

A System Design for Automated Tailoring of Behavior Change Recommendations Using Time-Series Clustering of Energy Consumption Data.

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Abstract

In this paper we describe our approach to address the challenges of tailoring and personalizing behavior change recommendations based on energy consumption data collected through smart meters and energy monitoring technologies. The approach uses time-series clustering techniques with dynamic time warping to group daily energy consumption curves into similar clusters, and then provides personalized recommendations for shifting energy behavior to each individual based on their predicted consumption pattern, the day-ahead energy prices and the resulting savings opportunities. The paper presents the methodology and discusses the suitability of this approach for improving traditional energy feedback and demand response interventions, and provides an outlook on the possibilities of artificial intelligence methods to further improve the concept.

Keywords

Tailored energy feedback, time-series clustering, demand response recommendations

1. Introduction

The increasing prevalence of smart meters and energy monitoring technologies has made it possible to collect large volumes of data on energy consumption patterns of households. This data can be used to provide feedback to users on their energy usage behavior and help them make more informed decisions about their energy consumption. However, one of the challenges in using this data for behavior change interventions is how to personalize the feedback and timing of the interventions to suit each individual's energy consumption patterns and preferences. This paper proposes using temporal clustering approaches to better understand the users' behavior patterns by grouping daily energy consumption curves into similar clusters and provide personalized feedback and timing of interventions to the individual participant based on the identified patterns. The paper introduces our approach and methodology and discusses its suitability for improving energy feedback and behavior change interventions. The findings of this analysis suggest that using temporal clustering can lead to more personalized and effective behavior change interventions for energy conservation

2. Related Work

2.1. Energy Feedback and Behavior Change

Energy Feedback is a key concept in the field of behavior change and sustainability, and refers to the process of providing information to consumers about their past energy consumption, allowing them to make more informed decisions about their energy usage. Energy feedback has been studied intensely over the last 40 years, and several meta-studies condensing the findings

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are available [1, 2, 3, 4, 5, 6, 7]. The findings suggest that energy feedback can be effective, with an impact of 5 to 15% of energy savings.

Tailored Energy Feedback. To make energy feedback more relevant and engaging more tailored approaches to provide feedback have been proposed [8, 9, 10]. Various studies have explored the effectiveness of tailored feedback in promoting energy conservation, including personalized energy feedback [11, 12, 13], context-aware feedback [14, 15], and normative feedback [16, 17, 18]. Personalized energy feedback is based on individual energy consumption data and provides feedback that is specific to the user's energy consumption patterns, while context-aware feedback takes into account contextual factors such as time of day, weather, and occupancy. Normative feedback provides information on how a user's energy consumption compares to that of similar households, which can help motivate behavior change. Some studies have also explored the use of gamification techniques, such as points, badges, and leaderboards, to incentivize energy conservation behaviors [19, 20, 21]. Overall, the literature suggests that tailored energy feedback can be effective in promoting energy conservation behaviors, but the effectiveness depends on the type and timing of the feedback and the individual's motivation and engagement.

Timing. The timing of energy feedback is a critical factor that needs to be carefully considered to ensure that the feedback is effective in promoting behavior change. Timely feedback that is delivered immediately after the energy-consuming behavior has been shown to be more effective in promoting behavior change than delayed feedback [1, 22]. The timing of the feedback should also take into account the user's daily routine and energy consumption patterns [23]. For example, providing feedback during peak energy consumption periods, such as in the evening when people are cooking and using electronic devices, may be more effective in promoting behavior change. The delivery mechanism of the feedback is also important, as different delivery mechanisms may be more effective at different times of day [24]. For example, mobile notifications may be more effective during the day when people are out and about, while email notifications may be more effective in the evening when people are at home. Overall, careful consideration of the timing and delivery mechanism of energy feedback is critical to ensure its effectiveness in promoting behavior change.

Shifting of consumption behavior. Research has shown that users are generally willing to shift their energy consumption in response to demand response programs, although the degree of willingness may vary depending on several factors [25, 26, 27]. One such factor is the type of demand response program being offered, with users being more likely to participate in programs that offer financial incentives or tangible benefits such as improved comfort or convenience. Another factor is the timing of the demand response event, with users being more willing to shift their energy consumption during off-peak hours or during times when energy costs are high [28]. The duration of the demand response event can also impact user willingness, with shorter events being generally more palatable than longer ones. Overall, understanding user willingness to participate in demand response programs is critical to the successful implementation of demand-side management strategies.

Users are willing to shift different types of energy-consuming activities in demand response programs [29, 30]. These activities may include adjusting heating or cooling settings, delaying the use of appliances such as washing machines or dishwashers, or even turning off non-essential appliances and lights. However, the specific activities that users are willing to shift may vary depending on factors such as their lifestyle, work schedule, and energy consumption habits. For example, users who work from home may be more willing to shift their energy consumption during the day, while those with rigid work schedules may prefer to shift their energy consumption in the evening or on weekends.

In the context of scheduling and shifting consumption behavior, it is also important to take into account the temporal horizon for rescheduling activities. Some activities, such as cooking, are inherently linked to specific times and cannot be easily rescheduled, while others can be more flexibly shifted to a different time slot, or delayed for a full day [31].

2.2. Clustering of Energy Consumption Data

Clustering of energy consumption profiles has been extensively studied in the literature as a means of identifying patterns in energy consumption data, e.g. [32, 33]. A variety of clustering algorithms have been applied to energy consumption data, ranging from traditional methods such as k-means clustering to more advanced methods such as hierarchical clustering, density-based clustering, and fuzzy clustering. Some studies have also explored the use of clustering with time-series data [34], frequently using dynamic time warping (DTW) [35] to account for slight misalignment of patterns. These clustering approaches have been used for various applications, including load forecasting [36, 37] and anomaly detection [38]. In our work we want to explore the effectiveness of clustering for personalization and timing of behavior change interventions in the context of energy conservation.

3. System Concept

In order to provide tailored demand response suggestions based on the individual users' consumption history we developed a system concept, which consists of four steps.

- First the existing consumption data of a household is clustered and typical daily patterns are identified.
- Second, the resulting clusters and their temporal occurrence are used to predict the most likely energy consumption pattern for the following day.
- Third, based on this prediction and the known day-ahead hourly energy prices obtained from the energy exchange opportunities for cost savings by temporal shifting of consumption activities are identified.
- Fourth, a detailed message and timing for sending a behavior recommendation to the user is carefully designed based on identified principles for persuasive message design.

Clustering. The starting point for the cluster analysis are the 15-minute electricity consumption values per household measured by smart meters, using data over the span of several months. The analysis is based on 24-hour periods, each starting at 4:00 a.m. This choice of the observation period makes it easier to combine different consumption profiles, as the transition from one pattern to the next falls into a period of low activity. The next step involves smoothing the temporal consumption curves by calculating the moving average over a period of 2 hours. Smoothing the consumption curves allows to ignore short fluctuations and helps identifying larger behavioral patterns. Using the smoothed data, a distance matrix comparing the daily load profiles to each other using dynamic time warping [35] is calculated. Using dynamic time warping when calculating the distance matrix allows to account for slight misalignment of patterns. The resulting distance matrix is then used to group the individual 24-hour periods into several prototypical clusters. The result is a set of characteristic temporal daily energy profiles, each of which describes a typical consumption pattern of the regarding household. The following graph below shows a sample result of this process for an individual household with data from two months. The thick dashed line depicts the identified trajectory of a calculated cluster, while the solid thinner lines represent the actual consumption patterns of the underlying days. Cluster 1 for example in this case is a very frequent pattern, and can be characterized by a slight increase in energy consumption in the morning hours, the absence of a mid-day peak, and a very pronounced increase in energy consumption in the evening. In contrast, Cluster 6 can be characterized by the absence of energy consumption in the morning, a strong mid-day peak, and slightly less pronounced energy consumption in the evening hours.

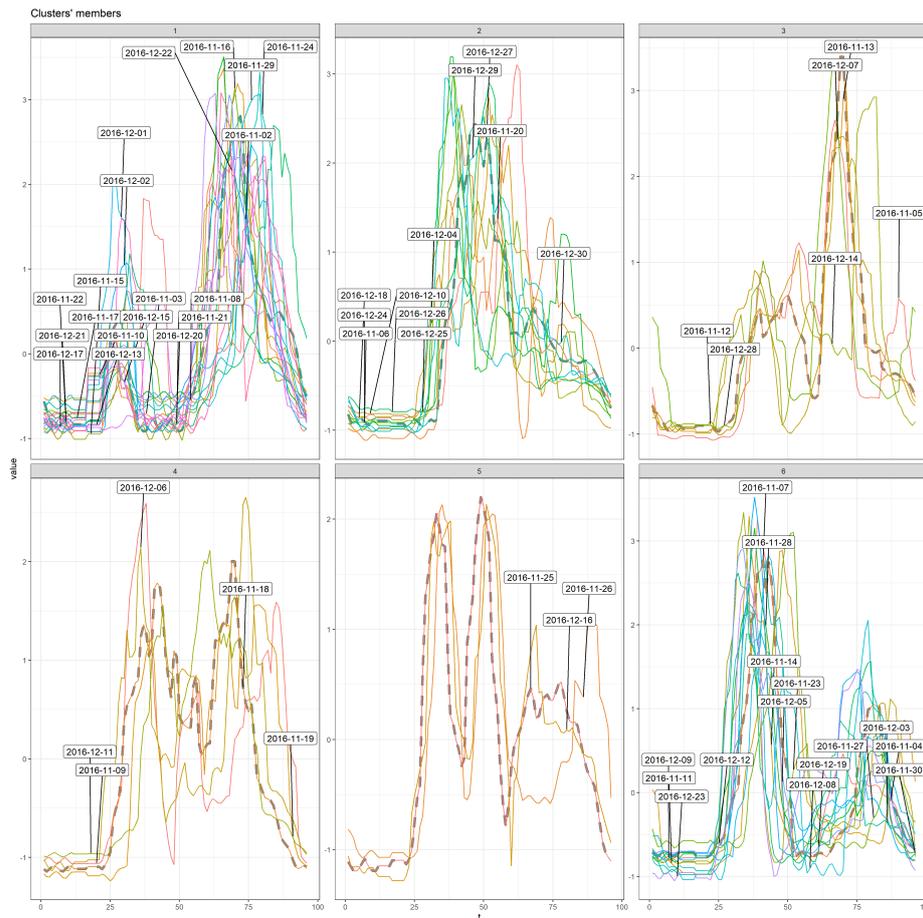


Figure 1: Example results of the clustering process for a selected household using historic consumption data. Six different patterns have been identified by the clustering procedure (thick dashed line). The horizontal axis shows the progression of the 96 15-minute-datapoints throughout the day, with 0 corresponding to 4h00 a.m. and 96 to 3h45 a.m. the following day.

Prediction. Once daily consumption patterns have been identified, each day in the consumption history is characterized by a single consumption profile, that best de-scribes the typical pattern for the regarding day. Together with calendar (school day, workday, day-of-week, month) and weather features (sunshine duration, precipitation) this classification is then used as a basis for a machine learning model describing the households using a random forest approach to learn a model of the users' typical daily behavior. The learned model was then used to predict the most likely consumption profile for the following day. This user model and prediction can be further refined over time as additional data becomes available and the algorithm learns more about the individual's consumption behavior.

Identification of relevant savings opportunities. Based on day-ahead-prices, predicted consumption pattern as well as constraints considering the users' willing-ness to shift energy consumption activities relevant saving opportunities for the next day are identified. In order to define these opportunities a set of guiding principles for the identification of regarding savings opportunities was developed based on prior research. In the following we first summarize these principles, explain the rationale for it and report the actual implementation of the principle for our system.

Principle 1: The corresponding period falls in a time span for which a relatively high energy consumption is predicted.

Rationale: Relatively high consumption is a good starting point for shifting measures for two reasons. First, a high initial consumption significantly increases the achievable savings potential. Second, the probability is higher that the user is actually at home at the regarding time, as higher

consumption is typically associated with activities that require the user to be present (e.g. cooking, cleaning, media consumption, showering, etc.).

Implementation: Only behavioral recommendations for those time periods will be considered where the electricity consumption is in the upper half of the daily consumption.

Principle 2: In the immediate temporal vicinity of the predicted high consumption period, there are areas with significantly lower energy costs.

Rationale: When it comes to bring forward or defer consumption-related activities, there are typically two time periods to consider. Either the activity is shifted by only a few minutes, or the activity is postponed at all until the next day. Since actual energy prices for the day after next are typically not available, we focus on those activities that can be shifted for a short period of time.

Implementation: The system only considers a time period of one hour prior or posterior for recommending shifting of consumption activities.

Principle 3: The achievable savings potential must be sufficiently high.

Rational: In order for users to perceive the suggestions as relevant and not experience them as a nuisance, it must be ensured that the achievable savings - when following the recommendations - reach a relevant order of magnitude.

Implementation: Only those behavioral recommendations are considered that have a potential for savings of at least 10%.

Principle 4: The addressed time falls within the typical daily activity rhythm of the participants.

Rational: Only recommendations that actually can be implemented by the user should be generated, therefore it is essential to exclude time periods in which users are typically at rest.

Implementation: Only those recommendations that relate to a time period between 7:00 a.m. and 11:00 p.m. are taken into account.

Generation of behavior recommendations. Based on the identified opportunities then tailored recommendations are designed to be communicated to the user. In order to achieve the best results and optimal user experience the following principles are applied:

Principle 1: Only a limited number of recommendations should be generated and communicated per day.

Rationale: It is important to avoid overwhelming or fatiguing users with too many recommendations. Providing users with an excessive number of recommendations can lead to decision fatigue, making it difficult for them to prioritize and follow through with the recommended actions. Additionally, overwhelming users can lead to a decrease in engagement and overall program effectiveness.

Implementation: At most one recommendation per day is communicated to the user.

Principle 2: Recommendations should be given with sufficient lead time.

Rationale: It is crucial that recommendations are given with sufficient lead time so that users have enough time to plan and implement behavioral changes into their daily lives in a way that is convenient for them. Additionally, users may not have enough time to adjust their schedules or routines to accommodate the recommended changes.

Implementation: Messages are delivered the day before.

Principle 3: Clear communication of possible benefits.

Rationale: Clear communication of the potential benefits of energy shifting behavior can help users understand the importance of their actions and motivate them to participate in the program. This can include providing information on how energy shifting can help reduce their energy bills and promote sustainable energy usage.

Implementation: The behavior recommendation also clearly specifies the amount of money that can be saved when following recommendations.

Principle 4: The basis for the recommendation (the predicted consumption) should also be communicated.

Rationale: When predictions are transparent, individuals can see the data and the algorithms used to generate the recommendations. They can also understand the assumptions and limitations of the data and algorithms, which allows them to assess the validity and reliability of the recommendations. Without transparency, individuals may not fully understand why they are being recommended certain behaviors or actions. This lack of understanding can lead to distrust in the recommendations and potentially negative outcomes if individuals choose to ignore or resist the recommendations.

Implementation: Together with the textual recommendations a graph containing the predicted consumption patterns as well as the day-ahead prices is shown.

Principle 5: Focus on opportunities with the best tradeoff between possible impact and effort

Rationale: In order to keep users motivated it is essential to focus on the areas where the users can achieve the highest impact with the lowest inconvenience.

Implementation: For the identification of savings opportunities therefore both the potential for savings and the length of the shifting period are taken into account for the rescheduling of activities, based on the assumption that longer delays represent a greater disruption to the user's usual routines and are therefore associated with more inconvenience.

Principle 6: Behavior recommendations should be clear and easy to follow and not require cognitive effort by the user.

Rationale: If recommendations are complex or require significant cognitive effort to follow users may become frustrated or overwhelmed and be less likely to adhere to the recommendations. Therefore, clear and easy-to-follow recommendations are more likely to be effective in promoting behavior change and improving outcomes.

Implementation: Behavior recommendations are expressed in a simple sentence providing clear instructions for shifting the consumption behavior.

4. Further opportunities for AI

Based on our system design and the conducted analysis we identify further promising development opportunities for the application of AI methods in the context of tailoring behavior recommendations for demand response.

4.1. Personalization of recommendations style

A promising approach for further using AI to improve persuasive systems we see in the improved personalization of messages. In our current work we have utilized a limited set of characteristics, primarily the consumption history and predicted consumption patterns, to tailor messages to individual users. Here AI-methods could help to further tailor behavior recommendations towards individuals, for example based on the users individual persuadability [9, 39] regarding different behavior change strategies, or by matching recommendations to the users preferred incentive system, or by mirroring the used language to the users' idiom [40].

4.2. Improve the timing of recommendation delivery

As discussed above proper timing and frequency of recommendations is essential for the perception and implementation of behavior recommendation systems. In our system concept we are currently using a very static approach, but more advanced scheduling of recommendations using AI-methods could help to better time message delivery.

We think that the utilization of activity recognition methods [41] can enhance the timing of messages, preventing them from arriving at inopportune moments for the user (i.e. when s/he is

engaged in other activities). As a result, notifications may be perceived as less disruptive, thereby increasing the likelihood of sustained system use.

Also, by matching behavior recommendations to the current activity of the users the likelihood of following the recommendations might be higher.

4.3. Disaggregated energy feedback

Research has shown that disaggregated energy feedback [42] might have several advantages over traditional aggregated energy feedback, as it provides users with a de-tailed breakdown of energy consumption by individual appliances or devices. Dis-aggregated feedback can provide more actionable information than aggregated feed-back, allowing users to make specific changes in their energy usage behavior.

As automatic disaggregation of energy profiles based on measured profiles (which doesn't require the installation of obtrusive energy metering devices) has made rapid progress [43] and commercial services become available, utilization of this knowledge for tailoring behavior recommendations to the individual appliances and their related usage practices and limitations seems to be a very promising approach for further tailoring of energy behavior recommendations.

4.4. Ongoing adaptation of recommendations using impact feedback

In the current system concept, only the learning of the typical energy profiles of the users adapt to possible changes over time. In a more elaborated system concept in-volving the constant monitoring of consumption levels as well as possibly activity recognition updating and further tailoring of the design of recommendations based on the observed consequences (i.e. did a recommendation induce a change in behavior) could be helpful. In short, AI could be used to learn which strategies and recommendations work, and adapt the future approach accordingly.

4.5. Improved clustering and prediction integrating additional data features

Another way to further improve the tailoring of our system concept we are exploring is the improvement of the clustering and prediction process by integrating additional data features. In the described concept we only integrated calendar and weather features due to simplicity of implementation, however adding information gained from additional sensor from the home could help to better model and predict users' consumption patterns. Especially with the increasing prevalence of smart homes and the associated increased availability of sensors and measurement data in various areas the integration of additional data sources becomes increasingly feasible.

5. Conclusion

In this paper we presented our system concept for the application of temporal clustering for tailoring persuasive messages to individuals based on their consumption characteristics. By analyzing a person's energy profile researchers and practitioners can identify opportunities for behavior suggestions, and also better design and possibly time messages. We think this approach also has potential applications in a variety of fields besides energy feedback and demand response, such as marketing, health pro-motion, and mobility. In our work we have implemented first applications of AI for improved behavior change recommendations, and also identified a number of promising research areas for further development of AI-based tailored behavior recommendations.

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