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Consumer Load Prediction and Theft Detection on Distribution Network Using Autoregressive Model

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Abstract— Load prediction is essential for the planning and management of electric power system and this has been an area of research interest recently. Various load forecasting techniques have been proposed to predict consumer load which represents the activities of the consumer on the distribution network. Commonly, these techniques use cumulative energy consumption data of various consumers connected to the power system to predict consumer load. However, this data fails to reveal the activities of individual consumers as related to energy consumption and stealing of electricity. A new approach of predicting consumer load and detecting electricity theft based on autoregressive model technique is proposed in this paper. The objective is to evaluate the relationship between the consumer load consumption vis-a-vis the model coefficients and model order selection. Such evaluation will facilitate effective monitoring of the individual consumer behaviour, which will be indicated in the changes in model parameters and invariably lead to detection of electricity theft on the part of the consumer. The study used the data acquired from consumer load prototype which represents a typical individual consumer connected to the distribution network. Average energy consumption obtained over 24 hours was used for the modelling and 5-minute step ahead load prediction based on model order 20 of minimum description length criterion technique was achieved. Electricity theft activities were detected whenever there are disparities in the model coefficients and consumer load data.

Index Terms— Autoregressive Model, Linear Prediction, Consumer Load prediction, Electricity Theft, Model Order Selection

1 Introduction

LOAD prediction is an important factor employed in the management of power system. It facilitates the estimation of future electricity demand by the utilities based on the past records, thus helps the utilities in decision making and operational planning such as routine maintenance, dispatch of generators, management of fuel and development of infrastructure. Moreover, it influences the consumers' decision in the management of energy such as load shedding and control of peak loads [1]. In the last decade, very short term load forecasting (VSTLF) which predicts load consumption from few minute to several hours has been proposed [2]. VSTLF is used in energy management for load frequency control, dispatch functions and areas that need forecast for short time leads Parameters such as the historical load data, weather data and seasonal data are the common input in load forecasting. However, instead of modeling the relationships between these variables, as in other types of load prediction, VSTLF extrapolates the recently observed load pattern to the nearest future [3]. VSTLF relied on real time data to predict future energy demand therefore, if it is employed at the consumer end it will facilitate the prediction of consumer load for few minutes step ahead and benchmarking this with actual load consumed will facilitate the detection of electricity theft.

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Electric load forecasting is currently restricted to energy management at generation and transmission level, but this has not been used to monitor the energy consumption of individual consumer connected to the distribution network. The conventional practice is to predict the energy loads based on the history of consumers' energy load data obtained over a period. These data are short of revealing individual consumer energy pattern which is essential in order to monitor consumers' activities such as electricity theft on the distribution network. The consequences of electricity theft has been well reported in terms of enormous loss of revenue, properties and lives on the part of the energy providers and consumers [4], [5], [6], [7], [8], [9]. The increasing prevalence of this menace has attracted attention although, it largely remains unabated despite various proposed methods for detecting and eliminating theft on the power network [10], [11], [12]. Thus, the need for a new method of detection to prevent and minimize these adverse impacts of electricity theft has attracted the interest of this study.

Load prediction as a tool for electricity theft detection has hardly been reported in the literatures, therefore this paper presents a novel 5-minutes step ahead consumer load prediction and theft detection using autoregressive model of time series technique.

2 Literature Review

Various techniques of predicting electricity load have been reported, however the techniques on very short term load prediction are limited. One of these techniques is statistical method which include multiple linear regression, exponential smoothing, time series, state space, and Kalman filter techniques [13]. Taylor [14] evaluated various methods of very short term load prediction between 10 and 30 minutes ahead using minute-by-minute British electricity demand load data. The study considered methods that capture both the intra-day and the intra-week seasonal cycles in the data. Similarly, the methods that do not attempt to model the seasonality were considered. The best results were achieved using the Holt-Winters' adaptation and the new intra-day cycle exponential smoothing method for very short-term prediction. Singh, et al. [15] proposed seasonal autoregressive moving average (SARMA) for home peak load and the study noted that ability to predict the stochastic activities of the consumer and routines are more significant for home load prediction. Furthermore, the study showed that historical based features are more effective than physical features such as temperature and time when hourly prediction is intended and a root mean square error of 30% accuracy was achieved.

Weekday based prediction model for electricity load forecasting using autocorrelation feature selection and machine learning algorithm, proposed by Koprinska, et al. [16], are considered as global model that predicts the load for all days of the week and local model that predict load for each day of the week. The two models were used to analyze a 5-minute electricity data obtained within two years from the State of New South Wales in Australia and the performances of the models were relatively good. However, local model performs better when used with linear regression algorithm and accuracy of 0.282% was obtained using the mean absolute percentage error (MAPE) criterion. Trudnowski, et al. [17] proposed a strategy for developing a very short-term load predictor using slow and fast Kalman estimators and an hourly forecaster load prediction for power system automatic generation control. The Kalman model parameters were determined by matching the frequency response of the estimator to load residuals. The design strategy was applied to a power system operated by the Bonneville Power Administration.

The other technique to VSTLF is the application of various artificial intelligent paradigms such as artificial neural network (ANN), fuzzy logic (FL) and knowledge based expert systems [18], [19], [20], [21]. A method of very short-term loads forecasting using wavelet neural networks with data pre-filtering 1-h into the future in 5-min steps proposed by Guan, et al. [22] used spike filtering technique to detect spikes in load data. The method removes spikes in real-time from the data before the load is decomposed into multiple components at different frequencies, where separate neural networks are applied to capture the features of individual components. Based on the results, 12 dedicated wavelet neural networks were used to form the final forecasts and data from ISO New England used for testing shows accurate predictions with small standard deviations.

Yang, et al. [23] proposed fuzzy neural system (FNS) for very-short-term electric load prediction based on chaotic dynamics reconstruction technique. The study applied Grassberger–Procaccia algorithm and least squares regression methods to obtain the value of correlation dimension for estimation of the model order. Based on this order, an appropriately structured FNS model was designed for the prediction of electric load and a dimension switching detector was devised to enhance the prediction performance of the FNS as well as to reduce the practical influences of the computation error on correlation dimension estimation. Load data from Shandong Heze Electric Utility, China was used for the experiment and satisfactory results are obtained for 15 min ahead prediction. A hybrid model of similar day and neural network for load forecast ranging from 15 minutes to few hours was proposed by Fok and Vai [24]. Hourly weather information which is not often considered in other VSTLF literatures was considered as one of input variables, while the results of VSTLF was used to adjust a day ahead STLF result which reduces the MAPE to 20%.

Charytoniuk and Chen [3] proposed load prediction up to dozen of minute based on ANN model and the forecasting was implemented as a set of neural networks to assure robust performance and training for on-line applications. Each network was assigned a task of predicting loads for a particular time lead and for a certain period of day with a unique pattern in load dynamics. This method has been implemented in a power utility in USA. Particle swarm optimization (PSO) based fuzzy inference method was applied to enhance the performance of a fuzzy system in prediction of building energy consumption [18]. The PSO algorithm was employed to optimize the fuzzy system's membership function while the scheme was used for identification of fuzzy models from the input-output data. The results obtained demonstrate that the developed model has better prediction scheme capabilities than a conventional fuzzy model for the same system with heuristically defined membership functions.

Detailed review of several techniques proposed and developed by various researchers for the detection and estimation of electricity theft have been reported by Abdullateef, et al. [25]. Automatic meter reading system incorporated with tampering detection and various communication media such as Global System for Mobile Communications (GSM) and Zigbee, have been proposed to track electricity theft [26], [27], [28]. Similarly, other researchers such as Nagi, et al. [29], Wang and Devabhaktuni [30] and Nizar and Dong [7] have repoted the application of Artificial Intelligent System (AIS) such as Support Vector Machine (SVM) for the detection of electricity theft based on the energy consumption pattern of the consumer.

In addition, the power line impedance technique proposed by Pasdar and Mirzakuchaki [12] considers the difference between network impedance and installed impedance which indicates electricity theft location with respect to the location of legitimate consumer. Bandim, et al. [10] proposed a central observer meter (COM) to monitor and identify the perpetrators while the method proposed by Cavdar [31], uses two energy meters to track illegal connection. Meter tampering detection based on changes between live and neutral currents as well as voltage monitoring at the meter input terminals has been proposed by Naiman, et al. [32] to depict electricity theft. The injection of unwanted harmonics into the distribution network in order to cause damage to the appliances of the suspected illegal users and application of smart resistance incorporated in smart meter as a mode of detecting illegal electricity usage, have been reported by Bat-Erdene, et al. [11] and Kadurek, et al. [33] respectively.

In this study, the energy consumed by a typical household was monitored and predicted based on data acquired from the Consumer Load Monitoring Prototype (CLMP) developed by Abdullateef, et al. [34]. Electricity consumption and theft scenario were imitated, while the theft detection was based on comparison between the predicted and theft data coefficients using the autoregressive (AR) model.

3 METHODOLOGY

3.1 Data Acquisition

The data used in this study were acquired from the Consumer Load Monitoring Prototype (CLMP) constructed at the Mechatronic Laboratory, International Islamic University Malaysia, for the purpose of studying electricity theft. The construction details and data acquisition procedure have been well-explained and presented [34]. Data obtained for a typical weekday representing both normal and theft situation was used.

3.2 Experimental Set Up For Data Load Monitoring

The CLMP was connected to power source and appliances such as refrigerator, incandescence bulb (100W), fluorescence lamp (80W), table fan (40W), electric kettle (1500W), induction cooker (1800W), microwave oven (700W), and electric iron (1000W) were connected to the CLMP, to represent a real life situation of typical consumer house hold electricity consumption. Current sensor (ACS785, Allegro MicroSystem Inc., USA) was connected to the live conductor to capture the current consumed by the loads connected to the prototype. The sensor provides galvanic isolation within the power network particularly, between the operator and other equipment connected to it. Data acquisition was carried out via LABVIEW hardware (National Instrument, USA) device linked to the PCI 6420E channel in the computer. The data acquired at a sampling frequency of 500Hz at 2×10^{-3} s interval were logged directly into the computer which displays the processes in real time and were stored for further analysis.

3.3 Analysis Technique

Linear prediction is a time series analysis technique that has been applied in speech signal processing, image processing and in communication [35], [36], [37]. It is based on the estimation of a signal from its present and past output samples. Time series data acquired from the CLMP is assumed to be generated from a linear filter excited by a white noise which can be expressed as

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

where $y(n)$ and $x(n)$ are the output and input signals respectively, while a_k, b_i, p, and q are the system parameters. Analysis of (1) leads to three different models: autoregressive model (AR), moving average (MA) model and autoregressive moving average model (ARMA).

3.3.1 Autoregressive Model

The current value of the time series $y(n)$ is expressed linearly in terms of its previous values and a white noise $\varepsilon(n)$ in the autoregressive process, so that

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

where $a_1, \ldots, a_p$ are the coefficients or weights to be determined, p is the model order and $\varepsilon(n)$ *is* the white noise with zero mean and variance σ^2. In the same manner, (2) is also referred to a "forward prediction". Similarly, the backward prediction is of this form

$$\hat{y}(n-1) = -\sum_{k=1}^{p} b_k y(n-k+1) \tag{3}$$

Various techniques such as covariance, Burg, Least Square and autocorrelation, have been used to estimate the coefficients of AR model in (2) [38]. In particular, estimation of AR coefficients is often based on solving Yule-Walker equations as epressed in Eq. (4) and in matrix form as in (5).

$$\sum_{k=1}^{p} a_k r_{xx}(l-k) = -r_{kx}(l) \quad ; \quad k = 1, 2, \ldots p \tag{4}$$

$$\begin{bmatrix} r_{xx}(0) & r_{xx}(-1) & r_{xx}(-2) & \cdots & r_{xx}(1-p) \\ r_{xx}(1) & r_{xx}(0) & r_{xx}(-1) & \cdots & r_{xx}(2-p) \\ \cdot & \cdot & \cdot & & \cdot \\ \cdot & \cdot & \cdot & \cdots & \cdot \\ \cdot & \cdot & \cdot & & \cdot \\ r_{xx}(p-1) & r_{xx}(p-2) & r_{xx}(p-3) & & r_{xx}(0) \end{bmatrix} \begin{bmatrix} a_1 \\ a_2 \\ \cdot \\ \cdot \\ \cdot \\ a_p \end{bmatrix} = - \begin{bmatrix} r_{xx}(1) \\ r_{xx}(2) \\ \cdot \\ \cdot \\ \cdot \\ r_{xx}(p) \end{bmatrix} \tag{5}$$

Concisely, (5) is expressed as

$$R_p a_p = -r_p \tag{6}$$

and

$$a_p = -r_p R_p^{-1} \tag{7}$$

The coefficients a_p is estimated by solving (7).

3.4 Model Order Selection

Optimum model order determination has been one of the challenges in linear prediction and time series modelling. Generally, in the evaluation of several model orders, the most appropriate is selected based on certain criteria such as Final Prediction Error (FPE), Akaike Information Criterion (AIC), Hannan-Quinn Information Criterion (HQC) and Schwaez Information Criterion (SIC), respectively, [39], [40], [41], [42], [43]. Despite wide application of the criteria as indicators of model order selection, their accuracies are relatively low [38].

3.4.1 Final Prediction Error

The final prediction error is a technique of selecting the model order by minimising the variance of the prediction error. FPE selects the system model order so that the average error variance for a one-step prediction is minimised [41], [44] and this is represented mathematically as

$$FPE(p)=\sigma_p^2\left(\frac{N+p}{N-p}\right) \quad (8)$$

when the sample mean is subtracted from the signal then (8) is adjusted as

$$FPE(p)=\sigma_p^2\left(\frac{N+p+1}{N-p-1}\right) \quad (9)$$

where σ_p^2 is the estimated error variance of the model, N is the number of data points, and p is the model order expressed as

$$\sigma_p^2=\frac{1}{N}\sum_{n=1}^{N}\varepsilon_p^2(n) \qquad =1,2,3,\ldots N) \quad (10)$$

and

$$\varepsilon_p=x_p(n)-\tilde{x}_p(n) \quad (11)$$

If M is the maximum model order that could be obtained, evaluating p from 1 to M increases the model orders (8) and this increases the uncertainty of the estimate of the predicted error variance. The optimum model order is the one that gives the minimum value of FPE (p), $1\leq p \leq$M.

3.4.2 Akaike Information Criterion (AIC)

The Akaike Information Criterion (AIC) is mathematically expressed as

$$AIC(p)=NIn(\sigma_p^2)+2p \quad (12)$$

The term '2p' represents the penalty for higher order selection that does not change in substantial reduction in the prediction error variance of the model. The inconsistency in model order estimation under this method has been reported by Kashyap [45], although, it is popularly used in model estimation. The performance of FPE and AIC model order selection methods is similar; however, AIC method is recommended for short data Ulrych and Ooe [46].

3.4.3 Hannan and Quinn Criterion (HQC)

Hannan and Quinn criterion technique is expressed as shown in (13). HQC counteracts the over fitting nature of AIC.

$$HNQ(p)=In(\sigma_p^2)+\frac{2pIn(InN)}{N} \quad (13)$$

3.4.4 Minimum Description Length (MDL)

Minimum description length (MDL) was developed to correct the irregularity associated with the FPE and AIC methods and is represented mathematically as

$$MDL(p)=NIn(\sigma_p^2)+pIn(N) \quad (14)$$

This increases the penalty factor incurred by using higher order as compare to AIC, thus favouring the selection of lower model order and it has been proven to be consistent statistically [44]. Equations 8, 10, 12, 13, and 14 were applied in this study to select appropriate model order for the AR model.

4 RESULTS AND DISCUSSION

The average current (amp) acquired from the appliances connected to the circuit at 10s interval for 24 hours is shown in Fig. 1. The spikes 'a-c' and 'm-o' indicate the starting of the refrigerator and the air conditioner loads during the morning and night respectively while spikes 'd-l' are due to the refrigerator starting point during the day. This is as a result of the single phase induction motor that drives the compressor, which is the major component that consumes energy in the refrigerator and air conditioner. The induction motor takes six to ten times its running current value at starting point [47].

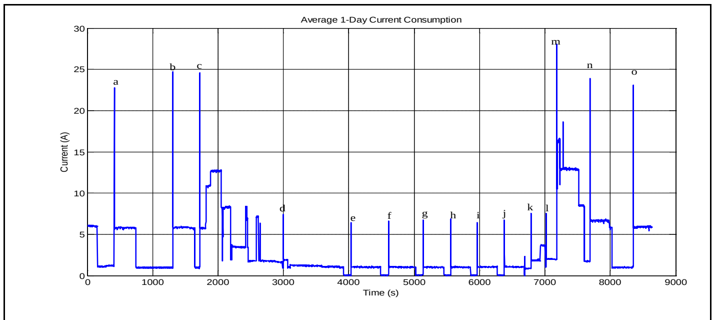

Fig. 1 . Average current acquired in 24hours

The average load consumption per day at 5min interval is depicted in Fig. 2. There was an increase in load consumption between the 285th and 370th minute as well as 1195th and 1280th minute with the peaks equivalence of 0.2156 kWh and 0.273 kWh, respectively. These developments indicate early morning and late evening energy demands by the consumer. However, the load consumption between 500th and 1155th minutes is relatively low and stable at 0.017kWh. This depicts the absence of the occupant at home and during this period, most appliances were switched off except the refrigerator. Furthermore, night and early morning electricity consumption with respect to the air conditioners ON and OFF cycle throughout the night is shown between 1st and 284th minutes as well as 1280th and 1440th minutes.

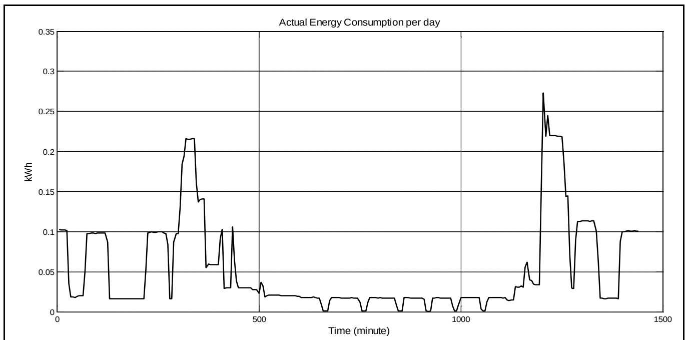

Fig. 2 . Energy Consumption in 24- hour

Fig. 3(a-d) depicts the model order selection criteria graphs, according to the order selection criteria discussed in section 3.4. Fig. 3a shows the MDL criterion graph with a sharp fall in the order and the minimum order occur at 20. It later picked up sharply and increases linearly as the order increased. The AIC graph (Fig. 3b) shows that the fall in the order is gradual and the minimum order occurs at 50. The model order was constant between 50 and 110 after which it increased gradually to the end. The minimum order according to HQC is 40 as depicted in Fig. 3c, there is a sharp fall in the order which later increased steadily from 40 to the end. Fig. 3d shows the FPE with an exponential fall in the model order as the error is minimised. Although the error decreases as the order increases, however the error is virtually constant from 50 to the end with no significant changes. Hence the minimum can be estimated at order 50. The outcome of the model selection criteria indicate that MDL with minimum order of 20 is preferable compared to others which indicates higher model order. This justifies higher penalty placed on this criteria according to session.

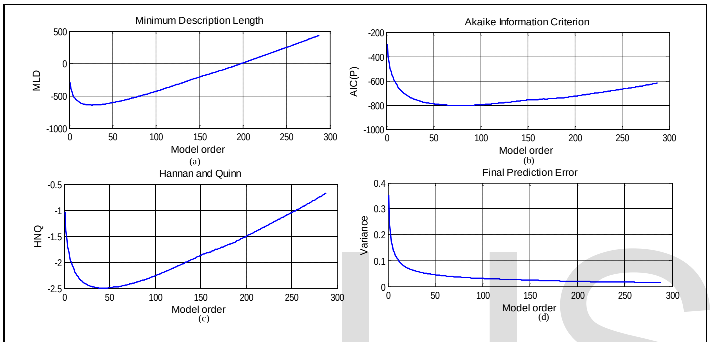

Fig. 3. Model order selection criteria

The consumer energy load prediction which is depicted by Fig. 4 shows the actual load and the predicted load based on model order 20 of MDL criterion. The dotted line indicates the predicted energy consumption while the continuous line specifies the actual energy consumption.

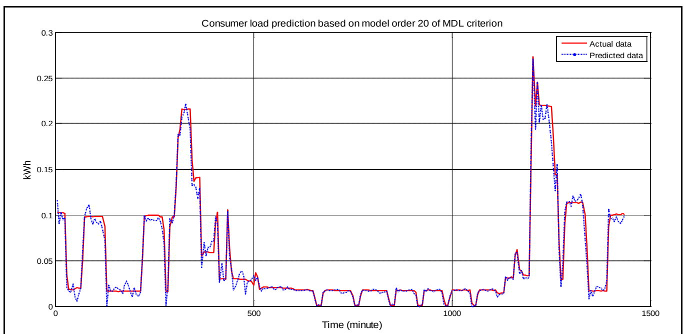

Fig. 4 . 24-hour consumer load prediction

Fig. 5 shows the graph of two energy data where ‘a’ indicates the actual energy consumed and ‘b’ shows the energy consumed as recorded by meter. It was observed that there are disparities in energy consumption between the 1st and the 375th minute, and between 1195th and 1440th minute. The variation is as a result of electricity theft carried out between these periods. These disparities are detected by the variance in the model coefficients and the registered load data coefficients are shown in Table 1. However, the consumed energy is the same between 375th and 1195th minute during the day which indicates normal condition hence the two graphs look the same.

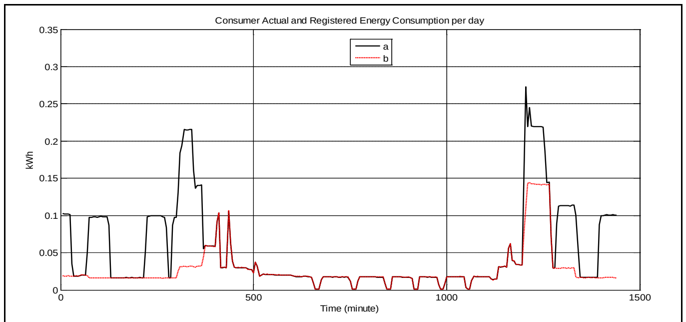

Fig. 5 . Comparison between 24-hour actual and registered energy consumption

TABLE 1
Model Coefficients Based on MDL Criterion

Order Number	Coefficients (a)	Coefficients (b)
0	1	1
1	-1.13098	-1.1502
2	0.244425	0.302929
3	-0.11689	-0.18113
4	0.079415	0.335079
5	-0.0376	-0.50806
6	0.011065	0.210142
7	0.023448	0.018369
8	-0.01949	0.082171
9	-0.06581	-0.17808
10	0.139161	0.084101
11	0.056493	0.059382
12	-0.06272	-0.01353
13	-0.07208	-0.02557
14	-0.11236	0.045213
15	0.163266	-0.00112
16	-0.09066	-0.00383
17	-0.05057	-0.05542
18	0.073731	0.042807
19	-0.0229	-0.07776
20	0.024456	0.045045

5 CONCLUSION

Prediction of consumer electricity load consumption using autoregressive model approach has been achieved in this study. Data were acquired at 500Hz sampling frequency over a period of 24h and average power consumption was computed over this period. A 5-minute step ahead consumer load prediction based on the data acquired was achieved using model order 20 of minimum description length criterion technique. The predicted load was used for the detection of electricity theft when the coefficients of the model varied in comparison with the coefficients of the theft data. This study is ongoing and further advanced signal analysis will be carried out in our future work to classify the theft.

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