Unlocking the flexibility of building energy consumption using machine learning

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Introduction

A major part of the energy consumption in the modern world takes place in buildings, and buildings are increasingly becoming equipped with sophisticated automation systems, sensors and ICT infrastructure. This opens new possibilities for value creation; Utilizing the buildings inherent flexibility in energy consumption to cover some of the increasing demand for flexibility from energy systems that are shifting toward stochastic generation from e.g. solar and wind.

- The buildings thus have the possibility to play an important active role in the energy systems of tomorrow
- Inspired by the recent advances with deep artificial neural networks for e.g. image recognition, natural language processing we seek ways to leverage these powerful techniques
- The methods are needed to adress the ever increasing volumes of data and go forwards in the energy transformation towards clean more sustainable energy systems

The EnergyLab Nordhavn - A Living Laboratory

The methods are developed for demonstration in the project EnergyLab Nordhavn that utilizes a rebuilt old harbour area as a living laboratory for integrated energy systems research and development.

- The methods thus need to be implementable in real value applications
- Consider the possible integration potential towards other parts of the energy systems
- Not sub-optimize for e.g. individual building benefits

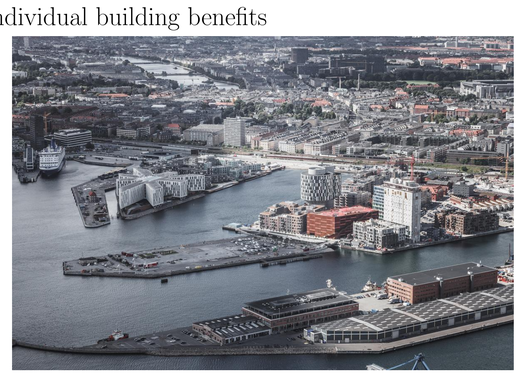


Figure 1: The Northern Harbour in Copenhagen, home of EnergyLab Nordhavn

A Machine Learning Approach to energy data analysis and predictions

In the investigation we combined feed forward neural networks with the fast Fourier transform to develop a novel classifier that determines the the presence of time of use pricing with residential electricity consumers. A Long Short-term memory recurrent neural network was trained to accurately predict aggregated electricity consumption. Both methods are expected to be implemented for use withing the Living Lab project.

- Data processing and cleaning were done in Python with SciPt
- Neural Networks were trained using Keras API with Tensorflow Back-end

Potential application and added value

The methods developed show promise towards real life applications by creating value from data that is often collected but rarely valorized.

- The classification methods can help validate the benefits of demand response programs and dynamic energy pricing by proving their efficacy
- Extract value from the smart meter roll-outs beyond billing services that mainly benefit utilities
- The ability to effortlessly predict energy consumption could be a key enabler for unlocking energy flexibility in the built environment
- The methods develop serve an important role in bringing value from the data deluge. A big gap still exists between the academic results for smart grids in showing the value that e.g. demand response program can bring

Application case

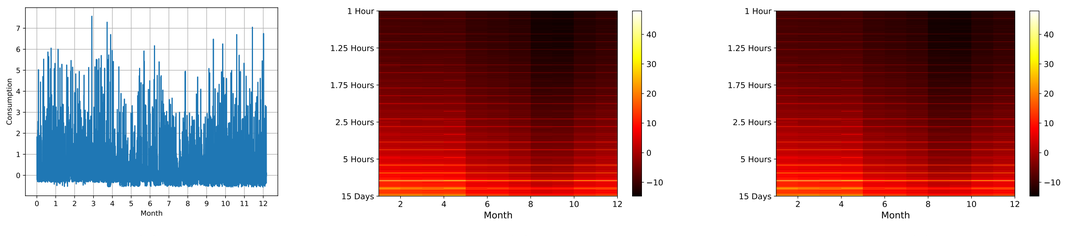
The data-set under investigation is electricity consumption data from UK, where a trial was run to investigate dynamic TOU pricing models. In the dataset there is included half hourly electricity consumption for a large number of households during the year 2013 where the dynamic time of use tariff trial was in effect. The data-set is publicly available [1] and summarized in table

Data description and pre-processing

Dataset	#samples	Length	TOU price	Unit
consumption_d	1025	17530	Dynamic	kWh
consumption_n	4173	17530	Fixed	kWh
tariff_d	1	17530	NA	£/kWh

Table 1: Data from residential electricity consumers

A matrix mean normalized single consumer consumption time-series is shown in figure along with the result of the fast Fourier transform as well as dynamic pricing information was used to as training data for the neural networks.



(a) (b) (c)

Figure 2: (a) Normalized Data for single customer
Yearly spectrogram of averaged consumption for (b) TOU customers (c) non-TOU customers

Implementations and results

Feed forward neural network with fast fourier transform We trained a feed forward neural network to correctly determine the Time of Use scheme for individual households. The accuracy of the trained network exceeds that of benchmark method logistic regression

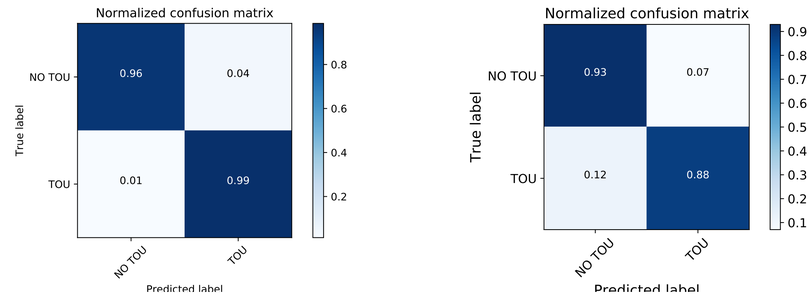
Layer	Units In	Units Out	Activation	Dropout
In	-	168	-	-
HL 1	168	128	ReLU	No
HL 2	128	64	ReLU	Yes
Out	64	2	Softmax	-

(a)

Parameter	Value
Optimizer	Adam
Learning Rate	0.0005
Regularization	0.0001
Batch Size	64

(b)

Table 2: (a) Layers of the Feed Forward Neural Network (b) Hyper-parameters

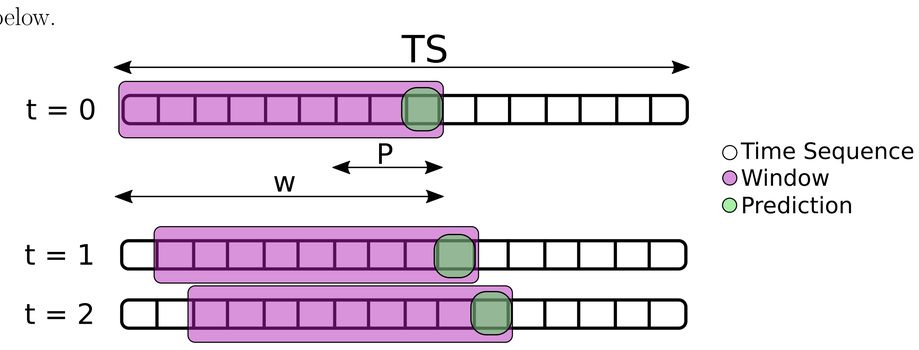


(a) (b)

Figure 3: Confusion matrix of binary clasifiers:
(a) Feed Forward Neural Network (b) Logistic regression benchmark

Long short-term memory

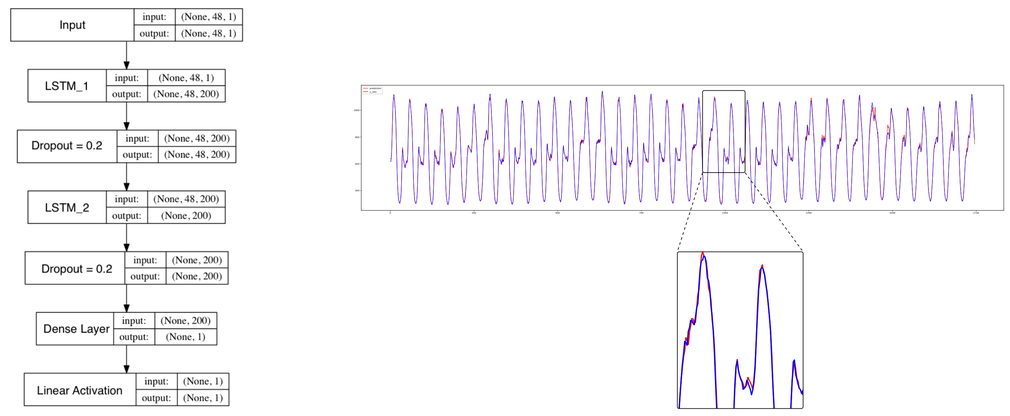
The Long short-term memory network was trained to predict the aggregated consumption based on previous day consumption. The knowledge of previous consumption was input to the LSTM network using a rolling window as shown below.



The implementation details and main results are shown below. A **grid search** was performed to derive the best combination of hyperparameters in the following manner:
We trained for 100 epochs models with the following combinations:

- `BATCH_SIZE` $\in [256, 512]$
- `WINDOW` $\in [1, 2, 7]$
- `NUMBER_OF_LAYERS` $\in [1, 2]$
- `NUMBER_OF_HIDDEN_UNITS` $\in [50, 100, 200]$

We saved all models, training logs, and "predicted vs expected" plots and chose as the best the one with the lowest *Test MSE*. The structure best forecaster for aggregated consumption based on day windows



(a) (b)

Figure 4: (a) Structure of best performing LSTM forecaster (b) Model fit to test data

Conclusions & Outlook

- We have shown how methods from the rapid-developing field of neural networks can be applied for analysis of the ever increasing volumes of Smart meter data. The methods show promise as early indicators of effective time of use schemes and forecasting of load.
- Similar data-sets from other studies are available. Since the results obtained are very promising,it would be interesting to see if transfer learning methods would ease the training of new models based on these datasets.
- Multi-task learning where we would train a set of shared and a set of individual layers for different customers is another approach that would be very interesting to apply.

[1] J Schofield, R Carmichael, S Tindemans, M Bilton, M Woolf, and G Strbac. Low Carbon London project: Data from the dynamic time-of-use electricity pricing trial, 2013 " Low Carbon London project: Data from the dynamic time-of-use electricity pricing trial UK Data Archive Study Number 7857 -Low Carbon London Project: Data from the Dynamic Time-of-Use Electricity Pricing Trial. 2015. URL `https://discover.ukdataservice.ac.uk/doi?sn=7857-1`.