Electricity theft detection framework based on universal prediction algorithm

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ABSTRACT

Electricity theft has caused huge losses over the globe and the trend of its perpetuation constantly evolve even as smart technologies such as smart meters are being deployed. Although the smart meters have come under some attacks, they provide sufficient data which can be analysed by an intelligent strategy for effective monitoring and detection of compromised situations. So many techniques have been employed but satisfactory result is yet to be obtained for a real-time detection of this electrical fraud. This work suggests a framework based on Universal Anomaly Detection (UAD) utilizing Lempel-Ziv universal compression algorithm, aimed at achieving a real-time detection in a smart grid environment. A number of the network parameters can be monitored to detect anomalies, but this framework monitors the energy consumption data, rate of change of the energy consumption data, its date stamp and time signatures. To classify the data based on normal and abnormal behaviour, Lempel-Ziv algorithm is used to assign probability of occurrence to the compressed data of the monitored parameters. This framework can learn normal behaviours of smart meter data and give alerts during any detected anomaly based on deviation from this probability. A forced aggressive measure is also suggested in the framework as means of applying fines to fraudulent customers.

Keywords: Anomaly detection, Botnets, Electricity theft, Lempel-ziv, Smart meters

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1. INTRODUCTION

The operations of every of our infrastructure and activities such as health care delivery systems; water and electricity; various marketing structures and platforms; manufacturing and all industrial processes; security systems and operations; education and researches etc. are mostly computer-based and are being thought of to be integrated in planned smart cities whose operation solely depends on an intelligent grid
known as smart grids (SGs). The introduction of smart grids (SGs) as the integration of digital computing and communication technology with the power infrastructure has improved the systems’ intelligence and has modernized the operation of the conventional power delivery schemes for improved reliability, flexibility, sustainability, security, resiliency, and energy efficiency [1-3] but are subjected to the risk of cyber-attacks and its related threats, especially with internet of things (IoT) taking over [4]. These attacks can change their patterns, appearance and are constantly evolving, hence, requiring a real-time solution to keep track and bring the attacks under control [5] the sooner they occur. Electricity infrastructure, the most targeted by cyber-attacks [6, 7] are commonly subjected to electricity theft.

Electricity theft is a global menace whose trend of perpetuation constantly evolves even as smart technologies are being deployed [8-10]. It occurs sporadically and inflicts huge economic losses and also threatens power systems’ sustainability [2]. World bank data reveal India loses about 25% of their generated power, Brazil faces about 16% loss while China and US reportedly lose 6% and 5%, respectively [1] with all countries worldwide having several bitter experiences. Northeast group LLC reported that worldwide, $89.3 billion are lost due to electricity theft on yearly basis [11]. So many approaches have been reported for energy theft detection using the data from conventional meters mainly by the application of artificial intelligence techniques [11-14] etc. but these solutions hardly focus on energy theft detection in real time which is a key aspect of the SGs. Nonetheless, the advent of smart electricity meters (SEMs) has helped greatly by mitigating the energy theft since customer’s meters can easily be monitored and its consumption pattern can easily be analysed for inferential judgement using various techniques and strategies some of which are as applied to the data obtained from conventional meters [15-18]. Although, the vulnerability of SEMs as a cyber-physical system remains a crucial concern due to their being able to change their patterns, appearances and constantly evolve, hence, demands critical monitoring by a real-time solution to keep track and bring the attacks under control [5] the sooner they occur. The current trend of ICT with its associated cyber-attacks dictates that proactive steps be taken in leveraging the technology for increased security [11] as electricity theft remains a key issue to be addressed.

In this paper, a framework for energy theft detection based on ‘anomaly detection technique’ employing a universal prediction algorithm, known as Lempel-Ziv algorithm (LZA), is proposed. The customers’ energy consumption data are to be classified by probability assignment of the LZA. Then, the probability assignment on the processed training data is carried out to build a statistical model which forms the basis for normal and abnormal behaviour classification to make decisions. A punishment for detected fraudulent customers to ease the on-site monitoring for utility officials is also suggested by a forced corrective technique. The next section of this paper explores smart meter data and electricity theft. Botnets and general intrusion detection systems are explained in Section 3 while anomaly detection and related works are presented in Sections 4 and 5 respectively. The universal prediction algorithm is explained in Section 6. Section 7 gives the details of the proposed framework and Section 8 concludes the study.

### 2. SMART METER DATA AND ELECTRICITY THEFT

The introduction of smart grids (SGs) as the integration of digital computing and communication technology with the power infrastructure has improved the systems’ intelligence and has modernized the operation of the conventional power delivery schemes for improved reliability, flexibility, sustainability, security, resiliency, and energy efficiency [1-3]. Fundamental to SGs, is the implementation of advanced metering infrastructure (AMI) with SEMs as its key components, for the monitoring and control of systems’ parameters [19-21]. This scheme helps to lessen energy theft risks but are vulnerable to cyber-attacks which could cause some adverse effects to customers and utilities. Such adverse effects include electricity service disruption, damage to infrastructure, electricity thefts etc. [1, 22].

SEMs are innovative energy meters deployed for the measurement of energy consumption data which in addition, provide real-time monitoring and basic information interchange between the customer and utility company. They securely communicate the stored data to advanced metering infrastructure (AMI) and are perfect replacements for the conventional analogue meters by the elimination of on-site monitoring and measurement reading by personnel [7, 18]. Additional functions of SEMs are as highlighted in Table 1 [7, 15, 21, 23-26]. Worldwide, SEMs are being gradually deployed with many nations setting landmark targets to completely replace their conventional meters [12, 27-29] own to these many functions and more.

The ability of SEMs to help in real-time collection of energy consumption data at regular intervals for advanced data analytics help energy theft detection at shorter periods which could have easily evade detection in longer periods (as applicable to conventional energy meters); and for further inference aimed at improving the power systems [2, 15, 30]. Its ability to detect fraud has helped in curbing theft but its vulnerability as applicable to any other cyber physical systems remain a major issue [1, 7]. A 24-hour test data obtained from a SEM is as shown in Figure 1.

*Electricity theft detection framework based on universal prediction algorithm (Abdulrahaman Okino Otuoze)*
Nonetheless, SEMs can be compromised by illegal direct connections to distribution lines; it could be via the utility service provider infrastructure by sniffing, large-scale meter take-over, emulation of own or foreign meter etc and; it could be via a web application e.g. for data injection, privacy breaches, billing errors [31]. Other ways by which energy theft is carried out include meter bypass, meter tampering, connivance with fraudulent staff, billing irregularities and any other physical or cyber engineered mechanism aimed at manipulating energy consumption to evade bill payment [11, 32, 33]. Unlike in the conventional mechanical meters which often suffer physical tampering, the digital SMs are exposed to alteration of metering data (locally or remotely) [22]. Various schemes have been proposed in the attempt to present a lasting solution to energy theft based on SEMs data analytics. Most of the schemes such as firmware security, key management security, source code development security etc. involve building a resilient defence mechanism by using these data [31]. Some of the methods employed in this analysis include statistical approach, development of some intelligent algorithms utilising machine learning classifiers e.g. support vector machines (SVM), Decision Trees, fuzzy classifications etc. [11, 34]. A fundamental issue related with machine learning classifiers as applicable to energy theft detection is the imbalance in the data resulting from the difference in normal and abnormal samples. This is because theft samples do not practically exist in wholistic as it is exposed to myriads of vulnerabilities. This vulnerability of SEMs has called for various dimensions of research input aimed at addressing the challenges. But these attacks, mainly for electricity thefts, are constantly evolving and in different modes, hence, the need for real time monitoring of the meters’ normal behaviours to distinguish it from abnormal behaviours. This is best achieved by the provision of network security offering protection against miscellaneous attacks. Most of the attacks ravaging computer systems today are mainly caused by botnets [35-37].

| Advantages of Smart Electricity Meters |
|---------------------------------------|
| • Real-time monitoring and response of energy consumption usage and dynamic billings |
| • Enhanced load control and revenue generation |
| • Improved supply monitoring and management as outages and faults are easily detected and reported |
| • Local reading ability and remote control for disconnect, dynamic pricing and general information from the utility etc. |
| • Automated power restoration |
| • Improved metering by detection of tampering and energy losses especially resulting from fraudulent activities |
| • Device and energy status capture by supporting a non-intrusive load monitoring for home automation |
| • Support for Home Area Networks |
| • Interoperability within the SGs network by renewable energy integration support |
| • Frequent sampling intervals and provision of adequate data used in processing and classifications for pattern identification and consequent decision support |

![Figure 1. 24-hr sampled data of power consumption of a customer from a SM](image)

### 3. BOTNETS AND INTRUSION DETECTION SYSTEMS

Botnets are compromised, and distributed software entities controlled by a server under the influence of a Bot-master using command and control (C&C) channel to infect machines while carrying out
malicious activities such as stealing and manipulations of data, cyberattacks, Denial of Service (DoS) etc. While the server may be infected websites, email attachments, file sharing etc., the host (i.e. the compromised machine) could be either computers, mobile phones etc. [5, 38-40]. Botnets attacks escalate geometrically as criminals have found them a safe-haven to perpetuate attacks for several reasons. These attacks are either server-based or host-based [38]. The severity of the attacks is very high because every compromised machine (known as bot) could also become a server for launching further attacks. Botnets account for over 85% of spam mails and about 20% ad clicks with associated heavy financial losses in billions of dollars [38]. Intrusion prevention techniques such as authentication, authorization and privacy are applied to secure systems from bot attacks, but they are random and prone to breaches. Hence, an intrusion detection systems (IDSs) are required as another level of protection [41]. An efficient IDSs must first uncover the behaviours of the bots to aid the design, detection and blocking mechanism [38, 39]. This is done by exploring the communication patterns of the bots C&C channel which is its weakest link, since it is the only link the bot-master communicates with its bots, and block them before any serious harm is done [5, 39, 42, 43].

IDSs are sometimes considered as either host-based or network-based. The host-based monitors a single host activity such as log files and applications activities while the network-based scans for any suspicious activity from the network traffic of a given part of the network. The boundary of the different segments of the network is usually the best place for the network-based. IDSs can be executed in offline or online mode. The offline mode involves manual periodic scanning to check for any possible intrusion since the previous scan. In this approach, scanning is carried out only at convenience but usually when suspicious activities are suspected. The online-based scanning is real time and able to run the scan at a pre-set interval of time [39, 44, 45]. IDSs can also be classified based on other techniques depending on the nature of the attacks and with respect to its detection principle. Several techniques are employed in botnets detection, but a basic approach is to view them from three angles namely; the honeynets approach, the signature-based detection and anomaly detection [5, 40]. While the honeynets approach utilises set traps to collect, study and reveal information about bots, the signature-based (sometimes called misuse-based) relies on using learned information stored on the database to locate bots and requires constant updates of the database since new attacks are not learnt and cannot be detected; the anomaly detection technique is targeted at recognising the presence of irregularities in any of the systems’ indicative parameters or in the network traffic [5, 45]. Figure 2 depicts a typical botnets and intrusion detection techniques as explained above. Undeniably, anomaly detection is more promising for the detection of botnets, since new attacks (also known as zero-day attacks) even without prior knowledge, can also be detected. Although the signature-based approach as discussed earlier works perfectly as a basis for detecting theft, the anomaly detection approach presents higher intelligence [22] since botnets are highly dynamic.

![Figure 2. Botnets and intrusion detection techniques](image)

4. ANOMALY DETECTIONS

Anomaly detections (ADs) involve the technique of finding outliers, intrusions or patterns in a given data set which do not conform to a defined normal or expected behaviour [45-47]. The anomalies (or outliers) are often induced in the data by adversaries for various purposes ranging from fraud, terrorism, cyber-attacks,
war etc. and hence, ADs have found applications in theft and fraud detection, intrusion detection for cybersecurity, fault detection in critical systems etc. [7, 45]. Anomalies in any given dataset could cause severe losses (financial and technical), failure, and breakdown of any system in context. In power systems, huge losses (in revenues) are incurred mostly due to electricity theft resulting from data manipulations by cyber-attacks on SMs. Worldwide, huge losses (in billions of dollars) are being reported in various cases of electricity thefts. Hence, the need for intensified research efforts by developing more intelligent frameworks and algorithms for detecting anomalies in energy consumption data especially.

In ADs, traffic analysis is used on both packet and flow data since attacks are assumed different from normal pattern. Metrics such as response time, date and time stamps, rate, volume, range etc. are used in identifying anomalous data [42]. Figures 3 and 4 show samples anomaly of an attack on a SM by infected data on the time and power utilised, respectively. The anomaly in Figure 2 presents same time and values over different instants and it is usually aimed at maliciously paying for only an instant (the first time before successful attack) of the periods while Figure 3 presents an instance where the power consumption remains flat at some very low value over a considerable long period of time. These types of attacks may last for days, months or even years without an intelligent algorithm for real-time detection. ADs are faced with possible high false alarm rate and so, it utilises prior knowledge based on statistical evaluations (e.g. ARMA or Markov model) on the normal data to achieve higher performance [42].

![Figure 3](image1.png)

**Figure 3. Time-infected data of a smart meter reading**

![Figure 4](image2.png)

**Figure 4. Power consumption infected data**

5. RELATED WORKS

The advent of smart meters with its steady provision of real-time customer consumption data has necessitated the applications of big data analytics and machine learning in the study of electricity theft detection. Machine Learning applications such as Support Vector Machines (SVM), Artificial Neural Networks (ANN), Recurrent Neural Networks (RNN), Self-organising Maps (SOM) etc. are often employed for data pre-processing, feature extraction and classification [44]. Some works have been reported by training and modelling datasets using ANN, fuzzy classification, SVM [12, 13, 22, 48-50] and other classification strategies.

An anomaly-based general detection framework clearly independent of botnets relying on the technique of deep packet inspection although could not establish a result standing the test of ever expanding data, was presented by Gu, et al. [51]. Spirić, et al. [52], using rough set theory, analysed customers’ invoice and some other registered data, and predicted a list of fraudulent customers based on the consumption pattern of suspected customers and then hinted the need for on-field corrective and penalty measures where
necessary. In another work, a temperature based predictive model was proposed for different types of circuit approximations to estimate technical losses which was tested on distribution feeders and linear circuits to detect power theft [18]. Depuru, et al. [32] introduced a high-performance computing by data encoding for speed detection of energy theft. Using SVM and Rule-based algorithms, the encoded data were then classified to uncover electricity theft.

A centralized energy detection scheme was proposed utilizing the Kalman filter by Salinas and Li [2]. They proposed a privacy-preserving energy detection-based algorithm to identify fraudulent customers while Soniya and Wilscy [39] proposed an intrusion detection technique capable of early and randomised detection utilising traffic analysis of an end-point host in identifying bot’s C&C communication. These algorithms depend on the systems’ parameters’ fore-knowledge. Universal anomaly detection algorithms able to learn and distinguish normal from abnormal pattern in a network traffic [5]. This algorithm has no fore knowledge of the system model or the characteristics of the threat or attack.

Despite the various efforts, issues of high false positive rates, the need for field inspection after determining suspected fraudulent customers, complicated data collection procedure, lack of real-time monitoring remain a major concern. These concerns can only be addressed by an effective anomaly detection technique as evident in the study presented by Siboni and Cohen [5]. In their work, Lempel-Ziv universal compression algorithm was utilised to assign optimally, probability assignments for normal behaviour (during learning) and able to estimate the likelihood of new data (during operation) and classify it accordingly. They tested a time-series data, enabling the network to be both protocol and encryption independent. They were able to suggest a system able to detect every hiding technique and concluded from their report that, LZA is applicable to any sequence of behaviours and not just the timing data and can be applied to detect anomalous behaviour in any given data set.

6. UNIVERSAL PREDICTION ALGORITHM

Provide a statement that what is expected, as stated in the "Introduction" chapter can ultimately result in "Results and Discussion" chapter, so there is compatibility. Moreover, it can also be added the prospect of the development of research results and application prospects of further studies into the next (based on result and discussion).

LZA, a lossless data compression algorithm is applied by a means of probability assignment to compress the data. It is characterised by a vanishing redundancy [5]. It is sometimes, considered a universal prediction algorithm and often referred to as an optimal universal compression algorithm [5, 42]. LZA is a parsing algorithm used to partition block of variables (or phrases) of sequence data such that a newly parsed block is the shortest variable not seen previously [53, 54]. Each phrase in this dictionary or block is usually represented by a rooted-tree defining paths to internal nodes with each phase containing suffixes of leaf-nodes added to the tree and can be used to define a statistical model for a given sequence [5, 42, 53]. Each sensor nodes is used to assign labels to the sensed data for instance, ‘0’ can be used to denote normal

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These parsing algorithms have found applications in numerous areas such as universal data compression scheme, entropy estimations, anomaly detections, data randomness test, statistical model estimations of given sequence, pattern matching [53, 54, 56, 57] etc. A good LZ dictionary or the sensed data contains the most useful aspect of the data and the compressed data based on the codewords of the phrases in the dictionary [58]. Using the principle of entropy in information technology, the most useful part of the sensed data is captured by extracting all the phrases in the file with the most frequent data stored into the dictionary [58]. Consider a phrase of length \( M \) symbols occurring \( n \) times in a file of length \( N \) symbols, its average entropy, \( H_M \) is as given in (1) [58]. This means \( H_M \) represents the components of the phrases with the higher length or more frequent in the file.

\[
H_M = \frac{1}{M} \log_2 \frac{N}{nN} \tag{1}
\]

Let the sensed data of the four parameters selected for monitoring by this framework, energy consumption data, its rate of change, its date stamp and time signatures be as represented by (2) to (5).

\[
E = E_1, E_2, E_3, E_4, E_5, E_6, ..., E_i \tag{2}
\]

\[
e = e_1, e_2, e_3, e_4, e_5, e_6, ..., e_i \tag{3}
\]

Electricity theft detection framework based on universal prediction algorithm (Abdulrahman Okino Otuoze)
\[ D(h, m, s) = D_1, D_2, D_3, D_4, D_5, \ldots, D_i \]  
(4)

\[ T = t_1, t_2, t_3, t_4, t_5, t_6, \ldots, t_i \]  
(5)

Assuming the assigned label of any of the parameters at any instance, \( i \) is \( S = 10010010011010101 \), then, the parsed sequence is \( S = 1|0|01|00|10|01|101 \) and Table 2 shows the code word and probability assignments for each of the parsed phrase contents in the sensed. The statistical model is depicted in Figure 5.

| Dictionary Location | Content (C) | Codeword | Probability Assignment (Pr(C/S)) |
|---------------------|-------------|----------|---------------------------------|
| 001                 | 1           | 0001     | 1/4                             |
| 010                 | 0           | 0000     | 3/4                             |
| 011                 | 01          | 0101     | 1/2                             |
| 100                 | 00          | 0100     | 1/4                             |
| 101                 | 10          | 0010     | 1/4                             |
| 110                 | 011         | 0111     | 1/4                             |
| 111                 | 010         | 0110     | 1/4                             |

Figure 5. LZA statistical model for 10010010011010101

### 7. THE UNIVERSAL ANOMALY DETECTION FRAMEWORK

In the study of electricity theft detection using smart meter data, customers’ energy consumption data are usually considered from an instant of time, say, \( t_i \) and at every interval of usually 1 minute but for analysis sake, the interval of say, \( t_i + j \) can be considered where \( j \) denotes an arbitrary interval of interest. This gives large volume of data for analysis because the training data usually require a minimum of one month of one-minute sample rate. Both training and test data are labelled by a suitable classification of data. As presented in the framework of Figure 6, the training and testing stage based on LZA is carried out and a statistical model is developed based on the set of discrete data. Training is done only on the normal set of discrete sequences and the testing sequences are separately quantized using similar quantization and approach though same set of centroids.

Based on the statistical model, the probability of the dataset is assigned, and classification carried out using a set threshold while sequential probability assignment is used in the probability assignment of each testing sequence. The anomalies are those testing sequence for which the probability is lower than the set threshold. The customers within this category are then listed as suspected fraudulent customers. To eliminate the need for on-site inspection of those customers, a forced aggressive measure is suggested in the framework. This extra measure assists the utility punish energy fraudsters to reduce the hectic tasks of the on-field measures. Any customer who feels cheated or billed wrongly can appeal whereas confirmed fraudulent customers are automatically fined or recommend for court hearing for further punishment depending on the regulations of the utility. With low false positive rate (FPR), the scheme is just a key model to mitigating energy thefts.
Electricity theft detection framework based on universal prediction algorithm

8. CONCLUSION
A framework for electricity theft detection utilising Lempel-Ziv probability assignment algorithm has been presented. This framework suggests a real-time monitoring of smart meter data at some pre-set interval. This eliminates the possibility of customers evading detection. Any abnormal behaviour or pattern in the Date, Time stamps, rate and the energy consumption data will be detected. A forced corrective/penalty measure is also suggested in the framework. When implemented, the utility staff would have been saved the stress of on-the-field monitoring and confirmation of fraudulent customers. The implementation of the framework gives a positive step in the fight against energy theft. The framework is however a maturity model and therefore, requires constant implementation and modification using real-time data to suit the efficient detection of ever-dynamic nature of electricity thefts.

ACKNOWLEDGEMENTS
My supervisor, Prof. M. W. Mustafa is highly acknowledged for his tutelage and UTM administration, for constantly subscribing to credible database.

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Indonesian J Elec Eng & Comp Sci, Vol. 15, No. 2, August 2019 : 758 - 768
Electricity theft detection framework based on universal prediction algorithm (Abdulrahaman Okino Otuoze)

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