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Understanding usage patterns of electric kettle and energy saving potential

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HIGHLIGHTS

- Time-of-use analysis to motivate kettle usage and consumption prediction.
- Identification of households whose kettle usage and consumption is outside the norm.
- Mathematical model to estimate water volume from consumed power measurements only.
- Quantification of energy savings if a household uses its kettle more efficiently.
- Kettle usage and demand prediction using an Adaptive Neuro Fuzzy Inference System.

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ABSTRACT

The availability of smart metering and smart appliances enables detecting and characterising appliance use in a household, quantifying energy savings through efficient appliance use and predicting appliance-specific demand from load measurements is possible. With growing electric kettle ownership and usage, lack of any efficiency labelling guidelines for the kettle, slow technological progress in improving kettle efficiency relative to other domestic appliances, and current consumer attitudes, urgent investigation into consumer kettle usage patterns is warranted. From an efficiency point of view, little can be done about the kettle, which is more efficient than other methods of heating water such as the stove top kettle. However, since a majority households use the kettle inefficiently by overfilling, in order to meet energy targets, it is imperative to quantify inefficient usage and predict demand. For the purposes of scalability, we propose tools that depend only on load measurement data for quantifying and visualising kettle usage and energy consumption, assessing energy wastage through overfilling via our proposed electric kettle model, and predicting kettle-specific demand, from which we can estimate potential energy savings in a household and across a housing stock. This is demonstrated using data from a longitudinal study across a sample of 14 UK households for a two-year period.

1. Introduction

An electric kettle is an electrical appliance, that has a self-contained heating unit, for heating water, and automatically switches off when the water reaches boiling point or at a preset temperature below 100 °C. It is thus different to the stove top kettle, which is less energy efficient and takes longer to boil the same volume of water as the electric kettle. In the rest of this paper, we refer to the electric kettle as kettle only.

The kettle is one of the most used appliances in the United Kingdom (UK) as well as the appliance with the highest rates of ownership; according to UKs Department for Environment, Food and Rural Affairs 2006 report [1], 97% of UK households own a kettle. Kettle ownership, and consequently kettle load demand, is also growing worldwide. For example, in Libya, 42% of homes owned a kettle in 2013, compared to 8% five years ago, with an estimated annual energy use of 374 kW h per household [2].

In the UK, more than nine in ten people (90%) use the kettle every day, with 40% doing this five times a day or more. Thus, the kettle has become a key domestic consumer. The 2012 annual electricity consumption of the kettle in the UK was 4489 GW h, which is roughly 34% of the total consumption attributed to cooking [3]. Moreover, the electricity demand from the kettle is increas-

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ing (at the expense of electric ovens and hobs due to changes in cooking practices and increased oven efficiency) and according to [3] will surpass, in the UK, the annual consumption of 5000 GW h by 2030, contributing close to 40% of the overall cooking electricity demand.

Though, overall, a lower consumer when compared to the electric heater or washing machine, the kettle is one of the appliances that has the highest wattage and requires the highest current when switched on [4]. This is evidenced by high spikes, caused by kettle usage, in the otherwise low to medium demand profile of a typical household [5]. Due to the spiky nature of its demand, the kettle can significantly influence electricity generation and the power distribution network, mainly due to the so-called "TV pick-up effect" that manifests itself through significant and synchronised usage of appliances, such as kettles and microwaves, during TV programme breaks [6].

The kettle is also one of the most inefficiently used appliances. In a survey of 86,000 homes in the UK, by the Energy Saving Trust [7], it was found that three-quarters of British households admit to overfilling their kettle when boiling water and are subsequently wasting GBP68 million each year. Similarly, in Libya [2], over 50% claim to overfill their kettle. However, both these statistics are based on interviews, instead of measurements. While kettle usage is generally assumed to be very regular and non-random [4,8], to the best of our knowledge, there has been no in-depth study which analyses patterns of kettle consumption. This is probably because of the assumption that kettle usage is highly routinized, monitoring kettle usage requires consumer engagement, and that the kettle is not considered a candidate for flexible domestic electricity demand [3], and as such, not of high interest to demand response measures.

Nevertheless, a clear trend in increased kettle usage [2,3], lack of any efficiency labelling guidelines, slow technological progress in improving efficiency (relative to other cooking appliances), and current consumers attitudes (86% of people do not choose kettles based on their features, but on looks to match a kitchen design/already owned products (see [1] and references therein)), all call for urgent investigation into consumer behaviour patterns with respect to kettle usage and energy conservation measures.

In this paper, we test the above assumption of regularity in kettle usage, quantify the actual and predicted contribution of energy consumed by the kettle in a household, and propose a method to determine energy waste from load measurements only. This is supported by a longitudinal study comprising a sample of 14 UK houses, of different occupancy and age groups (e.g., retirees, working couples, families with children and single occupants), some energy conscious and others not. The timestamped kettle power consumption was collected via an appliance-level smart plug monitor that measures active power every 6–8 s [9]. See [10] for details about the field study.

The main challenge in assessing energy waste due to overfilling the kettle is measuring fill water volumes in a non-intrusive way, since it is impractical to measure and record water volume for every kettle use. This paper overcomes the above problem by measuring the individual kettle consumption (kW h) and estimating the water volume from this measurement using mathematical modelling. In particular, using measurements with different kettle types, a generic mathematical model is built that relates the water volume of a kettle, its consumed power and water temperature.

We demonstrate how power consumption information and time of use information, together with the proposed mathematical model, can reveal a household's behaviour in terms of water overboiling and energy wastage, and identify established routines and usage synchronicity across the monitored households.

Furthermore, we study short-term and long-term load forecasting [11], which is useful for energy feedback, load balancing [12], effective planning and power plant management [13], demand response [14,15] and renewable energy systems and energy storage design [16]. Since consumers directly interact with appliances, appliance-level load forecasting is particularly challenging [14] as it depends on human behaviour, which is often stochastic and unpredictable. Moreover, energy efficiency measures and utility programs affect forecasting which is often a challenge to account for [17]. Adopting the established Adaptive Neuro Fuzzy Inference System (ANFIS) [18] prediction tool, we show that kettle usage and energy consumption can accurately be predicted, short- and long-term. Using this knowledge, we show how we can predict potential annual energy savings per household and for an entire housing stock if energy saving measures were taken.

In summary, the key contributions of the paper are:

- Time-of-use analysis to understand patterns of use and its implications for accurately predicting kettle usage and consumption.
- A method for identifying households whose usage is outside the norm through understanding energy consumption patterns to support energy conservation measures.
- A mathematical model of the kettle that relates water fill levels, consumed power, and change in water temperature to estimate water volume from consumed power measurements only.
- Quantification of energy savings if households use their kettle more efficiently by quantifying overfilling and reboils.
- Kettle usage and demand prediction using an Adaptive Neuro Fuzzy Inference System, which is also used to estimate energy savings for the next year if current patterns of use are maintained.

The paper is organised as follows. First, we discuss related work in the literature in Section 2. In Section 3, we present our findings with respect to temporal and energy usage analysis. In order to quantify energy waste due to overfilling, we describe our proposed modelling approach for estimating water volume and the results of our energy waste analysis in Section 4. Finally, Section 5 describes our prediction of usage and energy consumption methodology and its application to estimating energy savings if households take on board energy conservation measures of not overfilling the kettle.

2. Literature review

In this section, we briefly review prior work. We group the relevant literature into three categories: (1) understanding usage of different domestic appliances; (2) energy usage of the kettle; (3) appliance-level load prediction. Interestingly, despite the fact that the kettle has a non-negligible influence on electricity demand, modelling and forecasting methods to understand and predict demand, as well as calculating energy-wasteful usage, have not been analysed in detail so far for this appliance.

Many empirical studies on consumer attitudes and interactions with energy-consuming appliances have been reported recently, tackling this issue from consumer study [19], human computer interaction (HCI) [20], and energy [21,22] angles. For example, targeting autonomous load shifting, in [21], novel generic probabilistic models for wet-appliance usage are proposed that account for variability of patterns in usage. In [19], based on a longitudinal study in 29 countries, individual user attitudes towards manual and automatic dishwashing is considered, with the conclusion that dishwashers save water considerably more, and providing cleaner dishes with respect to manual dishwashing.

In [20], interactions with domestic appliances are studied through a qualitative longitudinal field-work with a sample of 12 households and an online survey, concluding that consumer behaviour is not the result of motivated actions, but instead it is strongly shaped by external factors. Appliance-level energy-conserving interaction is analysed with terminology that includes cutting (powering off when not used or reducing the usage), trimming (using at a lower setting), switching (using a more energy-efficient device that has slightly different functionality), upgrading (getting a more-energy efficient appliance with the same functionality) and shifting (shifting the use to a different time or place) the load.

Earlier studies on kettle efficiency are led by energy charities or government where the emphasis is on assessing overboil, minimum water volumes, and daily/monthly/annual costs based on average estimates [7]. Indeed, a recent survey [23] conducted across 2616 households showed that the percentage of households who admit to overfill their kettle is similar to the percentage of households who leave their television and computer on standby for long, but is significantly higher than the percentage of households who forget to switch off light when they leave a room. Hence, it is imperative to understand patterns of use, determine a methodology for accurate assessment of energy savings customised to a household and address eco-friendly behaviour when it comes to the kettle.

Improving usage efficiency and designing eco-feedback [20] to reduce energy wastage when using the kettle is considered by the HCI community in [24,8,4]. In [24], the effects of using adaptive aversive and appetitive stimuli to change consumer behaviour is discussed. Specifically, when the consumers use the correct amount of water, they are rewarded with a virtual gold star. On the other hand, when they draw too much water, they receive a negative reinforcement message. The method has not been tested in the field. In [8], a kettle prototype is designed, dubbed stroppy kettle, with a goal of changing bad habits of overfilling the kettle. The main idea is to impose on the user a punishment task if he/she is over-filling the kettle. Similarly, recognising that synchronous use of kettle can have significant negative impact on the grid, in [4], a new kettle design is proposed with a goal of achieving load management [12,25] and providing users with immediate feedback. None of these designs have been tested in a longitudinal study.

We note that none of the above work is focused on capturing and analysing household's habits w.r.t kettle usage. An exception is [26], where kettle usage patterns in the context of assisted living of people with early dementia was studied. However, focused on activity recognition, the work in [26] only considers the number of kettle uses without relating the findings to energy conservation and eco-behaviour.

Prediction of energy use is crucial in achieving energy conservation. Many prediction methods have been studied in the past for forecasting total load in residential settings. For example, in [13], all load forecasting methods are grouped as engineering, statistical and artificial intelligence methods, where the latter namely Support Vector Machines (SVMs) and neural networks, are shown to be the most accurate methods, but more complex and slower than statistical methods. In [27], wavelet transform and ANFIS are combined to provide high accuracy hourly prediction of large scale power system load. In [15], a short-term, day-ahead, demand prediction method for non-flexible loads is developed using clustering. [28] looks at a number of prediction algorithms including ANFIS for regional load prediction on a yearly basis for regional load in Taiwan, concluding that ANFIS is the most effective of the models trialled. In [29], ANFIS is applied to predict residential aggregate load profiles.

Appliance load modelling for forecasting has been studied extensively. See, for example, [30,21,31,5] and references therein, where different probabilistic models are developed for multi-state appliances. In [30,5], a high resolution modelling approach is developed to capture operations of kettle and similar appliances that have short durations but high impact on distribution network due to extremely peaky (spiky) nature of their demand. A generic framework for load forecasting at appliance level was studied in [14] based on recognising key energy-consuming activities. However, no performance results are presented. In [17], the effect of energy efficiency programs on long-term appliance load forecasting for demand response is studied, mainly focusing on lighting. In [32,33], different machine learning-based and stochastic methods are developed and compared to predict if a particular appliance is going to be switched on or off in the near future. We note that none of the previous approaches estimates the modelling/forecasting accuracy when applied to the kettle, nor quantifies energy efficiency or savings associated with energy-efficient usage of the appliance.

3. Longitudinal study: analysis and visualisation of patterns of use

In this section, we test the common assumption that kettle usage is non-random and predictable (see, e.g., [4,8]) by studying a sample of 14 UK households, with different occupancy over a period of about 2 years. We use the appliance-level kettle monitoring active power measurements from the REFIT electrical measurements dataset [9], using the same House ID, e.g., House 1,2, etc., for reproducibility. More details about the study and data collection tools can be found in [10].

Additionally, we present tools for quantifying and visualising kettle usage and its energy consumption in one household and across households using only appliance-level power sensors or smart metre data at the aggregate level and applying non-intrusive appliance load monitoring or disaggregating from the total load [34]. The work presented here builds on our earlier work [35], which performs an initial analysis of kettle usage across a few houses without looking into seasonal usage and factors affecting usage.

This section presents time-of-use patterns of use and energy consumption trends, trying to identify distinct usage patterns, household routines and possibly synchronicity between households to set the stage for the later tasks of estimating inefficient behaviour and predict consumption due to the kettle.

3.1. Time of use

We first verify that, within a house, patterns of kettle use are maintained throughout the year, embedded as the households steady routines, where only the number of kettle uses differ during weekday/weekends. A kettle use is defined as the number of times the kettle load data changes from zero to non-zero, representing each time the kettle was switched. Duration, water volume and energy consumption are not quantified here.

Fig. 1 shows that across the year the seasonal effect on kettle usage is minimal, with a general pattern showing slightly increased usage during winter which agrees with work done in [36]. We observe, however, that increase in usage occurs during UK holiday periods July, August, December, and January, when occupants are at home for longer periods of time. This warrants a study of weekday/weekend patterns, when occupants have different routines due to working/school hours.

Fig. 2 shows the total usage for all 14 houses during October 2014, which is not a holiday period. Fig. 2a shows the trend across all households of significantly higher usage at 7am, 1pm and 5pm (lunch is generally taken at 1–2pm and 5pm signifies the end of the working day). Fig. 2b shows the general shift that can be seen during the weekend: uses are more prominent later in the morning,

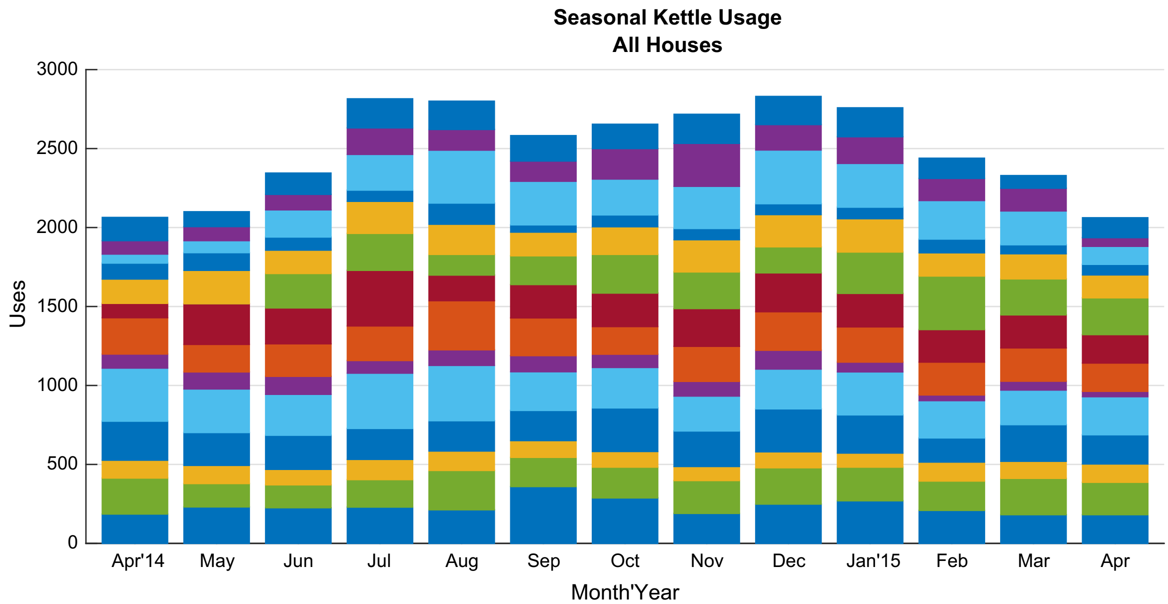


Fig. 1. Seasonal kettle usage for all 14 houses from April 2014 to April 2015. Each house is represented with a different colour. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

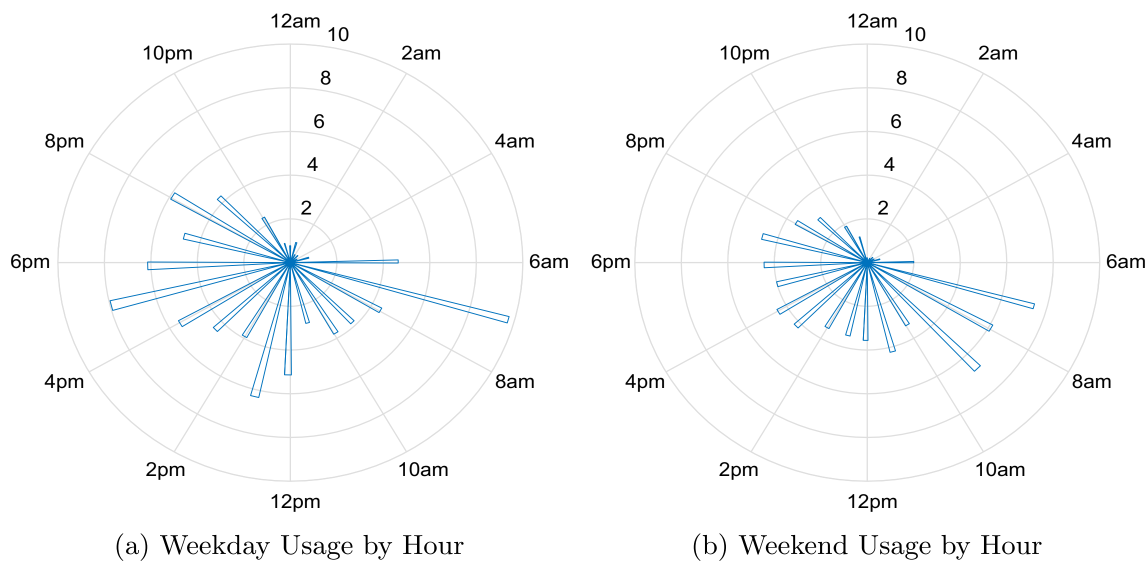


Fig. 2. Average daily usage of the kettle in October 2014 across all 14 houses, by hour.

and no significant peaks occur signifying more sporadic use of kettle, which, as will be shown in Section 5, affects prediction accuracy of kettle usage and consumption.

In Fig. 3 the houses in the study are grouped by their usage during the weekday: Those with high usage throughout the day (Houses 2, 5, 17, 19), those with low usage during work hours (Houses 7, 9, 12, 13, 20), and those which consist of retired or semi-retired occupants (Houses 3, 4, 6, 8, 11). Each group has a distinct pattern throughout the day. The houses in the high usage group all have at least one minor in the house, whereas those with low usage are less likely to have members below the age of 18. Retiree households have less of a distinct pattern with a morning peak later than those in working households and usage throughout the day. Additionally, the pattern of usage that continues late into the night for the group of retired households can be attributed to House 11, which has been discussed previously in [35].

3.2. Electricity consumption

While the number of uses explains patterns of use, it does not quantify how much energy each household consumes when using the kettle, nor identify variations in occupancy and energy waste due to overfilling the kettle. Table 1 shows the kettle consumption for each house over the month December 2014. It can be seen that consumption varies significantly even in households with a similar occupancy. kW h per use also varies indicating different levels of water in the kettle. For example, House 9, with close to 0.1 kW h per use (a relatively high value for a 2-person occupancy), requires a deeper investigation into their usage habits, to identify why they fill the kettle significantly more than other households with similar occupancy.

Fig. 4 shows the energy consumption of each household plotted against the number of times the kettle was switched on, i.e., the number of uses. The data is across all recorded months for each

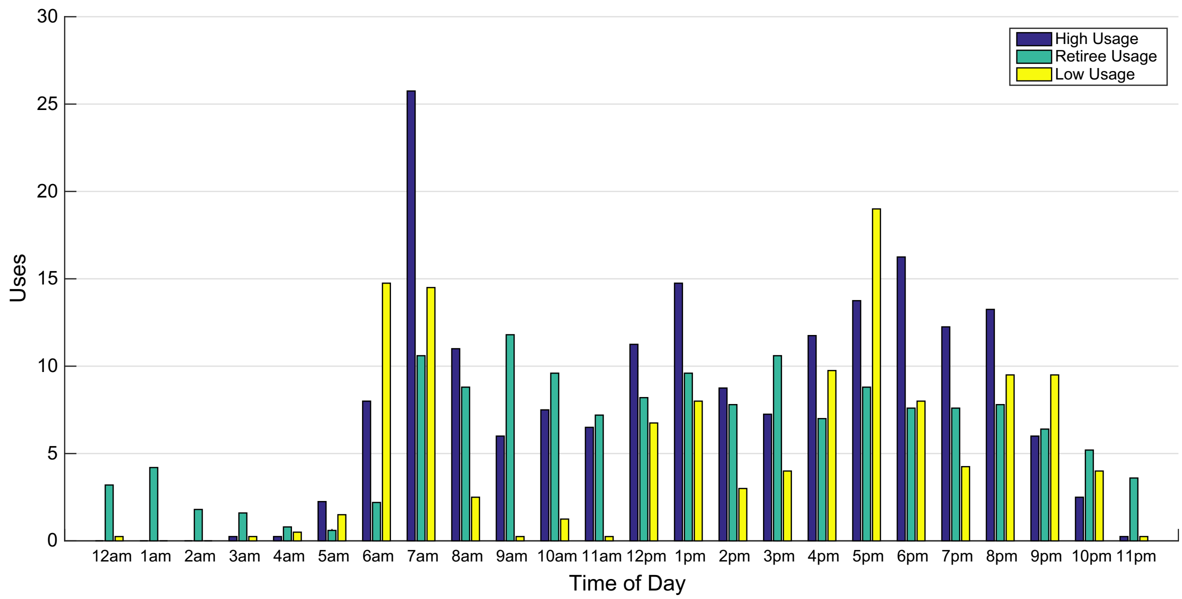


Fig. 3. Usage for all 14 houses grouped by occupancy type. The numbers present the average usage for October 2014 per house in the group.

Table 1
The number of occupants, total electrical consumption, and kettle electrical consumption for all 14 monitored houses. The data are given for December 2014.

House	Occupancy	Total kW h	Kettle kW h	Total monthly cost (GBP)	kW h per single kettle use	% of total energy consumption
2	4(2)	621.45	14.83	1.96	0.062	2
3	2SR	471.17	18.28	2.41	0.072	4
4	2R	270.59	6.87	0.90	0.068	3
5	4(2)	676.58	19.41	2.56	0.073	3
6	2SR	324.74	15.04	1.98	0.060	5
7	4(2)	514.88	8.69	1.14	0.075	2
8	2R	571.73	16.09	2.12	0.067	3
9	2	537.10	23.24	3.07	0.098	4
11	1R	152.51	12.02	1.58	0.072	8
12	3	305.78	19.07	2.52	0.097	6
13	4(2)	317.26	6.09	0.80	0.088	2
17	3(1)	324.57	21.01	2.77	0.062	6
19	4(2)	216.38	9.00	1.19	0.057	4
20	3	291.55	11.65	1.54	0.067	4

4(2) means there are 4 occupants including 2 minors. SR/R refers to (semi-(retired)) occupants. The consumption results are given for December 2014. Total monthly cost assumes 0.13GBP per 1 kW h.[a]

[a] Average tariff during field trial.

household. It can be seen that a clear linear trend is apparent (line of best fit $y = 0.0684x$), where 7 houses fall below this fitted line and 7 are above it. The houses that fall below the line of the best fit are prime candidates to help understand efficient kettle usage. On the other hand, House 9 far exceeds the mean consumption. With respect to the Energy Saving Trust's findings [7] we could expect 3–4 houses of the 14 not to overfill the kettle; it can be seen that, Houses 6, 17 and 19 appear to have kettle usage habits which do not excessively overfill.

A case study of a household that replaced their standard kettle with an eco-kettle during the recording period is described in Appendix A.

3.3. Findings summary

In this section, we confirm that while individual households have predictable patterns of use, there are weekday/weekend variations as well as seasonal variations, which we attribute primarily to holidays rather than weather changes. This findings are in accordance to [22], where it was shown that the usage of three user-dependent appliances (clothes washer/dryer and dishwasher) does not depend on the season but is not consistent over weekends and peak times and have more variations if there are occupants working from home. Secondly, we show various mechanisms by which kettle usage and energy consumption can be analysed and visualised, with a case study showing the impact of introducing an 'eco' kettle for the purpose of reducing energy consumption.

4. Energy waste estimation

While analysis of kettle usage and associated energy consumption can yield useful insights into patterns of use across a housing stock and over time, they do not reveal the amount of energy waste due to overfilling and re-boiling the kettle. In this section we describe the proposed mathematical modelling method used to estimate water volume based on measured consumed power, and then use the proposed model to estimate the amount of energy waste due to overfilling the kettle.

4.1. Mathematical modelling

The objectives of the proposed mathematical modelling are: (i) to determine whether there exists one generic model or equation that can estimate the water volume of a standard or smart kettle

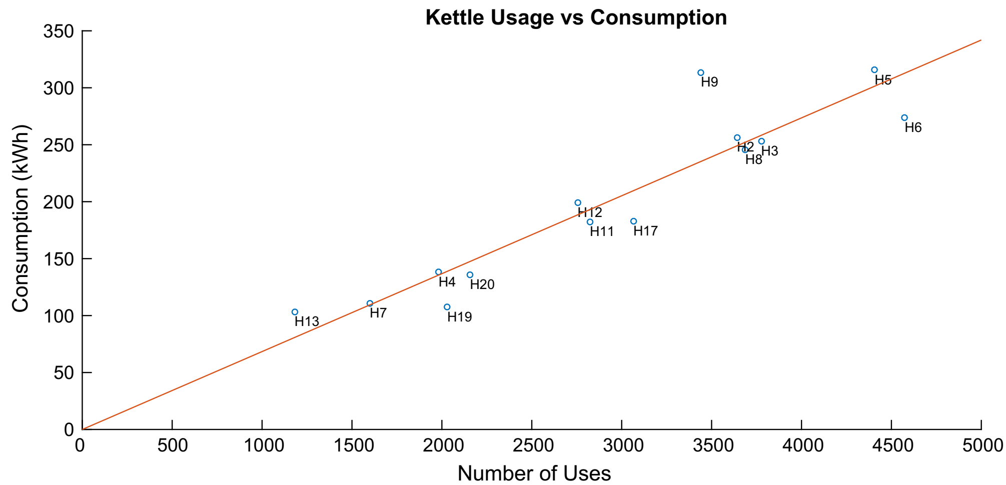


Fig. 4. Household consumption plotted against the number of kettle uses together with the fitted line.

using consumed power data only with high accuracy (a smart kettle would include additional heating temperatures 70–100 °C and/or a keep warm functionality), (ii) determine whether separate models for standard and smart kettles yield higher relative estimation accuracy, and (iii) assess its relative accuracy compared to the 'specific heat' physical model described in [37], where the kettle is treated as a classic heating element. The work presented here builds on [35] by producing a more robust model with more experiments, presenting a reproducible equation for the mathematical model and showing how this model can be used to assess energy waste in a housing stock.

The physical relationship between volume, temperature and consumed power for a heating element is given by [37]:

$$W = \frac{\alpha}{\beta * \Delta T}, \tag{1}$$

where W denotes water volume (represented in kg where 1 L = 1 kg), α is consumed power in kiloJoules (kJ), β is the specific heat capacity of water (= 4.19 kJ/kg °C) and ΔT the change in temperature after and before heating the water (in degrees Celsius). Density of the water is encapsulated in the value of specific heat [38]. We note that physical parameters such as heat capacity and density do not vary significantly for the temperature range of interest, i.e., from room temperature to boiling, and hence we do not consider these variations in the equation above.

Initial tests [35] with the physical model of (1) yielded large error during experimentation with the actual volume (see Table 2). This motivated the design of a more accurate mathematical model based on regression analysis [39] using experimental data, while still maintaining the objective of providing a scalable model that depends on load measurements, available non-intrusively and at little cost, and is fit for purpose.

Due to the simplicity of a kettle driven by a heating element, and our observation that the boil time is nearly linear with respect to the volume of water, we can reasonably assume a linear relationship between water volume and consumed power, taking starting temperature into account. That is:

$$W_{est} = a_0 + a_1 \Delta T_{meas} + a_2 P_{meas}, \tag{2}$$

where W_{est} is the water volume estimation, and ΔT_{meas} and P_{meas} are measured temperature difference and measured consumed power, respectively. ΔT_{meas} represents the difference in temperature after and before switching on the kettle, i.e., the difference between the temperature of the water in the kettle immediately before heating, and the temperature immediately after heating. The larger this difference, the more power will be consumed. Intuitively, lower volumes of water require less power to heat up than larger volumes. In practice, since we are proposing a scalable, non-intrusive model, ΔT_{meas} can be calculated as the difference between 100 °C and room temperature typical for the time measurements were taken. $a_i, i = 0, 1, 2$, are constants that need to be estimated to minimise the error between W_{est} and true, measured water volume W_{meas}, which is traditionally solved by linear regression.

Table 2
RMSE for the three kettle models and using Eq. (1).

	Linear interpolation	Polynomial	Locally weighted	Eq. (1)
Generic	120.79	94.79	147.67	173.24
Standard	217.32	53.69	153.85	136.75
Smart	74.40	72.64	133.78	203.28

Specifically, we tested three linear regression methods: standard polynomial method [40], locally weighted linear regression [40] (a 'memory-based' method that performs a regression around a point of prediction using only training data that are 'local' to that point), and the simplest linear interpolation method.

We performed experiments using four non-faulty kettles, namely 2 standard kettles and 2 smart kettles, measuring the following parameters: consumed power in [kW h], water volume, starting water temperature, finishing water temperature (⩽100 °C). A standard kettle is defined as a kettle that boils water to 100 °C with no additional 'boil' temperatures and no 'keep warm' or additional functionalities, unlike a smart kettle which allows water to be heated to temperatures less than 100 °C.

280 experiments were carried out, 140 with standard kettles and 140 with smart kettles. 5/7 of the data was used for training the model and the remaining 2/7 used for validation of the model. As a result, three kettle models were developed using surface fitting with the data obtained from the experiments, namely: (1) generic kettle model that combines smart kettle and standard kettle measurements, (2) standard kettle model, built with standard kettle data only, (3) smart kettle model, built with smart kettle data only.

The accuracy of the models is assessed by the root-mean square error (RMSE) given by:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(W_{est}^{i} - W_{meas}^{i})^2}{N}}, \tag{3}$$

where W^i_{est}, W^i_{meas} are i-th estimated water volume and measured in the testing dataset and N is the number of measurements in the testing dataset. The results for $N = 80$ for the generic model and physical model in (1) and $N = 40$ for the standard and smart kettle models are shown in Table 2.

Note from the table that the RMSE of Eq. (1) [37] is consistently larger than all other linear models evaluated. The polynomial linear interpolation method provides the lowest RMSE. As expected, the general kettle model performs worse than the bespoke standard and smart kettle models. Thus, the generic model should be used only if estimating the water volume of a kettle, whose type is unknown. This can happen if the type of kettle is unspecified during an appliance survey.

The resulting mathematical relationship using the best-performing polynomial linear method is defined as:

$$W(L) = a_0 - a_1 \Delta T + a_2 P_{meas}, \tag{4}$$

where the value of the coefficients a_0, a_1 and a_2 are shown in Table 3.

Table 3
Kettle model coefficients for (4).

	Generic	Standard	Smart
a_0	1.025	1.244	0.905
a_1	0.01595	0.02209	0.01401
a_2	12.34	14.54	11.82

4.2. Estimating energy wasted due to overfilling and reboiling

Equipped with the above model, we can estimate the amount of wasted energy due to overfilling the kettle using only the collected consumed power measurements, P_{meas}. Since, during the field trial, all households, apart from House 3, as discussed in Appendix A, were using standard kettles, the standard kettle model (4) is used to quantify waste due to overfilling.

First, we use kernel density estimation [41] to help better visualise the water filling patterns of the households. Kernel density estimation[1] is a non-parametric way to estimate probability density function of a random variable, and therefore does not assume an underlying distribution. It helps to visualise a higher number of uses for a particular value(s) of the random variable by creating a bump (s). Fig. 5 shows our results for five houses where the random variables are energy consumption and water volume estimated in the kettle per use. The negative volume scale represents re-boils, i.e., when the occupant uses the kettle before the water has cooled to room temperature. This is determined when a kettle use happens within 2 min of a previous use or its water volume is expected at less than 200 ml.

Obviously, different households have different preferred levels of water per boil, and consequently, consume differently per single kettle use. Houses 6 and 19 have a similar water-filling pattern: a very narrow boil range between 0.05–0.075 kW h; House 19 has a higher percentage of re-boils (hence, the second 0.025 kW h peak). The other end of the spectrum is House 12, peaking at more than 0.1 kW h with a wide bell curve on each side. This suggests that this house is the least efficient house in the survey group. House 9 has two peaks of relative magnitude, 0.05–0.075 kW h and 0.125 kW h, respectively. This wide range of consumption per usage suggests that the kettle is filled with little thought as to the purpose. House 5 is between the two extremes – no significant peak, but drops after 0.1 kW h at an equivalent rate to Houses 6 and 19, suggesting a slightly more economical usage with comparison to Houses 9 and 12.

It can be seen from Fig. 5b that House 6, which has been shown in the previous section to be an economical kettle user, has the lowest number of uses where the water level has been above 1 L and the usage peaks at just under 0.5 L. Similarly, House 9 has been shown to be one of the less economical users (see Table 1): Two distinct peaks are visible, one at −500 and 1250 with a slow tail off. House 19 which has the highest reboil peak, with 37% of all recorded uses estimated as re-boils consuming 15.14 kW h. House 12 which has a much larger number of uses has the lowest peak where 22% of uses are re-boils accounting for 10.77 kW h of consumption.

From Fig. 5, we can estimate how much energy could be saved assuming that the household cuts down on overfilling their kettle, as well as re-boils and assume a minimum of 500 mL (many kettles minimum fill), 275 mL per adult occupant for each household and 138 mL for each minor in the house. As an example, for House 9 which has 2 adult occupants, working from the assumption that a usage is minimum 500 mL, for two people ideal water volume will be 550 mL. Over the entire study period, House 9 had a recorded 3441 uses of which 1497 were above 1000 mL. This accounts for a consumption of 220.45 kW h of a total 313.48 kW h. The average kW h cost for 525–575 mL is 0.08 kW h. If all of the uses above 550 mL were reduced to 550 mL a saving of 102.13 kW h could have been made over the 18 months monitored for House 9, or 68.09 kW h per year. Similarly, House 12 which has 3 occupants should fill kettle to around 825 mL. House 12 has 2755 recorded usages with 907 of those usages being greater than 825 mL. This accounts for 113.97 kW h of a total 199.18 kW h recorded over the study period. Reducing these overboils to the maximum 825 mL could result in an annual saving of around 17.45 kW h.

The results for all 14 houses are summarised in Table 4, where estimated annual savings that could be obtained via more economical usage habits are up to 92 kW h per household. While the consumption difference may be insignificant to an individual household, it is significant for the whole housing stock, with clear impact on electrical demand and regional carbon footprint. Indeed the total consumption of the housing stock in our modest sample study adds up to 2181 kW h, which is not insignificant.

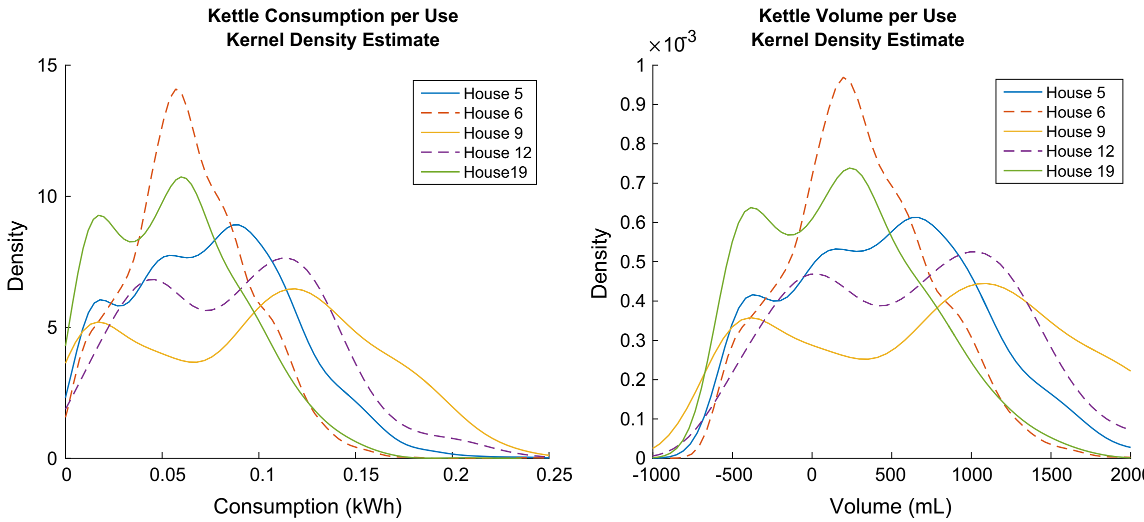
5. Demand prediction

As shown in Section 3, kettle usage patterns are part of established domestic daily routines (e.g., a high likeliness of usage early in the morning), and hence it is natural to assume that they can be accurately analytically predicted. In this section we present our findings on kettle use and energy demand predictability. We note that predicting kettle demand, to the best of our knowledge, has not been studied before.

By predicting kettle demand, one can quantify the amount of energy that could be saved (annually or monthly) if usage patterns change, for example, if the kettle is not overfilled. Moreover, appliance demand prediction is useful in time-use studies to understand routines and practices in the home.

To predict usage patterns we look at two different variables, namely energy consumption and uses. We adopt adaptive network-based fuzzy inference systems (ANFIS), which is well established for demand prediction and particularly suitable to this problem since, as has been shown previously, kettle data tend not to have a large variance, e.g., uses across any given hour will not vary greatly per household regardless of current day or month.

[1] A kernel is a type of probability density function which must be even.



(a) Energy consumption per use (b) Water volume per use

Fig. 5. Kernel density estimation of kettle consumption and water volume per use for five houses. The negative volume scale represents re-boils.

Table 4
Potential energy savings if householders did not overfill their kettle.

House	Occupants	Kettle consumption (kW h)	Household reduced fill volume (mL)	Consumption above volume (kW h)	Savings per year (kW h)	Savings per year (GBP)
2	4(2)	210.10	825	115.07	21.66	2.98
3	2SR	170.07	550	126.31	41.22	5.67
4	2R	95.88	550	59.55	10.97	1.51
5	4(2)	199.21	825	100.45	19.85	2.73
6	2SR	207.27	550	110.51	24.86	3.42
7	4(2)	72.84	825	31.65	6.56	0.90
8	2R	184.99	550	145.44	36.67	5.04
9	2	248.42	550	215.81	92.22	12.68
11	1R	157.58	500	98.44	30.83	4.24
12	3	162.60	825	93.63	21.33	2.93
13	4(2)	90.73	825	61.71	10.19	1.40
17	3(1)	166.49	550	107.97	26.00	3.58
19	4(2)	95.07	825	29.68	4.57	0.63
20	3	120.19	825	19.06	2.38	0.33

5.1. ANFIS demand prediction methodology

ANFIS is a type of artificial neural network that is based on the Takagi–Sugeno fuzzy inference system [18], suitable for time-series prediction. In our system we first use Fuzzy C-Means Clustering (FCM) [42] to extract rules from the input data. Once FCM has generated a fuzzy inference systems (FIS) structure [18], it is then trained for 20 epochs or until no further improvements can be made adjusting the initial rules.

In particular, to predict the consumption or usage in the next hour $(t+1)$ the FIS structure was generated using the following parameters:

$$[weekday(t), \quad x(t-24), \quad x(t-23), \quad x(t-22), \quad x(t-2)]$$

where x is a vector of the consumption(uses) in kW h/uses at time t [in hours], e.g., $x(t-24)$ is the consumption(uses) during the hour which is 24 h before to the current hour. $weekday(t)$ is the current weekday where Sunday is 1 and Saturday is 7.

These variables were chosen by using a sequential search method to find which $x(t-n)$ lend the most weight to prediction. As with any prediction method, ANFIS is limited by the quality of the historical data provided. Additionally, consumption prediction is affected by variation in water fill level, meaning that significantly higher usage in the month prior, e.g., holiday month, will result in an over prediction. Usage prediction is greatly affected by reboils and as such when they are included as input data cause over prediction; thus, since the consumption effect of reboils is small, they are not considered as a use for prediction.

5.2. ANFIS accuracy

Energy consumption prediction as the combined hourly predictions for each month over the yearly period for House 20 is shown in Fig. 6. A good agreement with the true consumption can be observed from the graph. The most significant error is in May, due to a sudden jump in consumption w.r.t the previous month.

Table 5 shows the results for all houses expressed by RMSE. RMSE is calculated between true consumption values [kW h] and predicted. A lower RMSE will show a more predictable pattern of usage while higher RMSE will show more erratic patterns of use.

It can be seen from the table that for most houses annual consumed energy prediction error is in the 2–3 kW h range. The exception is House 13 which shows a considerable error; this is explained by their considerably higher than usual usage during the months of Sept'14 and Feb'15.

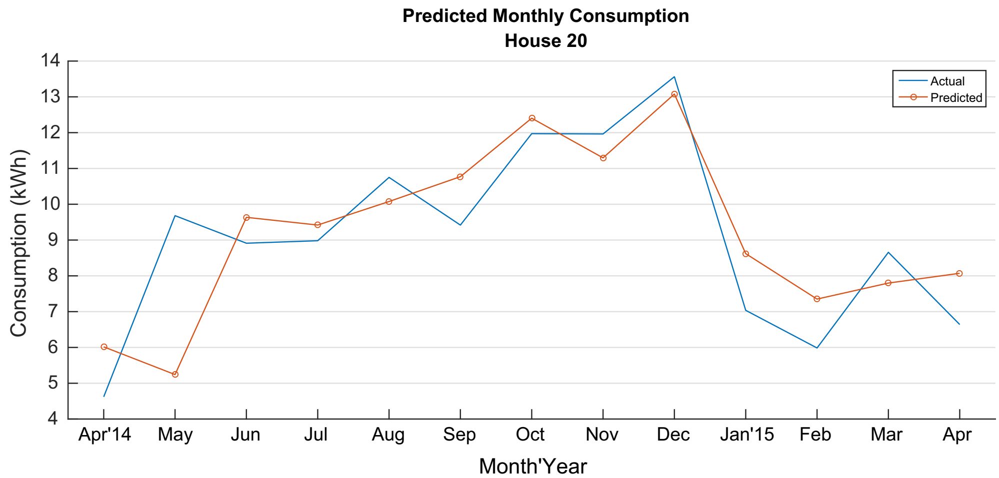


Fig. 6. Predicted kettle consumption, predicted hourly and summed.

Table 5
RMSE of hourly prediction summed over 12 months.

House	2	3	4	5	6	7	8	9	11	12	13	17	19	20
Hourly energy consumption	3.51	3.33	1.79	3.98	2.85	1.79	2.13	2.46	2.21	2.09	12.38	3.46	2.02	1.58

5.3. Cost saving estimation

Using the proposed ANFIS method we can estimate possible savings that could be made if kettle usage is adjusted to the recommended level defined in Table 4. To do this, we first predict the number of uses of kettle and multiply that by the power usage calculated via Eq. (4) for recommended water levels for the given occupancy (Table 4). This is compared with the energy consumption if the kettle use behaviour remains unchanged (that is, the household continues to use the same water levels). The difference between these values is then the estimated savings that could be made assuming that every kettle usage is filled to the recommended level.

Fig. 7 shows results for House 9, which was identified before as the least economical kettle. The results for the other houses in the study are shown Table 6.

In Table 6 predicted savings in kW h can be seen for the period April 2014–April 2015. House 20 can be seen to have a negative value associated with the saving. This can be explained by reference to House 20's economical usage habits. Indeed, House 20 must have many boils under their ideal fill level of 0.825L that assumes that all boils are for three people. Furthermore, across all households, the overall savings add up to a significant 548 kW h, which averages to 40 kW h per house.

6. Conclusion

This paper presents scalable tools for predicting and quantifying energy consumption due to the kettle and inefficient use due to overboiling using only widely available smart metre data. This is enabled by our proposed mathematical model that estimates water

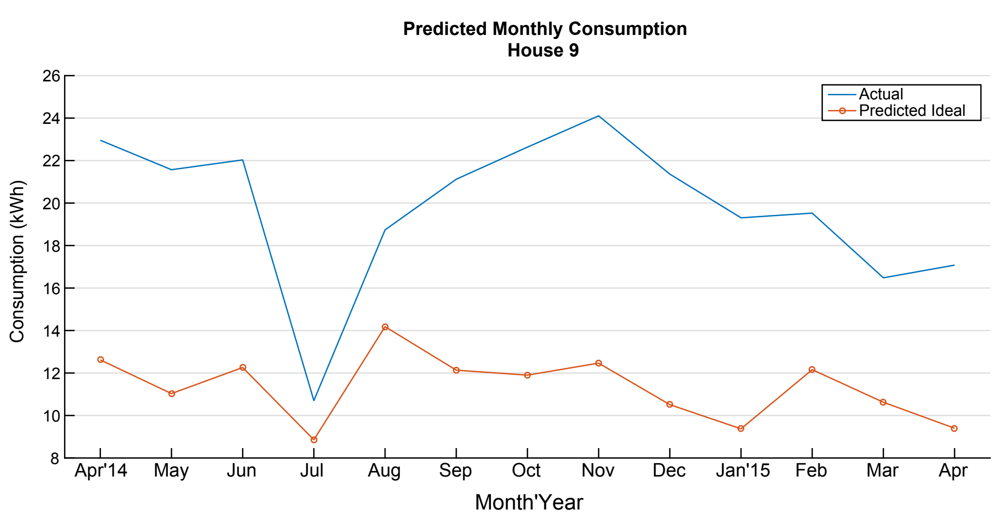


Fig. 7. Predicted consumption without overfilling for House 9.

Table 6
Yearly predicted savings for the period April 2014–April 2015.

House	2	3	4	5	6	7	8	9	11	12	13	17	19	20
Predicted savings (kW h)	8.92	62.9	10.34	6.71	33.56	16.60	54.74	108.00	1.47	18.30	71.02	130.27	45.84	−20.26
Predicted savings (GBP)	1.23	8.66	1.42	0.92	4.61	2.28	7.53	14.85	0.20	2.52	9.77	17.91	6.30	−2.79

fill levels of the kettle from the consumed power measurements. The proposed methods are based on regression analysis and ANFIS-based demand prediction.

Time of use analysis confirms well-defined patterns of use with respect to weekdays during standard "office hours", pattern variation depending on type of occupancy and general daily schedule, holiday periods and minor seasonal variation. Specifically, our analysis shows 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 studies, that a significant percentage of households do overfill their kettle. Another factor is reheating water soon after it has boiled. In these cases households that appear not to overfill, based on the number of occupants, waste energy on reheating or reboiling.

We demonstrate that due to well-defined patterns of use, it is possible to accurately predict kettle usage at a large scale using only smart metre readings, which could be of interest to network operators since synchronous kettle usage can have negative effects on the grid. An additional application of our proposed tools is to predict energy savings if water filling patterns change through, for example, more efficient behaviour of filling to ideal levels. The methods can also be used to enrich customer energy feedback and provide retrofit advice; an example is shown in Appendix A, where detailed feedback is provided to a householder to quantify energy savings incurred when they replaced their standard kettle with an 'eco' kettle.

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Appendix A. Effect of substituting an 'eco' kettle for a standard kettle

House 3 introduced a vacuum(eco) kettle as an energy saving measure during our study (Winter 2013 - Spring 2015). The vacuum kettle keeps water hot for longer, thus potentially reducing the number of uses. We can therefore look at their usage before and after the change to show the effect of usage and energy consumption of this new kettle.

The total uses per hour between the standard and vacuum kettle for the same household can be seen in Fig. 8. The standard kettle usage was much higher at 7am compared to the vacuum kettle. This can be attributed to the fact the vacuum kettle will be used once with a large amount of water and retain that heat throughout the hour. This pattern can also be seen at 3 pm in 2013 when there were uses in the following two hours. In 2014, the following two

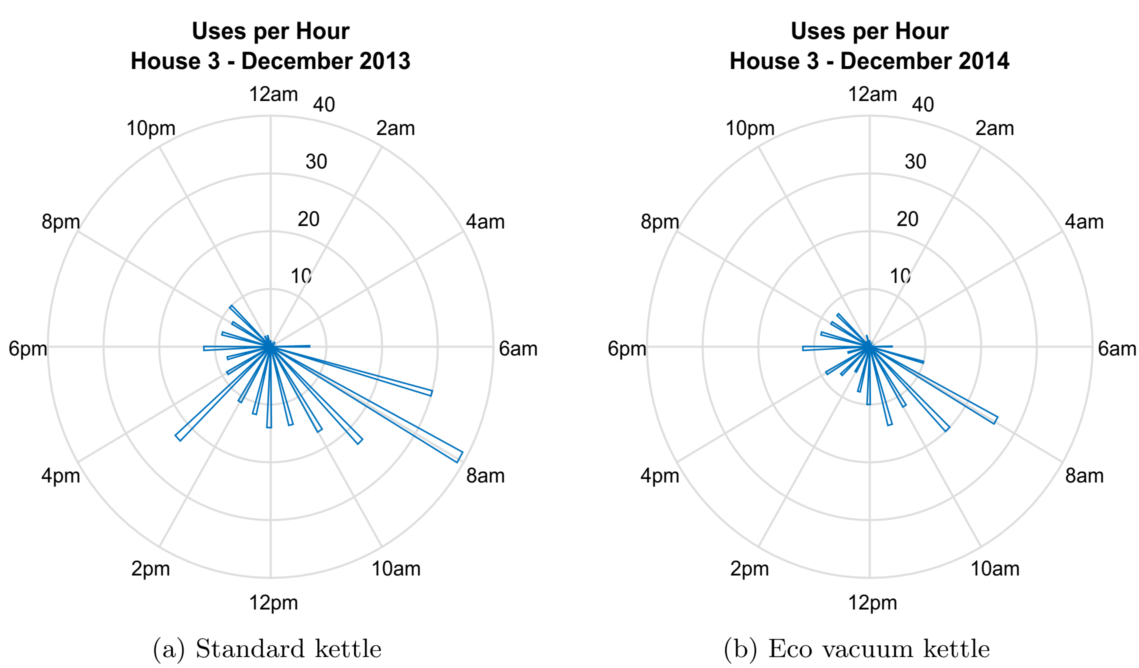

Fig. 8. Standard and eco kettle usage in House 3 over the month of December 2013 and 2014, respectively.

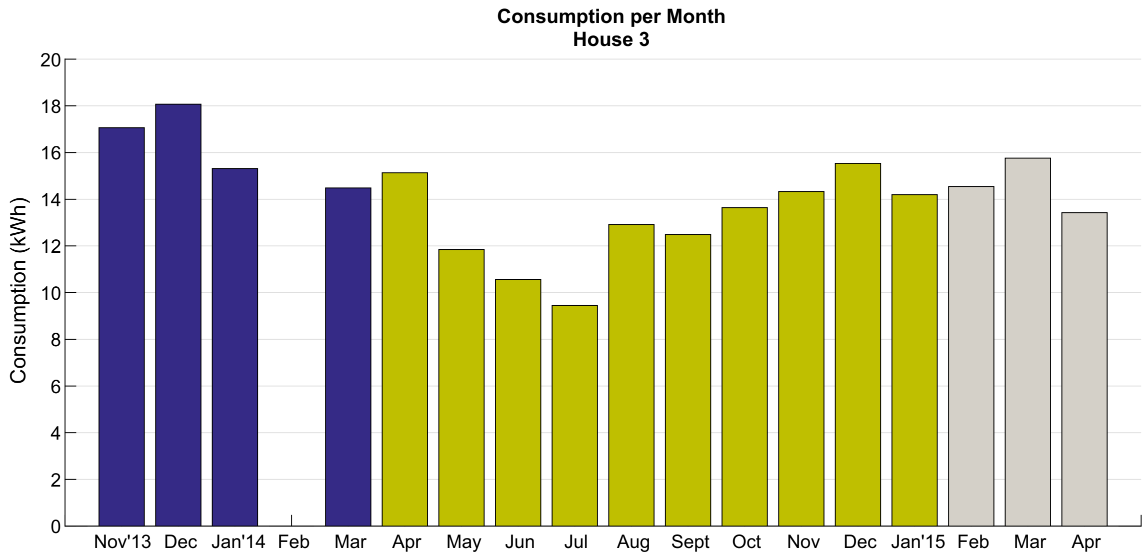

Fig. 9. Consumption due to kettle in House 3. Note, no data was available in Feb'13.

Table 7
Kettle usage and consumption in House 3 in December 2013 (using standard kettle) and December 2014 (using eco kettle).

Year	Uses	Consumption (megajoules)	kW h	Cost (13.52p/kW h)
2013December [standard]	241	63	17.57	2.38
2014December [eco]	199	45	12.52	1.69

hours have significantly less usage; the hour immediately after has a much smaller, and the following hour slightly more, possibly attributed to reheats where the water is not considered hot enough for the drink being prepared.

Fig. 9 shows the trend in relative energy consumption before the vacuum kettle was introduced in April 2014, while the vacuum kettle was used and after the vacuum kettle was removed in late January 2015. Consumption was lower in the period when vacuum kettle was used.

Table 7 shows that the eco-kettle has significantly fewer number of uses and therefore the associated cost has been reduced by close to GBP0.70 in the comparative months of December. Thus, the potential for annual savings by replacing a standard kettle with a vacuum kettle is around GBP8.00. This represents close to a 50% saving if we assume 1542 kettle uses per year, with an assumption of 0.11 kW h per use based on heating 1 L of water, resulting in a cost of GBP16.90.[2] The initial cost of the eco kettle, however, is around GBP80, therefore there is a significant period of time before the kettle will be cost effective.

Feedback: The residents of House 3 were provided with the above visual feedback, along with textual explanation of the findings. A survey was completed prior to feedback to assess the residents thoughts. The survey revealed a number of traits about the household. The residents 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.

As shown above, this can be seen in the comparisons made, in both usage and water consumption which led to a more economical usage style. They also made a note of the fact that they tried to avoid re-heating water and this is backed by the fact that only 7% of their kettle usage is within a 5-min window of a previous usage. The household stopped using this vacuum kettle due to a fault, which once fixed, never made it back into daily usage. Interestingly, this was not due to any effects on performance, but due to the noise the kettle made, which was annoying to the occupants. The feedback, however, was well received and the residents believed that this would be of benefit, and expressed that a monthly breakdown of appliance usage is beneficial toward supporting their efforts towards being eco-friendly.

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