

Design of Algorithms for Identification and State Inference of Home Appliances

Sukil Hong¹, Joongjin Kook^{2*}

¹Senior Research Engineer, Ph. D., Software Platform R&D Lab, Software Center, LG Electronics, Korea.

²Assistant Professor, School of Information Security Engineering, Sangmyung University, Korea.

*Corresponding Author

ORCID²: 0000-0002-0033-388X

Abstract

Many countries have used EMS as the national standard for the efficient use of energy. In particular, as the number of home appliances increases, the power consumption at home is rapidly increasing, and thus, IoT-based HEMS-related smart meter products have recently been released. However, smart metering products provide only the billing information through statistics on the on/ off status of home appliances and the accumulated power consumption. Better intelligent management requires automated reasoning for the types of home appliances and a good grasp of the management for divided states by device.

In this paper, we studied the methods of the identification and the inference of the states of home appliances that are first required for the management of intelligent home appliances, and verified them by using several kinds of products used at home.

Keywords: Smart home, Home appliance, ILM, NILM, HEMS

I. INTRODUCTION

Many countries, including the U.S, Denmark and the U.K, have established EMS as the national standard in order to use energy efficiently. Korea has also expanded the adoption of EMS. EMS is needed not only in energy-consuming factories and buildings, but also in households that use many kinds of home appliances. In particular, with the increase in home appliances, the power consumption at home has soared, and a burdensome in the electricity bill has also increased. This situation has led to the release of HEMS-related smart metering products are being released for home use.

Smart metering products used at homes generally consist of adapters, as shown in Fig. 1, and are connected to the Internet through a router. The amount of power consumption and the billing information measured by the device is stored and processed through the cloud and made available to users through PC applications and mobile apps. It also notifies the on/ off state of home appliances connected to each port and provides the function to control the states through the apps.

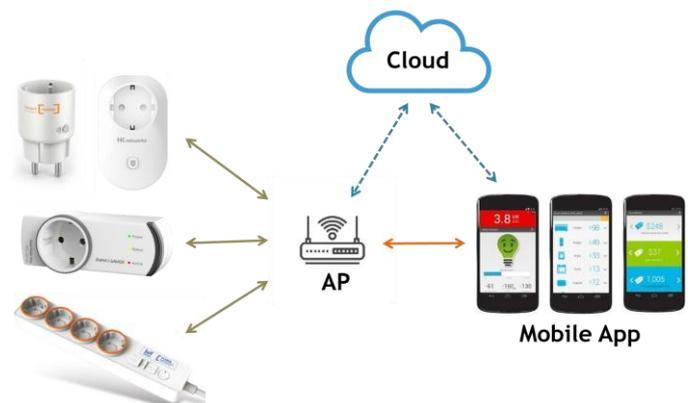


Fig 1. Smart Metering Devices and Services

Because these systems only measure the power consumption and do not manage information about home appliances, information about the products should be managed by the user. Of course, information about the home appliances can be stored by inputting it on the server, but there are problems that it is inconvenient because the user has to input it manually, and that the home appliance information needs to be modified when the device is replaced. Thus, in this paper, we studied the identification method of home appliances, which is the first requirement for intelligent power management.

In order to identify home appliances, we designed algorithms to detect the characteristics of products, generate information, and determine the active/ inactive/ idle state, and we verified the functions through several types of products used at home.

II. RELATED WORK

Even before the introduction of smart grid technology, the researches to monitor the power consumption of home appliances have been actively conducted. First of all, the methods of measuring the power consumption can be largely classified into ILM (Intrusive Load Monitoring) and NILM (Non-intrusive Load Monitoring) [1].

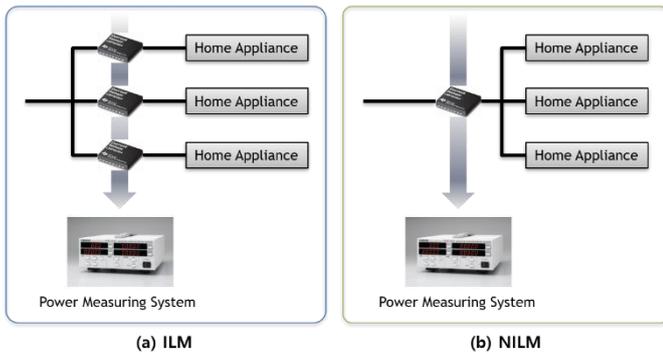


Fig 2. ILM vs. NILM

Fig. 2 shows the comparison between ILM and NILM methods for measuring the power consumption. In the case of ILM method, many power measurement sensors are individually attached to each home appliance, and data is collected by measuring power used. In the case of NILM, on the other hand, uses a single power measurement sensor to measure the main power line and collect data. ILM method is good at checking the amount of power consumed by each device, but it is expensive because it requires the use of multiple sensors. NILM method is low-cost and is easy to use even in non-specialized environments. In particular, the cost of installing EMS is not small unless the building is recently constructed.

Since all devices are connected to the main power line, the purpose of NILM method is to determine power consumption patterns of individual devices and to classify them by device. The AC power used by most home appliances is more cyclical than the DC power, so this pattern is analyzed and home appliances are identified. As for this pattern, the higher sampling period it has, the more unique signature of home appliances can be identified. A study to identify their signatures of random home appliances and to diagnose them through a single power meter [2-6] has been conducted. In addition, various studies have been carried out, such as applying the network to the demand management or monitoring overcurrent conditions in buildings [7-8].

In the past, the reason for measuring the power consumption was simply to collect measured quantities. Recently, the measured data is analyzed to identify home appliances and to find out detailed power consumption distribution [9-10]. The researches to identify home appliances mostly include NILM method, and the ability to identify home appliances enables efficient management of the home appliances, and builds an intelligent DR to shut off power from less frequently used appliances. NILM method uses the analysis of power consumption changes, of current waveforms, and of power consumption characteristics when the device is turned on/ off [11-13]. Special sensors need to be used to measure this data, but nowadays EMS smart metering devices are also used [14]. However, when using NILM method, it is very difficult to distinguish the same kind of home appliances.

Recently, both methods have been used to build EMS. In the case of the built-in outlet or adapter-type EMS client installed at home, ILM method to processes each measured data on EMS server is used. However, as for old houses, the installation cost of ILM method is too high, so NILM method is also used.

Meanwhile, as for multi-family houses or buildings, data is exchanged with external network such as remote meter reading through AMI by measuring with ILM method at each house or floor and by processing with NILM method in EMS. In this paper, we design the ILM-type HEMS to monitor the power consumption of home appliances and to identify home appliances based on general current values and power values rather than the frequency analysis.

III. PROPOSED SCHEME

III.I Appliances State

The states of home appliances refer to the state in which home appliances are in operation and is highly related to the power consumption. The states of home appliances are divided into two: the device is turned on/ off. The power consumption value of the state in which the device is turned off is 0A and the power consumption value of the state in which the device is turned on is greater than 0A. In addition, the state in which the device is turned off is defined as the static state, and the state in which the device is turned on is defined as the active state. All home appliances have a static state and an active state. All home appliances in the static state have the same power consumption value, but home appliances in the active state have different power consumption values. The active state can be divided into a single activity state and multiple activity states depending on home appliances. Devices with a single activity state can usually be expressed as a single power consumption value in the form of turning the power on/ off. On the other hand, devices with multiple activity state have irregular power consumption patterns in the active state, and cannot be expressed as a single power consumption value. The state of being active and consuming power without performing the main purpose of the device is called the idle state. This idle state is mainly used to wait for a remote control signal or to respond to a network. The idle state consumes less power than the active state, but it can prevent energy waste by shutting down the power.

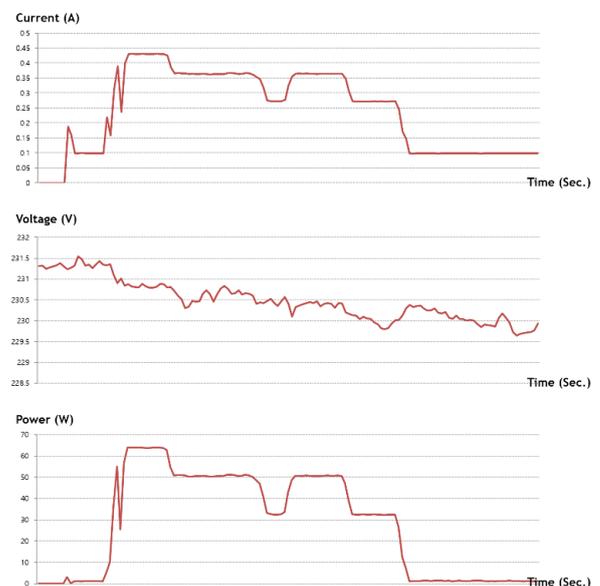


Fig 3. Power Consumption Pattern

Fig 3 shows a graphical representation by connecting TV to a client and by monitoring the power consumption on the server. Fig. 4 shows the state based on the current values that are relatively distinct among the power consumption information of the TV. The state before connecting the power to the client is the static state, and it is changed into the active state when the power is connected. At this time, the state of waiting for the input from the remote control is the idle state. Some home appliances need to maintain the idle state for charging. Except for these devices, the static state and the idle state are defined as being good even when shutting off the power.

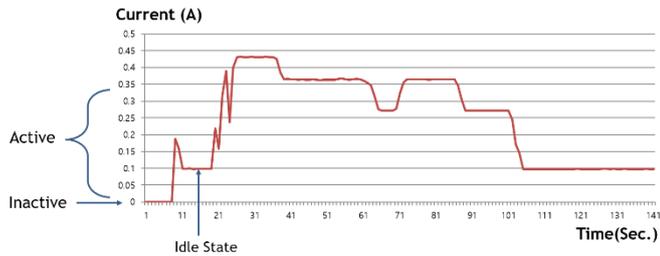


Fig 4. Active and Inactive State for TV

In order to store the information of home appliances in a database, the characteristics needs to be extracted by analyzing the power consumption patterns of home appliances. In order to extract these characteristics, a reference value for the power consumption of home appliances is first required, and the reference value needs to be defined in the power consumption pattern graph. Fig. 4 clearly shows the change of state of current consumption (I) and power consumption (P). However, the power consumption (P) graph uses the current consumption value (I) to distinguish the reference value because there is not much difference between the power consumption values (P) in the static state and in the idle state. However, because the power consumption value (P) is also used, the reference value mentioned in this paper is designed as a data structure that stores the current consumption value (I) and the power consumption value (P) together. Because the analog signal is converted to the digital value without a separate filter, it shows a noise-like shape instantaneously when the running current and the state change is made after the power is first turned on. And then, it remains stable values over time. Therefore, it is difficult to extract the reference values in the existing graph without processing, thus simplifying the graphs and using them as the reference values. First, the current consumption values (I) arbitrarily measured are defined as the reference values, and the current consumption values (I) within the range are determined as the reference values by setting the tolerance range as shown in Fig. 5. If they are outside the range of a certain number of times (N), a new reference value is defined to set the tolerance range again.

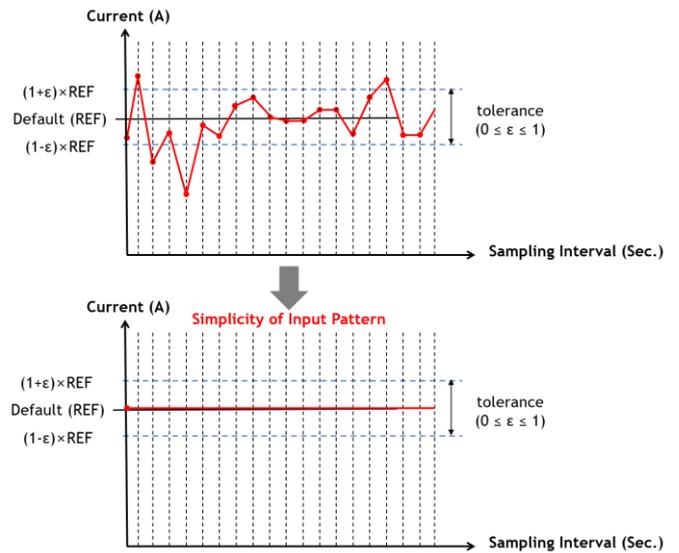


Fig 5. Simplicity of Current

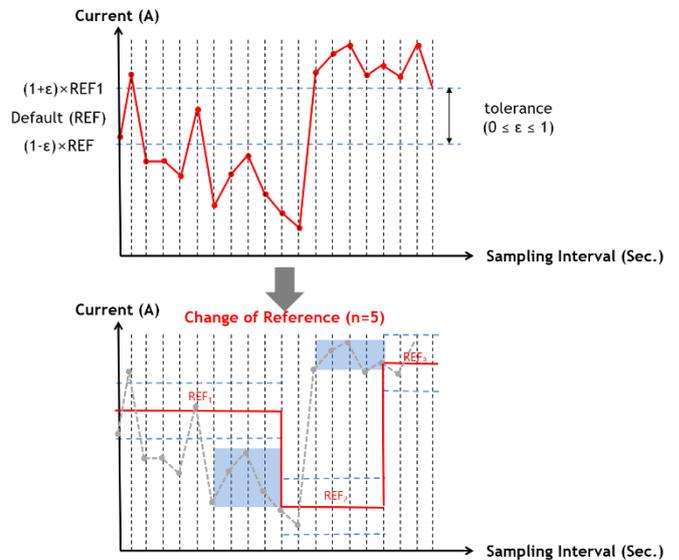


Fig 6. Change of Reference ($n = 5$)

Fig. 6 is an example of a change in the reference values for five consecutive deviations from the tolerance range. The reference values changed three times in total, and each reference value is characteristic value of the power consumption of the home appliance. These reference values are set only in the active state other than the static state and have various reference values depending on the type of home appliance.

The change in the reference values due to the change in the state of the home appliance is defined as an event, and the change in the state of the home appliance is detected. The event is divided into RISING event and FALLING event. The events that occur beyond the tolerance range 1 are called RISING events and the events that occur below the tolerance range 1 are called FALLING events, as shown in Fig.7.

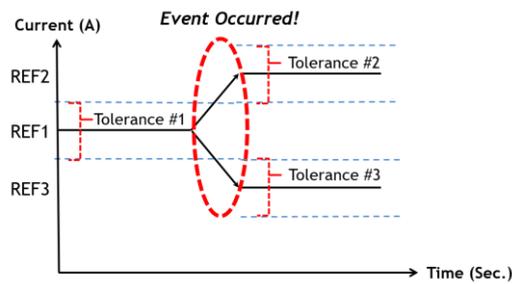


Fig 7. Event Detection

Whether or not an event occurs is checked using Equation (1) and (2) below, where REF represents a reference value, I represents an input value, and T_{Range} represents a tolerance range ratio. If the tolerance range ratio is too large, the event detection becomes too small. Otherwise, the event detection becomes too large. Thus, 5% is set as the basis through experiments and it can be modified using API.

$$REF + (REF \times T_{Range}) < I \quad (1)$$

$$REF - (REF \times T_{Range}) > I \quad (2)$$

When an event is detected, it is determined as a RISING event in case of Equation (1) and a falling event in case of Equation (2). Fig. 8 shows the algorithm for event detection.

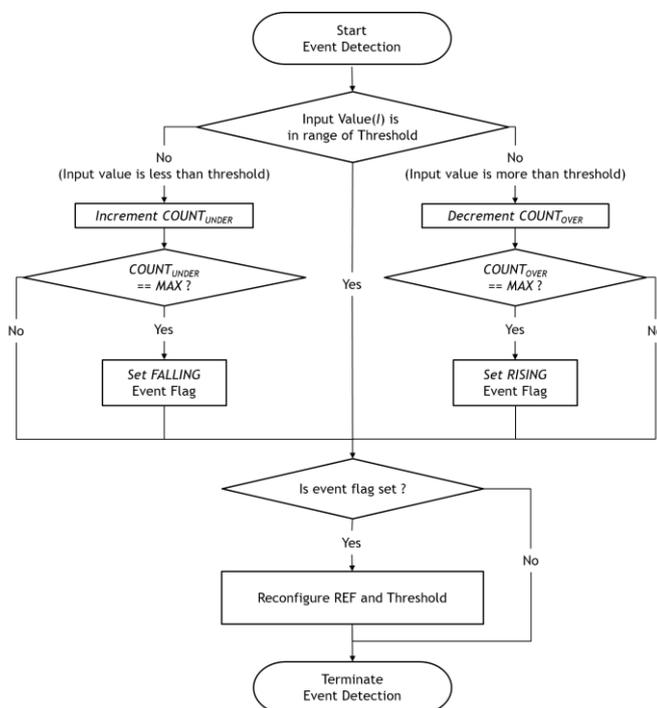


Fig 8. Flowchart for Event Detection

III.II Standby Power

The power consumption of home appliances in the idle state is called the standby power. In general, this power consumption is unnecessary power, and can be cut off by disconnecting the outlet from the home appliances. However, most users leave the standby power unattended because of the inconvenience of disconnecting and reconnecting the outlet. In this paper, if the idle state is maintained when automatically diagnosing the idle state of the home appliance and monitoring the power

consumption on the server, the standby power of the home appliance is cut off by sending a command to the device. The conditions for determining whether the home appliance is using the standby power are as follows. If the conditions are met, the standby power values are stored in the database.

Condition 1: If at least two reference values and REF_m (reference values of the power consumption) are called set R , then the set R must meet the following condition:

$$R = \{REF_1, REF_2, \dots, REF_m\}, (m \geq 2)$$

$$REF_1 < REF_2 < \dots < REF_m$$

Condition 2: The standby power value ($REF_{standby}$) is equal to the smallest reference value (REF_1).

$$REF_{standby} = REF_1 (REF_1 > 0)$$

Condition 3: The standby power value ($REF_{standby}$) is less than half of the largest reference value (REF_m).

$$REF_{standby} < \frac{REF_m}{2}$$

Condition 4: The standby power value ($REF_{standby}$) is less than the average value (AVG) of all reference value differences.

$$REF_{standby} < AVG$$

$$where, AVG = \frac{\sum_{r=1}^{m-1} |REF_r - REF_{r+1}|}{m-1}$$

In condition 1, the results of measuring the home appliance power consumption reference value needs to be two or more. If the reference value is one, it is classified as a single active device and it is determined that there is no idle state. Because home appliances in the idle state generally use the smallest standby power, the smallest reference value is used as the standby power value in condition 2. Because the power consumption of home appliances in the active state is the highest reference value and the standby power value is in the idle state, in condition 3, less than half of the power consumption value in active state is assumed. In condition 4, if there are more than one reference value of the power consumption, the average value of the differences in the all reference values is greater than the power consumption value in the idle state.

If all four conditions are satisfied, the home appliance is determined to be in the idle state, and the standby power value is recorded and stored in the database. If any of four conditions is not satisfied, it is determined that it has no idle state and the standby power value is recorded as 0. Later, while monitoring the power consumption of home appliances, the home appliances are used as a basis for determining the idle state, and if it remains in the idle state for a certain time ($T_{standby}$), it is cut off the power.

The device with the highest probability of matching is determined among the home appliances registered in the database, by analyzing the power consumption data of the home appliances currently being monitored. Home appliance matching probability (P_{MATCH}) is calculated in real-time every time the power consumption data is input. In this paper, the identification process is automatically terminated when there is a device that matches more than 80%. In addition, if the user

requests the identification manually during the device identification process, the identification process is terminated immediately and the device with the highest probability of matching is chosen.

$$P_1 = \frac{C_{Matched}}{C} \quad (3)$$

$$P_2 = \frac{N_{Matched}}{N} \quad (4)$$

$$P_{MATCH} = \omega P_1 + (1 - \omega)P_2, \text{ where } 0 < \omega < 1 \quad (5)$$

Equation (3) is the probability (P_1) of the home appliances that match the power consumption data, and is obtained by dividing the number of matching data ($C_{Matched}$) by the total number of input power consumption data (C). Equation (4) is the probability (P_2) of the home appliances that match the reference values recorded at the time of event, and is obtained by dividing the number of matching reference values ($N_{Matched}$) by the total number of recorded reference values (N). At this time, the matching reference values need to match the current consumption value (I) and the power consumption value (P), respectively. Equation (4.5) is an equation for calculating the probability ($P_{Matched}$) of matching home appliances, and is obtained by multiplying the probability of matching data (P_1) and the probability of matching reference value (P_2) by the weight (ω), respectively. The weight (ω) is used because the frequency and the importance of the probability of matching (P_1) and the probability of matching reference value (P_2) are different. In particular, the total number of reference values is different for each home appliance, and the current consumption value (I) and the power consumption value (P) need to be consistent. Therefore, in this paper, the weight (ω) is set to 0.2 to increase the proportion of the probability of matching reference value (P_2).

V. EXPERIMENTS AND RESULTS

The experimental environment and conditions proposed in this paper to verify the identification and the standby power cut-off of home appliances are as follows. First, Table 1 shows 10 home appliances used in the experiment.

Table 1. Home Appliances List

ID	Appliance	Manufacturer	Model
1	TV	LG	47G2
2	TV	LG	42LM6100
3	LCD Monitor	LG	M2762D
4	Laptop PC	ASUS	N55S
5	UMPC	SAMSUNG	Q1
6	Fan	LAMI	LM-12G
7	Microwave	SAMSUNG	RE-C20DV
8	Refrigerator	LG	R-B144GD
9	Lamp	SAMJUNG	SS-408
10	Blue-Ray Player	LG	BD 390

We connect each home appliance and use it for a certain period of time. At this time, the server receives the power consumption data for each home appliance, analyzes the characteristics of the home appliance, and generates the home appliance information. In addition, in the process of generating home appliance information, it checks for the idle state, informs the user the diagnosis results, and automatically builds a database by reflecting the feedback.

Table 2 shows the configuration of parameters for the identification of home appliances and for the evaluation of the idle state.

Table 2. Parameters for Evaluation

Parameter	Value (unit)	Description
N	5	The number of consecutive deviations from the reference value
T_{Range}	50 (= 5 %)	Tolerance of reference value (0~1000, 0~100%)
P_{MATCH}	80 (%)	Minimum match probability for identifying appliances
ω	0.2	Weight for data match probability (P_1)
$1 - \omega$	0.8	Weight for the criterion value match probability (P_2)
$T_{standby}$	180 (sec)	Minimum time to determine standby state

The power consumption data of home appliances is analyzed, and then the conditions for evaluating the idle state are checked. After diagnosing whether or not the idle state is, its result is informed to the user. Table 3 shows the information generated automatically by analyzing the information of 10 home appliances, and it also includes the idle state diagnosis results.

Table 3. Results

ID	Appliances Information		Idle State Diagnosis		
	Type	State (Level)	Idle State	Current (A)	Power (W)
1	TV	Multiple (5)	O	0.094	1.16
2	TV	Multiple (5)	O	0.098	1.34
3	LCD Monitor	Multiple (5)	O	0.068	4.23
4	Laptop	Multiple (8)	O	0.116	5.69
5	UMPC	Multiple (7)	O	0.195	16.99
6	Fan	Multiple (3)	X	-	-
7	Microwave	Multiple (3)	O	0.253	43.47
8	Refrigerator	Multiple (1)	X	-	-
9	Lamp	Multiple (1)	X	-	-
10	Blue-Ray Player	Multiple (4)	X	0.168	16.94

According to the generated information, home appliances are divided into multiple or single activity states. In the case of multiple activity state, the number of states and the reference value information for each state are recorded. In addition, the diagnosis of the idle state is performed normally, but there are also some home appliances, such as Blu-ray player, of which the power consumption value in the idle state is too large to meet the diagnosis conditions. In this case, however, there is no problem by reflecting the feedback of the user in the idle state. On the other hand, in the case of laptops and UMPS, even if the idle state is diagnosed, the power must not to be cut-off for charging, so they are classified and managed as charging devices.

VI. CONCLUSION

In this paper, we studied the identification methods of home appliances that are first required for the intelligent power management.

In order to identify home appliances, we designed algorithms to detect the characteristics of products, generate information, and determine the active/ inactive/ idle state, and we verified their functions through several types of products used at home.

For the accurate inference of their type and their state of home appliances, it is necessary to set unique parameters for each type, but it was limited to apply the parameters to all products due to products with similar characteristics and no clear difference. However, it is expected to be overcome these problems by using AI technology such as machine learning in the future.

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