Optimal Load Scheduling of Electric Vehicles in Distribution Networks

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https://github.com/fneum/ev_chargingcoordination2017

Agenda

Electric vehicles will add strain on distribution grids.

Targeted electrification of the transport sector entails

- unprecedented loads in distribution networks
- voltage drops and overloading of network equipment

Sustainability coupled to decarbonisation of electricity sector

- variable generation calls for active network management
- use EVs for demand side management as flexible loads

Consensus

Existing networks can accommodate substantial penetration levels of electric vehicles if charging is coordinated without reinforcement.

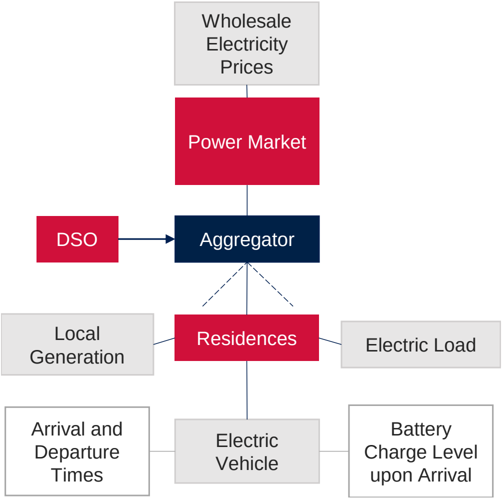
Joint market- and network-based scheduling is rare.

Much research has already been conducted. However,

1. market- and network-based optimisation is often disjunct;
   - cost-minimising algorithm disregards network constraints or
   - peak-shaving algorithm neglects potential economic benefits.

2. consideration of uncertainties about scenarios is more prevalent than recognition of individual uncertainties in mobility patterns, residential demand and market prices.

There are multiple sources of uncertainty in scheduling.



Research Objectives

- Develop a robust deterministic cost-minimising day-ahead scheduling routine that observes network and demand constraints in a stochastic environment.
- Model the uncertainties involved.
- Exploit knowledge about their distributions to hedge risks:
  - cost of charging
  - charging reliability
  - line overloading
  - voltage violations

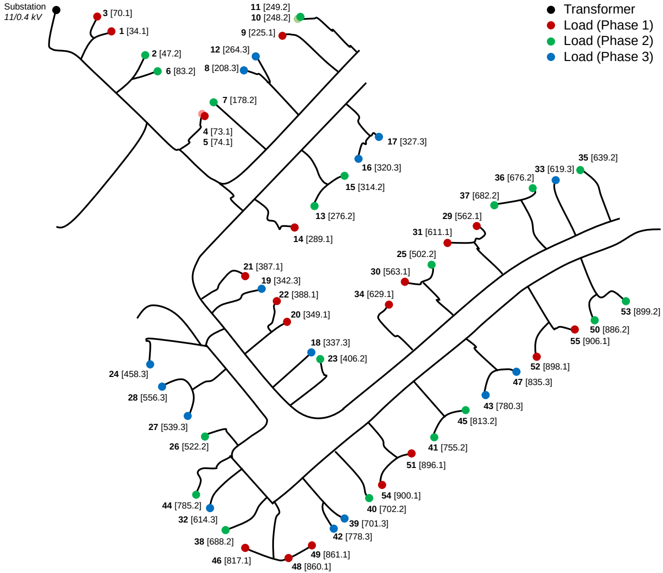
Research Questions

1. How can the major uncertainties involved in day-ahead scheduling of electric vehicles be modelled generically
2. How do they limit the reliability of unaware scheduling approaches in terms of meeting user requirements and observing network constraints?
3. What is the relative cost and benefit of increasing the robustness towards forecast deviations in day-ahead scheduling by applying more conservative forecast estimates?

Setting, Scope and Limitations of Analysis

- focus is on suburban low-voltage (400 V) distribution networks
- penetration of electric vehicles is 100% for the 55 households
- charging occurs exclusively overnight at home, not at work
- charging control is devised to one central aggregator with access to some abstract wholesale electricity market
- optimisation horizon is 24 h an is triggered daily at 1 pm (offline day-ahead scheduling)
- time resolution is 15 min
- uncertainty modelled via continuous distribution functions, in reality would use empirical distributions
- linear power flow

European low-voltage test feeder



Data and Parameters

Network topology

- European LV test feeder
- *Uncertainty: none*

Price time series

- UKPX Reference Price Data
- *Uncertainty: red-noise sequence*

Demand time series

- CREST demand model
- *Uncertainty: shifting peaks within 1 h*

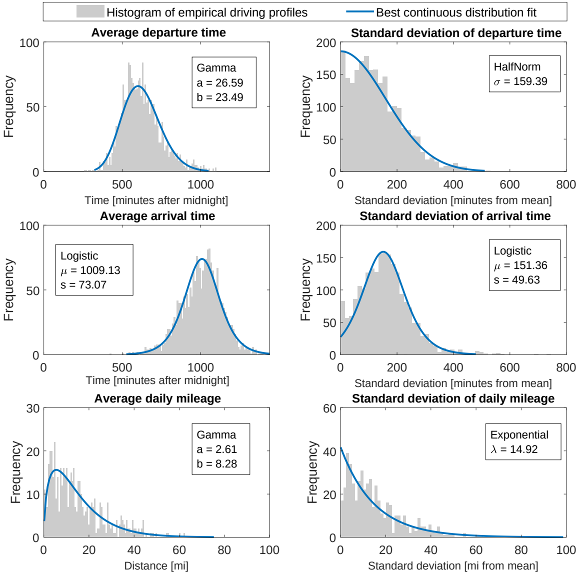
Mobility data

- UK National Travel Survey
- *Uncertainty: normal distributions, parameters individually assigned*

Vehicle specification

- EV consumption: 0.17 kWh/km
- Battery capacity: 30 kWh
- Charging mode: 3.7 kW
- Charging efficiency: 93%
- *Uncertainty: None*

How do people use their (electric) vehicles?



How is the travel pattern model built from the data?

Modelling

Data extraction from empirical data

Create 6 continuous distribution fits noting the average and standard deviation of

1) *end of last trip,*
2) *start of first trip, and*
3) *daily mileage*

of households participating in the survey.

for each participating household

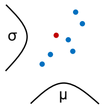
Preliminary Analysis ⇨

Scenario Generation

Assigning parameters describing the behaviour of EV owners

Sample parameter from all 6 model distributions

3 times



Each *(μ,σ)*-tuple describes an aspect of uncertain user behaviour via normal distribution

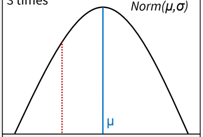
for each vehicle in the network

Optimal Scheduling ⇨

Realisation of Uncertainty

Sample from normal distributions to simulate observed behaviour

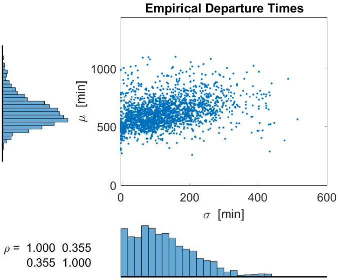
3 times

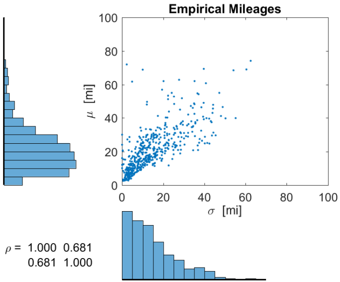


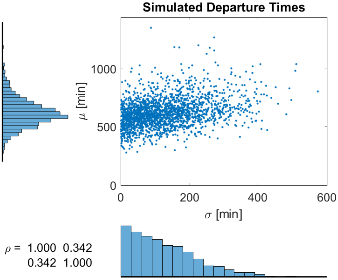
observation forecast

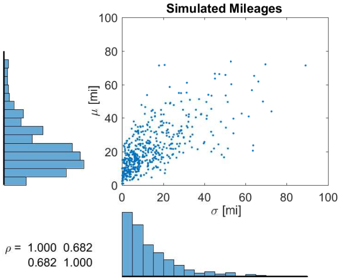
for each vehicle in the network

How do empirical data and simulated model compare?









Then availability probabilities look something like this:

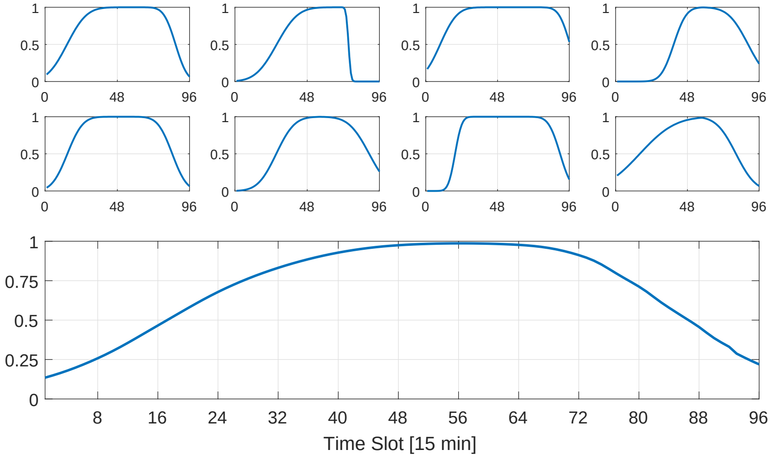
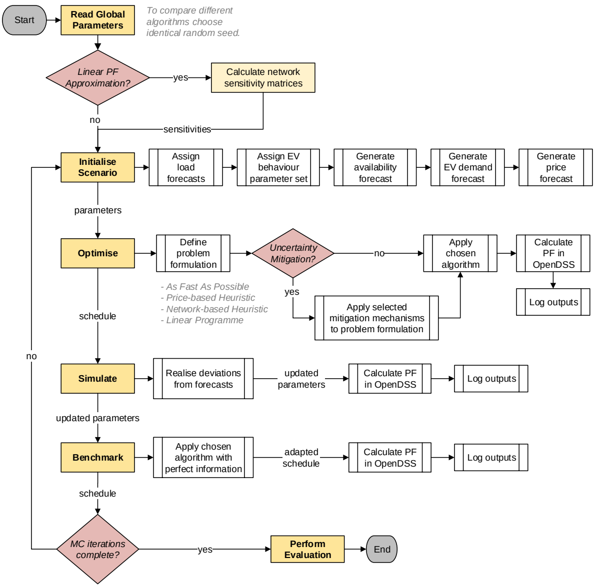


Figure: Illustration of availability probabilities on an individual (top) or aggregate level (bottom)

How were the charging approaches evaluated?



Plain Problem Formulation

$$\min_{\{P_{EV}\}} \quad C = \sum_{t=1}^{T} \sum_{k=1}^{K} \hat{\pi}_t \cdot \Delta t \cdot P_{k,t}^{EV}$$

$$
\begin{array}{lllcll}
\text{s.t.} & 0 & \leq & P_{k,t}^{EV} & \leq & P_{max}^{EV} \\
& & & \left(1 - \hat{\alpha}_{k,t}^{EV}\right) \cdot P_{k,t}^{EV} & = & 0 \\
& & & \hat{B}_k^{arr} + \sum_{t=1}^{T} \eta \cdot P_{k,t}^{EV} \cdot \Delta t & = & B_{max} \\
\text{PF} & V_{min} & \leq & V_{k,t}^{bus} & \leq & V_{max} \\
& & & I_{\ell,t}^{line} & \leq & I_{\ell}^{max}
\end{array}
$$

$$\forall k \in \{1, \ldots, K\} \quad \forall d \in \{1, \ldots, D\} \quad \forall t \in \{1, \ldots, T\} \quad \forall \ell \in \{1, \ldots, L\}$$

Substation had enough capacity by design.

How are the voltages and line loadings calculated?

Experimentally determine network sensitivities of household voltages and line loadings to additional loads.

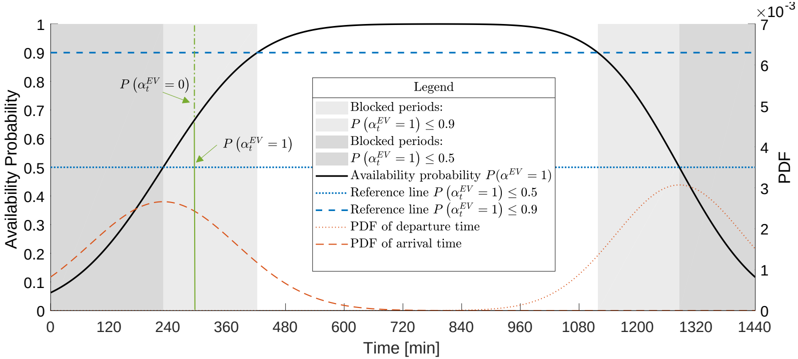
- series of unbalanced three-phase power flow calculations
- static load of 2 kW (max. avrg. demand winter)
- alternatingly increase one households load by 1 kW
- observe voltage and line loading change everywhere
- create sensitivity matrices λ and μ

$$\text{PF:} \quad V_{min} \leq V^{bus}_{k,t,init}\left(\hat{D}_{k,t}\right) + \sum_{j=1}^{K} \mu_{j,k} \cdot P^{EV}_{i,t} \leq V_{max}$$

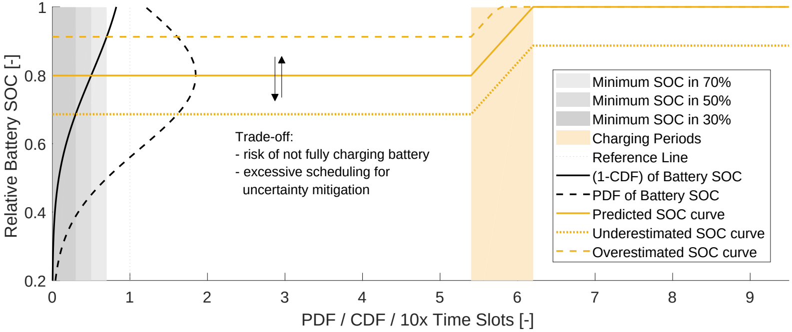
$$I^{line}_{\ell,t,init}\left(\hat{D}_{k,t}\right) + \sum_{j=1}^{K} \lambda_{j,\ell} \cdot P^{EV}_{i,t} \leq I^{max}_{\ell}$$

Low error for voltages ($\leq 0.5\%$) and lines ($\leq 2\%$) and rather overestimating the effect of additional load (uncontrolled EVs)!

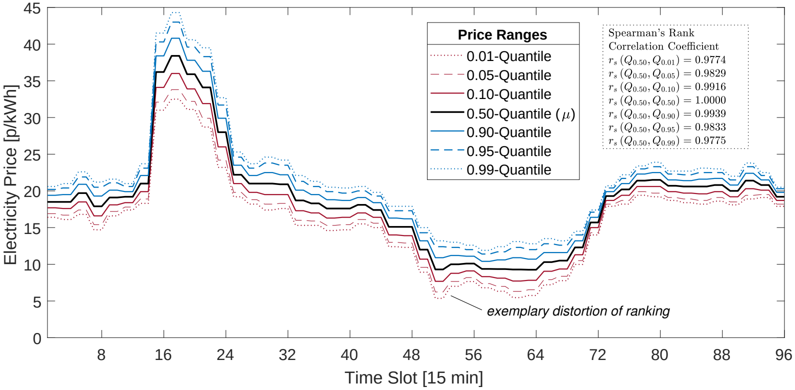
Mitigation of EV availability uncertainty



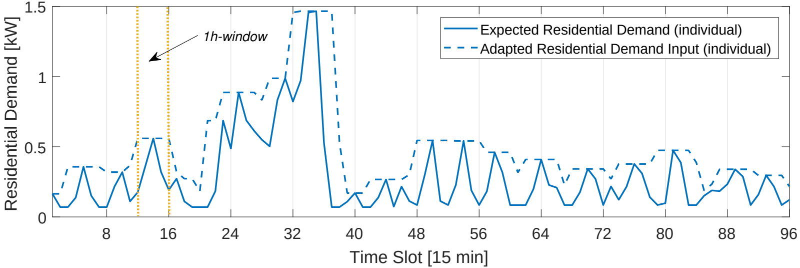
Mitigation of EV battery SOC uncertainty



Mitigation of price uncertainty



Mitigation of demand uncertainty



Evaluation Criteria

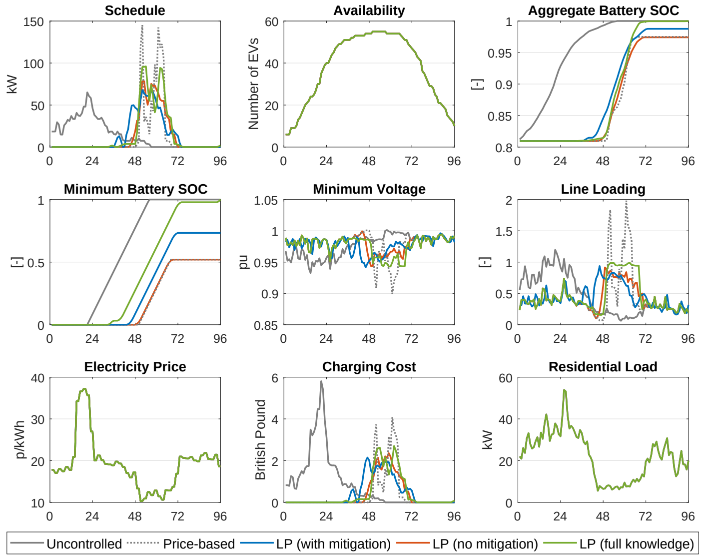
- **Relative charging costs**
  - economic benefit of coordinated vs. uncontrolled charging
  - interpretation of costs of introducing network constraints if compared to unconstrained price-based charging
- **Demand satisfaction**
  - average final battery state of charge
  - minimum final battery state of charge
- **Severity of constraint violations**
  - maximum line loadings
  - minimum bus voltages

How do the reference cases compare?

3 reference cases:

- no EVs
- uncontrolled
- price-based

Simulated performance w/wo uncertainty mitigation



Household-level view on scheduling and effect of controller

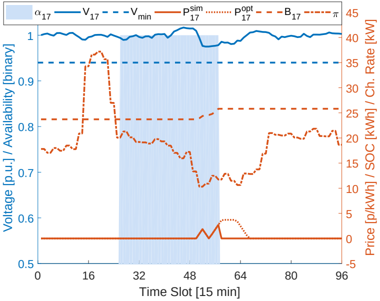
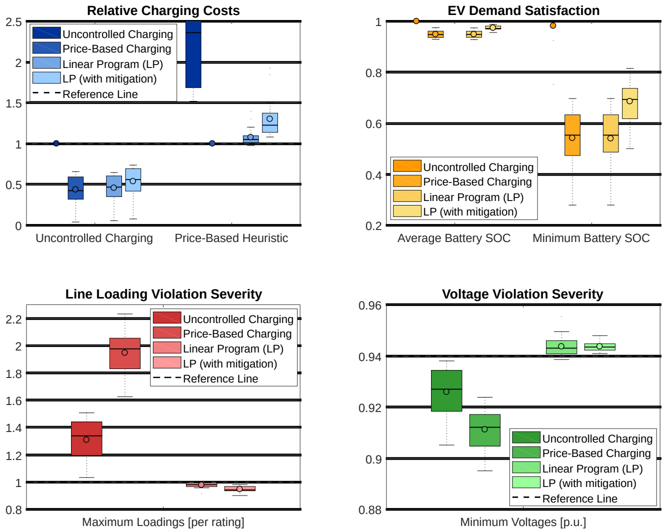
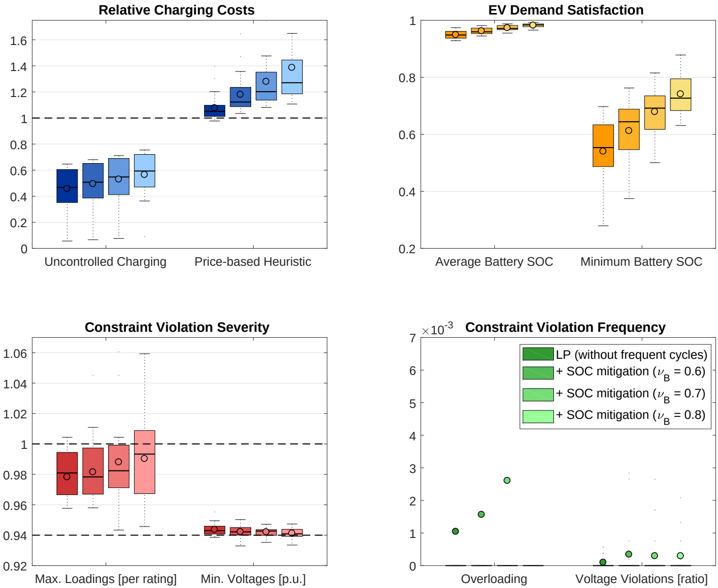


Figure: Two households close to (left) and far from substation (right)

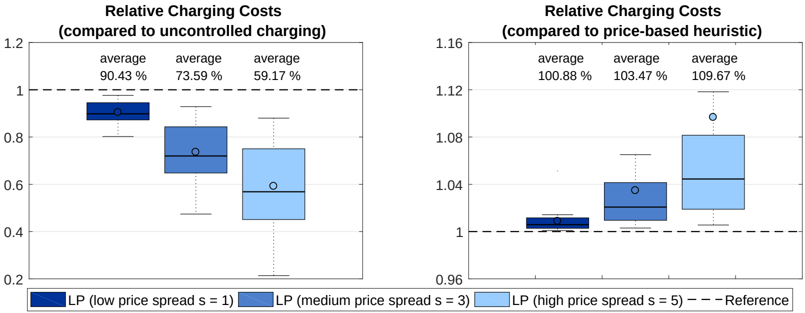
The main results summarised in one slide:



+: Sensitivities of SOC uncertainty mitigation parameters



+: Sensitivities of rel. charging costs to diff. price spreads



Summary

- **The cost of considering technical feasibility is confined to 10%** indicating that numerous alternative slots with similar charging costs and suitable network capacities are available.
- **Uncertainty could be mitigated**; particularly recognising total demand uncertainty of electric vehicles is effective (reserving more slots than actually needed). But obviously, this comes at a cost (plus 20 - 40 %).
- **Dynamic surcharges and levies incentivise participation in demand-side management** by amplifying the effect of variable electricity prices on the wholesale market *(something I didn't show today)*.