# Degree Project
# Specification and Schedule

Preliminary title:

## Non-Intrusive Load Monitoring using Machine Learning

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## BACKGROUND AND OBJECTIVES

In 2015, the residential sector accounted for around 27% of the total electricity consumed in the world and has increased by nearly 30% in a decade [1]. More specifically, in Sweden, the residential and service sector accounts for almost 40% of energy use [2]. It is estimated that there will be around 80% more buildings by the end of 2050 [3]. As a UN sustainability goal, Sweden wants to reduce its energy intensity by 20% compared to 2008, by 2020. Hence energy saving in the residential building will have a significant impact on the reduction of the overall energy consumption.

One approach to reducing energy consumption in residential building is to inspire positive behaviour change in the residents [4]. This can be achieved through real-time monitoring of end-use appliance consumption and providing real-time actionable feedback to its residents through an Appliance Load Monitoring (ALM) systems. ALM can be developed in two manners, one is Intrusive Load Monitoring (ILM) and another is Non-Intrusive Load Monitoring (NILM) [5]. The ILM is a traditional method of deploying sensors at each appliances and monitoring their consumption. This makes the system costly with large installation overheads. On the other hand in NILM, only one smart meter is required per home. The smart meter captures the aggregated data from a single point of source and then this data is disaggregated into appliances using various electric features, specific to each appliance. Hence, NILMs offers an economically viable solution for an ALM system.

After being formally proposed in 1980s, research in NILM has made rapid progress mainly adopting more accurate disaggregation algorithms from pattern recognition and machine learning. But even after three decades of research, NILM is far from being the perfect. There are several challenges present in state-of-the-art NILM that have prevented a large scale implementation in a real-world scenario.

One of the biggest roadblock for NILM implementation is quality data for creating models. Currently, European Union aims to replace at least 80% of the electrical meter around Europe to smart metering devices by end of 2020 [6]. These smart meters can provide aggregated real-power consumption for residential building with data sampling typically in range of 30 minutes to 10 seconds. But with just real-power is too coarse for disaggregation as algorithm cannot differentiate between appliances with similar power. In order to have more features, there is a need to develop a smart meter that can sample at much higher rate allowing extraction of multiple features from the aggregated data for disaggregation.

Another issue for NILM algorithm is applicability. A major focus in NILM research is on supervised and unsupervised learning methods. In the supervised learning methods, the NILM assume that the training data, either at the circuit level or the readings from sub-metered appliances, is available and the classifier can be trained on it. This assumption, however, reduces the practicality and scalability of the NILM as getting training data is often expensive and time-consuming. Unsupervised learning methods only need the aggregated data and can classify without any user intervention. However, these techniques can only learn the parameters of the different class of appliances, they are unable to assign a specific label to each class.

The state-of-the-art NILM algorithms do not focus on updating the appliance model database for classification/clustering on unseen data, hence are not scalable. Usually in the NILM research, there is an assumption that the dataset that have been used for creating models, represent the true world. Most of the publically available dataset have electrical signatures only for one house, or one appliance of each type. But that is not true for real-world, because of the following reasons:

- Each specific appliance in the same category can have different features. For example, a Samsung refrigerator will have different appliance signature from a LG refrigerator.
- The publically available dataset mostly contains 10-15 appliances, but a typical household can have upto 30-50 different appliances [7].

Also, most of the NILM algorithm present today do not work in real-time. The current system rely on either supervised or un-supervised methods that collects metered data, store them on cloud and then run inference on them. This raises several issues of privacy and cost. There are NILM algorithms that can perform inference/classification in real-time but they usually have high complexity and computation requirements. Therefore these algorithms are limited to run inference/classification only for low sampling data.

In light of the challenges presented above, the purpose of the thesis is to arrive at an NILM algorithm that can overcome the above mentioned limitations. For the thesis we focus on semi-supervised technique for NILM that can sufficiently be able to disaggregate the total power measured from household into individual appliance components. The algorithm can learn from a small set of data and then do self-learning to improve upon the appliance feature presented during training. Hence the self-learned models eventually will make better predictions for a specific house when compared to a general model. Also, the thesis focuses on the algorithms that are computationally cheap with small storage requirement so that that can be easily run on small embedded systems in real-time like Raspberry Pi. Running the algorithm on embedded device will then eliminate any need for cloud storage and hence will not have any privacy concerns.

## PRINCIPAL INTEREST

The project is intended to contribute to the vision of energy saving and creating awareness on household electricity consumption. In particular, the thesis is offered by Zyax AB (www.zyax.se), located in Stockholm. Zyax is developing a platform for combining security alarms, heating/ventilation and lighting control in one ecosystem. The system consists of a central gateway, mobile app, cloud server and communication interfaces to various sensors and actuators. In the same platform, there is a gateway that can sample three-phase voltage on the incoming electricity at high frequency. On this device, Zyax wants to develop an ALM system based on the electricity usage data. They want to create a service on the device which can measure the electric consumption of the entire house and then break it down to appliance specific information. The idea is to provide real-time actionable feedback to the residents on their electricity consumption and giving them insights on which appliances are used at given time instant, how long they have been used, how much electricity they consumed and if there are any potential defects in the appliance.

## OBJECTIVE and RESEARCH QUESTION

The research question we are trying to answer in the project is as follows,
*"Can a Re-learning algorithm improve the classification accuracy and estimation accuracy for an unseen house, when compared to the existing supervised and unsupervised load disaggregation algorithms running on low power embedded machines?"*

The goals of the thesis are listed below -:

1. Investigate on techniques to create an electrical feature model for each appliance that can be generalized across various brands and models of appliances.

2. Analyse different electrical features that can be used for the inference/classification of each appliance in the fast-sampling (> 1 Hz) load data.

3. Derive an algorithm for load inference/classification from an aggregated data that has low storage requirement and is computationally cheap, so that it can be easily run on small embedded systems like Raspberry-Pi.

4. Research the re-learning process to tune the general appliance model to represent the appliances with the specific house and improve on the classification accuracy when compared the classification done on general model.

5. Perform experimentation across the dataset and show that the proposed solution performs better that the state-of-the-art supervised and un-supervised techniques.

## EXAMINATION METHOD

The following figure shows the preliminary algorithm that will be used for the project.

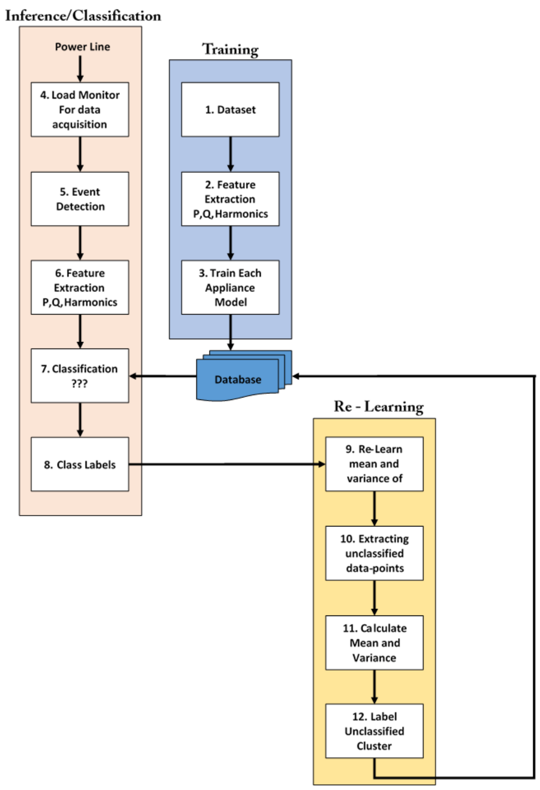


*Figure 1 Preliminary NILM Algorithm*

The proposed algorithm covers 12 steps that are divided into three sections-

1. Training
   1.1. Dataset: A dataset with the sub-metered data for each appliance will be used for the training and creating a general model for each appliance.
   1.2. Feature Extraction: For each appliance, first we have to extract the Active period for each appliance and then extract electrical signatures like Real Power, Reactive Power, Current, and Apparent power factor.
   1.3. Training: Once the features are extracted, then we will use these features for creating general model for the appliance. In the process, we will identify the states of operation foe each appliance and create a Gaussian Cluster for each operation state for each appliance.
   1.4. Database: The database will contain the model variables for each of the appliance that will be used for inference/classification on the aggregated data.

2. Inference/Classification:
   2.1. Load Monitoring: A load monitor that can measure multiple electrical features at a high sampling frequency (> 1Hz). From the monitor we will get the raw aggregated data.
   2.2. Event Detection: In order to classify the appliance, we have to know when they are switched on /off. The spike or dip in the total power tell us, the presence of the appliance. For the purpose, a event detection algorithm will be implemented
   2.3. Feature extraction: After an event is detected in the aggregated power source, the features are extracted from the signal. These are the exactly the same features that are used in the training period to create the appliance signature database.
   2.4. Classification/Inference: Based on the feature extracted in the last step, now the data point will be classified into one of the cluster group, and labelled. If the data-point does not belong to any of the cluster, then will be termed as un-classified point. The important thing is, that the data point will be checked across all the clusters. And same will be repeated for all the data points collected. This can be a slow operation
   2.5. Labelling: In this part, we just simply label all the points that are detected after the event detection, as either one of the cluster or un-classified points. These data-points are fed to the re-learning phase to update the database.

3. Re-Learning
   3.1. Re-adjust the appliance parameter: The mean and the variance of all the clusters will be readjusted based on the labelled data from a specific household. This step is only for the labelled data.
   3.2. Extracting unclassified data-points: The unclassified data points are then collected separately and are processed for the clustering algorithm.
   3.3. Clustering un-classified points: For the data-point we will run the clustering again, and see if there is a cluster that can be classified as an appliance. If yes, then there will be prompt saying that there is a new appliance found that has not been a part of the database yet.
   3.4. Label new cluster: There will be a prompt to the user to label the new cluster manually, and the points will the cluster values will be updated to the database for inference.

## EVALUATION

To evaluate the performance and the accuracy, several metrics are reported in the NILM literature. As reported in the several surveys on NILM [5, 8, 9], there has not been any consensus agreement in the NILM community on the metric suitable for evaluation. The following points outlines the metrics that are used in the NILM Toolkit (NILMTK) [10].

1. Error in Total energy: Difference between total energy assigned $(\tilde{y})$ and the actual energy consumed $(y)$ by an appliance $n$ for time period $t \in [1, N]$

$$\sum_{t=1}^{N} y_t^n - \tilde{y}_t^n$$

2. RMS in assigned power: The root mean square error between the assigned power $(\tilde{y})$ and actual power$(y)$ of appliance $n$ in each time $t \in [1, N]$.

$$\sqrt{\frac{1}{T}\sum_{t=1}^{N}(y_t^n - \tilde{y}_t^n)^2}$$

3. F – score: The harmonic mean of precision and recall. Precision is the time in which an appliance was correctly predicted to ON that it was OFF and Recall is the time which the appliance was correctly predicted ON that it was actually ON. They are calculated using metrics True Positive (TP), False Positive (FP), True Negative (TN) and False Negative FN).

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

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

$$F - score = \frac{2 * Precision * Recall}{(Precision + Recall)}$$

4. Overall Estimation Accuracy: Metric defined to measure the accuracy for the algorithm for all the appliances.

$$E_{Acc} = \left[1 - \frac{\sum_{t=1}^{T}\sum_{n=1}^{N}|y_t^n - \tilde{y}_t^n|}{2 * \sum_{t=1}^{T}\sum_{n=1}^{N}|y_t^n|}\right]$$

5. Appliance Estimation Accuracy: Using the above metric, estimation accuracy for each appliance can be derived by eliminating the summation for all appliances.

$$E_{Acc}^{(i)} = \left[1 - \frac{\sum_{t=1}^{T}|y_t^i - \tilde{y}_t^i|}{2 * \sum_{t=1}^{T}|y_t^i|}\right]$$

## Literature-Study

In 1980's, George Hart, Ed Kern and Fred Schweppe from MIT formally proposed the NILM process for load disaggregation using clustering algorithm on real and reactive power [11]. Shortly after their publication, the research in the NILMs made a rapid progress mainly adopting more accurate disaggregation algorithms from pattern recognition and machine learning. As mentioned above, the major focus in NILM research is on supervised and unsupervised methods. With supervised learning methods, the learning can be tackled either as optimization problem [12] or pattern recognition [13]. Several traditional classifiers have been used for the purpose of load disaggregation like Artificial Neural Networks (ANNs) [14, 15], Support Vector machines (SVM) [16, 17] and k-Nearest Neighbours [18]. As the load data is time-series, unsupervised learning methods present a natural solution. Different variants of Hidden Markov Models (HMM) like Viterbi Algorithm [19, 20] and Factorial HMMs [21] are commonly used in NILM. But because of a need for large amount of annotated training data in supervised methods and inability to assign a specific class to classified data in unsupervised methods, render then disadvantageous for NILM. A semi-supervised method presents an acceptable solution to overcome both these disadvantages. Ding Li *et al* [22] present promising techniques using Expectation-Maximization (EM) algorithm for semi-supervised learning. In a recent contribution by Parson [23], he creates a general model of the appliance that is built on the labelled data through Bayesian HMM and then it is tuned to a specific household using the unlabelled data. Leveraging this idea, more researchers have attempted at similar algorithms for semi-supervised learning with event-based classifier with Support Vector Machine and K-Nearest Neighbour [24], 1-NN using Gaussian Kernel to avoid abnormal training data with defined stopping point for training [25] or using wavelet design and Procrustes Analysis (PA) for NILM [26].

## Conditions and Schedule

The resources that are needed for the project are the dataset of appliances, load monitoring device for collecting aggregated data, high performance computer for training and cloud server for creating database. There are several datasets are available for the research purposes, mentioned in the survey [5, 8, 9]. A dataset that is suitable for the training purposes will be identified. A load monitoring system will be provided. I will also have the access to the load monitor designed by Zyax for testing and validation of the algorithm. Zyax will also provide me access to a cloud server, if needed, to create a database for appliance signature that can be accessed by the ALM system. I have a laptop which I deem powerful enough to train the model.

## Limitations

The project will focus exclusively on the appliance in a residential setting and only focusing on NILM methods. The algorithm developed will be tested, in a controlled setting, on a limited set of appliances for which we can get dataset and is available for testing. The focus of the project is to create an algorithm as a proof-of-concept and not aiming for an actual service to be provided to the consumers.

## Schedule

The following Gantt chart presents the schedule for the thesis, aiming to finish the project by 2nd week of June 2018.

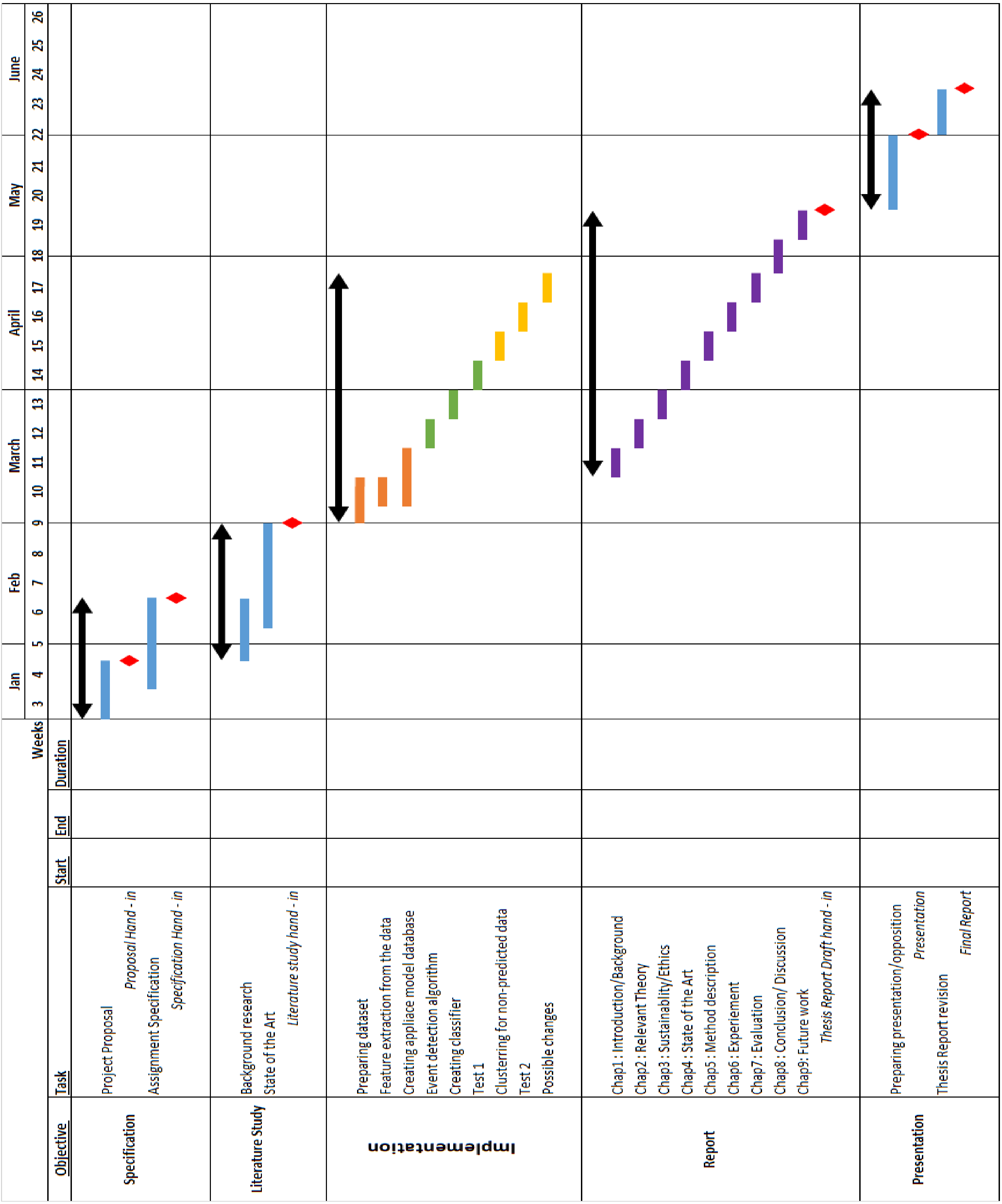


*Figure 2 Gantt chart for Thesis Schedule*

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