AI-POWERED PREDICTIONS FOR ELECTRICITY LOAD IN PROSUMER COMMUNITIES[1]

Aleksei KYCHKIN[2], Georgios CHASPARIS[3]

Motivation and Central Question

The flexibility in electricity consumption and production in residential buildings and communities, including those with renewable energy sources and energy storage (a.k.a., prosumers), can effectively be utilized through the advancement of short-term demand response mechanisms. It is known that flexibility can further be increased if demand response is performed at the level of communities of prosumers, since aggregated groups can coordinate electricity consumption in a Microgrid level. However, the effectiveness of such short-term optimization is highly dependent on the accuracy of the forecast values for the consumption of each building and the community, which have major differences in their profile structure. Structural variations in a load presented by time series can be associated with different contributions of the importance of exogenous factors, such as weather conditions, calendar information and day of the week, as well as user behavior. In this paper, we review a wide range of electricity load forecasting techniques, that can provide significant assistance in optimizing load consumption in prosumer communities. We present and test artificial intelligence (AI) powered short-term load forecasting methodologies that operate with black-box time series models, such as Facebook's Prophet and LSTM models; season-based SARIMA and smoothing Holt-Winters models; and empirical regression-based models that utilize domain knowledge. The integration of weather forecasts into data-driven time series forecasts is also tested. Results show that the combination of persistent and regression terms (adapted to the load forecasting task) achieves the best forecast accuracy.

Methodological Approach

The proposed methodologies for day-ahead electricity load forecasting are based on the recent article of the authors [1,2]. They are extended here by providing a comparative analysis over a wider range of Deep-Learning-based AI-powered methodologies, while we also include an investigation of the impact of forecast weather data.

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 sequence of predictions over the intervals of the following day). Measurements were collected from three residential buildings in the state of Upper Austria. In addition, an artificial community has been established by also considering the aggregated sum of the electricity load consumption as a predicted target variable. In this work, we provide a comparative analysis of AI-powered forecasting models with a collection of persistence models, auto-regressive based models, and their combinations.

Facebook`s Prophet model [2] and LSTM model [3,4] establish predictions based on average load consumption through sampling of similar sequences in the past. In a way, this resembles the persistence models N-days and N-same-days introduced in [1,2], where the predicted load for a future time interval is generated based on the load at similar time intervals in previous days. The machine learning models of Holt-Winters (HW) and SARIMA provide multi-step forecasting via smoothing, season, and trend decomposition. Furthermore, the persistence-based regression models, namely the persistence-based autoregressive model (PAR) and the seasonal persistence-based regressive models (SPR, SPNN) have

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[2] Softwarepark 32a, A-4232 Hagenberg, Tel: +43 50 343 813, Email: aleksei.kychkin@scch.at, Web: http://www.scch.at
[3] Softwarepark 32a, A-4232 Hagenberg, Tel: +43 50 343 857, Email: georgios.chasparis@scch.at, Web: http://www.scch.at

been introduced by the authors in [1] and combine persistence factors with auto-regressive and domain-specific features. In SPR and SPNN models, we expanded the set of features to capture phenomena that are specifically relevant to electricity load consumption in residential buildings (such as, maximum energy consumption over one day). Furthermore, using PAR as a basis model, we also introduced additional features capturing the weather conditions (which are also provided as forecasts), namely the *solar radiation* and *outdoor temperature,* which formulated the PAR-W model.

Results and Conclusions

In Figure 1, we present the load predictions for the community of buildings during the beginning of March 2016, after training the models for 2 consecutive months (Jan and Feb 2016). The overall accuracy of the models is also depicted in Table 1, which is calculated over 2016. In this table, we see a comparison of the relative average RMSE of several standard and modern AI-powered models.

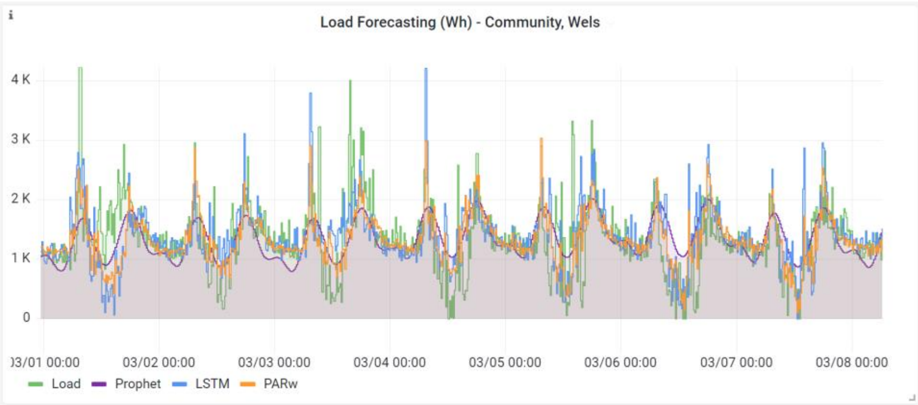

Figure 1 Load predictions for residential buildings community (Wels, Upper Austria) indicated by PAR-W, LSTM, and Prophet (March 2016)

AI-powered black-box model approaches, such as Prophet and LSTM, and machine learning models such as HW and SARIMA are generic time-series forecasting approaches that require computationally intensive training with several months of historical data and careful hyperparameter tuning as well. It is evident that the PAR and N-days models designed specifically for electricity load-forecasting exceed or match the performance of black-box forecasting models and are characterized by low computational complexity.

Table 1 Comparison of AI-powered electricity load prediction methods with respect to normalized average RMSE for the community of buildings.

Prophet	LSTM	N-same-days	N-days	HW	SARIMA	PAR	PAR-W	SPR	SPNN
0.667	0.653	0.731	0.621	0.678	0.634	0.543	0.532	0.682	0.681

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 the fact that the forecasting models without the weather data features are already adapting to the variations in the electricity load due to weather.

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