

# Electricity Load Forecasting - An Evaluation of Simple 1D-CNN Network Structures

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## 1 Introduction

An increasing number of apartment buildings have an autonomous power supply for both their electricity and heat. In order to operate the system in the most effective way, an accurate forecast of the electric and heat load is crucial.

The electric load of an apartment building is highly volatile and therefore difficult to predict by conventional statistical methods. We are proposing a novel forecasting method using a Convolutional Neural Network for iterative time series prediction and report the first results.

## 2 Conclusion

By varying the number of filters, the kernel size, and the size of one fully-connected layer, the influence of each parameter on the forecast and on each other were evaluated.

It can be shown that a reliable forecast, that outperforms the standard load profile, is possible with a rather simple CNN when the parameters are chosen correctly. For volatile load profiles, simplicity of the model seems to be a key for good forecasting results.

## 3 Supplying city districts

The research is embedded in the project MAGGIE [1,2], whose goal is to energetically modernise existing apartment buildings and draft a concept for sector coupling in city districts.

### Components in the houses:

- combined heat and power plant (CHP) → produces electricity and heat simultaneously
- heat pump → electricity to heat
- photovoltaics → provides electricity
- heat buffer → stores thermal energy (via H<sub>2</sub>O)
- power grid → receives surplus electricity and ensures availability of electricity

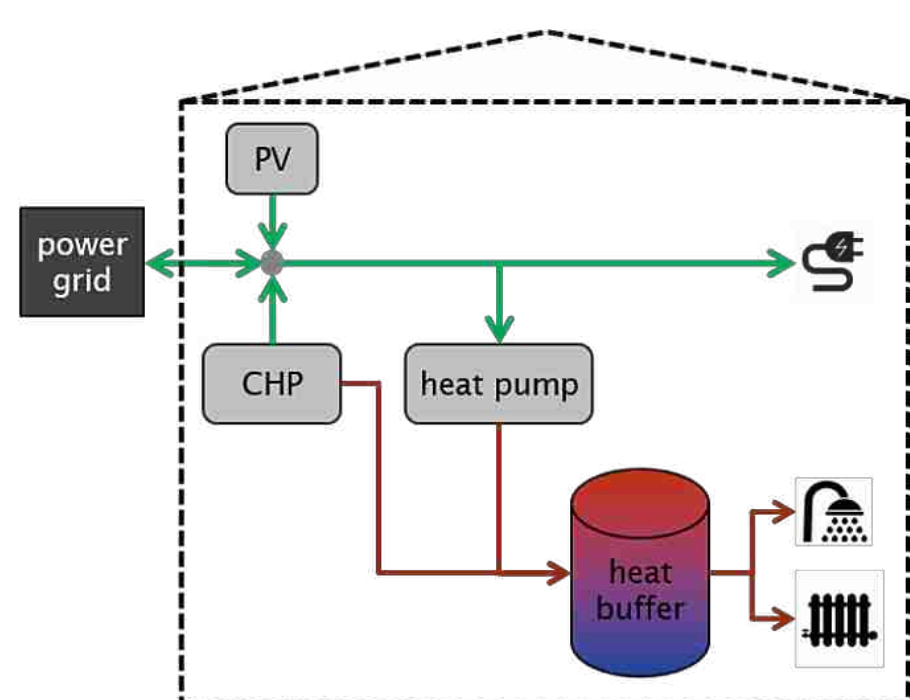


Fig.1: Schematic of the heating system. red=heat, green=electricity

All parts of the energy system can be controlled independently and in real-time

production and usage of heat and electricity can be shifted in time and between the components

flexibility in machine schedules

schedule optimisation possible (e.g. cost reduction, self-sufficiency)

Knowing the future energy loads is crucial for the schedule optimisation as deviations from the predicted load have to be absorbed by a changed production of the CHP or by the heat buffer.

## 4 Used dataset

In the research, data from the CER Smart Metering Trial in Ireland [3] were used. The dataset includes data from approx. two thousand private households in a 30 minute grid.

As the goal is to predict the electric load of apartment buildings, three aggregated load time series of randomly selected households were created:

- sum of 15 homes ≙ small apartment building
- sum of 40 homes ≙ big apartment building
- sum of 350 homes ≙ whole city district

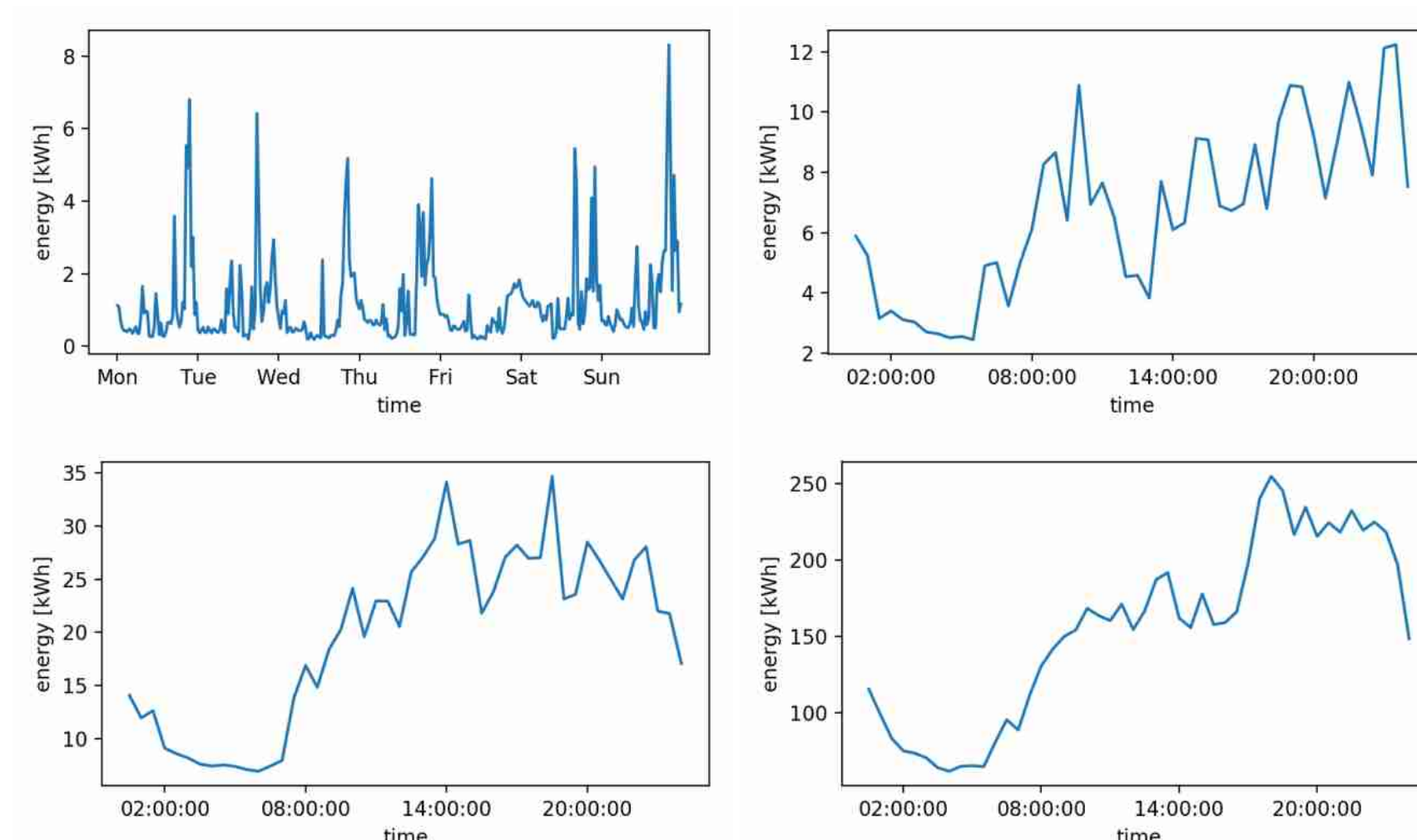


Fig.2: (a) shows an exemplary week of a single household. (b)-(d) show an exemplary day of the combined load of (b) 15, (c) 40, and (d) 350 households

## 5 Forecasting with CNNs

Forecasts are created iteratively, meaning that only one time step is predicted at a time by the network.

The idea of the network is that the 1D-CNN layer(s) create features that are then combined by one or more fully-connected layers, and finally a forecast is created based on the classification of the fully-connected layer. Pooling layers have been omitted.

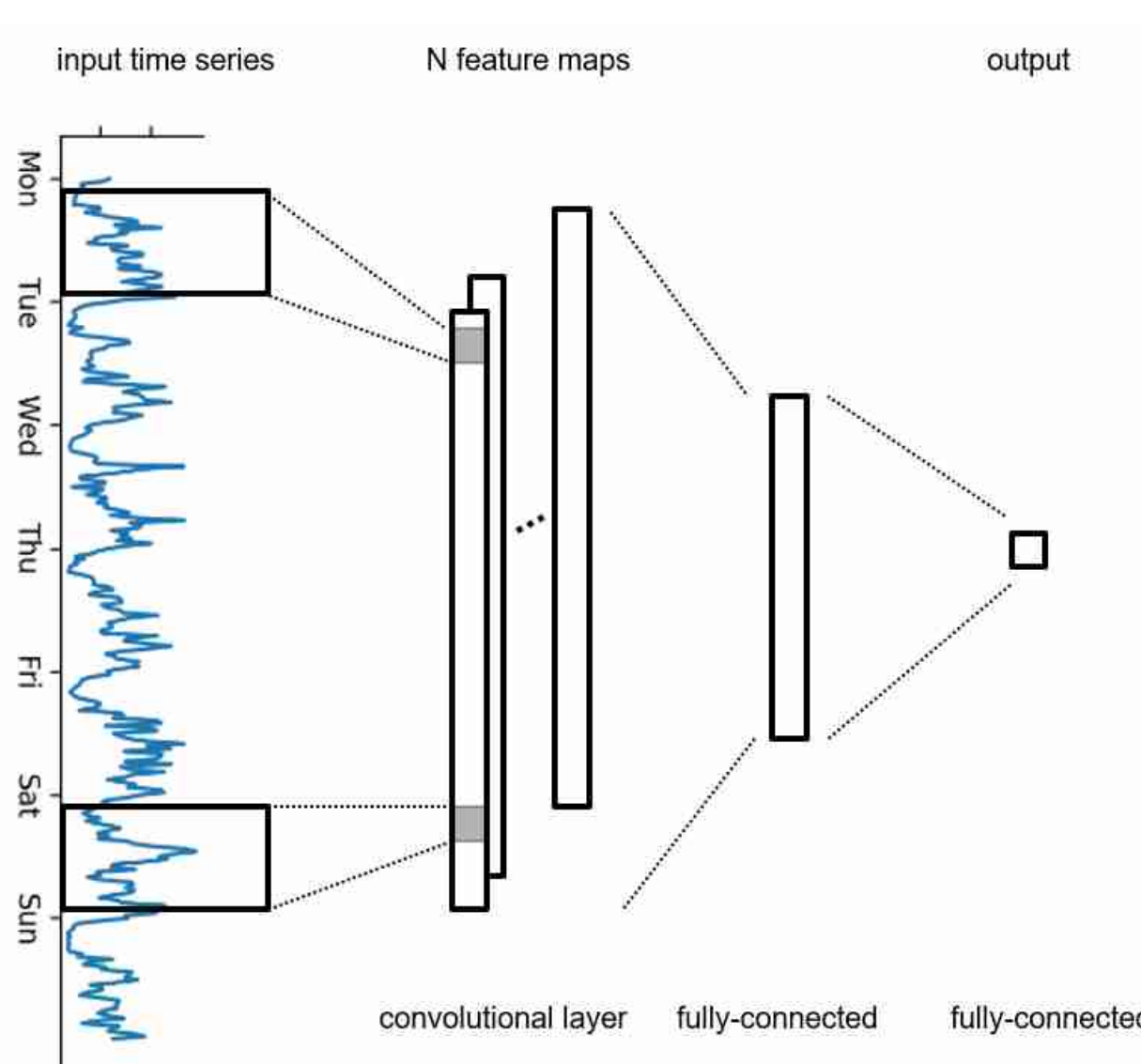
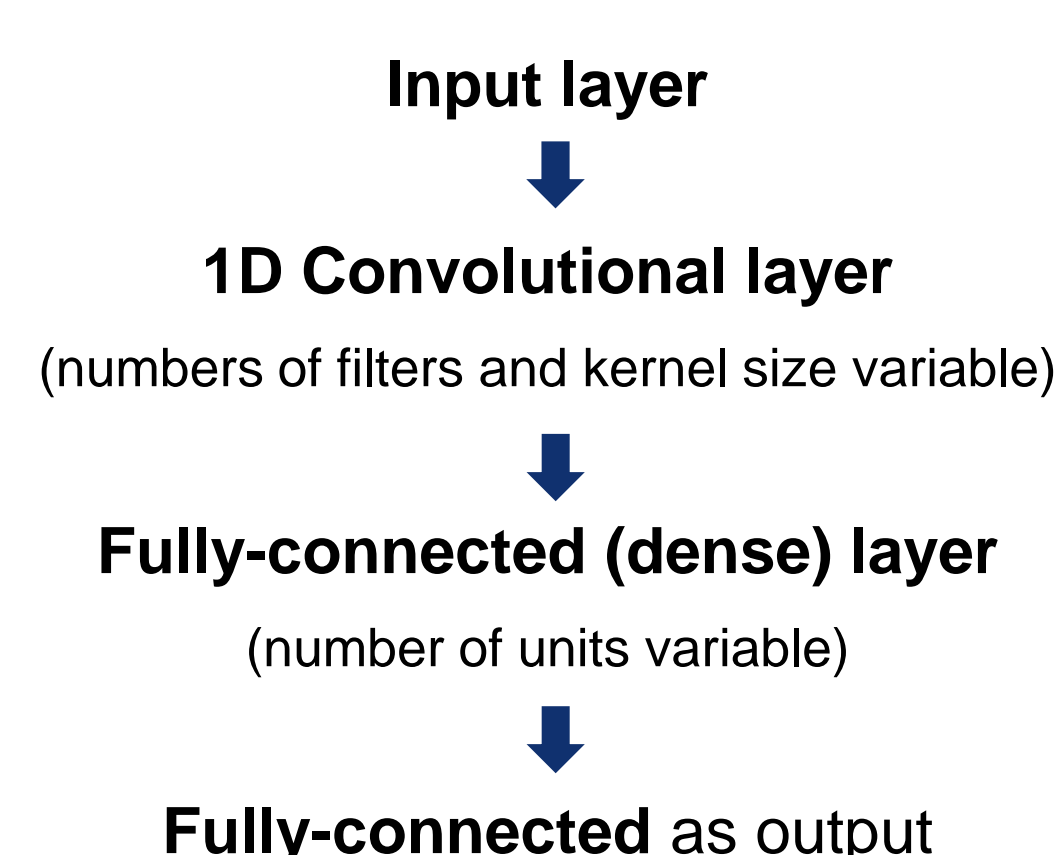


Fig.3: General architecture of the used neural network.

## 6 Results

Preliminary trials showed that simple networks produce already promising results. The following network structure was further tested in depth:



Variations of the following parameters in a grid search: number of filters, kernel size, dense size

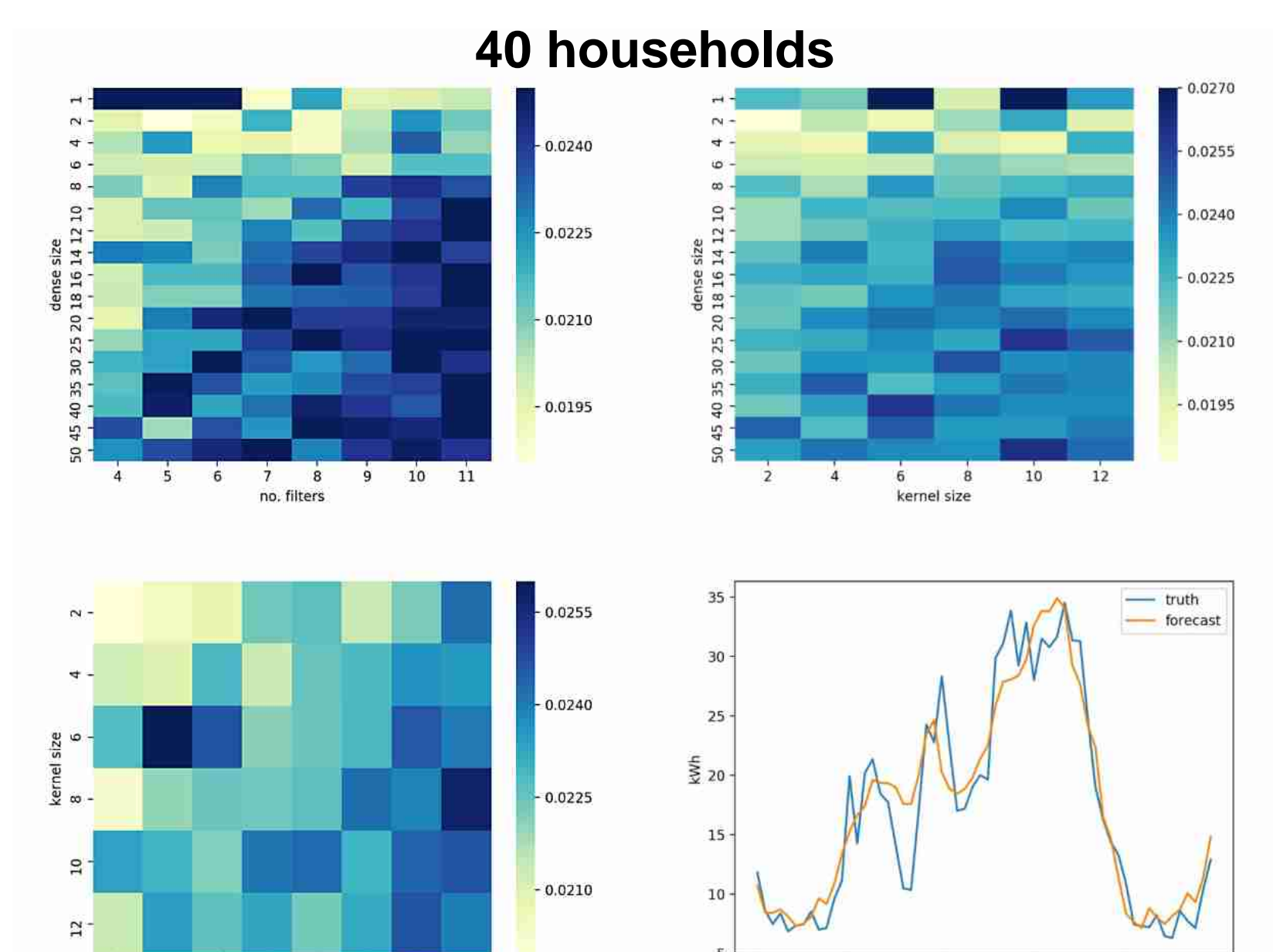


Fig.4: Heatmaps of the MSE. The values are mean values across the third parameter. (d) shows an exemplary forecast.

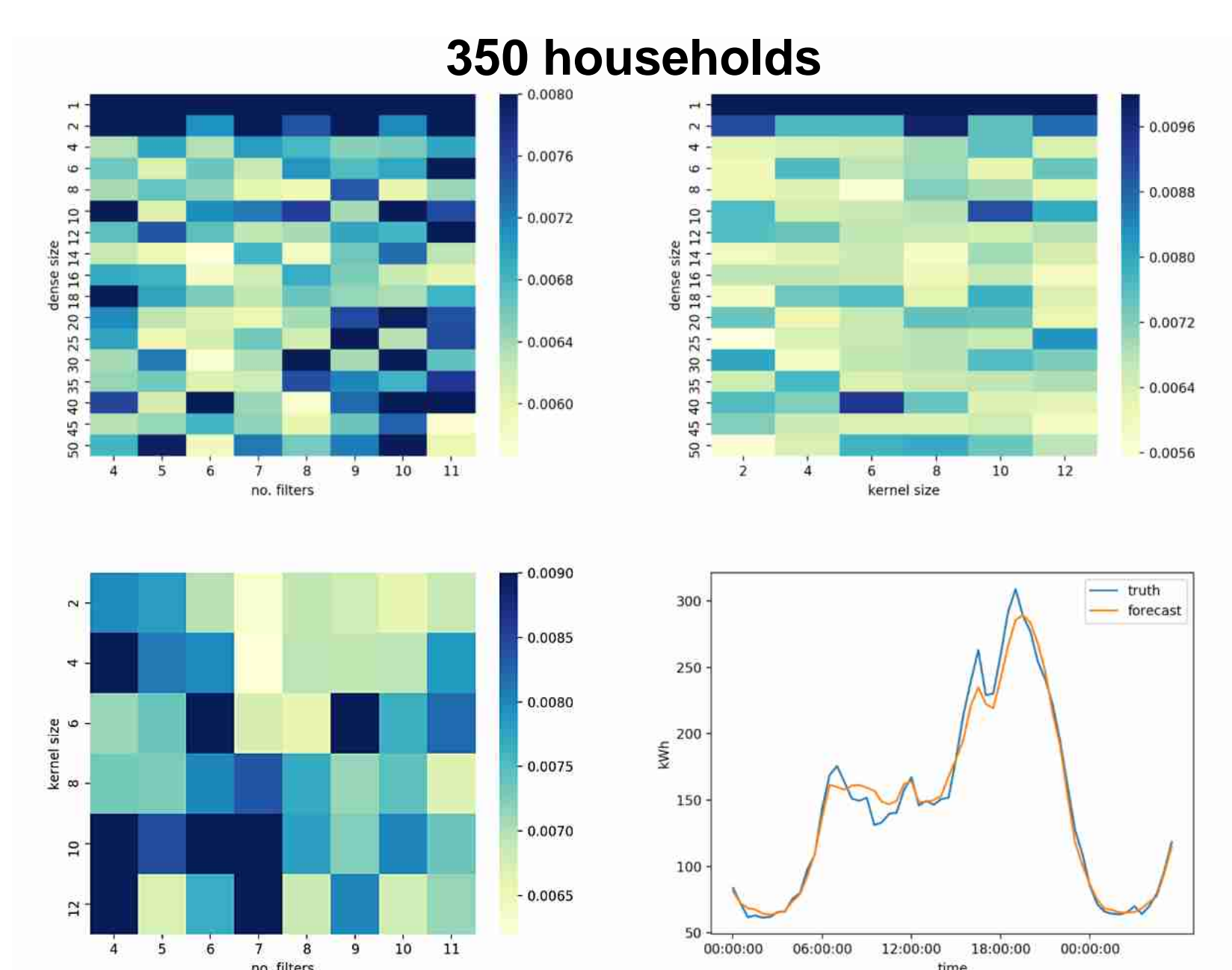


Fig.5: Heatmaps of the MSE. The values are mean values across the third parameter. (d) shows an exemplary forecast.

## 7 Discussion

### 40 households load series:

- best result with small dense layer, or else overfitting
- additional filters can compensate for a small dense layer and vice versa
- overfitting when dense size and no. filters too large
- worst results without dense layer (≙ dense=1)

### 350 households:

- only minor influences of no. filter and kernel size
- slightly better results with small kernel sizes
- for stable results → dense size > 2

## 8 Outlook

In the next step, combinations of different filter sizes and structural variations (e.g. increasing depth) will be investigated. Furthermore, the influence of external variables will be tested.

## 9 Bibliography

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- [3]: Commission for Energy Regulation (CER). (2012). CER Smart Metering Project - Electricity Customer Behaviour Trial, 2009-2010 [dataset]. 1st Edition. Irish Social Science Data Archive. SN: 0012-00. [www.ucd.ie/issda/CER-electricity](http://www.ucd.ie/issda/CER-electricity)