A Hidden Markov Model Based Procedure for Identifying Household Electric Loads

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Abstract- **In automated energy management systems, to make instantaneous decisions based on the appliance status information, continuous data access is a key requirement. With the advances in sensor and communication technologies, it is now possible to remotely monitor the power consumption data. However, before an appliance is actively monitored, it must be identified using the obtained power consumption data. Appropriate methods are required to analyse power consumption patterns for proper appliance recognition. The focus of this work is to provide the model structure for storing and distinguishing the recurring footprints of the household appliances. Hidden Markov model based method is proposed to recognize the individual appliances from combined load. It is found that the proposed method can efficiently differentiate the power consumption patterns of appliances from their combined profiles.**

I. INTRODUCTION

The critical nature of energy systems due to rapidly increasing energy demand is a much publicized issue nowadays. This happens due to the fact that generation resources and transmission infrastructure are approaching their limits [1]. One solution to this issue is to build new power generation plants. However, it requires many years along with huge capital investment. Despite this, the environmental concerns are also not favorable to building new generation plants. This situation has led the utilities to look at power production and utilization in a different way. As a result, they are focused not only on distributed generation based small power networks (known as microgrids) but also energy demand optimization.

The optimization of energy demand is a way to manage the demand according to the available generation resources so that a balance between demand and supply can be maintained. The most critical aspect of demand supply balance is the peak load which can be introduced for a few hours. Rather than shedding entire districts, the efficient mechanism is to selectively deactivate or shift the loads by taking into account the criticality of loads [1]. However, this method not only requires communication and load management infrastructure at the customer's end as a prerequisite. But also information about customer's processes (i.e. loads) so that a reliable algorithm which can optimize demand can be implemented.

Rather than influencing the customers' processes, another mechanism of energy optimization is to motivate the customers to adopt energy conservation behavior. For this purpose, on the one hand the customers are offered a time-of-use tariff [2, 3], while on the other hand direct energy consumption feedback is provided as a self-learning tool [4, 5, 6]. To design and evaluate such energy management programs, detailed end use energy consumption information is an essential requirement [7]. This information is typically acquired either by manual inspection or installing data loggers with appliances. Since the methods are laborious, cost-intensive and time consuming. Automated load monitoring system is required.

Therefore in the author's view point end-use energy consumption information is an essential requirement in order to optimize the energy utilization. In other words, knowledge about the energy consumption of individual appliances is key to meet the challenge of demand and supply imbalance. Since manual monitoring (using dedicated data loggers installed manually) provides outdated and costly information, the automated load monitoring system is vital.

The underlying goal of this work is to provide a model structure for detecting, storing and recognizing recurring power consumption patterns of household appliances. The load monitoring system should be capable to identify the individual appliances by observing the combined power that they have consumed collectively. In order to perform this task, the domain of machine learning provides a wide spectrum of methods. In [8], the authors unified several methods which can be used for the task of unsupervised learning under a single basic generative model. These methods include factor analysis, principle component analysis, and mixture of Gaussian clusters, vector quantization, Kalman filter models, and HMMs. The unification of all these different models is based on the fact that underlying principle behind the models is same. The decision when choosing appropriate model according to given task is mainly depended on whether if the data under observation is discrete or continuous in time and data space. For the task of load recognition, a model is required which can be used for discrete time and continuous valued data, so as the case with HMM. In HMM, patterns are thought of as product of sources which act statistically. The goal is to model the sources. In HMM, a state vector is used to model the underlying behavior of data source. The output of these states is modeled through emission probability distribution. This definition matches well with the way electric loads operate, i.e. each load have different states and each state

produce different outputs which are observed in the form of power values.

The remainder of the paper is organized as: Section II presents related work of the electric load recognition. Section III gives an introduction of the hidden Markov model. In Section IV, data acquisition and preprocessing is described. Section V contains methodology of building HMM for load recognition. In Section VI, it is given the procedure of load identification by using HMM. Finally scope and limitation of the proposed methodology is presented in Section VII.

II. RELATED WORK

During the last two decades, several load monitoring techniques have been proposed. These techniques can be viewed into two classes. One class contains techniques which operate on highly accurate date (low sampling rate and high resolution). In such data, signatures (harmonics or turn-on transients) of the appliances are very prominent therefore simple soft computing methods are used to extract these signatures. Such techniques are proposed in [9, 23]. Another class consists of techniques which operate on low accuracy data (high sampling rate and low resolution). In such data, the signatures of appliances are not very prominent therefore efficient soft computing methods are utilized to detect the appliances. Such techniques are proposed in [10, 19, 20, 21, 22, 24].

The soft computing methods used for second class of techniques are different machine learning methods. Machine learning (ML) provides a wide spectrum of methods for pattern extraction and recognition. So far different ML methods have been used for load recognition which includes clustering, support vector machine, Naïve Bayes, multi-layered perceptrons, radial basis function, support vector regression, neural networks and Genetic algorithm. The purpose of this paper is to present another ML technique (i.e. hidden Markov model) for load recognition. The reason for choosing hidden Markov model (HMM) is its relevant characteristics which makes it appropriate model choice for load recognition. For instance, for load recognition a model is required which can be used for discrete time and continuous valued data, so is the case with HMM. Moreover, power signals can be characterized as composed of stationary stochastic processes and typical HMM is known for modeling the combination of stationary stochastic processes.

III. HIDDEN MARKOV MODEL

The hidden Markov model (HMM) is considered as a two stage stochastic process. The first stage is discrete stationary stochastic process, used to model time series by using finite number of states. In this process, HMM can be considered as a finite state automaton where transition (or arcs) between the states (e.g. S_i and S_j) are modeled using a transition probability matrix A= $\{a_{ij}\}$, $a_{ij} = P(q_{t+1}= S_j | q_t= S_i)$. After describing the behavior of the system using discrete, casual and simple first stochastic process, another stochastic process is required to capture the underlying dynamics of the system. Therefore, the second stochastic process is used to model the generation of actual outputs or observation symbols at any time t. The associated probability density is only dependent on the current state and not the other predecessor states, i.e. $B = \{b_{ik} = P(O_t = k \mid q_t = S_i)\}$, where b_{ik} is the probability of emitting observation symbol k being in state S_i at time t. The symbols O_t and q_t are used to denote respectively the observation and state at any time t.

Formally, HMMs are characterized using five elements [11]: number of states, number of output symbols, transition probability matrix, emission probability distribution and initial state probability distribution.

The applicability of HMMs requires three tasks to be performed [11, 12, 25, 26]: evaluation, decoding and learning. The evaluation task deals with computing the probability of observation sequence by given the model. In decoding task, the most probable sequence of hidden states is found by given the observation sequence and model. Finally, the goal of learning task is to generate and optimize a HMM model, given the observation. The reason for the widespread usage of HMM technology is the availability of efficient algorithms which can performs all three tasks of HMMs in computationally efficient way. It includes respectively forward, Viterbi and forward and backward or Baum-Welch algorithms. For the purpose of this work, Viterbi algorithm is described below:

Viterbi algorithm is a dynamic programming algorithm, used to solve the decoding problem. It determines the most likely path of hidden states of a particular model, given an observation sequence. In order to describe the algorithm, a variable known as Viterbi path probability δ is defined. The Viterbi path probability is probability of reaching a particular intermediate state, having followed the most likely path.

$$\delta_t(i)= \max_{q1, q2, \ldots, qt-1} P(q_1, q_2, \ldots, q_t = S_i, O_1, O_2, \ldots, O_t \mid \square)$$

where $\delta_t(i)$ is the probability being in state S_i at time t. This is highest probability of all possible paths to that state. While computing the path probability, the Viterbi path probability variable is initialized as:

$$\delta_1(i)= \pi_i\, b_i\,(O_1)$$

where π_i is an initial state probability and $b_i\,(O_1)$ is an emission probability of initial symbol O_1 in state S_i. By expanding $\delta_t(i)$ from $t-1$ to t, the path with best probability to the next state can be estimated as:

$$\delta_t(j)= \max_{i,j} (\delta_{t-1}(i)\, a_{ij} b_j\,(O_t))$$

where, $\delta_t(j)$ is Viterbi path probability for each state S_j. Although Viterbi path probability gives the probability of best path by choosing the most probable next states along the model, the aim is to find the best path and not the probabilities. To find the best path, the predecessor state that optimally provoked the current state is required to be remembered. To remember predecessor states, a variable $\psi_t(i)$ is defined as:

$$\psi_t(i) = \arg\max_i (\delta_{t-1}(i)\, a_{ij})$$

The operator 'arg max' selects the index i to maximize the expression. Also, $\psi_t(i)$ does not require the computation of emission probabilities.

IV. DATA ACQUISITION AND PRE-PROCESSING

For the purpose of this work, power consumption data is monitored not only for individual appliances but also for their

combined load. Individual appliances are monitored to analyze and model their power consumption behavior. However, it was only required to build the load recognition system. Once the system is built there is no need to monitor individual appliances, only the combined load is required to be monitored in order to recognize the individual loads.

To collect the data, power consumption of the loads is monitored for several days with the sampling rate of 10 second. As the result, power consumption profiles of the loads are acquired with 8640 samples per profile in each day. This was done for: fridge, dishwasher, microwave, coffee machine, computer and printer. Typical load profiles of fridge and computer are shown in Figure 1 as an example.

After acquiring the power profiles, pre-processing is performed in order to acquire the features for designing recognition system. The methods used for this purpose are energy consumption, edge count and discrete Fourier transform (DFT). Due to no or less transitory behavior of power signals however DFT and edge count methods are found inefficient and discarded for next phase (recognition phase).

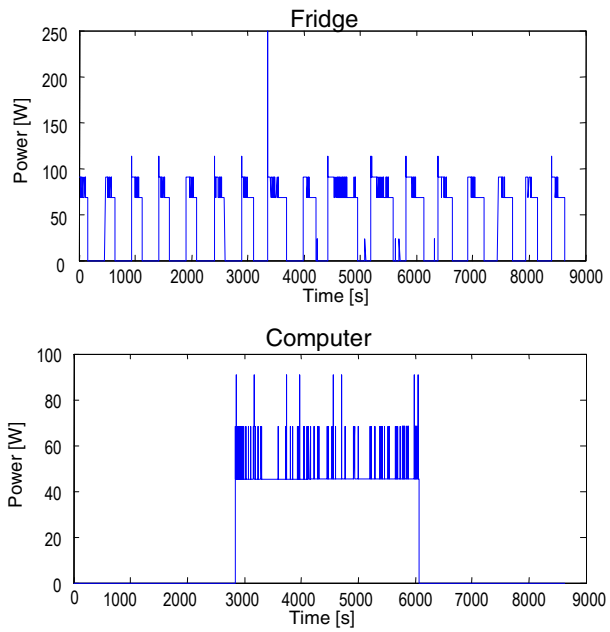


Figure 1: Examples of measured load profiles of fridge and computer.

V. HMM FOR LOAD RECOGNITION

In this work, using the framework of HMM, a model structure is described for storing, detecting and recognizing the recurring patterns (i.e. pre-processed load profiles) of electric loads.

Generally, the task of designing HMM based identification or recognition system is performed in two steps: structure modeling (i.e. determining the number of states and interconnection between states also known as topology of model) and parameter estimation (i.e. estimating transition and emission probabilities). The structure modeling is usually performed manually since there is no optimum method available for this task; the number of states and topology of the model is predetermined manually [13]. Although, there are exceptions where the models use automatic clustering algorithms in order to determine the number of states and their outputs, these methods still neglects transitional structure or topology of the model [14]. In this work, the structures of the HMMs are also determined manually and parameter estimation is performed using structural definition of the model on the basis of training data. The model is built in hierarchical fashion in a way that initially the HMMs are designed for individual loads. In the next phase, the individual HMMs are emerged to a single HMM which can describe the combined power.

A. *Building HMM for Individual Loads*

The structure of individual load is modeled by characterizing the power signal as a combination of steady state power levels. Since a steady state can be seen as a stationary stochastic process, the power signal can then be characterized as a combination of stationary stochastic processes. Although the variations exist [11], the typical HMM is a suitable modeling structure for the signals that are composed of stationary stochastic processes. The states of the HMM is used to model the stationary stochastic process and the state transition probability is used to describe the transition between the processes. Based on above intuition, the structure modeling approach is shown in the Figure 2 using a hypothetical power signal. The hypothetical signal is shown in Figure 2 (a) whereas a HMM of the signal is shown in the Figure 2 (b). Each steady state in the signal (represented with curve) is modeled as a separate state of HMM (represented with circle containing a curve; the curve in the circle shows that which steady state is modeled using which circle).

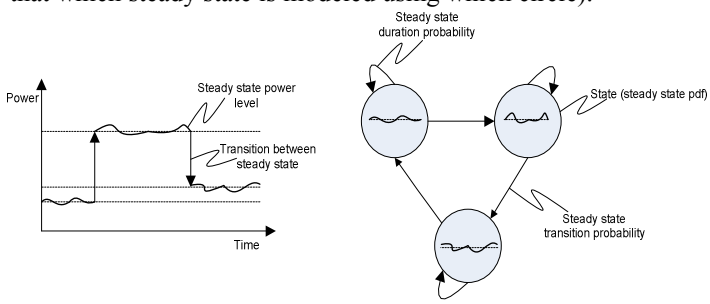


Figure 2: (a) A hypothetical power signal. (b) A symbolic hidden Markov model of power signal.

In order to illustrate the approach, below the pre-processed signal of fridge is shown in Figure 3.

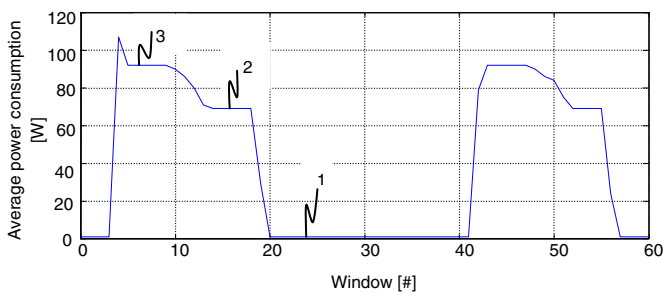


Figure 3: A preprocessed waveform of fridge for two hours. Three steady states power levels in the waveform are marked with labels 1, 2 and 3.

The fridge is a thermostatically controlled appliance which has a typical duty cycle of 40 minutes; 20 minutes ON and 20 minutes OFF. It can be seen that there are three steady states in the signal; numbered according to the level of power. As described above, three states HMM is suitable to model this signal.

After determining the number of states, in the next step topology of HMM model is required to be specified. In the main application areas of HMM-based modeling two topologies are more commonly used; left-right and ergodic [11, 15]. The schematic representation of these topologies is shown in Figure 4.

In the left-right topology, which is shown in Figure 4(A), the state transitions occur in the forward direction as time increase and state transition back to "past" states is not allowed. In contrast to left-right, the ergodic topology, which is shown in Figure 4 (B), allows arbitrary state transitions.

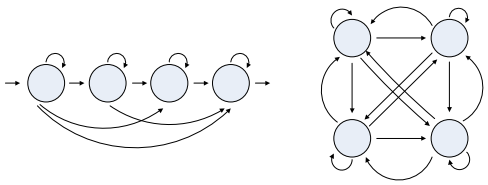


Figure 4: (a) left-right model (b) ergodic model [15]

Being a thermostatically controlled and automatically operated load, the waveform of fridge has a specific chronological structure which repeats over a period of time. By assuming that the load starts and ends its operation in same state (i.e. standby), the fridge waveform can be modeled using ergodic topology as shown in Figure 5.

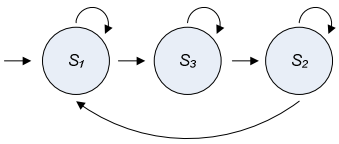


Figure 5: HMM of fridge waveform

It is also possible to model the load by using left-right topology. For this purpose, one can assume that starting and ending states of the model though are describing standby condition of the load but distinct due to their different chronological order of occurrence [26].

After determining structure of load models, the second step involves learning parameters of HMM. For this purpose, a separate function can be defined for each load which can map each value of training data over one of states of the load model according to structural definition of the load. For instance, if it is determined the steady state power levels of fridge which are described as states into its load model then a set of training data of fridge can be encoded into a set of states as:

$$S_t = \begin{cases} S_1, & 0 \le D_t \le 10 \\ S_2, & 11 \le D_t \le 69 \\ S_3, & 70 \le D_t \le 120 \end{cases} \; ; \; t = 1,2,\dots,length(D)$$

Where D_t denotes set of training data and S_t represents a set of states. Since D_t is a time series of power measurements, S_t is a time sequence of states. Once a state sequence is available, state transition probability of any state i transmitting into state j can be estimated by taking a relative frequency of number of transmission from state i to j with respect to total number of transmission from state i.

For initial state probability, the probability of first state of each load is set to one. This is because of the reason that first state of each load model describes off and standby status of the load. Since each load starts from off or standby state the HMM is also enforced to begin from initial state. Finally, based on the structural definition of each load model (as it is given above for load model of fridge), training data of each load can be segmented into different classes where each class belongs to a state of HMM of load. The segmented data can be used to estimate emission probability distribution (i.e. a Gaussian distribution model) of each state.

Since the goal behind defining the structure and estimating parameters of HMMs is to stochastically model the power consumption behavior of appliances. To show an artificially generated waveform from a modeled load source is a good way to visually verify that the model has actually learned underlying data generating process of load [16]. In Figure 6, it is shown an artificial power signals of fridge (of 100 samples) generated from HMM of fridge. It can be seen from the figures that the model operates in cyclic fashion (i.e. consecutive ON and OFF) while producing data samples (power consumption values) in a certain range as original signal.

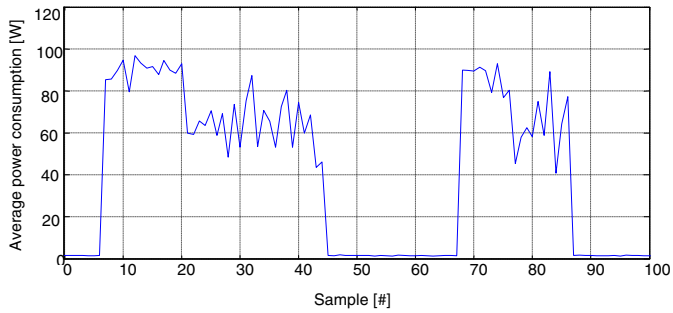


Figure 6: Artificially generated waveform of fridge from the HMM of fridge

B. *Building HMM for Combined Load*

After building the HMMs of individual loads, the combined load can be modeled by merging the individual HMMs into a single HMM. Intuitively, as individual load is described through steady state power levels, individual load (if operating) will be in a particular steady state at any time t. The combined load then can be characterized as combination of steady states of the individual loads that are operating at that time t. As the steady states of individual load are modeled as states in HMM, states of HMM of combined load can be described by merging the states of HMMs of individual load. In order to illustrate the combination of individual loads, consider the example of two load models i and j.

Using these load models, combined load model k is illustrated in Figure 8. Each state of the combined load model k is the combination of the states of load models i and j. The location of the state in combined load model tells about the corresponding states of individual loads.

Figure 7: (left) load model of load i (right) load model of load j

The combined load model shown in the figure describes all possible cases the load *i* and *j* operate in parallel. For example, when both the loads are activated simultaneously, the combined load model starts from state S_{k11}. Then depending on either load *i* or *j* changes their state first, the model will follow states S_{k12} or S_{k21} respectively.

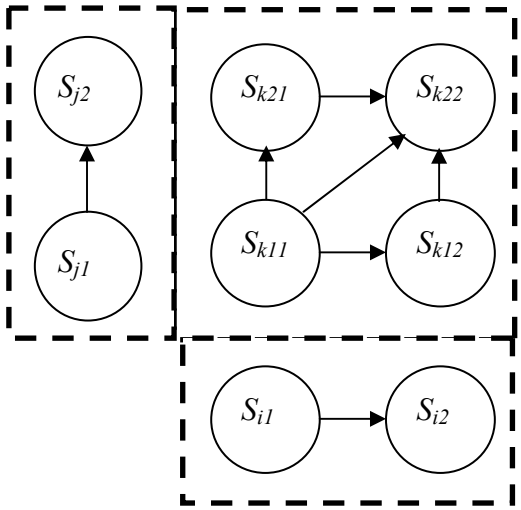


Figure 8: Illustration of combined load modeling (k) is shown for two hypothetical individual load models (i and j).

VI. IDENTIFYING LOADS USING HMM

Once a combined load model is built by following the procedure as described in above section, a given combined load profile can be decoded into states (by using the well known Viterbi algorithm). On the availability of sequence of states, it can be figured out which loads are contributing into the total power consumption profile by identifying the presence of finite state machines of individual loads (or specific state sequence where each state has a specific duration) within the decoded state sequence. Giving the combined load model, the load identification method can be characterized into three steps; pre-processing, state decoding and state sequence matching. These steps are shown in the form of block diagram in Figure 9.

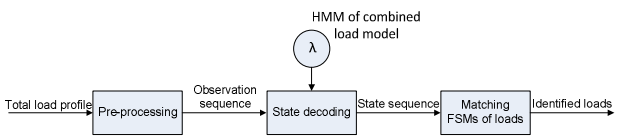


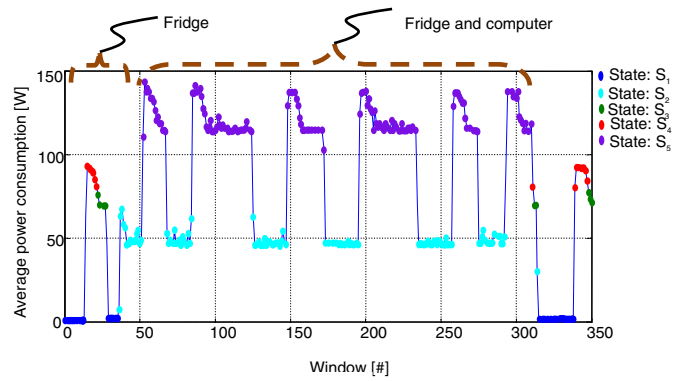
Figure 9: Block diagram of combined load based appliance identification system.

In the pre-processing phase, average power consumption pre-processing method is applied to pre-process the combined load profile. The pre-processing method is applied to make the data consistent with data which is used earlier to design and train the HMM. In state decoding phase, the pre-processed data (called here observation sequence) is translated into states by using Viterbi algorithm, given the HMM model of combined load. Finally, the loads are identified by detecting be the presence of specific state sequence patterns from the decoded state sequence.

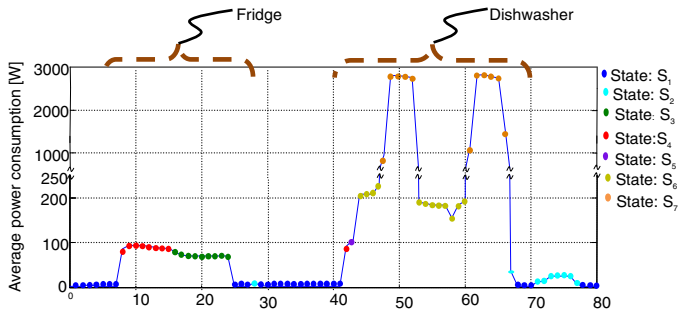
For sake of illustration, the combined load profiles of fridge and computer, and fridge and dishwasher are shown in Figure 10. These load profiles are decoded into the states. As the result, state vectors of same length as the load profiles are obtained. In figure, the state vector is represented with a color coding and plotted over the profiles. Since each state represents a certain steady state power level, it can be seen that different power levels have states in different colors. The consecutive states of a power level (consecutive states of same color) described the time duration of that power level. The recurring patterns of state sequences which are appeared when fridge, fridge and computer, and fridge and dishwasher are operating can also be seen from the Figure 10.

VII. CONCLUSION

A hidden Markov model (HMM) based combined load model is proposed to identify the presence of individual loads from total power consumption. The method is viable to utilize in order to obtain daily operational schedule (or time-of-day energy usage) and daily power consumption of household appliances which is a key requirement of demand side management applications and energy conservation programs.



(A)



(B)

Figure 10: (a) It is shown a waveform of combined load of fridge and computer. The decoded states are shown over the waveform. (b) It is shown a waveform of combined load of fridge and dishwasher. The states decoded over the waveform are also illustrated over the waveform.

The model can be used to identify thermostatically controlled automatic appliances (such as fridge, air conditioner and water heater), fixed operation humanly activated appliances (such as dishwasher and washing machine) and usage dependent humanly activated devices (such as computer, microwave and printer). Since the individual and combined power consumption waveforms of these appliance (electrically, the waveforms of individual loads are summed up to produce the waveform of total load) are composed of different steady state power levels and a steady state power level is a stationary stochastic process. The HMM based approach is suitable modeling approach to describe and identify these appliances due to the strength of HMM which lies in the fact that it models the combination of stationary stochastic processes [17]. However, generalization of this approach requires further refinement and extensibility of this method. In refinement phase, additional data will be collected in order e.g. to make model more flexible to deal with seasonal variations. In extensibility phase, additional types of household loads and their different brands will be considered. Although, the variants of HMM exist where they can be utilized to model continuously varying signals (not stationary stochastic), e.g. auto regression HMM [12]. However, the described approach is not viable to model the behavior of devices which vary their power continuously such as light dimmer and sewing machine. Since the power of these loads is continuously variable it is not easy to model their behavior as combinations of stationary stochastic processes. Because, these loads consume insignificant amount of energy in the households, they are not targeted in this work. The approach is modeled for combined load of fridge, dishwasher, microwave, computer and printer. Through the method performs significantly well after the training over several weeks' data. However, in future we are interested to perform a comparative analysis of this approach (in terms of estimation accuracy and scalability) with other conventional techniques.

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