Appliance Usage Detection from Smart Meter Data Using Supervised and Unsupervised Non-Intrusive Load Monitoring

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Climate change and awareness of energy efficiency encouraging end user and network operator towards management the load that needs diagnostic of the loads. Monitoring load of individual appliances using individual appliance sensors in a house or a commercial building is often impractical and expensive, load disaggregation via NILM (Non-Intrusive Load Monitoring) offers a non-intrusive, purely computational, software-based approach to separate aggregate load obtained from a single electricity meter into individual appliance loads. NILM methods can be divided into supervised and unsupervised techniques (though hybrid, semi-supervised approaches are also possible). Supervised NILM techniques require a labelled dataset of appliance consumption data for training and unsupervised approaches do not require training data.In this study, we evaluate the robustness of two unsupervised and two supervised methods for NILM for a range of appliances, namely kettle, oven, hob/cooker, fridge, freezer, fridge-freezer, washing machine, dishwasher, tumble dryer, microwave. Firstly, we validate our methods using the public REFIT and REDD datasets, training and testing on the same dataset, and compare results with the literature. We then resample all datasets to the sampling rate, carry out aforementioned NILM experiments in order to assess whether we can use transfer learning to detect these appliances in an unknown dataset obtained from industry. We present our findings in terms of which appliances can be disaggregated reliably using transfer learning from known public datasets, and which NILM methods are preferable.
This is the first step towards assessing safety in the house, e.g. due to appliances not being switched off or appliance malfunction. Indeed, in a study by the BBC following the Greenfell fires, it was found that malfunctioning appliances cause almost 12,000 fires in Britain in just over 3 years. These are attributed to washing machines, tumble dryers, dishwashers, cookers, fridge-freezers, toasters and microwaves. With NILM we hope to identify these faulty signatures and catch them before it is too late.

Key Words: NILM, ANN, Decision Tree, DBscan, K-Means

Paper type –Research paper

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