Energy Disaggregation with Specialized Hidden Markov Models

CIS 5930 Data Mining

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1. Preface

The original goal of our project was to replicate the Conditional Factorial Semi Hidden Markov Model (CFHSMM), a specialized dynamic Bayesian network, that is fairly effective at home energy disaggregation [1]. The goal proved infeasible due to the amount of coding required irrelevant to the task of data mining, discussed later in this report. As such, we shifted our goal to the development of a novel Hybrid HMM/KNN model. For brevity's sake, we will refer to the model as the Hybrid Hidden Markov Model (HHMM). Further, we analyze the usefulness of features for energy disaggregation that require additional, and possibly expensive, sensors throughout the home.

2. Introduction

We aim to improve the accuracy of home energy disaggregation by proposing a Hybrid Hidden Markov Model which makes use of two machine learning models, the Factorial Hidden Markov Model (FHMM) and the K Nearest Neighbors Model (KNN). Home energy disaggregation is the process of determining energy consumed by individual electronic appliances within a home from aggregate data of electrical signals from the circuit of the home.

In this paper, we explore the performance of a novel HHMM which makes use of a KNN classifier that is trained on predictions from the Factorial Hidden Markov Model (FHMM; a simple regression model for home energy disaggregation) along with measurements from additional sensors to achieve higher energy disaggregation accuracy. Further, we explore the difference in performance of the proposed classifier with features that do and do not require additional sensors. Data from additional sensors was chosen based on data availability and consist of light, temperature, and motion sensor measurements. We evaluate the proposed classifier on different combination of features and public energy disaggregation datasets [dataset references].

3. Relevant Literature Survey

Energy disaggregation is the process of determining energy consumed by individual electronic appliances from aggregate data of electrical signals on a circuit. Mechanical switches produce electrical noise in the current of a circuit [2], and the characteristics of the noise is unique among appliances [3]. Researchers have found the use of a dynamic Bayesian model, called the Factorial Hidden Markov Model (FHMM), and its variations are effective classifiers at analyzing power measurements to determine appliance level energy usage in a home. [1] Being able to determine appliance-level energy usage could create opportunities for energy conservation efforts. The data could also potentially be applied to detecting malfunctioning appliances [4].

The most significant feature in energy disaggregation is power consumption (W); however, considering additional input features improves accuracy of energy disaggregation models. [1] Additional input parameters could range from resident work schedules to ambient light readings; however, such data should be easily obtainable, e.g. without additional or special sensors, and minimally invasive for practical deployment of energy conservation efforts [1].

Additionally, the use of HHMMs have been utilized in a variety of other applications including speech recognition, where traditional HMM's do not perform optimally [5]. The purpose of a Hybrid HMM is to feed the results from an HMM to another classifier, resulting in better performance compared to the individual models. We applied this idea to energy disaggregation to analyze how effective such a model would be.

4. Methodology

Factorial Hidden Markov Model (FHMM)

The FHMM is provided as a standard energy disaggregation method in NILMTK. The FHMM is fed time series data about certain characteristics of the electrical currents in the circuit of a home. These characteristics include apparent and active power (W) or apparent and active energy (V). The REDD dataset provides apparent power readings for low frequency home energy disaggregation while the iAWE dataset provides active power readings for low frequency home energy disaggregation. These are the measurements we use to train the FHMM employed in the proposed HHMM, discussed in the next section.

Hybrid Hidden Markov Model (HHMM)

Our intuition behind a “chained model” instead of a standalone HMM was due to the trends we saw in the output of the FHMM on the REDD dataset [7]. We saw that the predictions of the FHMM could vary wildly; however, as seen in Figure 1, they also seem to follow a pattern. The model seems to repeat patterns seen in the ground truth, more than it should. Thus, the model seems sensitive to spikes in energy usage. Given this information, we considered the idea of passing the output from the FHMM to another classifier that could aim to minimize the models sensitivity to energy usage spikes. This is the motivation behind the HHMM, in addition to the road blocks mentioned in the implementation section.

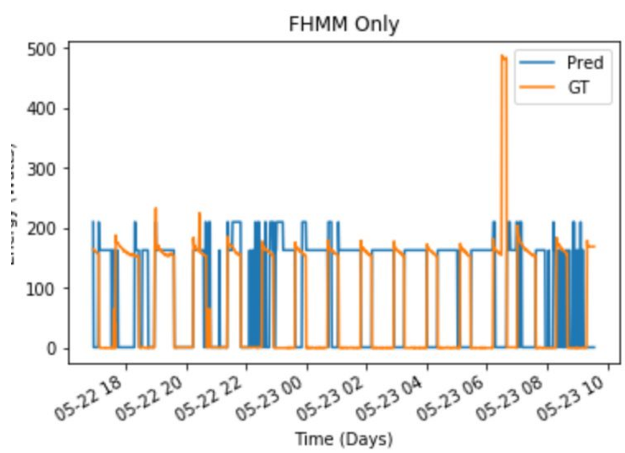


Figure 1. A Fridge from the REDD Dataset [7]. Notice how small spikes in the Ground Truth cause large spikes in the Prediction of the FHMM. This prompted us to try passing the output of a FHMM to another model.

The HHMM makes use of two machine learning algorithms, an FHMM and another classifier, on aggregate measurements from sensors strategically placed around a home. We experimented with passing the output of a FHMM that was trained on only the meter data from each appliance into other classifiers provided by SKLearn that could take extra input features. Given this setup, our team could train the new model with the output of an FHMM as one feature and other significant features such as temperature, light, and motion sensor data could also be added in. This enabled us to make use of the extra features we wanted without needing to use NILMTK to do so. These measures include light, motion, and temperature measurements from the iAWE dataset and electricity readings from both REDD and the iAWE dataset.

KNN VS Linear Regression

We decided to experiment with the Linear Regression (LR) and K Nearest Neighbor (KNN) classifiers. While the use of the Linear Regression classifier within the proposed HHMM produced results with similar SSE to that of the

HHMM using a KNN classifier, we found that a KNN based model performed much better when additional features are used compared to the LR based model. This can be seen in Figures 4 and 5.

Determining KNN with K = 9

To maximize the performance of our model, we aimed to determine the optimal number of nearest neighbors to consider in the HHMM. In order to determine the optimal number of neighbors to consider, we analyze the performance of the HHMM over different numbers of neighbors considered in the KNN classifier. More specifically, we maximize the accuracy of the model and minimize the sum of squared errors (SSE) when all features are utilized. We found that the K Nearest Neighbor (KNN) classifier with K = 9 nearest neighbors was the most accurate. The data used to come to this determination is shown in the experimental results section in figures 2 and 3.

Feature Importance

After determining the number of nearest neighbors to consider in the HHMM, we analyze the importance of extra features that come from additional sensors placed throughout the home. More specifically, we analyze the importance of light, temperature, and motion sensor readings is on the performance of our model. With 9 nearest neighbors considered, we evaluate the performance of our model on data from one home in the iAWE dataset, due to data availability. We found that considering these extra features greatly improved the accuracy of the HHMM model. We explore which features have the largest impact on the performance of our model by considering different combinations of features. This data is graphed in the Experimental Results section in figures 4 and 5.

5. Implementation

This section will discuss the implementation of both disaggregation methods. More specifically, we discuss the challenges we faced when attempting to replicate the CFHSMM [1] and the transition to the development of a novel disaggregation model, called the Hybrid Hidden Markov Model.

Conditional Factorial Hidden Semi Markov Model

The main challenge associated with the development of the CFHSMM [1] was the amount of changes to NILMTK the model required. NILMTK maintains a data structure that maintains measurements to feed disaggregation algorithms. The initial release of NILMTK had support for different types of meters; however, the current version of NILMTK only supports electric meter readings. This is a consequence of NILMTK undergoing major development changes due to being ‘revived’ as of June 2018. Attempting to make the required major changes to the open-source toolkit we are using, NILMTK [6], proved to be difficult and irrelevant to the objective of this project. Further, reverting to older versions that had support for information from different kinds of meters resulted in dependency roadblocks due to the initial release being over 5 years old. As a result, we could not get non-electric meter data into the disaggregation methods we were using with NILMTK. Finally, this led us to explore using a chain of two classifiers where appliance power usage predictions of the FHMM and additional sensor readings are passed into another classifier provided by SKLearn.

REDD Dataset

The REDD dataset [7] was the easiest to acquire and use with the FHMM, provided by NILMTK [6]. The limitation that came with REDD was the fact that it contained no additional features beyond timestamps and power usage. Since we couldn’t add more features, we used REDD as a starting ground due to its simplicity to use. Due to the lack of features we were forced to explore additional datasets.

iAWE Dataset

When attempting to use the iAWE [8] dataset we found a couple of limitations. One was the fact that India is subject to frequent (daily) power outages that occur for various lengths of time. Another is the fact that the data is collected in 1 second intervals where we are developing our model in 1 minute intervals. Our solution to this issue was to thoroughly clean the dataset using the following assumptions:

1. During outages, assumed as missing timestamps, fill the missing entries with previously recorded values.
2. To account for the different sampling rates, we took every 60th entry in the unclean data and generated clean data to be used with our model

The benefit of using iAWE was the fact that it contained more features than the REDD dataset [7]. The cost of using iAWE [8], after cleaning, is that there is only data for one home.

Dataport Dataset

The dataport dataset [9] had the largest amount of data available; that is by number of houses and features available. However, we faced the issue that not every house contained the same amount of usable features. Many homes had null entries in every feature. The task of simply acquiring data that could be then eventually cleaned became too daunting and we were faced to not utilize this dataset since we were only able to get one home to successfully download without extra features (only timestamps and power usage). At that point there was no difference in using dataport vs REDD [7], without using the additional features, or iAWE [8] and only accessing one home.

6. Experimental Results

Optimal Number of Nearest Neighbors

The two plots below illustrate the performance of the HHMM over varying number of nearest neighbors to consider.

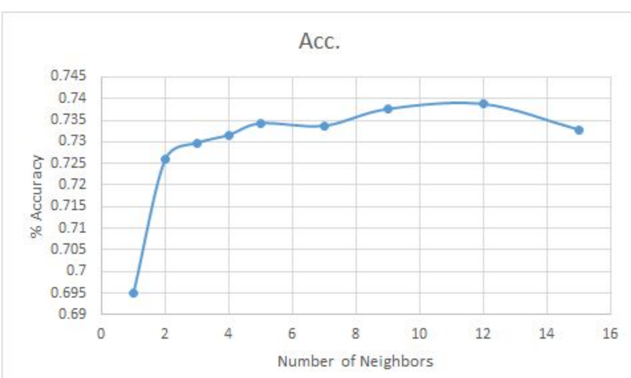


Figure 2: Accuracy of HHMM given different numbers of Neighbors

Figure 3: SSE of HHMM given different numbers of Neighbors

We concluded that using K = 9 neighbors yielded the best accuracy and also the lowest SSE; however, we did notice that when a lower number of neighbors are considered, the HHMM better predicts peaks in energy usage of appliances. However, lower numbers of neighbors considered also lends the model to spikes in energy usage in the prediction where there is no spike in the ground truth. We therefore choose the number of neighbors purely based on the accuracy and SSE.

Importance of Additional Features and Using HHMMs

Below are the results of the HHMM on data from the Indian Ambient Water and Energy dataset (iAWE) [8] for the top 5 most significant appliances in the home. Since the HHMM can take more than one input to train and generate predictions with, we use the prediction from the FHMM on the main meter data of a home along with permutations from the set of additional features. These features include ambient light, temperature readings, and motion sensors. We find that the HHMM with any of these extra features is significantly more accurate and has significantly less SSE than a simple FHMM. We also see that using all of the features available generates a model with the highest accuracy and lowest SSE, however, due to the cost and invasiveness of implementing a motion sensor, a model which uses only light and temperature data is sufficient.

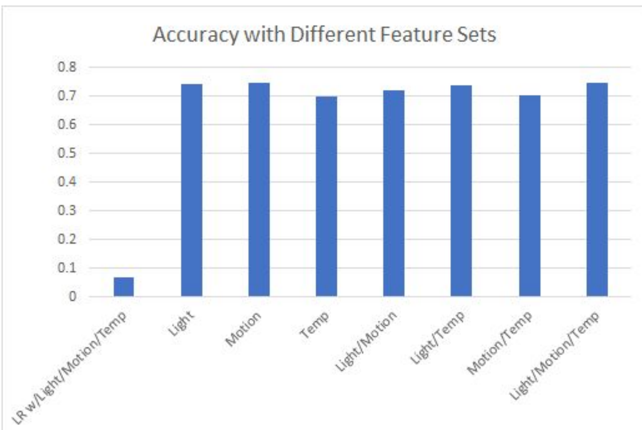


Figure 4: Accuracy of (in order) the LR based HHMM on all extra features and the performance of the KNN based HHMM on different combinations of extra features

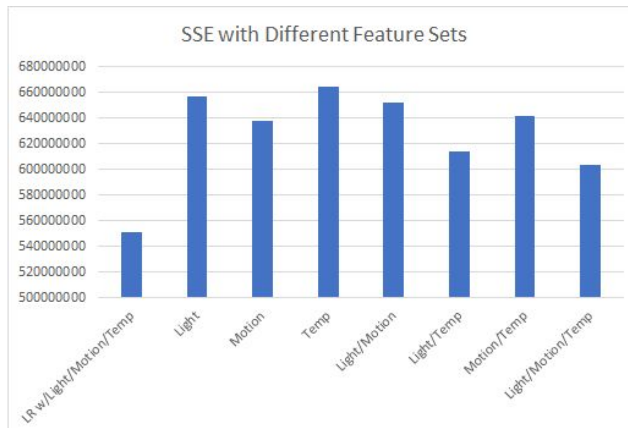


Figure 5: SEE of (in order) the LR based HHMM on all extra features and the performance of the KNN based HHMM on different combinations of extra features

Standalone FHMM VS HHMM

We found that the HHMM, which is composed of an FHMM and KNN, perform better than the FHMM alone. The following experiments were performed employing all available features for each classifier. That is, the standalone FHMM made use of only electric meter readings where the HHMM makes use electric meter readings as well as light, temperature, and motion measurement readings. These findings can be seen from the following figures:

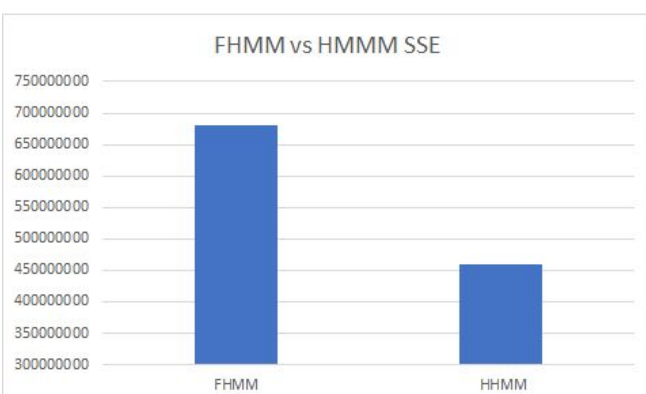


Figure 6: SSE comparison between FHMM and HHMM

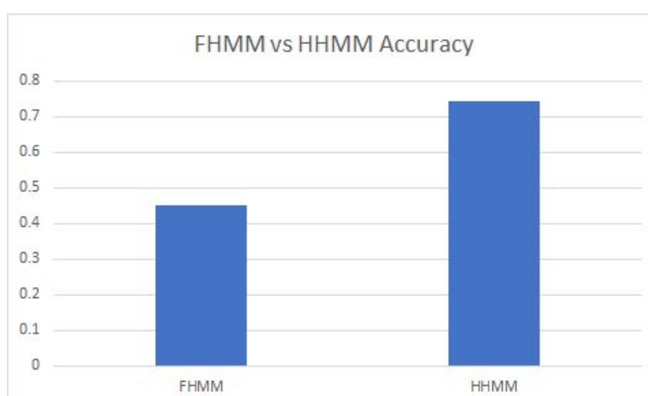
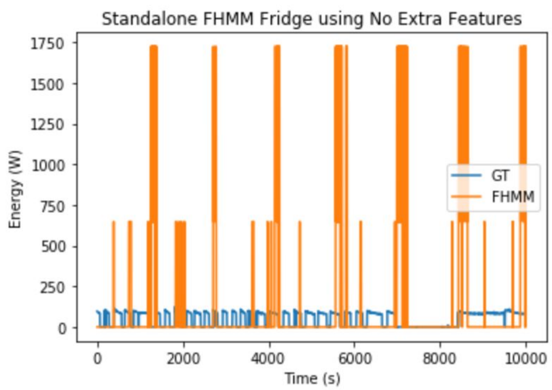


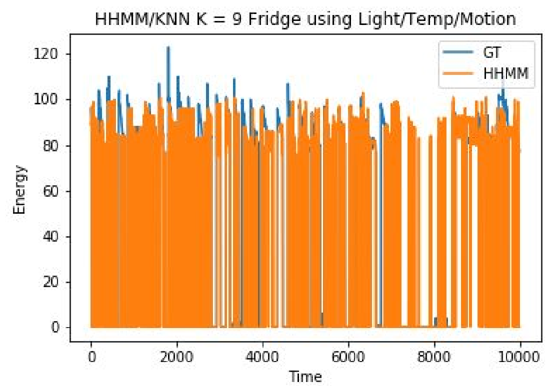
Figure 7: Accuracy comparison between FHMM and HHMM

The following diagrams illustrate the energy usage predictions of both the standalone FHMM and the HHMM for the top 5 most significant appliances in the iAWE dataset.

<u>Fridge</u>

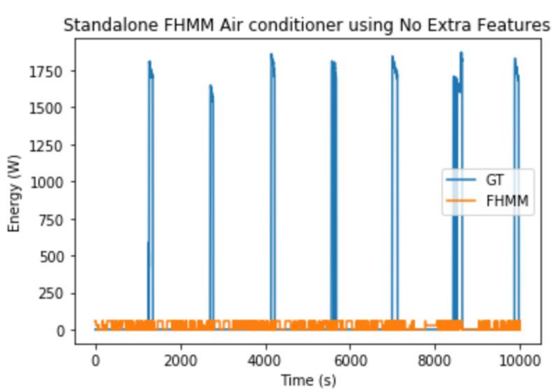
The sensitivity of the FHMM to energy spikes is emphasized can be seen when making predictions on refrigerator energy data provided by the iAWE dataset. As seen in left figure, the standalone FHMM predicts huge spikes in energy usage and the magnitude varies between 750 watts and 1750 watts. We show the improvement we achieved with our model that makes use of all additional sensor information provided by the iAWE dataset.

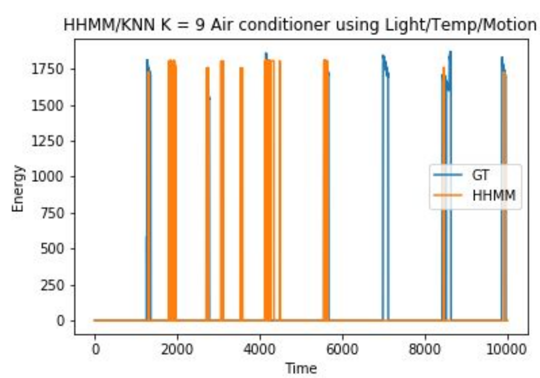


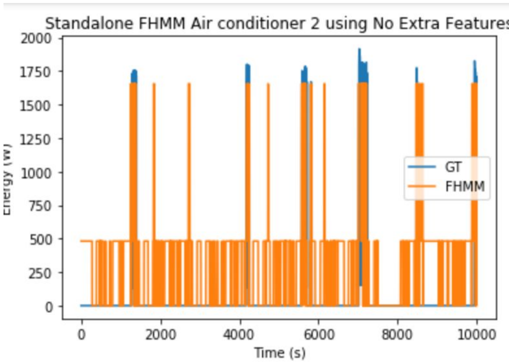


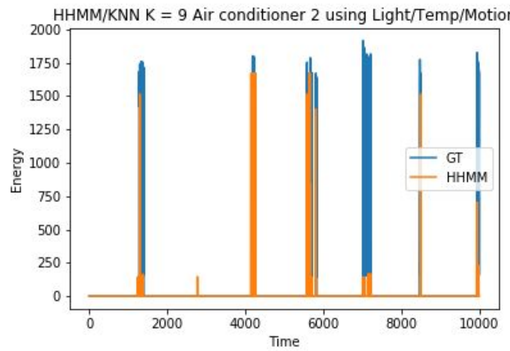
<u>Air Conditioner 1 & 2</u>

The improvement in energy usage predictions for these two appliance when using the proposed HHMM over the FHMM can be seen by the following four figures. The FHMM performed very poorly, for Air Conditioner 1, we believe is due to the lack of access to the additional features. More specifically, temperature measurements to detect when indoor temperature has increased above a certain amount. In the case of Air Condition 2, the proposed HHMM does a good job at minimizing predictions of spikes in energy usage not present in the ground truth; without sacrificing many correct spike in energy use predictions that are present in the ground truth.



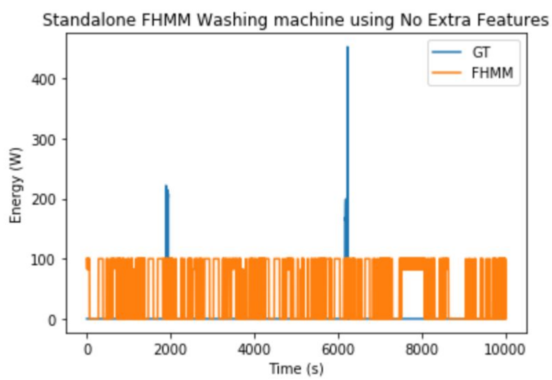


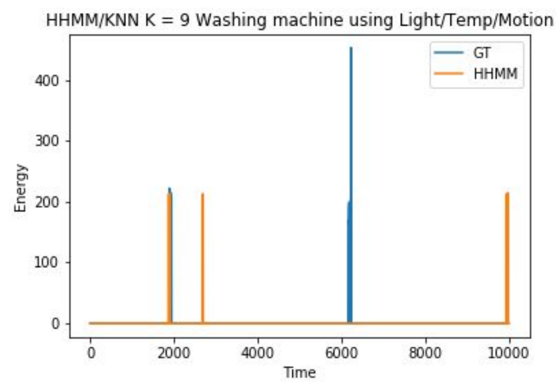




Washing Machine

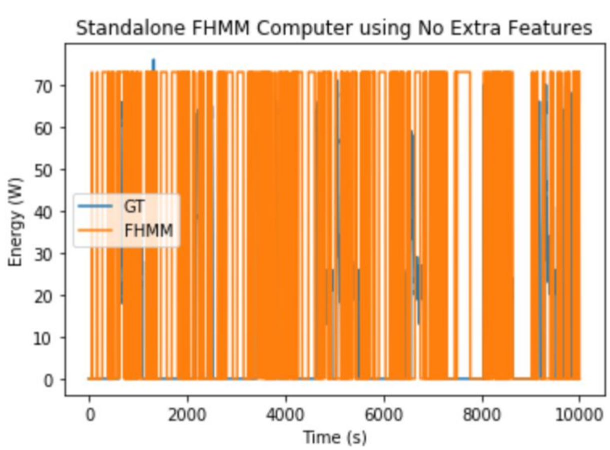
For this appliance, the FHMM predicts consistent energy usage of about 100 watts. This is odd, considering consistent energy usage for this appliance is not present in the ground truth. Regardless, the predictions from the proposed HHMM indicate that the model again is useful for minimizing high energy usage predictions of the FHMM. Further, it is better predicts peaks in energy usage for this appliance.

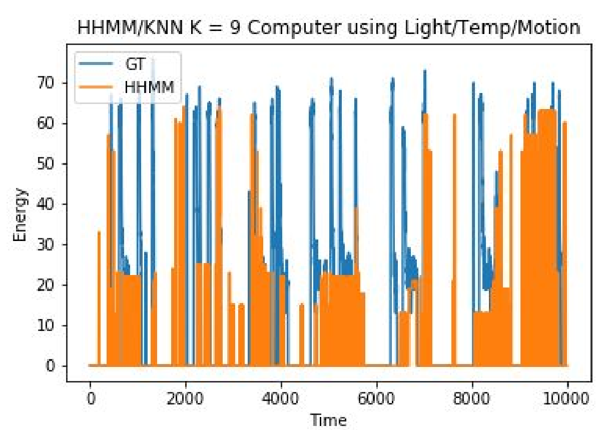




Computer

Finally, the fifth most significant appliance has many spikes in energy usage present in the ground truth. The FHMM as illustrated by the figure on the left illustrates the model performs poorly and predicts consistent high energy usage. The proposed HHMM performs better by minimizing the energy usage predictions while preserving high energy use that is present in the ground truth.





7. Conclusions

We found we can increase the accuracy of the FHMM at home energy disaggregation by utilizing its predictions as input to another model; we explored the use of the KNN and the LR classifiers. We maximized the performance of the modified FHMM, called the Hybrid Hidden Markov Model (HHMMs), to determine which classifier should be utilized in the HHMM. Overall, we found that the KNN based HHMM performed better than the LR based HHMM. Thus, the HHMM we propose makes use of a KNN classifier to improve upon the accuracy of the FHMM. Further, we analyzed the importance of features considered in the KNN classifier to maximize performance of the proposed HHMM. To do so, we created a model considering every combination of extra features, i.e. light, motion, and temperature. *Overall, we found the optimal HHMM makes use of a KNN for energy disaggregation, one should create a HHMM with K = 9 neighbors and use light and temperature data along with main meter data to train the model and generate predictions*. While adding motion did see minimal increases in accuracy and decreases in SSE, the likely cost of installing a motion sensor, and additional loss of the occupants' privacy, may not be worth the small increase performance.

8. Future Work

In the future, the proposed HHMM should be experimented on with other machine learning classifiers. Not only could the KNN be replaced with another model, but the FHMM could also be replaced with another energy disaggregation model such as a CFHSMM or a Neural Network. Testing possible combinations of models may yield useful information about energy disaggregation. In addition to this, these models should be tested on more datasets that contain features from different types of sensors. Doing so will reveal which would be most effective, with respect to the cost of the special sensor, in home energy disaggregation. We also would like to further test our current HHMM configuration on more houses and more datasets in order to be more confident in our results.

9. References

[1] Hyungsul Kim, Manish Marwah, Martin Arlitt, Geoff Lyon, and Jiawei Han, “Unsupervised Disaggregation of Low Frequency Power Measurements,” in *SIAM Int. Conf. on Data Mining*, 2011, pp. 747-758.

[2] M. Ito, R. Uda, S. Ichimura, K. Tago, T. Hoshi, and Y. Matsushita. A method of appliance detection based on features of power waveform. In IEEE Symposium on Applications and the Internet, Tokyo, Japan, 2004.

[3] R. Watson, M. Zinyousera, and R. M. (editors). Technologies, policies and measures for mitigating climate change. Technical report, 1996.

[4] R. Sexton, N.Johnson, and A. Konakayama. Consumer response to continuous-display electricity-use monitors in a time-of-use pricing experiment. Consumer Research, 14(1):55–62, 1987.

[5] X. Tang, “Hybrid Hidden Markov Model and Artificial Neural Network for Automatic Speech Recognition,” *2009 Pacific-Asia Conference on Circuits, Communications and Systems*, May 2009.

[6] Batra, Nipun, et al., "NILMTK: an open source toolkit for non-intrusive load monitoring," in *Int. conf. on Future energy systems*, 2014, 265-276.

[7] Kolter, J. Zico, and Matthew J. Johnson, "REDD: A public data set for energy disaggregation research," in *Workshop on Data Mining Applications in Sustainability*, 2011, pp 59-62.

[8] Nipun Batra, Manoj Gulati, Amarjeet Singh, and Mani Srivastava, “It's Different: Insights into home energy consumption in India,” in *Workshop on Embedded Systems For Energy-Efficient Buildings*, 2013, pp. 1-8

[9] O. Parson, G. Fisher, A. Hersey, N. Batra, J. Kelly, A. Singh, W. Knottenbelt, and A. Rogers, “Dataport and NILMTK: A building data set designed for non-intrusive load monitoring,” *2015 IEEE Global Conference on Signal and Information Processing (GlobalSIP)*, Dec. 2015.