An integrated simulation platform for assessing the integration of plug-in electric vehicles in electricity markets

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***Abstract*— In this paper an innovative, hierarchical, four-level optimization framework is proposed to model the optimal participation of Electric Vehicle Aggregators (EVAs) in day-ahead and real-time energy and regulation markets in conjunction with the optimal real-time charging management of the EV fleet. The scope of the framework is to incorporate in an integrated approach all the conjugated optimization tasks that an EVA should follow for cost-efficient and reliable market participation as well as for successful electric vehicles smart charging in real-time that will satisfy the EV owners. The PJM market design is modeled and a case study with 1000 PHEVs, represented by an EVA, is presented for one operating day. In the base case the EVA participates in the regulation market by following the dynamic regulation control signal. The base case is compared with one where the EVA follows the traditional regulation control signal and one where the EV fleet behaves in real-time differently than initially expected. The presentation of the main functionalities of the framework highlight its ability to model and evaluate the performance of the EV charging process in second-by-second time resolution in a market environment.**

***Index Terms*— ancillary services, dynamic regulation signal, electric vehicles, electricity market, regulation control signal, plug-in electric vehicles**

I. Introduction

The expected penetration of plug-in Electric Vehicles (EVs) in the near future creates prospects for a cleaner, more sustainable, and more decarbonized future. However, a large EVs penetration should be carefully addressed, since irregular charging management could have detrimental effects on power system and electricity market operation as well as on power quality at the distribution level. In this context, a vivid research interest on developing suitable tools for efficient solutions to these challenges is ongoing.

Most research works adopt the idea of an intermediary party, the plug-in Electric Vehicle Aggregator (EVA), as a market player that participates in the market arrangements on behalf of the EV fleet that he represents. However, besides the market operations, the EVA can control the EV charging process in real-time, can coordinate the charging management among the EV fleet and take advantage of the flexibility in the charging process by providing ancillary services to the System Operator (SO), for example provision of regulation by responding to the Regulation Control Signal (RCS) requests. Indicative works that focus on Day-Ahead Market (DAM), Real Time Market (RTM), real-time charging management approaches and RCS allocation algorithms can be found in [1]-[7]. In [8] and [9] rolling optimization processes for energy market participation are proposed, however regulation market and charging priority schemes are not included in the models.

This work goes beyond the recent works and proposes an integrated framework for detailed simulations down to second-by-second time resolution. The developed platform incorporates both market-oriented algorithms for the optimal bidding strategy of the EVAs in the DAM and subsequent RTM sessions as well as algorithms for the real-time charging management of the EVs during real-time in a coordinated manner. Through this platform, numerous qualitative and quantitative results can be derived, for example the efficiency of a candidate market design in integrating EVs can be evaluated or the efficiency of EVs integration in a specific market settlement can be assessed. To the best of our knowledge no such detailed approach has been proposed before. In section II the hierarchical structure of the platform is described, and in section III a detailed case study is set up. Conclusions are summarized in Section IV.

II. The Platform

In this paper an EVA manages a fleet of I EVs and participates in the short-term (DAM and RTM) wholesale electricity markets by submitting demand bids and regulation capacity offers. Unidirectional interaction with the grid is

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adopted, i.e. the EVs are not capable of discharging energy back to the grid: they can only deviate from their Preferred Operating Point (POP), by reducing or increasing their charging rate. The EVA has real-time control on the charging of each individual EV in the fleet: once an EV is plugged in, the EVA algorithm is responsible for modulating the EV charging power. In exchange, the EVA offers attractive tariffs to the EV owners by sharing part of his profits. The EV tariff structure is outside the scope of this paper.

The hierarchical, four-level optimization structure of the platform is described in brief below. Interactions between the involved parties and the optimization operations of the EVA are presented in Figure 1.

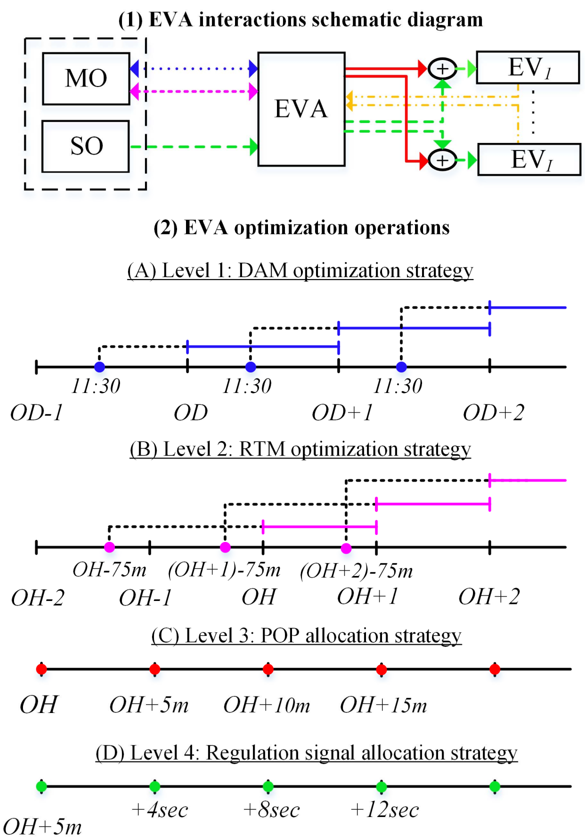

Figure 1: (1) Interactions between the EVA, the Market Operator, the SO, and the plug-in EVs. Level 1 (blue, dotted line), level 2 (purple, dashed line), level 3 (red, line) and level 4 (green, dashed line) interactions. In yellow, the EV information that is exchanged once with the EVA (e.g. desired State-of-Energy, EV battery size). The Market Operator and SO could be the same entity in some electricity markets. (2) Description of the EVA optimization problems. Time arrangements are parameterized for the PJM market. The colors are in line with the first diagram. Each dot declares the time that each problem is solved, and the solid part of line in levels 1 and 2 express the time interval for which binding decisions are produced.

A. Level 1: Optimal DAM participation strategy

The first optimization level includes the optimization strategy for participation in the DAM session of the Operating Day (OD) [Fig. 1(2A)]. The DAM optimization strategy of this paper is based on the framework developed in [1], where a two-stage stochastic, linear programming, optimization model is developed which produces optimal first-stage decisions for submission in the DAM (binding decisions) and second-stage scenario dependent, advisory schedules for submission in the RTM, 1 h before the Operating Hour (OH). The model can account for all uncertain DAM and RTM conditions as well as instructed and uninstructed (speculative) energy deviations between DAM and RTM. For the complete problem formulation, the reader is referred to [1].

B. Level 2: Optimal RTM participation strategy

In many contemporary market designs, besides the DAM, there is one or more market sessions much closer to the real-time operation. The EVA participates in these markets in order to take advantage of the latest updated information regarding his fleet portfolio and market conditions. The RTM optimization strategy of this paper is briefly described in [1]. This approach takes into account the DAM clearing results and optimizes the RTM quantities using two-stage stochastic, optimization on a rolling basis. The scheduled quantities are binding only for the first time interval and advisory for the remaining time horizon [Fig. 1(2B)]. Modeling and integration of level 2 problem that links DAM participation strategy (level 1) with the real-time charging management of the EV fleet (level 3 and 4) is one of the key innovations of this paper.

C. Level 3: Optimal POP allocation strategy

During real-time operation the EVA should allocate charging POPs to the EVs. The EV fleet POP ($\sum_{i\in I} POP_i$) where i is the set of EVs), is in line with the binding energy quantities calculated in level 2 problem. However, POP allocation is not arbitrarily selected but it is based on priority criteria. The priority criteria are expressed by priority weights and the smaller the weight, the higher the charging priority. Two main parameters determine the priority weight for the i^{th} EV (w_i): the energy required to complete the charging, E_i^r, and the time remaining until disconnection time, T_i^r. For example, two EVs with the same charging energy request will not be given the same priority if the first disconnects after one hour and the second disconnects after five hours. The first EV is given higher charging priority. The optimization framework for POP determination based on priority weights has been developed in [4]. The basic idea is that the combined priority weight is in the form of $w_i = (w_i^{Er})^{1/y} \cdot (w_i^{Tr})^{1/z}$, where (y,z) further tune the weights. An evaluation of the impact of the combined priority weight parameterization is carried out in [4]. Due to the evolving nature of priority weights the problem for POPs allocation should be solved very often. A reasonable value for this control level is 5min interval [Fig. 1, 2(C)].

D. Level 4: Optimal RCS allocation strategy

During real-time operation and after POP allocation to the EVs, the EVA receives RCS for provision of regulation. The allocation of the RCS request to the EVs is optimized every time the AGC system generates a new RCS (e.g., in PJM RTO every 2 s, in New York ISO every 6 s). A regulation up request from the SO implies charging rate reduction with respect to POP while a regulation down request from the SO implies a charging rate increase with respect to POP. The problem of this level determines the final charging SetPoints of the EVs. The scheme of priority weights of the previous step is also adopted here, i.e. when regulation down is requested, the EV with the higher charging priority charges first. The full optimization model is presented in [4].

III. CASE STUDY

In the presented residential, night charging case study the platform simulates the basic rules of PJM short-term energy and regulation market, where the EVA participates both in DAM and RTM sessions, while he modulates the charging of 1000 PHEVs during real-time operation. The EV parameters are created based on the distributions of Table I.

TABLE I
PROBABILITY DISTRIBUTIONS FOR THE EV FLEET PARAMETERS

	Distr.	Mean	St. dev	Min	Max
Battery capacity (kWh)	UD*	18	6.93	6	30
Arrival Time	TGD*	19:00	2 h	16:00	1:00
Departure Time	TGD*	7:00	2 h	5:00	12:00
Initial Battery SOE (%)	TGD*	75	25	25	95

* UD: uniform distribution, TGD: truncated Gaussian distribution

A. *PJM market rules*

Focusing on DAM participation, submission period for DAM offers/bids closes at 12:00 day-ahead [10]. The SO clears the day-ahead energy and schedules reserve market by co-optimizing energy and reserves using least-cost security constrained resource commitment and dispatch. The SO computes the cleared quantities system-wide and per participant as well as the day-ahead energy Locational Marginal Prices. EVAs are assumed to execute their optimal DAM participation program (level 1) at 11:30 day-ahead [Figure 1(2A)]. It is noted that in both DAM and RTM, the EVA is considered as a self-scheduled, price-taking market participant (rational assumption for small EV fleets) that submits quantity-only demand bids at the market price cap and regulation capacity offers at zero offer price ([10],[11]). It is assumed that the submitted regulation offers are fully cleared, therefore the assigned regulation capacity equals the submitted offer. The same is true for the submitted demand bids.

The resource owners that want to provide regulation in the PJM balancing area are required to submit no later than 18:00 day-ahead a) The maximum MW amount - Offer MW - of regulation capacity that the resource is willing to provide for the next operating day. b) a price - Offer Price - that should reflect the capability of the resource in \$/MW and the performance of the resource in \$/ΔMW[1]. Since the EVA is a self-scheduled participant, the Offer Price is zero. However, the above submissions are not binding. Until 60min prior to the beginning of the OH, when the regulation market actually closes, participants may submit revised regulation capacity offers (which are binding) with the following restrictions: a) Offer Price may not be changed; it is fixed to the one submitted before 18:00 day-ahead (in case of EVA it remains zero) b) Offer MW may be revised to reflect the most recent operating conditions; however, revised offer quantity may not be higher than the one submitted before 18:00 day-ahead. No penalties are imposed for revising the regulation capacity offers [11]. According to PJM rules, the resources must offer a regulation capacity band, i.e. the upward capacity equals the downward capacity [11]. The minimum accepted quantity is 0.1 MW. After collecting regulation offers, the SO adjusts them based on historical performance indices, ranks them in ascending order and calculates the regulation price components, the Regulation Market Capability Clearing Price (RMCCP), the Regulation Market Performance Clearing Price (RMPCP) and finally the Regulation Market Clearing Price (RMCP) and posts the results no later than 30 minutes prior to the beginning of the OH [11].

When a resource participates in the PJM regulation market, it can follow one of two candidate RCS; the traditional RCS (T. RCS) and the dynamic RCS (D. RCS). Actually, T. RCS is the low filter Area Control Error signal which is sent to the traditional regulating resources and D. RCS is the high filter Area Control Error signal sent to the dynamic regulating resources. D. RCS is designed for resources with high MW ramp rates and rapid turnaround, such as batteries and flywheels. T. RCS and D. RCS are complementary, that is, dynamic resources respond quickly but lack the ability to remain at that level for an extended period of time while traditional resources require time to follow the signal but have unlimited duration [11]. Figure 2 depicts T. RCS and D. RCS for one day. The difference in the energy bias of the signals and the requested resources movement (mileage) is obvious. PJM sends RCS every 2 sec. In this paper it is assumed that RCS is positive if the SO commands the provision of upward reserve (charging rate reduction in case of EVA) or negative if the SO commands the provision of downward reserve (charging rate increase in case of EVA).

Given a RCS time series, the 15min dispatch-to-contract ratio, R_{dc} coefficients, which express the ratio of real-time deployed energy to the assigned regulation capacity are calculated and incorporated into the DAM (level 1) and RTM (level 2) optimization models (see [1],[4]).

The actual regulation credits in PJM are dependent on the performance of the resource in providing regulation. In more details, the credits are proportional to the actual hourly performance score that the resource will achieve, which varies between 1 for perfect performance and zero (0) for no performance. The performance score consists of three factors, correlation, delay and precision score, weighted equally. Based on the very fast response capability of the lithium-ion batteries of EVs, correlation and delay scores can be assumed to be equal to 1 and the only factor that needs to be calculated is the hourly precision score, which is calculated at 10 sec samples from the absolute response error as a function of the resource's assigned regulation capacity in (1) and (2) where n is the number of samples (i.e. 360) in hour t. Finally, uninstructed energy deviations greater than 20% between DAM and RTM are penalized with the Balancing Operating Charge (BOR) which is considered 2.983 €/MWh.

[1] \$/ΔMW offer is part of the recent performance-based regulation mechanism that PJM has adopted, where the compensation for regulation provision is based on the performance of the providing resources. For more information, the reader is referred to ([11]).

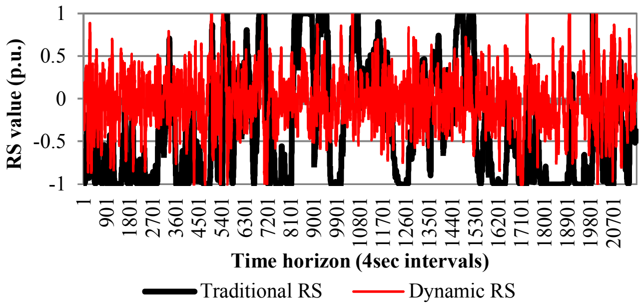

Figure 2: Dynamic and traditional PJM RCS (p.u.), April 22, 2014, [12].

$$\text{Precision score}_t = 1 - \frac{1}{n}\sum_{k \in t} \left| error_k \right| \tag{1}$$

$$\text{Error}_k = \frac{Response_k - RCS_k}{Assignment_t(MW)} \tag{2}$$

Three cases (A, B and C) are examined in this paper. In Case A (Base case) the EVA follows the D. RCS and perfect knowledge of the EV fleet behavior is considered, i.e. the EV fleet behavior in real-time is the same that estimated for the DAM. In case B, perfect EV fleet behavior is considered again but the EVA follows the T. RCS. Finally, in case C the EVA follows the D. RCS but uncertain EV fleet behavior is considered, i.e. the EV fleet behavior during real-time is not the same that estimated for the DAM. For case C it is assumed that 25% of the fleet (250 EVs) plug-in for charging 1 to 3 hours later than the expected time with an initial SOE deviation ranging between [-15%, +15%] from the expected, following a uniform distribution. Another 25% of the fleet will never plug-in and the rest 50% behaves exactly as it was expected. An EV scheduler/estimator has been developed that postpones the expected plug-in time when the EV does not plug-in as expected and if the EVs is not coming until the new, postponed expected time, the expected time is postponed again until a horizon limit, after which it is considered that the EV will not plug-in at all (the scheduler is not presented in more details due to space limitations). In all cases the rated charging power is 3kW and the desired final State-of-Energy (SOE) is set 97% for all the plug-in EVs.

B. *Input Data*

For the DAM optimization strategy forecasts or scenarios for the stochastic variables are necessary. Point forecasts are adopted for the DAM clearing price and RMCP, and scenarios are created for the RTM clearing price and for regulation deployment (R_{dc}). 04/22/2014 is considered as the operating day of the case study. The DAM cleared price (weighted prices for the PJM region) of the previous day (04/21/2014) is considered as a naïve forecast for the expected price trajectory of the operating day, since the load forecasts for those two days are very close. In addition, the price difference between DAM and RTM cleared price of the 10 previous days has been calculated and applied to DAM price forecast in order to create real-time, second-stage scenarios for level 1 optimization. RMCP of 04/20/2014 is considered as the RMCP point forecast. Finally, the calculated R_{dc} coefficients of the previous 10 days are used as 10 candidate scenarios. All data can be accessed in [12].

After the DAM clearing the EVA should optimize his strategy for participation in the RTM on a rolling, look-ahead basis every hour (level 2 optimization). Now the DAM hourly prices are known, however forecasts or scenarios are necessary for the RTM clearing price, the RMCP and for the regulation deployment for the rest of the time horizon. In this specific case the actual RTM clearing price and RMCP of the operating day (04/22/2014) are incorporated in the model considering perfect forecast of those prices. However, the uncertainty on regulation deployment calls is incorporated with RCS scenarios generation, created dynamically each time level 2 optimization problem is about to be solved, using an innovative scenario generation methodology based on ANNs [13]. A detailed description of the methodology is out of the scope of the current paper. After the RCS scenarios creation (10 scenarios) the 15min R_{dc} coefficients are calculated and incorporated into the RTM optimization model.

C. *Results*

In Figure 3 the hourly demand bids for submission in the DAM are presented, together with the 100 scenario-dependent second stage, advisory regulation capacity offers which highlight the diversity of different candidate scenarios realization due to the uncertainty on RTM clearing price and real-time regulation deployment. Based on the rule for symmetric regulation up and down capacity offering, the regulation capacity offers are symmetric. The EVA submits the maximum hourly capacity offer among all the scenarios before 18:00 day-ahead based on the PJM rules, as explained earlier. Another interesting result is the fact that although between 23:00 and 2:00 the EV fleet is expected to charge in real-time at a scenario-dependent, advisory fleet charging point no demand bid is submitted in the DAM. This is a result of the capability of the algorithm to optimize arbitrage between DAM and RTM, i.e. the EVA will purchase the necessary charging energy in the RTM market based on his expectations about cheaper energy price. In the specific case, arbitrage is profitable despite the BOR charge for uninstructed deviations greater than 20%. Finally, the aggregated rated charging power of the fleet is presented (purple color) which however gets reduced as the EVs State-of-Energy reaches high SOCs. The actual max. charging power of the fleet is also depicted in the figure (light blue). This reduction is a result of the incorporation into the optimization models of the Constant Current-Constant Voltage (CC-CV) charging mode which is very popular for li-ion battery systems. The SOE threshold for mode change is considered 85% for all the EVs. The reader is referred to [1] and [4] for detailed information of CC-CV modeling.

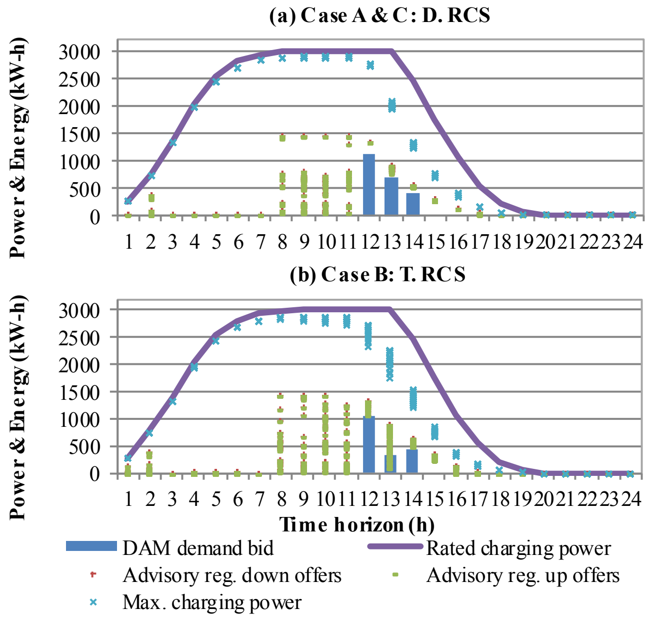

Figure 3: Results of the DAM optimization strategy (level 1).

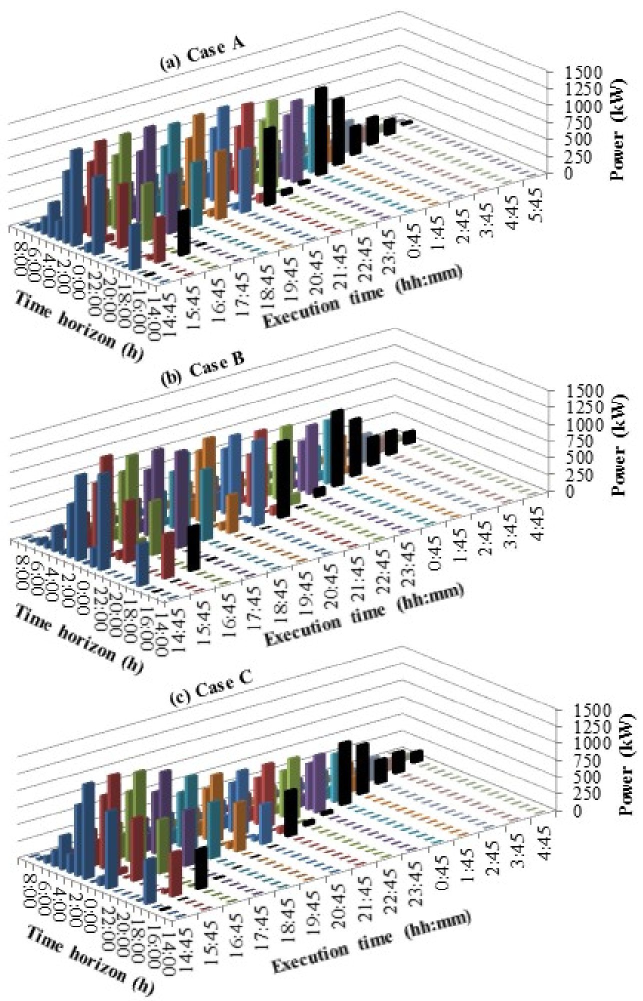

Figure 4: Regulation capacity offers produced from the RTM look-ahead optimization process (level 2), for scenario 1 out of 10. With black color the binding offers. With other colors the advisory, look-ahead schedules.

In figure 4 results from the rolling optimization process of level 2 are presented for one scenario. Binding and advisory regulation down capacity offers are depicted. The algorithms are solved 75 minutes before the OH and only the hourly capacity offer for the OH is binding. As an example, the problem solution at 15:45 creates binding schedules for the OH that begins at 17:00. The quantities for the subsequent hours are just advisory schedules which are replaced by the next rolling solutions (i.e. the solution at 16:45 creates binding schedules for the OH that begins at18:00). For case A, the regulation capacity offers for each OH are almost identical quantities. Results between cases A and B are very close, while in case C the advisory schedules for the first algorithm solution deviate noticeably from the final binding offers of the next hours, since level 2 problem optimizes the RTM bids and offers based on the updated information about the real-time behavior of the EV fleet.

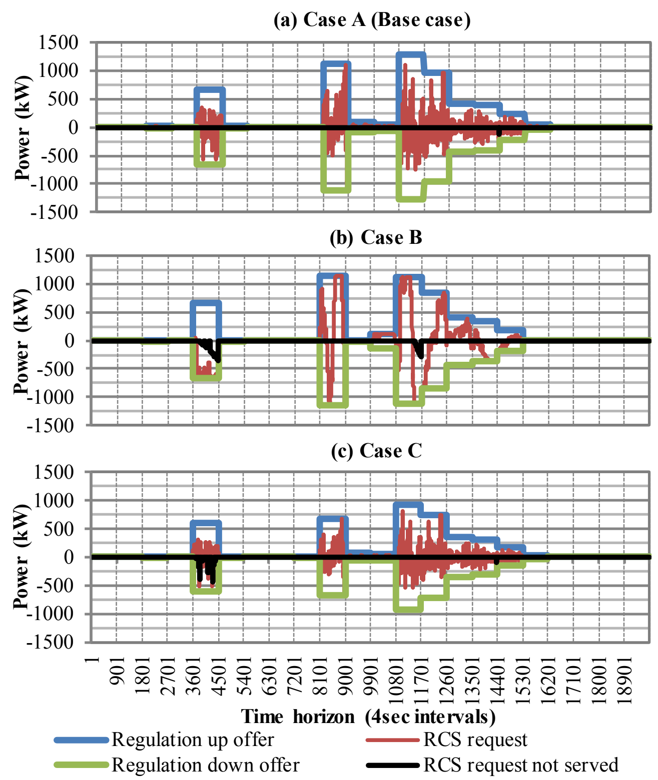

Figure 5: Binding regulation capacity offers, request for regulation provision and request that is not served during the whole time horizon.

In figure 5 the final binding regulation capacity offers submitted in the RTM are presented for the whole time horizon, together with the requests for regulation provision at a 4sec basis. In case A almost all RCS requests have been served. In case B the offering strategy is similar, however a different RCS trajectory is followed due to the T. RCS, while the non-served RCS request increases. Finally, in case C the overall market participation strategy is also similar, however a narrower regulation band is offered, since fewer EVs plug-in. In addition, there is a high percentage of unserved regulation requests during the first hour [Fig. 5(c)], since many EVs do not plug-in as initially expected. However, due to the rolling optimization strategy of level 2 the provision of regulation becomes reliable again. In figure 6 the actual charging program of one plug-in EV (out of 1000 EVs) is presented. The reduced charging power during CV charging above 85% SOE is obvious. The EV POP (calculated in level 3), is presented together with the up and down requests for regulation provision (calculated in level 4). The summation of POP and regulation requests results to the final EV charging SetPoint. Of course, up regulation requests hold for moments that the EV charges at a POP greater than zero.

Finally, in Table II numerical results for the three cases are presented. In the first five rows the different cost/revenue components and the total charging cost for the whole operating day is given. The revenues from the regulation market participation (third row) have been adjusted by the performance score which is presented in figure 7. In addition, regulation up and down requests are presented in the 6th and 7th rows. Finally, the total EV fleet energy request and the energy delivered are presented in the 8th and 9th rows. This energy difference results in a number of EVs that are not charged at the pre-specified level (last row). The number of those EVs indicates that the performance under D. RCS is more reliable than under T. RCS, and that the developed framework can treat well the uncertain EV fleet behavior in real-time.

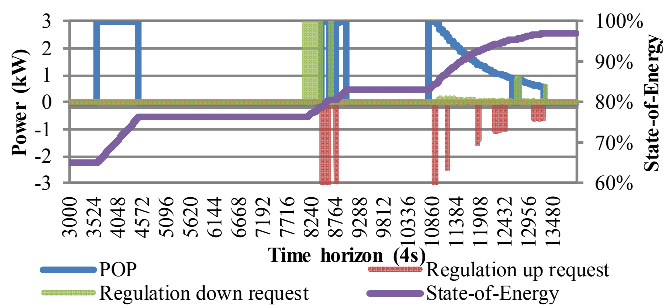

Figure 6: Charging power and SOE trajectories for one plug-in EV.

TABLE II
AGGREGATED EVA RESULTS OF THE OPERATING DAY

	Case A	Case B	Case C
DAM cost (€)*	62,3	49,8	62,3
RTM cost (€)*	107,4	123,5	68,0
Regulation capacity market revenue (€)**	89,7	79,8	66,7
Cost for uninstructed deviations >20%	16,1	15,1	12,0
Total charging cost (€)	**96,0**	**108,6**	**75,6*****
Reg. up request (kWh)	671,7	1491,4	490,6
Reg. down request (kWh)	630,4	1734,3	471,9
Fleet energy request (kWh)	5495,6	5495,6	4110,6
Fleet charged energy (kWh)	5472,0	5350,2	4086,6
EVs number with final SOE<92%	17	49	19

* Two-settlement system is adopted for financial settlements between DAM and RTM, **Adjusted with the performance score. ***The reader should bear in mind that in case C the EVA finally charges 750 and not 100 EVs.

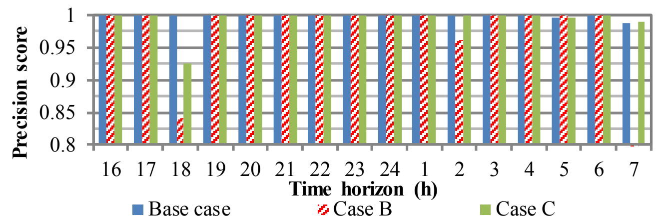

Figure 7: Precision score calculation.

IV. CONCLUSION

In this paper the main functionalities of an integrated, four-level optimization framework that models the optimal participation of Electric Vehicle Aggregators (EVAs) in day-ahead and real-time energy and regulation markets in conjunction with the optimal real-time charging management of the EV fleet are briefly presented. With the proposed optimization framework different market participation rules can be compared and detailed results regarding the reliability and viability of EVA participation in electricity markets can be deducted.

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