Trading Appliance Liveness for Home Electricity Consumption Privacy

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Abstract. Homes have been equipped with smart meters in recent years to automate the monitoring of energy usage to facilitate better scheduling of electricity generation and offer better billing of customers. This has increased the time resolution of energy consumption, which leads to privacy threats such as occupancy monitoring, pattern of live analysis, and device identification. Much work has been performed on using energy storage and renewable generation to obfuscate observations made via a smart meter. In this paper, we consider how appliance liveness can be traded-off to reduce behavioural distinguishability. We identify that liveness can be traded-off by undertaking an analysis of the REFIT smart home dataset and transforming the energy consumption of each day using a mixed integer programming model to and investigate all 512 combinations of liveness constraints of 9 appliances. The Pareto frontier is found for each subset of combinations where a single appliance must be live in order to demonstrate the trade-offs that occupants would need to make in order to reduce behavioural distinguishability. We identify that while it is possible to trade-off liveness for privacy, appliances which have a high usage in a day can limit the ability to reduce behavioural distinguishability. We also find a strong positive correlation between energy consumption and behavioural distinguishability, where reducing behavioural distinguishability leads to a reduction in energy consumption. This analysis helps identify which appliance categories have the greatest influence on behavioural distinguishability and highlights the trade-offs between appliance liveness and observability in smart meter data.

Keywords: Smart home energy privacy · optimisation · liveness constraints

1 Introduction

Smart meters are being widely deployed to enable detailed energy consumption monitoring with benefits to both home occupants and utility providers [7]. However, this information introduces privacy risks, as energy consumption can enable pattern of life analysis [2] and device identification due to the high time resolution of the data provided to energy suppliers [16]. To address this privacy threat, past work has explored countermeasures such as rechargeable batteries to smooth energy consumption [6,15], renewable generation to reduce the energy consumed via a smart meter [15], and demand-side management via scheduling appliance use [17] to obscure the true consumption of a home.

A commonly used strategy for finding a privacy-preserving transformation of power consumption is to use optimisation techniques such as linear programming to produce a modified energy profile that satisfies various constraints [9]. However, little attention has been given to the role of appliance liveness, that is, whether occupants should be directed to not use an appliance during certain time periods. This paper presents a retrospective analysis of real-world power consumption data [10]. We use an optimisation model to transform the half-hourly energy consumption of a day and investigate how appliance liveness influences the distinguishability of household behaviour from expected energy usage patterns. Rather than proposing a deployable scheduling system, the goal of this work is to explore the relationship between appliance liveness and behavioural distinguishability in smart meter observations, with the aim to answer the question of whether liveness (i.e., the ability for an appliance to be used at any time) can be traded-off to reduce behavioural distinguishability in energy measurement data.

The main contributions of this paper are:

- We perform a retrospective analysis of a real-world smart home dataset by transforming each day under all 512 appliance-liveness configurations.
- We investigate how appliance liveness influences behavioural distinguishability and energy consumption.
- We identify appliances that have a stronger influence on behavioural distinguishability when their activity is preserved during optimisation.

In this work, behavioural distinguishability is used as a proxy measure rather than a direct measure of privacy leakage. The objective is to understand how appliance liveness influences observable household behaviour in smart meter data. We therefore present the results as an exploratory retrospective analysis and discuss the limitations of this interpretation later in the paper. The rest of this paper is structured as follows. Section 2 reviews existing research on smart home energy privacy. Section 3 presents our methodology on dataset preparation and the formulation of the optimisation problem, the results of which are presented in Section 4, we discuss considerations of this work in Section 5, and we conclude in Section 6.

2 Related work

To provide energy privacy, optimisation algorithms have been used to shape energy use. For example, evolutionary optimisation methods have been used to improve the efficiency of device operation in Home Energy Management Systems [17]. Other work explores day-ahead optimisation to coordinate both programmable and non-programmable appliances, sometimes together with solar generation [11]. Multi-objective scheduling approaches such as peak-to-average ratio minimisation show that algorithmic control can improve energy efficiency by up to 7.25% [9]. Typically, these approaches focus on load shifting, bill reduction, and maintaining user comfort.

Privacy-aware scheduling has also received considerable attention in smart home energy management. Previous studies have shown that appliance scheduling can be used not only to reduce cost but also to reduce the amount of information revealed through smart meter observations. Li et al. [8] proposed a privacy-aware scheduling framework that jointly considers privacy and energy cost while accounting for both schedulable and non-schedulable appliances. Similarly, Chin et al. [3] investigated the use of flexible thermal loads, such as water heaters and space heaters, to reduce information leakage from smart meter data. Their results showed that flexible loads can provide privacy benefits without requiring dedicated energy storage, although the achievable protection depends on appliance constraints and occupant comfort requirements.

Several studies have also investigated privacy using information-theoretic measures. Sankar et al. [13] proposed a theoretical framework for analysing smart meter privacy using information leakage metrics. Other work has examined privacy-cost trade-offs through demand shaping and energy management approaches [14]. These studies demonstrate that appliance flexibility, scheduling decisions, and energy management strategies can influence the information revealed through smart meter observations.

These solutions may also use rechargeable batteries, renewable generation, or energy harvesting devices to reshape the load observed by a smart meter and reduce behavioural distinguishability [15]. Although these approaches can provide some protection, they come with purchase, installation, and maintenance costs. In addition, they often require additional hardware and infrastructure changes before deployment.

Privacy risks related to smart meters and non-intrusive appliance load monitoring are already well known. Previous studies show that appliance usage patterns can be inferred even from aggregated electricity measurements [7]. Other work also highlights the risk of over-sensing in domestic environments [2]. The results show that fine-grained energy data can reveal sensitive behavioural information. Despite this, most proposed solutions treat user behaviour as fixed and mainly focus on masking or hiding the observed energy traces.

Behaviour change has also been studied from an energy reduction perspective [5]. Previous work has explored appliance scheduling, flexible loads, energy storage, and demand shaping to reduce information leakage. However, most approaches focus on modifying energy consumption patterns while assuming that appliance availability remains unchanged. In contrast, this work investigates appliance liveness as the primary variable of interest. Rather than scheduling appliances to meet a particular objective, we study how keeping specific appliances live or allowing them to become non-live affects behavioural distinguishability and energy consumption. This provides a different perspective on privacy man-

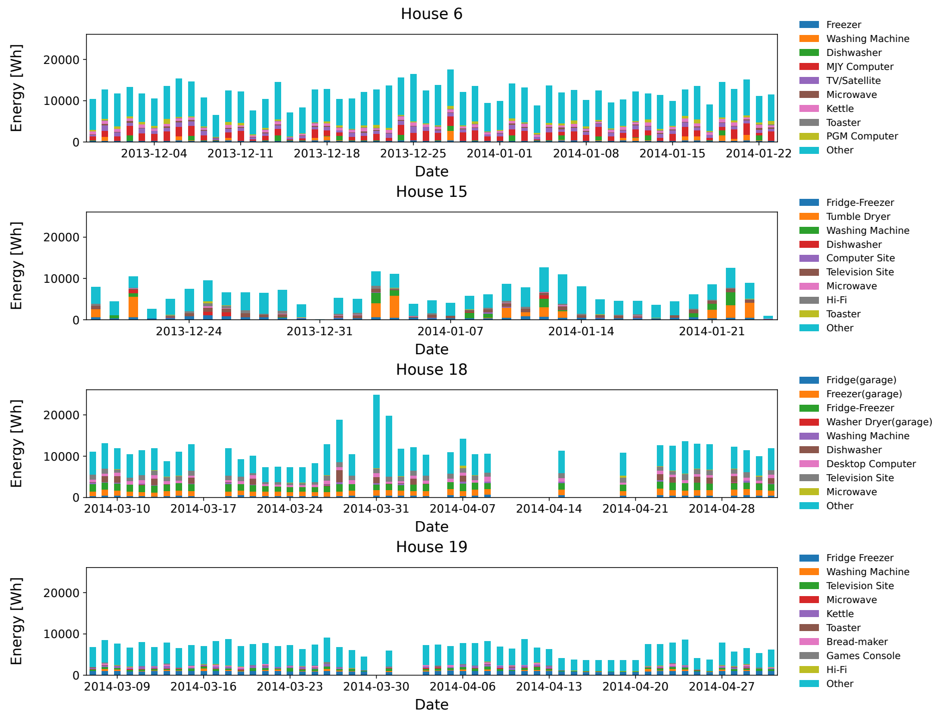

Fig. 1. Summary of energy consumption of investigated homes over a 55 day period

agement in smart homes and allows privacy-liveness trade-offs to be explored through a retrospective analysis of real-world energy data.

3 Methodology

In this work we wish to identify to what extent users can trade-off appliance liveness for greater privacy in the smart home. To do this we use real-world observations from the REFIT Smart Home Dataset [10] which includes energy consumption from appliances or groups of appliances in 20 UK homes between 2013 and 2015. This section describes how we use an optimisation algorithm to transform each day's energy consumption in each house to: (1) minimise the behavioural distinguishability, and (2) ensure the liveness of a subset of the appliances in the home. This is repeated for all combinations in the powerset of the appliances.

3.1 Dataset and Preprocessing

The REFIT Smart Home Dataset was selected due to its high-resolution appliance-level measurements and its widespread use in energy disaggregation and smart home studies. The dataset records power consumption at 8-second intervals [10] for nine appliances. These nine appliances are different in each home.

As a real-world dataset, there was inevitably some aspects of the data which meant that the data was unsuitable for our purposes, or needed additional cleaning. This lack of suitability falls into four categories:

1. Appliances were changed part-way through data gathering, making the maximum energy consumption unreliable (excluded: 1, 4, 5, 7, 8, 10, 17),
2. the homes themselves made use of renewable energy which impact what observations an adversary is capable of making leading to inaccurate behavioural distinguishability quantifications (excluded: 11, 21),
3. appliances were unknown or unused (excluded: 12), and
4. our data cleaning eliminated measurements of more than 30 consecutive days (excluded: 2, 3, 9, 16).

This leaves houses 6, 15, 18, and 19 over which the analysis will be performed. The energy consumption for these houses is summarised in Figure 1. Although this reduced the number of eligible houses, these exclusions were necessary to ensure that appliance-level observations remained consistent and comparable across all analysed households. This allows the optimisation results from different houses to be compared under the same assumptions and data quality requirements. Additional processing of the dataset was also required. The dataset measured appliance power consumption, this was converted to energy consumption by integrating over time. Sensor measurements are intended to be 8 seconds apart [10], however, we observed many measurements both less than and greater than 8 seconds. Any time between measurements greater than 60 seconds was clamped to 60 seconds when converting power readings into energy consumption. This prevents large gaps between measurements leading to high energy usage for a short time period. Houses containing extended periods of missing data were excluded from the analysis because these gaps could affect the calculation of daily energy consumption patterns. Measurements were aggregated into half-hourly intervals to reflect the sampling granularity typically available to smart meters [12]. Additionally, any day was excluded if (1) it was incomplete or (2) the aggregate energy consumption was less than the sum of the 9 appliances in any half-hour interval.

3.2 Formulation of Optimisation Problem

An optimisation model was implemented using GEKKO [1] which can solve linear integer programming problems and also implements certain non-linear functions. The optimisation algorithm takes a single day's activity in a single home in the REFIT dataset and transforms the activity of that day. The decision variable is $\mathrm{OPT}_{t,a}$, which represents the energy consumption for appliance a during the time-period t of that home and day. Each time period is 30 minutes long. This optimisation is repeated for all homes and all combinations in the powerset of appliances $\mathbb{P}(A)$ in that home for which liveness of those appliances is enforced. By doing so, this allows the liveness-privacy trade-offs to be explored.

Table 1. Notations used

Symbol	Description
P	behavioural distinguishability (difference between current day and the average day).
T	Set of 30-minute time windows; $T = \{\,00{:}00, 00{:}30, 01{:}00, \ldots, 23{:}00, 23{:}30\,\}$.
A	Set of appliances; $\|A\| = 9$ for every home.
$\mathbb{P}(A)$	The powerset of all appliances. $\|\mathbb{P}(A)\| = 2^{\|A\|} = 2^9 = 512$.
$L \in \mathbb{P}(A)$	A set of appliances that needs to be kept live.
D	The set of days.
$\mathrm{CUR}_{t,a}$	Current day energy use of appliance a during time window t for the single day which is being solved for.
$\mathrm{CUR}^d_{t,a}$	Current day energy use of appliance a during time window t for day d.
$\mathrm{AVG}_{t,a}$	Average energy use across all days of appliance a during time window t.
$\mathrm{OPT}_{t,a}$	Decision variable output for appliance a at time window t by the solver.
MAX_a	Maximum energy use across all days and time windows of appliance a.

Threat Model The adversary is observing energy consumption via a smart meter in a home. This means that the adversary is able to observe half-hourly energy consumption data over time. The adversary does not know the individual per-appliance energy consumption for these half-hour windows.

Over time, the adversary can collect historical smart meter observations and build an expectation of the household's normal energy usage behaviour. In this work, the average-day profile is used as a simplified representation of this expected behaviour. Days that differ from the expected energy pattern may be more noticeable to the adversary and could reveal unusual household activities. Therefore, we investigate how appliance liveness affects the ability to transform a day's energy profile towards the expected behaviour.

Behavioural Distinguishability Metric Behavioural distinguishability is measured as the difference between current-day and average-day energy consumption. The idea for this metric is that any difference from the usual behaviour is anomalous and of interest to an observing adversary. Alternative privacy metrics such as information-theoretic approaches using mutual information or divergence-based measures [13] can be used. However, these methods require probabilistic models of appliance behaviour which is challenging to integrate into optimisation problems. The behavioural distinguishability P is defined to be the absolute difference between the observed energy use $\mathrm{OPT}_{t,a}$ and the average behaviour $\mathrm{AVG}_{t,a}$ (in this instance acting as the adversary's expectation of what it expects to observe). The absolute function is used so a negative or positive difference between the average and current usage of an appliance a in an 30-minute time window t leads to a positive behavioural distinguishability. The intuition is that by transforming energy use to be closer to the average day, interesting events which lead to large changes (increases or decreases in energy use) are less visible.

$$P = \sum_{t \in T} \left| \sum_{a \in A} \mathrm{OPT}_{t,a} - \sum_{a \in A} \mathrm{AVG}_{t,a} \right| \tag{1}$$

The average-day profile is used as a simplified representation of the adversary's expectation of normal household behaviour. Larger deviations from this expected pattern may provide additional clues about unusual activities and therefore increase the distinguishability of the observed day. Many optimisation solvers do not support the absolute function due to it being non-linear. GEKKO provides the `abs2` function[1] using a complementarity constraint which we use to implement the objective function. An appliance is considered live when its observed energy usage must be preserved during optimisation. An appliance is considered non-live when the optimiser may modify its energy allocation within the optimisation constraints. Liveness is used as an analytical mechanism to understand how individual appliances influence behavioural distinguishability.

Intuition The intuition behind the following formulation is to find time periods which either:

1. exceed the half-hourly energy consumption which the adversary expects and thus the occupants would benefit from it being reduced, or
2. are below the expected half-hourly energy consumption, at which point additional energy should be consumed.

This optimisation does not aim to shape appliance use over time. For example, it would not direct a Kettle to be used over a 1 hour period to boil water. But instead it would indicate if the energy required to boil the water could or could not be used at that time, hence, why we have described the trade-off as a liveness trade-off, as the user may lose the ability to use appliances.

ct1 Liveness Constraint This constraint ensures that appliance activity is preserved whenever that appliance is in the subset of appliances $L \in \mathbb{P}(A)$ that must remain live.

$$\forall a \in L, \forall t \in T, \mathrm{OPT}_{t,a} \geq \mathrm{CUR}_{t,a} \tag{ct1}$$

ct2 Consumption Constraint For all appliances $a \in A$, it is not possible for a to consume more energy in a time window $t \in T$ than the maximum seen across all time windows or for an appliance to consume less than 0 energy. The maximum half-hourly energy consumption allows the optimisation to increase the amount of energy consumed by difference devices up to this maximum amount if needed to make the day being transformed more like the average day.

$$\forall a \in A, \forall t \in T, 0 \leq \mathrm{OPT}_{t,a} \leq \mathrm{MAX}_a \tag{ct2}$$

[1] https://gekko.readthedocs.io/en/latest/model_methods.html#logical-functions

The maximum consumption of appliance a is calculated as the maximum energy consumption seen for that appliance across all hours of every day.

$$\mathrm{MAX}_a = \max_{t\in T, d\in D} \mathrm{CUR}^d_{t,a} \tag{2}$$

As such for every time window $t \in T$, appliance $a \in A$, day $d \in D$, $\mathrm{CUR}^d_{t,a} \leq \mathrm{MAX}_a$.

Problem Formulation for a single home with a set of appliances A, on a single day, and the set of appliances $L \in \mathbb{P}(A)$ which are live:

$$\begin{aligned} \text{minimise} \quad & \sum_{t\in T} \left| \sum_{a\in A} \mathrm{OPT}_{t,a} - \sum_{a\in A} \mathrm{AVG}_{t,a} \right| \\ \text{subject to} \quad & \forall a \in L, \forall t \in T, \mathrm{OPT}_{t,a} \geq \mathrm{CUR}_{t,a} \\ & \forall a \in A, \forall t \in T, 0 \leq \mathrm{OPT}_{t,a} \leq \mathrm{MAX}_a. \end{aligned} \tag{3}$$

The *Other* energy measurement remains unchanged by the optimisation. This is because it is a collection of unknown appliances which could not be reasoned about wanting to trade-off their liveness because the appliances are unknown.

3.3 Optimisation Implementation

The optimisation model was implemented in Python using GEKKO. The APOPT solver was selected by setting `m.options.SOLVER = 1`. Optimisation was performed independently for each house, day, and appliance-liveness configuration. For each day, all 512 possible liveness configurations were generated using the powerset of the nine monitored appliances, including the empty set and the configuration where all appliances were live. These optimisation tasks were executed in parallel using Python multiprocessing.

The solver output was suppressed using `disp=False`. No custom convergence tolerances, iteration limits, or time limits were specified, therefore the default GEKKO/APOPT stopping criteria were used. Runtime was measured using `perf_counter()` for each day. Completed optimisation results were stored as pickle files and reloaded in subsequent executions to avoid recomputing previously solved optimisation problems. The optimisation operated on 30-minute energy intervals and minimised the absolute deviation between the optimised aggregate energy profile and the average-day aggregate profile using GEKKO's `abs2()` formulation.

4 Results

We now walk-through an example transformation of Day 1 of House 6, of which Figure 3 shows the actual energy consumption for this day. In order to transform this day, the average day (Figure 2) is calculated which acts as the target

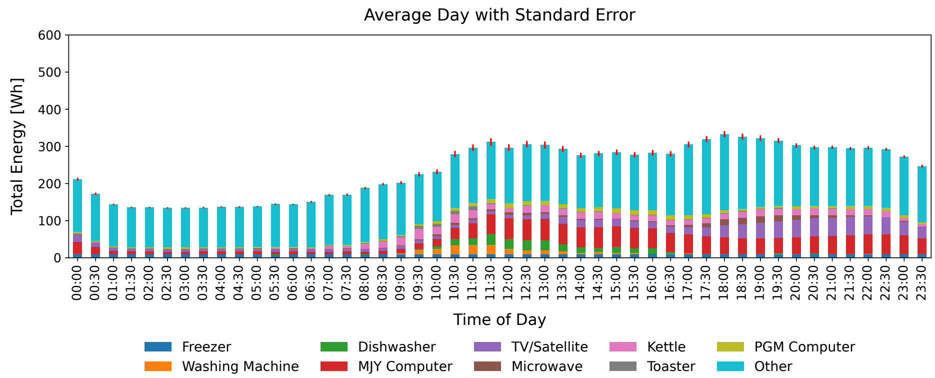

Fig. 2. The average day for House 6

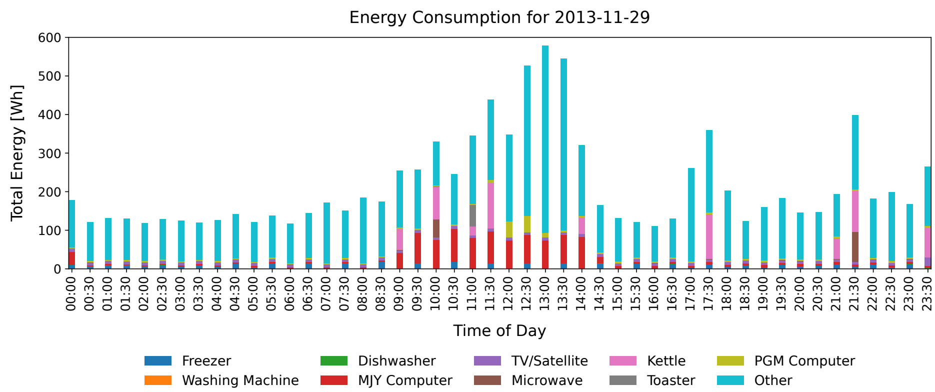

Fig. 3. The original Day 1 for House 6

energy consumption. The optimisation results for all 512 combinations of appliance liveness is shown in Figure 4. Of these we present the transformed day for when all devices' liveness is enforced (Figure 6) and when no devices' liveness is enforced (Figure 5). When no liveness is required a much greater similarity to the average day can be achieved (resp. lower behavioural distinguishability), and a higher liveness leads to greater divergence from the average day (resp. higher behavioural distinguishability).

On Figure 4 each point represents the outcome of one of the transformations of this day. The Pareto frontiers are drawn for when the liveness of one specific appliance is enforced and for when no liveness is enforced. All points on this line are the best trade-off between liveness and behavioural distinguishability for the configuration of which livenesses are enforced. The frontier for the MJY Computer shows higher behavioural distinguishability because this device uses a large amount of energy during peak energy consumption for the day. In contrast, the average day spreads energy usage for this appliance across much of the day. When the liveness of this device is enforced, the optimisation cannot change or reduce its activity during those peaks. Because of this, the energy profile can-

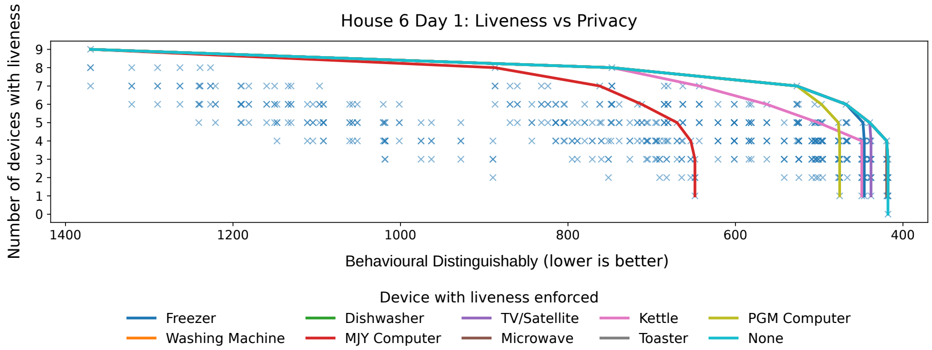

Fig. 4. The results from 512 different liveness transformations of Day 1 for House 6

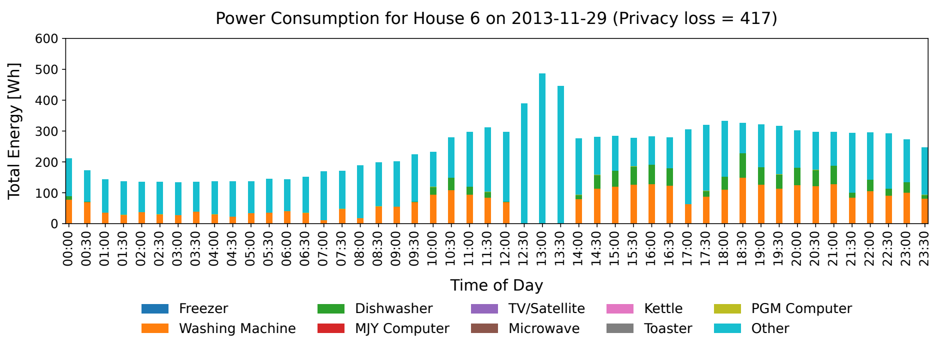

Fig. 5. Liveness enforced for no appliances

not move closer to the average day pattern. Since behavioural distinguishability measures the difference between the observed day and the average day, these remaining peaks lead to higher behavioural distinguishability compared to appliances whose energy usage is more evenly distributed across the day. This leads to MJY Computer having a Pareto frontier with a higher minimum behavioural distinguishability than other appliances.

4.1 High behavioural distinguishability

The distribution of behavioural distinguishability values obtained by the 512 transformations of each day in each home is shown in Figure 9 showing the observed behavioural distinguishability differing across homes. House 19 observes small changes in behavioural distinguishability, whereas House 18 shows larger variation. This corresponds to the high energy consumption observed in Figure 1 where a day in House 19 can consume over twice the energy of a day in House 18. Houses with high-energy devices usually show larger privacy differences, while houses with smaller appliances show less variation, this is because our privacy

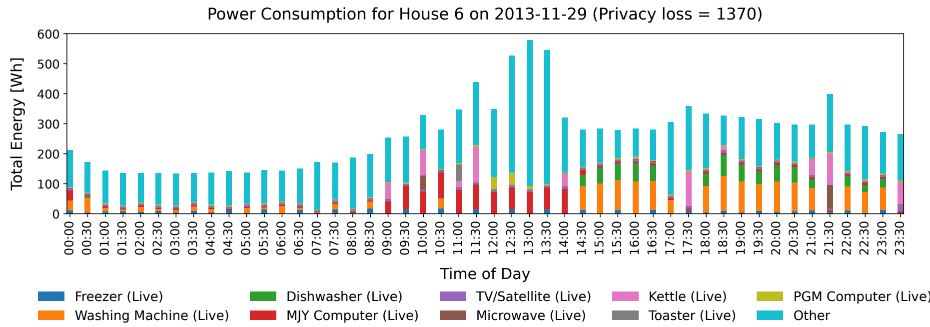

Fig. 6. Liveness enforced for all appliances

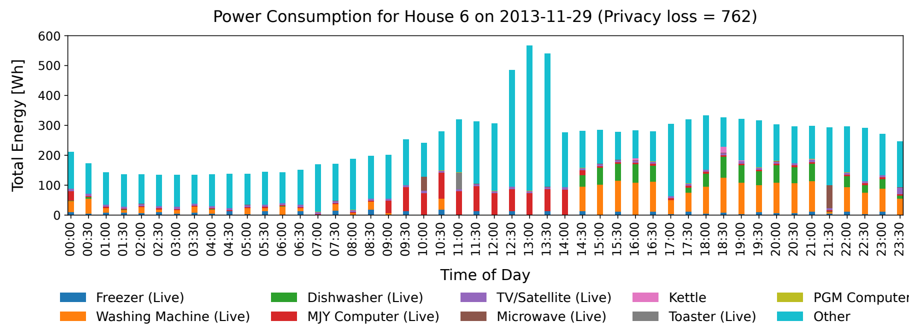

Fig. 7. Liveness enforced for 7 appliances including MJY Computer

metric is a measure of energy. Houses also have appliance-specific patterns[2], for example, in House 15 daily energy consumption peaks observed in Figure 1 correlate to high behavioural distinguishability days in Figure 9 due to the use of the Tumble Dryer (e.g., on 2013-12-21, 2014-01-03). The minimum behavioural distinguishability is low because when the Tumble Dryer is not live, it is possible to transform those days to be similar to the average day, however, when it is live, high behavioural distinguishability transformations are produced. This was seen in House 6 Day 1 where high energy use appliances that are live lead to a high behavioural distinguishability.

4.2 Liveness-Distinguishability Relationship

Across all houses and all days, when fewer devices are forced to stay live, the optimiser can produce a day with less behavioural distinguishability because it has more flexibility to reshape the energy consumption. When more devices must stay live, flexibility is reduced, leading to a higher behavioural distinguishability. From the Pareto frontier in Figure 4, we can also see that not all devices behave

[2] Please note that appliances are different between homes and are not comparable between them even if they have the same label.

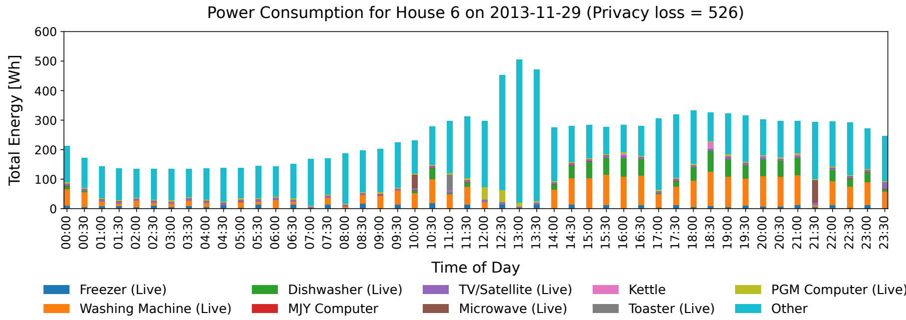

Fig. 8. Liveness enforced for 7 appliances excluding MJY Computer

the same. High energy consumption appliances have stronger impact on privacy. When high-energy devices must be live, behavioural distinguishability increases. When low-energy consumption appliances are live, the optimisation transformation is better able to produce a day with a low behavioural distinguishability. This means that the type of device and when it is used are crucial in considering trading-off appliance liveness for privacy.

4.3 Energy-Distinguishability Relationship

We calculated the Pearson correlation coefficient between energy overhead (Equation (4)) which is difference between the transformed day's total energy and the actual day's total energy use, and behavioural distinguishability (Equation (1)) to explore the relationship between energy consumption and privacy. Across almost all results show a strong positive correlation (both a Pearson correlation coefficient of 1 and slope of 1 with low variation (on the order of 10^{-6}). This has arisen as privacy is a measure of energy and is provided in this work by not enforcing liveness of devices. This relationship should be interpreted carefully because behavioural distinguishability is itself derived from energy consumption. Therefore, part of the observed correlation is a consequence of the metric definition rather than an independent finding, as such no conclusions should be drawn about the relationship between behavioural distinguishability and energy consumption in this work.

There was an exception on 2013-12-22 for House 15 with a Pearson correlation coefficient of -0.3, however, this has arisen due to low energy consumption on this day which led to a behavioural distinguishability between 0 and 2.5×10^{-14}.

$$\left(\sum\nolimits_{t \in T, a \in A} \mathrm{OPT}_{t,a}\right) - \left(\sum\nolimits_{t \in T, a \in A} \mathrm{CUR}_{t,a}\right) \tag{4}$$

5 Discussion

Alternate Formulation of Liveness Constraint In Section 3.2, the liveness constraint in Equation (ct1) is formulated using an inequality rather than an

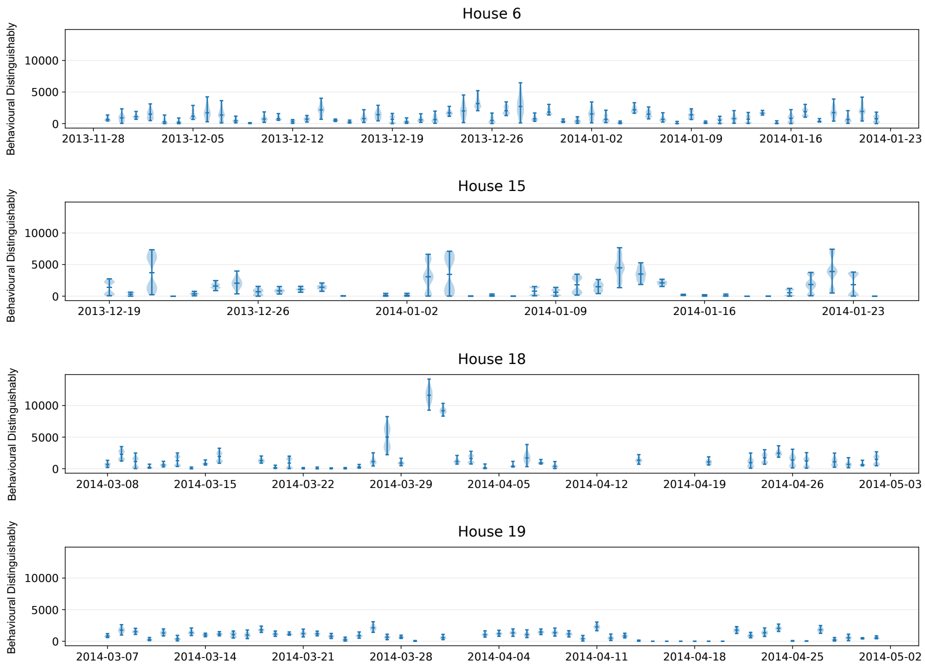

Fig. 9. Summary of transformed days' behavioural distinguishability distribution for each home

equality. This is an intentional choice in our model. When an appliance is live, the optimiser cannot reduce its energy consumption below the amount observed in the original data. However, it can increase the consumption up to the appliance's maximum value defined in Equation (ct2). For example, if a live appliance consumed 100 Wh during a 30 minute period, the optimiser must keep at least this 100 Wh, but it may increase the consumption up to the maximum if needed. In this way, the original appliance activity is not removed by the optimisation, while additional consumption is still allowed. This gives more flexibility to reduce the difference between the transformed day's energy consumption and the household's average day consumption. Future work could investigate broadening the designation of live and not-live appliances to also include appliances whose liveness is maintained but uses more energy than typical.

Home Excluded Due to Renewable Use In Section 3.1 homes 11 and 21 were excluded as they made use of renewable energy. The aggregate power measurements of houses 11 and 21 were affected by solar panel generation. The solar generation was not separately measured by the installed individual appliance monitors. It would have been interesting to see how renewables impacted the decisions made by the optimiser, however, we were unable to do as the dataset did not include how much energy was generated by the renewable sources. An additional energy source that varies throughout a day could have been considered and could potentially lead to different outcomes, especially if when a renewable was most available aligns with when an appliance needs to be used. However, much of this has already been investigated by previous work [4,15], such as by using a battery to shape the load of a home.

6 Conclusions

The results show that appliance liveness affects behavioural distinguishability in smart home energy data. Unlike approaches that use batteries or energy storage, this work looks at how appliance activity changes the visibility of daily energy usage patterns. When fewer appliances are required to stay live, the optimiser has more flexibility to reshape the daily energy profile and reduce behavioural distinguishability. However, when many appliances remain live, or when high-energy appliances must remain live, the transformation becomes more limited and behavioural distinguishability increases.

In this paper, we used real-world smart home data to carry out a retrospective analysis of the relationship between appliance liveness, energy consumption, and behavioural distinguishability. The results show that different liveness configurations lead to different trade-offs and that some appliances have a greater impact on distinguishability than others. By analysing all appliance combinations we identified the potential to trade-off between liveness and behavioural distinguishability. These results help us understand how appliance behaviour affects what can be observed from smart meter data.

This study has some limitations. The analysis uses only four households from the REFIT dataset, so the results may not represent all smart homes. The optimisation is retrospective and does not consider appliance continuity, such as washing machines, dishwashers, or ovens running over multiple time periods. In addition, behavioural distinguishability is used as a proxy measure and does not directly measure privacy leakage. In addition, behavioural distinguishability is derived from energy consumption, which contributes to the strong correlation observed between energy overhead and distinguishability. Therefore, the results should be viewed as an exploratory analysis of the potential to use a change in which devices are kept live as an alternate mechanism to obscure information from an observing adversary.

Future work should investigate whether occupants are willing to accept different liveness trade-offs and how these trade-offs fit with daily household routines. Future studies could also include appliance continuity constraints and larger smart home datasets. The findings from this work may also help the development of real-time recommendation or scheduling approaches that balance appliance usage, energy consumption, and behavioural distinguishability.

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