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The Influence of State-of-Charge Estimation Errors on Electric Vehicle Aggregator Benefits in Frequency Containment Reserves

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***Abstract*—In recent years, variable renewable energy sources (RES) have been integrated into electricity generation to reduce reliance on fossil fuels. RES integration into conventional power systems diminishes rotational inertia, causing frequency fluctuation vulnerability. Following the rapid increase in electric vehicle (EV) sales, an EV fleet can contribute to an automatic frequency reserve service in balancing markets through an EV aggregator. However, the benefits of an EV aggregator directly depend on the energy availability of each EV in an aggregator, represented by the state-of-charge (SoC). In the wider literature, SoC estimation is conventionally calculated using the ampere-hour (Coulomb counting) method. However, this approach is vulnerable to estimation errors, such as initial SoC and power measurement errors, that can positively or negatively affect aggregator benefits. Although previous studies have examined several ways to maximize aggregator benefits, none has explored the effect of SoC estimation errors on aggregator benefits. Therefore, this study aims to preliminarily explore the influence of SoC estimation errors on aggregator benefits in the frequency containment reserve (FCR) market. The regulatory framework and the FCR market are modeled in the European context. The simulation results demonstrate that SoC estimation errors affected the FCR provision period and forced charging activation, resulting in positive and negative changes in EV aggregator revenues.**

***Index Terms*—balancing market, electric vehicles, frequency containment reserve, state-of-charge.**

I. Introduction

A power system's frequency is a critical variable for system stability, as it is directly linked to balancing generation and consumption. Variable renewable energy source (RES) integration has continuously increased in recent years, expediting a transition toward sustainability in electricity production and reducing reliance on traditional fossil fuel-based energy sources [1]. Moreover, power system inertia diminishes significantly with the rapid growth of RES installations, resulting in frequency instability [2]. In particular, photovoltaic (PV) penetration has increased considerably due to strong market growth and a substantial price reduction. Hence, PV generation fluctuations are tremendous challenges encountered by transmission system operators (TSOs) and distribution system operators (DSOs) [3]. Global electric vehicle (EV) purchases have increased due to high petrol prices and fossil fuel depletion, reaching 6.6 million vehicles in 2021 and expected to reach over 15 million by 2030, according to the International Energy Agency [4]. Therefore, an EV fleet can provide ancillary services in balancing markets [5]. In European electricity markets [6], the balancing market includes four reserve types: frequency containment reserve (FCR), automatic frequency restoration reserve (aFRR), manual frequency restoration reserve (mFRR), and replacement reserve (RR). However, this study focuses on an EV aggregator providing an FCR or primary frequency regulation.

Previous studies have focused on developing EV aggregator models as an FCR service provider to maximize aggregator benefits. Luo et al. [7] explored an EV aggregator's potential financial return in frequency regulation markets. Shafie-khah et al. [8] developed a new model to optimize EV aggregator performance in FCR markets, considering short- and long-term horizons. Thingvad et al. [9] assessed the potential economic revenue of an EV aggregator with unidirectional and bidirectional charging technologies providing frequency control in Denmark. Borne et al. [10] investigated different technical requirements in an FCR provided by an EV aggregator in different balancing markets. Arias et al. [11] analyzed the practical issues associated with Frederiksberg Forsyning's first commercial EV aggregator in the Danish frequency regulation market. The study suggests that delays, measurement errors, and physical equipment constraints should be considered to implement realistic frequency regulation. Herre et al. [12] developed a two-stage stochastic optimization to maximize risk-averse EV aggregator profits in energy and FCR markets. Pavic et al. [13] developed an EV aggregator model for the day-ahead market and FCR bidding to assess the potential challenges arising during such service provision. Guzman et al. [14] proposed a smart EV aggregation strategy allowing aggregator participation in the reserve market to maximize aggregator profits while guaranteeing the energy required for EV transportation. Diaz Londono et al. [15] introduced a conceptual framework coordinating flexible loads and EV aggregators as balancing service providers. Tepe et al. [16] investigated the FCR market's flexibility to make the market more economically attractive for EV aggregators. Cai and Matsuhashi [17] proposed a model predictive control scheme for EV aggregators that forecasts the regulation capacity price in the FCR market to increase aggregator revenues. Schlund et al. [18] considered the stochastic behavior of EV drivers based on real data in an EV aggregator in FCR markets under different charging control modes: unidirectional and bidirectional. Pavic et al. [19] presented stochastic and robust models of an EV aggregator providing FCR and aFRR services, considering EV and market uncertainties.

Based on the current literature, previous studies have devoted their efforts to developing EV aggregator models based on unidirectional and bidirectional charging modes to provide an FCR in the balancing markets. Additionally, uncertainties associated with market prices, technical infrastructure limitations, and EV owners' preferences were considered. However, the benefits of EV aggregators in providing an FCR depend on EV availability, represented by the state-of-charge (SoC). Typically, SoC estimation is based on an ampere-hour (Coulomb counting) method, which is vulnerable to three inevitable errors: initial SoC level, power measurement from noise, and energy capacity [20]. Although previous studies have examined several ways to maximize aggregator benefits, none has explored the effects of SoC errors. Therefore, this study preliminarily explores the influence of SoC errors on aggregator revenue in the FCR market. The regulatory framework and FCR market are modeled in the European context. Although an ampere-hour method has main three inevitable errors, this study does not consider electrochemical reactions inside batteries that affect the reduction in energy capacity. Therefore, the first two error sources (initial SoC level, power measurement from noise) are merely focused.

The remainder of this paper is organized as follows. Section II describes the FCR market structure. The SoC estimation errors are detailed in Section III. The simulation results are provided in Section IV. Finally, the key conclusions are summarized in Section V.

II. FCR MARKET STRUCTURE

A. FCR requirements

This study focuses on European balancing markets because several FCR implementations exist, especially in Nordic countries and central Europe. In particular, this study only considers an EV aggregator providing an FCR (referred to as European markets) or primary frequency regulation (referred to as the North American markets). The FCR is automatically activated within a few seconds to mitigate the imbalance between generation and consumption (load), allowing the system frequency to be regulated around its nominal value of 50 or 60 Hz. The EV aggregators participating in FCR markets must provide up- and downregulation with sufficient energy and power capacity. The FCR control algorithm is conventionally designed using a droop-based controller. A pre-defined dead-band is also assigned and set to ± 0.02 Hz from the nominal frequency, and the allowable frequency limits are set to ± 0.1 Hz from the nominal frequency. When the system frequency deviates within the pre-defined dead-band, the FCR is not activated. When the system frequency decreases below the dead-band, the TSO sends an FCR request as upregulation to the EV aggregator to inject power into the grid. In contrast, downregulation is activated by the TSO when the system frequency increases above the dead-band. Consequently, the aggregator absorbs power from the grid. If the frequency leaves the deadband, the aggregator injects or absorbs power at its maximum capacity. Since the aggregator's availability depends on the EV SoC, the EVs cannot participate in an FCR when their SoC reaches the allowable limit, indicating that the EV is over-discharged or under-charged [21]. However, the driving purpose is a critical concern for EVs participating in an FCR. In addition, the aggregator decides whether the EVs participate in the FCR or are charged at their rated power to achieve the expected SoC (forced charging). This decision is based on the minimum plug-in duration available. If the minimum available plug-in duration is reached, forced charging is activated. Further details of the EV aggregator providing the FCR can be referred to in the study proposed by Jamroen et al [22].

B. FCR remuneration

In this study, the FCR remuneration model is designed according to European balancing markets and has five components: i) revenue from power capacity to provide an FCR, ii) penalty cost due to aggregator unavailability, iii) revenue from energy delivered to provide upregulation, iv) cost of energy bought to provide downregulation, and v) aggregator forced charging cost. Since increased RES integration results in decreased adjustable production, a transition to a 15-minute market time resolution and imbalance settlement period (ISP) is not only a solution for increased RES integration but also supports low reserve capacity demand, reserve power optimization, reduced deterministic imbalance, wider access to balancing, and day-ahead and intraday markets [23]. According to the European network of transmission system operators for electricity (ENTSO-E) [24], nine European countries implemented a 15-minute ISP in 2022, including Germany, Netherlands, Belgium, and Austria. The Nordic balancing markets will switch to a 15-minute ISP in May 2023. Spain and Portugal will move to a 15-minute ISP in October 2023, while the Baltics have a derogation granted until 2024. Therefore, this study applied a 15-minute ISP to the FCR remuneration model. It should be noted that the FCR remuneration is calculated every 15 minutes but the simulation is conducted based on a minutely basis. Consequently, the FCR remuneration model is expressed as follows:

$$\mathrm{REV} = \sum_{\tau=1}^{T} \left(R_p(\tau) - C_p(\tau) + R_e^{\mathrm{up}}(\tau) - C_e^{\mathrm{down}}(\tau) - C_e^{\mathrm{ch}}(\tau) \right) \tag{1}$$

where REV is the total revenue for the aggregator providing an FCR over simulation time T (€), $R_p(\tau)$ is the power capacity revenue for FCR at time step τ (€), $C_p(\tau)$ is the power capacity penalty cost at time step τ (€), $R_e^{\mathrm{up}}(\tau)$ is the delivered energy revenue for upregulation at time step τ (€), $C_e^{\mathrm{down}}(\tau)$ is the charging energy cost for downregulation at time step τ (€); and $C_e^{\mathrm{ch}}(\tau)$ is the aggregator's forced charging cost at time step τ (€).

The FCR's power capacity is remunerated when the aggregator provides the FCR power requested by the TSO in both up- and downregulation. Hence, the power capacity's absolute value is applied. The power capacity revenue for time step τ is expressed as follows:

$$R_p(\tau) = \frac{\pi_{\mathrm{FCR}}}{4} \cdot \frac{\sum_{m=1}^{15} |P_{\mathrm{FCR}}(m)|}{15} \tag{2}$$

where π_{FCR} is the power capacity price (€/MW/h), and $P_{\mathrm{FCR}}(m)$ is the power capacity provided by the aggregator at minute m (MW).

A penalty is applied if the aggregator partially or completely fails to provide the power capacity requested by the TSO, expressed as follows [25], [26]:

$$C_p(\tau) = \frac{\pi_{\mathrm{pen}}}{4} \cdot \left(|P_{\mathrm{bid}}(\tau)| - \frac{\sum_{m=1}^{15} |P_{\mathrm{FCR}}(m)|}{15} \right) \tag{3}$$

where π_{pen} is the penalty price (€/MW/h), and $P_{\mathrm{bid}}(\tau)$ is the power capacity required by the TSO at time step τ (MW).

The delivered energy is only remunerated when the aggregator provides upregulation (discharge power to the grid) and is expressed as follows:

$$R_e^{\mathrm{up}}(\tau) = \frac{\pi_{\mathrm{up}}}{4} \cdot \sum_{m=1}^{15} P_{\mathrm{uFCR}}(m) \tag{4}$$

where π_{up} is the energy price for upregulation (€/MWh), and $P_{\mathrm{uFCR}}(m)$ is the power delivered for upregulation at minute m (MW).

Although the aggregator consumes power from the grid to provide downregulation, the aggregator is still charged by the TSO based on the downregulation price. The cost of energy bought from the balancing market to provide downregulation for time step τ is calculated as follows:

$$C_e^{\mathrm{down}}(\tau) = \frac{\pi_{\mathrm{down}}}{4} \cdot \sum_{m=1}^{15} P_{\mathrm{dFCR}}(m) \tag{5}$$

where π_{down} is the energy price for downregulation (€/MWh), and $P_{\mathrm{dFCR}}(m)$ is the power consumed for downregulation at minute m (MW).

When the EVs have reached the minimum available plug-in duration, the aggregator allows them to charge to meet their desired SoC (forced charging). Hence, the aggregator buys energy from the grid. The aggregator's charging cost for time step τ is expressed as follows:

$$C_e^{\mathrm{ch}}(\tau) = \frac{\pi_{\mathrm{ch}}}{4} \cdot \sum_{m=1}^{15} P_{\mathrm{ch}}(m) \tag{6}$$

where π_{ch} is the price of energy bought from the grid (€/MWh), and $P_{\mathrm{ch}}(m)$ is the charging power at minute m (MW).

III. SoC ESTIMATION ERRORS

Lithium-ion rechargeable batteries currently dominate the market for portable electronics and have a widespread application in the booming automotive and stationary energy storage market due to their increased power and energy densities, safety, and lifetime [27]. Consequently, lithium-ion batteries are the most common type of battery used in EVs. With vehicle-to-grid (V2G) technology, EV charging control is a promising solution to providing an FCR as a new flexibility source. As discussed in Section II, aggregator availability for FCR provision depends on EV availability, represented by the SoC. The SoC represents the remaining energy stored in a battery. Since batteries are complex electrochemical devices with distinct nonlinear behavior, accurate SoC estimation is a challenging task depending on various internal and external conditions. According to current literature, the SoC is determined indirectly by measuring battery parameters such as voltage and current [28]. However, the ampere-hour (Coulomb counting) method can estimate the SoC due to its low computational complexity. Coulomb counting SoC estimation can be expressed in terms of current or power integration as follows:

$$\mathrm{SoC}(m) = \mathrm{SoC}_0 - \left(\frac{\eta_c \sum_{m=1}^{15} I_{\mathrm{EV}}(m)}{Q_{\mathrm{EV}}^{\mathrm{rated}}} \times 100\% \right) \tag{7}$$

$$\mathrm{SoC}(m) = \mathrm{SoC}_0 - \left(\frac{\eta_c \sum_{m=1}^{15} P_{\mathrm{EV}}(m)}{E_{\mathrm{EV}}^{\mathrm{rated}}} \times 100\% \right) \tag{8}$$

where $\mathrm{SoC}(m)$ is the current EV SoC level (%); SoC_0 is the initial EV SoC level (%); $Q_{\mathrm{EV}}^{\mathrm{rated}}$ and $P_{\mathrm{EV}}^{\mathrm{rated}}$ are the actual EV capacity represented in ampere integration (Ah) and power integration (kWh), respectively; $I_{\mathrm{EV}}(m)$ is the EV's discharging or charging current (A), which is positive while discharging but negative while charging; $P_{\mathrm{EV}}(m)$ is the EV's discharging or charging power (kW), which is positive while discharging but negative while charging; and η_c is the Coulombic efficiency (%).

In this study, Eq. (8) represents the SoC estimation errors. Eq. (8) contains three possible error sources that cause SoC estimation errors: initial SoC, power measurement, and EV capacity. This study does not consider electrochemical reactions inside batteries that affect the reduction in energy capacity, and EV energy capacity takes a certain time to decrease [29]. These error sources are summarized as follows:

- Initial SoC estimation error: this study considers a deterministic error that shifts the true initial SoC value by a constant value [30]. This error can be corrected when the battery has rested for a long period [31]. However, this may not be practical for EVs in a charging station. The measured initial SoC is expressed as follows:

$$\mathrm{SoC}_0^{\mathrm{meas}} = \mathrm{SoC}_0^{\mathrm{act}} + \beta \tag{9}$$

  where $\mathrm{SoC}_0^{\mathrm{meas}}$ and $\mathrm{SoC}_0^{\mathrm{act}}$ are the measured and actual SoC values (%), respectively, and β is the deterministic constant error.
- Power measurement error: current and voltage measurements are required to measure power. These measurements also create noise to calculate power. This study considers a random error that also shifts the true measurement value. The power value was added with random noise [32]. The measured EV power is expressed as follows:

$$P_{\mathrm{EV}}^{\mathrm{meas}} = P_{\mathrm{EV}}^{\mathrm{act}} + \gamma \tag{10}$$

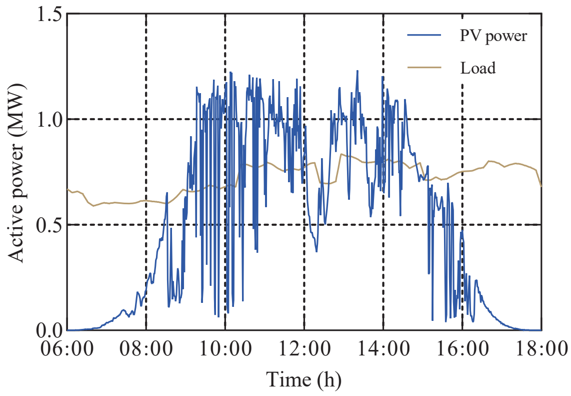

Fig. 1. PV and load profiles used in the simulation.

where $P_{\text{EV}}^{\text{meas}}$ and $P_{\text{EV}}^{\text{act}}$ are the measured and actual EV power (kW), respectively, and γ is the random noise.

IV. Results and Discussion

A. Simulation setup

A simplified single-area power system was operated using DIgSILENT PowerFactory software. The system was connected to the external grid via a step-down transformer and a feeder. The transformer was rated at 69/22 kV. The feeder length was 50 km with a resistance component of 0.328 Ω/km and a reactance component of 0.509 Ω/km. The network included a load, a PV system, and an EV aggregator. This study focuses on a system with high PV penetration due to a substantial increase in global PV system installations. Therefore, a PV system is merely a RES system integrated into the system. The PV and load profiles used in this study are based on a previous study by Jamroen et al. [22] and illustrated in Fig. 1. The EV aggregator and frequency regulation settings are detailed in Table I. This study assumes that the EVs are parked at a charging station (as an aggregator) during the daytime for work. Therefore, the EVs can participate in the FCR, particularly high PV power fluctuations. Additionally, this study aims to maximize FCR revenue. Thus, it is assumed that the aggregator can make an accurate bid in response to the FCR request. The FCR market prices and penalty are listed in Table II. Since the total simulation period is 12 hours (which is 720 in minutely basis and 48 in 15-minute basis), T in Eq. 1 is set to 48 because the FCR remuneration model is designed using a 15-minute ISP.

B. Impact of initial SoC error

This section evaluates the impact of initial SoC errors. Different β values (0%, ±5%, and ±10%) were set in Eq. (9) and subsequently in Eq. (8). Fig. 2 illustrates the comparative variations in EV aggregator power based on different initial SoC errors. In addition, comparative variations in EV SoC based on different initial SoC errors are presented in Fig. 3. Since this study considered a system with high PV penetration, Fig. 2 demonstrates that the EV aggregator frequently provided downregulation but occasionally supplied upregulation. Consequently, the EV SoC tended to increase in response

Table I
EV aggregator and system parameter configuration

Parameter	Specification
Rated EV power capacity	10 kW
Rated EV energy capacity	25 kWh
Number of EVs	200
Initial EV SoC level	50%
Expected EV SoC level	80%
Maximum EV SoC level	100%
Minimum EV SoC level	20%
Coulombic efficiency	98%
Departure time	16:00
Nominal frequency	50 Hz
Frequency deadband	±0.02 Hz
Maximum allowable frequency	±0.1 Hz
Nominal voltage	22 kV

Table II
FCR market prices and penalty

Parameter	Specification
Power capacity price	37.56 €/MW/h
Power capacity penalty	37.56 €/MW/h
Upregulation energy price	39.62 €/MWh
Downregulation energy price	15.03 €/MWh
Charging price	15.03 €/MWh

to frequent downregulation (indicated in Fig. 3). This study considered the aggregator without an initial SoC estimation error (0%) as a reference. This EV aggregator stopped providing an FCR at 15:45. Subsequently, forced charging was activated (as demonstrated in Figs. 2 and 3) to charge the EVs to the expected SoC value (80%) at the departure time (16:00). However, when forced charging was activated, the aggregator was unable to provide further FCR, resulting in a penalty. Moreover, this situation led to increased charging costs due to forced charging. The EV aggregator's revenue and penalty are summarized in Table III. Without an initial SoC estimation error, the EV aggregator received revenue for the sold power capacity. However, this revenue was €2.99. Notably, increasing the initial SoC estimation error to 5% led to a positive revenue of €19.06 because this EV aggregator could provide an FCR for a longer period (lower minimum plug-in duration available), as indicated in Fig. 2. Although the downregulation energy cost increased marginally due to a longer FCR period, the penalty cost significantly decreased, resulting in positive revenue. Nevertheless, when the initial SoC estimation error reached 10%, the SoC quickly attained the expected value at 13:20 due to frequent downregulation. Although the charging energy cost was zero, because forced charging was not activated, the EV aggregator was unable to provide an FCR after 13:20, resulting in a considerable penalty cost. Consequently, this EV aggregator's revenue was the lowest at –€36.74, which was economically infeasible. When negative initial SoC errors were assigned, the power capacity revenue decreased slightly because forced charging was activated early, resulting in a shorter FCR period and a penalty cost. Similarly, the downregulation energy cost also

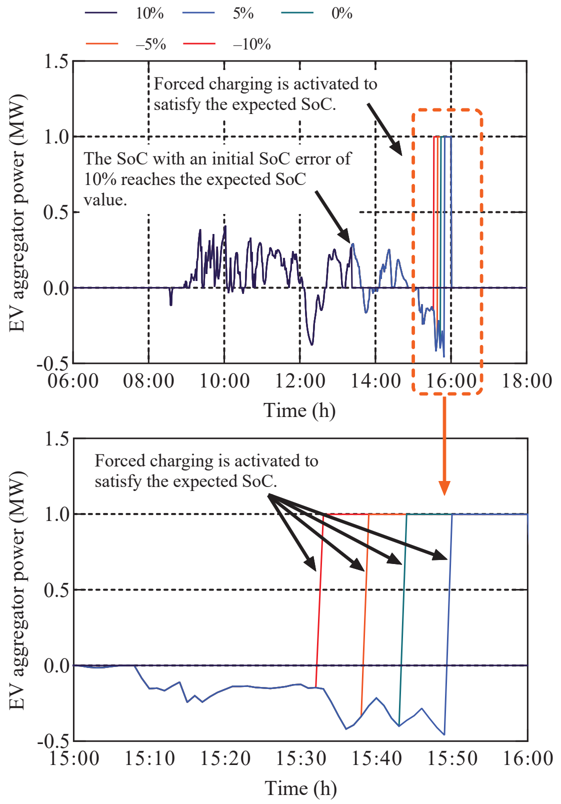

Fig. 2. EV aggregator power deviations in different initial SoC errors while providing the FCR service.

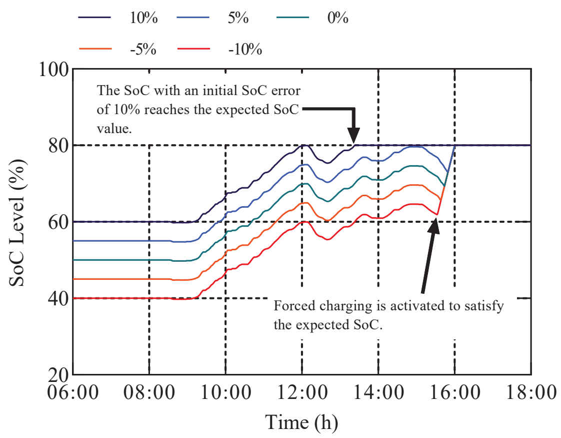

Fig. 3. Evolutions of EV SoC levels in different initial SoC errors.

decreased slightly. It was noted that the initial SoC errors did not affect upregulation energy revenue because downregulation was frequently activated, and the EVs had sufficient stored energy. Since the EV aggregators with negative initial SoC errors had a shorter FCR period due to forced charging, the charging energy cost increased marginally. Therefore, the EV aggregators' revenue deteriorated compared to the reference case.

C. Impact of power measurement error

The power measurement error's impact on EV aggregator revenue was evaluated by applying different power measurement error values (0%, 2%, 4%, 6%, 8%, and 10%) in (10) and, subsequently, in (8). Table III gives the EV aggregator revenues and costs following different power measurement errors. An increase in the power measurement error increased the EV aggregator revenue to €10.87 because the EV aggregator could provide a longer FCR period, similar to the small positive result in the initial SoC error estimation case. The revenue remained unchanged when the power measurement error was increased to 4%. Furthermore, the EV aggregator revenue increased slightly when the power measurement error was increased to 6% and remained unchanged when the power measurement error was increased to 8%. It can be concluded that the power measurement error's influence appears to be less than that of the initial SoC estimation error because the error induced by the power measurement error is cumulative, gradually increasing over time. Since this study focused on a single day, the cumulative error was small. However, it tends to be significant when a longer period is considered (such as several months or years), as discussed by Movassagh et al. [29].

V. Conclusion

This study evaluated the influence of different SoC estimation errors (i.e., initial SoC level and power measurement errors) on EV aggregator revenues in FCR market participation, focusing on the Coulomb counting SoC estimation method. The regulatory framework and FCR market were modeled in the European context. The simulation focused on a system with high PV penetration frequently activated by downregulation. The key study findings are summarized as follows. The simulation results reveal that the initial SoC error affected the FCR provision period and forced charging activation. A small positive initial SoC error could lead to positive EV aggregator revenue. However, an initial SoC error of 10% caused EV unavailability sooner than the lower positive SoC error, resulting in substantial negative revenue. Nevertheless, the small negative initial SoC errors slightly decreased revenue and became more influential than the large initial SoC error. The power measurement error positively affected EV aggregator revenue, although only a small increase in revenue was observed.

The study has focused on the influence of different SoC estimation errors on EV aggregator revenues in FCR market participation. Nevertheless, a one-day simulation with high PV production was selected. Thus, a one-year simulation should be considered in future studies to capture the variability of PV generation and better clarify the influence of different SoC estimation errors on EV aggregator revenues. Additionally, the influence of interactions among SoC estimation errors on EV aggregator revenues should be analyzed.

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Table III
IMPACT OF SOC ERRORS ON EV AGGREGATOR REVENUE AND COST

Error type	Error level	Power capacity revenue (€)	Penalty cost (€)	Upregulation energy revenue (€)	Downregulation energy cost (€)	Charging energy cost (€)	Total revenue (€)
Initial SoC errors	10	24.37	57.09	8.42	4.40	0	–36.74
	5	35.06	14.32	10.34	11.42	2.76	19.06
	0	32.44	24.81	10.34	9.97	4.26	2.99
	–5	32.75	23.55	10.34	8.98	5.51	2.34
	–10	31.58	28.24	10.34	7.75	7.01	–6.26
Power measurement errors	0	32.44	24.81	10.34	9.97	4.26	2.99
	2	33.92	18.90	10.34	10.21	4.01	10.87
	4	33.92	18.90	10.34	10.21	4.01	10.87
	6	34.13	18.06	10.34	10.43	3.76	12.40
	8	34.13	18.06	10.34	10.43	3.76	12.40

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