Firm-level optimisation of EV workplace charging:

Trade-offs, impacts, and tools

E-Mobility Power System Integration Symposium — Berlin, Germany

Session: Charging Infrastructure Planning II

October 6th, 2025

Speaker: Marcel Seger, DPhil Student, ECI Energy Group, University of Oxford
Collaborators: Christian Brand, Christoph Clement, James Dixon, Charlie Wilson

My educational background blends entrepreneurship w/ operations research

Study Background & DPhil Research Group

Marcel Seger

DPhil (PhD) **Student** (final year)

Environmental *Change* Institute

iDODDLE

Research Project

Educational Track

2022 - today

DPhil (PhD) in Geography & the Environment at the Environmental Change Institute (ECI), University of Oxford

2019 - 2022

Honours Degree in Technology Management at Center for Digital Technology & Management (CDTM)

2014 - 2022

B.Sc. & M.Sc. In Management & Technology (Industrial Engineering) at TU Munich

Key Information & Context

Research Objective

Studying the impacts of digitalised daily life on climate change across the domains food, home, energy, and mobility

Funding

This research was supported by European Research Council ERC Consolidator Grant, #101003083 (2021 – 2025)

Funded by the European Union

European Research Council

Established by the European Commission

iDODDLE

The Impacts of Digitalised Daily Life on Climate Change

Today’s talk is structured in eight main sections

Overview

1 | **Motivation**
Problem context: Decarbonising transport

2 | **Background**
Case study: Context-relevant information

3 | **Model Structure**
Approach: Outlining four-step structure

4 | **Methodology**
Methods: Drawing from operations research (OR)

5 | **Results**
Analysis: Scenario analyses

6 | **Discussion**
Review: Main findings, limitations & further research

7 | **Web Application**
Demonstration: Development of interactive tool

8 | **Q&A**
Appendix: References and back-up slides

Increased uptake of EVs requires extensive build-out of charging infrastructure

Problem context: Decarbonising transport

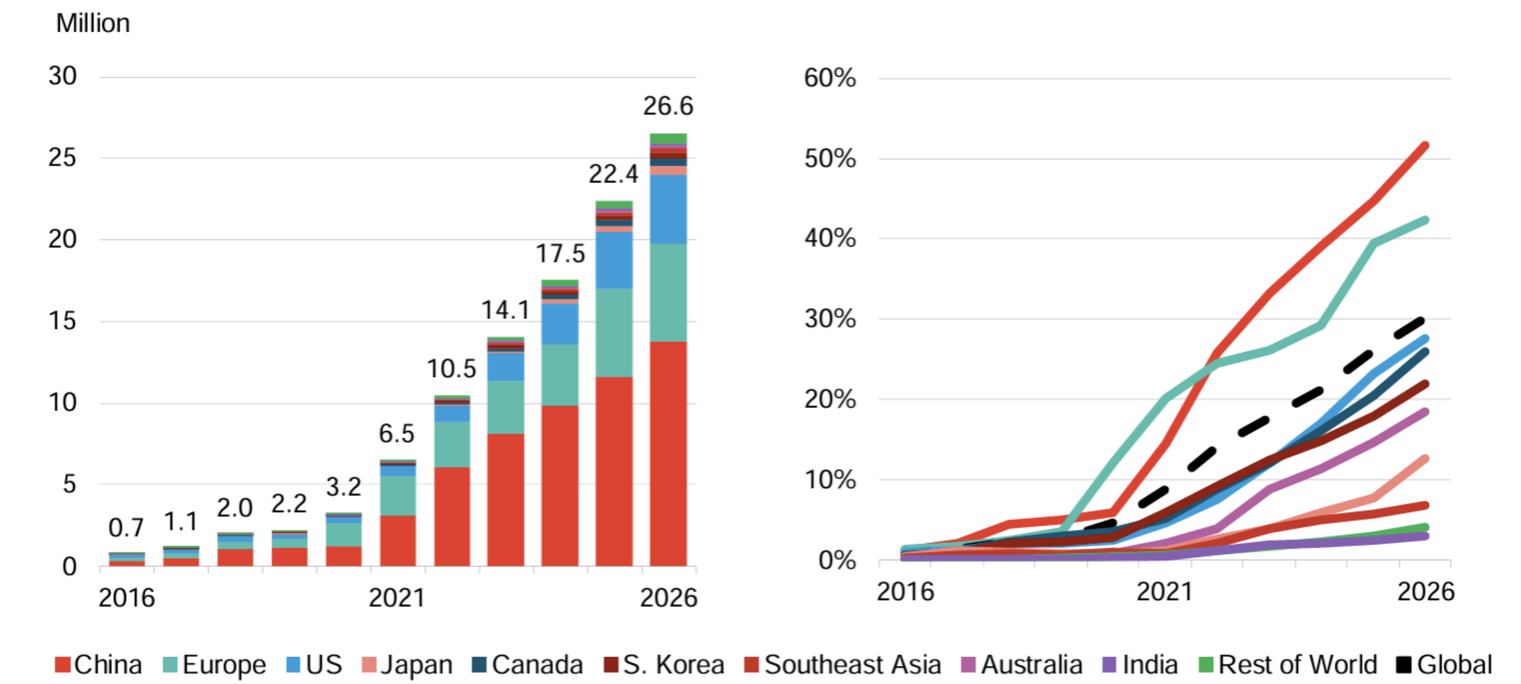


Fig. 1 | Global near-term EV sales (l.) and share of new passenger vehicle sales by market. Note: Europe includes the EU, the UK and EFTA countries. EV includes BEVs and PHEVs. Figure taken from [1].

Further notes

- **88%** of GHG emissions are covered by net-zero legislation as of 2023 [2].
- Mitigation efforts in **transport sector** feature strong focus on road vehicle electrification.
- **65%** of commitments in nations' revised nationally determined contributions (NDCs) as of the **Glasgow Climate Pact (2021**) are focused on electrification & fuel-switching [3].
- Helping deliver these commitments requires widespread **charging infrastructure** at **workplaces** and public places to bring 'convenience parity' between EVs and internal combustion vehicles (ICVs) [4].

Number of workplace chargers is projected to grow fivefold (UK) / double (DE) by 2030

Future drivers & outlook to 2030

8 million EVs

Annual sales volume by 2030 [+400% (2024)] [5]

82 GWh

+300% electricity demand for EV charging by 2030 [5]

Workplace chargers

+500% forecasted for UK / +200% in DE by 2030 [6,7]

Scope 3 emissions

Firms' reporting obligation of employee commute [8]

Decision support system

Identified need for data-driven decision support to plan and operate EV workplace charging infrastructure [9]

Roll-out of extensive EV charging infrastructure on employee car park

Case study: Context-relevant information

RQ1 What are the benefits of coordinated EV workplace charging for firms?

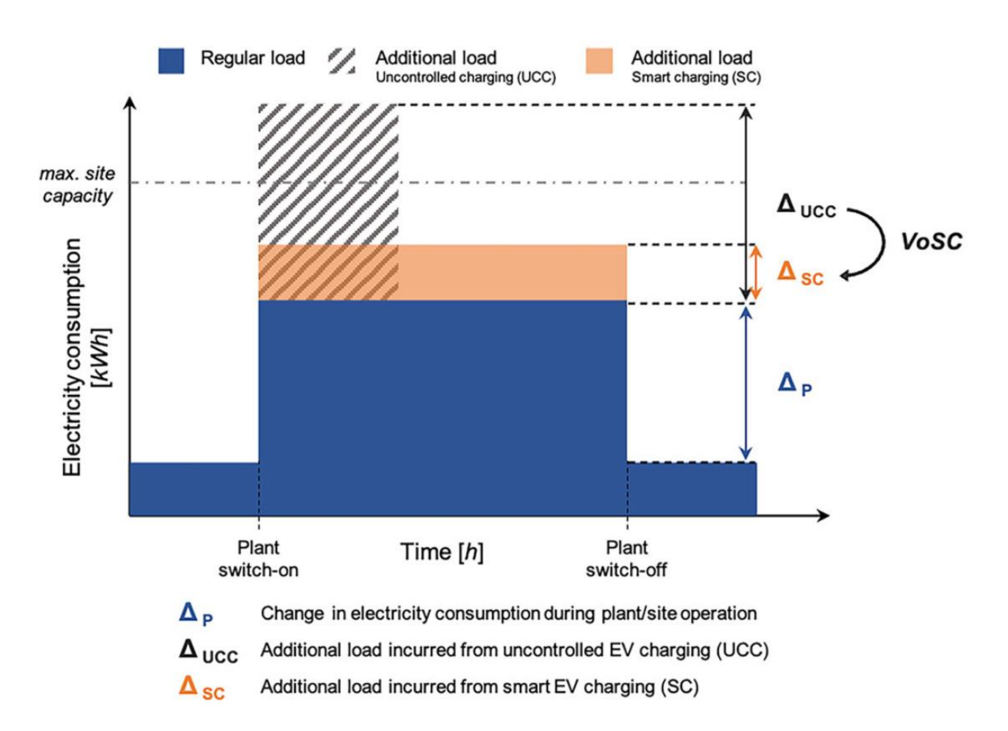


Fig. 1 | Schematic electricity consumption profile of industrial site.

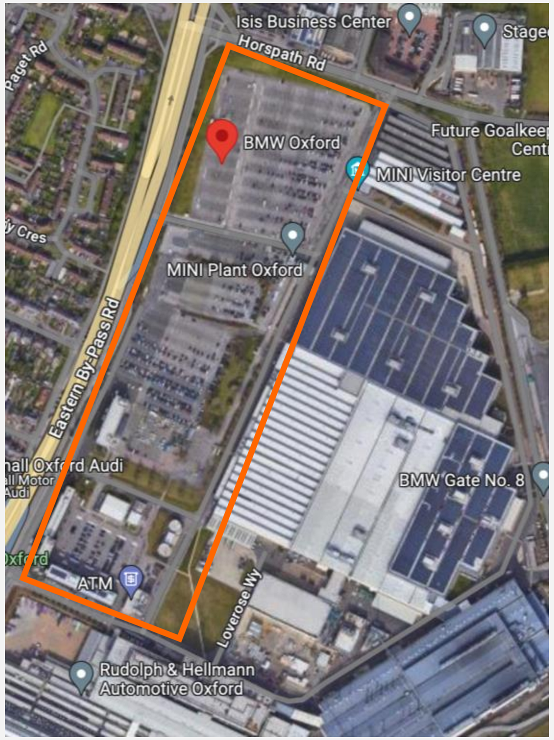


Fig. 2 | Aerial image of employee car park.

Motivation: regulatory context

- Enforcement of recent EU laws add regulatory pressure for firms
  - **Corporate Sustainability Reporting Directive (CSRD)**: more stringent reporting of Scope 3 emissions, including employees' commute practices to the workplace
  - **Energy performance of buildings (EPBD)**: legal requirement to provide min. 1x charging station on business car parks w/ >20 parking spots ('GEIG' in Germany – in effect since 01.01.2025)

We benchmark each model type against uncontrolled charging (UCC) [%Δ]

Approach: Outlining four-step structure

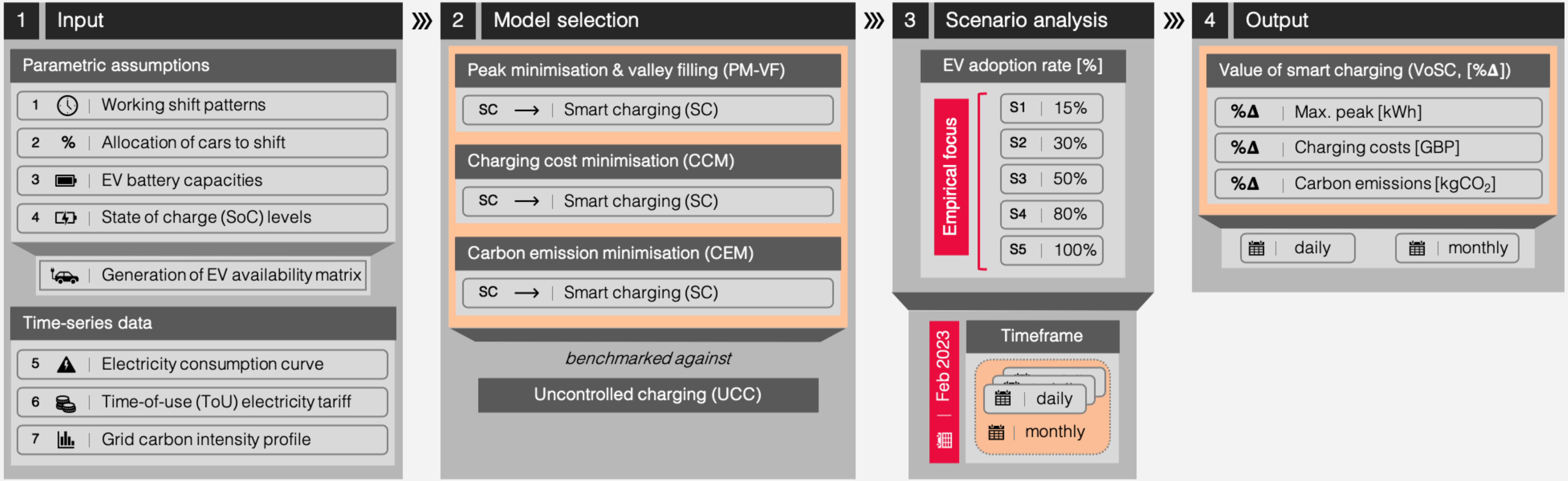


Fig. 4 | Schematic overview of our modelling framework. Step 1: Specification of input parameters. **Step 2:** Selection of model, assessing (i) peak minimisation & valley filling (PM-VF), (ii) charging cost minimisation (CCM), or carbon emission minimisation (CEM). **Step 3:** Scenario analysis with varying EV adoption rates [%] and temporal scale. **Step 4:** Computation of model results for each objective function in relative terms (%Δ).

Parametric assumptions and time-series data are used as model inputs

Step 1: Input

Electricity demand curve P_t

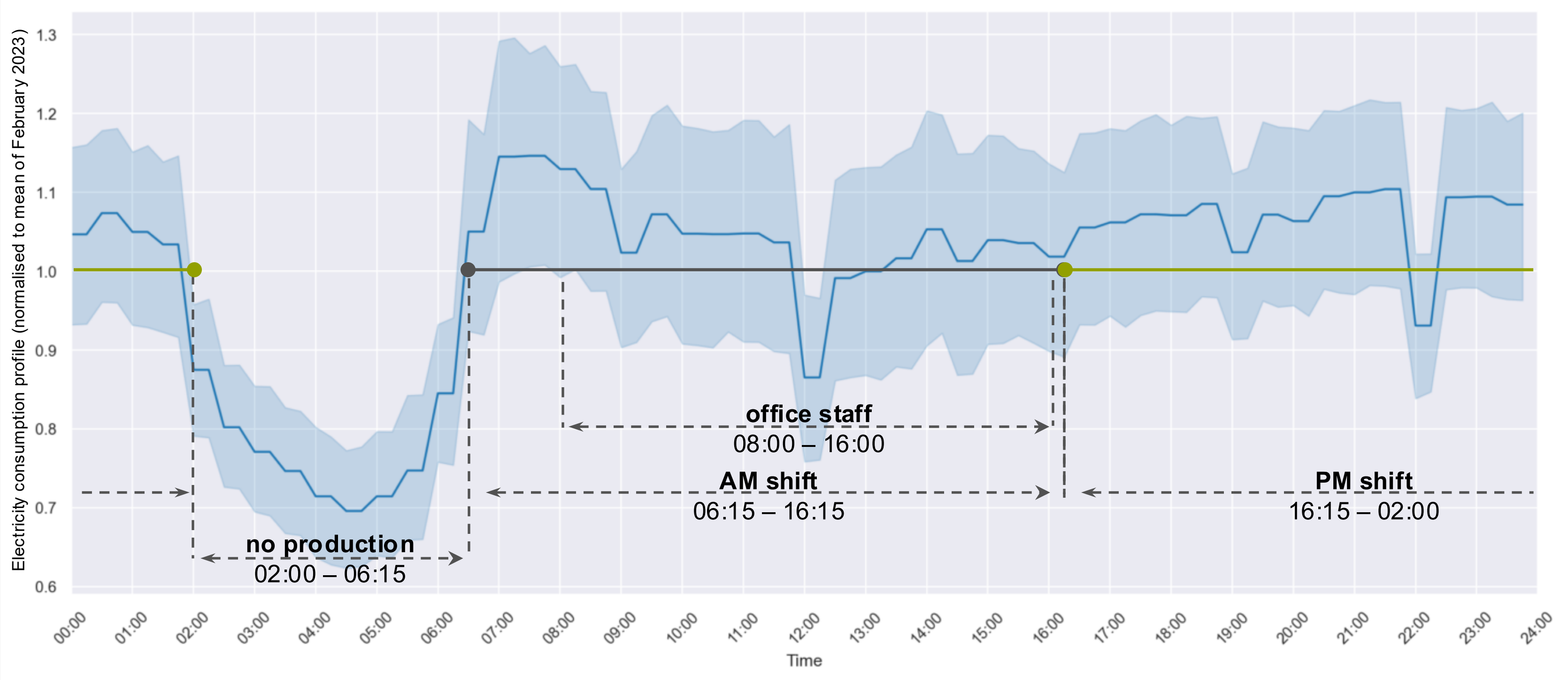
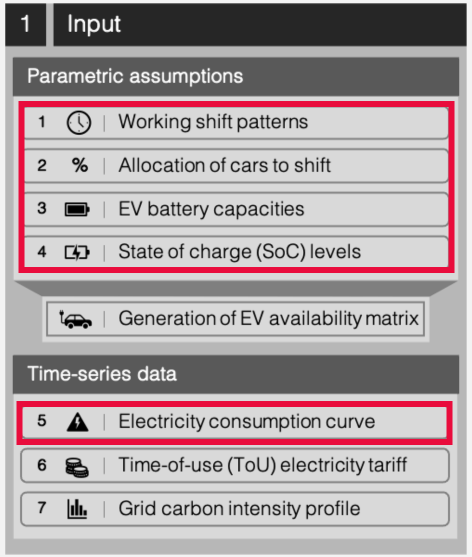


Fig. 5 | Electricity consumption profile of industrial production site in Feb 2023. Note: Time-series data has been normalised to mean of Feb 2023 for data sensitivity reasons. Shaded area represents 95%-confidence interval.



Real-world data + assumptions

	AM	PM	OFFICE	#CARS
2 |	63%	27%	10%	1,100
3 |	48 kWh	71 kWh	100 kWh	uniformly distributed
		LB	UB	
4 |	E_{ini}	10%	80%	
	E_{fin}	80%	100%	

Each model pursues a different optimisation goal, yet w/ identical constraints

Methods: Drawing from operations research (OR)

Peak min. & valley filling (PM-VF):

$$min \ \ z_{PM-VF} = \sum_{t \in T} (P_t + y_t - C)^2$$

Charging cost min. (CCM):

$$min \ \ z_{CCM} = \sum_{t \in T} y_t * \lambda_t$$

Carbon emission min. (CEM):

$$min \ \ z_{CEM} = \sum_{t \in T} y_t * \gamma_t$$

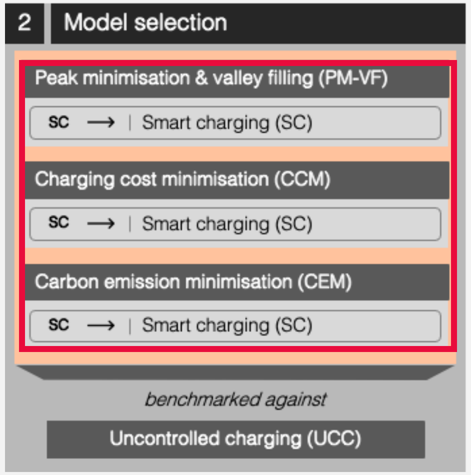
[1]	$s.t. \quad y_t = \sum_{m \in M} x_{mt} f_{mt}$	$\forall \, t \in T$	Total charging load
[2]	$-p_{max} \leq x_{mt} \leq p_{max}$	$\forall \, t \in T; \ m \in M$	Charging power restrictions
[3]	$0 \leq E_m^{ini} + \sum_{k \in T \mid k \leq t} x_{mt} f_{mt} \leq E_m^{cap}$	$\forall \, t \in T; \ m \in M$	Battery capacity restrictions
[4]	$E_m^{fin} = E_m^{ini} + \sum_{k \in T \mid k \leq t} x_{mt} f_{mt} \geq E_{T+1}$	$\forall \, t \in T; \ m \in M$	Minimum state-of-charge (SoC) requirement
[5]	$0 = x_{mt}(1 - f_{mt})$	$\forall \, t \in T; \ m \in M$	Logical operator ensuring car availability

$$C = \frac{max(P_t) + min(P_t)}{2}$$

Constant C

$$f_{mt} = \begin{cases} \mathbf{1}, if \ \ EV \ \ m \in M \ is \ parked \ at \ workplace \ at \ time \ t \in T, \\ \mathbf{0}, \qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad otherwise \end{cases}$$

Definition of car availability matrix



C	Average of peak and minimum power consumption of building
E_{T+1}	Energy needed for next trip
E_m^{cap}	Battery capacity of EV m
E_m^{fin}	Final battery energy of EV m
E_m^{ini}	Initial battery energy of EV m
F	EV presence matrix
M	Set of EVs
N	Set of time intervals
P_{ui}	Power consumption of building in interval i
$Q^{(i)}$	Set of intervals prior to interval i
T_m	Charging/discharging period of EV m
m	Electric vehicle (EV)
p_{max}	Maximum charging or discharging power
t_m^{arr}	Arrival time of EV m
t_m^{dep}	Departure time of EV m
x_{mi}	Charging/discharging power of EV m in interval i
y_i	Total load for charging/discharging the available EVs in interval i
i	Time interval

For further references, see [10, 11].

Each model pursues a different optimisation goal, yet w/ identical constraints

Methods: Drawing from operations research (OR)

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$$min \quad z_{PM-VF} = \sum_{t \in T} (P_t + y_t - C)^2$$

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Carbon emission min. (CEM):

$$min \quad z_{CEM} = \sum_{t \in T} y_t * \gamma_t$$

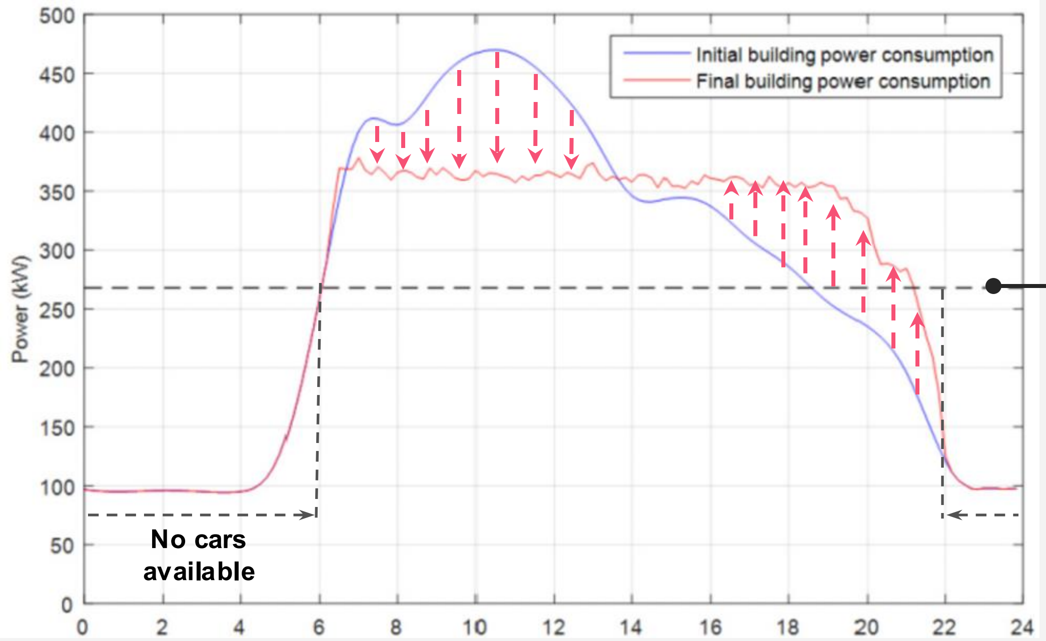


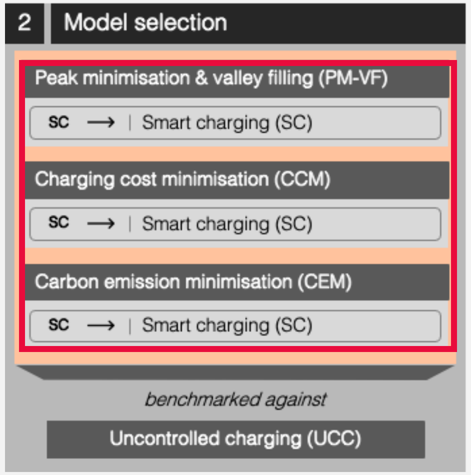
Fig. 6 | Schematic power curve. Figure taken from [10].

$$C = \frac{max(P_t) + min(P_t)}{2}$$

Mathematical Objective Function

Minimising the least square difference:

$$min \quad z_{PM-VF} = \sum_{t \in T} (P_t + y_t - C)^2$$



PM-VF reduces peaks by -21.3% measured against UCC [%Δ] | EV rate = 50%

Analysis: Scenario analysis for varying EV adoption rates

Peak minimisation & valley filling (PM-VF) | EV adoption rate = **50%**

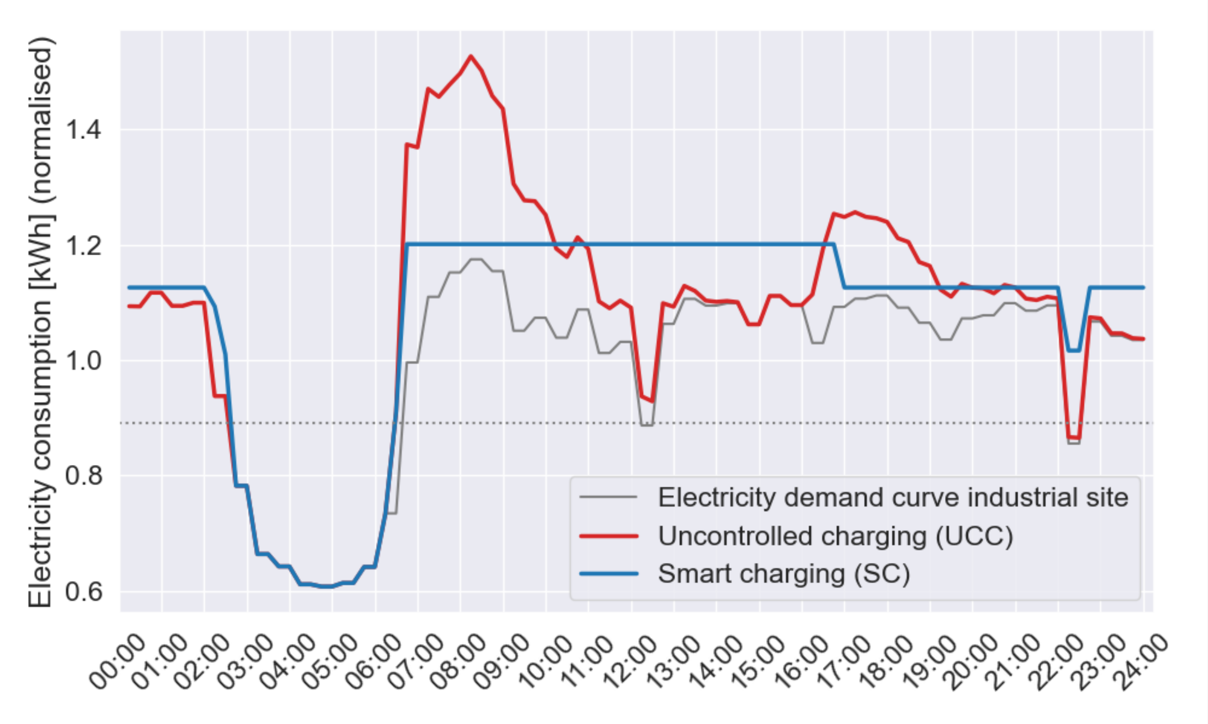
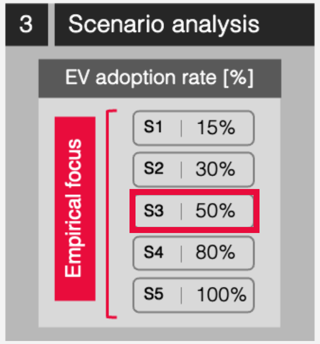


Fig. 7 | Resulting electricity demand profile from EV charging. Note: Graph shows results for model type PM-VF for EV rate = 50%, exemplarily for 01 Feb, 2023.



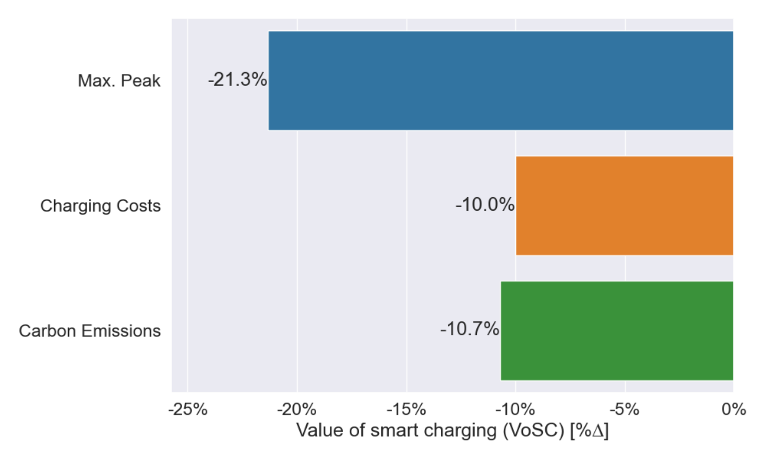
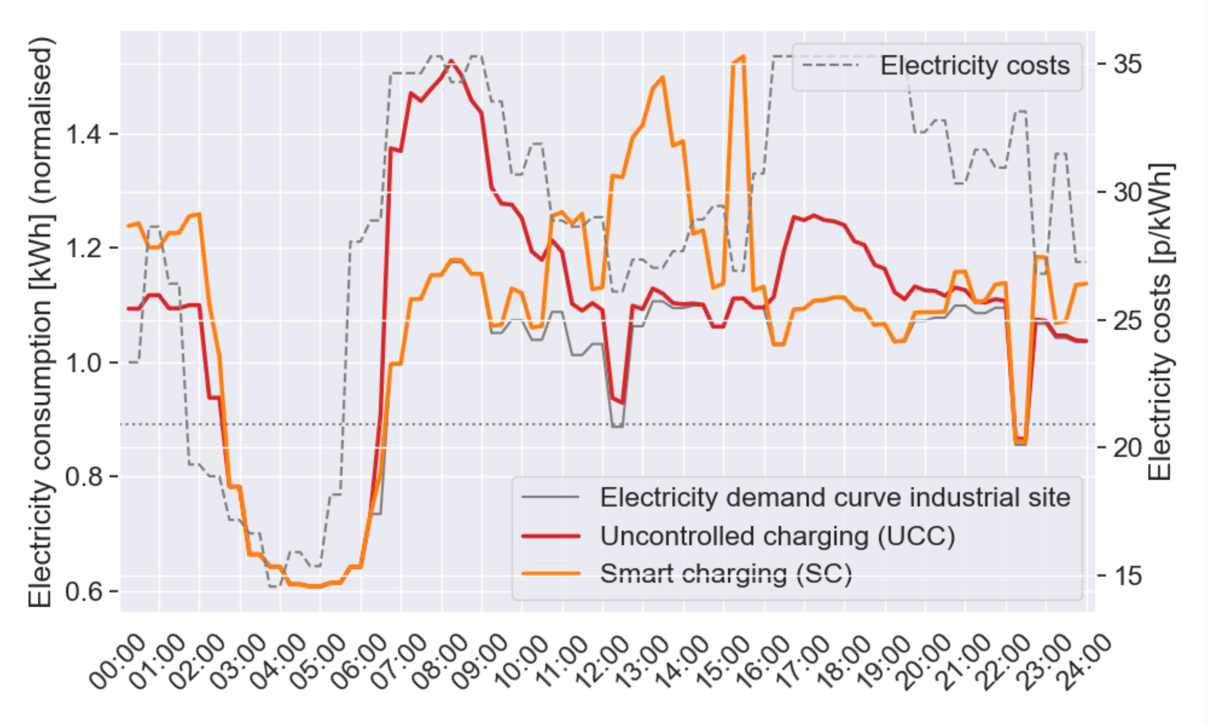


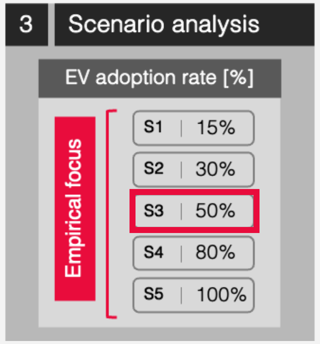
Fig. 8 | Relative performance of PM-VF. Note: Bar charts capture change in output cf. to UCC (VoSC) [%Δ].

CCM reduces costs by -19.6% measured against UCC [%Δ] | EV rate = 50%

Analysis: Scenario analysis for varying EV adoption rates

Charging cost minimisation (CCM) | EV adoption rate = 50%





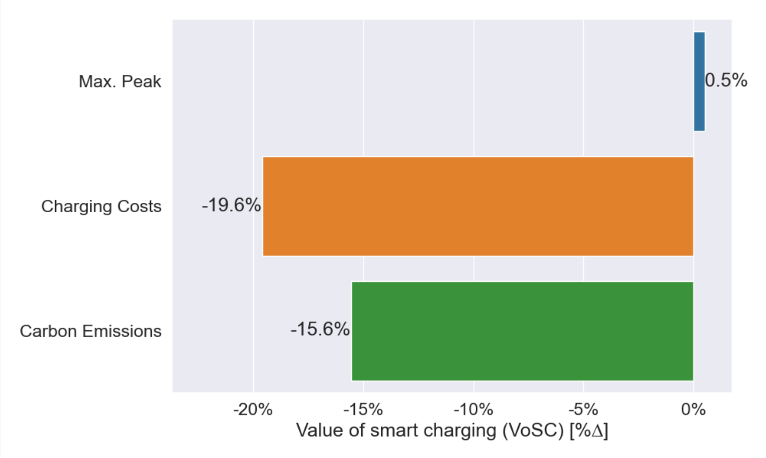


Fig. 9 | Resulting electricity demand profile from EV charging. Note: Graph shows results for model type CCM for EV rate = 50%, exemplarily for 01 Feb, 2023.

Fig. 10 | Relative performance of CCM. Note: Bar charts capture change in output cf. to UCC (VoSC) [%Δ].

CEM reduces CO_2 by -19.3% measured against UCC [%Δ] | EV rate = 50%

Analysis: Scenario analysis for varying EV adoption rates

Charging emission minimisation (CEM) | EV adoption rate = **50%**

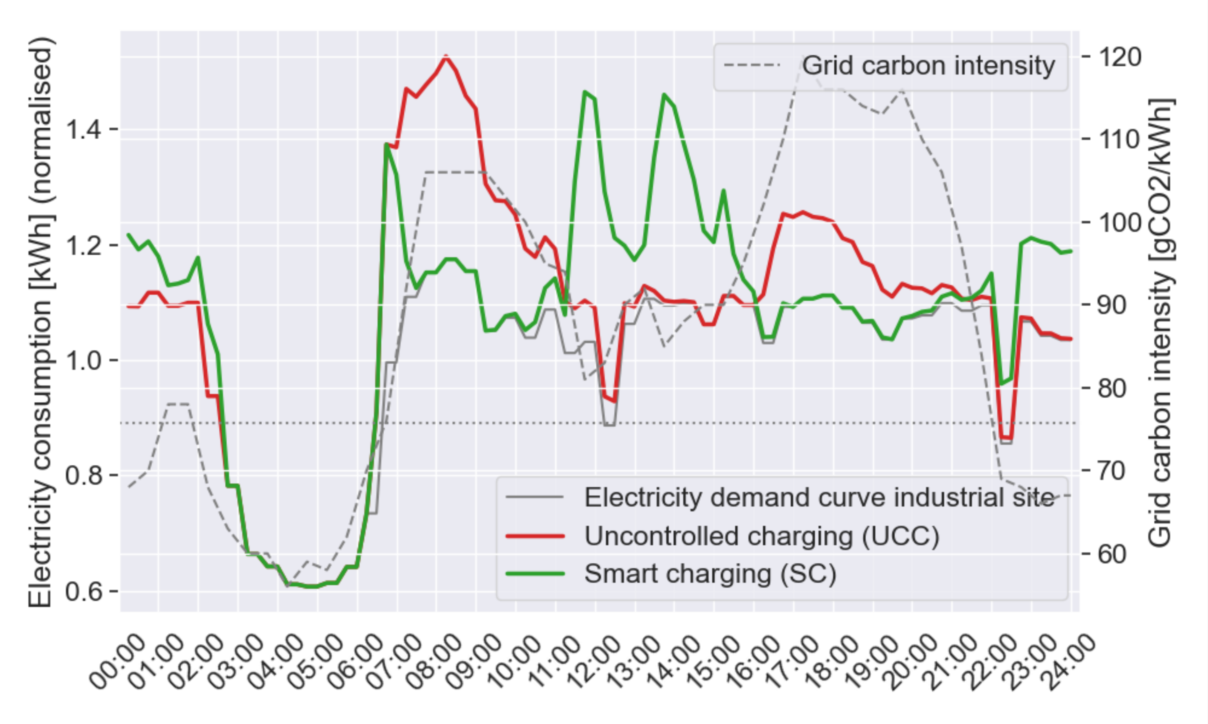
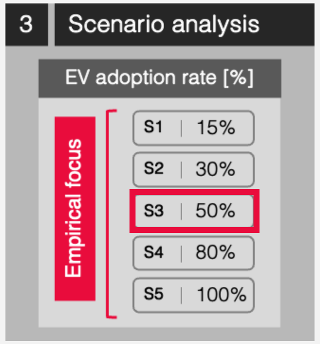


Fig. 11 | Resulting electricity demand profile from EV charging. Note: Graph shows results for model type CEM for EV rate = 50%, exemplarily for 01 Feb, 2023.



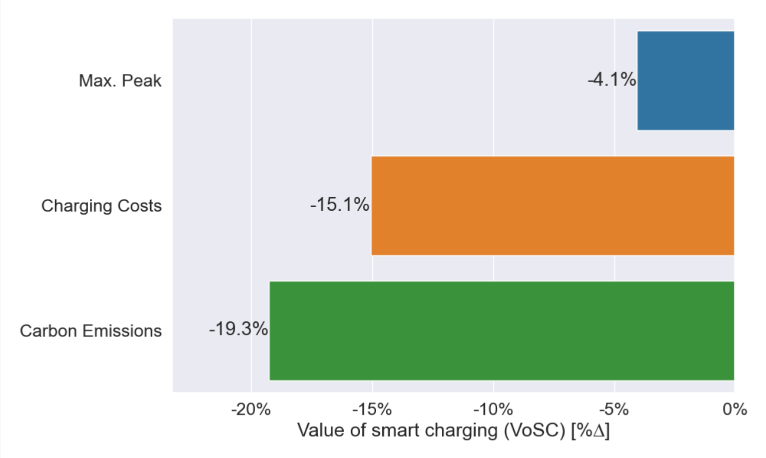
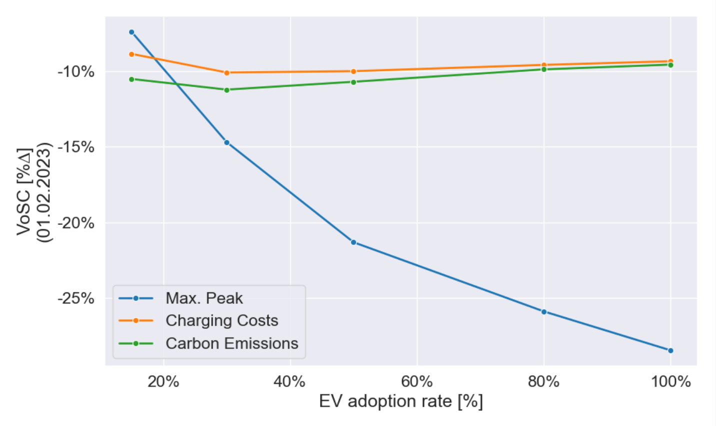


Fig. 12 | Relative performance of CEM. Note: Bar charts capture change in output cf. to UCC (VoSC) [%Δ].

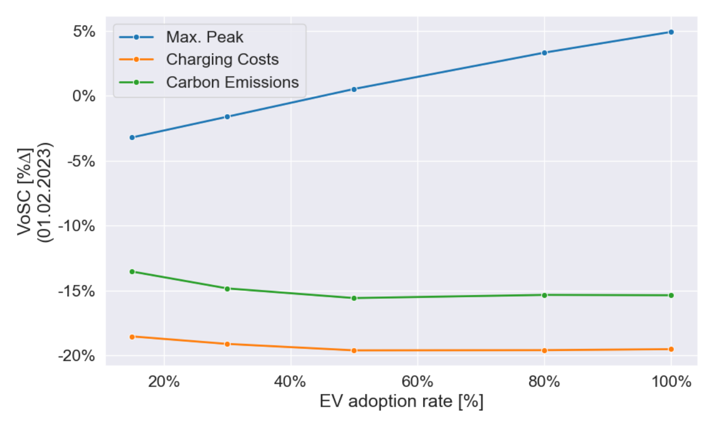
Results reveal trade-off space betw. max. peak, charging costs & CO_2 emissions

Analysis: Scenario analysis for varying EV adoption rates (summary)

Peak minimisation & valley filling (PM-VF):



Charging cost minimisation (CCM):



Carbon emission minimisation (CEM):

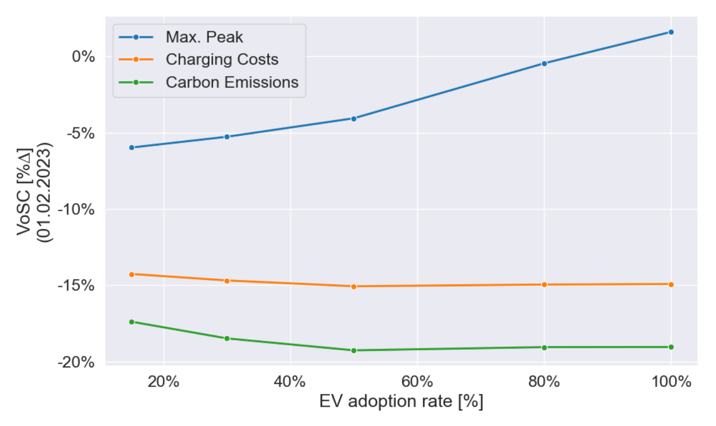
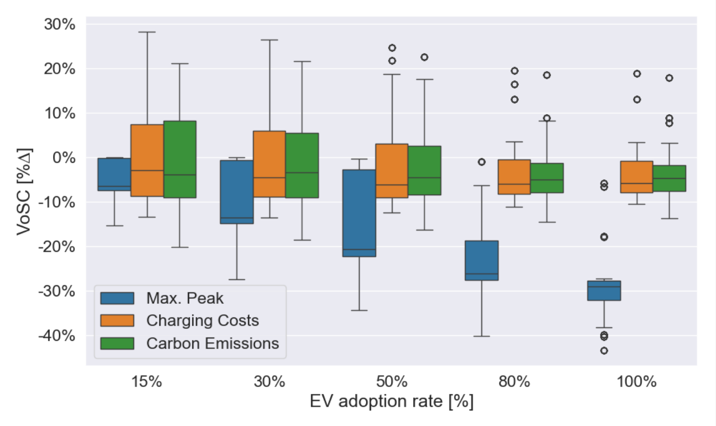


Fig. 13 | Visual summary of key metrics max. peak, charging costs and carbon emissions differentiated by model type | EV rates [S1-5: 15–100%].
Note: Quantitative assessment of output changes (VoSC) [%Δ], measured against UCC, for PM-VF (l.), CCM (m.), and CEM (r.), exemplarily for Feb. 2023.

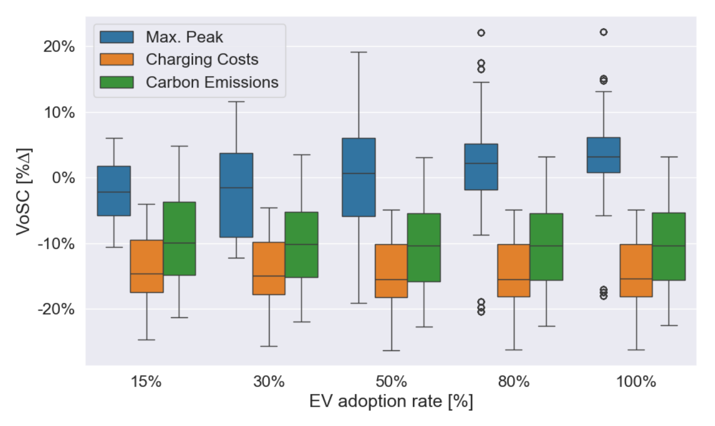
Deployed models yield robust outcomes to time-variant parameters

Analysis: Temporal sensitivity analysis (28 single-day model runs for Feb 2023)

Peak minimisation & valley filling (PM-VF):



Charging cost minimisation (CCM):



Carbon emission minimisation (CEM):

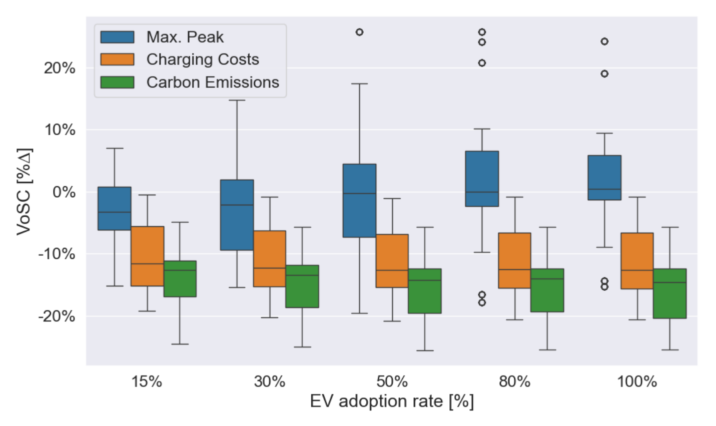


Fig. 14 | Overview of model results, grouped by model type, for increasing EV rates [S1–5: 15–100%], computed over a 4-week long time frame [Feb 2023]. Note: Statistical analysis of 28 single-day model results, capturing output changes (VoSC, [%Δ]), measured against UCC, for each model type (a) PM-VF, (b) CCM and (c) CEM by plotting the variability of the key output metrics (i) max. peak (blue), (ii) charging costs (orange) and (iii) carbon emissions (green) using boxplots as visualisation tool. Note: Lower %Δ numbers (y-axis) refer to higher saving potentials

Reflections and outlook

Review: Main findings, limitations & further research

Summary of main findings

- **Optimal solution space**
  - Optimising for respective model objective (PM-VF, CCM, CEM) yields lowest overall objective value across model types
- **Trade-offs between key metrics**:
  - In turn, trade-offs between objectives for achieving key metrics (max. peak, charging costs, carbon emissions) are indispensable
- **Robustness of results**:
  - Temporal sensitivity analysis reveals robustness of results

Model limitations

- **Model implementation**
  - Model assumes perfect foresight of EV availability and parameter inputs, which can be justified given a workplace setting
- **Technical limitations**
  - Model does not incorporate physical charging power constraint, for SoC > 80% to reflect change from constant current to constant voltage.
- **Behavioural travel assumptions**
  - Further model parametrisation to reflect travel patterns of commuters

Further research

- **Integration of Vehicle-to-Building**
  - Model expansion to include bidirectional charging capabilities by including negative range of decision variable x_{mt} to allow for discharging
- **Access to charging infrastructure**
  - Advancing model to cover sensitivity analysis of employees' access to charging infrastructure and the implication on firms' power demand
- **Computation of cost-benefit analysis**
  - Integrating net-present value (NPV) analysis to facilitate decision making

Full paper is available in npj sustainability mobility and transport

Publication reference

npj | sustainable mobility and transport Article

https://doi.org/10.1038/s44333-025-00032-w

Firm level optimisation strategies for sustainable and cost effective electric vehicle workplace charging

Check for updates

Marcel Seger[1], Christian Brand[1,2], Christoph Clement[3], James Dixon[4] & Charlie Wilson[1,5]

Expanding electric vehicle (EV) charging infrastructure is essential for transitioning to an electrified mobility system. With rising EV adoption rates, firms face increasing regulatory pressure to build up workplace charging facilities for their employees. However, the impact of EV charging loads on businesses' specific electricity consumption profiles remains largely unknown. Our study addresses this challenge by presenting a mathematical optimisation model, available via an open-source web application, that empowers business executives to manage energy consumption effectively, enabling them to assess peak loads, charging costs and carbon emissions specific to their power profiles and employee needs. Using real-world data from a global car manufacturer in South East England, UK, we demonstrate that smart charging strategies can reduce peak loads by 28% and decrease charging costs and emissions by 9% compared to convenience charging. Our methodology is widely applicable across industries and geographies, offering data-driven insights for planning EV workplace charging infrastructure.

Fig. 15 | Screenshot of published study in *npj sustainable mobility and transport*

Full publication available here:
https://www.nature.com/articles/s44333-025-00032-w

Open source web app allows firms to compute bespoke scenario analyses

Demonstration of open-source web application for firm-specific decision support

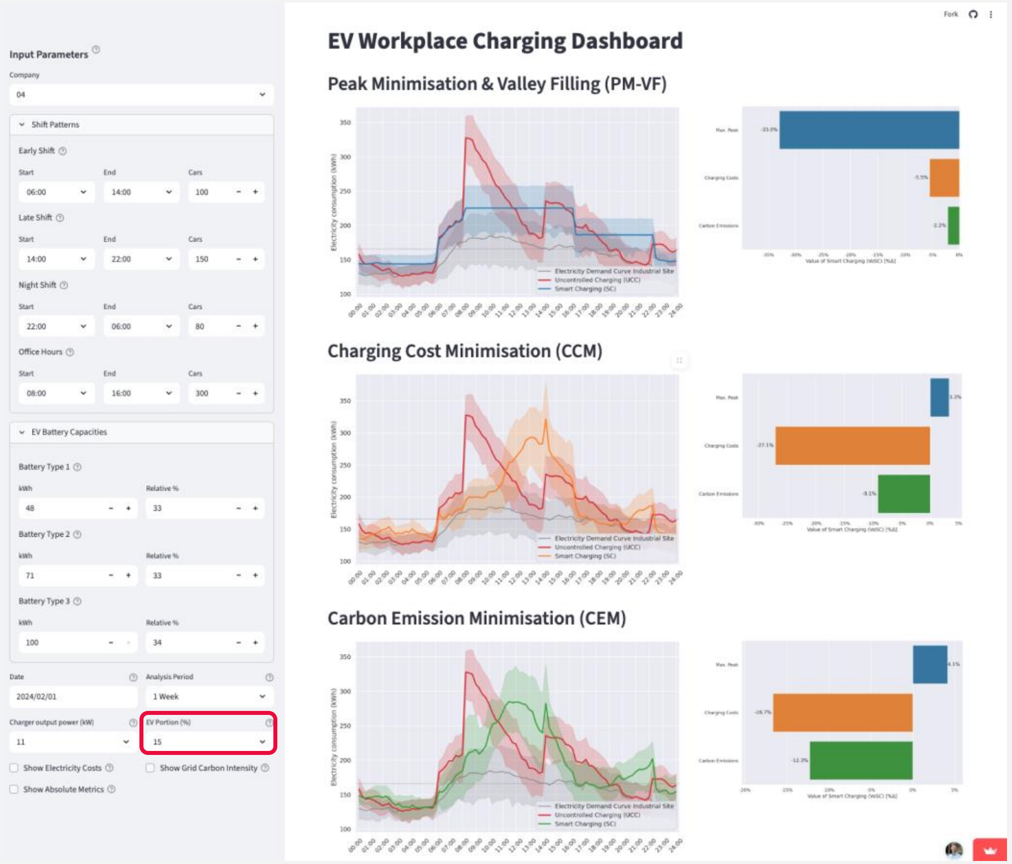


Fig. 16 | Screenshot of interactive web application built in Streamlit [12].

Programming languages & tools

Data pipeline — python

Model formulation — PYOMO

Optimisation — GUROBI OPTIMIZATION

Visualisation — Streamlit

GitHub

Available open-source

Live Demo

Add-on: Evaluation of web application using Design Science Research (Paper 2)

Semi-structured interviews w/ business executives

Summary

- We build a **digital artefact** using Streamlit to assists workplace decision makers to more accurately predict the impact of EV workplace charging
- We developed, demonstrated, and evaluated the prototype through **three rigour design & evaluation cycles**, collecting qual. + quant. data from eight case study partners (medium- to large-sized firms in Germany)
- With a total SUS score of 82%, we deemed the prototype as acceptable.
- Going forward, we will open-source the web application to the public.

Contribution to theory

- Decision type: '**Decision support system**'
  - Guiding workplace decision makers with building and operating EV workplace charging infrastructure
- Core contribution through '**exaptation**', i.e. repurposing existing optimisation algorithms for dedicated applications in workplace charging decision contexts

Selected quotes: perceived usefulness

*"I actually find this **really useful**. Because I think a lot of companies still have no real idea of the challenges that come with electrification in general, and with reducing CO_2 emissions. And just getting an overview of what's basically out there and how things can be optimised is, I think, a huge help for any company."*

Case study ID: **4a** [Pharma]

*"But it's just nice to be able to argue using valid data, and **I think data will become increasingly relevant** in the future anyway. And of course, all this information is something I'd otherwise have to gather myself with a lot of effort. Having it all from a single source—just entering my own values, which I already have—**that's a great solution**."*

Case study ID: **2a** [Office supply manufacturer]

Q&A

*…and a special ‘**thank you**’ to:*
*my collaborators **Dr Christoph Clement** and*
***Dr James Dixon** and my supervisors*
Prof Dr Charlie Wilson** and **Prof Dr Christian Brand

Thank you for your attention!

Any Questions?

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Please **reach out** to discuss potential further collaboration

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Electricity cost curve based on Octopus Agile Tariff for February, 2023

Model Structure | Step 1: Time-series input data (1 / 2)

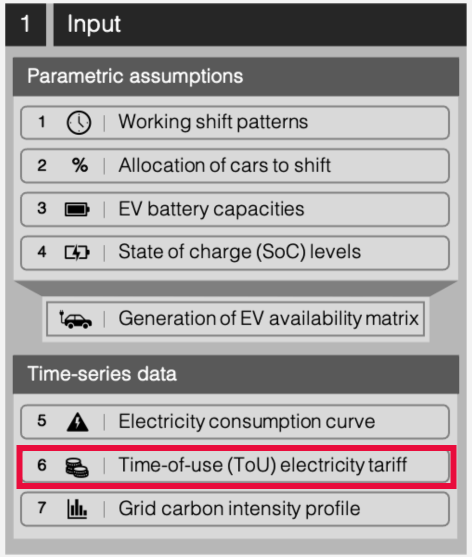
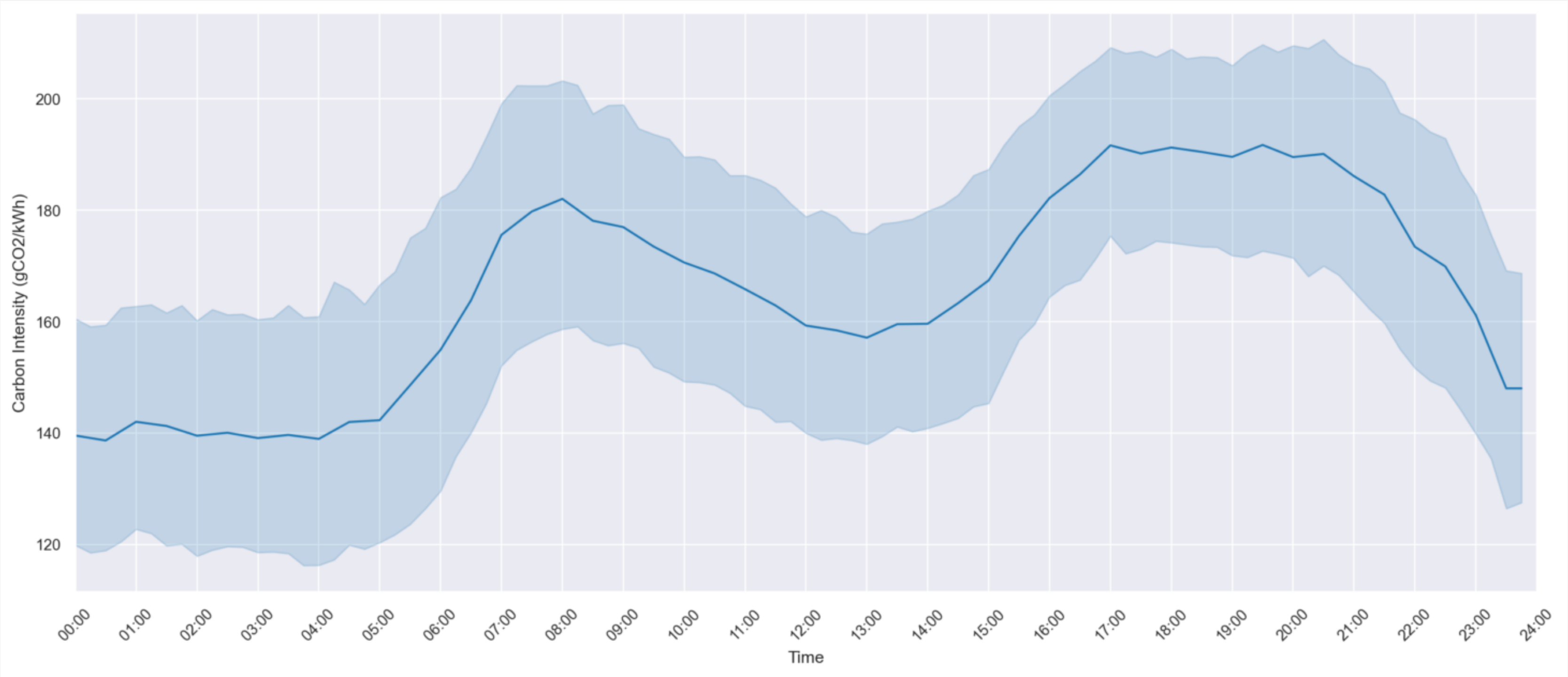


Fig. A1 | Time-series data of electricity costs in Feb 2023. Note: Graph depicts evolution of half-hourly electricity prices [p/kWh], taken from Octopus Agile Tariff (Nov 2022 v1) [13]. Shaded area represents 95%-confidence interval.

Grid carbon intensity profile in South-East England for February, 2023

Model Structure | Step 1: Time-series input data (2 / 2)



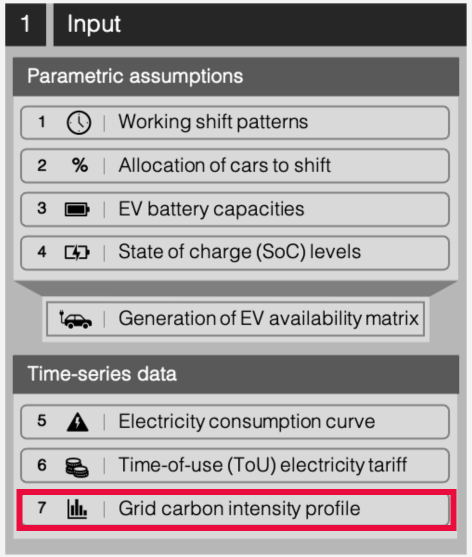


Fig. A2 | Time-series data of grid carbon intensity in Feb 2023. Note: Graph depicts evolution of half-hourly grid carbon intensity [gCO_2/kWh], taken from nationalgridESO [14]. Shaded area represents 95%- confidence interval.

PM-VF reduces peaks by -7.4% measured against UCC [%Δ] | EV rate = 15%

Analysis: Scenario analysis for varying EV adoption rates

Peak minimisation & valley filling (PM-VF) | EV adoption rate = **15%**

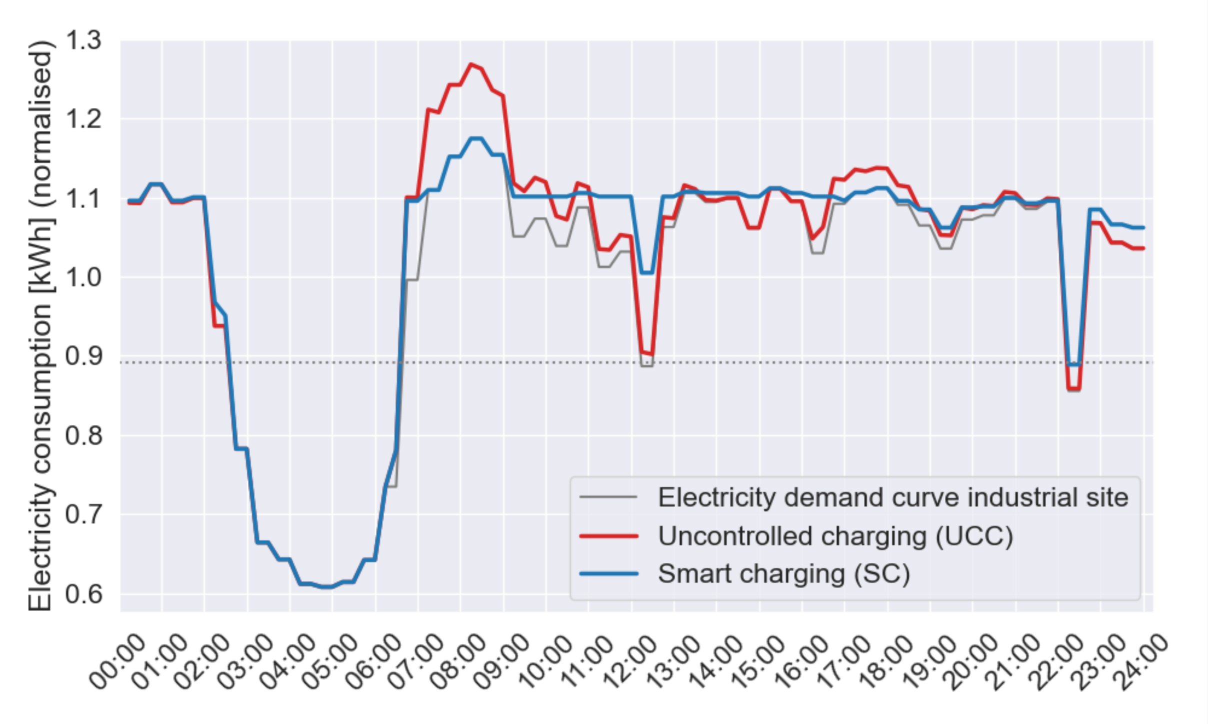
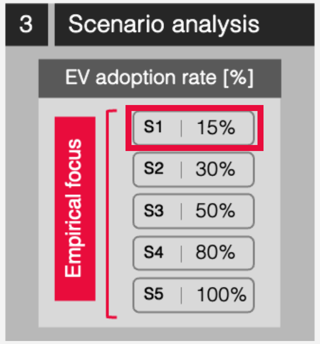


Fig. A3 | Resulting electricity demand profile from EV charging. Note: Graph shows results for model type PM-VF for EV rate = 15%, exemplarily for 01 Feb, 2023.



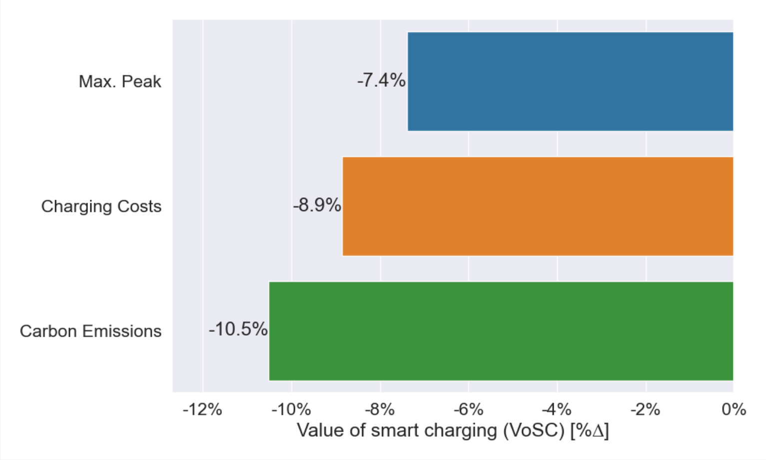


Fig. A4 | Relative performance of PM-VF. Note: Bar charts capture change in output cf. to UCC (VoSC) [%Δ].

PM-VF reduces peaks by -21.3% measured against UCC [%Δ] | EV rate = 50%

Analysis: Scenario analysis for varying EV adoption rates

Peak minimisation & valley filling (PM-VF) | EV adoption rate = **50%**

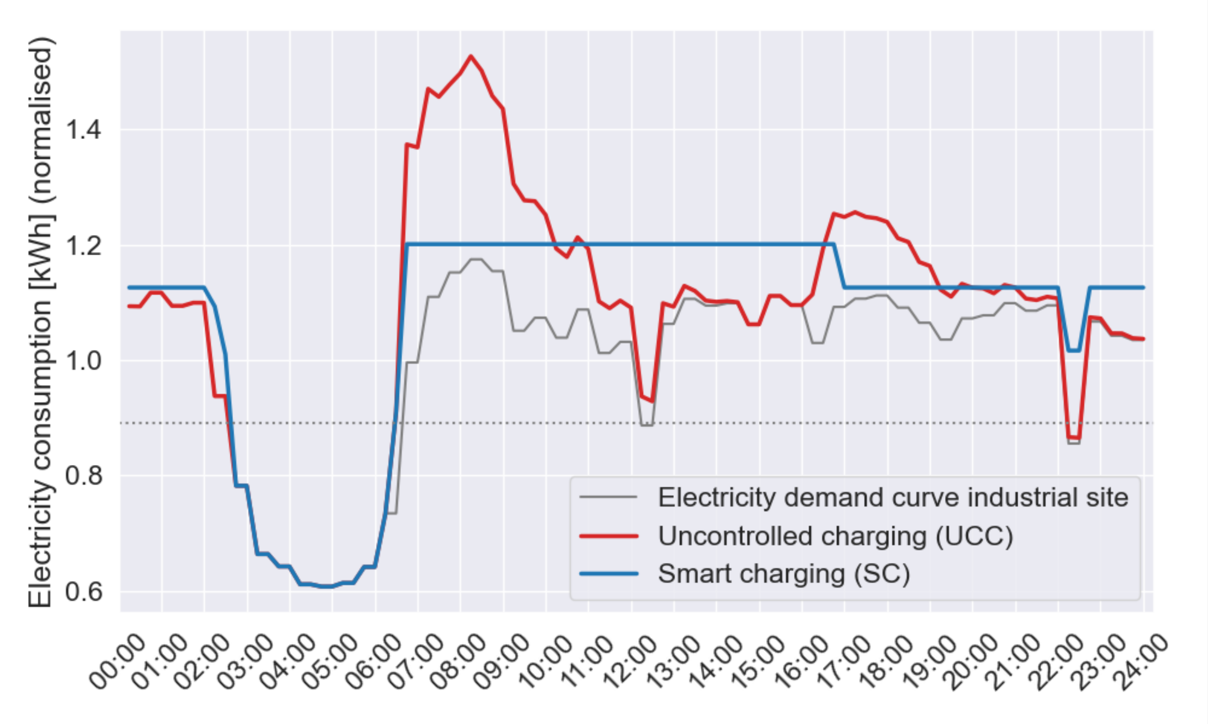


Fig. A5 | Resulting electricity demand profile from EV charging. Note: Graph shows results for model type PM-VF for EV rate = 50%, exemplarily for 01 Feb, 2023.

3	Scenario analysis
EV adoption rate [%]	
Empirical focus	S1 | 15%
	S2 | 30%
	S3 | 50%
	S4 | 80%
	S5 | 100%

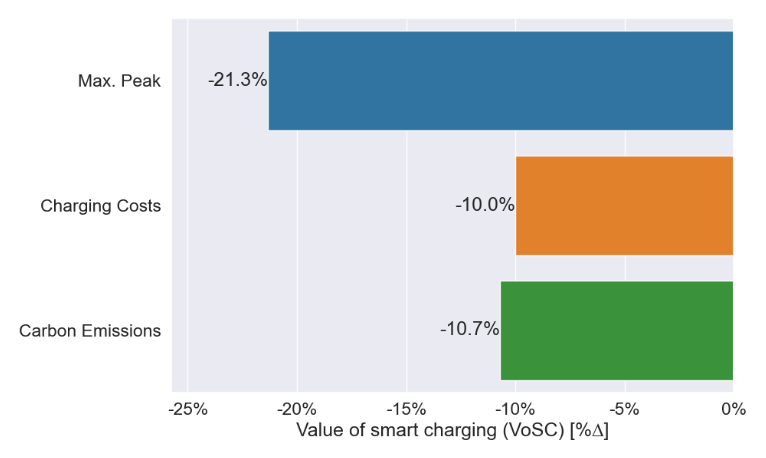


Fig. A6 | Relative performance of PM-VF. Note: Bar charts capture change in output cf. to UCC (VoSC) [%Δ].

PM-VF reduces peaks by -28.5% measured against UCC [%Δ] | EV rate = 100%

Analysis: Scenario analysis for varying EV adoption rates

Peak minimisation & valley filling (PM-VF) | EV adoption rate = **100%**

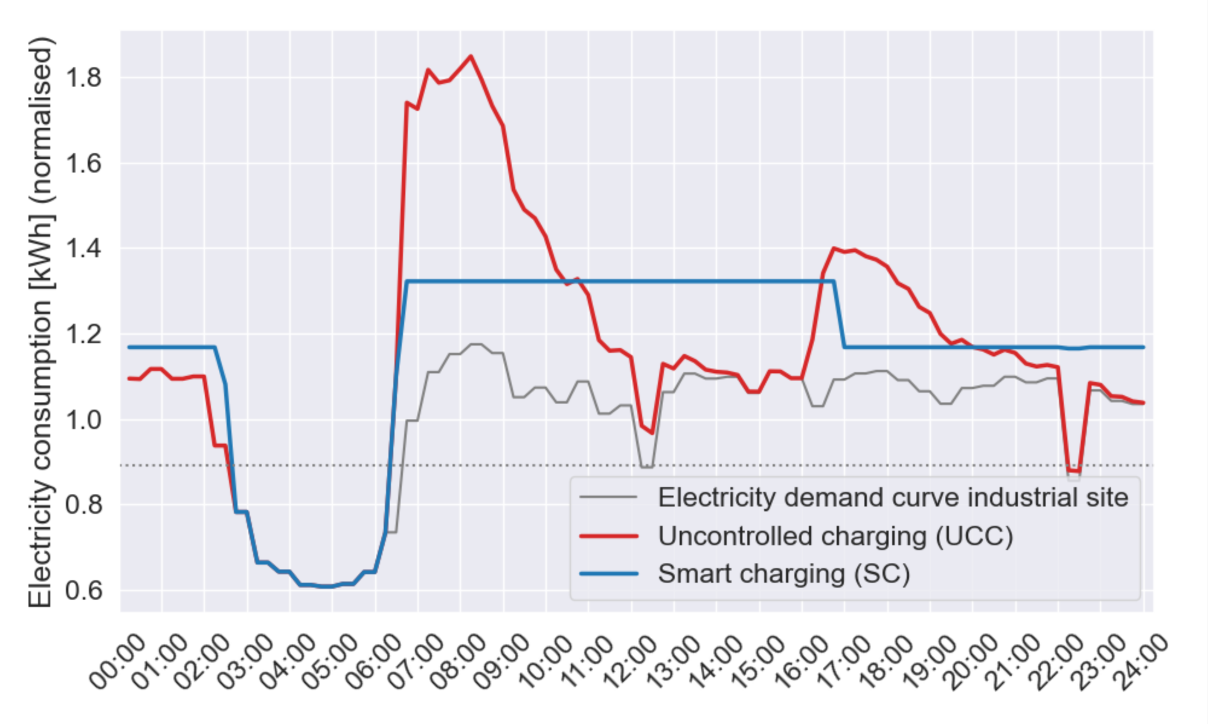
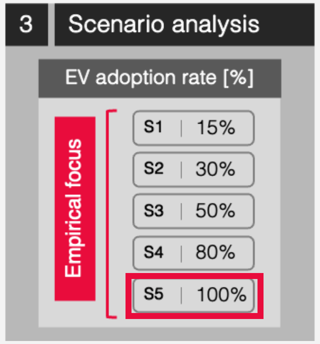


Fig. A7 | Resulting electricity demand profile from EV charging. Note: Graph shows results for model type PM-VF for EV rate = 100%, exemplarily for 01 Feb, 2023.



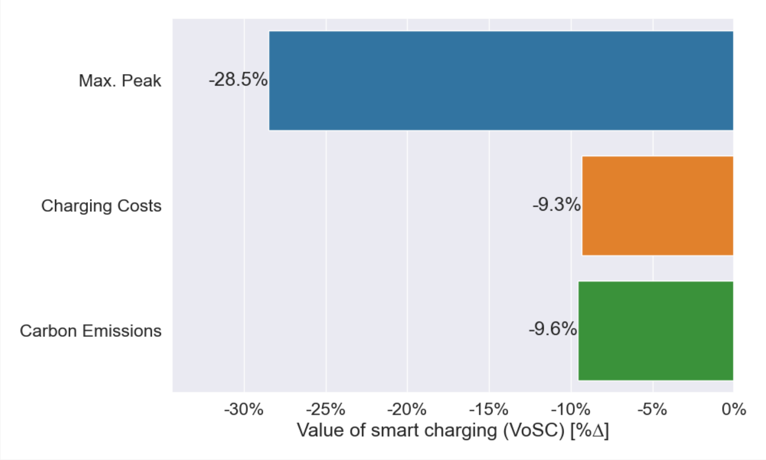


Fig. A8 | Relative performance of PM-VF. Note: Bar charts capture change in output cf. to UCC (VoSC) [%Δ].

CCM reduces costs by -18.5% measured against UCC [%Δ] | EV rate = 15%

Analysis: Scenario analysis for varying EV adoption rates

Charging cost minimisation (CCM) | EV adoption rate = **15%**

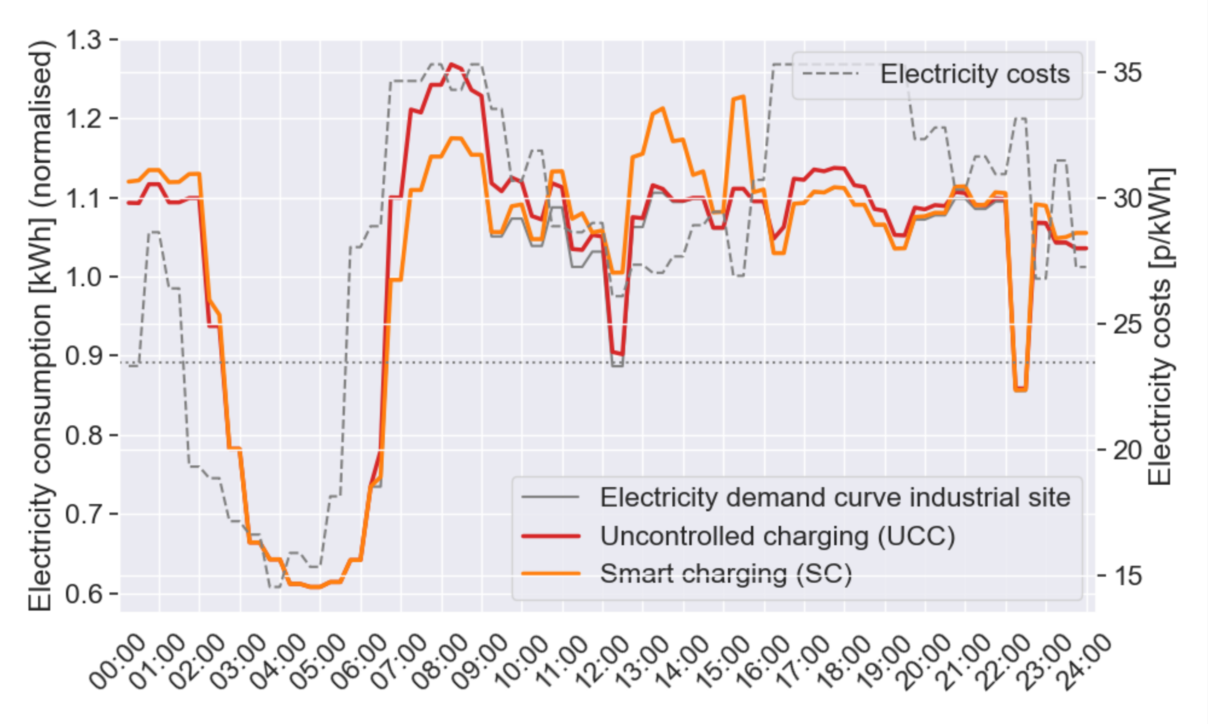
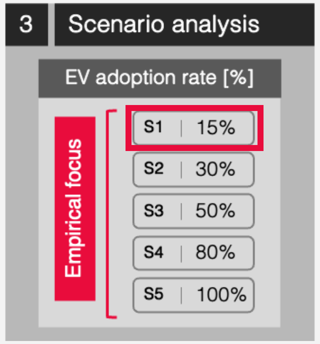


Fig. A9 | Resulting electricity demand profile from EV charging. Note: Graph shows results for model type CCM for EV rate = 15%, exemplarily for 01 Feb, 2023.



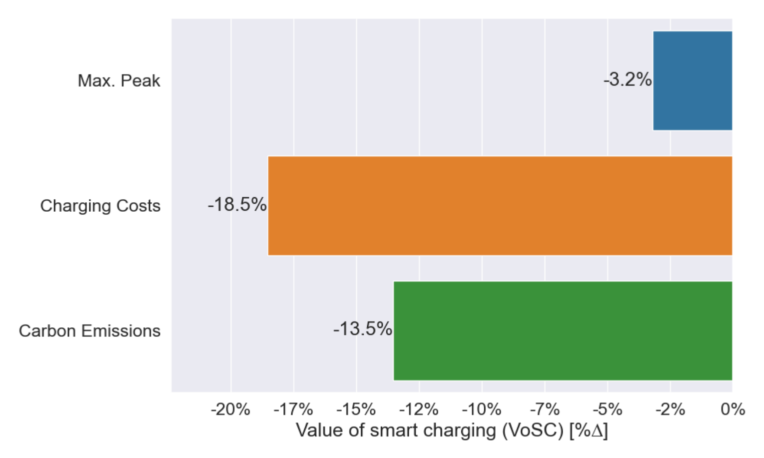


Fig. A10 | Relative performance of PM-VF. Note: Bar charts capture change in output cf. to UCC (VoSC) [%Δ].

CCM reduces costs by -19.6% measured against UCC [%Δ] | EV rate = 50%

Analysis: Scenario analysis for varying EV adoption rates

Charging cost minimisation (CCM) | EV adoption rate = 50%

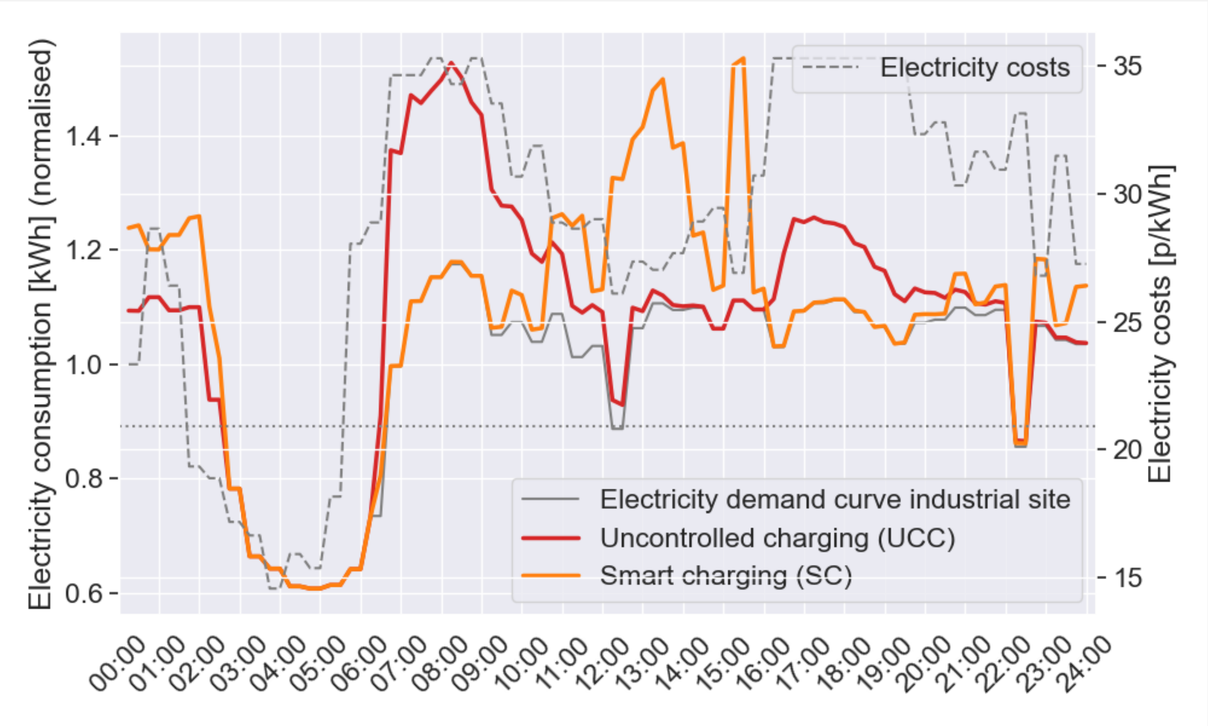
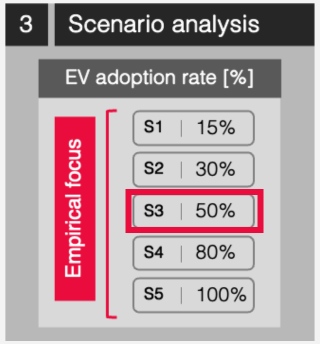


Fig. A11 | Resulting electricity demand profile from EV charging. Note: Graph shows results for model type CCM for EV rate = 50%, exemplarily for 01 Feb, 2023.



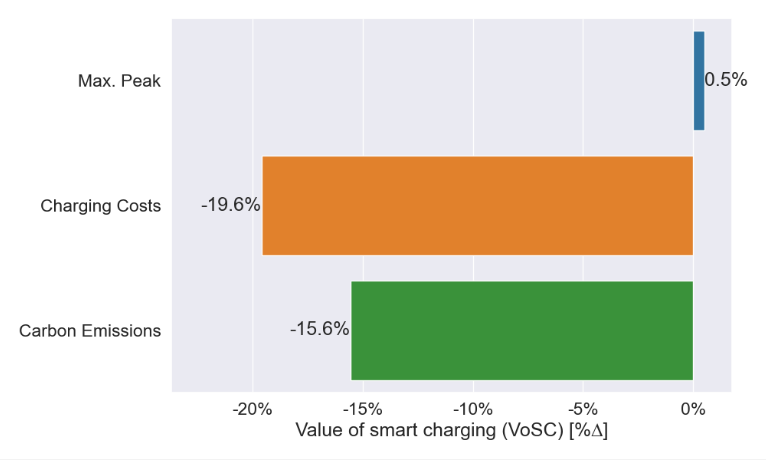


Fig. A12 | Relative performance of PM-VF. Note: Bar charts capture change in output cf. to UCC (VoSC) [%Δ].

CCM reduces costs by -19.5% measured against UCC [%Δ] | EV rate = 100%

Analysis: Scenario analysis for varying EV adoption rates

Charging cost minimisation (CCM) | EV adoption rate = **100%**

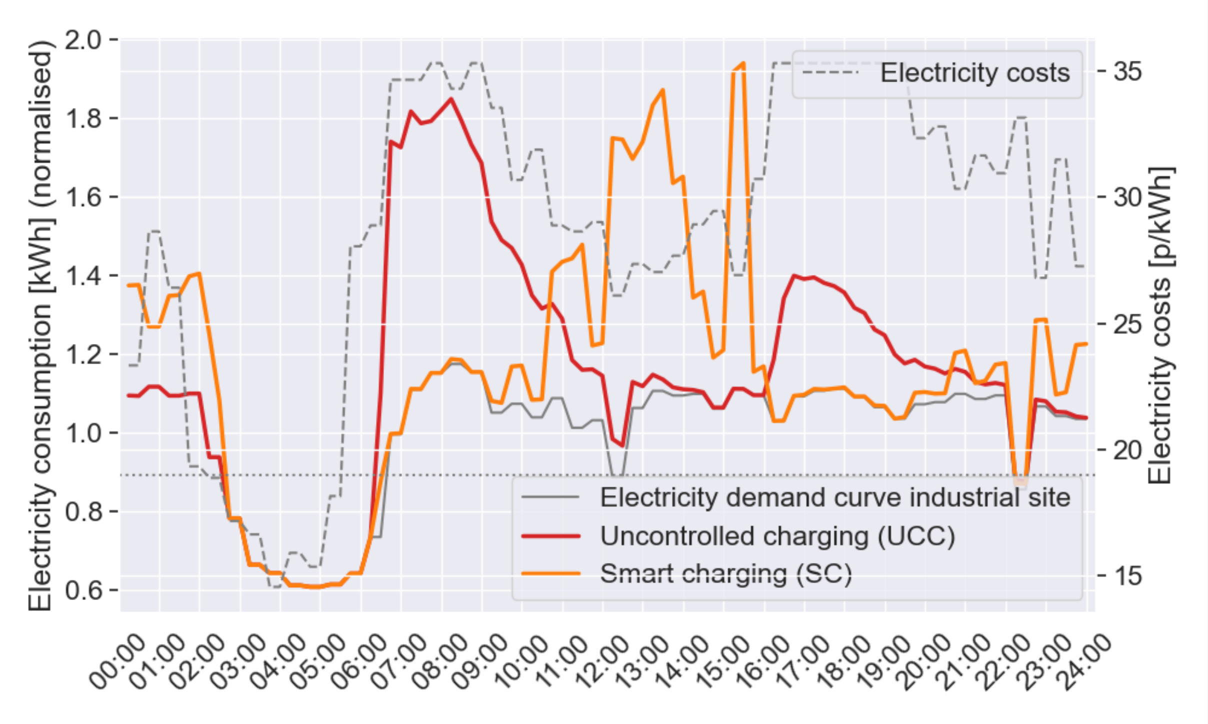
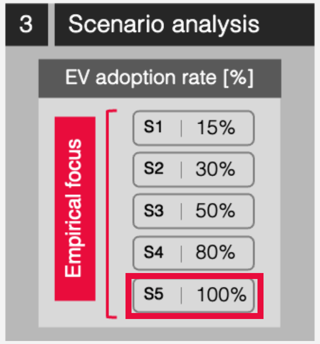


Fig. A13 | Resulting electricity demand profile from EV charging. Note: Graph shows results for model type CCM for EV rate = 100%, exemplarily for 01 Feb, 2023.



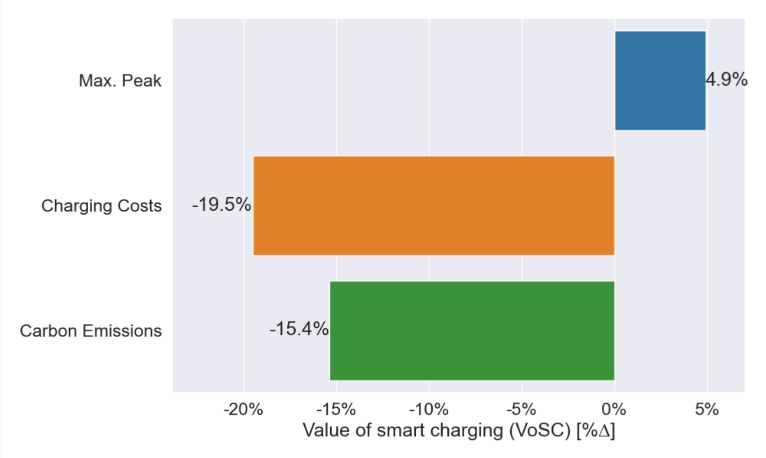


Fig. A14 | Relative performance of PM-VF. Note: Bar charts capture change in output cf. to UCC (VoSC) [%Δ].

CEM reduces CO_2 by -17.4% measured against UCC [%Δ] | EV rate = 15%

Analysis: Scenario analysis for varying EV adoption rates

Charging emission minimisation (CEM) | EV adoption rate = 15%

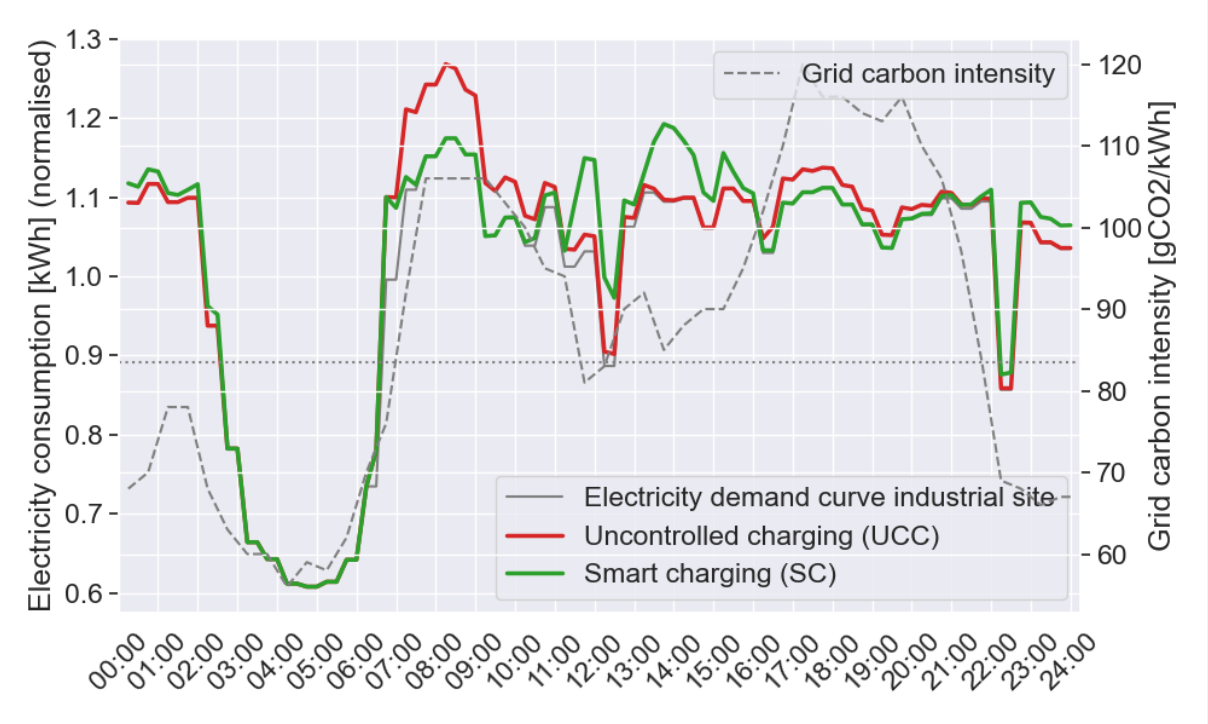
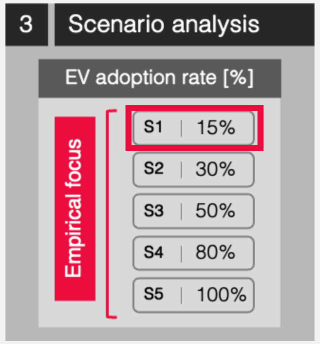


Fig. A15 | Resulting electricity demand profile from EV charging. Note: Graph shows results for model type CEM for EV rate = 15%, exemplarily for 01 Feb, 2023.



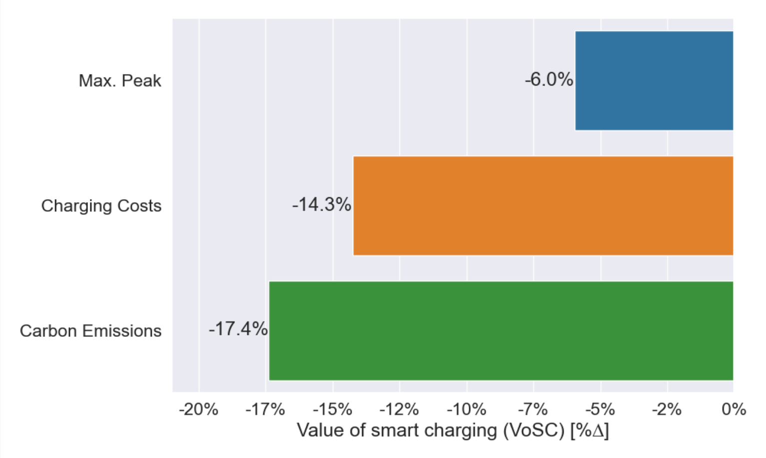


Fig. A16 | Relative performance of PM-VF. Note: Bar charts capture change in output cf. to UCC (VoSC) [%Δ].

CEM reduces CO_2 by -19.3% measured against UCC [%Δ] | EV rate = 50%

Analysis: Scenario analysis for varying EV adoption rates

Charging emission minimisation (CEM) | EV adoption rate = **50%**

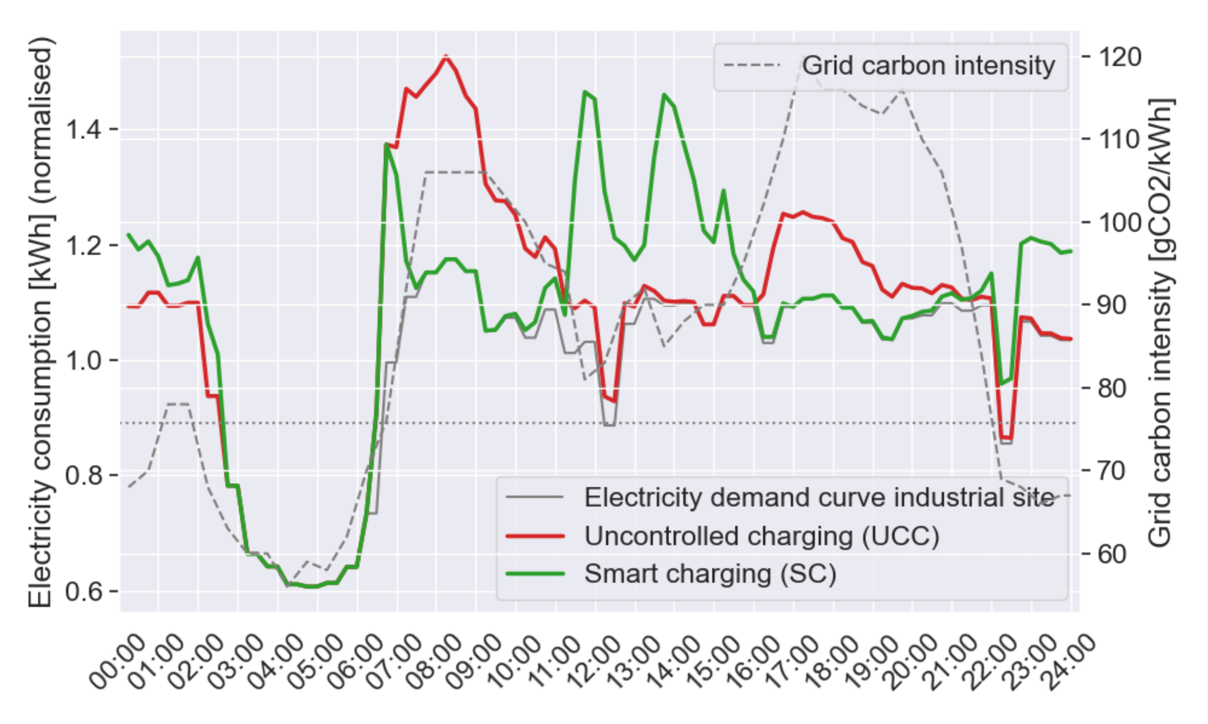
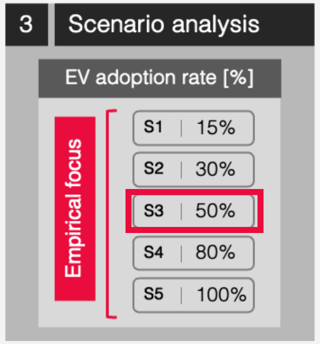


Fig. A17 | Resulting electricity demand profile from EV charging. Note: Graph shows results for model type CEM for EV rate = 50%, exemplarily for 01 Feb, 2023.



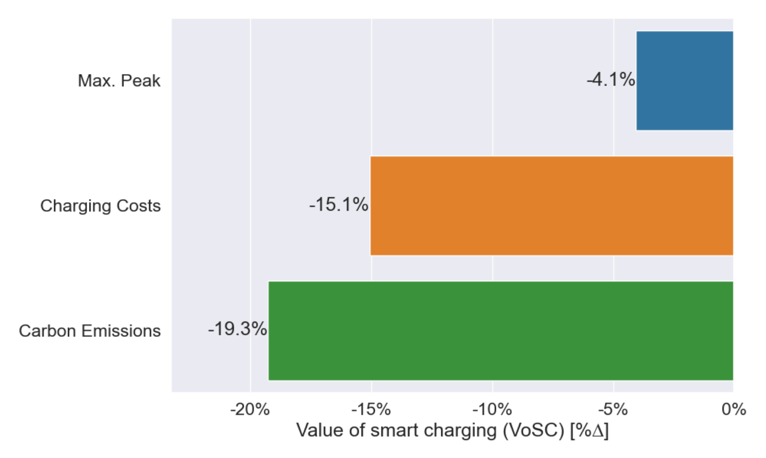


Fig. A18 | Relative performance of PM-VF. Note: Bar charts capture change in output cf. to UCC (VoSC) [%Δ].

CEM reduces CO_2 by -19.0% measured against UCC [%Δ] | EV rate = 100%

Analysis: Scenario analysis for varying EV adoption rates

Charging emission minimisation (CEM) | EV adoption rate = **100%**

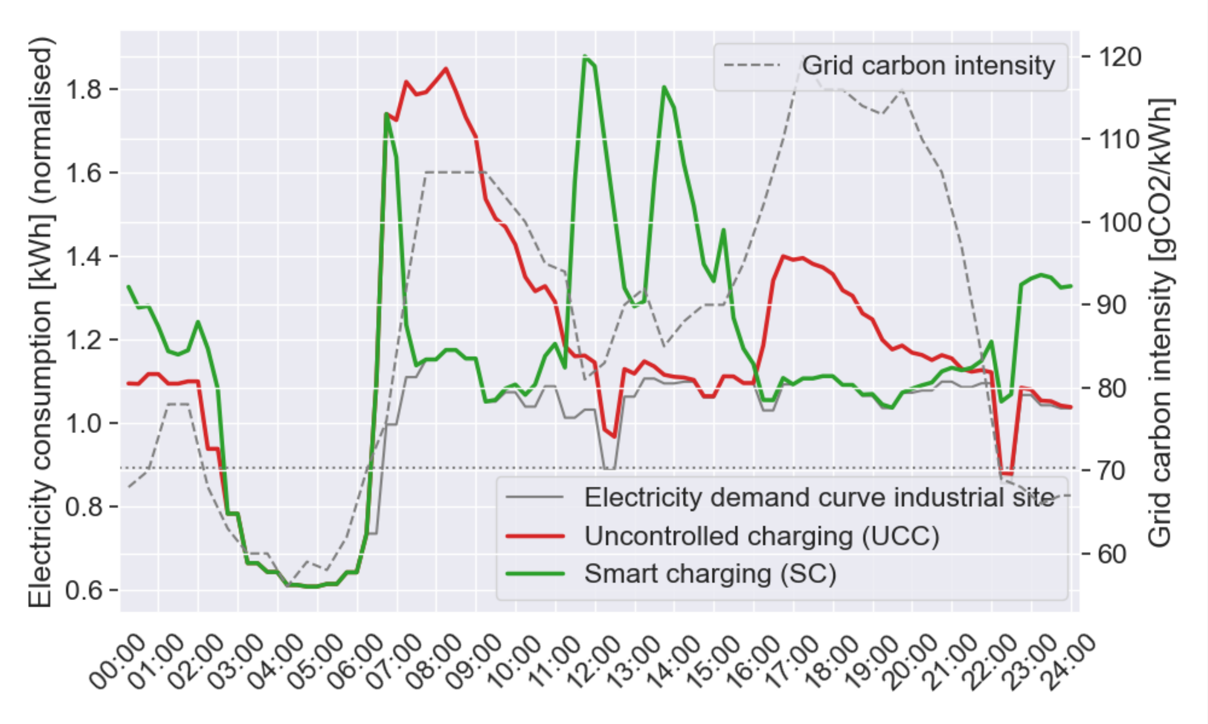
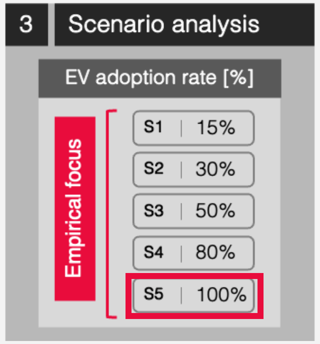


Fig. A19 | Resulting electricity demand profile from EV charging. Note: Graph shows results for model type CEM for EV rate = 100%, exemplarily for 01 Feb, 2023.



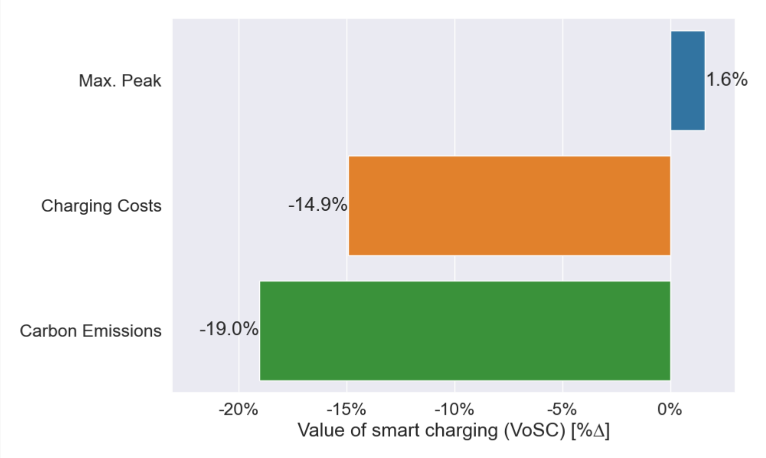


Fig. A20 | Relative performance of PM-VF. Note: Bar charts capture change in output cf. to UCC (VoSC) [%Δ].

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