J Electr Eng Technol Vol. 8, No. 3: 572-580, 2013
http://dx.doi.org/10.5370/JEET.2013.8.3.572

ISSN(Print) 1975-0102
ISSN(Online) 2093-7423

Load Profile Disaggregation Method for Home Appliances Using Active Power Consumption

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Abstract – Power metering and monitoring system is a basic element of Smart Grid technology. This paper proposes a new Non-Intrusive Load Monitoring (NILM) method for a residential building sector using the measured total active power consumption. Home electrical appliances are classified by ON/OFF state models, Multi-state models, and Composite models according to their operational characteristics observed by experiments. In order to disaggregate the operation and the power consumption of each model, an algorithm which includes a switching function, a truth table matrix, and a matching process is presented. Typical profiles of each appliances and disaggregation results are shown and classified. To improve the accuracy, a Time Lagging (TL) algorithm and a Permanent-On model (PO) algorithm are additionally proposed. The method is validated as comparing the simulation results to the experimental ones with high accuracy.

Keywords: Non-Intrusive Load Monitoring, Home electrical appliance, Signature Identification

1. Introduction

Development of renewable energy and communication technologies bring a new era of Smart Grid. Advanced Metering Infrastructure (AMI) and Home Area Network (HAN) are one of the Smart Grid technologies. They are applied in a residential building sector to provide intelligent power metering service to home occupants. Before these technologies existed, the power metering had been mostly oriented to electricity suppliers. By acquiring and estimating information of energy consumption and demand of home occupants, the suppliers can improve reliability, security, and efficiency of their service [1-2].

However, as the infrastructure of user level's monitoring service by AMI and HAN is established, the users are more available to access to the information of their energy consumption. For example, the information can be sent to monitoring devices which are closed to the users, such as a computer monitor, a television, or a cell phone. Then, it makes the users can recognize their energy consumption as well as knowledge on performance of their electrical appliances. Moreover, it provides awareness of energy consumption to the users and leads them to act useful feedbacks in order to reduce their energy consumption [3].

As these monitoring techniques become widely being used, the users will demand more detailed and continuous monitoring data. The demand will include not only the total energy consumption in real time but also the operation time or the duration of each electrical appliance.

Over the past two decades, a number of electrical load monitoring methods have been developed [4-11]. Fig. 1 shows an example of measured power consumption data of each home appliance and their total power consumption profiles. In order to obtain these profiles, two main approaches can be chosen: Intrusive Load Monitoring (ILM) and Non-Intrusive Load Monitoring (NILM). The ILM needs separate measured data of power consumption profiles of each electrical appliance. Many sensors and channels are therefore necessary to gather each of them. It gives accuracy of the information. However, it needs more time and high costs in order to install and maintain the measuring equipment and devices [4-5].

Conversely, the NILM preliminary needs digital algorithms and proper signature determinations for identifying the power consumption profiles of each appliance. Without intrusive measuring devices adapted to each load, power consumption and occupied periods of each load can be

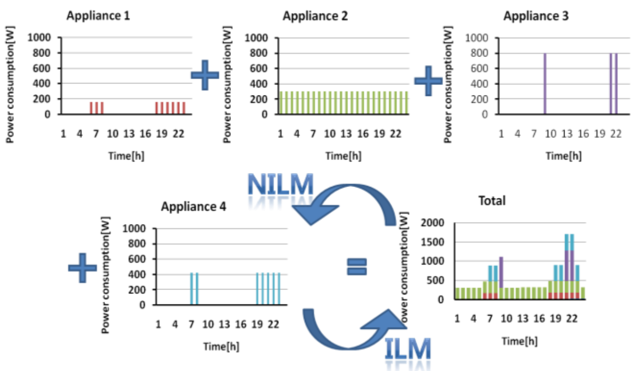

Fig. 1. An example of power consumption data of home appliances treated by intrusive load monitoring (ILM) and non-intrusive load monitoring (NILM)

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Received: November 9, 2011; Accepted: January 14, 2013

identified from total load profiles. Digital algorithms are developed to disaggregate the operations of each electrical appliance. The used proper signatures to distinguish each operation are power, current, or admittance at fundamental frequency, harmonic currents for steady-state [4, 6-8], and shape, size, duration, or time constant for transient state [4, 9-10].

To reduce errors of the estimation and improve the accuracy and the performance of the analysis, regression algorithms [2], artificial neural networks [5], genetic algorithms [11], and optimization algorithms are applied in literature [6, 11].

Previous works on NILM in a residential building sector treat the active power and reactive power as load signatures in order to determine each operation state of home electrical appliances at each time [4,6-8,12]. However, most of residential buildings do not dispose metering devices which measure both active and reactive powers. The measured active power is normally informed to consumers. For a simple and cost effective metering, several studies which only use the active power were also presented in [3,8]. Although the method is quite simple as it does not need the information of reactive power profiles, it is yet difficult to identify the operations of multi-state appliances, permanently-on appliances, continuous variable appliances, or identical power consuming appliances.

This paper proposes a new algorithm to disaggregate the power consumption of electrical appliances in a residential building sector. We used only active power profiles as a necessary load signature. The proposed algorithm identifies not only Permanently-On models, two states (ON/OFF) models but also Multi-state models. To identify each state of models, binary codes are generated by a switching function. Then a truth table matrix and a matching process are proposed to distinguish each state. For improving disaggregation accuracy, a time lagging (TL) algorithm for transition period is used and a removing Off state of Permanently-On appliance (PO) algorithm are additionally developed. Proposed algorithms are also verified by a case study in practice.

2. Model Algorithms

2.1 A. On/off model algorithm

To define operation states of home electrical appliances, a switching function [4, 8] is used in this paper. Let $A = [a_1\, a_2 \ldots a_n]$ be an appliance matrix. Let $P = [P_1\, P_2 \ldots P_n]$ be an active power consumption matrix of each element of matrix *A*. Here, *n* is a number of the appliances. For example, an appliance a_1 consumes P_1[W] at ON state. The matrix *P* lists the ON state power consumption of all appliances. To express ON and OFF states of each appliance, we use the switching function, $s_i(t)$. It is defined at any time *t*, as follows

$$s_i(t) = \begin{Bmatrix} 0, if\ a_i\ is\ off \\ 1, if\ a_i\ is\ on \end{Bmatrix} \tag{1}$$

where $i = 1, 2, \cdots, n$. If $s_1(t)$ is equal to 1, then, it means the appliance a_1 consumes P_1 [W].

In sequence, we present a truth table matrix S_{on} which is generated by the switching function. It shows all possible combinations of the operation states of *n* appliances. It describe as

$$S_{on} = \begin{bmatrix} 0 & 0 & 0 & \cdots & 0 \\ 0 & 0 & 0 & & 1 \\ & \vdots & & \ddots & \vdots \\ 1 & 0 & 1 & \cdots & 1 \\ 1 & 1 & 1 & & 1 \end{bmatrix} \tag{2}$$

The dimension of S_{on} is a $(n \times 2^n)$. The row of the matrix is a set of the states of appliances. If all of the appliances except a_2 are off, the second column of the matrix becomes an array of 1. Using the transpose of this matrix and the matrix *P*, the truth table matrix P_{on} is then derived as follows

$$\begin{aligned} P_{on} &= P \cdot {S_{on}}^T \\ &= [P_1\, P_2\, P_3\ \ldots\ P_n] \cdot \begin{bmatrix} 0 & 0 & 0 & \cdots & 0 \\ 0 & 0 & 0 & & 1 \\ & \vdots & & \ddots & \vdots \\ 1 & 1 & 1 & \cdots & 0 \\ 1 & 1 & 1 & & 1 \end{bmatrix}^T \\ &= [P_1\, P_2\, P_3\ \ldots\ P_n] \cdot \begin{bmatrix} 0 & 0 & & 1 & 1 \\ 0 & 0 & \cdots & 1 & 1 \\ 0 & 0 & & 1 & 1 \\ \vdots & & \ddots & & \vdots \\ 0 & 1 & \cdots & 0 & 1 \end{bmatrix} \\ &= [0\ P_n \cdots\ P_1{+}P_2 + \cdots + P_{n-1}\ \ P_1{+}P_2 + \cdots + P_n] \end{aligned} \tag{3}$$

The truth table matrix P_{on} describes all possible combinations of the active power consumption of *n* appliances. The matrix has 2^{nd} elements. The number of elements also means the number of possible combinations of the power consumption of all selected electrical appliances.

Now, we introduce a matching process. Let $P_{T\_on} = [P_{T1}\, P_{T2}\ \ldots\ P_{Tm}]$ be a total active power consumption value during $t = t_1 \sim t_m$. The first element of this matrix P_{T1} is the total power consumption of *n* electrical appliances at initial time t_1. Then, P_{T2} is the total power consumption of *n* electrical appliances at $t_2 (= t_1 + \Delta t)$. Here, Δt is the time interval of data acquisition. Similarly, P_{Tm} is the total power consumption of *n* electrical appliances at final time $t_m (= t_{m-1} + \Delta t)$. At any time, each total power consumption value can be matched to an element of the matrix P_{on} as mentioned above. The element of P_{T_on} which is matched to P_{on} can be automatically addressed to an element of S_{on} because all elements of P_{on} are chained to S_{on}, respectively. As a result, the matching matrix S_{match} is generated. This matrix is a $(n \times m)$ matrix, where n is a number of appliances and m is a number of sampling data.

$$S_{match} = \begin{bmatrix} S_{11} & S_{12} & \cdots & S_{1m} \\ S_{21} & S_{22} & & S_{2m} \\ \vdots & & \ddots & \vdots \\ S_{n1} & S_{n2} & \cdots & S_{nm} \end{bmatrix} \quad (4)$$

It describes ON/OFF states of all the appliances versus time with binary code. i.g. S_{11}, S_{22} respectively represent the states of appliances a_1, a_2 at $t = t_1, t_2$. S_{nm} represents the state of appliance a_n at $t = t_m$.

From S_{match}, the power consumption profile of a home appliance a_i, $(P_{Profile\_on})_i$ versus time is generated as follows

$$(P_{Profile\_on})_i = P_i \cdot [S_{i1}\ S_{i2}\ \cdots\ S_{im}] \quad (5)$$

where $i = 1, 2, \cdots, n$ is the number of appliances, $j = 1, 2, \cdots, m$ is the number of sampling time. Regarding on this data, we can also graphically show the power consumption of each appliance $P_{Profile\_on}$. Its total power consumption $(P_{cons\_on})_i$ is calculated by

$$(P_{cons\_on})_i = \sum_{j=1}^{m} P_i \cdot S_{ij} \quad (6)$$

Then, total power consumption matrix of all appliances, $P_{cons\_on\_T}$ is calculated as

$$P_{cons\_on\_T} = \sum_{i=1}^{n} \sum_{j=1}^{m} P_i \cdot S_{ij} \quad (7)$$

2.2 Multi-state model algorithm

Some of the home appliances such as hair drier, clothes washer and drier, microwave, and toaster have multi-state operations. Each state can be described as ON/OFF state using a switching function. Let $a_{ik} = [a_{i1}\ a_{i2}\ \ldots\ a_{is}]$ be a multi-state matrix of an electrical appliance a_i which has multi-operation states ($k = 1, 2, \cdots, s$), and $P_{ik} = [P_{i1}\ P_{i2}\ \ldots\ P_{is}]$ be its active power consumption matrix at each operation state, from 1st to sth. A truth table matrix of Multi-state model a_i, S_{multi} is then described as follows :

$$S_{multi} = \begin{bmatrix} 0 & 0 & 0 & \cdots & 0 \\ 0 & 0 & 0 & & 1 \\ & \vdots & & \ddots & \vdots \\ 1 & 0 & 1 & & 1 \\ 1 & 1 & 1 & \cdots & 1 \end{bmatrix} \quad (8)$$

The dimension is a $(s \times 2^s)$. As using the switching function, each element of a_i can be considered to be an individual electrical appliance. However, unlike S_{on} adapted to ON/OFF appliances, the Multi-state model does not operate two or three states at the same time. Therefore, we have to remove some rows which have double or tautological ON, that is 1, in this truth table matrix. S_{multi} is finally derived as a $(s \times s)$ diagonal matrix.

$$S_{multi} = \begin{bmatrix} 1 & 0 & 0 & \cdots & 0 \\ 0 & 1 & 0 & & 0 \\ & \vdots & & \ddots & \vdots \\ 0 & 0 & 0 & & 0 \\ 0 & 0 & 0 & \cdots & 1 \end{bmatrix} \quad (9)$$

A power consumption matrix $P_{multi}$of an appliance a_i is then derived as

$$(P_{multi})_i = P_{ik} \cdot [S_{multi}]^T = [P_{i1}\ P_{i2}\ \cdots\ P_{is}] \quad (10)$$

where $k = 1, 2, \cdots, s$. s is the number of the operation states of an electrical appliance. Since the switching function matrix of this case is a diagonal matrix, every possibility of the power consumption of an appliance a_i is the same to the matrix $(P_{multi})_i$. Through a matching process, each element of P_{T_multi}, the power consumption matrix of the Multi-state model versus time can be matched to an element of P_{multi} like an ON/OFF model. All matched elements can be automatically addressed to an element of the switch truth table matrix S_{multi}. Then, the power consumption of a_i at any time t, $(P_{profile\_multi})_{ij}$ is obtained by

$$(P_{profile\_multi})_{ij} = \sum_{k=1}^{s} P_{ik} \quad (11)$$

As indicated above, $j = 1, 2, \cdots, m$ is time series of the number of sampling time. Then, the total power consumption of an appliance a_i, $(P_{cons\_multi})_i$, and all of the Multi-state models, $P_{cons\_multi\_T}$ during $t = t_1 \sim t_m$ are calculated as follows

$$(P_{cons\_multi})_i = \sum_{j=1}^{m} \sum_{k=1}^{s} P_{ik} \quad (12)$$

$$P_{cons\_multi\_T} = \sum_{i=1}^{n} \sum_{j=1}^{m} \sum_{k=1}^{s} P_{ik} \quad (13)$$

2.3 Composite model algorithm

Based on overall principles, for the case of the composite model algorithm, matrix A includes all of the ON/OFF models and the Multi-state models. Its truth table matrix S_{all} composes $S_{on}$of ON/OFF models and S_{multi} of Multi-state models. i.g. n, the number of elements of matrix A and P is the sum of the numbers of ON/OFF models and all states of Multi-state models.

$[S_{all}]^T$	$[P_{all}]$
...	...
00111	530
01001	580
01010	650
01011	730
01100	800
01101	880
...	...

	t_1	t_2	t_3	t_4	t_5	t_6	t_7
P_T	800	800	880	580	730	730	880

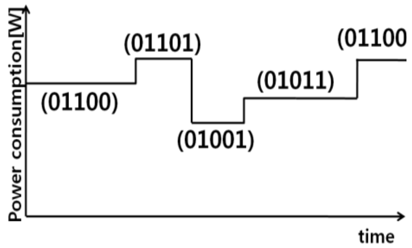


Fig. 2. An example of switching function, truth table matrix, total power consumption matrix and matched value

The truth table matrix S_{all} becomes $(n \times 2^n)$ matrix. However, as discussed before, to avoid synchronous operations in any duplicated appliances, we remove some rows which have double or tautological 1 at the multiple-state columns of the matrix S_{all}.

After obtaining S_{all}, we can also obtain its power consumption matrix P_{all} in the same way to above process. The matrix P_{all} has the rows of P_{on} and the rows of P_{multi}. Then, every element of P_{all} is matched to an element of the end-use power consumption matrix versus time P_T. Finally, we can get disaggregated load profiles of each electrical appliance. The power consumption of a_i at any time t is calculated as Eqs. (5) and (11). The total power consumption of each appliance and all of the considered appliances in total period can be calculated as (6, 7), (12), and (13), respectively.

Fig. 2 shows a basic concept of this algorithm. We can generate the truth matrix S_{all} and the power consumption matrix P_{all} as knowing the number of each state of appliance and its consuming power P_i. Then, P_T can be matched to P_{all} and be addressed to S_{all}.

3. Methodology

In order to apply the presented algorithm to the load monitoring of home appliances within a residential building sector, we propose a disaggregation framework. It is illustrated in Fig. 3. There are five layers of the framework: data acquisition, quantization, matching process, error adjustment, and disaggregation data analysis.

At the first layer, power consumption profiles of each electrical appliance and ensembles of electrical appliances are measured. Then the acquired data is applied to the algorithm proposed in Section 2 for quantization and matching process. In order to reduce the errors of the process, error adjusting algorithms are additionally developed. Finally, disaggregation results are analyzed. The details of the framework are explained as follows.

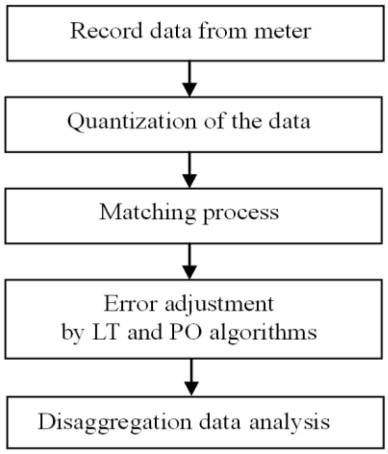


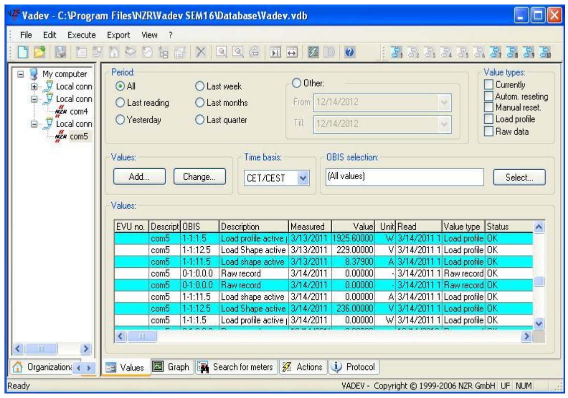
Fig. 3. Flowchart of the methodology

3.1 Data acquisition

Total power consumption profiles of electrical appliances are acquired by NZR Standby-Energy-Monitor 16 (NZR SEM 16). This device measures and stores the following values of a home appliance: current, voltage, active power, energy consumption, energy costs, and maximal/ minimal power during the measurement. The sampling time is 1 [min].

The load profiles, such as current, voltage, and power consumption of each electrical appliance are firstly

(a) NZR SEM 16 device



(b) VADEV Distance meter reader

Fig. 4. Electrical power monitoring device and meter reading system

acquired by NZR SEM 16 device. It leads to define typical load profiles of ON/OFF models (e.g. a lamp, a kettle, a modem, etc.), Multi-state models (e.g. a hair dryer, a television, a monitor, a heater, a fan, etc.), and Cyclic models (e.g. a rice cooker, a refrigerator, etc.). Then, the load profiles of ensembles of electrical appliances which are selected by their function modes are measured. The data will be disaggregated at the final layer of the study.

All the data measured by NZR SEM 16 device are transferred to the data reading program VADEV Distant meter reading system installed in a host computer via an USB interface. The features of the measuring device and the distant meter reading system are shown in Fig. 4.

3.2 Quantization

Each load profile of electrical appliances is not constant due to the supplied voltage variation which causes the variations of current and power consumption. Moreover measuring device captures the average values which measured during a certain sampling time. Therefore, it is not necessary to keep all of the various values. Thus, we chose the most frequent active power value of each state of each appliance, as a representative value. With these modal values, matrix *P* and P_{all} are generated.

Then, each element of P_T are compared with each element of P_{all} matrix which shows the all usage possibility of electrical appliances included in the matrix *A*. After that, it is replaced to the nearest element of P_{all}. Author calls this process a quantization.

3.3 Matching process

After the quantization of measured total load profiles, each data at each time is matched to an element of matrix P_{all}. Since all of the elements of P are addressed to one of the rows of the truth table S_{all}, the treated data also have an address which describes the state of all appliances as discussed in Section 2.

In this process, errors of quantization can be observed and be detected. Although we avoided the identical power consuming appliances, there would be any appliance consumes relatively small power comparing with other appliances. It may cause the error of quantization. Moreover, unexpected data during the transition because of the sampling time appears and causes an uncorrected matching.

3.4 Error adjustment

In order to adjust the errors during the above process, we developed two additional algorithms. Firstly we applied a Time Lagging (TL) algorithm during transition periods. If a value at $t = t_1$ differs from its previous two values (at $t = t_1 - 2\Delta t, t_1 - \Delta t$) and its later ones (at $t = t_1 + 2\Delta t, t_1 + \Delta t$), we call this moment a transition period. Since the value at $t = t_1$ does not reached to the stable point, this value is replaced by the previous value. In the same way its inverse state maybe exists, the sum of total consumption of the appliance will not be fatally changed.

Secondly, we used a permanently-On (PO) algorithm. It searches permanently-On state models to exclude their OFF states. It removes any row which has useless state on the truth table matrix.

3.5 Disaggregation data analysis

After the error adjustment process is done, we can get each appliance's usage profiles versus time. This disaggregation data provides the detailed information of power consumption of each electrical appliance and their performance to the electricity suppliers and the consumers. Furthermore, the information can be reproduced for calculating economical and environmental impact of the buildings. Moreover, it can be also used for analysis on the user's presence or behavior patterns of the buildings, etc.

4. Applications

In this section, we present the experimental procedures, the experimental results, and the simulation results. The experiments were conducted in an author's residential building, and the proposed algorithms were implemented in Matlab® in order to validate the proposed methodology.

4.1 Experimental procedures

The selected home appliances relevant to this study are a kettle, a lamp, a modem, a television, a computer monitor, a hair dryer, a battery charger, a refrigerator, a laptop computer, and a desktop computer. Overall experimental procedures are illustrated in Fig. 5. As stated in Section 3.1, measurements of each appliance were firstly achieved in order to acquire their preliminary data. It aims to determine the typical load profiles of each appliance and further disaggregate them. Among the tested appliances, a modem, a lamp, a television, a kettle, and a hair dryer were then selected according to the functions of each appliance. Since we used ON/OFF models and Multi-state models for using switching function, the appliances which consume the

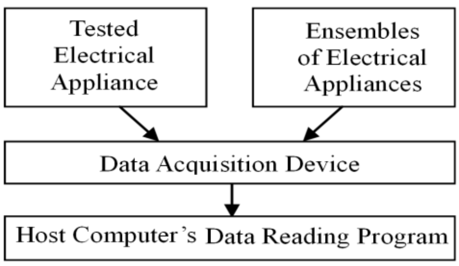


Fig. 5. Overall experimental procedures

same quantity of power to other appliances were excluded. Measurements of the ensembles of appliances were then acquired in an author's residential building. The measured data were finally transferred to the host computer.

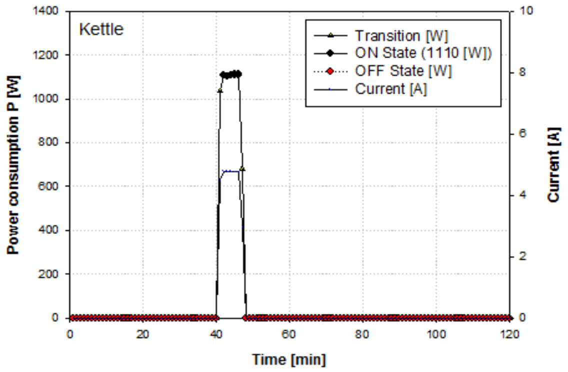
4.2 Experimental results

The measured current and the measured power consumption data of these appliances are shown in Figs. 6 (a)-(e).

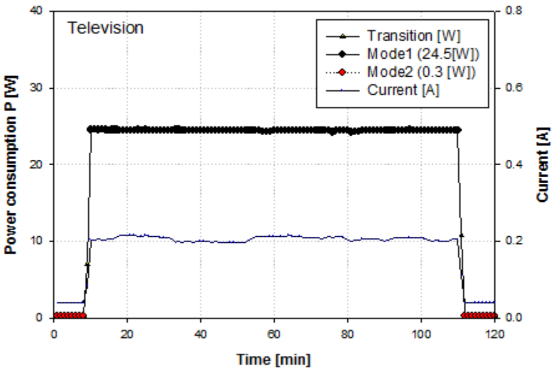
ON/OFF state of a kettle is shown in Fig. 6(a). The On state lasts during five minutes. Then, a transition period is observed when the state of the kettle is changed from the OFF state to the ON state, and vise versa. A lamp, an iron, and a modem have the similar forms to the kettle with different magnitudes of the voltage and the current. However, the modem permanently functions at the On state by user's necessity.

Fig. 6(b) depicts two modes of a television which indicate the normal On state (mode 1) and the standby state (mode 2). A computer monitor has also the standby state and the On state. While these appliances are not turned on, they remain at the standby mode and continuously consume the small powers less than 0.6 W except to the unplugged situation.

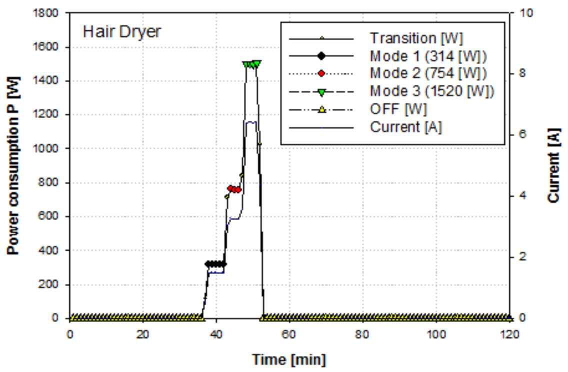
Figs. 6(c), (d) describe profiles of a hair dryer and a rice cooker. They represent the Multi-state model. Although they have the same number of modes, their functions are



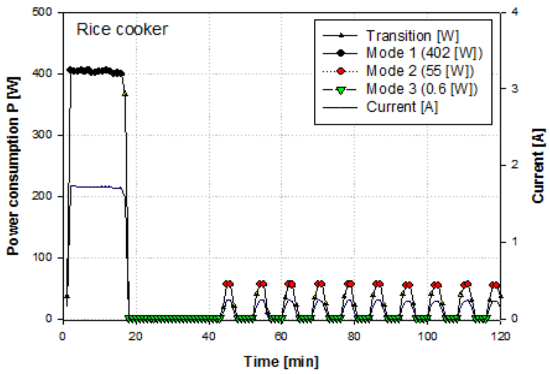
(a) Kettle



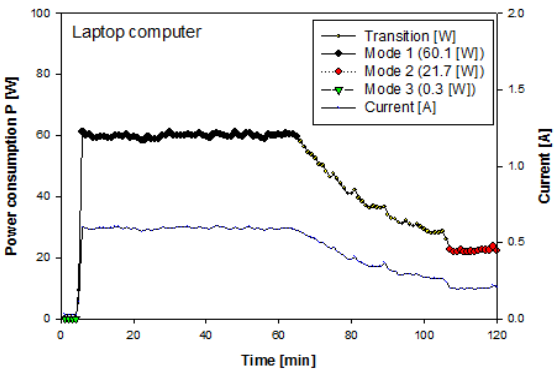
(b) Television



(c) Hair Dryer



(d) Rice Cooker



(e) Laptop computer with electric charger

Fig. 6. Measured current and active power of electrical appliances

different. In the case of the hair dryer we can select its state according to our need or preference, but the rice cooker automatically functions with its own cyclic period. During the first seventeen minutes, the rice cooker consumes about 402 W to boil the rice. During the next twenty five minutes, the standby mode remains. After this first cycle, it has another cycle which repeats heating and keeping warmth every 8-9 minutes. A refrigerator also has the cyclic period.

Fig. 6(e) shows the load profile of a laptop computer which is connected to its battery charger. This profile has three modes and especially has a long transition period. Since this period is long and various, it gives a difficulty to determine its state for generating a truth table and to disaggregate it from the total power consumption data. Moreover, it can include several power consumption values which are the same to the values of other electrical appliances.

Based on these measured data, we classified their function as described in Table 1. The ON/OFF model is classified by two characteristics as 'Permanently-On' model and 'Controllable' model. The 'Permanently-On' model always remains at On state by user's necessity. The 'Controllable' model means that user can select appliance's state. The Multi-state model has four characteristics: 'Permanently-On' model, 'Controllable' model, 'Cyclic' model, and 'Continuously various' model. 'Cyclic' model has its own cyclic patterns of power consumption and 'Continuous varying' model has also its own patterns but has no cyclic function. Examples of the electrical appliances according to this classification are also listed in Table 1.

Table 1. Classification of Home appliances

Model	Characteristics	Appliance
ON/OFF	Permanently-On	Modem
	Controllable	Lamp, Kettle, Iron
Multi-state	Permanently-On (Standby)	TV, Monitor
	Controllable	Hair dryer
	Cyclic	Rice cooker, Refrigerator
	Continuously various	Laptop computer, Desktop computer, Charger

We selected several appliances to adopt our proposed disaggregation framework. Table 2 describes the selected home appliances and their active power consumptions. The appliances which consume small power, like a modem or a television which is on standby state can be still included in Table 2. It is an advantage of the truth table matrix which considers every combination of appliance states. However, since our model algorithms are based on the switching function and the truth table matrix, we excluded the cyclic Multi-state model and the continuous varying Multi-state model. They are not able to be adapted to the used principles.

Table 2. Selected Home appliances

Model	Appliances	Active Power consumption [W]
ON/OFF	Modem	6.9
	Lamp	25.2
	Kettle	1150
Multi-state	Television	0.3
		23.8
	Hair dryer	310
		754
		1500

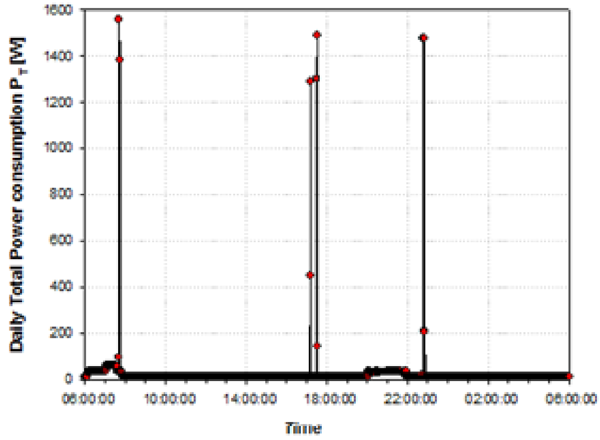


Fig. 7. Measured total power consumption profile of selected appliances during a day

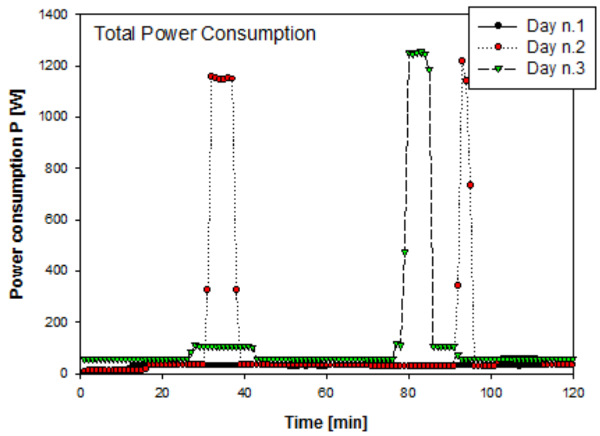


Fig. 8. Measured power consumption of ensembles of selected appliances during short term periods

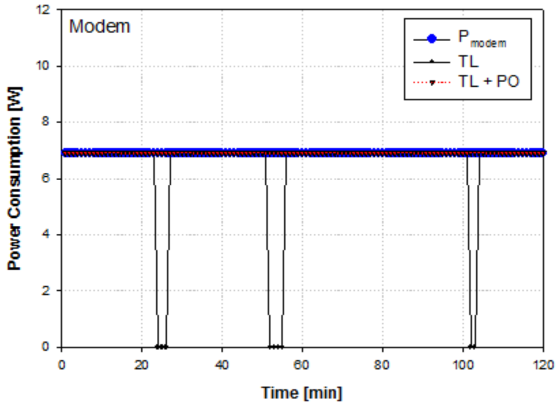
Fig. 7 shows a measurement result of whole day end use profile of the selected electrical appliances. The total usage profiles of the home appliances are related to user's schedule and patterns. Since the appliances do not operate all the times, we conducted on the experiment during two hours while the appliances are more frequently used. Fig. 8 displays the measured data of total power consumption profiles of selected electrical appliances. We measured the data three times because the profiles are different according to the usage patterns.

4.3 Disaggregation results

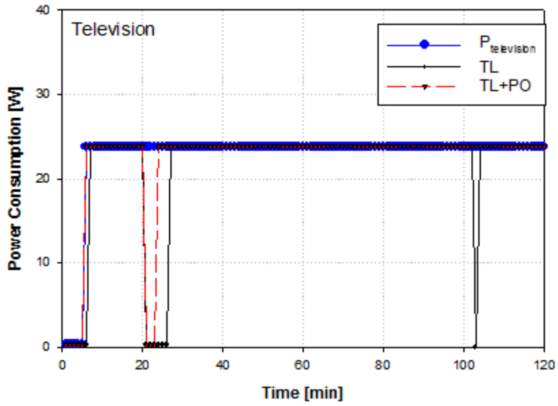
The proposed algorithms were implemented in Matlab® . Then each disaggregated load profile of the ensembles of the selected electrical appliances was obtained by the sequential framework proposed in Section 3. Figs. 9 (a)-(f) display the disaggregation results of the Composite model of selected home appliances.

In order to adjust errors revealed on quantization, we used a Time Lagging (TL) algorithm in transition periods. Then, we reduced the errors by prohibiting the Off state of the Permanently-On model (PO). After applying these error adjustment processes, we compared the results with the real states and real power consumption of each electrical appliance.

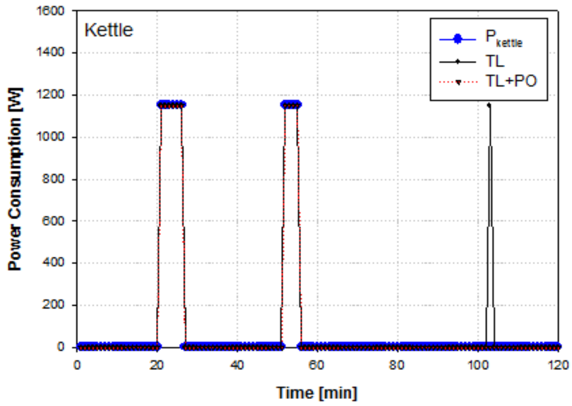
As a result, the accuracy of each case are obtained as follows: 92.62 %, 94.26 %, 99.18 %, 93.44 %, 98.36 % with TL adjustment and 100 %, 97.54 %, 100 %, 97.54 %, 100 % with TL+PO adjustment for the modem, the lamp, the kettle, the television, and the hair dryer. The measured



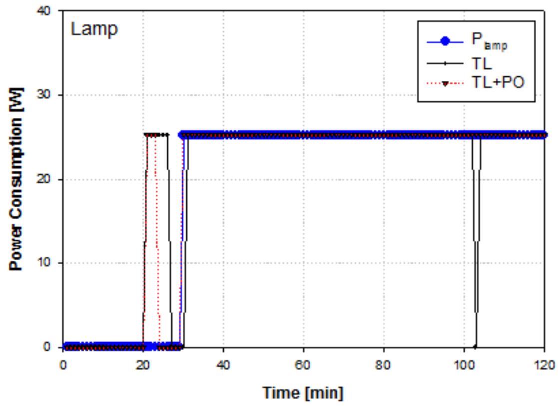
(a) Model



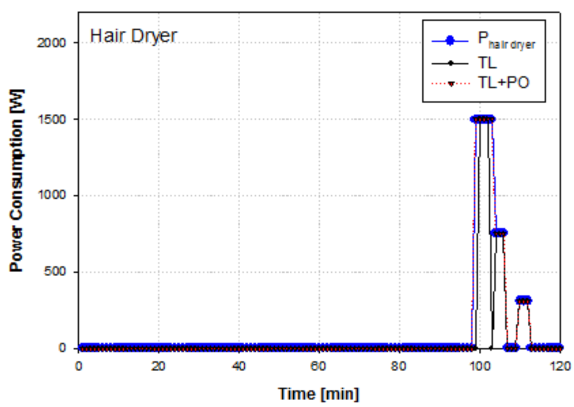
(b) Television



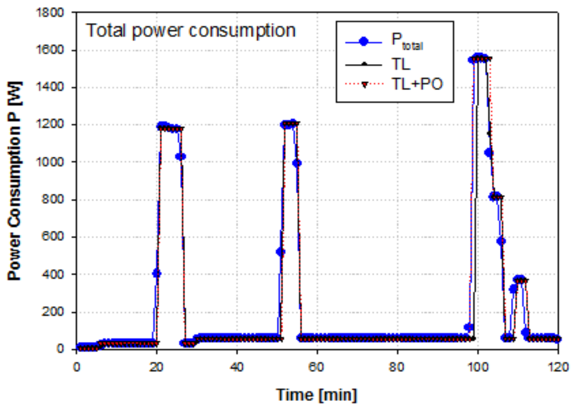
(c) Kettle



(d) Lamp



(e) Hair dryer



(f) Total power consumption

Fig. 9. Disaggregation results

end use total power consumption is 28,113.2 W. The obtained total power consumptions by the simulations using TL and TL+PO are 26,113.6 W, and 28,118.2 W, respectively. The accuracy of the total measured power consumptions are each 92.88% and 99.98%.

5. Conclusions

This paper proposed a new algorithm to disaggregate the power consumption of electrical appliances in a residential building sector. The active power profiles were selected as the load signature for identifying each electrical appliance. The proposed algorithm disaggregates Permanently-On models, ON/OFF state models as well as Multi-state models. To identify each state of the models, binary codes were generated by a switching function. Then a truth table matrix and a matching process were proposed to distinguish each state. For improving disaggregation accuracy, a time lagging (TL) algorithm adapted for transition periods and a removing Off state of Permanently-On appliance (PO) algorithm were additionally developed. The proposed algorithms were evaluated by a case study in practice. The comparisons of the results obtained by experiments and simulations were achieved. Finally, the proposed algorithms were validated with a high accuracy. However, continuous variable appliances and identical power consumption appliances were not yet disaggregated because of the possibility of duplication of power profiles among electrical appliances. It will be the next topic of our investigation.

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