Combined PV Power and Load Prediction for Building-Level Energy Management Applications

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DLR Institute of Networked Energy Systems
DLR-Institute of Networked Energy Systems

• Institute of the German Aerospace Center (DLR)
  – Institute of Networked Energy Systems

• Located in Oldenburg and Stuttgart, Germany

• Topics we cover:
  – Design and operation of energy systems with focus on sector coupling
  – Development of ML-based energy management approaches
  – Simulation of electricity and heat grids
  – Smart City applications and demonstration
Motivation

• What?
  – Limit the global average temperature increase to 2 °C against pre-industrial levels
  – Low or zero-emission building stock in the EU countries by 2050.

• How?
  – Increase the share of renewable energies at building level.
  – Supporting the rollout of e-mobility infrastructure in buildings, such as e-charging points in buildings.
  – More automation and control systems for energy efficient buildings.
  – Combined PV power and load demand forecasting for load management applications.
Methodology – Definitions

- **Residual load R (lat. residuum „rest“)**
  
  \[ R = \text{grid load} - \text{feed in from renewables (fluctuating) sources} \]

- **Local residual Load LR in kW**
  
  \[ LR = \text{local demand} - \text{local generation} \]

- Available capacity in kW
  
  \[ P_{\text{available}} = \text{house connection point power limit} - LR \]
Methodology – The Combined Prediction Model

- PV-power forecast model from Maitanove et al. [3] and [4].
- Standalone Load forecast model from Steens et al. [5]
- As input data only local PV power measurements, load measurements and free available weather reports from Openweathermap was used.
  - LSTM Network from Python toolbox Keras [6]
  - Hyperparameter optimization with Python toolbox Talos [7]
Methodology – The Case Study

• Commercial building (offices and worspaces):
  – Roof-top PV-system with 99.9 kW installed capacity
  – Dataset from April 1st to December 31st
  – House connection point limit 112 kW
  – Maximum peak load without BEV: 85 kW
  – Ten three phases AC charging points each with maximum 22 kW

• Assumptions for BEV charging demand simulation:
  – Charging powers 11 kW (16 A) at a maximum of 22 kW (32 A).
  – The battery capacities of the BEV were randomly assigned between 25 kWh and 75 kWh.
  – SoC of the BEV was known at its arrival time and was randomly calculated in the range between 10% and 50%.
Methodology – Evaluation

**Metrics**

\[
RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (P_f - P_i)^2} \tag{1}
\]

\[
MAE = \frac{1}{n} \sum_{i=1}^{n} |P_f - P_i| \tag{2}
\]

\[
MASE = \frac{MAE}{\frac{1}{n-m} \sum_{i=m+1}^{n} |P_i - P_{i-m}|} \tag{3}
\]

**Forecast benchmark**

- As a benchmark for the developed prediction model, a persistence model was chosen to evaluate forecast accuracy.
  - This model uses the power values of the same weekday of the previous week at the same time points.

**Case Study benchmark**

- As case study benchmark we used the case of „unscheduled charging“
  - Charging processes are classified into “unscheduled” and “forecast based”
  - Unscheduled: A car that arrives starts immediately with the charging
Forecast Results – Separate PV power and Load Forecast

- Simulation period: April 1st 2019 to 31st December 2019

<table>
<thead>
<tr>
<th></th>
<th>Mean MAE</th>
<th>Mean RMSE</th>
<th>Median MAE</th>
<th>Median RMSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>PV ML</td>
<td>5.12</td>
<td>8.95</td>
<td>4.62</td>
<td>8.43</td>
</tr>
<tr>
<td>PV persistence</td>
<td>6.58</td>
<td>11.86</td>
<td>5.76</td>
<td>11.30</td>
</tr>
<tr>
<td>Load ML</td>
<td>4.10</td>
<td>6.35</td>
<td>3.64</td>
<td>5.76</td>
</tr>
<tr>
<td>Load persistence</td>
<td>6.12</td>
<td>8.88</td>
<td>4.20</td>
<td>6.14</td>
</tr>
</tbody>
</table>
Forecast Results – Local Residual Forecast

- Mean absolute scaled error
- Influence of load and PV on residual load
Forecast Results – Seasonal Dependencies

- Higher MAE in summer are related to the higher PV production compared to transition and winter periods
- Public holidays or changed load demand behavior affecting the forecasting accuracy
- Extreme weather changes affection the PV power forecast accuracy.
Forecasted Based Charging Strategies

• Optimized PV self-consumption in summer

<table>
<thead>
<tr>
<th>Charging strategies</th>
<th>Number of injuries (&gt;= 112 kW)</th>
<th>Max. peak power [kW]</th>
<th>PV self-consumption rate [%] (87% without BEV)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Unscheduled Charging</td>
<td>2494</td>
<td>177.30</td>
<td>92 %</td>
</tr>
<tr>
<td>Forecast based charging</td>
<td>70</td>
<td>122.74</td>
<td>94 %</td>
</tr>
</tbody>
</table>
Conclusion & Outlook

**Conclusion:**

- Definition of local residual load
- Residual load forecasting model
- Forecasting results
- Case study results

**Outlook:**

- Validation dataset / transferability of the model
- Uncertainty quantification
- Further application possibilities
- Optimized Very Short-Term Load Demand
Thank you for your attention!

Questions?

If you have further questions please feel free to contact me:

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References


