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Energy feedback enabled by load disaggregation

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Abstract

Motivated by recent advances in load disaggregation, we discuss innovative tools for understanding household appliance energy consumption and patterns of appliance use for energy feedback generation, developed as part of the EPSRC REFIT project. We show how analytical tools applied on disaggregated data can lead to a variety of energy feedback ranging from appliance usage patterns analysis, appliance upgrade/retrofit advice, opportunities for load shifting and assessing tariff suitability, and understanding household routines through time use and energy consumption studies of daily activities in the home, such as cooking or laundering. Our analysis is based on the publicly-available REFIT electrical measurements dataset that was populated by a 2-year longitudinal study in UK houses and is supplemented by qualitative data. Namely, we collected electricity data, aggregate data and individual appliance consumption, with an 8-second sampling rate for active power, similar to that provided by a Consumer Access Device that reads measurements from a smart meter directly. This implies that our feedback generation approaches could potentially be used in conjunction with smart meters that will be present in all UK homes by 2020. Furthermore, we summarise the findings collected during exit interviews from the test households about the usefulness of smart metering and energy feedback.

1. Introduction

Smart meter roll-outs have been implemented or planned across the world to better manage residential energy demand, conserve energy, improve billing accuracy, and help users understand the energy implications of their appliance usage habits. Bundled with In-Home Display devices, smart meters will provide real-time aggregate energy consumption information and access to historical aggregate consumption.

In this paper we explore enhanced energy feedback methods, beyond live and historical aggregate consumption, that are only possible from appliance-level consumption data. Non-Intrusive appliance Load Monitoring (NILM) is an attractive load disaggregation option, since it does not require any physical, appliance-level sensors to be installed and can potentially estimate energy consumption of each appliance in a home using only smart meter data. Indeed, up to 20% energy consumption reduction is expected via appliance-feedback and specific appliance upgrade programs (Armel, Gupta, Shrimali, & Albert, 2013).

The extended abstract is organised as follows: firstly, we briefly describe NILM techniques, recently developed specifically by the authors to operate with high accuracy on smart-meter type data; secondly, we demonstrate how to use the disaggregated data obtained from NILM to provide enhanced feedback to customers, such as individual appliance consumption, energy consumption broken down to activity level (e.g., cooking, laundering), appliance mining and upgrade/retrofit advice, and suitability for different variable tariffs; thirdly, we present a summary of findings from 20 households on their thoughts about the previously discussed feedback methods.

The paper is based on a field study conducted as part of the EPSRC REFIT project, where 20 homes in the Loughborough area were monitored for about 2 years.

2. Load disaggregation: background and summary of approaches

Though founded over 30 years ago (see Hart, 1992), NILM has generated renewed interest recently, due energy conservation programmes and large-scale smart meter deployments worldwide. Recent challenges for NILM are high accuracy disaggregation from smart-meter type low sampling rate electrical measurements, and robustness to noise manifested from a the very large number of household appliances in a home, many with similar electrical signatures. Most popular ‘low-rate’ NILM approaches are based on Hidden Markov Models (HMMs) which usually require expert knowledge to initiate appliance state models and a very large ‘noiseless’ training set to build//refine the models.

In order to overcome the disadvantages of HMM-based approaches, we have developed a range of NILM methods that are of low complexity without compromising on accuracy, that work with active power measurements at low sampling rates (in the order of seconds or minutes) - see (Liao, Elafoudi, Stankovic, & Stankovic, 2014), (Elafoudi, Stankovic, & Stankovic, 2014), (Altrabalsi, Stankovic, Liao, & Stankovic, 2016), and (Zhao, Stankovic, & Stankovic, 2016).

Our two supervised NILM approaches are based on adaptive thresholding for event detection with a Decision Tree (Liao et al., 2014) and combined K-means and Support Vector Machine for event classification (Altrabalsi et al., 2016). However, both approaches require a training period, albeit small compared to HMM-based approaches, when each appliance is operating with minimum noise from other appliances. Since, for such training, either plug-level sensors or time-diaries are needed, these approaches might not be suitable for widespread deployment.

In (Liao et al., 2014) and (Elafoudi et al., 2014), we proposed an unsupervised method based on Dynamic Time Warping, which does not require a labelled dataset for training and has competitive performance to supervised approaches. However, the method of (Elafoudi et al., 2014) compares each newly extracted electrical signature with a database of signatures which is populated on-the-fly; this may result in high complexity if there are many appliances contributing to the aggregate load.

Finally, in (Zhao et al., 2016), we developed a ‘training-less’ approach based on Graph Signal Processing (GSP) that does not require any training and can start disaggregating measurements immediately. Due to the inherent properties of the underlying GSP design, this approach can capture signal patterns that occur rarely (as opposed to machine learning based methods), is robust to noisy data and outliers and has low computational complexity.

All above approaches have been tested on a range of datasets and demonstrated competitive accuracy with respect to state-of-the-art approaches.

3. Going beyond load disaggregation: Enhanced feedback on consumption habits

While NILM can identify when an appliance is used and how much electricity it consumes, this is hardly sufficient for motivating energy conservation. We conducted two types of detailed analysis based on disaggregated appliance-level data:

a) Appliance usage monitoring, i.e., analysis of appliance usage patterns, including seasonal effects, suitability for load shifting and suitability of variable tariffs;
b) Domestic activity recognition, i.e., analysing energy consumption through the lens of activities, potentially more meaningful to consumers as it is tied to their lived experience.

3.1 Appliance usage monitoring

By characterising appliance use in a household, it is possible to quantify energy savings through efficient appliance use and predict appliance-specific demand from load measurements. Specifically, we carried out: (i) time-of-use analysis to understand patterns of use of appliances and comparison of appliance usage and consumption patterns among households (Murray, Liao, Stankovic, & Stankovic, 2015b); (ii) analysis to quantify energy savings if appliances were used more efficiently and predict appliance-load demand (Murray, Liao, Stankovic, & Stankovic, 2016); (iii) analysis of suitability of variable tariffs stemming from households-specific consumption (Murray et al., 2015a).

The time-of-kettle-use analysis for 14 REFIT households in (Murray et al., 2015b) confirms that kettle usage patterns are regular at peak times (morning, evening around dinner) and mainly sporadic otherwise during the day. Additionally, we show quantitatively, in-line with previous other studies, that a significant percentage of households overfill their kettle. Additionally, households that appear not to overfill, based on household occupancy, waste energy on reheating or re-boiling soon after a boil. We demonstrate in (Murray et al., 2016) that due to well-defined patterns of use, it is possible to accurately predict kettle usage at a large scale using only disaggregated smart meter readings. An additional application of our proposed tools is the prediction of quantifiable energy savings if water filling patterns change through, for example, more efficient behaviour by filling to ideal levels.

Following the approaches discussed above, we provided one household with energy feedback (see (Murray et al., 2016, Appendix A) for more details and visual feedback examples) about changes in energy consumption incurred by replacing their standard kettle with an ‘eco’ vacuum kettle. A survey was completed prior to feedback to assess the residents’ thoughts. The survey revealed a number of traits about the household: they were committed to being eco-friendly and were positive about buying other products aimed at reducing energy, they believed that they had changed their habits significantly as they actively incorporated the vacuum kettle into their routine. The feedback was well received and a monthly breakdown of appliance usage deemed beneficial towards their energy saving goals. Our findings showed close to 50% energy savings caused by the switch to the vacuum kettle, a reduction in the number of re-heats and a continued economical usage style even when the vacuum kettle was replaced due a fault.

Energy feedback that incorporates time-of-use of appliances, is useful in determining suitability of different variable energy tariffs, such as the Economy 7 tariff, for those open to the flexibility of shifting white goods schedules. For example, while one energy-conscious household on the Economy 7 tariff used their washing machine mostly overnight (off-peak usage), it could have benefitted more by shifting the rest of its usage at off-peak times - see Figure 4 in (Murray et al., 2015a) for details and an example of visual feedback. While assessing tariff suitability, we found that only 40% of the households who were on the Economy 7 off-peak tariff were benefitting from this. The other 60% were paying more than if they were on a standard tariff.

3.2 Activity-based feedback

Recent studies of energy-related feedback have found that electricity consumption data, aggregated or disaggregated down to appliance level, is not often meaningful to households as it is not tied to their lived experience (Hargreaves, Nye, & Burgess, 2013), (Wilson, Hargreaves, & Hauxwell-Baldwin, 2015a). Activities such as cooking, washing, listening to music or playing computer games are more consistent with households' own experiences of life at home. Activities are a simple descriptive term for these common ways in which households spend their time (Wilson et al., 2015b). Thus, in (Wilson et al., 2015b) and (Stankovic et al., 2015), through analysis of qualitative and quantitative disaggregated appliance-level data, we relate electricity consumption to domestic activities.

We first disaggregate a household’s total electricity load down to appliance level, generating the start time, duration, and total electricity consumption for each appliance use. We then make inferences about activities occurring in the home by combining these disaggregated data with an ontology that formally specifies the relationships between electricity-using appliances and activities. Our method was tested on six households, making reliable inferences on four to nine activities over the course of a month. Results presented in (Stankovic et al., 2015) show that the time profile of domestic activities has routine characteristics but these tend to vary widely between households with different socio-demographic characteristics, with unique weekday and weekend time profiles and also reveals certain households to be large energy users across a range of activities - see (Stankovic et al., 2015, p. 9-11) for visual feedback examples.

Activity-centric feedback using smart meter disaggregated data has important implications for providing meaningful energy feedback to households, comparing the energy efficiency of households' daily activities, and exploring the potential to shift the timing of activities for demand management.

4. Participants’ feedback

After the REFIT study period, when the smart meters and home automation devices were taken out of the 20 REFIT homes, householders were asked to fill a questionnaire to gauge their experience and perceptions about the usefulness of smart meters, types of feedback, smart home automation and what motivated them towards energy conservation. We summarise some of the responses below. Note that 80-85% of households responded that their energy bill and being eco-friendly were the primary factors that motivated them towards energy conservation.

In-home display: While 60% of households rarely looked at the real-time in-home display (IHD), which presented in real time total electricity usage in their home, as well as that of nine selected appliances, 89% were open to having a smart meter installed in their home. Those who looked at the IHD daily, responded a heightened awareness of how much electricity their appliances were consuming and changed the way they used their appliances or carried out their daily activities.

Temporal granularity of feedback: All households said they would like to see how their consumption compared with that of the previous month or year, and 65% stated that their monthly consumption was useful feedback, whereas only 25% stated that daily or weekly consumption feedback would be useful. 50% said it was useful to see how they compared with other similar households, whilst only 10% responded that they would like to breakdown appliance-specific energy use to the highest consuming appliances in their home.

Breaking the bill down to appliance level: 70% of households said that consumption broken down to appliance use would be useful.

Load shifting and variable tariffs: 65% of households said they would consider adjusting the timing of their activities to benefit from a better tariff. The activities or appliances they said they were willing to shift include dishwashing, laundering including washing machine and tumble dryer, hobbies, charging devices, bread-maker, computing, and charging their car.

5. Conclusion

This paper discusses how load disaggregation from smart meter data can be instrumental in designing enhanced energy feedback, beyond that possible from an IHD only. Besides presenting an appliance-itemised electricity bill, load disaggregation together with additional data analytics can support different appliance usage analysis feedback, including wasteful usage habits, suitability of different tariffs, and activity-centric energy usage for common domestic activities such as cooking or laundering. The feedback generated from load disaggregated data and analytical methods can be found in (Murray et al., 2015a), (Murray et al., 2015b), (Murray et al., 2016), (Wilson et al., 2015b), (Stankovic et al., 2015), (Zhao et al., 2016).

The initial feedback from a relatively small study of 20 REFIT households showed the potential of these types of energy feedback. However, the views were mixed and more detailed studies and visualization methods need to be investigated to evaluate the value of the proposed feedback mechanisms.

6. References

Altrabalsi, H., Stankovic, V., Liao, J., & Stankovic, L. (2016). Low-complexity energy disaggregation using appliance load monitoring. *AIMS Energy*, 4, 884-905. doi:10.3934/energy.2016.1.1.

Armel, K. C., Gupta, A., Shrimali, G., & Albert, G. (2013). Is disaggregation the holy grail of energy efficiency? The case of electricity. *Energy Policy*, 52, 213–234. doi:10.1016/j.enpol.2012.08.062.

Elafoudi, G., Stankovic, L., & Stankovic, V. (2014). Power disaggregation of domestic smart meter readings using Dynamic Time Warping. *Proc. ISCCSP-2014 IEEE International Symposium on Communications, Control, and Signal Processing*, 36-39. doi: 10.1109/ISCCSP.2014.6877810.

Hargreaves, T., Nye, M., & Burgess, J. (2013). Keeping energy visible? How householders interact with feedback from smart energy monitors in the longer term. *Energy Policy*, 52, 126–134. doi: 10.1016/j.enpol.2012.03.027.

Hart, G.W. (1992). Nonintrusive appliance load monitoring. *Proc. IEEE,* 80, 1870-1891. doi:10.1109/5.192069.

Hauxwell-Baldwin, R., Hargreaves, T., & Wilson, C. (2016). *REFIT smart home interviews*. [Dataset]. ReShare Data Repository, UK Data Service. https://discover.ukdataservice.ac.uk.

Liao, J., Elafoudi, G., Stankovic, L., & Stankovic, V. (2014). Non-intrusive appliance load monitoring using low-resolution smart meter data. *Proc. IEEE SmartGridComm-2014*, 535-540. doi: https://dx.doi.org/10. 2790/012477.

Murray, D., Liao, J., Stankovic, L., Stankovic, V., Hauxwell-Baldwin, R., Wilson, C., Coleman, M., Kane, T., & Firth, S. (2015). A data management platform for personalised real-time energy feedback. *Proc. EEDAL-2015 8th Int. Conf. Energy Efficiency in Domestic Appliances and Lighting*, 1293-1307. doi: https://dx.doi.org/ 10.2790/012477.

Murray, D., Liao, J., Stankovic, L., & Stankovic, V. (2015). How to make efficient use of kettles: Understanding usage patterns. *Proc. EEDAL-2015 8th Int. Conf. Energy Efficiency in Domestic Appliances and Lighting*. 743-755. doi: https://dx.doi.org/10. 2790/012477.

Murray, D.M., Liao, J., Stankovic, L., & Stankovic, V. (2016). Understanding usage patterns of electric kettle and energy saving potential. *Elsevier Applied Energy*, 171, 213-242. doi: 10.1016/j.apenergy.2016.03.038.

Stankovic, L., Stankovic, V., Liao, J., Wilson, C., Hauxwell-Baldwin, R., & Coleman, M. (2015). Understanding domestic appliance use through their linkages to common activities. *Proc. EEDAL-2015 8th Int. Conf. Energy Efficiency in Domestic Appliances and Lighting*.

University of Strathclyde (2016). *REFIT: Electrical load measurements dataset 2013–2015*. [Dataset]. doi: http://dx.doi.org/10.15129/31da3ece-f902-4e95- a093-e0a9536983c4.

Wilson, C., Hargreaves, T., & Hauxwell-Baldwin, R. (2015). Smart homes and their users: A systematic analysis and key challenges. *Pers. Ubiquitous Computing*, 19, 463-476. doi:10.1007/s00779-014-0813-0.

Wilson, C., Stankovic, L., Stankovic, V., Liao, J., Coleman, M., Hauxwell-Baldwin, R., Kane, T., Firth, S., & Hassan, T. (2015). Identifying the time profile of everyday activities in the home using smart meter data. *ECEEE Summer Study Proceedings: First fuel now.* Lindström, T. L. (ed.), 933-946 5-046-15.

Zhao, B., Stankovic, L., & Stankovic, V. (2016). On a training-less solution for non-intrusive appliance load monitoring using graph signal processing. *IEEE Access*, 4, 1784-1799. doi:10.1109/ACCESS.2016.25574/460.

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http://www.refitsmarthomes.org. The REFIT Electrical Load Measurements dataset can be accessed at http://dx.doi.org/10.15129/31da3ece-f902-4e95- a093-e0a9536983c4. The qualitative data, collected by University of East Anglia team, with the same house numbering is available at: https://discover.ukdataservice.ac.uk.