# Trace Recovery: Inferring Fine-grained Trace of Energy Data from Aggregates

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Abstract: Smart meter data is collected and shared with different stakeholders involved in a smart grid ecosystem. The fine-grained energy data is extremely useful for grid operations and maintenance, monitoring and for market segmentation purposes. However, sharing and releasing fine-grained energy data induces explicit violations of private information of consumers (Molina-Markham et al., 2010). Service providers do then share and release aggregated statistics to preserve the privacy of consumers with data aggregation aiming at reducing the risks of individual consumption traces being revealed. In this paper, we show that an adversary can reconstruct individual traces of energy data by exploiting *consistency* (similar consumption patterns over time) and *distinctiveness* (one household's energy consumption pattern is significantly different from that of others) properties of individual consumption load patterns. We propose an unsupervised attack framework to recover hourly energy consumption time-series of individual users without any prior knowledge. We pose the problem of assigning aggregated energy consumption meter readings to individuals as an assignment problem and solve it by the Hungarian algorithm (Xu et al., 2017; Kuhn, 1955). Using two real-world datasets, our empirical evaluations show that an adversary is capable of recovering over 70% of households' energy consumption patterns with over 90% accuracy.



# 1 INTRODUCTION

Smart meters, an integral component of metering infrastructures in smart grids, have been widely deployed in homes around the world. Smart meter consumption measurements are used for monitoring, operations and management of grids (Knirsch et al., 2016). Individual household smart meter data is aggregated into a cluster (e.g., from the same neighbourhood) and communicated to the energy providers over a secure channel for the purposes of demand forecasting and analytics without compromising the privacy of individual households (Sankar et al., 2012; Erkin and Tsudik, 2012). Many mechanisms based on such secure aggregation have been proposed to protect the privacy of consumers (Buescher et al., 2017). Although aggregation itself is cryptographically protected, the electricity providers have access to the decrypted aggregated form of energy consumption over a cluster (group) of households (Buescher et al., 2017).

Due to the nature of smart meter data, two types of aggregations can be performed: temporal and/or spatial. Temporal aggregation is one of the most naive forms of data aggregation and is performed over a long period of time, for example, monthly or quarterly (Dong et al., 2016). The aggregated monthly or quarterly consumption of individual households is performed for billing purposes. On the other hand, in spatial aggregation (Dong et al., 2016) multiple households' load patterns are combined together into a cluster in order to mask individual consumption patterns to prevent information leakage (Farokhi, 2020).

This aggregated form of individual consumption data can be shared with other stakeholders (e.g., retailers and marketing companies) (Liu et al., 2018) or can be released publicly to benefit businesses and research, with assumption that aggregated statistics of individual households' energy consumption data, do not infringe the privacy of customers. However, this assumption on aggregation providing enough privacy

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requires further exploration. In this paper, we show an attack where an adversary (e.g., curious service provider, a third-party stakeholder or an external malicious entity) is capable of recovering fine-grained energy consumption traces of individual customers through having access to the aggregated statistics of energy consumption time-series data. The essential elements of our attack are based on the attack from Xu et al. (Xu et al., 2017) on de-aggregating user location traces from aggregated mobility traces, and a similar argument is often used about privacy via aggregation.

In essence, we show that an attacker can infringe the privacy of individuals by exploiting two key attributes of their load patterns. First, the load pattern of a household is consistent, which makes their load pattern highly predictable. Second, the load pattern of each household can be uniquely distinguished from each other with high probability. Combining the two observations, we could split the aggregated energy data to different traces of energy consumption iteratively (by the first observation), then link the recovered traces to most of the individual households (by the second observation).

***Contributions***. In this paper, we aim to quantitatively investigate the privacy implications of releasing aggregated statistics of smart meter energy consumption data of individual customers without any prior knowledge. Our contributions are as follows:

- We construct an unsupervised adversarial model based on aggregated statistics of energy consumption data. The adversarial framework does not require any background information about the individuals to reconstruct their fine-grained energy consumption records from aggregates. The adversary exploits the *consistency* and *distinctiveness* property in day-to-day energy consumption load patterns. Then we present the problem as a mathematical balanced assignment problem and construct cost matrices (Xu et al., 2017) based on expected energy consumption change at each time step. Our quantitative analysis shows that the households' consumption patterns are similar over time and most of them are different from each other. We compute expected energy consumption changes from one time step to another, which help to estimate energy consumption in the next time steps and formulate a cost matrix to optimise the assignment of households to energy consumption traces (see Section 4).
- We use two real-world smart meter reading datasets to empirically evaluate the adversary's capability to reconstruct individual users' fine-grained energy usage load patterns. We show that the adversary recovers energy consumption patterns with high accuracy (between 80% and 95%) averaged over all target households and the entire time period. We observe that 70% of households' load patterns can be inferred from aggregated statistics with an accuracy over 90%. Finally, we show that the adversary recovers 60% of households' energy consumption by incurring a 0.4 kWh or less error from the actual (ground truth) consumption traces.

A key feature of our attack on aggregated energy data is that it does not rely on any background knowledge of any individual household's consumption. This is unlike other attacks on smart-meter aggregation, for example, (Buescher et al., 2017), as detailed in the next section.

The rest of the paper is organised as follows. In Section 2 we review the state-of-the-art of privacy related issues in energy data and possible solutions to safeguard the privacy of customers. Then we explain the background of the threat model for recovering energy consumption traces in Section 3. In Section 4, we discuss key features of two real-world datasets that are used to evaluate the performance of the adversary. Further, we analyse the feasibility of privacy breach using two key concepts: *consistency* and *distinctiveness*. In Section 5, we propose the attack framework and inference strategies based on our observations discussed in Section 4. We then demonstrate the experimental configurations and analyse the performance of the adversary using two different metrics in Section 6. Finally, conclude the paper by discussing our key findings and future work in Section 7

## 2 RELATED WORK

In this section, we review some related work pertaining to privacy preserving energy data analytics, issues in energy data sharing with third-parties, releasing aggregated data, adversarial models and privacy enhancing technologies that are widely used to protect the privacy of individuals while leveraging aggregated data analytics.

*Privacy Preserving Data Analytics:* A massive amount of energy consumption data from millions of households and generated on a daily basis is being collected and shared with third-parties and different stakeholders involved in the smart meter ecosystem (Yang et al., 2014). Smart meter data analytics involve descriptive, predictive (Habtemariam et al., 2016) and prescriptive analyses, it also includes many critical applications, such as as load analysis, load forecasting and load management (Wang et al., 2018). The main objective of privacy friendly data analytics is to safeguard the users (households) from private information leakage while leveraging the utility of the data (Shateri et al., 2019). Many other schemes have been proposed to facilitate privacy preserving data collection, sharing and analytics (Makhdoom et al., 2020). Sirojan et al. (Sirojan et al., 2019) envisaged an edge computing based architecture to provide a variety of energy data analytic services such as event detection, down-sampling and load identification, however, this architecture does not guarantee the privacy of user specific sensitive data. Cloud based hierarchical architectures are conceived as facilitating access control mechanisms that help manage to share and analyse data while keeping sensitive information hidden (Lee et al., 2017). Shateri et al. (Shateri et al., 2019) studied the privacy-utility tradeoff in privacy preserving energy data analytics using an information theoretic approach. Chen et al. (Chen et al., 2018) reviewed some learning based methods that leverage efficient privacy-aware energy data analytics. Wen et al. (Wen et al., 2013) proposed a privacy preserving query-based cloud server model for encrypted consumption data.

*Non-Intrusive Load Monitoring:* A myriad of study has been conducted on how fine-grained energy consumption data can reveal an enormous amount of private information about individual households. Non-intrusive load monitoring (NILM) has been a prolific research area in the last decade. NILM has shown that the individual appliance specific energy consumption can be separated from the load pattern of a household using different statistical methods (Herrero et al., 2017; Zhang et al., 2019) and deep learning algorithms (Kelly and Knottenbelt, 2015). Therefore, information about personal activities can be discovered from their electricity consumption patterns. This constitutes a severe privacy threat to individual consumers (Reinhardt et al., 2015). Note that, NILM is successful only if an adversary has access to the load patterns of individual consumers. All the aforementioned studies rely on individual households' energy consumption time-series data to retrieve appliance specific consumption or to derive appliances' ON/OFF states at different point of time. However, in this paper, we attempt to recover each individual household's fine-grained energy consumption traces from an aggregate, which is the combination of a cluster (group) of households' energy consumption time-series data without relying on any prior knowledge and/or access to individual's load patterns.

*Privacy of Aggregation Models:* Aggregation is widely used to safeguard the privacy of individual households by masking the individual specific consumption (Farokhi, 2020). More generally, two types of privacy preserving aggregation methods exist in the literature: many solutions rely on trusted third-party based services using cryptographic protocols (e.g., homomorphic encryption) (Efthymiou and Kalogridis, 2010; Abdallah and Shen, 2016; Vahedi et al., 2017) and decentralised techniques, relying on blockchain technology (Habtemariam et al., 2016; Xu et al., 2020). Hong et al. (Hong et al., 2017) proposed a streaming algorithm that safeguards the implications of information leakage from the readings of a meter on the state of a specific appliance. A study by an industrial body suggests that aggregation of two load patterns of two different households is sufficient to protect the privacy of individuals in aggregated data (ENA-Report, 2015). However, this study was revisited and its findings disputed in (Buescher et al., 2017), which shows that individuals in an aggregate of size two are distinguishable with high accuracy. Moreover, Buescher et al. (Buescher et al., 2017) demonstrated the risk of being distinguishable for different size of aggregates. However, one of the limitations of this distinguishability attack model is that the adversary knows the load profiles contained in the aggregate and past consumption records of all aggregators (Buescher et al., 2017). The key difference between our attack model and the work in (Buescher et al., 2017) is that our attack model does not rely on any prior knowledge about the individual energy consumption records.

Our work has been inspired by (Xu et al., 2017) that recovers individuals mobility data (trajectories) by exploiting *consistency* and *distinctiveness* features of mobility patterns of users. Authors posed and verified that most mobile users follow explicit moving patterns, with little mobility during night time and stable (and hence predictable) mobility patterns during daytime. In (Xu et al., 2017), Xu et al. considered that during day time users' velocities are uniform which may not be a realistic assumption. While our work on Energy data consumption is different, we additionally took into consideration changes in consumption (analogous to speed or velocity in mobility data) from one time window to the next over the entire population.

# 3 BACKGROUND AND THREAT MODEL

In this section we define the notation that will be used throughout the paper, and precisely describe the threat model behind energy consumption data recovery.

### 3.1 Notation

The energy reading of household $i$ by a smart meter at time step $t \in \mathbb{N}$ is denoted by $x_i^{(t)}$.[1] Energy data of household $i$ over horizon $T$ (i.e., $T$ time steps) is represented as a time-series, and denoted by the $T$-element vector $\mathbf{x}_i$, whose $t$-th element is $x_i^{(t)}$.

The aggregate (sum) consumption of $n$ number of households over a time period $T$, defined as a set of one or more time steps, is given by

$$x_{agg} = \left[ \sum_{i=1}^{n} x_i^{(1)},\ \sum_{i=1}^{n} x_i^{(2)},\ \ldots,\ \sum_{i=1}^{n} x_i^{(T)} \right] \quad (1)$$

The notations used throughout the paper are summarised in Table 1.

Table 1: Notation.

| Symbol | Description |
|---|---|
| $\mathcal{A}$ | Adversary |
| $\mathcal{B}$ | *Bucket* of energy |
| $\Delta\mathcal{B} = e$ | Size of a *bucket* |
| $\hat{\mathcal{B}}$ | Estimated/predicted *bucket* of energy |
| $C$ | Cost Matrix |
| $c_{ij}^{(t)}$ | Cost of $i^{th}$ household at $j^{th}$ *bucket* at time $t$ |
| $\Delta^{(t)}$ | Expectation of energy consumption change at time $t$ |
| $k$ | Total number of buckets |
| $n$ | Total number of households |
| $T$ | Overall time period |
| $X$ | Decision Matrix |
| $x_{ij}^{(t)}$ | Value of $i^{th}$ household at $j^{th}$ *bucket* at time $t$ |
| $\mathbf{x}$ | Vector of actual energy consumption traces |

### 3.2 Energy Trace Recovery: Threat Model

We now describe an adversary ($\mathcal{A}$) who wishes to reconstruct fine-grained energy consumption patterns of individual households from aggregate statistics. First, the adversary $\mathcal{A}$ accumulates aggregated statistics of $n$ number of households in a neighbourhood over $T$ period of time from a publicly released aggregated dataset or through querying a database via a user interface. The queries to the database may include but not be limited to the following: *(i) What are the maximum and minimum consumption in kWh in a neighbourhood at each time step t over the horizon of time T?*, *(ii) How many households consume x kWh of energy at a specific time of a day?*, *(iii) How many households' consumption is in a given range of energy (e.g., how many households' energy consumption is between 0 and 1 kWh at time t)* and *(iv) How many households' electricity usage increases or decreases at different hourly of a day and how much?*. There could be many other possible queries which are beyond the scope of this paper.

The adversary $\mathcal{A}$ then analyses the aggregated statistics to construct an attack strategy that helps reconstruct the energy consumption patterns of individual households. A key consideration here is that the adversary might not be able to reconstruct the energy consumption of each household at very fine granularity levels. This is due to the fact that even though the energy consumption of a household may show *similar* trends over time, these trends are not expected to be precisely the same due to small fluctuations in energy consumption. We therefore propose the idea of energy consumption within buckets. More precisely, given the answers to the above queries, adversary $\mathcal{A}$ divides the energy consumption at each time step into different equal sized intervals (semi-closed) which are defined as buckets throughout the paper. The idea of *bucket* describes the granularity of users in each interval of energy consumption at every time step over the horizon $T$. For instance, at each hour during the night-time most households consume between 0.50 kWh and 1 kWh (i.e., (0.5, 1]), so we state that most of the users' consumption is taken place from $\mathcal{B}_1$ and when households are on holidays, they do not consume any electricity, thus we state that during that period of time energy consumption took place from $\mathcal{B}_0$.

*Energy Buckets.* Formally, we illustrate the concept of *bucket* as follows. A *bucket* of energy consumption is denoted by $\mathcal{B}$ and value of each *bucket* represents a half-open interval (i.e., energy consumption range in kWh), where the interval size, i.e., *bucket* size, is denoted by $\Delta\mathcal{B} = e$. We denote buckets by $\mathcal{B}_0 = [0], \mathcal{B}_1 = (0, e], \mathcal{B}_2 = (e, 2e], \mathcal{B}_3 = (2e, 3e]$ and so on, and we try different *bucket* sizes to test the attacker's accuracy. We say a household is in a *bucket* $\mathcal{B}_i$ at time $t$ if the household's energy consumption falls into the interval of $\mathcal{B}_i$. Note that when a user does not consume any electricity at a specific time of a day this falls under *bucket* $\mathcal{B}_0$. We have considered a *bucket* with 0 consumption because an adversary could be interested to know when her target home is not occupied.

## 4 DATASET AND FEASIBILITY OF PRIVACY BREACH

In this section, we first explain the datasets which are used to evaluate the performance of the adversary $\mathcal{A}$, then show the key features behind the load patterns of households energy consumption.

[1] In general, time steps $t$ and $t+1$ represent consecutive, potentially equally-spaced, times. In this paper, they represent hours.

## 4.1 Data

We use two real-world datasets that capture the fine-grained (i.e., “disaggregated”) energy consumption (time-series) records of households: the UK Power Networks (London Dataset)[2] and Ausgrid households dataset[3]. We then aggregate these datasets to perform analyses and attacks on them. The actual-“disaggregated”-datasets serve as ground truth against the estimated consumption data.

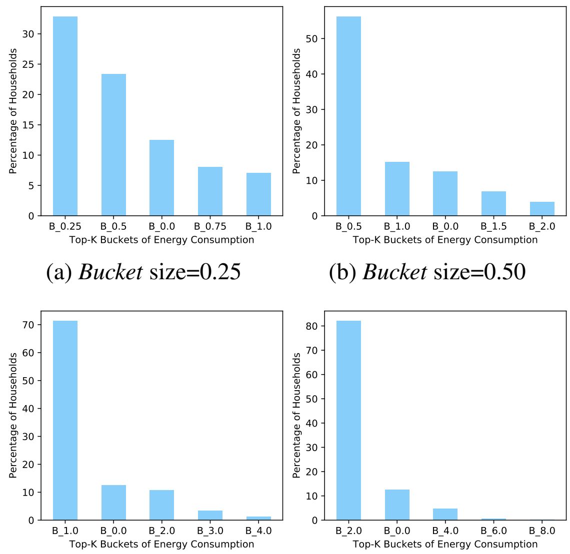
These publicly available datasets contain different numbers of households with a variety of smart-meter reading frequencies over various periods of time. We use these datasets primarily because of their different characteristics, such as different meter-reading resolutions, geographic locations of the households, time periods and number of households. Note that the actual datasets contain more households over a greater period of time. We discarded the rest as they are inconsistent or incomplete. A brief summary of the datasets, which were used in our evaluation, is presented in Table 2.

## 4.2 Consistency and Distinctiveness Properties of Energy Consumption

By performing analysis on the raw (find-grained, dis-aggregated) data for both London and Ausgrid datasets, we argue that each household follows a consistent energy consumption pattern and hence the households can be uniquely distinguished with a high probability.

To comprehensively understand the *consistency* of energy consumption patterns of all households over the entire period of time, we study the percentage of households that consume energy from Top-5 buckets over four sizes of buckets in $\{0.25, 0.5, 1.0, 2.0\}$ for both datasets. Figure 1 shows the results in the Ausgrid dataset. We observe that the percentage of households that consume from the top buckets increases with the increase of *bucket* size. When the *bucket* size is 0.25, around 40% and 25% of households consumer energy from Top-1 and Top-2 buckets, respectively. Furthermore, we observed over 12% of households' consumption is from Top-3 *bucket*. Note that number of buckets and the hourly/daily/monthly maximum value of the buckets are varying over the population and the entire time period.

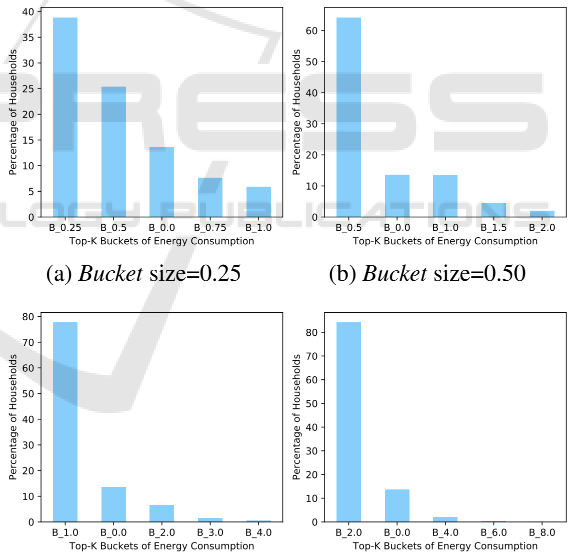
Doubling the *bucket* size to 0.5 and 1.0, around 60% and 70% of households' energy consumption




(a) *Bucket* size=0.25 (b) *Bucket* size=0.50

(c) *Bucket* size=1.0 (d) *Bucket* size=2.0

Figure 1: The percentage of households that consume energy from top buckets for four different size of buckets over the period of one year in Ausgrid dataset.




(a) *Bucket* size=0.25 (b) *Bucket* size=0.50

(c) *Bucket* size=1.0 (d) *Bucket* size=2.0

Figure 2: The percentage of households that consume energy from top buckets for four different size of buckets over the period of one year in London dataset.

remains in Top-1 buckets respectively. Increasing the *bucket* size to 2.0, over 90% of the households consume energy from Top-2 buckets. We also observe similar pattern in consuming energy in London dataset (see Figure 2).

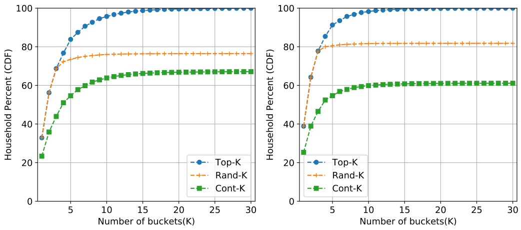
Observations from both the datasets suggest that most of the households tend to consume from the same (top) buckets consistently. Thus, the consump-

[2]https://data.london.gov.uk/dataset/smartmeter-energy-use-data-in-london-households

[3]https://data.gov.au/data/dataset/smart-grid-smart-city-customer-trial-data

Table 2: Some features of the datasets used in the experiments are summarised.

| Dataset | Number of Households | Location | Year | Meter Reading Interval |
|---|---|---|---|---|
| London Dataset | 4681 | London, UK | 2013 | 30 min |
| Ausgrid Dataset | 6981 | NSW, Australia | 2013 | 30 min |




(a) Ausgrid Dataset (b) London Dataset

Figure 3: The percentage of households that can be distinguished by $K$ buckets of energy consumption for the bucket size 0.25.

tion patterns are highly *consistent*. Note that with the increase of *bucket* size, the top buckets are accommodating more users as the buckets include more coarse-grained meter readings within their boundaries.

To evaluate the *distinctiveness* of households' energy consumption patterns, we first generate a vector containing $K$ energy consumption buckets, then investigate the percentage of households not sharing the same given buckets vector. We use three different strategies to obtain the buckets vector, that is, selecting the Top-$K$ frequently used buckets by the households (Top-$K$), randomly selecting $K$ buckets belonging to the households' energy consumption patterns (Rand-$K$) and randomly selecting $K$ consecutive buckets (Cont-$K$). Under these three strategies, we show the percentage of (consumption patterns of) households that can be distinguished from other households by the selected patterns in Figure 3.

In the Ausgrid dataset (Figure 3a), we observe that within the Top-5 buckets 80% of households have unique Top-5 energy consumption buckets. Whereas a smaller number of households (73% and 55%) can be distinguished from Rand-5 and Cont-5 buckets respectively. Further, considering the Top-15 buckets, almost all households can be distinguished. However, only 55% and 70% of households can be distinguished when we consider Rand-15 and Cont-15 buckets. Similar observations are observed in the London household dataset (Figure 3b).

The above results quantitatively show that the energy consumption patterns of households are consistent and distinct. This finding helps us construct an attack model to reconstruct the consumption patterns of individual households.

## 4.3 Capturing Energy Consumption Speed

Since we know that the energy consumption of households are consistent and distinct, in this section, we study the energy consumption speed. Prior to showing the results of consumption speed, we first show that the energy consumption speed is also stable over the whole time period.

Figure 4 depicts the average percentage of time when the households consume from Top-20 buckets at different hour of a day in the Ausgrid dataset.

The top left figure in Figure 4 reports that the percentage of time that the households consume energy from top buckets during the night-time (i.e., 12:00 am - 6:00 am). We observe that over 80% and 90% of the time households consume electricity from Top-3 buckets and Top-5 buckets respectively. We also observe that almost 100% of the time Ausgrid households' consumption patterns revolve within Top-10 energy buckets. The figures show that energy consumption over six consecutive hours (from 12 am - to 5 am) were quite consistent. These observations are presumably due to the natural sleeping cycles, energy consumption patterns of households remains consistent during night-time in the Ausgrid dataset.

The top right figure in Figure 4 shows the percentage of time that the households consume energy from top buckets in the morning (i.e., 6am - 12 am). We observe that over 80% of the time households' energy consumption occurred from top-5 buckets. Moreover, over 95% of the time energy is consumed from Top-10 buckets from 7 am to 11 am. Interestingly, the consumption patterns during this time interval are quite uniform. Further, the consumption patterns in the morning are more diverse than that in the night-time.

The bottom left figure in Figure 4 illustrates the cumulative percentage of households consumption duration from each of the frequently used buckets. Top-5 and Top-10 buckets are used by the households over 80% of the time for the first consecutive 4 hours, whereas the rest of the time energy consumption patterns are somewhat more diverse. During this 3-hour period in the afternoon, however, energy consumption remains very consistent (i.e., households consume a constant amount of energy from 12 pm to 3 pm), and this is similar to the trend from 7 am to 11 am. This could reflect the fact that usually people tend to go to their workplace during the day-time.

The consumption patterns in the evening are much more diverse though it keeps increasing until midnight (see bottom right figure in Figure 4). Then, the usage time of the top buckets decreases as people tend to go to bed, which reduces the use of energy.

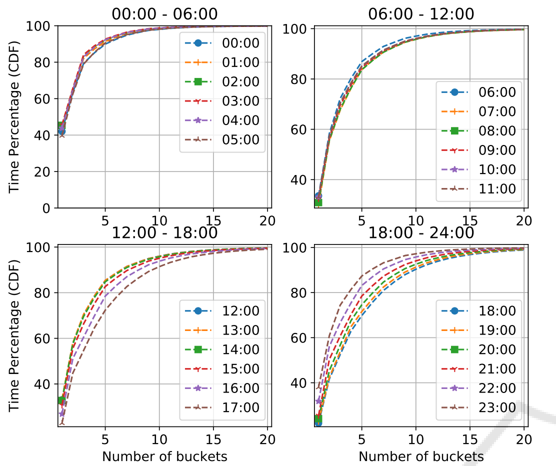



Figure 4: Percentage of time (on an average) a household uses top buckets of energy where *bucket* size is 0.25, over the entire period of time in Ausgrid dataset.

Similarly, in the London dataset (see Figure 5), the average percentages of time when the households consume the top buckets of energy also remains steady. Households usually consume from Top-5 buckets over a whole natural day. Although the specific consumption pattern is quite different than that of in the Ausgrid dataset.

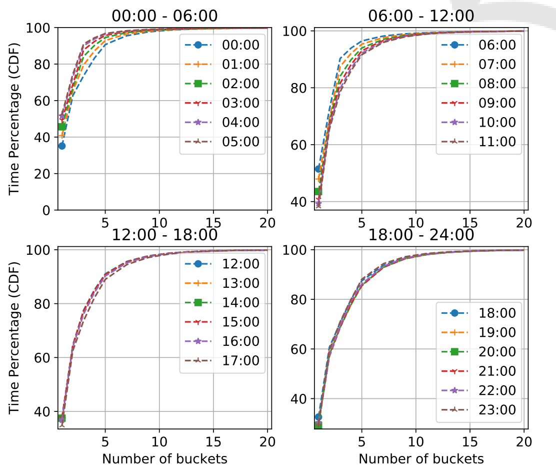



Figure 5: Percentage of time (on an average) a household uses top buckets of energy where *bucket* size is 0.25, over the entire period of time in London dataset.

We now demonstrate how different households' energy consumption varies from one time step to another. We show the results for 2 consecutive hours of a day using the London dataset. Figure 6 depicts what percentage of households fall in which range of energy consumption variation (increase or decrease) from one time step to the next. For example, we observe that at Hour-1, we see around a 10% increase in the percentage of households that showed an increase by $0-10\%$ of their energy consumption than its previous time step. Moreover, at Hour-2, we observe that most of the households' (around 60%) energy consumption showed an increase by $0-10\%$.

Note that the negative percentage change refers to decrease in percentage. Based on such an observation, we calculate the expected energy consumption speed for each given *bucket*. The detailed calculation given in the next section.

To conclude, all of the aforementioned observations indicate that from the aggregated dataset, we could take advantage of the consistence, *distinctiveness* and expected energy consumption speed to recover the energy consumption traces of the individual households.

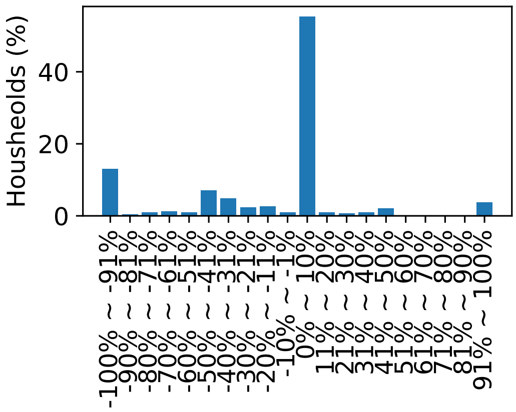
## 5 UNSUPERVISED ATTACK MODEL

In this section, we present our unsupervised attack model for individual energy consumption recovery from an aggregated dataset.

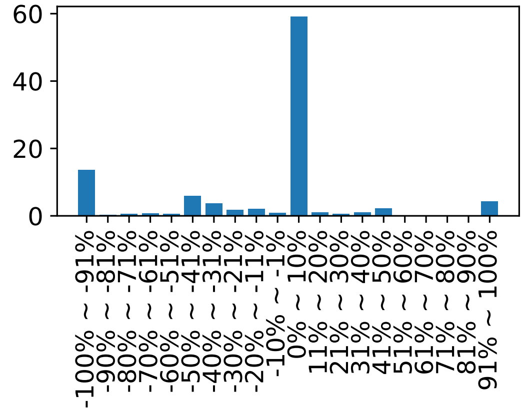
### 5.1 Overview

We consider a realistic scenario (Buescher et al., 2017) where a data curator releases time-series energy consumption data aggregated from a set of $n$ households over a time period $T$. To recover the trace of individual energy consumption over the entire time period, we extract individual energy consumption from the aggregated data time by time. In general, once given a *bucket* size, we can assign the aggregated data to different buckets. The salient point here is that at a single moment, one *bucket* contains only one household. Formally, we can derive the energy consumption buckets $B^{(t)} = [B_1^{(t)}, B_2^{(t)}, \ldots, B_k^{(t)}]$ at time step $t$ with $k$ buckets. Recovering a consumer's energy usage load pattern is equivalent to associating anonymised buckets that are consumed by the same consumer across different time slots. We now explain how to identify the energy consumption buckets that can be linked to the same load pattern of a household.

To address this problem, we propose an unsupervised attack model inspired by the work in (Xu et al., 2017) that iteratively associates the same house-




(a) Hour-1




(b) Hour-2

Figure 6: Percentage of households in each threshold (i.e., the energy consumption variation in percentage in the given ranges) of energy consumption change at consecutive two hours of a day in London dataset.

holds' load patterns from its following time steps, and the adversary then recovers the entire load patterns (by linking consumption buckets). At each point in time, the adversarial method can be divided into two steps. First, we estimate the likelihood of the next energy consumption *bucket* that belongs to a given load pattern by exploiting the characteristics of household energy consumption patterns. Second, we derive an optimal solution to link households' energy consumption buckets with the next consumption bucket which maximises the overall likelihood. We first discuss how we can estimate an optimal association between recovered and actual energy consumption traces through having access to the estimated likelihood.

We define the cost matrix at time $t$ as $C^{(t)} = \{c^{(t)}_{i,j}\}_{k\times k}$, where $c_{i,j}$ corresponds to the inverse of likelihood of connecting a load pattern of household $i$ to the next consumption *bucket* $B^{(t+1)}_j$. The load pattern reconstruction problem is equivalent to solving an optimal match between the rows and columns, which minimises the overall cost. Let us suppose the decision matrix $X^{(t)} = \{x^{(t)}_{i,j}\}_{k\times k}$, where, $x^{(t)}_{i,j} = 1$ denotes that the load pattern gets linked with next consumption *bucket* $B^{(t+1)}_j$ and $x^{(t)}_{i,j} = 0$ otherwise. Now, we construct the energy consumption recovery problem as follows.

$$\text{minimise} \quad \sum_{i=1}^{k}\sum_{i=1}^{k} c^{(t)}_{i,j} \cdot x^{(t)}_{i,j} \tag{2}$$

$$\text{subject to:} \quad x^{(t)}_{i,j} = \{0,1\} \tag{3}$$

$$\sum_{i=1}^{k} x^{(t)}_{i,j} = 1 \text{ and } \sum_{j=1}^{k} x^{(t)}_{i,j} = 1 \tag{4}$$

Such an optimisation problem could be solved by the Hungarian algorithm (Xu et al., 2017; Kuhn, 1955).

## 5.2 Recovering Fine-grained Energy Consumption Patterns

We propose a scheme inspired by the work in (Xu et al., 2017) based on our observations discussed in Section 4 to formulate the cost matrix over the 24 hours of a day. The steps are as follows.

1) We calculate the expected changing for a given *bucket* at time $t$ by our observation about the energy consumption speed. We use $\Delta^{(t)} = \{\delta^{(t)}_1, \ldots, \delta^{(t)}_k\}$ to indicate the matrix of such expectations for all possible buckets under given *bucket* size. Note that, once given a *bucket* size, all the energy consumption values can be assigned to a specific *bucket*.

According to what we have in Figure 6, we calculate $\delta^{(t)}_j \in \Delta^{(t)}$ for *bucket* $B^{(t)}_j$ as

$$\delta^{(t)}_j = \sum_{i=1}^{20} \Pr_i \times change_i, \tag{5}$$

where $change_i$ indicates the $i$th changing step (x axis) shown in Figure 6, $\Pr_i$ is the corresponding probability measured by the percentage of households (y axis) in Figure 6, 20 is a predefined value for the steps of energy consumption changing from time $t$ to $t+1$. Then for a given *bucket* $j$ at time $t$, we estimate its value for time $t+1$ as

$$\hat{B}^{(t+1)}_j = B^{(t)}_j \times \delta^{(t)}_j \tag{6}$$

2) We consider $\Delta^{(t)}$ at each time step $t$ as the thresholds that have been discussed in Section 4.3.

We used the above discussed assumption to construct the cost matrix $C^{(t)}$. Thus, we use the Euclidean distance between the estimated/predicted *bucket* $\hat{B}^{(t+1)}_{u_i}$ of households $i$ and each unassigned *bucket* $B^{(t+1)}_j$ at the next time slot to formulate the

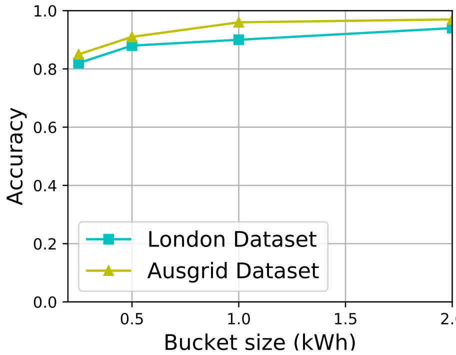
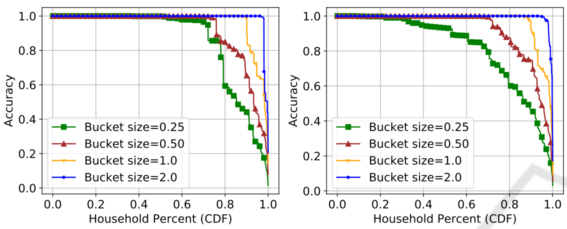



Figure 7: Mean recovery accuracy of energy consumption buckets for different size of buckets.




(a) Ausgrid Dataset (b) London Dataset

Figure 8: Adversarial performance (accuracy) of the attacker in recovering energy consumption patterns of individual households using both datasets.

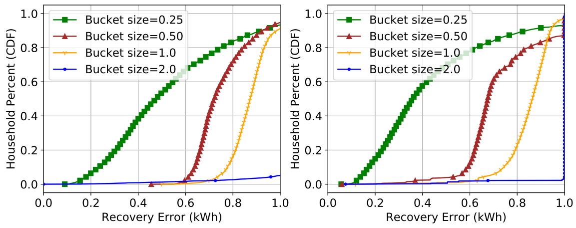
cost matrix $C^{(t)}$. The cost for each household for consuming energy from each *bucket* is illustrated in the following equation.

$$c_{ij}^{(t)} = |\hat{B}_{u_i}^{(t+1)} - B_j^{(t+1)}|. \tag{7}$$

For example, let the corresponding *bucket* of Alice's energy consumption be $x$ at time $t$. We first calculate the estimated *bucket* $\hat{x}$ for time $t+1$ based on current time $t$. Let the unassigned *bucket* at time $t+1$ be $y_1$ and $y_2$. Then we have to decide whether we move Alice from *bucket* $x$ to $y_1$ or $y_2$. We calculate the cost of such a movement by calculating the distance between $\hat{x}$ and $y_1$, $y_2$ respectively. Solving the optimisation problem in last section with the cost matrix would provide us with a decision as to whether Alice moves to *bucket* $y_1$ or $y_2$, that is, the energy consumption of Alice at time $t+1$.

# 6 EXPERIMENTAL EVALUATION

In this section, we first introduce the configurations, together with the metrics used in our experimental analysis of the attack model, then report the attack performance against two famous real-world datasets of individual's energy consumption data.




(a) Ausgrid Dataset (b) London Dataset

Figure 9: Cumulative errors (recovery error) in estimating energy consumption trace of individual households using both datasets.

## 6.1 Experimental Configurations

First, we aggregate the half hourly reading to hourly readings for both datasets. We split the datasets randomly into five samples where each sample contains 1000 households over 2 months. One month of data is chosen from the beginning of the year and another month of data from the middle of the year because the households' energy consumption distribution in the middle of the year is different from that of at the beginning and end of the year for both the datasets.

This variation in energy consumption distribution could be caused by seasonal change (e.g., winter to summer) over time. We choose four values of $l$ = [0.25, 0.50, 1.0, 2.0] to check how user percentages vary from one *bucket* size to another. We then generate buckets for each value of $l$ for each sample of the data. We also calculate the number of households in each *bucket* at each time step to observe how consistent the households are in consuming energy from different size of buckets. Then we compute the percentage of households at different ranges of energy consumption change (as a percentage) (see Figure 6). We then convert the range of percentage changes into discrete values (e.g., if the percentage change of energy consumption remains between 0 to 10%, we map this range into 0.1, and if the range is between 11-20%, we map this into 0.2 and so on). We then compute the expected speed of energy consumption that is, expected energy consumption change over each hour of the day by multiplying the mapped value with its corresponding user percentage, as explained earlier in Section 4.3. This $\Delta$ helps us construct the cost matrices to reconstruct energy consumption patterns in terms of buckets. Then we apply the Hungarian algorithm to optimise the assignment problem using `linear_sum_assignment` solver imported from a python library `scipy.optimise`. The entire project is implemented in Python3.

## 6.2 Metrics

We evaluate the attack performance of the adversary by considering the following two metrics: accuracy in recovering buckets which the households consuming the energy from and recovery error. First, we pair the recovered energy consumption patterns in terms of buckets with the most similar actual load patterns (i.e., the ground truth buckets) using a greedy approach. Let the actual load pattern buckets of $i^{th}$ household be $B_i = \{B_i^{(1)}, B_i^{(2)}, \ldots, B_i^{(T)}\}$ and the $j^{th}$ recovered load pattern buckets be $\hat{B}_i = \{\hat{B}_i^{(1)}, \hat{B}_i^{(2)}, \ldots, \hat{B}_i^{(T)}\}$ over a period of time $T$. Thus, the average accuracy is denoted by $\mathscr{A}$ is defined as follows.

$$\mathscr{A} = \frac{1}{n}\sum_{i,j}^{n} \frac{|\hat{B}_j \cap B_i|}{|B_i|}, \tag{8}$$

where, $\hat{B}_j \cap B_i$ refers to the common energy consumption buckets between the estimated buckets and the actual buckets, and $|*|$ refers to the total number of buckets in $*$.

Secondly, we compute the recovery error (RE) by measuring the distance between the estimated buckets and the actual energy consumption traces (not the actual buckets) of households as follows.

$$\mathrm{RE} := \frac{1}{T}\begin{bmatrix} \sum_{t=1}^{T} |x_1^{(t)} - \hat{B}_1^{(t)}| \\ \vdots \\ \sum_{t=1}^{T} |x_n^{(t)} - \hat{B}_n^{(t)}| \end{bmatrix}, \tag{9}$$

where, $\hat{B}_i^{(t)}$ is the estimated *bucket* of a household $i$ at time $t$ and $x_i^{(t)}$ is the actual energy consumption trace of a household $i$ at time $t$.

## 6.3 Adversarial Performance

We empirically quantify the performance of the adversary $\mathcal{A}$ in recovering energy consumption buckets. We first present the average recovery accuracy of reconstruction attack on the two above discussed datasets.

Figure 7 shows that the average recovery accuracy (over all target households) averaged over the entire period of time, varies between 80% and 95% for the different sized buckets. We observe that the buckets (i.e., energy consumption patterns) recovery accuracy in the Ausgrid dataset is a small amount higher than in the London dataset. The accuracy increases with the increase of the size of buckets because the top buckets are accommodating more users as the buckets include more coarse-grained meter readings within their boundaries.

We now demonstrate the cumulative accuracy (see Figure 8) of the attacker in recovering the energy consumption patterns of households using both datasets for four different size of buckets. Figure 8a shows that over 90% of the households' consumption patterns can be recovered accurately when the *bucket* size is between 1 and 2. Reducing the size of the *bucket* to 0.50, we observe the cumulative accuracy falls, though still achieving more than 95% accuracy for around 75% of households in reconstructing their load patterns in terms of buckets. When we set *bucket* size to 0.25, we observe that the adversary is still capable of recovering over 70% of the households' energy consumption patterns with over 95%accuracy. Moreover, 80% of the households' load patterns can be inferred with at least 80% accuracy. In using the London smart meter dataset, we observe similar results for all size of buckets except the 0.25 bucket. Setting the *bucket* size to 0.25, we observe that 50% and 70% of households' load patterns can be inferred from aggregated statistics with around 90% and 80%, respectively, or higher accuracy.

Thus, our experimental evaluations show that the adversary successfully recovers most of the households' energy consumption load patterns (i.e., the quantity of households that consume from which buckets). These findings show that the privacy threat is severe and this attack paves a way for other possibilities of inferring minute private information about occupancy levels and the activities of target households.

Finally, we report how far the estimated buckets of energy consumption patterns deviate from the ground truth energy consumption traces. Figure 9 shows the recovery errors in kWh (x-axis) and the y-axis represents the households' percentage. We observe that increasing the size of the buckets, increases recovery errors, whereas a smaller *bucket* size decreases recovery errors for both smart meter energy datasets. For the smallest *bucket* the adversary recovers 60% of households' energy consumption by incurring 0.6 kWh or less error from the actual (ground truth) consumption traces in the Ausgrid dataset. The adversary **A** incurs less errors in the London dataset compared to that of in Ausgrid dataset. The attacker recovers energy consumption traces of 40% and 80% households and incurs only 0.4 kWh and 0.6 kWh or less deviation from the ground truth traces, respectively.

We conclude from the above discussed empirical evaluations that our adversarial strategy is effective in inferring the fine-grained energy consumption load patterns of individual households from aggregated statistics. Our study deduces that private information such as household occupancy level and home activities can be gleaned from the estimated fine-gained energy consumption data with high accuracy and low recovery errors. These findings suggest that releasing or sharing the aggregated statistics of energy consumption records of individual households, is not privacy protective. A malicious entity can infringe the privacy of individuals by exploiting the *consistency* and *distinctiveness* properties of consumption patterns. Therefore, data owners must quantify the risks in aggregated statistics before releasing publicly or sharing with third party stakeholders.

# 7 DISCUSSION AND CONCLUDING REMARKS

We have shown that an adversary is capable of reconstructing individual energy consumption traces from aggregated statistics with very high accuracy. Thus, any aggregated energy consumption datasets are not resilient to such attack. As a consequence, the privacy of individual households is at risk. However, we considered only a limited number of queries to assess the adversary's inference capabilities, which could be countered as a weakness in the adversarial model. To address this weakness we will attempt to construct a generic attack model in the future work. Further, we discussed a potential privacy preserving scheme that can be deployed in a privacy preserving data analytics framework to mitigate such privacy attacks while leveraging the aggregated utility of the data. One of the promising privacy preserving technologies is differential privacy (Dwork and Roth, 2014) (DP) that could be used to mitigate the effect of the proposed attack on aggregated consumption. DP is an efficient way to protect the privacy of individual users and can also be used to attenuate the implications of reconstruction attacks. In future work, we would investigate how local differential privacy (LDP) (Kasiviswanathan et al., 2011) could be deployed when collecting data from the smart meters. However, it is still challenging to achieve an optimised trade-off between privacy and utility. Following this paper, we would try to employ LDP under a min-max game that minimises the accuracy loss against protecting from adversaries having maximum background knowledge of the households' energy consumption patterns.

We studied the privacy implications of the aggregated statistics of energy consumption data that is collected from smart meter reading. We empirically evaluated an adversary's performance without having any external information to recover individual users' fine-grained energy consumption on an hourly basis. We offer an example of how an adversary can formulate an unsupervised attack method; we pose the problem as a balanced assignment problem and solve it using the Hungarian algorithm to find the optimal match by minimising the cost. Overall, our work presents a novel methodology to assess privacy risks in aggregated smart meter data. Moreover, our methodology can be used to quantify the privacy implications in other real-world settings such as transaction data, health data and web search data.

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