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AI-Powered Predictions for Electricity Load in Prosumer Communities

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Aleksei Kychkin

www.scch.at
aleksei.kychkin@scch.at

Georgios Chasparis

www.scch.at
georgios.chasparis@scch.at

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Contents

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Introduction: Serve-U Project

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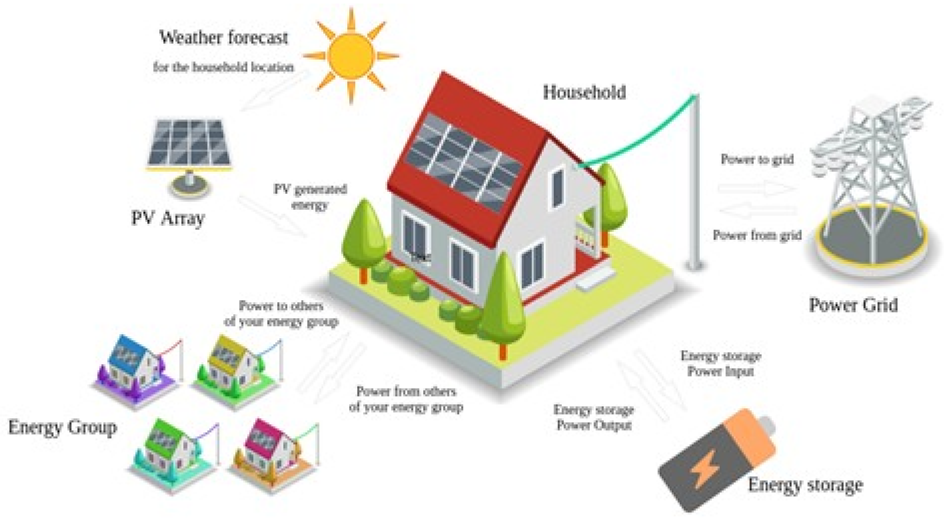
- Serve-U project (FFG):
  - Web: https://serve-u.at
  - User-centered energy service platform
  - Enable energy communities to access forecasts
  - Influence energy-optimized utilization options



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Introduction: Short Term Load Forecasting

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- Short Term Load Forecasting (STLF):
  - Needed for energy-utilization optimal decisions
  - Day-ahead (DA) electricity load forecasting
  - 15-min granularity of energy data
  - Several model possibilities (black-box, naive persistence, regression-based models)

Related work

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- Black-box standard Models
  - Standard averaging techniques [*Haben et al., 2014; Kychkin, 2016*]
  - Auto-regressive models, e.g., AR/ARMA/ARIMA/SARIMA [*Haben et al., 2019; Clements et al., 2016*]
  - Exponential smoothing approach, e.g., Holt-Winters method [*Alfares and Mohammad, 2002*]
- Models specifically tailored for STLF
  - Including influence data, e.g., weather [*Cancelo, 2008*]
  - Regression analysis, as a tool for estimating the relationships among variables [*Hong et al., 2010*]
  - A set of relevant features that can be extracted from the time series [*Christ et al., 2017-2018*]
  - Advanced models like artificial neural networks, fuzzy logic and knowledge-based models [*Chitsaz et al., 2015; Hippert, 2005; Alfares, 2002*]

Related work (cont)

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- Optimally combining models for STLF
  - Wavelet (trigonometric regressions sensitive to seasonality effects)-ARMAX-Winters Model [*Chen et al., 2004*]
  - Online Sequential Extreme Learning Machine for ensemble learning [*Ye and Dai, 2018*]
  - Two-level Seasonal Autoregressive model (TLSAR) that combines calculations for potential and irregular load [*Soares and Medeiros, 2008*]
  - Dummy-Adjusted SARIMA with day type variables [*Soares and Medeiros, 2008*]
  - Combinations of naive, smoothing and regression models [*Hippert et al., 2005*]
  - Deep Neural Networks Using LSTM [*Hochreiter, 1997; Kwon et al., 2020*]
  - Prophet Algorithm based on Seasonality and Exogenous Features [*Parizad, 2020*]

Standard Models – Persistence Models

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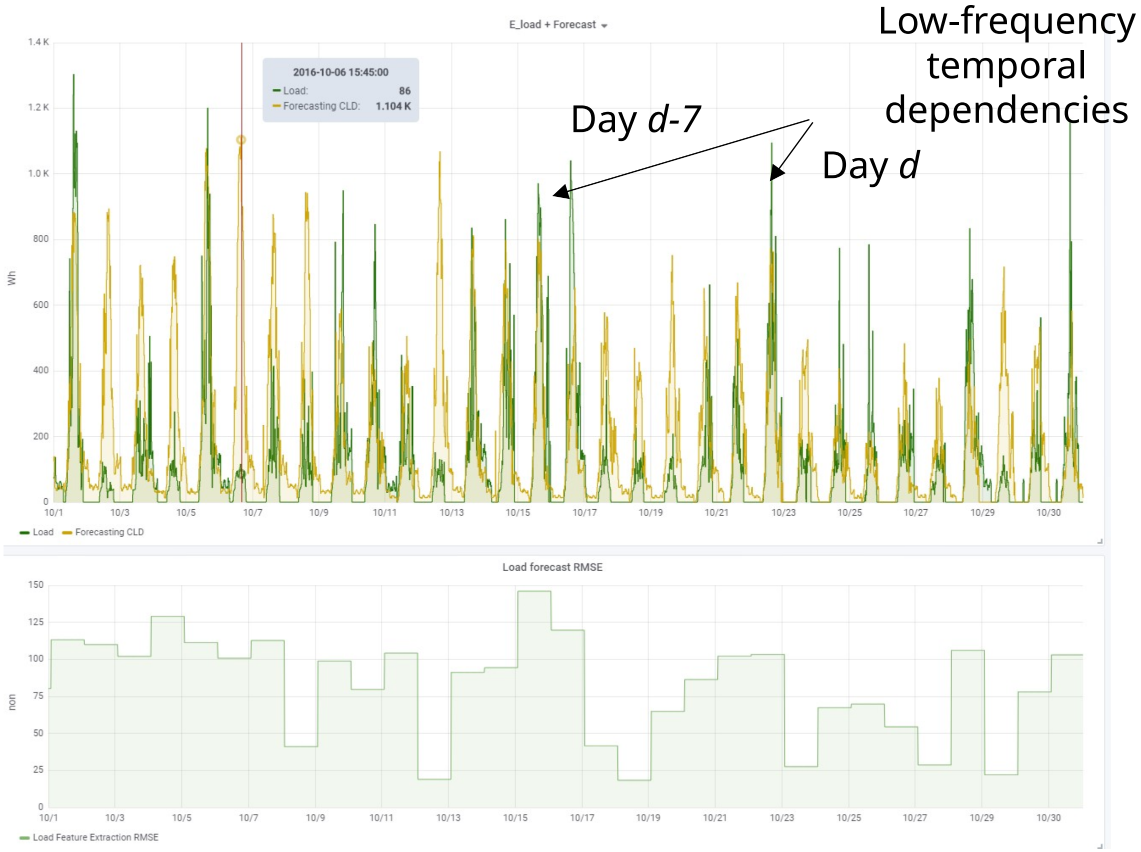
- “N-days” persistence model (*N-days*)
  - It takes an average of the load of N previous days and at exactly the same time
- “N-same-days” persistence model (*N-same-days*)
  - It tries to exploit residents’ schedule
  - Average consumption at the same time on N previous same days



Standard Models – Regression-based Models

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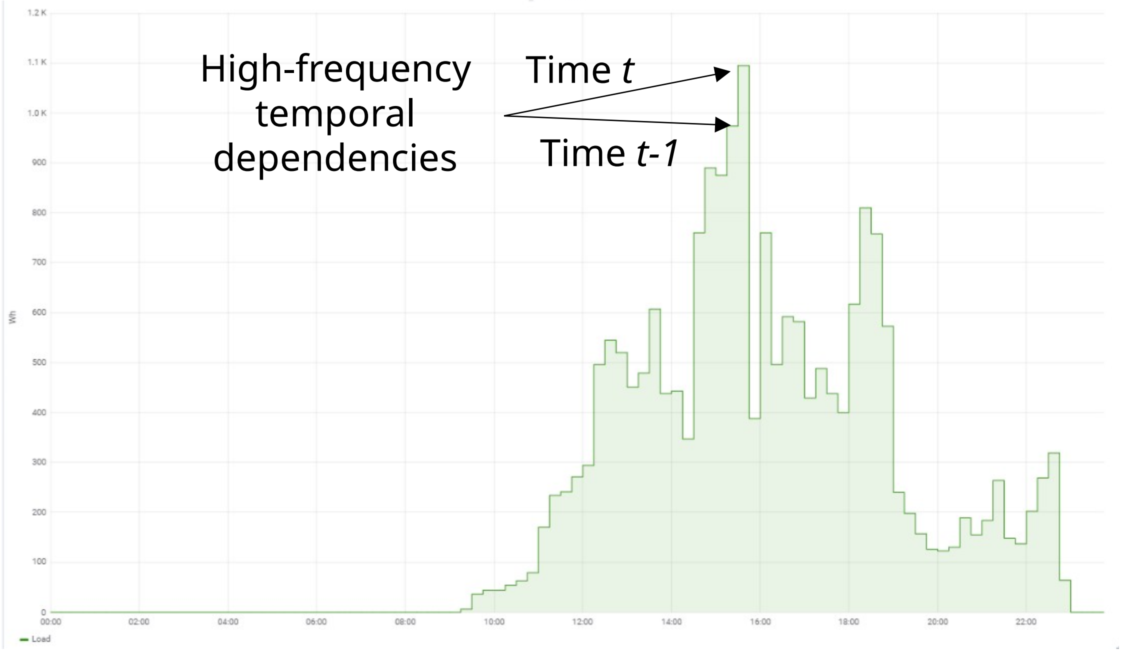
- Auto-regressive Model (AR)
  - Captures temporal dependencies of the load within the same day
  - Linear combination of the load at previous time instances



Electricity consumption for one building over a time period of one day (25 April 2017)

Standard Models – Regression-based Models (cont.)

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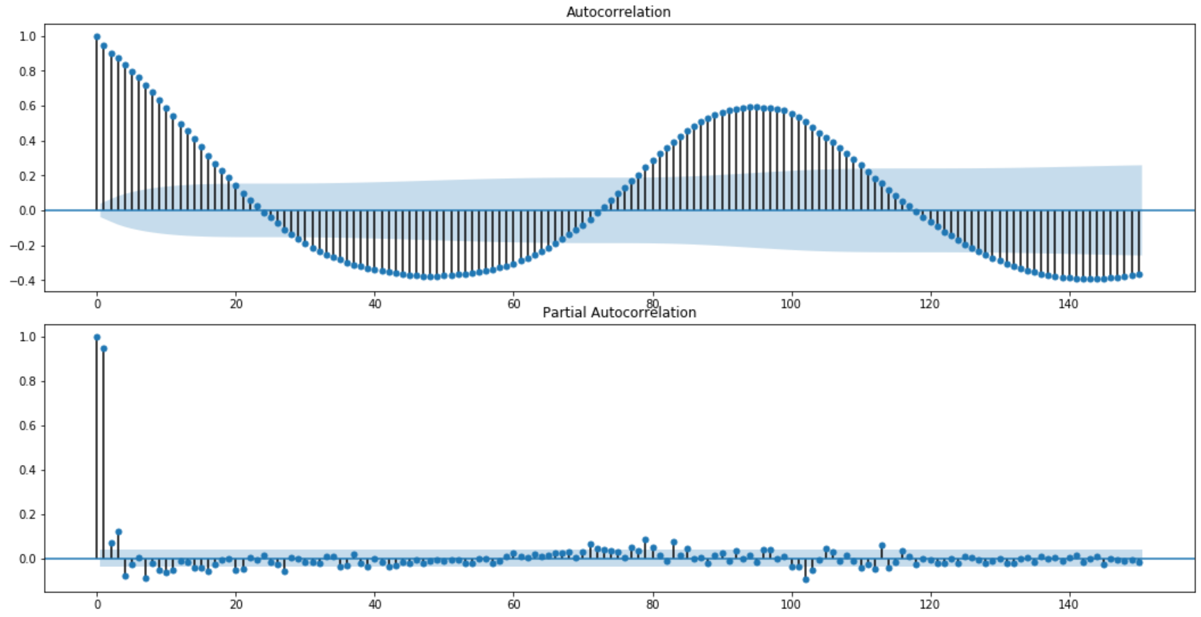
- Auto-regressive Model (AR)
  - Captures temporal dependencies of the load within the same day
  - Linear combination of the load at previous time instances

- Season auto-regressive integrated moving-average model (SARIMA)
  - It is based on ARIMA model (auto-regressive, integration, moving-average part)
  - Captures stationarity in the process through the Moving Average (MA) part
  - Captures trends (in the form of differences in time) through the Integration (I) part
  - Captures seasonality (day-season or week-season) through the (S) part



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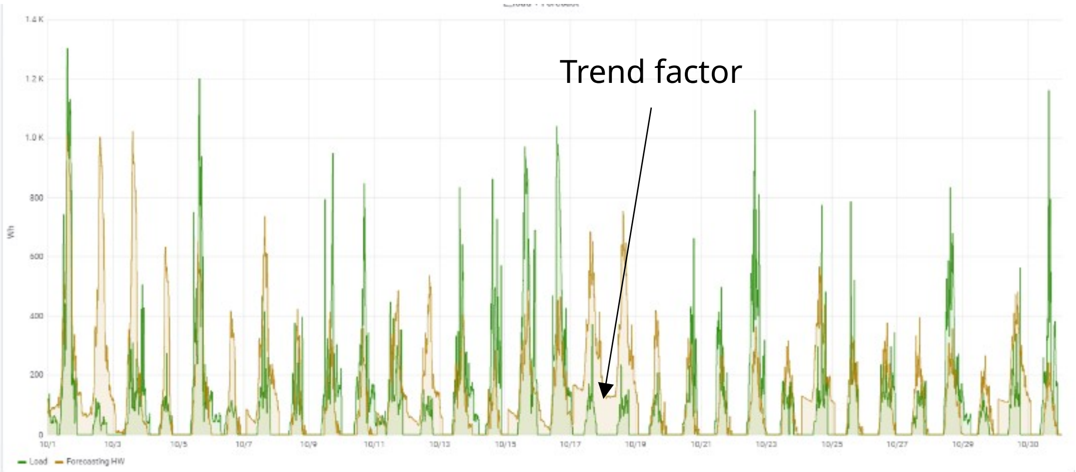
Standard Models – Exponential Smoothing

- Holt-Winters model (HW)
  - Captures repeated fluctuations as well as temporal trends
  - Seasonal component is characterized by the length of the season (here, 1 week)

$$\hat{y}_d^{\mathrm{HW}}(t) = L(t-n) + nP(t-n) + S(t-T)$$

  - L : level component (baseline)
  - P : trend component (low-pass filter)
  - S : season component



Persistence-based Auto-Regressive Model (PAR)

- Persistence-based auto-regressive model (PAR):
  - Persistence models capture low-frequency temporal dependencies (over several days)
  - Auto-regressive models capture high-frequency temporal dependencies (within the same day)
  - Combination of two types of models

$$\hat{y}_d^{\mathrm{PAR}}(t|a_1,\ldots,a_j,b_0) = a_1 \cdot \hat{y}_d^{\mathrm{AR}}(t-1) + \cdots + a_j \cdot \hat{y}_d^{\mathrm{AR}}(t-j) + b_0 \cdot \hat{y}_d^{\mathrm{PM}}(t)$$

  - In the spirit of “Expert-based forecasting methods” of [Cesa-Bianchi and Lugosi, 2006]

A. Kychkin, G. Chasparis, “Feature and model selection for day-ahead electricity-load forecasting in residential buildings,” *Energy and Buildings*, vol 249, 2021.
N. Cesa-Bianchi, G. Lugosi, Prediction, Learning, and Games, Cambridge University Press, New York, NY, USA, 2006.

Persistence-based Auto-Regressive Model with Weather Data (PAR-W)

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- Persistence-based auto-regressive model (PAR):
  - Persistence models capture low-frequency temporal dependencies (over several days)
  - Auto-regressive models capture high-frequency temporal dependencies (within the same day)
  - Combination of two types of models

$$\hat{y}_d^{\mathrm{PAR}}(t|a_1,\ldots,a_j,b_0) = a_1 \cdot \hat{y}_d^{\mathrm{AR}}(t-1) + \cdots + a_j \cdot \hat{y}_d^{\mathrm{AR}}(t-j) + b_0 \cdot \hat{y}_d^{\mathrm{PM}}(t)$$

  - In the spirit of “Expert-based forecasting methods” of [Cesa-Bianchi and Lugosi, 2006]

  - *Additional features were included to capture the weather conditions*

A. Kychkin, G. Chasparis, “Feature and model selection for day-ahead electricity-load forecasting in residential buildings,” *Energy and Buildings*, vol 249, 2021.
N. Cesa-Bianchi, G. Lugosi, Prediction, Learning, and Games, Cambridge University Press, New York, NY, USA, 2006.

Seasonal Persistence-based Regressive Model (SPR and SPNN)

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- Exploiting causal effects specific to user-behavior
  - e.g., users consume about the same energy every morning or in certain periods
  - e.g., users consume about the same energy every day
- Introduce Additional features:
  - Load from previous timestamps
  - Rolling sum of electricity load with 1h window
  - Hourly Load (total energy load) within the last hours
  - Low/High energy consumption flag
  - Weekend flag
  - Part of the mean daily Load
  - Difference between hourly Loads
- In other words,
  - we reduce the level of uncertainty in the user-behavior
  - we try to exploit patterns in user behavior

$$\begin{aligned}\hat{y}_d^{\mathrm{SPR}}(t|a_0,a_1,\ldots,a_{14}) = a_0\cdot f_d + a_1\cdot y_{d-1}(t) + a_2\cdot y_{d-7}(t) + a_3 \\ \cdot y_{rs,d-1}(t) + a_4\cdot y_{rs,d-7}(t) + a_5\cdot y_{h,d-1}(t) \\ + a_6\cdot y_{h,d-7}(t) + a_7\cdot y_{d,d-1}(t) + a_8 \\ \cdot y_{d,d-7}(t) + a_9\cdot y_{dh,d-1}(t) + a_{10} \\ \cdot y_{dh,d-7}(t) + a_{11}\cdot y_{\mathrm{low},d-1}(t) + a_{12} \\ \cdot y_{\mathrm{low},d-7}(t) + a_{13}\cdot y_{\mathrm{high},d-1}(t) + a_{14} \\ \cdot y_{\mathrm{high},d-7}(t).\end{aligned}$$

Seasonal Persistence-based Neural Network Model (SPNN) detect non-linear dependences by using MLP artificial neural network

A. Kychkin, G. Chasparis, "Feature and model selection for day-ahead electricity-load forecasting in residential buildings," *Energy and Buildings*, vol 249, 2021.

Generalized Additive Model (FBProphet)

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Generalized Additive Model (Prophet):

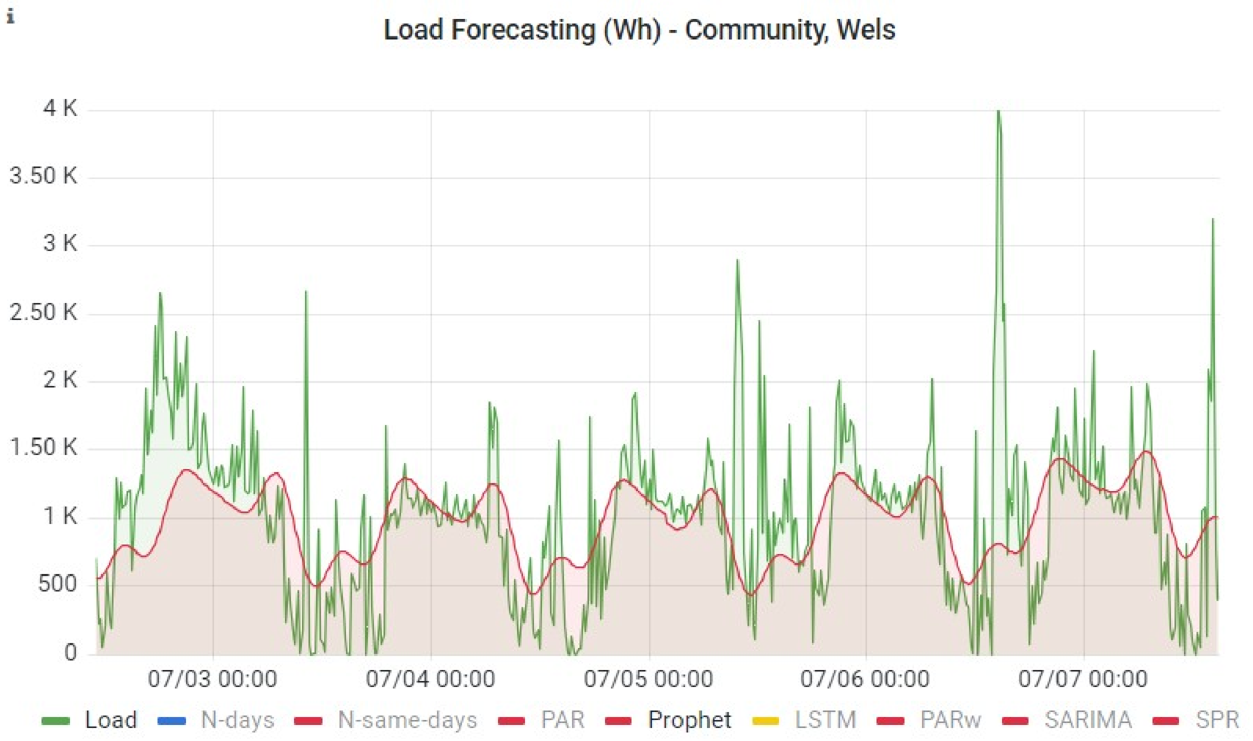
- Bayesian approach allows uncertainty estimation in the predictions
- Capture complex patterns in the Load:
  - seasonality

$$s(t) = \sum_{n=1}^{N} \left(a_n \cos\left(\frac{2\pi nt}{P}\right) + b_n \sin\left(\frac{2\pi nt}{P}\right) \right)$$

  - trends

$$g(t) = (k + \sum_{i:t>s_i} \delta_i)t + (m + \sum_{j:t>s_j} \gamma_j)$$

  - effect of holidays



A. Parizad and C. J. Hatziadoniu, "Using Prophet Algorithm for Pattern Recognition and Short Term Forecasting of Load Demand Based on Seasonality and Exogenous Features," *2020 52nd North American Power Symposium (NAPS)*, Tempe, AZ, USA, 2021, pp. 1-6, doi: 10.1109/NAPS50074.2021.9449743.

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Long Short-Term Memory (LSTM)

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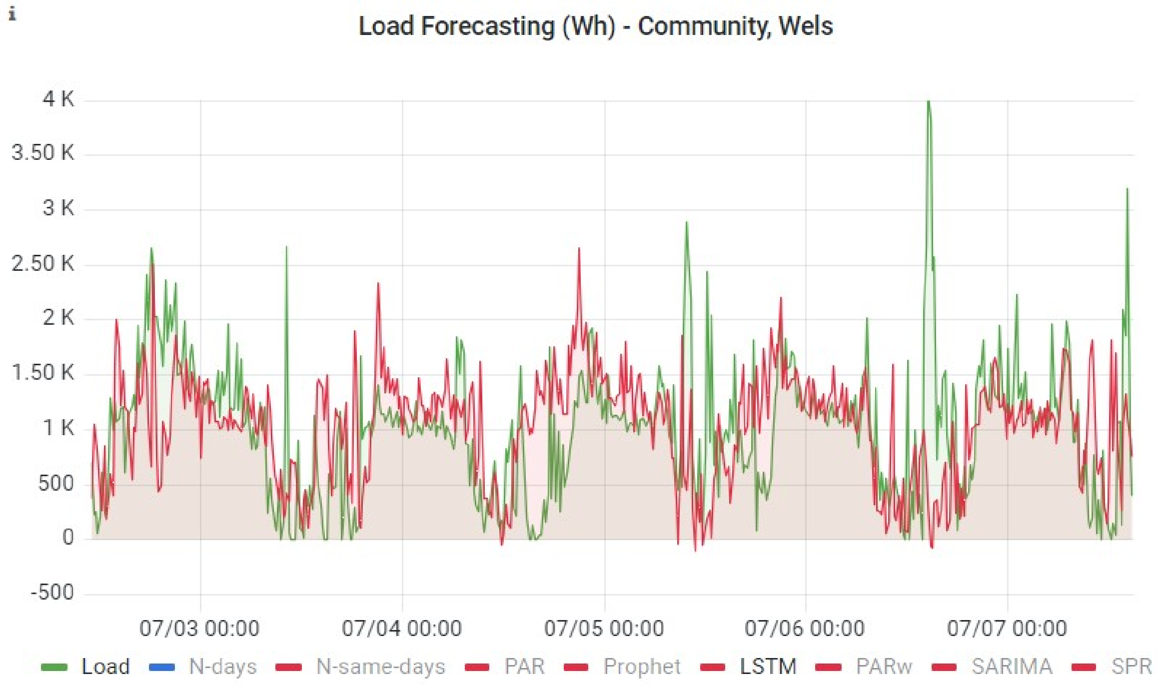
Recurrent neural network Long short-term memory (LSTM):

- Capture long-term dependencies within sequence predictions
- Configuration:
  - daily retraining
  - learn day patterns via a week
  - number of neurons:
    - input layer - 96*7
    - first hidden recursive layer - 96*5
    - second hidden recursive layer - 96*3
    - output layer – 96
  - optimizer – “Adam”, 40 epochs



Hochreiter, Sepp & Schmidhuber, Jürgen. (1997). Long Short-term Memory. Neural computation. 9. 1735-80. 10.1162/neco.1997.9.8.1735.

Software Architecture

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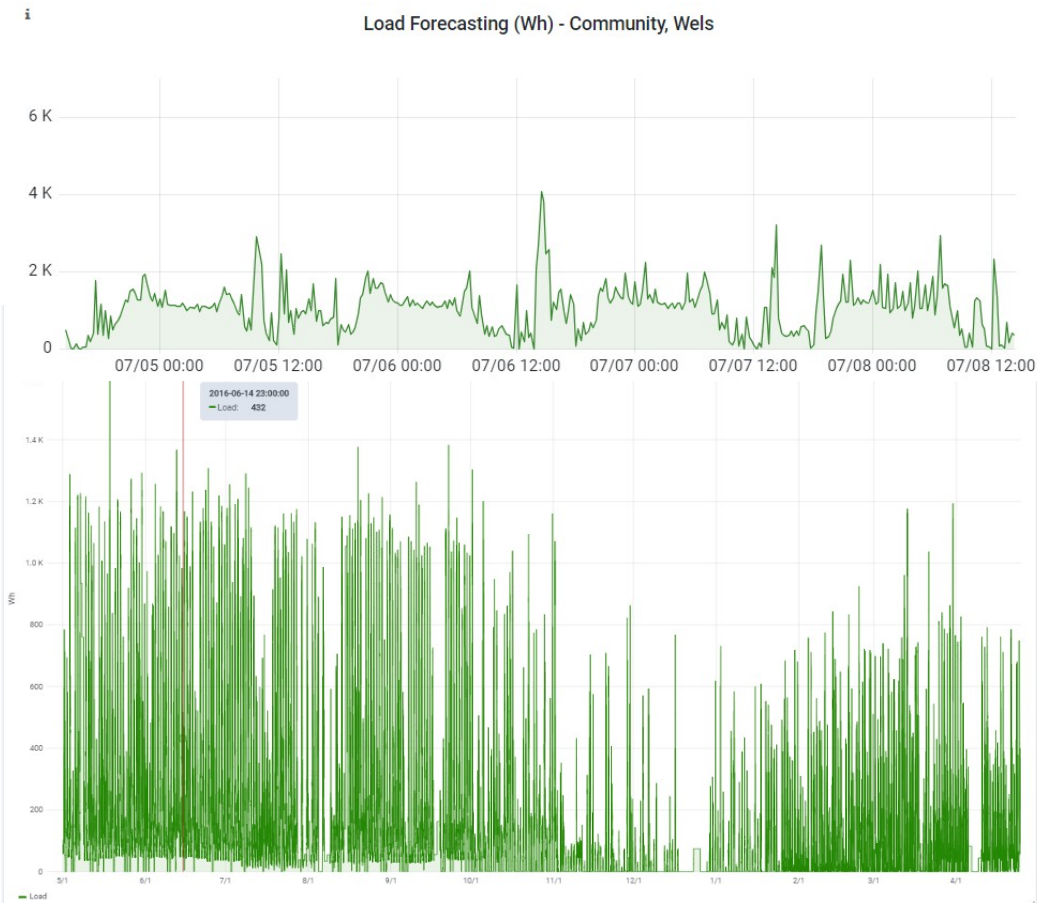
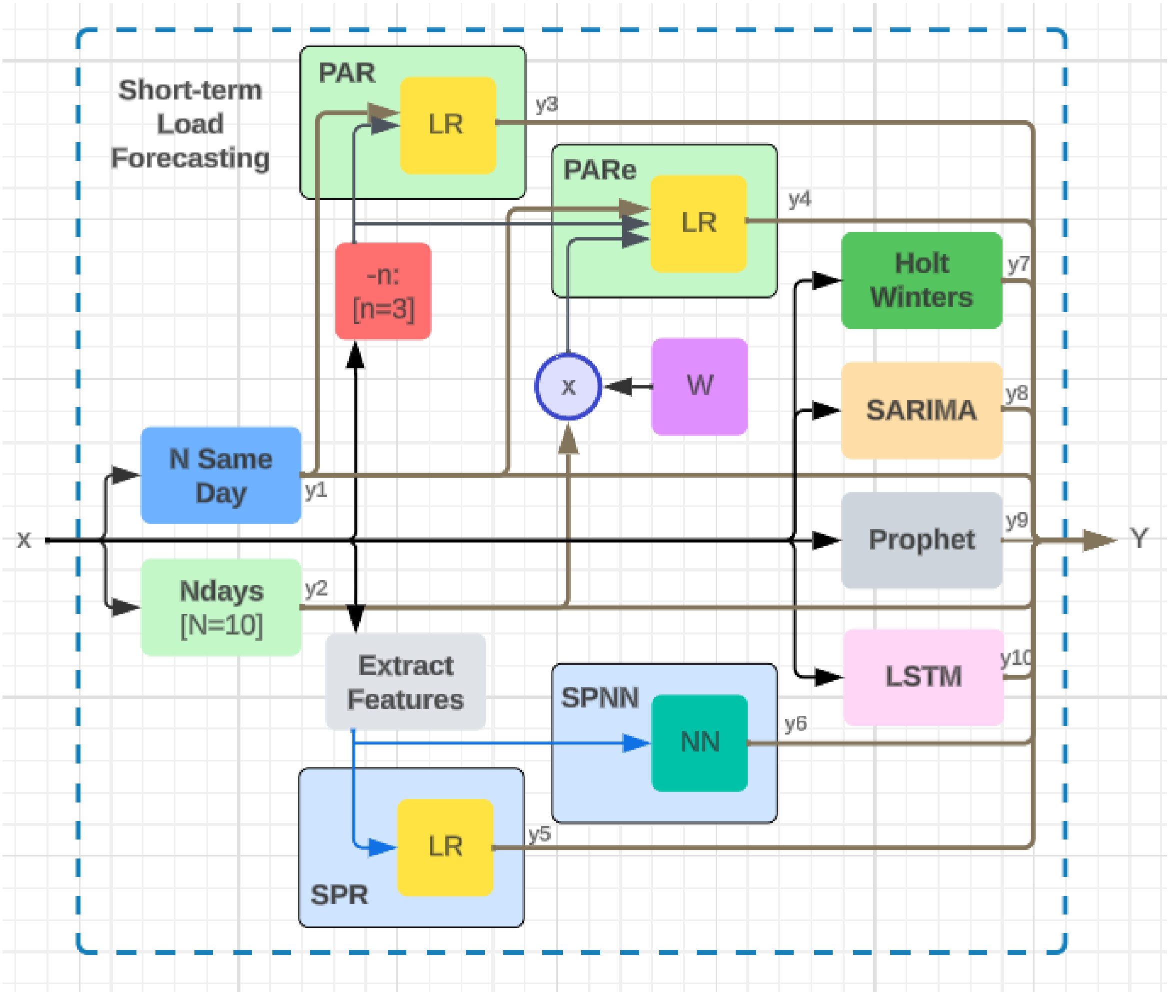


Electricity Consumption Snapshot



- Time-series database – InfluxDB
- Visualization tool – Grafana
- Data Analytics – Python

- Period of measurements = 15min
- Simulation period = 1 year

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Community Load Forecasting

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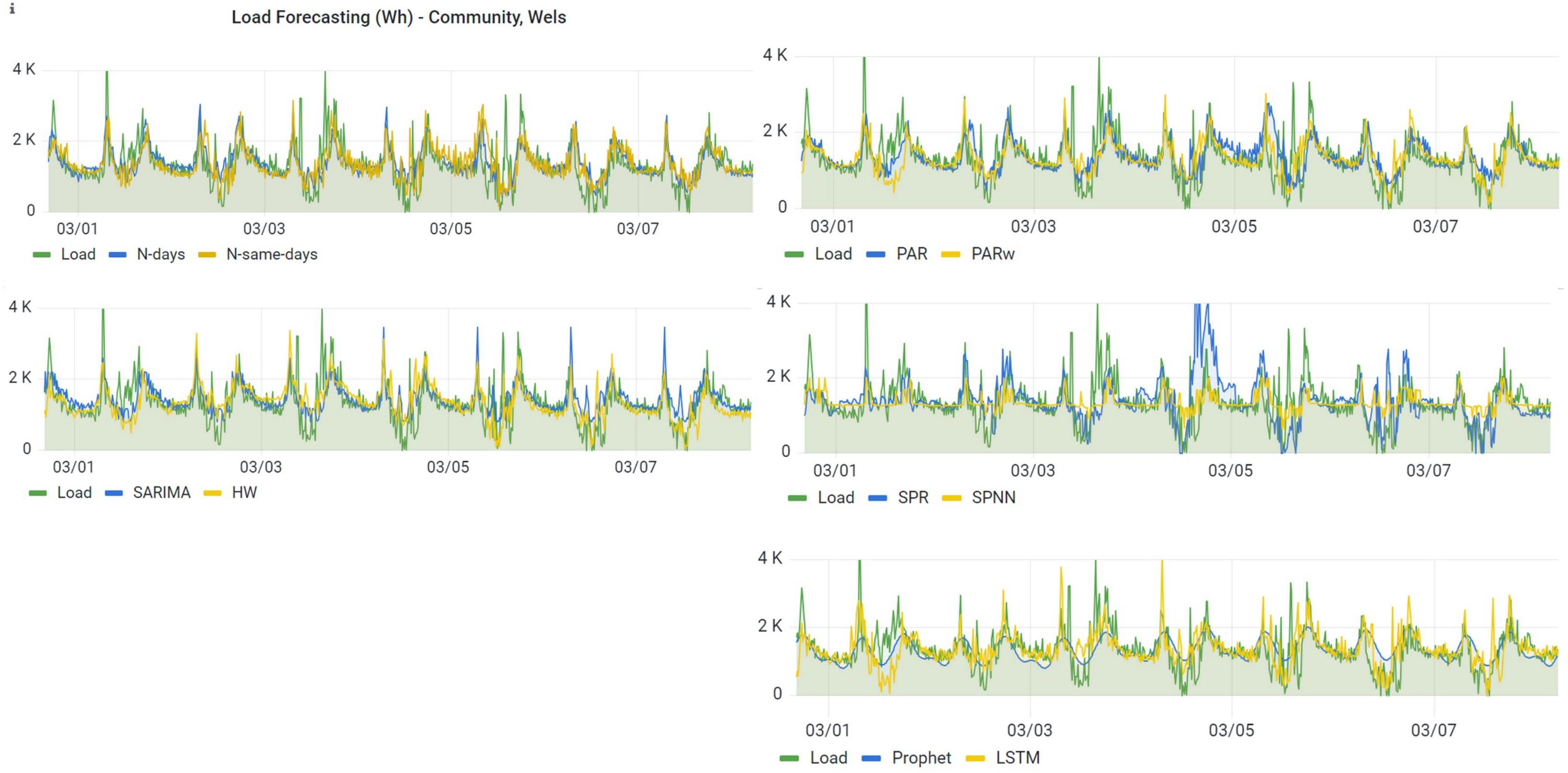
- Investigate forecast RMSE in energy communities
  - Exploit averaging effects for better load forecasting
  - Community load should exhibit lower variability (smaller size of load picks)
  - Community RMSE should be lower than average RMSE
- Experiments
  - Tests were performed in a community of 3 buildings in Upper Austria



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Community Load Forecasting – Performance

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- Remarks:
  - Relative RMSE for a community of 3 buildings
  - Better performance was observed by PAR-W and PAR models
  - AI-powered models also improved in comparison to N-same-days persistence, SPR and HW models
  - SARIMA is not able to improve in comparison to N-days persistence model
  - LSTM and SARIMA require much more computation resources than other models

Duration	Feb 2016	July 2016	Dec 2016	2016
N-days	0,664	<u>0,752</u>	<u>0,467</u>	<u>0,621</u>
N-same-days	0,843	0,868	0,546	0,731
HW	0,713	0,846	0,527	0,678
SARIMA	0,632	0,801	0,497	0,634
PAR	<u>0,500</u>	<u>0,724</u>	<u>0,474</u>	<u>0,543</u>
PAR-W	**0,489**	**0,711**	**0,455**	**0,532**
SPR	0,669	0,852	0,533	0,682
SPNN	0,789	0,803	0,487	0,681
FBProphet	0,766	0,768	0,490	0.667
LSTM	<u>0,616</u>	0,843	0,535	0.653

Community Load Forecasting – Performance (cont)

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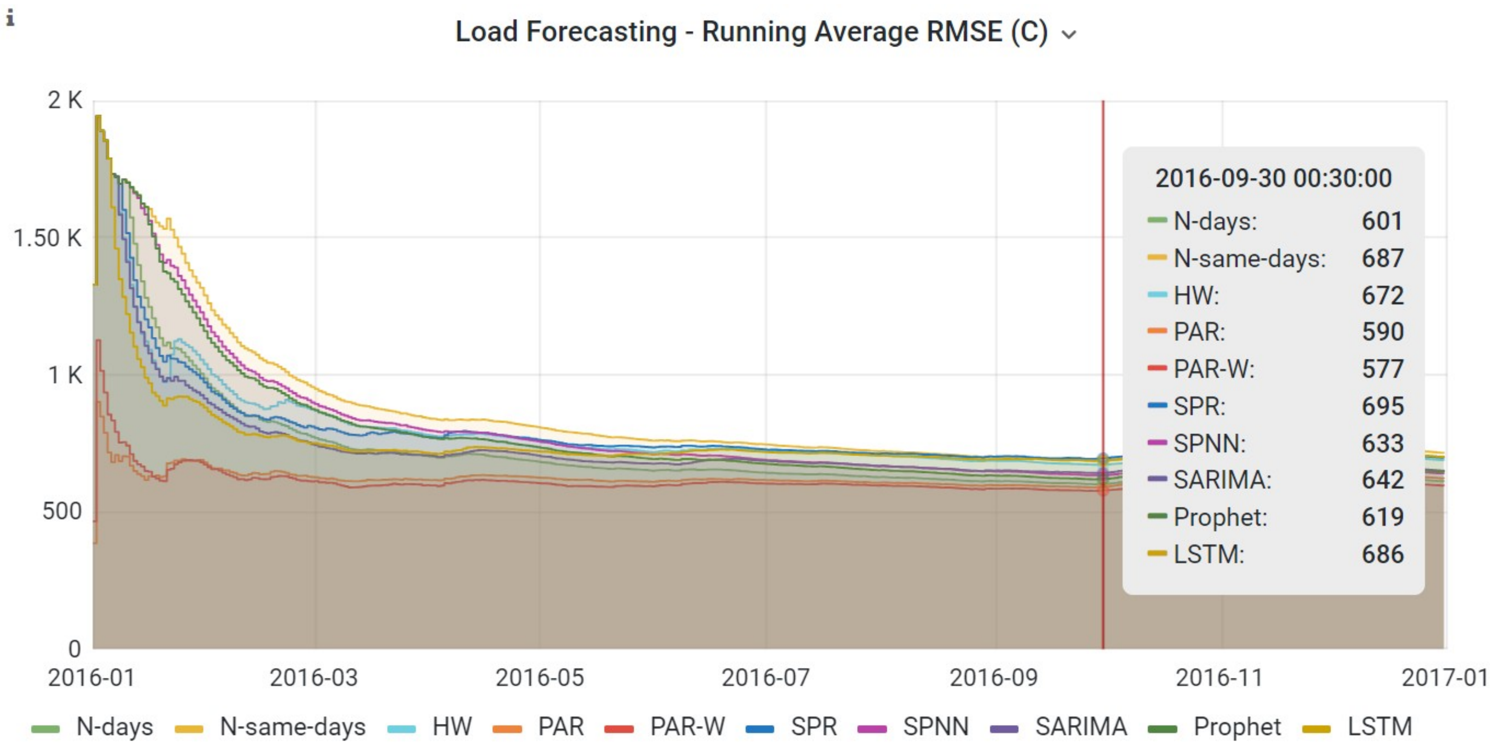
- Remarks:
  - AI-powered black-box model as well ML models such as HW and SARIMA require computationally intensive training
  - High performance of LSTM at the beginning is significantly reduced after 3 months
  - Overfitting could be reduced by careful hyperparameter tuning within multiply repeated sets of experiments
  - FBProphet provides the Human-in-the-loop approach based on manual configurations of day patterns, like holidays. Expert knowledge is required
  - SPR and SPNN models are limited in the amount of statistical information
  - PAR and PAR-W attain the best forecasting accuracy



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Conclusions

- Evaluation of day-ahead load forecasting models
  - Evaluated performance of basic and AI-powered models to load forecasting
  - Persistence-based Model (PAR) provided the best performance
  - PAR and SPR also exhibit computational efficiency
  - Incorporating of weather data slightly improved predictions
  - LSTM shows better result than FBProphet
  - AI-based models require careful hyperparameter tuning

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Dr. Georgios Chasparis
Key Researcher Data Science
email: georgios.chasparis@scch.at
Tel: +43 50 343 857

Dr. Aleksei Kychkin
Researcher and Senior Data Scientist
email: aleksei.kychkin@scch.at
Tel: +43 676 852488813

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