Predictive Modeling for Flexibility Load Forecasting in Prosumer Communities[1]

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Motivation und zentrale Fragestellung / Motivation and Central Question

Recently there has been a great need for demand response mechanisms to increase the flexibility in electricity consumption of residential buildings or *prosumers*. Such flexibility can further be increased when demand response is performed at the level of *prosumer communities*. This is because prosumer communities can optimize and coordinate electricity consumption at a local level, by better exploiting the renewable energy generation available at the participating prosumers. However, the performance of such short-term optimization relies heavily upon the accuracy of several forecast quantities, including forecasts of the electricity-load profile both at the prosumer and the community level. At the same time, capturing the dependencies of the electricity load consumption to exogenous factors, such as the weather conditions, may significantly improve the quality of such forecasts. In this paper, we focus on a wide selection of methodologies for electricity load forecasting, the combination of which may provide significant assistance to the optimization of electricity load in communities of prosumers. We present and test standard data-based load forecasting methodologies, including black-box time-series models as well as time-series models specifically tailored for load forecasting. The integration of weather forecasts into data-based time-series forecasts is also tested. The results demonstrate that a combination of persistence and regressive terms (tailored to the load forecasting problem) can attain the best forecasting accuracy. Instead, generic black-box models are not able to provide equally good forecast accuracy.

Methodische Vorgangsweise / Methodological Approach

The proposed methodologies for day-ahead electricity load forecasting are based on the recent article of the authors [1]. They are extended and analyzed here in the context of prosumer communities. Furthermore, the impact of weather forecasts in the accuracy of the load forecasts is investigated.

Measurements of the electricity load over a period of several months are sufficient to establish reliable day-ahead forecast models, where forecasts of the electricity load are provided over the following day (i.e., a series of $n = 96$ predictions over the $15\,min$ intervals of the following day). Measurements were collected from three residential buildings in the state of Upper Austria, indicated by B1, B2, and B3. In addition, a virtual community (indicated by C) has been established by considering also the aggregated (sum) of the electricity load consumption as a predicted target variable. This further allows for investigating forecasts over the total electricity consumption of the whole community. In Figure 1, we provide a sample of the available time-series data for the three buildings and the community over a period of one month (Jan, 2016).

In this paper, we are investigating a collection of persistence models, auto-regressive based models, and combinations of the two model categories. The list of considered models is as follows:

- Persistence models
- Autoregressive (AR) based models
- Holt-Winters (HW) model
- SARIMA model
- Persistence-based autoregressive model (PAR)
- Seasonal persistence-based, regressive model (SPR)
- Seasonal persistence-based neural-network model (SPNN)

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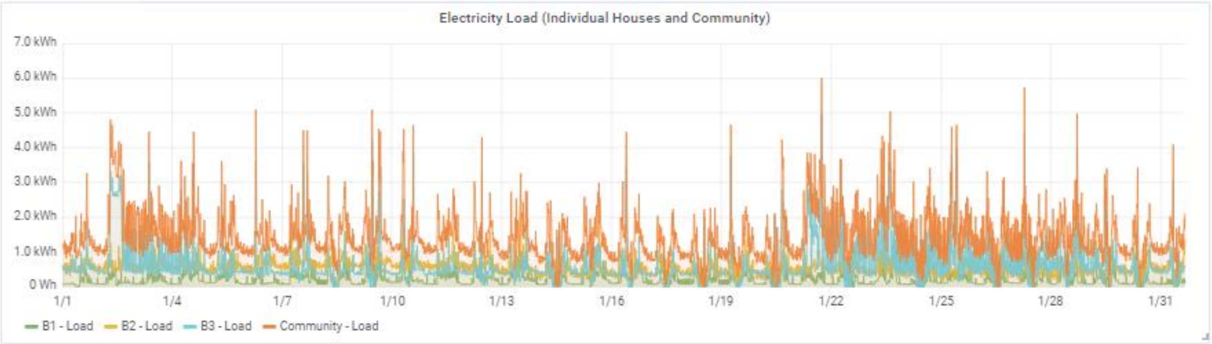

Figure 1 Load consumption from three residential buildings (from Wels, Upper Austria), indicated by B1, B2, and B3, within a single month (from 01.01.2016 to 31.01.2016).

Persistence models [2] establish predictions based on average load consumption at "similar" time periods in the past (e.g., similar time periods during previous calendar days). Autoregressive (AR) based models [3], [4] can be used to capture higher frequency temporal dependencies in the load consumption within the same calendar day. The models HW [5] and SARIMA [6]–[8] are standard models used for time series forecasting that try to capture seasonal trends. The persistence-based models (PAR, SPR, SPNN) have been introduced by the authors in [1] and combine persistence models with auto-regressive features. In SPR and SPNN we further expanded the set of features to capture phenomena that are specifically relevant for electricity load consumption in residential buildings. In this paper, we analyze their performance also in the context of prosumer communities. Furthermore, in the case of PAR, we also introduced additional features capturing the weather conditions (which are also provided as forecasts), namely the *solar radiation* and *outdoor temperature*. We indicate the new model by PAR-W, and we perform a comparative analysis of the forecast accuracy with the models of the above list.

Ergebnisse und Schlussfolgerungen / Results and Conclusions

In Table 1, we present the normalized daily-average RMSE over a different simulation period for all data-based forecast methods when the target value is the electricity consumption of the overall community (i.e., buildings B1, B2, and B3, together). The performance has been recorded after 2 months of training (during Feb 2016), 7 months of training (during July, 2016) and 12 months of training (during Dec 2016). We also present the overall daily-average RMSE over the whole year (2016). Normalization of the RMSE is performed with respect to the average daily electricity load consumption. It is evident that the PAR and SPR models, which are persistence- and regression-based models outperform all other (black-box) standard forecasting models. This should be attributed to the fact that both PAR and SPR models have been designed specifically for electricity load-forecasting, incorporating both low and high frequency factors. On the other hand, black-box model approaches, such as SARIMA and HW are generic time-series forecasting approaches that require careful configuration. Furthermore, we should mention that SARIMA requires computationally intensive training with several months of historical data. Its performance gets rather close to the performance of PAR and SPR models (if we compare their performance in July 2016), however this is achieved after six months of training.

Table 1 Comparison of standard electricity load prediction methods with respect to normalized RMSE for the community of buildings (i.e., when the target value is the sum of the electricity load consumption of all three participating buildings B1, B2, and B3).

Duration	Feb 2016	July 2016	Dec 2016	2016
N-same-days	0,808	0,717	0,521	0,690
N-days	0,636	0,621	0,446	0,586
HW	0,751	0,755	0,532	0,694
SARIMA	0,694	0,644	0,455	0,616
PAR	0,461	**0,579**	**0,429**	0,488
PAR-W	**0,460**	**0,579**	**0,429**	**0,487**
SPR	0,505	0,609	0,450	0,526
SPNN	0,762	0,666	0,466	0,646

These results are further confirmed when we analyze the running average RMSE over the whole training period as depicted in Figure 2. In this figure, we observe that the behavior of the models is rather consistent across all individual buildings, even though the load consumption differs significantly across buildings (i.e., small consumption in B1, medium consumption in B2, and large consumption in B3). It is important to also note that the daily-average RMSE of the community load consumption is significantly smaller than the arithmetic mean of the daily-average RMSE of the individual buildings. This demonstrates that forecasting at the community level provides higher accuracy, which can further be exploited for more reliable decision making at the community level. Finally, we also observe that incorporating the weather forecasts in the PAR-W model maintained or slightly increased the forecasting accuracy, however the improvement is rather limited. This should be attributed to fact that the forecasting models without the weather data features are already adapting to the variations in the electricity load due to weather.

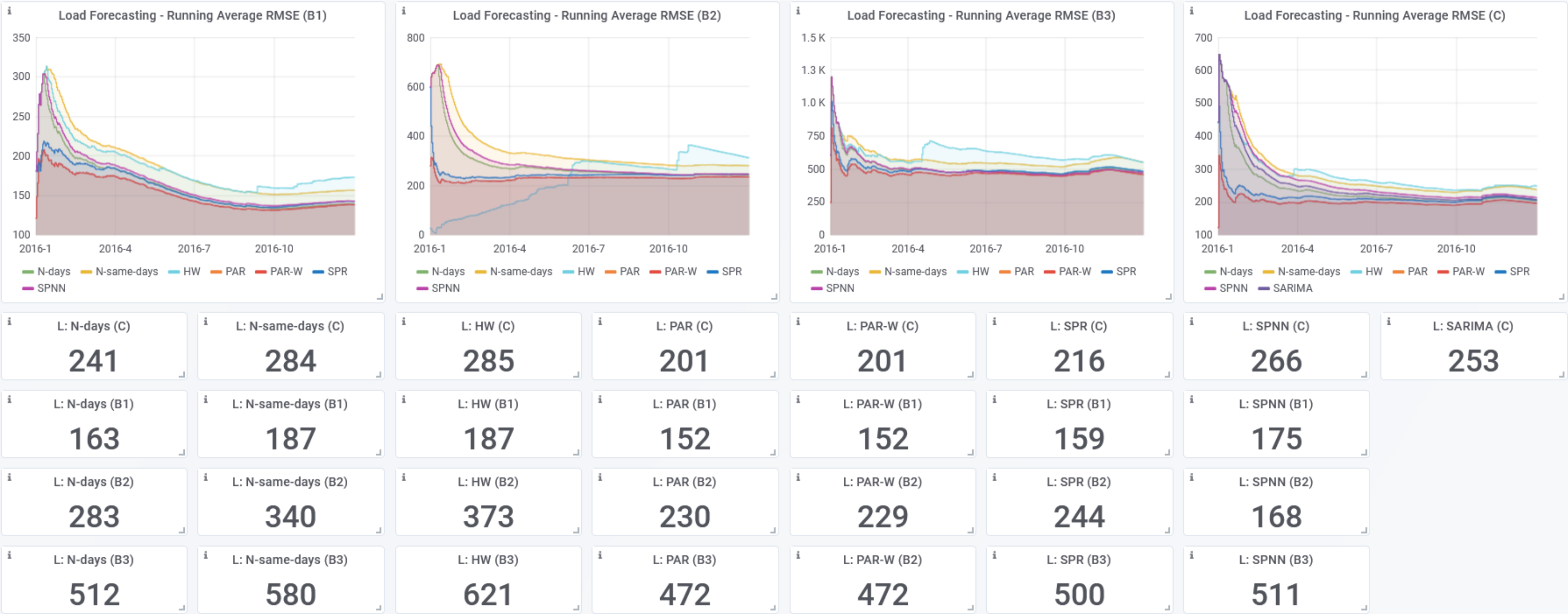

Figure 2 Running average RMSE in Wh of standard models over a period of one year (from 01.01.2016 to 31.12.2016). Predictions are provided for three residential buildings (B1, B2 and B3) as well as for their community (C). In the case of the community, the target/predicted variable is the average load consumption over the three individual buildings (i.e., B1+B2+B3/3). For the case of SARIMA only the performance of the community is presented due to the computational complexity of the training process. We observe that in all cases (B1, B2, B3, and C), the best models correspond to PAR and PAR-W.

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