Methodology for Managing Cost-Effective Demand Response Campaigns Based on Demand Elasticity Profiles

Angeliki Anastopoulou Costas Kalogiros George D. Stamoulis
Department of Informatics, Athens University of Economics and Business, Greece
{aanastop, ckalog, gstamoul}@aueb.gr

***Abstract*—We develop and evaluate a methodology for running manual implicit and explicit Demand Response campaigns in order to improve the sustainability of smart grids. Initially, we introduce a flexibility profiling engine that relies on the correlation among end-user's consumption, prices and environmental conditions. Then, we investigate two mechanisms so that an Aggregator, acting as an intermediate between the Distribution System Operator or Retailer and the consumers, achieves the desired demand flexibility. More precisely we introduce: (i) a price-based mechanism that determines the new price that consumers will be paying during the DR campaign, and (ii) a reward-based mechanism that determines which set of consumers should participate in the campaign, along with the load flexibility to be asked from each one and the reward offered. The proposed methodology is evaluated using a publicly-available dataset. It is seen that the CES model achieves high estimation accuracy. Also, the economic metrics obtained using both price-based and reward-based mechanisms, are more favorable than the ones obtained by the dynamic prices actually applied and by a naive reward-based method rewards, respectively.**[1]

I. Introduction

In recent years, the concept of smart grid has begun to materialize, leading to more flexible and reliable power distribution systems. In this setting, Demand Response (DR) methods constitute a core element, transforming end-users from passive consumers to active grid actors, that play a significant role in the operation of the distribution grid. Consumers that participate in DR campaigns modify their electricity usage in response to time-based rates or other forms of financial and/or behavioral incentives, at times of high wholesale market prices, when the system reliability is jeopardized or in order to achieve certain environmental benefits.

In this context, this paper proposes a methodology for running implicit (price-based) and explicit (reward-based) DR campaigns. A flexibility profiling engine is developed that produces a profile for each end-user, reflecting real-time demand flexibility as a function of multiple parameters, such as environmental conditions, energy retail prices and individual preferences. End-users are characterized by their price elasticities, i.e. (i) own-price elasticity that is a measure of load curtailment and (ii) elasticity of substitution that measures load shifting, weather sensitivity and other end-user and period (peak, off-peak) specific constant parameters.

The engine is based on the Constant Elasticity of Substitution (CES) model [1], that will be described in the sequel. Based on the calculated elasticities the enginel can predict changes in load consumption as function of prices and temperature and vice versa, i.e. it can estimate the pricing structure that is capable to achieve the utility-defined objectives for peak load alleviation, under a given set of temperatures.

Based on flexibility profiling engine's capabilities two mechanisms for running DR campaigns are proposed. One for implicit DR campaigns that can be employed by an Aggregator for helping a Retailer in estimating the new retail price that should be announced to consumers enrolled in a dynamic pricing program, so that the desired demand reduction is met. In addition, we describe a mechanism for explicit DR campaigns that enables an Aggregator to select the subset of consumers for possible load curtailment, decide on the portion of load to curtail from each one of them and calculate personalized rewards that will appropriately compensate end-users for the incurred loss in their net benefit.

The proposed methodology is evaluated using a publicly available data set from a dynamic pricing program that was extensively applied in London [2]. We round out this work by providing information regarding the data preprocessing we performed, along with simple approaches for calculating missing core elements of the CES model, such as individual end-user baseline, when dealing with an incomplete data set. This evokes the assumption that

A. CES model motivation and other approaches

A large number of empirical studies deals with price elasticities of residential electricity demand based on data from dynamic-pricing pilot programs applied in US and Europe: e.g. see [3] and [4]. The data sets used in these studies usually include repeated observations of time-varying electricity prices and respective electricity consumption, without consumer's budget constraints. Thus, in order to estimate demand functions that are consistent with the theory of consumer's utility maximization (a typical assumption in microeconomics), we need to assume that the household decides the total amount to be spent on electricity along with how much to spend on other

[1]This research has been partly funded by the European UnionâĂŹs Horizon 2020 research and innovation programme under the grant agreement NÂž 646184 NOBEL GRID.

978-3-901882-99-9

commodities. This necessitates the assumption of homothetic separability in consumer preferences, i.e. the ratio of peak to off-peak consumption does not depend on the amount being spent on electricity, but on relative electricity prices only. The CES model allows the elasticity of substitution to take on any value, it has been found to be well-suited to Time of Use (TOU) pricing studies and is computationally simple [4].

The authors in [5] and [6] use the CES model to estimate price elasticities during summer period in a pilot site in California and in Baltimore, respectively. Their results reveal the effectiveness of dynamic pricing, i.e. end-users actually reduce their peak period loads and these reductions do not wear off when the pricing plans are implemented over two consecutive summers. The work presented in [7] uses the CES model to estimate price elasticity of large commercial or industrial users that participate in the first large-scale application of real-time pricing in a competitive retail market in the U.S.

B. DR campaigns and incentives for participation

There are two broad categories of DR schemes; Automated methods that rely on smart devices that can be remotely controlled, as well as Manual ones where end users decide whether to conform to the incoming signal or ignore it. In this paper we focus on the latter type of DR campaigns, which can be further clustered into (i) *Implicit DR*, i.e. price-based and (ii) *Explicit DR*, i.e. reward-based. Implicit DR schemes refer to dynamic *retail* pricing schemes that guide consumers towards reducing their demand when prices are high, while they reduce their electricity bill. The work presented in [8] presents incentive-based consumption scheduling solutions towards this goal. Reward-based incentives, on the other hand, give either financial incentives to users for curtailing their load during peak-demand [9], or promote collaboration and competition for encouraging renewable and sustainable energy use and pro-environmental behaviour more broadly [10].

II. Flexibility Profiling Engine

In this work, we study a flexibility profiling engine that is based on CES model and relies on the correlation among end-user's consumption, prices and environmental conditions. The proposed engine generates price elasticity profiles, i.e. each endpoint i is characterized by its own-price elasticity of demand, elasticity of substitution, weather sensitivity and other endpoint and period (peak, off-peak) specific constant parameters that will be analyzed in the sequel.

Own-elasticity ε_i, measures the reduction of the consumer's demand in a certain time interval due to the increase in the price of that interval. It is always negative; usage goes down as price goes up. The own-price elasticity equation is:

$$\ln q_i^{p_k} = n_i + \varepsilon_i \ln p_k + \delta_i HDH_i^{p_k} , \tag{1}$$

where: p_k is the applied price during time interva kl, $q_i^{p_k}$ is the respective demand of end-point i, δ_i is weather sensitivity, n_i is a period constant term, $HDH_i^{p_k} = H \times BT_i^{p_k} - T_i^+$ is the number of heating degree hours (HDH) of end-point i, taking into account the average outside temperature T_i at the premises of consumer i and the base temperature $BT_i^{p_k}$ (see section III-A) and H is the duration in hours of the period during which the price p_k is applied. Note that own-elasticity is calculated separately for peak and off-peak period.

Elasticity of substitution σ_i, in the energy domain, is a measure of load shifting and reflects the rebound effects that possibly take place after a change in price during the previous period(s). More formally, is defined as the relative change in usage in the two periods (e.g., the ratio of the peak to off-peak usage) for a certain percentage of change in the relative prices in those periods (the ratio of the off-peak to peak price). Note that the price term uses the inverse price ratio, which is why substitution elasticities are positive (e.g., a higher peak price decreases the off-peak to peak price ratio, causing the peak load to be reduced, and the peak to off-peak load ratio to decline). We denote peak period with p and off-peak period with op. The elasticity of substitution equation is:

$$\ln \frac{q_i^p}{q_i^{op}} = \alpha_i + \sigma_i \ln \frac{p_k^{op}}{p_k^p} + \beta_i (HDH_i^{p,p_k^p} - HDH_i^{op,p_k^{op}}) , \tag{2}$$

where: β_i is weather sensitivity and α_i is a constant term.

A regression model is applied to Equations 1 and 2 in order to calculate the elasticity profiles for both peak and off-peak period. Then, based on these elasticity profiles the flexibility profiling engine can project peak and off-peak period loads for each end-user i, for certain dynamic prices applied and outside temperatures. More details can be found in [1].

III. Accuracy

A. Dataset

In order to evaluate the performance of the proposed flexibility profiling engine a dataset from a dynamic pricing program that was applied in a large ($\sim$ 1100) number of households (endpoints) in London, from 01/01/2013 until 31/12/2013 was used. This dataset included half-hourly consumption data for each endpoint (no sub-metering data were available) for each of the three different price bands. More specifically, three price bands were used: $p_0 = 0.1176£/kWh$, $p_1 = 0.0399£/kWh$ and $p_2 = 0.672£/kWh$ as baseline, low and high price, respectively.

Preprocessing was performed on the dataset in order to estimate for each day and for each endpoint: (i) for the 6-hour peak period (17:00 – 23:00) and (ii) for the 18-hour off-peak period (23:00 – 17:00), the average price that was applied and average outside temperature, respectively. Thus, after preprocessing, the data we obtained included for each day of the year 2013, for each endpoint and for both peak and off-peak period the time stamped aggregated energy consumption data from the energy meter, the average value of the applied dynamic price and the average outside temperature.

B. Projection of peak and off-peak period loads

1) Training of the flexibility profiling engine: From the one-year dataset presented in the previous section we considered a two-month training period, from 01/02/2013 until 31/03/2013.

By making use of this subset we calculated the elasticity values and other endpoint specific parameters for each endpoint.

Peak and off-peak baseline calculation: In order to calculate the baseline energy consumption for both peak and off-peak periods, we considered for each endpoint the consumption data that are associated with an average dynamic price equal to the base price p_0 only. Then, the peak (resp. off-peak) consumption data are averaged over these periods to calculate the peak (resp. off-peak) consumption baseline.

Base temperature calculation for various dynamic prices: Base temperature for heating is the minimum outside temperature in $^{\circ}C$ for which heating is not activated by a certain endpoint for a certain retail price of energy (e.g., p_1). This parameter is endpoint specific and depends also on the new dynamic price p_1 that is applied, instead of p_0, since this is the price that consumers would pay and which could determine whether to turn the heating on. Thus, for each price $p_k(p_0 = 0.1176£/kWh$, $p_1 = 0.0399£/kWh$ and $p_2 = 0.672£/kWh)$ that is applied and for each endpoint, the respective base temperature for heating is extracted.

In a complete data set where sub-metering for AC consumption would also be included and each dynamic price p_k would be applied for a sufficient number of times during the testing period, the base temperature for heating for each endpoint would be calculated based on the AC consumption data, i.e. based on whether the AC is activated or not, and the outside temperature. Base temperature for heating will be equal to the minimum outside temperature for which AC is not activated.

However, extracting such information from our dataset was quite challenging due to: (i) absence of sub-metering data (AC consumption data), (ii) non-baseline prices (p_1 and p_2) were applied a very limited number of times and (iii) endpoints were located in London where gas is mainly used for heating. Thus, we assumed that only in very low temperatures it is possible that an endpoint will also use an electrical device for heating, and we calculate base temperature as follows:

Starting with the base price p_0 for which we had sufficient data, we considered for each endpoint all peak period temperatures for which the following two conditions are met: (i) the dynamic price that is applied is equal p_0 and (ii) the consumption is smaller than peak baseline consumption. Then, for each endpoint i, those temperatures were averaged to calculate the corresponding base temperature for heating BT_i^0. Then, the base temperature for each one the rest of the applied dynamic prices $BT_i^{p_k}$ was calculated: (i) in a similar way if a substantial number of data was available and (ii) by using BT_i^0 as the reference temperature and decreasing/increasing it moderately depending on whether the new price was greater/smaller than the base price p_0.

Peak and off-peak elasticity profiles calculation: Own-price elasticity ε_i, weather sensitivity δ_i and the constant term n_i were extracted for each endpoint i and for both peak and off-peak period by applying a regression model to equation 1. As input we used all peak and off-peak period data from each endpoint, i.e. data for each day t of the training period, regardless the dynamic price applied (p_0 and $p_k \neq p_0$).

Elasticity of substitution σ_i, weather sensitivity β_i and constant term α_i are extracted for each endpoint i by applying a regression model to equation 2. As input we select for each endpoint the data that meet the following condition: the price applied in the peak period is greater than the price applied in the off-peak period that follows the peak period, $p_k^p > p_k^{op}$.

Note: We assume that dynamic prices are announced a few hours before they are actually applied and thus, load shifting is considered to take place only in the off-peak period that follows and not the one that precedes the peak period.

2) Accuracy estimation: Based on the outputs from the training period we assess the proposed engine's accuracy. To achieve this, we used a subset of our initial dataset that includes data from 01/11/2013 until 31/12/2013 for 145, randomly selected, endpoints. The aforementioned months were selected since they are characterized by similar weather conditions with the months considered in the testing period.

According to [12] load forecasting on the individual household level is a challenging task due to the extreme system volatility as a result of dynamic processes composed of many individual components. Home loads can be influenced by a number of factors, such as: operational characteristics of devices, behaviours of the users, economic factors, time of the day, day of the week, weather conditions, holidays etc.

The forecasting accuracy at the individual level of each endpoint i is determined by calculating the Mean Absolute Persentage Error (MAPE) as follows:

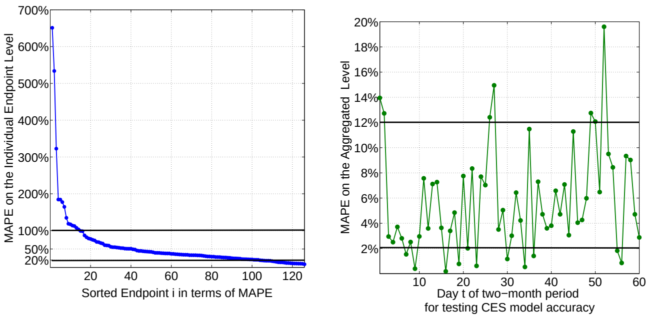
$$MAPE_i = \frac{100}{T}\sum_{1}^{T} \mid \frac{L_{forecasted}^t - L_{actual}^t}{L_{actual}^t} \mid , \qquad (3)$$

where:L_{actual}^t and $L_{forecasted}^t$ are the actual and forecasted values of peak period aggregated consumption of endpoint i at day t, T is the number of fitted points, i.e. in our case 61 days of the two-month period.

Extraction of forecasted values for peak period: The peak period loads for each endpoint i and for each day t of the accuracy dataset are projected by solving equation (1) taking into account the calculated values of price elasticities, the price that is applied p_k and the average outside temperature $T_i^{p,t}$ that are included in the dataset. Similarly, we project the off-peak period loads taking also into account possible load shifting from the peak period by solving equation (2).

According to [12], the forecasting performance at the individual level shows much higher errors (20% to 100% and even higher), and depends on dwelling lifestyle and regularity of appliance usage as described above. In Figure 1a we depict the calculated MAPE for each endpoint that was considered. As expected, we observe that for the majority of endpoints, the MAPE is lower than 50% while it exceeds 100% for only a few endpoints. More specifically, 18.28% of users (23 out of 126) have error below 20%, for 64.29% of participants (81 in total) the error ranges from 21% up to 70% and for 6.3% (8 out of 126) the error is between 71% and 100%.

Aggregation on the other hand reduces the inherent variability in electricity consumption resulting in increasingly smooth



(a) Individual endpoint level

(b) Aggregated Level

Fig. 1: Forecasting accuracy during peak periods in terms of MAPE.

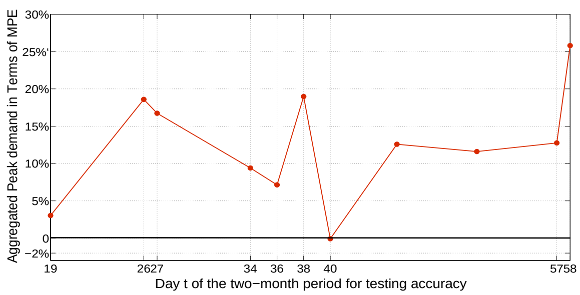


Fig. 2: Forecasting accuracy on the Aggregated Level during peak period in terms of MPE.

load shapes, and as a result, the relative forecasting errors typically seen at the level of substations have been quite low in terms of MAPE (1% âĹŠ 2%) [13] and in cases higher (12%-30%) [14]. Figure 1b presents the calculated MAPE of aggregated peak demand of all endpoints in each day of the two-month period used for testing accuracy. As expected the forecasting accuracy substantially improved. More specifically, 18.33% of the days (11 out of 60) have error below 2%, for 70% of participants (42 in total) the error ranges from 2% up to 8%. The days with high errors (>12%) are holidays, which could explain the comparatively higher errors.

In Figure 2 we depict the Mean Percentage Error (MPE) of aggregated peak demand only when a dynamic price $p_k^p > p_0$ is applied. We observe that all except one values of MPE are positive, i.e. the forecasted peak load is greater than the actual or in other words the forecasted demand reduction is lower than the actual under a certain dynamic price. According to this it could be argued that endpointsâĂŹ elasticities are underestimated (end-users seem to be more elastic eventually)

IV. Mechanisms for Managing DR Campaigns Based on Price Elasticity

In this Section we introduce two mechanisms for running DR campaigns: (i) a mechanism for implicit DR campaigns that can be employed by a Retailer to estimate the new retail price in order to achieve a certain amount of demand reduction and (ii) a mechanism for explicit DR campaigns that enables a DSO/Retailer to select the subset of consumers for possible load curtailment, decide on the portion of load to curtail from each one of them and calculate personalized rewards.

A. Implicit DR (price-based)

Initially, we assume that a Retailer has to attain a reduction in the consumption by ΔQ_{target} (in KWh) during the next peak period. To achieve this target the Retailer has to employ a new price $p_k > p_0$ to a set of N consumers with dynamic pricing contracts. The Retailer would use the flexibility profiling engine, for characterizing the demand function for each consumer, and then by performing Algorithm 1 he can find the new price p_k that would lead to the desired demand reduction. Algorithm 1 works as follows. For a certain price the total demand reduction ΔQ is calculated. Then, the price is increased/decreased, depending on whether ΔQ is smaller/-greater than the desired demand reduction, respectively. The algorithm ends when the desired demand reduction is met.

Algorithm 1 Mechanism for Implicit DR

set $step$, $p_{test} = p_0 + step$, ΔQ_{target},
while $\Delta Q > \Delta Q_{target}$ **do**
  set $\Delta Q = \sum_i (q_i^{p_0} - q_i^{p_{test}})$
  if $\Delta Q > \Delta Q_{target} + threshold$ **then**
    set $p_{old} = p_{test}$
    set $p_{test} = p_{test} - step$
  else if $\Delta Q < \Delta Q_{target} + threshold$ **then**
    set $p_{old} = p_{test}$
    set $p_{test} = p_{test} + step$
  end if
  Set $step = \frac{(p_{old} + p_{test})}{2}$
end while
set $p_k = p_{test}$

B. Explicit DR (reward-based)

We assume that a DSO/Retailer wishes to achieve a demand reduction by ΔQ_{target} (in KWh) during the next peak period, but we focus on the case of N consumers for which a change in price is not foreseen and introduce a consumer–selection mechanism for managing explicit DR campaigns. In this context, in order to obtain a certain amount of flexibility from consumer i, an appropriate reward should be offered to her. A traditional way in microeconomic theory for monetary incentives is to offer a payment that will make her (at least) as happy as before the DR signal [11].

Figure 3 presents the Net Benefit of a single endpoint during the peak period depicted for simplicity but without loss of generality, for the case of linear demand function. In the peak period, when the price is p_0, the consumption is expected to be q_0 for a total charge given by the area $D+E$, and thus the Net Benefit is the sum of the areas A, B and C. Raising the price to p_k results in reduced consumption q_k and a total charge equal to the area $B+D$. In this latter case, the Net Benefit is equal to area A. Thus, $NB_{baseline} = A+B+C$, while $NB_{new} = A$, and thus the Net Benefit difference for endpoint i is $r_i = B+C$. Assuming that the (inverse) demand function that is

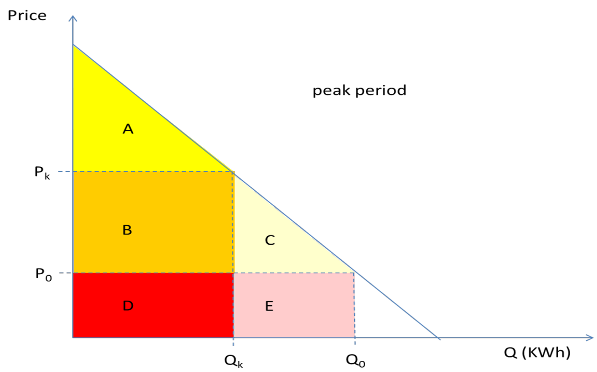


Fig. 3: A graphical representation of the Net Benefit of a single endpoint for different prices during the peak period

characterized by the endpoint's profile parameters is indeed linear, we can compute each of the terms in r_i as follows:

$$B = q_k * (p_k - p_0) \tag{4}$$

$$C = (q_0 - q_k) * (p_k - p_0)/2 \tag{5}$$

Based on the above the reward that would result in a flexibility that equals the flexibility obtained when price p_k is announced can be calculated as follows.

$$r_i = q_i^{p_k} \times (p_k - p_0) + (q_0 - q_i^{p_k}) \times (p_k - p_0)/2 \tag{6}$$

The proposed mechanism: (i) selects which consumers will be targeted for load curtailment, (ii) estimates the amount of flexibility that should be requested by each one of them to achieve a certain amount of demand reduction $\Delta Q_{target} = \sum_j dq_j, j \in K$ (with K we denote the set of selected consumers) and (iii) calculates the DR compensation r_i that should be offered to each selected consumer if she ultimately achieves the demand reduction. In contrast to the previous case, where a uniform (for all consumers) retail price is announced, both q_i and r_i are personalized. The pseudocode of the proposed mechanism is presented with Algorithm 2.

Algorithm 2 Consumer-Selection Mechanism for Explicit DR

```
set step, virtual price p_i = p_0 + step ∀i ∈ N, ΔQ_target
calculate q_i^{p_i}, r_i^{p_i}, R_i^{p_i} = r_i^{p_i} / q_i^{p_i} and dq_i^{p_i} = q_i^{p_0} − q_i^{p_i}, ∀i ∈ I
select endpoint i* = argmin_i R_i^{p_i}
set ΔQ = dq_{i*}^{p_{i*}}
while ΔQ_target < ΔQ do
    set virtual p_{i*} = p_{i*} + step for selected consumer i*
    calculate q_{i*}^{p_i^*}, r_{i*}^{p_i^*}, R_{i*}^{p_{i*}} = r_i^{p_{i*}} / q_i^{p_{i*}} and dq_i^{p_i}
    select endpoint i* = argmin_i R_i^{p_i}
    ΔQ = Σ_j^k dq_j^{p_j}, j ∈ K selected endpoints
end while
Total Reward = Σ_j^k r_j^{p_j}
```

Note: In both scenarios described above, a third party Aggregator could act as intermediate between the DSO/Retailer and the end-users. In such a case, the Aggregator employs the proposed mechanisms and helps the DSO/Retailer to achieve the desired demand reduction in return for a compensation.

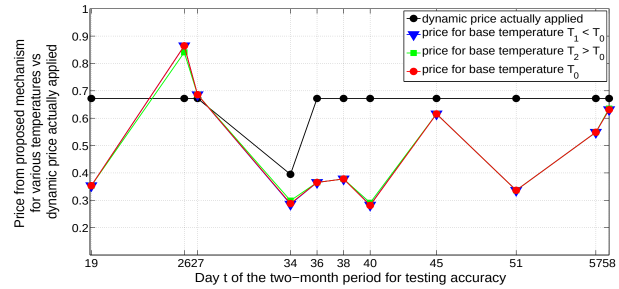


Fig. 4: Comparison of the dynamic prices as outcome of the proposed price-based mechanism vs actual dynamic prices applied during testing period.

V. Evaluation of the Proposed Mechanisms

We assume that a DSO/Retailer wishes to achieve a demand reduction during the next peak period, which is equal to the total demand reduction that was actually obtained in each day t of the testing peak period, during which a dynamic price $p_k > p_0$ was applied. Thus, the DSO/Retailer employs the proposed mechanisms based on endpoints' elasticity profiles and estimates the dynamic prices/rewards that should be announced to achieve the desired demand reduction.

A. Implicit DR (price-based)

In Figure 4 we compare the dynamic prices for various base temperatures (red, green, blue lines) as outcome of the proposed mechanism. We observe, as expected, that the base temperature plays a less significant role for the data set we examine, since endpoints were located in London where gas is mainly used for heating. In addition, we depict the dynamic prices actually applied during testing period (black line). As we observe the dynamic prices extracted by means of the proposed mechanism are in most cases significantly lower than the actual prices. Taking into account that endpoints' elasticities are underestimated (see Figure 2) we can reasonably expect that if the proposed methodology were used by a Retailer, along with adequate training, then an amount equal to the demand reduction actually achieved could be attained by employing a lower dynamic price. This would make the dynamic-pricing program more attractive to end-users.

Please note that DR mechanism for implicit DR campaigns during days 26, 27 of the testing period lead to higher dynamic prices and rewards respectively. This could be due to endpoints' elasticities are underestimated, particularly for days 26, 27 MPE is significantly high (Figure 2).

B. Explicit DR

Due to absence of real reward values, in Figure 5 we compare the total reward, extracted by means of the mechanism introduced, that should be offered to selected consumers for load curtailment in order for the DSO/Retailer to achieve the desired demand reduction, with the total reward calculated based on a naive approach, i.e. we calculate a uniform virtual

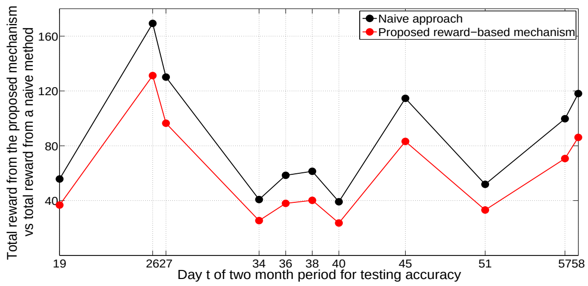


Fig. 5: Comparison of the total daily rewards as outcome of the proposed mechanism vs the total daily rewards calculated by a naive approach.

dynamic price that if announced to all participating end-users the desired demand reduction would be achieved. Based on this virtual dynamic price the respective rewards are calculated. Our approach outperforms the naive method.

VI. Conclusions

In this work, we developed in detail an approach for managing manual DR campaigns. Initially, we described a flexibility profiling engine that implements the CES model for producing a profile for every end-user. Each profile reflects demand for electricity as a function of multiple parameters, such as environmental context/conditions, energy retail prices at peak and off-peak periods and individual/group preferences.

An entity acting as an Aggregator can use these profiles for calculating the expected flexibility obtained by each end-user for a certain price, outside temperature and period (peak/off-peak). In order to do so, we provided guidance on how to calculate a) the baseline load and b) the base temperature. These steps, although not emphasized in the literature, are important especially in the absence of sub-metering data. Furthermore, we evaluated the accuracy of CES model in a very challenging scenario. In particular, we used a publicly available data set from a dynamic pricing program that took place in London, where electricity is rarely used for heating purposes, while few new prices were announced to avoid fatigue effects. Despite the challenges, the CES model achieves high accuracy compared to bibliography and particularly on the aggregate case which is of high importance in DR schemes.

Our second contribution is documenting how these profiles can be used by an Aggregator in order to define key aspects of a successful manual campaign. In the case of implicit DR the objective is to help a Retailer find a price that, if announced to all customers under a dynamic pricing contract, such that the target flexibility will be met. In the case of explicit DR we seek to meet the target flexibility requested by a DSO or Retailer, while reducing the total cost of DR campaign in terms of the monetary rewards. Given that users have a fixed tariff scheme, we do so by gradually finding the set of users that are more sensitive to prices and ask them to provide a certain flexibility for a personalized reward, which will make the consumer (at least) as happy in terms of net benefit as before the DR signal.

In both cases we see that dynamic price or monetary rewards obtained using the proposed mechanisms are more favorable compared with the respective dynamic prices actually applied and rewards calculated by a naive method. Assuming a fixed markup for Aggregator's profit, the low cost of the campaign will render demand-side management schemes that are more attractive for traditional players in the electricity market, such as DSOs and Retailers. At the same time by participating in DR campaigns, end-users will have a more active role and enjoy either higher bill savings (since dynamic prices in most cases will be below the flat price) or an additional revenue stream from the rewards.

Overall, our work explains how the proposed methodology is going to be applied in practice. In the future we plan to evaluate the accuracy of the CES-based profiling engine in real world demonstration activities performed in three pilot sites of the Nobel Grid EU-funded project, namely Manchester, Flanders and Terni.

References

[1] D. Ton, M.A. Biviji, E. Nagypal and J. Wang "Tool for determining price elasticity of electricity demand and designing dynamic price program", *Innovative Smart Grid Technologies (ISGT), 2013 IEEE PES*, pp.1–6, 2013.

[2] J.R. Schofield, R. Carmichael, S.Tindemans, M. Bilton, M. Woolf and G. Strbac "Low Carbon London Project: Data from the Dynamic Time-of-Use Electricity Pricing Trial, 2013", [data collection]. UK Data Service. SN: 7857, <http://doi.org/10.5255/UKDA-SN-7857-2>http://doi.org/10.5255/UKDA-SN-7857-2

[3] M. Filippini "Short-and long-run time-of-use price elasticities in Swiss residential electricity demand", *Energy policy*, vol.39, no.10, pp.5811–5817, Elsevier, 2011.

[4] A. Faruqui, and S. Sergici "Household response to dynamic pricing of electricity – a survey of the experimental evidence", 2009. [Online].http://www.hks.harvard.edu/hepg

[5] Charles River Associates "Impact Evaluation of the California Statewide Pricing Pilot", [Online].https://www.smartgrid.gov/files/Impact_Evaluation_California_Statewide_Pricing_Pilot_200501.pdf

[6] A. Faruqui, and S. Sergici "Dynamic pricing of electricity in the mid-Atlantic region: econometric results from the Baltimore gas and electric company experiment", *Journal of regulatory economics*, vol.40, no.1, pp.82–109, Springer, 2011.

[7] C. Goldman, N. Hopper, R. Bharvirkar, B. Neenan, R. Boisvert, P. Cappers, D. Pratt and K. Butkins "Customer Strategies for Responding to Day-Ahead Market Hourly Electricity Pricing", 2005

[8] A.R. Mohsenian, V. Wong, J. Jatskevich, R. Schober, and A. Leon-Garcia, "Autonomous demand-side management based on game-theoretic energy consumption scheduling for the future smart grid", *IEEE Trans. Smart Grid*, vol. 1, no. 3, pp. 320-331, 2010.

[9] L. Chen, N. Li, S. H. Low, and J. C. Doyle, "Two market models for demand response in power networks", In Proc. *IEEE SmartGridComm*, 2010.

[10] E. R. Frederiks, K. Stenner and E. V. Hobman "Household energy use: Applying behavioural economics to understand consumer decision-making and behaviour', *Renewable and Sustainable Energy Reviews*, vol. 41, pp. 1385–1394, 2015, Elsevier.

[11] M. Minou, G. Stamoulis, G. Thanos and V. Chandan "Incentives and targeting policies for automated demand response contracts", *IEEE International Conference on Smart Grid Communications (SmartGridComm)*, pp. 557–562, IEEE, 2015.

[12] K. Gajowniczek and T. Zkabkowski "Electricity forecasting on the individual household level enhanced based on activity patterns", *PloS one*, vol. 12, no. 4, 2010, Public Library of Science.

[13] K. Siwek, S. Osowski and R. Szupiluk "Ensemble neural network approach for accurate load forecasting in a power system", *International Journal of Applied Mathematics and Computer Science*, vol. 19, no. 2, pp. 303–315, 2009.

[14] M. Ghofrani, M. Hassanzadeh, M. Etezadi-Amoli, M and MS. Fadali "Smart meter based short-term load forecasting for residential customers", In Proc. *North American Power Symposium (NAPS)*, pp. 1–5, 2011, IEEE.