Adaptive Non-Intrusive Load Monitoring Model using Bayesian Learning

Nur Iksan[1], Suhono Harso Supangkat[2]

[1,2]Sekolah Teknoik Elektro dan Informatika, Institut Teknologi Bandung

Jalan Ganesha 10 Bandung 40132, Indonesia

nur.iksan@students.itb.ac.id[1], suhono@stei.itb.ac.id[2]

***Abstract*—NILM is an electrical energy monitoring system that can be used in smart home/building. The system is equipped with sensors to measure the voltage and electric current large installed in the electrical panel. NILM methods are designed to measure the total power consumption signals at the entry point of the main electrical panel of a building, and then disaggregate it into the power consumption of individual appliances. This paper will take an approach relies on low frequency acquisition and steady state feature extraction and using Bayesian learning method for power disaggregation. In order to adapt to the change in the environment and to detect unknown state, this paper using an adaptive module that applied in the monitoring system.**

Keywords*—context awareness; home energy management; energy saving.

I. Background

Energy consumption has been increasing over the last half century. This is due to the increase in population and economic development throughout the world. On the other hand, the use of energy in buildings (residential and commercial) continued to increase that reached nearly 40% of total energy consumption in the world [1]. With the increase in energy consumption need to be done efforts to meet the demand for energy. Currently, efforts are being made to address the increased use of energy in Indonesia is only focused on increasing the supply of energy through the addition of energy generation both fossil and non-fossil. This effort is very ineffective, because it will bring new problems related to the increase in energy costs, the cost of government energy subsidies and carbon emissions in the air.

One of appropriate effort is by saving energy consumption or energy conservation. Energy conservation can be implemented by monitoring energy usage through accurate measurements on energy consumption of appliances and providing real-time energy usage information to consumers. Nagesh [3] using smart meters that are directly connected to each of appliances. Although energy consumption information of each appliance can be obtained, a number of smart meters must be installed on each of appliances. The initial cost needed is high enough that covering the cost of production of smart meters, installation, integration and operation. In addition, the ability of this approach is decreases when the number of smart meters installed increases.

Therefore, to address these problems, non-intrusive Load Monitor (NILM) methods are used. NILM methods are designed to measure the total power consumption signals at the entry point of the main electrical panel of a building, and then disaggregate it into the power consumption of individual appliances. Some of approach [4-8] have been developed to disaggregate power consumed. This paper will take the model relies on low frequency acquisition and steady state feature extraction and using Bayesian learning method for power disaggregation. In order to adapt to the change in the environment and to detect unknown state, this paper using an adaptive module that applied in the monitoring system.

The paper is organized as follows. In Section II, we describe details the important works related to our proposal, allowing positioning the contribution. In Section III, we describe NILM method, architecture and present the problem of power disaggregation. The experimental setup is presented in Section IV. Finally, conclusions are drawn in Section V.

II. Related Works

Research on monitoring system on the electrical circuit start studied since the 1990s. George Hart [4] found a steady-state analysis approach to non-intrusive Appliance Load Monitoring (NIALM) System to monitor the status of on/off based on steady-state behavior and energy load consumed by each device. However, this approach has limitations because it does not able to distinguish the real and reactive power consumption of the similar equipment.

Cole [5] using an approach based on the harmonic context of a non-linear load to identify the burden of multiple appliances. However, this approach can only identify some of the appliances in small quantities. Suzuki [6] using an approach based on integer programming techniques and Laughman [7] using transient properties of the appliances to identify each appliances. However, this approach does not involve algorithms for training data, so the results from identification is inaccurate. Chang [8] using the variable features of transient energy and some elements of the steady state (the real power consumption, distortion current/voltage harmonics, distortion amount of current/voltage harmonics). These variables then analyzed using a neural network algorithm to identify the load. However this approach is not adaptive and the required computational load increases when monitoring a large number of load operations.

III. NON-INTRUSIVE LOAD MONITOR METHOD

Fig. 1 shows the framework of NILM system on smart building. The system consists of three processes, i.e.; data acquisition, data preprocess, recognition process and diagnosis process.

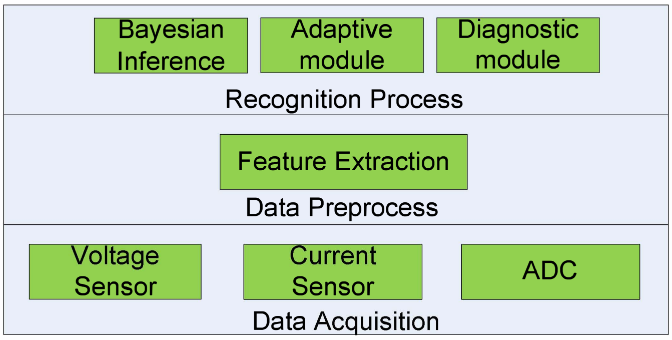

Fig. 1. NILM Framework

Data acquisition require some hardware, ie; current and voltage sensors that used to get values of current and voltage of an electrical panel and then these values converted by ADC (Analog Digital Converter) into a signal that can be processed. In the data preprocessing, feature extraction process occurs to process the raw data in the form of waves, currents and voltages into the power matrix, ie the active power and reactive power. The data acquisition module is using low frequency with 1Hz, and feature extraction is in steady-state. Recognition process is the core of adaptive NILM system. This process divided into three parts, i.e.; the Bayesian inference, an adaptive module and the diagnosis module. Bayesian inference is used as a load disaggregation. An adaptive module is used as unknown state detection and environment changing adaptation. The diagnosis module is used to diagnoses the state load.

A. Feature Extration

After acquiring the aggregated loads signal, and then continued the process of feature extraction. The extraction process uses a method for recognition of steady-state signature. This method is deduced from the difference between the two signal conditions. First, the condition before turning on appliances and second, the conditions at the time appliances is on. Steady-state method is simpler than the transient method because lower frequency sample rates can be used.

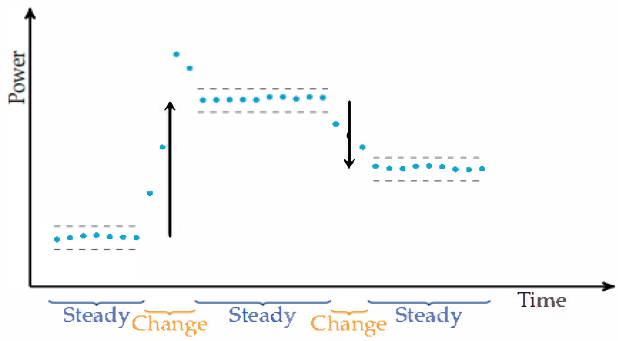

Fig. 2. Illustration of Three steady-states

According to Hart [4], a set of sequential samples represents a steady-state if the distance any two samples of the set is less than a given value, called tolerance. This threshold depends on the input signal that could be the active power (measured in Watts) or the reactive power (measured in VAR). Other variable is the minimum number of sample, S_{min}. The minimum number of consecutive samples needed to identify a steady-state depends on the sampling frequency: when it is low, a small number of samples is enough; otherwise, a bigger number is needed. For instance, Hart considered the minimum number of samples is three ($S_{min} = 3$)for a sampling rate of 1 Hz. Fig. 2 illustrates an example where the steady-states are identified with two dashed line segment, while the remaining sample belong to a change state.

To recognizes steady-states, this paper using the MinMaxSteady-State algorithm, as used in [9]. Consider a sequence of n consecutive sampling values, $Y = \{y_i, i = 1, \ldots, n\}$ already identified as a steady-state. By definition, $|y_i - y_j| \leq \epsilon\, \forall i, j = 1, \ldots, n$ and $i \neq j$, where $\epsilon > 0$ is the defined tolerance. Then, $y_m = \max\{y_i\}$ and $y_m = \min\{y_i\}$, $\forall i = 1, \ldots, n$ be the maximum and minimum values, respectively, for Y, and that $y_r (r = n + 1)$ is the next sample value.

Theorem 1. In the condition above, the n+1 consecutive values form a steady-state if $y_M - \epsilon \le y_r \le y_m + \epsilon$, i. e.,

$|y_i - y_j| \le \epsilon, \forall i, j = 1, \dots, n+1.$

Proof. In fact $y_m \le y_r \le y_M$, then $|y_i - y_r| \le |y_m - y_M| \le \epsilon$, for all $i = 1, \dots, n$.

Consider now that $y_M < y_r \le y_m + \epsilon$. For any $y_i \epsilon [y_m, y_M]$, $i = 1, \dots, n$, we have,

$|y_i - y_r| \le |y_m - y_r| \le |y_m - y_m + \epsilon| = \epsilon.$

Thus, the sequence of the $n + 1$values, $y_i, i = 1, \dots, n+1$, forms a steady-states with a new maximum value: $y_M = y_{n+1} = y_r$.

If we assume that $y_M - \epsilon < y_r \le y_m$, then, using a similar reasoning, we prove that $y_r = y_n + 1$ maintains the stability of the state, and the steady sequence $y_i, i = 1, \dots, n+1$ has a new minimum value: $y_M = y_{n+1} = y_r$.

In all the other cases, that $y_r < y_M - \epsilon$ or $y_r > y_m + \epsilon$, y_r does not belong to the steady-state y since exceeds the maximum tolerance.

In conclusion, the MinMaxSteady-state algorithm considers that a consecutive sample point y_r belongs to the steady-state immediately before if $y_M - \epsilon < y_r \le y_m + \epsilon$ such that y_m and y_M are the minimum and maximum values in the state.

B. Bayesian Disaggregation

After the features extraction process in accordance with the defined steady-state signature the next step is appliance identification. The appliances are identified via a classification model. The main goal of the classification problem is to learn a model able to correctly assign an appliance class label to a given feature vector (appliance signature). In this paper, these extracted features are classified by Bayesian classifier for load disaggregation. This algorithm would use the history of power measurement in a household to identify the possible ratings of the electric appliances. The algorithm requires that the prior probabilities of individual, i.e. $P(L_1)$, .., $P(L_N)$ and the power ratings of the load (W_{L_x}) are available [10]. The boards steps in the algorithm can be describe as,

1. Identifying and eliminating impossible load combinations, i.e. $\bar{L}_a$, for $1 \le a < 2^N$, where $\bar{L}_a$ refer to the load combination vector.
2. Computing the likelihood of the observation for each possible load combination i.e. $P(W = \omega | \bar{L}_a)$.
3. Obtaining the Maximum a Posteriori probability for individual loads combination i.e $P(\bar{L}_a | W = \omega)$.
4. Obtaining the Maximum a Posteriori probability for individual loads by marginalization i.e $P(\bar{L}_k = ON | W = \omega)$, for k=1, ..., N

C. Identification and detection

Chou [11] paper proposed a method about steady-state loads that present a failure detection index (FDI) based on statistical method. All new data have unique FDI for each single Gaussian distribution when they enter into the system, and we chose the minimum as its index. Then we set the threshold for identification, such as following:

$\min FDI_k \le threshold$, k=1,…,K

By controlling the threshold, we can adjust adaptation failure performance. It will distinguish between the new state or unknown state and the existing state.

IV. Experiment and Discussion

The monitoring system in smart building using NILM approach is built on a cloud computing platform. This system consists of 3 parts, namely smart building environment, cloud services and access devices. Smart building environment consists of electrical equipment, which is equipped with ZigBee NILM wireless and gateways.

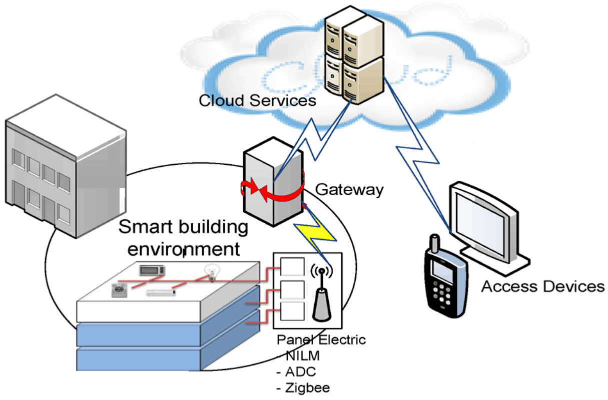

Fig. 3. Energy Monitoring System Using NILM

Fig. 3 above is the architecture of the monitoring system of Smart Building that is equipped using NILM. The system is integrated in the cloud service to provide services automation, intelligent and monitoring, either through the web or a smartphone. NILM will detect the voltage and current in electrical panels and sends it to the gateway to be analyzed. The results of the analysis of information and the status of energy consumption of electrical appliances are sent to the cloud server via an Internet connection to be stored on the storage server. The information is then processed to provide monitoring services and can be accessed through a web interface and a smartphone.

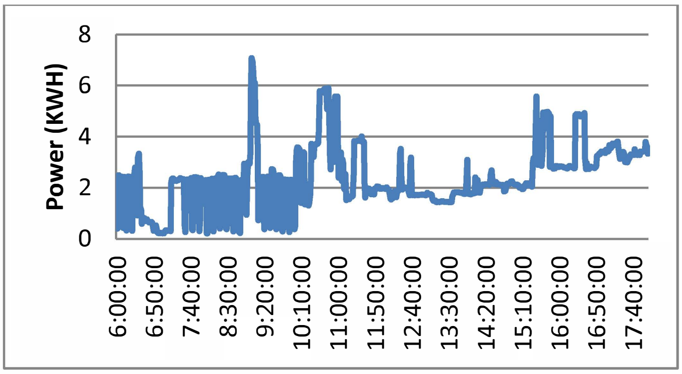

Fig. 4. Simulated data of consumed power (KWH)

NILM techniques will be tested through simulations using a dataset as input data. This dataset is provided by EDF Energy [12] which was released in 2012 Measurements were performed in a home with the duration measurement for 4 years. Average of measurements made every 1 minute. This dataset consists of a collection of data in the form of active power, reactive power, voltage and current. In addition, the amount of data and some other electrical sub-metering values available. Here's an example data set from the dataset.

Parameters:

Date; Time; Global_active_power; Global_reactive_power; Voltage; Global_intensity; Sub_metering_1; Sub_metering_2; Sub_metering_3

```
16/12/2006;17:24:00;4.216;0.418;234.840;18.400;0.000;1.000;17.000
16/12/2006;17:25:00;5.360;0.436;233.630;23.000;0.000;1.000;16.000
16/12/2006;17:26:00;5.374;0.498;233.290;23.000;0.000;2.000;17.000
16/12/2006;17:27:00;5.388;0.502;233.740;23.000;0.000;1.000;17.000
16/12/2006;17:28:00;3.666;0.528;235.680;15.800;0.000;1.000;17.000
16/12/2006;17:29:00;3.520;0.522;235.020;15.000;0.000;2.000;17.000
16/12/2006;17:30:00;3.702;0.520;235.090;15.800;0.000;1.000;17.000
```

The simulated data was generated by choosing a set of appliance ratings and randomizing their transitions from one state to another, allowing at most one change at a time. A typical simulated data will look as in Fig. 4. Based on the simulated data, some appliances in this experiment corresponds to the kitchen (containing mainly a dishwasher, an oven and a microwave), laundry room (containing a washing-machine, a tumble-drier, a refrigerator and a light), and electric water-heater and an air-conditioner as showed on Table 1.

TABLE I. APPLIANCES LIST

Appliance	Power (Watt Hours)
Dishwasher	200
Oven	1200
Microwave	750 – 1100
Washing-machine	700
Tumble-drier	1800
Refrigerator	500 – 1400
Light	60
Electric water-heater	1200
Air-conditioner	900

V. CONCLUSION

This paper have described an model relies on low frequency acquisition and steady state feature extraction and using Bayesian learning method for power disaggregation. Then, this paper has described the model of adaptive module to adapt the change on the environment and to detect unknown states. Further work will test and analyses the result of these method.

ACKNOWLEDGMENT

We would like to thank Blackberry Innovation Center-Institute of Technology Bandung for their assistance in facilitating education and research.

REFERENCES

[1] WBCSD, Energy Efficiency in Buildings Facts & Trends. Bussiness Reality and Opportunity: WBCSD, 2008

[2] Ueno Tsuyoshi, Nakano Yukio. 2006. Effectiveness of Displaying Energy Consumption Data in Residential Buildings: To Know Is to Change. Summer Study on Energy Efficiency in Buildings: ACEEE.

[3] Nagesh DYR, Krishna JVV, Tulasiram SS. 2010. A real-time architecture for smart energy management. Innovative Smart Grid Technologies (ISGT): IEEE.

[4] Hart, G.W. 1992. Nonintrusive appliance load monitoring. IEEE.

[5] Cole, A.; Albicki, A. 2000. Nonintrusive Identification of Electrical Loads in a Three-Phase Environment Based on Harmonic Content. Instrumentation and Measurement Technology Conference.

[6] Suzuki, K.; Inagaki, S.; Suzuki, T.; Nakamura, H.; Ito, K. 2008. Nonintrusive Appliance Load Monitoring Based on Integer Programming. SICE Annual Conference.

[7] Laughman, C.; Lee, K.; Cox, R.; Shaw, S.; Leeb, S.; Norford, L.; Armstrong, P. 2003. Power signature analysis. IEEE Power and Energy Magazine: IEEE.

[8] Chang HH, Lin CL, Lee JK. 2010. Load identification in nonintrusive load monitoring using steady-state and turn-on transient energy algorithms. International conference on computer supported cooperative work in design.

[9] Figueiredo, Marisa; Almeida, Ana; Ribeiro, Bernardete. 2012. Home electrical signal disaggregation for non-intrusive load monitoring (NILM) system. Neurocomputing Journal. Elsevier.

[10] Srinivasarengan, Krishnan. 2013. A Framework for Non Intrusive Load Monitoring using Bayesian Inference. Seventh International Conference on Innovative Mobile and Internet Services in Ubiquitous Computing: IEEE

[11] Chou, Po-an. 2013. Unsupervised Adaptive Non-Intrusive Load Monitoring System. International Conference on Systems, Man, and Cybernetics: IEEE

[12] http://archive.ics.uci.edu/ml/dataset/