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OLM software data set for Nonintrusive Load Monitoring (NILM)

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Abstract

A Nonintrusive Load Monitoring system (NILM) is an energy demand monitoring with load identification system. The NILM can use only one instrument installed at main power distribution board for the monitoring and load identification. In this paper, we present the Operating Load Model data set (OLM), a software data set containing detailed electricity consumption that can be adjusted by user, which is aimed at furthering research on energy disaggregation. This paper points to six appliances in household including air conditioner, television, refrigerator, rice cooker, fluorescent lamp and electric iron. Moreover the paper implemented a low sampling rate of monitored data to detect any change of power signal that obtained a 1 Hz sampling rate of active power from OLM software data set. The proposed OLM used 5 points of recorded data with steady-state real power and reactive power signatures to disaggregation. From the results showed that the proposed OLM software data set can be used to test NILM algorithm and the proposed NILM algorithm can disaggregation energy of the OLM software data set in 6 cases with accuracy percentage of energy consumption is approximately 91.76%.

Keywords: Nonintrusive Load Monitoring (NILM), Operating Load Model (OLM), disaggregation load

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1. Introduction

The traditional load monitoring method uses electricity meters at different points of the electrical installation to measure all possible variables that called intrusive load monitoring system [1, 2] shown as Figure 1. Various drawbacks are presented when applying this method such as the division of the load circuits, the cost of the electricity meters, the cost of installation, the available space for installing the hardware, among others. The Nonintrusive Load Monitoring (NILM) method focuses on using the user's electricity meter to identify the operation state of electrical devices, and the characteristics of the consumption and the load [3]. This monitoring method has been applied for different type of installations, being most common for residential users. Nonintrusive Load Monitoring has become more important with the growing use of smart meters at electrical installations. Significant savings in energy consumption can be achieved by improved energy management and real-time information on appliances in buildings [4]. In [4], researchers investigated the effects of electricity consumption feedback. Type of feedback has the effect of saving electricity. Furthermore, the greatest saving can be achieved by providing electricity consumption broken down to the specific appliances of a household. Real-time energy consumption on appliances can be used to plan to improve efficiency of load such as cleaning air conditioner or defrosting refrigerators. A continuous feedback on load power draw can lead to significant energy saving. One of the classifications of NLIM is sampling rate that they rely on: very low sampling rate (1 h - 15 min), low sampling rate (1 min - 1 s) and high sampling rate (< 1 s) methods. Very low sampling rate methods are to get data from Automatic Meter Reading (AMR) that complies with 10, 15, 30 and 60 minutes [5, 6, 7]. Low sampling rate methods are to get data from smart meter with port communication that obtained data at a 1 Hz [8, 9]. High sampling rate data allows NILM algorithms to use more complex features including transients, current harmonics and voltage-current trajectory that get data from special meter [10]. This research uses a single energy meter of main point to obtain a 1 Hz sampling rate of active power. To test NILM algorithm we need data set of electricity consumption. In recent years, several real-world electricity

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consumption data sets have been made available to the public. One of the most used and well-known data sets is the Reference Energy Disaggregation Data set (REDD) that provided the electricity consumption data at 1 Hz [8]. For instance, the Building-Level fully-labelled data set for Electricity Disaggregation (BLUED) [11] includes the electricity data of one household over a time period of 8 days, whereas the Almanac of Minutely Power data set (AMPds) [12, 13] provide one and two years of data measured at 1 minute intervals. Electrical loads in a power system may be modeled in one of three ways: constant impedance, constant power, or constant current sink [14]. Electrical loads in households can be classified according to the power factor of the load as follows: unity power factor (resistive electrical loads), lagging power factor (combination of resistive and inductive electrical loads) and leading power factor (combination of resistive and capacitive electrical loads) [15]. The choice of modeling depends on the degree of accuracy required.

In this paper, we present our work on developing a software data set, termed Operating Load Model (OLM). Three types of load model that is classified by power factor are used in this paper namely unity power factor, lagging power factor and leading power factor. Starting, steady and stopping characteristic of load are modeled. The advantages of OLM software data set are: various situations can be simulated, saving time and no cost of instrument installation. We used 5 points of recorded data with steady-state real power and reactive power (PQ) signatures to disaggregation to test our NILM algorithm. Figure 2 shows an electricity system of household with NILM embedded system that only uses one instrument installed at main power distribution board. The user interface can read all information from cloud by internet and direct read from NILM embedded system.

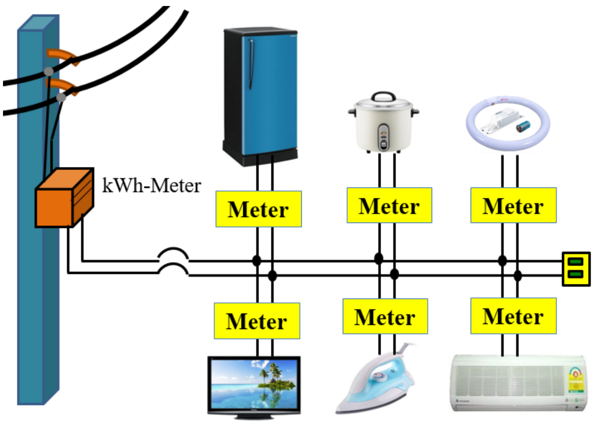

Figure 1 Intrusive Load Monitoring

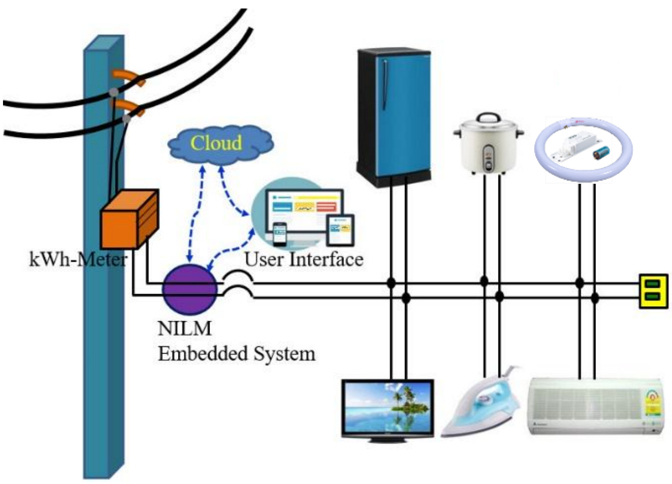

Figure 2 Nonintrusive Load Monitoring

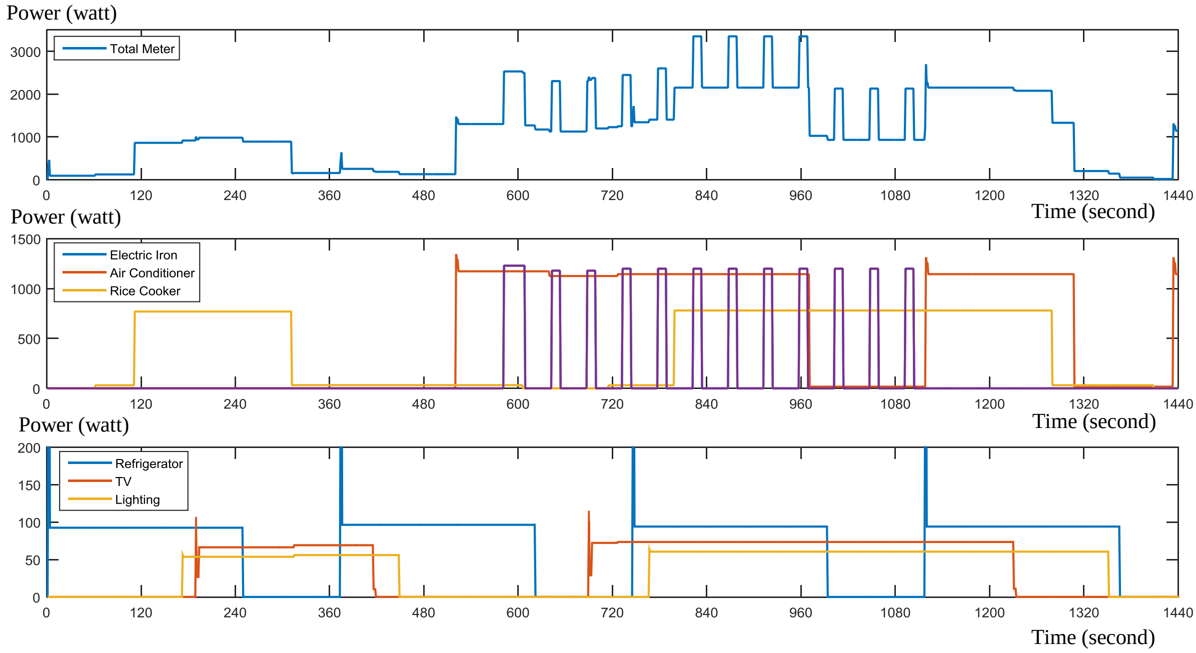

Figure 3 Example of disaggregation of main input signal into individual appliances signal

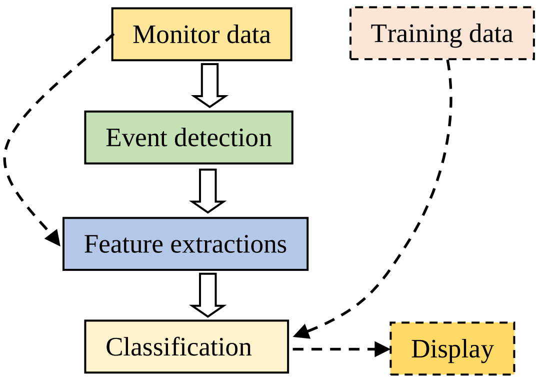

Figure 4 NILM system elements

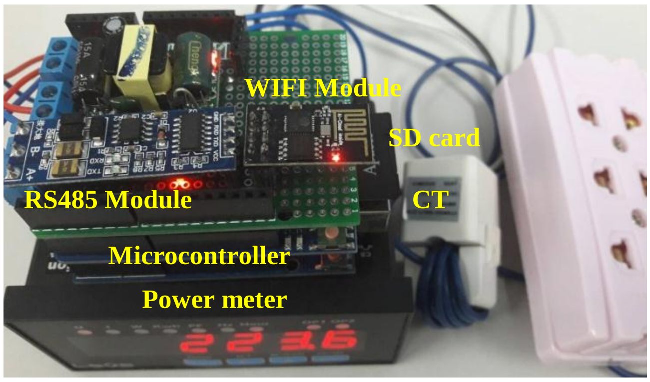

Figure 5 Smart power meter module

2. Materials and methods

2.1 Nonintrusive Load Monitoring

To monitor status and energy consumption of appliances in household with non-intrusive are the main concept of nonintrusive load monitoring. The data of electricity in household is collected at the main circuit, and then disaggregated data to obtain power draw and operational time of appliances that system classification. Figure 3 shows an example of amain active power signal and individual appliances signal that corresponding with main active power. The main active signal consist with 6 loads in household including television, rice cooker, air conditioner, refrigerator, fluorescent lamp and electric iron. In this illustration, the reconstructed operational time of television is from 198 s to 423 s and step 698 s to 1239 s with the power draw is about 59 W, electric iron is from step 586 s to 1090 s (on and off in this period) with the power draw is about 1000 W and refrigerator is on and off all day with the power draw is about 75 W. In this example, the appliances are modeled as on/off load that consume constant active power at a single steady state.

NILM system can be divided into four main parts as shown as Figure 4 [16]:

Monitor Data: This part is data logger that is used to measure and record data from system. There is a wide variety of power meters designed to measure the aggregated load of the building [17, 18] such as smart meter.

Event Detection: To detect the change of electricity data used in detection part, that is software part such as active power (P) as its input and returns a list of timestamps of detected events [19].

Feature Extractions: Feature extraction is the extraction of some features out of those timestamps that read from main signal.

Classification: Classification part acts as grouped or disaggregation the appliances status used training data to classifier with timestamps.

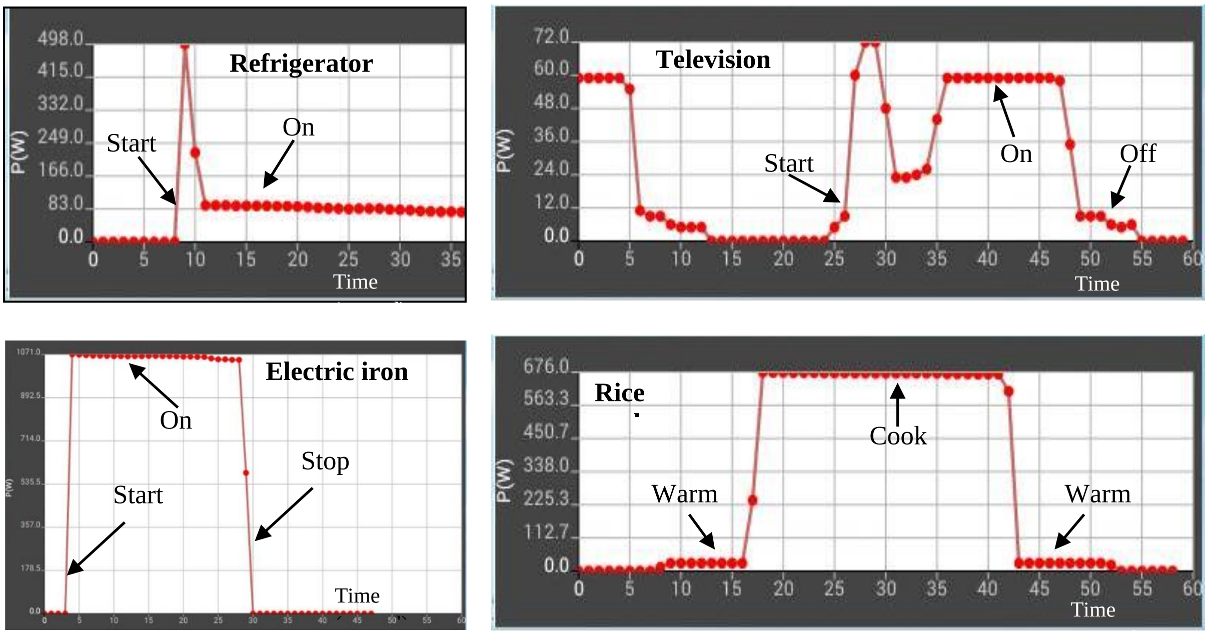

Figure 6 Characteristic of appliances from energy meter

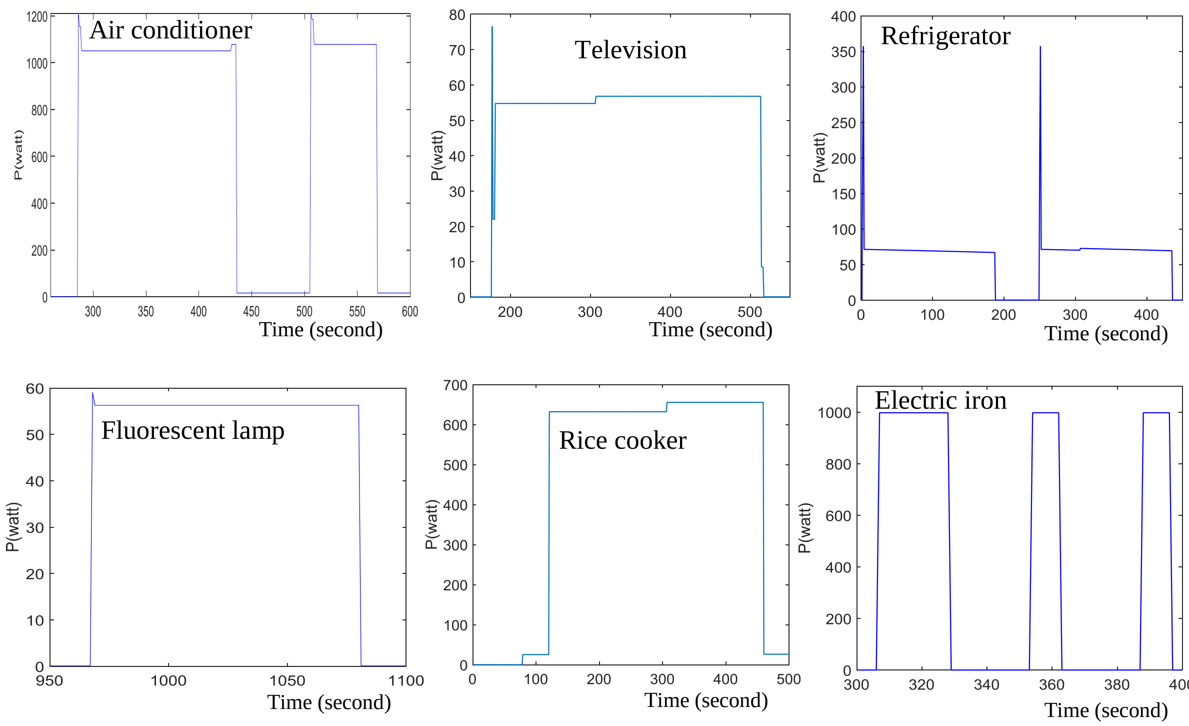

Figure 7 Characteristic of appliances from operating load model

To present power consumption of appliances to user has to have display part such as internet smart phone.

2.2 Operating Load Model

This paper has introduced the Operating Load Model (OLM), a software data set for research energy disaggregation. We have chosen MATLAB as programming language to build operating load model because it is widely used both in industry and education and it is especially popular in the engineering and applied mathematics communities. Six appliances in household are build including air conditioner, television, refrigerator, rice cooker, fluorescent lamp and electric iron. To record the characteristic of appliances to build a model in MATLAB, we used the smart power meter module that include power meter with 0.5% power accuracy [20] that connect to microcontroller with RS485 communication shown as Figure 5. Electricity parameters namely active power, reactive power and voltage that obtained from energy meter have been save in memory of microcontroller and a micro-SD card with timestamp and send data to smart phone or computer by wireless communication a rate of 1 Hz. To design model of load, we consider about characteristic at start-stop time and power consumptions. Examples of data that record with the smart power display as Figure 6 and Figure 7 show the characteristic of appliances that build from MATLAB programming.

Signature of appliances can be illustrated:

- Air conditioner is overshoot at start time. The operational pattern is on-off with temperature setting. First on period have long time more than other. Power of air conditioner is a combination of both inductive reactive power and active power.

- The operational pattern of television is changing active power high and low before steady state. Power of television is a combination of both capacitive reactive power and real power.

- Refrigerator is high overshoot at start time. The operational pattern is on-off with thermostat setting. Power of refrigerator is a combination of both inductive reactive power and active power. When compressor on it decreases power in function of time defined formally as

$$P_{Ref}(t) = 0.1446t^2 - 2.6826t + P_{to} \qquad (1)$$

where $P_{Ref}(t)$ denotes the active power for time t, P_{t0} denotes the steady state active power at on start time, t denotes time in second (start when compress or on).

- The operational pattern of rice cooker is warm and cook step. It has only active power.

- Fluorescent lamp is little overshoot at start time. Power of fluorescent lamp is a combination of both inductive reactive power and active power.

- The operational pattern of electric iron is on-off with heating of bimetal switch. First on period have long time more than other. It has only active power.

Figure 8 shows system that include OLM of appliances main meter and sub meter for test accuracy with NILM. Figure 9 shows the OLM of air conditioner and block parameters.

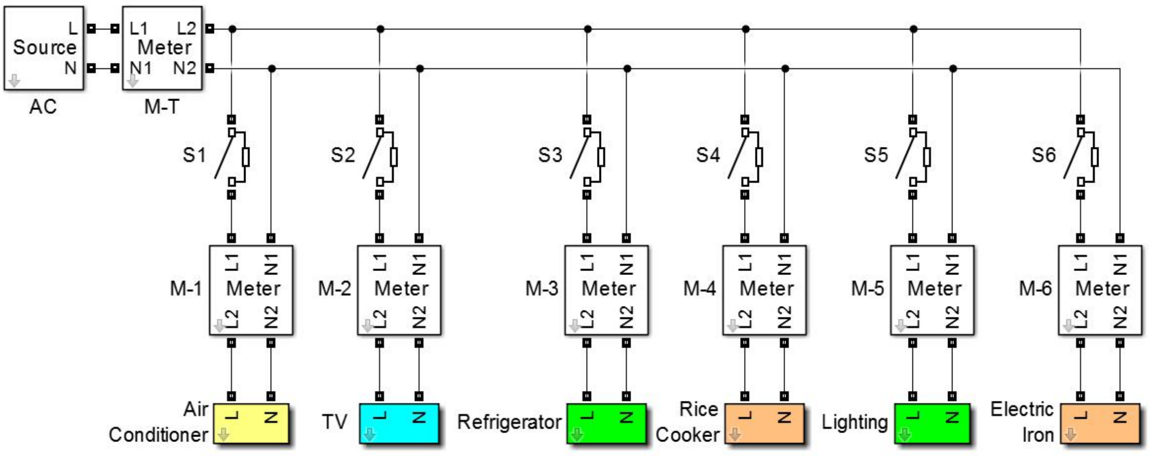

Figure 8 Operating Load Model system

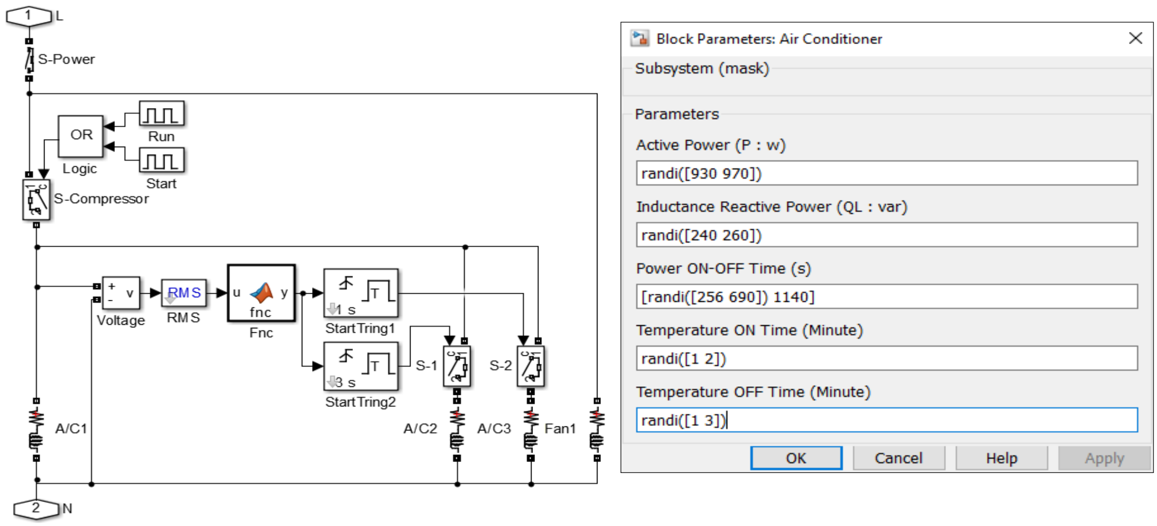

Figure 9 OLM of air conditioner and block parameters

2.3 NILM algorithms

The NILM algorithm in this paper extracts main data every 1 second when detected the change of active power from the OLM data set and assigns each event to the appliance with the best match in a signature database. The algorithm is based on the approach developed by [1, 21, 22]. Five points of monitor data used to event detection to detect positive and negative change of active power. If data of 5 point (P1, P2, P3, P4 and P5) are in the steady state find a change of real power (ΔP) by comparing with last the steady state of real power. Used ΔP ΔQ and pattern of last 10 point before get the steady state to find best match in a signature database. Pattern of last 10 point used to classifier load that on and off more than 1 load. It can be mathematically expressed as Eq. 2:

$$\Delta P = P_{t2} - P_{t1} \tag{2}$$

where ΔP is a change of active power, P_{t1} is the steady-state active power at time t_1 and P_{t2} is the steady-state active power at time t_2.

For load identification, the transition of steady-state active poweris mapped into a space of P-Q. Find the 3 minimum of error index (S) after that used pattern of last 10 points to find the best of error index (S). It can be mathematically expressed as Eq. 3:

$$e_k = \sqrt{(\Delta P - sP_k)^2 + (\Delta Q - sQ_k)^2} \tag{3}$$

where ΔP is a change of active power, ΔQ is a change of reactive power, sP_k is the sum of active power at index k, sQ_k is the sum of reactive power at index k and e_k is error of power at index k.

On-off status was used to determine status of appliances from the best of error index (k) and calculate active power that have on status defined formally as

$$Pon_i = \left(1 + \frac{\sum_{m=1}^{2n} P_m K_m - \Delta P}{\sum_{m=1}^{n} |P_m K_m|}\right) P_i \tag{4}$$

where Pon_i is active power of load i that status is on, P_i, P_m are setting active power of load i and load m, K_m is status of load m, n is number of load.

We used the energy consumption to evaluate the performance of the method with 60 seconds of interval time and 1,440 seconds and 14,400 seconds of period time defined formally as

$$Acc^k = 1 - \frac{\sum_{n=0}^{\frac{N}{T}} \left| \sum_{t=nT+1}^{nT+T} \hat{P}_t^k - \sum_{t=nT+1}^{nT+T} P_t^k \right|}{\sum_j^N \hat{P}_j^k} \tag{5}$$

$$Acc = 1 - \frac{\sum_{n=0}^{\frac{N}{T}} \left| \sum_{t=nT+1}^{nT+T} \bar{P}_t - \sum_{t=nT+1}^{nT+T} \sum_{k=1}^{m} P_t^k \right|}{\sum_{j=1}^N \bar{P}_j} \tag{6}$$

where Acc^k is energy accuracy of load k, Acc is total energy accuracy, $\hat{P}_t^k$ is active power of load k that read from meter at the tth time step, P_t^k is active power of load k that can be estimated from NILM at the tth time step, $\bar{P}_j$ is total active power that read from meter at the tth time step, m is number of load, T is interval time and N is period of testing time.

3. Results and discussion

To evaluate the method, we used 1,440 seconds of data from the OLM software data set with 5 cases study shown as Figure 10. Figure 11 shows active power of OLM that read from meter and Figure 12 shows active power of NILM algorithms that disaggregate from main power of the 5th case study. Switching events of the 5th case study detect different of active power that have 42 switching events shown as Figure 13 and Figure 14 shows energy consumption from OLM and NILM of the 5th case study.

Testing time of the 6th case study is 14,400 seconds that shown as Figure 15 and Figure 16. The energy consumption of different type of appliances from the simulation result shows in Table 1. Table 2 shows accuracy percentage of energy consumption with accuracy percentage of energy consumption is approximately 91.76%.

In addition to OLM used to test the NILM method, the OLM software data set can be simulated to study different aspects of loads: reactive power compensation, power quality and efficiency, load shedding and system planning such as planning of TOU (time of use) in electric bill system. Blocks of OLMs that were created in this paper can be added to MATLAB Simulink in other related manner.

4. Conclusions

This paper presents the Operating Load Model data set (OLM), a software data set for application research in the Nonintrusive Load Monitoring system (NILM). To identify the energy consumption in various types of appliances can conduct an essential real impact on energy saving and sustainability energy use. We have introduced 6 operating appliance models as air conditioner, television, refrigerator, rice cooker, lighting (fluorescent lamp) and electric iron. We constructed a smart power display module to record the characteristic of appliances to build the OLMs. The great advantages of proposed OLM software data set are that various situations can be simulated, saving time and no cost of installed instrument moreover the model can be adjusted various parameters such as voltage, power and time of on-off state. The results showed that proposed OLM software data set can be used to test the NILM algorithm. The proposed NILM algorithm can disaggregation energy of the OLM software data set in 6 study cases with the average accuracy is 91.76%.

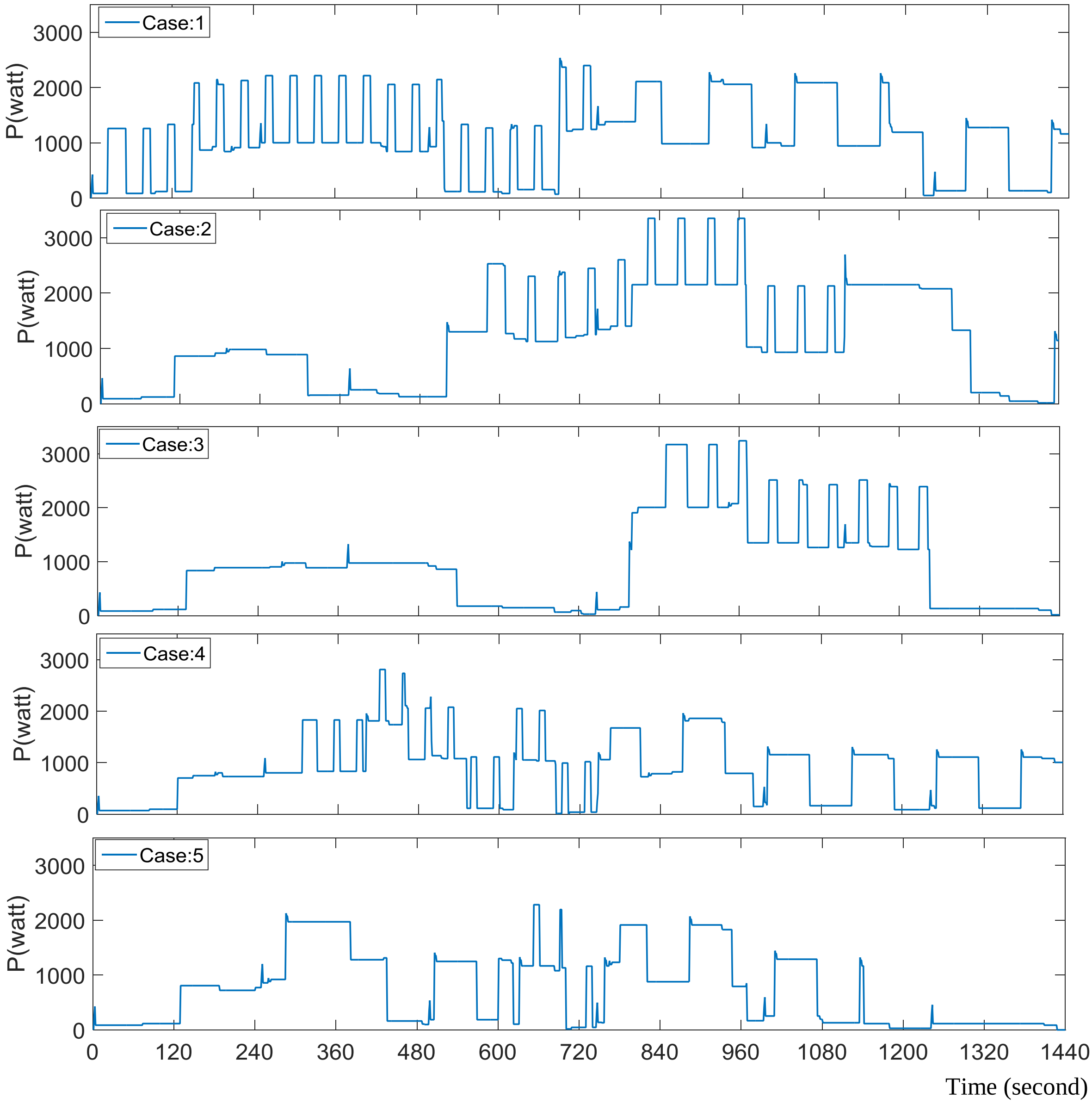

Figure 10 Total active power from main meter of OLM

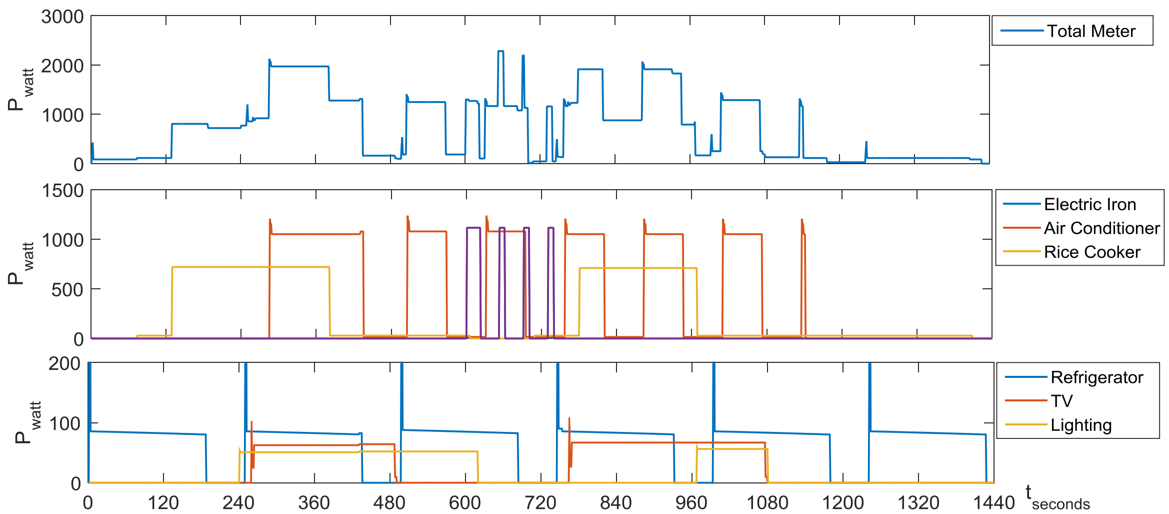

Figure 11 Active power from OLM of the 5th case study

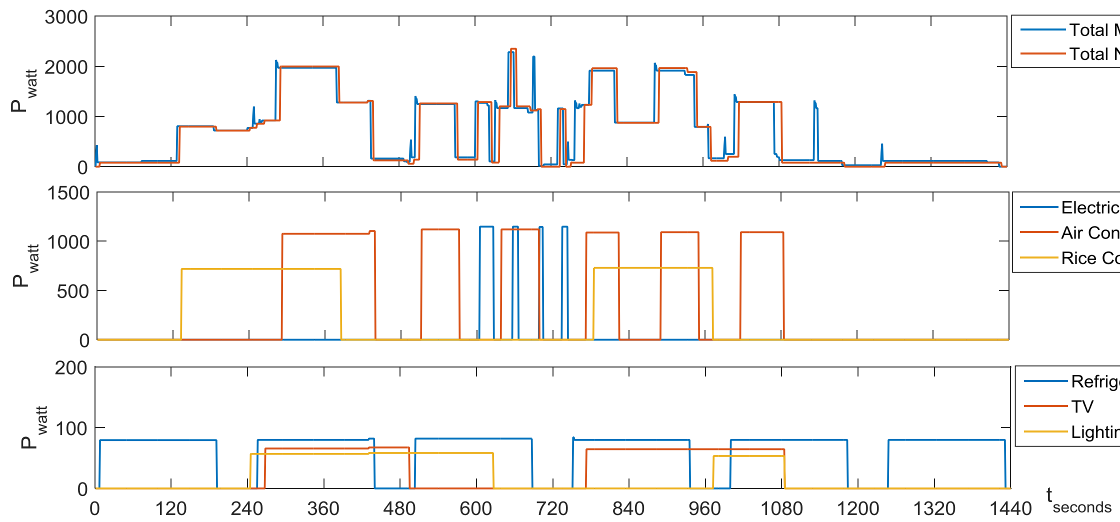

Figure 12 Active power from NILM of the 5th case study

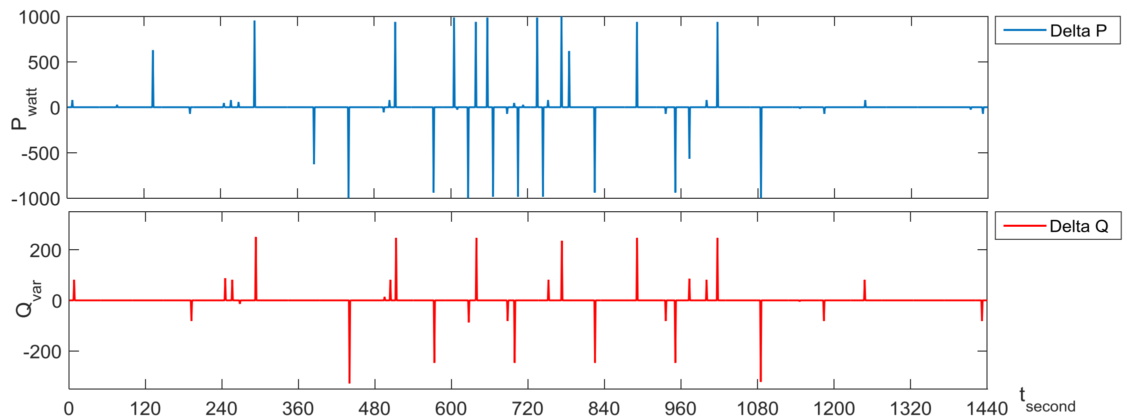

Figure 13 Power detection (ΔP and ΔQ) of the 5th case study

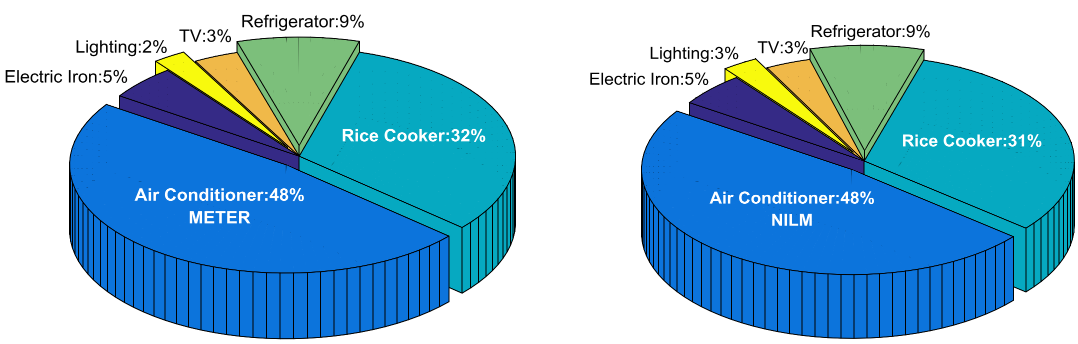

Figure 14 Energy consumption from OLM and NILM of the 5th case study

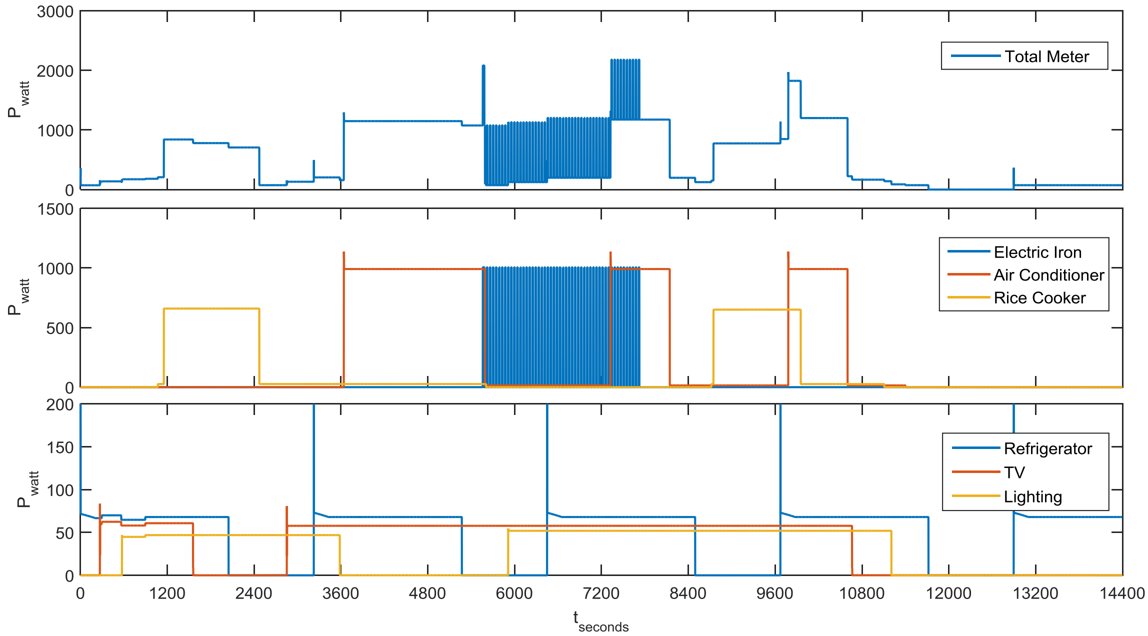

Figure 15 Active power from OLM of the 6th case study

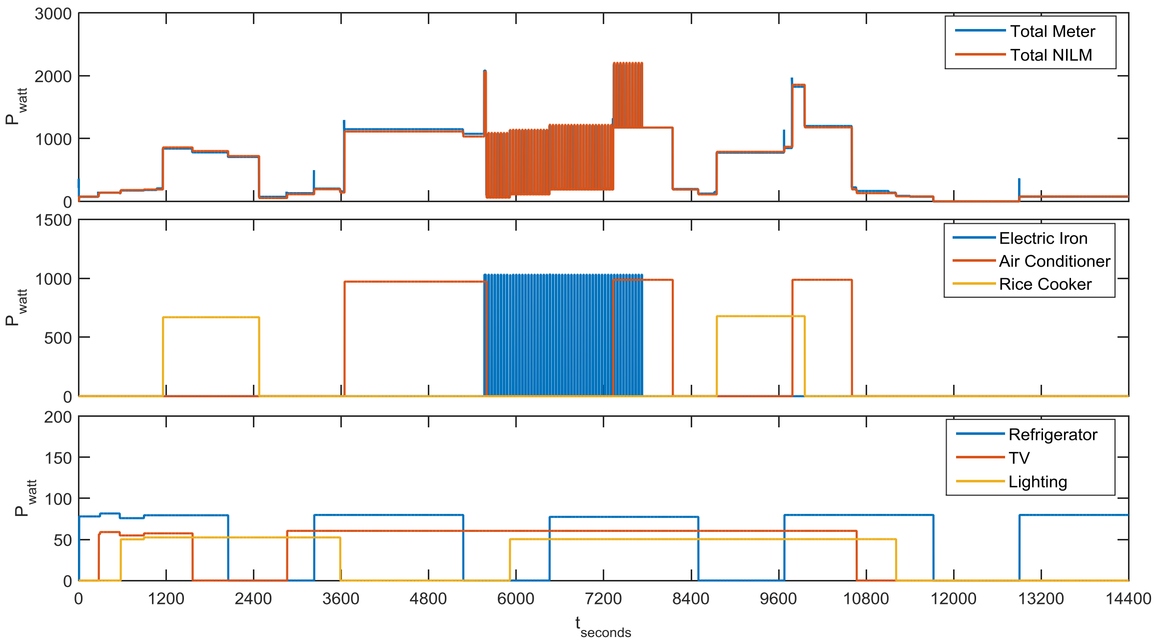

Figure 16 Active power from NILM of the 6th case study

Table 1 Energy consumption of different type appliances from meter/NILM

Appliances	Energy consumption (w-hr) [meter/NILM]					
	Case: 1	Case: 2	Case: 3	Case: 4	Case: 5	Case: 6
Electric iron	78.2 / 75.5	49.4 / 50.3	44.0 / 46.7	35.9 / 35.6	15.1 / 14.6	134 / 137
Air conditioner	139.3 / 129.2	207.3 / 210.3	139.7 / 142.2	165.3 / 157.2	140.8 / 135.8	1,005 / 973
Rice cooker	162.4 / 165.9	151.9 / 150.3	126.4 / 125.0	104.4 / 103.6	93.8 / 88.4	492 / 472
Refrigerator	26.7 / 28.8	26.6 / 24.3	28.5 / 30.3	23.0 / 23.6	26.7 / 24.5	184 / 212
Television	15.4 / 11.0	15.2 / 15.1	12.7 / 12.0	8.2 / 8.6	9.7 / 9.7	147 / 152
Lighting (FL)	9.8 / 9.8	14.0 / 14.2	10.8 / 12.4	8.9 / 10.3	7.2 / 7.7	115 / 117
Total	432.8 / 432.0	464.5 / 464.5	363.6 / 362.0	346.5 / 345.8	294.5 / 293.7	2,091 / 2,064

Table 2 Accuracy percentage of energy consumption

Appliances	Accuracy % of energy consumption						
	Case: 1	Case: 2	Case: 3	Case: 4	Case: 5	Case: 6	Average
Electric iron	90.64	88.39	92.65	86.55	87.70	93.88	89.97
Air conditioner	94.63	95.27	96.54	95.61	91.21	96.80	95.01
Rice cooker	94.16	94.86	93.28	92.47	92.08	90.79	92.94
Refrigerator	89.02	91.58	90.55	90.76	91.96	84.16	89.67
Television	70.76	94.64	94.04	92.42	95.56	95.12	90.42
Lighting (FL)	93.68	91.49	85.29	83.95	88.72	93.85	89.5
Total	94.98	95.66	95.67	91.94	93.52	96.90	94.78
Average	89.70	93.13	92.57	90.53	91.54	93.07	**91.76**

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