Data-driven Method for Providing Feedback to Households on Electricity Consumption

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***Abstract*—The building sector is a major energy consumer and CO_2 emitter, being responsible for approximately 40% of the total consumption in the EU. Active demand side participation of electricity customers is seen as crucial in the management and reduction of the building sector's CO_2 emissions. However, today's electricity markets are often lacking strong incentives for active demand side participation. Understandable customer specific comparison information and easy-to-use energy displays can be used to influence customer behaviour and encourage customer participation. This paper presents a data-driven method for producing household level comparison information, based on hourly interval smart meter data and additional household information. Firstly, the customers are segmented by the heating system and the type of housing, followed by weighted clustering that is used to refine the comparison group. In the weighted clustering, normalized load profiles together with properties of the dwelling and the residents are considered, and weights are assigned to the properties according to how much they contribute to the electricity consumption. In this paper, the initial experimental results are presented and discussed, and future development ideas are laid out. The method is under development and testing as a part of the Finnish SGEM-project.**

***Index Terms*—smart grid, energy efficiency, demand side management, customer behaviour, load profiling, smart metering, energy displays**

I. Introduction

Energy companies selling electricity to the private households have traditionally provided feedback to their customers on electricity consumption merely via billing, that is based on an estimated consumption and is validated once a year. The estimation of consumption is typically based on few variables, that do not necessary explain the consumption satisfactorily. Hence, the customers encounter difficulties in monitoring their electricity consumption and detecting the overall logic behind it. In addition, the customers usually do not have any tools to benchmark their consumption with similar households, making it difficult to determine whether their consumption is on the high or low side.

In these circumstances, households have not been able to effectively evaluate their energy efficiency, and consider the potential in decreasing their consumption by altering personal behavior or, for instance, upgrading the heating system. Consequently, it is difficult for the customers to cut their electricity expenses and reduce the CO_2 emissions.

It has been estimated that approximately 40% of the total energy consumption in the European Union is produced by the building sector, making it a notable CO_2 emitter [1]. As the concern about climate change is increasing, numerous actions have been taken in order to control the CO_2 emissions. Among these actions, in 2006, the European Union set a directive demanding that all the energy companies, managing distribution grids or retailing electricity, should provide detailed feedback to their customers [2].

In order to build the infrastructure that can be used for hosting the required information systems, several member states in the European Union have taken actions in order to bring automatic meter reading (AMR) systems into wide use. These systems can be used for reporting the electricity consumption to the energy companies almost in real-time, enabling simultaneously a set of new services. For example, in Finland it is required that 80% of energy consumption sites have remote meter reading technology by the end of 2014 [3]. The data produced by the emerging AMR technology is actively used in research, for instance, in user segmentation and load prediction [4], [5]. However, it has not been extensively discussed how the AMR data could be applied for producing feedback to the consumers. Nevertheless, in order to fulfill the requirements of the legislation, energy companies are building their own customer portals that offer comparison information.

In this paper we propose a method that can be used to produce personalized feedback to the electricity customers on their consumption compared to similar households. The method considers customers' dwelling properties and the family compositions, but also normalized load profiles, and benchmarks a given household against similar households having a) the same or b) different heating system. The purpose is to provide feedback on customers' energy efficiency and demonstrate the benefits of an alternative heating system, such as ground-source heat pump.

II. Related literature

Numerous studies have analyzed the effect of feedback on electricity consumption. Surveys [6], [7] and [8] are comprehensively reviewing these studies. Typically, the experiments are carried out in a rather small set of prototype households, reducing credibility of the results. There is also great variation in how the feedback is formulated and displayed, making the results difficult to compare. However, [7] concludes that such feedback can effectively reduce the consumption by up to 10-15%. The comparison can be historical, based on the earlier personal consumption, or normative, based on the consumption on similar households. In [7], historical comparison is found to be more effective than normative one. A potential reason presented in [9] is that customers are suspicious about the validity of their comparison group. This indicates that the choice of the comparison group should be justifiable and easily understood.

In [10], consumer preferences for feedback are analyzed by developing a set of feedback prototypes and conducting interviews of consumers. The results can be summed up as follows: a) cost savings are found more compelling than reduction on power consumption or CO_2 emission, b) appliance-specific breakdown is appreciated as well as c) comparison with own prior consumption. In [10], the normative feedback did not cause much interest among the participants, due to similar reason as in [7]. That is, the presented total consumption compared to the similar households did not reveal what could cause the higher consumption and it was not explained how the calculations were carried out. For instance, participants had concerns whether the number of residents was taken into account. However, opposite results have also been discovered in [11] and [12], reporting that consumers were interested about benchmarking with similar households.

Despite the fact that feedback on normative consumption is mentioned on several articles, there seems to be very limited amount of information available on the methodology that is used to generate such feedback [6]. That is, how comparison group is selected, taking into account the numerous factors that together explain the consumption. In addition, in the previous studies the feedback has only considered the total consumption, ignoring the distribution within a day that contains valuable information to the customers [7], [10].

The different properties of the dwelling and residents are contributing to the energy consumption in various ways and are analyzed in many studies such as [13], [14], [15] and [16]. In addition, various methods for segmenting the electricity consumers, based on the smart meter data, are presented in the literature. A comprehensive survey on the methods is available in [4]. However, as far as we know, these two aspects have not been combined earlier in order to produce comparison information.

III. Data-driven method for providing feedback

In this section, we present method that can be used to provide normative feedback to the electricity consumers. That is, how the electricity consumption of a given household relates to the consumption in similar households. The feedback describes one's total consumption and its distribution within a typical day side-by-side with the mean consumption in the comparison group.

Special attention is paid to the feedback regarding to heating systems as the heating system dominates the electricity consumption in regions having colder climate, such as in Finland [18]. Thus, the method can be used to compare the electricity consumption of a given customer against consumption in similar households having a different heating system.

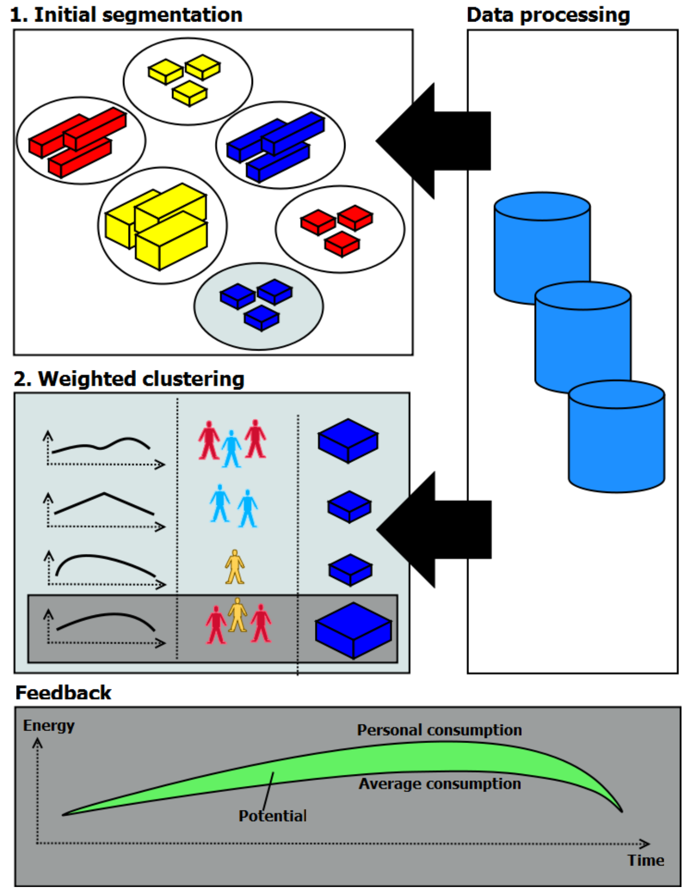

Fig. 1. Outline of the method

The proposed method is outlined in Fig. 1. The data collected from various sources is applied to support the two-level clustering of the electricity consumers. In the first level, a rigid segmentation of the households is done based on the type of housing and the heating system. In the second level, weighted clustering is applied within the groups defined in the first level. The clustering considers several properties of the households and gives them weights according to how much they contribute to the electricity consumption. Three aspects are taken into account: electricity load profiles, residents and dwellings. Finally, the feedback to a given household is produced by benchmarking with the similar households defined by the two-level clustering.

A. Data processing

The proposed data-driven method makes use of several data sources: 1) smart meter data from electricity consumption sites (metering points), 2) background data about the households connected to these sites, and (3) meteorological data.

The smart meter data (1) covers hourly electricity consumption of the households. We are arguing that the distribution of the consumption within a typical day reveals details regarding the household that should be considered when a comparison group is selected. Such details are, for instance, heavy usage of the night-time electricity due to the lower rates or variation in the intraday activity due to different socio-economical positions, namely employed versus unemployed or retired residents, and so forth.

The background data (2) covers details regarding the dwellings and also socio-economical details regarding the residents. Both of them are substantially affecting the consumption, as pointed out in [13] and [14], and unfair comparison is concerning customers as reported in [7].

The meteorological data (3) covers hourly outdoor temperatures measured in several weather stations near to the electricity consumption sites. The data is applied to perform temperature normalization of the smart meted data. Heating dominates the electricity consumption in countries having colder climate, such as in Finland, and load profiles representing households in different regions are not comparable without the temperature normalization.

Smart meter data were recorded during the year 2008 by a local energy company Savon Voima Oyj in Northern Savonia, Finland, and contains hourly electricity consumption of 4554 customers. The data can be incomplete due to setting-up of new sites or termination of old ones, as well as power failures and other interruptions. To avoid invalid results we are omitting the customers that do not have a complete time-series covering all the 366 days in the year 2008. Thresholds were applied in order to filter out customers having unusually low or high total consumption. Additional filtering of outliers is also done during the clustering process as presented in III-D.

The background data are acquired from a questionnaire directed to the household customers of the energy company Savon Voima Oyj. The questionnaire was conducted during the year 2009 and, in total, 869 responses were collected. In the questionnaire, the customers were given written answers to questions regarding the properties of their dwelling, heating system, lighting and appliances. The general attitude towards the energy consumption was also investigated. Socio-economical details of the residents were not comprehensively investigated. The number of residents in different age groups is presented, though.

The meteorological data was acquired from the Finnish Meteorological Institute. The hourly temperatures were measured in 13 weather stations near to the electricity consumption sites. The normalization requires hourly temperature data for all electricity consumption sites that are considered. Thus, linear interpolation is applied in order to generalize the data to all electricity consumption sites.

In order to simplify the presentation, the proposed method is demonstrated by including only a few variables from the background data. The selected variables are the gross floor area of dwellings and the family composition (the number of residents in different age groups). The variables are representing properties of the dwellings and socio-economical properties of the residents and both of them are shown to have significant impact on the electricity consumption [13], [14]. However, the proposed method is flexible and the selection of variables can be altered based on the requirements. The selection of the variables should be considered carefully, though. For instance, level of income is shown to have correlation with the electricity consumption [16]. Thus, by including the variable, level of income, households with higher standard of living would get justification for lower energy efficiency as in the comparison group the mean consumption is high.

B. Initial segmentation

After the data preprocessing, the first step of the proposed method is to perform a rigid segmentation of the households based on the type of housing and the heating system. Both of them tend to have a significant impact on the electricity consumption and cross-comparison would not be well-grounded [15].

In apartment and terraced houses, electricity is consumed in apartments but part of the consumption can be collective and not recorded by smart meters. For instance, water heating can be centralized and costs are distributed equally to all residents. On the contrary, in single-family detached houses, each family is directly charged based on the overall consumption.

In regions, such as in Finland, where intensive heating is required during majority of the year, the heating system has crucial effect to the overall electricity consumption [18]. Meaning that, if electricity heating is used, it dominates the electricity consumption, leaving the remaining consumption rather irrelevant. On the other hand, if the dwelling is equipped with a less electricity-driven heating method, such as district heating or ground-source heat pump, the potential in saving energy comes from lighting, appliances and so forth.

The initial segmentation is carried out by connecting the smart meter data and responses to the questionnaire by IDs of the electricity consumption sites and grouping the households that are uniform in type of housing and heating system.

C. Load profiling

Mutanen et al. [17] have presented a method to cluster electricity consumers into groups having similar load profiles. In this step III-C we are applying those ideas in order to prepare the load profiles to be used in the weighted clustering in the step III-D.

As the hourly temperatures differ between the electricity consumption sites, the smart meter data are normalized by the temperature prior to the clustering step. That is, the portion of the load that is correlating with the outdoor temperature is detected and altered to correspond to the equivalent temperatures in all sites.

Firstly, temperature dependencies α_x^i are defined for each customer x, and for each month $i = 1, 2, ..., 12$ separately. This is done by linear regression in the fashion presented in [17]:

$$\bar{E}_x^i = \alpha_x^i \bar{T}_x^i + \beta, \tag{1}$$

where the response variable $\bar{E}_x^i$ denotes the vector for the percent errors between the daily energy consumption and the average daily energy consumption on similar days. The predictor variable $\bar{T}_x^i$ denotes the vector for the differences between the daily average temperatures and the average temperature on similar days. Least-squares estimation is used to define α_x^i, that is the temperature dependency parameter, and β is the constant term.

The similar day stands for a same day of the week in a time window of four weeks, that is, three days in total. The selection of the response variable and predictor variable is conducted in order to avoid the systematic error due to the variation in customer activity within a typical week. As the demand of heating does not immediately follow changes in the outdoor temperature, a one day difference was used to connect $\bar{E}_x^i$ and $\bar{T}_x^i$ in order to simulate the delay.

The temperature dependencies α_x^i (unit: %/C°) are applied to normalize the smart meter data to reference temperatures. In this study, temperature data linked to a randomly selected electricity consumption site r was used as the reference. For each electricity consumption site x, and for each month $i = 1, 2, ..., 12$, the normalization is carried out by:

$$E'^i_x = E_x^i(1 + \alpha_x^i(T_x^i - T_r)), \tag{2}$$

where vector E'^i_x denotes hourly electricity consumption, that is normalized by the temperature. Vectors E_x^i and T_x^i denote the hourly electricity consumption and temperatures. Vector T_r denotes the reference temperatures and scalar α_x^i denotes the temperature dependency defined by the equation 1.

After the temperature normalization, load pattern vectors E'^p_x are constructed for each household x by defining the mean intraday consumption for each hour, that is, 24 values in total. In this study, we chose to provide monthly feedback to the households. Thus, separate vectors are constructed for each month. Moreover, as on weekdays, Saturdays and Sundays residents are expected to have different daily routines, these cases are also treated separately.

Finally, the load pattern vectors are normalized by the total consumption in order to ignore the amplitude of the consumption and to perform the clustering considering only the profile of the load. For each electricity consumption site x, the normalization is done by:

$$\widehat{E}_x^p = \frac{E'^p_x}{\sum E'^p_x}, \tag{3}$$

where $\widehat{E}_x^p$ denotes the pattern vector with 24 values representing the load profile, and E'^p_x denotes the pattern vector with 24 values representing the electricity consumption in watt-hours.

D. Weighted clustering

In our experiments, clustering of the load profiles constructed in III-C did not segregate some relevant properties, such as the gross floor area of dwellings and the family composition, satisfactorily. Thus, we are also including properties of the dwellings and residents to the pattern vectors that are used to determine the relevant comparison group. In addition, during the clustering, the individual properties are weighted. The weights are assigned according to how much each property contributes to the total electricity consumption.

Firstly, the pattern vectors describing the households are constructed by combining the load profile, and the corresponding gross floor area together with the number of residents in different age groups. As the attributes have different units and ranges, the data are standardized ($\mu = 0$ and $\sigma = 1$) prior to clustering.

Linear regression analysis is applied to define regression coefficients for the properties of the dwellings and residents:

$$E_\Sigma = \sum_{i=1}^{n} \alpha_i^B X_i + \beta, \tag{4}$$

where the response variable E_Σ is the vector for the total electricity consumption during a typical day (E'^p_x) for each customer. The predictor variables X_i are vectors for the gross floor area of dwellings and the family composition, for each customer, correspondingly. Least-squares estimation is used to define α_i^B, that are the regression coefficients, for $i = 1, 2, ..., n$, and β is the constant term.

The coefficients for the 24 values in the load profile are not defined by the equation 4 as the profile describes the consumption but does not explain it. However, the similarity of load profiles within the comparison group is essential as the feedback concerns intraday behavior. Thus, it is required that weights are assigned to the load data, too. A reasonable balance between the load and the background data is achieved by:

$$\alpha^E = \frac{\sum_{i=1}^{n} \alpha_i^B}{24}, \tag{5}$$

where scalar α^E denotes the fixed weight for every 24 value in the load profile. Scalars α_i^B, for $i = 1, 2, ..., n$, denote the coefficients assigned to the properties of the dwelling and residents by equation 4.

The coefficients defined by the equations 4 and 5 are transformed into weights for the refined clustering. This is done by scaling the coefficients to the interval $[0, 1]$ so that they sum up to one:

$$w_i = \frac{\alpha_i}{\sum \alpha^B + 24\alpha^E}, \tag{6}$$

where scalar w_i denotes the weight for the property i, for $i = 1, 2, ..., n$. Scalars α^B and α^E denotes the coefficient for the property i defined by the equations 4 and 5, correspondingly, and scalar α_i denotes the coefficient (either in α^B or α^E) in respect to i.

In the table I, an example of weights w_i and coefficients α_i, are given. In the example, the segment of single-family detached houses, that are heated by electricity directly, is considered. As the weights w_i are defined by linear regression analysis, correlations among predictor variables could make the weights unstable. The variance inflation factor (VIF) was used to define the multicollinearity among the variables. In our experiments, VIF values were lower than five suggesting that weights are reasonable stable [19].

TABLE I
AN EXAMPLE OF WEIGHTS

variable	weight w_i	coef. α_i	VIF
<8 years old	0.03	510	1.41
8–15 years old	0.05	1030	1.24
16–30 years old	0.03	540	1.61
31–50 years old	0.06	1180	4.50
51–65 years old	0.10	1930	4.42
66–75 years old	0.03	670	2.25
>75 years old	0.05	1030	1.28
area (m^2)	0.16	3160	1.23
load profile (24x)	0.02	419	–
total	**1.00**		

K-means clustering algorithm is applied in order to cluster the pattern vectors into similar groups. The weights are taken into account by modifying the Euclidean distance that k-means is based on. The distance of households x and y is defined by:

$$\mathrm{d}(x, y) = \sqrt{\sum_{i=1}^{n} (w_i(x_i - y_i))^2}, \tag{7}$$

where x_i and y_i denote the ith elements in the pattern vectors, and w_i denotes the weight associated with the elements, correspondingly.

Due to the potential irregularities in the data, outliers are filtered out prior to the final clustering. This is done by a repeating k-means procedure and omitting the pattern vectors that are unorthodox enough to form their own cluster, that is, no other item in the data is a member of the same cluster. The number of iterations was set to $N/2$, where N is the number of households. In our experiments, 5 – 10 % of the pattern vectors were treated as outliers.

The final clustering is performed similarly by the k-means. The number of clusters k is determined according to the Davies–Bouldin index that is a metric for evaluating the quality of the clustering. The value of k was altered and several iterations of k-means were scored by the Davies–Bouldin index until the optimal value was found. The final clustering was also repeated several times as the performance of the k-means varies due to the random initialization.

IV. RESULTS

The proposed method is demonstrated by providing feedback to a randomly selected household in two cases: a) benchmarking with similar households, and b) benchmarking with similar households that have a different heating system. In the case b), benchmarking with households primarily heated by ground-source heat pump was carried out. The feedback in both cases concerns a typical weekday in January.

The example household dwells in a single-family detached house that is heated by electricity directly. The gross floor area of the dwelling is 120–140 m^2 and the three residents belong to the age groups, 16–30, 31–50 and 51–65 years old, respectively.

In Fig. 2, feedback in the case a) is presented. The mean consumption in the example household is shown by the black line and the mean consumption in the comparison group is shown by the blue line. It can be seen that during the night, the consumption of the example household is lower than the average one, but the high consumption during the morning and evening hours reduces the energy efficiency; so much so, that the total consumption is higher than in the comparison group. The difference in an average weekday is 1664 Wh or, if a tariff rate of 15 cents per kilowatt hour is applied, 25 cents.

In Fig. 3, the feedback in the case b) is presented. Ground-source heat pumps are obviously less electricity-driven heating systems reducing the average consumption in the comparison group by 10 % or so. Thus, the comparison shows that in the example household, the electricity consumption exceeds the average one in the comparison groups throughout the day. The potential to save energy and money increases approximately by 50 % totalling 3508 Wh or 53 cents in a day. The result clearly indicates the benefits the less electricity-driven heating system presents to the example household.

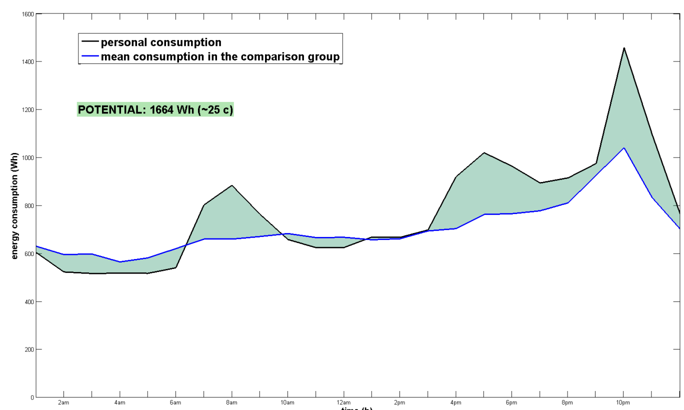

Fig. 2. Feedback in the case a)

V. DISCUSSION

The results demonstrate that the proposed method can be used to provide informative feedback to households on their electricity consumption. The feedback visualizes the development of one's electricity consumption during a typical day and the energy efficiency compared to the similar households. In addition, the properties of the desired comparison group can be adjusted. For instance, comparison with similar households having a different heating system provides interesting information regarding the benefits that could be achieved by upgrading the heating system.

We are arguing that valid benchmarking requires consideration of various aspects affecting to the electricity consumption.

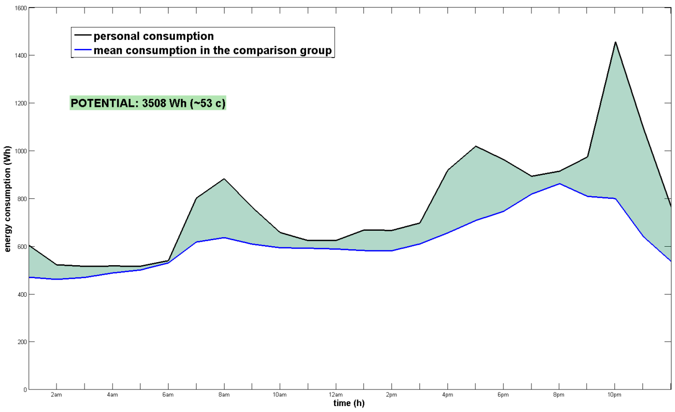

Fig. 3. Feedback in the case b)

The customers having similar load profiles are reasonable base of the comparison group but only if properties of the dwellings and socio-economical properties of the residents are also taken into account. The weighted clustering proposed in this paper takes these aspects into account and assigns the weights according to the impact on the total consumption that each property has. Therefore, the method constructs homogeneous comparison groups to ensure fair benchmarking.

The proposed method is presented by exploiting only a few properties of the dwellings and the residents. However, the method is flexible and set of variables can be altered. The selection of properties should be considered carefully, though, as pointed out in the section III-A.

In the future research, the proposed method will be refined. Segregation of the loads is also studied in order to provide more detailed feedback, concerning different subloads, such as heating, lighting or appliances, separately.

One interesting direction would be the exploitation of open data that is increasingly available due to the INSPIRE directive of the European Union [20].

VI. Conclusion

In this paper we proposed a data-driven method for providing normative feedback to the households regarding their electricity consumption. Such feedback is expected to trigger changes towards improved energy efficiency in the households. This is beneficial for the customers in terms of the cost savings, but also in the wider scope due to the reduction of CO_2 emissions. However, the selection of a reasonable comparison group is not trivial as various reasons are affecting the consumption and fair benchmarking is essential. The proposed method takes into account several aspects, namely, the load profiles of the households, properties of the dwellings and socio-economical properties of the residents, in order to ensure the meaningful comparison. The first results are presented and discussed in this paper. Further research is carried out in order to refine the method.

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