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Optimal non-zero Price Bids for EVs in Energy and Reserves Markets using Stochastic Optimization

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Abstract—**In power systems, demand and supply always have to be balanced. This is becoming more challenging due to the sustained penetration of renewable energy sources and their inherit uncertain production. Because of the increasing amount of electrical vehicles (EVs), and the high capacity and flexibility of their charging process, EVs are a good candidate for providing balancing services to electric systems. We propose a stochastic optimization method for an EV aggregator that models the uncertainty of the imbalance price, the reserve prices and the probability of acceptance and deployment of reserves. The model results in an optimal charging and discharging strategy considering day-ahead purchase, imbalance trading and reserve bids. Unlike previous studies, the reserve bids consists of both a quantity and an optimal price using a novel efficient formulation for the price bids. Experimental evaluation shows that the proposed stochastic opti-mization method results in lower costs than determin-istic and quantity-only bid solutions.**

Index Terms—**Electrical vehicles, stochastic opti-mization, reserve markets, day-ahead markets, mixed integer programming.**

I. Nomenclature

The expected value of a variable is denoted by omitting the scenario index ω. The superscript$\pm$means that either up ($\ddagger$ or down ( ) reserves are meant. The superscript $\updownarrow$ means that either charging ($\downarrow$) or discharging ($\uparrow$) is meant.

Indices and Sets:

$i \in \mathcal{I}$	Electric vehicles, from 1 to I.
$t \in \mathcal{T}$	Programme time unit (PTU), from 1 to T.
$h(t) \in \mathcal{H}$	Hourly periods. Every PTU t belongs to a specific hour $h(t)$.
$t(h) \in \mathcal{T}$	A set of PTUs t, within one hour h.
$\omega \in \Omega$	Set of all scenarios, from 1 to W.

EV Parameters:

E_i^{A}	State of Charge (SOC) at arrival [kWh].
E_i^{D}	Required SOC for departure [kWh].
$\bar{E}_i$	Battery energy capacity [kWh].
$\bar{P}_i^{\updownarrow}$	Maximum (dis)charging speed [kW].
T_i^{A}	Time of arrival [h].
T_i^{D}	Time of departure [h].
α_{it}	Availability: $\alpha_{it} = 1 \Leftrightarrow t \in [T_i^A, T_i^D]$.
$\eta_i^{\updownarrow}$	(Dis)charging efficiency [p.u.].

System Parameters:

Δ	Duration of a PTU [h].
$\varepsilon_{\omega t}^{\pm}$	Deployed reserves [%].
κ	Battery degradation cost [€/kWh].
$\lambda_{\omega t}^{\mathrm{imb}}$	Imbalance market price [€/kWh].
$\lambda_{\omega t}^{\pm}$	Reserve capacity market price [€/kW].
λ_h^{DA}	Day ahead (DA) energy price [€/kWh].
ϕ_ω	Probability of scenario ω.
	Penalization of unmet SOC demand [€/kWh].
$\chi_t^{\pm}$	Bid-acceptance probability (deterministic model).

First-stage Decision Variables:

$b_t^{\pm}$	Reserves capacity price bid [€/kWh].
d_{it}	Charging (0) or discharging (1).
$f_{i\omega}$	Planned unmet SOC demand [kWh].
$p_{it}^{\updownarrow}$	(Dis)charging power [kW].
p_h^{DA}	Energy bought in the DA market [kWh].
p_t^{imb}	Imbalance power[1] bought [kW].
$r_{it}^{\updownarrow\pm}$	Reserves capacity bid [kW].

Second-stage Decision Variables:

$e_{i\omega t}$	State of charge (SOC) [kWh].
$u_{\omega t}^{\pm}$	Binary variable that is used to determine the price bid $b_t^{\pm}$, according to $u_{\omega t}^{\pm} = 1$ iff $\lambda_{\omega t}^{\pm} \leqslant b_t^{\pm}$.

II. Introduction

The balancing of supply and demand in power systems is challenging and even more with increasing use of renewable resources. Because of the flexibility of the EV charging process, and their high capacity, EVs are good candidates for providing balancing services. In the Netherlands for example, a number of EVs equal to approximately 0.8% of the total Dutch car pool would suffice to solve the average imbalance [1], [2]; and at the moment that EV share is already 0.3%. Also, EVs can be used to attain a higher utilization of renewable energy sources, such as wind and solar power, which are sources of uncertainty. The result is that fewer fossil fuel sources would be required as a backup for these renewable energy sources [3].

An aggregator can participate on behalf of EV owners in balance regulation by following the imbalance price signal, but also by providing ancillary services to the power

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[1]In reality, energy is bought/sold, not power. The amount of energy is determined by multiplying with Δ.

system. However, a number of uncertain parameters, such as the energy price, and demand and supply of both the power system and the EV fleet, make this problem challenging to solve. We propose a Stochastic Optimization (SO) method that models electricity prices and reserve acceptance and deployment stochastically. The method decides on 1) what energy to buy day-ahead, 2) what energy to buy in the imbalance market, 3) what reserve capacity to commit, 4) what reserve price bids are made, and 5) when to provide vehicle to grid (V2G) services. Unlike previous studies, the reserve bids consist of both a quantity and an optimal price.

Some studies on this subject have focused on deterministic approaches [4], [5]. Among those, Sarker et al. [4] have developed a model that results reserves consisting of quantity and price. Other studies have developed an SO method [6]–[8]: Vagropoulos et al. [6] built an SO model for an aggregator participating in the ancillary services. They provide quantity-only reserve bids, and assume that those bids are always accepted and deployed. Sánchez-Martín et al. [7] model the uncertainty of consumer behavior stochastically. They model market prices deterministically. Alipour et al. [8], model the uncertainty of market prices, EV driving patterns and reserve deployment. Both [8] and [7] provide quantity-only reserve bids. Quantity-only bids can lead to unprofitable situations, because reserves then have to be provided for any price that is offered.

Shafie-khah et al. [9] propose an iterative approach to identify market clearing prices, and optimal bidding strategies. Their model captures the uncertainty associated to EV owners' behavior, being called to provide reserves, and other market participants behavior. In [10] a similar problem is solved with SO. Instead of EVs, however, their source of flexibility is an aluminum smelter, and their main focus is on optimal DA bidding, and not on optimal reserve bid prices.

Therefore, our main contributions are:
- An SO model for an EV aggregator that models the uncertainty of electricity prices and reserve deployments.
- A novel method for obtaining optimal reserve price bids by use of SO.

This remainder of this paper is organized as follows. First, the stochastic model is introduced. This model is different to typical stochastic models. This can be observed from the fact that a deterministic variant cannot trivially be obtained. So the next section explains how to obtain a deterministic variant. The aim of the evaluation that follows is to study the advantage of SO in comparison to the deterministic approach, and the advantage of reserve bids with optimal prices.

III. Stochastic optimization model

The SO model optimizes EV charging and discharging costs for an aggregator, while providing balancing services to the grid. The market model that is assumed here is a general electricity market with a DA market, an imbalance market and reserves which are committed DA. The aggregator is assumed to be a price-taker. For accepted reserve services, a capacity payment is paid, and when deployed the imbalance price is paid. A reserve bid is considered to be accepted only when its price is below the market capacity clearing price. An accepted bid is deployed only when reserves are needed.

This Stochastic model for DA, Imbalance and Reserves (SDIR) is as follows:

$$\min \sum_{h \in \mathcal{H}} p_h^{\mathrm{DA}} \lambda_h^{\mathrm{DA}} + \sum_{t \in \mathcal{T}} p_t^{\mathrm{imb}} \lambda_t^{\mathrm{imb}} \Delta +$$

$$\sum_{i \in \mathcal{I}} \sum_{\omega \in \Omega} \phi_\omega \Bigg(\sum_{t \in \mathcal{T}} \Big((r_{it}^{\downarrow -} + r_{it}^{\uparrow -})(\lambda_{\omega t}^- + \varepsilon_{\omega t}^- \lambda_{\omega t}^{\mathrm{imb}}) u_{\omega t}^- -$$

$$(r_{it}^{\downarrow +} + r_{it}^{\uparrow +})(\lambda_{\omega t}^+ + \varepsilon_{\omega t}^+ \lambda_{\omega t}^{\mathrm{imb}}) u_{\omega t}^+ +$$

$$(p_{it}^\uparrow - r_{it}^{\uparrow -} \varepsilon_{\omega t}^- u_{\omega t}^- + r_{it}^{\uparrow +} \varepsilon_{\omega t}^+ u_{\omega t}^+) \kappa \Big) \Delta + f_{i\omega} \psi \Bigg) \quad (1)$$

subject to:

$$\sum_{i \in \mathcal{I}} (p_{it}^\downarrow - p_{it}^\uparrow) = p_{h(t)}^{\mathrm{DA}} + p_t^{\mathrm{imb}} \quad \forall t \quad (2)$$

$$p_{h(t)}^{\mathrm{DA}} p_t^{\mathrm{imb}} \geqslant 0 \quad \forall t \quad (3)$$

$$p_{it}^\downarrow + r_{it}^{\downarrow -} u_{\omega t}^- \leqslant \overline{P}_i^\downarrow (1 - d_{it}) \alpha_{it} \quad \forall i, \omega, t \quad (4)$$

$$p_{it}^\downarrow - r_{it}^{\downarrow +} u_{\omega t}^+ \geqslant 0 \quad \forall i, \omega, t \quad (5)$$

$$p_{it}^\uparrow + r_{it}^{\uparrow +} u_{\omega t}^+ \leqslant \overline{P}_i^\uparrow d_{it} \alpha_{it} \quad \forall i, \omega, t \quad (6)$$

$$p_{it}^\uparrow - r_{it}^{\uparrow -} u_{\omega t}^- \geqslant 0 \quad \forall i, \omega, t \quad (7)$$

$$e_{i\omega t} = \eta_i^\downarrow \left(p_{it}^\downarrow + r_{it}^{\downarrow -} u_{\omega t}^- \varepsilon_{\omega t}^- - r_{it}^{\downarrow +} u_{\omega t}^+ \varepsilon_{\omega t}^+ \right) \Delta$$
$$- \frac{1}{\eta_i^\uparrow} \left(p_{it}^\uparrow - r_{it}^{\uparrow -} u_{\omega t}^- \varepsilon_{\omega t}^- + r_{it}^{\uparrow +} u_{\omega t}^+ \varepsilon_{\omega t}^+ \right) \Delta$$
$$+ e_{i\omega, t-1} \quad \forall i, \omega, t \quad (8)$$

$$e_{i\omega, T_i^{\mathrm{A}}} = E_i^{\mathrm{A}} \quad \forall i, \omega \quad (9)$$

$$e_{i\omega t} \leqslant \bar{E}_i \quad \forall i, \omega, t \quad (10)$$

$$e_{i\omega, T_i^{\mathrm{D}}} \geqslant E_i^{\mathrm{D}} - f_{i\omega} \quad \forall i, \omega \quad (11)$$

$$b_t^- \leqslant \lambda_{\omega t}^- u_{\omega t}^- + \bar{\lambda}_t^- \left(1 - u_{\omega t}^- \right) \quad \forall \omega, t \quad (12)$$

$$b_t^- \geqslant \lambda_{\omega t}^- \left(1 - u_{\omega t}^- \right) + \underline{\lambda}_t^- u_{\omega t}^- \quad \forall \omega, t \quad (13)$$

$$b_t^+ \leqslant \lambda_{\omega t}^+ u_{\omega t}^+ + \bar{\lambda}_t^+ \left(1 - u_{\omega t}^+ \right) \quad \forall \omega, t \quad (14)$$

$$b_t^+ \geqslant \lambda_{\omega t}^+ \left(1 - u_{\omega t}^+ \right) + \underline{\lambda}_t^+ u_{\omega t}^+ \quad \forall \omega, t \quad (15)$$

$$p_{it}^\uparrow, p_{it}^\downarrow, r_{it}^{\uparrow +}, r_{it}^{\downarrow +}, r_{it}^{\uparrow -}, r_{it}^{\downarrow -} \geqslant 0 \quad \forall i, t \quad (16)$$

$$e_{i\omega t} \geqslant 0 \quad \forall i, \omega, t \quad (17)$$

$$u_{\omega t}^+, u_{\omega t}^- \in \{0, 1\} \quad \forall \omega, t \quad (18)$$

$$d_{it} \in \{0, 1\} \quad \forall i, t \quad (19)$$

The objective function (1) minimizes the expected cost for charging the EV pool of an aggregator. This cost is
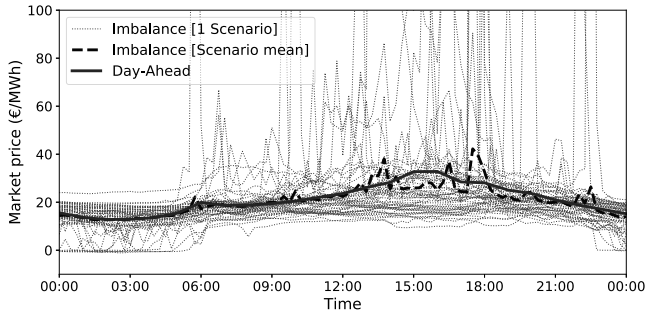
Fig. 1. Historic price data from ERCOT[11].

Fig. 2. Historic reserve deployment data from ERCOT[12].

subdivided in the cost of DA purchase and imbalance trading, and the expected costs over all scenarios. The costs per scenario consist of the reserve capacity payment, reserve deployment payment, and battery degradation costs. In addition, the objective function also penalizes unmet demand. Constraint (2) balances the total charge to the amount of energy bought and sold in different markets. Constraint (3) guarantees that the aggregator does not intend to sell/buy on the imbalance market what it bought/sold DA. This is required to avoid gaming.

Constraints (4)-(7) limit the (dis)charge and up and down reserve amounts. Each EV can be in two states ($d_{it} = 0$ means charging and $d_{it} = 1$ means discharging) and in both states it can provide up and down reserves. The constraints guarantee that (dis)charging limits are never exceeded.

For each scenario, (8) keeps track of the SOC. The SOC in time step t is equal to the SOC of time step $t-1$ plus (minus) the planned (dis)charging amount and deployed reserves. The SOC $e_{i\omega t}$ is further limited by (9)-(11), so that it never exceeds the battery limit and is charged to a minimum SOC at departure time. The variable $f_{i\omega}$ is added to (11), so that the aggregator can specify the risk it is willing to take of not fulfilling the required SOC levels.

What is most special about this model is how the optimal price bids are obtained. The optimal reserve capacity price bids b_t^+, b_t^- are obtained from (12)-(15) (with $\bar{\lambda}_t^- = \sup_\omega \lambda_{\omega t}^-$, $\underline{\lambda}_t^- = \inf_\omega \lambda_{\omega t}^-$, and $\bar{\lambda}_t^+ = \sup_\omega \lambda_{\omega t}^+$, $\underline{\lambda}_t^+ = \inf_\omega \lambda_{\omega t}^+$). Constraints (12) and (13) represent the optimal down-bid by requiring that a given price bid b_t^- is accepted if and only if it is lower than the market price $\lambda_{\omega t}^-$, i.e., $b_t^- \leqslant \lambda_{\omega t}^-$. Similarly, the up-bid logic is represented by (14) and (15).

For a charging speed that depends on the SOC, one can add (20), as proposed in [6]. The variable E_i^{crit} is the critical amount of charge from which the EV cannot be charged at full power:

$$p_{it}^\downarrow + r_{it}^{\downarrow-} u_{\omega t}^- \leqslant \bar{P}_i^\downarrow \frac{\bar{E}_i - e_{i\omega t}}{\bar{E}_i - E_i^{\mathrm{crit}}} \quad \forall i, \omega, t \qquad (20)$$

Notice that (1), (4)-(8) and (20) include multiplications of binary and continuous variables. These can easily be linearized, as done in [4], by introducing big-M constraints.
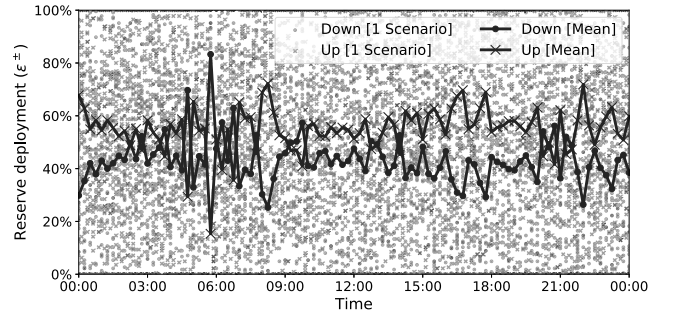
This requires the substitution $r_{i\omega t}^{\updownarrow\pm} = r_{it}^{\updownarrow\pm} u_{\omega t}^\pm$, for all i, ω, t. Additionally, constraint (3) needs to be rewritten to linear constraints, by adding binary variables q_h which take care that p_t^{imb} and $p_{h(t)}^{\mathrm{DA}}$ are either both positive or both negative. The result is shown in (21) with $M_t = \sum_{i\in\mathcal{I}} \alpha_{it} \max(\bar{P}_i^\uparrow, \bar{P}_i^\downarrow)$.

$$\begin{aligned} p_t^{\mathrm{imb}} &\geqslant -M_t(1 - q_{h(t)}) \quad \forall t & p_t^{\mathrm{imb}} &\leqslant M_t q_{h(t)} \quad \forall t \\ p_{h(t)}^{\mathrm{DA}} &\geqslant -M_t(1 - q_{h(t)}) \quad \forall t & p_{h(t)}^{\mathrm{DA}} &\leqslant M_t q_{h(t)} \quad \forall t \quad (21) \end{aligned}$$

IV. DETERMINISTIC MODEL

In order to evaluate the advantage of SO for this problem, this section introduces a deterministic variant of the same model, called DDIR. This deterministic model cannot trivially be obtained from the SO model, i.e. by using one scenario based on expected values for all parameters. This is because of the way the price bids are obtained in SDIR. Instead, as done in [4], DDIR determines the bid prices from the desired bid-acceptance probability, $\chi_t^\pm$. The deterministic model then chooses a price that according to historic data will obtain that probability $\chi^\pm$. The values $\lambda_t^{*\pm}$ and $\lambda_t^{*\mathrm{imb}}$ are the expected accepted prices given the price bid, based on $\chi^\pm$.

The DDIR model is as follows:

$$\begin{aligned} \min \sum_{h\in\mathcal{H}} p_h^{\mathrm{DA}} \lambda_h^{\mathrm{DA}} &+ \sum_{t\in\mathcal{T}} p_t^{\mathrm{imb}} \lambda_t^{\mathrm{imb}} \Delta + \\ \sum_{t\in\mathcal{T}} \sum_{i\in\mathcal{I}} \Big(&(r_{it}^{\downarrow-} + r_{it}^{\uparrow-})(\lambda_t^{*-} + \varepsilon_t^- \lambda_t^{*\mathrm{imb}})\chi_t^- - \\ &(r_{it}^{\downarrow+} + r_{it}^{\uparrow+})(\lambda_t^{*+} + \varepsilon_t^+ \lambda_t^{*\mathrm{imb}})\chi_t^+ + \\ &(p_{it}^\uparrow - r_{it}^{\uparrow-} \varepsilon_t^- + r_{it}^{\uparrow+} \varepsilon_t^+)\kappa \Big) \Delta \quad (22) \end{aligned}$$

subject to (2)-(7), (9)-(11) with the ω index omitted of the variables and parameters, with $u_{\omega t}^\pm$ removed from (4)-(7), and also subject to

$$\begin{aligned} e_{it} = \eta_i^\downarrow &\left(p_{it}^\downarrow + r_{it}^{\downarrow-} \chi_t^- \varepsilon_t^- - r_{it}^{\downarrow+} \chi_t^+ \varepsilon_t^+ \right) \Delta \\ &- \frac{1}{\eta_i^\uparrow} \left(p_{it}^\uparrow - r_{it}^{\uparrow-} \chi_t^- \varepsilon_t^- + r_{it}^{\uparrow+} \chi_t^+ \varepsilon_t^+ \right) \Delta \\ &+ e_{i,t-1} \quad \forall i, t \quad (23) \end{aligned}$$

TABLE I
Specification of the EV used in the experiments

Arrival time:	20.00h	Arrival SOC:	3kWh
Departure time:	7.15h	Required SOC:	27kWh
(Dis)charging speed:	7kW	Battery capacity:	30kWh
(Dis)charging efficiency:	90%		

V. Experimental evaluation

The aim of the experimental evaluation is to evaluate the advantages of SO and of optimal reserve price bids. The obtained schedules are evaluated based on resulting charging costs and on robustness. An evaluation of the effects of market participation and providing ancillary services is also shown for comparison reasons.

A. Experimental setup

The experimental setup is as follows: The uncertain parameters in the proposed models are $\lambda_{\omega t}^{\text{imb}}$, the imbalance price, $\lambda_{\omega t}^{\pm}$, the market capacity price of down and up reserves, and $\varepsilon_{\omega t}^{\pm}$ the proportion of a PTU during which reserves are deployed (for every time step t and scenario ω). Historic data of 2016 from ERCOT [11], [12] is used to make 52 scenarios: one scenario from every week in the historic data set. This scenario data is also shown in Fig. 1 and Fig. 2. These figures show values for $\lambda_{\omega t}^{\text{imb}}$ and $\epsilon_{\omega t}^{\pm}$ for one day. The SO is obtained from subsets of this whole set of scenarios. These subsets are created in such a way that the difference between the complete and subset mean and variance is minimal.

Because the experiments do not consider consumer behavior uncertainty, all experiments are run for one EV, with the properties as specified in Table I. Based on [13], the battery degradation cost κ is set to €0.042/kWh.

In Fig. 3-6, the average operation costs are computed by evaluating the schedule against all 52 scenarios. Because all evaluated schedules are made day-ahead, they may fail to satisfy the demand in some scenarios. Therefore, these figures also show the average unmet demand. A more conservative schedule results in less unmet demand. To take the unmet demand in account when evaluating costs, all unmet demand is penalized by €60/MWh, and added to the other costs.

For the aggregator it is possible to choose different strategies concerning risks of unmet demand. Fig. 3 shows the effect of setting the risk penalization parameter. Because of these results, the risk penalization ψ is set to €60/MWh for the rest of the experiments.

B. Stochastic optimization and optimal price bids

SO is excepted to give better results than a deterministic approach. Additionally, optimal price bids should be better than quantity-only bids. Both these statements are evaluated here by comparing the SDIR and DDIR methods both with optimal bids, and with quantity-only bids.

The desired bid-acceptance probability is an important parameter
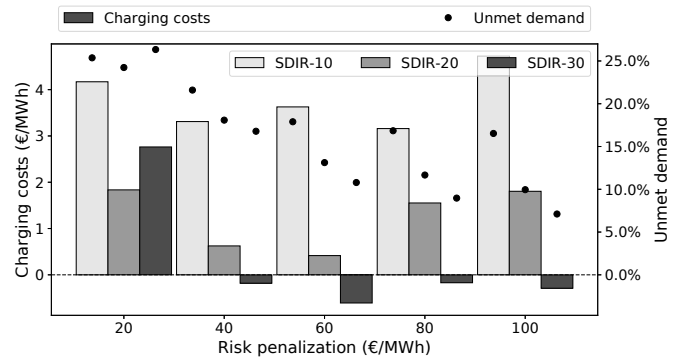

Fig. 3. Effect of the risk penalization parameter on the expected charging costs and unmet demand, computed with SDIR and different numbers of scenarios.
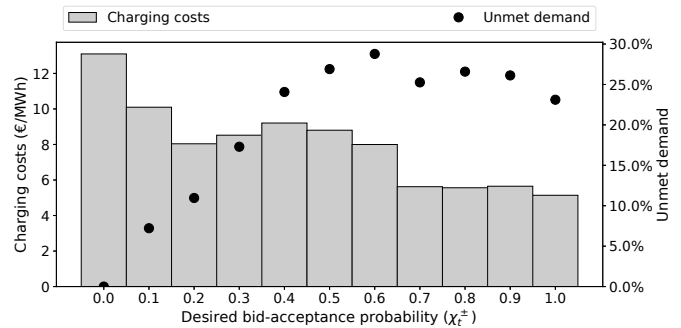

Fig. 4. Evaluation of an optimal bid-acceptance probability parameter for DDIR.

for DDIR. Fig. 4 shows the effect of this parameter on the charging costs and the unmet demand. The results show that DDIR gives best cost performance with $\chi_t^{\pm} = 1$. This means that DDIR performs best when providing quantity-only bids. With $\chi_t^{\pm} = 0.2$, there is a good balance between unmet demand and charging costs. For the following experiment, $\chi_t^{\pm}$ is set to 0.2.

Fig. 5 shows the average costs of the schedules obtained by the deterministic and SO approach with increasing number of scenarios. It also shows the effect of optimal reserve bids in comparison to quantity-only bids. A quantity-only version of the models is made by forcing all $u_{\omega t} = 1$ for the SO, and $\chi_t^{\pm} = 1$ for the deterministic approach. The effect is that the model returns reserve bids that are always assumed to be accepted.

Fig. 5 shows that SDIR gives lower charging costs than DDIR. Especially the results for SDIR-30 are much better, with lower costs and less unmet demand than DDIR. SDIR-30 with optimal bids performs better both in terms of charging costs and unmet demand when compared to SDIR-52 that provides quantity-only bids.

C. Effect of market participation

To put the cost benefits into perspective, Fig. 6 shows the effect of smart charging strategies on the operational costs for an aggregator, compared to direct charging. All results are obtained with SDIR-30. In Fig. 6 'Imbalance'
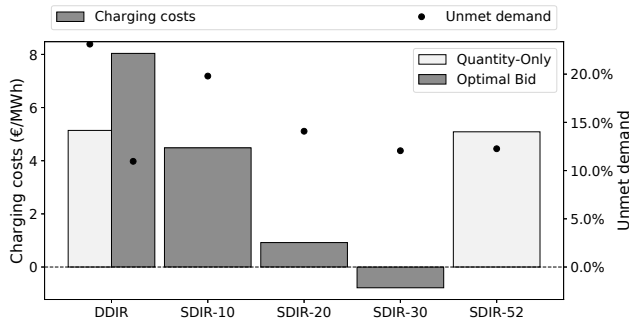
Fig. 5. A comparison of the deterministic approach vs the SO approach with increasing number of scenarios. The plot shows the results for optimal price bids, and for quantity-only bids. Unmet energy demands are penalized with €60/MWh.
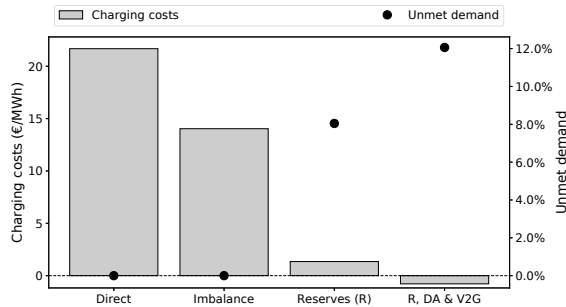

Fig. 6. Effect of market participation on the operation costs for an aggregator, computed with SDIR-30.

means that only trading on the imbalance market is possible. The next column adds the possibility of providing reserves, and the last column also allows for trading on the DA market and for providing V2G. Fig. 6 shows that each added feature decreases the operational costs of the aggregator.

From Fig. 5 and Fig. 6 we can also conclude that the cost savings from SO and optimal bids are also considerable when compared to the cost savings that can be made by including for example DA and V2G.

VI. Conclusion

This paper presents a model to minimize operational costs for an EV aggregator that considers both electricity prices and reserve deployment to be uncertain, by using Stochastic Optimization (SO). The model also chooses what energy to buy day-ahead, what energy to buy real-time, and what reserve capacity and price to bid. As expected, SO in comparison to the deterministic approach, results in schedules with lower costs and better robustness. The SO also showed the benefit of reserve bids that consist of quantity and price, in comparison to quantity-only bids.

As a future work, we suggest to extend the evaluation to include a rolling horizon and the possibility to update schedules. In the evaluation presented here, no changes can be made from the schedule which is decided day-ahead. Also all reserve bids are now made day-ahead. A rolling

horizon evaluation would result in a better penalization of unmet demand.

Another important extension of the model is uncertainty in EV staying patterns. When the model is used for multiple EVs, run time becomes also more important. The binary variables used to obtain optimal reserve price bids have an impact on the run time. Therefore, we suggest as a future work to search for ways to reduce to the run time of this model. This would enable an EV aggregator to use the advantages of SO and optimal reserve price bids in providing balancing services.

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