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Real-Time Privacy-Preserving Data Release for Smart Meters

Mohammadhadi Shateri, Francisco Messina, Pablo Piantanida, and Fabrice Labeau

Abstract—Smart Meters (SMs) are a fundamental component of smart grids, but they carry sensitive information about users such as occupancy status of houses and therefore, they have raised serious concerns about leakage of consumers private information. In particular, we focus on real-time privacy threats, i.e., potential attackers that try to infer sensitive data from SMs reported data in an online fashion. We adopt an information-theoretic privacy measure and show that it effectively limits the performance of any real-time attacker. Using this privacy measure, we propose a general formulation to design a privatization mechanism that can provide a target level of privacy by adding a minimal amount of distortion to the SMs measurements. On the other hand, to cope with different applications, a flexible distortion measure is considered. This formulation leads to a general loss function, which is optimized using a deep learning adversarial framework, where two neural networks—referred to as the releaser and the adversary—are trained with opposite goals. An exhaustive empirical study is then performed to validate the performances of the proposed approach for the occupancy detection privacy problem, assuming the attacker disposes of either limited or full access to the training dataset.

Index Terms—Privacy-preserving mechanism, Deep learning, Adversarial training, Time series data, Recurrent Neural Networks, Long-Short Term Memory (LSTM) cell, Directed information, Privacy-utility trade-off, Smart meters privacy.

I. INTRODUCTION

SMART Meters (SMs) are a cornerstone for the development of smart electrical grids. These devices are able to report power consumption measurements of a house to a utility provider every hour or even every few minutes. This feature generates a considerably amount of useful data which enables several applications in almost real-time such as power quality monitoring, timely fault detection, demand response, energy theft prevention, etc. [1], [2]. However, this fine-grained power consumption monitoring poses a threat to consumers privacy. As a matter of fact, it has been shown that simple algorithms, known in general as NonIntrusive Load Monitoring (NILM) methods, can readily be used to infer from the smart meter data the types of appliances being used at a household at a given time [3]. Since these features are highly correlated with the presence of people at the dwelling and their personal habits, this induces serious privacy concerns which can have an impact on the acceptance and deployment pace of SMs [4]. The natural challenge raised here is: how can privacy be enhanced while preserving the utility of the SMs

data? Although the privacy problem has been widely studied in the field of data science [5], the time series structure of SMs data requires a particular treatment [6]. For a recent survey about SMs privacy, the reader is referred to [7].

Simple approaches for preservation of privacy in the context of SMs include data aggregation and encryption [8], [9], the use of pseudonyms rather than the real identities of users [10], downsampling of the data [11], [12] and random noise addition [13]. However, these methods often restrict the potential applications of the SMs data in an uncontrolled way. For instance, downsampling of the data may incur time delays to detect critical events, while data aggregation degrades the positioning and accuracy of the power measurements.

A formal approach to the privacy problem has been presented in [14] from an information-theoretic perspective, where it has been proposed to assess privacy by the Mutual Information (MI) between the sensitive variables to be hidden and the power measurements distorted by a privatizer mechanism. More specifically, the authors model the power measurements of SMs with a hidden Markov model in which the distribution of the measurements is controlled by the state of the appliances, and for each particular state, the distribution of power consumption is assumed to be Gaussian. This model is then used to obtain the privacy-utility trade-off using tools from rate-distortion theory [15]. Although this approach is very appealing, it has two important limitations for its application to real-time privacy problems using actual data. First, the privacy-preserving data release mechanism works with blocks of samples, which is not well-suited for real-time processing. Second, the Gaussian model may be quite restrictive to model SMs signals. We address the first limitation by proposing a causal sample by sample data processing mechanism and the second one by taking a data-based approach in which no explicit constraints on the distributions or statistics of the involved variables are needed.

More sophisticated approaches consider the use of Rechargeable Batteries (RBs) and Renewable Energy Sources (RES) in homes in order to modify the actual energy consumption of users with the goal of hiding the sensitive information [16]–[19]. The main motivation to introduce the use of physical resources into the privacy problem comes from the observation that this strategy does not require any distortion in the actual SMs measurements, which means that there is no loss in terms of utility. However, the incorporation of physical resources may not only make the problem more complex and limited in scope, but can also generate a significant cost to users due to the faster wear and tear of the RBs as a consequence of the increased charging/discharging rate [7]. On the other hand, the required level of distortion for a

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specific privacy goal in a realistic scenario in which the attacker threatening privacy has only partial information is still an open question. Thus, the need and convenience of these solutions is still questionable. In this work, we show that under some conditions the privacy-utility trade-off may be much less severe than expected. However, it is also important to note that these approaches are complementary to the ones based on distorting the power measurements. For simplicity, we assume that no RBs and/or RESs are available and thus, the distortion on power measurements is the only mean to achieve a desired privacy level.

The use of neural networks to model a privacy attacker has been considered in [20]. However, a more powerful formulation of the problem is obtained if one assumes that both the releaser (i.e., the privatizer) and the attacker are deep neural networks (DNNs). In this framework, the releaser can be trained by simulating an attacker based on a minimax game, an idea that is inspired by the well-known Generative Adversarial Networks (GANs) [21]. This concept can be referred to as Generative Adversarial Privacy (GAP) [22] and is the basis for the approach taken in the present work. It should be mentioned that the concept of GAP has been studied for different applications related to image classification [23], [24] but, to the best of our knowledge, not in the context of SMs. In these works, the authors consider independent and identically distributed (i.i.d.) data and deep feed-forward neural networks for the releaser and attacker, while in this paper we consider deep Recurrent Neural Networks (RNNs) to capture and exploit the time correlation. The idea of time-series generation with an adversarial approach has been considered in [25] for medical data based in the principle of differential privacy. As we mentioned previously, our approach is instead based on an information-theoretic measure of privacy.

The main contributions of this work, which is an extension of a short version in [26], are the following:

- (i) We applied Directed Information (DI) as a privacy measure and show its theoretical relevance for the privacy problem under consideration. It is worth to mention that DI was first used in [27] but in a different manner. In addition, unlike this and other works, we impose no explicit assumptions on the generating model of the power measurements, but take a more versatile data-driven approach.
- (ii) We study different distortion measures to provide more flexibility to control the specific features to be preserved in the released signals, i.e., the relevant characteristics for the targeted applications of the data.
- (iii) For the sake of computational tractability, we propose a loss function for training the privacy-preserving releaser based on an upper bound of the DI. Then, considering an attacker that minimizes a Kullback-Leibler divergence between the true and approximate distributions of the sensitive variables given the released signal, we implement an adversarial framework based on two RNNs to train the releaser.
- (iv) We perform an extensive statistical study with actual data to characterize the utility-privacy trade-offs and the nature of the distortion generated by the releaser network.
- (v) We investigate the data mismatch problem in the context of SMs privacy, which occurs when the data available to the attacker is not the same as the one used for training the releaser mechanism, and show that it has an important impact on the privacy-utility trade-off.

Notation and conventions

The reader is referred to [15] for the definition of basic information-theoretic concepts such as mutual information and entropy, while the definition of directed information can be found in [28]. The main conventions used in the paper are as follows:

- $X^T = (X_1, \dots, X_T)$: A sequence of random variables, or a time series, of length T ;
- $x^T = (x_1, x_2, \dots, x_T)$: A realization of X^T ;
- $x^{(i)T} = (x_1^{(i)}, x_2^{(i)}, \dots, x_T^{(i)})$: The i^{th} sample in a minibatch used for training;
- $\mathbb{E}[X]$: The expectation of a random variable X ;
- p_X : The distribution of X ;
- $I(X; Y)$: Mutual information between X and Y ;
- $H(X)$: Entropy of random variable X ;
- $I(X^T \rightarrow Y^T)$: Directed information between X^T and Y^T ;
- $X \circlearrowleft Y \circlearrowleft Z$: Markov chain among X , Y and Z .

II. PROBLEM FORMULATION

There are four main types of variables that should be clearly defined in the privacy-preserving data release setting: (i) the private/sensitive attribute which we aim to hide X^T (e.g., occupancy state of a house over time); (ii) the useful process for the utility provider Y^T (e.g., actual electricity consumption of the household), which is generally highly correlated with the private data; (iii) the observed signal W^T , a combination of private and useful variables which is the input to the data release system; (iv) and the released process Z^T , a sanitized version of Y^T which is the output of the data release system.

We assume that X_t takes values on a fixed discrete alphabet \mathcal{X} for each $t \in \{1, \dots, T\}$. At each time t , a releaser produces the released process Z_t based on the observation W^t , while an attacker attempts to infer X_t based on Z^t by using an approximation of $p_{X^t|Z^t}$, which we shall denote by $p_{\hat{X}^t|Z^t}$. Notice that the releaser must be causal in order to avoid delays in the smart meter data report process. In addition, we treat the case in which the attacker is performing the inference in real-time, so that it is also causal. This assumption is reasonable for scenarios in which the sensitive information is valuable in a timely manner (e.g., in the case of targeted burglary based on occupancy detection [6]). However, it should be noted that not all privacy threats fall under this umbrella. Alternative attacker structures, which may be interesting in other scenarios, are left for future work and are out of the scope of this paper. Note that due to the previous assumption the distribution $p_{Z^T \hat{X}^T | W^T}$ can be decomposed as follows:

$$p_{Z^T \hat{X}^T | W^T}(z^T, \hat{x}^T | w^T) = \prod_{t=1}^T p_{Z_t | W^t}(z_t | w^t) p_{\hat{X}_t | Z^t}(\hat{x}_t | z^t). \quad (1)$$

In abstract terms, the goal of the releaser is to minimize the information leakage of the sensitive process X^T while

simultaneously keeping the distortion between the released time series Z^T and the useful signal Y^T small. On the other hand, the goal of the attacker is to infer $p_{X_t|Z^t}$, for each t , as accurately as possible. Note that after the approximation $p_{\hat{X}_t|Z^t}$ is obtained, the attacker can estimate the private information x^t from observations z^t in an online (causal) fashion, by solving

$$\operatorname{argmax}_{\hat{x}_t \in \mathcal{X}} p_{\hat{X}_t|Z^t}(\hat{x}_t|z^t), \quad (2)$$

at each $t = 1, \dots, T$. Thus, the attacker can be interpreted as a classifier or hypothesis test, as stated in [29]. However, in the present case, we consider the more realistic and general scenario in which the statistical test is sub-optimal due to the fact that the attacker has no access to the actual conditional distributions $p_{X_t|Z^t}$ but only to its approximation $p_{\hat{X}_t|Z^t}$.

In order to take into account the causal relation between X^T and \hat{X}^T , the information leakage is quantified by the DI [28]:

$$I(X^T \rightarrow \hat{X}^T) := \sum_{t=1}^T I(X^t; \hat{X}_t | \hat{X}^{t-1}), \quad (3)$$

where $I(X^t; \hat{X}_t | \hat{X}^{t-1})$ is the conditional mutual information between X^t and \hat{X}_t conditioned on \hat{X}^{t-1} [15].

The normalized expected distortion between Z^T and its noisy (or disturbed) observation Y^T is defined as:

$$D(Z^T, Y^T) := \frac{\mathbb{E}[d(Z^T, Y^T)]}{T}, \quad (4)$$

where $d : \mathbb{R}^T \times \mathbb{R}^T \rightarrow \mathbb{R}$ is any distortion function (i.e., a metric on \mathbb{R}^T). To ensure the quality of the release, it is natural to impose the following constraint: $D(Z^T, Y^T) \leq \varepsilon$ for some given $\varepsilon \geq 0$. In previous works, the normalized squared-error was considered as a distortion function (e.g., [14], [26]). Nevertheless, other distortion measures can also be relevant within the framework of SMs. For instance, demand response programs usually require an accurate knowledge of peak power consumption, so a distortion function closer to the infinity norm would be more meaningful for those particular applications. Thus, for the sake of generality and to keep the distortion function simple, we propose to use an ℓ_p distance:

$$d(z^T, y^T) := \|z^T - y^T\|_p = \left(\sum_{t=1}^T |z_t - y_t|^p \right)^{1/p}, \quad (5)$$

where $p \geq 2$ is a fixed parameter. Note that this distortion function leads to the root-mean-squared error when $p = 2$, while it converges to the maximum error between the components of z^T and y^T as $p \rightarrow \infty$.

Therefore, the problem of finding an optimal releaser subject to the optimal (Bayesian) attacker and distortion constraint can be formally written as follows:

$$\inf_{p_{Z^T|W^T}} I(X^T \rightarrow \hat{X}^T) \quad \text{subject to} \quad D(Z^T, Y^T) \leq \varepsilon. \quad (6)$$

Note that the solution to this optimization problem requires a balance between the attacker $p_{\hat{X}^T|Z^T}$ and the releaser $p_{Z^T|W^T}$, where the optimal attacker consists in inferring the private information $\hat{X}^T \approx X^T$ and thus, the attacker attempts to

minimize the Kullback-Leibler divergence [15] between the corresponding predictors:

$$\inf_{p_{\hat{X}^T|Z^T}} \text{KL}(p_{X^T|Z^T} \| p_{\hat{X}^T|Z^T}) = \inf_{p_{\hat{X}^T|Z^T}} \mathbb{E} \left[\log \frac{p_{X^T|Z^T}(X^T|Z^T)}{p_{\hat{X}^T|Z^T}(X^T|Z^T)} \right], \quad (7)$$

where the expectation is with respect to $p_{X^T|Z^T}$. Note that solving (7) is equivalent to minimizing $\mathbb{E}[-\log p_{\hat{X}^T|Z^T}(X^T|Z^T)]$, the so-called cross-entropy.

Unfortunately, the optimization problem (6) is, in general, computationally intractable. For instance, simply computing the DI would take $O(|\mathcal{X}|^T)$ operations, where $|\mathcal{X}|$ is the size of \mathcal{X} , which makes it not scalable for large sequences of data. However, it can be exploited to obtain a more convenient surrogate objective function for the releaser, by considering the following simpler upper bound:

$$\begin{aligned} I(X^T \rightarrow \hat{X}^T) &= \sum_{t=1}^T [H(\hat{X}_t | \hat{X}^{t-1}) - H(\hat{X}_t | \hat{X}^{t-1}, X^t)] \\ &\stackrel{(i)}{\leq} \sum_{t=1}^T [H(\hat{X}_t | \hat{X}^{t-1}) - H(\hat{X}_t | \hat{X}^{t-1}, X^t, Z^t)] \\ &\stackrel{(ii)}{=} \sum_{t=1}^T [H(\hat{X}_t | \hat{X}^{t-1}) - H(\hat{X}_t | Z^t)] \\ &\stackrel{(iii)}{\leq} T \log |\mathcal{X}| - \sum_{t=1}^T H(\hat{X}_t | Z^t), \end{aligned} \quad (8)$$

where (i) is due to the fact that conditioning reduces entropy; equality (ii) is due to the Markov chain $(X^t, \hat{X}^{t-1}) \circlearrowleft Z^t \circlearrowleft \hat{X}_t$, which follows from (1); and (iii) is due to the trivial bounds $H(\hat{X}_t | \hat{X}^{t-1}) \leq H(\hat{X}_t) \leq \log(|\mathcal{X}|)$. Note that minimizing the upper bound (8) corresponds to maximizing $\sum_{t=1}^T H(\hat{X}_t | Z^t)$, which amounts to maximizing the total uncertainty of the attacker. In fact, from Fano's inequality [15], we have that

$$f(P_{e,t}) := h(P_{e,t}) + P_{e,t} \log(|\mathcal{X}|-1) \geq H(\hat{X}_t | X_t) \geq H(\hat{X}_t | Z^t), \quad (9)$$

where $P_{e,t} := \mathbb{P}(X_t \neq \hat{X}_t)$ and $h(p) := -p \log(p) - (1-p) \log(1-p)$ is the so-called binary entropy function. In addition, the bound is tight (i.e., it can not be strengthened without further assumptions) [15], [30]. It should be noted that this bound constrains $P_{e,t}$ to be in an interval around $P_{e,t} = (|\mathcal{X}|-1)/|\mathcal{X}|$, which corresponds to the performance of an attacker that does uniform random guessing to infer the value of X_t . Indeed, in the extreme case in which $H(\hat{X}_t | Z^t) = \log(|\mathcal{X}|)$, we have that $P_{e,t} = (|\mathcal{X}|-1)/|\mathcal{X}|$. Physically, this means that Z^t is not providing any information to the attacker to infer X_t . Moreover, the length of this interval decreases monotonically when $H(\hat{X}_t | Z^t)$ is increased (see Fig. 1 for an illustration). Therefore, a releaser which attempts to maximize $H(\hat{X}_t | Z^t)$ is trying to constrain $P_{e,t}$ to be close to random guessing performance. This can be considered as a universal privacy guarantee and justifies the usefulness of the DI and, in particular, the surrogate upper bound (8).

Therefore, in this work, the information leakage is measured by the following average conditional entropy

$$-\frac{1}{T} \sum_{t=1}^T H(\hat{X}_t | Z^t), \quad (10)$$

where the factor $1/T$ has been introduced for normalization purposes. It is interesting to notice that this is different from the formulation in [14], in which the authors consider the MI $I(X^T; Z^T) = H(X^T) - H(X^T|Z^T)$ as the information leakage measure, which can be equivalently written as follows:

$$-\frac{1}{T} \sum_{t=1}^T H(X_t|Z^T, X^{t-1}). \quad (11)$$

By comparing (10) and (11), the differences between the two privacy measures are clear. The fact that we have assumed that the attacker has a causal structure explains why Z^t appears in (10) instead of Z^T as in (11). More fundamentally, the expression (11) corresponds to assuming that the attacker is optimal (i.e., $p_{\hat{X}_t|Z^t} = p_{X_t|Z^t}$) and has access to X^{t-1} to infer X_t . These latter assumptions are not expected to hold in practice.

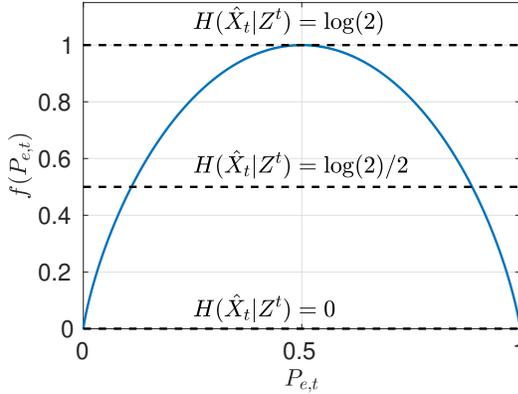


Fig. 1. Plot of the Fano's function $f(P_{e,t})$ for the case $|\mathcal{X}|=2$. Notice that as $H(\hat{X}_t|Z^t)$ increases, the interval over which $P_{e,t}$ lies shrinks. Also, in the extreme case in which $H(\hat{X}_t|Z^t) = \log(2)$, Fano's inequality (9) implies $P_{e,t} = 1/2$, which corresponds to the performance of random guessing the value of X_t , meaning that Z^t does not provide any valuable information.

III. PRIVACY-PRESERVING MODEL

We now shift the focus from the abstract theoretical formulation to a practical one based on deep learning ideas. In particular, in this section, we model the releaser $p_{Z^T|W^T}$ and attacker $p_{\hat{X}^T|Z^T}$ as Recurrent Neural Networks (RNNs), which are well-suited for the time-series structure of the SMs data and online processing. In the following, we describe in detail the loss functions, the network architectures and the learning algorithm used to train the releaser mechanism.

A. Loss Functions

Considering (6) and (10), the loss function for the releaser is defined as follows:

$$\mathcal{L}_{\mathcal{R}}(\theta, \phi, \lambda) := D(Z^T, Y^T) - \frac{\lambda}{T} \sum_{t=1}^T H(\hat{X}_t|Z^t), \quad (12)$$

where $\lambda \geq 0$ controls the privacy-utility trade-off, θ are the parameters of the releaser and ϕ the parameters of the attacker. It should be mentioned that for $\lambda = 0$, the loss function $\mathcal{L}_{\mathcal{R}}(\theta, \phi, \lambda)$ reduces to the expected distortion, being independent from the attacker. In such scenario, the releaser

offers no privacy guarantees. Conversely, for very large values of λ , the loss function $\mathcal{L}_{\mathcal{R}}(\theta, \phi, \lambda)$ is dominated by the second term, so that privacy is the main goal of the releaser. In this regime, we expect the attacker to fail in inferring X^T , i.e., to approach to random guessing performance.

On the other hand, from (7), the attacker loss function is defined as follows:

$$\mathcal{L}_{\mathcal{A}}(\phi) := \frac{1}{T} \sum_{t=1}^T \mathbb{E} \left[-\log p_{\hat{X}_t|Z^t}(X_t|Z^t) \right], \quad (13)$$

where the expectation is with respect to $p_{X_t|Z^t}$.

It should be mentioned that for training the previous loss functions are approximated by evaluating the expectations empirically as shown next. Let $\{(x^{(b)T}, y^{(b)T})\}_{b=1}^B$ be a sample of B examples and $\{z^{(b)T}\}_{b=1}^B$ the corresponding outputs of the releaser. Then, the loss functions are approximated as follows:

$$\begin{aligned} \mathcal{L}_{\mathcal{R}}(\theta, \phi, \lambda) &\approx \frac{1}{BT} \sum_{b=1}^B d(z^{(b)T}, y^{(b)T}) \\ &+ \frac{\lambda}{BT} \sum_{b=1}^B \sum_{\hat{x}_t^{(b)} \in \mathcal{X}} p_{\hat{x}_t^{(b)}|z^{(b)T}}(\hat{x}_t^{(b)}|z^{(b)T}) \log p_{\hat{x}_t^{(b)}|z^{(b)T}}(\hat{x}_t^{(b)}|z^{(b)T}), \end{aligned} \quad (14)$$

$$\mathcal{L}_{\mathcal{A}}(\phi) \approx -\frac{1}{BT} \sum_{t=1}^T \sum_{b=1}^B \log p_{\hat{x}_t|Z^t}(x_t^{(b)}|z^{(b)T}). \quad (15)$$

B. Recurrent Neural Networks and Long Short-Term Memory

Recurrent Neural Networks (RNNs) are a class of neural networks that are able to process sequential data by modeling the temporal correlation in data. Therefore, the output of an RNN network at time step $t-1$ generally affects the output at time t . Training of the RNNs is generally performed by gradient descent using the backpropagation through time algorithm [31]. However, learning long-term dependencies of time series data by RNNs may lead to the gradient vanishing or exploding problems, thus preventing successful training [32]. To resolve this issue, the so-called long short-term memory (LSTM) cell was introduced in [33] and further improved in [34]. Fig. 2 represents the architecture of a LSTM cell in detail. For more information on RNNs and LSTMs, the reader is referred to [35, Chapter 10] and references therein.

C. Privacy-Preserving Adversarial Learning

Based on the previous formulation, an adversarial modeling framework consisting of two RNNs, a releaser \mathcal{R}_{θ} and an attacker \mathcal{A}_{ϕ} , is considered (see Fig. 3). Note that independent noise U^T (with dimension m) is appended to W^T in order to randomize the released variables Z^T , which is a popular approach in privacy-preserving methods. In addition, the available theoretical results show that, for Gaussian distributions, the optimal release contains such a noise component [14], [23]. For both networks, a LSTM architecture is selected. Training in the suggested framework is performed using the Algorithm 1 which requires k gradient steps to train \mathcal{A}_{ϕ} followed by one gradient step to train \mathcal{R}_{θ} . It is worth to emphasize that k should be large enough in order to ensure that \mathcal{A}_{ϕ} represents

Algorithm 1 Algorithm for training privacy-preserving data releaser neural network.

Input: Data set (which includes samples of useful data y^T , sensitive data x^T); seed noise samples u^T ; seed noise dimension m ; batch size B ; number of steps to apply to the Adversary k ; gradient clipping value C ; ℓ_2 regularization parameter β .

Output: Releaser network \mathcal{R}_θ .

- 1: **for** number of training iterations **do**
- 2: **for** k steps **do**
- 3: Sample minibatch of B examples $\{w^{(b)T} = (x^{(b)T}, y^{(b)T}, u^{(b)T})\}_{b=1}^B$ and generate releases $\{z^{(b)T}\}_{b=1}^B$.
- 4: Compute the gradient of $\mathcal{L}_{\mathcal{A}}(\phi)$, empirically approximated with the minibatch \mathcal{B} , with respect to ϕ .
- 5: Update ϕ by applying the RMSprop optimizer [36] with clipping value C .
- 6: **end for**
- 7: Sample minibatch of B examples $\{w^{(b)T} = (x^{(b)T}, y^{(b)T}, u^{(b)T})\}_{b=1}^B$ and generate releases $\{z^{(b)T}\}_{b=1}^B$.
- 8: Compute the gradient of $\mathcal{L}_{\mathcal{R}}(\theta, \phi, \lambda)$, approximated with the minibatch \mathcal{B} , with respect to θ .
- 9: Use Ridge(L_2) regularization [37] with value β and update θ by applying RMSprop optimizer with clipping value C .
- 10: **end for**

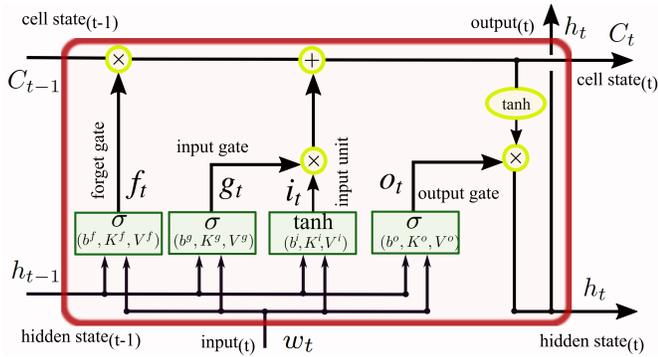


Fig. 2. LSTM recurrent network cell diagram at time step t . The cell includes four gating units to control the flow of information. All the gating units have a sigmoid activation function (σ) except for the input unit (that uses a hyperbolic tangent activation function (\tanh) by default). The parameters b, V, K are respectively biases, input weights, and recurrent weights. In the LSTM architecture, the forget gate $f_t = \sigma(b^f + K^f h_{t-1} + V^f w_t)$ uses the output of the previous cell (which is called hidden state h_{t-1}) to control the cell state C_t and remove irrelevant information. On the other hand, the input gate $g_t = \sigma(b^g + K^g h_{t-1} + V^g w_t)$ and input unit $i_t = \sigma(b^i + K^i h_{t-1} + V^i w_t)$ add new information to the cell state $C_t = f_t C_{t-1} + g_t i_t$. Finally, the output gate $o_t = \sigma(b^o + K^o h_{t-1} + V^o w_t)$ generates the output of the cell from the current input and cell state: $h_t = o_t \tanh(C_t)$.

a strong attacker. However, if k is too large, this could lead to overfitting and thus a poor attacker. After the training of both networks is completed, a new network is trained from scratch in order to test the privacy achieved by the releaser network.

IV. RESULTS AND DISCUSSION

We will validate our results on the Electricity Consumption & Occupancy (ECO) dataset. ECO is collected and published by [38], which includes 1 Hz power consumption measurements and occupancy information of five houses in Switzerland over a period of 8 months. Occupancy labels are determined as 1 for the case that someone is at home and 0 otherwise. Thus, for this application, the privacy attacker is a binary classifier that attempts to infer if a household is occupied or not at a given time. In this study, we re-sampled the data to have hourly samples. We model the time dependency over each day, so the data set is reshaped to sample sequences of length 24. A total number of 11225

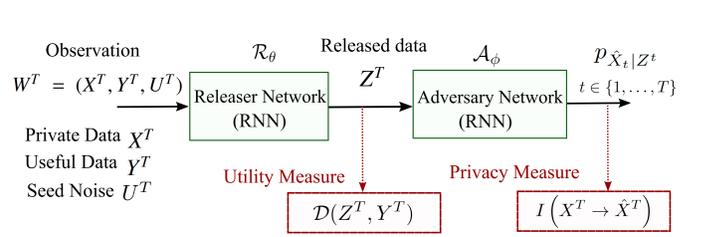


Fig. 3. Privacy-Preserving framework. The seed noise U^T is generated from independent and identically distributed (i.i.d.) samples according to a uniform distribution: $U_t \sim U[0, 1]$.

sample sequences were collected. The data sets are split into training and test sets with a ratio of roughly 85:15 while 10% of training data is dedicated to validation which intended to set the hyperparameters. The network architectures and hyperparameters values are summarized in Table I. A stronger attacker composed of 3 LSTM layers is used for the test.

To clearly assess the distortion with respect to the actual power consumption measurements, we define the Normalized Error (NE) for the different ℓ_p distortion functions as follows:

$$NE_p := \frac{\mathbb{E}[\|Y^T - Z^T\|_p]}{\mathbb{E}[\|Y^T\|_p]}. \quad (16)$$

In addition, performance of the attacker on inferring the private attributes is quantified based on the balanced accuracy. This is common in classification problems to deal with the data imbalance problem, which occurs when the number of samples for each class is quite different. Balanced accuracy is defined as the average recall calculated for each class [39]. Concretely, let c_{ij} represent the fraction of examples of class i classified as class j . Then, the balanced accuracy can be defined as

$$\text{Balanced Accuracy} := \frac{1}{2} \left(\frac{c_{11}}{c_{11} + c_{12}} + \frac{c_{22}}{c_{22} + c_{21}} \right). \quad (17)$$

This metric provides a fair assessment of the quality of the attacker independently from the degree of data unbalance. Thus, simplifying the analysis of the results. In the following we use the term accuracy to refer to the balanced accuracy.

TABLE I
MODEL ARCHITECTURES AND HYPERPARAMETERS VALUES.

Releaser	Adversary	Attacker	B	k	m
4 LSTM layers each with 64 cells and $\beta = 1.5$	2 LSTM layers each with 32 cells	3 LSTM layers each with 32 cells	128	4	8

TABLE II
ERRORS IN POWER QUALITY INDICATORS ALONG THE PRIVACY-UTILITY TRADE-OFF.

NE_2	Accuracy(%)	Absolute relative error of quality indicators(%)				
		Mean	Skewness	Kurtosis	Std. Dev./Mean	Max./Mean
0.04	78	1.42	1.06	0.70	0.67	0.46
0.12	65	9.69	4.32	5.81	4.58	4.92
0.18	57	13.26	12.83	2.57	16.44	13.89

A. ℓ_2 Distortion

In this section, we consider the ℓ_2 distortion function (i.e., $p = 2$ in (5)). Fig. 4 shows the empirically found privacy-utility trade-off for this scenario. Note that by increasing the distortion of the release, the accuracy of the attacker changes from more than 80% (almost no privacy) to 50% (full privacy).

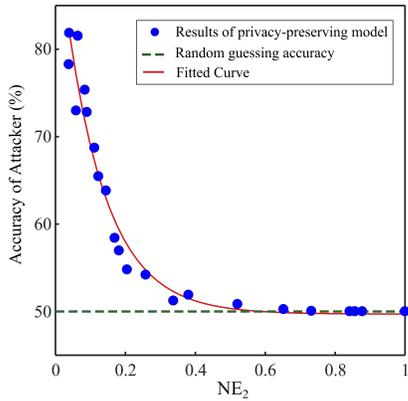


Fig. 4. Privacy-utility trade-off for house occupancy inference using ℓ_2 distortion function. The fitted curve is based on an exponential function and is included only for illustration purposes.

To assess the quality of the release signal, utility providers may be interested in several different indicators. These include, for instance, the mean, skewness, kurtosis, standard deviation to mean ratio, and maximum to mean ratio [40]. Thus, for completeness, we present these indicators in Table II for three different cases along the privacy-utility trade off curve. We observe that in general the errors in these indicators are small when the privacy constraints are lax and increase as they become stricter. Nevertheless, no simple relation can be expected between NE_2 and the values of those indicators.

B. ℓ_p Distortion

As already discussed in Section II, the distortion function should be properly matched to the intended application of the released variables Z^T in order to preserve the characteristics of the target variables Y^T that are considered essential. In this

section, we consider the ℓ_p distortion (5) with $p = 4, 5$ as an alternative to the ℓ_2 distortion function used in the previous section and study their potential benefits.

The privacy-utility trade-off curve for these distortion functions is shown in Fig. 5. As a first observation, it is clear that the choice of the distortion measure has a non-negligible impact on the privacy-utility trade-off curve. In fact, it can be seen that for a given amount of normalized distortion, the releaser trained with the ℓ_4 and ℓ_5 distortion measures achieve a higher level of privacy than the one trained with the ℓ_2 distortion function. It should also be mentioned that we also considered other norms, such as the ℓ_{10} , and the privacy-utility trade-off was observed to be similar, but slightly different, than the one corresponding to the ℓ_4 norm.

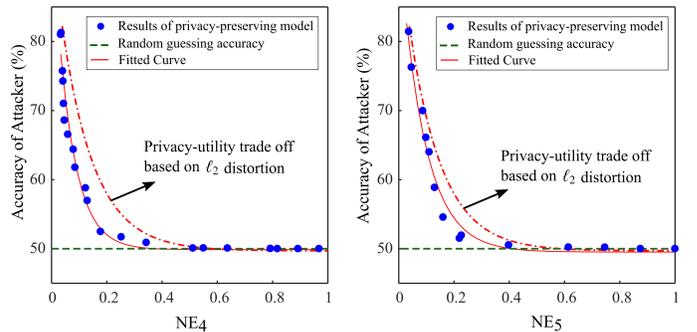


Fig. 5. Privacy-utility trade-off for house occupancy inference based on the different ℓ_p distortion functions. For each figure, the dashed line, shown for comparison purposes, is the fitted curve found in Fig. 4 for the ℓ_2 distortion function.

As we discussed in Section II, in some applications, such as demand response programs, the utilities are mostly interested in the peak power consumption of the customers. It is also expected that higher-order ℓ_p norms are better at preserving these signal characteristics than the ℓ_2 norm. To verify this notion, we considered 60 random days of the ECO data set in a full privacy scenario (i.e., with an attacker accuracy very close to 50%) and plotted the actual power consumption along with the corresponding release signals for both the ℓ_4 and ℓ_2 distortion functions. Results shown in Fig. 6 clearly indicate that the number of peaks preserved by the releaser trained with

the ℓ_4 distortion function is much higher than the ones kept by the releaser trained with the ℓ_2 distortion function. This suggests that for these applications, higher order ℓ_p distortion functions should be considered.

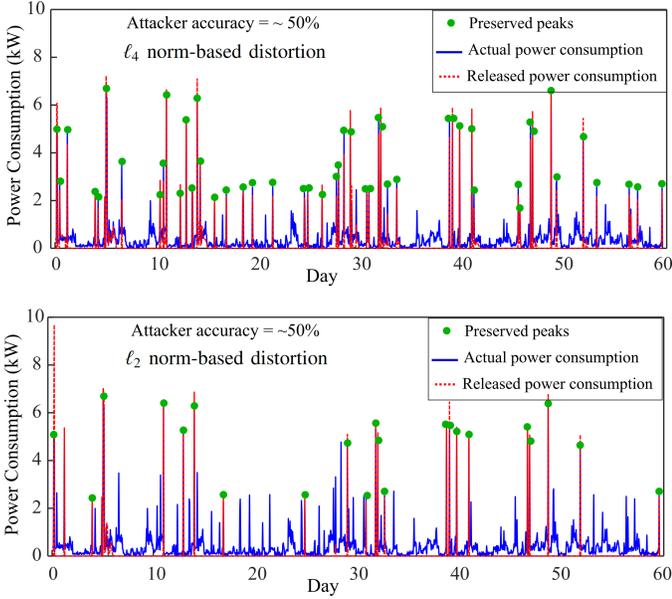


Fig. 6. Example of the release power consumption in the time domain compared with the actual power consumption over 60 random days with almost full privacy for the ℓ_4 and ℓ_2 distortion functions.

C. Attacker with Data Mismatch Problem

All the previous results are based on the assumption that the attacker has access to exactly the same training data set used by the releaser-adversary system. This case should be considered as a worst-case analysis of the performance of the releaser. However, this assumption may not be true in practice. To examine the impact of this hypothesis, we consider two different cases. It should be noted that the total number of samples used for training and testing was kept fixed in all the different scenarios. In the first case, we assume that, out of the data set of the five houses in the ECO data set, the releaser uses the data of all the houses for training while the attacker has only access to the data of houses 1 and 3. In the second case, we assume that releaser is trained with the data of houses $\{1, 2, 4, 5\}$ but the attacker has only access to data from house 3. These scenarios try to capture different degrees of the data mismatch problem, which could have an impact on the privacy-utility trade-off due to the different generalization errors. The results are presented in Fig. 7 along with the worst-case scenario. We conclude that the overlapping of the training data sets of the releaser and the attacker can strongly affect the performance of the model. In fact, in the case where the attacker does not have access to the same data set as the releaser, its performance largely degrades, which means that a target level of privacy requires much less distortion. In the extreme case where the attacker has no access to the releaser training data set, a very high level of privacy can be achieved with negligible distortion. It should be mentioned that

we repeated this experiment with different choices of these 5 houses and similar results were obtained.

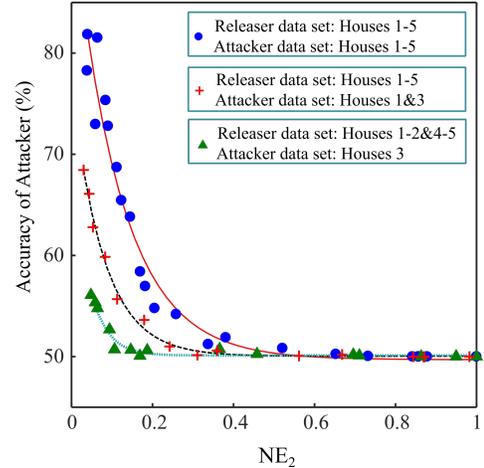


Fig. 7. Effect of data mismatch between the releaser and the attacker on the privacy-utility trade-off for house occupancy inference.

V. DISCUSSION AND CONCLUDING REMARKS

Privacy concerns associated with smart meters measurements are an important problem since these can have an impact on their deployment pace and the advancement of smart grid technologies. As a consequence, it is essential to understand and to palliate real privacy risks in order to provide an adequate solution to conveniently share SM data.

In this paper, we proposed to measure the privacy based on the Directed Information (DI) between the sensitive time series and its inference by a potential attacker optimized for the dedicated task. This captures the causal time dependencies present in the time series data and its sequential processing. For the sake of computational tractability, we propose an upper bound to the DI which leads to our training objective. Then, using Fano's inequality, it was shown that this bound can constrain the performance of the optimal (Bayesian) attacker. Unlike previous approaches, the proposed method does not impose explicit assumptions to the statistics or distributions of the involved random quantities. We believe that this data-driven approach, using state-of-the-art methods, can provide a more accurate assessment of the leakage in practice than purely theoretical studies based on restrictive models.

We explored a data release framework that balances the trade-off between privacy of the sensitive information and distortion of the useful data. The desired releaser was then trained in an adversarial framework using RNNs to optimize such objective, while an artificial attacker was trained with an opposite goal. After convergence, a new attacker was trained to test the level of privacy achieved by the releaser.

A detailed study of the inference of households occupancy using actual SMs data set was performed. We showed that the choice of the distortion measure can have a significant impact on the privacy-utility trade-off curve. Indeed, it is shown that the ℓ_4 distortion measure generates a release that preserves most of the power consumption peaks even under a

full privacy regime, which is not the case for the ℓ_2 distortion function. This result may be of considerable importance for some applications such as demand response. More generally, our formulation is amenable to train different release systems tailored for several potential applications based on SMs data.

Finally, we studied the impact of the data mismatch problem in this application, which occurs when the training data set of the attacker is not exactly the same as the one used by the releaser. These results have shown that this effect can greatly affect the privacy-utility trade-off. Since this phenomenon is expected in practice, at least to some degree, these findings suggest that the level of required distortion to achieve desired privacy targets may be negligible in several cases of interest.

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