patterns are sufficient to significantly increase demand side control.

The rest of the paper is organized as follows. Section II offers a brief overview of existing modeling techniques, including agent-based approaches. Section III introduces the proposed formal models and methodology while Section IV contains the agent architecture and modules’ analysis. Section V presents the experimental evaluation of the proposed approach while Section VI concludes this work and provides directions for further research.

II. STATE OF THE ART

Significant research on modeling of individual household energy consumption has been conducted in the context of bottom-up modeling approaches. Contrary to top-down methods that perceive the entire housing sector as a whole, bottom-up approaches use individual household models and aggregate the results. Aggregation is achieved by extrapolating models to group households, neighborhoods, cities, etc by combining measurements with demographic data. Bottom-Up

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modeling can be classified into two main categories: Statistical Methods and Engineering Methods (EM).

Statistical Methods model the aggregated household consumption without mapping the load curve to consumer end-uses. Thus, these approaches cannot be used for designing effective demand response programs. On the other hand, Engineering Methods rely on more detailed housing information but the models are built by assumptions made by human experts and demographics and do not rely on historical values, although historical data can be used for calibration. The most apparent drawback of the EM is that occupant behavior models are static and in most cases are not originated from data.

An interesting set of methods that model consumer behavior and allow a level of parametrization is a sub-category of EM called in the bibliography as Distributions [1]. This technique utilizes distributions of appliance ownership and usage with common appliance ratings to calculate the energy consumption of each end-use. The first publication of this method is the work of Walker et al. [2]. Their models develop the concept of an "availability" function which statistically estimates the number of people in a household available to use an appliance, and of a "proclivity" function which gives the probability an individual will use that appliance at any given time of day. The most well known Distribution method was however presented in the work of Capasso et al. [3], who utilized distributions based on demographic surveys over appliance ownership, family types and lifestyle to create an appliance use profile of the Italian residential sector and compare them to the existing load recordings.

In another important publication, Paatero and Lund [4] presented a simplified but efficient bottom-up model. The model was used to generate realistic domestic electricity consumption data on an hourly basis from a few up to thousands of households. The model used input data that is available in public reports and statistics. Their analysis showed that the generated load profiles correlate well with real data. In recent years, Firth et al. [5] made a monitoring study of the electricity consumption of a sample of UK domestic buildings, in order to investigate the ongoing patterns of different energy user groups (low, medium and high) and their contribution to the overall consumption. Finally, Armstrong et al. [6] have created detailed Canadian household electrical demand profiles, using a bottom-up approach from available inputs, including a detailed appliance set, annual consumption targets and occupancy patterns. These profiles were used in the simulation of residential co-generation devices to examine the issues of system performance, efficiency and emission reduction potential.

Special mention should made of several recently published approaches which are based on high-resolution domestic building occupancy models in order to predict the overall energy consumption and the inter-relations between household members that may exist [7], [8], [9], [10], [11], [12], [13], [14]. The major drawback of most of these approaches is that they are based on consumer data collected from diaries, meaning that the experiment participants had to fill his daily activities in 10 or 15 minute intervals for the duration of the tests, which can be a highly intrusive and error-prone procedure.

Agent-Based Approaches

Agent Technology (AT) and especially multi-agent systems have been successfully applied to model Power Markets (see [15] by Zhou et. al. for a survey). However there are not many published works that approach residential electrical power consumers as individual and autonomous entities.

In 2006, Sonnenschein et al. [16] described an agent-based simulation tool for examining the impact of real-time pricing methods upon the power consumption of domestic users (houses). The main entities within the model are electricity suppliers and electricity consumers scheduling their demand according to real-time prices for electricity. In [17] a hybrid econometric and social influence model was implemented for evaluating the influence of pricing and public education policies on residential habit of electricity using in power resources management. Abras et al. [18] implemented a multi-agent Home Automation System (MAHAS) dedicated to power management that adapts power consumption to available power resources according to inhabitant comfort and cost criteria.

Karnouskos et al. [19] presented the emergent concept of a future Smart City Grid. They designed and built a simulator, based on software agents, that attempts to capture the behavior of a smart city, by simulating discrete heterogeneous devices that consume and/or produce energy, able to act autonomously and collaborate. Similarly, in [20], [21] residential consumers are modeled as autonomous agents (SmartHome) which are responsible for shifting their consumption in order to maximize the residential revenue in addition to several social welfare factors. These works do not attempt to model consumer behavior, since their goal is the decentralized control of shiftable loads and the optimal utilization of renewable energy sources.

The approach presented in this paper deviates from most related work, since it is based on power consumption measurements to build accurate consumer behavior models. By following a bottom-up approach, individual appliance usage models are built that describe in detail the consumption activities. This type of detailed models allow the change estimation in each installation’s daily power curve for each slight alteration in end-use behavior. Appliance control is therefore left to the end consumer, making the proposed modeling methodology appropriate for designing effective demand response programs, targeting changes in appliance end-use that can lead to significant peak reduction.

III. FORMAL CONSUMER MODELS

This Section presents the fundamental elements that are used to describe residential power consumption in the proposed framework. These include the Residential Consumer, Appliance and Behavior models.

A. Residential Consumer

A residential consumer is defined as the set of tuples:
\[ \mathcal{R} = \{(c_{a,\theta}(t), B_{a,\theta}) : a = 1, \ldots, L\} \] (1)

for each appliance \(a\), where \(c_{a,\theta}(t)\) is the consumption model (i.e., how the appliance consumes power when it is switched on) and \(B_{a,\theta}\) is the behavior model (i.e., how the appliance is operated by the residential consumer). Appliance consumption and end-use behavior may depend on a set of parameters \(\theta\), such as external temperature, time of year, working/non-working day, etc. In the following sections, we consider a simplified version of the models that is independent of \(\theta\), due to the limited amount of available training data. One can directly extend the proposed approach by producing a set of models, one for each value of \(\theta\).

**B. Appliance Models**

The electrical appliances are categorized by type (e.g., cooking oven, washing machine) [22]. The appliance type does not only characterize its usage, but also its consumption, since appliances of the same type have similar power consumption patterns.

In this work, each appliance is fully defined by a *Consumption Model*, \(c_a\). There are two main categories of consumption models.

1) **Single Operation Cycle Consumption Model (SOC):** the consumption of the appliance remains the same during appliance operation. There may be several operating scales, depending on the appliance type or the manufacturer. Examples of such appliances include boilers, TVs, light bulbs and toasters. In SOC models, \(c_a\) is defined as:

\[ c_a(t) = \begin{cases} 1 \cdot P_{\text{nom}} & T_{\text{on}} < t < T_{\text{off}} \\ 0 & \text{elsewhere} \end{cases} \] (2)

where \(P_{\text{nom}}\) is the nominal operating power consumption, \(T_{\text{on}}\) and \(T_{\text{off}}\) are the starting and stopping operation points and \(l\) is the level of operation of the appliance. A constant model is a special case of the model with \(l = 1\).

2) **Multiple Operation Cycles Consumption Model (MOC):** More complex appliances (washing machines, ovens, dishwashers etc.) do not have only one operation cycle. In fact, the number of operation cycles may differ for each appliance type and each cycle may have its own pattern of electrical consumption, making modeling more intricate in these cases. In MOC models, \(c_a\) is defined as:

\[ c_a(t) = \begin{cases} l \cdot P_1 & T_{1\text{start}} < t < T_{1\text{end}} \\ \vdots \\ l \cdot P_n & T_{n\text{start}} < t < T_{n\text{end}} \\ 0 & \text{elsewhere} \end{cases} \] (3)

These fully describe a consumer’s end-use of a certain appliance. Load shaping, in the presented context is achieved by slight modification of the probability density functions of \(B_a\), as described in Section [IV-D].

**C. Consumer Behavior Model**

**Consumer Behavior Models** encapsulate the habits concerning the end-use of an appliance for the realization of a household task. These behavior models need to be expressive enough to capture different usage patterns of household occupants for each appliance, while at the same time simple enough to be constructed with a relatively small amount of electrical measurement data.

Formally, the *Consumer Behavior Model* of appliance \(a\) is defined as the set of three random variables

\[ B_a = \{n_a, s_a, d_a\} \] (4)

where \(n_a\) is the number of times appliance \(a\) is operated during a day, \(s_a\) is the time index the appliance is switched on, in minute intervals during a day (i.e., up to 1440 minutes) and \(d_a\) is the duration of operation of the appliance. These random variables are described by their corresponding probability density functions (PDF)

\[ n_a : N(a) \quad (n = 0, 1, \ldots) \] (5)

\[ s_a : S(a) \quad (s = 0, \ldots, 1440) \] (6)

\[ d_a : D(a) \quad (d = 0, 1, \ldots) \] (7)

**IV. HOUSEHOLD AGENT ARCHITECTURE**

We encapsulate the models presented in Section [III] in an autonomous household agent, that (i) builds consumer behavior models from electrical consumption measurements, (ii) simulates consumption behavior of the implemented models and (iii) responds to incentives/messages by adapting its behavioral models and altering consumption patterns accordingly. The proposed agent employs a modular architecture, shown in Figure [1].
1) Event Detection Module (EDM): EDM processes available datasets, prepares training sets and applies the Event Detection Algorithm, discussed in Section IV-A. The input needed for the aforementioned analysis, meaning the measurements from appliances, is collected either from files provided by the user, or directly from device interfaces (smart devices). In case smart meters are installed that measure the overall household consumption, disaggregation methods can also be utilized to identify the consumption of individual appliances[23].

2) Event Analysis and Modeling Module (EAMM): EAMM analyzes the event dataset extracted from EDM and derives consumer behavior models that can simulate the appliances’ consumption patterns. These models are passed on to the next module to be tested and applied.

3) Simulation Module (SM): The SM module is used for estimating power consumption based on the appliance and behavior models of the EAMM.

4) Aggregation and Shaping Module (ASM): ASM allows the agent to respond to pricing incentives by altering the EAMM models, leading to change in the appliance end-use and, ultimately, to load curve smoothing.

The following Sections provide details about the operation of the more important modules of our architecture.

A. Event Detection Module

A Consumption Event (or simply Event) is defined as a pair \((T_{on}, d)\) of the start time and the duration of appliance operation by the end consumer, where \(d = T_{off} - T_{on}\). Given a stream of power consumption measurements, one from each appliance, the goal of the EDM is to automatically identify the parameters \((T_{on}, d)\) of all events from the data. To this end we employ a two-step heuristic algorithm:

1) The initiation of an appliance’s operation \(T_{on}\) is marked when the appliance consumption exceeds a pre-specified threshold. Obviously, this threshold differs for each appliance. In order to achieve high noise tolerance, the threshold is usually set as a fraction (1/3 or 1/5) of the nominal operating power of the appliance.

2) The end of the operation \(T_{off}\) is marked differently for each appliance type. In most appliances, zero or near zero consumption means the end of the use. Nevertheless, there are several appliance types whose operation cycle demands pausing for certain time intervals, meaning (almost) zero consumption during that time. Based on the appliance consumption model \(c_{on}\), a counter of these cycles or a time duration threshold is used to identify the end of operation.

An outliers detection and removal step follows, where erroneous values are identified and removed. These can be identified as events with power consumption excessively greater than the nominal value of the appliance, or as events lasting significantly longer than they normally do.

B. Event Analysis and Modeling Module

The consumption events for the selected appliance are used to build the residential consumer model. We use two types of probability density function estimation approaches, frequency histograms and Gaussian Mixture Models (GMMs).

While the frequency histogram approach is straightforward and widely understood histograms are less accurate when a limited number of samples is available for estimation [24]. In our approach, histograms are used for the estimation of the PDFs \(N_a(n)\) and \(D_a(d)\) (the number of events per day and duration for appliance \(a\), respectively).

For \(S_a(s)\), parametric estimation approaches are more appropriate, especially in cases of limited data availability. These PDFs are estimated using Gaussian Mixture Models defined as a weighted sum of \(M\) Gaussian component densities [25]:

\[
f(x) = \sum_{i=1}^{M} w_i N(x|\mu_i, \sigma_i)
\]

where \(x\) are the values of a random variable \(x\) (\(s\) or \(d\) in our case), \(w_i\), \(i = 1, \ldots, M\) are the mixture weights, and \(N(x|\mu_i, \sigma_i)\), \(i = 1, \ldots, M\) are the component Gaussian densities.

GMM parameters are estimated from the event time indices (for \(T_{on}\)) and durations (for \(d\)) detected from the EDM (Section IV-A). Estimation is carried out using iterative Expectation-Maximization (EM) algorithm with Maximum Likelihood Parameter Estimation [26] for selecting the optimal GMM parameters \((w_i, \mu_i, \sigma_i)\) and KL-divergence distribution distance for selecting the number of mixtures \(M\).

Based on the above, the EAMM produces the models \(R\) of the residential consumers. These models can be directly used by the Simulation Module in conjunction with the appliance consumption models to observe the household agent’s power consumption.

C. Simulation Module

Simulation module is responsible for assessing the extracted behavior models’ accuracy. This is achieved by creating a realistic environment where the appliances are operated by a “person” based on the behavior models for a time interval equal to the sampling period and the results are compared with the actual levels of use and consumption.

More details over the followed simulation procedure are provided in the Experimental Results Section [V].

D. Aggregating and Shaping Module

Expected Power: Having generated and applied the residential consumer models, the next step is to estimate the aggregate consumption of the household for a specific day. Appliance \(a\) may be triggered at time \(t\) of a day by an event \((T_{on}, d)\) given that:

\[
(T_{on} = t)\vee((T_{on} = t-1)\land(d \geq 1))\vee((T_{on} = t-2)\land(d \geq 2))\ldots
\]
We can therefore compute the Expected Power $P_a(t)$ as:

$$P_a(t) = \sum_{\tau=0}^{\tau_{\text{max}}} S_a(T_{on} - \tau)D_a(d \geq \tau)c_a(\tau)$$  \hspace{1cm} (10)

where $\tau_{\text{max}}$ is an upper bound to the appliance $a$ event duration and $S_a$, $D_a$ as described in Equations (5) and (7). It should be noted that even though the distribution $N_{a}$ of the daily number of times is also affecting appliances’ Expected Power by a constant, it is not affecting the shifting and response behavior of the models. Thus, it is omitted from the equation (10) above.

Thus, the Expected Energy Consumption $E_a$ for a day ($t \in \{1, \ldots, 1440\}$) is computed as:

$$E_a = \sum_{t=1}^{1440} P_a(t)$$  \hspace{1cm} (11)

**Peak Detection and Analysis:** A Peak Detection algorithm has been implemented (Figure 2) to identify the global maximum (or several local maxima) in the time series of the daily Expected Power. These peaks are used as input to the subsequent shifting operations.

```plaintext
Collect Expected Power Time Series
for i = 0:Minutes per day
left := value[i]
middle := value[i+1]
right := value[i+2]
if ( middle - left > K && middle - right > K )
    Add local maximum to List
end for
Remove peaks covered by larger "neighbors"
Return list ordered by Expected Power
```

Fig. 2. Peak Detection Algorithm

In the Peak detection algorithm, $K$ is an arbitrarily small value used as a threshold. In the step of peak removal from the list, we try to keep the list short by keeping the maximum of the local maxima that are close in time.

The analysis of the peak (or peaks) of interest is the next task of the ASM. The percentage of participation of each appliance of the household on this excessive load is therefore estimated from the following formula:

$$\text{Perc}_a(t_p) = \frac{P_a(t_p)}{\sum_{j=1}^{M} P_j(t_p)}$$  \hspace{1cm} (12)

where Perc$_a$ is the percentage of participation of the $i$-th appliance, $t_p$ is the peak time index, and $P_j$ is the Expected Power as defined above.

1) **Shifting Operations:** Given the observed peaks in the Expected Power, incentives (rewards and/or penalties) may be provided to the agent to alter its end-use behavior. These have the form of price variation (rise or drop) within a time window $W$, while the agent responds by altering its consumption patterns according to a set of shifting operations. These operations introduce alternations to the start time distribution $S_a(s)$ of the behavior model [4]. In the proposed work, the alternations in $S_a(s)$ are inversely proportional to the price change in $W$ and the residual probability $P_r = \sum W(S_a(s) - S_r(s))$ is distributed to the rest of the time points of the new distribution $S_a(s)$ according to three different types of response models:

1) **Response 1 (best case):** $P_r$ is distributed proportionally to the values of $S_a(s)$ outside of $W$: $S'_a(s) = (1 + P_r)S_a(s)$ for all $s$ outside $W$. This scenario is realistic for price aware smart appliances that can automatically shift their operation in time periods with lower prices.

2) **Response 2:** $S_a(s)$ is increased right before and after the window $W$ (assuming the agent will minimize his activity shift as much as possible). This behavior is simulated by the application of a Moving Average Algorithm.

3) **Response 3 (worst case):** In some cases, consumers respond by shifting their activities to the other day-time intervals they prefer to do this activity. To simulate this behavior the agent distributes the residual $P_r$ proportionally to the next largest peaks (up to three).

V. **Experimental Results**

This section presents a series of experiments that were realized using electrical consumption measurements from different installations and appliances. The results illustrate the effectiveness of the proposed small-scale consumer models and show how agent response to incentives can lead to peak power reduction.

Raw measurement data was obtained from the Digital Environment Home Energy Management System (DEHEMS) project. The data was collected from May 2010 up to August of 2011 from different installations across 5 different European cities. From the large databases of DEHEMS project we were able to extract a useful measurements’ dataset containing plug-wise consumption from 63 households: Plug-wise devices were connected with most installed household appliances in order to acquire detailed measurements of their consumption over different time-spans (minute, day, week, month and year).

The following two groups of experiments were realized:

1) Single appliance measurements from several households were compared with their simulated models’ consumption, to evaluate the effectiveness of EDM, EAMM and SM (Section IV).

2) Peak reduction scenarios by using the ASM, which were evaluated based on the overall household Expected Power.

A. **Single Appliance**

The first stage of model evaluation is the comparison between simulated and actual appliance power consumption. We manually constructed a set of consumption models $c_a(t)$ based on the nominal load consumption of the appliances under examination.

In order to evaluate the precision of our end-use models for each appliance we used the Mean Percentage Error,

$$MPE = \frac{1}{n} \sum_{i=1}^{n} \frac{|v_i - p_i|}{v_i} \times 100\%$$  \hspace{1cm} (13)
where $n$ is the number of time series samples, $v_i$ is the observed value for each time step $i$ and $p_i$ is the respective predicted value.

This error is estimated for three different time intervals: Daily MPE (DMPE), Weekly MPE (WMPE) and Monthly MPE (MMPE). Percentage Deviation was used as a standard deviation metric for the above mean error:

$$PD = \frac{1}{n} \sum_{i=1}^{n} \frac{\sigma_i}{v_i} \times 100\%$$  \hspace{1cm} (14)

where $\sigma_i$ is the standard deviation for each time step $i$.

Finally, in order to measure the accuracy of the proposed models for finer temporal granularity, we compared the simulated Expected Power with the real Expected Power extracted from the available data measurements. The metric used to evaluate the results is the Symmetric Mean Absolute Percentage Error (SMAPE) \cite{27}, which is an accuracy measure based on relative percentage errors. The formula for the estimation of SMAPE is

$$SMAPE = \frac{1}{n} \sum_{t=1}^{n} \frac{|A_t - F_t|}{A_t + F_t} \times 100\%$$  \hspace{1cm} (15)

where $A_t$ is the expected power extracted from the real measurements for ten minutes interval $t$ of the day and $F_t$ is the simulated expected power. Both errors can be easily calculated with the time series provided for analysis.

Table I presents the errors measured for different household appliance types. The Table displays the average and standard deviation of the different error measures (DMPE, WMPE, MMPE and SMAPE) over 100 runs, where for each run 75% of days are used for training the models and the rest 25% is used for evaluation. A different training set is selected in each run. Given the complexity of each model, it is easily seen that simple appliances (boiler, toaster, microwave oven) have small Percentage Errors ($\sim 5.98 \pm 4.29\%$, $\sim 8.16 \pm 7.31\%$ and $\sim 8.74 \pm 6.44\%$ in this example), while prediction errors of the more complex appliances, such as oven and washing machine are larger, though small enough to consider the models accurate in the proposed consumer behavior modeling context ($\sim 14.24 \pm 7.78\%$ and $\sim 11.08 \pm 9.66\%$ respectively). The average SMAPE value for all appliances in our experiments was 10.51\%, while its standard deviation was 1.28\%. Figure 3 compares the actual and estimated power consumption for a representative appliance example (boiler), where the proposed models provide very accurate peak time index forecasting and closely follow the trends of the real expected power.

Given the tolerance levels of transmission and distribution segments of the power system, a 10\% SMAPE is considered as acceptable error. Furthermore, as the goal of the proposed framework is not focused on consumption forecasting but the modeling of consumer behavior (e.g., appliance operation statistics), this error level is more than adequate to characterize and/or group consumers and support the design of effective demand side management programs.

It is important to note that for some of the appliances (e.g.
Washing Machine) very few events were detected in the data. By increasing the sample size, the constructed models have greater prediction capacity. Figure 4 illustrates how error is reduced as the number of samples increases for an example appliance. Similar results are obtained for other appliances. As power utilities have access to an abundance of measurement data from the smart grid, there is the potential to build highly accurate and more granular end-use models that can describe consumer behavior over different seasons of the year or different day types (e.g., weekend/weekday).

B. Load Shaping Simulations

Apart from end-use behavior analysis, the presented agent can use the consumer models for residential load shaping (Section IV-D). After processing the raw data from the DEHEMS dataset with EDM and EAMM, the agent computes the Expected Power of each appliance power consumption using Eq. (10).

The second series of experiments implemented penalty incentives for a single appliance around the time interval where its load demand was peaked. A 20% price increase in a window around the appliance peak power was applied. In the best case scenario (Figure 5(a)), the average observed reduction over all the appliances was 42% ± 8%, while the level of the expected power for the rest of the day remained the approximately the same, since only a small portion of residual power had transferred to each minute. In the second case (Figure 5(b)), the average reduction was 29% ± 12% and the residual power was naturally shifted to the time intervals near the penalized timezone, increasing the surrounding region’s power up to 15% ± 4%. In the third and worst case scenario (Figure 5(c)), the mean reduction was equally significant with the previous case (29%±12%), but there was an average increase of 25% in other peaks of the daily expected power (although in absolute values, the peaks remained lower).

The results of all the scenarios examined indicate that a significant decompression in the peak area is feasible without having to increase the prices too much and heavily penalizing the customers who choose not to accept the behavior change. This approach also reveals a significant benefit of the presented bottom-up modeling: By having detailed small-scale models, it is possible to send different incentives to each consumer agent, leading to very fine control of the power curve at a macroscopic level. However, incentives to some consumers may lead to response behaviors that reduce the positive results of others or void them altogether. The proposed consumer agent can be used in a multi-agent system to solve this problem (although this could not be done in this work due to lack of data).

VI. CONCLUSION AND FUTURE WORK

This work presented a detailed bottom-up small-scale consumer modeling methodology that was embodied in autonomous consumer agents. By providing appliance-level power consumption data, the agent builds detailed models and can simulate the observed end-use behavior. Furthermore, the agent encapsulates a Demand Shaping mechanism, responding to incentives provided by altering its consumption pattern. Using the proposed agent, the observed power consumption can be mapped to consumer activities and activity shifting responses and can therefore model and simulate a wide range of DSM scenarios for load shaping.

A number of experiments were carried out using measurements that were collected by different households from 5 cities in Europe. These experiments illustrated the accuracy and applicability of our consumer agent for various levels of temporal granularity and also outlined the proposed load shaping process.

In the future, we aim at extending this work by using detailed appliance models and context adaptive behavior models that will be sensitive to varying parameters (weather, location, week...
of year etc). Another aspect worth researching is the possibility of having dynamic pricing schemes that may change over time, which would require an automated procedure encapsulated on the consumer-agents. Finally, when more Smart Grid measurement data become available, it will be very interesting to examine the construction of multi-agent systems of consumer agents and experiment on different types of incentives and consumer response models.

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