Electricity Theft Prediction on Low Voltage Distribution System Using Autoregressive Technique

A.I. Abdullateef, M.J.E. Salami, M.A. Musse, A.M. Aibinu, and M.A.Onasanya

***Abstract*—** Electricity consumers tend to avoid the payment of electricity dues through various methods such as tampering with energy meter and illegal tapping via direct connection to the distribution feeder. This has led to huge revenue losses by the electricity supplying corporation and the related government or private agencies. A new approach of detecting electricity theft on low voltage distribution systems, either single or three phase, based on the advanced signal processing using linear prediction is presented in this paper. Consumer data were analyzed using Autoregressive (AR) model in order to predict the quantity of power consumed within the specified interval and consequently, compare the result obtained with the actual data recorded against the consumer under study. Thus the model developed was used to predict power consumption at 30minutes interval ahead, thereby facilitating the detection of electricity theft if there is a wide variation between the actual and the predicted data.

***Keywords*—** autoregressive model, electricity theft, linear prediction, low voltage distribution system.

I. INTRODUCTION

ELECTRICITY theft, which is the practice of using electricity from the utility company without the company's authorization or consent, is a major problem challenging power utilities worldwide. Usually, this menace occurs between the distribution networks that links the consumers' ends to the power network and could be inform of billing irregularities, meter tampering and upaid bills [1]. However, since electricity is indispensable to domestic and industrial development activities of a nation, thus it needs to be protected and monitored for effective and efficient power delivery to the consumers. Various reports have shown the prevalence of electricity theft in developing countries range from 20 to 30% losses in the distribution network [2]. Wang et al [3] reported a wider range of 10 - 40%.

Furthermore, the prevalence of this menace is also evident in developed countries such as the USA and Canada which recorded huge revenue loss, amounting to $6 billion and $100 million, respectively, to electricity theft in 2010 [4], [5]. Similarly, fast developing countries, such as Malaysia, reported a revenue loss ranging from RM150 to 500 million, between 2010 and 2011 [6], [7], while South Africa recorded a loss ranging between R2.5 and R3.6 billion [8], [9].

Billing irregularities, non-payment by the consumer, and metering error, have been identified as widespread operations under electricity theft [10], however, the most prominent include illegal connection and meter tampering. Various ways of tampering the meter has been elucidated in [11]. Basically, electricity theft often resulted to overloading of the generation units and this adversely affects the utility company [12] in terms of revenue. In addition, electricity theft raises safety concerns such as electric shocks leading to death and maiming of personnel's [13] -[16], hence the need to prevent and minimize the adverse impact of electricity theft has attracted the interest of this study.

Diverse schemes have been designed, in various studies, to solve the problem [17], [18] yet, recent reports indicate that the menace has not been managed efficiently enough, because the prevalence of the electricity theft is currently occurring at an alarming rate and the perpetrators are becoming sophisticated as technology advances [19]. One of the major challenges in the distribution network, in recent time, is the detection and elimination of electricity theft. However, several methods proposed for the detection of this phenomenon are either not implementable in real time or yet to be applied in real situations.

This paper discusses the problem of electricity theft as well as proposed a new method for its prediction and detection. Similarly, autocorrelation algorithms for computing AR parameters, as applied to electricity consumer data, were also investigated and the preliminary studies indicated that AR techniques can be used to predict power consumption. The structure of the paper is as follows: review of electricity theft described in section II. Linear prediction technique is explained in section III. Section IV elucidates results obtained while section V discusses the conclusion.

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II. REVIEW OF ELECTRICITY THEFT

The summary of a few of the several techniques proposed and developed by various researchers, over the years, for the detection and estimation of electricity theft are illustrated in this section. Detail review can be found in our previous work [20].

Automatic meter reading system incorporated with tamper detection and different communication media such as Global System for Mobile Communications (GSM) as well as Zigbee to track electricity theft was proposed [21]-[23]. Some studies employed artificial intelligent system such as Support Vector Machine (SVM) to classify electricity theft based on the energy consumption pattern of the consumer and pre-select suspected consumers for inspection [2], [24] -[27].

In addition, the power line impedance technique was proposed [28], where all subscribers are disconnected and a low voltage signal of 2V at high frequency of 150Hz was transmitted to the network to detect impedance of the network and comparisons were made with the installed impedance values. The difference indicates the theft location with respect to the location of legitimate consumer. On the other hand, Bandim et al. [29] proposed Central Observer Meter (COM) to monitor the consumer’s meters and in this technique, the value of energy read by the observer meter and the consumer’s meter was compared in order to identify the fraud and the perpetrator. The method proposed in [30] uses two energy meters to track illegal connection.

Furthermore, meter tampering detection based on monitoring the live current, neutral current and the voltage at the meter input to detect various tampering, was proposed by Naiman et al.[31] any changes in their values depict electricity theft. Depuru et al. [32], proposed injecting of unwanted harmonics into the distribution network in order to cause damage to the appliances of the suspected illegal users while Bat-Erdene et al. [33] proposed application of smart resistance incorporated in smart meter as a mode of detecting illegal electricity usage. Other proposed techniques include smart metering development [34].

III. LINEAR PREDICTION

Linear prediction is a time series technique and most significantly used tool in speech processing [35] and its prediction of the output of a linear system is often based on its input and past outputs. The parameters of the system are determined by analyzing the systems inputs and outputs using linear prediction method.

3.1 *Mathematical Derivation*

If the input signal in a linear system is denoted by x (n) and the past output by y (n-1), y (n-2),…….. y (n-p) then such a system can be represented by a general

difference equation of a linear system ;

$$y(n) = \sum_{k=0}^{q} b_k x(n-k) - \sum_{k=1}^{p} a_k y(n-k) \tag{1}$$

where 'b_k' and 'a_k' are autoregressive moving average coefficients model and p and q are the model order respectively. This leads to three distinct types of linear model such as:

i) Autoregressive Model (AM) which is represented by equation 2, below

$$y(n) = -\sum_{k=1}^{p} a_k y(n-k) + u(n) \tag{2}$$

where u(n) is a white noise

ii) Moving Average Model (MAM) represented by equation 3

$$y(n) = \sum_{k=0}^{q} b_k y(n-k) \tag{3}$$

iii) Autoregressive Moving Average (ARMA) with a transfer function indicated in equation 4

$$H(z) = \frac{Y(z)}{X(z)} = \frac{\sum_{k=0}^{q} b_k z^{-k}}{1 + \sum_{k=1}^{p} a_k z^{-k}} \tag{4}$$

However, the All-pole Model (AR) remains the simplest and most widely study with respect to parameter estimation which leads to linear equations [36], [37]. It has computational advantages over ARMA and MA parameter estimation techniques.

3.2 *Autoregressive (AR) model*

A signal $y(n)$ can be predicted by a combination of its past weighted value $y(n\text{-}1)$, $y(n\text{-}2)$,…….. $y(n\text{-}p)$

$$\tilde{y}(n) = -\sum_{k=1}^{p} a_k y(n-k) \tag{5}$$

where a_k is known as the prediction coefficients of order p and the difference between the value $y(n)$ and the predicted value $\tilde{y}(n)$ is called predicted error denoted by $e(n)$

$$e(n) = y - \tilde{y}(n) = y(n) + \sum_{k=1}^{p} a_k y(n-k) \tag{6}$$

The total squared error is given in (7) where the range of sample specification depends on the method used for coefficient estimation.

$$\varepsilon = \sum_{n} |e(n)|^2 \tag{7}$$

$$\varepsilon = \sum_{n} \left| y(n) + \sum_{k=1}^{p} a_k y(n-k) \right|^2 \tag{8}$$

If (8) is minimized by setting

$$\frac{\partial \varepsilon}{\partial a_i} = 0, \; 1 \le i \le p \tag{9}$$

A set of equations known as normal equations can be obtained from equation (8) and (9) as;

$$\sum_{k=1}^{p} a_k \sum_{n} y(n-k)y(n-i) = -\sum_{n} y(n)y(n-i) \quad (10)$$

$$1 \le i \le p$$

The minimum total square error ε_p is obtained by expanding equation (8) and substituting (10),

$$\varepsilon_p = \sum_n y^2(n) + \sum_{k=1}^{p} a_k \sum_n y(n)y(n-k) \quad (11)$$

without specifying the range of the summation, the range of summation is usually specified based on the method used. The challenge of the equation (5) is solving for coefficient 'a_k', which can be carried out in a number of ways such as Prony's, autocorrelation and covariance methods. However this work focuses on autocorrelation method to estimate the coefficient because of the short data available.

3.3 *Autocorrelation method*

The autocorrelation method applies a rectangular window to the signal such that the signal x(n) is known over interval [0, N] and the values outside this interval is assumed to be equal to zero, thus the coefficient 'a_k' is evaluated while the error is minimized over the interval of $-\infty < n < \infty$.

Equations (10) and (11) can then be reduced to

$$\sum_{k=1}^{p} a_k r(i-k) = -r(i), \quad 1 \le i \le p \quad (12)$$

$$\varepsilon_p = r(0) + \sum_{k=1}^{p} a_k r(k) \quad (13)$$

where

$r(i) = \sum_{n=-\infty}^{\infty} y(n)y(n+i)$ is the autocorrelation function of the signal $y(n)$ and is an even function

$$r(i) = r(-i)$$

Writing equations 12 and 13, in matrix form is shown below:

$$\begin{bmatrix} r(0) & r^*(1) & r^*(2) & \cdots & r^*(p-1) \\ r(1) & r(0) & r^*(1) & \cdots & r^*(p-2) \\ r(2) & r(1) & r(0) & \cdots & r^*(p-3) \\ r(3) & r(2) & r(1) & \cdots & r(p-4) \\ \vdots & \vdots & \vdots & & \vdots \\ r(p-1) & r(p-2) & r(p-3) & \cdots & r(0) \end{bmatrix} \begin{bmatrix} a(1) \\ a(2) \\ a(3) \\ a(4) \\ \vdots \\ a(p) \end{bmatrix} = - \begin{bmatrix} r(1) \\ r(2) \\ r(3) \\ r(4) \\ \vdots \\ r(p) \end{bmatrix}$$

This is a Hermitian Teoplitz matrix and could be solved by Levinson Durbin recursion algorithm.

IV RESULTS OBTAINED

Typical domestic consumer data were obtained in Ilorin, (8°30'00"N, 4°32'59"E) Nigeria (Table 1) for 5 days, between Monday 2-4-2012 and Friday 6-4-2012.

TABLE I
DOMESTIC POWER CONSUMPTION DATA

Time (am)	Power Consumption (kW) Mon. 2/4/12	Tues. 3/4/12	Wed. 4/4/12	Thur. 5/4/12	Fri. 6/4/12
12.30	5	4	3	3	3
1.00	5	3	4	3	3
1.30	5	4	3	3	2
2.00	5	3	4	3	2
2.30	4	3	3	3	3
3.00	4	3	3	3	3
3.30	5	3	3	3	3
4.00	4	3	3	3	2
4.30	14	3	4	3	3
5.00	15	3	5	2	2
5.30	4	7	17	12	15
6.00	9	15	14	14	12
6.60	5	9	10	11	15
7.00	4	11	6	5	7
7.30	5	4	6	4	5
8.00	4	5	4	2	3
8.30	5	5	4	2	3
9.00	9	4	5	3	3
9.30	3	5	4	3	3
10.00	6	4	3	4	3

The data were widowed between 12.30am and 9.00am at 30 minute interval making 18 data points. Moreover, Data for Wednesday 4th April 2102 was modeled using the AR Modeling technique and the best model order coefficients was selected by plotting the Mean Square Error (MSE) against the Model Order. The result obtained indicated Model order 4 is appropriate in this case (Fig.1). The model order was then used to predict the load consumption 30minute ahead, similarly the result showed that the predicted value signal was close to the actual (Fig. 2). The data correlates with the actual value when compared (Table 2)

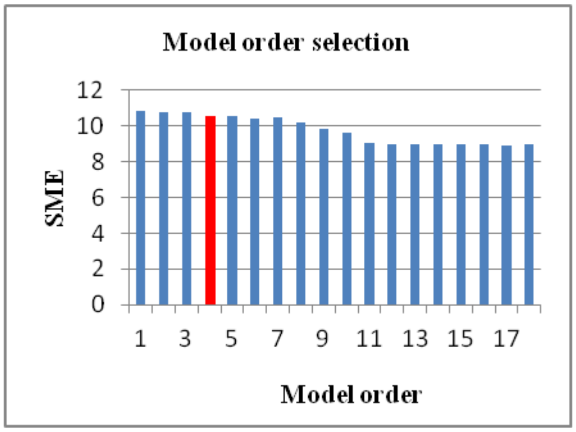

Fig. 1 Mean square error vs model order

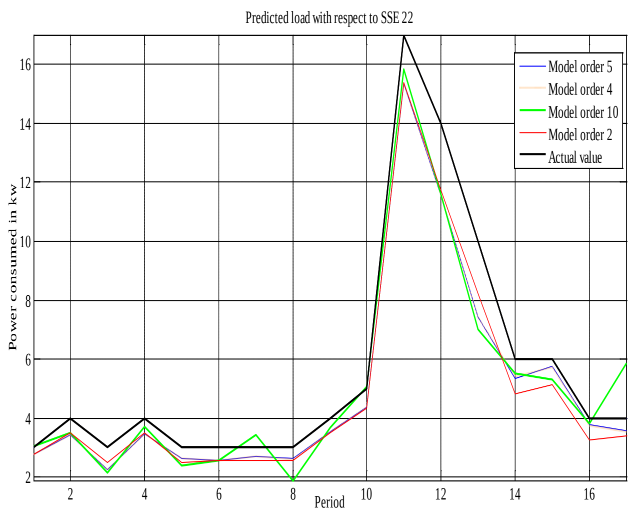

Fig. 2 Actual and predicted load with different model order

The Coefficients obtained for model order 4 are:
a_1= -0.9261, a_2 = 0.0866, a_3 = 0.0636, a_4 = -0.0944

$$\tilde{y}(n) = -\sum_{k=1}^{p} a_k y(n-k)$$

TABLE II
ACTUAL AND PREDICTED VALUES

Actual value	Predicted value
4	4.5961

V. Conclusion

Since the load ahead could be predicted, this could be benchmarked to monitor the power consumed by the consumer such that if the quantity of power consumed varies widely with respect to the predicted load, the consumer is suspected as a potential theft on the distribution network hence electricity theft activities could be predicted and detected. This study in on-going, it is expected that the use of more data will show the robustness of the model developed and more models are expected to be developed for effective detection and prediction of electricity theft on the distribution networks.

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