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A Distributed Software Solution for Demand Side Management with Consumer Habits Prediction

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***Abstract*—Future smart grids will open the marketplace to novel services for grid management, such as Demand Side Management (DSM). To achieve energy saving in distribution systems, DSM aims at modifying load profile patterns of electricity demand by involving actively customers. In particular, residential customers can participate to this service by shifting their energivourous appliances (e.g. washing machine and dishwasher).**

In this paper, we present a novel DSM service to manage a day ahead balance. It exploits a human-in-the-loop approach to provide suggestions on shifting their appliances based on *Latent Dirichlet Allocation* algorithm combining both i) the probability density function of each customer's appliance usage and ii) the cost function. To assess our DSM service, we present our experimental results performed in a realistic environment where we simulated a virtual population of about $1'000$ families.

***Index Terms*—Demand Side Management, Human-in-the-Loop, Smart Metering Infrastructure, Smart Grid, Latent Dirichlet Allocation**

I. INTRODUCTION

The transition to the new smart grid paradigm opens the energy marketplace to novel services for flexible demand [1]. Demand flexibility aims at modifying the energy consumption behaviour of customers to balance the electricity in grids. This is a powerful solution to solve operation limit violations in distribution networks and to flatten energy peaks by shifting some loads over the day [2]. Services for demand flexibility are categorized into Demand Side Management (DSM) and Demand Response (DR) [3]. In both cases, demand flexibility is achieved through various approaches (e.g. financial incentives, dynamic tariffs, Time of Use tariffs) to encourage participation of customers in consuming less energy during peak hours even by shifting their loads during off-peak periods. Possible shiftable appliances for residential customers are washing machine, dishwasher and tumble dryer that are typical energivorous appliances. To achieve this purpose, we need novel smart appliances that are Internet-connected devices ready to send different information about their operational status and to remotely receive actuation commands, for instance, from authorized actors (e.g. energy aggregators, utilities or retailers). However, such smart appliances are not yet widespread deployed in our homes. Thus, we need alternative and non-invasive human-in-the-loop solutions to convey tips and suggestions to customers [4].

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Müller et al. [5] states that Information and Communication Technologies (ICT) play a crucial role in future power systems. Indeed, future smart grids will be complex systems where various actors constantly exchange heterogeneous information. For example, new generation smart meters are becoming the main actors in Advanced Metering Infrastructure (AMI). Thus, they will drive new services for DSM and DR, which need to be accurately tested in a realistic simulation scenario before their massive deployment in real-world distribution systems [6].

In the last years, different solutions have been proposed for engaging residential customers to foster novel strategies for both management and control of distribution networks. Sajjad et al. [3] present an energy flexibility indicator for aggregated residential loads. Such indicator is based on the binomial model that designates the flexibility of aggregate customers in terms of probability of increasing and/or decreasing the demand. In [1], authors present a module to micro-forecast energy flexibility of end-users. This module, which is embedded in their AMI, exploits different forecasting techniques, such as exponential smoothing, ARIMA and Neural Networks. Mishra et al. [7] propose a novel methodology to asses DSM with renewable energy based on the wards agglomerative heretical clustering technique. In [2], Blaauwbroek et al. present a methodology to model DSM appliances and their applications into an optimization strategy based on grid requests. LeMay et al. [8] describe a Meter Gateway Architecture for enabling energy aggregators to an integrated control of loads. Babar et al. [9] present Energy Flexometer a monitoring and controlling communication node that can be integrated in an energy management system. It provides a functional block to forecast a state of an agent for an expected action by using the price flexibility of demand. In [10], authors present a cloud-based platform to exploit demand flexibility and to provide customers with price incentives. SEMIAH [11] is a solution to deal with residential DR events to shift smart appliances by allowing a bidirectional communication between their AMI and a Home Energy Management Gateway. Bhattarai et al. [12] present a solution to perform three levels of control and actuation. It manages residential appliances by applying different rules for management of appliances (i.e. direct load control, price based, demand dispatch and autonomous) to each of the proposed layers. Finally, Mashima et al. [4] proposed a human-in-the-loop framework to provide customers with control policies allowing a remote control of smart appliances based on a mobile app. In our view, the reviewed literature solutions for DSM lacks on analyzing the behaviour of customers that strongly affect the use of appliances at home [13]. Indeed, providing suggestions on shifting appliances based on usage patterns of customers can increase the acceptance towards these new services and therefore be more effective.

With respect to literature solutions, in this paper, we propose a DSM algorithm that leverages upon our advanced metering infrastructure, a.k.a. *Flexmeter* [14], [15]. The proposed DSM service is based on the *Latent Dirichlet Allocation* (LDA) algorithm [16], [17] and deals with the day ahead balance of the aggregated daily load trend in cities. Through a human-in-the-loop approach, it actively involves residential customers by sending suggestions to shift their loads based on their behavioral patterns. Moreover, it considers also the cost function representing the need of balancing the energy in the grid. In designing and developing this solution, we addressed the following challenges highlighted by Rajabi et al. [18]: i) bidirectional communication between the DSM algorithm and the customers through the *Flexmeter* platform by exploiting consolidated communication protocols; ii) shift loads based on behaviours and appliances usage patterns of customers. It is worth noting that, through *Flexmeter*, DSM algorithm can send either commands directly to smart appliances or suggestion to customers via mobile apps in case they own traditional appliances. Finally, through *Flexmeter*, that provides also feature for realistic co-simulations, we tested the whole system to evaluate its performance in different scenarios. Thanks to the proposed solution, Energy Aggregators can become active actors in the marketplace for day-ahead energy balancing. Indeed, they can create a virtual power plant [19] consisting of aggregated customers that can follow DSM suggestions by receiving rewards, such as economic incentives.

The rest of the paper is organized as follows. Section II briefly introduces *Flexmeter*, our advanced metering infrastructure. Section III presents the proposed algorithm, which is the core of our DSM service. Section IV reports the experimental results performed in a realistic environment where we simulated a virtual population of about $1'000$ families. Finally, Section V discusses the concluding remarks and future works.

II. *Flexmeter* Platform

As mentioned in the previous section, our DSM service leverages upon *Flexmeter*, which is our advanced metering infrastructure [14], [15]. *Flexmeter* provides also features to design and co-simulate general purpose services in smart grid scenarios. As shown in Figure 1, *Flexmeter* consists of three main layers: i) the *Device Integration Layer*, ii) the *Middleware Layer* and iii) the *Application Layer*.

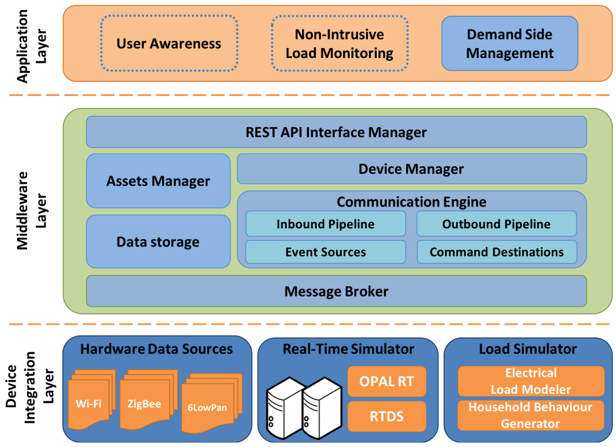

Fig. 1. Scheme of *Flexmeter* platform.

The *Device Integration Layer* ensures interoperability among real and simulated devices (e.g. novel smart meters), supporting a bidirectional real-time data transmission. It integrates also different simulators either hardware (e.g. OpalRT, RTDS) or software (e.g. LoadSim [20] in the figure). Real-time hardware simulators, like OpalRT and RTDS, are in charge of reproducing realistically the electromagnetic transient in distribution networks. LoadSim [20] generates realistic power profiles of residential customer with multi-level aggregations (i.e. individual appliance, house, district and city) starting from statistical information.

The *Middleware Layer* collects, stores and retrieves data coming from devices and smart meters. It provides authorized developers with Web Services to access measurements and send commands to appliances compliant with standard communication protocols and data-formats.

The *Application Layer* consists of a set of general purpose services that can share information between them. For example, the DSM service, that belongs to this layer, can either receive inputs directly from smart appliances or exploit results of other services, such as *Non-Intrusive Load Monitoring service* (NILM) [21] in case customers own traditional appliances. The NILM service derives load profiles of individual appliances starting from a single point of measurement, the smart meter at home. Then, the outputs of the DSM Service are sent either to remote smart appliances, as actuation commands, or to customers through the *User Awareness* app [22], as suggestions.

III. Latent Dirichlet Allocation for Appliance Usage Pattern Prediction

The proposed DSM service is based on the *Latent Dirichlet Allocation* (LDA) algorithm [16], [17]. LDA reverses a generative probabilistic model for collections of discrete data that,

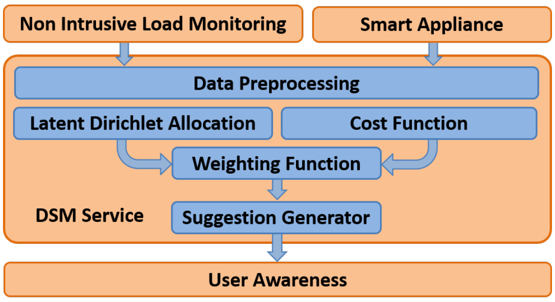

Fig. 2. Schema of the DSM service.

in our case, are applied to forecast appliance usage patterns based on customers' behaviours. It predicts the appliance usage patterns as a probability density function (PDF) for each monitored household and then provides suggestions on shifting residential loads according to a cost function representing the need of balancing the energy in the grid.

Human behaviours strongly affect the use of appliances at home and, often, such behaviours are periodically repeated over the week [13]. Thus, we need a time series data-set with activation of appliances over the week. These time series intrinsically report the user behaviour patterns and are discretized into a histograms of counts within a fixed time interval. The time interval should be i) fine enough to intercept the different behavioural patterns of customers and ii) coarse enough to derive statistical features without noise.

Hence for each week, we chose a 30-minute time interval, resulting in 336 time-bins per week. Each appliance usage pattern can be conveniently represented as a histogram of counts where most of them will be zero under the assumption of sparsity of data. The generated data-set consists of a set of histograms pertaining to the appliance under consideration (e.g. washing machine). It can be represented as a matrix of counts, where rows reefer to each customer and columns represent the weekly time intervals (i.e. 336 time-bins). This process is handled by the *Data Preprocessing* module in Figure 2.

In this context, the data-set $\mathbf{D}$ is a collection of appliance usage patterns $\{d_1, ..., d_M\}$, and $d = \{w_1, ..., w_N\}$ is the usage pattern histogram on temporal bins w from an indexed vocabulary $\{1, ..., N\}$. The v^{th} bin of the vocabulary is represented as a N-vector w such that $w^v = 1$ and $w^u = 0$ for $v \neq u$. The generative model describes how each usage pattern d obtains its active bins w:

1) Choose $N \sim Poisson(\xi)$
2) Choose $\Theta \sim Dir(\alpha)$
3) For each of the N bins w_n:
    a) Choose a micro-habits $z_n \sim Multinomial(\Theta, \beta)$
    b) Choose a bin w_n from $P(w_n \mid z_n, \beta)$

where N are the generated bins from a generic Poisson distribution with parameter ξ; Θ is a Dirichlet distribution with parameter α; $Multinomial(\Theta, \beta)$ is a multinomial distribution generated over Θ with parameter β; and $P(w_n \mid z_n, \beta)$ a multinomial probability conditioned to micro-habits z_n and parameter β. In this model, all the usage patterns share the same set of micro-habits with different proportions.

Assuming this generative model for a collection of usage patterns, LDA tries to backtrack from the usage patterns to infer a set of micro-habits $\widetilde{\mathbf{z}}$ that likely generated the data-set. The main issue for modeling these micro-habits $\widetilde{\mathbf{z}}$ consists on using the observed patterns to infer the structure of hidden micro-habits. This can be achieved by applying the collapsed Gibbs sampling, as described in Algorithm 1.

Algorithm 1 Gibbs sampling

for $\forall d : d \in \mathbf{D}$ **do**
  for $\forall w : w \in d$ **do**
    $w \leftarrow \widetilde{z} \in \widetilde{\mathbf{z}}$
for $\forall d : d \in \mathbf{D}$ **do**
  for $\forall w : w \in d$ **do**
    for $\forall \widetilde{z} : \widetilde{z} \in \widetilde{\mathbf{z}}$ **do**
      Compute $P(\widetilde{z} \mid d)$
      Compute $P(w \mid \widetilde{z})$
      Compute $P(\widetilde{z} \mid d) \cdot P(w \mid \widetilde{z})$
      Choose $\widetilde{z}$ *maximize* $P(\widetilde{z} \mid d) \cdot P(w \mid \widetilde{z})$

According to Gibbs sampler, $P(\widetilde{z} \mid d)$ is the proportion of bins w in a usage pattern d that are currently assigned to micro-habits $\widetilde{z}$. $P(w \mid \widetilde{z})$ represents the proportion of a micro-habits $\widetilde{z}$ over the all usage patterns that come from a bin w. Then, we reassign to w a new micro-habit $\widetilde{z}$ to maximize the probability $P(\widetilde{z} \mid d) \cdot P(w \mid \widetilde{z})$. According to the generative model, this is the probability that a $\widetilde{z}$ generates a bin w. So, it makes sense to re-sample the current proportion of bin's micro-habits that maximize such probability. After repeating the previous step in a loop for several times, the Gibbs sampler will reach a steady state where the assignments reflect the actual distribution of the data.

Our histogram matrix $\mathbf{D}$ with collection of appliance usage patterns can be reconstructed as $\widetilde{\mathbf{D}}$ by an inner product of the bin relevance for each micro-habits $P(w \mid \widetilde{z})$ and a mix of micro-habits $P(\widetilde{z} \mid d)$ for each usage pattern. As shown in Figure 3, the matrix $\mathbf{D}$ is decomposed into $P(w \mid \widetilde{z})$ and $P(\widetilde{z} \mid d)$ to obtain the characteristic bins for each micro-habit and the mix of micro-habits for each usage pattern.

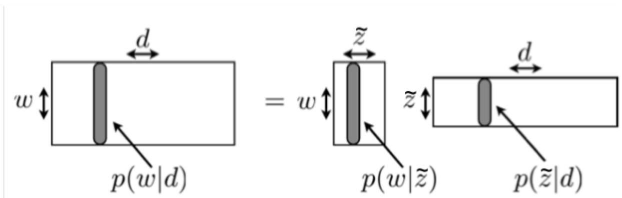

Fig. 3. Reverse Generative Process.

The reconstructed matrix $\widetilde{\mathbf{D}} = P(w \mid z) \cdot P(z \mid d)$ estimates the data-set $\mathbf{D}$ and is the PDF of each user's appliance usage. All this computation is accomplished by the *Latent Dirichlet Allocation* module in Figure 2.

Weighting Function module combines the resulting $\widetilde{\mathbf{D}}$ with a cost vector, which is a time series with the price of electricity over the time. This cost vector is provided by the *Cost*

Function module. The *Weighting Function* module needs as input an additional parameter α that weights the cost function with the PDF of using appliances over the day. The resulting weighting function is a linear combination of the cost function and the user u discomfort. It is expressed by the Equation 1:

$$combined(t,u) = \alpha \cdot discomfort(t,u) + (1-\alpha) \cdot cost(t) \quad (1)$$

where

$$discomfort(t,u) = 1 - \widetilde{\mathbf{D}}(t,u) \quad (2)$$

This is needed to generate suggestions giving more priority to user behaviours or to the cost vector. Figure 4 shows an example of four washing machines in four different houses, where $\alpha = 0.5$.

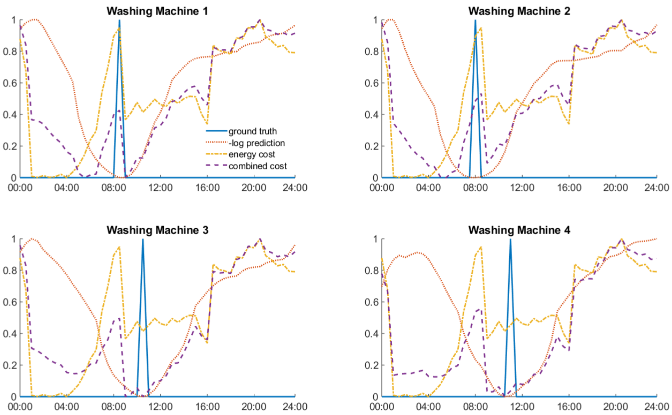

Fig. 4. Results of *Weighting Function* module for four washing machines in four houses.

The output of *Weighting Function* module is given as input to *Suggestion Generator* module that will generate suggestions for customers. This module takes the combined cost matrix and extracts the generated suggestion for each user. This is achieved by applying Equation 3 for all active users U_{active}.

$$\arg\min_t combined(t,u) \;\forall u \in U_{active} \quad (3)$$

IV. Experimental Result

In this section, we present the experimental results performed in a realistic environment where we simulated a virtual population of about $1'000$ heterogeneous families with their appliances. We used LoadSim [20], which is a multi-scale simulator to generate realistic residential load profiles at different spatial-temporal resolutions. LoadSim simulate activities and behaviours of customers starting from results of national *Time Use* surveys and *Census data*. Furthermore, the distribution of appliances among families is given by considering the national statistics reported in [23]. Thus, virtual families are statistically coherent with the distributions of family-size, people categories and distribution of appliances. Then, LoadSim translates these activities into energy consumption. We simulate a period of about 8 weeks.

To simulate the behavior of a realistic smart grid, results from LoadSim are collected by *Flexmeter* and then retrieved and pre-processed by the DSM service. For each shiftable appliance (i.e. washing machine and dishwasher, typical energivorous loads), the DSM service will generate a $\mathbf{D}$ matrix (see Section III). To assess the results of our LDA-based algorithm compared to reference data (i.e. ground truth of the real appliance activation), we exploited the following indexes, that are widely used in descriptive statistics: i) the *Root Mean Square Error* (RMSE) defines the standard deviation of the difference between the predicted values and the ground truth of the real appliance activation; ii) the *Perplexity Index* describes how a probability distribution predicts a sample. A lower Perplexity Index indicates a better generalization; thus, the PDF is good in predicting a sample.

Performance indicators for washing machine and dishwasher are shown in Table I. RMSE for both appliances is very low, about 5%. Whilst, the Perplexity Index is about 100 and 39 for washing machine and dishwasher, respectively. This is due to the different usage patterns of each appliance. Indeed, dishwasher typically presents a more regular pattern for each family that is better predicted. Whilst, washing machine presents a more heterogeneous pattern, thus, a higher Perplexity Index.

TABLE I
Performance indicators for washing machines and dishwashers.

Appliance	RMSE [%]	Perplexity Index
Washing Machine	5.2%	100.31
Dishwasher	5.1%	39.42

After these preliminary assessments, we simulated different scenarios varying the α parameter and the suggestion acceptance rate of customers. Thus, our scenarios vary according to different weights given to the cost function and the PDF of using appliances over the day, following the Equation 1. In particular, we varied α in $[0\%, 25\%, 50\%, 75\%, 100\%]$ and the acceptance rate in $[33\%, 66\%, 100\%]$. The cost function is set equal to the aggregated power profile of a typical day, as shown in Figure 4. In the case of low α, the resulting suggestions will smooth the aggregated power profile of the whole virtual population. Thus, shiftable loads are moved during off-peak periods.

Figure 5 shows the aggregated power profiles of the whole virtual population with and without the DSM event (blue dashed-line and red solid-line, respectively) for the different α and acceptance rate. As shown in the figure, accepted suggestions change the power profile moving some loads to the early morning. This is clearly pointed out when $\alpha = [0\%, 50\%]$. In particular, Table II reports the energy shifted for washing machine and dishwasher for the different combinations of α and acceptance rate.

When $\alpha = 0\%$ and acceptance rate is 100%, the DSM service generates suggestion considering only the cost function. In this case, the energy shifted is about $400\ kWh$ in the

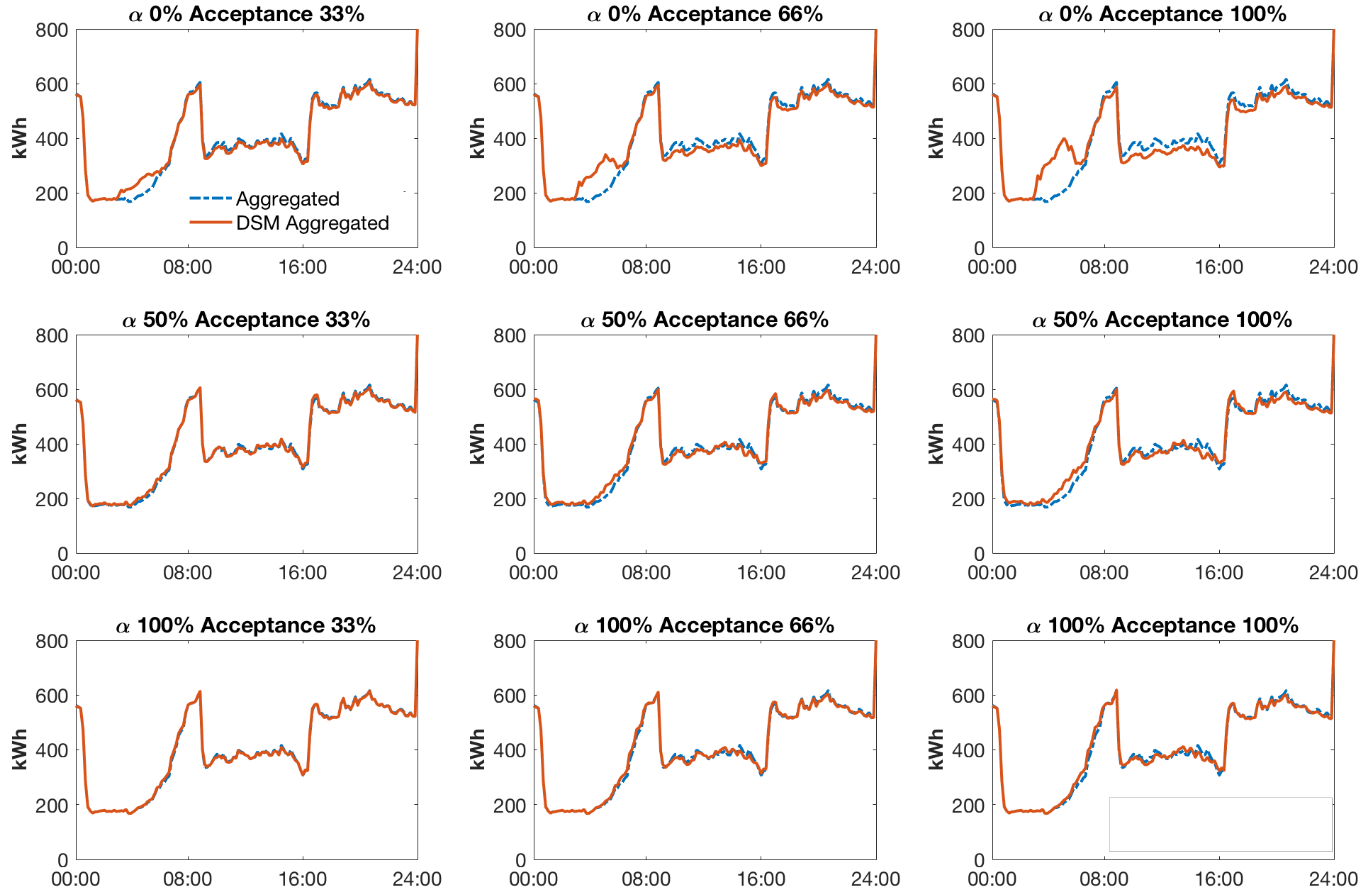

Fig. 5. Aggregated power profiles of the virtual population with and without DSM event (blue dashed-line and red solid-line, respectively).

TABLE II
RESULTS OF DSM SERVICE ON THE DIFFERENT SIMULATED SCENARIOS.

α [%]	Acceptance Rate [%]	Total Shifted Loads [kWh]	Shifted Washing Machine [kWh]	Shifted Dishwasher [kWh]
0	33	132.46	99.15	33.31
	66	264.05	197.42	66.62
	100	402.74	299.31	103.44
25	33	134.11	99.05	35.06
	66	265.10	196.73	68.37
	100	401.62	298.18	103.44
50	33	74.67	52.89	21.78
	66	148.40	105.08	43.32
	100	220.72	153.13	67.60
75	33	50.83	31.06	19.77
	66	86.73	53.25	33.48
	100	130.18	83.12	47.06
100	33	46.41	31.90	14.51
	66	88.55	59.40	29.15
	100	131.22	87.13	44.09

period between 4:00 AM and 6:00 AM (see Figure 5). When the acceptance rate is 66% and 33%, the energy shifted is about 264 kWh and 132 kWh, respectively.

As expected, the results when $\alpha = 25\%$ are comparable to $\alpha = 0\%$ because this parameter still assigns a higher weight to the cost function (see Equation 1).

When $\alpha = 50\%$, the total energy shifted ranges between 74 kWh and 220 kWh proportionally to the acceptance rate.

With $\alpha = 100\%$ and $\alpha = 75\%$, the DSM service generates suggestions giving a higher weight to the PDF of the appliance usage over the day. This means that the DSM service produces an aggregated power profile of the whole population that follows the one without the DSM event, as shown in Figure 5. In this scenario, the energy shifted ranges between 46 kWh and 131 kWh for the different acceptance rates. This confirms the accuracy of the DSM service in learning the appliance usage patterns and generating consistent suggestions.

V. CONCLUSION

In this paper, we presented a DSM service to manage a day ahead balance of the aggregated daily load profile in cities. This service is based on the *Latent Dirichlet Allocation* algorithm. It follows a human-in-the-loop approach by considering the customer behaviour patterns and cost functions to shift loads and modify the aggregated energy profile over the day. This energy balance is achieved by shifting some appliances, either smart or traditional, belonging to residential customers.

First, we discussed the motivations that drive the demand flexibility in smart grid management, including the challenges addressed by the proposed DSM algorithm which is a service of our *Flexmeter* platform. After we introduced the mathematical formulation of the proposed algorithm, we discussed the experimental results giving by performing different simulation scenarios for a virtual population, statically consistent. Such scenarios differ in suggestion acceptance rate of customers. As future work, we plan to test this service in a real-world environment by involving real customers to verify their willingness to participate and accept suggestions.

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