Optimal Charging of Electric Vehicle Aggregations Participating in Energy and Ancillary Service Markets

Shuang Gao, *Member, IEEE*, Hailong Li, Jakub Jurasz, and Ruxin Dai

***Abstract*—Providing ancillary services through flexible electric vehicle (EV) charging has the potential to offer extra market benefit for EVs. EV aggregator controlling a fleet of EVs can play a significant role in managing the considerable EV charging demand and bid in the electricity markets. The increasing penetration of EVs has created the feasibility of participating in both the day-ahead energy market and frequency regulation market. This article presents a multimarket optimization model for minimizing the net operation cost of EV charging considering the benefit from performing frequency regulation. A two-level optimization algorithm for EVs controlled by the aggregator is proposed to determine optimal operation strategies of EV aggregations and the charging power of each individual EV. The optimization is able to merge revenue from frequency regulation with the cost reduction objectives of traditional EV charging management. The effectiveness of optimization algorithm is demonstrated by simulating EVs charged at the workplace and residential areas. The operation of EV aggregator is studied considering the diverse charging need of individual EV and market prices acquired from Nord Pool real-time market and Swedish power system operator. The increased profitability of participation in the sequential electricity markets has been illustrated. Net operating cost of EV aggregations can be significantly reduced considering both capacity and energy remunerations in the regulation market and the charging demand in the energy market.**

***Index Terms*—Electric vehicle (EV) aggregator, electricity market, frequency regulation (FR), vehicle-to-grid (V2G).**

Nomenclature

Subscripts

k	EV number.
n	Aggregation number.
t	Time interval.
RU	Regulation up.
RD	Regulation down.
RC	Regulation capacity.
Chr	Scheduled charging.
max	Maximum value of variables.
min	Minimum value of variables.

Variables

F_{Chr}	Energy cost of EV charging.
F_{RC}	Capacity payment of frequency regulation.
F_{RP}	Energy payment of frequency regulation.
$p_{\mathrm{Chr}}(t)$	Charging power on the day-ahead market.
$P_{\mathrm{RC}}(t)$	Capacity of frequency regulation.
$p_{\mathrm{RU}}(t)$	Regulation-up power.
$p_{\mathrm{RD}}(t)$	Regulation-down power.
$p_{\mathrm{EVA}}(t)$	Charging power of all EV aggregations.
$p_{\mathrm{EVA}}^{n}(t)$	Charging power of EV aggregation n.
$p_{\mathrm{EV}}^{nk}(t)$	Charging power of EV k in the EV aggregation n.

Parameters

$r_{\mathrm{Chr}}(t)$	Day-ahead price.
$r_{\mathrm{RC}}(t)$	Capacity price of frequency regulation.
$r_{\mathrm{RU}}(t), r_{\mathrm{RD}}(t)$	Regulation up and down prices.
$\boldsymbol{T}_{\mathrm{in}}^{nk}$	Set of EV plug-in time intervals.
$\boldsymbol{T}_{\mathrm{out}}^{nk}$	Set of EV plug-out time intervals.
$P_{\max}^{nk}$	Rated EV charging rate.
$\mathrm{SOC}_{\mathrm{set}}^{nk}$	Target SOC by the departure of EV.
$\mathrm{SOC}_{\mathrm{Ini}}^{nk}$	Initial SOC of EV.
u	Charging efficiency.
B^{nk}	EV battery capacity.
σ, μ	Mean and deviation of the Gaussian distribution.

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I. Introduction

OPERATING a reliable and effective electric power system requires the procurement and trading of resources in several electricity markets on different time scales. The day-ahead (DA) energy market secures the availability of adequate resources to meet the expected customer demands one day ahead, whereas intraday (ID) trading adjusts the hourly power generation according to the unexpected changes from the DA scheduling during the operation day. In addition to scheduled amount of resources, the mismatch between the generation and load during the operating hour must be compensated by the frequency regulation (FR) reserves [1]. Electric vehicles (EVs) that are connected to and charged in the power grid have been studied to support the power system operation as mobile energy storage [2]. The charging load of EVs is exploited for demand response to smooth the load profile, i.e., peak shaving and valley filling.

Additional benefits from incorporating flexible EV charging demand into electricity markets may be obtained to encourage the participation of EVs in the vehicle-to-grid (V2G) operation [3]. When EV charging participates in multiple electricity markets, it is necessary to estimate the quantity of regulation service that is able to be provided by EVs. It is also necessary to develop operational strategies of EVs in an aggregation manner to deliver considerable power to the sequential DA energy and FR markets.

In order to aggregate the power from individual EVs to bid in the electricity market, the EV aggregator (EVA) is introduced as the intermediate control unit to interact with power system operator [4]. For this purpose, intelligent charging algorithms for providing demand response and spinning reserves have been developed for the aggregator [5]. EVs charged at the feeders of the distribution network are aggregated as the additional load and controlled to level the total load profile. The EV charging demand has been included into the optimal dispatch problem of the power system, which is solved by sequential quadratic programming [6]. In the optimal dispatch, EV charging is modeled as the adjustable bus load in the power network. The power balance constraints of the power network can be simplified and solved by mixed integer linear programming [7]. If EVs are used for FR as battery energy storage in the power system, the charging and battery status of EVs are monitored and controlled by EVA in response to the frequency deviation of the power system [8]. For instance, to maintain the real-time balance between the generation and load, automatic generation control (AGC) signals are issued by the power system operator. The procured frequency reserves, including the regulation capacity of EV charging power, are controlled to follow the AGC signal. A droop control based EVA is developed for a cluster of EVs to accurately track the FR signals [9]. In consideration of expanding renewable energies, a distributed control method of EVA is proposed to reduce the control complexity of numerous EVs. The EVA regulates the total charging power of EVs to compensate for the intermittent power generation of renewable energies [10]. An extension to EV charging control has also been made to consider the battery discharging in the V2G operation [11]. However, unlike the generic battery energy storage devices in the power system, EV owners have concerns on the lifetime of the battery engaged in the V2G service. In the bidirectional V2G operation, substantial numbers of charging and discharging reduce the battery lifetime, which is generally estimated by depth of discharging and cycle number [7]. Severe battery degradation from discharging may prevent EV owners to join the V2G program. However, modulating the charging process of battery does not affect the lifespan, and in most of previous studies on EV smart charging, it is considered negligible in the cost of battery degradation [12]. Moreover, the practical application of bidirectional V2G operation is unlikely to be available in the near future, since the existing charging facility does not have the bidirectional charging capability. Unidirectional V2G operation scheme can be readily implemented without updating the power electronic hardware and protection equipment. Thus, only unidirectional charging control of EVs is taken into account in this article.

With respect to the EV charging control in the electricity markets, previous works have demonstrated the increased profit from utilizing the regulation capability of EV charging power to follow the market signals [13]. EV charging models have been incorporated into the optimization routines of the power system in different electricity markets. EV charging demands can be shifted to minimize the cost of purchasing electricity in the DA market according to the time-of-use rates and peak demand charges [14]. In order to perform demand response in the electricity markets, the market prices replace the load variation to be the signals that direct the EV charging power to maintain the reliable and economic operation of the power system. The EV charging control has also been modeled as the adjustable load and included in the security constrained economic dispatch of the power system, aiming to reduce the total operation cost in the spot energy market [1]. Aside from the benefits achieved through load shifting and price response in the DA energy market, EV charging control may also be well-suited to provide ancillary services due to its fast and accurate power regulation capabilities and low standby cost [15]. The cost to install battery energy storage can be saved by employing the grid-connected EVs in the frequency reserves. FR provided by EVs with aggregator through modulating the charging rates has also been investigated in the recent work [16]. In order to get paid in the FR market, the FERC Order 755 "pay-for-performance" rule must be fulfilled, which has been implemented by the majority of the US power system operators, e.g., PJM and CAISO. The quick response time of EV battery ensures the accurate tracking of FR signals and, thus, making more profit in regulation market [17]. Nevertheless, there are only very few references dealing with the participation of EV charging in the sequential DA and FR markets based on the market mechanism and real-time prices. A mathematical model for optimizing energy dispatch of EV charging in the DA market combined with capacity bid and regulation power in regulation market has not been presented so far.

Compared to the literature on EV smart charging that maximizes the benefit from electricity markets, the contributions of this article include the following:

1) to investigate the economic potential for EVs from trading in multiple electricity markets by adopting real-world market mechanism in the modeling;
2) to develop a multistage optimal operation model for EV aggregations that considers the chronological sequence of DA energy dispatch, FR capacity bidding, and power regulation;
3) to simultaneously optimize the EVA charging plan for FR capacity bidding, DA energy dispatch, and power regulation in sequential DA and FR markets, since these decisions cannot be taken separately;
4) to propose a multimarket optimization for aggregated EVs taking into account the diverse charging need of each individual EV controlled by EVA;
5) to solve the proposed optimal charging problem of EVs by applying the two-level optimization algorithm in the EVA-based hierarchical control framework.

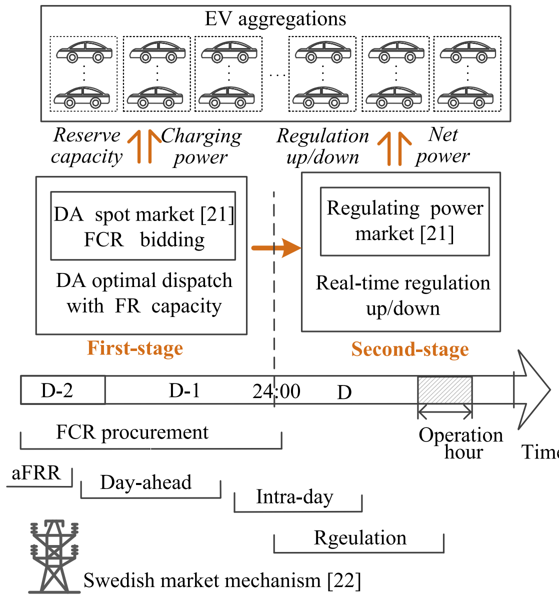

Fig. 1. Multimarket optimization of EVA and market mechanism.

II. Modeling of EV Aggregation in Electricity Markets

A. Market Opportunities and Revenues

The market mechanism applied to this study is based on the real-world electricity market in Europe. The electricity is first traded in the DA and intraday markets. In order to maintain the real-time balance of the power system, an ancillary service market, which is also called power balancing market, is needed. The following ancillary services are available: frequency containment reserve (FCR), automatic/manual frequency restoration reserve, and replacement reserve [18]. The market data are taken from Nord Pool, a joint market of the four Nordic countries [19], and the proposed concept is illustrated using the example of Swedish DA spot market and frequency reserve markets [20]. Considering the technical characteristic of EV battery charging, which is basically the most flexible power regulation source, a provision of FCR is guaranteed even though it is the fastest FR service [21]. In order to control the EV charging process according to benefit potential in the electricity markets, the sequential operation process of different markets need to be analyzed. A crucial factor is the timing of FR capacity setting and power regulation after the predefined DA dispatch plan. The market revenue of FCR in Sweden includes both capacity and energy payment, as depicted in Fig. 1. The capacity remuneration is for preserving the capacity for power balancing activated in real time by power system operator. In addition, an energy price is paid for the regulating power that is actually delivered during the day. The capacity is procured one and two days ahead of the hour of delivery [20], which means that FR capacity must be reserved before DA energy dispatch.

The cost to purchase electricity for EV charging and capacity remuneration of FCR is calculated by

$$F_{\mathrm{Chr}} = \sum_{t=1}^{T} r_{\mathrm{Chr}}(t) \times p_{\mathrm{Chr}}(t) \tag{1}$$

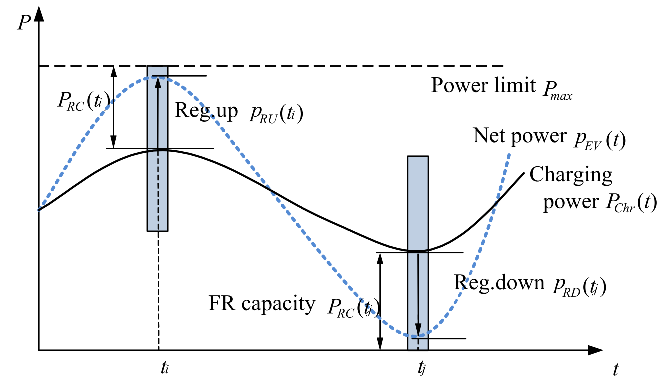

Fig. 2. Control diagram of EV charging power in electricity markets.

$$F_{\mathrm{RC}} = \sum_{t=1}^{T} r_{\mathrm{RC}}(t) \times P_{\mathrm{RC}}(t). \tag{2}$$

In an up-regulation situation, the power price is higher than the DA price. EVs reduce the charging power and sell the surplus charging power at a higher price. On the contrary, when the regulation-down price is lower than DA prices, EVs increase the charging power so as to benefit from charging at a lower price. Thus, the benefit obtained from regulation market is calculated by

$$F_{\mathrm{RP}} = \sum_{t=1}^{T} [r_{\mathrm{RU}}(t) \times p_{\mathrm{RU}}(t) - r_{\mathrm{RD}}(t) \times p_{\mathrm{RD}}(t)]. \tag{3}$$

B. FR Capabilities of EVA

To fully exploit revenue potentials, the charging control of EVs engaged in the DA and FR markets has to be optimized simultaneously. For this purpose, the charging power scheduled for DA market, reserved FR capacity, and actual regulation-up/down are optimized together in a multistage decision-making process, as illustrated in Fig. 2. The first-stage decision is the quantities bid in the FR market. The capacity reserved for FR determines the remaining volumes that can be dispatched in the DA market, which is modeled as second-stage decision. At this stage, an economic dispatch of EV charging power for the next day is implemented. Third-stage decisions are the regulation-up/down on the top of dispatch DA volumes according to the regulation up/down prices in the regulating power market.

A large amount of EVs must be aggregated to provide considerable regulating power at the power system level. The charging power of EV aggregation is given by

$$p_{\mathrm{EVA}}^{n}(t) = \sum_{k=1}^{K_n} p_{\mathrm{EV}}^{nk}(t) \tag{4}$$

$$p_{\mathrm{EVA}}(t) = \sum_{n=1}^{N} p_{\mathrm{EVA}}^{n}(t). \tag{5}$$

The actual charging power of EV is the sum of the trading power in both DA and FR markets

$$p_{\mathrm{EV}}^{nk}(t) = p_{\mathrm{Chr}}^{nk}(t) - p_{\mathrm{RU}}^{nk}(t) + p_{\mathrm{RD}}^{nk}(t). \tag{6}$$

The plug-in time of EV is simulated by a truncated Gaussian distribution for the uncertain driving and parking behaviors of EVs, which is written as

$$f_{\text{in}}(t_{\text{in}}^{nk}) = \frac{1}{\sigma_{\text{in}}^{n}\sqrt{2\pi}}\exp\left[-\frac{(t_{\text{in}}^{nk}-\mu_{\text{in}}^{n})^2}{2\sigma_{\text{in}}^{n\,2}}\right],$$
$$T_{\text{start}}^{n} < t_{\text{in}}^{nk} < T_{\text{end}}^{n}. \tag{7}$$

The initial SOC and plug-out time are generated similarly.

As shown in Fig. 2, the regulation-up/down capacities have the same volumes since the FR capacity product is symmetrical. The power regulation of EV charging is subject to

$$p_{\text{EV}}^{nk}(t) + P_{\text{RC}}^{nk}(t) \le P_{\max}^{nk} \tag{8}$$
$$p_{\text{EV}}^{nk}(t) - P_{\text{RC}}^{nk}(t) \ge 0. \tag{9}$$

III. Multimarket Optimization of EVA

A. Objective Function

The objective is to minimize expected operation cost of EVA, which is defined as EV charging costs in the DA energy market subtracted by revenues from frequency reserve market. EV charging costs are given as the electricity purchased from the DA energy market, whereas capacity and upward/downward regulation power are remunerated with the corresponding FR market prices. Thus, the objective function is

$$\min f = \sum_{n=1}^{N} F_{\text{Chr}}^{n} - F_{\text{RC}}^{n} - F_{\text{RP}}^{n}. \tag{10}$$

EVA charging variables are optimized in a multistage decision-making process for a combined planning of DA and FR market. A certain percentage of EV charging capacity should be reserved for FR biddings and the remaining capacity is exploit in DA energy dispatch. The operational constraints for the two markets are given in the following sections.

B. Operational Constraint in the DA Energy Market

As the charging of EVs is principally operated to fulfill the drive needs of EV owners, appropriate restrictions have to be implemented to ensure the charging demand of EVA. Since EVs have to be charged to the target SOC set by each customer, the total charging energy has to be fulfilled before the departure from the parking and charging facilities. The total demand of charging (DOC) for EVAs can be computed by

$$\text{DOC}_{\min}^{n} \le \sum_{t=1}^{T} p_{\text{Chr}}^{n}(t) \le \text{DOC}_{\max}^{n} \tag{11}$$

where $\text{DOC}_{\min}^{n}$ is the DOC of EV aggregation *n*, which is defined by the summation of charging demand of each individual EV in the aggregation. $\text{DOC}_{\max}^{n}$ is the maximum DOC limit corresponding to maximum target SOC by departure set by EV owner

$$\text{DOC}_{\min}^{n} = \sum_{k=1}^{K_n} \frac{(\text{SOC}_{\text{set.min}}^{nk} - \text{SOC}_{\text{Ini}}^{nk}) \times B^{nk}}{u\Delta t} \tag{12}$$

$$\text{DOC}_{\max}^{n} = \sum_{k=1}^{K_n} \frac{(\text{SOC}_{\text{set.max}}^{nk} - \text{SOC}_{\text{Ini}}^{nk}) \times B^{nk}}{u\Delta t}. \tag{13}$$

The plug-in time period of EV is also taken into account to define the power regulating range of EVA

$$p_{\text{Chr}}^{n}(t) + P_{\text{RC}}^{n}(t) \le \sum_{k=1}^{K_n} p_{\text{lim}}^{nk}(t) \tag{14}$$

$$p_{\text{lim}}^{nk}(t) = \begin{cases} 0 & t \in \boldsymbol{T}_{\text{in}}^{nk} \\ P_{\max}^{nk} & t \in \boldsymbol{T}_{\text{out}}^{nk} \end{cases} \tag{15}$$

$$p_{\text{Chr}}^{n}(t) - P_{\text{RC}}^{n}(t) \ge 0. \tag{16}$$

Constraints (14)–(16) model the assumption that the FR capacity is first reserved and the remaining EV charging capacity is exploited in the DA market.

C. Operational Constraints in the Regulation Market

Regulation up/down powers are within the regulatory range of capacity reserved for FR. For each period *t*, decision variables are the regulation-up/down power that depends on the current scheduled EV charging in the DA market and the reserved FR capacity

$$p_{\text{RU}}^{n}(t) \le P_{\text{RC}}^{n}(t) \tag{17}$$
$$p_{\text{RD}}^{n}(t) \le P_{\text{RC}}^{n}(t) \tag{18}$$
$$0 \le -p_{\text{RU}}^{n}(t) + M \times P_{\text{bin1}}^{n}(t) \le M - 1 \tag{19}$$
$$0 \le -p_{\text{RD}}^{n}(t) + M \times P_{\text{bin2}}^{n}(t) \le M - 1 \tag{20}$$
$$P_{\text{bin1}}^{n}(t) + P_{\text{bin2}}^{n}(t) \le 1. \tag{21}$$

Constraints (18)–(20) model that either regulation up or down is delivered for each *t* period using auxiliary variable M, and two binary variables $P_{\text{bin1}}^{n}(t)$ and P_{bin2}^{n}.

Due to participating in FR market, EVA charging is forced to deviate from its formerly scheduled DA plan. EVA charging should compensate the changes in the required charging energy for EV batteries during the planning time horizon. The net charging power also satisfies the charging demand constraint

$$\text{DOC}_{\min}^{n} \le \sum_{t=1}^{T} p_{\text{net}}^{n}(t) \le \text{DOC}_{\max}^{n} \tag{22}$$

$$p_{\text{net}}^{n}(t) = p_{\text{Chr}}^{n}(t) - p_{\text{RU}}^{n}(t) + p_{\text{RD}}^{n}(t). \tag{23}$$

IV. Two-Level Optimization Algorithm

A. Solving EVA Multimarket Optimization

The multimarket optimization of EVA is solved by a two-level optimization algorithm, as described in [22]. The upper level optimizes the charging power of EVAs, whereas the lower level optimization manages the charging plan of each individual EV. A distributed solving method for EVA power control, as described in [23], is applied to lower level model. The upper level and lower level optimizations run iteratively several times to determine the final optimum.

The upper level optimization rewrites (9) to

$$\mathrm{Min}F = \mathrm{Min}(F_{\mathrm{Chr}} - F_{\mathrm{RC}} - F_{\mathrm{RP}}) + \alpha \sum_{n=1}^{N} G_n[p_{\mathrm{net}}(t), p_{\mathrm{EVA}}(t)] \tag{24}$$

where $\alpha \sum_{n=1}^{N} G_n[p_{\mathrm{net}}(t), p_{\mathrm{EVA}}(t)]$ is the penalty term for the difference between scheduled power of EV aggregation in the upper level and the actual EVA charging power given in the lower level optimization, α is the penalty coefficient. The objective function is subject to constraints (10)–(22).

In the lower level model, EVA minimizes the power deviation from the scheduled charging power of upper level optimization. The objective function of the EVA optimal control is written by

$$\mathrm{Min}G_n(p_{\mathrm{net}}(t), p_{\mathrm{EVA}}(t)) = \mathrm{Min} \sum_{t=1}^{T} \left[\sum_{k=1}^{K_n} p_{\mathrm{EV}}^{nk}(t) - p_{\mathrm{net}}^{n}(t) \right] \tag{25}$$

where G_n is the power difference between the sum of actual EV charging power and the scheduled amount of EVA.

For each individual EV, target SOC by departure from the charging facility set by each EV owner needs to be fulfilled

$$\mathrm{SOC}_{\mathrm{min}}^{nk}(T) \leq \mathrm{SOC}^{nk}(0) + \sum_{t=1}^{T} \frac{p_{\mathrm{EV}}^{nk}(t)\Delta t}{B^{nk}u} \leq \mathrm{SOC}_{\mathrm{max}}^{nk}(T) \tag{26}$$

$$\mathrm{SOC}^{nk}(t) = \mathrm{SOC}^{nk}(0) + \frac{p_{\mathrm{Chr}}^{nk}(t)\Delta t}{B^{nk}u}. \tag{27}$$

Again, all associated variables should be bounded by their maximum and minimum values, according to technical constraints. The charging power of EV is limited by the rated charging power of EV and the charging facility

$$0 \leq p_{\mathrm{Chr}}^{nk}(t) \leq P_{\mathrm{max}}^{nk} y^{nk}(t) \tag{28}$$

where $y(t)$ is the binary variable corresponding to the plug-in status of EV with $y(t) = 1$ when EV is connected to charging facility and available for charging control, 0 otherwise. EVA must maintain the SOC within the minimum and maximum capacities at all times

$$\mathrm{SOC}_{\mathrm{min}}^{nk} \leq \mathrm{SOC}^{nk}(t) \leq \mathrm{SOC}_{\mathrm{max}}^{nk}. \tag{29}$$

The lower level optimization of EVA is to eliminate the deviation from upper level schedule amount of charging power. The iterative process between upper and lower optimizations ends as $||p_{\mathrm{net}}(t) - \sum_{n=1}^{N} p_{\mathrm{EVA}}^{n}(t)|| \ \leq \varepsilon$.

B. Workflow of the Two-Level Optimization Algorithm

In the operation process, the market data for DA and FR are collected first and EVA acts for a group of EVs to engage in multiple markets. The upper level optimization is performed to determine the optimal dispatch of EVA in the power system, and then EVA allocates the power to each individual EV controlled by the aggregator. The final optimum is corrected as the iterative process ends, so that the actual EVA charging power can be computed to estimate the market benefits and minimum net cost.

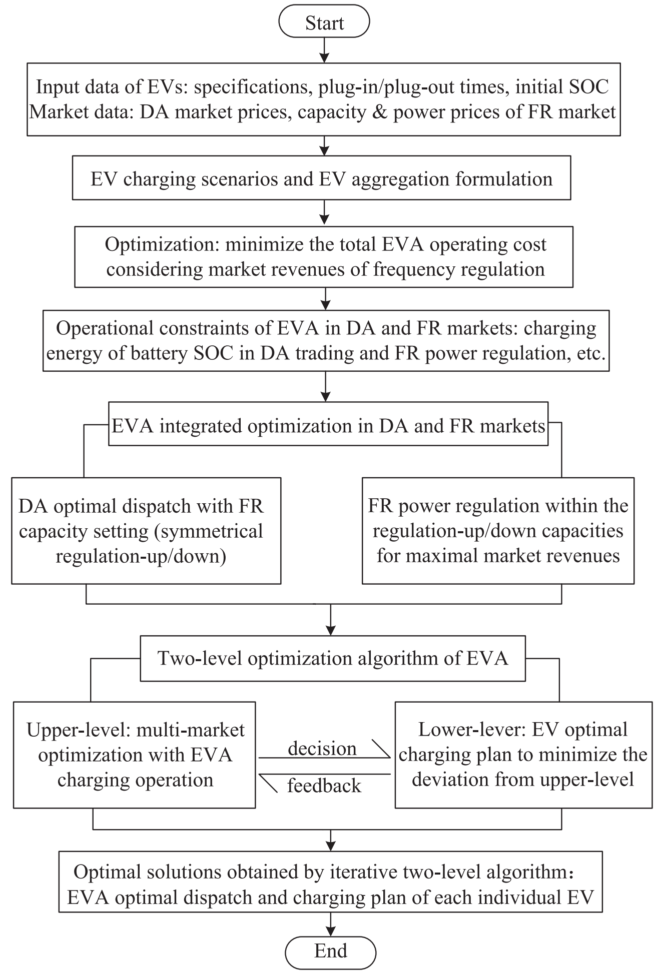

Fig. 3. Flowchart of EVA bilevel solving algorithm for the proposed multi-market optimization.

The workflow of the proposed EVA multimarket optimization model and solving method is shown in Fig. 3. At the beginning of the two-level optimization program, the penalty term of power deviation between upper and lower levels is not added to the upper level optimization algorithm, as the actual EV charging plans have not been given by the lower level EVA optimal control.

V. Case Study

A. Cost Analysis With the Revenues From FR

The case study is the operation control of EVAs for a large number of EVs mainly for commuter purposes. EVs are assumed to charge at household charger in the residential area and the charging facilities at the parking lots located in the commercial and office buildings. For each type of charging facilities, an EVA is assigned to control the EV charging parked at residential area and the workplace, i.e., EVA_R and EVA_W, respectively. The parameters of EV models and EVA are given in Table I. The electricity price profile of DA market [19] and the prices for capacity and regulation power of FR market in Sweden [21] on November 6, 2019 are given in Fig. 4. Three scenarios are

TABLE I
PARAMETER OF EVS

EV aggregation	EVA_W		EVA_R	
EV type	TOYOTA C-HR EV	PORSCHE Taycan	CHERY eQ1	ROEWE MARVEL X
Charging power [kW]	8.35	9.9	6.6	6.2
Battery capacity [kWh]	54.3	79.2	30.6	52.5
Quantity	250	250	250	250

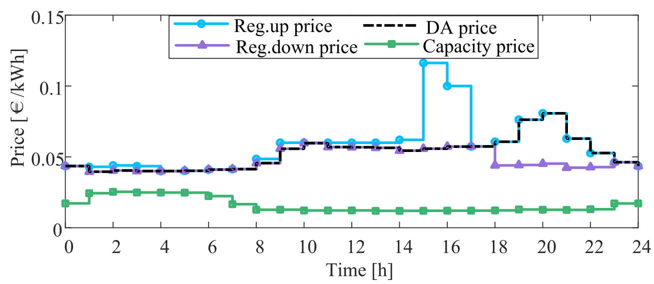

Fig. 4. Electricity market prices [19], [21].

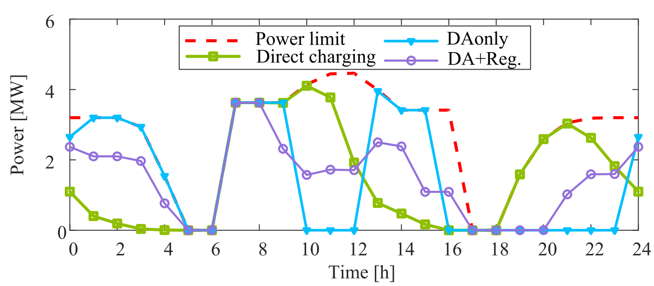

Fig. 5. EV charging power in different control scenarios.

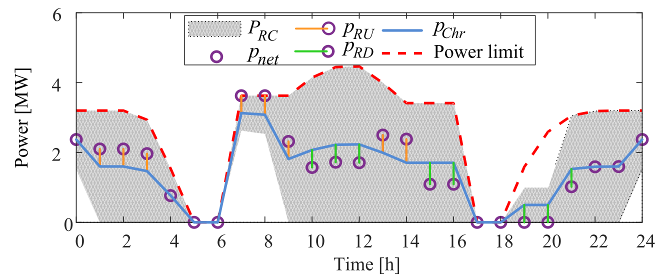

Fig. 6. EV charging power of DA+Reg in different electricity markets.

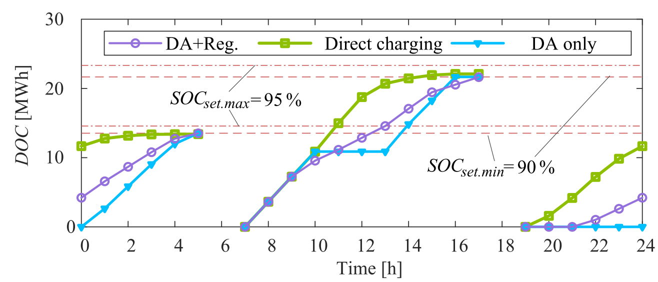

Fig. 7. DOC curves of EVA in different control scenario.

compared regarding expected net EVA operation cost, the actual charging power considering performing FR, and the corresponding cost and revenues from market trading.

Scenario 0: Conventional paradigm of direct charging (DC). The operation of EVA to satisfy the diverse charging needs of EV owners is simulated without any trading opportunities in the electricity markets considered. The EVs are charged as soon as it is plugged into the charging facilities at the rated power till reaching the target battery SOC. The DC charging scenario serve as a reference case to compare with the two controlled charging scenarios.

Scenario 1: New paradigm of DA market optimization (DA only). A sole participation in the DA energy market is analyzed to minimize the charging cost in response to the price signals.

Scenario 2: New paradigm of proposed multimarket optimization (DA+Reg.). EV charging power is controlled to engage in both the DA energy market and FR market.

In the absence of market incentives, EVA charging power is solely conducted according to the EV owners' diverse charging needs. Compare with the DC charging curve, DA only leads to a market-price-oriented operation of EVA. As displayed in Fig. 5, the charging of EV is preferred to be conducted in times of low DA energy prices. Consequently, if DA prices are high, charging power is decreased and the EVs' charging demand is fulfilled by purchases from the low-price periods. This can be observed, e.g., in 10–13 h, where the charging of EVs is avoided. The sudden increasing charging power of EVs in the adjacent time periods indicates that the charging power is shifted to the low-price times to satisfy the required charging demand for EV drive needs. Compared to the reference case, the net operation cost of EVA decreases by 23% when operating on the DA energy market.

Offering FR in the FR market improves the profitability of EVA operation for the optimal EV charging control. Fig. 6 shows the amount of regulated charging power contributed in the DA market, FR capacity, and regulation markets. The market prices determine whether the regulation up and down is offered. It can be seen that either regulation up or down is performed within the same time interval and the regulation power is adjusted within the EV charging capacity reserved for FR. The dispatched amount of EV charging in the DA market determines the capacity that can be offered to the FR market. Instead of charging EVs at low prices in the DA energy market, EVA decreases the EV charging power to secure higher regulating capacity in the FR market. These findings indicate that in this case study, devoting EV charging regulation to FR market is more profitable than economic dispatch of EV charging power in the DA energy market. Avoiding the high variation of EV charging in the DA energy market, thus raising the level of FR capacity bidding, simultaneously increases the maximum possible regulation up/down in the regulation market. This double remuneration of FR capacity and energy results in further net cost reduction with revenues from FR market. As a whole, the net operation cost of EVAs in the DA+Reg scenario decreases by 40% compared to the reference case and by 22% compared to optimizing EV charging only in the DA energy market. Additionally, the DOC, as described in optimization model for EVAs in the DA+Reg scenario during the day, is depicted in Fig. 7. As the target battery SOC of EV charging is set to 90%–95%, the final DOC must be

TABLE II
EVA CHARGING COST IN DIFFERENT CONTROL SCENARIOS

EV aggregation	Direct Charging	DA only	DA+Reg.
EVA_W [€]	1166	1123	885
EVA_R [€]	817	547	374
Total [€]	1983	1607	1259

TABLE III
BREAKDOWN OF EVA NET COST IN DA+REG

EV aggregation	Charging cost [€]	Capacity profit [€]	Energy profit [€]
EVA_W	1150	194	72
EVA_R	648	216	57
Total	1798	410	129

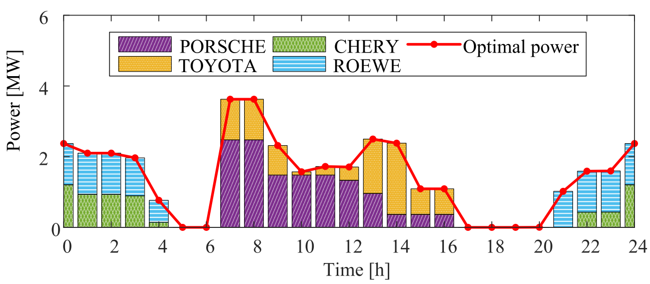

Fig. 8. Charging power for the four EV types and the optimal daily charging.

maintained within this range even though different EVAs have a wide variety of charging demands.

EV charging engages in DA and FR markets requires adapting the EVA operation according to revenue potentials in different markets. Comparing the case of a sole participation in the DA energy market in Table II with the DA+Reg given in Table III, charging cost changes in the DA market show that DA only scenario is more effective in cost minimization in DA energy market. Table III shows the economical revenue from participation in FR market as well as the operation cost in the DA energy market. As seen, reserving a percentage of EV charging capacity for playing in FR market (DA+Reg.) will not increase the cost in the DA market significantly. However, considerable market revenue from FR is obtained, which not only make up for the extra operation cost in the DA market but will decrease the net cost to the maximum extent. The results in this section illustrate the potential of participating in both DA energy market and FR for EVA control of massive connected EVs.

B. Operation of EVA Power Control

The EVA is operated to achieve the scheduled charging power in the multimarket optimization, as described in the two-level algorithm. The optimal charging power in the DA+Reg scenario, as shown in Fig. 5, is met by the charging powers contributed by the four 250 EVs fleet of a certain EV type specified in Table I. Fig. 8 clearly depicts the total charging power of the four types of EVs' tracks the EVA scheduled charging quantity at all times.

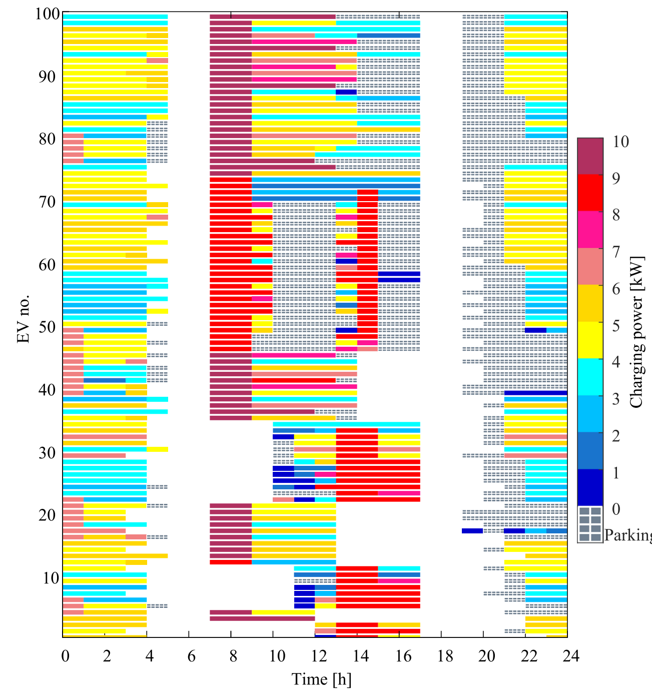

Fig. 9. Charging power and plug-in duration of sample EVs.

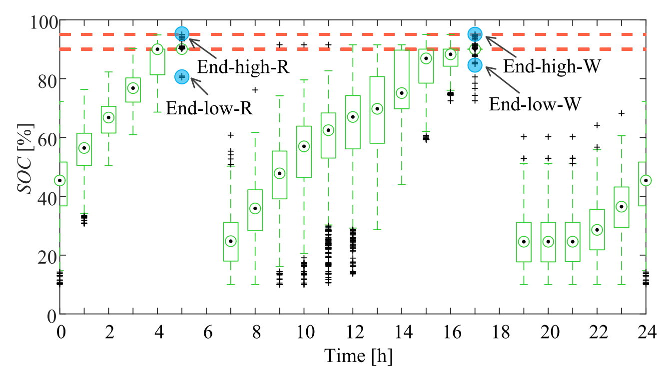

Fig. 10. Statistics of SOC changes for all controlled EVs during the day.

The temporal distribution of EV plug-in time at the charging facilities is simulated in the probabilistic mode described in Section II. The charging power of EVs within the plug-in time in the multimarket optimization is shown in Fig. 9. Due to the large number of EVs, only 10% of EVs are presented to show the charging behaviors of all 1000 EVs involved in the optimization. The EVs are first ranked by the length of plug-in time, and then each one out of ten EVs is selected in sequence. The charging and idle durations of 100 EVs are recorded by colorful bars. The simulation results show that all EVs are regulating the charging power only if EV is plugged into the charging facility; however, the charging pattern of different EV varies a lot. For most of EVs, idle and low-power times take up a large portion of total plug-in duration, which indicates the capability to adjust the charging power. Thus, the EV charging flexibility can be exploited for optimal control strategy in the electricity markets.

The statistics of the corresponding SOC caused by EV charging during the day is given in Fig. 10. Most of EVs can be

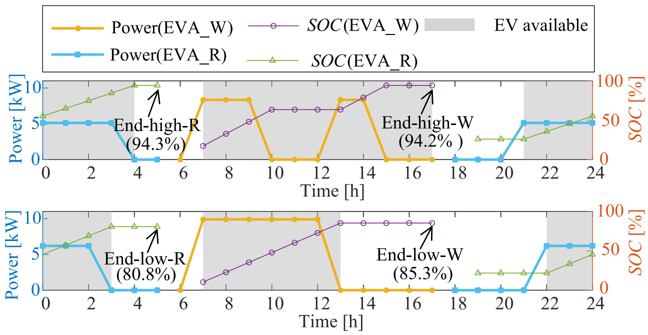

Fig. 11. Charging power and SOC curves of selected EVs.

charged to the target SOC and the final SOC varies within the range from 90% to 95%. Since the objective of EV charging control is to minimize the cost, it is reasonable to stop charging at the minimum acceptable SOC level. The EVs with the high final SOC is selected, as shown in Fig. 10, to analyze it charging behaviors in detail. As shown in Fig. 11, the surplus charging power occurs in times of extremely low regulation-down prices in the FR market and high scheduled charging power of EVA. The charging of EV is increased to reach the maximum target SOC to make more profit from DA and FR markets. Moreover, EVs that fail to reach the minimum target SOC are also picked from Fig. 10, and the charging behavior of these EVs is shown in Fig. 11. It is because the plug-in duration is too short to fully charge the EV probably due to the abrupt departure even though the charging power is maintained at the maximum rate. EV charging curve changes considerably according to revenue potentials in multiple electricity markets.

A few other scenarios of EVA daily operation with different EV behaviors and market prices were simulated in this study. However, the results are mostly similar to the ones shown here and, therefore, omitted for considerations of space.

VI. Conclusion

In this article, we studied the participation of aggregated EVs in the DA energy and FR markets in the context of Swedish power system and Nord Pool real-time market. A multistage optimal control of EV charging has been developed to optimize the market opportunities considering both cost and revenues in two sequential electricity markets. Optimizing the operation of EV aggregations for the charging control of a large number of EVs while fulfilling the customer's diverse charging and drive needs constitutes a complex task. The methodology presented in this article seems promising to handle this complexity by adopting two-level optimization algorithm for EVA-based EV charging control. Results of the case study illustrate how EVA multimarket optimization can lead to a significant decrease of net operation cost by performing FR. Furthermore, the results of bilevel EVA control algorithm exemplify how aggregator manages the charging of each individual EV to participate in electricity markets to achieve the overall optimum of EVA and EV charging strategies.

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