SearchFromFree: Adversarial Measurements for Machine Learning-based Energy Theft Detection

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Abstract—Energy theft causes large economic losses to utility companies around the world. In recent years, energy theft detection approaches based on machine learning (ML) techniques, especially neural networks, are becoming popular in the research community and shown to achieve state-of-the-art detection performance. However, in this work, we demonstrate that the well-trained ML models for energy theft detection are highly vulnerable to adversarial attacks. In particular, we design an adversarial measurement generation approach that enables the attacker to report extremely low power consumption measurements to utilities while bypassing the ML energy theft detection. We evaluate our approach with three kinds of neural networks based on a real-world smart meter dataset. The evaluation results demonstrate that our approach is able to significantly decrease the ML models’ detection accuracy, even for black-box attackers.

Index Terms—energy theft detection, power grid, adversarial machine learning

I. INTRODUCTION

As one of the primary non-technical losses (NTL) in the power systems, energy theft happens when an attacker deliberately manipulates his/her electricity data to reduce the electricity bills. To date, energy theft causes high financial losses to electric utility companies around the world. It is estimated that up to $6 billion of electricity is stolen (around 1% to 3% annual revenue) in the United States each year [1], and the loss can be larger in developing countries [2].

In recent years, with the development of advanced metering infrastructure (AMI), two-way data communications between customers and utilities are enabled by the deployment of smart meters. However, recent studies demonstrated that the data communication facilities of AMI introduce new vulnerabilities that can be exploited by the attackers to launch energy theft [3]. Meanwhile, the smart meters are also shown to be vulnerable to physical penetration [4], and there are even video tutorials online on smart meter hacking [5]. Therefore, the energy theft problem is serious and the corresponding detection approaches are needed.

Different approaches were proposed to detect and mitigate energy theft. In general, the detection approaches can be categorized into two classes, sensor-based and consumption profile-based. The sensor-based approaches require the deployment of extra equipment and will increase the maintenance costs while the profile-based approaches utilize the customers’ power usage patterns to detect the abnormal variations [3]. Among the profile-based approaches, detection methods that employ machine learning (ML) techniques, especially deep neural networks (DNN), are becoming popular in the research community [3] [6]–[9]. Enabled by the AMI, ML-based approaches take advantage of the statistical properties of the massive fine-grained smart meter data as a whole and achieve state-of-the-art detection performances. Meanwhile, the ML detection schemes are purely data-driven without additional equipment, which makes it compatible with current infrastructures in the power systems.

However, recent studies in the computer vision domain have demonstrated that ML models are highly vulnerable to adversarial attacks [10]–[13]. By adding well-crafted perturbations to the legitimate inputs, the attacker is able to deceive the well-trained ML models to output the wrong classification results. In addition, the adversarial attacks are also shown to be effective in power systems applications [14]–[16]. As the ML approaches become popular in detecting energy theft, the threat from adversarial attacks need to be investigated to prevent potential financial losses.

In general, the process to generate adversarial examples can be represented as an optimization problem. The adversarial perturbations in the computer vision domain are expected to be small enough to avoid being noticed by human eyes. However, such a constraint is not suitable to a ‘smart’ energy thief. In particular, the attacker needs to generate a small energy consumption measurement to reduce his/her bill while bypassing the utilities’ energy theft detection.

In this work, from the attacker’s point of view, we study the reliability of ML models used for energy theft detection. We analyze and formulate the properties of adversarial attacks in energy theft detection and propose a general threat model. Meanwhile, we design and implement an adversarial measurement generation algorithm that maximizes the attacker’s profit.

The evaluation of a real-world smart meter dataset shows that our algorithm can generate extremely low fake measurements while bypassing the well-trained ML detection models, even for black-box attackers. The main contribution of this paper can be summarized as follows:

- We highlight the potential risks of adversarial attacks on ML-based energy theft detection.
- We analyze and summarize the properties of adversarial measurements in energy theft detection and propose a general threat model.
- We design an adversarial measurement generation algorithm to maximize the attackers’ profit, we name the
algorithm the SearchFromFree algorithm.

• We evaluate our algorithm with three kinds of neural networks that trained with real-world smart meter data. The evaluation results demonstrate that our algorithm generates extremely small fake measurements that can still successfully bypass the ML models’ detection. We open-source the related source code on Github [17].

Related research is discussed in Section II. After that, we format the attack and present the threat model in Section III. Section IV and V present the algorithm design and the experiment evaluations respectively. We discuss the future work in section VI. Finally, section VII concludes the paper.

II. RELATED WORK
A. ML-based Energy Theft Detection

In 2009, Nagi et al. utilized the support vector machine (SVM) to detect abnormal power usage behaviors based on historian consumption data [18]. After that, Depuru et al. extend their approach and introduce more information, such as the type of consumer, geographic location, to train the SVM classifier [19]. Meanwhile, SVM can also be combined with other techniques, such as a fuzzy inference system [20] and decision tree [21], to increase the detection performance. In 2015, Jokar et al. generated a synthetic attack dataset and trained a multiclass SVM classifier for each customer to detect malicious power consumption [7]. Recently, detection approaches based on deep neural networks become popular and achieves promising performance. In 2017, Zheng et al. [9] firstly employed deep convolutional neural networks trained by a dataset released by State Grid Corporation of China (SGCC) and achieved high detection accuracy and low false-negative rate. After that, in 2018, a deep recurrent neural network was employed in [6] for energy theft detection. They train the RNN with daily smart meter data and randomly search for the appropriate model parameters. Besides the consumption domain, attackers may also claim higher supplied energy and overcharge the utilities in the smart grid to make a profit, such as through photovoltaic solar cells. [22] investigated the energy theft attack in the distributed generation domain and utilized a hybrid neural network to detect such attacks. More related work on the ML-based energy theft detection can be found in [23].

B. Adversarial Attacks

The effect of the adversarial examples was firstly discovered in the computer vision domain by Szegedy et al. in 2013 [10]. They found that by adding a small crafted perturbation that is imperceptible to human eyes, the attacker can deceive the ML models to output the wrong classification result. Moreover, the same perturbation is transferable in different ML models. After that, different perturbation generation algorithm was proposed, such as the Fast Gradient Sign Method by Goodfellow et al. [11], Fast Gradient Method by Rozsa et al. [12], and DeepFool by Moosavi-Dezfooli et al. [13]. In recent years, the threat of adversarial attacks to power system applications also drew more and more attention. In 2018, Chen et al. demonstrated that adversarial examples are effective in both classification and regression ML applications in the power systems [16]. After that, Liu et al. studied the effect of adversarial attacks on neural network-based state estimation [15]. In 2020, [14] demonstrated that the attacker can easily bypass the ML-based false data injection detection under the physical constraints. In [24], Marulli et al. studied the data poisoning attacks to ML models in energy theft detection using the generative adversarial network (GAN). However, they did not consider the evasion attacks and the profit of the attackers.

III. ATTACK FORMATION
A. Mathematical Presentation

In this paper, we consider the scenario that the utilities employ an ML model $f_0$ to detect energy theft based on the customers’ power consumption measurements. The model $f_0 : M \rightarrow Y$ maps the measurement vector $M$ to its label $Y$ (Normal, Malicious) and is trained with the dataset ${M, Y}$. The energy thief is assumed to be able to compromise his/her electricity meter and freely modify the meter’s measurement. The purpose of the energy thief is to launch a false-negative evasion adversarial attack to $f_0$ by generating malicious measurement vectors $A$ so that $f_0(A) \rightarrow Normal$. Different from the general adversarial attacks which require the adversarial perturbations to be small. In the energy theft problem, the attacker only needs to focus on the size of $A$ in order to minimize his/her electricity bills. Therefore, the adversarial attacks in energy theft detection can be formally represented as follow:

$$
\min \|a\|_1 \quad \text{s.t. } f_0(a) \rightarrow Normal \quad a_i \geq 0
$$

where $a$ represents a specific adversarial measurement vector, $\|a\|_1 = \sum a_i$ is the $L_1$-Norm of $a$. The constraint (1c) requires all the power consumption measurement $a_i$ in $a$ must be non-negative to be feasible.

B. Threat Model

We propose a practical threat model for the adversarial attacks in energy theft detection.

• We assume the attacker is able to compromise his/her electricity meter and can freely modify the meter measurements. In practice, this can be achieved by physical penetration.

• We consider a black-box adversarial attack since the energy thief usually cannot access the ML model $f_0$ and training dataset ${M, Y}$ owned by the utilities. However, we allow the attacker to obtain an alternative dataset $\{M', Y'\}$, such as a historian dataset, to train his/her model $f_{0'}$ to generate adversarial measurements.

• As demonstrated by (1c), the attacker needs to generate non-negative adversarial measurements in order to be practical.
In addition to the black-box attacks described above, we will also evaluate the attack performance in the white-box scenario that allows the attacker to access the full ML model \( f_\theta \). As presented by the Kerckhoffs’s principle in cryptography, such evaluation can demonstrate the vulnerability of the detection system under the worst-case scenario and allow us to learn the upper bound performance of the adversarial attacks.

IV. SearchFromFree Algorithm Design

Based on our threat model, we propose the design of the SearchFromFree algorithm to generate valid adversarial measurement vectors \( A \) that can deceive the ML model \( f_\theta \). Our algorithm assumes the attacker trained his/her local ML model \( f'_\theta \) with an alternative dataset, such as a public historian dataset. The assumption behinds our approach is the transferability of adversarial examples. Similar to the \textit{DeepFool} algorithm [13], our algorithm is gradient-based and iteratively searches for a valid \( a \).

Algorithm 1: SearchFromFree Algorithm

```plaintext
1 Input: \( f'_\theta, \) step, size, \( \lambda, \sigma \)
2 Output: \( a \)
3 function advGen(\( f'_\theta, \) step, size, \( \lambda, \sigma \))
4 define \( L_{total} = L(f'_\theta(a), Y_a) - \lambda \cdot \|a\|_1 \)
5 initialize \( a \sim N(0, \sigma^2) \)
6 set all negative elements in \( a \) to zero
7 initialize stepNum = 0
8 while stepNum \leq step - 1 do
9     if \( f'_\theta(a) \rightarrow \text{Normal} \) then
10        return \( a \)
11     end
12     calculate gradient \( G = \nabla_a L_{total} \)
13     \( r = G \cdot \text{size} / \max(\text{abs}(G)) \)
14     update \( a = a + r \)
15     set all negative elements in \( a \) to zero
16     stepNum = stepNum + 1
17 end
18 return \( a \)
```

As shown in Algorithm 1, the \textit{advGen} function has five inputs, including the local ML model \( f'_\theta \), and four positive constant parameters. The constant \textit{step} limits the maximum number of search iteration while \textit{size} defines the maximum modifications of \( a \) in each iteration. It is obvious that the energy thief’s bill amount from the utilities is approximately linear (consider the various electricity price) to \( \|a\|_1 \), the \( L_1 \)-norm of \( a \). In order to maximize the attackers’ profit, we add a regularization item \( \lambda \cdot \|a\|_1 \) to the loss \( L_{total} \). We employ a constant \( \lambda \) to represent the compromisation between the attack success rate and the attacker’s bill amount. Therefore, \( \lambda \) should be carefully tuned according to specific attack scenarios. As shown by Line 5 of Algorithm 1, we empirically initialize \( a \) according to a Gaussian distribution with a zero mean value, which indicates a zero amount (free) bill for the energy thief. The intuition behind this is that the search iteration process will gradually increase \( \|a\|_1 \) to a normal measurement vector that has a higher probability to bypass the detection. Therefore, a small initial \( a \) will finally lead to a smaller \( \|a\|_1 \) so that the attacker can make more profit. The perturbation \( r \) generated from the loss gradient may cause negative measurements in \( a \). Therefore, as shown by Line 6 and 15, we set all negative values to zero to generate a feasible adversarial measurement vector \( a \).

V. Simulation Implementation

A. Dataset

We utilize the smart meter data published by the Irish Social Data Science Data Archive (ISSDA) [25] as it is widely used as a benchmark for energy theft detection in related literatures [3][6][8]. The dataset contains the smart meter energy consumption measurement data of over 5000 customers in the Irish during 2009 and 2010. The customers agreed to install the smart meters and participated in the research project. Therefore, we assume all the measurement data in the dataset are normal and there is no energy theft. There are missing and illegal measurements in the original dataset. We pre-process the raw dataset by removing the incomplete measurements. We then regulate the time-series measurement data into daily reading vectors and obtain dataset \( D_{daily} \). As the smart meters recorded every 30 minutes, each daily vector will contain 48 measurements.

| Table I: Energy Theft Attack Scenarios [3] |
|-------------------------------------------|
| Attack Scenario                         |
| \( h_1(m_t) = \alpha m_t, \alpha \sim \text{Uniform}(0.1,0.8) \) |
| \( h_2(m_t) = \beta m_t, \beta \sim \text{Uniform}(0.1,0.8) \) |
| \( h_3(m_t) \in \{ \alpha m_t | \forall t \in [t_i,t_j], m_t \} \) |
| \( h_4(m_t) = E(m_t) \) |
| \( h_5(m_t) = \beta E(m_t) \) |
| \( h_6(m_t) = \beta m_{24-t} \) |

However, there is a shortage of real-world energy theft dataset. To solve this, we employ the false measurement data generation approach proposed in [3] to simulate the energy theft measurements. As shown in Table I, [3] presents six energy theft scenarios. The first attack \( h_1 \) multiplies the real meter reading with a constant while \( h_2 \) with random constant generated from a uniform distribution. The \( h_3 \) assumes the energy thief reports zero consumption during a period. The fourth scenario happens when the attacker constantly reports the mean consumption. \( h_5 \) is similar to \( h_2 \) but multiplies the random constant with the mean value instead of the real measurements. At last, \( h_6 \) reverses the records of a day so that low measurements will be reported during periods whose electricity price is lower.

We generate a synthetic dataset based on the regulated daily smart meter dataset. We firstly randomly sample 180,000 daily records from \( D_{daily} \) and pollute half records in the sample...
dataset according to the attack scenarios described in Table I. We label all normal records as 0 and polluted records as 1. We finally obtain the defender’s dataset $D_{\text{defender}} : \{ M_{180,000 \times 48}^1, Y_{180,000 \times 1}^1 \}$. We generate the dataset $D_{\text{attacker}}$ for the attacker in the same process. We note that the normal records in both $D_{\text{attacker}}$ and $D_{\text{defender}}$ are sampled from $D_{\text{daily}}$ and there are a portion of the same records in the two datasets. However, since there are over 2.5 million records in $D_{\text{daily}}$, they can be regarded as different datasets.

### B. Evaluation

We evaluate our algorithm with three kinds of neural networks, feed-forward Neural networks (FNN), recurrent neural network (RNN), and convolutional neural network (CNN). We train three neural networks for the utilities as the defender models and three separate neural networks with different structures for the attackers. The structures of the corresponding neural networks are shown in Table II.

All our ML models are trained with the TensorFlow and Keras library. We conduct our experiments on a Windows 10 PC with an Intel Core i7 CPU and 16 GB memory. An NVIDIA GeForce GTX 1070 graphic card is employed to accelerate the training process. The related source code of this paper is available on Github [17].

We manually tuned the parameter of the model training and the performances of different models are shown in Table III. From the table, we can learn that the RNN (LSTM) achieves the best performance in both metrics, followed by the CNN and FNN. This is because RNN has an inherent advantage in learning the pattern of time-series data. Meanwhile, we can also learn that the performances of attackers’ models are very similar to the defenders’, which indicates that our sampled dataset can represent the overall manifold of the raw dataset.

We set two metrics to evaluate the performance of our attacks. The first metric will be the detection accuracy of the defender’s ML models. Meanwhile, it is straightforward that a fake measurement vector with a smaller profit to the energy thief will have a higher probability to bypass the energy theft detection. For example, if the attacker just set the parameter $\alpha$ of $h_1$ in Table I to $1 - 10^{-5}$, the adversarial measurement vector will hold a very high probability to be classified as normal by the utilities’ ML model. However, this will lead to a small profit of the attacker. Therefore, we will select the average $L_1$-Norm of fake measurement vectors as the second evaluation metric. In our experiment, the average $L_1$-Norm of all normal measurement records in $D_{\text{defender}}$ is 32.05 kWh.

In order to demonstrate the effectiveness of our algorithm, we set up two **vanilla black-box attackers** as baselines. The first vanilla attacker $V A_1$ will simply gradually try different $\alpha$ of $h_1$ as defined in Table I while the second vanilla attacker $V A_2$ generates uniformly distributed measurement vector between 0 and a variable $u$. The performances of the vanilla attackers of 1,000 fake measurement vectors are demonstrated in Fig. 1 and Fig. 2 respectively.

![Figure 1: Vanilla Attacker 1](image)

From Fig. 1, we can learn that the detection accuracy of the defenders’ models decreases with the parameter $\alpha$ increases under $V A_1$ attack. As analyzed above, this indicates that energy theft has a higher success probability if the attacker

### Table II: Model Structures

| Networks | FNN | RNN | CNN |
|----------|-----|-----|-----|
| Models   | $f_{\text{FNN}}$ | $f_{\text{FNN}}'$ | $f_{\text{RNN}}$ | $f_{\text{RNN}}'$ | $f_{\text{CNN}}$ | $f_{\text{CNN}}'$ |
| Layer 0  | input 48 | input 48 | input 48 × 1 | input 48 × 1 | input 6 × 8 | input 6 × 8 |
| Layer 1  | 128 Dense | 168 Dense | 256 LSTM | 246 LSTM | 128 Conv2D | 156 Conv2D |
| Layer 2  | 256 Dense | 328 Dense | Dropout 0.25 | Dropout 0.25 | 128 Conv2D | 214 Conv2D |
| Layer 3  | 125 Dense | 168 Dense | 165 LSTM | 148 LSTM | MaxPooling2D (2,2) | MaxPooling2D (2,2) |
| Layer 4  | Dropout 0.25 | 128 Dense | Dropout 0.25 | Dropout 0.25 | Dropout 0.25 | Dropout 0.25 |
| Layer 5  | 32 Dense | Dropout 0.25 | 128 LSTM | 108 LSTM | flatten | flatten |
| Layer 6  | Dropout 0.25 | 64 Dense | 2 Dense Softmax | 2 Dense Softmax | 32 Dense | 48 Dense |
| Layer 7  | 2 Dense Softmax | Dropout 0.25 | - | Dense 2 Softmax | Dense 2 Softmax | - |
| Layer 8  | - | 2 Dense Softmax | - | - | - | - |

The models $f_*$ act as the defenders while $f_*'$ as attackers. The activation function of each layer is $\text{ReLU}$ unless specifically noted.

### Table III: Model Performance

| Model | Accuracy | False Positive Rate |
|-------|----------|---------------------|
| $f_{\text{FNN}}$ | 86.9% | 10.01% |
| $f_{\text{FNN}}'$ | 86.87% | 14.01% |
| $f_{\text{RNN}}$ | 97.5% | 2.58% |
| $f_{\text{RNN}}'$ | 97.48% | 2.62% |
| $f_{\text{CNN}}$ | 93.49% | 7.79% |
| $f_{\text{CNN}}'$ | 93.28% | 6.41% |
was willing to decrease his/her stolen profit. Overall, CNN and RNN are more vulnerable to VA1 attack compared with FNN. This is because the RNN and CNN can learn the time-series pattern more accurately than FNN. However, by comparing the two figures in Fig. 1, if the attacker wants to have a relatively high success probability for energy theft, such as over 65%, she/he will need to pay an over 20 kWh power consumption bill ($\alpha > 0.65$).

Figure 2: Vanilla Attacker 2

The performance of the VA2 attack is demonstrated in Fig. 2. We can learn that the detection accuracy of RNN and CNN remains high (over 95%) with parameter $u$ increases. Again, this verifies our analysis that the RNN and CNN can learn the daily electricity consumption patterns, and a uniform distributed consumption measurement vector is obviously abnormal. However, the performance of the FNN decreases dramatically if the attacker generates larger fake measurements. Overall, the VA2 attack is not effective on energy theft for the attacker.

We then evaluate the effectiveness of the SearchFromFree algorithm. Fig. 3 and Fig. 4 demonstrate the energy theft detection accuracy of different ML models under the white-box attacks and black-box attacks. The experiments were also conducted with 1,000 generated adversarial measurement vectors per case. From the left figure of Fig. 3 we can learn that the detection accuracy drops dramatically with the step increase. When step becomes larger, the RNN models’ detection accuracy is close to zero under white-box attacks and is around 20% under black-box attacks. The FNN’s detection accuracy is even worse under our adversarial attacks. The right figure in Fig. 3 shows that the FNN models have no energy theft detection ability under both white-box and black-box attacks.

Figure 3: The detection accuracy of the RNNs and the FNNs. The parameter $size = 0.01$ while $\lambda = 10$.

Figure 4: The detection accuracy of the CNNs. The parameter $\lambda = 10$ in white-box attacks and $\lambda = 0$ in black-box attacks. The white-box attack has a $size = 0.01$ while the black-box attack sets $size = 0.1$.

The L1 Norm of daily adversarial consumption

Figure 5: The $L_1$-Norm of adversarial measurement vectors (white-box attacks). The parameters $size = 0.01$ and step = 14 for all three models.

By comparing Fig. 5 and Fig. 6 with Fig. 3 and Fig. 4, we can summarize the performance of our attacks in Table IV. The worst attack performance in our experiments in from the black-box attack of $f_{CNN}$ (31% Accu, 1.59 kWh), which is still effective enough for energy theft, compared with the vanilla attacks and the 32.05 kWh normal daily consumption.

VI. DISCUSSION AND FUTURE WORK

We investigate the vulnerability of ML energy theft detection from the attacker’s perspective. A more reliable ML
solution that is resistant to the adversarial attacks needs to be studied in the future. The state-of-the-art defense approaches, such as adversarial training and input reconstruction, will be evaluated for ML-based energy theft detection in our future work. On the other hand, energy theft is inevitable even if ML-based detection is employed since energy thieves can just modify the $h_1$ attack defined in Table I with a relatively larger $\alpha$. Therefore, defense mechanisms that can significantly decrease the energy theft profit of the attackers should also be investigated.

VII. CONCLUSION

The ML-based energy theft detection mechanisms are highly vulnerable to well-designed adversarial attacks. In this paper, we study adversarial attacks in energy theft detection and propose a general threat model. We then design the SearchFromFree algorithm to maximize the attacker’s profit. We evaluate our attacks with three kinds of neural networks trained on a real-world smart meter dataset, and the results demonstrate that energy thieves can effectively bypass the detection of the well-trained ML models with extremely low reported energy consumption measurements, even in black-box attack scenarios.

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