

Forecasting of Smart Meter Time Series Based on Neural Networks

Thierry Zufferey^{1,2}, Andreas Ulbig^{1,2}, Stephan Koch^{1,2}, Gabriela Hug¹
¹Power Systems Laboratory, ETH Zurich; ²Adaptricity AG



1 Introduction

Traditional power networks

- Distribution System Operators (DSOs) monitor energy flows on a medium- or high-voltage level for an ensemble of consumers
- Low-voltage grid is regarded as a black box

Modern power networks

- Smart meters (SMs) record the consumption of individual customers connected to the low- and medium-voltage grid with high temporal resolution
- Previously unattainable degree of detail in state estimation
- The behaviour of (an aggregation of) single consumers can be predicted

2 Method overview

Project context

- Based on the work of Zufferey *et al.*¹
- SM data gathered from about 30k residential loads by IWB, the DSO of the City of Basel
- SM data processed by the ETH spinoff Adaptricity²

Features extraction (residential loads)

- Value on previous day(s) at the same time
- Mean of previous week(s) on the same weekday and at the same time
- Calendar features, i.e. hour of the day, weekday, month and public holiday

Note: very limited influence of weather data

Artificial Neural Networks (ANNs)

- most successful machine learning algorithm for short-term load forecasting³

Software support	H2O ⁴ + Azure VM
ANN model	Multilayer Perceptron (MLP)
# hidden layers	1
# neurons (hidden)	200
Activation function	rectifier $\max(0, x)$
Training algorithm	stochastic gradient descent with backpropagation

Fig. 1. Characteristics of the forecasting analysis

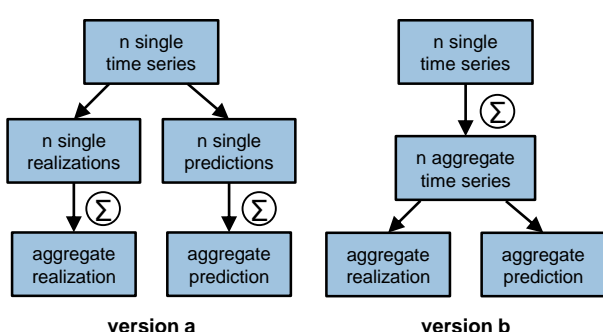


Fig. 2. Two ways of combining forecasting and aggregation

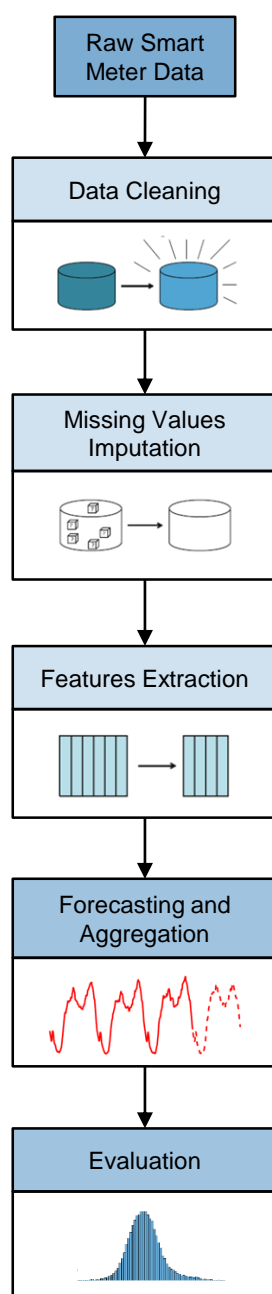


Fig. 3. Forecasting approach

3 Results and discussion

Key results

- Low accuracy with individual residential loads due to stochastic home appliances
- Constant performance (MAPE \approx 5%) from an aggregation of 1,000 loads and larger
- Underestimation of the actual aggregate consumption at the weekend
- Very similar performance of versions a and b for any aggregation size

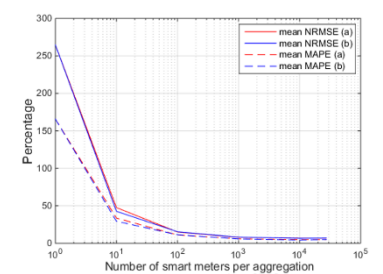


Fig. 4. Performance evaluation

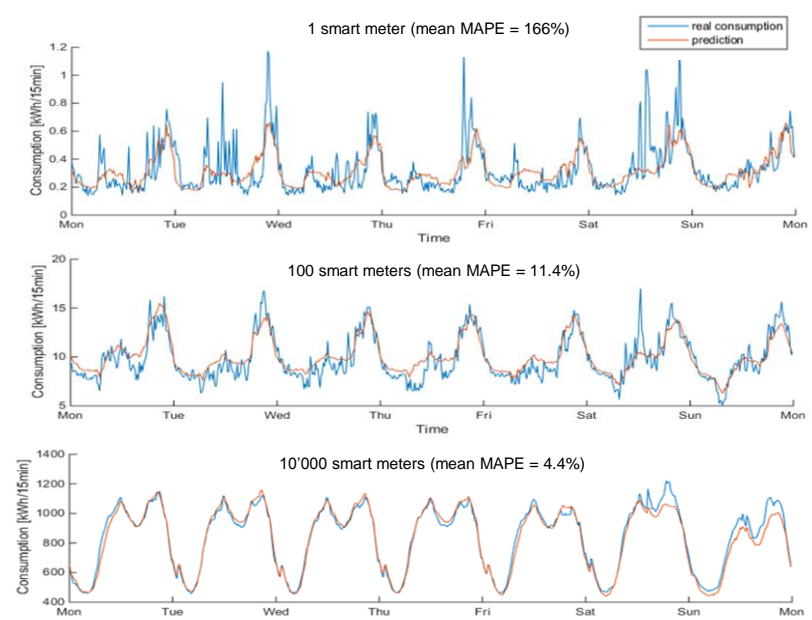


Fig. 5. Prediction outcomes according to the spatial aggregation level (version b)

4 Conclusion

Here are the main outcomes of this poster and the related paper¹:

- Considerably improved forecasting accuracy with aggregate load profiles in comparison to individual households, even for small aggregation sizes
- Reduced computational cost and no loss of accuracy by aggregating profiles before the neural network performs forecasting (version b)
- Better performance by aggregating profiles of similar shapes
- Analogous results for commercial and industrial loads as well PV systems, assuming an appropriate features selection

5 References

1. T. Zufferey, A. Ulbig, S. Koch, G. Hug: *Forecasting of Smart Meter Time Series Based on Neural Networks*. In: Data Analytics for Renewable Energy Integration, 19-23 September 2016, Riva del Garda, Italy
2. Adaptricity AG, <https://www.adaptricity.com/>
3. P. Koponen, A. Mutanen, H. Niska: *Assessment of Some Methods for Short-Term Load Forecasting*. In: IEEE PES ISGT Europe 2014
4. H2O.ai, <https://www.h2o.ai>