Disaggregation of community energy consumption data to households

Author
Stan Verlaan
S.Verlaan@student.tudelft.nl

Responsible professor
Luciano Cavalcante Siebert
L.CavalcanteSiebert@tudelft.nl

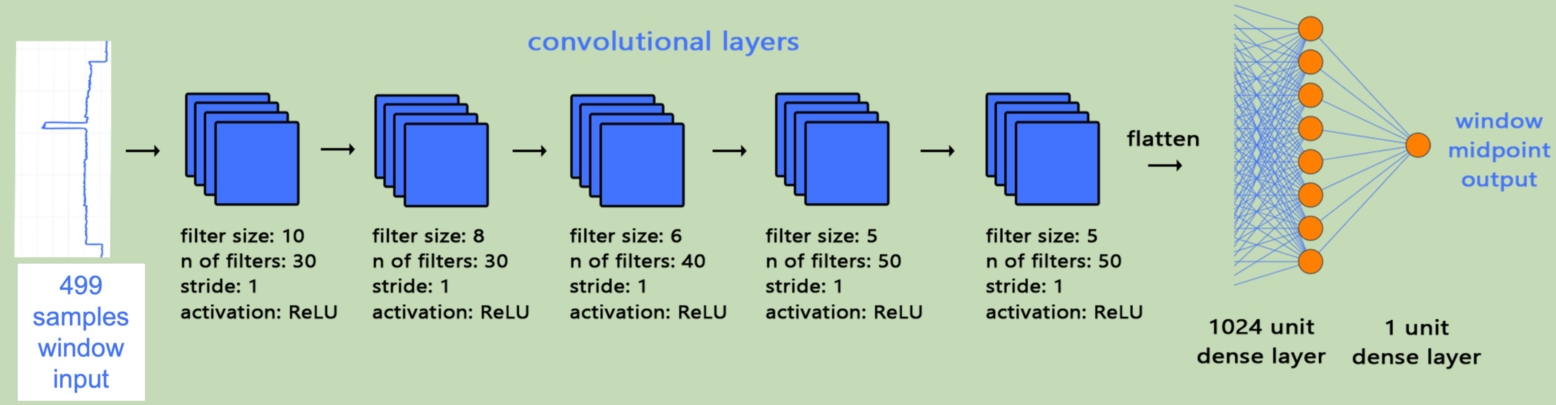
Supervisor
Sietze Kuilman
S.K.Kuilman@tudelft.nl

Research question

Is possible to apply the concept of NILM to communities to get information about households?

Motivation

1. Privacy
2. Fraud detection
3. Apartment buildings
4. Forecasting



Methodology

1. Data processing

Selection	Discard negative energy appliances (e.g. solar panels).
Outlier detection	Apply the empirical rule.
Missing feature detection	Fill the first five missing features else fill with 0.
Aggregation	Aggregate the data to households and communities.
Normalisation	Normalise using standard deviation and mean.

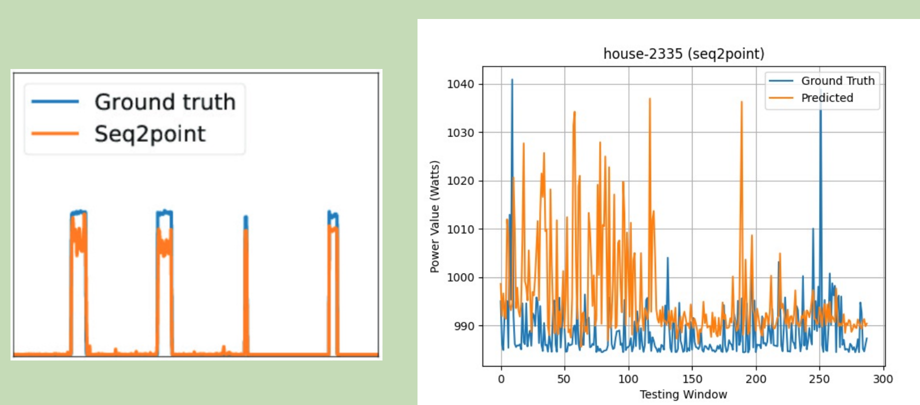
2. Sequence-to-point learning

A machine learning technique for mapping an input sequence to another output sequence.

Results

The results in terms of error look good, they perform better than Zhang et al. (2018). They used seq2point for NILM and got a Mean Absolute Error of 15.472 ± 7.718. When we look at the graphs below we see that the seq2point network is able to learn the load signature of a kettle, but when applied to a community it does not quite capture the load signature. It just oscillates around the mean.

Mean Absolute Error (MAE)	Root-Mean-Square Error (RMSE)
11.592 ± 6.331	16.135 ± 8.755



On the left we see the result of training a kettle in a NILM domain. On the right we see a result of disaggregating from communities to households.

Conclusions

Although the error results are promising the output can not be of any significant use. As the concept has valuable applications it is worth more exploring. In future works the following can be researched:

1. Use of a bigger dataset.
2. Use of more frequent data.
3. A different machine learning model.

These suggestion show potential, but might not result in better performance. Therefore, another explanation is that the data does not follow distinctive enough patterns. In NILM, appliances have a recognisable load signature. For example, a kettle can be either ON or OFF, therefore it has two consumption levels in its signature. For households, there are many irregular levels making it harder to disaggregate

TUDelft