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Home Electricity Consumption Monitoring Enhancement Using Smart Device Status Information

Sung-Yong Son

Department of Electrical Engineering, Gachon University,
Seongnam-Si, Gyeonggi-Do, 461-701, Korea
xtra@gachon.ac.kr

Abstract

Electricity consumption monitoring to understand energy consumption status and patterns is the first step in reducing the electric cost for a house. Conventional electricity consumption monitoring systems usually rely on specially designed power measuring equipment such as a smart meter or sub-metering device. However, it is not easy to obtain enough information for energy monitoring because the limited number of measuring equipment can be installed due to their costs and privacy issues. Therefore, the status of devices could be usually inferred from limited information using the technology called non-intrusive appliance load monitoring. However, the limited information causes inaccuracy in estimating operation status of the devices. Many efforts have been performed to improve the estimation accuracy. Smart devices including smart appliances have been deployed recently to provide more advanced services at home. Network connectivity is one of the essential functions for the smart devices. When the operation information of those smart devices can be shared with energy monitoring devices, it can improve the energy consumption monitoring. In this paper, a hybrid approach is proposed to improve energy consumption status estimation. Devices' status information is shared via ubiquitous home networks in addition to the conventional energy consumption monitoring. This approach makes the energy consumption inference more simple and accurate for the rest of unknown devices.

Keywords: *Disaggregation, NALM, appliance, smart meter*

1. Introduction

An electricity consumption pattern of a house includes lots of information such as lifestyle, the number of families, and appliance possession. The information can be used to develop more advanced and various services. Understanding of energy consumption patterns is also important for energy management. However, the information we can obtain to infer the detailed energy usage of individual devices is usually limited because it is in the private space. Therefore, energy usage estimation for devices at home from single measured metering data that is also called disaggregation becomes important. There have been many studies for non-intrusive appliance load monitoring (NALM) that pursues finding individual appliance usage from aggregated energy consumption data since proposed by Hart in [1]. In addition to power consumption, other features such as harmonics, power factors, and high frequency are adopted to improve the energy consumption estimation accuracy [2-5]. However, to extract these additional features additional functions and cost are required.

Wide deployment of smart meters and advanced metering infrastructure (AMI) enables access to electricity usage data. However, the main purpose of smart meters is in billing for utilities. It means that the data we can obtain from the meters may be limited in the sampling resolution and type of data handled. For example, fifteen

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minutes is commonly accepted for metering purposes [6]. On the other hand, smart devices such as smart appliances and home automation devices support network connectivity for advanced services. Even though not all devices would be smart, the smart ones can communicate in almost real time with other devices. If we can share the information of the smart devices' status by using the connectivity, energy usage monitoring would become easier and more precise for the entire house. Recent interests of sensor networks can also accelerate smart device distribution [7]. In this research, appliance status information is used in addition to metering information to improve the accuracy and to reduce computational complexity.

2. System Model

2.1. System Configurations

Home energy monitoring systems can be implemented with various models. As shown in figure 1, a smart meter measures aggregated power consumption of a house. The smart meter can be a conventional billing meter installed by a power company or an additionally installed power consumption measuring device. The measured metering information is a fundamental signal to estimate individual device status. An energy consumption monitoring (ECM) module estimates the status of individual devices at home with the data obtained from the smart meter. The ECM can be located anywhere within home premise or outside home so long as it can provide enough performance. When ECM is located within home area network (HAN), it can exist as a separate device or locate within TV or residential gateway. Configuration (a) would be a common model for energy consumption monitoring. The ECM is located in HAN, and the smart meter is also connected to the ECM via HAN. Energy consumption information with high sampling rate can be obtained in this model so long as the smart meter supports. There are two types of devices within a house: smart and legacy devices. The smart devices support network connectivity to HAN and can send their operation status information to the ECM. Both broadcast and unicast can be used to deliver the operation information. If the smart device can measure its energy consumption in addition to the operation information, the energy consumption estimation can be more accurate.

In many cases, the smart meter is owned by a power company, and the direct connection to the smart meter is restricted. The power company collects smart meter information via AMI network to a meter data management system (MDMS). The ECM needs to connect MDMS or equivalent services to access the collected metering data. Configuration (b) shows the case of separate AMI while the ECM is in HAN. In this case, the smart meter and AMI usually do not support high sampling rate, much information would disappear because of the averaging effect. Configuration (c) shows the case that ECM is located outside the home. When the operation information of individual smart devices can be provided to ECM without concerning the physical locations, there are not many differences between configuration (b) and (c) except for the communication reliability.

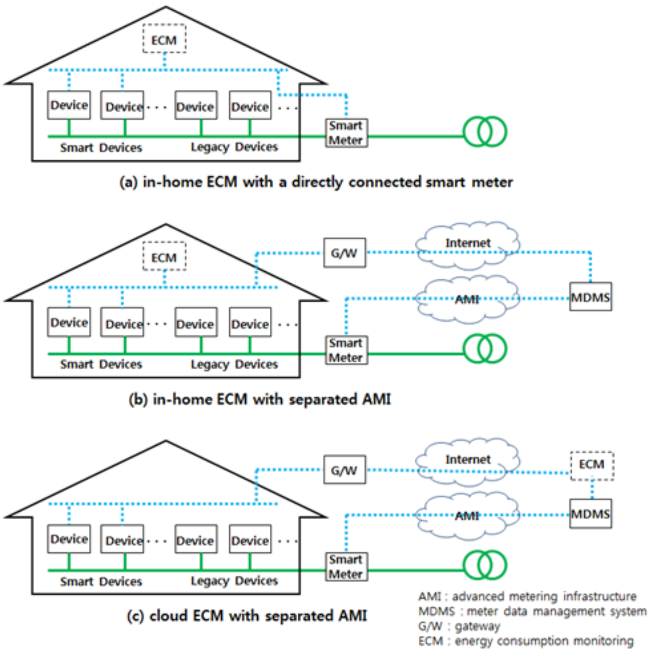

Figure 1. Configuration Types for Energy Consumption Monitoring

2.2. Home Device Operation Status Estimation

Once devices existing inside a house is recognized, home device operation status are estimated based on the measured metering data throughout time. Figure 2 shows the concept of the device status changes for state estimation. A horizontal line means the sequence of status change of an individual device. The devices can be divided into two sets: "known" and "unknown". Here, a device in "known" set means that the status of the device is deterministically known to the ECM because its operation information is provided from the device directly via a communication network. A device within "unknown" set means that it is a legacy device or operation status is not provided properly at the moment even though it is a smart device. Therefore, the status of a device can be changed from "unknown" to "known" and vice versa as shown in the figure based on the obtained operation information at each sequence. Circles with solid line mean they are in "known" status, and circles with dotted line mean they are in "unknown" or estimated status. A color in a circle means the status of the corresponding device such as "ON" and "OFF". The solid color means the definite status, and the patterned color means the estimated status of the devices.

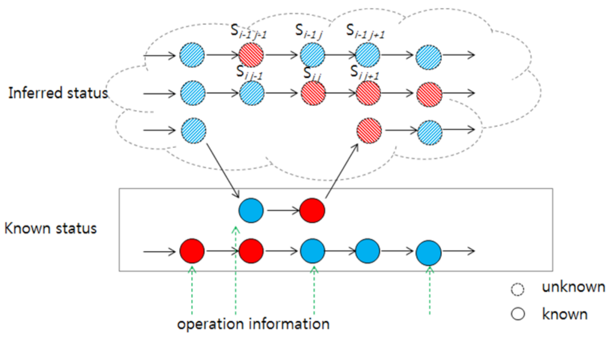

Figure 2. The Concept Diagram of Device Status Changes

2.3. Message Handling Process

A smart device can either make a direct connection and send its operation status to the ECM or broadcast their operation status to the HAN. Both approaches would deliver similar results in HAN environment. If the ECM is outside the home, the direct connection would be appropriate. The smart devices send the changes in their status when major status transitions occur such as on and off. In addition, they send current status periodically to compensate the case of communication error. Otherwise, a missing message can bring a misunderstanding of the ECM about the device`s status.

Figure 4 shows the message handling flow of the ECM to distinguish the status of smart device *i* whether it is in “known” or “unknown”. When the ECM receives a status message from a device, then it renews the status information of the corresponding smart device as known. The status of the device at the moment is determined from status information included in the message. If the ECM does not obtain any messages from the smart device for a predetermined period ($T_{i\ limit}$), then the ECM considers that the status of the device is unknown. And the ECM performs a regular estimation process including the device. In this way, unknown state estimation of devices can be improved by reducing unknown variables.

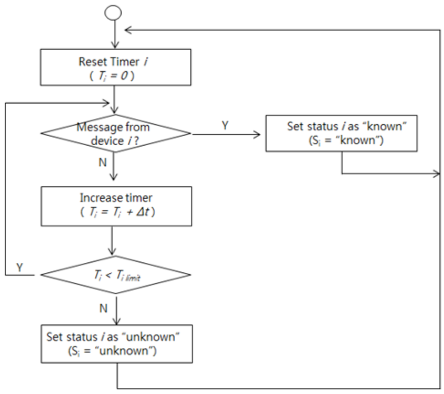

Figure 3. Message Handling Flow of ECM for Device i

3. Results and Discussions

The difficulty of disaggregation exists when there are similar feature change characteristics between more than two devices, or a feature change of a device is too small to distinguish from other device`s variance. While some devices consume high energy with a large amount of variance, others spend low energy with the small amount of variance. Some devices have very complex characteristics with intermittent operations and very large variance. In this paper, three types of signals are considered depending on metering period; 1 second, 5 minutes and 15 minutes. One second sampling period means almost real time observation. Five and fifteen minute sampling periods mean delays in the main metering. They are reasonable assumptions when considering separate AMI environment. The metering value is obtained after the accumulation period of five and fifteen minutes with the mean value.

Five common devices in Korea are used for the experiment: a water purifier, a monitor, a refrigerator, an air conditioner and a washer. The individual patterns of the devices for three types of sampling periods are shown in Figure 4. The monitor has the flat power consumption pattern having distinguished the “On” and “Off” status. The water purifier has a pattern combined with a heater and a cooler altogether to provide hot and cold water simultaneously. The heater and cooler operate independently depending on their temperature. Therefore, there can be four patterns with the combination of heater and cooler cycles. The refrigerator has a cooling cycle operated intermittently to keep the temperature. However, other complex patterns are combined altogether. A defrost process is one of the common non-regular patterns. Although the air conditioner looks like repeating on and off periodically, the period and duty cycle would be affected by outdoor temperature. The cloth washer has relatively complex patterns combined by short term on and off cycle and long term washing processes. The five and fifteen-minute interval signals show different patterns from original ones making pattern detection more difficult as expected. Especially, when a status change occurs during metering cycle or the duty cycle of an operation is less than the metering cycle, the signals become ambiguous.

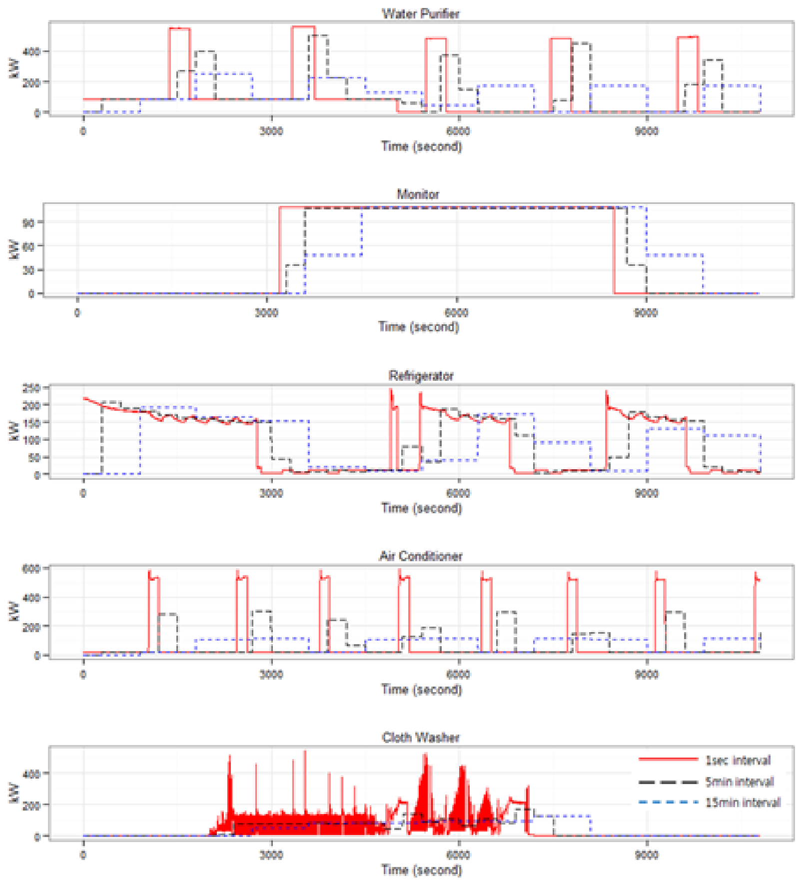

Figure 4. Energy Usage Patterns Used in the Case Study

Figure 5 shows an example used in the case study based on the patterns in Figure 4. The signal is simulated by combining individual energy consumption patterns for three hours. The figure includes 1 second, 5 minutes and 15 minutes metering signals. In the example, 36 events are correctly detected among 47 real status changes when a simple differential detection algorithm is used for the one-second interval signal. When the cloth washer is excluded, most status changes are detected appropriately. By using the cloth washer operation signal, the result is improved detecting 42 status changes.

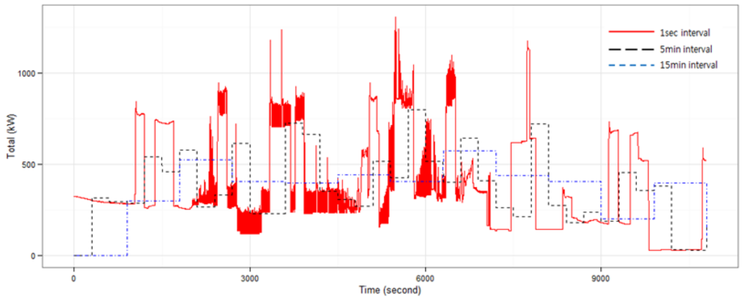

Figure 5. An Example of the Mixed Energy Use Pattern

For 5 and 15-minute interval measuring signals, only 30 and 15 status changes are detected, respectively, because of the resolution of the measurement. The result also includes fault decisions. When a status change due to a high energy-consuming appliance with a short-term duration such as an air conditioner occurs during a sampling period, then the change may affect the very period partially. By having the status change information from appliances, we can compensate such a case. Even though not all appliances can be connected to the ECM, the more connections we have, the more the estimation can be improved.

If all devices and appliances become intelligent, and they can share their operation information, complex disaggregation process would not be necessary. However, limited devices would support connectivity in the real world. Most disaggregation service requires the agreement of data usage from customers for the privacy issues. Therefore, an assumption about sharing operation information of appliances would be still reasonable.

4. Conclusions

In this study, a smart device operation status information sharing model is proposed to improve energy consumption monitoring accuracy. Smart devices share their operation information in real time with an energy consumption monitoring module using their network connectivity. Their operation status is updated when the operation signal is transferred and maintained until another status change signal arrives, or no signal is received for a predetermined period. The approach is helpful especially when the metering interval is long. By combining metering and appliance status information, disaggregation becomes simpler than the case with metering information only.

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Author

Sung-Yong Son, received the B.S. and M.S. degree from Korea Advanced Institute of Science and Technology (KAIST), Korea in 1990 and 1992, respectively, and Ph.D. degree in Mechanical Engineering from University of Michigan, Ann Arbor, in 2000. From 2000 to 2005, he worked at 4DHomeNet and Icross-technology, respectively. He is currently working as an associate professor at the Department of Electrical Engineering, Gachon University, Korea. His research interests are smart grid and smart home.

