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***Abstract*—Smart-Charging of Electric Vehicles (EVs) is able to provide frequency regulation capacity services to the System Operator (SO) upon an automation generation control (AGC) signal. While the amount of available regulation capacity is offered in the Day-Ahead Market (DAM), there is high uncertainty on the actual amount of reserves that will be called in the Real-Time Market (RTM). This work focuses on aiding EV smart-charging to offer a consistent and reasonable amount of regulation capacity, taking into account the impact of potential future instantaneous called regulation reserves while also maintaining simplicity. The work also analyzes the results of different charger types with different characteristics and shows that they play an important role on the regulation provision. Finally, it has been shown that even though the regulation income is inevitably reduced (up to 66%), the Energy Management System (EMS) can still successfully charge the EVs and simultaneously provide regulation reserves with remuneration.**

***Index Terms*—regulation reserves, smart charging, electric vehicles, rolling horizon, ancillary services**

I. Introduction

The integration of a large number of Electric Vehicles (EVs) in the future electricity grid allows smart charging to be involved, apart from the main purpose of sustainable EV charging with minimum charging cost, with the provision of ancillary services to the System Operator (SO). Such ancillary services can be Regulation Reserves (categorized to up and down), Spinning or non-Spinning Reserves, Load Following, Voltage Control, etc [1]. Frequency Regulation Reserves are a very important type of ancillary services that the EVs can provide upon an automated generation control (AGC) signal for frequency stabilization [2]. Moreover, EV fleets' charging is also very suitable for providing fast frequency regulation due to their extremely high ramp-up and down rates (even as less as 200 milliseconds according to Chademo and Combo EV charging standards) [3], [4].

Several works in the literature have already proposed the combination of EV smart charging with regulation reserves provision. For example, optimal strategies for offers of primary and secondary frequency reserves have been proposed in [5] and [6], respectively, for maximization of regulation revenue. However, both of these works are not combined with thoroughly optimal EV smart charging. Furthermore, deterministic and stochastic optimal bidding strategies have been formulated in [7] and [8], respectively. In [7], the authors have shown that the provision of positive automatic Frequency Restoration Reserves (aFRR) in Germany from 30 October 2018 to 31 July 2019 can accomplish a positive net return. In addition, primary regulation provision by EV chargers and battery systems has been proven to increase lifetime cost savings by 36% in [9]. However, these works do not consider the impact on the provided regulation capacity of EV fleets with different characteristics. Moreover, the scheduling of regulation capacity is often treated with multiple levels of optimization. In this regard, bi-level optimizations have been proposed in [10] and [11], aiming to submit the best offering strategies to Day-Ahead and Real-Time markets (DAM and RTM) while simultaneously improving the EV owners' revenues. On the contrary, authors in [12] utilized a 3-level hierarchical charging management model. The first control layer interacts with the DAM, while the second and third layers aim to cope with the dynamics of the RTM. Only a few smart-charging works, such as [3], investigated scheduling and deployment of regulation reserves, avoiding complex multiple optimization levels. However, the authors in [3] ignored the impact of future potential called regulation reserves on the instantaneous EV SOCs, assuming that the net up and down called amount is close to zero. The same neglect can also be seen in other works, such as [7], [9] & [13].

This work focuses on regulation reserves provision by smart-charging while simultaneously addressing the impact of the future instantaneous regulation calls (every 5'). Building upon the rolling-horizon model in [3] (considered as representative of works with this limitation), the work aids EV smart charging to offer a consistent and reasonable amount of regulation capacity, with the use of the expected future calls. Similar concepts have only been proposed in [1], [2] & [14]. However, this work utilizes the rolling-horizon capability and integrates different concepts of regulation reserves in the optimization horizon. Hence, it is maintained as single-level and avoids complex sequential optimization levels. This work's contributions can be summarized as follows:

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1) Natural, offered & expected regulation reserves (concepts will be further explained in Section II) are integrated as three different decision variable series in the optimization. Each one takes different responsibilities in the smart-charging optimization for consistent and reasonable regulation capacity provision. The problem is maintained as single-level in order to reduce complexity and avoid multiple optimization levels.

2) The work considers the impact of future regulation calls on the instantaneous EV SOCs, simultaneously quantifying it by comparing it with the initial model [3].

3) The work investigates the concept on different types of chargers, aiming to reveal also the impact on the regulation provision of different characteristics of EV fleets.

The rest of the work is divided into the following categories: Section II integrates the methodology of development of the improved smart charging and regulation provision models. Section III consists of the results and discussion of this work, while Section IV integrates the conclusions and recommendations for future research.

II. Methodology

A. Initial Smart Charging Algorithm & Regulation Model

A summary of the important parts of the initial smart-charging work's concept and model (1) - (7) is presented here. The reader should refer to [3] for further explanations. The initial model is formulated as a rolling-horizon MILP problem of timestep Δt. It describes an Energy Management System (EMS) of an EV parking garage that aims to maximize EV charging by an integrated PV park, covering the EV-requested charging demand and the base electric load with minimum cost. The garage is also connected to the main grid for power exchange during power mismatch. The EMS updates the optimization horizon upon every EV's arrival. Moreover, it integrates chargers at nodes at three different locations: a "Home", a "Semi-Public" & a "Public" node, which in the investigated example encompass 3, 5 & 3 chargers, respectively.

$$\begin{aligned}\min C_n = \Delta t(&-\sum_{t=1}^{T}\sum_{j=1}^{J}(P_{up}^{n,j,t}C_{up}^{t} + P_{dn}^{n,j,t}C_{dn}^{t}) \\ &+\sum_{t=1}^{T}(P_{im}^{n,t}C_{buy}^{t} - P_{ex}^{n,t}C_{sell}^{t})) \\ &+\sum_{j=1}^{J}(B_a^{n,j} + d^{n,j} - B_d^{n,j})C_{pen}^{n,j}\end{aligned} \tag{1}$$

Equation (1) represents the objective function of the EMS, where $P_{up}^{n,j,t}, P_{dn}^{n,j,t}, P_{im}^{n,t}, P_{ex}^{n,t}$ are the dynamic PV generation, up & down regulation and imported & exported power respectively, expressed in kWs. The EMS tries to minimize for every node n over a horizon T, the overall charging cost, which is an outcome of $C_{up}^{t}, C_{dn}^{t}, C_{buy}^{t}, C_{sell}^{t}$ & $C_{pen}^{n,j}$, which are the up & down regulation revenue, imported power cost, exported power revenue and penalty cost, respectively. It must be noted that all revenues (earnings) are introduced with a negative sign, while all costs (expenses) are introduced with a positive sign. Moreover, all costs and revenues are expressed in €/kWh. Additionally, the penalty cost is produced when the departure capacity $B_d^{n,j}$ of a driver at charger j is less than the sum of the arrival capacity $B_a^{n,j}$ and the requested charging demand $d^{n,j}$ and is equal to [10€/1%(uncharged SOC)].

$$P_{im}^{n,t} - P_{ex}^{n,t} = P_{dif}^{n,t} = \sum_{j=1}^{J}\frac{P_{ch}^{n,j,t}}{h_{ch}^{n,j}} + P_{l}^{n,t} - P_{PV}^{n,t} \tag{2}$$

$$B^{n,j,t} = B_a^{n,j} + \Delta t \sum_{T_a^{n,j}}^{t}(P_{ch}^{n,j}h_{ev}^{n,j}) \tag{3}$$

$$P_{up}^{n,j,t} \leq \frac{P_{ch}^{n,j,t}}{h_{ch}^{n,j}} \tag{4}$$

$$P_{ch}^{n,j,t} + P_{dn}^{n,j,t}h_{ch}^{n,j} \leq P_{max_{ch}}^{n,j} \tag{5}$$

$$\sum_{j=1}^{J}\frac{P_{ch}^{n,j,t}}{h_{ch}^{n,j}} + P_{dn}^{n,j,t} + P_{l}^{n,t} - P_{PV}^{n,t} \leq G_{in}^{n}, \text{ if } P_{dif}^{n,t} \geq 0 \tag{6}$$

$$P_{PV}^{n,t} - P_{l}^{n,t} - \sum_{j=1}^{J}\frac{P_{ch}^{n,j,t}}{h_{ch}^{n,j}} - P_{up}^{n,j,t} \leq G_{out}^{n}, \text{ if } P_{dif}^{n,t} < 0 \tag{7}$$

Equations (2) & (3), defined as charging functions, dictate the power balance and the dynamics of EV SOCs, respectively, where $P_{PV}^{n,t}, P_{ch}^{n,j,t} \& P_{l}^{n,t}$ are the PV generation, charging & base load power and $h_{ch}^{n,j}$ & $h_{ev}^{n,j}$ the charger's & EV Battery Management System's (BMS) efficiency, respectively, assumed here both 0.95. Finally, (4)-(7) dictate the charging limits according to the charger's maximum power $P_{max_{ch}}^{n,j}$ and grid import & export limits G_{in}^{n} & G_{out}^{n}, which are here considered 87kW and 22kW, respectively, for all the grid nodes. They dictate that the sum of EV charging, regulation & grid exchange power always comply with the related limits. Finally (1) - (7) apply for every node n and charger j. However, (1), (2, (4), (6) & (7) apply for every t in horizon T, while (3) & (5) apply for every t between EV arrival and departure times $[T_a^{n,j}, T_d^{n,j}]$.

Observing the initial model (1) - (7), the EMS only computed the ideal (or natural) reserves according to the various power limits. It was assumed that, on the one hand, the EMS offers, and on the other hand, the market accepts and remunerates the EMS for all the natural capacity. As stated, the regulation model ignored the future instantaneous impact of regulation calls on the EV SOCs, assuming that the net reserves capacity called by the SO was zero. The integrated initial regulation provision model can be seen in Fig. 1 ("Initial Regulation Provider").

B. New concepts of Regulation Reserves & Regulation Model

However, the net called capacity is not always zero. Moreover, the called reserves' dynamics are highly uncertain and can directly impact the decisions of the EMS. Finally, the Balance Service Providers (BSPs), such as the proposed EMS, offer predefined regulation capacities and are obliged to be capable of actually providing a lower or equal amount of

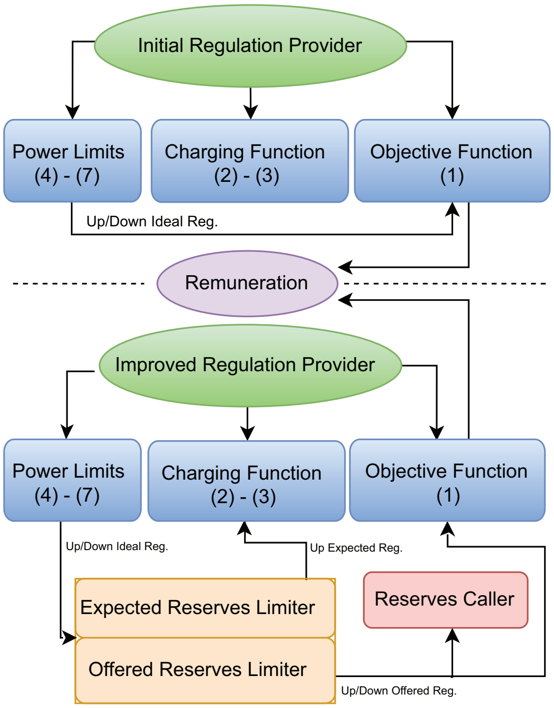

Fig. 1. Initial and Improved Regulation Provider Concepts

the offered reserves for the entire delivery period [1]. These services will be remunerated even if the SO does not call the reserves in real time. In this regard, this work utilizes four different concepts of regulation reserves, which are defined and explained as follows:

- "Natural-Ideal" Regulation Reserves: Capacity that could be ideally provided during EV smart-charging. This capacity is utilized in the initial provision model.
- "Offered" Regulation Reserves: Optimal Capacity decided to be offered to the reserve market and maintained available in real-time. This capacity is considered totally accepted and equal to the natural capacity in the initial regulation provider.
- "Expected" Regulation Reserves: A reasonable amount of offered reserves, expected to be called by the SO in the future and considered in the optimization horizon.
- "Called" Regulation Reserves: Uncertain Capacity "called" by the SO in real-time, whose net amount is considered zero in the initial regulation provider.

This work is maintained as a single-level MILP problem by integrating the natural, offered, and expected regulation capacities as different decision variables' series within the same optimizer in order to avoid the transition to multiple sequential optimization levels. With the integration of expected regulation reserves in the charging functions (2)-(3), the work accounts for the impact of the future instantaneous regulation calls. Additionally, it uses them to moderate the offered reserves and provide a consistent and reasonable amount. The

[1] https://www.tennet.eu/balancing-markets

reformulation of the regulation provider, depicted in Fig. 1 ("Improved Regulation Provider"), is summarized below:

1) The natural reserves $P_{up}^{n,j,t}$ & $P_{dn}^{n,j,t}$ are integrated in all power limit constraints (the EMS should be capable of providing them), hence (4)-(7) remain unmodified.

2) The offered reserves are integrated into the objective function for remuneration. Hence, $P_{of_{up}}^{n,j,t}$ & $P_{of_{dn}}^{n,j,t}$ replace $P_{up}^{n,j,t}$ and $P_{dn}^{n,j,t}$ respectively in (1).

3) The expected reserves are integrated into the charging functions: the power balance & EV SOCs' equations (2) & (3), to take into account the estimated instantaneous future calls in the EV charging. As already stated, the improved regulation provision concept intends to aid the optimizer in seeking for a reasonable trade-off between charging and regulation provision. While high offered reserves are desired for high remuneration, they simultaneously constitute a risk for the optimization. Upon potential call, the EMS is obliged to provide them, giving second priority to the EV charging. For that reason, expected down regulation reserves are favorable for the minimum charging cost since the chargers can charge the EVs without paying for imported grid power. Therefore they are taken out so that the EMS does not always choose to charge the EVs with down regulation reserves. Hence, only up expected reserves $P_{exp_{up}}^{n,j,t}$ are integrated in the (8) and (9), which replace the (2) and (3), respectively.

$$P_{im}^{n,t} - P_{ex}^{n,t} = \sum_{j=1}^{J} \left(\frac{P_{ch}^{n,j,t}}{h_{ch}^{n,j}} - P_{exp_{up}}^{n,j,t}\right) + P_{l}^{n,t} - P_{PV}^{n,t} \quad (8)$$

$$B^{n,j,t} = B_{a}^{n,j} + \Delta t \sum_{T_a^{n,j}}^{t} \left(\left(P_{ch}^{n,j,t} - \frac{P_{exp_{up}}^{n,j,t}}{h_{ch}^{n,j}}\right) h_{ev}^{n,j}\right) \quad (9)$$

4) By the definition of different types of reserves: the up and down natural reserves are always higher or equal to the offered reserves, which are higher or equal to the expected reserves for every node n and timestep Δt, which is dictated by (10).

$$P_{exp_{up}}^{n,j,t} \leq P_{of_{up}}^{n,j,t} \leq P_{up}^{n,j,t} \;\&\; P_{of_{dn}}^{n,j,t} \leq P_{dn}^{n,j,t} \quad (10)$$

5) The expected up reserves must be forced to be bound to the offered up reserves. Otherwise, the EMS offers up reserves uncontrollably for remuneration but chooses not to expect. The expected capacity is bound to be within $a = 5.35\%$ & $b = 10\%$ of the offered capacity, dictated by (11), considering historical data of dutch regulation reserves available in the ENTSO-E platform.

$$a \sum_{t=1}^{T} P_{of_{up}}^{n,j,t} \leq \sum_{t=1}^{T} P_{exp_{up}}^{n,j,t} \leq b \sum_{t=1}^{T} P_{of_{up}}^{n,j,t} \quad (11)$$

6) The offered up reserves are now bound, but not the offered down reserves. Therefore, the EMS decides to offer much higher down reserves than up reserves, which are bound to the expected up reserves. Hence, the offered up and down reserves should also be bound. The up reserves are set to exceed a

$c = 25\%$ amount of the down reserves in every optimization horizon, which is dictated by (12).

$$\sum_{t=1}^{T} P_{of_{up}}^{n,j,t} > c \sum_{t=1}^{T} P_{of_{dn}}^{n,j,t} \tag{12}$$

7) Finally, a randomized percentage of offered up or down reserves (also zero) is actually called for deployment by the SO at every timestep after the optimization is finished. For the investigated study case of this work (see Section IV), the probability and magnitude of the instantaneous called reserves are set so that the net amount resembles the total expected amount.

Overall, the EMS with the improved regulation provider is formulated by the initial EMS & provider (1) - (7) as follows:

- Substitution of (2) and (3) by (8) and (9), respectively
- Integration of (10) - (12)

C. Description of Data Inputs & Study Cases

The utilized PV generation distribution profiles have been developed with the use of weather data from the Royal Netherlands Meteorological Institute (KNMI), scaled at 2.5 kW rated power, while base load consumption profiles have been downloaded by the NEDU Dutch load database. Finally, stochastic profiles of EV driving patterns (arrival SOC, arrival and departure time, requested energy) have been used by the ElaadNL open database for the generation of the EV consumption profiles. As already stated, the EMS comprises of chargers of nodes at Home, Semi-Public & Public locations. With the use of Monte-Carlo Simulation (MCS), 200 different EV datasets have been stochastically generated for each of the different locations.

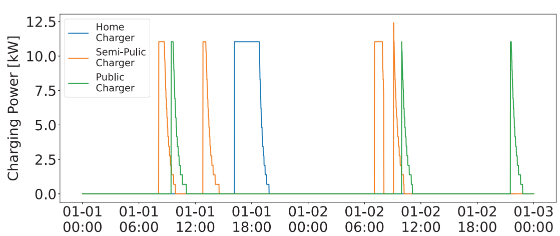

Fig. 2. Typical Uncontrolled Charging of EV fleets at Home, Semi-Public & Public Chargers (2 days)

In Fig. 2, typical uncontrolled charging events of EV fleets at the nodes of the three different locations are depicted. Charging at Home chargers usually lasts longer because of high requested amounts of energy, low arrival SOCs, and higher connection time. However, the frequency of EV arrivals is greatly lower than at Semi-public and Public chargers, typically 3-4 times per week. In comparison, Semi-public and Public chargers can have even 3 EV arrivals per day.

Two study cases have been constructed for the validation of the functionality of the improved regulation provider. The results of the two study cases are compared to the initial regulation provider and also to uncontrolled charging.

- Improved Case 0: The first study case (Case 0) represents a neutral case where no regulation reserves are called. This study case tests the successful operation of the EMS with the improved regulation provider in terms of the decided offered amount and the resulting revenue (earnings from regulation provision), independently from what is actually called.
- Improved Case 1: In the second study case, an amount of the node up or down offered reserves at every timestep $P_{of_{up(dn)}}^{n,t}$ is actually called $P_{cal_{up(dn)}}^{n,t}$. The SO (caller) checks what has been offered at every timestep and randomly chooses to call or not. The called regulation probability has been set at similar levels to the expected regulation capacity. Finally, the contribution of every EV charger to the node called reserves $P_{cal_{up(dn)}}^{n,j,t}$ is equal to its contribution to the offered reserves $P_{of_{up(dn)}}^{n,j,t}$, as dictated by (13).

$$P_{cal_{up(dn)}}^{n,j,t} = \frac{P_{of_{up(dn)}}^{n,j,t}}{P_{of_{up(dn)}}^{n,t}} P_{cal_{up(dn)}}^{n,t}, \ \forall t \in T \ \& \ j \in n \tag{13}$$

III. Results and Discussion

A. Different Regulation Concepts at different Nodes - Case 1

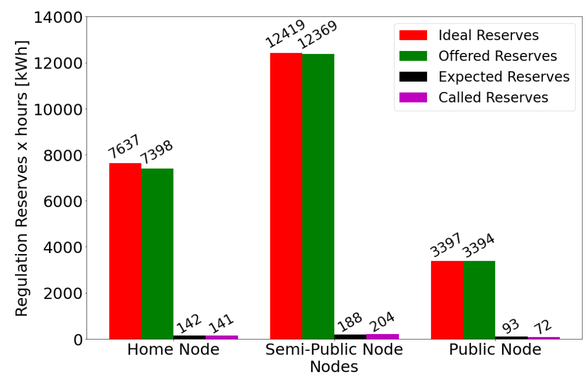

Fig. 3. Total Ideal, Offered, Expected & Called Reserves per Node (Case 1)

Fig. 3 presents the total amounts of the four types of reserves for every node. While the total ideal and the offered

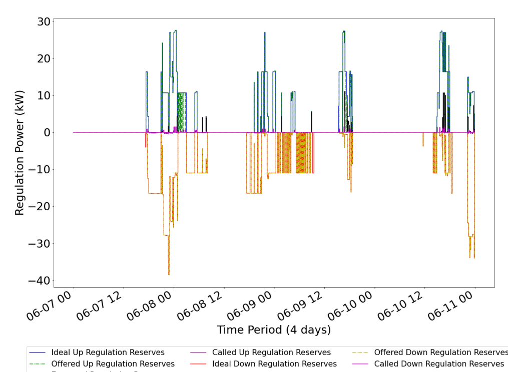

Fig. 4. Ideal, Offered, Expected & Called Regulation: Home Node, Case 1

reserves are of a similar magnitude, there is a notable difference, especially at the Home node (239 kW in 4 days). Furthermore, the Semi-Public node offers a higher amount of regulation (and hence earns the highest revenue) since it comprises of more chargers. The Home Node offers an approximately higher by 217% regulation capacity compared to the Public node, despite comprising the same number of chargers. This is justified by the longer parking periods of the EVs at the Home chargers, as seen in Fig 2. When EVs are parked for a time period much longer than the needed charging period, there is more ”room” for regulation offers. This is also, however, the reason behind the notable difference between the ideal-offered amount at the Home node. Mainly for the up regulation amount, the Home node is in the position naturally to offer a higher amount of up reserves, compared with the other two nodes. However, it decides to offer a lower amount because high offers risk the optimal EV charging.

Finally, in Fig. 4, an example of all the aforementioned regulation reserves' concepts is depicted for the Home node in Study Case 1. The preference of the EMS to offer more down than up regulation reserves, as explained in the Methodology section of the work, is also seen in Fig. 4. The amount of down regulation reserves is vastly higher than the respective amount of up reserves. This is because, with the use of down reserves, the EMS can charge the EVs with imported power from the grid and receive remuneration for regulation simultaneously. Therefore, down expected reserves are not integrated into the optimization horizon, so the EV charging can be optimized only with the expectation of the worst-case scenario of only up called reserves.

B. Regulation Revenue and Charging Cost in different Cases

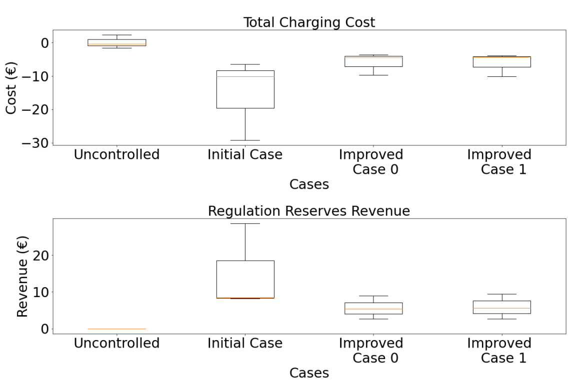

Fig. 5. Total Node Charging Cost C_n & Regulation Revenue R_n per Case

Fig. 5 depicts the total regulation revenue R_n and charging cost C_n (from (1)) for all three nodes in the four different cases: Study Cases 0 & 1, the initial case and the uncontrolled charging case. The total node charging cost integrates the total cost of the imported grid power $C_{n,buy}^{tot}$, the total revenues by exported grid power $C_{n,sell}^{tot}$ and regulation R_n (these are introduced with a negative sign because they represent earnings) and the total penalty cost $C_{n,pen}^{tot}$. When the total charging cost results negative, it means that the node in total has earnings when everything is summed up.

Firstly, no penalty cost has appeared; hence the charging is successful in all four cases. Secondly, the lowest charging cost (highest actual revenue, since it is negative), which can reach for the Semi-Public node up to 28€, belongs to the initial case, as expected. Moreover, this case also has the maximum regulation revenue (10€ on average). The uncontrolled case has the highest charging cost. However, it is close to zero because the EMS can still use PV power and export it to the grid when there is excess PV generation. As expected, Study Cases 0 & 1 present moderate results, receiving remuneration up to 9€ (for the Semi-Public node), which is always lower than the initial case but remains steady in both new cases. Hence, the impact of future potential calls on the improved provider remains low if the total called reserves are close to the expected. Moreover, the results for every node are less dispersed with the improved regulation provider than with the initial one. The highest difference between nodes' remuneration is 4€, compared with the 23€ of the initial case. This is another outcome of the moderate offers of the improved provider, controlled by the integration of expected reserves in (8) & (9) .

Table I further explains the reduced offered reserves and regulation revenue of the two cases, compared to the initial case for every node. Therefore, the impact of considered potential future instantaneous called reserves is quantified. The regulation provider offers more reasonable regulation amounts to avoid high real-time potential calls, which can be a risk for EV charging. The Semi-Public & Public nodes suffer the most from offered reserves and income reduction, which can reach up to 66.52% & 66.4%, respectively. On the contrary, the Home node is less affected (only a 2.7% reduction of offered reserves in Case 1). Hence, the difference between nodes' remuneration decreases. This difference between the nodes is again due to EV fleets' higher frequency and lower parking times at Semi-public and Public chargers. Forcing the EMS to expect (higher) called regulation reserves during a limited available time impels the EMS to offer a lower regulation amount and focus more on the charging. On the contrary, Home nodes typically have a lot of time to focus on both.

C. Testing the Regulation Provider against uncertainties

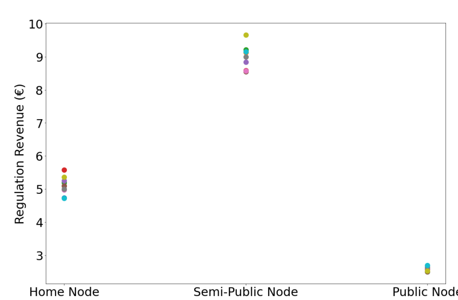

Fig. 6. Regulation Revenue per Node for 10 different simulations: Case 1

TABLE I
COMPARISON OF REGULATION REVENUE & OFFERED RESERVES BETWEEN INITIAL & IMPROVED PROVIDER

Node Type	Case 0		Case 1	
	Income Reduction %	***Offered Reserves Reduction %***	***Income Reduction %***	***Offered Reserves Reduction %***
Home Node	43.9	8.58	39.4	2.7
Semi-Public Node	66.4	66.52	65	64.68
Public Node	55.6	65.62	56.9	66.1

Study Case 1 has been repeatedly simulated ten times in order to test the provider against the uncertain regulation calls. The regulation revenue results of the three nodes are summarized in Fig. 6. The EMS provided successful charging (no penalty costs) for all nodes, receiving similar regulation revenue with low scarcity (up to 2.6 € at Semi-Public Node). Therefore, we can conclude that the regulation provision of the EMS is robust against uncertain calls. Moreover, we can see that the characteristics of the different nodes play a notable role also in this section. The higher number of chargers at the Semi-public node and the longer EV parking periods at the Home node increase the scarcity of the revenue results.

IV. CONCLUSIONS & FUTURE WORK

This paper focused on providing regulation, addressing the impact of future instantaneous regulation calls on smart charging, and using them to decide the offered amount. Binding offered and expected regulation capacity motivates the EMS-provider to offer reasonable regulation in favor of successful EV charging. While the initial case's offers and regulation revenue have been inevitably reduced, EV charging remains successful against uncertain potential calls, also providing earnings from regulation. The value of these earnings has been quantified by comparison with uncontrolled charging. The concept is also formulated, avoiding complex sequential optimization levels by integrating the different regulation concepts within the same optimizer. This work has also shown that, compared with up regulation, expecting and offering down regulation is more favorable for EV charging. Finally, the node type is also very significant for regulation. The higher parking times and time flexibility of the Home node favor offered regulation capacity. However, the improved regulation provider moderates the different nodes' offered capacity and revenue differences.

The limitations of this work are recommended for future research. Firstly, the model should be tested for equal up and down reserves, which applies in several reserve markets. Secondly, this work, as formulated, is more suitable for providing automatic Frequency Restoration Reserves (aFRR) in the US reserves market, which are firstly offered and consequently called by the Independent System Operator (ISO). The concept should also be modified to offer different ancillary services (e.g Frequency Containment Reserves) due to the fast ramping EV capability or function in European markets. Moreover, the model should also consider in detail the specifications of the different services, such as the contracted, activation, and maintenance time of reserves. Finally, the integration of the battery degradation is also recommended for future work.

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