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Energy disaggregation in NIALM using hidden Markov models

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ENERGY DISAGGREGATION IN NIALM

USING HIDDEN MARKOV MODELS

by

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ABSTRACT

This work presents an appliance disaggregation technique to handle the fundamental goal of the Non-Intrusive Appliance Load Monitoring (NIALM) problem i.e., a simple breakdown of an appliance level energy consumption of a house. It also presents the modeling of individual appliances as load models using hidden Markov models and combined appliances as a single load model using factorial hidden Markov models. Granularity of the power readings of the disaggregated appliances matches with that of the readings collected at the service entrance. Accuracy of the proposed algorithm is evaluated using publicly released Tracebase data sets and UK-DALE data sets at various sampling intervals. The proposed algorithm achieved a success rate of 95% and above with Tracebase data sets at 5 second sampling resolution and 85% and above with UK-DALE data sets at 6 second sampling resolution.

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Many thanks to my cheerful lab mates Thomas Roth for proof-reading my thesis work, Li Feng, Stephen Jackson, Gerry Howser and my dear friend Aaron Scott Pope, for their thoughtful guidance and help and all the stimulating discussions in the lab.

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1. INTRODUCTION

Non-Intrusive Appliance Load Monitoring (NIALM), is a process for analyzing the voltage and current going into a house and deducing what appliances are in the house as well as their individual energy consumption [1]. Appliance level energy consumption information is considered extremely valuable to consumers, utilities, public policy makers and appliance manufacturers, in order to improve energy efficiency. NIALM offers feedback to the utility companies, to know in advance the maximum energy consumed by each appliance. This is very beneficial in identifying electricity usage of individual appliances thereby generating the required power supplied to the consumer households.

The United States is the world's 2nd largest energy consumer behind China in terms of total use. Energy consumption in the United States was 25,155 TWh and 82 TWh per million persons in 2009 [2]. Energy consumption is classified into four broad sectors by U.S. Department of Energy such as industrial sector, transportation sector, residential sector and commercial sector. Buildings account for a large portion of both U.S. primary energy (almost 40%) and electricity (73%) consumption [3]. Prior studies suggest that energy efficient solutions for domestic electrical appliances can be deployed that reduce consumer energy waste between to 10 to 15% [1]. One of the solutions is to provide a detailed breakdown of contributing appliance's energy consumption to the consumers. Also by providing this information, inspires positive consumer behavioral change.

The aim of this work is to develop a NIALM method that provides a breakdown of energy consumption of household appliances. The research problem addressed in this work is to investigate ways in which machine learning techniques can be used in developing a NIALM model that disaggregates combined household load into individual appliance loads. With the data recorded at the service entrance, the goal is to detect the appliances functioning in the household according to their individual load characteristics. This paper mainly focuses on the applications of the probabilistic methods for appliance energy disaggregation with smart meter data collected at the service entrance. A novel appliance disaggregation technique is proposed, where the granularity of the disaggregated appliance power readings matches with that of the readings collected at the service entrance.

The full problem of energy disaggregation is treated and a solution is provided to the NIALM problem fully, in a three stage procedure. In the first stage, individual load characteristics of appliances are well studied, and all the appliances are trained on their individual characteristics identical to the method proposed in [4]. In the second stage, a combined load model is build using the trained individual appliances. This combined load model will contain all the possible state transitions between appliances in a house. In the third stage, a mathematical algorithm disaggregates the power readings obtained from a service-entrance of a house into its individual appliances. The proposed disaggregation technique is tested with publicly released UK-DALE [5] and Tracebase [6] data sets. Indeed in the Section 5.1 and the Section 5.2, we present the success rate of the proposed approach where it showed a 95% success rate of 1-minute data samples and a success rate of 85% and above for 15-minutes data samples of Tracebase [6] data sets. It also showed a success rate of 85% and above for 6-seconds data samples of the UK-DALE data sets.

2. BACKGROUND: APPLIANCE LOAD MONITORING

State-of-the-art approaches divide appliance load monitoring into two distinct categories, i.e. intrusive appliance load monitoring and non-intrusive appliance load monitoring. Hart (1992) explains intrusive-monitoring as a complex data-gathering hardware but simple software process. Each appliance of interest is monitored using specific appliance type hardware and data is collected at a central location using separate data paths, so the software merely has to tabulate the data arriving over these separate hardware channels. Conversely, Hart defines non-intrusive monitoring as a simple hardware but complex software process. Complex software is required for the processing and analysis of appliance signals. This is the reason non-intrusive monitoring is considered as a cost-effective trade off, which is a major advantage of NIALM.

2.1. INTRUSIVE APPLIANCE LOAD MONITORING

Intrusive appliance load monitoring is commonly referred to as a distributed monitoring approach. It is more accurate in measuring appliance specific energy consumption, but it requires configuration of multiple sensor(s) as well as installation on individual appliances. It is this intrinsic intrusive nature that favors the use of non-intrusive monitoring especially for the case of large scale deployments. Intrusive monitoring is further divided into electrical sub-metering and appliance tagging categories.

Electrical sub-metering refers to the monitoring of the electrical consumption of individual appliances within a household. In addition to the main-load meter used by utilities to determine overall household electric consumption, electrical sub-meters allow building and facility managers to have visibility into the energy use and performance of their appliances, creating an opportunity for energy saving. Although this approach allows an accurate measurement of the energy consumed by an appliance, it has many practical disadvantages. The significant cost and time required per installation are often cited as reasons why this approach is impractical to deploy for a large user base. This is the reason why electrical sub-meters for long-term appliance monitoring are not considered in current literature [1].

In appliance tagging, each device has an RFID tag that emits a signal, whenever an appliance turns on or off. These signals are detected by a central data-gathering hub which estimates each appliance’s energy consumption. McWilliam and Purvis (2006) demonstrate the use of transmitting an RFID signal through the main circuit to a central recorder in order to uniquely identify appliances. However, each appliance is customized in addition to the installation of a central signature detector. As with electrical sub-metering the installation time and cost per household is considerable and is therefore not considered by the researchers [1].

2.2. NON-INTRUSIVE APPLIANCE LOAD MONITORING

Non-intrusive appliance load monitoring refers to the process of monitoring an electric circuit that consists of a number of appliances which switch on and off independently of each other. Hart [1] demonstrates that NIALM requires a sophisticated analysis of the current and voltage waveforms of the total load, to estimate the number and nature of the individual loads, their individual energy consumption and other relevant statistics. This provides a time and cost-efficient method of gathering load data when compared to traditional IALM approaches. The NIALM monitors the total load, checking for certain appliance "signatures" that provides information about the state (activity) of the appliances which contributes the total load. Types of appliances and a detailed analysis of each of these appliances are discussed in the further sections.

2.3. TYPES AND ANALYSIS OF APPLIANCES

Appliances are classified into three models. Hart [1] classifies them as on/off, multi-state and continuously variable from the NIALM perspective. An appliance which is on or off at any given moment and draws a constant power in each state is considered as an ON/OFF appliance. Example of such an appliance is a light-bulb. An appliance that possesses multiple types of ON state is considered as a multistate appliance. An example of such an appliance is a washing machine with distinct ON states such as fill, rinse, spin, pump, etc. An appliance with a continuous range of ON states is considered a continuously variable appliance. An example of such appliance is a light dimmer. Hart explains that the former two types can be monitored non-intrusively and the later cannot as such appliances do not generate step changes in power. Therefore, these continuously variable appliances will not be considered further in this work. Hart [1] implies that an appliance state (e.g. fan speed) is user observable and draws a constant power. However this model is not applicable to all appliances, as it makes no provision for electrically distinct types of ON states. For example, a modern washing machine might operate on a predefined cycle (e.g. fill, agitate, spin), but the power drawn at each state of this cycle might constantly alternate between two or more levels. Therefore, a more expressive model is required to represent the distribution of power drawn by an appliance for each of its operating states, which is inadequately represented by an ON/OFF model.

There are many factors that result in an appliance changing its operational state. There is a clear distinction between the state changes that are caused either by a human or the appliance itself. A human can control the state transitions of an appliance (e.g. television). Alternatively an appliance can control the state transitions of an appliance itself. An appliance might turn on at a time determined by the appliance (e.g. refrigerator), or turn off at a time determined by the appliance (e.g. toaster). Also, an appliance might change its operating state accordingly to a cycle determined by the appliance. (e.g. washing machine). It is easier to predict state transitions that are caused due to an appliance, since it is predetermined by an appliance itself, and it is highly likely that an appliance will follow similar state transitions, according to the predefined set. Therefore, an appliance model should exploit such predictability when disaggregating a household.

2.4. TEMPORAL GRAPHICAL MODELS

A temporal graphical model is a probabilistic model where a graph denotes the conditional dependence structure between consecutive time-slices of a distribution. State-of-the-art approaches in this area use a principled probabilistic model to represent the NIALM problem. The model should recognize that premise-level power readings are drawn from a continuous time series, and are not independent of each other. In general, appliances are far more likely to stay in their current state, and state changes are comparatively rare. NIALM can also be considered as an on-line learning problem in which disaggregation must occur after each individual premise-level power value has been received. These two assumptions map directly on to the modeling of such a problem as a factorial hidden Markov model.

A hidden Markov model (HMM) is a stochastic Markov model. A first-order Markov chain is a sequence of conditionally dependent variables, where the variable at each time slice is dependent only on the variable immediately preceding it. A HMM is made up of a Markov chain of discrete variables, each of which is responsible for a corresponding observation [7]. The HMM is a well-studied probabilistic model, and it is considered as a novel approach for appliance disaggregation. It has been successfully applied to the fields of speech recognition, natural modeling and online handwriting recognition [7]. According to the NIALM scenario, the simplest problem is one in which we wish to determine the state of a single multi-state appliance, such as those described in Section 2.3, given its power demand. This can be represented using a hidden Markov model as follows:

$$p(x,z|\theta) = p(z_1|\pi)\prod_{t=2}^{T} p(z \mid z_{t-1}, A) \prod_{t=1}^{\pi} p(x_t \mid z_t, \phi) \tag{1}$$

Where z represents observations of power, π is a vector of probabilities of starting values for z_1, A is a matrix of transition probabilities between states, ϕ is a vector of distributions for the observations and θ is a set of model parameters $\{\pi, A, \phi\}$. Elements of π are probabilities that relate to each of the discrete states, and therefore must satisfy:

$$\sum_{k=1}^{K} (\pi_{n,k}) = 1 \tag{2}$$

where $0 \leq \pi_{n,k} \leq 1$. Similarly, A is a matrix of probabilities where rows, denoted by i, represent the probabilities of transitions from one state to each other state, represented by columns, j, and therefore must satisfy:

$$\sum_{j=1}^{J} \left(A_{n,i,j}\right) = 1 \qquad (3)$$

for each i, where $0 \leq A_{n,i,j} \leq 1$. The elements of the main diagonal correspond to the probability that appliance will stay in the same state it is already in; while the surrounding elements correspond to the probability that it will change to each other state. These transition probabilities model appliance switching as a Markov process, in which the appliance's immediate future transition is dependent only on the appliance's current state. Also, an assumption is made that an appliance in a given state will draw power normally distributed about a mean μ_n, with some variance, σ_n.

$$\emptyset_n = \mathrm{N}(\mu_{n,k}, \sigma_{n,k}) \qquad (4)$$

Therefore, the power demand of each appliance, y_n, is modelled by one set of Gaussian functions:

$$y_n = \sum_{k=1}^{K} z_{n,k} \mathrm{N}\left(\mu_{n,k}, \sigma_{n,k}\right) \qquad (5)$$

where the switching variable satisfies $z_{n,k} \in \{0,1\}$. Knowledge of the model parameters θ, or π, A and $\emptyset$, is necessary to calculate the probability of a sequence of variable assignments in a HMM. Initial probability of the state of an appliance can be determined by hand, or can be learned during model training. To disaggregate the power drawn by many appliances into individual appliances, we need multiple HMMs that can represent multiple appliance states and their sequence of observations. A factorial Hidden Markov Model (FHMM) is used to represent multiple appliances in one model.

In a FHMM, there are multiple independent chains of hidden variables. According to the NIALM scenario, these are the current operating states of each appliance. At each time slice, there is also an observed variable that is dependent on the states of all the corresponding hidden variables, which according to NIALM, is the service-entrance power value. The goal of an NIALM solution is to evaluate the state of appliances, and power demand of appliances in that state. We are therefore interested in modelling the probability of an appliance being in a certain state, given the appliance's state in the previous time slice and the observed variable for that time slice: $p(z_t|z_{t-1}, x_t)$.

3. EXISTING SOLUTIONS

This section primarily focuses on existing solutions that aimed at solving the NIALM problem.

Event detection techniques are considered to be one of the existing approaches for non-intrusive load monitoring and disaggregation. In [8] the author proposed an Approximate Power Trace Decomposition Algorithm (APTDA) that exploits the nature of the power signal by power consumption level. This approach considers K ranges of power consumption and defines each E_k to represent the energy consumed by appliances that consume power in the K^{th} range. E_0 represents the total energy used by the background devices, E_1 represents the total energy used by the devices that consume power in the range of 0-105W, E_2 represents the total energy used by appliances that consume power in the range of 105-720W, and E3 represents the total energy used by devices that consume power at a rate of greater than 720W. Although the modeling of power consumption ranges for a power consumption-based decomposition is somewhat similar to our proposed approach in Section 4, the power ranges that are modeled using the APTDA approach do not tell the user what devices have contributed to each range. Also this approach deviates from the full problem of energy disaggregation and only focuses on estimating the energy used by the different ranges of devices.

An interesting model is proposed in [9], in which there are two observation sequences, instead of the one that is used in standard HMM. One observation sequence corresponds to the household aggregate power demand measured at the service entrance, while the other corresponds to the step changes in the aggregate power demand. The second observation sequence is therefore dependent on the appliance state in both the current and previous time slice. Hence, the second observation sequence corresponds to the change in aggregate power that is generated by the two consecutive appliance states. In later stages, this approach detects some appliances switching on and off at certain time windows, based on the edge signature of each of the appliances using the Expectation-Maximization (EM) algorithm. The essential step considered in this approach, is to subtract the estimated usage of an appliance load from the aggregate load before the disaggregation of a new load. The Viterbi algorithm is a dynamic programming algorithm that determines the optimal sequence of state transitions in a hidden Markov model, given the sequence of observation of the model. Also the extended Viterbi algorithm used in [9] does not take into consideration that the observation sequence of the aggregated signal is a linear combination of the appliance loads. While [9] iteratively disaggregates some appliances for which prior behavior models are known, there is a possibility of introducing errors by disaggregating the high energy consuming appliances with more energy than they actually consume. It means wrongly detected instances of an appliance lead to errors that are carried out by the algorithm in its next iteration of disaggregation. Such disaggregation excludes information of low energy consuming appliances, as their instances will be lost in the signatures of the high energy consuming appliance instances. A similar unsupervised HMM based approach is proposed in [10] which claims that, given the inferred consumption of the whole set of devices, it is possible to perform an optimatization step adjusting the calculated states, as the measured aggregated electrical usage is a linear combination of these loads.

Two new disaggregation algorithms in [11] focus on energy disaggregation at low-sampling rates (at 6 sec and at 1 min) using only active power measurements for training and testing. During the training phase of these algorithms, the load of each appliance is estimated at specific time instances of appliances, and is fed into a library of appliance signatures. The training phase needs to be re-executed whenever an appliance changes it states. Edge detection is used by comparing the power from current and previous time instances to detect an event that occurs when an appliance changes its state. Classification of appliances is performed by pattern matching, for the DTW method. This approach is directly compared against our proposed approach in Section 5.2 and the results are presented in Section 5. The proposed algorithm achieved higher success rate in direct comparison to the existing algorithms [11].

Another approach to monitor appliances without installing smart meters is through conditional demand analysis (CDA). CDA utilizes the energy bills generated for the households. In addition, CDA would require information about consumer, household and weather. Data collected from many households is then analyzed using a multivariate regression technique to learn what appliances are contributing in the aggregate power demand. Using CDA would require a large participant base, and each of them is asked to complete a detailed questionnaire; which could be an intrusion of their privacy. Furthermore, CDA does not capture unusual cases which are not accounted for by such questionnaires, e.g. when the dryer runs four times a day.

One essential problem with event detection algorithms is that they deviate from the main goal of appliance level energy disaggregation, instead focus on disaggregating detected events in appliances. These algorithms later perform an optimization step by linearly combining the respective events of an appliance in order to obtain the energy consumption of individual appliances. Instead the proposed algorithm in Section 4 aims at solving the fundamental problem of NIALM, a complete appliance level energy disaggregation from the aggregated load collected at the service entrance. The proposed approach in Section 4 takes an edge over the existing approach [9] where the existing approach [9] disaggregates those periods during where a single appliance turns on and off without any other appliances changing state. This produces a signature in the aggregate load which affects the baseline load. Also, only specific instances of an appliance are obtained, instead of the complete behavior of an appliance (complete state transition sequence). The general models of appliances are tuned to specific appliance instances, by using those disaggregated periods. This approach deviates from the fundamental problem of energy disaggregation, i.e., a simple appliance level breakdown of energy consumption, and it focus on disaggregating those times windows of an appliance, when other appliance states remain constant (i.e., it aims to disaggregate specific appliance instances instead of the complete behavior).

4. PROPOSED DISAGGREGATION TECHNIQUE FOR NIALM

This section primarily focuses on the application of probabilistic methods for appliance energy disaggregation using smart meter data collected at the service entrance. First, individual device HMMs and combined load HMMs are modeled from the locally collected data set. Then, a novel appliance disaggregation method is proposed, where the granularity of the disaggregated appliance power readings matches with that of the readings collected at the service entrance.

4.1 MODELING INDIVIDUAL LOAD HIDDEN MARKOV MODEL

To build a non-intrusive solution for appliance monitoring, it is first necessary to evaluate the range of appliance loads the system is required to disaggregate. Similar individual appliance load modeling is carried out as mentioned in [4]. The load profile that is collected from active power consumption using a Power Standards Lab PQube measurement device is converted into sequence of observations by bucketing power levels. Bucketing is a design decision made, where the input of each bucket is a range of power values, and each bucket outputs a corresponding sequence of observations based on the specified bucket size. Similar power measurements within a load profile are considered as one observation condensed to a single state or value. State is an operational mode of a device. Each state emits a range of power values

State of an appliance is often defined with a human insight into the appliance's pre-defined nature. For instance, we know prior to looking at the washing machine's data set that a washing machine has various states (OFF state, rinse state, spin state etc.). So the washing machine's data set will have a corresponding sequence of observations at various states. 'OFF' state will have observations falling into bucket zero, the 'rinse' state will have observations falling into comparatively much higher buckets than off state, and spin state will have observations falling into the superlatively highest bucket. Each bucket corresponds to a state, with bucket 0 mapping to state 1. If an appliance has new observations falling beyond the current highest bucket, then these observations are allocated to a new bucket. Once the states are determined, a known test Viterbi sequence of that appliance is generated. Modeling of individual load appliances is carried out in the Algorithm 4.1 in a step-wise manner.

1. An appliance's original sequence of observations along with the appliance's known test Viterbi sequence are given as inputs to the maximum likelihood estimation (MLE) algorithm.
2. MLE estimates the number of i to j transitions for an observation sequence, and also the number of observations at state i, to output the best log likelihood transition and observation probabilities of transition (T) and observation (O) matrices. Transition probability ($T_{i,j}$) is defined as the probability of going from state i to state j and observation probability ($O_{i,s}$) is defined as the probability of finding an observation s at state i. A similar method is employed to generate all the T and O matrices for all the variants of an appliance.
3. Generated T and O matrices are averaged over the number of variants of an appliance resulting in the trained T and O matrices. The trained T and O

matrices modeled this way are expected to have the best log likelihood probabilities of an appliance.

4. To ensure the confidence in the trained T and O matrices, an appliance's original sequence of observation along with the trained T and O matrices are given as an input to the Viterbi algorithm. The Viterbi algorithm then outputs the optimal state sequence of an appliance which is similar to the known test Viterbi state sequence of that appliance provided as an input to the algorithm. Figure 4.1. (a) shows the known test Viterbi sequence for a hair dryer and Fig. 4.1. (b) and Fig. 4.1. (c) shows the hair dryer's corresponding Viterbi state sequence and its original sequence of observations (active power measurement) respectively.

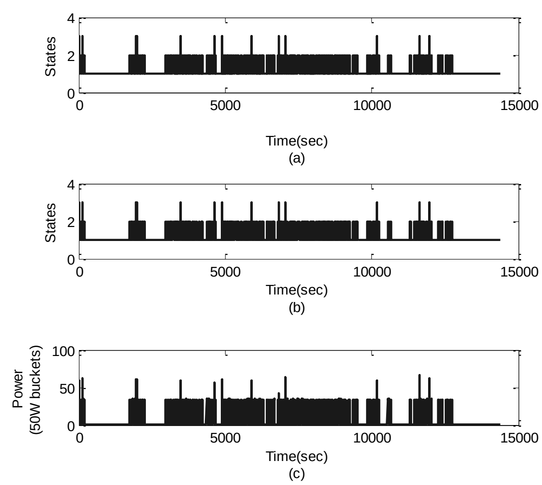

Fig. 4.1. Individual Load Modeling of Hair Dryer, Hair Dryer known test Viterbi state sequence (a), Optimal state sequence by Viterbi algorithm (b), active power measurement (c)

4.2 MODELING COMBINED LOAD HIDDEN MARKOV MODEL

To build a combined load hidden Markov model, the three basic HMM problems are addressed. First, the likelihood of the combined observation sequence $P(O|\lambda)$ is evaluated given the combined load hidden Markov model $\lambda = (T, O, \pi)$. Second, the parameters of the combined load hidden Markov model are adjusted to maximize the likelihood of the combined observation sequence $P(O|\lambda)$. Third, the optimal state sequence is deduced by the Viterbi algorithm given the combined observation sequence and the model. To model a combined Viterbi state sequence of all the appliances, transition and observation matrices are required that represent all possible combinations of the appliances state transition and observation probabilities. Kronecker operators are employed to describe all the possible state transitions of a combined load HMM. Transition matrices of individual appliances are combined using a Kronecker product in equation (6), where $T_{combined}$ is the transition matrix of a combined load HMM, and T_1 and T_2 are the transition matrices of individual HMMs. Although it is highly unlikely that switching off a washing machine would result in a refrigerator turning off, but even such transitions between states are still represented in the combined state space with either a very low probability, or zero probability. Emission matrices are also combined using a Kronecker product and the columns corresponding to equal combination of symbols are summed in equation (7) where O_{full} is the observation matrix of a combined load HMM, and O_1 and O_2 are the observation matrices of individual HMMs. The $\hat{\otimes}$ operator performs a Kronecker product with summation over equal columns of observations.

$$T_{combined} = (((T_1 \otimes T_2) \otimes T_3) \otimes T_4) \quad (6)$$

$$O_{combined} = (((O_1 \hat{\otimes} O_2) \hat{\otimes} O_3) \hat{\otimes} O_4) \quad (7)$$

In equation (6), the key point is the composition of transition matrices of various appliances. When doing so, the order in which the transition matrices of appliances are composed is particularly critical for the proposed disaggregation algorithm. This is because the resulting Viterbi state sequence from the combined transition and observation matrices and combined load observation sequence is given as an input to the disaggregation algorithm. Figure 4.2 (a) represents the combined Viterbi state sequence for combined load observation sequence in Fig 4.2 (b), comprising of seven appliances in the specified order (dishwasher, hair dryer, kettle, microwave, gas-oven, toaster and washing machine).

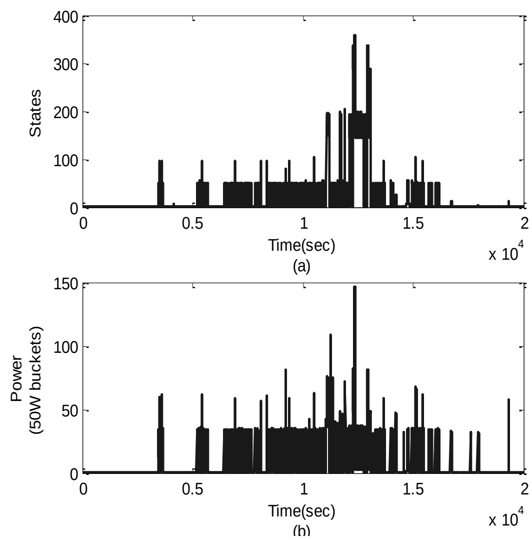

Fig. 4.2. Combined Load Modeling, Comparison of combined load observation sequence (a), combined Viterbi state sequence (b).

4.3 DISAGGREGATING THE COMBINED LOAD HIDDEN MARKOV MODEL

The disaggregation task aims to extract individual hidden Markov models from the combined load hidden Markov model. A mathematical extension of a Viterbi algorithm is proposed to disaggregate the individual Viterbi sequences of appliances from the combined load Viterbi sequence using their respective state sizes. State size corresponds to the number of states present in an individual appliance. The input of the disaggregation algorithm is the combined Viterbi state sequence generated using the combined transition and observation matrices. The order in which these matrices are composed is of paramount concern in disaggregating the combined Viterbi state sequence. This is because, the proposed algorithm disaggregates the combined Viterbi state sequence with respect to the state sizes of the remaining appliances added in the order it is modeled. So if an appliance is added to the combined load model which consists of three other appliances, then the proposed algorithm disaggregates the combined Viterbi state sequence with respect to the state size of the disaggregating appliance.

To disaggregate an appliance that is first added in the order of the combined model of four appliances, the algorithm first divides the combined Viterbi state sequence over all the added over appliances' state sizes. The remaining combined Viterbi sequence is disaggregated with respect to the disaggregating appliance's state size. Unlike existing disaggregation algorithms that focus on incremental improvements in the accuracy, the proposed disaggregation algorithm handles the full problem of energy disaggregation i.e., a simple appliance-level breakdown of home energy consumption.

Figure 4.3, Fig 4.4, Fig 4.5, Fig 4.6, Fig 4.7, Fig 4.8 and Fig 4.9 illustrates the disaggregation process of seven appliances (dishwasher, hair dryer, kettle, microwave, gas-oven, toaster and washing machine). Since dishwasher is added first in the combined load model, the combined Viterbi state sequence is divided over the states sizes of hair dryer, kettle, microwave, gas-oven, toaster and washing machine, later it is disaggregated with respect to its own state size to generate the dishwasher's Viterbi state sequence. To obtain the microwave's Viterbi state sequence, the proposed algorithm divides the combined Viterbi state sequence over the state sizes of gas-oven, toaster and washing-machine (since these appliances are added into the model after the microwave is added), and later it disaggregates the resulting Viterbi state sequence with respect to microwave's state size. The main difference between the existing algorithms to the proposed algorithm is that, the disaggregation process is not iterative. This means that at any instance of time in the disaggregation process, an appliance can be disaggregated with respect to its state size, to obtain a complete state sequence of an appliance.

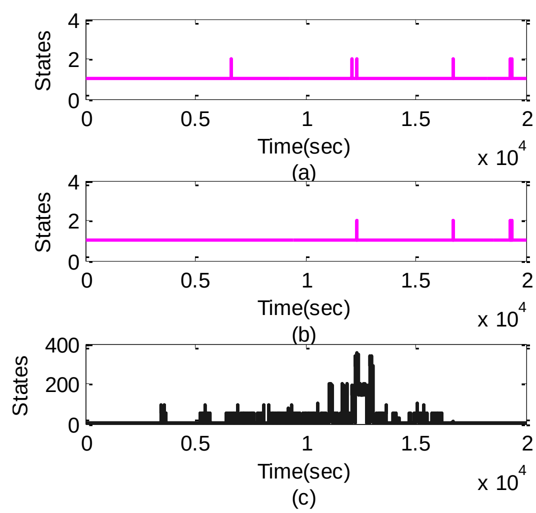

Fig 4.3. Microwave's disaggregation, Disaggregated Microwave's Viterbi state sequence (a) from combined Viterbi state sequence(c), and known test microwave's Viterbi state sequence (b)

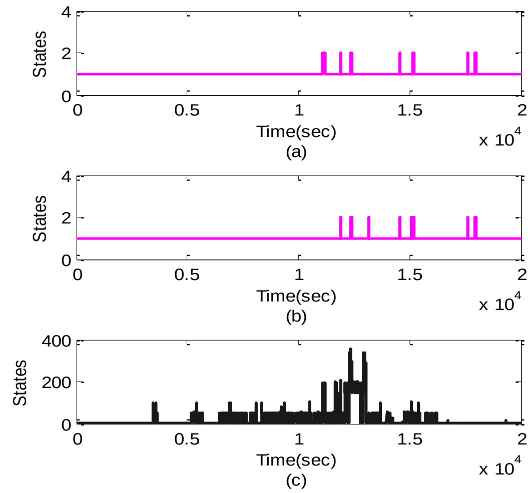

Fig 4.4. Toaster’s disaggregation, Disaggregated Toaster’s Viterbi state sequence (a) from combined Viterbi state sequence(c), and known test toaster’s Viterbi state sequence (b)

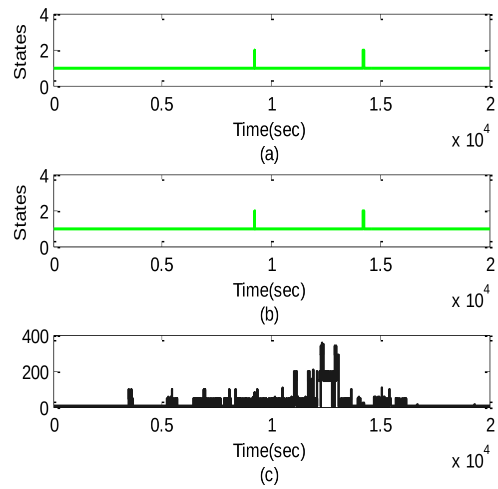

Fig 4.5. Kettle’s disaggregation, Disaggregated Kettle Viterbi state sequence (a) from combined Viterbi state sequence(c), and known test kettle’s Viterbi state sequence (b)

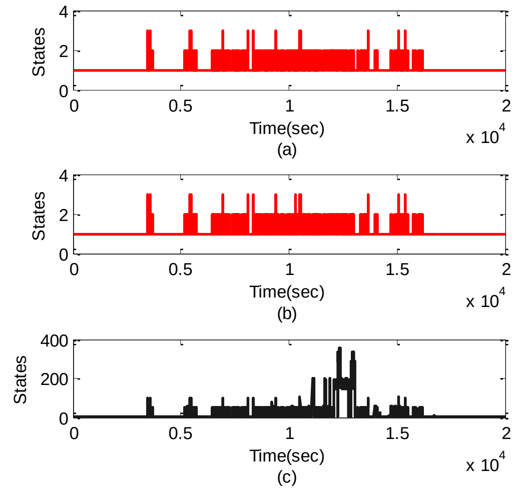

Fig 4.6. Hair Dryer's disaggregation, Disaggregated Hair Dryer Viterbi state sequence (a) from combined Viterbi state sequence(c), and known test Hair Dryer's Viterbi state sequence (b)

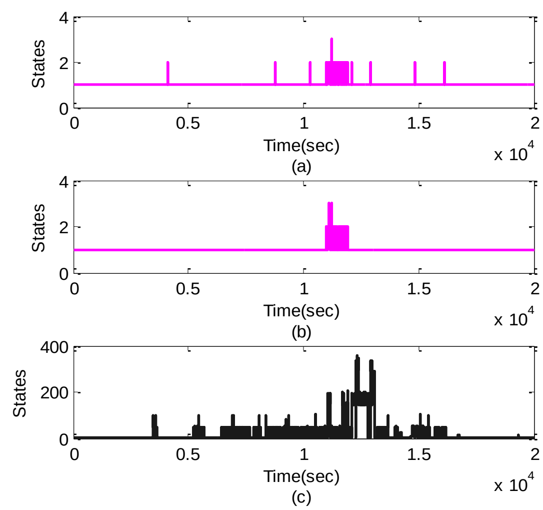

Fig 4.7. Washing-machine's disaggregation, Disaggregated Washing-machine's Viterbi state sequence (a) from combined Viterbi state sequence(c), and known generated washing-machine Viterbi state sequence (b)

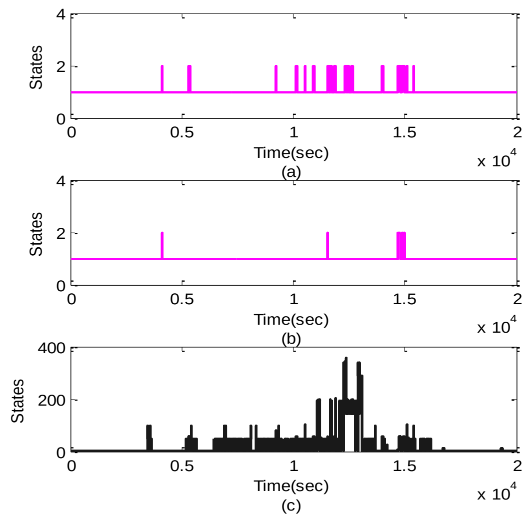

Fig 4.8. Gas-oven's disaggregation, Disaggregated Gas-Oven's Viterbi state sequence (a) from combined Viterbi state sequence(c), and known test gas-ovenViterbi state sequence (b)

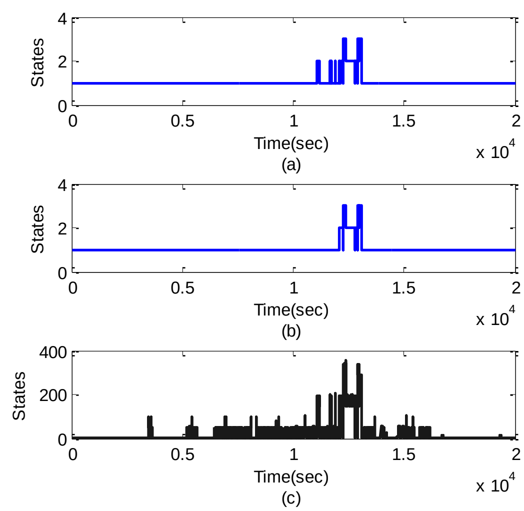

Fig 4.9. Dishwasher's disaggregation, Disaggregated Dishwasher Viterbi state sequence (a) from combined Viterbi state sequence(c), and known test dishwasher Viterbi state sequence (b)

5. EVALUATING THE PROPOSED MODEL

In this section, the success rate of the proposed disaggregation algorithm is evaluated through the following two data sets and experiments. First, the accuracy of the proposed disaggregation algorithm is estimated with publicly released Tracebase [6] data sets. Second the proposed algorithm results are compared directly against the results [11] with the UK-DALE [5] data sets. The evaluation metrics used for the first experiment using the Tracebase data set are the K-fold cross validation techniques and calculated the correlation coefficients for individual appliances and the proposed model. For the second experiment using the UK-DALE [5] data set, the metrics used are precision (PR), recall (RE) and F-Measure (FM) as defined in the [9][11].

5.1 ESTIMATING THE ACCURACY USING TRACEBASE DATA SETS

The K-fold cross validation technique is employed to validate the proposed model for assessing how robust the model is to an independent data set. In K-fold cross validation, of the K-data sets, a single dataset is retained as the validation data for testing the model, and the remaining k-1 data sets are used for training the model. The proposed approach has been evaluated using the Tracebase [7] data set. This data set was chosen as it is a public data set collected specifically for evaluating NIALM approaches. Tracebase comprises a collection of various electrical appliance power traces, collected using the plug-wise system to capture the real power demand of an appliance at a resolution of several samples per second. Both aggregate and appliance-level data were down sampled to one sample per five seconds.

To estimate the accuracy of the defined model, data is sampled at different resolutions, using a zero-order hold technique. The zero-order hold (ZOH) is a signal reconstruction technique that converted the originally sampled data into specified sampling interval data by holding each sample value for one sample interval for missed samples. Various samples of data with different resolutions at different bucket sizes are considered. Data from the Tracebase data sets is relaxed at different sampling rates, ranging from 1 sec to 15 minutes between different bucket sizes ranging from 5W to 100W. The correlation between the disaggregated Viterbi sequence and a known test Viterbi sequence are calculated by measuring the degree of correlation between these two sequences. Correlation coefficient is defined as a measure that determines the degree to which the two sequences (known test Viterbi sequence and disaggregated Viterbi sequence) are associated with each other. The correlation coefficient will vary from -1 to +1, indicating perfect negative correlation and perfect positive correlation respectively. Figure 5.1 represents the information graph obtained calculating the accuracy of proposed model.

$$Accuracy_{calculated,known} = \frac{Covariance(calculated,known)}{\sigma_{calculated}\sigma_{known}} \tag{8}$$

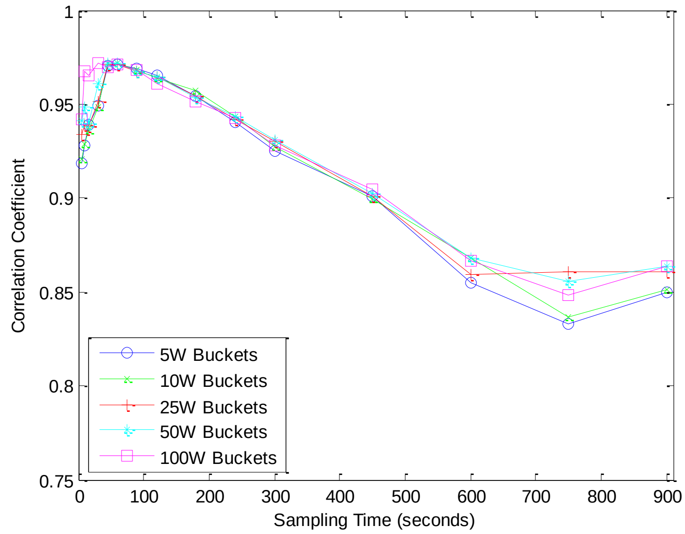

Fig. 5.1. Information Graph representing the correlation between known and disaggregated Viterbi sequences

From the information graph in the Figure 5.1, it is observed that the disaggregated Viterbi sequences have high correlation with the known test Viterbi sequences. At 5 seconds sampling intervals, the correlation between known Viterbi sequences and disaggregated Viterbi sequences is found to be around 95% which means 95% of variation in the disaggregated Viterbi sequences is explained by the known Viterbi sequence. At 15 minutes sampling intervals, the correlation is found to be around 85%. As sampling interval increases from 5seconds to 15minutes, the information obtained from the graph decreases because a lot of information about the appliances which are operated at smaller duration of time is obtained at higher sampling resolutions. For higher sampling resolution such as 5 seconds, there should be a lot of scope to detail, (microwave's events such as turning on and off, toaster turning on and off etc.) which is exactly reflected by the information graph. Events such as microwave turning on and off (for 5 minutes duration), will go unnoticed for smaller sampling resolution as of 15 minutes. So this information is excluded in the information graph.

5.2 EVALUATING THE MODEL USING UK-DALE DATA SETS

The proposed disaggregation method is evaluated by calculating the common performance metrics precision (PR), recall (RE) and F-Measure (F_M) and accuracy.

$$PR = TP/(TP + FP) \tag{9}$$

$$RE = TP/(TP + FN) \tag{10}$$

$$F_M = 2 * (PR * RE)/(PR + RE) \tag{11}$$

where true positive (TP) measures the actual positives that are correctly identified, false positives (FP) measures the actual positives that are incorrectly identified and false negative (FN) measures the actual negatives that are incorrectly rejcted. Actual positive (p) is defined as an appliance being in an ON state (beyond state 1) and actual negative (n) is defined as an appliance being in an OFF state (state 1). So TP presents a claim that an appliance was used in the original combined state sequence and correctly identified in the disaggregated Viterbi sequence, FP presents a claim that an appliance was not used in the original combined state sequence yet identified in the disaggregated Viterbi sequence, and FN presents a claim that an appliance was used in the original combined state sequence but not identified in the disaggregated Viterbi sequence. Seven appliances from the UK-DALE data sets (dishwasher, hair dryer, kettle, microwave, gas-oven, toaster and washing machine) were trained as discussed in the Section 4.1. Dishwasher, hair dryer and washing machine were trained as three state appliances while microwave, kettle, gas-oven and toaster were trained as two state appliances. In their ON state, the two state appliances except for gas-oven had power consumption ranging from 1500W to 2500W. When the power levels are separated into 50W buckets, these values span between 30-50 buckets. The gas-oven in its ON state had a power consumption range from 100W to 150W, so it was bucketed into three 50W buckets. Power measurements falling into the second bucket are considered as an ON state for the gas-oven. Known test Viterbi sequences for each of these appliances were generated as described in the Section 4.1. Later the bucketed-power sequences along with the known test Viterbi sequences were given as an input to the MLE algorithm, to obtain their T and O matrics. These T and O matrices were combined as discussed in the Section 4.2, in the specified order (dishwasher, hair dryer, kettle, microwave, gas-oven, toaster and washing machine) into the $T_{combined}$ and $O_{combined}$ matrix. The $T_{combined}$ matrix represents all the possible state transitions between the combined appliances. These $T_{combined}$ and $O_{combined}$ matrices along with the combined sequence of power observations are given as an input to the Viterbi algorithm to generate the optimal sequence of state transitions between the appliances. Finally, the full Viterbi state sequence of the combined appliances was given as an input to the proposed disaggregation algorithm as discussed in the Section 4.3. Indeed the proposed algorithm disaggregated the combined Viterbi sequence into individual load Viterbi sequences with a total precision (PR) of 85.93% , recall (RE) of 95.30% and F-Measure (F_M) of 88.67% as showed in Table 5.1.

Table 5.1. Comparison between the existing disaggregation methods and the proposed algorithm

	Precision PR(%)				Recall RE(%)				F-Measure F_M(%)			
Appliances	DTW [12]	DT [12]	HMM [12]	Proposed Algorithm	DTW [12]	DT [12]	HMM [12]	Proposed Algorithm	DTW [12]	DT [12]	HMM [12]	Proposed Algorithm
Microwave	98.33	87.01	64.9	80.85	69.21	95.04	69.5	84.44	81.24	90.95	67.12	90.69
Toaster	69.16	87.5	67.21	100	96.1	71.01	58.57	98.44	80.43	78.4	62.6	97.33
Kettle	95.04	100	94.23	100	95.83	87.76	50	100	95.43	93.48	65.33	100
Oven	100	41.18	100	41.68	100	87.5	62.5	98.41	100	56	76.92	82.61
Washing Machine	100	88.89	0	97.66	100	100	0	91.26	100	94.12	0	58.56
Hair Dryer	50	66.67	25	95.42	66.67	50	25	99.3	57.13	57.14	25	99.21
Dishwasher				83.11				99.79				94.35
Total	85.42	78.54	58.55	85.93	87.96	81.88	44.26	95.30	85.70	78.34	49.45	88.67

Table 5.1. represents the comparison between the existing disaggregation methods and the proposed disaggregation algorithm using the PR, RE and F_M metrics using the 6-second data from UK-DALE data sets. The proposed algorithm had higher results in direct comparison with the existing algorithms proposed in [11]. The author in [11] developed two algorithms: Decision Tree (DT) algorithm is a supervised learning algorithm with low-complexity, and Dynamic Time Wrapping (DTW) is an unsupervised learning algorithm. A direct comparison is also made with the state-of-the-art Hidden Markov Model (HMM) based approach. It showed a success rate of 85% and above for 6-sec UK-DALE [5] data sets with six appliances as opposed to the existing disaggregation algorithms used in the comparison. The existing algorithms did not train their model with dishwasher appliance, and hence dishwasher wasn't used in calculating the overall PR, RE and F_M scores of the proposed algorithm.

6. CONCLUSION

This work handled the fundamental goal of NIALM problem i.e., an appliance level disaggregation of house hold data. Individual appliances were modeled as hidden Markov models using their active power measurements. Then a method to model the aggregate load was discussed and an appliance disaggregation technique was proposed. The proposed algorithm was evaluated using both Tracebase [6] data sets and the UK-DALE [8] data sets at different sampling intervals. Using Tracebase data sets [6], the accuracy of the disaggregation technique was calculated to be at 95% for higher-sampling resolutions as of 5 seconds. A comparison of existing disaggregation algorithm [11] with the proposed disaggregation algorithm was made, and the proposed algorithm indeed showed a success rate of 85% and above with 6-second sampled UK-DALE data set [5].

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VITA

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