A Study on Data Requirements for Power Disaggregation

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***Abstract*—While much research is being done on power disaggregation analysis, there is a lack of discussion on the data requirements of the appliance under analysis. In this paper, we present four new data requirements for power disaggregation analysis and explain implementation methods to verify them. The experimental results applied to the test appliance data are also introduced. In conclusion, this paper insists that validation of the data requirements should be an essential prerequisite step prior to developing a power disaggregation analysis model.**

Keywords-component; power disaggregation; non-intrusive load monitoring(NILM); data requirement; dynamic time warping(DTW)

I. INTRODUCTION

Disaggregation also known as Non-Intrusive Load Monitoring (NILM) analysis is a technique for extracting individual home appliance usage from total power consumption data as shown in Figure 1. It was introduced by George W. Hart [1] in 1992 and has been continuously studied [2]-[10]. The technology is useful for energy cost reduction guides, smart home services, prediction of failures, and has a potential value in that it can provide lifestyle analysis by understanding usage of home appliances.

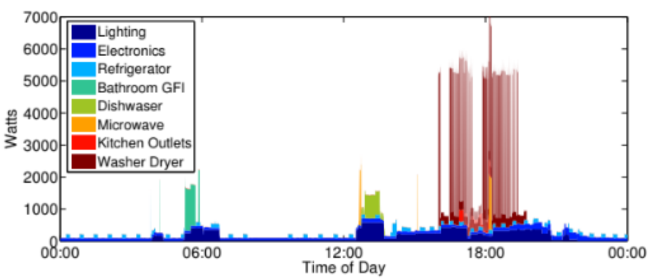

Figure 1. Example of Energy Disaggregation [2].

The existing data requirement mentioned in related work is that active power, reactive power, and voltage data should be measured at least one second sampling for developing power disaggregation analysis model [9]. However, while various analysis models have been developed based on the criteria, the performance is still less than 10 home appliances that can be disaggregated [5, 10]. Thus, we assume that if additional proper data requirement is adopted and validated for disaggregation analysis model, performance in terms of accuracy and possible number of home appliances to be identified can be improved. This is why we try to find new data requirements for power disaggregation.

The organization of the paper is as follows. Section II addresses the problem that we focus on. Section III explains our approach in detail. Some experimental results are given in Section IV. The concluding remark is presented in Section V.

II. PROBLEM DEFINITION

Disaggregation technology currently identifies a relatively small number of home appliances out of many home appliances. Without the whitelist (i.e., targeting list) of home appliances, disaggregation is a very difficult problem. Therefore, it is desirable to examine whether a home appliance is possible for power disaggregation or not in advance. According to the result, some are included in the whitelist and others are excluded for not being participated in machine learning for developing analysis model. It may be the key to improve accuracy.

For this, we propose a methodology to pre-verify candidate home appliance data that is suitable for power disaggregation analysis by checking the newly introduced data requirements. That is our main contribution to the literature. Unlike this study, the previous work as in [3] selected candidate home appliances without knowing whether they could be identified or not.

III. OUR APPROACH

We derive the characteristics that power usage data of home appliances should basically have for power disaggregation analysis. They are related to consistency. In order to develop a general disaggregation model and identify the same kind of home appliances, all the requirements must be met. In addition, practical implementation scheme for checking the requirements should be explained.

A. New Data Requirements

The power usage data of a specific home appliance must satisfy the following four criteria. For our study, active power data is only examined. Since reactive power data is highly correlated with active power data and voltage is not a suitable due to too little change in value, they are not to be used.

1) Reproducibility: The same power usage pattern should be shown when repeatedly running certain appliances in the same mode.

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2) Multiplicity: The power usage pattern should maintain multiple characteristics when the specific appliance is operated such as in strong, medium or weak mode.

3) Similarity: Similar power usage pattern should be shown between the same kind products.

4) Inconsistency: Some part of an appliance data should not appear within the other appliances data.

B. Verification Method

In order to verify satisfaction of the above data requirements, we use Dynamic Time Warping (DTW) technique [11], which is designed to investigate similarity between the time series data. Power usage data is also time series data, and DTW is suitable for this study because similarity can be checked even if there is a difference in the data length to be compared or the starting point of the comparison does not match.

How DTW works and why it is better than Euclidian distance calculation is illustrated in Figure 2. The cost (C) of each cell is calculated by (1). Starting from (0, 0), the calculation proceeds to the upper left direction and moves to right. After all cells have been filled in, DTW path is determined by moving from (n, n) to (0, 0) and selecting the smallest value in left, diagonal left and bottom order based on the greedy search algorithm.

$$C(i, j) = Dist(i, j) + min[C(i\text{-}1, j), C(i, j\text{-}1), C(i\text{-}1, j\text{-}1)] \quad (1)$$

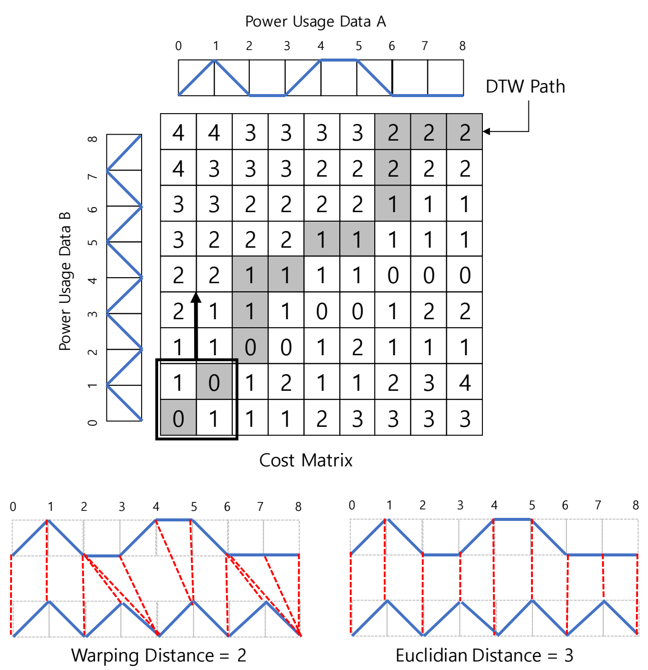

Figure 2. DTW concept and example.

In the example, DTW path is determined as (0, 0), (1, 1), (2, 2), (2, 3), (2, 4), (3, 4), (4, 5), (5,5), (6, 6), (6, 7), (6, 8), (7, 8), (8, 8). DTW distance is the sum of the distance values of the cells in DTW path. Therefore, it is 2(= 0 + 0 + 0 + 1 + 0 + 0 + 0 + 0 + 0 + 1 + 0 + 0 + 0). The result shows how DTW distance comparison is performed at the bottom of Figure 2. It is different from Euclidian distance method. Eventually, DTW distance value is used to determine the degree of similarity of the two power usage data.

There are previous studies as in [12, 13] related to DTW performance improvement and the widely used open source libraries that implement them. However, since it has no performance gain on time series data of length less than 100, it is not adopted in this study.

C. Preparation of Test Data

Active power, reactive power, and voltage data of 20 test home appliances are measured at every second. Operating each home appliance is done three times. As a power usage meter device, the commercial product, ADPOWER's Wattman (HPM-100A) is used.

Test data set is composed of the following three CSV files. The last file is automatically generated by Wattman. The others are manually written by tester.

- #1 Appliance Description
  {Type, Type Name, Product, Product Name, # of Modes}
- #2 Activation History
  {Start Time, End Time, Product, Mode (0...N)}
- #3 Power Consumption Data
  {Timestamp, Active Power, Reactive Power, Voltage, ⋯}

D. Implementation

The verification module implemented in python reads test data into memory and Z-normalizes the underlying data. The Z-normalization is necessary for equality comparison [13] because there is a difference in absolute value of power consumption data between the same kind products.

Then, each module is consecutively called to check the data requirements and generates output as shown in Figure 3.

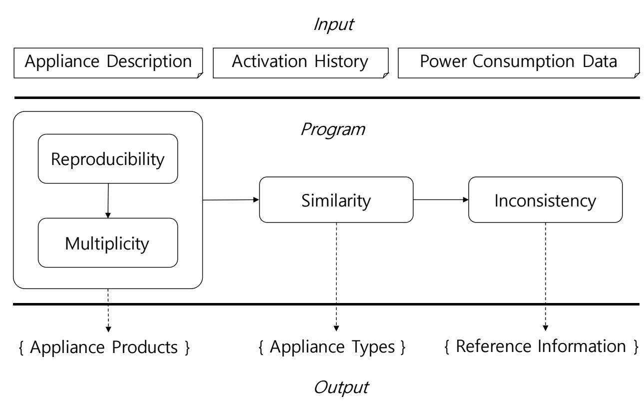

Figure 3. System configuration and order of execution.

Of the data requirements, reproducibility and multiplicity are the fundamental characteristics. The output is a list of appliance products. Similarity is essential for developing a general disaggregation analysis model. Qualified appliance types are given as the result. Inconsistency is a partial matching verification to confirm whether some part of data such as 5- second, 10-second, and etc. does not appear in the total data of other kinds of home appliances. If the previous step is not successfully done, it does not move to the next step.

But here, there is the important issue that should be considered in advance. It is necessary to define a criterion for objectively interpreting DTW distance that is a relative value. The value itself is not known to what extent. Therefore, Margin of Error (MOE) is introduced and defined as follows. MOE is the allowable percentage of the difference. It can be regarded as similar only if DTW distance is smaller than the baseline (2). They are defined as (3) and (4) with the same distance formula.

$$DTW\ distance \leq Baseline \tag{2}$$

$$DTW\ distance\ = \sqrt{\sum_{(i,j)\in P}(Xi - Yj)^2} \tag{3}$$

$$Baseline\ = \sqrt{(Max * MOE)^2 * Length} \tag{4}$$

In Figure 4, data compared with the center line source data is determined to be similar only when it is within MOE range. It is heuristically set to 0.3 (= 30%) criterion as the MOE. It is determined by considering error in data measurement and possibility of overcoming dissimilarity and developing disaggregation analysis model in other ways.

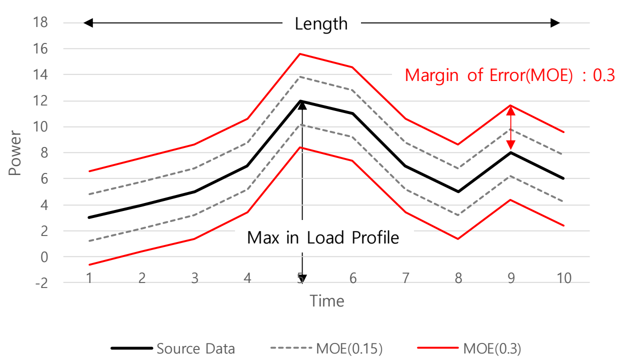

Figure 4. Acceptable distance specified by MOE.

IV. Experimental Results

We verify reproducibility, multiplicity, and similarity of test data from 20 home appliance products in 10 types (hair dryer, vacuum, notebook, light, electric blanket, microwave, TV, electric fan, monitor, and iron) and present the result as shown in Figure 5.

Figure 5 includes a single result like notebook, and multiple results like hair dryer for reproducibility. This is because notebook has a single ON/OFF mode while hair dryer has a plurality of modes such as strong, medium and weak. Hair dryer, vacuum, and notebook meet all the requirements but for the rest of the appliances, it is found that DTW distance is over the baseline in some verifications.

Unexpectedly, there are some cases that do not satisfy reproducibility. It is not possible to identify the home appliance that does not maintain reproducibility. In the case of electric blanket, microwave, and iron, reproducibility can fail due to the previous operation. When they are turned on, temperature is checked and properly operated according to it. It means that same pattern may not be guaranteed.

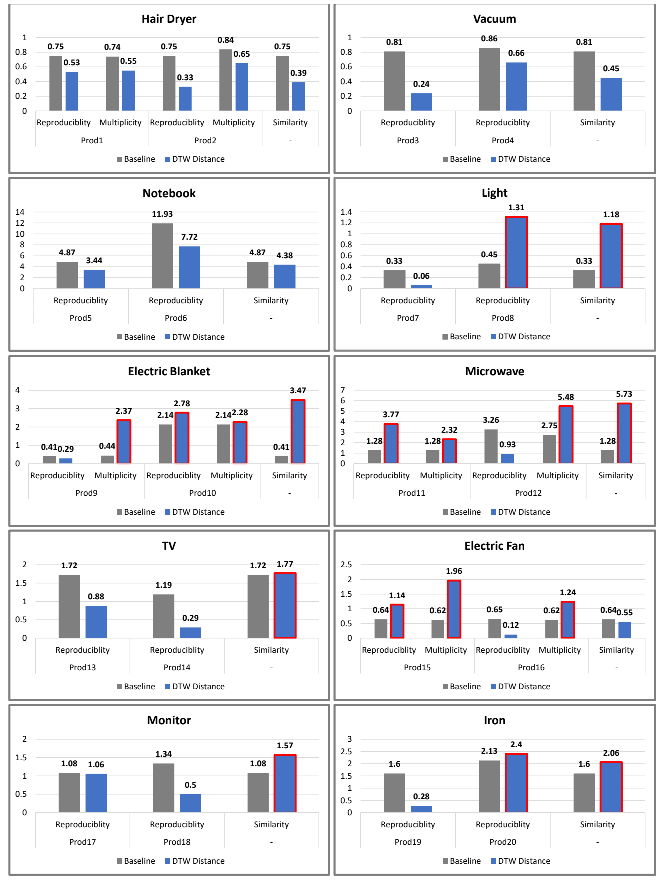

Figure 5. Experimental result (reproducibility, multiplicity, and similarity).

Multiplicity verification is to see if the z-normalized data in different modes show a similar pattern. Only hair dryer is passed and electric blanket, microwave, and electric fan are not successful for this test.

Verification of similarity addresses not only verification between products of the same manufacturer but also verification between products of different manufacturers. Therefore, it is difficult to meet this requirement. If the similarity test is not satisfied, it leads that it is impossible to develop a general disaggregation analysis model. TVs and monitors are unsuccessful for this test. Although the TVs used in the experiment were made by same manufacturer, they did not satisfy the requirement. Therefore, result might be worse between different manufacturers. Furthermore, since TV and Monitor can embed different display panels, it seems that possibility of developing a common disaggregation analysis model for them is low.

In Figure 5, the case where DTW distance exceeds the baseline is highlighted separately. If there appears such a case in a product, it is regarded as unqualified.

Examination of inconsistency has a different purpose. The result does not directly indicate whether it is possible to disaggregate or not. Instead, it provides useful information to refer when developing disaggregation analysis model. For example, although the partial usage data of a particular home appliance appears in the usage data of other products, such coincidence can be eliminated by increasing length of the query data. By doing so, the optimal length of data to avoid coincidence can be found. Inconsistency is executed only on product 1 to 6 that satisfy all the previous requirements. As shown in Figure 6, except for product 6, when the data length is 10, the least overlapping pattern is found. Therefore, it is determined that at least 10 data (i.e. 10-second data) need to be examined for disaggregation analysis.

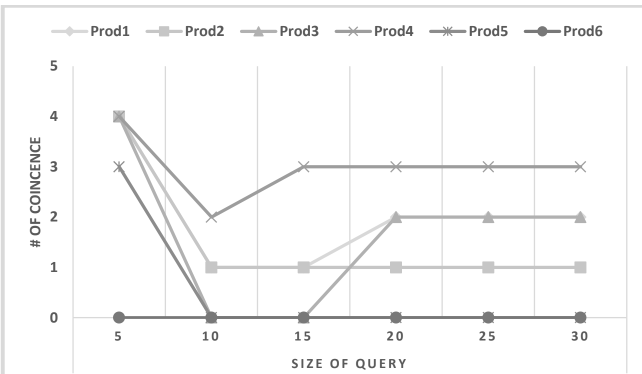

Figure 6. Experimental result (inconsistency).

V. Conclusion

In this paper, we propose that reproducibility, multiplicity, similarity, and inconsistency as new data requirements should be pre-verified for developing more accurate disaggregation analysis model. Implementation detail using DTW is also presented. Test results of 20 home appliances are explained. As a result, only hair dryer, vacuum, and notebook out of 10 home appliance types passed all the verification. It means that they are likely to be identified by disaggregation analysis model.

By targeting disaggregation-enabled home appliances as whitelist and excluding the others as blacklist, disaggregation analysis model can be more effective since negative information is blocked during exploratory data analysis and feature selection for developing analysis model. Therefore, verification presented in this paper is necessary.

Many home appliances could not be examined in the study. However, we are going to continue to test and verify more home appliances to update valid list. Although it is determined that a small number of home appliances can be disaggregated, the result is still meaningful. It is because they can be utilized for smart home services. For example, identifying use of hair dryer may indicate the time to go out, use of vacuum may reveal whether or not it is in the house, and use of notebook may be notified and controlled by parents.

Future work is to develop a disaggregation analysis model based on the result presented in this study and prove the effect by comparing with other approaches.

Acknowledgment

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