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Electric Vehicle Scheduling Strategies to Reduce the Imbalances due to User Uncertainties

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ABSTRACT

There has been an increase in the adoption of electric vehicles (EVs) due to growing environmental concerns, technological advancements, and supportive government policies. This rapid increase in EVs necessitates energy providers to procure sufficient power to meet the charging demands. However, uncertainties in EV usage due to variable driving patterns and charging preferences make it challenging for energy providers to predict the charging demand. To address these uncertainties, energy providers can use stochastic models and trade in multiple short-term electricity markets. Moreover, when smart charging, energy providers can use the EV flexibility to charge the vehicles during lower market price periods, reducing procurement costs. Despite these strategies, there is a time lag between trading and delivery during which users could change their EV usage patterns, leading to new user requirements during delivery. This update in the user requirements creates discrepancies between procured and updated power needs, causing imbalances. Our study analyzes whether EVs possess enough flexibility to overcome their uncertainties, satisfy user energy requirements, and reduce imbalance costs. We develop a two-step approach: 1) procuring energy in the day-ahead market and 2) rescheduling across each EV to meet updated requirements. We test three rescheduling strategies across 51 scenarios, reflecting the updated user requirements. Our findings reveal that, despite uncertainties, EVs have enough flexibility to meet user needs and reduce imbalance costs, with the potential for additional revenues.

Keywords: Smart charging, Electric vehicle flexibility, Optimization, Day-ahead market, Imbalance costs

NOMENCLATURE

Abbreviations	
DA	day-ahead
EV	electric vehicle
reBAP	imbalance price

1. INTRODUCTION

In recent years, there has been a surge in the adoption of electric vehicles (EVs) [1]. This growth is expected to continue, compelling energy providers to meet the escalating power demands of EV charging. Typically, energy providers can use EV demand forecasts based on historical driving and charging patterns to help them better predict the demand and procure the power required to satisfy the charging demand [2].

However, diverse driving patterns and charging preferences create uncertainties in EV usage, posing challenges to energy providers [3]. Factors such as EV user trip distances, parking durations, arrival and departure times, and energy requirements contribute to these uncertainties, making accurate prediction difficult for the energy providers [4, 5]. To address these challenges, energy providers can utilize Monte Carlo simulation models based on probability functions [6, 7] or Markov chain models [8]. These modelling techniques enable the representation of stochastic EV usage patterns and facilitate better estimation of charging demand.

Furthermore, the actual charging duration of EVs is often less than their plugin duration, especially in the case of residential charging, which is the focus of this paper. This makes EV charging temporally flexible [9]. This temporal flexibility allows the energy providers to control and adjust the EV charging schedule within a specific period [10, 11]. Thus, when smart charging energy providers can leverage the flexibility provided by EVs to minimize their procurement costs by scheduling the EV charging when the market prices are lower [12, 13].

To handle the EV uncertainties while trading in day-ahead (DA) market, energy providers can use stochastic optimization models [14]. These models aim to minimize the expected costs while satisfying user requirements. Authors in [15] developed a stochastic optimization model with the objective to minimize the energy provider's expected cost in DA market. Within the optimization model, they considered the EV uncertainties by modelling different demand scenarios. Additionally, authors in [16, 14] include risk measures such as conditional value at risk (CVar) in their stochastic models. The inclusion of risk measures to mitigate the financial risks

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incurred due EV uncertainty while trading in DA market.

Two-stage optimization models enable energy providers to optimize the EV charging in both DA and intraday markets [17]. The first-stage decisions usually correspond to DA market scheduling to minimize the costs of the energy provider. The second-stage decisions usually correspond to intraday markets where the objective function is to reduce the power imbalances and minimize the energy provider's costs [18]. Furthermore, authors in [19] developed a sequential trading strategy to trade in both DA and intraday markets. They developed a rolling window optimization model to deal with uncertainties while trading in the intraday market.

While the above studies effectively handle uncertainties by integrating them into their models and trading in multiple markets, a time lag exists between trading and the delivery period. During this interval, the initial user requirements predicted during the trading time may change; for instance, users may update their plugin duration and energy requests. This update in user requirements would lead to discrepancies between the procured power while trading and the updated power demand during delivery time, causing imbalances. In Europe, energy providers must settle these imbalances in the imbalance market and pay additional costs. However, if EVs possess sufficient flexibility, energy providers can reschedule the allocated power to each EV to meet the updated EV requirements and reduce imbalance costs. Therefore, our research paper aims to answer the following research questions:

- RQ 1) To what extent can energy providers use the EV flexibility to satisfy the updated energy requirements at delivery time?
- RQ 2) Do EVs possess enough flexibility to reduce the energy provider's overall imbalance costs?

To answer the above research questions, we develop a two-step optimization approach. In the first step, we procure the aggregated power required for EV charging from the DA market using the initial user requirements. We develop a linear optimization model to facilitate trading in DA market to minimize the procurement costs. In the second step, we update the user requirements and reschedule the power allocated to each EV. We use three rescheduling strategies and evaluate the imbalance costs for each strategy. In the first strategy, we assume that the energy provider tries to satisfy the updated energy requirements by reallocating the power to each EV using the aggregated power from DA market. In this strategy, the energy provider settles in the imbalance market only if they have excess power. In the second strategy, the energy provider settles all the imbalances in the imbalance market to satisfy the updated energy requirements while minimizing the overall imbalance volume. The third strategy is similar to the second, but we minimize the energy provider's overall imbalance costs in this strategy.

2. METHODS

Figure 1 gives an overview of our two-step optimization approach. The first step is related to the DA scheduling based on initial user requirements, where the energy provider procures the aggregated power required for EV charging while trading in DA market. Section 2.1 presents our optimization model and relevant data required for trading in DA market. The second part

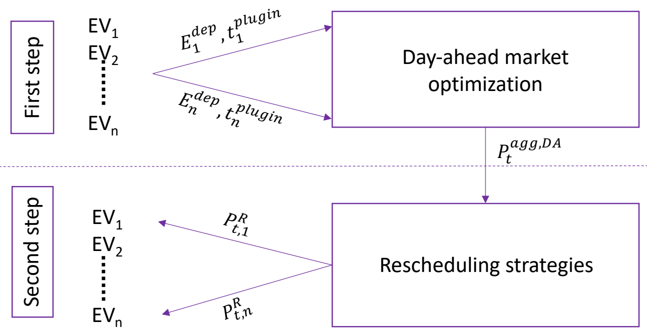

Fig. 1 Overview of our two-step optimization approach.

relates to rescheduling, where the energy provider allocates the power to each EV based on the updated user requirements using three strategies for which we develop three optimization models. Section 2.2 presents the optimization models and relevant data required to reschedule the power allocated to each EV.

2.1 Day-ahead market optimization model

We develop a linear optimization model to minimize energy provider's procurement costs incurred for charging the EV fleet while trading in DA market. The input data for our optimization model are DA market prices (C_t^{DA}), EV specifications and user requirements. The EV specifications include the maximum charging power of each EV (P_v^{max}) and maximum battery capacity (E_v^{max}). The user requirements include plugin duration (t_v^{plugin}) and energy level requested at departure ($E_v^{\mathsf{dep,DA}}$). We assume perfect foresight of DA prices in line with [20].

Our objective function aims to minimize the energy provider's DA procurement costs (see Equation 1). The objective function considers the variable $P_t^{\mathsf{agg,DA}}$ and parameter C_t^{DA}, which are the aggregated power procured from DA market for charging the EVs and the DA price at time t, respectively.

$$\min \sum_t C_t^{\mathsf{DA}} \times P_t^{\mathsf{agg,DA}} \times \Delta t \tag{1}$$

The aggregated power procured from DA market ($P_t^{\mathsf{agg,DA}}$) should be equal to the power allocated to each EV while trading in DA market ($P_{t,v}^{\mathsf{DA}}$) and this is ensured by Equation (2).

$$\sum_{v} \left(P^{\text{DA}}_{t,v}\right) = P^{\text{agg,DA}}_{t} \quad \forall t \tag{2}$$

Since $P^{\text{DA}}_{t,v}$ is the power with which each vehicle is charged, its value should always be within the limits of the maximum charging capacity of the EV. Thus, the constraint in Equation (3) ensures that $P^{\text{DA}}_{t,v}$ value is between 0 and P^{max}_{v} during the plugin duration.

$$0 \leq P^{\text{DA}}_{t,v} \leq P^{\text{max}}_{v} \quad \text{for } t \in t^{\text{plugin}}_{v} \quad \forall v \tag{3}$$

$E^{\text{DA}}_{t,v}$ is the energy level of the vehicle at time t, and it should be within the battery capacity limits, which is ensured by Equation (4).

$$0 \leq E^{\text{DA}}_{t,v} \leq E^{\text{max}}_{v} \quad \text{for } t \in t^{\text{plugin}}_{v} \quad \forall v \tag{4}$$

The constraints in Equations (5), (6), and (7) ensure the energy balance of EVs at the time of arrival (t^{arr}_{v}), throughout the plugin duration (t^{plugin}_{v}) and at the time of departure (t^{dep}_{v}).

$E^{\text{DA}}_{t,v}$ gives the energy level of an EV at timestep t, $E^{\text{arr,DA}}_{v}$ is the energy level of an EV at t^{arr}_{v} which we obtain from user input, $E^{\text{DA}}_{t-1,v}$ gives the energy level of an EV at previous timestep, η_{ch} is the charging efficiency, $E^{\text{dep,DA}}_{v}$ is the energy level of EV at t^{dep}_{v}.

$$E^{\text{DA}}_{t,v} = E^{\text{arr,DA}}_{v} \quad \text{for } t = t^{\text{arr}}_{v} \quad \forall v \tag{5}$$

$$E^{\text{DA}}_{t,v} = E^{\text{DA}}_{t-1,v} + \eta_{\text{ch}} \cdot P^{\text{DA}}_{t,v} \cdot \Delta t \quad \text{for } t \in t^{\text{plugin}}_{v} \quad \forall v \tag{6}$$

$$E^{\text{DA}}_{t,v} = E^{\text{dep,DA}}_{v} \quad \text{for } t = t^{\text{dep}}_{v} \quad \forall v \tag{7}$$

2.2 *Rescheduling optimization model*

Trading in the DA market occurs up to 36 hours before energy delivery, in our case, before EV charging. During the time between trading and delivery, the users might change their arrival time, departure time and energy level requested at departure. This update in the user requirements would mean that there might be a mismatch between the procured power from DA markets (aggregated DA power schedule) and updated power needs for charging, causing imbalances. The energy providers can reschedule the power allocated to each EV to address these imbalances. In our paper, we propose three rescheduling strategies for energy providers:

- First strategy: uses the same aggregated DA schedule to satisfy the updated user requirements without settling in the imbalance market. We reallocate the power to each EV to minimize the deviation between their updated energy level requirement at departure and the actual energy level resulting from the updated power we allocate to each EV.

- Second strategy: settling the imbalances in the imbalance market to satisfy the updated user requirements while minimizing the imbalance volume. By doing this, we change the aggregated power schedule at delivery (updated power schedule), ensuring we meet the updated energy requirements.

- Third strategy: settling the imbalances in the imbalance market to satisfy the updated user requirements while minimizing the imbalance costs. By doing this, we change the aggregated power schedule at delivery time (updated power schedule), ensuring we meet the updated energy requirement.

The following subsections will describe each of the strategies in more detail.

2.2.1 First strategy: Minimizing energy deviation

In the first strategy, we assume that energy providers reschedule the power allocated to each EV using the same aggregated power procured from DA market. Instead of procuring additional power from the imbalance market, the energy provider reallocates the power to each EV to reduce the deviation of the energy level requested by EV users at departures. Thus, the objective of the energy provider is to minimize the sum of the difference between the updated energy level request of the user at the departure ($E^{\text{dep,R}}_{v}$) and the actual energy level of the user at departure time after the delivery ($\tilde{E}^{\text{dep,R}}_{v}$) for all vehicles. Equation (8) represents the mathematical formulation of the objective function.

$$\min \sum_{v} \left(E^{\text{dep,R}}_{v} - \tilde{E}^{\text{dep,R}}_{v}\right) \tag{8}$$

The constraint in the Equation (9) ensures that the sum of the updated power allocated to each EV ($P^{\text{R}}_{t,v}$) is equal to the updated aggregated power schedule ($P^{\text{agg,R}}_{t}$).

$$\sum_{v} \left(P^{\text{R}}_{t,v}\right) = P^{\text{agg,R}}_{t} \quad \forall t \tag{9}$$

In this strategy, energy providers use the same DA aggregated power schedule to meet users updated energy requirements by utilizing the flexibility provided by EVs. Ideally, if all the updated energy requirements are satisfied, $P^{\text{agg,R}}_{t}$ should equal $P^{\text{agg,DA}}_{t}$. However, with updated requirements, $P^{\text{agg,R}}_{t}$ might be higher or lower than $P^{\text{agg,DA}}_{t}$. Since we assume that the energy provider does not procure additional power from the imbalance market, $P^{\text{agg,R}}_{t}$ can never exceed $P^{\text{agg,DA}}_{t}$. Instead, $P^{\text{agg,R}}_{t}$ can be less than $P^{\text{agg,DA}}_{t}$ to ensure feasibility if the overall $P^{\text{agg,R}}_{t}$ needed is less than the overall $P^{\text{agg,DA}}_{t}$. When $P^{\text{agg,R}}_{t}$ is less than $P^{\text{agg,DA}}_{t}$, the energy provider settles the excess power in the imbalance market. Equation (10) ensures the power balance between $P^{\text{agg,R}}_{t}$ and $P^{\text{agg,DA}}_{t}$.

$$P_t^{\text{agg,R}} \leq P_t^{\text{agg,DA}} \quad \forall t \tag{10}$$

Furthermore, the objective function is subject to updated constraints given by (11), (12), (13), (14), and (15).

$$0 \leq P_{t,v}^{\text{R}} \leq P_v^{\text{max}} \quad \text{for } t \in t_v^{\text{plugin}} \quad \forall v \tag{11}$$

$$0 \leq E_{t,v}^{\text{R}} \leq E_v^{\text{max}} \quad \text{for } t \in t_v^{\text{plugin}} \quad \forall v \tag{12}$$

$$E_{t,v}^{\text{R}} = E_v^{\text{arr,DA}} \quad \text{for } t = t_v^{\text{arr}} \quad \forall v \tag{13}$$

$$E_{t,v}^{\text{R}} = E_{t-1,v}^{\text{R}} + \eta_{\text{ch}} \cdot P_{t,v}^{\text{DA}} \cdot \Delta t \quad \text{for } t \in t_v^{\text{plugin}} \quad \forall v \tag{14}$$

$$E_{t,v}^{\text{R}} \leq E_v^{\text{dep,R}} \quad \text{for } t = t_v^{\text{dep}} \quad \forall v \tag{15}$$

The only major difference compared to DA optimization model is the energy balance equation at t_v^{dep} that is relaxed. We depict this using Equation (15). This constraint ensures that the actual energy level at departure can be less than the requested one.

$$E_{t,v}^{\text{R}} = \tilde{E}_v^{\text{dep,R}} \quad \text{for } t = t_v^{\text{dep}} \quad \forall v \tag{16}$$

The Equation (16) gives the mathematical representation of how we calculate the actual energy level at departure ($\tilde{E}_v^{\text{dep,R}}$), which is also the decision variable of the objective function (see Equation 8)

2.2.2 Second strategy: Minimize power deviation

In this strategy, we assume that the energy provider settles all the imbalances in the imbalance market and reallocates the power to each EV. While doing so, the energy provider tries to reduce the imbalance volumes whilst satisfying the user requirements. Accordingly, we formulate our objective function in Equation (17), which is to minimize the sum of the absolute power difference between the updated aggregated power schedule ($P_t^{\text{agg,R}}$) and aggregated DA power schedule ($P_t^{\text{agg,DA}}$).

$$\min \sum_t \left| P_t^{\text{agg,R}} - P_t^{\text{agg,DA}} \right| \tag{17}$$

We can observe that the objective function (Equation (17)) is non-linear as we are minimizing an absolute value. To make the objective function linear, we introduce an auxiliary variable for each time t denoted by z_t and additional constraints formulated in Equations (19) and (20). Accordingly, we present the modified optimization problem with an updated objective function in Equation (18) to minimize the sum of variable z_t.

$$\min \sum_t z_t \tag{18}$$

The constraints (refer to Equations (19) and (20)) ensure that z_t is at least as large as the absolute value of the expression inside.

$$z_t \geq \left(P_t^{\text{agg,R}} - P_t^{\text{agg,DA}} \right) \quad \forall t \tag{19}$$

$$z_t \geq -\left(P_t^{\text{agg,R}} - P_t^{\text{agg,DA}} \right) \quad \forall t \tag{20}$$

The objective function is subject to the same constraints as the first strategy (refer to Section 2.2.1) given by Equations (9), (11), (12), (13), and (14). However, the constraint in Equation (21) is different compared to the first strategy as the energy provider must ensure that they satisfy the EV user's energy requirements.

$$E_{t,v}^{\text{R}} = E_v^{\text{dep,R}} \quad \text{for } t = t_v^{\text{dep}} \quad \forall v \tag{21}$$

2.2.3 Third strategy: Minimizing imbalance costs

In the third strategy, we assume that the energy provider has perfect foresight of imbalance prices and aims to reduce the imbalance costs. Accordingly, our objective function (refer to Equation 22) is to minimize the energy provider's imbalance costs when settling in the imbalance market.

$$\min \sum_t \left(P_t^{\text{agg,R}} - P_t^{\text{agg,DA}} \right) \times C_t^{\text{reBAP}} \times \Delta t \tag{22}$$

The objective function is subject to the same constraints as in the second strategy (refer to Section 2.2.2), given by Equations (9), (11), (12), (13), (14), and (21).

3. DATA AND SIMULATION SETUP

3.1 Mobility data

We use existing synthetic mobility data to derive the user requirements for each EV [21]. The synthetic mobility data stems from a German mobility survey [22]. The mobility data consists of 200 unique mobility profiles of residential EVs. We analyze only the home charging case with the following assumptions:

- All vehicles are always plugged in when parked at home.
- All vehicles are charged until they reach E_v^{max}, or the maximum energy level they can reach when the users plugin their vehicle.
- The battery capacity of all vehicles is 75 kWh
- We consider a Level 2 charger with a mean power rating of 7.4 kW and charging efficiency (η) of 95%, typically used for home charging [23].

We divide the mobility dataset, containing individual profiles for the entire fleet of 200 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. Out of the 52 new datasets, we use one dataset to reflect the predicted (initial) user requirements while trading in DA market, and we use the other 51 datasets to reflect the change in user requirements and to test our rescheduling strategies for each of the 51 datasets separately.

3.2 Market data

We use the German DA market's one week's price data from January 2024 for trading in DA [24]. The resulting price data is from 15th January 2024 to 21st January 2024. We obtain imbalance price (reBAP) prices from ENTSOE-E Transparency Platform [25] for the same period as that of DA market data. We calculate the imbalance costs for all strategies ex-post using the reBAP price data. Equation (23) gives the formula we use to calculate the total imbalance costs for each rescheduling trading strategy.

$$\sum_{t} \left(P_t^{\text{agg,R}} - P_t^{\text{agg,DA}} \right) \times C_t^{\text{reBAP}} \times \Delta t \qquad (23)$$

4. RESULTS AND DISCUSSION

In this section, we present the results to answer our research questions. Section 4.1 presents the aggregated power schedule resulting from the DA optimization and updated aggregated power schedules resulting from the three rescheduling strategies. In Section 4.2, we compare the three strategies by calculating the energy deviation incurred for the EVs across all the charging sessions. Section 4.3 compares the three strategies, calculating the imbalance costs incurred while settling in the imbalance market.

4.1 Aggregated EV schedules

We first present the aggregated power schedule from the DA optimization. To illustrate our rescheduling process, we plot the updated aggregated power schedules from our three strategies and compare them with the DA aggregated power schedule. We present the aggregated power schedules for a single day: January 18, 2024.

Figure 2 presents the aggregated DA power schedule ($P_t^{\text{agg,DA}}$) based on DA market optimization (refer to Section 2.1) and DA market prices (C_t^{DA}). As the objective of the DA market optimization model is to minimize the overall costs, it tries to procure the power when prices are lower. Therefore, we can observe that most of the power procured for EV is between 02:00 and 04:00 when the prices are lower.

Figure 3 presents two aggregated power schedules - $P_t^{\text{agg,DA}}$ and $P_t^{\text{agg,R1}}$. $P_t^{\text{agg,R1}}$ is the updated aggregated power schedule based on the first strategy (refer to Section 2.2.1). We can observe that both power schedules are overlapping each other, indicating that $P_t^{\text{agg,R1}}$ is the same as that of $P_t^{\text{agg,DA}}$. This is because, in the first strategy, the model tries to allocate the power to each EV while still using the $P_t^{\text{agg,DA}}$.

Figure 4 presents two aggregated power schedules -

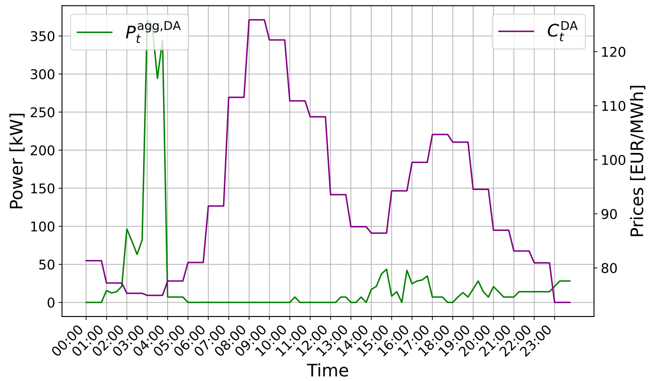

Fig. 2 Day-ahead schedule on 18th Jan 2024.

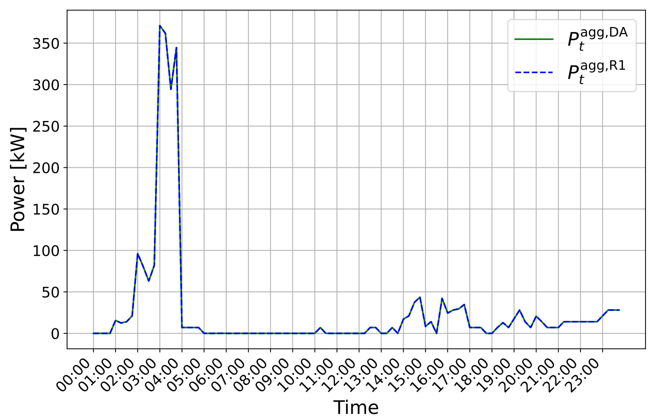

Fig. 3 Updated schedule based on first strategy on 18th Jan 2024.

$P_t^{\text{agg,DA}}$ and $P_t^{\text{agg,R2}}$. $P_t^{\text{agg,R2}}$ is the updated aggregated power schedule based on the second strategy (refer to Section 2.2.2). The objective of the second strategy is to minimize the power deviation. Therefore, we can observe that $P_t^{\text{agg,R2}}$ profile is very similar to $P_t^{\text{agg,DA}}$ albeit, there are few instances where the magnitude of $P_t^{\text{agg,R2}}$ is different to that of $P_t^{\text{agg,DA}}$ to account for imbalances caused due to the change in user requirements. One instance where the imbalance occurs is around 05:00. This is a negative imbalance since the $P_t^{\text{agg,R2}}$ value is higher than that of $P_t^{\text{agg,DA}}$ during this instance (at 05:00), which means the energy provider has to procure more power to satisfy the users' updated energy requirements.

Figure 5 presents the results for the third strategy (refer to Section 2.2.3). In the figure, we present $P_t^{\text{agg,DA}}$, $P^{\text{agg,R3}}$ - the updated aggregated power schedule based on the third rescheduling strategy, and imbalance prices (C_t^{reBAP}). We can observe that $P^{\text{agg,R3}}$ is quite different from $P^{\text{agg,DA}}$. The difference is because the third rescheduling strategy aims to minimize the imbalance costs. Therefore, the model utilizes the EV flexibility to create a negative imbalance when the imbalance prices are lower and procure the power from the imbalance market, and create a positive imbalance when the im-

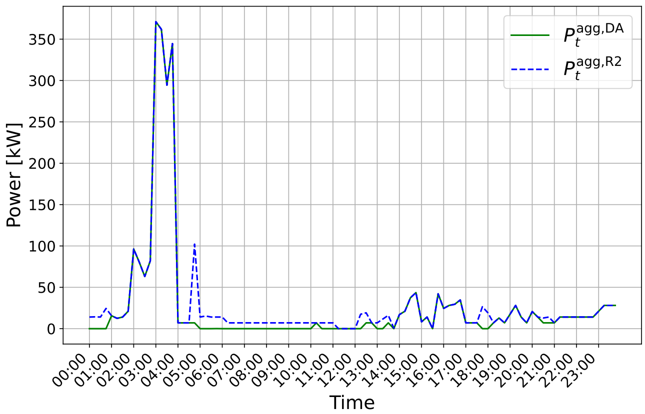

Fig. 4 Updated schedule based on second strategy on 18th Jan 2024.

balance prices are high and sell the imbalance power to the market. A few instances where we can observe instances of negative imbalance are around 02:00, 04:00 and 23:00. One instance of positive imbalance is around 03:00.

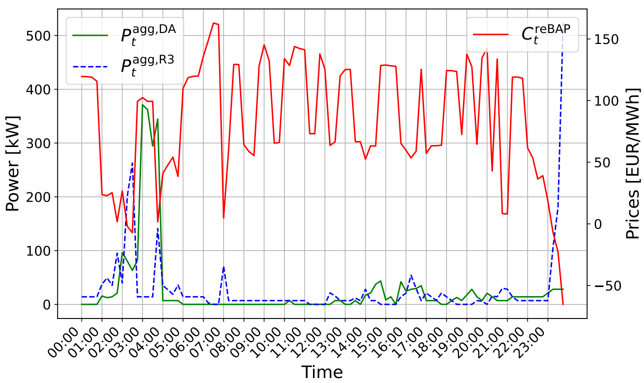

Fig. 5 Updated schedule based on third strategy on 18th Jan 2024.

4.2 Deviation in requested energy

The energy level deviation gives the difference between the updated energy level requested by users and the actual energy level that EVs have at the departure time after the rescheduling. Figure 6 shows the histogram of energy level deviations for all EVs at departure time in all 51 scenarios over one week for the first trading strategy. The x-axis represents the energy level deviation of each EV in kWh, and the y-axis represents the percentage of occurrences. We limit the x-axis data to 25 kWh to better illustrate the distribution of values. From the figure, we observe that in about 85% of cases, the energy level deviation is zero; for the remaining 15%, the deviation is spread from 1 kWh to 60 kWh, most of which are under 15 kWh. These results indicate that using the first strategy, the energy providers could satisfy the energy requirements of users for about 85% of the cases.

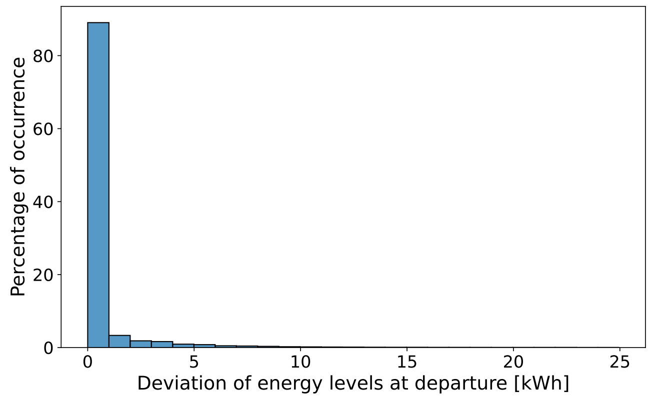

Fig. 6 Energy level deviation across all scenarios.

The energy level deviation for all EVs across all scenarios in the second and third strategies is equal to zero. The value is zero because the model allocates the power to each EV in a way that satisfies the user requirements, which means that the actual energy level is equal to the updated energy level requested by the user.

In the first strategy, energy deviations primarily occur in scenarios where overall energy requirements significantly exceed the anticipated levels during DA trading, resulting in insufficient power to meet the demand. In our study, we assume that all EVs would be charged until they reach their maximum battery capacity, which translates to EV users requesting 100% battery capacity at the time of departure. Often, EV users do not need 100% of their battery for their daily driving needs. For example, the average daily distance in Germany is around 33 km, which requires approximately 9% of the total battery capacity for a vehicle with a 75 kWh battery. In the 15% of instances where the updated energy requirements were not satisfied, the energy deviation is less than 15 kWh for most instances. The 15 kWh deviation implies that their battery percentage is at least 80%, which is sufficient for most of the trips and thus might not hinder user comfort in terms of their driving needs.

4.3 Imbalance costs

Figure 7 depicts the distribution of imbalance costs incurred across all scenarios for each rescheduling strategy. In the first strategy, the imbalance costs vary from around -71 to 0 EUR for a week across all scenarios. The imbalance costs are negative because, in the first strategy, the model uses EV flexibility and tries to reallocate the power to each EV based on DA. In case of potential imbalance, the energy provider only settles in the imbalance when there is a positive imbalance, i.e., aggregated DA power is higher than updated aggregated power. As most imbalance prices are positive, the overall imbalance cost is negative (refer to the formula in Equation 23).

In the second strategy, the imbalance costs vary from around -50 EUR to 200 EUR for one week across all sce-

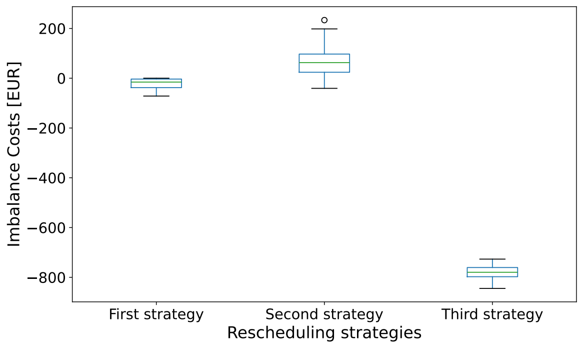

Fig. 7 Distribution of imbalance costs for each strategy.

narios, with a median value of around 60 EUR. Though the model tries to use the EV flexibility to minimize the power deviation from the aggregated DA power schedule while rescheduling, there could be several instances where there is a positive or negative imbalance. The positive imbalance occurs when the aggregated rescheduled power is less than the aggregated DA power. During the positive imbalance period, the energy provider settles (sells) the excess power in the imbalance market. If the price during the positive imbalance period is positive, the imbalance cost is negative (the provider makes revenue); else, the imbalance cost is positive (refer to the formula in Equation (23)).

The negative imbalance occurs if the aggregated rescheduled power exceeds the aggregated DA power. During the negative imbalance period, the energy provider settles (buys) the excess power in the imbalance market. If the price during the negative imbalance period is positive, the imbalance cost is positive; else, the imbalance cost is negative (the provider makes revenue) (refer to the formula in Equation (23)).

Therefore, overall imbalance costs are negative in some scenarios because there are more periods with a combination of positive imbalance and negative price and/or negative imbalance and positive price. Similarly, overall imbalance costs are negative in some scenarios because there are more periods with a combination of positive imbalance and positive price and/or negative imbalance and negative price. Therefore, creating a positive imbalance by procuring more power in DA does not always create revenues.

In the third strategy, the imbalance costs are negative, ranging from -850 EUR to -750 EUR, with a median value of -780 EUR. This strategy assumes perfect foresight of imbalance prices, allowing the model to utilize the flexibility provided by EVs to create positive and negative imbalances during periods that minimize costs. Consequently, the imbalance costs are negative in all scenarios.

However, the third strategy is purely theoretical since providers cannot predict imbalance prices upfront and thus cannot reschedule power to EVs to generate such revenues. These results highlight that advanced knowledge of imbalance prices could help minimize overall imbalance costs. However, this strategy illustrates that energy providers can harness EV flexibility to provide balancing energy services to system operators, helping to minimize overall system imbalances and generate additional revenues for suppliers or EV owners. This is because balancing energy prices is used to establish imbalance prices in the first place.

4.4 Discussion

Using the first strategy, energy providers could meet most users' energy needs. There is a risk that they might not fully satisfy the user's energy requirement, reducing the charging reliability and impacting user comfort regarding their driving needs. Suppose users offer more flexibility by reducing their energy requirements. In that case, energy providers can allocate power in a way that ensures all EVs have enough energy to complete their next trip without significantly impacting user comfort. In cases where there is still a high deviation between the energy levels at departure for the EVs, causing substantial discomfort and preventing users from meeting their driving needs, the energy provider can then resort to the second strategy. The second strategy involves settling the imbalances through the imbalance markets to meet the user's energy requirements. Thus, using the second strategy would not impact the user's comfort and charging reliability as they would have the requested energy by the end of the charging session. Furthermore, though the third strategy is impractical to implement directly, it illustrates that EVs possess enough flexibility to provide balancing energy services to system operators, helping to minimize overall system imbalances and generate additional revenues for energy providers or EV owners.

In our study, we recognize several limitations that highlight opportunities for future research. We used price data for one week to test our strategies and calculate the imbalance costs. We could extend our study for longer periods, allowing us to capture the seasonal effects. From the wholesale market model perspective, we only considered DA market because it is more liquid than the intraday market. However, for future work, we can also consider trading in the intraday market, where trading goes on until a few minutes before delivery, and analyze if trading multiple markets would reduce the imbalance costs. However, these limitations will not significantly impact our overall result, which is that despite uncertainties, EVs possess enough flexibility to meet user requirements and reduce imbalance costs.

5. CONCLUSION

Our paper analyzed if EVs possess enough flexibility to overcome the uncertainties arising due to variable EV usage, satisfy the user requirements, and reduce the energy provider's imbalance costs. We proposed a two-step scheduling approach. The first step relates to DA scheduling, where we developed a linear optimization model to procure the power required for EV charging based on the predicted initial user requirements while minimizing the energy provider's procurement costs. The second step relates to rescheduling, where we proposed three strategies to reallocate the power allocated to each EV to satisfy their updated user requirements. The first strategy reallocated power to EVs without settling in the imbalance market, minimizing deviation from updated energy requirements. The second strategy minimized imbalance volume by adjusting the aggregated power schedule at delivery. The third strategy focused on minimizing imbalance costs and adjusting the power schedule to meet updated energy requirements.

Our analysis demonstrated that energy providers could meet most of the users' energy needs by leveraging EV flexibility. Additionally, we found that providers could minimize user impact and imbalance costs by adjusting power allocation and utilizing the imbalance markets. Although the third strategy assumed perfect foresight of imbalance prices and was impractical for direct use, it illustrated that EVs possessed enough flexibility to provide balancing energy services, minimize system imbalances, and generate additional revenue. These findings highlighted the potential of EV flexibility to overcome their own uncertainties and use this flexibility to satisfy user energy requirements and reduce imbalance costs - potentially generating additional revenues.

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