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Poster abstract: grid-level short-term load forecasting based on disaggregated smart meter data

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Abstract The rollout of smart meters and steadily increasing sample rates lead to a growing amount of raw data available for short-term load forecasting (STLF). While the original motivation for high resolutions has been the enabling of non-intrusive load monitoring (NILM), so far their value for STLF has been limited. We propose a novel approach, which allows the exploitation of high resolution data for STLF, by incorporating NILM and subsequent clustering of similarly behaving appliances as a preprocessing step.

Keywords STLF · NILM · Clustering · Smart grid

1 Introduction

To enable a stable and efficient management of the energy system, each distribution network operator is legally bound to offer a one day ahead prediction of the grid's expected load. This *short-term load forecasting* (STLF) minimizes the necessary amount of balancing energy, as it allows to timely adjust the power stations' schedules.

With the rollout of smart meters and advances in metering technology, the availability of data has improved significantly from quarter-hourly aggregated data on the grid level to household-specific data with a sample rate in the order of seconds. It is not obvious, however, whether high resolution data can lead to better forecasts. This fine granularity, though, enables the identification of single appliances within the overall load of households, a paradigm known as *disaggregation* or *non-intrusive load monitoring* (NILM). With these prerequisites, our work proposes an innovative approach, using disaggregation for STLF. Based on household-level NILM, clusters of appliances with similar behavior are built across all households. The research hypothesis is that individual forecasts per cluster and their subsequent aggregation is superior to one single forecast.

We base the hypothesis on the observation that different classes of appliances are sensitive to different features (e.g., usage of lamps correlates to daylight, while air conditioning correlates with temperature). The clustering of appliances should enable STLF techniques to determine more meaningful relations, which were hidden inside the aggregated power flow before.

2 Background and related work

STLF has been extensively investigated [4]. Traditional approaches, whether they are statistical, regression- or machine learning based, do only rely on (grid-level) aggregated consumption data. These forecasting methods extrapolate from the past load profile, typically taking into account additional features such as season or temperature. Even recent approaches, e.g. using deep learning [1], are still designed for coarse grid-level data.

Due to smart meters, however, current STLF can also take advantage of more precise household-level consumption data. Clustering households according to their energy signatures, individually forecasting for each cluster, and aggregating these forecasts outperforms a single prediction over all facilities [5].

For clustering households, the 15-min sample rate provided by any smart meter is sufficient. More fine-granular measurements (i.e., in the order of seconds) have so far

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mainly been used for NILM [2] and subsequent user feedback. To the best of our knowledge, high resolution data has not yet been used for STLF.

3 Method

Starting from household data, our method introduces NILM-based clustering as a preprocessing step for applying standard STLF afterwards. The prediction pipeline is summarized in Fig. 1.

In step 1, NILM is used to disaggregate the load profile of each household into its different appliances. Under the constraint that it has to be an unsupervised solution, any NILM algorithm can used. For our implementation, we follow an event-based approach, which identifies comparable loads by the similarity of their slopes when switched on or off [2]. The outcome of the disaggregation step are the load profiles of single appliances complemented by one additional load profile per household, containing all remaining unclassified loads.

Step 2 first calculates the obtained load profiles' historical correlation to those quantities, which are later used as input features in the STLF step. For each load profile, the resulting set of correlation coefficients is combined into a single vector. Clustering is then performed on this vector to group together appliances which correlate in a similar way to the different features.

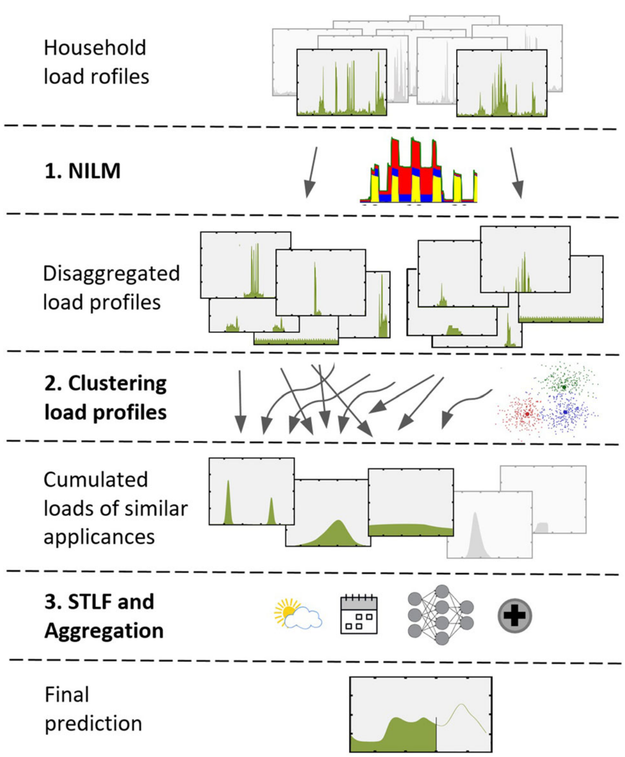

Fig. 1 All steps of the prediction pipeline

Finally, in step 3, STLF is used to forecast the load of the following day for each cluster. The available load profiles of the clusters are downsampled to a resolution equal to that of the targeted prediction. Existing STLF algorithms that assume a 15-min resolution can then be used for the individual cluster predictions. The selection of interesting input features does not require adaptations either. The final prediction for all households is determined by summing together all forecasts.

4 Status and outlook

To verify our hypothesis, we use a previously unpublished data set from a German metering point operator. The anonymized data set comprises load profiles from more than 3500 households distributed over Germany. For each household, we have been provided data for more than one year, for all three phases, and with a resolution of two seconds. Each time series is annotated by its zip code's first 3 numbers (out of 5). This allows the incorporation of weather data and other locality-dependent features. The NILM implementation is already available and we are proceeding with the clustering step. By the time of the conference, we will be able to present first predictions and to make an early assessment of the value of our approach. Unsupervised disaggregation is unsatisfactorily solved today. This limitation notwithstanding, ever higher sampling rates, as well as new approaches based on deep learning [3], are likely to lead to a continuously improving precision of NILM. This would yield increasingly accurate appliance clusters, improving as a consequence the accuracy of the overall forecast.

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