Simulating Plug-in Electric Vehicle Charging for AutoML-Based Prediction of Regional Energy Demand

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About the Presenter

- Matthias Schneider (presenter and author)
- Software Developer at Daimler TSS (Germany)
  - Area Digital Vehicle Products
- Graduated in September 2020 (Bachelor)
  - Computer Science at the
    Corporate State University Baden-Württemberg (DHBW)

Overview

PEV

ML/AutoML

Charging

Prediction

Agenda

1. PEV Charging Simulation
2. Regional Energy Demand Prediction
3. Evaluation
4. Conclusion

Agenda

1 **PEV Charging Simulation**

2 Regional Energy Demand Prediction

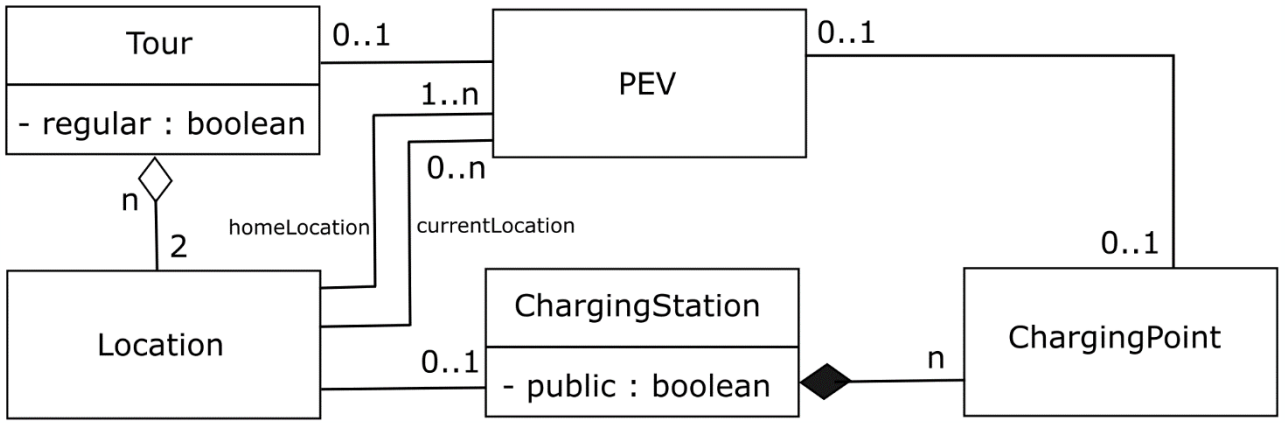
3 Evaluation

4 Conclusion

PEV Charging Simulation

- Overview

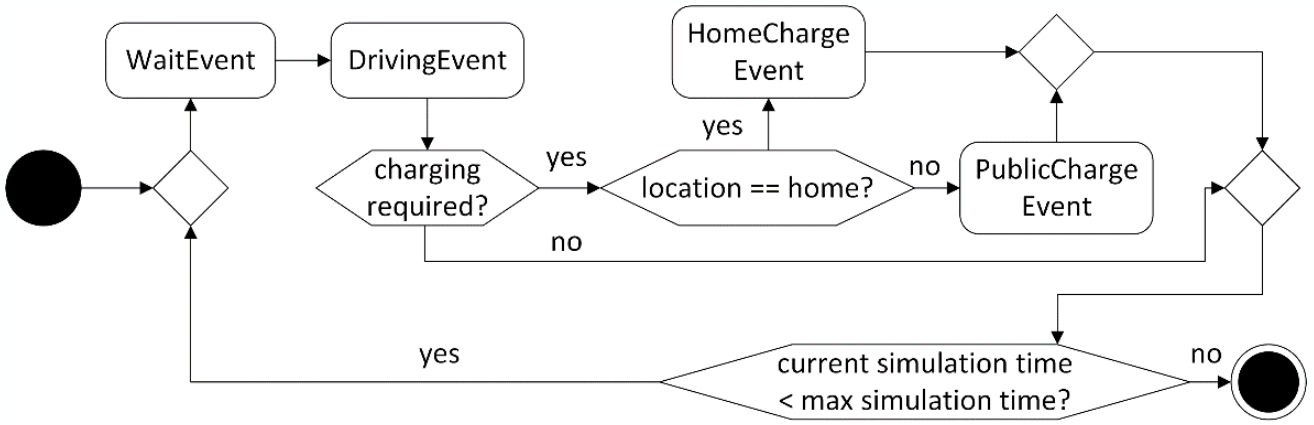
- DES simulation (framework SimPy)
- Five major simulation entities
  - Tour
  - PEV
  - Location
  - ChargingStation
  - ChargingPoint



PEV Charging Simulation

- Basic Simulation Flow

- Most important assumptions
  - PEV reaches destination and next tour cannot be performed with current SoC → charging
  - PEV cannot finish tour due to low SoC → charging
  - PEV reaches home location → charging
  - Tours to work start around 5am (maximum at 8am)
  - Tours back from work around 3-4pm
  - Less tours on weekends
- Two categories of tours (regular, irregular)
- Two types of charging stations (public, home)
- Distinction between weekday, weekend and vacation periods



PEV Charging Simulation
- Simulation Input

- Configurable simulation input parameters → adjustment of simulation
- 71 degrees of freedom
- Usage of normal distributions
  - Configurable mean and standard deviation (e.g. StartOfWork in table)

Simulation Input Parameters (Excerpt)

Name	Description
ChargingStation.Location	Location of the charging station
ChargingStation.MaxCPower	Max. charging power of charging station
ChargingStation.NrCP	Nr. of charging points at charging station
Context.NrPEV	Nr. of simulated PEVs
Home.Location	Home location of the PEV's owner
StartOfWork.NDist.Mean	Mean start time of work
StartOfWork.NDist.Sd	Standard deviation start time of work

PEV Charging Simulation
- Simulation Output

- Simulation output in CSV file
- Output contains relevant information of executed charging operations
  - e.g. duration, charged amount, location, start time, if charging took place during a vacation period, etc.

Simulation Output Parameters (Excerpt)

Name	Description
ChargingOperation.Duration	The duration of the charging operation
ChargingOperation.Kw	The charged energy amount in kW
ChargingOperation.Location	Location of corresponding charging point
ChargingOperation.Start	Start time of the charging operation
Vacation.Present	Vacation period present during charging?

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Regional Energy Demand Prediction

ML input example:

StartTime	DayOfWeek	Partition Id	ChargedKwh	MajorityChargingType	IsVacation	SumChargingTime	AvgChargingTime
1590364800	monday	6449	39.88	public	true	36723.46	36723.46
1590451200	tuesday	6449	55.18	private	true	50814.11	25407.05
1591660800	tuesday	6449	41.54	public	false	38255.0	12751.66

- Utilizing simulation output for short-term and regional energy demand prediction
  - Simulation configuration in this article reflects city Stuttgart (Germany)
- Feature engineering as pre-requirement for training ML models
  - Aggregation by partitions
  - Aggregation by time
  - Aggregation and averaging of remaining values (e.g. average charging time)

Regional Energy Demand Prediction

- AutoML library auto-sklearn used for model creation
  - AutoML: Automated process for creating ML models
  - 75% training data, 25% testing set
  - Vanilla (out-of-the-box) AutoML

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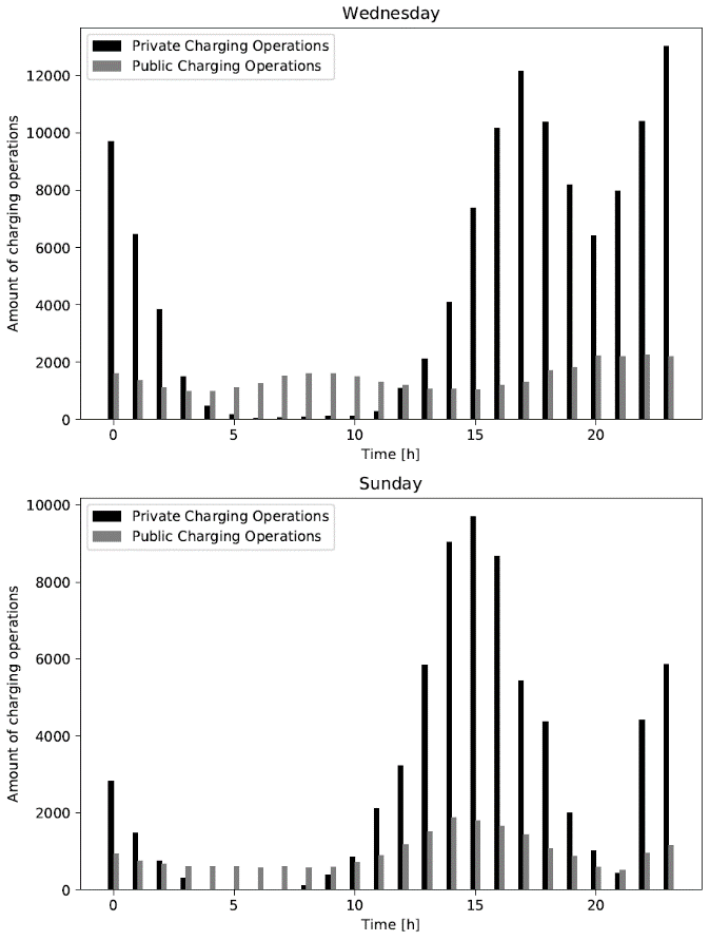
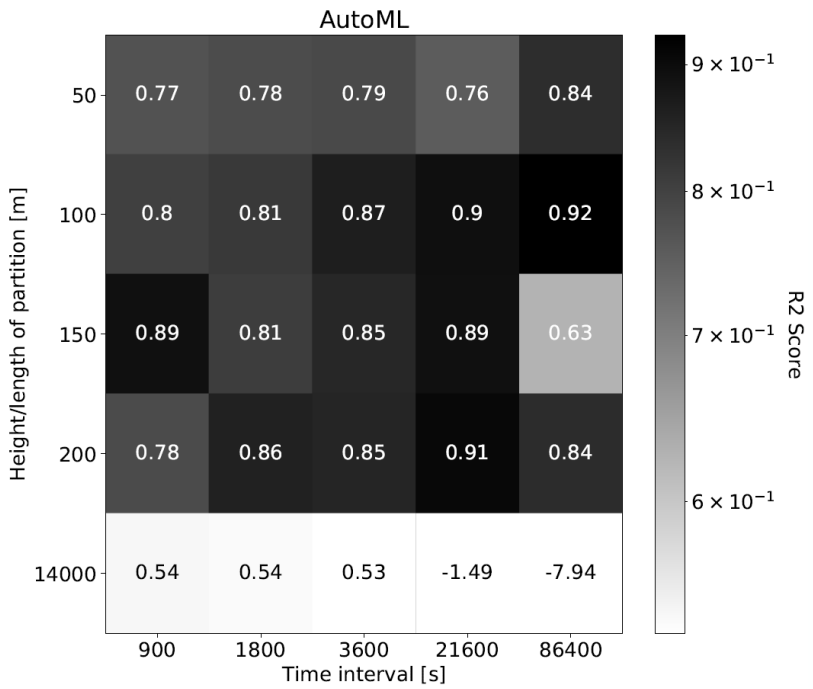
Evaluation

- Weekdays and weekend days with different charging patterns
- Weekday (e.g. Wednesday)
  - Tours to work (start around 5am) → Reduction of private charging
  - Tours back home (around 3-4pm) → Increase of private charging
- Weekend day (e.g. Sunday)
  - Strong increase of private charging at around 3pm → return from leisure trips
  - Only one high peak → not as much tours as on weekdays took place



Evaluation

- $R^2(y, \hat{y}) = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \overline{y})^2}$
  - y_i: true value of the i-th sample
  - $\hat{y}_i$: predicted value of the i-th sample
  - $\overline{y}$: arithmetic mean
- Highest partition size provides worst models → other models perform well
- Best model: partition size 100m and time interval 24 hours



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4 **Conclusion**

Conclusion

- PEV charging behavior simulation
  - Usable for multiple different use cases in the context of electric mobility
- Training of useful ML models based on simulation output
  - Application example: prediction of regional energy demand
  - AutoML capable to provide very good predictions for the short-term, regional energy demand
- Future work
  - Improve simulation’s underlying physical model
  - Take additional parameters into account (e.g. outside temperature, battery temperature, PEV’s charging curve)

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