Machine Learning and Multimedia Content Generation for Energy Demand Reduction

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***Abstract*—Domestic energy demand accounts for about 30% of overall energy use. The IDEAL project uses a variety of IT methods to investigate whether, and in which social groups, feedback of personalised, household-specific and behaviour-specific information results in greater reduction in energy use than overall consumption information reported by Smart Meters. It is a sociotechnical study, concentrated on existing housing, with a strong social science component and an experimental design that looks at income levels and household composition as primary factors. Temperature and humidity data related to behaviour is gathered using a small number of wireless sensors in the home, together with data on weather, building factors and household composition. This data is streamed over the internet to servers where it is analysed using Bayesian machine-learning methods to extract household-specific behaviours in near-realtime. Information on the cost, carbon content and amount of energy used for specific behaviours is reported back to the householders via a dedicated wireless tablet. This interactive content is automatically generated using multimedia methods based on natural language generation techniques. The project is in its design phase, with the main project planned (and funded) to run 2013-2016. It is anticipated to demonstrate whether such low-cost sensing, analysis and feedback is significantly more effective than standard Smart Meters in reducing demand, and a business opportunity for green service organisations.**

***Keywords*-demand reduction; building energy efficiency; machine learning; human-computer interaction; natural language generation**

I. Introduction

Reducing energy demand from existing dwellings through occupant behaviour change is crucial to meet 2050 carbon emission reduction targets. In the UK, dwellings account for 32% of energy consumption, and corresponding emissions. A focus on existing dwellings is essential: 80% of the 2050 stock already exists. Heat is key, accounting for 80% of domestic demand. Attention to behaviour change is important: behaviour is estimated to account for 60% of the variance in demand. Using an interdisciplinary sociotechnical conceptual framework, our team of computer scientists, building engineers and sociologists, are working together to explore the dynamic roles, interactions and boundaries of energy technologies and householder behaviours. Household energy demand will be analysed in great detail across a large number of homes and the effect of behavioural feedback evaluated over a multi-year period.

Previous work in behaviour change for domestic demand reduction through digital means focussed mainly on electricity (often excluding heating) and supplied feedback on overall energy consumption and normative comparisons with other households ([1], [2], [3], [4]). Overall consumption feedback creates a loop in which the householder interprets consumption graphs to determine which household practices waste energy, then changes her behaviour to reduce that waste.

Although such feedback can reduce demand, consumption information fails to meet an important precondition of successful behavioural change: it does not explicitly identify the specific behaviours that are wasting energy, but leaves it up to the householder to infer these. Successful change requires recipients of the feedback to realise there is a problem, understand how their behaviour is related to it, and become aware that they can influence it[2]. The CHARM project found that householders used hourly consumption charts to identify the behaviours responsible for the greatest fluctuation in consumption[3]. In a study of how householders interact with consumption feedback from smart meters, Hargreaves found that householders used the monitors to detect specific events, e.g., when a computer had been left on[4]. In contrast, this project examines the effect of providing *personalised behavioural feedback* to occupants: explicitly identifying the behaviours (e.g., showering and bathing, room heating, major appliance use) that account for energy use/expenditure; and how these could be reduced.

We are creating the following enhanced digital intelligent loop: a) detailed in-home sensing, sufficient to b) infer specific demand-related behaviours, enabling c) timely personalised behavioural feedback. We hypothesise that this loop can be tuned to improve reduction in

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energy demand from dwellings compared to the state-of-the-art consumption feedback methods, especially where behaviours are not easily identified from consumption feedback by non-experts (heating, cooling, etc). An exciting aspect of this loop over the length of the study is that we will be able to modify the feedback we give householders, using the behaviour changes that we observe and infer as due to our feedback–we will be getting feedback about our feedback!

II. Research Hypothesis and Objectives

Our main hypothesis is that an intelligent personalised behavioural feedback loop can be tuned to significantly affect behaviours and so reduce energy demand from dwellings more than a consumption feedback loop. There are four specific components to this hypothesis:

1) *People will change their behaviours more if they can see the connection between their behaviours and their energy use.* We are designing and will execute a controlled study to compare the demand reducing effect of the intelligent behavioural feedback loop with that of the consumption feedback provided by Smart Meters.
2) *A small number of non-invasive sensors per dwelling can provide the data required to infer behaviour.* We are developing and will deploy internet-enabled wireless sensor technology in 576 dwellings; will acquire real-time data on energy demand and occupant behaviour; and will gather related data on the dwelling and its occupants and their relevant attitudes and behaviour patterns.
3) *Probabilistic models are capable of inferring behaviours from such sensor data.* We are applying and extending such models for this data and associated metadata (e.g., weather) to infer energy-related occupant behaviours.
4) *Automated personalised natural language feedback, supported by interactive graphics, is effective in informing occupants of the connection between behaviour and energy use, and in motivating changes.* We are applying and extending such methods to produce tailored feedback relating occupants' energy use to behaviours, enabling them to reduce demand/cost without reducing quality of home life.

III. Programme and Methodology

The different disciplinary strands of the project are integrated using the "glue" of a shared conceptual framework, namely a set of sociotechnical theories (actor-network theory, sociotechnical transitions, innovation studies) about people, energy and housing, which have demonstrated the complex interactions between individuals and energy technologies in the home [5], [6], [7]. This conceptual framework will provide a shared language for the team and partners enabling a truly multidisciplinary focus on a common objective.

A. Research Design

Our main hypothesis is that a personalised behavioural feedback loop is more effective in inducing demand-reducing behaviour change than the consumption feedback loop, so the main independent variable is feedback type, in three categories: a *control* group receiving only household consumption feedback equivalent to that produced by Smart Meters, an experimental group receiving *individual* household consumption and behavioural feedback, and another experimental group receiving additionally *social feedback* on household consumption and behaviour. Social feedback will include, for example, normative comparisons with people in similar households[3]. The control group will be recruited with the same offer and receive the same treatment as the experimental groups. Thus the effects of repeated social interaction with the research team are controlled for, allowing us to rule out "Hawthorne" effects of social interaction *per se*. In order to simplify and standardise the feedback interface (a dedicated tablet computer, supported by a personalised website), we will select households that are broadband-equipped.

Our design uses 576 UK households divided into the three feedback types (192 in each category), as shown below. Beyond testing the main hypothesis with this

Feedback	Individual	Social	Control	All
N	192	192	192	576

design, we will evaluate the feedback loop's differential effectiveness in relation to the independent variables of household income (above and below UK median income) and household composition (single person; two or more adults; family of one or two parents and one or more children)–a 2x3 within-feedback-category design as shown below with 32 in each sub-cell. Household income

Variables	1 Adult	2+ Adults	Family	N
Lower £	32	32	32	96
Higher £	32	32	32	96
N	64	64	64	192

and composition are expected to be a significant intervening variable in the impact of personalised behavioural feedback on energy demand. The size of the data set will also enable us to model, and differentiate, the interacting effects of social class, education and age [8]; building type and existing energy-efficiency measures may also impact the effect of behavioural feedback.

The design includes households from demographics of significant social and environmental interest: 1) affluent/technically able, with the potential for high carbon savings, 2) low-income/fuel-poor, with the potential for significant social benefits as well as some carbon savings. The outcome will be a set of conclusions useful for policy setting, for commercial offerings targeted at different market segments and households, and for further studies.

Quantitative Measurement will determine:

1) Baseline and final energy consumption and user profiles for each household.
2) The impact of repeated visits, surveys and standard consumption feedback measures.
3) The impact of sensor-derived, personalised behavioural feedback during the course of the study.

These will enable quantitative assessment of:

1) Differential effects of social/normative and individual household feedback.
2) Differential impact of feedback due to household income, education, ages, composition, building type, and energy performance (regression).
3) The extent to which reductions in energy demand are sustained over time in different households.

Qualitative Measurement will examine why and how different forms of personalised behavioural feedback influence energy-related behavior, and explore the impact of household composition and dynamics. Six-monthly surveys (online and/or via the dedicated feedback tablet) over the course of 3 years will collect data on changes in attitudes to energy use and cost, carbon footprint of energy, the presence of the sensors, and responses to personalised feedback. When the sensors have been in place for 12 months, the attitudinal data will be used to identify a subset of around 50 households–selected for contrasting attitudes to feedback, and household composition–to participate in small scale evaluation of feedback presentations using semi-structured interviews. Household composition is important because responses to feedback will be affected by the dynamics of multi-person households. The qualitative dataset will provide insight into the complexity of interacting factors which modulate energy demand in households, and allow us progressively to optimise the design of feedback for different household types.

B. Data Acquisition

1) Recruitment and Householder Journey: Social enterprises focused on demand reduction in the community will be managing the critical householder journey, encompassing trust, a household focus, and an ethical data stance. Staged recruitment will target, characterize, qualify, filter and allocate participants to study design groups, using a variety of channels including Registered Social Landlords and large corporations We will provide a hotline support phone number for all issues. Household engagement will be maintained with twice yearly short project newsletters, 6-monthly online follow-up surveys, and opportunities for householders to interact with the team and each other via e.g., online discussion boards, Facebook groups, etc.

2) Installation and initial data acquisition: Data collection will exploit wireless networked sensors. For each dwelling, sensors will be installed and initial data gathered, including:

1) Energy related property attributes including building fabric, heating systems and controls, solar gain, meter types, and installed renewable energy technologies. A RDSAP survey will generate an Energy Efficiency Rating as part of an Energy Performance Certificate.
2) Household characteristics, including composition, ownership/control of domestic electrical appliances, individual heating patterns, room temperatures and energy related behaviours.

3) Real-time sensors: The sensors are small wireless devices with 3-year battery power which communicate timestamped data at 1 minute intervals to a base station. Room sensors attached securely measure temperature ($\pm 0.5\,^{\circ}$C), humidity ($\pm 2\%$) and light level (> 6 Lux). Electricity and gas demand is measured with a current clamp (240 Hz) and a magnetic or optoelectric sensor, respectively. Heating demand is assessed with temperature sensors on radiator and hot-water tap supply pipes.

4) Post-installation data acquisition: The mains-powered base station collecting sensor data will communicate to a high-reliability commercial cloud service via broadband once per minute; from there it will be downloaded to the project database frequently. External datasets downloaded to the database will include average monthly fuel prices, Met Office weather data including both forecasts and actual hourly readings, and carbon intensity of grid electricity. The 6-monthly online follow up surveys, and close collaboration with RSLs, will capture changes to factors influencing (1) the property energy performance such as retrofits of energy efficiency measures or microgeneration technologies, or (2) the household characteristics including holidays, variations in house occupancy, changes in attitudes, or changes in energy supplier. This will allow us to quantify actual energy savings of retrofit measures, and any "rebound" effect [9].

C. Computational Modelling

We are developing methods to convert the stream of sensor data into a description of the household's energy-using behaviours that can be used for feedback. The available data will include time-series for electricity and gas demand, room temperatures, humidities and light-levels, and the temperature of key hot water pipes, and additional data such as weather, number of occupants, etc. The information sent to the feedback generator will include standard household consumption statistics, such as energy used (kWh), carbon footprint (kg CO2*e*) and imputed cost (£), aggregated over the preceding day, week and month; but the key will be computed inferences about behaviour, including:

1) Thermostat setting and, if there are TRVs, the settings for each room, with changes inferred using change point detection [10].
2) Whether people are using each room and if they are awake or sleeping, using survey and sensor data (e.g., lights tend to be off when people are sleeping; humidity and temperature tend to go up a little when people are in a room).
3) Hot water behaviours such as washing-up, showers, and cooking, which can be inferred from sensor data from hot-water pipe and rooms (temperature and humidity) sensors.
4) Behaviours related to electricity use such as major appliances (refrigerator, dishwasher, etc.), disaggregated from the load profile.

For each behaviour, we automatically infer when the behaviour takes place, its duration, and its consumption of energy. The key technique we use is probabilistic graphical models, which provide a principled means for integrating uncertain information of different modalities, such as the room sensor streams and the electricity/gas load which both embody indirect information about behaviour. The model for gas demand is designed to infer whether gas is being used for space heating, for hot water, or cooking. This will be done by combining the measured gas demand, the room and weather data (to detect space heating), and humidity sensors in bathroom and kitchen (to detect bathing, showering and cooking). The model for electricity is designed to disaggregate overall demand into the demand created by each appliance, which is possible because different appliance classes have different demand profiles (e.g., [11]).

Intuitively, the models will segment the sensor stream according to where it changes sharply, for example, when the gas demand and the bathroom humidity both increase. Crucially, this segmentation can be done in a minimally supervised fashion. That is, we do not expect that training the models will require us to collect a detailed log of behaviour times. Instead, we are developing unsupervised models that simultaneously segment the stream and cluster segments with a similar profile. Then we manually label the resulting clusters, assigning labels to the clustered segments, such as "shower" and "refrigerator", by combining our own expert knowledge with the survey data about the households.

We are addressing two additional practical challenges. The first is the need to keep up with the continuing data stream. Here we will use advanced approximation techniques, such as online variational inference and sequential Monte Carlo (e.g., [12]). A second challenge will be in handling anomalies in the sensor data, e.g., due to sensor failure, and long-term changes, such as new household occupants. We will deal with anomalies using a combination of heuristics (e.g., ignore sensors that stop reporting) and probabilistic approaches (e.g., look for individual sensor readings that are extremely unlikely according to our model), and with long-term changes using change-point detection[10], combined with information from the 6-monthly surveys.

D. Feedback

To generate feedback we are developing methods for delivering timely personalised, multimodal feedback about energy related behaviours based on the description of these behaviours and other data produced by the inference algorithms. We are also produce the feedback for control households, modeled on that provided by standard utiility Smart Meters.

Previous studies have displayed graphs showing energy consumption (in some cases compared to social norms) and generic pre-authored feedback tips such as "If your energy consumption is high at night, consider turning thermostats down in any unoccupied rooms." In contrast, we are using techniques from user modelling (e.g., [13]) and natural language generation (e.g., [14]) to automatically generate feedback tailored to occupant behaviours, household characteristics, and, in later stages of the project, recipient preferences for type and/or mode of feedback. To determine what information to include in the feedback, the system employs general rules, elicited from household energy advisors, which will be instantiated with information about the current household and behaviours. For example, a rule such as, "If a room is heated when unoccupied, advise changing the heating timer for the room." may be personalised to produce, "Your 2nd bedroom is unoccupied at night, but is being heated to 21C. If you reset the heating controls to switch off that bedroom at night, you could reduce your gas bill by £5/week". The system will then present the information in coordinated text and information graphics (e.g., graphs, bar charts, pie charts), using multimodal information presentation methods (e.g., [15].

Because of the length of this study–three full years of data gathering and feedback in years 2-4, we expect to be able to evaluate multiple feedback strategies over time. Hargreaves indicates that the reaction to feedback provided by Smart Meters changes over time, and initial positive effects fade[4]. The CHARM study [3] suggests that normative comparisons can help maintain householder interest, but this could not be validated due to the short duration of the trial (4 months). Initially we plan to compare two types of personalised behavioural feedback (*individual* household and *social*/normative) against the control group receiving only consumption feedback, with refinements in later years.

By collecting statistics on which data is viewed on the tablet, and what options are selected, we expect to be able to improve and focus the feedback on the information of interest to the householder. In addition, by monitoring inferred behaviour changes and reinforcing positive changes, we hope to be able to use this "feedback on our feedback" to improve the long-term effectiveness of feedback for maintaining energy-saving behaviour changes, within and across households.

IV. Conclusion

The IDEAL project is in the design phase, with pilot studies and recruitment planned in 2013 and the main studies in 2014-16. The project will accrue a uniquely large, detailed and temporally extensive dataset related to household energy demand in two representative areas of the UK (Milton Keynes and Edinburgh). This database, suitably anonymised, will be made available to the research community. It will be an invaluable resource that will offer opportunities in ICT (machine learning, intelligent agents, human computer interaction) and social science (sociology, sociotechnical systems, policy studies), including the possibility of reanalysing previously acquired datasets and enabling comparisons with similar studies in other countries. Many extensions will be possible–for example to study the creation of occupant-centred (vs. engineering-centred) domestic energy systems.

IDEAL contributes directly to a number of key societal challenges. Most prominently, various greenhouse gas targets for 2050 require significant reductions in projected residential energy demand. The project will deliver refined recommendations for methods to improve residential energy demand reduction through behaviour change. Demand reduction contributes to other sociotechnical energy-related challenges: replacing the current power-station fleet (less new generation capacity needed); improving energy security (by reducing imports); and addressing fuel-poverty (comfort with less). Residential demand reduction also contributes indirectly to future economic success. Energy efficiency (the energy intensity of GDP) will become a key indicator of sustainability; residential demand reduction contributes to this through feedback in the economy. If we demonstrate that substantial savings are achievable through behavioural feedback, this could be the stimulus for commercial offerings that provide such feedback to households, which would enable large-scale roll out of these interventions without taxpayer funds.

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