scch {
software
competence
center
hagenberg
}

scch { }

Predictive Modeling for Flexibility Load Forecasting in Prosumer Communities

IEWT 2023, Wien 16-02-2023

Georgios Chasparis

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

SCCH is an initiative of

JOHANNES KEPLER UNIVERSITY LINZ

Bundesministerium
Digitalisierung und Wirtschaftsstandort

Bundesministerium
Klimaschutz, Umwelt, Energie, Mobilität, Innovation und Technologie

Contents

scch { }

- Introduction
  - Software Competence Center Hagenberg (SCCH)
  - Serve-U FFG project
  - Short Term Load Forecasting (STLF)
- Standard Forecasting Models
- Persistence-based Regressive Models
- Evaluation to Energy Communities
- Evaluation when Incorporating Weather Data

Software Competence Center Hagenberg

scch { }

- Non-profit institution for Data Science & Software Science
- Founded by the Johannes Kepler University Linz in 1999
- ~ 100 Employees (over 120 with partners)
- ~ 8.5 Mi Euro Revenue
- COMET competence center

JKU JOHANNES KEPLER UNIVERSITÄT LINZ

UAR Upper Austrian Research GmbH

Introduction: Serve-U Project

scch { }

- 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

Introduction: Short Term Load Forecasting

scch { }

- 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

- 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*]

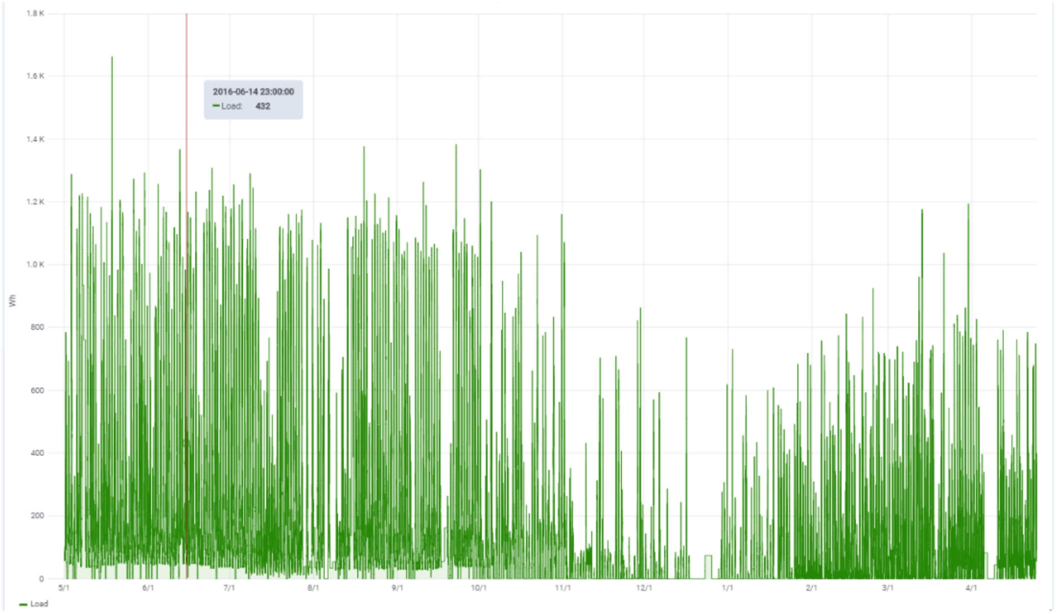
Related work (cont)

- 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]*
  - Neural networks

Software Architecture

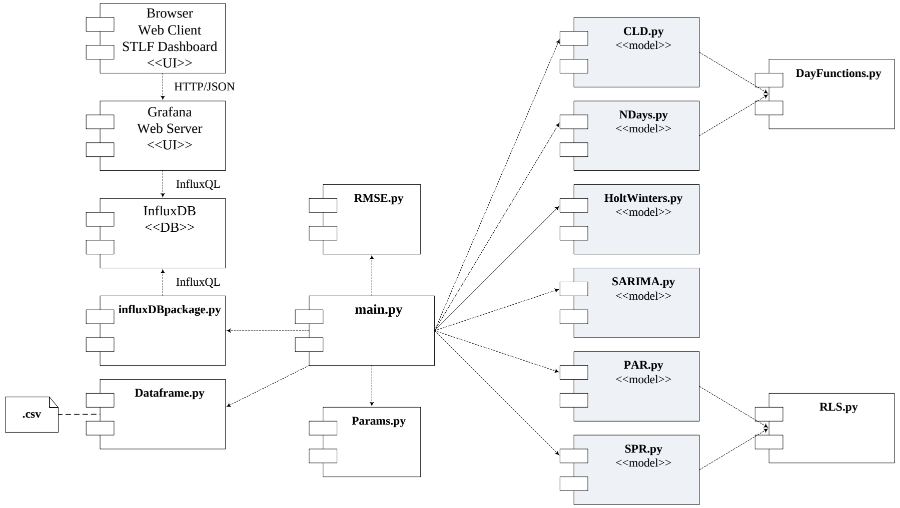
scch { }

- Period of measurements = 15min (96 measurements/day)



Electricity Consumption Snapshot

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

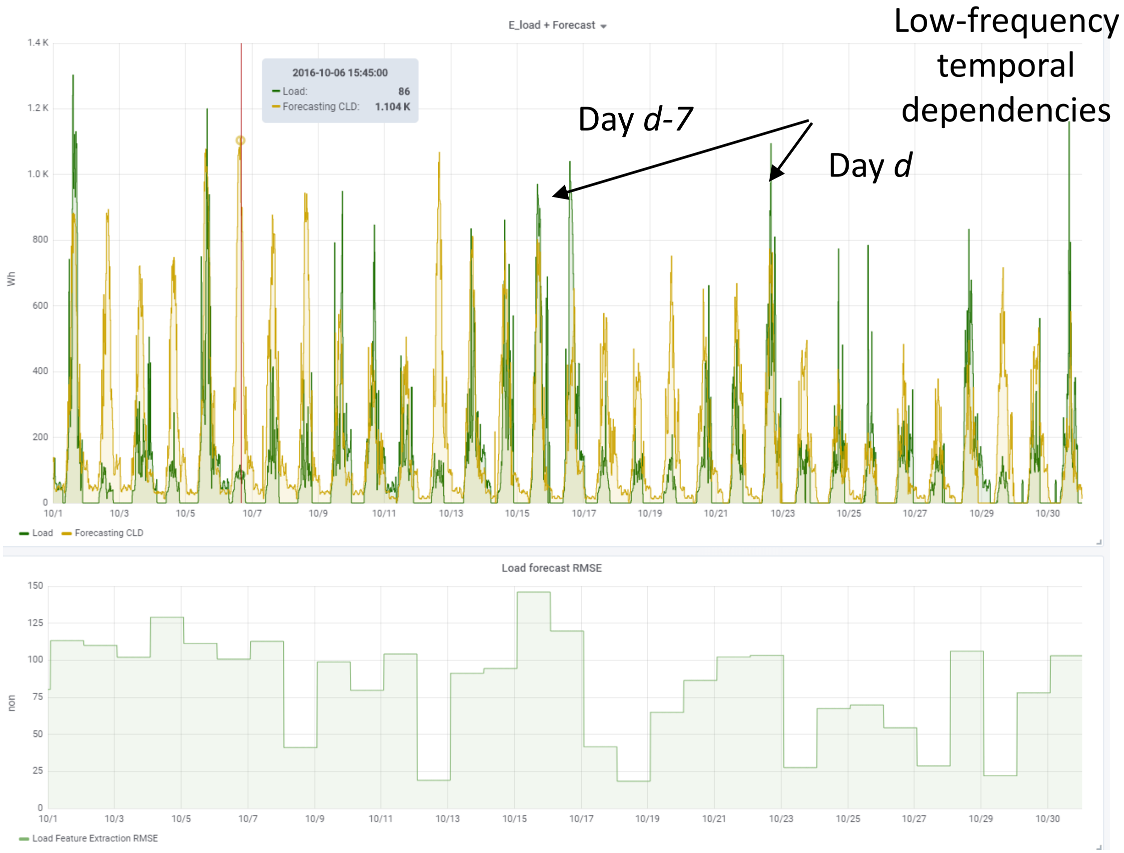


Software Architecture

Standard Models – Persistence Models

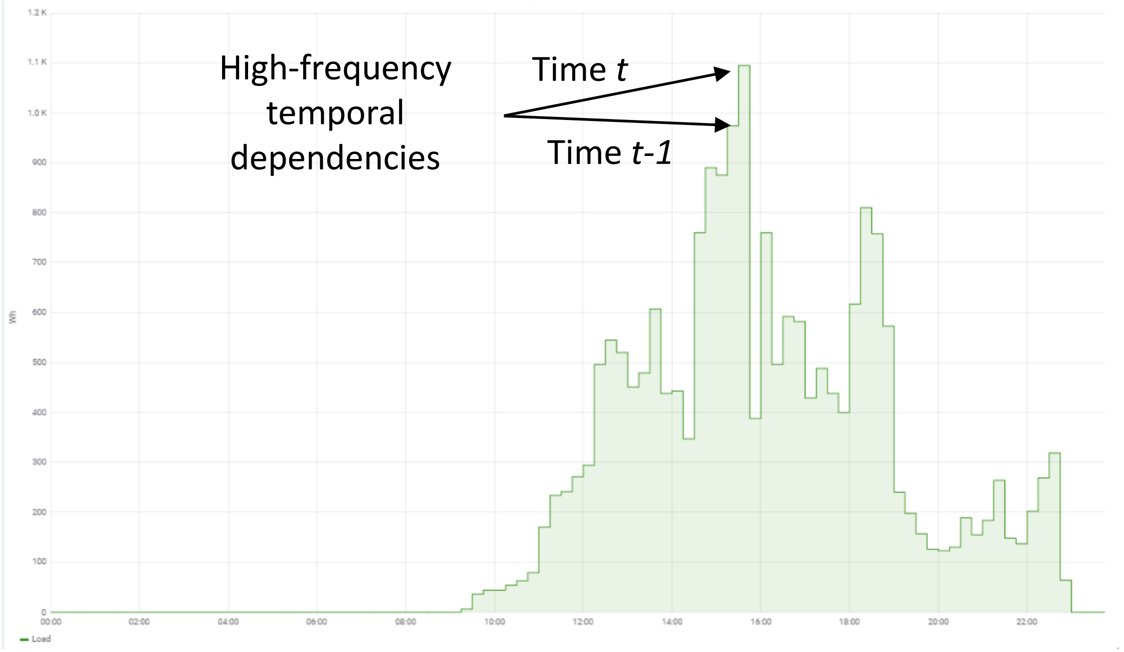
scch { }

- “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

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

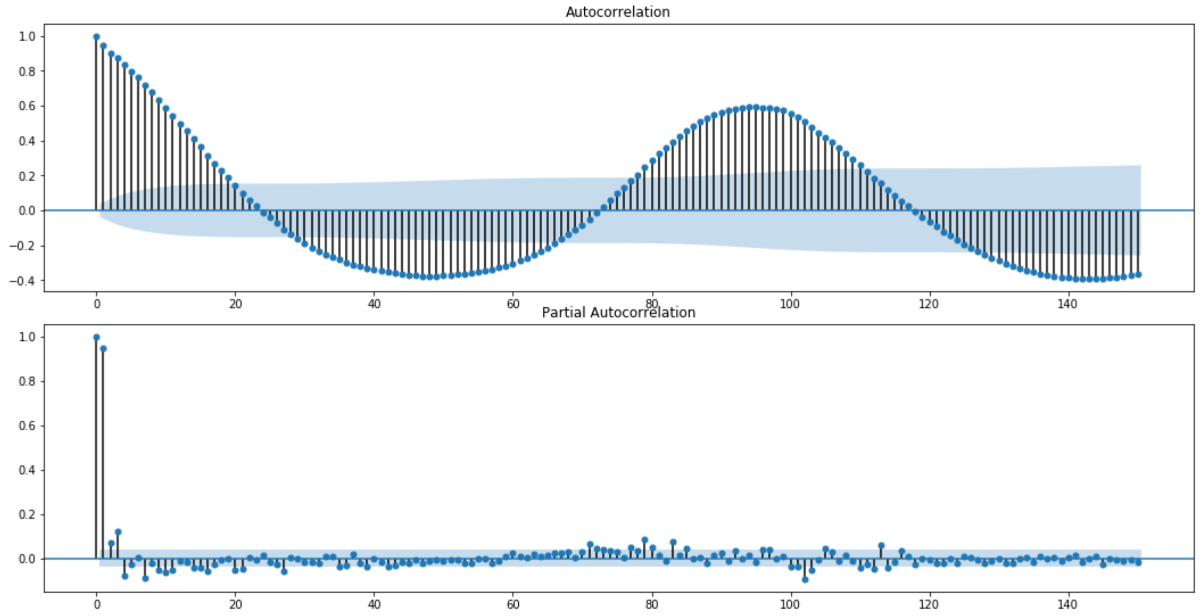


Electricity consumption for one building over a time period of one day (25 April 2017)

Standard Models – Regression-based Models (cont.)

scch { }

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



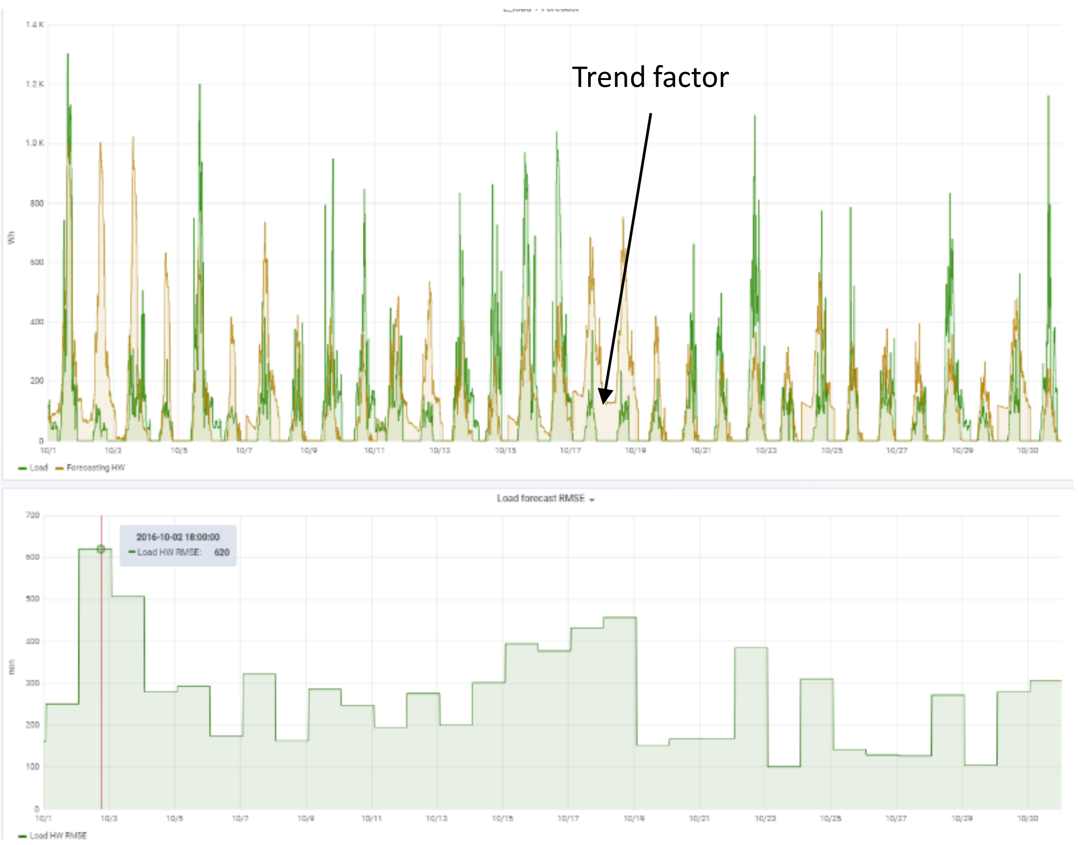
- Season auto-regressive integrated moving-average model (SARIMA)
  - It is based on ARIMA model (auto-regressive, integration, moving-average part)
  - Captures stationarity in the process through the Moving Average (MA) part
  - Captures trends (in the form of differences in time) through the Integration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

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)

scch { }

- 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)

scch { }

- 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)

scch { }

- 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:
  - Total energy load within the last hours
  - Low/High energy consumption flag
  - Rolling-sum of electricity load
  - ...

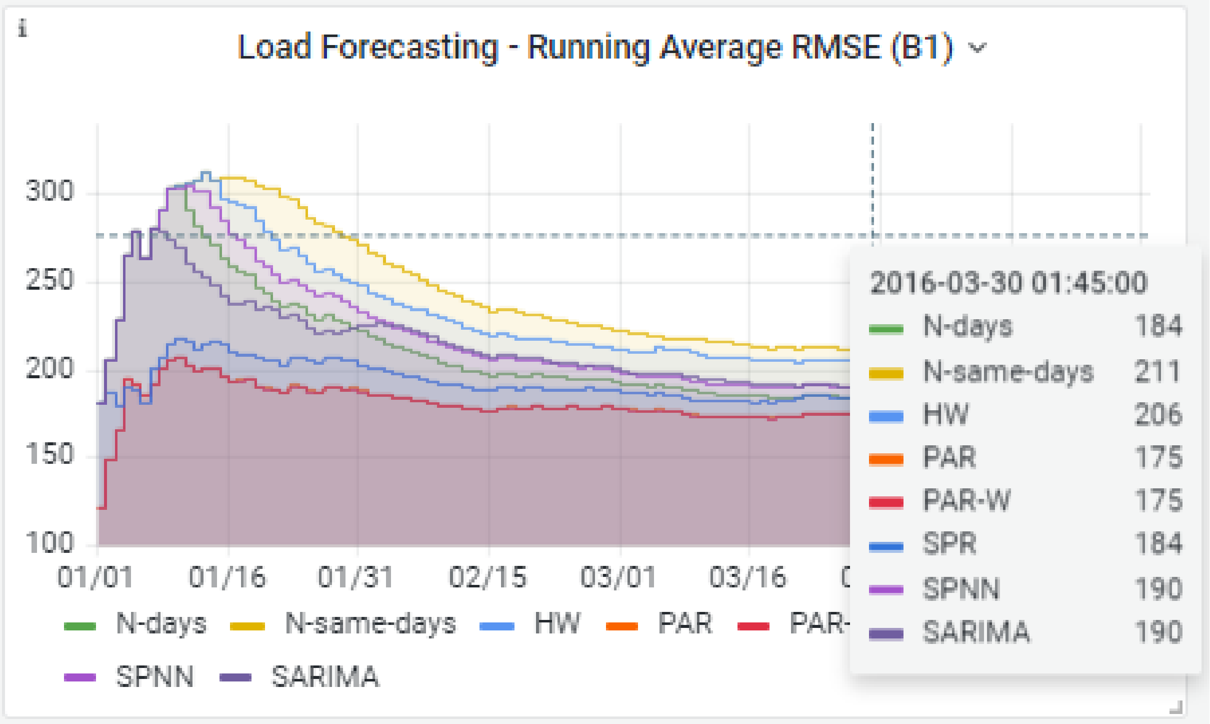
$$\hat{y}_d^{\mathrm{SPR}}(t|a_0, a_1, \ldots, a_{14}) = a_0 \cdot f_d + a_1 \cdot y_{d-1}(t) + a_2 \cdot y_{d-7}(t) + a_3 \cdot y_{rs,d-1}(t) + a_4 \cdot y_{rs,d-7}(t) + a_5 \cdot y_{h,d-1}(t) + a_6 \cdot y_{h,d-7}(t) + a_7 \cdot y_{d,d-1}(t) + a_8 \cdot y_{d,d-7}(t) + a_9 \cdot y_{dh,d-1}(t) + a_{10}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

- In other words,
  - we reduce the level of uncertainty in the user-behavior
  - we try to exploit patterns in user behavior

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

Performance on Individual Buildings

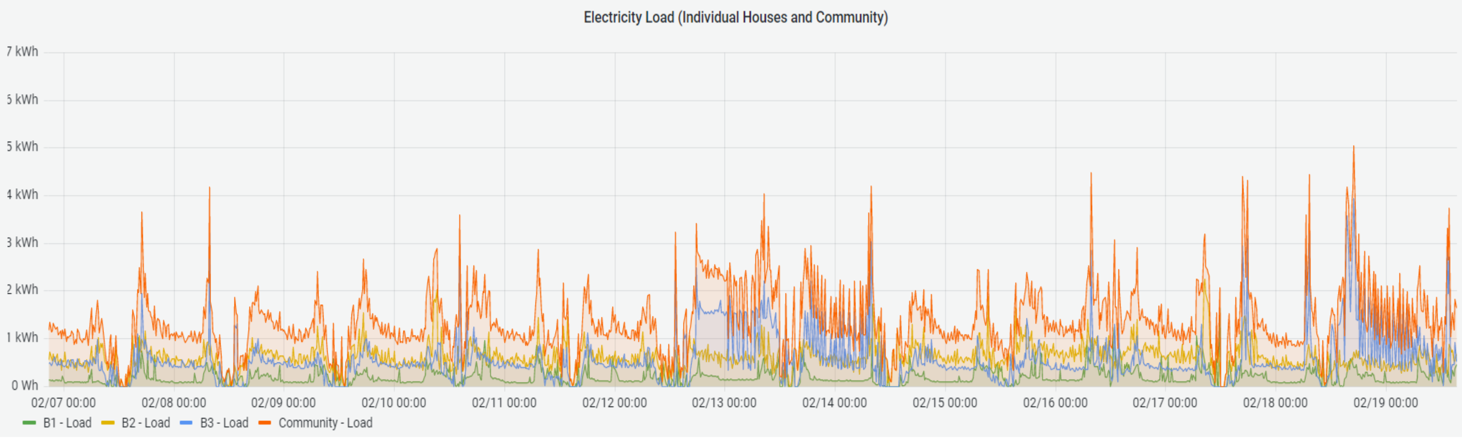
- Standard models may not perform better than naive persistence models
  - e.g., N-days vs HW / SARIMA
- Combined models (PAR) improve performance over naive persistence models
- Weather data may very slightly improve forecasts
  - see, e.g., PAR vs PAR-W
- Accuracy vs computational complexity
  - e.g., SARIMA vs PAR

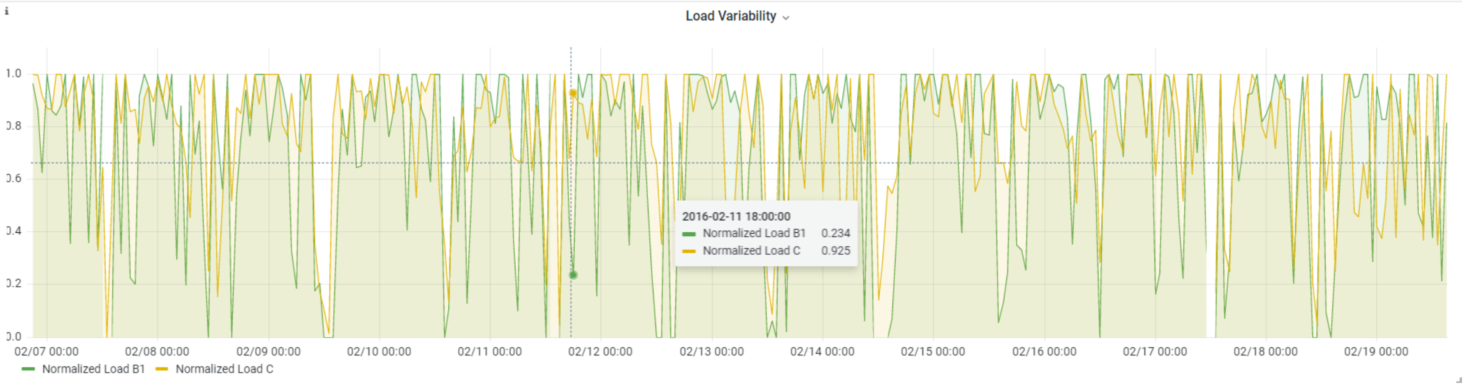


Community Load Forecasting

scch { }

- 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
  - Individual buildings demonstrate larger relative load variation than community load





Community Load Forecasting – Performance

scch { }

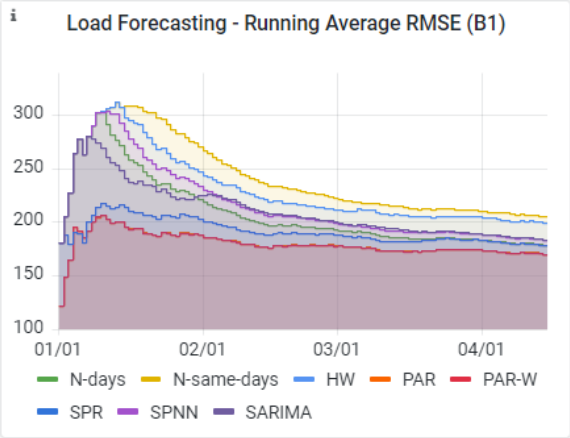
- Remarks:
  - Relative RMSE for a community of 3 buildings
  - Better performance was observed by PAR and PAR-W models
  - SPR models also improved in comparison to naive persistence models
  - SARIMA is not able to improve in comparison to N-days naive persistence model

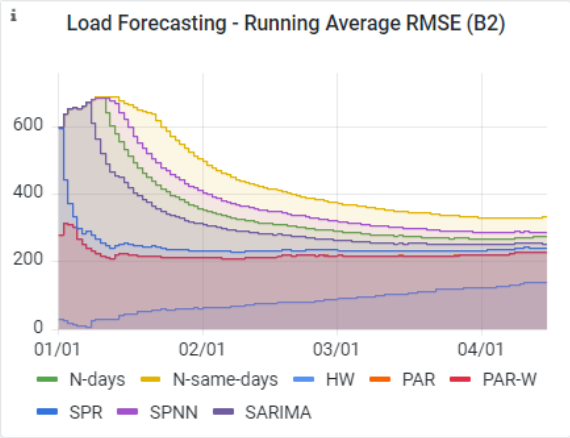
Duration	Feb 2016	July 2016	Dec 2016	2016
N-same-days	0,808	0,717	0,521	0,690
N-days	0,636	0,621	0,446	0,586
HW	0,751	0,755	0,532	0,694
SARIMA	0,694	0,644	0,455	0,616
PAR	0,461	**0,579**	**0,429**	0,488
PAR-W	**0,460**	**0,579**	**0,429**	**0,487**
SPR	0,505	0,609	0,450	0,526
SPNN	0,762	0,666	0,466	0,646

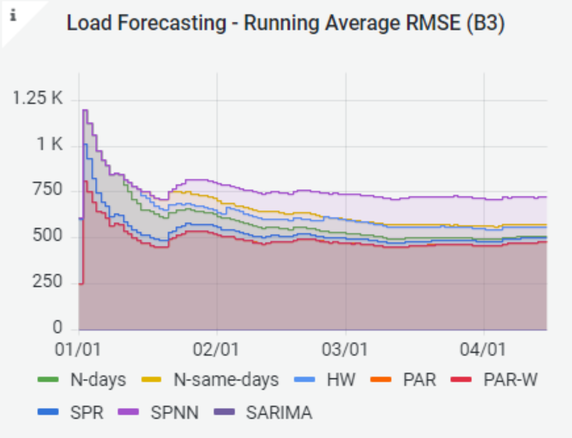
Community Load Forecasting – Performance (cont)

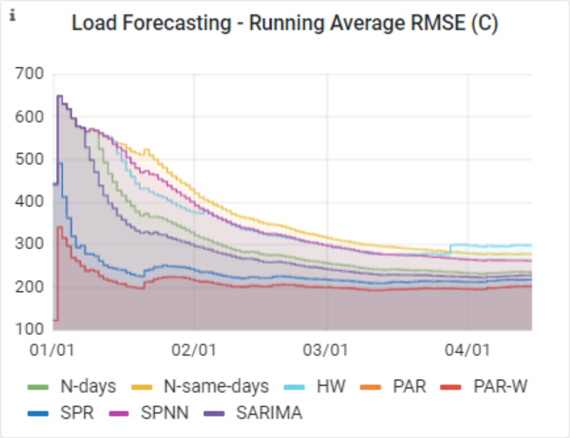
- Remarks:
  - Poor performance in individual building DA forecasts is significantly reduced in the community forecasts
  - For example, for the PAR-W model, individual buildings forecasts (rRMSE=1.050, 0.433, 0.914) are worse on average than the community forecasts (rRMSE=0.490)
  - Optimization at the community level can exploit such robustness!

L: PAR-W (C) 0.490	L: SPR (C) 0.551
L: PAR-W (B1) 1.05	L: SPR (B1) 1.12
L: PAR-W (B2) 0.433	L: SPR (B2) 0.477
L: PAR-W (B2) 0.914	L: SPR (B3) 0.983









Conclusions

- Evaluation of day-ahead load forecasting models
  - Evaluated performance of basic and combined models to load forecasting
  - Persistence-based Regression Models (PAR, SPR) provided the best performance
  - PAR and SPR also exhibit computational efficiency
  - Incorporating of weather data slightly improved predictions
  - Community forecasting exhibits robustness to individual bad forecasts

- Causal-inference-based load-forecasting
  - PAR and SPR further exploit causal effects in user-behavior
  - Causality needs to be exploited further, especially in hourly forecasts

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

SCCH ist eine Initiative der

SCCH befindet sich im