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2016

Aiad, M., & Lee, P. H. (2016). Unsupervised approach for load disaggregation with devices interactions. *Energy and Buildings*, 116, 96-103.

<https://hdl.handle.net/10356/82926>

<https://doi.org/10.1016/j.enbuild.2015.12.043>

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Unsupervised approach for load disaggregation with devices interactions

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ABSTRACT

Energy savings is one of the hottest issues and concerns nowadays due to high oil prices and global warming as a result of CO₂ emissions. Non-intrusive appliances load monitoring (NIALM) is a methodology that aim to breakdown the total power consumption measured by the smart meter in each household into the power consumed by the individual appliances. These detailed information on individual appliances consumptions can influence the users to follow better energy usage profiles so as to achieve energy savings. We introduce a novel energy disaggregation model that consider mutual devices interactions and embed the information on devices interactions into the Factorial Hidden Markov Models (FHMM) representations of the aggregated data. The hidden states in the FHMM were inferred by means of the Viterbi algorithm. Devices interactions is a power quality issue that affects the measured power consumed by a device when there are other devices connected to the network. We tested our model using a selected house from the REDD public data set. Our proposed approach showed enhanced results when compared with the standard FHMM. Devices interactions, when observed, enabled us to disaggregate and assign energy consumption for individual devices more accurately.

Keywords: non-intrusive appliance load monitoring, energy disaggregation, devices interactions, Factorial Hidden Markov Models, Viterbi algorithm.

1. INTRODUCTION

It is becoming an established fact that the world faces many challenges regarding energy matters such as resources limitation, sustainability, carbon emissions, etc. Therefore, techniques for energy savings and energy management are necessary to assist in resolving some of these issues.

In residential homes, energy smart meters give information about the total aggregated household consumption of energy. This information is insufficient to inform inhabitants about consumption by individual devices. It is believed that giving detailed information about the energy consumed by each device will influence users on energy usage that would lead eventually to the decrease in energy consumption [1]. Studies conducted had shown energy savings from 9% to 20% (see e.g. [1, 6] in this aspect). Energy disaggregation, or non-intrusive appliance load monitoring (NIALM), is the task of decomposing the aggregate consumption readings of a house smart meter into its individual devices consumptions.

Formally, this problem can be defined as follows: Given the total power consumption $p(t)$ at any time instant t , we have

$$p(t) = p_1(t) + p_2(t) + \dots + p_n(t) \quad (1)$$

The problem is to estimate each $p_j(t)$, the individual power consumption of the device j at time instant t , where $j=1, 2, \dots, n$, $t=1, 2, \dots, T$ and n is the total number of active devices within the time period T [2]. Applications of load disaggregation also include energy management systems and faults troubleshooting [3].

To simplify the task of load disaggregation, a load inside a house is considered to fall into one of the following four categories [4]:

- Base load or always ON devices: these are loads which are operating at all time instants. These devices do not switch to the OFF state and they usually have constant active and reactive power draws. Smoke detector is a typical example for this category.
- ON/OFF devices: these are loads with only two possible states (operating/ not operating). Examples of such devices include light bulb, television, toaster, etc.
- Finite State Machines (FSM): these are appliances with finite number of possible states. An appliance in this category usually draws different amount of power at each state. Examples of this category include stand and ceiling fans, washing machine, etc.
- Continuously variable devices: these are loads without fixed number of states and consumes variable amount of power based on their usage manner. An example of this category is the light dimmer.

It is important to notice that in the NIALM process, there is no need to install additional sensors to report devices states because we deal directly with the total measurements from the main smart meter. In intrusive load monitoring techniques, the installations of sensing devices made the energy disaggregation process more costly, complex and less practical in applications [2].

2. BACKGROUND

Non-intrusive load monitoring was first proposed by Hart in 1992 [5]. His study showed the possibility to detect appliances operations by inspecting their signatures in the total consumption signal. The main work of disaggregation consisted of two steps. Firstly, to measure significant features whenever an event is detected (devices switch ON or OFF) as shown in Figure 1 [5]. Then, to cluster these features (distinct signatures) into different clusters or groups that represent different appliances. It was observed that high power consuming devices are easier to be classified since they are placed far from other devices in the features space. Meanwhile, there are overlapping points in low power consuming devices, which require additional decision criteria to assign them correctly into devices clusters.

Influenced by Hart's work, researchers started to extend the work by investigating new methodologies to enhance disaggregation accuracy. There is mainly two paths to improve the disaggregation process: extracting new significant features and improving the clustering algorithms [4].

Fig. 1. Total load showing step changes due to individual appliance events [5].

2.1. Low and high frequency sampling features

The number and nature of features that can be extracted from the aggregated total signal obtained from the smart energy meter depend essentially on the sampling frequency used in the measurement stage. High frequencies sampling measurements, which usually use frequencies of several kHz, can capture fine features such as harmonics, transient characteristics, voltage current V-I trajectory shapes, electromagnetic interference (EMI) and noise Fast Fourier Transform (noise FFT) [2]. Although high frequency measurements can provide more fine and detailed signatures, it is still not a practical solution due to the need of installations for new equipment. Currently installed, or to be installed, smart meters usually report power usages at low frequency intervals such as every 1 second interval. Therefore, the solutions for the energy disaggregation problem based on low frequencies signatures are more practical and promising. Main features that can be captured by low frequency measurements are generally macroscopic ones like active and reactive power measured at transition instants of states [4]. Our approach make the use of the measurements from the smart meters without the need of additional sensors installations.

Some non-electric signal features can help in the disaggregation process. These are usually related to users' behavior or outside environmental factors such as ambient temperature, time of use, duration of use, interdependency between appliances, etc. [6].

2.2. Supervised and unsupervised learning algorithms

In supervised learning algorithms, there is a training phase for the proposed models before it is set to work. In this phase, a database of all possible devices along with their features are recorded. The disaggregation process is done later either through optimization or pattern recognition approaches. In optimization methods, the system tries different combinations of known devices that will result in minimized error between actual and estimated total consumptions. In pattern recognition approaches, different methodologies were used to classify devices into their relevant groups such as Bayesian Classifiers, Neural Networks, Hidden Markov Model and its extensions [2]. Supervised learning approaches require training for the models of each device, which make it less applicable in actual system deployment since individual consumption patterns are unavailable in normal situations. Therefore, research has been directed to unsupervised approaches to gain better scalable, time and cost effective solutions [6].

Unsupervised approaches perform models training phase online while the disaggregation process is running such that whenever a new possible device is defined, it will be added to the database of devices. This process is usually done by probabilistic analysis and classification methods [6, 7].

Hidden Markov Models (HMMs) and their extensions were used in many proposed disaggregation models due to their good representations of devices. The hidden states chain in HMMs represents the operation state/states of a device and the emission or observation sequences represent the measured total power consumption [8].

Kim *et al.* [6] tested different extensions of Hidden Markov Model (HMM) for better representations and disaggregation outcomes. These models were

- Factorial Hidden Markov Model (FHMM) in which there are several independent hidden state chains evolving in parallel and the observation is a joint function of these chains [9].
- Factorial Hidden Semi-Markov Model (FHSMM), in which states are explicitly assigned to occupancy duration periods that could fit to exponential or gamma distributions.
- Conditional FHMM (CFHMM), in which states changes are constrained to fulfill some conditions based on current state.
- Conditional FHSMM (CFHSM) that combines both FHSMM and CFHMM models.

Kolter and Jaakola [7] expressed a new approximate inference method based on FHMM. They utilized two complementary models, the additive and the difference FHMM. The additive FHMM captures well the total aggregate output signal while the difference FHMM encodes the signal differences between subsequent levels (when a device switches ON or OFF).

Parson [8] proposed an approach in which a one-time supervised learning process with already labeled data set was used to create general probabilistic models of appliances. Thereafter, these general models can be tuned to previously unseen households in an unsupervised manner. The tuning process resulted in specific models of devices that were present in the testing households.

2.3. Public data sets for energy disaggregation research work

Recently, data sets were made available for the public to test and compare the different proposed approaches. The largest and detailed public data set available is the Reference Energy Disaggregation Data Set (REDD) [10]. REDD includes both low and high frequency measurements of six real houses for an approximate period of two weeks. Consumptions of individual appliances are also provided for the purpose of training (in supervised approaches) or for algorithms validation and accuracy calculations. Although REDD satisfies most research needs, it is noted that the summation of individual consumptions often is not equal to total consumption at the same time instant. This indicates unmeasured or hidden devices. Moreover, the devices are not grouped to belong either to mains 1 or mains 2 phase circuits. This requires additional manual work for grouping in order to perform validation more accurately. In this paper, the REDD data set was used to build models and to test our approach.

2.4. Accuracy metrics

An important issue among the different proposed energy disaggregation techniques is that there is no one agreed metric where the different approaches can be compared with. From the literature, there were commonly five different metrics used to evaluate disaggregation accuracy and they are described briefly as follows

2.4.1. Total energy correctly assigned to individual devices. This accuracy metric is defined as

$$Acc = 1 - \frac{\sum_{t=1}^T \sum_{i=1}^n |\hat{y}_t(i) - y_t(i)|}{2 \sum_{t=1}^T \bar{y}_t} \quad (2)$$

where $\bar{y}_t$ refers to the observed total power consumption at time t , $y_t(i)$ is the true power consumed at time t by device i , and $\hat{y}_t(i)$ is the estimated power consumption at time t by device i and n is the total number of active devices operating during the period T . The factor of 2 in the denominator comes from the fact that the absolute value will “double count” errors [10, 11]. This metric is used in this paper as it gives a better evaluation in terms of how close the estimated energy consumed by a device is to its actual consumption.

2.4.2. Using *Precision*, *Recall* and *F-measure* of detected events (devices switchings) [7]. In this metric, events detected and classified are categorized into four groups based on reality and algorithm outcomes as shown in Table 1.

Table 1. Actual Vs. concluded events.

Test conclusion	Real event occurred	Real event did not occur
Detected	True Positive (<i>TP</i>)	False Positive (<i>FP</i>)
Not detected	False Negative (<i>FN</i>)	True Negative (<i>TN</i>)

Precision is a measure that describe the relevance ratio of the detected elements (percentage of truly detected events from all detected events) and it is given by

$$Precision = \frac{TP}{TP + FP} \quad (3)$$

Recall is a measure of how many of relevant elements (events occurred in reality) were detected and it is given by

$$Recall = \frac{TP}{TP + FN} \quad (4)$$

F-Measure is a measure that combines precision and recall as the harmonic mean. It is given by

$$F = 2 \left(\frac{Precision \times Recall}{Precision + Recall} \right) \quad (5)$$

2.4.3. Kim *et al.* [6] also used the previous metric in 2.4.2 but they have redefined the *Precision* and *Recall* by subdividing the true positive (*TP*) group into accurate true positive (*ATP*) and inaccurate true positive (*ITP*) as follows

$$TP \begin{cases} ATP, & \text{where } \frac{|\hat{P} - P|}{P} \leq \rho \\ ITP, & \text{where } \frac{|\hat{P} - P|}{P} > \rho \end{cases} \quad (6)$$

$$Precision = \frac{ATP}{ATP + ITP + FP} \quad (7)$$

$$Recall = \frac{ATP}{ATP + ITP + FN} \quad (8)$$

where, $\hat{P}$ is the estimated power consumption and P is the actual consumption. Usually, power consumption fluctuate within 20% of the mean power, thus a ρ threshold can be taken as 0.2 [6].

2.4.4. Liang *et al.* [12] differentiated between detection and classification accuracy as follows: if detected events include all true and false detections, then detection accuracy is the percentage number of those classified correctly from detected events. Classification accuracy is the percentage of number of those classified correctly from truly detected events. Overall accuracy is the percentage number of those classified correctly to events that actually occurred [4, 12].

2.4.5. Parson [8] used receiver operating characteristic (*ROC*) curves to trade-off between true positive rate (*TPR*), which is same as *Recall* defined in 2.4.2, and its complementary false positive rate (*FPR*).

3. ANALYSIS OF DEVICES INTERACTIONS

In residential houses, devices are often connected in parallel to the main feeder line. In the ideal case of operation, a device should operate like an isolated entity such that its operation neither is affecting other devices nor is affected by others. Unfortunately, the design of devices allowed the presence of mutual interactions effects between devices and other components connected to the electricity network.

3.1. Interpretation of devices interactions from statistical perspective

We consider an experiment model where the output observations (responses) are directly driven by a set of controllable factors and a set of non-controllable factors (such as noise) as shown in Figure 2.

Fig. 2. General experiment model.

In factorial design of an experiment, each factor (device) A and B can be either High (ON) or Low (OFF). The response y is the output of the system that intuitively depends on the states of these factors. To detect if an interaction AB exists between factors A and B , we firstly define the notations for different responses y (measured power outputs) at different possible states of A and B as shown in Table 2. It is noted that even when both factors A and B are OFF, we may still have a response i due to unknown factors or noise effect.

Table 2. Response y at different A, B states.

Factor A state	Factor B state	y
OFF	OFF	i
ON	OFF	a
OFF	ON	b
ON	ON	ab

In some experiments, the difference in response between the levels (Low/High) of one factor is not the same when the other factors are at different levels. When this occurs, there is an interaction between the factors [13, 14]. The main factors effects (A and B) and the two-way interaction effect (AB) can be estimated from the average of differences between High and Low levels as follows

$$A = (ab + a - i - b)/2 \quad (9)$$

$$B = (ab + b - i - a)/2 \quad (10)$$

$$AB = (ab + i - a - b)/2 \quad (11)$$

As an illustration, suppose when all factors (devices) are OFF we have a response i of 20 W, a response a (when A is ON alone) of 120 W, a response b (when B is ON alone) of 250 W and response ab (when A and B are ON together) of 360 W. Therefore, main and interaction effects can be evaluated using equations (9) to (11). Hence, we have the main effects A and B to be 105 W and 235 W respectively. The two-way interaction AB can also be evaluated to be 5 W.

3.2. Sparsity of effects principle

In experiments with many factors, there could be higher orders (3^{rd} , 4^{th} , etc.) interactions beside the main factors effects. The sparsity of effects principle states that the system is usually dominated by the main factors effects and low-order interactions (e.g. 2^{nd} order interactions). The 3^{rd} and higher order interactions are usually neglected [14]. In other words, higher order interactions such as three-factor interactions are very rarely significant. This is sometimes referred to as the hierarchical ordering principle. This property in factorial designs can be useful in the screening of significant factors from the insignificant ones (see [13]).

In view of the above, in our proposed method on energy disaggregation, we only estimate the main factors effects (main power consumption by devices) and the two-way interactions (where possible) between two operating devices. These interactions were embedded into a FHMM as additional hidden state chains.

3.3. Devices interaction as a power quality issue

Modern electricity networks are becoming more sophisticated due to, for example, the increased use of power electronics devices. These devices introduce distortions in the power system due to their nonlinear characteristics. Moreover, the electrical equipment have become more complex in terms of their functionalities and the way in which they interact with other equipment connected to the same network [15]. Generally, there is a possibility for two circuits to interact if they share a common point of connection. Due to the electronic devices and low power quality in the operation of some devices, this point of common connection allows the flow of different interference components such as harmonics and electromagnetic interference currents. The design or manufacturing of a device is considered to have low power quality issues when its operation does not satisfy the desired case. This includes emissions of harmonics, interference currents, being affected by the operation of other devices, etc.

Gil-de-Castro *et al.* [16] studied harmonic interactions between different devices (LED lamp, microwave oven and TV) and how different combinations of these devices could affect the charging process of an electric vehicle (EV). It was found that the presence of a neighboring device could have a strong influence on the harmonics emitted by the EV. In addition, the EV was found to be affected by different emissions (amplitudes and frequencies) coming from different nearby devices. They concluded that to understand the current flowing through an electronic device, the interactions between connected devices must be understood.

Gil-de-Castro *et al.* [17] investigated harmonic emission of different domestic equipment combined with different types of lighting. Their study showed that the total emissions produced by equipment depended on the lamps that were connected in the background.

Pavas *et al.* [18] carried out a statistical analysis of power quality disturbances propagation by means of the method of disturbances interactions. Their study was performed on a large scale to estimate possible interactions between two buildings. The measurements were done at the medium/low voltage level substation that feed the two buildings. The presence of disturbances was found to be responding to possible interactions of the two buildings circuits and all connected devices.

In residential households, devices are usually connected in parallel as shown in Figure 3. To investigate if two neighboring devices are interacting in terms of consumed power, the power consumptions should be measured at different states of devices *A* and *B*. That is, measuring the power consumptions when only one device is operating and when both are operating together.

Fig. 3. Parallel connection of devices in residential households.

In the ideal case, the devices should show zero interaction value i.e. power consumption when both are operating is equal to the summation of the two individual consumptions. On the other hand, when there is a difference between the two, it indicates that the devices have an amount of mutual interaction.

Thus, whenever

$$p_A + p_B \neq p_{AB} \quad (12)$$

where p_A and p_B are the power consumed when device A or device B is operating alone respectively and p_{AB} is the power consumed when both A and B are operating simultaneously. Then, the interaction effect AB is not zero and could be estimated along with main factors effects using equations (9) to (11) as explained earlier. It is noted that main factors effects must be always positive as devices always consumes power. However, interactions can, theoretically, hold a positive or a negative value depending on the behavior of devices under study. The interaction value is positive when we observe p_{AB} to be larger than the summation of $p_A + p_B$. On contrary, the interaction value is negative when we observe p_{AB} to be less than the summation of $p_A + p_B$.

4. PROPOSED MODEL FOR ENERGY DISAGGREGATION

We adopted a FHMM, with added chains for possible interactions, to represent the time series of states and observations sequences as shown in Figure 4.

Fig. 4. FHMM with interactions chains.

The observations (X_1 through X_T) chain represent the observed total aggregate signal from the smart meter measurements. The main factors (A , B , etc.) in hidden state chains represent a single state device or a single state in Finite State Machine (FSM), since FSM can be encoded as a multi single-state device [6]. The two-way interactions chains (e.g. AB , BC , etc.) represent the interaction between the corresponding respective devices. An interaction AB is considered only when both main factors A and B are operating in the ON state and so on for the other factors. The interaction AB holds the amount of change in power consumptions when both A and B are ON than that when any operates alone. This happens due to behavior change of a device consumption when other devices are present in the background. The observed aggregate signal is ultimately the additive responses of all active factors effects and their interactions at any time instant. Three-way and higher order interactions were neglected in accordance to the principle of sparsity.

The infrastructure and properties of FHMM is well described in the literature (see e.g. [8, 19]). Here, we focus on how the presence of interaction effects could enhance the energy disaggregation process. The problem is to find the most probable sequence of hidden states that resulted in the given sequence of observations. This problem can be solved by the Viterbi algorithm [19].

4.1. Models of power consumptions by devices

Since the power consumed by a device is not constant during its operations in many cases, e.g. refrigerators and heating devices, we have chosen to model the power consumed by a device (or a state of a device) with three power levels: initial, average and final power consumption levels. Initial power level is the level of power consumed directly when a device switches to ON state. We have used a period of five seconds after a device is switched on to estimate the initial power consumption level. Conversely, the final power is the power consumed five seconds before a device goes OFF. The average power level is the mean power level during the entire period of operation. For example, Figure 5 shows a consumption pattern of a refrigerator in house 2 from the REDD public data set [10]. It is clear that the power consumed at the beginning of operation is larger than that before going into OFF state, and it keeps decreasing during the operation period. Therefore, the proposed method gives a more accurate model of assigning power consumptions to a device than that of assuming only one constant consumption level. A contrary example is shown in Figure 6 for the consumption pattern of a central air conditioner [20]. It shows that the power consumed by the central air conditioner starts at some value and then keep increasing during operation.

Fig. 5. Consumption pattern by a refrigerator from REDD [10].

Fig. 6. Consumption pattern by a central air conditioner [20].

It is noticeable also that a device power consumption has natural fluctuations above/below the mean value of the consumed power. Therefore, we have considered the devices consumptions as a *Normal* distribution random variable to represent natural fluctuations as in [6]. The *Normal* distribution for each device was considered with a mean value that is the same as the mean power level and a standard deviation of 20% of the mean power level to represent the natural fluctuations.

4.2. Devices identification when a transition in total aggregate signal is detected

When a transition up is detected in the aggregate signal, the model will search for the most probable device that has been switched ON by comparing the transition with the initial power of the

recorded devices in the database obtained in step 1 of the disaggregation algorithm in subsection 4.3. In addition, the interaction effects between this possible device and currently operating devices are considered. The new device will be detected by means of the Viterbi algorithm. Similar manner was used to work with detected transitions down in the aggregate total signal.

That is, when a transition up is detected in aggregate signal, we search for a device x such that

$$x^* \sim \arg \min \left| \left(X_i + 2 \cdot \sum_Y XY \right) - |tx| \right| \quad (13)$$

Similarly, when a transition down is detected, we search for a device x such that

$$x^* \sim \arg \min \left| \left(X_f + 2 \cdot \sum_Y XY \right) - |tx| \right| \quad (14)$$

where, X_i is the main factor initial power level of the possible device x , X_f is the main factor final power level of the possible device x , Y is all currently ON devices, XY represents the pair interactions of devices x and y and $|tx|$ is the absolute value of the transition caused by the switching of device x . The above two equations were derived from the fact that when a device turns ON, its main effect (power consumption) will be added to the aggregate signal plus all possible interactions with already operating devices. The contrary behavior happens when a device goes into OFF state.

To illustrate the above, we can rewrite equation (11) as

$$ab - b = (a - i) + 2 \cdot AB \quad (15)$$

Since the term $(a - i)$ gives an approximate value for the main factor A , we can write

$$|tx| = ab - b \approx A + 2 \cdot AB \quad (16)$$

Therefore, the algorithm searches for the most probable device x that caused the transition in the total aggregate signal considering interactions with currently operating devices. Algorithms such as [1, 5 and 7] search for the device x without considering others devices that are already in operation. Our proposed method have considered devices interactions which aid in the disaggregation process. Test results on the public REDD data set showed an improved accuracy on disaggregation as illustrated in section 5.

Since power measurement has normal fluctuations, we only considered significant transitions larger than some threshold. A threshold of 25 W was used in our approach testing. We used this moderate threshold because a lower value will make the system very sensitive to small changes in the aggregate signal, while a higher threshold may result in missing smaller changes and low power consuming devices may not to be detected.

4.3. Procedure of the energy disaggregation algorithm

Our energy disaggregation approach can thus be summarized in the following steps:

- Step 1: using an initial portion of the aggregate total signal, models of devices were built and devices interactions were estimated. It is possible to estimate an interaction between two devices only if we can observe each device when operating alone and when both are operating together at different time instants.
- Step 2: the process of disaggregation was performed on the remaining part of the aggregate total signal.

- Step 3: accuracy of disaggregation was evaluated by comparing the resulting estimates to actual individual consumptions of devices obtained from the REDD public data set. The accuracy metric in 2.4.1 was used to assess our approach.

As in many other proposed approaches [4], we are still unable to detect or classify continuously variable devices. Only single state or FSM devices can be disaggregated by our approach. Since unsupervised approaches result in unlabeled groups, manual matching of the devices was performed at the end of the process.

5. RESULTS

We used the low frequency data measurements of house 2 available in REDD public data set [10] to carry out and test the proposed approach. House 2 was used to illustrate our approach as it includes only nine devices, which made it easier to investigate interactions per pair of devices. The nine devices are microwave, refrigerator, outlet 1, outlet 2, washer dryer, lights, stove, dishwasher and disposal. These devices are fed by two phases, which are labeled as mains1 and mains 2.

Firstly, the base load was determined by observing the minimum level of consumed power in both mains 1 and mains 2 circuits. They were found to be as shown in Table 3. The base loads here represent the response i in Table 2 when all other devices are assumed to be in the OFF state.

Table 3. Base load for mains 1 and mains 2.

Circuit	Mains 1	Mains 2
Base load (W)	15.7	22.8

Although the base load could include devices that are always ON, we considered this as the response i because all significant devices to be detected are still in the OFF state. The always ON devices are lumped together to represent the response when all other significant devices (to be detected) are OFF.

Using the disaggregation procedure described in subsection 4.3, the energy disaggregation was carried out. In step 1, models were built according to the detected devices in a two-day portion of aggregate data. Unseen or rarely used devices can be added during the disaggregation process (step 2). In step 1, we were able to estimate three interactions between corresponding observed devices and they are as shown in Table 4.

Table 4. Estimated interactions between observed devices.

Device A	Device B	Interaction AB (W)
Outlet 1	Outlet 2	-27.7
Outlet 2	Unknown (≈ 40 W)	-12.5
Refrigerator	Microwave	-31.5

In step 2, the disaggregation task was performed on the measured total signal of one-day length sequences separately. As an illustration, consider the microwave and refrigerator case. In step 1 of the disaggregation procedure described in subsection 4.3, we observed that the average power consumptions of the microwave and the refrigerator are 1935 W and 238 W respectively. Thereafter, these amounts were assigned to their consumption estimates whenever they were detected in the disaggregation process. The only exception was when they were detected to be operating together simultaneously. In this case, their individual consumptions were estimated to be decreased by 31.5 W (see Table 4).

In step 3, comparisons of outcome estimates of power consumptions to actual consumptions per device was done to find the disaggregation accuracy for individual devices. They are as shown in Table 5. We have repeated the experiment twice, once considering the interactions in hidden Markov chains and another by ignoring them (setting to zero) as in the standard FHMM. The accuracy of the estimated

consumption of each device was evaluated in order to understand the impact of considering their interactions specifically.

Table 5. Disaggregation accuracy for devices with/without interaction models.

Device	FHMM (Interaction ignored)	FHMM (Interaction considered)
Microwave	54.26%	57.29%
Outlet 2	78.66%	81.40%
Refrigerator	64.11%	64.57%
Outlet 1	68.66%	68.80%
Washer dryer	77.26%	77.26%
Lights	51.62%	51.66%
Stove	81.56%	81.56%

Figures 7 shows the estimated and the actual consumption patterns of the washer dryer in a given time period, respectively. As can be seen from the figure, the proposed method of energy disaggregation gives quite good estimation of the actual consumption pattern of the washer dryer.

Fig. 7. Estimated and actual power consumption of the washer dryer.

6. DISCUSSION

The addition of interaction property chains to the FHMM in our proposed approach considers the behavior of a device when there are different other devices operating in the background. The proposed model showed an improvement in the disaggregation accuracy whenever a mutual interaction between two devices was observed and estimated.

In step 1 of the proposed disaggregation procedure described in subsection 4.3, we were able to observe and estimate a limited number of interactions. This is because to estimate an interaction between

two devices, we must be able to observe each device operating alone in different time instants, in addition to observing when both are operating simultaneously. These conditions limits the probability to estimate interactions between a pair of devices. In reality, each pair of devices could interact, either with small or significant amount. Whenever we are able to estimate the interactions, they will help to improve the accuracy of disaggregation process as illustrated in our example. The transition of the unknown device in Table 4 was detected but we were unable to match with any of known devices in the household. It could belong to an unmeasured device since all other devices have no such transition in their consumptions at the same time instant. Hence, it was given a generic unknown device name.

From the disaggregation results, it can be seen that embedding interaction characteristics to FHMM improved the disaggregation accuracy for a set of devices such as the microwave, refrigerator, outlet 1 and outlet 2. No significant change in accuracy was obtained for the rest of other devices as no interaction was observed from the set of measured data for these devices. This showed that energy consumption was assigned more accurately to devices with known interaction properties. It is observed that either we embed interaction chains to FHMM or not, devices with unknown mutual interactions were not significantly affected in terms of the disaggregation accuracy. The results showed a noticeable enhancement to accuracy for devices with known interaction property. For reasonable comparisons, we may compare our results to those obtained in literature where the same accuracy metric is used (e.g. in [10, 11]). In [10], achieved accuracies were in the range of 59.6% to 71.5%. In [11], only 5 devices were considered. Thus, achieved accuracy range was increased to be 77.7% to 84.8%. Our proposed method can thus provide improved estimations of daily and monthly consumptions of the different devices in the household. This is useful when giving advice to home users about the energy consumptions of different devices and possible recommendations for energy savings.

Two other devices in house 2, the dishwasher and the disposal, were not shown in Table 5. From the individual power consumption data in REDD, it can be seen that the dishwasher operated only once during the entire two weeks period when data was collected. This may be sufficient to build a model but the device was not used again for the rest of the two weeks period for detection by our proposed disaggregation algorithm. The disposal consumed varying powers over the period of data collection and such device cannot be detected by our proposed algorithm.

7. CONCLUSION

The property of devices interactions was estimated and embedded in a FHMM representation to improve energy disaggregation accuracy. Although devices interactions would mean low power quality in their design or in electricity network components, we utilized this characteristic to further enhance the energy disaggregation. The new approach was tested in a selected home from available public data. Models were first built and possible interactions were observed from a portion of aggregate total signal. Then, the disaggregation process was performed on the remaining portion. It was found that devices with known mutual interactions were detected with higher accuracy than those with unknown interactions. The new model contributed in assigning consumed energy to devices more accurately. The essential impact of this work is to influence the house's occupants to adopt better energy saving usage for devices that would lead to valuable savings. For the future work, we look to evaluate and test our algorithm in different houses so as to increase the confidence about the proposed algorithm.

8. ACKNOWLEDGMENT

The authors would like to acknowledge the Singapore International Graduate Award (SINGA) for the support in carrying out this work.

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