Uncovering Hidden Demand Flexibility Using Non-Intrusive Load Monitoring (NILM) A Case for Southern Africa – Preliminary Results for Erongo RED, Namibia

Partnership: University of Strathclyde, Heriot-Watt University and Erongo Regional Electricity Distributor (RED) Company (Pty) Ltd, Namibia

R. S. Mollel, A. I. Elombo, L. Stankovic, V. Stankovic, J. Hambata G. Thiel, “Uncovering Hidden Demand Flexibility Using Non-Intrusive Load Monitoring (NILM): A Case for Southern Africa – Namibia,” to appear in 12th Int. Conf. Energy Efficiency in Domestic Appliances and Lighting (EEDAL-2024) Proc., Oct 2024, Japan

Problem Statement

- Our partner, Erongo RED, an electricity distributor for the Erongo Region of Namibia, distributes electricity to major towns in the Erongo Region, supplying approximately 21% of the entire country's electricity.
- Looking to improve active network management such as demand-side management.
- To do so, there is a need to exploit demand flexibility.
- Energy end-use building-level granular energy consumption data needed.
- Very limited availability of household-level labelled energy consumption datasets in African countries, mainly due to low rate of adoption of smart metering.

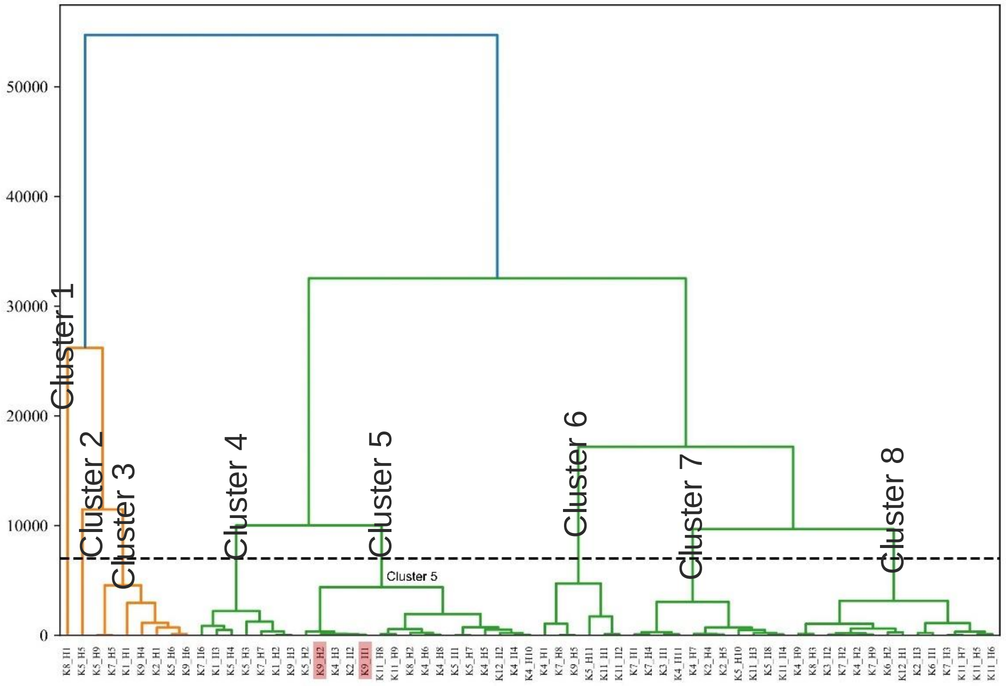
Approach

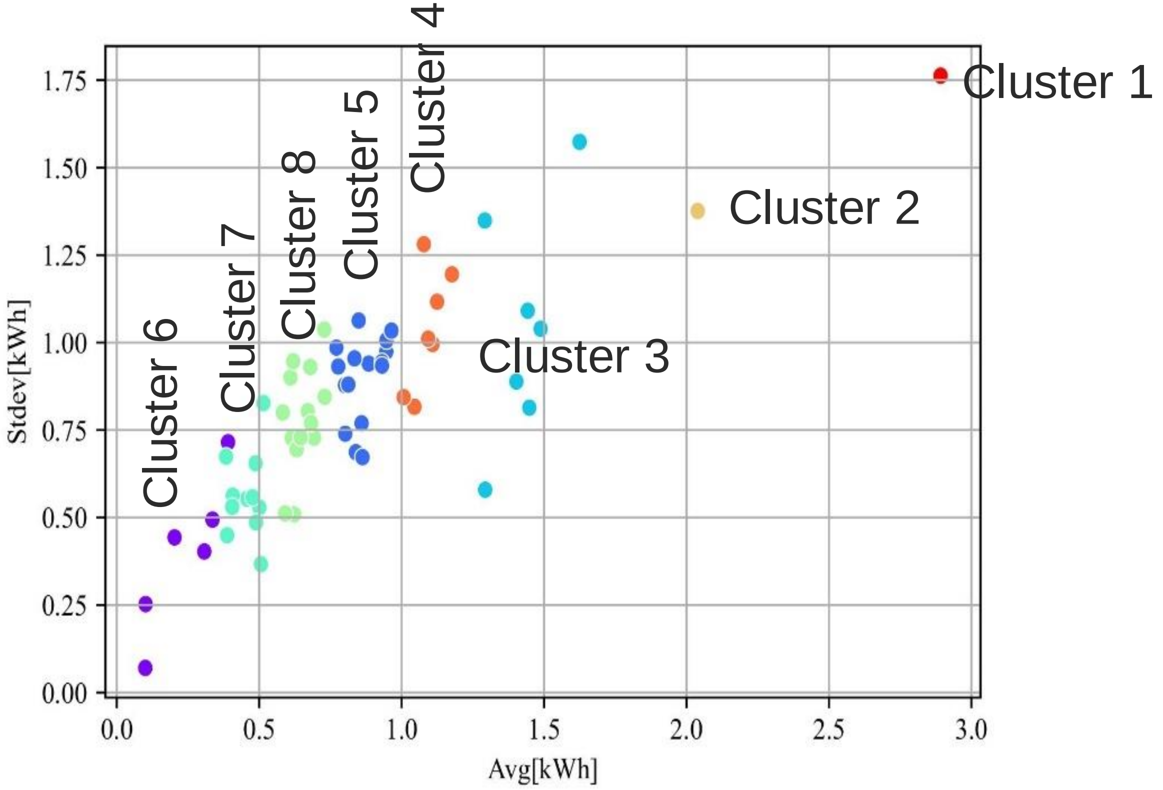
- Therefore, this paper proposes a data-driven methodology through NILM (essential tool for behind-the-meter visibility) to uncover demand flexibility.
- Erongo RED provided smart meter energy consumption data, representing house-level aggregate energy consumption of 63 residential homes within the Meersig Area of Walvis Bay.
- The data is sampled in kWh at a 30-minute sampling rate over 10 months, starting from 01/07/2021 until 30/04/2022.
- Leverage on hierarchical clustering to gain insights on aggregate load profiles across 63 residential homes.

Approach

- First, a clustering analysis is performed on the dataset to categorise the respective homes into groups of similar consumption patterns.
- To do this, we used the average energy, standard deviation, and total energy demand as criteria for clustering.
- The first two criteria provided a measure of the average and spread of energy consumption in the home across the day, whereas the latter criterion gave an indicative level of energy consumption in the home.

Key findings: categorisation of homes with similar energy consumption profiles





- Cluster 5 has the most houses and although averaging at 0.75kWh, the stdev is high, load profiles are spread out and hence the need to drill down what makes these houses different to explore flexibility potential.

Approach

- Qualitative appliance ownership and time-of-use surveys to design and validate unsupervised load disaggregation in the absence of submetering data.
- Our proposed unsupervised K-means approach aims to identify individual appliances or a group of appliances with similar energy consumption.
- This approach takes $E_{t,m}$ samples and groups them into “K” number of clusters based on their similarities.
- The number of clusters need to be predefined, and, in this paper, K was set to reflect the number of known appliances in the dataset.

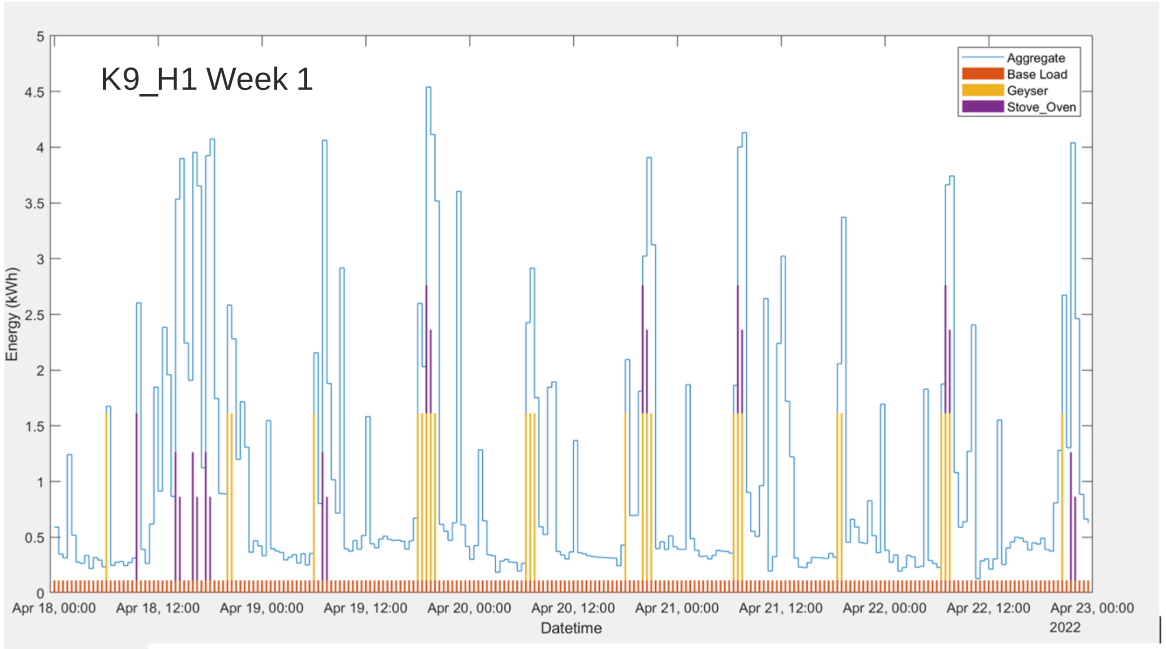
Approach

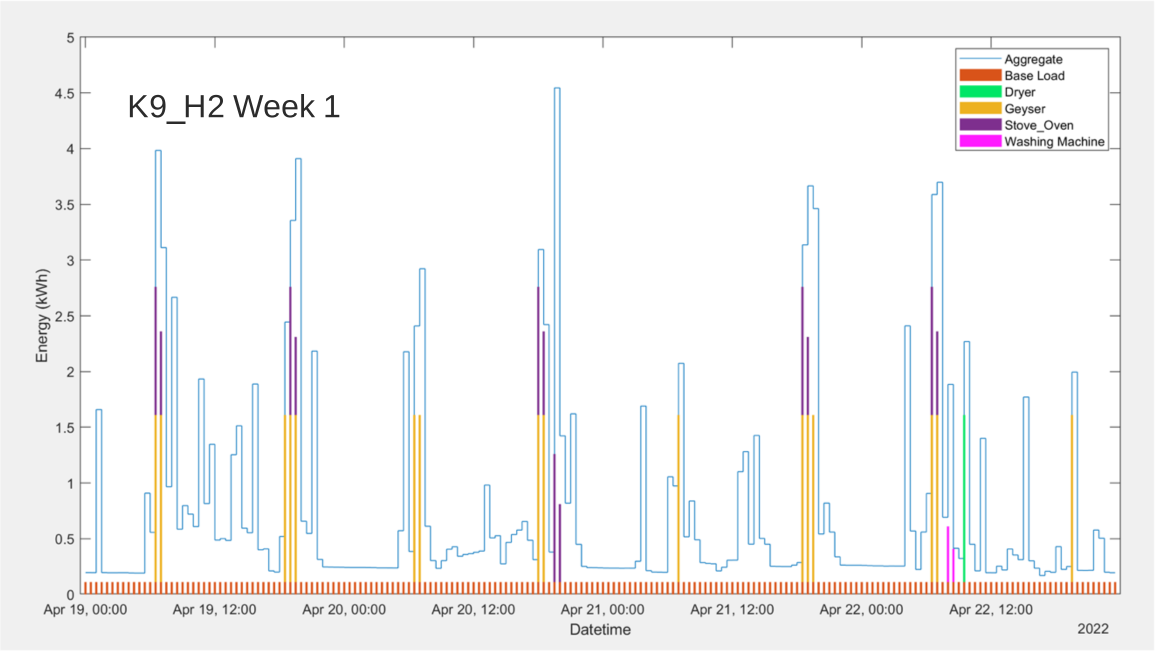
- The appliances were disaggregated and labelled according to the information obtained from surveys and their estimated energy consumption per run (a product of appliance power and average duration per use), for each 30 min sample; washing machine (0.5;0.2,0.1 kWh), Geyser (1.5 kWh), Stove/Oven (1.15,0.75 kWh), dryer (1.5,0.75 kWh) and base load from always-on loads.
- To validate our approach, we first evaluated the proposed methodology on the public resampled REFIT (UK) dataset, benchmarked against state-of-the-art very low-frequency NILM methods, viz. Graph Signal Processing (GSP), Convolution Neural Network (CNN), Factorial Hidden Markov Model (FHMM), Combinatorial Optimization (CO), Discriminative Disaggregation Sparse Coding (DDSC), and Optimisation-based (OPT) approaches.

Approach

- K-means shows comparable performance for washer-dryer, washing machine and Kettle, Microwave and Toaster, whilst performance is slightly worse for refrigeration devices.
- This gives us confidence in proceeding with disaggregating the Erongo RED houses to gain further insights on energy use in Namibia at household level.

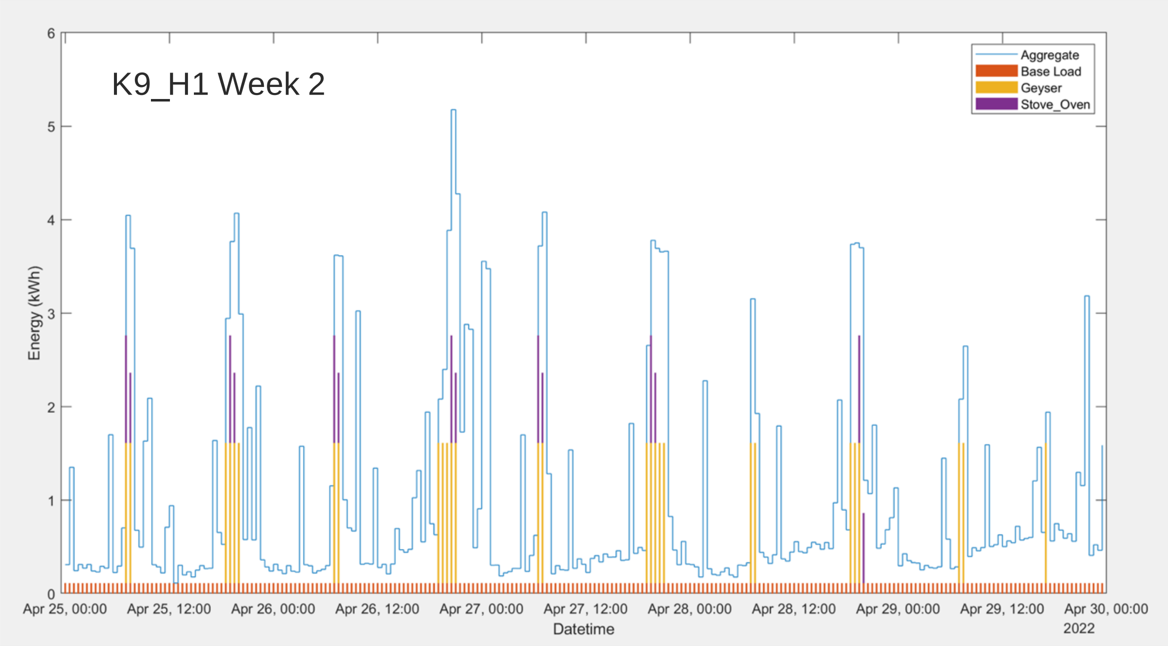
Key findings: Visualisation of disaggregated loads against total energy consumption

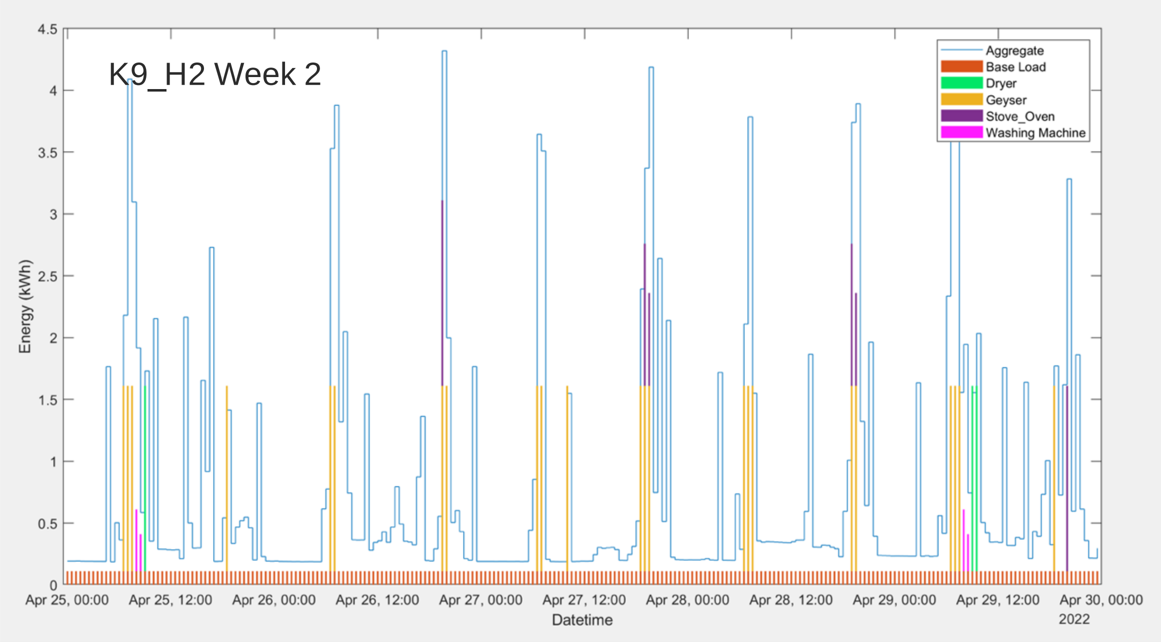




- Although both houses show similar energy usage pattern and aggregate consumption between 2kWh – 4.5kWh especially in the morning and evening, the appliance usage is different;
- Stove/Oven & Geyser being used mornings and evenings; but,
- H2 has used Washing Machine and Dryer on a weekday morning unlike H1.

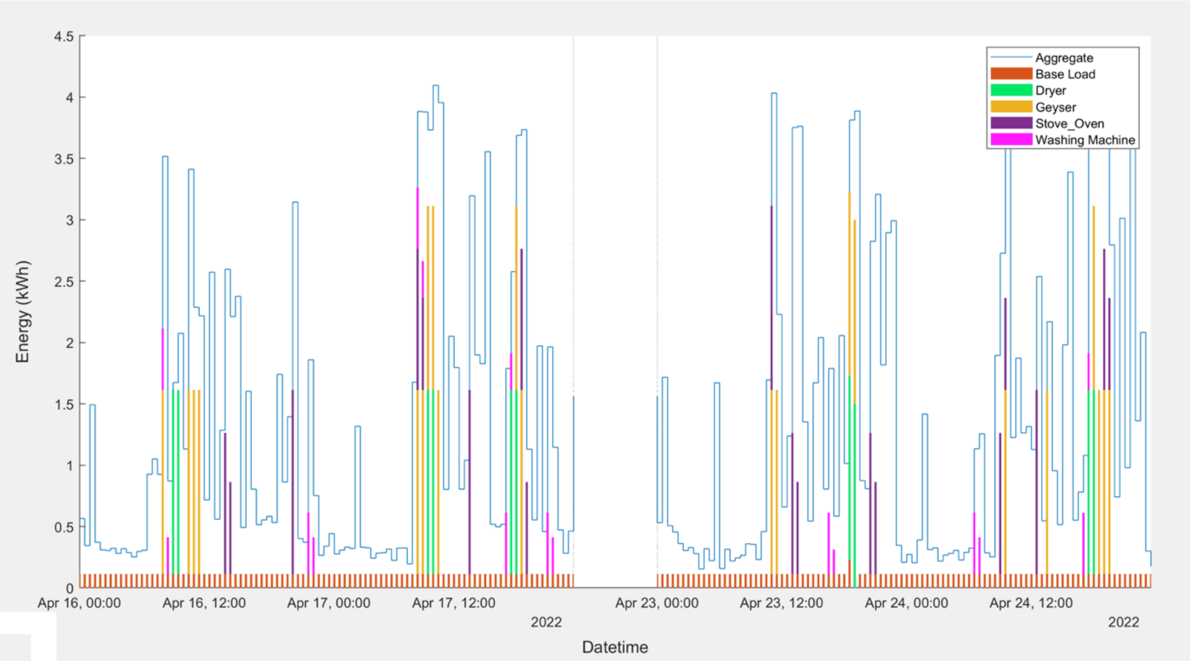
Key findings: Visualisation of disaggregated loads against total energy consumption



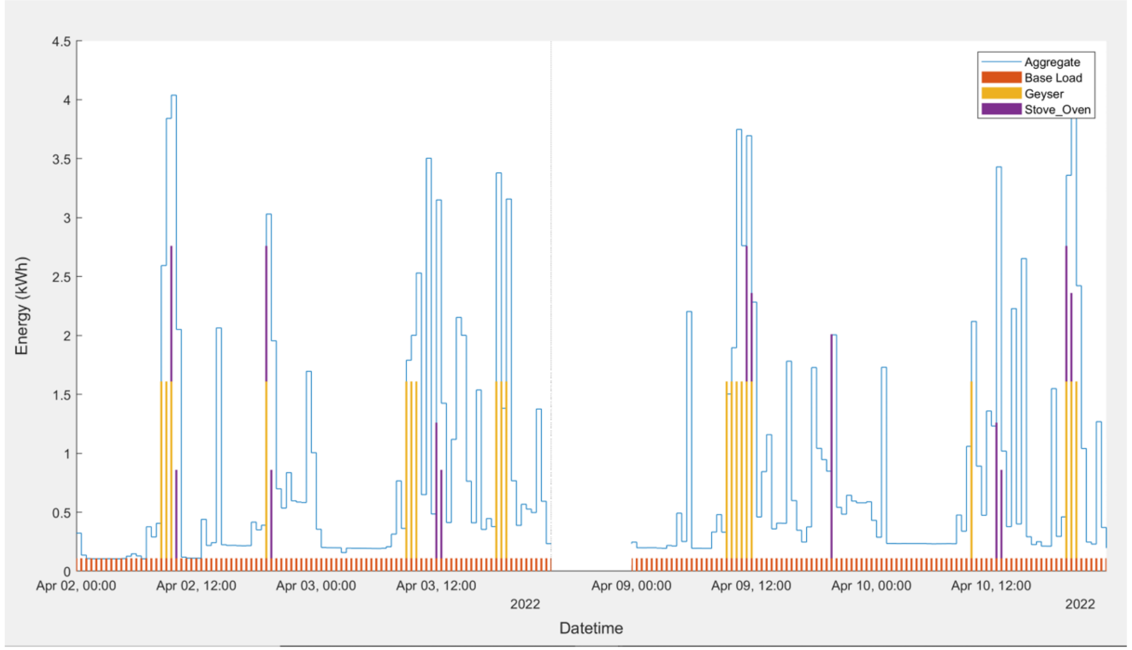


- Similar energy usage pattern – Stove/Oven & Geyser being used mornings and evenings. More Stove/Oven usage in H1.
- H2 has used Washing Machine and Dryer on a weekday morning unlike H1.

Key findings: Visualisation of disaggregated loads against total energy consumption



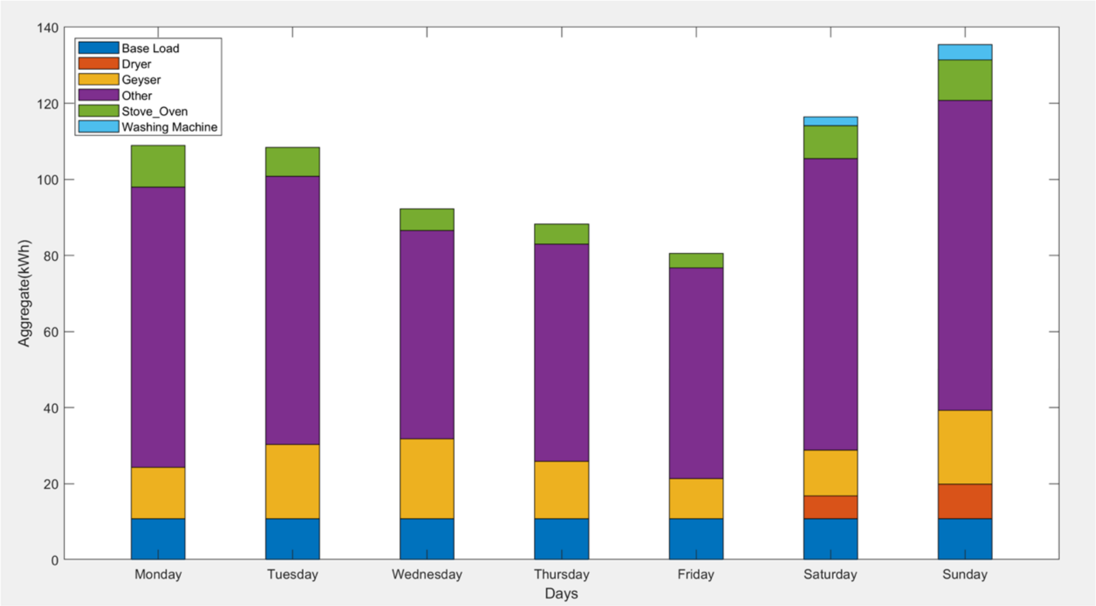
(a) K9_H1 Weekend



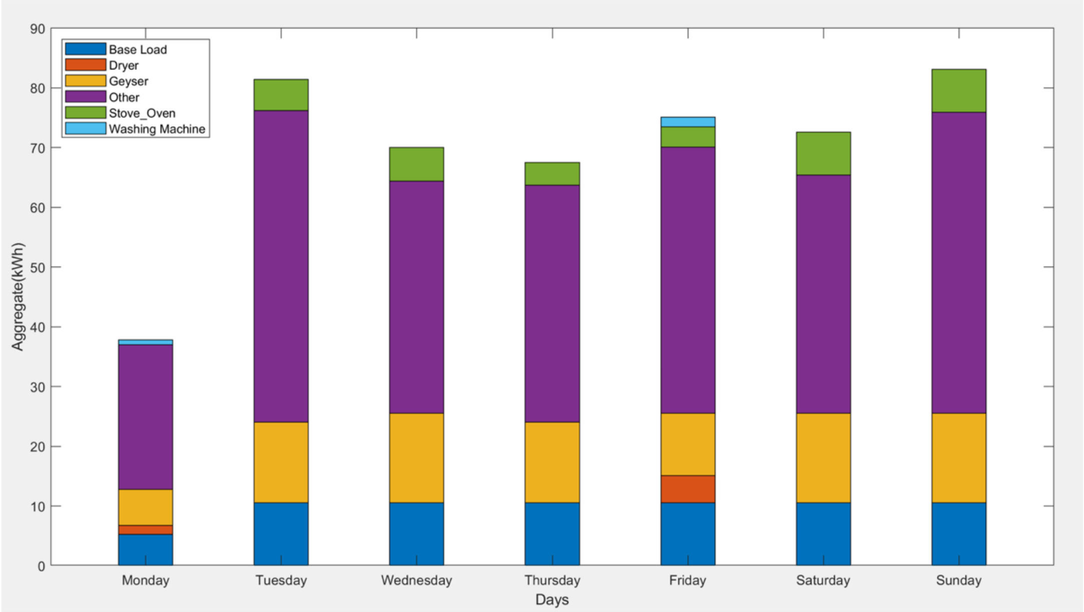
(b) K9_H2 Weekend

- More usage levels in terms of aggregate consumption (both mornings and evenings) unlike weekdays for both houses.
- H1 has used Washing Machine and Dryer on a weekend mornings and evening.
- More appliance usage in H1 unlike H2.

Key findings: Appliance Energy Distribution Per Day



K9_H1



K9_H2

- Different levels of base load can be observed in the two homes.
- K9_H1 uses washing machine and dryer on weekends rather than weekdays unlike K9_H2.

Conclusion

- The core value of NILM in terms of active network management is that it allows network operators to gain visibility into dynamic energy demand composition of the network.
- This network visibility enables the network operator to exploit the full benefits of demand flexibility, which would otherwise be hidden if the operators could only see the aggregate energy consumption.
- A flexibility-driven demand-side management intervention can be implemented by the network operator to manage limited energy supply or mitigate network capacity during times of peak demand.
- Since the plots provide a granular view of appliance-level energy consumption in the home, it also helps households gain a detailed understanding of the energy consumed by each appliance.
- This helps in managing energy bills by either reducing usage of specific appliances or shifting the use of specific appliances to the time of the day when tariffs are affordable.

Future Work

- Future work will include the utilisation of feedback from users on disaggregation results to improve our methodology – this will mitigate the potential inconsistencies caused by human error when completing the user-survey questionnaires .
- Additionally, we will investigate other unsupervised and/or supervised methods as well as explore the generalisability of the proposed methodology across more houses in the Erongo RED dataset.

THE PLACE OF USEFUL LEARNING

University of Strathclyde Engineering