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ELECTRICITY CONSUMPTION PATTERN DISAGGREGATION USING NON-INTRUSIVE APPLIANCE LOAD MONITORING METHOD

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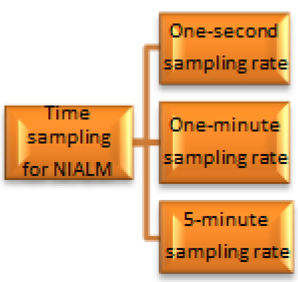
Graphical abstract



Abstract

In practice, a standard energy meter can only capture the overall electricity consumption and estimating electricity consumption pattern of various appliances from the overall consumption pattern is complicated. Therefore, the Non-Intrusive Appliance Load Monitoring (NIALM) technique can be applied to trace electricity consumption from each appliance in a monitored building. However, the method requires a detailed, second-by-second power consumption data which is commonly not available without the use of high specification energy meter. Hence, this paper analyzes the impact of different time sampling data in estimating the energy consumption pattern of various appliances through NIALM method. This is so that consumers will have an overview of time sampling data which is required in order to apply the NIALM technique. As for the analysis, air-conditioning systems and fluorescent lamps were used in the experimental setup. One minute sample rate was the minimum time interval required by NIALM carried out in this analysis. Through the study presented in this paper, it can be established that higher time sampling led to uncertain appliance detection and low accuracy.

Keywords: Non-intrusive load monitoring; energy management; power consumption disaggregation; energy saving

1.0 INTRODUCTION

Consumers' energy consumption in a building can be identified by using a smart meter where each meter directly interacts with intelligent appliances and decomposes the total electricity energy consumption. Known as the Intrusive Load Monitoring, this method is one of the most reliable and accurate systems to identify load consumption of an individual appliance. However, this type of smart meter requires a large amount of meters for each appliance and each meter to be installed results in high installation and maintenance cost [1]. Therefore, the Non-Intrusive Appliance Load Monitor (NIALM) technique was introduced in [2], where it is proven that the technique is able to disaggregate the energy consumption of each appliance by monitoring one electrical circuit that contains a number of electrical appliances without using separate sub-meters. . The NIALM method grows rapidly as the system requires fewer sensors with a single point of measurement and low installation cost.

The physical task that the load performs influences the transient behavior of a typical electrical load. The signature of turn ON transients associated with a fluorescent lamp and an induction motor, for example, are distinct because the physical tasks of igniting an illuminating arc and accelerating a rotor are fundamentally different. This observation led to the study of a transient event detector for non-intrusive load monitoring [3]. The transientevent present in the data is isolated by an algorithm to detect which device is turning ON, OFF or otherwise changing state. Therefore, the transients present in the event need to be captured so that the occurrence of the appliance during the time interval can be observed. However, to capture the transient that occurs in a certain period of time, the data frequency captured by a power meter need to be as small as possible. Power meters with this type of capability are available in high specification but are very expensive. In practice, common residents would not be able to afford power meters such as these.

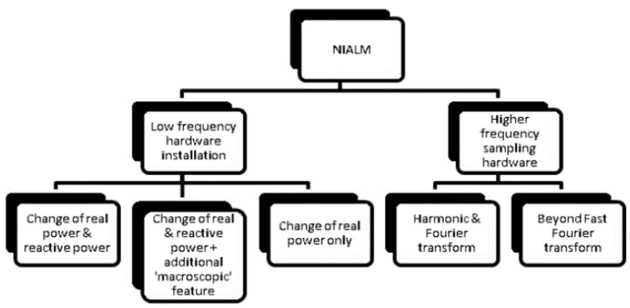


Figure 1 NIALM division

Figure 1 shows the different types of NIALM method separated into several divisions, depending on the frequency of input data. As for the low frequency hardware installation method, its minimum requirement is still data per second. Thus, this paper is focused on the analysis of data time sampling that will be needed to avoid the use of high specification device which is expensive and costly. This is so that, using a certain data captured interval proposed in this paper, NIALM method can still be applied by the regular user. Different time sampling is compared and analyzed to investigate its suitability in estimating occurring events involving air-conditioning system and fluorescent lamps that will contribute to NIALM method. However, the accuracy of NIALM technique is not the main priority in this study where the decrease of data frequency will reduce the accuracy of appliance detection.

2.0 NON-INTRUSIVE APPLIANCE LOAD MONITORING

Basically, NIALM is a process to detect changes of the voltage and current going through a house and predict the type of appliances used in the house, as well as their individual energy consumption based on a single set of sensors. Normally, the system is installed at the main electric entrance of the house to monitor the changes of desire features. Then, the electric signal is analyzed to disaggregate the total energy consumption.

Most of the existing methods consider electrical power into their system as the main feature. In that case, real and reactive powers are taken into account as a feature to distinguish power consumption drawn by certain appliances. These features will be used for clustering data into their group. Non-intrusive load monitoring was initially proposed by G.W Hart [4]. Massachusetts Institute of Technology (MIT) suggested four types of appliance models that represent NIALM technique which are:

I. ON/OFF appliances
II. Finite State Machines (FSM),
III. Continuously Variable Consumer Device
IV. Permanent Consumer Device.

The study proposed by MIT concentrated on ON/OFF appliances and FSM categories and considered two signatures, which were steady state analysis and transient analysis

Most of complex residential loads are investigated to have turn-on on appliance that can be characterized by three phases: an initial upward spike in power, slower changing variations, and a settled power level. Thus, Cole and Albicki proposed a method which relates edges, slopes, and steady-states respectively according to the phase [5]. However, only edges and slopes are unique features that differentiate loads.

[6] proposed that a specialized variant of Hidden Markov Model (HMM) known as Factorial HMM (FHMM) which is a different method to recognize appliance-specific load patterns from the aggregated power measurements. This solution made use of circuit-level power measurements and was applied to low-power appliance particularly. Nevertheless, the performance severely degraded in case of devices switching to intermediate states.

On the other hand, development in NIALM by using artificial intelligence methods were tremendous [7]. Artificial Intelligence is applicable in pattern recognition problems. Wavelet Transform [8-10] was upgraded by combining the existing method producing high accuracy load detection. Most of these methods emphasized the accuracy of load identification. Neural Network [11-13] is another load identification technique that is convincing to attain more accuracy result. However, most of these methods depend on high sampling data collection which requires extra cost for installation.

Table 1 show various methods which currently exist in practice. These methods focuses on non-intrusive load monitoring to trace active appliances in a given time scale, as well as on home equipment with different types of appliances usage.

Table 1 Comparison of various method for load identification [14]

Learning Algorithm	Features	Accuracy (%)	Training	Online/ Offline	Appliance Type
Support Vector Machine	Steady State & Transient	75-98	Supervised	Online	I, II, III & IV
Bayes	Steady State	80-99	Supervised	Online or Offline	I & II
Hidden Markov Model	Steady State	75-95	Supervised or Unsupervised	Offline	I & II
Neural Network	Steady State & Transient	80-97	Supervised	Online	I & II & III
K-Nearest Neighbour	Steady State & Transient	70-90	Supervised	Online or Offline	I & II & III
Optimization	Steady State	60-97	Supervised	Offline	I & II & III

3.0 CASE STUDY

The objective of this case study is to test the impact of different time sampling in estimating the energy consumption pattern of various equipment through NIALM.

3.1 Test System

Experimental setup consisted of one unit of air-conditioning system and 10 units of fluorescent lamps and all fluorescent lamps were connected in parallel. Figure 2 shows the schematic circuit of the test system. The chosen fluorescent lamps were cool daylight, T8 type. Power rating for each fluorescent lamp was TLD 36W/865 (Cool-daylight). As for air-conditioning system(Hesstar HAC-AE120), the power rating was 1500W with cooling capacity of 1.5 HP (12000btu). A Kyoritsu Power Quality Analyzer was used to record the electricity consumption data.

The analysis was carried out for 40 minutes. During the time interval, the air-conditioning system and fluorescent lamps were switched ON and OFF with various combination in accordance with Table 2. Whenever the appliance's state changed, the time of transition will be recorded. Each fluorescent lamp was connected to a switch. The temperature of air-conditioning system was neglected in this study since the main purpose of the analysis was to monitor the pattern of power drawn by each appliance as the state changes. Next, the data obtained by the meter was plotted in time series graph to observe the step changes. Individual appliance events were analysed by referring to the time series plot. Then, the shape of power changes for fluorescent lamps and air-conditioning system were used to differentiate these two appliances. The measured current pattern was considered as additional feature for the analysis.

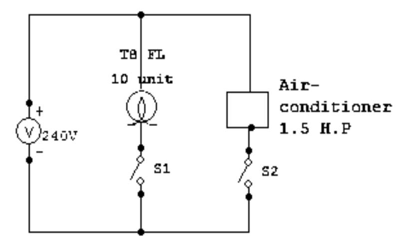


Figure 2 Schematic circuit of test system

3.2 Results and Discussion

3.2.1 One-Second Time Sampling

The electrical power consumption and current data for the test system are shown in Figure 3 and Figure 4 respectively. It can be seen that both real power and current drawn change as the states of fluorescent lamp and air-conditioning system change. When the air-conditioning system is turned ON or OFF, the changes are obvious.

The turn ON transients associated with the air-conditioning system and fluorescent lamp are different because switching on a compressor in air-conditioning system is fundamentally different from heating a lamp filament. There is not much difference in pattern between the real power and current profiles. However, the existence of inrush current at the starting point for current profile in Figure 4 is an additional feature for differentiating the equipment in NIALM.

Table 2 Number of fluorescent lights switched on and air-conditioning system state at the corresponding time

Time elapsed	Number of T8 switched ON	Air-conditioning system Status
0:00:18	6	OFF
0:01:42	6	ON
0:05:16	10	ON
0:07:15	4	ON
0:10:47	8	ON
0:13:32	2	ON
0:14:45	0	ON
0:16:44	4	ON
0:18:03	8	ON
0:19:09	10	ON
0:20:51	6	ON
0:21:25	4	ON
0:21:53	4	OFF
0:22:41	2	OFF
0:23:10	0	OFF
0:23:33	2	OFF
0:24:05	4	OFF
0:24:26	6	OFF
0:24:48	8	OFF
0:25:10	10	OFF
0:26:21	2	OFF
0:26:40	2	ON
0:27:15	4	ON
0:27:58	6	ON
0:28:32	8	ON
0:28:59	10	ON
0:30:38	9	ON
0:30:52	8	ON
0:31:08	7	ON
0:31:26	6	ON
0:31:41	5	ON
0:31:55	4	ON
0:32:23	3	ON
0:32:56	2	ON
0:33:18	1	ON
0:33:38	0	ON
0:34:39	0	OFF
0:35:16	1	OFF
0:36:01	2	OFF
0:36:16	3	OFF
0:36:31	4	OFF
0:36:44	5	OFF
0:37:01	6	OFF
0:37:17	7	OFF
0:37:39	8	OFF
0:37:58	9	OFF
0:38:14	10	OFF
0:38:51	10	ON

Through real power consumption pattern analysis, the load profile in Figure 3 is interpreted in Figure 5. At the beginning of the load profile, six fluorescent lamps were switched ON and the step changes can be seen around the 0:00:18 time mark. Next, air-conditioning system was turned ON around 0:01:42 and a large portion of power change are clearly observed. The air-conditioning system consumed about 1440W to reach steady-state phase once it is switched ON. At this time, the data shows the total power consumption for six fluorescent lamps and an air-conditioning system (with constant temperature). A high step-down transition is observed around 0:21:53 from the load profile and according to the power rating of the appliances, this indicates that the air-conditioning system had been turned-OFF. Between the time intervals, the fluorescent lamps were variously switched ON and OFF for a certain number of times, the presence of air-conditioning system is predictable due to the high power rating compared to fluorescent lamps. The load disaggregation can be estimated as shown in Figure 6.

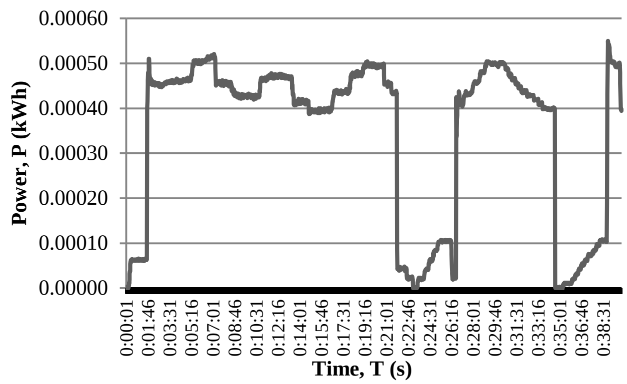


Figure 3 Power drawn by randomly switching ON/OFF individual equipment

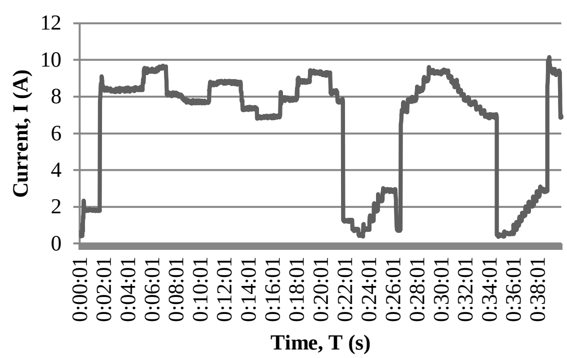


Figure 4 Instantaneous current drawn by randomly switching ON/OFF individual equipment

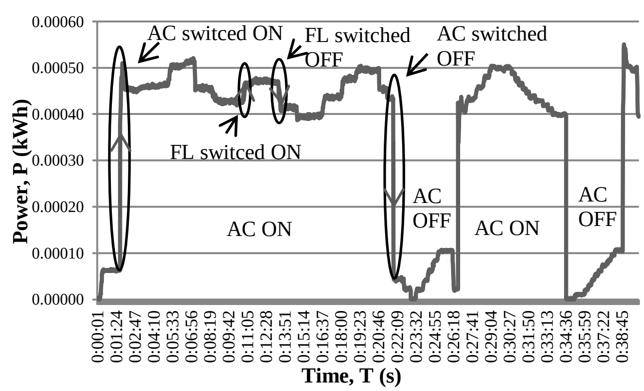


Figure 5 Power vs. time plot shows step changes due to individual appliance events

Based on Figure 5, the detail of AC was referring to Air-conditioning system while FL indicated Fluorescent Lamp on the load profile.

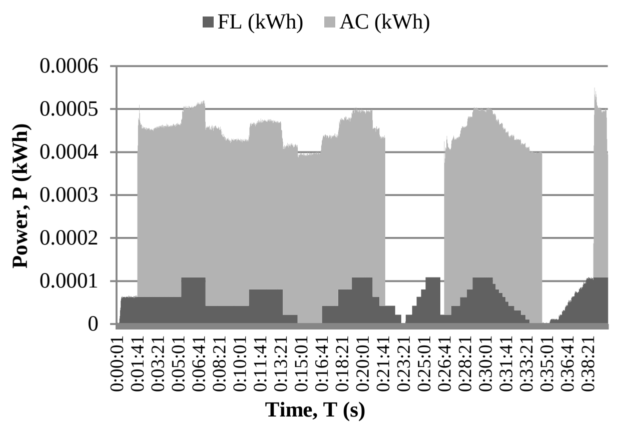


Figure 6 Disaggregation of power consumption load profile with 1 second time sampling data for Fluorescent lamps (FL) and air-conditioning system (AC)

3.2.2 One-Minute Time Sampling

Figure 7 shows the time series plot for the power consumption data of the previously mentioned test system with time sample of one-minute. It can be seen that the occurrence of the two appliances can still be predicted through NIALM approach i.e. through real power consumption pattern analysis. Nevertheless, the existence of fluorescent lamps consumption might be undetectable at certain times (due to merged consumption data of the two appliances within 1 minute),hence the accuracy of prediction will be reduced. The load disaggregation for the load profile in Figure 7 is given in Figure 8.

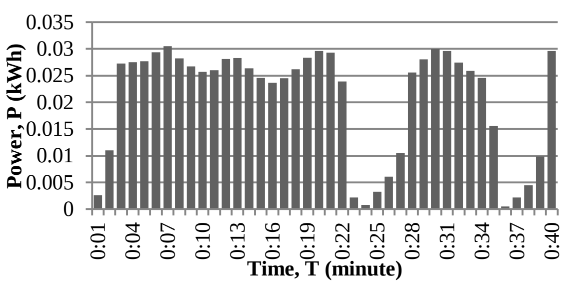


Figure 7 Power vs. time data plotted in one-minute time sampling

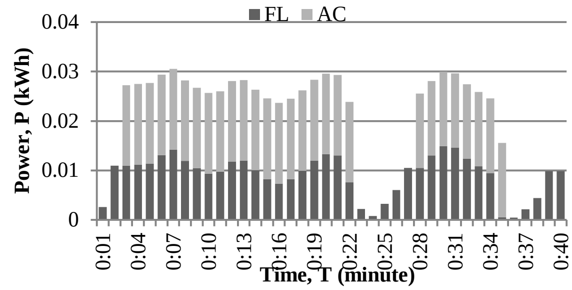


Figure 8 Disaggregation of power consumption load profile with 1 minute time sampling for Fluorescent lamps (FL) and air-conditioning system (AC)

3.2.3 Five-Minute Time Sampling

Figure 9 shows the real power consumption pattern captured for every 5 minutes. Based on Figure 9, the graph shows a significant change in a specific time period. However, the pattern is not sufficient to determine energy consumption of the respective appliance because the presence of active appliance cannot be predicted through the load profile. Even though the existence of air-conditioning system can still be predicted due to the significant power consumption change, nevertheless it is uncertain whether fluorescent lamps also contributed to the consumption at that specific time. Thus, the load disaggregation prediction based on five minutes time sampling will be inaccurate. Figure 10 shows the load disaggregation in five-minutes intervals.

The overall contribution of fluorescent lamps and air-conditioning system from the estimated load disaggregation with different time sampling is shown in Figure 11. It can be seen that as the time sampling increases, the accuracy in estimating appliance contribution towards electricity consumption decreases. Thus, to disaggregate the measured load profile data using NIALM, the data sampling should be as small as possible. Data sampling with one minute time interval is also acceptable especially in estimating individual appliance consumption pattern (Figure 8). One minute time sampling is preferred in practice since the size of consumption data that needs to be stored by the meter is greatly reduced. Higher sampling rate may be applicable if the overall load consumption is high and appliances' states (ON or OFF) do not change frequently.

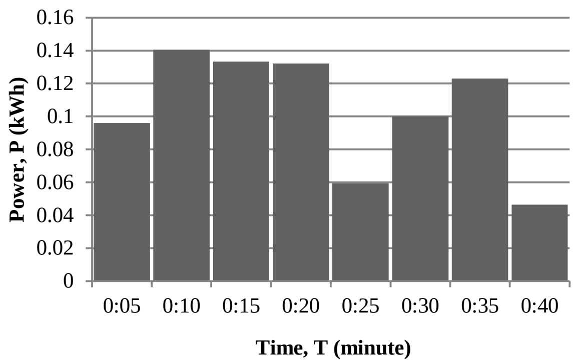


Figure 9 Power vs. time data plotted with 5 minute time sampling

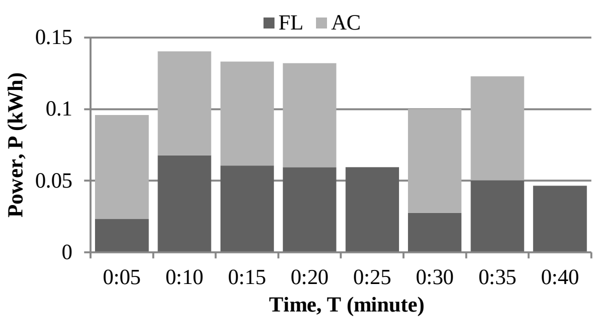


Figure 10 Disaggregation of power consumption load profile with 5 minute time sampling for Fluorescent lamp (FL) and air-conditioning system (AC)

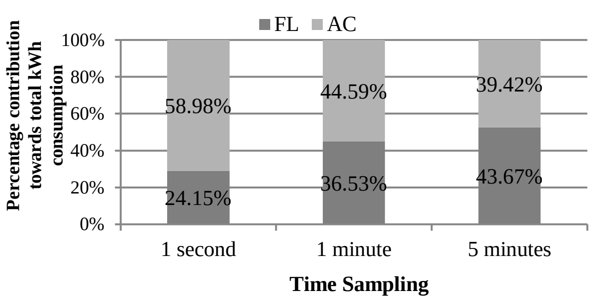


Figure 11 Contribution of Fluorescent lamp (FL) and air-conditioning system (AC) to the overall electricity consumption

4.0 CONCLUSION

Air-conditioning system and fluorescent lamps are appliances that contribute the most in electricity consumption. NIALM method can be used to estimate the load pattern of various appliances from the recorded load profile data. The estimation accuracy depends on the time sampling of the recorded data. Obviously, smaller time sampling will result in better estimation. However, in practice, selecting smaller time samples will put a burden on the meter as it needs larger memory storage to store extensive data. Thus selecting appropriate time sampling value that does not compromise the accuracy and practicality of the NIALM-based load disaggregation method is required. Based on the study, one minute is the minimum sample rate required to perform appliance detection for NIALM method. Five minute time sampling is not recommended but might be applicable if additional information such as number of appliances, user usage patterns etc. are provided.

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