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Uncertain electric vehicle charging flexibility, its value on spot markets, and the impact of user behaviour

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HIGHLIGHTS

- Integration of behavioural factors while estimating the user charging preferences.
- Focus on two charging preferences: minimum state of charge and charging frequency.
- Flexibility model to quantify the flexibility provided by electric vehicles.
- Robust optimisation model facilitating energy providers to trade in spot markets.
- Flexible charging offers high economic value with minimal user inconvenience.

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ABSTRACT

Simultaneous charging of electric vehicles (EVs) increases peak demand, potentially causing higher electricity prices and increased procurement costs for charging, making EVs less economically appealing. Smart charging addresses this challenge by utilising EVs as flexible assets, adjusting their charging behaviour in response to both power system conditions and user requirements. In our paper, we take the perspective of an energy provider using smart charging algorithms to reduce their electricity procurement costs (EPC) by charging the EVs when the electricity prices are lower. However, EV usage uncertainties introduce variability in the flexibility EVs provide and subsequently impact the energy providers' EPC when trading in electricity markets. Our paper considers uncertainties arising due to variable driving patterns and charging preferences. Within the charging preferences, we specifically focus on two charging preferences such as a minimum state of charge (SOC^{min}) requirement – the percentage of the battery up to which EV needs to be charged immediately at full power when connected to the charging point; and the frequency of EV connection to the charging point – how often EV users connect their EV to the charging point. We develop a flexibility model that quantifies the flexibility in terms of energy and power as a function of time. To calculate the energy provider's EPC, we develop a scenario-based robust optimisation model, minimising the energy provider's EPC while trading in German day-ahead and intraday markets. As expected, an increase in SOC^{min} requirements and a decrease in frequency of EV connections results in reduced EV flexibility and subsequently increases the EPC. However, our cost sensitivity analysis reveals that even with an 80 % SOC^{min}, EPC can be reduced by up to 33.5 % and 36.9 % for the years 2022 and 2023, respectively, compared to fully uncontrolled charging. When EVs offer full flexibility (0 % SOC^{min}), the cost reduction is only slightly higher, at around 43.6 % and 49.6 % for the years 2022 and 2023, respectively. Flexible EV charging, even with low flexibility, thus possesses high economic value, allowing energy providers to achieve substantial monetary gains with minimal impact on user convenience.

1. Introduction

Electric vehicles (EVs) are a cornerstone of transport decarbonisation as they aid in reducing greenhouse gas emissions, particularly when charged with renewable energy sources (RES). The positive impact on the environment and targeted political measures have led to a significant rise in EV market penetration in recent years. This trend is expected to gain even more traction in forthcoming years [1]. However,

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Nomenclature

Indices/sets

t	Index of time step
T	Set of time steps
w	Index of electric vehicle uncertain scenarios
W	Set of electric vehicle uncertain scenarios

Parameters

$E_{t,w}^{\min,agg}$	Aggregated minimum energy flexibility metric at time t for scenario w, in MWh
$E_{t,w}^{\max,agg}$	Aggregated maximum energy flexibility metric at time t for scenario w, in MWh
$P_{t,w}^{\min,agg}$	Aggregated minimum power flexibility metric at time t for scenario w, in MW
$P_{t,w}^{\max,agg}$	Aggregated maximum power flexibility metric at time t for scenario w, in MW
$E_{t,w}^{vehicles,dis}$	Cumulative energy transferred to EVs disconnected from charging point at time t for scenario w, in MWh
C_t^{DA}	Day-ahead market price at time t, in EUR/MWh
C_t^{ID}	Intraday market price at time t, in EUR/MWh
Δt	Length of time step, in hour

Variables

β	Auxiliary decision variable to capture worst scenario in intraday market
P_t^{DA}	Power procured from day-ahead market at time t, in MW
$P_{t,w}^{ID}$	Power procured from intraday market at time t, in MW
$P_{t,w}^{agg}$	Aggregated charging power procured for the electric vehicle fleet at time t for scenario w, in MW
$E_{t,w}^{agg}$	Cumulative energy transferred to the electric vehicle fleet at time t for scenario w, in MWh

the simultaneous charging of multiple EVs raises concerns, as it contributes to higher peak power demand, leading to increased wholesale prices [2,3]. These factors can increase electricity procurement costs (EPC), potentially affecting users' bills and making the transition to EVs less economically appealing.

Smart charging addresses the challenges of simultaneous charging by utilising EVs as flexible assets, adjusting their charging behaviour in response to both power system conditions and user mobility requirements [4,5]. In this paper, we take the perspective of the energy provider (such as aggregators and energy suppliers), who uses smart charging algorithms to control the charging behaviour of EVs. Typically, electricity market prices are lower during off-peak periods. Smart charging algorithms leverage the flexibility of EVs by scheduling their charging during these periods of low electricity prices, thereby reducing EPC for energy providers and possibly overall peak demand [6]. These algorithms can employ linear optimisation models, assuming deterministic EV usage behaviour, with the objective of minimising EPC while trading in electricity markets such as day-ahead markets [7,8].

EV usage is subject to several uncertainties due to diverse driving patterns and charging preferences. Uncertainties stem from EV user trip distances, parking durations, arrival and departure times, and energy requirements [9]. Being inherent in EV usage, uncertainties introduce variability in the flexibility offered by EVs, posing challenges for energy providers in predicting and managing the EV schedules [10,11]. Energy providers can employ stochastic or robust optimisation models to address the challenges associated with EV uncertainties. Stochastic optimisation models represent uncertainties using probability distribution functions (PDFs), allowing energy providers to account for a spectrum of scenarios and minimize their average EPC while trading in electricity markets [12]. Conversely, robust optimisation models characterize uncertainties using an uncertainty set or range of scenarios to minimize EPC while preparing for worst-case scenarios [13,14]. However, while modelling the uncertainties due to charging preferences, authors often assume that users would provide full flexibility - meaning no minimum state of charge (SOC^{min}) requirement, and that users always connect their EVs to the charging point when the vehicle is parked [10–14].

However, EV users could be reluctant to provide flexibility for smart charging due to behavioural aspects such as range anxiety and loss of control [15–17]. As a countermeasure, authors have introduced the concept of the minimum state of charge (SOC^{min}) [18–20]. SOC^{min} represents the percentage of the battery capacity up to which an EV is charged at full power immediately upon connection to the charging point. SOC^{min} provides users with a sense of security, as it ensures that their required battery capacity will be available to them as soon as possible. The SOC^{min} values that EV users choose could vary, introducing uncertainty in energy requirements.

Moreover, users might not always connect their EVs to the charging point whenever it is parked, especially in the context of residential charging, which is the primary focus of our paper [21]. The frequency of EV connections can vary due to various factors. Users with higher range anxiety opt for more frequent charging and vice versa [21]. While, some users could plug in their vehicles less frequently due to concerns about potential battery damage [22]. The frequency of EV connections influences the energy requirements and the total number of EVs connected to the grid.

Both the SOC^{min} and the frequency of EV connections to the charging point introduce uncertainties in the EV usage and impact the overall flexibility available to the energy provider. Consequently, these additional behavioural uncertainties pose significant challenges for energy providers in accurately assessing the monetary value of EV flexibility while trading in the spot markets (day-ahead and intraday electricity markets). Thus, in our paper, we aim to answer the following two research questions:

- RQ1: What is the impact of behavioural uncertainties on overall EV flexibility?
  - RQ1a: What is the impact of SOC^{min} requirements on overall EV flexibility?
  - RQ1b: What is the impact of the frequency of EVs connections to the charging point on overall EV flexibility?
- RQ2: What is the impact of behavioural uncertainties on the monetary value of EV flexibility in spot markets?
  - RQ2a: What is the impact of SOC^{min} requirements on the monetary value of EV flexibility in spot markets?
  - RQ2b: What is the impact of the frequency of EVs connections to the charging point on the monetary value of EV flexibility in spot markets?

To answer RQ1, we propose a flexibility model that quantifies flexibility in terms of energy and power as a function of time. This model provides insights into the dynamic power adjustment at each time step while ensuring the necessary energy levels to meet user requirements. To evaluate the flexibility model, we use an existing mobility dataset based on German mobility behaviour for driving patterns [23]. Additionally, we derive user charging preferences, such as SOC^{min} requirements and the frequency of EV connections to the charging point, from the "large scale survey data on behavioural aspects of charging" [17]. We first represent the variability in driving patterns by generating distinct scenarios. We assume different user charging preferences and calculate the flexibility for each scenario. In our paper, we assume unidirectional charging and accordingly calculate the flexibility of the EVs in each scenario. We then incorporate these flexibility scenarios into our optimisation model for evaluating the monetary value of EV flexibility.

To answer RQ2, we develop a scenario-based robust optimisation model with the objective of minimising the EPC while participating in both day-ahead and intraday markets. By implementing a robust optimisation approach, we optimise the EPC over the worst scenario, helping energy providers to clearly assess the financial viability of trading EV flexibility in spot markets. We used the German day-ahead and intraday electricity market data to evaluate our optimisation model and to test the impact of EV user uncertainties on the technical and financial indicators of flexibility provision.

The remainder of the paper is structured as follows. In Section 2, we discuss the literature on modelling EV usage patterns, EV scheduling algorithms, and different user charging preferences. Section 3 introduces our flexibility and scenario-based robust optimisation models. Section 4 gives an overview of scenarios and the data used for our simulations. Section 5 presents our results, and we discuss them in Section 6. Section 7 concludes the paper.

2. Related work

In this section, we first outline the different methods employed in the previous publications for modelling EV usage, accounting for inherent uncertainties. We then present how different papers utilised these EV usage models to estimate EV flexibility and develop smart charging algorithms. We primarily focus on optimisation/scheduling models that optimised the EV charging with the objective to minimise the EPC or maximise the revenue of the energy provider while participating in electricity markets. Lastly, we explore the impact of behavioural factors on charging preferences, highlighting their potential effects on the provision of EV flexibility and its corresponding monetary value.

2.1. EV usage models

The models to generate EV usage patterns are classified into annual mileage models and daily pattern models based on their time resolution [9]. Annual mileage models typically model vehicle usage as annual distances travelled by vehicles [24]. In contrast, daily pattern models, employed to develop EV scheduling algorithms typically focus on modelling the usage metrics such as the number of trips, daily mileage, daily activity-travel schedules (i.e., trip chains interspersed with non-travel activities) [9,25]. Daily pattern models are usually referred to as short-period models, as the time resolution typically ranges from hours to quarter hours [26,27].

Due to the limited availability of EV data, short-period models often rely on conventional vehicle usage patterns to generate EV usage patterns. These patterns, extracted from travel journals, are obtained through travel surveys, questionnaires, or GPS data. Authors [28–31] analyse these conventional patterns, focusing on parameters such as trip distance, trip frequency, trip duration, trip start and end times, and parking duration. The two predominant approaches to capture the variability in these parameters are PDFs and Markov chains [32]. In the first approach, authors in [33] used different types of PDFs such as uniform, normal, exponential, Gaussian, and Rician. Authors in [33] fit these PDFs to the observed data to find the distribution that best represents the different parameters. To simulate the stochastic behaviour of EV usage, authors in [11,29–31] employed Monte Carlo simulations, drawing random samples from the PDFs of various EV parameters.

The second approach to model the stochastic usage of EVs is by using a Markov chain. A Markov chain's next state is solely determined by the current state, based on the Markov property [34]. To generate a consistent EV usage pattern, authors in [10,35] used discrete time state Markov chain, which gives the state of each EV for each time interval (e.g., 15 min, 30 min, 1 h) over a defined period (e.g., week, month, year). These EV states can include information on whether the EV is driving, parked at work, at home, or in commercial areas. Transition probabilities, which indicate the likelihood of moving from one state to another for a given period, are usually derived from statistical information on traffic patterns in the region of analysis [23,26].

The energy that an EV consumes while driving can be estimated by multiplying its consumption rate by the distance travelled. To calculate the consumption rate, authors in [23,36,37] developed complex models that consider several factors like average velocity, aerodynamic efficiency, ambient temperature, and power consumption of auxiliary equipment. To estimate the charging demand of EVs, authors in [38–40] often assume an uncontrolled charging regime, where an EV is charged at full power until its energy requirement is fulfilled. The energy required for a charging session is assumed to be either equal to the estimated energy consumption of the EV for its next trip or the energy needed to reach maximum battery capacity. The required charging time is calculated based on the maximum charging power and the needed energy. In reality, EV maximum charging power is not always equal to the rated charging capacity of the charging point. The charging process typically involves various stages, including constant current and voltage, to preserve battery health and safety [41]. For simplicity, the authors [42] usually assume that maximum charging power is constant throughout the charging process and equal to the maximum rated charging capacity. The load profile for each EV, which gives the electricity consumption pattern of each EV, is computed and superimposed, representing the overall EVs demand at each time step for a given period.

2.2. EV charging scheduling algorithms

The actual charging duration of EVs is usually less than their parking duration, which makes the EV charging temporally flexible. This flexibility allows the energy providers to alter the EV charging schedule within a specific time period [43]. Consequently, using smart charging, energy providers can leverage the flexibility provided by EVs to minimise their EPC by scheduling the charging at times when market prices are low [44]. To smart charge, the EVs, the EV charging schedule can be formulated as a mathematical optimisation problem while considering various uncertainties [45]. Smart charging can be formulated as an optimisation problem because it typically involves allocating resources (i.e., charging power) to optimise the objectives (such as minimising energy supplier EPC) while satisfying constraints (e.g., user requirements). The performance of these optimised charging schedules is then compared with an uncontrolled charging schedule derived directly from the EV usage models [6,46].

Energy providers can use stochastic optimisation models to deal with uncertainties associated with EV usage in EV scheduling problems [12,47]. The stochastic optimisation model utilises probability distributions to represent uncertainties in EV behaviour, enabling the model to account for a spectrum of potential scenarios [48,49]. The energy provider could implement diverse approaches to formulating objective functions to minimise EPC when trading in electricity markets. For example, authors in [49] formulated the objective function to maximise the expected revenue of the energy provider in the reserve market by calculating the average performance across different EV demand scenarios based on their respective probabilities. Additionally, some stochastic optimisation models incorporate risk measures such as conditional value at risk (CVaR) [12,48,50] or variance [47] into the objective function. This inclusion serves to maximise energy provider's revenue in the day-ahead market [12,48,50] or reserve markets [47] while penalising outcomes with high variability or undesirable characteristics. Authors in [31,51] proposed two-staged stochastic optimisation models. The goal of these optimisation models is to minimise the expected EPC of energy providers while trading in both day-ahead and real-time/intraday markets. In the first stage, decisions aim to minimise the energy provider's EPC in the day-ahead market scheduling [51]. In the second stage, decisions correspond to the real-time/intraday markets where energy providers minimise the expected EPC of the anticipated energy procured in the real-time/intraday markets markets [31,51,52]. Trading in both day-ahead and intraday markets enables energy providers to fully utilise the flexibility offered by EVs across time horizons and market conditions [53].

In contrast to stochastic optimisation, energy providers can employ robust optimisation models in EV scheduling problems to adopt a more conservative and resilient strategy to address the uncertainties [13,14]. Within robust optimisation models, energy providers can model the uncertainties in EV usage [14] and market prices [13] by considering a set of uncertain scenarios without explicitly relying on probability distributions. While robust optimisation does not rely on probability distributions as stochastic optimisation does, its effectiveness is highly dependent on the chosen uncertainty set. A narrowly defined uncertainty set may only protect against a limited range of outcomes, similar to how scenario selection in stochastic optimisation can restrict the model's scope [54]. This connection parallels chance-constrained optimisation approaches, which address uncertainty without assuming a single probability distribution function and extend the applicability and robustness of the model [55]. The uncertainties related to EV usage could be, for example, the number of vehicles charging, the arrival or departure times, and the required energy [56]. Robust optimisation models aim to optimise the EV charging schedules to perform well under the worst-case scenarios. In this notion, authors in [57,58] formulated the objective function as a "min-max" model, aiming to minimise the energy provider's EPC for the worst-case scenario across all scenarios while trading in day-ahead markets. Another approach to model the objective function in robust optimisation models is by introducing a penalty term or robustness term in the original objective function [14]. Introducing a penalty or robustness term would penalise the deviations from the expected values within the uncertainty set. Authors in [59] proposed scenario-based robust optimisation to facilitate trading in day-ahead and intraday markets. Their scenario-based robust optimisation model aims to minimise the worst scenarios EPC, which could include day-ahead EPC and intraday worst scenario costs.

Our literature review reveals that most papers primarily relied on statistical models to derive the charging requirements and, consequently, to estimate the flexibility provided by EVs. They did not comprehensively consider the effect of behavioural factors on the charging preferences, such as $\mathrm{SOC}^{\mathrm{min}}$ requirements and frequency of charging events, and consequently their influence on the EV flexibility potential.

2.3. Charging preferences as an uncertainty

In our paper, the primary objective is to address limitations in previous research by integrating more realistic behavioural uncertainties into our charging algorithms. In this subsection, we elaborate on how specific behavioural factors can shape charging preferences, subsequently impacting both EV flexibility provision and EPC.

First, as previously mentioned, papers indicate that users are reluctant to participate in smart charging programs and thus provide flexibility [15,16]. Some users feel they lose control of the charging process and are concerned that the charge provided by the energy provider will not be sufficient in an emergency [15], such as a night-time hospital visit. To counteract this range anxiety, papers introduced the concept of $\mathrm{SOC}^{\mathrm{min}}$ [18,20]. $\mathrm{SOC}^{\mathrm{min}}$ offers users assurance that their EV will be instantly charged to their desired $\mathrm{SOC}^{\mathrm{min}}$, ensuring sufficiency in emergency situations [15]. By implementing this $\mathrm{SOC}^{\mathrm{min}}$ requirement, energy providers anticipate that users will provide some flexibility for smart charging from $\mathrm{SOC}^{\mathrm{min}}$ to the required state of charge at departure $\mathrm{SOC}^{\mathrm{dep}}$. However, the decisions of EV users are susceptible to behavioural factors like range anxiety [60], which is related to risk aversity – a personality trait in which individuals tend to prefer lower risks over higher risks, even if there is a good chance of a more advantageous outcome [61]. Risk-averse individuals may choose higher $\mathrm{SOC}^{\mathrm{min}}$ values than risk-prone individuals, impacting EV flexibility provision and the energy provider's EPC.

Second, papers indicate that EV users do not charge daily, but rather two to four times a week [21,62]. The charging frequency might depend on objective and subjective reasons. Regarding objective reasons, charging frequency correlates with the number of kilometres people drive per day [63]. It may also depend on other driving habits, such as the radius they drive from home and the number of trips they make. Weather and temperature as external factors could also influence the charging behaviour of EV users [64]. When the sun is shining, those with photovoltaic installations and the ability to charge at home can charge for free. Besides objective reasons, a subjective reason influencing the charging frequency might be range anxiety [21], which might be influenced by risk aversity [17]. Risk-averse people might tend to charge their EV more often to reduce the risk that the range will not be sufficient for upcoming trips. The frequency of EV connections influences the number of EVs connecting to the grid and their energy requirements, consequently impacting the EV flexibility potential.

3. Mathematical framework

In this section, we present the mathematical formulation of our flexibility model, which quantifies the EV flexibility in terms of power and energy flexibility metrics as a function of time. These flexibility metrics convey information on the amount of power that can be varied in each time step while maintaining the required energy level to meet the users' requirements. We then present the mathematical formulation of our scenario-based robust optimisation model, which uses this flexibility information for different scenarios and electricity market price data as an input to minimise the EPC for EV charging.

3.1. Flexibility model

The necessity of developing our flexibility model is twofold. Firstly, to evaluate the EV flexibility potential and secondly, to aid in EV flexibility trading. Within our model, we calculate individual flexibility metrics for each EV based on the user requirements. These flexibility metrics include time-dependent power and energy metrics, providing insights into how much power can be varied while maintaining energy levels required to meet EV user needs. By aggregating these individual flexibility metrics, we derive aggregated flexibility metrics. These aggregated flexibility metrics give a comprehensive view of the fleet's capacity to adjust power levels while maintaining energy requirements, allowing us to estimate the flexibility potential. Furthermore, these aggregated metrics serve as direct inputs to our optimisation model, reducing the complexity of our optimisation model by eliminating the need for individual-level computations for each EV.

3.1.1. Input data to quantify individual EV flexibility

The level of flexibility an EV offers varies with each charging session, influenced by the user's driving patterns and charging preferences, EV battery and charging point specifications.

To quantify EV flexibility, we require maximum charging power, energy requirements and parking duration. The maximum charging power (P^{max}) is the maximum power at which an EV can be charged. We derive the energy requirements from the user's $\mathrm{SOC}^{\mathrm{min}}$ and $\mathrm{SOC}^{\mathrm{dep}}$ requirements. $\mathrm{SOC}^{\mathrm{min}}$ represents the battery percentage up to which an EV will be charged at full power immediately upon connection to the charging point. $\mathrm{SOC}^{\mathrm{dep}}$ is the battery percentage requested by the user that should be fulfilled at departure time (t^{dep}). E^{SOCmin} denotes the energy that should be transferred to satisfy the $\mathrm{SOC}^{\mathrm{min}}$ requirement. The energy that should be transferred to satisfy the user's $\mathrm{SOC}^{\mathrm{dep}}$ requirement is denoted by E^{dep}. Plugin duration is the time throughout which the EV is connected to the charging point. We calculate the plugin duration using the user's arrival time (t^{arr}) and departure time (t^{dep}).

In Fig. 1, we illustrate the typical EV battery with different energy values at the time of arrival. E^{max} is the total battery capacity of the EV, E^{arr} is the energy level of EV battery at t^{arr}, and E^{dep} is the energy that should be transferred to satisfy the $\mathrm{SOC}^{\mathrm{dep}}$ requirement.

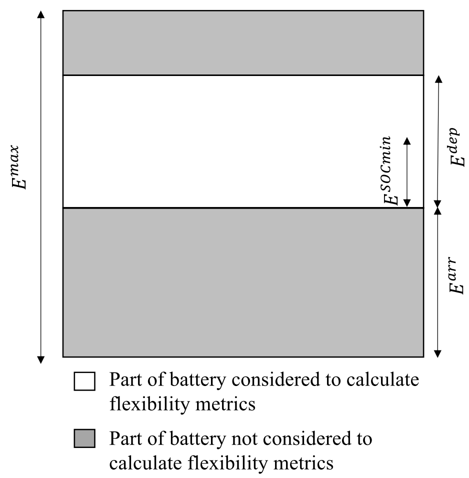


Fig. 1. Typical EV battery and different energy values.

As we only consider unidirectional charging, the overall energy capacity of the battery can never drop below E^{arr}. Furthermore, the user might not always request 100 % SOC^{dep}. This would mean that the sum of E^{arr} and E^{dep} would not always be equal to E^{max}. Therefore, when evaluating the flexibility metrics, we only consider the part of the battery that can be charged, i.e., E^{dep}.

3.1.2. Mathematical formulation to quantify individual EV flexibility

We derive time-dependent energy and power flexibility metrics to quantify the flexibility provided by an EV during its plugin duration, using the parameters introduced in the previous Section 3.1.1. The energy flexibility metrics are minimum energy (E_t^{min}) and maximum energy (E_t^{max}) at time t. The power flexibility metrics are minimum power (P_t^{min}) and maximum power (P_t^{max}) at time t. These flexibility metrics will convey the amount of power with which an EV can be charged while maintaining upper and lower limits of cumulative energy transfer. E_t^{min} represents the minimum cumulative energy that must be transferred to the EV at time t to fulfil the user's energy requirements, i.e. E^{dep} and E^{SOCmin}. The process to determine E_t^{min} is divided into three phases within its plugin duration as we illustrate in Fig. 2. The first phase is between t^{arr} and the time taken to transfer E^{SOCmin}, which is t^{min}. In the first phase, the vehicle is charged at full power until E^{SOCmin} is transferred. The second phase is between t^{min} and t^{c}, where t^{c} is the time after which the P_t should be maximum to transfer the remaining energy to fulfil E^{dep}. In the second phase, the vehicle is in an idle state. The third phase is the time between t^{c} and t^{dep}. In the third phase, the vehicle is charged at full power until it transfers the remaining energy required to fulfil E^{dep}. We present the mathematical formulation for the process to determine E_t^{min} in Eqs. (1) and (2).

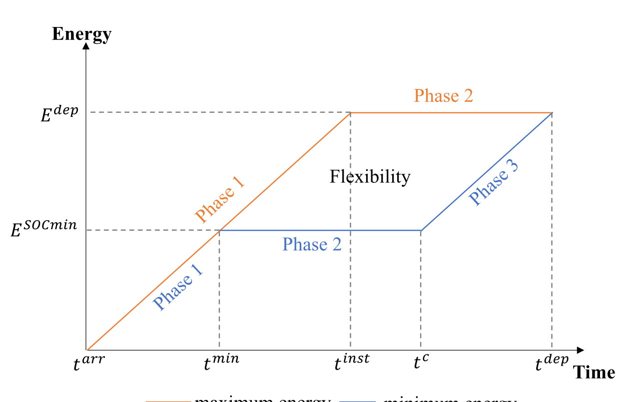


Fig. 2. Representing EV flexibility in energy vs. time graph.

$$E_t^{\text{min}} = E_{t-1}^{\text{min}} + P_t \times \eta \times \Delta t \tag{1}$$

$$P_t = \begin{cases} P^{\text{max}}, & t^{\text{arr}} < t \leq t^{\text{min}} \quad \text{(Phase 1)} \\ 0, & t^{\text{min}} < t \leq t^{\text{c}} \quad \text{(Phase 2)} \\ P^{\text{max}}, & t^{\text{c}} < t \leq t^{\text{dep}} \quad \text{(Phase 3)} \end{cases} \tag{2}$$

In reality, EV charging is not linear and involves different stages, such as constant current and voltage, to optimise the charging process for battery health and safety [41]. However, for simplicity, we assume a linear charging of the EV where the charging power takes continuous values. Therefore, we calculate E_t^{min} using the Eq. (1), where charging power at time t is P_t, and η is the charging efficiency to account for power losses while charging. The value of P_t to calculate E_t^{min} in the first phase, second phase, and third phase is P^{max}, 0, and P^{max} respectively, as depicted in Eq. (2).

E_t^{max} represents the maximum cumulative energy that can be transferred to the EV at time t to satisfy the user's energy requirement, i.e., E^{dep}. The process to determine E_t^{max} is divided into two phases as illustrated in Fig. 2. The first phase is between t^{arr} and t^{inst}. t^{inst} is the time it takes to transfer E^{dep} when charged at full power. The second phase is between t^{inst} and t^{dep} where there is no energy transfer. We present the mathematical formulation to calculate E_t^{max} in Eqs. (3) and (4).

$$E_t^{\text{max}} = E_{t-1}^{\text{max}} + P_t \times \eta \times \Delta t \tag{3}$$

$$P_t = \begin{cases} P^{\text{max}}, & t^{\text{arr}} < t \leq t^{\text{inst}} \quad \text{(Phase 1)} \\ 0, & t^{\text{inst}} < t \leq t^{\text{dep}} \quad \text{(Phase 2)} \end{cases} \tag{4}$$

As we assume a linear charging of EV, E_t^{max} is calculated by Eq. (3). The value of P_t to calculate E_t^{max} in the first and the second phase is equal to P^{max} and 0, respectively, as depicted in Eq. (4).

When plotting E_t^{min} and E_t^{max} on the energy vs time graph, the region bounded by these two energy metrics represents the flexibility (see Fig. 2). From the Fig. 2, we can observe that EV does not provide any flexibility until t^{min}.

P_t^{min} represents the minimum allowable power at which EV can be charged at time t. When there is no flexibility, until t^{min}, P_t^{min} is equal to P^{max}. When EV offers flexibility, from t^{min} to t^{dep}, P_t^{min} is equal to 0.

P_t^{max} represents the maximum allowable power at which EV can be charged at time t. Therefore, P_t^{max} for the whole plugin duration equals P^{max}.

3.1.3. Aggregated flexibilities for an EV fleet

In our paper, we consider different scenarios where the energy requirements, time of arrival and time of departure of the EVs are different in each scenario. For each scenario, we calculate the aggregated flexibility of the EV fleet as depicted in Fig. 3. We compute the individual flexibilities for each EV separately using user input data (refer to Section 3.1.2) for each specific scenario. We then aggregate the flexibility metrics of the EV fleet for a given scenario by summing up the individual flexibility metrics of each EV.

We repeat the same process for all scenarios and calculate the aggregated flexibility metrics for each scenario. The corresponding aggregated energy and power flexibility metrics for each scenario w are denoted as $E_{t,w}^{\text{min,agg}}$, $E_{t,w}^{\text{max,agg}}$ and $P_{t,w}^{\text{min,agg}}$, $P_{t,w}^{\text{max,agg}}$ which serves as an input to our optimisation model. We will present our optimisation model in the next Section 3.2.

3.2. Optimisation model

Our paper aims to assess the monetary value of EV flexibility in electricity spot markets considering inherent uncertainties in EV usage. To

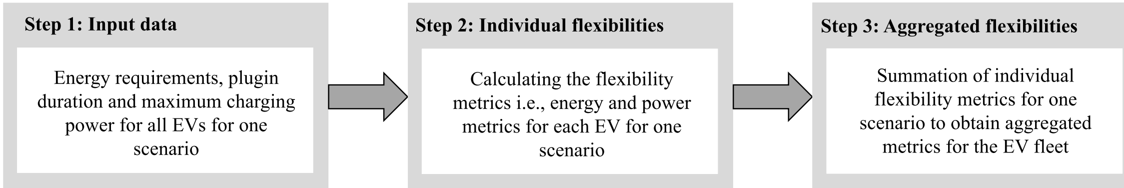


Fig. 3. Flexibility model to calculate aggregated flexibilities.

achieve this, we opt for a scenario-based robust optimisation model to minimise the EPC for the worst case while trading in day-ahead and intraday markets. We consider predetermined scenarios across which we calculate the aggregated flexibility metrics by varying the time of arrival, time of departure and energy requirements of each EV as discussed in Section 3.1.3

The robust optimisation model enables us to evaluate the worst-case scenario in terms of cost, providing a conservative estimate of the value of flexibility. Moreover, the robust optimisation approach allows us to develop charging schedules by considering various potential scenarios, providing resilience against different uncertainties related to EV usage. By accounting for these uncertainties in the optimisation model and optimising for the worst-case scenario, we can further ascertain if it is worthwhile to trade EV flexibility in electricity markets despite the uncertainties.

In line with prevalent scenario-based robust optimisation models, we assume that power acquired in the day-ahead market is the same for all scenarios, and the power is varied for each scenario while trading in the intraday market [59]. We assume perfect foresight of day-ahead and intraday market prices. Fig. 4 gives an overview of our optimisation model, illustrating the input data, objective function, relevant constraints and the resulting output.

Accordingly, we formulate the objective function of our optimisation model using Eq. (5). The first part is the energy provider's EPC of the day-ahead market, and β is an auxiliary decision variable used to capture the worst scenario intraday market EPC. In other words, β is a robustness variable that identifies the solution optimised for the worst scenario among all the modelled scenarios in the robust optimisation framework. The variable P_t^{DA} represents the power procured from the day-ahead market at time t, while C_t^{DA} denotes the corresponding day-ahead market price at time t. T gives the set of time steps, and Δt gives the length of the time step. In our paper, the time resolution is 15 min, and the time period is one week. Thus, the set $T = \{1, \dots, 672\}$, and value of Δt is equal to 0.25 h

$$\min \sum_{t \in T} (P_t^{\mathrm{DA}} \times C_t^{\mathrm{DA}})\Delta t + \beta \tag{5}$$

We formulate the constraint that relates the decisions taken in the intraday market to the objective function using Eq. (6). This constraint ensures that intraday EPC for all scenarios are less than or equal to the auxiliary decision variable . $P_{t,w}^{\mathrm{ID}}$ represents the power procured from the intraday market at time t for scenario w, and the parameter C_t^{ID} represents intraday market prices at time t. W is the set of scenarios; we model 52 EV flexibility scenarios, which we describe in detail in Section 4.1. Thus, the set $W = \{1, \dots, 52\}$.

$$\sum_{t \in T} (P_{t,w}^{\mathrm{ID}} \times C_t^{\mathrm{ID}})\Delta t \le \beta \ \forall w \in W \tag{6}$$

As we assume P_t^{DA} to be the same for all the scenarios, the power balance between day-ahead and intraday market for each scenario w is attained using the Eq. (7). $P_{t,w}^{\mathrm{agg}}$ is the variable for the aggregated charging power of EVs for scenario w at time t.

$$P_t^{\mathrm{DA}} + P_{t,w}^{\mathrm{ID}} = P_{t,w}^{\mathrm{agg}} \quad \forall\, t \in T, w \in W. \tag{7}$$

The number of vehicles connected to the charging point limits the variable $P_{t,w}^{\mathrm{agg}}$. The constraint, which we illustrate in the Eq. (8), ensures the $P_{t,w}^{\mathrm{agg}}$ is always within the values of aggregated power flexibility metrics. $P_{t,w}^{\mathrm{min,agg}}$ and $P_{t,w}^{\mathrm{max,agg}}$ are the aggregated power flexibility parameters at time t for each scenario w within which $P_{t,w}^{\mathrm{agg}}$ can vary. We determine these power flexibility metrics using the flexibility model described in Section 3.1.

$$P_{t,w}^{\mathrm{min,agg}} \le P_{t,w}^{\mathrm{agg}} \le P_{t,w}^{\mathrm{max,agg}} \quad \forall\, t \in T\ w \in W. \tag{8}$$

As we trade the aggregated flexibility of the EV fleet, we assume that all the EVs connected to their respective charging points at the residential level create a large virtual battery [65]. This virtual battery can describe the connected vehicles' characteristics while properly understanding the mathematical modelling of EVs. The variable $E_{t,w}^{\mathrm{agg}}$ illustrates the cumulative energy transferred to this virtual battery at time t for each scenario w. $E_{t,w}^{\mathrm{agg}}$ is restricted by the aggregated energy flexibility metrics as illustrated in the Eq. (9). $E_{t,w}^{\mathrm{min,agg}}$ and $E_{t,w}^{\mathrm{max,agg}}$ are

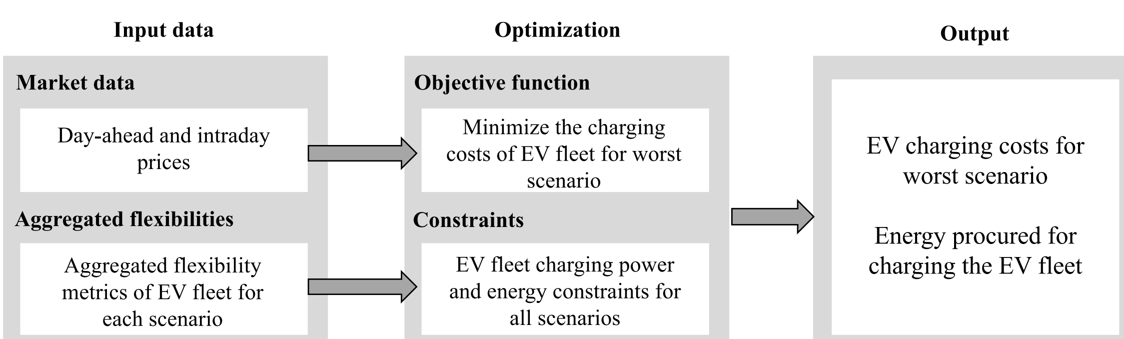


Fig. 4. Optimisation model.

the aggregated energy flexibility metrics at time t for scenario w. We determine these energy flexibility metrics using the flexibility model described in Section 3.1.

$$E_{t,w}^{\min,\text{agg}} \leq E_{t,w}^{\text{agg}} \leq E_{t,w}^{\max,\text{agg}} \quad \forall\, t \in T\; w \in W \tag{9}$$

The following Eq. (10) depicts the energy balance of the virtual battery:

$$E_{t,w}^{\text{agg}} = E_{t-1,w}^{\text{agg}} + P_{t,w}^{\text{agg}} \times \Delta t - E_{t,w}^{\text{vehicles,dis}} \;\forall\, t \in T, w \in W. \tag{10}$$

$E_{t,w}^{\text{agg}}$ is the variable illustrating the cumulative energy transferred to this virtual battery at time t for each scenario w. Its value is affected by $E_{t-1,w}^{\text{agg}}$, $P_{t,w}^{\text{agg}}$, and $E_{t,w}^{\text{vehicles,dis}}$. $E_{t-1,w}^{\text{agg}}$ is the cumulative energy transferred to the virtual battery in the previous time step for scenario w. $P_{t,w}^{\text{agg}}$ is the aggregated charging power of EVs or power procured to charge the virtual battery at the current time step t for scenario w. $E_{t,w}^{\text{vehicles,dis}}$ is the cumulative energy transferred to EVs disconnected from the charging points at the current time step t for scenario w, respectively.

4. Scenario generation and datasets

This section describes the approach and relevant datasets for generating flexibility scenarios and calculating the EPC.

We model uncertainties due to driving patterns by generating scenarios with different EV user driving patterns. We explain the methodology used to generate different scenarios in Section 4.1. These driving patterns provide information on the plugin duration of individual EV across different scenarios. We also need energy requirements to calculate flexibility for each scenario, which depends on charging preferences. Section 4.2 outlines the different charging preferences we assume, from which we derive the energy requirements for each EV across the scenarios. The information on plugin duration and energy requirements, derived from driving pattern scenarios and charging preferences, serves as input to the flexibility model, allowing us to calculate the aggregated flexibility metrics for each scenario.

Section 4.3 provides an overview of the electricity market price data used in our optimisation model to calculate EPC.

4.1. Modelling uncertainties due to driving patterns

To model uncertainties stemming from diverse driving patterns, we generate diverse scenarios reflecting various EV user driving patterns. We create the scenarios using synthetic mobility data derived from the German mobility survey [23]. We consider the mobility data of 1000 EVs. The mobility data comprises one-year mobility profiles for each EV. Each mobility profile represents a year-long time series capturing vehicle location, distance travelled, and energy consumption at 15-minute intervals. Our paper exclusively focuses on home charging, assuming all EVs charge when parked at home. Additionally, we assume the following specifications for all EVs.

- The battery capacity $E^{\max}$ of all vehicles is 75 kWh, which is similar to Tesla Model S [66].
- As per IEC 61851–1:2017 standard, we consider a Level 2 charger with a mean power rating of 7.4 kW, typically used for home charging [67].
- The charging efficiency η is 95 % which is within the efficiency range of Level 2 charger [68].

Fig. 5 outlines our approach to generate 52 scenarios to capture the uncertainties arising from variable driving patterns. We divide the mobility dataset – which contains individual profiles for the entire fleet (1000 EVs) over one year, into weekly datasets. This results in 52 datasets comprising the individual mobility profiles for the entire EV fleet over one week each. We utilise weekly datasets to better represent real-world charging behaviour, as EV users commonly plan their charging schedules every week. It also allows us to capture variations in charging behaviour between weekdays and weekends, which can differ significantly. Each weekly dataset is assigned to a unique scenario, totalling 52 scenarios. This approach introduces uncertainties in arrival and departure times, trip distances, and trip start and end times.

These driving pattern scenarios allow us to estimate the energy consumed by an EV during driving and the plugin duration for charging sessions in different scenarios. However, to quantify flexibility across all scenarios, we also require the energy requirements of EV users. The energy requirements depend on different charging preferences, which we discuss in the next section.

Overall, using our approach, we generate 52 different flexibility scenarios to model the uncertainty. These 52 scenarios serve as potential scenarios for one week that energy provider should consider while making the procurement decisions for that week. These scenarios serve as inputs for our robust optimisation model, which calculates the EPC for the worst scenario over the week (refer to Section 3.2).

4.2. Use cases for charging preferences

4.2.1. Definition of the use cases

EV users' charging preferences include SOC^{dep}, SOC^{min}, and the frequency of EV connection to the charging point. To determine SOC^{dep}, we assume that all EV users charge their vehicles until they reach either 100 % SOC or the maximum SOC at departure. Various possibilities exist regarding SOC^{min} and the frequency of EV connection to the charging point. For instance, the SOC^{min} requirement might vary between different EV users; some EV users may connect to the charging point every time they park with/without SOC^{min} requirement; some EV users may not connect to the charging point every time they park with/without SOC^{min} requirement. To deal with these different possibilities, we develop four different cases to cover all these possibilities.

- Case 1: We assume that all EVs are connected to the charging point whenever they are parked at home and offer full flexibility, i.e. 0 % SOC^{min} requirement.
- Case 2: We assume that all EVs are connected to the charging point whenever parked at home, each having a unique SOC^{min} requirement. We explain the methodology used to derive the SOC^{min} values in Section 4.2.2.
- Case 3: We assume that EVs are not always connected to the charging point when parked at home and offer full flexibility (i.e., no SOC^{min} requirement) when connected to the charging point. Connection occurs when state of charge at arrival SOC^{arr} values drop below a certain state of charge (SOC) value, which we define as the charging threshold. Thus, we assume that EV users plugin the vehicle when the SOC^{arr} is below the charging threshold. The charging threshold is unique for each EV, and Section 4.2.2 explains the approach to derive this value.
- Case 4: We assume that EVs are not always connected to the charging point when parked at home and have an SOC^{min} requirement when connected. In other words, here we consider both SOC^{min} and irregular EV connection to the charging point.

Table 1 provides an overview of the assumed charging preferences for each case. We consider Case 1 as the base case with no SOC^{min} requirement and with the assumption that EVs are always connected to the charging point when they are at home. Hence, we compare the results of other cases with Case 1 to analyse the impact of charging preferences on EV flexibility potential and its monetary value.

4.2.2. Deriving input data for each use case

We obtained the values for SOC^{min} requirements and charging thresholds from our large-scale survey data [17]. The survey, detailed in the paper by Marxen et al. [17], gathered data on various variables, including risk aversion, from $n = 289$ participants. To derive SOC^{min} requirements and charging thresholds, we used participants' responses to the question: "Which battery percentage should your EV always have as a minimum in case of unforeseen emergencies? (This implies that

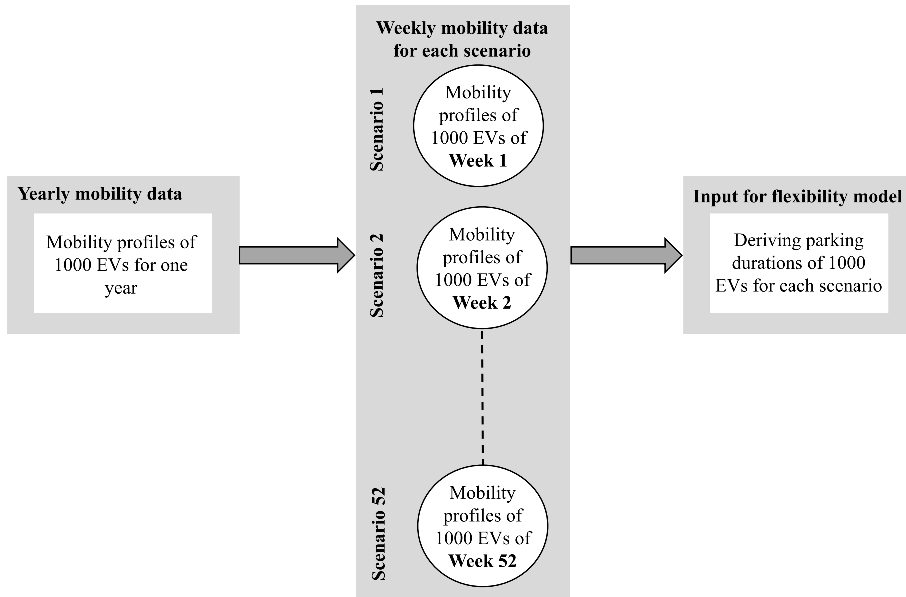


Fig. 5. Our approach to generating different scenarios.

Table 1
Charging preferences for different cases.

	SOC^{min} requirement	Irregular connection
Case 1	✗	✗
Case 2	✓	✗
Case 3	✗	✓
Case 4	✓	✓

your EV would always be charged to that level at maximum charging power when plugged in.)" Participants selected values between 0 % and 100 %. We then created a frequency distribution of their responses and randomly assigned SOC^{min} and charging threshold values to the 1000 EVs. In our survey, we also asked the participants about the battery capacity of their EV and the kilometres which they daily drive their EV. As these values did not correlate with SOC^{min}, we randomly assigned the SOC^{min} values for the scenarios. Fig. 6 illustrates the distribution of SOC^{min}/charging threshold values for 1000 EVs.

This distribution guides the definition of both SOC^{min} and charging threshold values, as the rationale behind the charging threshold is similar to that of SOC^{min}. The charging threshold also represents the battery percentage users would like to have for a sense of security. Therefore, we assumed that the values of SOC^{min} and the charging threshold would be the same for an individual EV. An assumption in our study is that the SOC^{min} values are based on survey data, which reflect behavioural intentions rather than actual behaviour. While behavioural intentions are generally considered a good proxy for actual behaviour [69], we acknowledge that a gap may exist between intentions and actual behaviour.

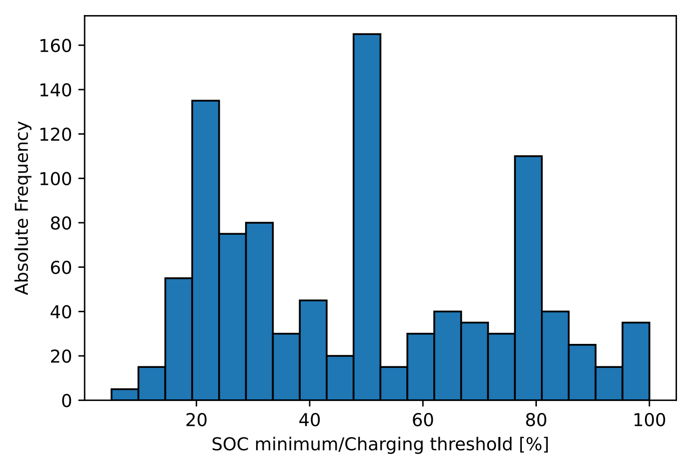


Fig. 6. Frequency distribution of SOC^{min} and charging thresholds derived from our survey data.

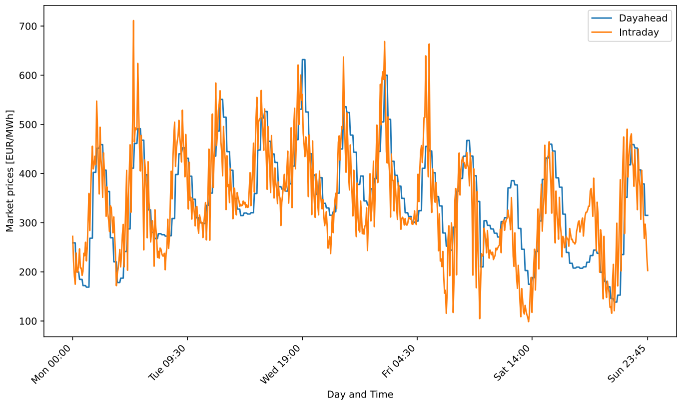
4.3. Electricity market price data

We use German wholesale electricity market price data from the day-ahead and intraday (ID3 index) markets for the years 2022 and 2023 [70] to calculate EPC. We include 2022 due to its high prices and increased market price volatility and analyse its impact on EPC [71]. The resolution of the prices is a quarter-hour.

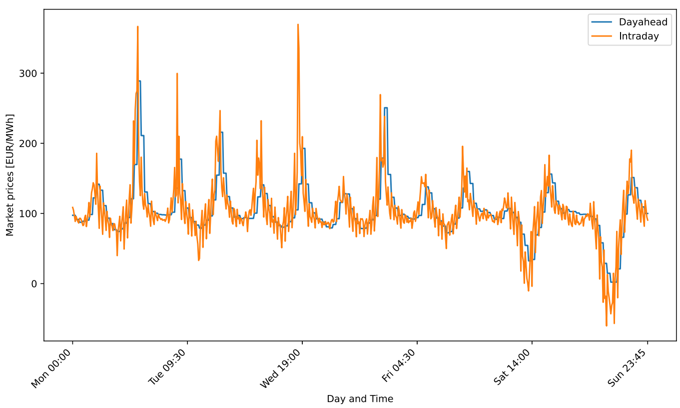
Since our uncertain EV flexibility scenarios are modelled over a one-week period (refer to Section 4.1), we perform the optimisation for a single week to determine EPC over that time frame. To avoid bias from choosing a specific week, we use the weekly median price for a given month as input to our optimisation model. The weekly median price is calculated with a 15-minute resolution. For each 15-minute interval within the week, we take the corresponding prices from all weeks in the given month and calculate their median. To analyse the seasonal price impact on EPC, we run the optimisation separately for each month. For each run, we use that month's weekly median price data to calculate the EPC incurred by the energy provider to charge the vehicles for one week. Fig. 7 illustrates the price data (median value) for a typical week in September 2022 (see Fig. 7(a)) and September 2023 (see Fig. 7(b)).

4.4. Simulation setup

Fig. 8 gives an overview of our methodology for calculating aggregated flexibilities and EPC for a single use case. We generate different scenarios and obtain the plugin duration of all EVs for each scenario (refer to Section 4.1). By considering one of the four charging preference use cases (refer to Section 4.2, we determine the energy requirements of all EVs for each scenario. These user requirements, such as plugin duration and energy requirements, serve as an input to calculate the aggregated flexibility metrics for each scenario using our flexibility



(a) September, 2022



(b) September 2023

Fig. 7: Electricity market price data for a typical week.

model (refer to Section 3.1). Subsequently, we employ our optimisation model to compute the worst scenario EPC (refer to Section 3.2) for one week in a specific month. We run the optimisation model separately for one month based on the weekly price input in each month (refer to Section 4.3) and calculate the worst-scenario EPC costs for all months in both 2022 and 2023.

We replicate this approach for each charging preference use case, determining flexibility scenarios for each use case separately.

5. Results

This section addresses our two research questions by presenting the results. We begin in Section 5.1 with the aggregated flexibility metrics calculated for all use cases using our flexibility model (refer to Section 3.1). Section 5.2 presents the EPC incurred for charging the EVs across all use cases. Finally, Section 5.3 explores the results of our cost-sensitivity analysis, where we determine the EPC incurred by varying the SOC$^{\min}$ and charging threshold values.

5.1. EV flexibilities

In this section, we present quantile distribution graphs illustrating aggregated flexibility metrics for all cases (refer to Section 4.2) we consider in our paper. As we describe in Section 3.1.3, the aggregated flexibility metrics are energy metrics - $E_{t,w}^{\max,agg}$ and $E_{t,w}^{\min,agg}$; power metrics - $P_{t,w}^{\max,agg}$ and $P_{t,w}^{\max,agg}$. We create these quantile distribution plots for typical weekdays and weekends to showcase the variability of EV flexibility across the 52 scenarios. To analyse the impact of SOC$^{\min}$ requirements and frequency of EV connections to the charging point on the flexibility, we compare the aggregated flexibility metrics of different cases with Case 1, the base case.

For the quantile distribution plots, we group weekdays (Monday to Friday) and weekends (Saturday and Sunday) separately and calculate the median value of the aggregated flexibility metrics for each scenario. We then plot the quantile distribution of these medians for weekdays and weekends. We use these typical plots to generalise the results across all weekdays and weekends. A solid red/orange line represents each flexibility metric's median (q50) value in these quantile distribution plots. Different shades of green around the central line indicate various quantile values for the flexibility metric. For example, in Fig. 9(c), the red line represents median (q50) of $E_{t,w}^{\max,agg}$ metric, and adjacent green shades are different quantiles of $E_{t,w}^{\max,agg}$ metric.

In the subsequent subsections, we detail the quantile distributions of all flexibility metrics for Cases 1–4, depicted in Figs. 9–12, respectively.

5.1.1. EV flexibilities for case 1

Figs. 9(a) and (b) illustrate the quantile distribution of power metrics for Case 1 on a typical weekday and weekend, respectively.

The $P_{t,w}^{\max,agg}$ metric displays slight variability for weekdays and weekends. Variability occurs due to different arrival and departure times of EVs in different scenarios, resulting in the difference in the number of vehicles connected to the charging point for a given period in different scenarios. On weekdays, the median value of $P_{t,w}^{\max,agg}$ is highest (7 MW) between midnight and 06:15 when most EVs are at home and connected to the charging point. Then it decreases as many people go to work. The median value increases again after 15:00 as people return home from work. On weekends, the median value of $P_{t,w}^{\max,agg}$ is highest (7 MW) just after midnight and remains constant until 08:45, when most EVs are at home. Its value drops slightly after 08:45, possibly due to short leisure trips some EV users take on weekends.

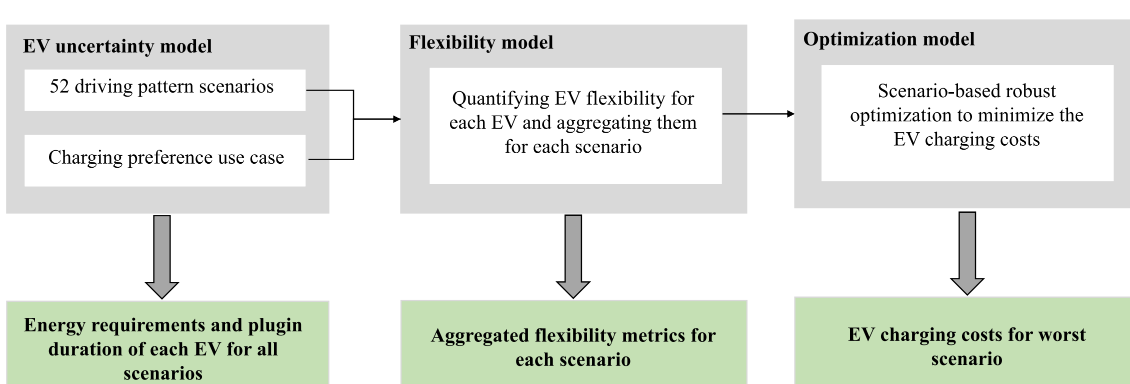
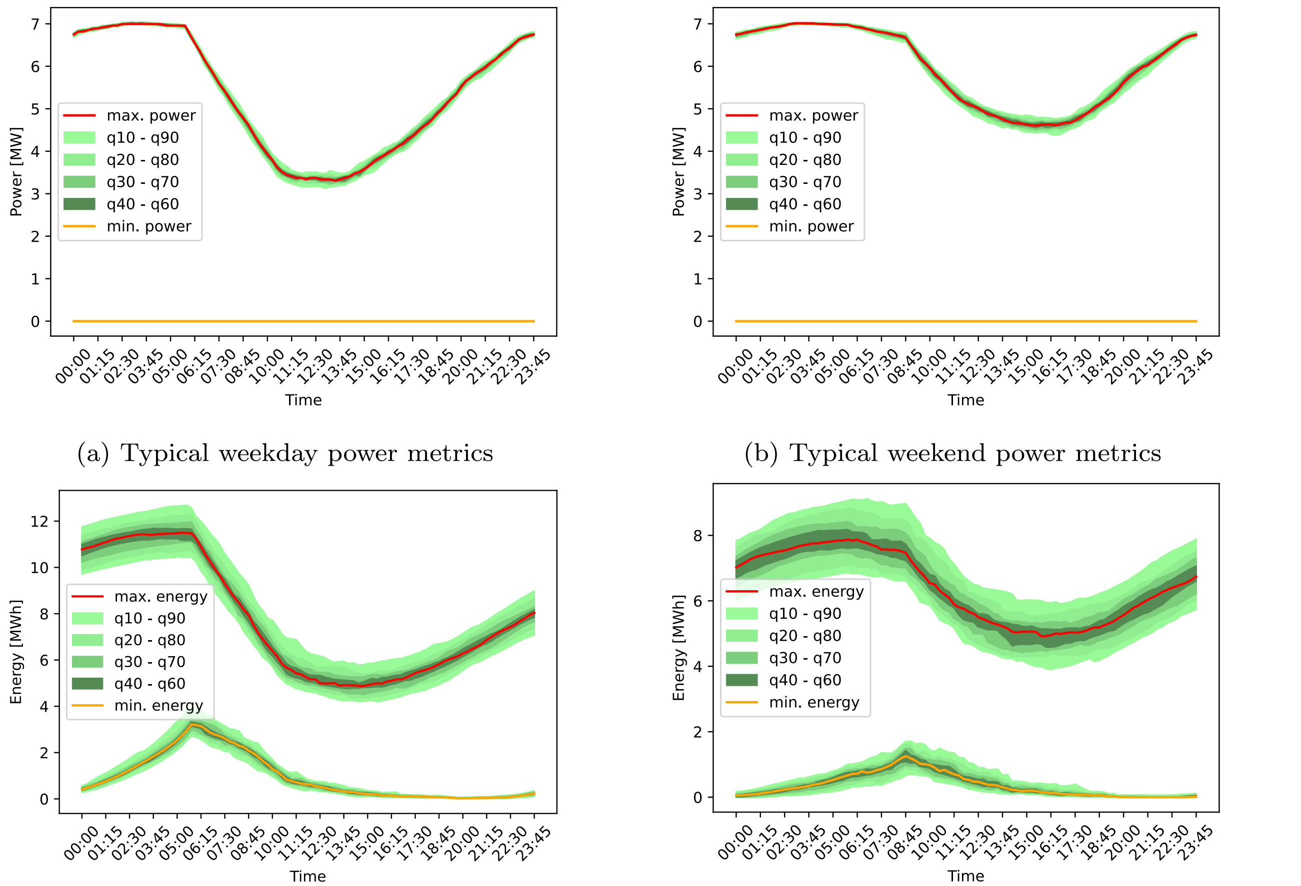


Fig. 8. Overview of our methodology for one use case.



(a) Typical weekday power metrics (b) Typical weekend power metrics

(c) Typical weekday energy metrics (d) Typical weekend energy metrics

Fig. 9. Quantile distribution of flexibility metrics for Case 1.

$P_{t,w}^{\max,\text{agg}}$ is zero during both weekdays and weekends during all hours, as all EVs offer full flexibility throughout the plugin duration.

The energy metric for Case 1, especially $E_{t,w}^{\max,\text{agg}}$, exhibits some variability throughout the day, with its values varying by ± 1 MWh from the median value for both weekdays (refer to Fig. 9(c)) and weekends (refer to Fig. 9(d)). The variability is predominantly due to the different energy requirements (E^{dep}) caused by variable driving patterns of each EV across the scenarios. The median values are highest around 06:15 (11 MWh) and 08:45 (7 MWh) for weekdays and weekends, respectively. $E_{t,w}^{\max,\text{agg}}$ is the sum of the maximum cumulative energy that could be transferred to all connected EVs. Therefore, its value increases when more vehicles start connecting to the charging point, reaches a peak, and decreases when the number of vehicles leaving is relatively higher than the number of connected vehicles. The $E_{t,w}^{\max,\text{agg}}$ values are higher on weekdays than weekends. These high values at weekends can be attributed to the fact that many EVs are more active on weekdays than weekends.

For weekdays, the median value of $E_{t,w}^{\min,\text{agg}}$ is almost close to zero from 17:30 to 23:45 and only increases after midnight with a peak (3 MWh) around 06:15, although many users connect their EVs to their charging points. The increase in the value only after midnight suggests that most EVs only need to be charged for a fraction of their plugin time. On weekends, the $E_{t,w}^{\min,\text{agg}}$ curve is much flatter than on weekdays, with a small peak (1 MWh) around 08:45, and the values are also much lower. These low values are because the energy requirements of the EVs are much lower on weekdays, likely due to short leisure trips taken by the EV users on weekends.

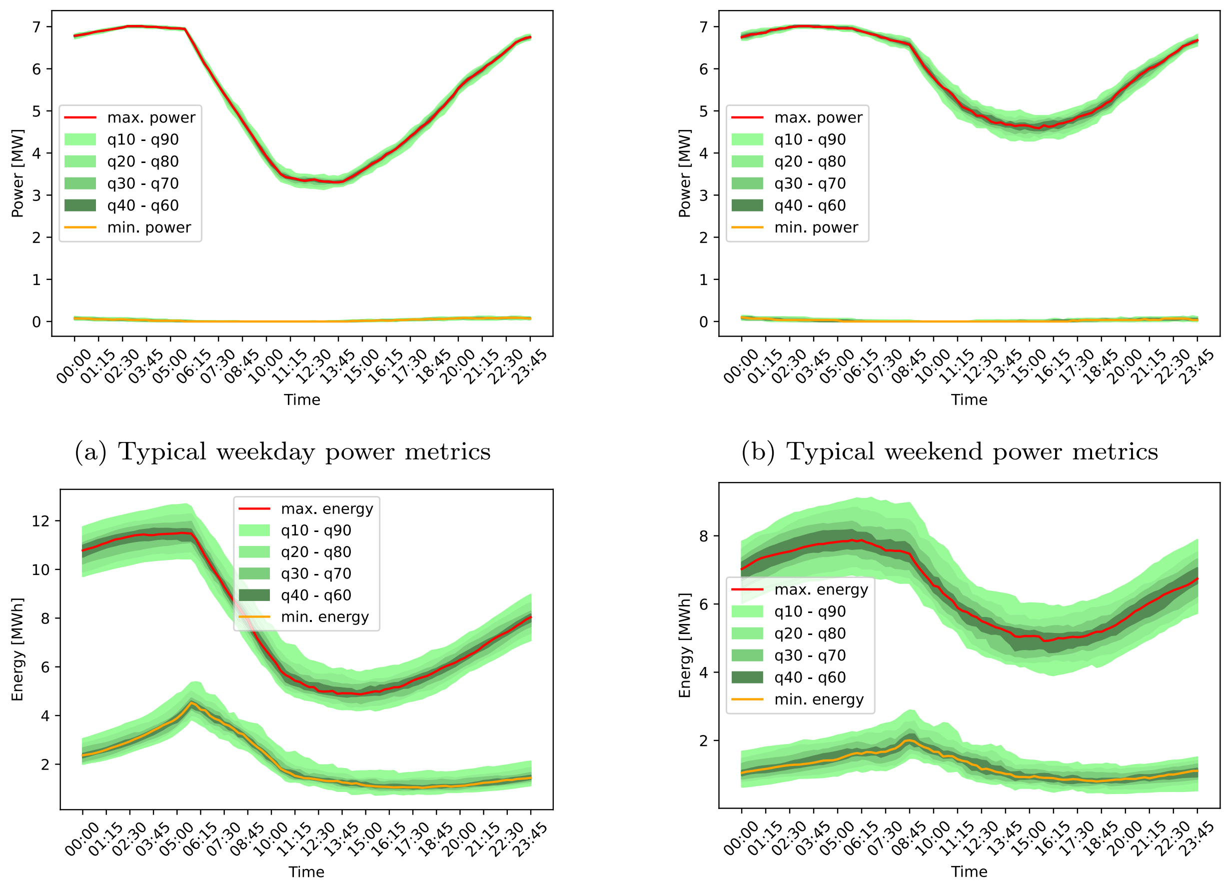
5.1.2. EV flexibilities for case 2

For Case 2, the $P_{t,w}^{\max,\text{agg}}$ values for both weekday (refer Fig. 10(a)) and weekend (refer Fig. 10(b)) are the same as those of Case 1. The similarity is because the number of EVs connected in Case 2 is identical to that in Case 1.

However, the $P_{t,w}^{\max,\text{agg}}$ values are slightly higher in Case 2 compared to Case 1 for weekdays and weekends. The increase in $P_{t,w}^{\max,\text{agg}}$ values is due to the $\text{SOC}^{\min}$ requirement in Case 2, which mandates that EVs charge at full power until their SOC value reaches $\text{SOC}^{\min}$. Nevertheless, the increase in $P_{t,w}^{\max,\text{agg}}$ is marginal, with a median value just above zero. This minimal increase could be attributed to two main factors: first, most EVs already have SOC^{arr} values greater than or equal to $\text{SOC}^{\min}$; second, for EVs where SOC^{arr} is less than $\text{SOC}^{\min}$, the power required to meet $\text{SOC}^{\min}$ is not very high.

The $E_{t,w}^{\max,\text{agg}}$ values for both weekdays (refer Fig. 10(c)) and weekends (refer 10(d)) are the same as in Case 1. The similarity is because $E_{t,w}^{\max,\text{agg}}$ is the sum of the maximum cumulative energy of all the EVs, and the number of EVs connected and their E^{dep} requirements are similar to those of Case 1.

The $E_{t,w}^{\min,\text{agg}}$ values for both weekdays and weekends are higher than those of Case 1 due to the $\text{SOC}^{\min}$ requirement. The peak median value of $E_{t,w}^{\min,\text{agg}}$ is 4 MWh and 2 MWh for weekdays and weekends, respectively,



(a) Typical weekday power metrics (b) Typical weekend power metrics

(c) Typical weekday energy metrics (d) Typical weekend energy metrics

Fig. 10. Quantile distribution of flexibility metrics for Case 2.

which is 1 MWh higher than in Case 1. The values are higher in Case 2 because, unlike Case 1, the amount of energy (E^{SOCmin}) needed to meet SOC$^{\text{min}}$ requirement should be immediately transferred to each EV. Since $E_{t,w}^{\text{min,agg}}$ represents the minimum cumulative energy transfer, this additional transfer of E^{SOCmin} for each EV at the start of the plugin duration contributes to higher overall values.

5.1.3. EV flexibilities for case 3

For Case 3, the shape of the $P_{t,w}^{\text{max,agg}}$ quantile distribution is similar to that of Case 1, both for weekdays (refer Fig. 11(a)) and weekends (refer Fig. 11(b)), due to similar driving patterns. However, there is slightly higher variability in the quantile distribution, and the values of $P_{t,w}^{\text{max,agg}}$ metric are notably lower than those of Case 1. The peak median value of $P_{t,w}^{\text{max,agg}}$ is 2.25 MW and 1.75 MW for weekdays and weekends, respectively, 4.75 MW and 5.25 MW lower than in Case 1.

The variable frequency of EV connections means that most users do not connect their EVs to the charging point daily, which was the situation in Case 1. This varying number of connected vehicles leads to variability in the $P_{t,w}^{\text{max,agg}}$ metric. Consequently, these irregular connections also lead to a reduced number of EVs connected to the charging point, contributing to lower $P_{t,w}^{\text{max,agg}}$ values.

$P_{t,w}^{\text{max,agg}}$ values are equal to zero, which is similar to those of Case 1 because EVs offers full flexibility throughout the plugin duration.

The variability of different quantile values of $E_{t,w}^{\text{max,agg}}$ in Case 3 is slightly higher than that of Case 1, both for weekdays (refer to Fig. 11(c)) and weekends (refer to Fig. 11(d)). This difference could be primarily due to the varying number of EVs connected to the charging point on a given day, with more diverse energy requirements (E^{dep}) across different scenarios.

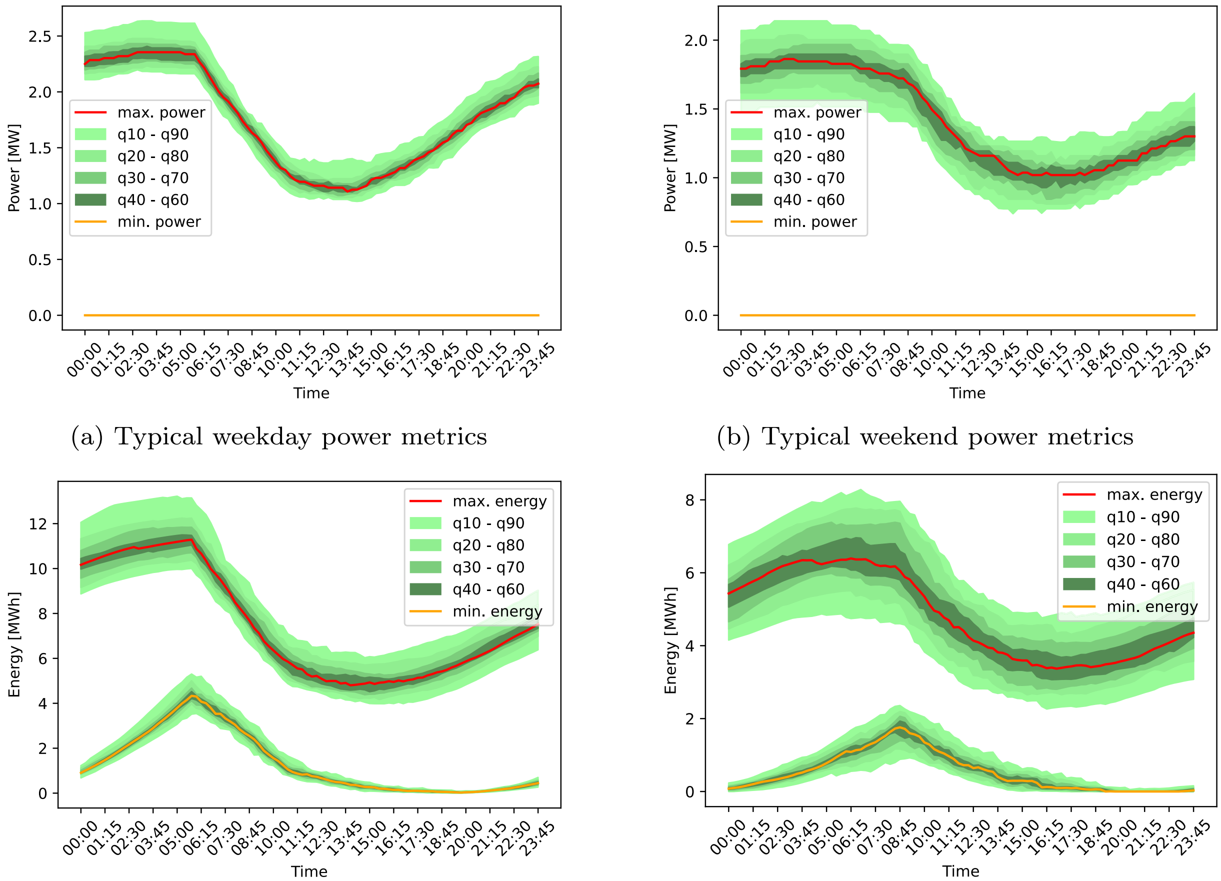
However, the peak median value of $E_{t,w}^{\text{max,agg}}$, particularly for weekdays, is similar (11 MWh) to that of Case 1. Although the number of connected EVs is lower than in Case 1, their energy requirement, i.e., E^{dep} value, within a charging session is higher than in Case 1. In Case 3, the E^{dep} value for each user is higher because they have to meet the energy required for their weekly driving needs in fewer charging sessions than in Case 1. Therefore, at the aggregate level, the total energy could be similar.

The values of $E_{t,w}^{\text{min,agg}}$ are significantly higher for weekdays and weekends in Case 3 than in Case 1. The peak median value of $E_{t,w}^{\text{min,agg}}$ is 4 MWh and 2 MWh for weekdays and weekends, respectively, 2 MWh and 1 MWh higher than in Case 1. This disparity is due to the higher energy requirements (E^{dep}) of EVs in Case 3, where these vehicles need more time to meet their energy requirements compared to Case 1.

5.1.4. EV flexibilities for case 4

For Case 4, the values of $P_{t,w}^{\text{max,agg}}$ are similar to those of Case 3, both for weekdays (refer to Fig. 12(a)) and for weekends (refer to Fig. 12(b)). The values in both cases are similar because the number of EVs connected to the charging point is similar to Case 3. Therefore, the reason for the difference in values compared to Case 1 is similar to Case 3.

However, the $P_{t,w}^{\text{max,agg}}$ values are slightly higher in Case 4 compared to Case 1 for both weekdays and weekends. This increase could be



(a) Typical weekday power metrics

(b) Typical weekend power metrics

(c) Typical weekday energy metrics

(d) Typical weekend energy metrics

Fig. 11. Quantile distribution of flexibility metrics for Case 3.

primarily attributed to the $\mathrm{SOC}^{\mathrm{min}}$ requirement, which forces EVs to charge at full power until the $\mathrm{SOC}^{\mathrm{min}}$ requirement is met. Nevertheless, the increase in $P_{t,w}^{\mathrm{max,agg}}$ is marginal, with a median value just above zero. The increase in $P_{t,w}^{\mathrm{max,agg}}$ is minimal because the power required to meet $\mathrm{SOC}^{\mathrm{min}}$ is low.

The $E_{t,w}^{\mathrm{max,agg}}$ values for Case 4 are the same as those in Case 3, both for weekdays (refer to Fig. 12(c)) and weekends (refer to Fig. 12(d)). The similarity in both cases is because the number of EVs connected to the charging point and the energy requirement (E^{dep}) of EVs is similar to that of Case 3. Therefore, the rationale behind the differences in values compared to Case 1 is similar to that of Case 3.

The $E_{t,w}^{\mathrm{min,agg}}$ values for weekdays and weekends are higher than in Case 1. The peak median value of $E_{t,w}^{\mathrm{min,agg}}$ is 6 MWh and 3 MWh for weekdays and weekends, respectively, 4 MWh and 2 MWh higher than in Case 1. The values in Case 4 are higher because the combination of irregular charging and $\mathrm{SOC}^{\mathrm{min}}$ leads to higher energy requirements (E^{SOCmin} and E^{dep}) within a charging session, which would mean that the minimum cumulative energy that should be transferred to EV would be higher compared to Case 1.

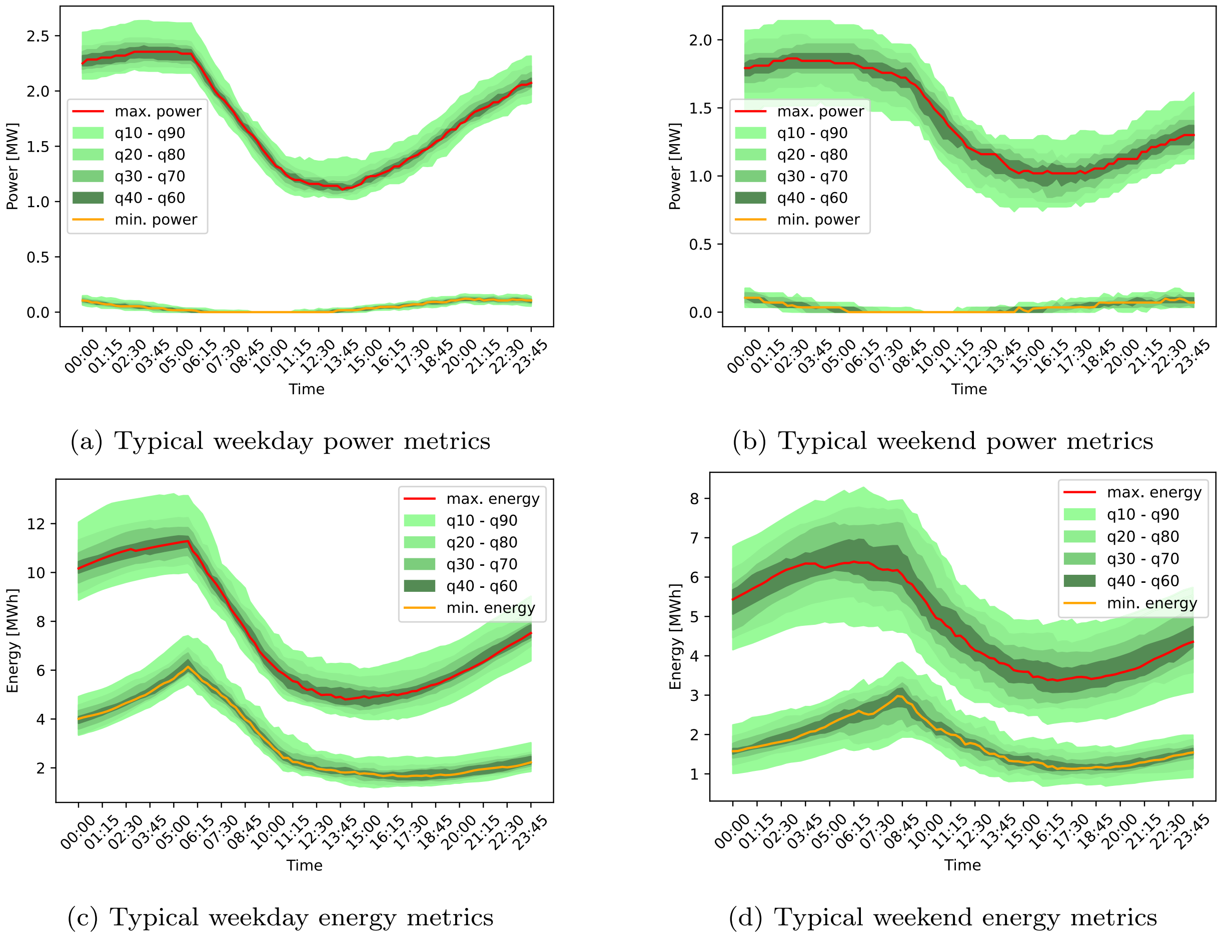
5.1.5. Comparison of EV flexibilities for all cases

When comparing the aggregated flexibility of cases with Case 1, we observe changes in both power and energy flexibility metrics for all three cases. Specifically, Case 2 exhibits an increase in $P_{t,w}^{\mathrm{max,agg}}$ and $E_{t,w}^{\mathrm{min,agg}}$ values compared to Case 1, attributed to the requirements of $\mathrm{SOC}^{\mathrm{min}}$. Case 3 exhibits a decrease in $P_{t,w}^{\mathrm{max,agg}}$ and an increase in $E_{t,w}^{\mathrm{min,agg}}$ values, compared to Case 1, owing to irregular EV connection to the charging point. Case 4 indicates a decrease in $P_{t,w}^{\mathrm{max,agg}}$ and an increase in both $P_{t,w}^{\mathrm{max,agg}}$ and $E_{t,w}^{\mathrm{min,agg}}$ values, compared to Case 1, influenced by $\mathrm{SOC}^{\mathrm{min}}$ requirements and irregular EV connections to the charging point.

Considering that we model aggregated flexibility metrics, we can assume that all EVs connected to the charging point create a sizeable virtual battery. Hence, $E_{t,w}^{\mathrm{min,agg}}$ and $E_{t,w}^{\mathrm{max,agg}}$ represent the minimum and maximum energy capacity of this virtual battery, while $P_{t,w}^{\mathrm{max,agg}}$ and $P_{t,w}^{\mathrm{max,agg}}$ signify its minimum and maximum charging capacity. Any increase in $P_{t,w}^{\mathrm{max,agg}}$ or decrease in $P_{t,w}^{\mathrm{max,agg}}$ suggests a reduction in the power capacity of this virtual battery, indicating decreased flexibility. Similarly, an increase in $E_{t,w}^{\mathrm{min,agg}}$ or a decrease in $E_{t,w}^{\mathrm{max,agg}}$ implies a reduction in the energy capacity of the virtual battery, signifying decreased flexibility. Thus, observed increases in $P_{t,w}^{\mathrm{max,agg}}$ and $E_{t,w}^{\mathrm{min,agg}}$ for cases with $\mathrm{SOC}^{\mathrm{min}}$ requirements indicate a reduction in flexibility due to $\mathrm{SOC}^{\mathrm{min}}$ requirements. A decrease in $P_{t,w}^{\mathrm{max,agg}}$ and an increase in $E_{t,w}^{\mathrm{min,agg}}$ for cases with irregular EV connections to the charging point, indicate reduced flexibility due to irregular EV connections to the charging point.

5.2. Monetary value of EV flexibility

Fig. 13 illustrates the corresponding EPC incurred for procuring the energy required (87.16 MWh) to charge the EVs for one week in each month across the years 2022 and 2023. The bars represent the absolute EPC and the dashed lines represent the average EPC incurred for each case.



(a) Typical weekday power metrics

(b) Typical weekend power metrics

(c) Typical weekday energy metrics

(d) Typical weekend energy metrics

Fig. 12. Quantile distribution of flexibility metrics for Case 4.

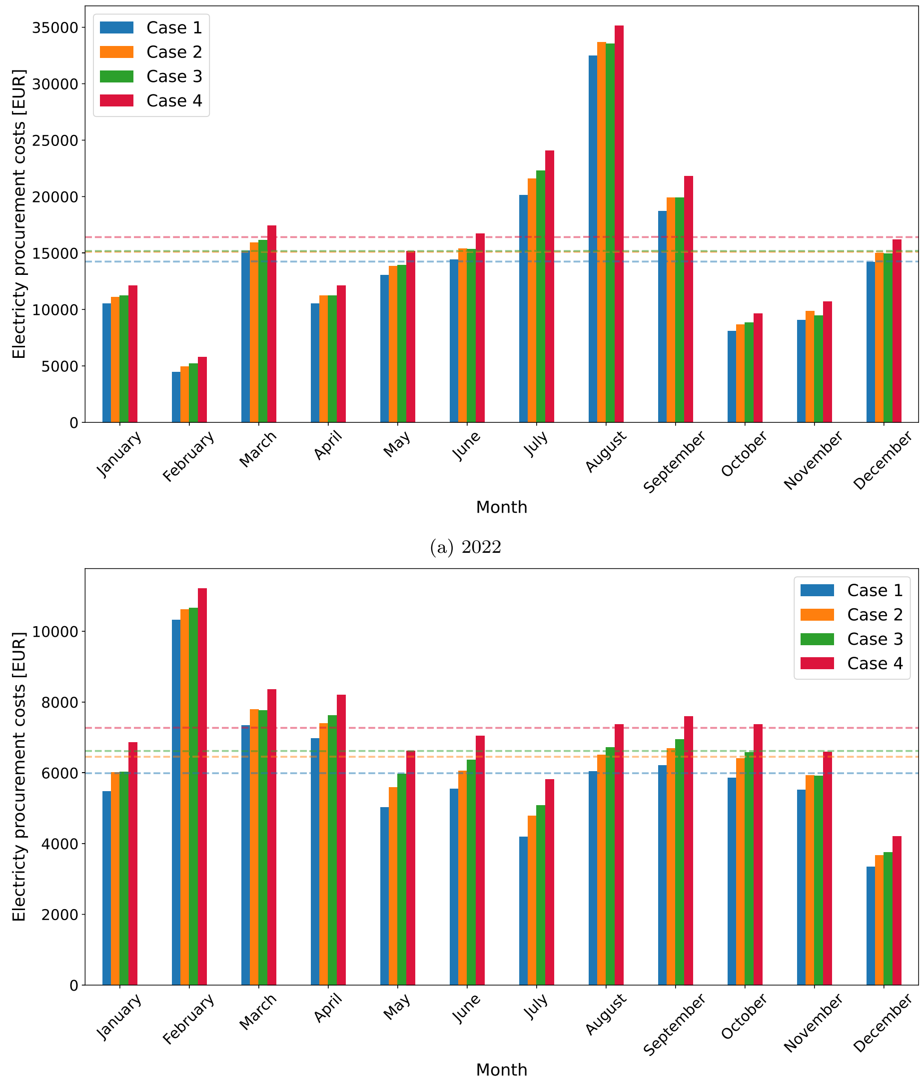
From Fig. 13(a), we can observe that in 2022, EPC are highest for August and lowest for February. In all cases, the EPC exhibit a similar trend for all three months. This trend persists in all three months, with EPC increasing for cases with SOC^{min} requirements and irregular EV connection frequency to charging points. To analyse the impact of SOC^{min} requirements and charging frequency on EPC, we compare the EPC of the different cases with Case 1, which is the base case. We selected August and February for a detailed comparison, as these months depict the lowest and highest cost increases, respectively, compared to other months in 2022 (Appendix A illustrates the relative increase in EPC when compared to Case 1 for all the months in the year 2022).

First, comparing Case 2 with Case 1 reveals that EPC increases by 3.6 % (1166 EUR) in August and 11.3 % (505 EUR) in February, demonstrating the effect of SOC^{min} requirements. Second, comparing Case 3 with Case 1 exhibits a rise of 3.3 % (1075 EUR) in August and 16.5 % (736 EUR) in February, demonstrating the effect of the frequency of EV connection to the charging point. Third, comparing Case 4 with Case 1 reveals an increase of 8.1 % (2644 EUR) in August and 30.3 % (1350 EUR) in February, demonstrating the effect of the SOC^{min} requirement and charging frequency.

From Fig. 13(b), we can observe that in 2023, EPC are highest for February and lowest for December. In all cases, the EPC exhibit a similar trend for all the months. Although the EPC for the different cases exhibit a similar trend as in 2022, the EPC are much lower than those of 2022. Similar to the year 2022, to analyse the impact of SOC^{min} requirements and charging frequency on EPC, we compare the EPC of the different cases with Case 1, which is the base case. We selected February and July for detailed comparison, as these months depict the lowest and highest cost increases, respectively, compared to other months in 2023 (Appendix A illustrates the relative increase in EPC when compared to Case 1 for all the months in the year 2023).

First, comparing Case 2 with Case 1 reveals that EPC increases by 2.8 % (296 EUR) in February and 14 % (589 EUR) in July, demonstrating the effect of SOC^{min} requirements. Second, comparing Case 3 with Case 1 exhibits a rise of 3.3 % (341 EUR) in February and 21 % (882 EUR) in July, demonstrating the effect of the frequency of EV connection to the charging point. Third, comparing Case 4 with Case 1 reveals an increase of 8.6 % (891 EUR) in February and 38.4 % (1613 EUR) in July, demonstrating the effect of the SOC^{min} requirement and charging frequency.

In both years, the EPC are higher for the cases with SOC^{min} requirements, variable frequency of the EV connection, and combination of SOC^{min} and variable frequency of the EV connection when compared to Case 1. The increase in EPC implies that as the EV flexibility decreases, the EPC increases. When comparing the EPC between the two years, the EPC are much higher for 2022 due to high market prices, yet we still observed a notable reduction in the EPC for the cases offering higher flexibility.



(a) 2022

(b) 2023

Fig. 13. Electricity procurement costs for one week across all months.

5.3. *Cost sensitivity analysis*

We perform a sensitivity analysis to assess how varying the SOC^{min} and charging threshold values will affect the EPC. In our cost sensitivity analysis, we vary the charging thresholds and SOC^{min} values for all EVs. We vary the charging threshold values from 20 % to 100 % in 20 % increments, while SOC^{min} values vary from 0 % to 100 % in the same increments. The higher charging threshold implies that users connect their EVs more frequently. An SOC^{min} requirement of 100 % is similar to uncontrolled charging, where an EV does not offer flexibility, whereas 0 % is when the EV offers full flexibility i.e., energy provider can control the charging throughout the plugin duration.

Fig. 14 illustrates the EPC incurred for different combinations of charging thresholds and SOC^{min} values for February 2022 and July 2023. We selected February and July for our detailed analysis, as these months depict the highest cost variation compared to other months in 2022 and 2023, respectively (refer to Appendix B for the analysis of other months). From the sensitivity analysis of two months (refer to Figs. 14(a) and (b), we observe a trend where EPC decreases as the charging threshold value increases, and conversely, EPC tends to rise with higher SOC^{min} requirements.

From the sensitivity analysis, it is evident that the EPC varies considerably. We observe the highest EPC is 7917.68 EUR and 8335.05 EUR for February 2022 and July 2023, respectively, reflecting uncontrolled charging where EVs provide no flexibility. The lowest EPC are 4464 EUR and 4197.37 EUR, for February 2022 and July 2023, respectively, representing the combination with the highest overall flexibility (0 % SOC^{min} and 100 % charging threshold).

Furthermore, we observe a notable trend in the EPC variations concerning SOC^{min} values. The EPC remains relatively stable for certain charging thresholds until a particular value of SOC^{min}, after which the EPC escalates rapidly. For instance, for charging thresholds 80 % and 100 %, EPC is almost similar up to 80 % SOC^{min}, after which it increases significantly. This is because higher charging thresholds entail a higher SOC^{arr} value, which means that for most of EVs when they arrive, the SOC^{arr} might be already higher than SOC^{min} requirement, thus not having much impact on the EPC.

Expanding our cost sensitivity analysis, we evaluate the relative reduction of EPC for the cases with 0 % SOC^{min} and 80 % SOC^{min} compared to the EPC of 100 % SOC^{min} across various charging threshold values. With 0 % SOC^{min} reflecting a full flexibility and 80 % SOC^{min} a low flexibility case. This comparison allows us to estimate a range for potential EPC reductions when EVs provide flexibility for smart charging as opposed to uncontrolled charging where EVs provide no flexibility (100 % SOC^{min}).

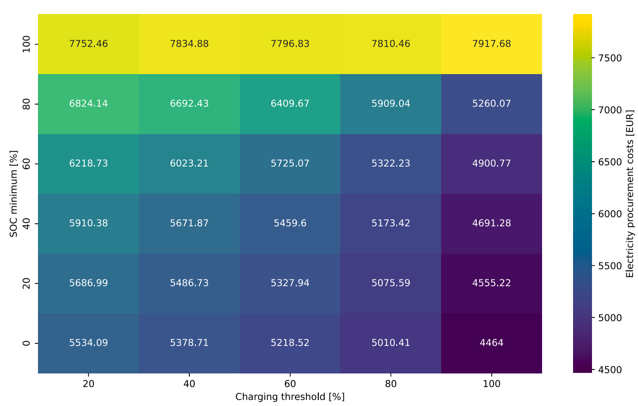
Fig. 15 illustrates the relative EPC reduction for February 2022 and July 2023 (refer to C for the analysis of other months). For 0 % SOC^{min}, the EPC reduction ranges from 28.6 % to 43.6 % in February 2022 (refer to Fig. 15(a)) and from 33.9 % to 49.6 % in July 2023 (refer to Fig. 15(b)).

Even with low flexibility (80 % SOC^{min}), we observe a substantial reduction in EPC compared to uncontrolled charging. The EPC reduction ranges from 11.9 % to 33.5 % for February 2022 (refer to Fig. 15(a)) and from 11.8 % to 36.9 % for July 2023 (refer to Fig. 15(b)).

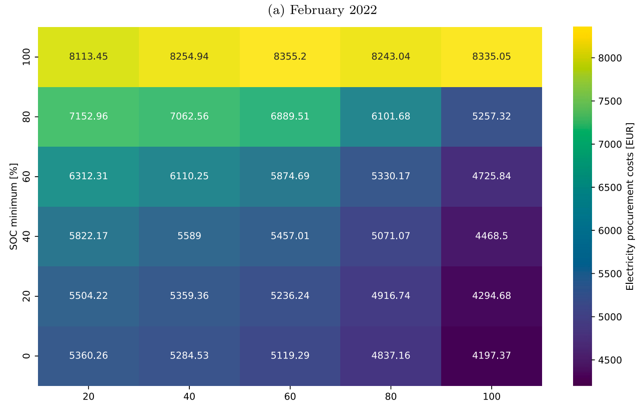
6. Discussion and limitations

6.1. Implications to energy providers

In our analysis, an increase in SOC^{min} requirements and a decrease in the frequency of EV connections to the charging point result in reduced EV flexibility, which subsequently increases overall EPC. Therefore, high flexibility, i.e., low SOC^{min} requirements and high frequency of EV connections, is desirable for energy providers. While energy providers cannot directly control the EV user charging preferences, they can incentivise users to adapt their preferences in a certain way, resulting in higher flexibility provision. Thus, users could be persuaded with monetary incentives to provide low SOC^{min} values and frequently connect their EV to the charging point.

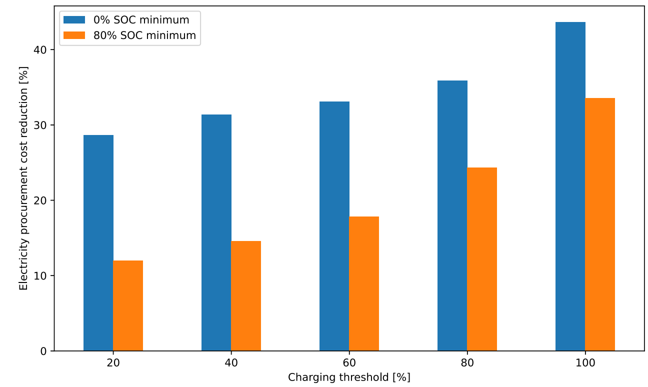


(a) February 2022

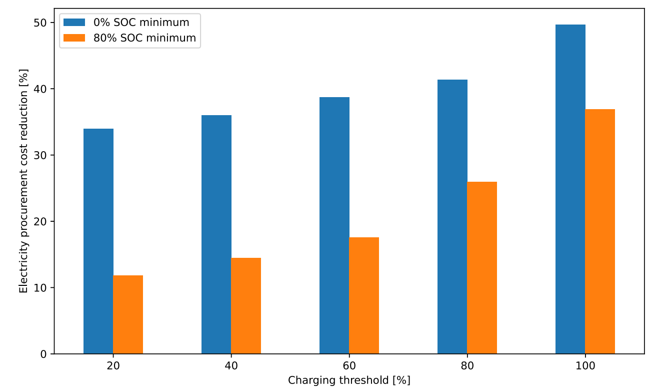


(b) July 2023

Fig. 14. Electricity procurement costs of one week for different SOC^{min} and charging threshold combinations.



(a) February 2022



(b) July 2023

Fig. 15. Relative cost reduction of different SOC^{min} values compared to 100 % SOC^{min} values across different charging thresholds.

With regard to our cost sensitivity analysis, we would like to define three cases for the SOC^{min} values to guide the discussion. We distinguish these three cases in terms of their flexibility and convenience to the users. First, we define 0 % SOC^{min} as the case offering full flexibility but low convenience. This case gives energy providers full control over charging during the plugin duration, but it can be inconvenient for users as they are unsure when their energy needs will be met. Second, we define 100 % SOC^{min} as the case offering no flexibility but high convenience. Here, users retain full control over their charging, ensuring their energy requirements are met immediately but providing no flexibility to energy providers. Third, we define 80 % SOC^{min} as offering low flexibility and maximum convenience. Energy providers can control charging only after EV reaches 80 % of the total battery, but users are assured that 80 % of their battery will be charged immediately. For most EV users, an 80 % SOC^{min} is nearly as effective as 100 %, as 80 % of the battery is sufficient for most trips, even in emergencies such as a nighttime trip to a nearby hospital. Therefore, this case also does not affect the user's convenience to a large extent.

Energy providers are concerned that users might set a high SOC^{min} to preserve their convenience, which would reduce flexibility and increase the EPC. However, our cost sensitivity analysis illustrates that even with low flexibility, energy providers can reduce their EPC up to

33.9 %, compared to no flexibility case. The EPC reduction at full flexibility is only slightly higher, at around 49.6 %. These results indicate that energy providers could achieve a similar magnitude of reduction as full flexibility, even with low flexibility, without causing much inconvenience to the users.

Our cost sensitivity analysis suggests that considerable cost reductions in low flexibility cases can be achieved when EVs connect more frequently to the charging point. The cost reductions for low flexibility are notably higher for higher charging thresholds (60 %–100 %). Many EV owners tend to plug in their vehicles less frequently, i.e., at lower battery thresholds, fearing potential battery degradation. However, the preferable operating range is typically between 20 % and 80 % [22]. Hence, energy providers could incentivize users to plug in their vehicles when their battery is between 60 % and 80 % (which is still within the preferable operating range), benefiting both users and energy providers.

6.2. Limitations and Outlook

There are several limitations in our study that we intend to address in future research.

We assumed linear charging when calculating EV flexibilities. In reality, charging power decreases as the battery's SOC approaches full capacity, which may extend charging times and slightly reduce flexibility. Additionally, battery degradation over time may affect charging efficiency and usable capacity, further influencing available flexibility. However, when flexibility is aggregated across multiple EVs, these individual discrepancies are minimized, resulting in a relatively small impact on the monetary value of EV flexibility in spot market trading. Future research could incorporate more realistic charging profiles to improve the accuracy of the flexibility modelling.

Beyond charging dynamics, our flexibility estimations rely on synthetic mobility data based on German driving patterns. While this approach provides a structured dataset, it does not fully capture real-world uncertainties, such as seasonal variations. For example, holiday mobility patterns often differ significantly from typical workdays, influencing driving and charging behaviours. Additionally, our estimations do not account for variability in vehicle specifications, such as battery size. Since battery capacity can influence user charging preferences—particularly their SOC^{min} thresholds—it may affect both the flexibility provided by EVs and overall user behaviour. Future studies could integrate real-world data to enhance modelling accuracy, refining scenarios and adapting them to specific periods.

Moreover, while we provide general recommendations to energy providers on incentivizing users to adapt their charging preferences for greater flexibility at an aggregated level, we did not differentiate between demographic factors such as income, urban versus rural location, or access to home charging. Different demographic groups may respond differently to incentives for flexible EV charging. Future research could explore how various user segments react to different levels of monetary incentives, enabling more tailored strategies that optimise flexibility provision across diverse demographic profiles.

When estimating the monetary value of flexibility, our model assumes perfect foresight for electricity prices for simplicity. However, in reality, energy providers face price uncertainty. Future research could address this limitation by incorporating uncertain price scenarios or integrating price forecasting techniques into the optimisation process, making the model more reflective of real-world market conditions.

The role of bidirectional charging (V2G) also warrants further exploration. With V2G, providers could arbitrage price differences across markets, potentially increasing revenue compared to unidirectional charging, as demonstrated in [25,31]. However, revenue potential depends on users' willingness to allow battery discharge, which varies and should be considered in future assessments. Integrating these behavioural aspects into flexibility modelling could provide a more realistic assessment of V2G's benefits.

Beyond economic optimisation, aligning EV charging with periods of high renewable energy availability enhances sustainability by reducing reliance on fossil-based electricity. While our approach indirectly captures this effect—since lower electricity prices often coincide with higher renewable generation—future studies could explicitly integrate renewable energy forecasts into optimisation models. A multi-objective approach that balances cost-efficiency with sustainability considerations could provide deeper insights into effectively managing EV charging under real-world conditions.

Our study focuses on energy providers who leverage aggregated EV flexibility to minimize costs while trading in the market and procuring power for the entire fleet. Yet, when allocating power to individual EVs, grid constraints may restrict the ability to shift all charging to lower-cost periods, potentially leading to additional redispatch costs, thereby diminishing the financial benefits of flexible charging. Future research could integrate these constraints into optimisation models to better assess their impact on cost savings and the feasibility of flexible charging strategies in real-world applications.

Despite these limitations, they do not diminish the key conclusion of our study: EVs possess significant flexibility that energy providers can utilise to reduce their EPC, even under the uncertainties considered in this work.

7. Conclusion

Our paper evaluated the impact of uncertain user behaviour on the EV flexibility potential and its monetary value in both day-ahead and intraday markets. We consider uncertainties arising from variable driving patterns and charging preferences. We introduced 52 distinct scenarios to model uncertainties in driving patterns effectively. Regarding charging preferences, our paper considered variations in both the SOC^{min} requirement and the frequency with which users connect their EVs to charging points. By assuming four use cases that reflect different possibilities of these charging preferences, we computed flexibility for each scenario using a dedicated flexibility model. We then used these flexibility scenarios as input to our scenario-based robust optimisation model to calculate the EPC for each use case. We calculated the EPC for each use case for one week across all months for 2022 and 2023.

Our findings indicate that a decrease in the frequency of EV connections to the charging point and an increase in the SOC^{min} requirement resulted in reduced EV flexibility, subsequently leading to increased EPC. The cases' EPC were much higher in 2022 than in 2023 due to high market prices. Nevertheless, we still observed a notable reduction in the EPC for the cases offering higher flexibility in 2022.

We also performed a cost sensitivity analysis, where we varied the charging thresholds- below which users plugin their EVs and SOC^{min} values and calculated the corresponding EPC for all months in the years 2022 and 2023. We observed the highest reductions in EPC for the months of February and July in 2022 and 2023, respectively, when EVs offer flexibility as opposed to uncontrolled charging where EVs offer no flexibility.

The reductions in EPC when EVs offer high flexibility (0 % SOC^{min} and 100 % charging threshold) were up to 43.6 % for February 2022 and 49.6 % for July 2023. Furthermore, we found that the EPC reduces up to 33.5 % for February 2022 and 36.9 % for July 2023 even when SOC^{min} values are as high as 80 % when compared to 100 % SOC^{min} values. These results indicate that an 80 % SOC^{min} achieves nearly the same EPC reduction as when 0 % SOC^{min} values. Our findings outline that flexible EVs charging thus possesses high economic value, allowing energy providers to achieve substantial monetary gains with minimal impact on user convenience.

CRediT authorship contribution statement

Raviteja Chemudupaty: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Ramin Bahmani:** Writing – original draft, Validation, Methodology, Conceptualization. **Gilbert Fridgen:** Writing – review & editing, Supervision, Funding acquisition. **Hanna Marxen:** Writing – review & editing, Writing – original draft, Conceptualization. **Ivan Pavić:** Writing – review & editing, Validation, Supervision, Conceptualization.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used Grammarly and ChatGPT in order to improve readability and language. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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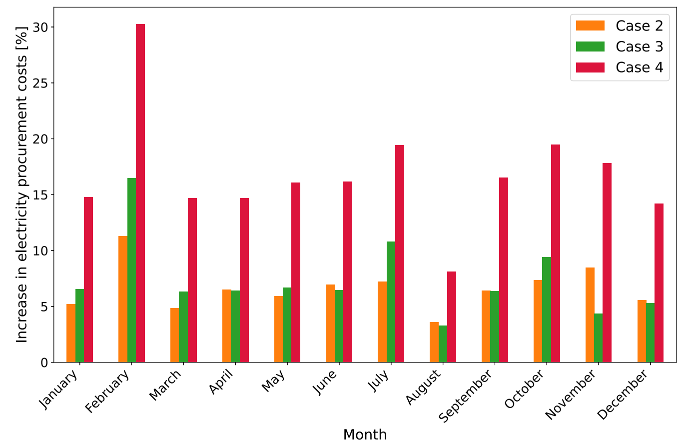
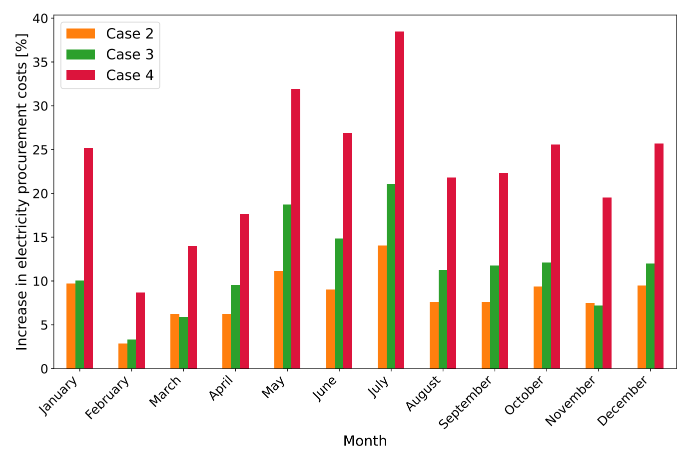
Appendix A. Relative values of increase in EPC for different use cases

See Fig. A.16(a) and (b).



(a) 2022



(b) 2023

Fig. A.16. Electricity procurement cost reduction for different cases when compared to Case 1 for one week across all months.

Appendix B. Cost sensitivity analysis for all months across the years 2022 and 2023

See Figs. B.17 and B.18.

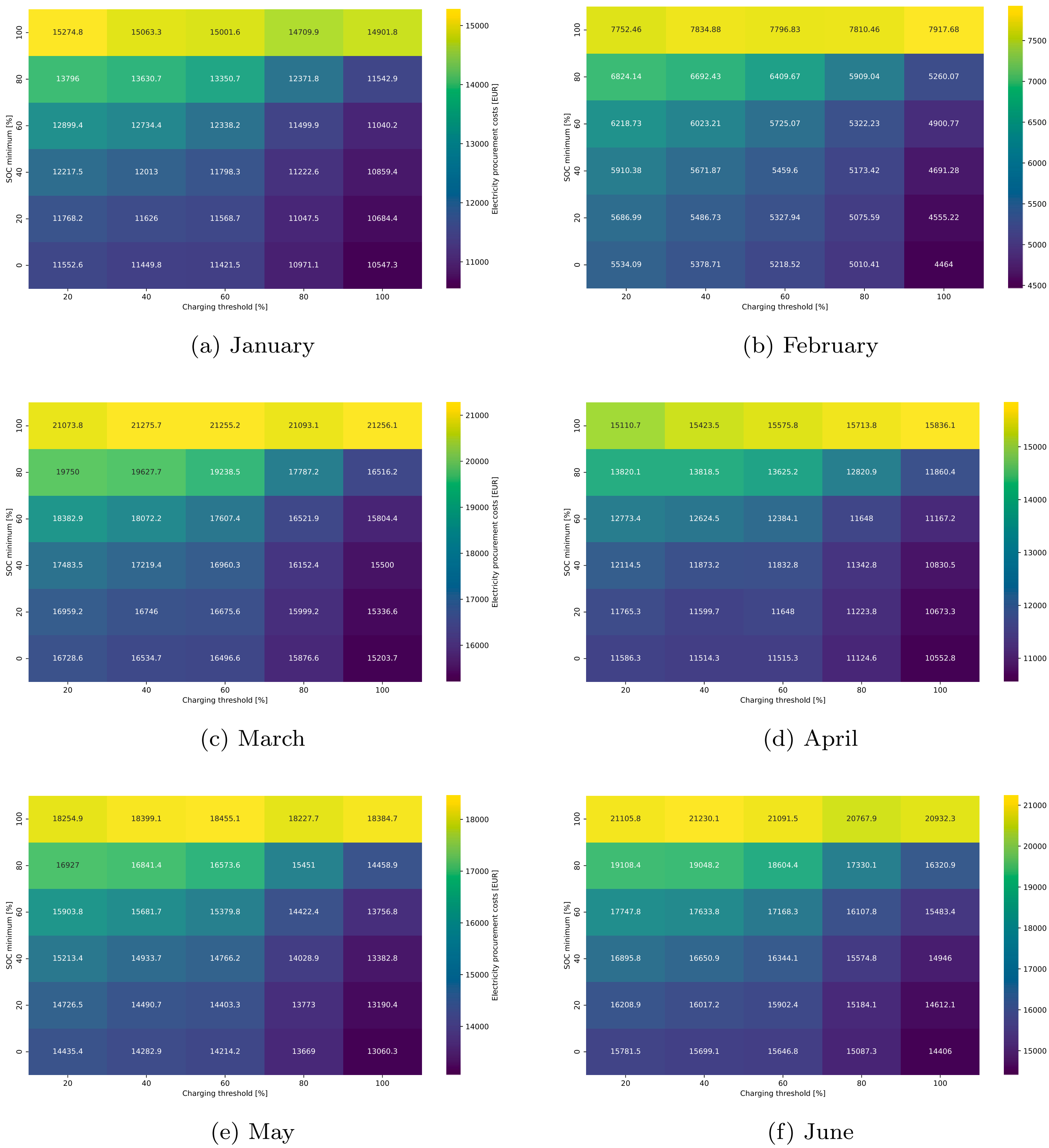
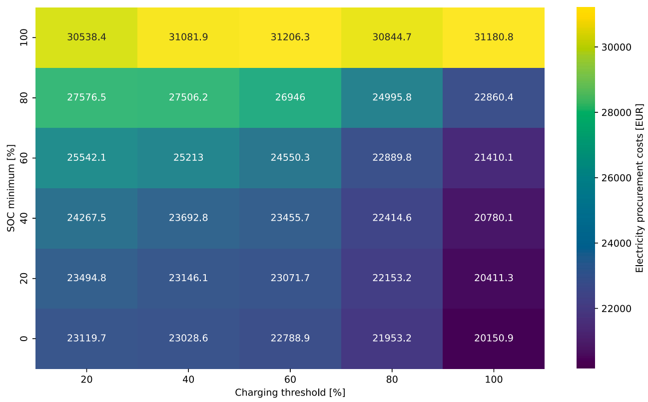
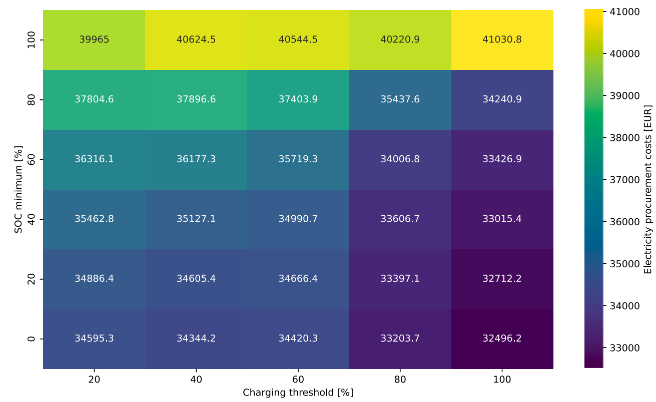


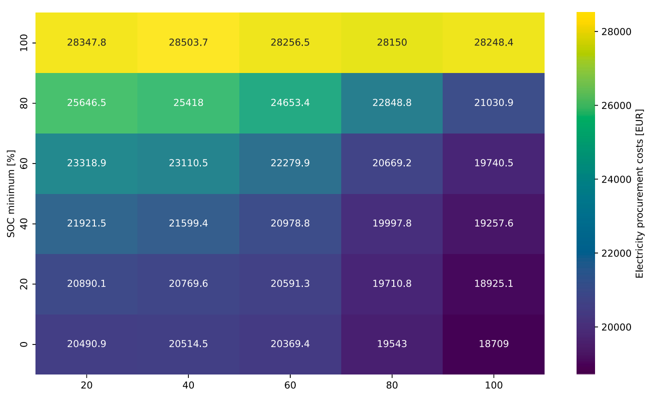
Fig. B.17. Electricity procurement costs of one week for different SOC^{min} and charging threshold combinations for each month in 2022.



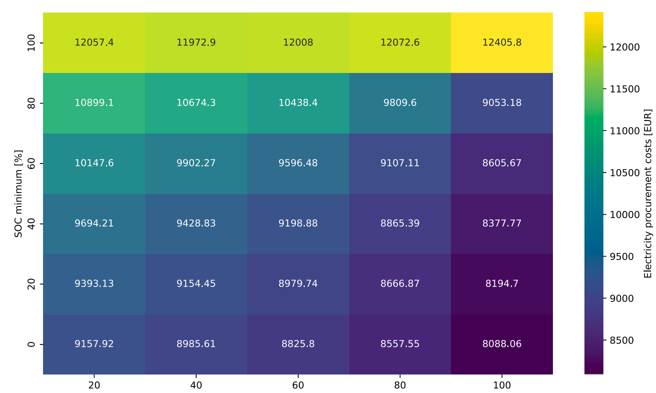
(g) July



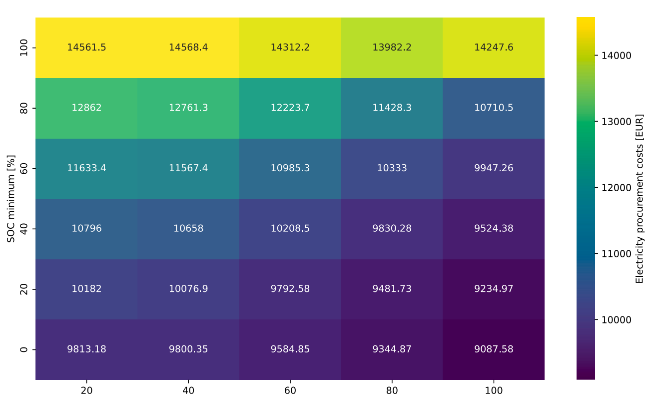
(h) August



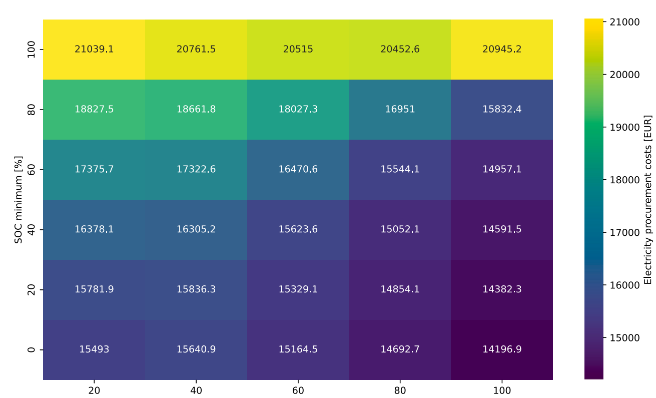
(i) September



(j) October

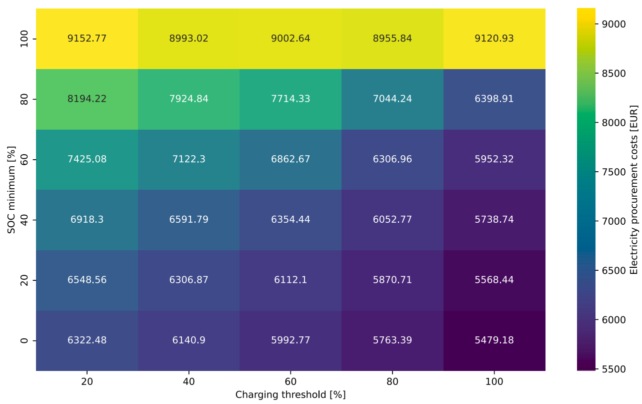


(k) November

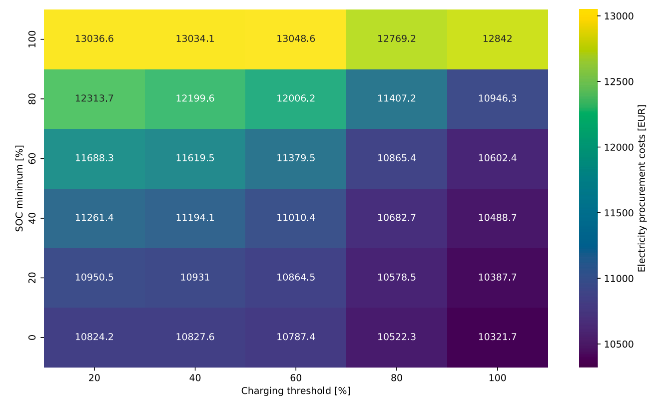


(l) December

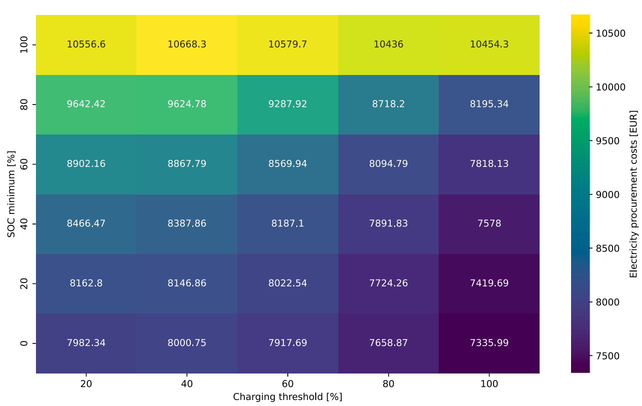
Fig. B.17. (*Continued*)



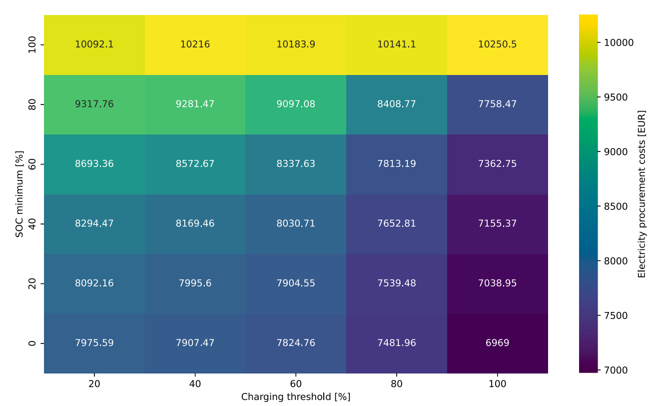
(a) January



(b) February



(c) March



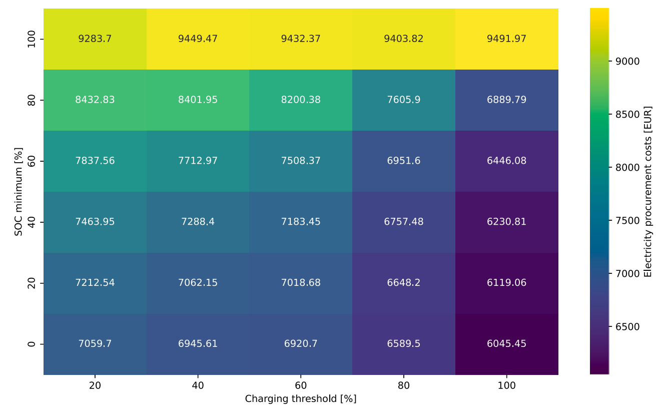
(d) April

(e) May

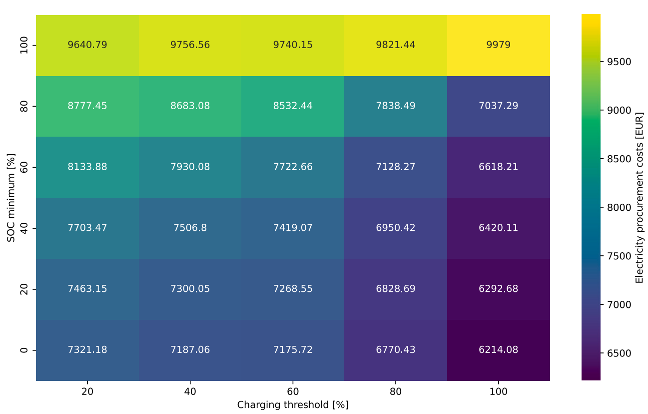
(f) June

Fig. B.18. Electricity procurement costs of one week for different SOC^{min} and charging threshold combinations for each month in 2023.

(g) July



(h) August



(i) September

(j) October

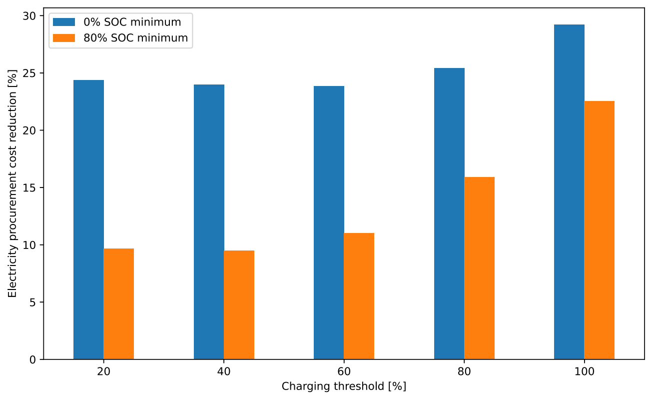
(k) November

(l) December

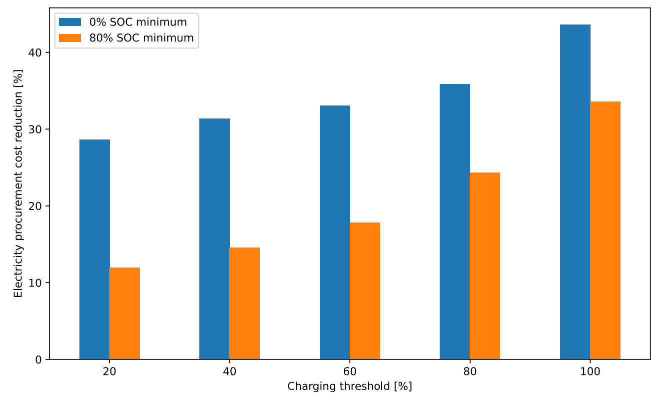
Fig. B.18. (*Continued*)

Appendix C. Relative reduction of EPC for different SOC^{min} for all months across the years 2022 and 2023

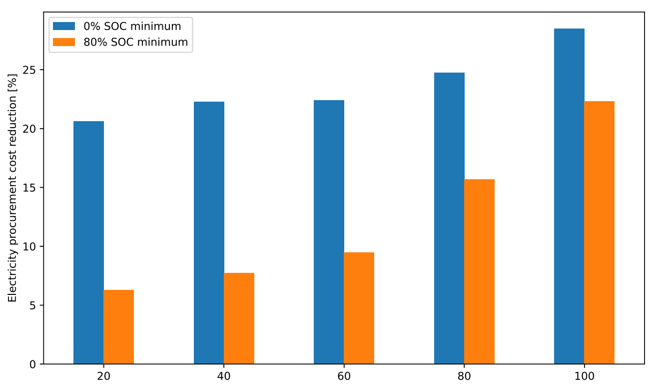
See Figs. C.19 and C.20.



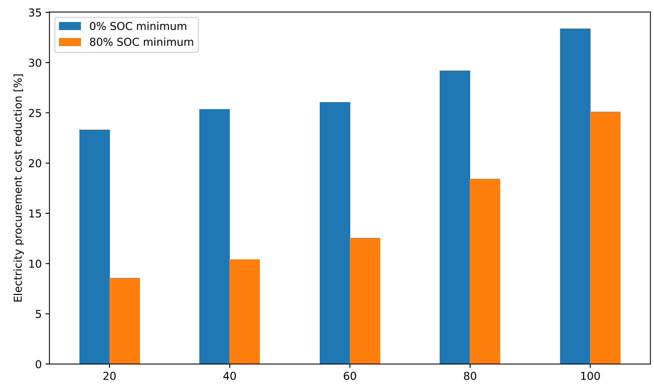
(a) January



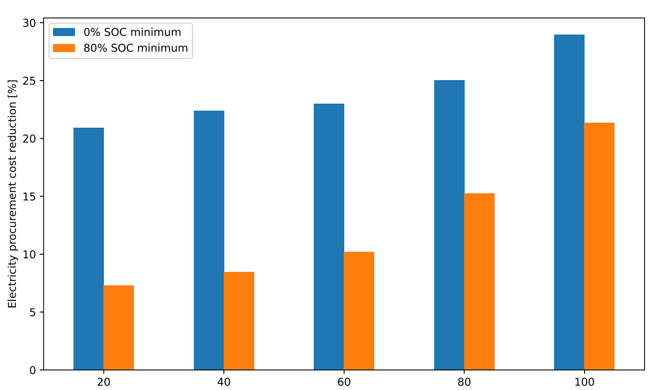
(b) February



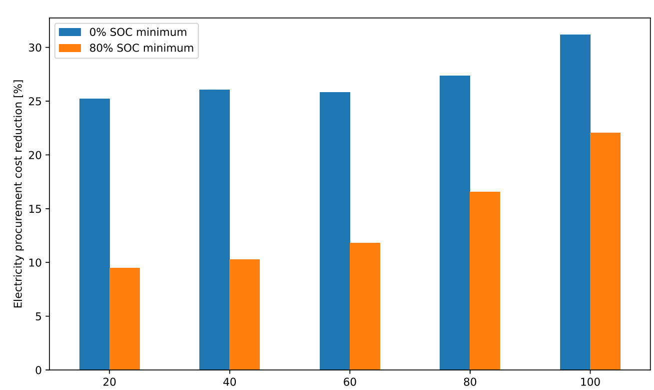
(c) March



(d) April

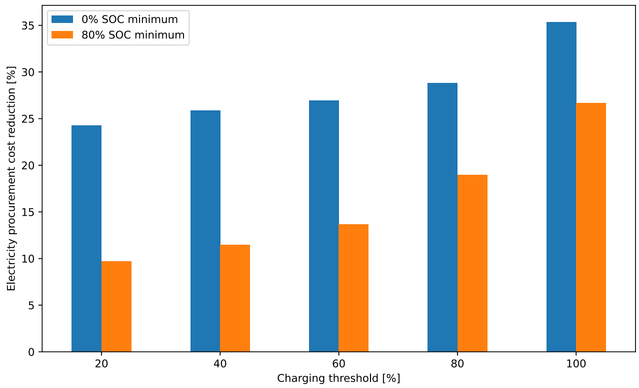


(e) May

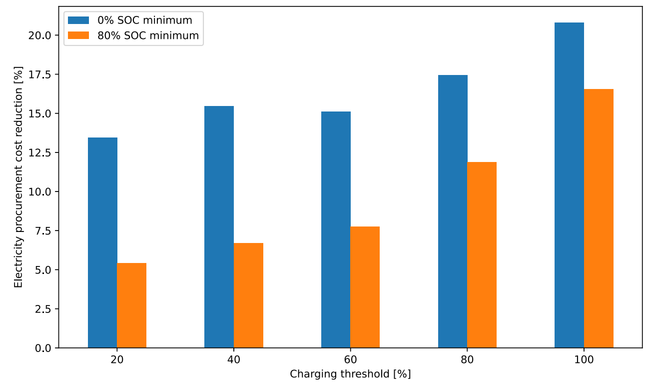


(f) June

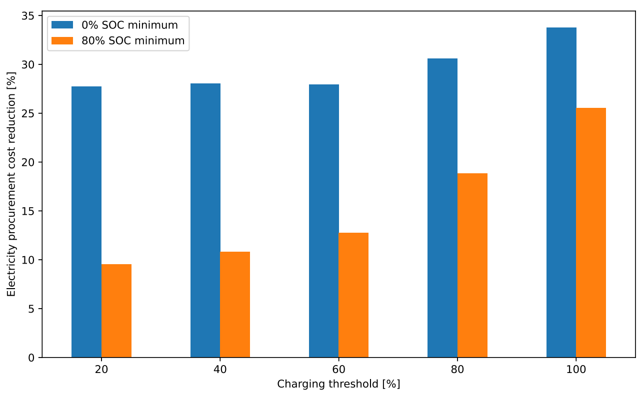
Fig. C.19. Relative cost reduction of different SOC^{min} values compared to 100 % SOC^{min} values across different charging threshold for each month in 2022.



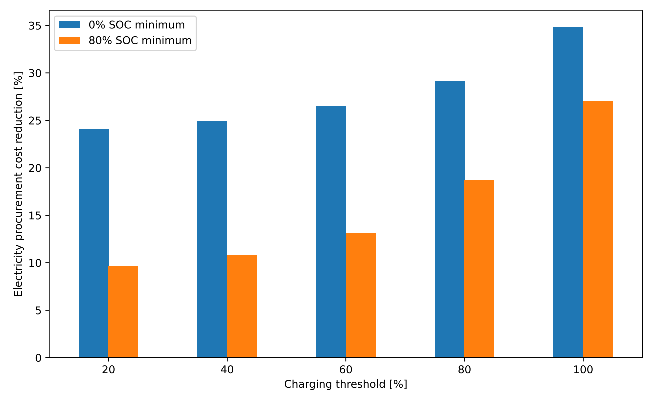
(g) July



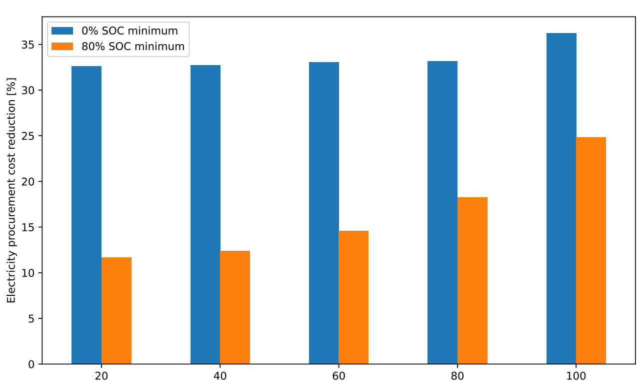
(h) August



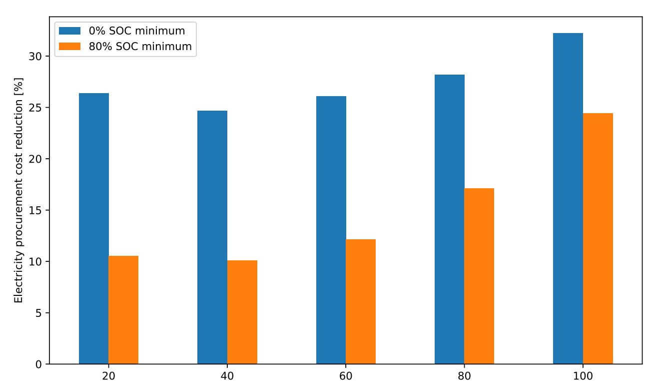
(i) September



(j) October

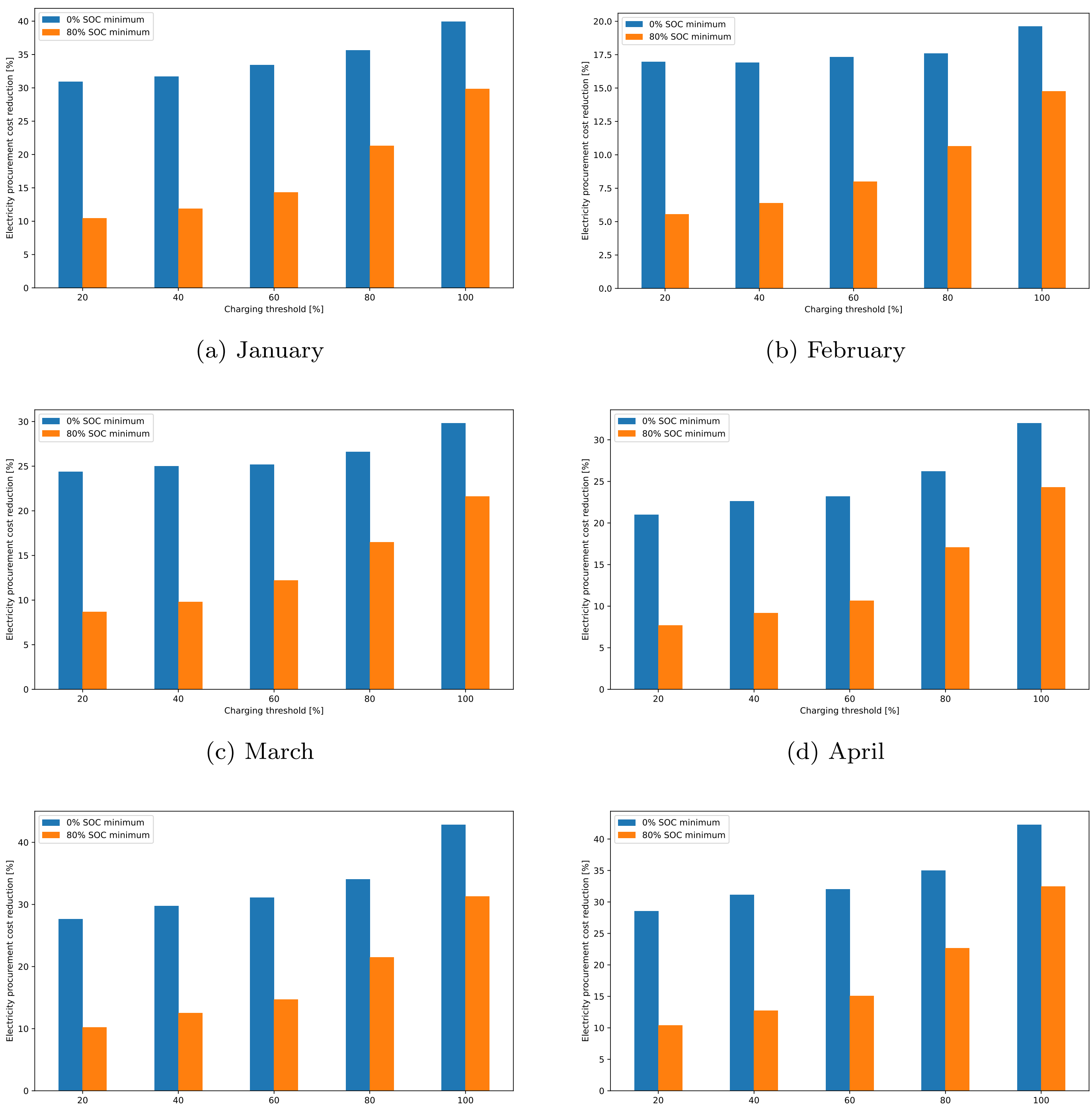


(k) November



(l) December

Fig. C.19. (*Continued*)

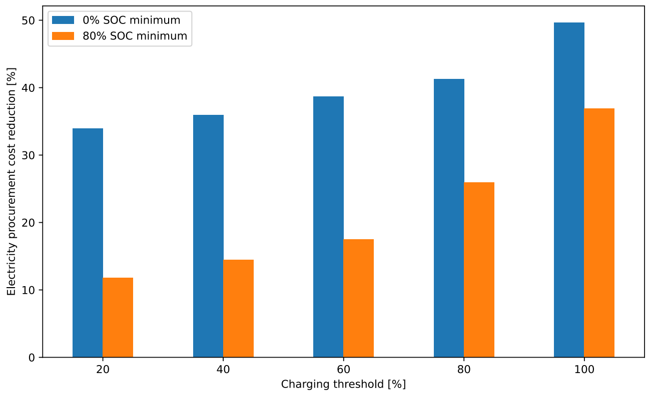


(a) January (b) February

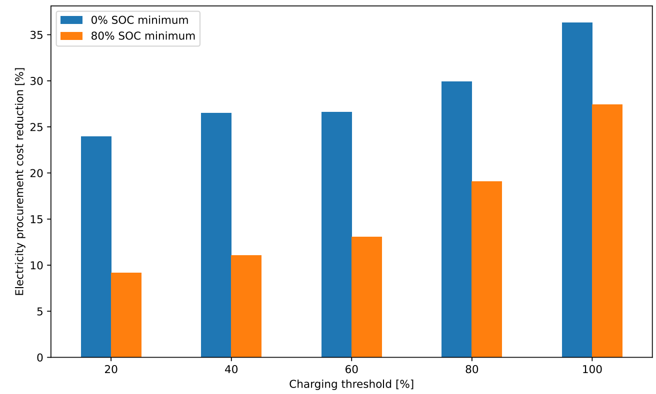
(c) March (d) April

(e) May (f) June

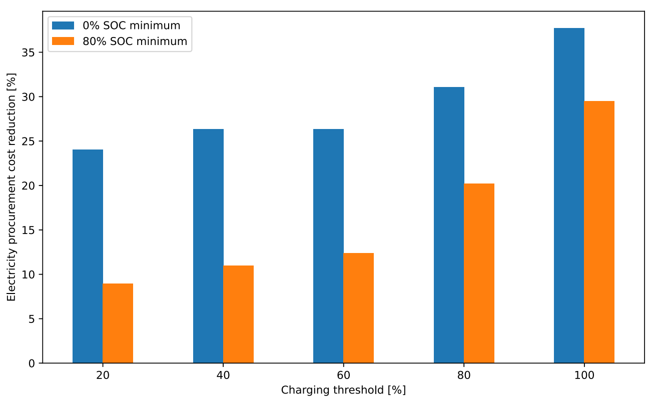
Fig. C.20. Relative cost reduction of different SOC^{min} values compared to 100 % SOC^{min} values across different charging threshold for each month in 2023.



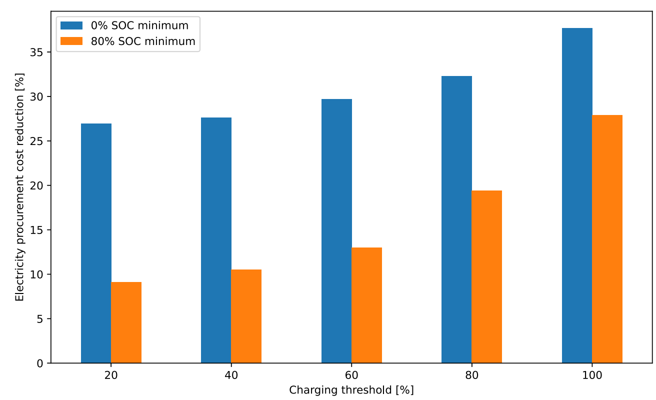
(g) July



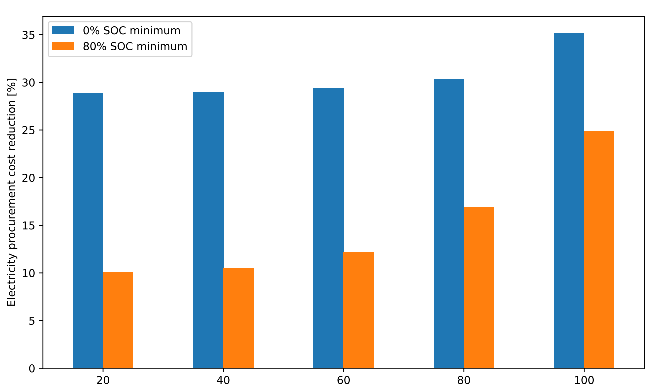
(h) August



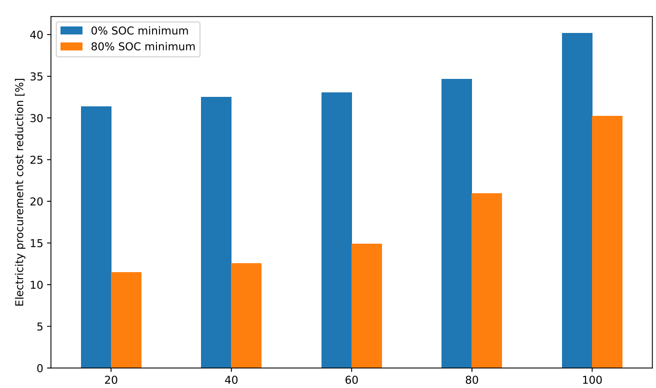
(i) September



(j) October



(k) November



(l) December

Fig. C.20. (*Continued*)

Data availability

Data will be made available on request.

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