Electric Vehicle Intraday Load Forecasting with Artificial Intelligence

Mathias Renner
inno2grid GmbH

Problem definition

- Rising demand for EVs increases energy demand in low voltage grid.
- Charging multiple EVs concurrently results in excessive power peaks.
- High power peaks are penalized by higher costs for the investment and operation of a smart grid (higher costs when energy exchanged with public grid, higher installation costs, higher performance price).
- High peaks can be buffered with batteries as in the Micro Smart Grid at EUREF, but its capabilities are limited and its costs are high.

Solution approach

- Load management: EV charging power is dynamically adapted according to energy production of locally deployed renewables or public grid capacity.
- Load is controlled by changing power of the charging points depending on supply at time intervals \(i\).
  
  \[
  \text{Charging Power}_i = f(\text{Power Supply}_i)
  \]

- Energy demand of an EV shall be covered while it is parked.
  
  \[
  \sum_{i=0}^{\infty} \text{Energy Supplied}_i = \text{EV Energy Demand}
  \]

- Thus, forecasts of energy demand and parking durations have to be calculated at the onset of a charging event (definition of \(f(\text{Power Supply}_i)\)) is not part of this work).

- To calculate the forecasts, 14 machine learning algorithms have been selected, trained, evaluated and compared according to their performance.

Results

- Out of several algorithms incl. Support Vector Machines and Artificial Neural Nets with few layers, the random forest regression algorithm performed best.
- The most meaningful metric for the performance of results (KPI) is the „Mean Absolute Error“ (MAE), defined as the difference between the forecasted value and the real value.
- The deployed prediction models can forecast an EV’s parking time with an MAE of 2.5 h and its energy demand with an MAE of 3.5 kWh.
- Only 5 data points are required as input to calculate one forecast (!).
- Machine learning algorithms greatly outperform simplistic approaches like averaging historical values by 33% (EV energy demand) and 72% (parking time).

Next steps

- The deployed machine learning model will be further tested in different environments to investigate its generalization performance.
- Day-ahead forecasts will be added to further support load management, in cooperation with Distributed Artificial Intelligence Laboratory, Berlin.

---

Table 1: Distribution characteristics

<table>
<thead>
<tr>
<th>EV Energy Demand</th>
<th>Parking Duration</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average overall</td>
<td>14.43 kWh</td>
</tr>
<tr>
<td>Standard deviation</td>
<td>9.81 kWh</td>
</tr>
<tr>
<td>10.92 h</td>
<td>7.49 h</td>
</tr>
</tbody>
</table>

Table 2: Performance of best forecast model (Random Forest)

<table>
<thead>
<tr>
<th>EV Energy Demand</th>
<th>Parking Duration</th>
</tr>
</thead>
<tbody>
<tr>
<td>MAE without machine learning</td>
<td>5.34 kWh</td>
</tr>
<tr>
<td>MAE with machine learning</td>
<td>3.58 kWh</td>
</tr>
</tbody>
</table>

Required input data for machine learning algorithm:

- Weekday
- Hour
- Month
- Max. Power
- User category (private, car-sharing etc.)

---

Fig. 1: Energy demand of EVs, 10/2016 - 10/2017 at Micro Smart Grid

Fig. 2: Energy supply by local renewables (PV)

Fig. 3: Energy demand by EVs (unmanaged)

Fig. 4: Expected result: Balanced supply & demand (green) vs. imbalanced (red)