Electric Vehicle Intraday Load Forecasting with Artificial Intelligence

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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.

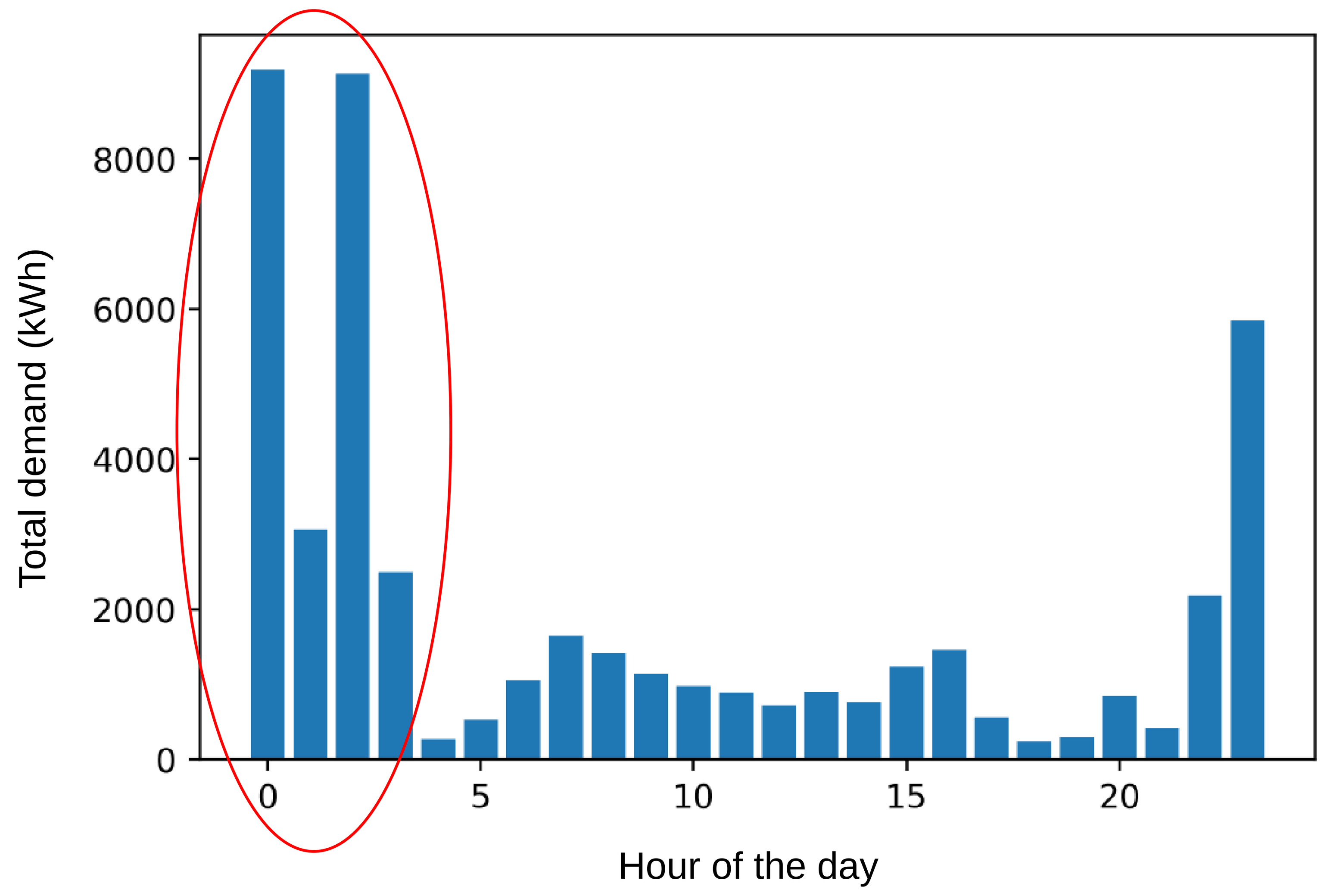

Fig. 1: Energy demand of EVs, 10/2016 - 10/2017 at Micro Smart Grid

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*.

$$Charging\ Power_i = f(Power\ Supply_i)$$

- Energy demand of an EV shall be covered while it is parked.

$$\sum_{i=0}^{Parking\ Duration\ (end)} Energy\ Supplied_i = EV\ Energy\ Demand$$

- Thus, forecasts of energy demand and parking durations have to be calculated at the onset of a charging event (definition of $f(Power\ Supply_i)$ 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.

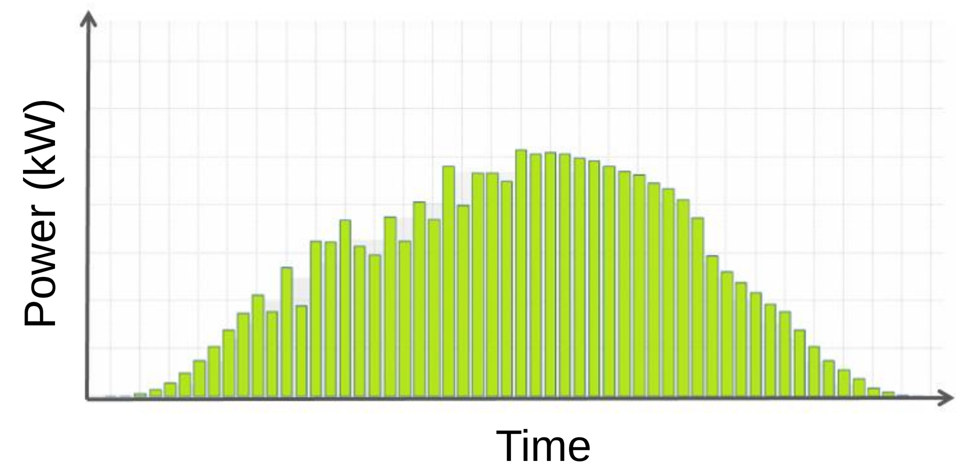

Fig. 2: Energy supply by local renewables (PV)

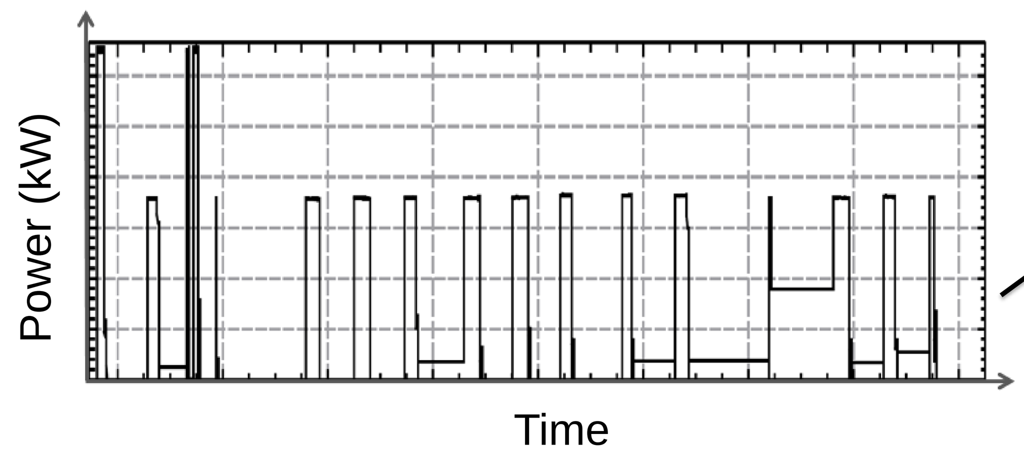

Fig. 3: Energy demand by EVs (unmanaged)

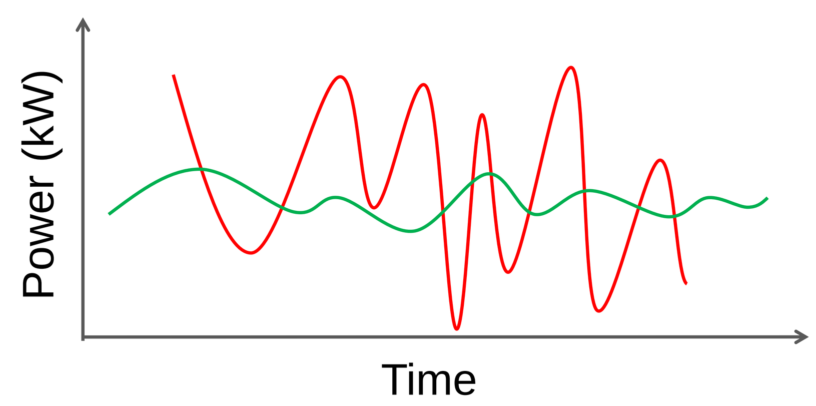

Fig. 4: Expected result: Balanced supply & demand (green) vs. imbalanced (red)

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).

Table 1: Distribution characteristics

	EV Energy Demand	Parking Duration
Average overall	14.43 kWh	10.92 h
Standard deviation	9.81 kWh	7.49 h

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

	EV Energy Demand	Parking Duration
MAE without machine learning	5.34 kWh	8.99 h
MAE with machine learning	**3.58 kWh**	**2.47 h**

Required input data for machine learning algorithm:

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

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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.