A heuristic for bi-directional charging of fleet EVs

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***Abstract*—The growing adoption of electric vehicles (EVs) as company cars significantly amplifies charging demand and produces large power flows that must be carefully controlled. The advent of bi-directional charging opens up opportunities while simultaneously adding layers of complexity to the design of charging plans. Concurrently, installing photovoltaic (PV) systems at the company premises enhances sustainability but also introduces fluctuations in power generation, posing challenges to effective energy management. These complexities are compounded by the inherent uncertainties in forecasting EV behavior, PV output, and energy pricing, which further complicate the design of smart charging solutions. This paper introduces a heuristic bi-directional smart charging algorithm that generates charging station assignments for limited bi-directional charging stations and creates charging plans in real-time while being robust to prediction error. The simulation results demonstrate that our approach yields considerable advantages compared to benchmarks, including cost reductions, peak demand management, and improved PV energy utilization.**

Keywords—Smart grid, optimization, electric vehicles, bi-directional charging, renewable energy

I. Introduction

Climate change and resource depletion are driving forces accelerating the adoption of electric vehicles (EVs) and renewable energy resources. Global EV sales reached an unprecedented ten million by the end of 2023, compared to a mere one million previously [1]. Additionally, worldwide renewable energy capacity experienced a 50% growth last year, reaching 510 gigawatts in 2023 [2]. In this context, two significant challenges emerge: First, the uncoordinated charging of EVs often leads to substantially higher peak loads, which can strain local infrastructure and the broader power grid [3]. Second, the challenge of integrating renewable energy into existing electrical systems is complicated by its intermittent and variable nature. To address these challenges, smart charging offers a promising solution. By intelligently managing when and how much EVs are charged, smart charging can help to mitigate peak loads, balance the fluctuations of renewable generation, and also reduce charging costs [4], [5].

Smart charging can be categorized into two types: uni-directional and bi-directional. Uni-directional smart charging strategies address key issues such as minimizing demand and energy charges [6], correcting phase load imbalances [7]-[9], employing peak shaving [9], [10], and optimizing PV and EV sizing for enhanced cost efficiency [11]. Studies on bi-directional smart charging explore its implementation in both front-of-the-meter [12]-[15] and behind-the-meter applications [14]-[17] broadening its applicability and potential benefits.

Despite these advancements, research on bi-directional smart charging at company premises remains limited, especially for systems with PV and company-owned EVs that allow centralized control. This area is important since a large number of EVs results in significant energy flows and presents unique challenges: Cable capacity limitations often prevent simultaneous charging for all EVs, even if they are assigned to a station. Additionally, specific arrival and departure patterns further restrict effective energy management. Furthermore, not all charging stations support bi-directional charging, and assigning bi-directional vehicles to limited bi-directional stations poses another significant challenge.

This study presents a renewable- and cost-aware (ReCo) smart charging heuristic algorithm that dynamically generates charging station assignments and charging plans in real-time, utilizing bi-directional charging for behind-the-meter use cases. Additionally, the algorithm adapts to prediction errors in energy prices, PV generation, and early EV departures. The main contributions of our work are as follows:

- We developed a real-time bi-directional charging simulator and designed a heuristic algorithm to optimize the charging plans. The algorithm is fast, scalable for real-time implementations, and robust to prediction errors.
- A strategy is developed to assign bi-directional EVs in scenarios with limited bi-directional charging stations. Effectively utilizing available charging infrastructure while accommodating the specific charging needs of each EV.
- Simulations demonstrate that our approach has considerable advantages over benchmark algorithms, including cost reduction, peak shaving, and utilization of PV-generated energy.

II. Scenario

Generally, EV users and charge point operators have differing interests, which can complicate the adoption of centralized charging plans. To effectively utilize bi-directional charging, our study focuses on a company premise with company-owned cars and PV panels (Fig. 1). The key elements are:

Charging station: includes uni-directional and bi-directional charging stations, with a power range from 4 to 22 kilowatts.

EV: supports bi-directional charging with same discharge and charging power ranges. Furthermore, we model the charging and discharging behaviors of EV batteries to be linear [18]. We utilize historical data from a German company to establish two discrete probability distributions for EV arrival and departure times. These times are modeled as normal distributions, with peak times at 08:00 and 17:00 and a standard deviation of one hour each. Acknowledging the uncertainty of knowing the actual departure time of each EV upon its arrival, we simplify our optimization model by predicting that every EV would leave at exactly 17:00.

PV: The on-site PV generation data (Fig. 2) used in our study is derived from weather conditions observed in Dresden, Germany, during a summer day in 2023. This data has been appropriately scaled to match our simulation needs, with peak production reaching 340 kilowatts. Additionally, the generation data is treated as predicted values, and is updated each 15-minute timeslot to reflect the changing conditions and prediction errors.

Energy costs: Electricity prices are derived from historical data from the intraday energy market, as shown in Fig. 3. We simplify the pricing model by assuming a constant price for each 15-minute timeslot. The cost is calculated based on these prices and the total energy used. Similarly, the energy prices used in our study are treated as predicted data. It's worth mentioning that our analysis does not include any system usage charges related to peak consumption.

Hierarchy of power network: The car park infrastructure is represented by a tree of fuses, with each node depicting a fuse that can connect to additional nodes, charging stations, or the PV system, forming a hierarchical structure. Each charging station is connected to the tree via three-phase alternating current. The tree is structured with a depth of three levels, mirroring real-world installations, as illustrated in Fig. 4.

Time of planning: This work focuses on real-time planning. EV's information is received upon its arrival at the company, for instance, via an app integrated into the EV. The data includes arrival time, estimated departure time, and initial state of charge (SoC), in addition to user-specified preferences

Fig. 1. Company premise with a parking lot and PV panels.

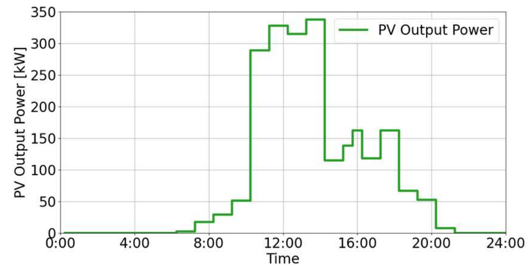

Fig. 2. PV output power generated from weather conditions in Germany.

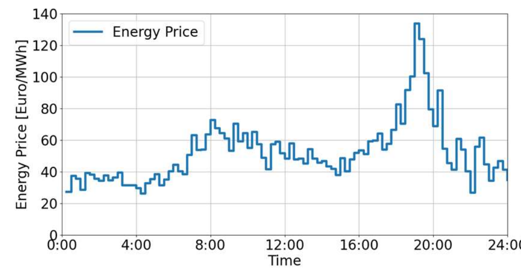

Fig. 3. Electricity prices from the intraday market in Germany.

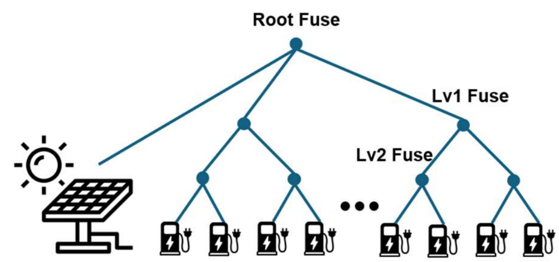

Fig. 4. Hierarchy of power network in the parking lot, showing the three-level fuse tree structure.

such as desired departure SoC, minimum SoC, and the maximum energy that can be discharged. Once this information is received, the assignment and charging plan is generated.

III. Method

This work introduces a heuristic approach to minimize charging energy costs and increase PV utilization while maintaining peak power within a specified range and satisfying the EVs' charging needs. The decision variables $P_n(t)$ describe the power of EV n at timeslot t. There are a total of N EVs, and the duration of each timeslot t is denoted as τ. In our study, t is set to 15 minutes. The objective function is outlined in (1), weight factors $w1$ and $w2$ have the units (1/€) and (1/kWh), respectively. The total charging cost from the grid C^G is calculated over the timeslot from 1 to T, where T represents the last timeslot of the day, as detailed in (2). The charging energy utilized from the PV system, E^{PV}, is specified in (3). Additionally, $c^{Grid}(t)$ *represents* the unit cost of grid energy at any given time t, and $P^{PV}(t)$ is the output power of the PV system.

The constraints are as follows: the total power drawn from the grid must not exceed P^{Peak} (4). Furthermore, the total power of all EVs connected to a fuse F_i must not exceed the maximum allowable power P_{F_i} for each fuse in the fuse tree (5). For an individual EV, the charging process is determined by (6), considering the charging and discharging efficiencies denoted by η^C and η^D, respectively, E_n^{max} the maximum capacity of the EV's battery. Additionally, the ranges for charging and discharging power are specified in (7). During discharging, the total discharged amount must not surpass $\Delta E_n^{D,max}$, and discharging should not reduce the SoC below the minimum threshold SoC_n^{min} (9). Most critically, each EV must depart with its desired SoC enforced by (10).

$$\text{Minimize: } w_1 C^G - w_2 E^{PV} \tag{1}$$

$$\text{where:} C^G = \sum_{t=1}^{T} [c^{Grid}(t)\cdot \tau\cdot \max(\sum_{n=1}^{N} P_n(t) - P^{PV}(t), (0)] \tag{2}$$

$$E^{PV} = [\tau\cdot \min(P^{PV}(t),\ \sum_{n=1}^{N} P_n(t))] \tag{3}$$

$$\text{s.t: } \sum_{n=1}^{N} P_n(t) - P^{PV}(t) \le P^{Peak} \tag{4}$$

$$\sum_{n\in F_i} P_n(t) \le P_{F_i} \tag{5}$$

$$SoC_n(t+1) - SoC_n(t) = \frac{\tau\cdot \max(P_n(t), 0)\eta^C}{E_n^{max}} + \frac{\tau\ .\ \min(P_n(t), 0)}{E_n^{max}\ \eta^D} \tag{6}$$

$$P_n^{min} \le |P_n(t)| \le P_n^{max} \tag{7}$$

$$-\tau\cdot \sum_{t=0}^{t_{max}} \min(P_n(t), 0) \le \Delta E_n^{D,max} \tag{8}$$

$$SoC_n^{min} \le SoC_n(t) \le SoC_n^{max} \tag{9}$$

$$SoC_n(t = t_n^{Leave}) \ge SoC_n^{Target} \tag{10}$$

Due to the limited number of bi-directional stations, an assignment strategy is essential upon the arrival of each EV, as detailed in Fig. 5. When an EV arrives, we calculate the charging priority σ_n^C and discharging priority σ_n^D according to (11) and (13); Δt_n represents the remaining parking time, while $\Delta E_n(t)$ denotes the total required energy. σ_n^C indicates the urgency of the EV's need for charging. Larger charging requirements and limited parking time result in a higher priority. δ_n^D quantifies the maximum potential energy of the EV for discharging (12). σ_n^D is calculated based on δ_n^D, by scaling it down to a range between 0 and 1 with weight factor w_3. EVs with a higher potential to discharge more energy are prioritized for assignment to a bi-directional station. After calculating the priority values, σ_n^C and σ_n^D are compared against respective thresholds, θ^C and θ^D. Based on these comparisons, the EV is assigned to an appropriate charging station and a charging plan is created.

$$\sigma^C = \min\left(\max\left(\frac{\Delta E_n(t)}{\Delta t_n\cdot P_n^{max}\cdot \eta^C}, 0\right), 1\right) \tag{11}$$

$$\delta_n^D = \min\left(\frac{\Delta t_n\cdot P_n^{max}\cdot \eta^C - \Delta E_n(t)}{2}, \Delta E_n^{D,max}\right) \tag{12}$$

$$\sigma_n^D = \min\left(\max\left(\frac{\delta^D}{w_3}, 0\right), 1\right) \tag{13}$$

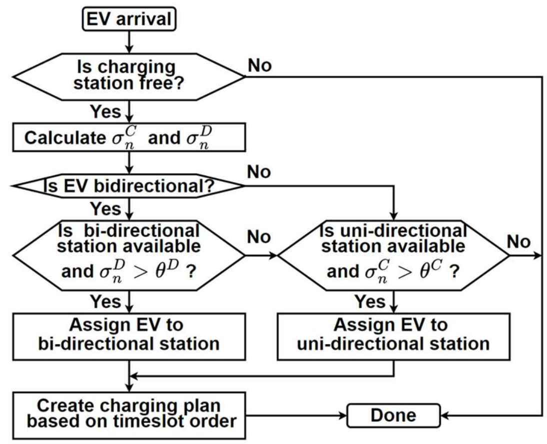

Fig. 5. Flow chart of the charging station assignment strategy.

In this work, we model grid energy, PV energy, and energy discharged from EVs as resource blocks, each characterized by its available amount, timeslot, source, and priority index which is calculated according to (14), (15), and (16). A lower priority index indicates that the resource block has a higher priority. σ^{Grid} is associated with the cost of grid energy, while σ^{PV} is linked to the remaining amount of PV energy. For σ^{EV}, we assume that the discharging cost is constant, denoted as c^{EV}. To optimize the use of discharging opportunities during periods of high grid costs and low PV availability, σ^{EV} includes a small negative component. This component serves to differentiate between EV resource blocks at different times, ensuring there is a distinction even when the discharging costs remain constant.

After station assignment, a charging plan for the EV is generated. All resource blocks available between the EV's arrival time and the predicted departure time are sorted based on their priority index, from lowest to highest. Then the charging plan is filled with these resource blocks until the desired amount of energy is reached, considering the constraints (7), (9), and (10). This ensures that the charging strategy is both cost-effective and aligned with the EV's specific energy requirements and schedule.

$$\sigma^{Grid}(t) = c^{Grid}(t) \tag{14}$$

$$\sigma^{PV}(t) = -\max\left(P^{PV}(t) - \sum_{n=1}^{N} P_n(t), 0\right) \tag{15}$$

$$\sigma^{EV}(t) = c^{EV}(t) - \left(\frac{\sigma^{Grid}(t)}{\sigma^{Grid,max}} + \frac{\sigma^{PV}(t)}{\sigma^{PV,max}}\right) \tag{16}$$

Following the creation of the charging plan, potential violations of the power peak (4) and fuse capacity (5) are checked. If any violations occur at specific timeslots, they are addressed sequentially. For each violating timeslot, we block it and identify the relevant EVs present during that slot. Then re-calculate the charging and discharging priorities for these EVs and select them from lowest to highest priority. After that, for each EV, actions are taken based on its current state: if it is charging, we stop it; if it is idle, we initiate discharging. The missing energy of the EV during this timeslot due to the adjustment is rescheduled to other timeslots by following a similar method to the initial charging plan generation. This process is repeated until the violation at the current timeslot is resolved.

For a bi-directional EV assigned to a bi-directional charging station, once the charging plan is generated, the EV can potentially provide energy resources during its idle timeslots by discharging. The discharging resource blocks are generated while taking into account constraints (7), (8), and (9). These blocks are then added to the resource block pool and made available for selection by other EVs. If an EV is discharged at maximum power during a timeslot, it will take more than one timeslot to fully recharge due to the charging efficiency. Additionally, discharging an EV near its predicted departure time heightens the risk of failing to reach the target SoC. Consequently, the last two timeslots before the EV's expected departure time are reserved and cannot be used for discharging.

In this work, prediction errors are modeled as unexpected events, such as early EV departures, PV generation changes, and energy price fluctuations. We introduce a randomness value $r \in [0,1]$ to reflect the uncertainties in the predictions. The magnitude of the prediction error is directly tied to the value of r, where $r = 0$ indicates no error and increasing values of r lead to more significant deviations. Fig. 6 illustrates how these unexpected events are managed: we first block the timeslot and then calculate the charging and discharging priorities for all relevant EVs (11), (13). Afterward, we assess the type of event and determine whether we need to increase total power (Case I) or reduce total power (Case II). For Case I, we prioritize EVs with the highest priority and start charging or stop discharging when they are either idle or in the process of discharging. In Case II, we use a similar approach to the one previously described for solving the violation problem. After the action, any violations of (4) and (5) will be checked and addressed as necessary.

IV. RESULTS

The testing environment for evaluation (Fig. 7) is implemented in Python and composed of a data generator, a real-time charging simulator, and smart charging algorithms including the ReCo algorithm and other benchmark algorithms.

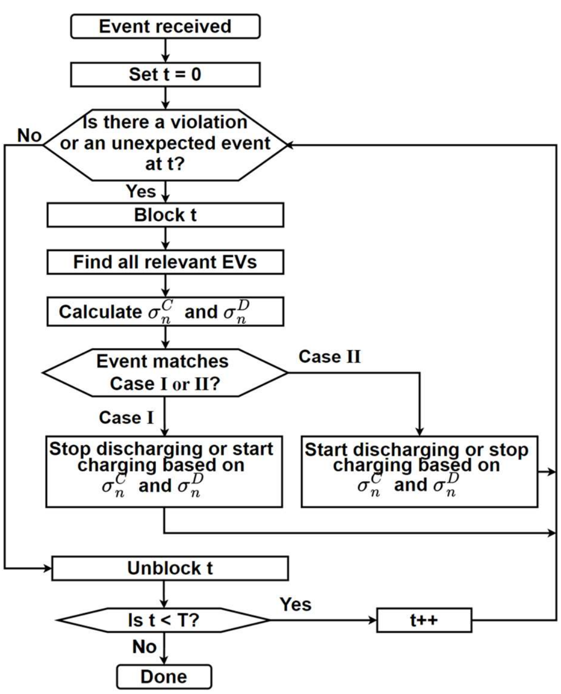

Fig. 6. Flow chart of handling violations and unexpected events.

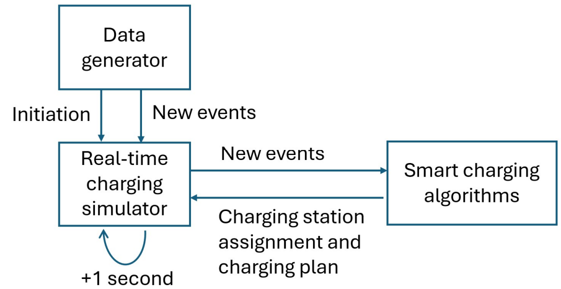

Fig. 7. Block diagram of the simulator.

The data generator is based on historical data to generate the predicted departure times, electricity prices, and PV generation, as discussed in Section II. When a prediction error occurs, the data generator produces an unexpected event, which could be an early EV departure, a fluctuation in energy prices, or a change in PV production. The charging simulator uses a time-sequencing simulation, where each timestep is one second. Various events may occur throughout the simulation, such as EVs arriving or departing, EVs reaching their maximum or minimum SoC, and unexpected events. Our algorithm responds to these events by dynamically adjusting or creating new charging plans or charging station assignments.

Table I gives an overview of the most important simulation parameters that describe the scenario. Table II shows the list of algorithms where greedy charging and schedule guided heuristic (SGH) [9] algorithm are included as benchmarks. To reduce noise, each simulation is repeated 20 times with different seeds. The results are averaged and the 95% confidence interval is provided. Simulations run on a

TABLE. I. Simulation parameters

Parameter	Value
Number of EVs, charging stations	50/50
Charging/Discharging efficiency	0.9/0.95
Min/Max charging power	4/22kW
Min/Max discharging power	4/22kW
Max capacity of EV battery	85kWh
Target SoC	0.8
Min SoC	0.4
Max discharged energy in SoC	0.8
Root/Lv1/Lv2 fuse size	600/80/40kW

TABLE. II. Overview of algorithms

Label	Method
Greedy	A first-come-first-serve approach as benchmark.
SGH	EVs are optimized based on the heuristic algorithm in [9].
ReCo Uni	Proposed approach with only uni-directional charging and no charging station assignment.
ReCo Bidi	Extends from ReCo Uni which assigns EVs to bi-directional charging stations based on their potential and supports bi-directional charging plans.

machine with Intel(R) Xeon(R) W-2125 CPU and 32 GB RAM.

Simulation results detailed in Table III compare the performance of various algorithms during a single day. To offer a clearer view of the scheduling, Fig. 8 illustrates the aggregated power consumption of all charging sessions throughout the day for different algorithms.

While benchmark algorithms, Greedy and SGH, reveal higher peak power and limited adaptability to PV generation, the ReCo algorithms demonstrate significant advantages. They effectively reduce peak power and respond to changes in PV generation and electricity prices, as evidenced by the highest PV self-sufficient ratios and the lowest average costs among the compared algorithms. Notably, ReCo Bidi outperforms ReCo Uni by utilizing EVs' discharging capabilities, allowing for greater flexibility and efficiency in energy management. It is also important to highlight that, despite these enhancements in performance, the ReCo algorithm still successfully meets the drivers' charging needs at levels comparable to other algorithms.

In practice, prediction errors are inevitable. To assess the impact, Fig. 9 demonstrates how different algorithms perform under various levels of randomness, with the ReCo Bidi algorithm consistently showing the lowest average cost. As randomness increases, ReCo Bidi not only maintains lower costs but also manages to charge more compared to other algorithms. This is primarily due to its effective response to cases such as significantly lower energy prices and higher-than-predicted PV production, which frequently occur with increased levels of randomness.

Fig. 10 illustrates the grid energy consumption for different algorithms under varying PV system sizes. In this context, a PV scaling factor of 50 corresponds to a peak production of 680 kilowatts. As PV generation increases, all strategies reduce their reliance on grid energy. Both ReCo algorithms adjust their charging plans to align more closely with PV output power patterns, finally reducing grid energy use to zero. The ReCo Bidi algorithm shows a steeper decline indicating a more flexible and responsive adaptation to available PV energy.

As shown in Fig. 11, when the number of bidirectional stations increases, we observe a noticeable reduction in costs. However, this cost reduction becomes small beyond 20 stations, indicating that equipping a parking lot fully with bidirectional stations may not be cost-effective when considering the installation and purchase expenses. Furthermore, our assignment algorithm significantly improves station utilization compared to randomly assigning

TABLE. III. Performance comparison of different algorithms over a single day.

Algorithm	Greedy	SGH	ReCo Uni	ReCo Bidi
EVs reached target SoC	42	**50**	48	49
Energy from grid (kWh)	1510	1530	**795**	822
Average cost (€/MWh)	60.65	47.89	46.97	**43.97**
Energy from PV (kWh)	714	1169	1585	**1619**
Self-sufficient ratio	38%	62%	84%	**86%**

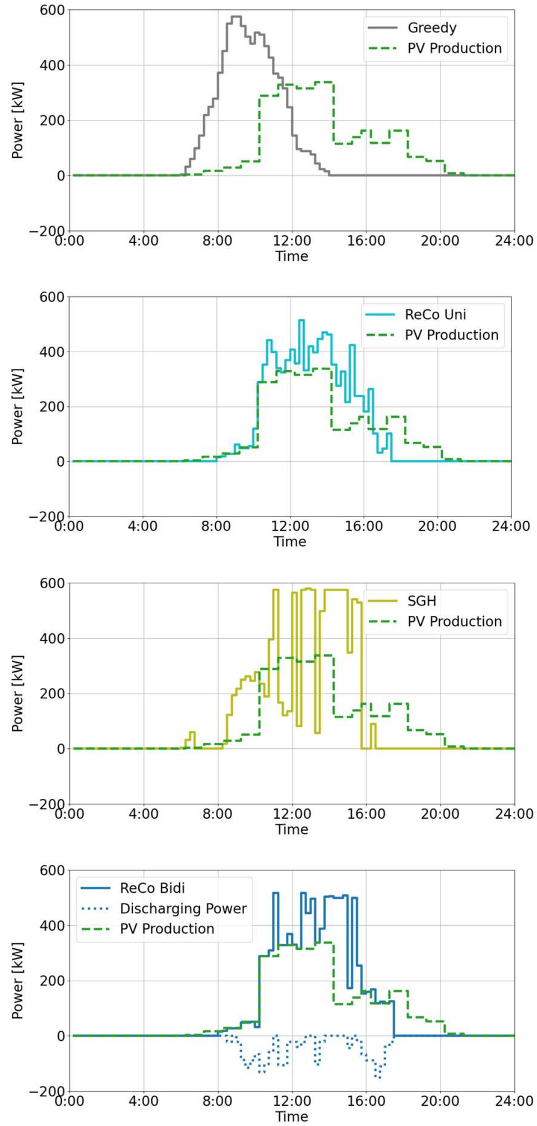

Fig. 8. Aggregated power of all charging sessions in the day for different algorithms.

EVs to bidirectional charging stations. With the same number of bidirectional stations, our approach results in lower costs.

Table IV presents the computation time of our algorithm across different fleet sizes. The results confirm that the increase in computation time is manageable even as the number of EVs scales up, demonstrating the scalability of our algorithm.

V. Discussion

The smart charging system model presented in this work is intended to accurately represent electrical engineering constraints to allow solutions to be effectively integrated with OCPP 2.0.1 [19] in the future. However, it must be recognized that the model contains certain simplifications and limitations.

Our methodology employs a heuristic approach that does not guarantee a globally optimal solution, and due to prediction errors, it does not quantify the gaps to this unknown optimal. The heuristic model emphasizes managing intraday

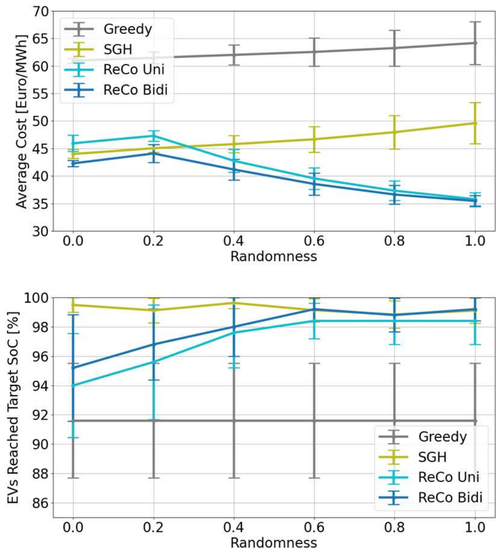

Fig. 9. Performance for different randomness values.

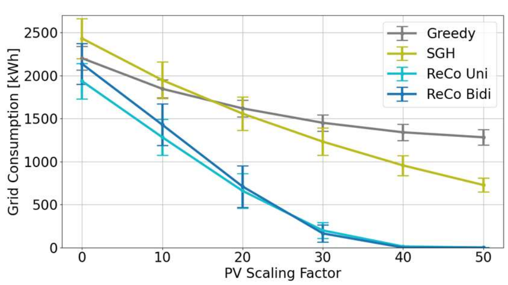

Fig. 10. Grid energy consumption from different PV sizes.

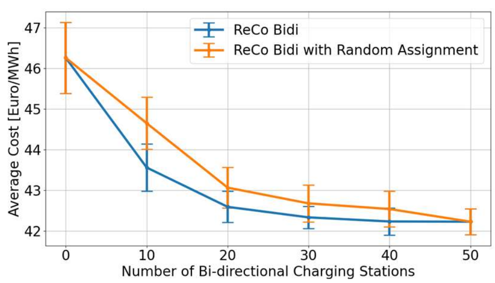

Fig. 11. Average cost for different number of bi-directional charging stations.

TABLE. IV. Computation time for various fleet sizes.

Number of EVs	50	100	150	200	250
Computation time of each EV (s)	0.19	0.30	0.43	0.56	0.68

event randomness and aims for near-optimal outcomes by balancing cost, PV utilization, and peak shaving.

The model assumes linear charging and discharging behavior; however, these processes are non-linear in reality. For example, during the 80%-100% charging phase using CCCV [20], the charging speed becomes progressively slower compared to a linear case, leading to sub-optimal use of the charging infrastructure. Similarly, the discharging process exhibits non-linearity, which results in further mismatches between planned and actual energy flows. Furthermore, discharging at low power levels can result in inefficiencies as high as 65%. Therefore, prioritizing high-power discharging for individual EVs is preferable over uniformly distributing low-power discharging across many EVs.

The charging plan often involves numerous starts and stops, which may harm the vehicle's battery life and the associated charging components. Vehicles are typically not designed for frequent charge-discharge cycles. Designing a smoother charging curve could mitigate this issue.

Our model assumes that the company buys electricity only from the intraday market, which may not accurately reflect the case of all companies. Moreover, the discharging price is supposed to be constant throughout the day, a simplification that warrants further analysis to understand its financial implications better.

While it is possible to obtain some of the data in advance, such as the arrival and departure times of certain workers, leveraging this information to pre-design charging plans can optimize operations and provide additional time for scheduling. This approach could improve resource management and enhance the charging process's efficiency.

The current model is tailored to the company premises and only considers behind-the-meter usage. The pattern of vehicle arrivals and departures is centered on early mornings and afternoons, respectively. This setup does not fully utilize the capabilities of bi-directional charging. Broadening the scenarios and use cases could substantially enhance the overall effectiveness of bi-directional charging.

VI. CONCLUSION

This study focuses on the real-time optimization of EV charging in a company premise equipped with PV, and both uni-directional and bi-directional charging stations. The main challenges include meeting drivers' charging needs, managing peak loads, reducing costs, maximizing PV utilization, and addressing prediction errors such as early departure, energy cost change, and PV generation change.

We present a novel heuristic algorithm that creates charging station assignments and charging schedules, utilizing the discharging capabilities of EVs to make efficient use of limited resources. The algorithm is scalable, robust to prediction errors, and capable of real-time operation, essential for real-life implementations. Experimental results demonstrate that our ReCo Bidi algorithm substantially outperforms benchmarks by effectively reducing costs and peak demands, tailoring charging schedules to driver requirements and PV availability, and dynamically adjusting to prediction errors. However, it's important to note that the potential of bi-directional charging is not fully exploited. Future work will explore broadening the application of charging and discharging strategies across multiple locations, considering the mobility of cars that allow charging at one location and discharging at another. Additionally, we plan to extend our use cases to include front-of-the-meter scenarios, enhancing grid stability.

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