A Novel Detector to Detect Colluded Non-Technical Loss Frauds in Smart Grid

Wenlin Han, Yang Xiao*

Abstract—A Non-Technical Loss (NTL) fraud occurs when a fraudster tampers with a smart meter so that the meter registers less electricity consumption than the actual consumed amount, and therefore the utility becomes the victim who suffers the corresponding economic loss. In the literature, many detection schemes have been proposed to detect NTL frauds. However, some NTL frauds are far more complicated than what the existing schemes expect. We recently discovered a new potential type of frauds, a variant of NTL frauds, called Colluded Non-Technical Loss (CNTL) frauds in the Smart Grid. In a CNTL fraud, multiple fraudsters can co-exist or collaborate to commit the fraud. Existing detection schemes cannot detect CNTL frauds since these methods do not consider the co-existing or collaborating fraudsters, and therefore cannot distinguish one from many fraudsters. In this paper, we propose a CNTL fraud detector to detect CNTL frauds. The proposed method can quickly detect a tampered meter based on recursive least squares. After identifying the tampered meter, the proposed scheme can detect different fraudsters using mathematical models. Our experiments show that our method is effective in detecting CNTL frauds.

Index Terms—Smart Grid Security, Smart Meter, Non-Technical Loss, Colluded Fraud, Malicious Meter.

I. INTRODUCTION

Smart Grid is the new generation of power grid with two-way electricity flows and two-way communication links [1], [2]. The system losses in Smart Grid can be classified into two types [3]: technical loss and non-technical loss. Technical loss is the loss during the generation, transmission, distribution, and redistribution processes, and it is due to the loss of energy in power lines, transformers, and other devices. Generally, Non-Technical Loss (NTL) is referred as to the loss other than technical loss, including unpaid bills, electricity theft, inaccurate metering, etc. An NTL fraud occurs when a fraudster tampers with a smart meter so that the meter registers less electricity consumption than the actual consumed amount, and this causes non-technical loss to the utility [4], [5].

Utility companies have experienced huge economic loss because of NTL frauds. NTL frauds cause yearly \$89.3bn economic loss world-wide as reported by Northeast Group LLC [6]. Among the \$89.3bn loss, \$58.7bn loss is reported in the 50 emerging market countries, including India, China, etc. These 50 countries planned an investment of totally \$168bn

to make Smart Grid more reliable and to reduce NTL frauds. In the U.S., the annual loss due to NTL frauds is \$6bn, and it is reported by law enforcement in Houston that probably 60% to 70% of meters have been tampered with [7].

NTL frauds not only exist in Smart Grid, but also in the old power grid [8]. In the traditional power grid, people have a long history of using physical methods to steal electricity [3], [9]. A typical method is to use an additional power line to bypass a meter. Smart Grid brings novel technologies to the power grid. However, when meters become electronic and smart, there are much more ways to commit an NTL fraud. Examples are given as follows: smart meters could be remotely controlled [10]; the communication between the meters and the utility could be intercepted; moreover, those physical methods can be still applied in Smart Grid.

Traditional NTL fraud detection methods attempt to identify a tampered meter or multiple tampered meters among meters [11], [12]. However, an NTL fraud can be very sophisticated. In our recent studies, we discovered a new potential type of frauds, a variant of NTL frauds, called Colluded Non-Technical Loss (CNTL) frauds in the Smart Grid. In a CNTL fraud, more than one fraudster can co-exist or collaborate to commit the fraud. In other words, in a single tampered meter, there are multiple fraudsters. They may not realize the existence of other fraudsters, and we call them co-existing fraudsters. On the other hand, they may realize the existence of other fraudsters and collaborate to commit an NTL fraud, and then we call them collaborating fraudsters. We study the behaviors of the co-existing and collaborating fraudsters and analyze the features of CNTL frauds. We classify CNTL frauds into four types: segmented CNTL frauds, fully overlapped CNTL frauds, partially overlapped CNTL frauds, and combined CNTL frauds.

To combat NTL frauds, many schemes have been proposed including intrusion detection based methods [13]–[16], industrial control based methods [17], [18], physical methods [19]–[22], profiling based methods [23], [24], statistical methods [25], [26] and comparison based methods [3], [11], [27]–[30]. These schemes can detect NTL frauds and identify the tampered meters, but they cannot detect CNTL frauds since these methods do not consider the co-existing or collaborating fraudsters, and therefore cannot distinguish one from many fraudsters.

In this paper, a novel detector, called Colluded Non-Technical Loss Fraud Detection (CNFD), is proposed to address the CNTL fraud problem in Smart Grid. CNFD has two steps to detect CNTL frauds: 1) NTL fraud detection and 2) fraudster differentiation. In the NTL fraud detection

Wenlin Han is with the Department of Computer Science, the University of Alabama, Tuscaloosa, AL 35487-0290, USA. E-mail: whan2@crimson.ua.edu.

Yang Xiao is with both School of Computer and Software, Nanjing University of Information Science and Technology, Nanjing, 210044, China, and with the Department of Computer Science, the University of Alabama, Tuscaloosa, AL 35487-0290, USA. E-mail: yangxiao@ieee.org.

Yang Xiao is the corresponding author. E-mail: yangxiao@ieee.org.

step, CNFD quickly identifies the tampered meter within a group of meters. In the fraudster differentiation step, CNFD differentiates multiple fraudsters in the tampered meter. CNFD adapts Recursive Least Square (RLS) [31] to model fraudsters' behaviors using linear functions. Different fraudsters have different models to represent themselves. CNFD is lightweight and requires only a small amount of data. CNFD can even predict the behaviors of fraudsters which they may not realize by themselves. We have conducted various experiments to test the effectiveness and performance of CNFD. The experimental results show that CNFD can effectively detect four types of CNTL frauds and describe the behaviors of different fraudsters clearly.

The main contributions of this paper include:

- We recently discovered a potential type of frauds in Smart Grid, called the CNTL frauds;
- We study the features of different CNTL frauds and categorize them into four types;
- We propose a novel detector CNFD to detect CNTL frauds in Smart Grid;
- Our experiments show that CNFD is effective.

The rest of the paper is organized as follows. The problem definition, the CNTL attack model, and the four types of CNTL frauds are introduced in Section II. In Section III, we introduce the CNFD algorithm. In Section IV, experiments and experimental results are presented to show the effectiveness of CNFD. In Section V, we introduce related works and conclude the paper in Section VI.

II. COLLUDED NTL FRAUD

In this section, we first define the problem that we are trying to solve, and then present the attack model of CNTL frauds. Furthermore, detailed analysis on the features of these frauds is then presented, and based on the analysis, we classify CNTL frauds into four types.

A. Problem definition

Alabama Power, a utility company headquartered in Birmingham, is responsible for providing electricity service for southern Alabama where Alabama is a state located in the southeast (SEC) region of USA. Consider a community with N households in total served by Alabama Power. As shown in Fig. 1, these households have smart meters installed outside their houses, and each household has one smart meter. Some households may have multiple meters, but there is always one meter that is responsible for recording the total energy consumption and providing data for the billing purpose. Alabama Power keeps records of the total amount of electricity supplied to this community. However, the total billed amount is always smaller than the supplied amount if there are some compromised meters.

Alabama Power checks technical problems during the transmission and distribution processes. Electricity losses of power lines and transformers are deducted from the total loss. But the amount of loss is still large. Alabama Power suspects that at least one meter was tampered with in this community, and one or more than one customer are fraudsters who stole

electricity. The problem is how to identify the tampered meters and fraudsters.

In this paper, we only consider the case that the total billed amount is smaller than the consumed amount, i.e., it is an NTL fraud; we do not consider the case that the total billed amount is larger than the consumed amount, i.e., it is not an NTL fraud.

B. Attack model

There are two types of fraudsters in general: inside fraudsters (fraudsters inside the households) and outside fraudsters (fraudsters outside the households). Inside fraudsters have the ability to physically tamper with smart meters, such as slowing down the meters using magnets. They also have the ability to impersonate smart meters using simulation software or overwrite the firmware of the meters. Outside fraudsters have the ability to remotely control smart meters, intercept the communication between smart meters and head-end systems in the utility, and extract encryption keys or passwords from network traffic. If the fraudsters are from the outside, the owner of the tampered meter may not realize the fraud. In a single tampered meter, the outside fraudsters and the inside fraudsters may co-exist.

As shown in Fig. 1, some smart meters are normal, while some other smart meters are tampered with. In a tampered meter, there may be one or multiple fraudsters. Collaborating fraudsters are those fraudsters who cooperate with each other to tamper with a meter and are aware of the existence of other fraudsters. Co-existing fraudsters are those fraudsters in a single tampered meter who just co-exist and are not aware of the existence of other fraudsters. Typically, collaborating fraudsters are either from the outside or from the inside. It is not common for the inside fraudsters to collaborate with the outside fraudsters. But for co-existing fraudsters, inside fraudsters may co-exist with outside fraudsters.

C. Colluded NTL Fraud

A CNTL fraud occurs when multiple fraudsters tamper with a meter so that the meter records less electricity than the consumed amount by the household, and the fraudsters gain illegal benefit by paying less money. After further analyzing these fraudsters, we find that they have different behaviors which they may not realize themselves. Moreover, the behaviors of how they collude the frauds can be different.

Sometimes, when a meter is tampered with by multiple fraudsters, these fraudsters may commit the malicious manipulation at different time segments. As shown in Fig. 2(a), we name this kind of CNTL frauds as segmented CNTL frauds. In a segmented CNTL fraud, fraudsters usually do not realize the existence of other fraudsters. Thus, these fraudsters are co-existing fraudsters, and are not collaborating fraudsters.

During most of the time, CNTL frauds are not segmented. Different fraudsters can manipulate the same meter at the same time, or at least part of the manipulation time overlaps. We call this kind of colluded NTL frauds as overlapped CNTL frauds. Overlapped CNTL frauds can be classified into partially overlapped CNTL frauds and fully overlapped

Fig. 1. The attack framework of CNTL frauds. Each household has a smart meter installed. The status of each meter could be ‘normal’ or ‘tampered’. In a single tampered meter, there may be multiple fraudsters. These fraudsters could collaborate or just co-exist. The problem is that the total amount of billed electricity is much smaller than the total amount supplied.

CNTL frauds, as shown in Figs. 2(b) and (c), respectively. The difference between partially overlapped CNTL and fully overlapped CNTL is that there is one fraudster who overlaps all other fraudsters in a fully overlapped CNTL fraud. This feature can easily fool a detector and can make the detector believe that there is only one fraudster in this meter.

Some frauds are even more complicated since they have both segmented CNTL and overlapped CNTL, and we name them as combined CNTL frauds, shown in Fig. 2(d). In an overlapped CNTL fraud or a combined CNTL fraud, fraudsters may or may not realize the existence of other fraudsters. Thus, these fraudsters could be co-existing fraudsters, or they could also be collaborating fraudsters.

III. CNTL FRAUD DETECTION

In this section, we will introduce how to detect CNTL frauds using our proposed CNFD method, and the algorithm of CNFD is also presented.

A. Observer meter

We install an observer meter to record the total amount of electricity supplied to n ($n \leq N$) households in this community. The observer meter is installed at the pole side keeping a distance to the properties of these households. Among these n households, one or multiple meters are suspected to be tampered with. To guarantee the safety of the observer, we attach a tamper-resistant device to the observer and monitor it intensively using a camera. The tamper-resistant device is to protect the observer from cyber attacks. Camera surveillance is to protect the observer from any physical tampering. The observer meter is shown in Fig. 1. There are two reasons that we cannot secure all the meters using the way that we secure

the observer. One reason is the limited budget. Another reason is privacy consideration [32]–[35].

The smart meters owned by the households are responsible for keeping records of the energy consumptions of the households. The metering system will automatically read these meters, including smart meters and the observer. The interval of meter reading is fixed, but the length of the interval is adjustable, e.g. from several minutes to several months. A typical interval is 15 minutes [1], [36]. Now, we have two set of known values. One set is the energy consumption reported by smart meters. Note that the reported value may be smaller than the amount of the actual energy consumption of the household due to the fraud. Another value is the total amount supplied to the n ($n \leq N$) households. Our objective is to figure out which meters have CNTL frauds.

B. Tampered meter detection

CNFD includes two steps. The first step is to detect tampered meters. We list notations used in this paper as follows:

- T_j : j -th measurement time period;
- m : the total number of measurements;
- E_{ij} : the electricity actually consumed by Meter i , during the time period T_j ;
- E_j : the total electricity recorded at an observer meter, during the time period T_j ;
- E : the column vector of E_j of all meters;
- x_{ij} : the electricity recorded by Meter i , during the time period T_j ;
- X_j : the row vector of x_{ij} of all meters, during the time period T_j ;
- X : the column vector of X_j ;
- a_{ij} : the coefficient of Meter i , during the time period T_j ;
- a_i : the coefficient vector of Meter i ;

Fig. 2. Four different types of CNTL frauds that we discovered. a) Segmented CNTL fraud; b) Partially overlapped CNTL fraud; c) Fully overlapped CNTL fraud; d) Combined CNTL fraud.

- A : the row vector of a_i of all meters;
- S_i : the coefficient set of all different fraudsters in Meter i ;
- e : the user defined error.

The values of $(E_{ij}, j = 1, 2, \dots, m)$ are not available although the values of $(x_{ij}, j = 1, 2, \dots, m)$ are available. For a value pair (x_{ij}, E_{ij}) , there is a corresponding point, such as Point B, at the coordinate as shown in Fig. 3. Each meter has a group of points of its own, and we can find a line closet to these points to represent this meter. Let us denote this line as:

$$f_i(x) = a_i x. \quad (1)$$

Note that each line starts from $(0, 0)$, since the recorded value must be 0 if the consumed energy is 0.

If Meter i is a normal meter, either $E_{ij}/x_{ij} = 1$ holds or $|E_{ij}/x_{ij} - 1|$ is very small. If $|E_{ij}/x_{ij} - 1|$ is large, this indicates that Meter i is an abnormal (tampered) meter. Define

$\alpha_{ij} = E_{ij}/x_{ij}$ which indicates the accuracy ratio, i.e., the error committed by Meter i during the period j . For simplicity and without losing generality, we assume that if Meter i is a normal meter, its α_{ij} should be in the range as follows:

$$\alpha_{ij} \in [\alpha_{min}, \alpha_{max}], (1 \leq i \leq n).$$

The accuracy of metering is affected by many factors, including connection type, power factor, current, standards in different countries, etc. A typical metering system accuracy is $\pm 1.55\%$ [37]. To accommodate rounding error and data noise, we choose $\pm 2\%$ as the accuracy class, i.e., $\alpha_{min} = 0.98$ and $\alpha_{max} = 1.02$. We also assume that if one meter is tampered with (abnormal), we have $\alpha_{ij} > \alpha_{max}$. In other words, we assume that all of the normal meters have the same accuracy range as the above, and all of the abnormal (tampered) meters have higher accuracy values above the range. Generally speaking, α_{ij} could be less than α_{min} , and

Fig. 3. Modeling the behavior of fraudsters mathematically and differentiating them. Each value pair, e.g. (the recorded amount of electricity, the actually consumed amount of electricity) has a point to represent it at the coordinate. Each meter has a dataset containing a series of value pairs obtained from several measurements. The dataset has a set of corresponding points. In CNFD, a line which represents the set of points is used to represent the meter. For tampered meters, their lines are above the line of $f_1(x) = \alpha_{max}x$. For normal meters, their lines are between the lines of $f_1(x) = \alpha_{max}x$ and $f_4(x) = \alpha_{min}x$. Some lines can be reshaped into multiple lines.

this means that the billing amount of electricity is larger than the consumed amount so that the customer has to pay more money. The customer herself (himself) will never tamper with a meter in this way. It only happens when a meter is manipulated by outside attackers and the meter readings are altered to be higher than the actual values. However, it is not an NTL fraud in this situation, and it is out of the scope of this paper.

As shown in Fig. 3, a tampered meter has a line above the line of $f_1(x) = \alpha_{max}x$, and a normal meter has a line between the lines of $f_1(x) = \alpha_{max}x$ and $f_4(x) = \alpha_{min}x$. A line below the line of $f_4(x)$ is a sign of working error. We can figure out which meters are tampered with and obtain the coefficient vector A . We notice that

$$E_j = \sum_{i=1}^n E_{ij}, \quad (2)$$

and E_j is available. We re-write it as follows:

$$E_j = \sum_{i=1}^n a_i x_{ij}. \quad (3)$$

Let X_j be the values of the j -th measurement. Let A be the array of all coefficients. We have:

$$A = (a_1, a_2, \dots, a_n). \quad (4)$$

$$X_j = (x_{1j}, x_{2j}, \dots, x_{nj}). \quad (5)$$

Suppose that we have an estimation of A after $j-1$ times of measurements, A_{j-1} . Now we obtain a new measurement X_j and E_j , and want to update the estimation with this new measurement. According to the theory of Recursive Least Square (RLS), to get a new estimation A_j , we have:

$$A_j = A_{j-1} + W_j(E_j - X_j A_{j-1}), \quad (6)$$

where

$$W_j = P_{j-1} X_j^T (\lambda + X_j P_{j-1} X_j^T)^{-1}, \quad (7)$$

$$P_j = (I - W_j X_j) P_{j-1} / \lambda, \quad (8)$$

$$P_j^{-1} = \lambda P_{j-1}^{-1} + X_j^T X_j. \quad (9)$$

Here, W is a weight array. I is the identity matrix. P is the degree of precision of the measurement, and is initialized with $P_0 = kI$, where k is a high value constant. λ is a forgetting factor with a value between 0 and 1 ($0 < \lambda \leq 1$). In order to reduce the influence of old values, we should choose a lower value of λ .

Let us set j as 1, since we have no historical data, and thus have no knowledge of A . As shown in Alg. 1, the process is repeated until the value of A does not change. Then, each a_i in A is compared to α_{min} and α_{max} . If a_i is larger than

α_{max} , Meter i is identified as ‘tampered’. Then the value of i is assigned to t .

C. Fraudster differentiation

The second step of CNFD is fraudster differentiation. We identified the tampered meter, Meter t , in the first step, and the value of the coefficient vector A is known. In this step, CNFD will try to find out whether there are multiple fraudsters in the tampered meter and differentiate them. An illustrative example is shown in Fig. 3. In the first step, the red points are used to generate a red line, $f_2(x)$, which is above the line of $f_1(x) = \alpha_{max}x$. Thus, the meter represented by the red points is identified as the tampered meter. After further analysis, we find that the red points can be reshaped into two lines which are $f_{2,1}(x)$ and $f_{2,2}(x)$. The red dot points are closer to $f_{2,1}(x)$ rather than $f_2(x)$, and the red star points are closer to $f_{2,2}(x)$ rather than $f_2(x)$. In fact, there are two fraudsters and their behaviors are represented by $f_{2,1}(x)$ and $f_{2,2}(x)$, respectively.

Algorithm 1 CNFD: CNTL fraud detection

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1: Initiation: set initial values of  $e, n, m, \alpha_{min}, \alpha_{max}, A_{j-1},$ 
    $\lambda$  and  $k$ . Set  $P_{j-1} = kI$ .  $j$  starts from 1. Set  $S_t = \{\}$ ,
    $t = -1$ .
2: repeat
3:   record the value of observer meter  $E_j$  in each time
     period  $j$ ,
     record the value array of all other meters  $X_j$  in each
     time period  $j$ ,
      $W_j \leftarrow P_{j-1}X_j^T(\lambda + X_jP_{j-1}X_j^T)^{-1}$ ,
      $A_j \leftarrow A_{j-1} + W_j(E_j - X_jA_{j-1})$ ,
      $P_j \leftarrow (I - W_jX_j)P_{j-1}/\lambda$ 
4: until  $A_j$  doesn't change
5: for each  $a_i$  in  $A_j$  do
6:   if  $a_i > \alpha_{max}$  then
7:     identified as ‘tampered’
8:      $t \leftarrow i$ 
9:   if  $\alpha_{min} \leq a_i \leq \alpha_{max}$  then
10:    identified as ‘normal’
11:   else
12:     report ‘error’ and exit
13: if  $t = -1$  then
14:   report ‘normal’ and exit
15: for each  $j \leq m$  do
16:    $a_{tj} = \frac{E_j - \sum_{i=1}^n a_i x_{ij}}{x_{tj}} (i \neq t)$ 
17:   for each  $a_k$  in  $S_t$  do
18:     if  $a_{tj} \geq a_k + e$  or  $a_{tj} \leq a_k - e$  then
19:        $S_t = S_t \cup \{a_{tj}\}$ 
20: Output:  $S_t$ .
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The algorithm of CNFD is shown in Alg. 1, which includes the two steps. The codes from Line 15 to Line 20 in Alg. 1 show the process of fraudster differentiation. The basic idea of fraudster differentiation is to calculate the coefficients at every interval after isolating the tampered meter, and analyze the similarity of these values within a given error e . Finally, these

values are identified as belonging to different fraudsters. Here, e is a given value of error that defined by users. S_t contains the output coefficients of all the fraudsters in Meter t . S_t is set initially to be an empty set. If the output coefficients in S_t are very similar, within the range of e , it means that there is only one fraudster. In other words, it is not a CNTL fraud.

IV. EXPERIMENTS

In this section, we will introduce four experiments to show the effectiveness of CNFD. These four experiments show results of detecting segmented CNTL frauds, fully overlapped CNTL frauds, partially overlapped CNTL frauds, and combined CNTL frauds, respectively. The user defined error e is set to 0.5%. There are 30 measurement records in each experiment, but we only list the first 20 records to save space. The value of k is 100, λ is 0.01, and a_i is 2. We set the measurement accuracy class as 2%, i.e., $\alpha_{min} = 0.98$ and $\alpha_{max} = 1.02$. If a meter's line falls in the range between $y = 0.98x$ and $y = 1.02x$, it is a normal meter. Any line of a meter that is above $y = 1.02x$ is a tampered meter's line. It indicates that an error occurs if there is any line of a meter is below $y = 0.98x$. The data used in the experiments are synthetic data. We obtained normal electricity consumption data based on a real-world dataset [38], and increased the consumption of some meters randomly. The measurement interval is one month.

A. Experiment 1: segmented CNTL

In the first experiment, there are 10 meters under the observation of one observer meter. The recorded values and the total supplied value of electricity are listed in Table I.

As shown in Fig. 4, this is the tampered meter detection process in Exp. 1, which shows that Meter 4 is a tampered meter and the line of $y = 2.216x$ represents its fraudster's behavior. After further analysis, we find that there are two fraudsters in this meter. Their behaviors are represented by $y = 1.22x$ and $y = 2.22x$, which are shown in Fig. 5. Each of the two fraudsters dominates a time segment of the whole process, and therefore it is a segmented CNTL fraud.

B. Experiment 2: fully overlapped CNTL

In the second experiment, there is one observer meter, and it monitors 10 other meters. We list the first 20 measurement records in Table II.

As shown in Fig. 6, this is the detection process in Exp. 2. The coefficient of Meter 2 converges to 2.51 while the coefficients of other meters converge to 1, and this indicates that Meter 2 is a tampered meter. We further analyze this meter using CNFD, and we find that this fraud is colluded by two fraudsters. However, the behavior of Fraudster 1 is fully covered by Fraudster 2. Therefore, it is a fully overlapped CNTL fraud. As shown in Fig. 7, the behaviors of these two fraudsters are represented by $y = 1.33x$ and $y = 2.51x$, respectively.

TABLE I
THE RECORDED ELECTRICITY CONSUMPTION (kWh) IN EXPERIMENT 1

Meter 1	2	3	4	5	6	7	8	9	10	Observer
2790	3970	5540	2960	3440	9950	5550	4340	5740	6700	51631.2
3400	4200	6510	3620	2360	9970	6030	3590	5310	6840	52626.4
2910	4460	7650	3910	3240	1017	6290	2500	5710	6980	54680.2
3370	3760	6880	3180	4060	1089	6190	6230	7670	8080	61009.6
3690	3940	6600	3580	6090	9780	6830	3280	6200	5320	56097.6
2350	5170	7150	3540	6600	10530	7330	4690	6270	6920	64868.8
3820	3390	7310	4290	3130	9170	6430	4270	6270	6560	59873.8
3120	4930	5550	2180	4110	9790	5820	5200	3350	7570	54279.6
4580	4320	5720	3040	4480	9440	6350	4250	6320	7230	59438.8
2300	4220	4560	3920	3280	9830	5500	4860	6630	5840	55722.4
3350	3900	5850	2990	6120	8760	5650	4720	6670	6220	57877.8
3320	4180	5550	2990	6620	8470	6800	3580	5900	5290	56347.8
2780	3310	5800	3870	4850	8560	6700	3210	3900	4030	51731.4
2980	4900	6560	2520	6130	10350	8000	3620	4660	4900	57694.4
3010	4100	7210	4460	5480	9530	8260	4080	5620	7260	64451.2
4260	3470	7290	5330	4630	9790	8460	3650	4730	6920	65032.6
3610	3640	5740	4140	4870	9730	6630	3590	5870	7420	60290.8
3190	4690	5930	4140	6240	10710	6870	4620	6060	6800	64300.8
3060	5800	6450	3790	3290	11190	7510	4700	5080	6760	62253.8
3660	4050	7010	3610	5160	9810	6670	5520	6250	6440	62584.2

Fig. 4. The tampered meter detection process in Exp. 1: the converging process of the coefficients of 10 meters. Among these 10 meters, the coefficient of Meter 4 converges to 2.216 while others converge to 1, and this indicates that Meter 4 is a tampered meter.

C. Experiment 3: partially overlapped CNTL

In this experiment, there are still 10 meters which are monitored by one observer meter. Table III shows 20 measurements of data of the recorded values of electricity.

The tampered meter detection result is shown in Fig. 8. Coefficients of all other meters converge to 1 while the coefficient of Meter 3 converges to 3.11, and this indicates that Meter 3 is a tampered meter. We analyze Meter 3 using CNFD, and find that there are two fraudsters who manipulated this meter. Their manipulation behaviors overlapped in some time segments, but not in the whole process. Thus, it is a partially overlapped CNTL fraud. These two fraudsters' behaviors are

$y = 1.88x$ and $y = 3.11x$ in terms of mathematics, which are shown in Fig. 9.

D. Experiment 4: combined CNTL

This is the last experiment. In this experiment, we still employ 10 meters and an observer. Table IV shows their recorded data in 20 measurements.

The result of the first step, tampered meter detection, of CNFD is shown in Fig. 10. Meter 6 is a tampered meter because the curve of its coefficients finally converges to 1.972. The other 9 meters are normal since the curves of their coefficients finally converge to 1. In the second step, three

Fig. 5. The final detection result of CNFD in Exp. 1. CNFD detection shows that there are two different fraudsters who collude the fraud in Meter 4.

TABLE II
THE RECORDED ELECTRICITY CONSUMPTION (KWH) IN EXPERIMENT 2

Meter 1	2	3	4	5	6	7	8	9	10	Observer
3500	3480	6300	2990	3640	9200	5240	4270	5150	6500	51418.4
3420	3960	6730	3250	2950	9580	5770	3380	5790	6880	57689.6
2830	4380	7210	3800	3060	9480	5740	2850	5740	6490	53025.4
3040	4060	7640	3020	3800	1109	6930	6610	7760	8020	63309.8
4170	3510	6370	3740	6000	9970	7380	3380	6240	5350	61410.1
2640	4800	7530	4030	6620	10120	7760	4090	5890	6240	66968
3210	3830	7860	3750	2610	9600	6570	4400	5720	6490	55303.9
2860	4240	5850	2460	4040	9840	6100	4270	3470	7390	56922.4
3760	4200	5580	3610	3880	9930	6040	4350	7080	7100	56916
2750	4230	5030	3720	3550	10540	5270	4970	6730	6020	54205.9
3440	3830	5530	3070	6790	9180	5860	3930	6090	5900	59403.3
3520	3680	6190	3120	6360	7820	6730	3540	6120	4700	57336.8
2120	3150	6300	4160	4480	7940	7320	3190	3690	3930	51036.5
2940	4930	6610	2110	6370	10520	7890	4080	4640	5330	62864.3
3400	3910	6940	4500	5890	9530	7880	3980	4640	6900	63474.1
4410	3320	7130	5050	4860	10120	7950	3300	5530	7500	64183.2
3250	3800	6060	4990	4680	9300	6780	3370	6130	7080	61178
3120	4780	6010	4290	5780	10240	7670	4060	6470	7010	66647.8
2370	5810	7070	3450	3230	11480	7050	4220	5380	6900	65733.1
3580	3580	6710	3670	5010	10270	7170	5030	6420	7130	63975.8

different fraudsters are identified, and they are represented by $y = 1.45x$, $y = 1.19x$, and $y = 1.98x$, respectively. Fraudster 3 partially overlaps Fraudster 2, while Fraudster 1 and Fraudster 2 are segmented. Thus, it is a combined CNTL fraud shown in Fig. 11.

V. RELATED WORK

The physical method has the longest history in combating NTL fraud. In the traditional power grid, surveillance staffs are hired to examine power lines and get rid of bypasses routinely [39]. In Smart Grid, monitoring is still a good choice to deal with bypassing and other types of physical tampering. In the paper [19], video surveillance by drones is used to analyze

the suspected segments in the feeder line, and a control center is employed to identify NTL frauds and notify the nearest vigilance staff. Some research focuses on designing secure modules installed along each smart meter. The paper [22] introduces a smart prepaid metering system employing a special energy meter which can protect against meter bypassing. The main drawback of these physical methods is that they either cannot pinpoint a tampered meter, or they are expensive when they can pinpoint a tampered meter. In Smart Grid, automatic power line examination cannot only help to maintain the functionality of the power line but also help to address NTL fraud problems. A power line impedance technique is proposed in the papers [20], [21] to locate tampered meters. By

Fig. 6. The tampered meter detection process in Exp. 2: the converging process of the coefficients of 10 meters. Among these 10 meters, the coefficient of Meter 2 converges to 2.51 while others converge to 1, and this indicates that Meter 2 is a tampered meter.

Fig. 7. The final detection result of CNFD in Exp. 2. CNFD detection shows that two different fraudsters collude the fraud on Meter 2.

using two different operating frequencies, the phase angle of the transmission lines and the impedance values are measured and used to locate the tampered meters.

Physical methods have three shortcomings. The first shortcoming is that the monitoring methods are expensive and inefficient. The monitoring methods need humans involved. Video surveillance still needs staff to watch these videos. The second shortcoming is that they are mainly used to detect NTL frauds committed via physical methods, such as power line bypassing. They cannot detect NTL frauds committed via cyber attacks, such as manipulating a billing message and changing the values of the billing amount. The third shortcoming is that customers easily complain about privacy

invasion [33], [40]–[42].

Profiling is a typical method used to detect NTL frauds, and a method using profiling typically obtains energy consumption profiles of different types of users. The mostly used technologies are Artificial Intelligence (AI) enabled technologies, such as Pattern Recognition [43], [44], Machine Learning [45], [46], Data Mining [47], etc. In the paper [23], Support Vector Machines (SVMs) are trained with energy consumption data that represent all possible types of energy theft. A dataset that contains the energy consumption patterns of users is generated based on historical data. Then energy consumption profiles of these customers are built and classified according to some given rules, and the suspicious profiles are grouped. The

TABLE III
THE RECORDED ELECTRICITY CONSUMPTION (kWh) IN EXPERIMENT 3

Meter 1	2	3	4	5	6	7	8	9	10	Observer
3440	4220	6220	2930	3690	9130	5270	4400	5140	6140	56053.6
3550	4180	7050	4190	2690	9670	6000	3300	5840	6810	59484
3530	4650	7600	4140	3400	10140	5710	2760	6330	6440	61388
3330	3470	7560	2720	4030	10360	6600	5900	7560	7630	75111.6
4170	3650	6700	3780	5410	9290	6910	3630	5710	5900	69287
2090	5410	7930	3570	6480	10260	7140	3960	5750	6260	75582.3
3870	3550	7950	4230	3080	9400	6290	4750	5980	6180	72054.5
3440	4390	6370	2220	4430	9210	6340	5160	3230	7520	57915.6
4530	4150	5550	3340	4730	9700	5780	3790	7240	6920	60614
2230	3900	4560	4020	3080	10510	5890	5220	6280	5230	54932.8
2970	3820	6010	3780	5920	9030	6090	4480	6470	5720	66971.1
2980	3770	6360	2730	6220	8460	6570	3740	5910	4400	64559.6
2440	3380	5760	3830	4670	8010	6390	3570	3240	3680	57123.6
3170	4750	6630	2670	5740	10090	8010	3630	5260	4660	68599.3
3080	3370	7190	3930	5540	10260	8220	3790	5440	6480	72470.9
4470	3950	6560	5080	5050	9280	8640	3100	4990	6890	71851.6
3560	4460	5770	4880	4670	9460	6210	2940	5560	7010	66694.7
3590	5040	6500	4430	6200	10390	7680	4310	5920	7000	74775
2900	5440	6970	3080	3940	10850	7200	4750	5520	7200	72556.7
3880	4360	7380	2730	4880	9840	7090	4980	6260	7230	74201.8

Fig. 8. The tampered meter detection process in Exp. 3: the converging process of the coefficients of 10 meters. Among these 10 meters, the coefficient of Meter 3 converges to 3.11 while others converge to 1, which indicates that Meter 3 is a tampered meter.

authors in [24] introduce how to deal with the characterization of customers in utility companies to detect NTL frauds. They propose a new framework to find relevant knowledge of the particular characteristics of the customers.

Profiling methods have three drawbacks. The first drawback is that these methods often need lots of data to generate user profiles. The second drawback is that they are sensitive to variations, such as traveling or buying a new home appliance. The third drawback is that they can only detect frauds that have known patterns.

Comparison based methods [11], [27]–[30], [48] are to record a correct value of energy usage and compare the reading of a meter with this value. We have proposed NFD [29] and

FNFD [30], [48] which are comparison based methods. Both NFD and FNFD use an observer meter to record a correct value of energy usage for the purpose of comparison. The benefit of comparison based methods is that they usually require a small amount of data and lightweight. Both NFD and FNFD can detect NTL frauds, but they cannot detect CNTL fraud. NFD employs polynomial functions to build models, and thus it is more accurate than FNFD. FNFD employs linear functions to build models, and thus it is faster than NFD. Note that a short version of this paper was presented in the conference [12].

Fig. 9. The final detection result of CNFD in Exp. 3. CNFD detection shows that there are two different fraudsters who collude the fraud in Meter 3.

TABLE IV
THE RECORDED ELECTRICITY CONSUMPTION (KWH) IN EXPERIMENT 4

Meter 1	2	3	4	5	6	7	8	9	10	Observer
2920	3590	6470	2300	3490	9550	5530	4110	5830	6310	54397.5
3560	3710	6980	3930	2650	9070	6280	2920	5440	6320	54941.5
3100	4540	7140	3160	3230	9600	6380	2210	6020	6540	56240
2660	4350	6860	3230	3540	10410	6800	6200	8210	7430	64374.5
3380	4430	6100	3060	5220	9330	7380	3800	6510	5510	56492.7
2240	5260	7360	4110	6740	10370	7270	4740	5820	6770	70842.6
3670	3500	7920	4300	2570	9590	6260	4040	6330	6850	64428.2
3000	4530	6250	2940	3760	9740	6500	4530	3280	7590	53970.6
4590	4600	5600	3560	4270	9230	5980	4130	6650	7140	57503.7
2920	4210	5150	3430	3190	10260	5460	4680	6910	5710	53869.4
3640	3260	6150	3270	6430	9200	5860	4740	6540	5630	63736
3050	3680	5430	3440	6470	8020	7190	3560	6610	4610	59919.6
2220	3140	5930	4180	4940	8550	6760	2890	3710	3700	54399
2720	4710	5990	2380	6340	10090	7620	3900	5160	4680	63478.2
3480	3870	7280	4670	5270	9500	8380	3980	5220	6920	67880
4228	3948	6678	5348	4780	10188	8088	3668	4818	7480	68976.4
3840	3750	6090	4710	4870	9570	6840	3110	6270	7350	65778.6
3740	5100	6410	4850	5570	9770	7430	4310	5670	6920	69344.6
3060	5520	7180	3630	3900	10590	6920	4240	5580	6480	67478.2
3630	3790	6820	3520	4580	9850	6670	5740	6130	7280	67663

VI. CONCLUSION

In this paper, we introduced a potential type of frauds that we recently discovered in the Smart Grid. Since this type of fraud is a variant of NTL frauds and multiple fraudsters co-exist or collaborate to commit a fraud, we named them Colluded NTL (CNTL) frauds. We presented our study on the features of this type of frauds, and categorized them into four types: segmented CNTL frauds, fully overlapped CNTL frauds, partially overlapped CNTL frauds, and combined CNTL frauds. We further proposed a detector, named CNFD, to detect CNTL frauds in Smart Grid. We conducted various experiments and the results showed that CNFD can detect four types of CNTL frauds.

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REFERENCES

- [1] J. Gao, Y. Xiao, J. Liu, W. Liang, and C. L. P. Chen. A survey of communication/networking in smart grids. (*Elsevier*) *Future Generation Computer Systems*, 28(2):391404, 2012.

Fig. 10. The result of the first step, tampered meter detection, of CNFD in Exp. 4. It shows the converging process of the coefficients of 10 meters. The coefficient of Meter 6 converges to 1.972 and the coefficients of other meters converge to 1 showing that Meter 6 is the tampered meter.

Fig. 11. The result of CNFD after the second step, fraudster differentiation, in Exp. 4. It shows that there is a CNTL fraud on Meter 6 which are committed by three fraudsters.

- [2] J. Mu, W. Song, W. Wang, and B. Zhang. Self-healing hierarchical architecture for zigbee network in smart grid application. *International Journal of Sensor Networks*, 17(2):130–137, 2015.
- [3] Z. Xiao, Y. Xiao, and D. Du. Non-repudiation in neighborhood area networks for smart grid. *IEEE Communications Magazine*, 51(1):18–26, Jan. 2013.
- [4] W. Han and Y. Xiao. Non-technical loss fraud in advanced metering infrastructure in smart grid. In *The 2nd International Conference on Cloud Computing and Security (ICCCS 2016)*, July 2016.
- [5] W. Han and Y. Xiao. Combating TNTL: Non-technical loss fraud targeting time-based pricing in smart grid. In *The 2nd International Conference on Cloud Computing and Security (ICCCS 2016)*, July 2016.
- [6] Northeast, Group, and LLC. Emerging markets smart grid: Outlook 2015. available at: <http://www.northeast-group.com/reports/Brochure-Emerging%20Markets%20Smart%20Grid-Outlook%202015-Northeast%20Group.pdf>, Dec. 2014.
- [7] P. Detwiler. Electricity theft: A bigger issue than you think. available at: <http://www.forbes.com/sites/peterdetwiler/2013/04/23/electricity-theft-a-bigger-issue-than-you-think/#6a262d5272eff>, Apr. 2013.
- [8] D. Kundur, X. Feng, S. Mashayekh, S. Liu, T. Zourntos, and K.L. Butler-Purry. Towards modelling the impact of cyber attacks on a smart grid. *International Journal of Security and Networks*, 6(1):2–13, 2011.
- [9] J. Zhang and C. A. Gunter. Application-aware secure multicast for power grid communications. *International Journal of Security and Networks*, 6(1):40–52, 2011.
- [10] J. Liu, Y. Xiao, S. Li, W. Liang, and C. L. P. Chen. Cyber security and privacy issues in smart grids. *IEEE Communications Surveys & Tutorials*, 14(4):981–997, Fourth Quarter 2012.
- [11] Z. Xiao, Y. Xiao, and D. Du. Exploring malicious meter inspection in neighborhood area smart grids. *IEEE Transactions on Smart Grid*, 4(1):214–226, Mar. 2013.
- [12] W. Han and Y. Xiao. Cnfd: A novel scheme to detect colluded non-

- technical loss fraud in smart grid. In *Proceedings of The 11th International Conference on Wireless Algorithms, Systems, and Applications (WASA 2016)*, August 8-10, 2016, Bozeman, Montana, USA., pages 47–56, Aug. 2016.
- [13] R. Berthier and W. H. Sanders. Monitoring advanced metering infrastructures with amilyzer. *Cyber-security of SCADA & industrial control systems*, 2013.
- [14] S. McLaughlin, B. Holbert, S. Zonouz, and R. Berthier. AMIDS: A multi-sensor energy theft detection framework for advanced metering infrastructures. In *Proceedings of the 2012 IEEE Third International Conference on Smart Grid Communications (SmartGridComm'12)*, pages 354–359, Nov. 2012.
- [15] W. Han, W. Xiong, Y. Xiao, M. Ellabidy, A. V. Vasilakos, and N. Xiong. A class of non-statistical traffic anomaly detection in complex network systems. In *Proceedings of the 32nd International Conference on Distributed Computing Systems Workshops (ICDCSW'12)*, pages 640–646, June 2012.
- [16] Z. A. Baig. Rapid anomaly detection for smart grid infrastructures through hierarchical pattern matching. *International Journal of Security and Networks*, 7(2):83–94, 2012.
- [17] D.J. Gausshell and H.T. Darlington. Supervisory control and data acquisition. *Proceedings of the IEEE*, 75(3):1645–1658, 2005.
- [18] J. Gao, J. Liu, B. Rajan, R. Nori, B. Fu, Y. Xiao, W. Liang, and C. L. P. Chen. Scada communication and security issues. *Security and Communication Networks Security Comm*, 7(1):175–194, 2014.
- [19] P. Rengaraju, S. R. Pandian, and C. Lung. Communication networks and non-technical energy loss control system for smart grid networks. In *Proceedings of the 2014 IEEE Innovative Smart Grid Technologies - Asia (ISGT ASIA)*, pages 418–423, May 2014.
- [20] J.V. Wijayakulasooriya, D.M.I.S. Dasanayake, P.I. Muthukumarana, H.M.P.P. Kumara, and L.A.D.S.D. Thelisinghe. Remotely accessible single phase energy measuring system. In *Proceedings of the 1st Int'l Conf. on Industrial and Information Systems*, pages 304–309, Aug. 2006.
- [21] A. Pasdar and S. Mirzakuchaki. A solution to remote detecting of illegal electricity usage based on smart metering. In *Proceedings of the 2nd Int'l workshop on Soft Computing Applications*, pages 163–167, Aug. 2007.
- [22] N. Mohammad, A. Baru, and M.A. Arafat. A smart prepaid energy metering system to control electricity theft. In *Proceedings of the Int'l Conf. on Power, Energy and Control*, pages 562–565, Feb. 2013.
- [23] S.S.S.R. Depuru, L. Wang, and V. Devabhaktuni. Support vector machine based data classification for detection of electricity theft. In *Proceedings of IEEE/PES Power Systems Conference and Exposition (PSCE)*, pages 1–8, Mar. 2011.
- [24] F. Biscarri, I. Monedero, C. Leon, and J. I. Guerrero. A mining framework to detect non-technical losses in power utilities. In *Proceedings of 11th International Conference on Enterprise Information System (ICEIS'09)*, May 2009.
- [25] C. Lin, S. Chen, C. Kuo, and J. Chen. Non-cooperative game model applied to an advanced metering infrastructure for non-technical loss screening in micro-distribution systems. *IEEE Transactions on Smart Grid*, 5(5):2468–2469, Sept. 2014.
- [26] S. Huang, Y. Lo, and C. Lu. Non-technical loss detection using state estimation and analysis of variance. *IEEE Transactions on Power Systems*, 28(3):2959–2966, Aug. 2013.
- [27] X. Xia, W. Liang, Y. Xiao, M. Zheng, and Z. Xiao. Difference-comparison-based approach for malicious meter inspection in neighborhood area smart grids. In *Proceedings of the 2015 International Conference on Communications (ICC'15)*, pages 802–807, June 2015.
- [28] X. Xia, W. Liang, Y. Xiao, and M. Zheng. BCGI: A fast approach to detect malicious meters in neighborhood area smart grid. In *Proceedings of the 2015 International Conference on Communications (ICC'15)*, pages 7228–7233, June 2015.
- [29] W. Han and Y. Xiao. NFD: A practical scheme to detect non-technical loss fraud in smart grid. In *Proceedings of the 2014 International Conference on Communications (ICC'14)*, pages 605–609, June 2014.
- [30] W. Han and Y. Xiao. FNFD: A fast scheme to detect and verify non-technical loss fraud in smart grid. In *Proceedings of the International Workshop on Traffic Measurements for Cybersecurity (WTMC'16)*, May–June 2016.
- [31] M. H. Hayes. Recursive least squares. In *Statistical Digital Signal Processing and Modeling*, chapter 9.4, page 154, Wiley, 1996.
- [32] W. Han and Y. Xiao. IP2DM for V2G networks in smart grid. In *Proceedings of the 2015 International Conference on Communications (ICC'15)*, pages 782–787, June 2015.
- [33] W. Han and Y. Xiao. Privacy preserving for v2g networks in smart grid: A survey. *Computer Communications*, 91-92:17–28, 2016.
- [34] G. Kalogridis, S.Z. Denic, T. Lewis, and R. Cepeda. Privacy protection system and metrics for hiding electrical events. *International Journal of Security and Networks*, 6(1):14–27, 2011.
- [35] F. Li, B. Luo, and P. Liu. Secure and privacy-preserving information aggregation for smart grids. *International Journal of Security and Networks*, 6(1):28–39, 2011.
- [36] P. Jokar, N. Arianpoo, and V. C. M. Leung. A survey on security issues in smart grids. *Security and Communication Networks*, 9:262–273, June 2012.
- [37] SATEC Power Solutions. Accuracy class: a small s that makes a big difference. available at: <http://www.satec-global.com/sites/default/files/ApplicationNote-Accuracy-Class-Dec2012.pdf>, 2012.
- [38] Georges Habrail and Alice Barard. Individual household electric power consumption data set. available at: <https://archive.ics.uci.edu/ml/datasets/Individual+household+electric+power+consumption>, 2012.
- [39] S. Ma, Y. Yang, Y. Qian, H. Sharif, and M. Alahmad. Energy harvesting for wireless sensor networks: applications and challenges in smart grid. *International Journal of Sensor Networks*, 21(4):226–241, 2016.
- [40] Z. Fu, X. Sun, Q. Liu, L. Zhou, and J. Shu. Achieving efficient cloud search services: Multi-keyword ranked search over encrypted cloud data supporting parallel computing. *IEICE Transactions on Communications*, E98-B(1):190–200, 2015.
- [41] Z. Fu, K. Ren, J. Shu, X. Sun, and F. Huang. Enabling personalized search over encrypted outsourced data with efficiency improvement. *IEEE Transactions on Parallel and Distributed Systems*, DOI: 10.1109/TPDS.2015.2506573, 2015.
- [42] Z. Xia, X. Wang, X. Sun, and Q. Wang. A secure and dynamic multi-keyword ranked search scheme over encrypted cloud data. *IEEE Transactions on Parallel and Distributed Systems*, 27(2):340–352, 2015.
- [43] B. Gu, V. S. Sheng, K. Tay, W. Romano, and S. Li. Incremental support vector learning for ordinal regression. *IEEE Transactions on Neural Networks and Learning Systems*, 26(7):1403–1416, 2015.
- [44] W. Ma, M. Liu, H. Huang, and D. Su. An efficient algorithm for finding frequent and diverse subgraph patterns in ppi networks. *International Journal of Sensor Networks*, 16(4):210–216, 2014.
- [45] B. Gu, X. Sun, and V. S. Sheng. Structural minimax probability machine. *IEEE Transactions on Neural Networks and Learning Systems*, DOI: 10.1109/TNNLS.2016.2544779, 2016.
- [46] Y. Zheng, B. Jeon, D. Xu, Q.M. J. Wu, and H. Zhang. Image segmentation by generalized hierarchical fuzzy c-means algorithm. *Journal of Intelligent and Fuzzy Systems*, 28(2):961–973, 2015.
- [47] H. Yang, S. Fong, K. Cho, and J. Wang. Atmospheric pattern recognition of human activities on ubiquitous sensor network using data stream mining algorithms. *International Journal of Sensor Networks*, 20(3):147–162, 2016.
- [48] W. Han and Y. Xiao. Design a fast non-technical loss fraud detector for smart grid. (*Wiley Journal of Security and Communication Networks*, accepted).