Optimal V2X operation of EV fleets with PV-battery charging station for demand-side flexibility provision

Federica Bellizio, *Member, IEEE,* Philipp Heer, *Member, IEEE*

***Abstract*—The increasing number of electric vehicles expected on the road in the coming years poses new threats to the reliability of the power system. However, it can also play a key role as a source of demand-side flexibility to support the system in managing uncertainty resulting from the integration of renewable and distributed energy resources. In this paper, a novel operational tool for vehicle-to-everything operation of electric vehicle fleets with photovoltaics-battery charging station for demand-side flexibility provision is proposed. The tool provides electric vehicle aggregators with a risk-aware flexibility quantification, robust market bids and real-time control decisions. The approach was tested on real demonstrators in Switzerland, highlighting the cost-benefits of demand-side flexibility provision, which resulted in a net revenue for aggregators of CHF 3'142 over a month. These revenues, generated from providing flexibility as a service in the form of availability, significantly exceeded the energy costs of the charging station.**

***Index Terms*—Electric Vehicles, Vehicle-to-Everything, Demand-side Flexibility, Uncertainty, Model Predictive Control.**

I. Introduction

THE current regulatory policies aimed at promoting the transition from fossil fuel to low emission transportation have incentivized significant technological advancements, leading to reduced electric vehicle (EV) cost, increased EV range and denser charging infrastructure. Consequently, EVs are becoming more popular, with the global EV fleet projected to reach 145 million units by 2030 [1]. On the one hand, the added energy demand from the growing EV supply equipment required for charging poses new threats to the reliability of the power system [2]. On the other hand, the increasing number of EVs on the road can play a key role as a source of flexibility for a more reliable system operation if their charging scheduling is properly optimised. The additional storage capacity offered by EVs can support the system to deal with the operational uncertainty resulting from the integration of renewable and distributed energy resources. This would allow for an improved utilization of the existing grid assets and a consequent reduction of the investment costs to reinforce the network equipment [3]. However, for flexibility provision in new emerging demand-response (DR) markets, there are participation requirements on minimum bid sizes that could be challenging to meet for EV fleets [4].

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The onsite coupling between photovoltaics (PVs), battery energy storage systems (BESS) and EV fleets with vehicle-to-grid (V2G) technology has shown extremely promising performance in terms of demand-side flexibility provision [5], [6]. In a vehicle-to-everything (V2X) operation, EV fleets can be used for site self-consumption maximization by storing electricity surplus produced by PVs and releasing it during peak hours [7], for load peak shifting in grid congestion occurrences or for voltage and frequency regulation by consuming or injecting power when the grid constraints are violated [8]. By aggregating the EV fleet and BESS capacity, the requirement of minimum bid size can be easily met, enabling the participation of EVs in DR markets, and hence the generation of new revenue streams for aggregators [9]. To avoid overbidding in such markets, aggregators need new operational tools: i) to quantify the available flexible energy in advance for accurate flexibility market bidding and, ii) to operate the charging station cost-efficiently while reserving flexible energy in case of accepted bids.

Several approaches have been proposed for demand-side flexibility quantification, most of them distinguishable into direct and indirect quantification [10], [11]. Direct approaches aim to quantify the flexibility directly at the level of individual technologies in a bottom-up manner. Conversely, indirect approaches assume a specific market and control strategy and evaluate the impact of energy flexibility according to standardized metrics [12], e.g. operational cost savings, peak power, or carbon emission reductions. In particular, model predictive control (MPC) has been widely used to indirectly quantify the flexibility [13], [14], and most studies have observed that the uncertainty coming from weather forecasts or user behaviours can play a key role in terms of comfort and grid constraint violations [15], [16]. To overcome the challenge of considering uncertainty when quantifying energy flexibility, sampling-based approaches or stochastic MPC-based schemes have been investigated extensively [17], [18]. Similarly, due to the uncertain nature of market conditions, stochastic approaches to the aggregator's optimal bidding problem seem necessary. In [19], a two-stage stochastic linear programming was used to evaluate the optimal bidding strategy model for an EV aggregator participating in the day-ahead energy and regulation markets. Conversely, Monte Carlo (MC) simulation was used to evaluate optimal bidding in German secondary reserve market in [20]. When operating EV fleets with PV-battery charging station for flexibility provision, the uncertainty stems from onsite generation and load forecasts, and EV user behaviour, i.e. EV arrival and departure times at the station and the required energy demand [21]. Such uncertainties need to be considered both when quantifying the flexibility in advance for market bids and when operating the station in real-time.

A. Proposed approach

This paper proposes a novel operational tool for EV aggregators with PV-battery charging station aiming at reducing their energy costs and generating new revenues from the provision of demand-side flexibility. The flowchart of the proposed approach is shown in Fig. 1. The first step is the time-ahead prediction of the available flexibility based on forecasts of the charging station generation and load, as well as EV arrival and departure times and energy demand [22]. Subsequently, such forecasts are fed as input to a multi-site optimizer that provides 15-hour ahead optimal charging/ discharging schedules for an onsite BESS and an EV fleet moving between different sites during the day, thus being able to provide flexibility services at different locations. An example of the EV daily trip is shown in Fig 2. The EV fleet moves between the charging station and another site for daily services, which is also equipped with charge points (CPs). The available flexible energy capacity resulting from the optimization can then be bid in intraday DR markets. Finally, in real-time operation, a controller adjusts the BESS and EV schedules based on real-time measurements and acceptance of the market bids.

The contribution of this paper is twofold:

- A chance-constrained intraday optimization of the BESS and EV fleet charging scheduling for indirect flexibility quantification under uncertainty and robust flexibility bidding in DR markets;
- A flexibility-aware MPC-based real-time controller to account for operational uncertainty while reserving the flexible energy to provide in case of accepted bids.

A case study on the NEST and move demonstrators at Empa, in Switzerland, was used to investigate the aggregator's cost-benefits of adopting the proposed tool in real-time operations [23]. The test system representing the PV-battery charging station included 168 kWh battery and 110 kWp PV systems, and 4 CPs. A fleet of 4 EVs with V2G technology moving between the charging station and the service site was sampled from real charging data provided by TotalEnergies [22]. The flexibility market framework shown in Fig. 3 was assumed [24], [25]. In such a framework, transmission and distribution operators can procure flexibility in two respective and competitive DR markets, i.e. a local market for congestion management and a national market for frequency response services. The flexibility providers participate in the most profitable market, i.e. higher availability (or reservation) prices per MWh of provided energy flexibility.

The rest of the paper is structured as follows. Sections II and III describe the methodologies for the indirect flexibility quantification and the implementation of the MPC-based real-time controller. Subsequently, section IV presents the case study with the main assumptions related to the test system and the market framework, the main results, and a few limitations of the approach. Section V finally draws the conclusions.

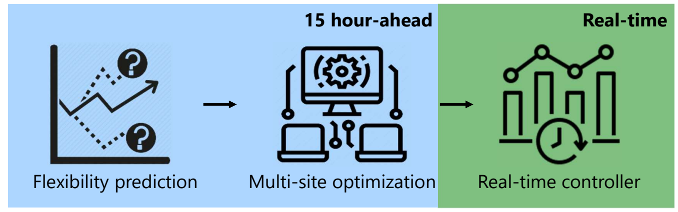

Fig. 1. The proposed operational tool for demand-side flexibility provision.

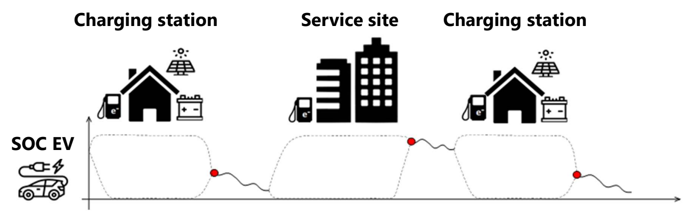

Fig. 2. An example of daily EV trip.

II. Flexibility Quantification

This section first describes the deterministic intraday charging schedule optimization with the operating constraints related to all the assets available at the charging station and the EV fleet moving between the station and the service site. Subsequently, the chance-constrained formulation is provided to account for forecast errors and quantify the flexibility in terms of an envelope for robust DR intraday market bids [26], [27]. The flexibility envelope provides the aggregators with the maximum, hourly flexible energy that is available to bid at 9am every morning for the next 15 hours. The aggregators can decide whether to bid the maximum available flexible energy or less according to their risk management strategies.

A. Multi-site optimization

In this section, the schedules for a charging station equipped with a battery, PV generation and a fleet of K EVs over a finite time horizon with hourly time step is provided. Let $\mathcal{T} = \{0, \ldots, T-1\}$ where T is the length of the horizon considered with a time discretization t. The EV $k \in [1, K]$ can charge (C_t^k) and discharge (D_t^k), acquiring energy needed for each trip ($E_t^{k,tr}$), as well as providing an upward service by reducing charging ($A_t^{k,c,n}, A_t^{k,c,l}$ for national and local service, respectively) or increasing discharging ($A_t^{k,d,n}, A_t^{k,d,l}$ for national and local service, respectively) in the form of availability, whenever it is connected to the grid, at the charging station ($T_t^{k,sta}$) or at the service site ($T_t^{k,ser}$) [28]. The charging/discharging power of the EV can be regulated between 0 and a maximum power level allowed by the charger (P_{max}^k). Similarly, the state of charge (SoC) of each EV at each timestep SoC_t^k is limited between $10\% - 90\%$ of the maximum EV energy capacity E_{cap}^{EV}. The same input and control variables are considered for the onsite battery. The battery can charge (C_t^B) and discharge (D_t^B), as well as providing an upward balancing service by reducing charging ($A_t^{B,c,n}, A_t^{B,c,l}$ for national and local service, respectively) or increasing discharging ($A_t^{B,d,n}, A_t^{B,d,l}$ for national and local service, respectively) in the form of availability. The

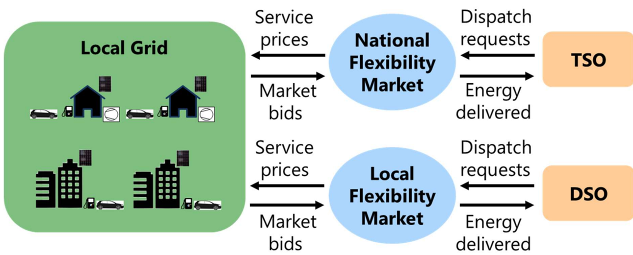

Fig. 3. The assumed market framework.

charging/discharging power of the battery can be regulated between 0 and a maximum allowed power level (P^B_{max}). Finally, the battery SoC at each timestep SoC^B_t is limited between $10\%-90\%$ of the maximum battery energy capacity E^B_{cap}. The electricity prices π^{el}_t, the national and local flexibility service prices for availability, $\pi^{A,n}_t$ and $\pi^{A,l}_t$, are known ahead of the time horizon. The trips that the EVs need to take, including the length of the trip in hours and the energy required, the onsite generation and load of the station are forecasted for the whole time horizon, thus they are considered as given in the deterministic formulation.

The objective function maximizes revenues from flexibility service provision, while meeting the station energy and EV energy trip requirements and maximizing the station self-consumption (i.e. minimizing the energy imported from the grid E^{imp}_t), as shown below:

$$\begin{aligned}\max \sum_{t\in\mathcal{T}} \Bigg(& \sum_{k=1}^{K} \Big((A^{k,c,n}_t + A^{k,d,n}_t + A^{B,c,n}_t + A^{B,d,n}_t) \cdot \pi^{A,n}_t \\ & + (A^{k,c,l}_t + A^{k,d,l}_t + A^{B,c,l}_t + A^{B,d,l}_t) \cdot \pi^{A,l}_t \\ & - C^k_t \cdot \pi^{el}_t \cdot T^{k,ser}_t - \epsilon^p \cdot D^k_t \Big) \\ & + (A^{B,c,n}_t + A^{B,d,l}_t) \cdot \pi^{A,n}_t + (A^{B,c,l}_t + A^{B,d,l}_t) \cdot \pi^{A,l}_t \\ & - E^{imp}_t \cdot \pi^{el}_t - \epsilon^p \cdot D^B_t \Bigg)\end{aligned} \tag{1}$$

where $T^{k,ser}_t, T^{k,sta}_t = 1$ if the EV is connected to a CP at the service site or at the charging station, respectively, otherwise $T^{k,ser}_t, T^{k,sta}_t = 0$. ϵ^p is a penalty factor that penalizes onsite battery and EV discharging, thus minimizing battery cycling, while only minimally affecting revenues from providing availability as a service. A zero feed-in tariff is assumed, indicating that no revenues are generated for selling energy E^{exp}_t back to the grid [29].

The operating models of the station, battery, and EVs include several constraints [26]. The energy balance of the entire charging station is given by:

$$\begin{aligned} E^{exp}_t - E^{imp}_t = E^l_t - E^{PV}_t - D^B_t + C^B_t \\ + \sum_{k=1}^{\mathcal{K}} (C^k_t - D^k_t) \cdot T^{k,sta}_t, \quad \forall t \in \mathcal{T}\end{aligned} \tag{2}$$

with E^l_t and E^{PV}_t being the onsite load and generation, respectively.

The constraint seen in Eq. (3) describes the EV battery's energy balance, taking into account the energy needed for mobility purposes as well as the losses caused by charging and discharging efficiencies, η^{EV}_c and η^{EV}_d.

$$\begin{aligned}\text{SoC}^k_t = \text{SoC}^k_{t-1} + \eta^{EV}_c \cdot C^k_t \\ - \frac{D^k_t}{\eta^{EV}_d} - E^{k,tr}_t, \quad \forall t \in \mathcal{T}, k \in [1, K]\end{aligned} \tag{3}$$

When the EVs are not connected to the grid, the charging, discharging and availability for services are zero:

$$\begin{aligned} C^k_t = D^k_t = A^{k,c,l}_t = A^{k,d,l}_t = A^{k,c,n}_t = A^{k,d,n}_t = 0, \\ \forall t \in \{T^{k,sta}_t, T^{k,ser}_t = 1\}, k \in [1, K]\end{aligned} \tag{4}$$

The constraint seen in Eq. (5) limits the SoC of each EV between the lower and upper bounds of the battery's energy content, which is assumed to be the same for each EV:

$$0.1 \cdot E^{EV}_{cap} \leq \text{SoC}^k_t \leq 0.9 \cdot E^{EV}_{cap}, \quad \forall t \in \mathcal{T}, k \in [1, K] \tag{5}$$

Moreover, each EV battery cannot charge and discharge at the same time:

$$C^k_t \cdot D^k_t = 0, \quad \forall t \in \mathcal{T}, k \in [1, K] \tag{6}$$

When committing to service availability, the maximum power allowed by the charger P^k_{max}, as well as whether the EV is charging or discharging, need to be taken into account:

$$\begin{cases} A^{k,d,n}_t + A^{k,d,n}_t + D^k_t \leq P^k_{max} \\ A^{k,c,n}_t + A^{k,c,n}_t \leq C^k_t & \forall t \in \mathcal{T}, k \in [1, K] \\ (D^k_t - C^k_t) + (A^{k,d,n}_t + A^{k,d,n}_t + A^{k,c,n}_t + A^{k,c,n}_t) \leq P^k_{max} \end{cases} \tag{7}$$

Simultaneously, when the bid is accepted and the service is called on, it is important to ensure that the committed energy is available for the service to be sustained for the required time t_s:

$$\begin{cases} x^k_t + C^k_t \cdot \eta^{EV}_c - \frac{(D^k_t + A^{k,d,n}_t + A^{k,d,n}_t) \cdot t_s}{\eta^{EV}_d} \geq 0.1 \cdot E^{EV}_{cap} \\ x^k_t \leq \text{SoC}^k_t & \forall t \in \mathcal{T}, k \in [1, K] \\ x^k_t \leq \text{SoC}^k_{t-1} \end{cases} \tag{8}$$

where x^k_t is an auxiliary decision variable introduced for linearisation. The flexibility service provision only considers availability, rather than utilization, which occurs infrequently [30]. Finally, the EV battery's energy level is at the required level E^{EV}_{req} set by aggregator at the end of each day:

$$\text{SoC}^k_{T-1} = E^{EV}_{req} \tag{9}$$

Similarly, all the constraints in Eqs. (3)-(8) are imposed for the battery $\forall t \in \mathcal{T}$, as follows:

$$\text{SoC}^B_t = \text{SoC}^B_{t-1} + \eta^B_c \cdot C^B_t - \frac{D^B_t}{\eta^B_d} \tag{10}$$

$$C^B_t = D^B_t = A^{B,c,l}_t = A^{B,d,l}_t = A^{B,c,n}_t = A^{B,d,n}_t = 0 \tag{11}$$

$$0.1 \cdot E^B_{cap} \leq \text{SoC}^B_t \leq 0.9 \cdot E^B_{cap} \tag{12}$$

$$C^B_t \cdot D^B_t = 0 \tag{13}$$

$$A^{B,d,n}_t + A^{B,d,n}_t + D^B_t \leq P^B_{max} \tag{14}$$

$$A^{B,c,n}_t + A^{B,c,n}_t \leq C^B_t \tag{15}$$

$$(D_t^B - C_t^B) + (A_t^{B,d,n} + A_t^{B,d,n} + A_t^{B,c,n} + A_t^{B,c,n}) \leq P_{max}^B \quad (16)$$

$$x_t^B + C_t^B \cdot \eta_c^B - \frac{(D_t^B + A_t^{B,d,n} + A_t^{B,d,n}) \cdot t_s}{\eta_d^B} \geq 0.1 \cdot E_{cap}^B \quad (17)$$

$$x_t^B \leq \mathrm{SoC}_t^B \quad (18)$$

$$x_t^B \leq \mathrm{SoC}_{t-1}^B \quad (19)$$

$$\mathrm{SoC}_{T-1}^B = E_{req}^B \quad (20)$$

where x_t^b is the auxiliary decision variable introduced for linearisation, and η_c^B and η_d^B are the battery's charging and discharging efficiencies, respectively.

B. Accounting for uncertainty

In order to mitigate the effect of uncertainty on the market bidding strategy, an intraday chance-constrained optimization is formulated [31]. The uncertainty derives from the forecasts of onsite load and PV generation, and EV charging sessions (i.e. arrival and departure times, and charging energy demand). Chance-constraints are probabilistic constraints that ensure that the limits will hold with a pre-described probability $1-\epsilon$, where ϵ is the acceptable violation probability. This is done by replacing the original constraints with tightened constraints, where tightenings represent security margins against uncertainty and are evaluated using MC simulations. The optimization, shown in Fig. 4, is solved using an iterative algorithm which alternates between solving a deterministic optimization with tightened constraints, and evaluating the following tightenings at each iteration m:

$$\begin{aligned} \Omega_m^{EV} &= |\mathrm{SoC}_t^{EV,1-\epsilon}| - |\mathrm{SoC}_t^{EV,0}| \\ \Omega_m^{B} &= |\mathrm{SoC}_t^{B,1-\epsilon}| - |\mathrm{SoC}_t^{B,0}| \end{aligned} \quad (21)$$

with $\mathrm{SoC}_m^{EV} = \sum_{k=1}^{K} \mathrm{SoC}_t^k$ and superscript 0 indicates the solution with zero forecast error. If the maximum changes in the tightenings between two subsequent iterations are below a certain threshold η^Ω, the algorithm has converged and a feasible solution has been found. The solution represents the maximum, hourly flexible energy that is available to bid while ensuring the station operational constraints and the user comfort boundaries.

III. Real-time Controller

A finite horizon MPC-based controller to account for real-time operational uncertainty while reserving the flexible energy to provide in case of accepted bids is formulated in this section. The full formulation is given by:

$$\min \sum_{t \in \mathcal{T}} \left(\sum_{k=1}^{K} \left(C_t^k \cdot \pi_t^{el} \cdot T_t^{k,ser} + \epsilon^p \cdot D_t^k \right) + E_t^{imp} \cdot \pi_t^{el} + \epsilon^p \cdot D_t^B \right)$$
$$\text{subject to} \qquad \text{Eqs. (4)-(9), Eqs. (11)-(20)} \quad (22)$$

The following two constraints are also added to provide the flexible energy when the bids are accepted:

$$\mathrm{SoC}_t^k = \mathrm{SoC}_{t-1}^k + \eta_c^{EV} \cdot C_t^k - \frac{D_t^k}{\eta_d^{EV}} - E_t^{k,tr} - E_t^{k,bid} \cdot T_t^{k,bid}, \quad \forall t \in \mathcal{T}, k \in [1, K] \quad (23)$$

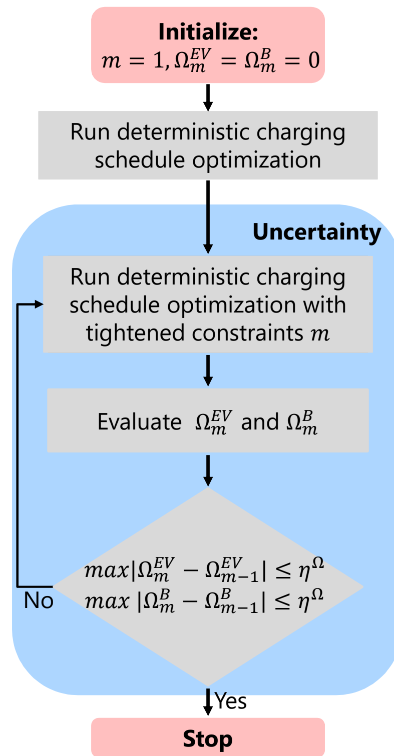

Fig. 4. The proposed chance-constrained optimization.

$$\mathrm{SoC}_t^B = \mathrm{SoC}_{t-1}^B + \eta_c^B \cdot C_t^B - \frac{D_t^B}{\eta_d^B} - E_t^{B,bid} \cdot T_t^{B,bid}, \quad \forall t \in \mathcal{T} \quad (24)$$

with $E_t^{k,bid}, E_t^{B,bid}$ representing the flexible energy from EVs and battery, respectively, bid in the intraday DR markets, $T_t^{k,bid}, T_t^{B,bid} = 1$ in case of accepted bids, otherwise $T_t^{k,bid}, T_t^{B,bid} = 0$. No revenues are assumed for flexibility provision in the form of utilization.

At each time step t, the optimization in Eqs. (22)-(24) takes the real-time measurement and the acceptance of market bids as inputs, and determines the optimal charging/discharging schedules for the EV fleet and onsite battery for the full horizon $\mathcal{T} = \{t, ..., t+T-1\}$ using the updated forecasts of onsite load and PV generation, and EV charging sessions. However, only the optimal schedules at time step t are applied.

IV. Case Study

This section provides an overview of the performance of the proposed tool in terms of energy cost reduction and generation of new revenues from demand-side flexibility provision. Additional studies were conducted to investigate the optimal technical and social settings to fully exploit the demand-side flexibility, leading to higher cost-benefits for the aggregators.

A. Test system and assumptions

A case study was conducted on the NEST and move demonstrators at Empa, in Switzerland [23]. This test system representing the PV-battery charging station included a 168 kWh battery, 110 kWp PV systems, and 4 CPs. Historical data for PV generation and load for August 2022 were used to test the proposed tool. Charging data for a fleet of 4 EVs with V2G technology and 40 kWh battery each, moving between the charging station and the service site, was sampled from real data provided by TotalEnergies with over 2 million charging sessions and 5317 CPs across the Netherlands [22]. The V2X operation of the EV fleet was considered exclusively at the charging station, as described in Eq. (2). A maximum allowed power level $P^k_{max} = 15$ kW and $P^B_{max} = 80$ kW were assumed for the EVs and onsite battery, respectively. The required battery level set by the aggregator at the end of each day was $E^{EV}_{req} = 0.9 \cdot E^{EV}_{cap}$ and $E^B_{req} = 0.9 \cdot E^B_{cap}$. Electricity and national flexibility service prices for availability, π^{el}_t and $\pi^{A,n}_t$, were taken from [28] for August 2022. In such a price modeling, the prices for national flexibility services reflect the need for inertia of transmission operators following the integration of renewable sources. Higher prices are modeled when the hourly share of renewable integration if higher, thus corresponding to lower system's inertia and a higher need for the system operator [32]. The same price variation of national flexibility services was assumed for local flexibility services, as the congestion risk increases when the hourly share of renewable integration is higher, similar to the inertia need in national flexibility price modeling. However, for local services, different mean values were considered based on the locations of the charging station or service site, i.e. higher mean values for locations with a higher congestion risk. In this work, the service site, which is located in urban areas, has a higher congestion risk than the charging station, resulting in higher local service prices. The assumed prices are shown in Fig. 5 for one week. Dynamic containment [33] and congestion management [34] were considered as national and local flexibility services, respectively. A finite time horizon of 15 hours with time step $t = 1$h was used for both the multi-site optimization and real-time controller. The electricity and flexibility prices were assumed to be known ahead of this horizon, which is in line with the current intraday energy and balancing service market arrangements. The required time for the flexibility service to be sustained when called on was $t_s = 1$h. The multi-site optimization was performed once every day for the horizon 9am-11pm to calculate the intraday market bids, with $\epsilon^p = 0.05$ to minimize battery cycling. Conversely, the real-time MPC controller was run hourly with a 15 hour horizon. However, the aggregator becomes aware of accepted bids only after the intraday market clearing at 9am every day. The forecasts of onsite load and PV generation, and EV charging sessions are fed as inputs to both the multi-site optimization and the real-time controller. Long short-term memory (LSTM) neural networks with 3 layers and 15 neurons per layer were used for these forecasts. The input and output rolling windows of the LSTM models were one week and 15 hours, respectively. In order to capture the seasonal trend, historical data from June to July 2022 was used to train and test the LSTM models for onsite load and PV generation. Synthetic data from January to July 2022 was used for the prediction of EV charging sessions. The training and testing split was 80%/20%, while the data from August was used for the validation of all predictive models. Weather data were used

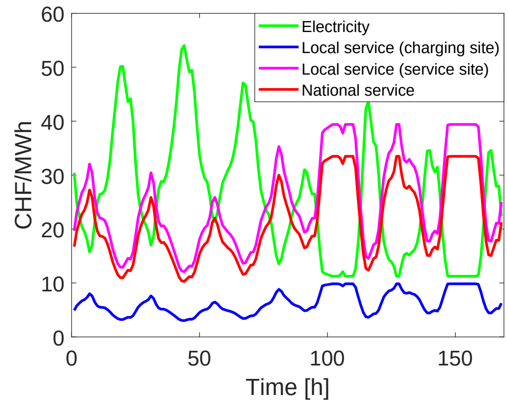

Fig. 5. The assumed prices for electricity, availability for local (charging station and service site), and national flexibility services over a week.

as additional features to improve the predictive performance. More specifically, for the EV charging sessions, categorical features such as the day of the week were also considered, and new features were created to capture the charging behaviour of each EV in the fleet [22]. Subsequently, a causality-based feature selection approach was used to select the most relevant features for training, thus enhancing the performance. As an example, the forecast error distribution of the charging station load is shown in Fig. 6. The error distributions of onsite load and PV generation, charging session duration and energy demand, were used for the MC simulations to account for uncertainty, enforcing the chance constraints with an $\epsilon = 5\%$ violation probability.

B. The flexibility envelope

This section focuses on evaluating the flexibility envelope through which aggregators can make robust flexibility bids in intraday DR markets according to their risk management strategies.

The optimal charging schedule resulting from the chance-constrained, multi-site optimization for a single EV over the time horizon 9am-11pm is shown in Fig. 7. The EV was at the charging station (indicated in the grey box area), on a trip and at the service site (in the red and light blue box area), respectively. Following the trips, the battery SoC decreased due to the energy consumed for travelling. When the EV charges, it gets paid for offering availability to reduce its charging and increase its discharging. As a result, the EV charged at the service site when the price for local service provision was significantly higher. Subsequently, the EV charged again upon returning to the charging station in the evening, as constrained by Eq. (9). The optimization resulted in a similar charging schedule for the onsite battery, which provided only national service availability, as the prices for such services were always higher than the local ones at the charging station. Simultaneously, the chance-constrained optimization aimed at reducing the overall electricity costs of the charging station, as shown in Fig. 8. No electricity was imported from the grid when the PV generation was sufficient to satisfy the load. Subsequently, when no PV generation was available in the evening, the battery was first discharged to meet the load as the

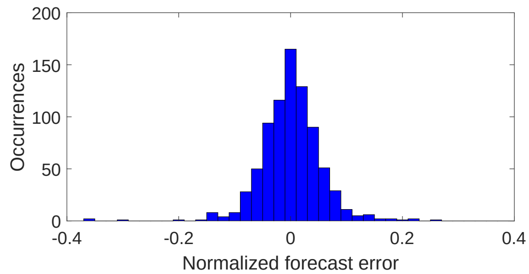

Fig. 6. Histogram of normalized forecast errors for the charging station load.

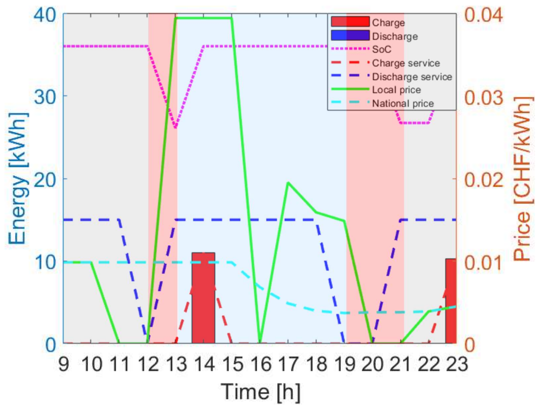

Fig. 7. The optimal charging schedule for a single EV over the time horizon 9am-11pm.

electricity price was high. Finally, when the electricity price decreased, the battery was charged by importing energy from the grid to fulfil the constraint in Eq. (20).

The chance-constrained, multi-site optimization resulted in a net revenue (i.e. revenues net of electricity costs) of CHF $3'142$ for August 2022. The available flexible energy from EVs and the onsite battery to bid in DR markets is aggregated and shown in Fig. 9 in the form of a flexibility envelope for the whole considered month. Here, the envelope resulting from the proposed chance-constrained optimization, indicated as approach i), was compared against: ii) the naive forecast-based approach in which the forecasts are assumed to be perfectly accurate and considered in the deterministic optimization, iii) the deterministic approach in which real measurements are used as inputs to the optimization, providing the true flexibility potential.

The proposed approach i) resulted in more conservative estimates of the available flexible energy, preventing over-bidding in DR markets, thus avoiding penalties. The errors in the hourly estimates of the available flexible energy for approaches i)-ii) against the true values provided by approach iii) are shown in Fig. 10, highlighting the better performance of the proposed chance-constrained optimization in terms of estimating the true flexibility potential. In terms of net revenues, the proposed approach i) decreased the revenues only by CHF 11 compared to the true revenues resulting from approach iii). Conversely, approach ii) increased the revenues by CHF 114, but this increase needs to be offset by overbidding penalties, resulting in a significantly lower net revenue.

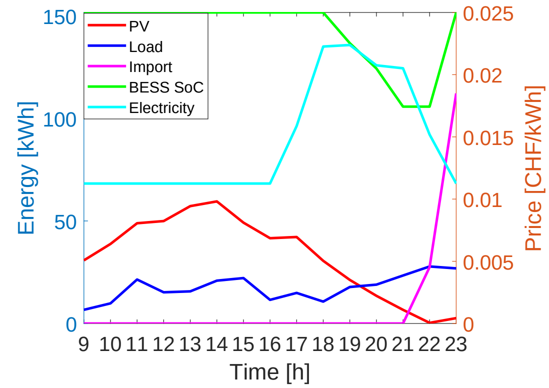

Fig. 8. The cost-optimization for the charging station over the time horizon 9am-11pm.

Additional studies were conducted to investigate the best technology, i.e. unidirectional smart charging (V1G) and V2G, to fully exploit the demand-side flexibility and quantify the cost-benefits of a more interactive involvement of EV users in flexibility provision schemes. Using the proposed multi-site, chance-constrained optimization, different settings were compared in terms of net revenues against the described baseline approach with V2G technology in Table 10: i) only V1G was available, ii) the EVs were flexible on arrival and departure times by 1 hour, iii) EVs were flexible on arrival and departure times by 2 hours. The results highlighted that with a small fleet of 4 EVs the net revenues over a month could be increased by up-to 14% when considering V2G technology and by up-to 5% by asking the EV users in advance if they would be flexible with their parking times. This resulted in a single user's revenue increasing by-up to CHF 40 in a month, significantly incentivizing their participation in flexibility provision. Such revenue increase could be interpreted as the minimum discomfort price of EV users, i.e. the minimum price at which individual EV users would be willing to reschedule their trips in exchange for higher revenues.

C. The real-time performance

In this section, the performance of the MPC controller in responding to real-time measurements and acceptance of the intraday market bids was analzyed. In Fig. 11, the changes in the aggregated SoC of the EVs and onsite battery following the acceptance of the bids are shown over a week. It was assumed that one bid was accepted per day. It is worth noting the main discrepancies relate to the provision of the bid flexible energy and the following recharging of the batteries. This resulted in an energy cost increase of CHF 516 as no revenues for flexibility utilization were considered. However, such an increase was significantly lower than the net revenue resulting from providing availability as a service in intraday DR markets, highlighting the cost-benefits of providing flexibility services for the aggregators.

D. Discussion

The proposed novel operational tool reduced the energy costs of EV aggregators with PV-battery charging station and

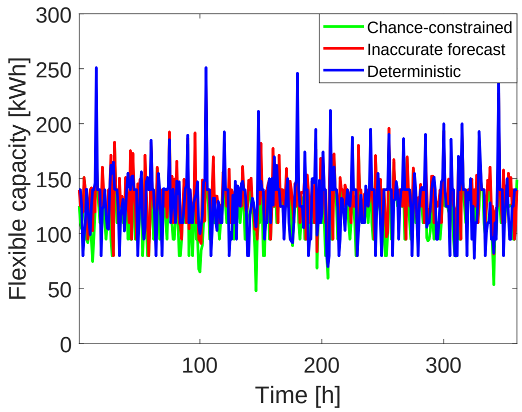

Fig. 9. The flexibility envelope for August 2022 according to three different approaches.

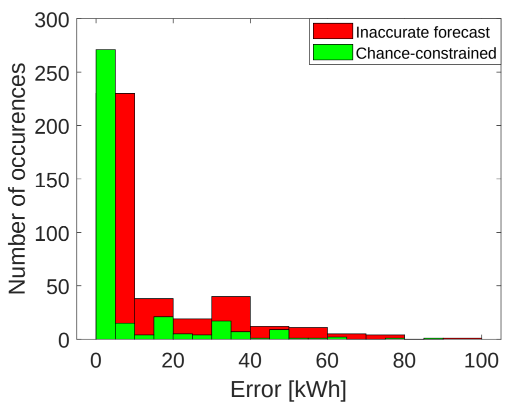

Fig. 10. The error histogram of the hourly estimates of the available flexible energy for approaches i)-ii) against the true values provided by approach iii).

enabled the generation of new revenues from the provision of demand-side flexibility. The case study showed that such new revenues offset and exceeded the energy costs of the charging station, resulting in a net revenue of CHF $3'142$ over a specific month. Considering the uncertainty when quantifying the available flexible energy to bid in markets slightly reduced the revenues because of the increased robustness of the approach, but prevented overbidding. The additional studies on the optimal technical and social settings to fully exploit the demand-side flexibility showed that the net revenues could be increased by up to 14% over a month using V2G technology and by up to 5% with EV users flexible with their parking times, resulting in an individual user's revenue increase of up to CHF 40. While the acceptance of market bids marginally increased the energy costs of the charging station, the resulting net revenues from flexibility provision significantly surpassed such an increase.

The proposed approach still has a few limitations that need to be considered. The resulting net revenues strictly depend on the assumed market framework, electricity, and flexibility service prices. While flexibility markets show promise in managing local congestion or supporting the transmission grids, only a few pilot projects currently exist, and it is challenging to foresee their development in the coming years. With the integration of more renewable generation sources into future power systems, leading to higher operational uncertainty, the prices of ancillary services, and consequently the revenues from flexibility provision, are likely to rise [32]. Nevertheless, the proposed tool can adapt to various market frameworks and prices, technical and social settings, consistently leading to reduced energy costs and new revenue generation. The case study only showed the benefits of using a fleet of 4 EVs, but the tool can easily scale to larger fleets as the approach iteratively solves a deterministic optimization with tightened constraints and the resolution of a deterministic optimization generally requires only a few seconds, specifically less than 60s in this work using a standard machine with 12 CPU cores and 64GB RAM. A constant charging power per hour was assumed for both the EVs and onsite battery. However, in practice, the charging power is higher initially and gradually decreases as the battery approaches the maximum SoC. In terms of predictive model training for onsite load and PV generation, and EV charging sessions, a single data split was used, but performing more random splits might better prevent biased models. However, the models were also tested on different validation sets, such as different months of the year, showing similar predictive performance. Similarly, training the models using historical data from several years may enhance such performance as allows to capture seasonal or yearly patterns. However, using larger training datasets can significantly increase the training time, posing a challenge for real-time applications where the predictive models would need to be periodically updated to incorporate newly collected data. There are several solutions to reduce the training computational times, such as the feature selection approach we used in this work. Such an approach can significantly reduce the training computational times however, it requires a large number of CPU cores to quickly identify the relevant

TABLE I
COMPARISON OF NET REVENUES WITH DIFFERENT TECHNICAL AND SOCIAL SETTINGS

	Settings			
	Baseline	V1G	1h Flex User	2h Flex User
Net revenue [CHF]	$3'142$ –	$2'692$ (-14%)	$3'207$ $(+2\%)$	$3'300$ $(+5\%)$

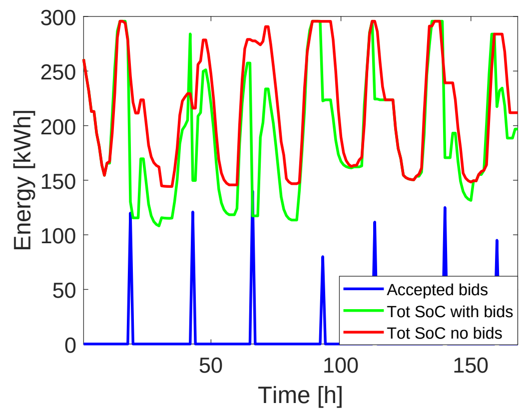

Fig. 11. The aggregated SoC of the EVs and onsite battery over a week with and without accepted intraday market bids.

features. In all our studies, a zero sell price for energy was assumed. Making energy arbitrage profitable could further increase the net revenues, albeit with higher battery cycling. Similarly, the aggregator's net revenues could be significantly enhanced if the flexibility provision in the form of utilization is remunerated.

V. Conclusion

The electrification of urban mobility can support grid decarbonization through the provision of demand-side flexibility. However, there is a need for novel operational tools for EV aggregators to facilitate such provision while reducing their energy costs. This paper proposes leveraging data-driven techniques and physics models in a novel tool for optimal V2X operation of EV fleets with a PV-battery charging station. The tool is designed to minimize aggregator's energy costs and maximize new revenues from the provision of flexibility, by providing risk-aware flexibility quantification, market bids, and real-time control decisions. Using a case study on the NEST and move demonstrators at Empa, in Switzerland, we showed that the revenues stemming from the provision of flexibility in the form of availability significantly exceeded the energy costs of the charging station, even when the market bids were accepted in real-time operation with no revenues from utilization as a service. Results also showed that V2G technology and a more interactive involvement of EV users in the provision schemes can significantly enhance the overall cost-benefits. This highlights the need for implementing new incentives for the installation of V2G chargers and reshaping the regulatory framework to incentivize active participation of EV users, either by staying within the boundaries of their comfort or by appropriately compensating for their discomfort. Future work will focus on sector coupling by equipping the charging station with both electrical and thermal resources, enabling a more comprehensive cost-benefit and feasibility analysis of V2X operations for demand-side flexibility provision.

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