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An optimized trading strategy for an energy storage systems aggregator in an ancillary service market

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ABSTRACT

With increasing proportion of intermittent renewable energy sources in the electric power system, the system operator (SO) is facing a challenge of maintaining the demand-supply balance which is more dynamic and uncertain than before. To manage the balance, the SO procures different services from balancing service providers like balancing mechanism units and distributed energy resources aggregators. In this work, we propose a model for an aggregator of energy storage systems (ESS). The distributed small size ESS can be grouped and utilized by an aggregator for trading of multiple services with different specifications and bidding rules in ancillary service markets. ESS, being flexible and having quick response time, can contribute in both directions for all the services and assist in maintaining the real time demand-supply balance of the system. The trading strategy proposed in this work captures the regulations and the bidding characteristics of all the services individually. This proposed solution is a Mixed Integer Linear Programming (MILP) problem which becomes computationally complex as the size of ESS dataset of the aggregator increases. Hence, we also propose an alternate approximation method which is scalable, comparatively easy to solve and takes less computation time while giving comparable optimal schedules. These proposed methods have also been compared with an intuitive baseline method. We have demonstrated the efficacy of the proposed methods with real world data of France balancing market.

1. Introduction

The System Operator (SO) has the responsibility of managing the demand-supply balance in the electric power system network in real-time. Growing proportion of intermittent renewable energy sources (RES) in the power system has been a concern for SOs world-wide. Not only is the power generated by these sources intermittent due to their dependency on weather, but the rapid rate of change of power output makes it difficult for the SO to manage the demand-supply balance with only conventional balancing mechanism units (BMU) which are typically rotating synchronous generators. Though the RES help in achieving the sustainability goals of decarbonization of the power system, there are new challenges in forecasting the generation and managing rapidly changing demand-supply imbalances in real-time. The low/no inertia of the RES necessitates flexible mechanisms/services to help the SO.

The SO must always ensure a balance between supply and demand in real time, while considering the consumption and generation variability. To maintain this balance, the SO requires dispatchable power reserves of certain capacity in both directions — upward and downward, within its geographical area. These reserves are a reactive means to level out the frequency deviations in the power grid and can be traded through ancillary service markets/balancing markets [1–3]. Balancing markets include capacity markets and energy markets. Balancing energy is the energy utilized by the SO to manage the frequency deviations and maintain demand-supply balance. Balancing capacity is the flexible capacity which is made available or kept on standby by balancing service providers (BSPs) for a certain duration in order to provide balancing energy whenever required.

1.1. Contributions

In many European markets, a distributed energy resources (DER) aggregator participating as a BSP faces the problem of optimizing its

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Nomenclature

Parameters

$P_b^{\text{dsg max}}$	Maximum discharge rate of battery b
$P_b^{\text{chg max}}$	Maximum charge rate of battery b
Δ_t	smallest time duration
η^{chg}, η^{dsg}	Charging/Discharging efficiency of battery
γ	Linear approximation of degradation slope
$\hat{\text{AP}}_t$	Forecasted activation prices at time t
$\hat{\text{CP}}_t$	Forecasted capacity prices at time t
$\mathcal{T}^{\text{aFRR}}$	Pre-defined blocks for aFRR bidding
$\mathcal{T}^{\text{FCR}}$	Pre-defined blocks for FCR bidding
$\mathcal{T}^{\text{manual}}$	Pre-defined blocks for mFRR and RR bidding
π_t	Probability of activation in balancing energy markets at time t
σ_1, σ_2	Weights of penalty functions
C_b^{inv}	Investment cost of battery b
k	Bidding block index
SoC_b^{min}	Minimum SoC limits of battery b
Cap_b	Battery capacity of b

Variables

$\mathsf{afrr}_t^{\mathsf{Up}}$, $\mathsf{afrr}_t^{\mathsf{Dn}}$	Bidding volume scheduled for $aFRR$ product at time t
$\alpha_{t,b}$	Binary variable to decide the state of charging of b at time t. 1:charging, 0:discharging
β	Binary variable to implement minimum volume requirement. 1:volume geq 1 MW, 0: no bidding
$\mathsf{fcr}_t^{\mathsf{Up}}$, $\mathsf{fcr}_t^{\mathsf{Dn}}$	Bidding volume scheduled for FCR product at time t
$\mathcal{R}_t^{\text{aFRR}}$	Revenue earned from aFRR at time t
$\mathcal{R}_t^{\text{FCR}}$	Revenue earned from FCR at time t
$\mathcal{R}_t^{\text{mFRR}}$	Revenue earned from mFRR at time t
$\mathcal{R}_t^{\text{RR}}$	Revenue earned from RR at time t
$\mathsf{mfrr}_t^{\mathsf{Up}}$, $\mathsf{mfrr}_t^{\mathsf{Dn}}$	Bidding volume scheduled for $mFRR$ product at time t
$\mathsf{rr}_t^{\mathsf{Up}}$, $\mathsf{rr}_t^{\mathsf{Dn}}$	Bidding volume scheduled for RR product at time t
C_b^{deg}	Degradation cost of battery b
$p_{t,b}^{\text{chg}}$, $p_{t,b}^{\text{dsg}}$	Volume scheduled for charging and discharging of battery b at time t
$soc_{t,b}$	State of charge of battery b at time t

resources with complex inter-temporal constraints of various services. A typical balancing market timeline is shown in Fig. 1. The BSP who wishes to provide a particular balancing service for a day, can first bid for balancing capacity either through annual tenders or daily tenders [4,5]. When bidding for day D, a BSP can submit its bids in capacity markets for the entire day on $D-1$ by gate closure of 11 a.m. Market clearing for balancing capacity is merit order based with the objective of procurement cost minimization. This clearing is done immediately and the result of clearing is relayed back to the BSPs on $D-1$ by 12 p.m. If the bid is cleared and procured by the SO, it has to keep the procured capacity available (on standby) for the entire cleared duration and bid the entire volume in balancing energy markets. The bids for a slot T of the actual delivery day D in balancing energy markets can be updated till the previous time slot $T-1$. Activation of the procured capacity in energy markets is subject to real time *system imbalances*. There are two streams of revenues from these markets: (1)capacity payment for being available and (2)activation payment for actual deployment of balancing energy. The balancing markets have defined services or products based on different activation methods, activation speeds and activation response timescales for which a BSP can bid for. Some of standard balancing services present in the European markets are [1,3,6,7]:

1. Frequency Containment Reserve (FCR)
2. automatic Frequency Restoration Reserve (aFRR)
3. manual Frequency Restoration Reserve (mFRR)
4. Replacement Reserve (RR)

An Energy storage system (ESS) is an ideal resource to provide balancing services due to its high flexibility. It can provide these services in both directions, upward direction by discharging and downward direction by charging. Also, it has quick response time, i.e., it can instantaneously start charging or discharging. If multiple ESS are aggregated together to get some specified capacity and are operated appropriately, they can participate in balancing markets and provide services while earning revenue. Our aim in this paper is the development of trading algorithms to enable the ESS aggregator to provide such services.

Though some models for ESS (direct or with aggregators) participating in energy and/or balancing markets have been discussed in literature (see Section 1.2), there are some gaps which we address in this work. Our goal is to develop a scalable, mathematical optimization framework for an ESS aggregator to optimize large and heterogeneous storage resources across various services. With the focus on developing a model for an ESS aggregator whose goal is to participate in balancing markets and appropriately bid for multiple services simultaneously with an objective of earning maximum revenue, our contributions are:

- Since each service has different specifications, the proposed formulation captures the regulations and bidding characteristics of all the four services individually. The proposed formulation is a Mixed Integer Linear Programming (MILP) problem. To the best of our knowledge, this problem of optimizing a battery storage's simultaneous participation in all the frequency regulation services has not been attempted before.
- There is a continuous rise in the number of small size batteries (standalone or solar-ESS combination) being installed across the distribution network by the residential users. An aggregator can aggregate them and use them for trading in markets. However, large number of ESS with the aggregator will lead to increase in binary variables in the original MILP formulation which will increase its computational complexity. Hence, we have also proposed an alternate approximation method which is scalable and takes significantly less computation time while giving comparable results.
- Previous literature considers a constant probability of activation (real time deployment ratios) in balancing energy markets for the entire day in their models. However, it varies over time slots and is different for different services as it depends on values of real time system imbalances and the duration of each event. We estimate the activation probability of each time slot for each service to get a robust schedule which will give less deviations for unknown activation calls in real time.

The proposed model is evaluated on a set of 500 ESS using real world regulation market data traces from France SO. It successfully gives an output schedule which bids its available aggregator capacity into multiple services such that the net profit earned is maximized. The discussed approximation method reduces the computation time by almost 50% while giving comparable optimal results with respect to the original method.

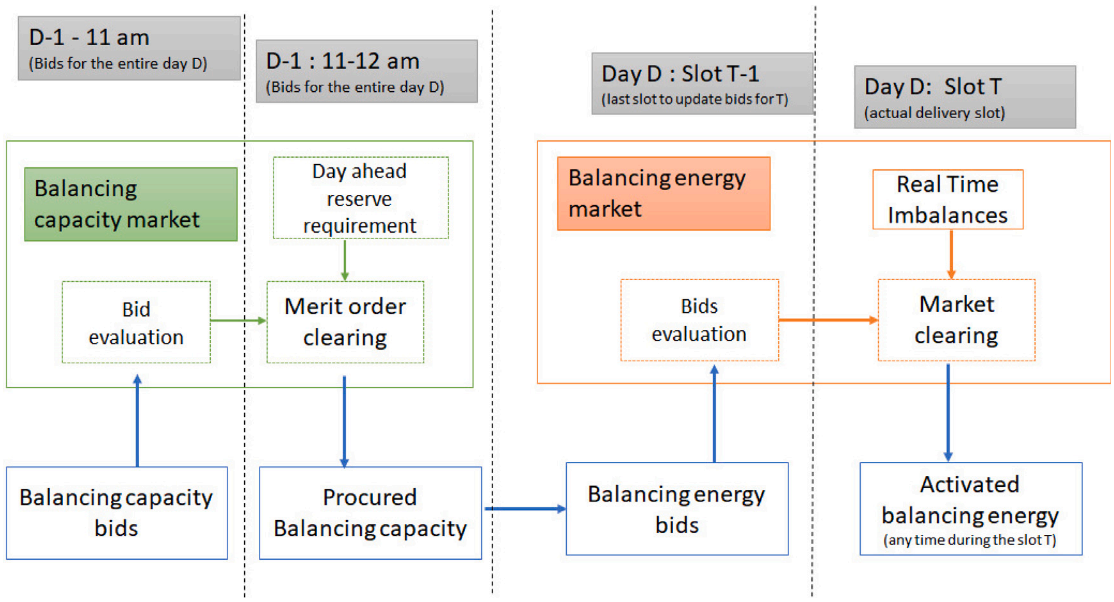


Fig. 1. A typical balancing market timeline.

1.2. Related works

Participation of energy storage in energy and reserve markets have been discussed in the literature [8,9]. An energy storage provider can make profit by energy arbitrage or by helping the grid operator in managing the reliability and demand-supply balance. Xu et al. [9] proposed a bi-level optimization problem to find out location and size of energy storage participating in energy arbitrage and regulation services. Hosseini et al. [10] proposed a two stage stochastic optimization model for a wind power plant participating in a joint day-ahead energy and reserve market.

As the distributed energy resources (DER) like battery and electric vehicles (EVs) are increasing on the low voltage side of the grid, aggregators of the these resources can also participate in the energy and regulation markets without actually owning any of the asset [11]. The roles and models for DER aggregators are being talked about a lot in research and as well as in practice [12]. DER aggregators help in better utilization of the distributed asset and can have a win-win situation for both the aggregator and the subscribers [13]. Some references of aggregators participating in energy and/or ancillary service markets are mentioned here.

Attarha et al. [14] proposed a bidding model for participation in energy and FCAS (frequency control ancillary service) markets by a DER aggregator. The model considers network constraints. The model has been developed for Australian market scenario where energy and FCAS are co-optimized. In a similar work [15], an MILP optimization model for a ESS to participate in energy and reserve markets in the USA with flexible ramping product. Iria et al. [13] proposed a two-stage stochastic optimization model for bidding strategies for aggregator of prosumers with heterogeneous DERs. The aggregator participates in the day-ahead energy and secondary reserve markets. Stochasticity of variables like the renewable generation, consumption, outdoor temperature, behaviors, and preferences of the prosumers are modeled through a set of scenarios. The model considers sequential market rule as in European markets where reserve market scheduling is done after the day-ahead market clearing. The model has continuous variables only and is modeled as a linear programming problem. Another work on solar-battery systems aggregator participating in ancillary service market discusses about an MILP optimization model for up and down regulation services [16]. The Italian market rules are being considered in the proposed model.

EVs can also provide similar flexibility as a battery energy storage systems, however, they may have some constraints like, mobility, availability etc. Providing ancillary services by an EV aggregator has also been addressed in the literature with similar ideas. Ref. [17] developed an optimal strategy to participate in energy and reserve markets considering their trade offs and their effect on battery degradation. The proposed model is an MILP formulation to maximize the profits of the aggregator by participating in DA and reserve markets simultaneously in ERCOT market. The objective function has revenue terms (– revenue from DA market, revenue from capacity being accepted in reserve markets and revenue from accepted capacity being deployed) and cost terms (cost of buying from RT in case of deployment not being met and degradation cost). Probability of capacity acceptance and deployment considered in the formulation. In DA, the aggregator acts as price taker. In reserve markets, the non linear price–quantity (price being a function of quantity) linearized in step wise fashion (PQP price-quantity-probability curve). Vatandoust et al. [18] proposed a stochastic MILP optimization model for the participation of an aggregator controlling a fleet of electric vehicles and an energy storage in day-ahead regulation and energy markets in CAISO. The model determines the optimal size of the aggregator's bids while considering Conditional Value at Risk (CVaR) model for uncertainties in energy and frequency regulation prices. The proposed model also includes linear load flow formulation to investigate the impact of network limits on the bids.

2. Specifications and bidding rules of the balancing services

This section gives a brief introduction of the four services and describes their bidding rules and timelines on offer in balancing markets. Out of the four services, FCR and aFRR are fast response services which are activated automatically upon frequency deviation by automatic generation control (AGC) signal without any intervention of the SO. FCR is the instantaneous response while aFRR is the secondary response which takes over FCR if the deviation persists beyond the time scope of FCR. mFRR and RR are activated manually by the BSPs upon receiving signal from the SO. These services are called to intervene when there are long lasting deviations which cannot be tackled by FCR and aFRR

Table 1
Specifications of technical characteristics of standard products.

Characteristics	FCR	aFRR	mFRR	RR
Mode of Activation	automatic	automatic	manual	manual
FAT	30 sec	5 min	12.5 min	30 min
Minimum quantity	1 MW	1 MW	1 MW	1 MW
Maximum quantity	25 MW	–	9999 MW	–
Bid granularity	1 MW	1 MW	1 MW	1 MW
Minimum duration of delivery period	–	5 min	30 min	30 min
Maximum duration of delivery period	15 min	15 min	120 min	90 min

alone. Their main responsibility is to restore the frequency to system's nominal frequency. Each of these services are defined by the following characteristics [19].

1. Full activation time (FAT): This is the period between the activation request by the SO and full delivery of requested MW power. It is the sum of preparation period (the period between the activation request by the SO and start of the ramping period) and ramping period (the time required for the active power output to increase or decrease from the current set point)
2. Mode of activation: Can be either automatic or manual and represents the way the system operator can activate the relevant bid.
3. Minimum and maximum quantity: It is the change of power output offered by BSPs. It is necessary that the offered change can be reached within the activation time.
4. Minimum and maximum duration of delivery period: The minimum and maximum period for which the BSP is capable of delivering requested change of power to the system
5. Bid granularity: Minimum step of power that is offered by the BSP.

The standard specifications of technical characteristics of all the four services are summarized in Table 1 (see Table 1).

Remarks:

- The automatic reserves are activated for a shorter duration of 15 min per event but are called upon more frequently for deployment.
- The manually activated services are deployed for a longer duration but are called upon less frequently as compared to the two automatic reserves.

The capacity requirement of the system for each service is published by the SO beforehand through annual and daily tenders. Also, the bidding rules/regulations outlined by ENTSO-E (the European Network of Transmission System Operators of SO in Europe) are disclosed in detail [20]. In this paper, we focus on the balancing market managed by RTE (the SO of France).

2.1. *Contracting for* FCR

Procurement of FCR capacity is done by means of cross border call for daily tender which is common to 11 SOs from 8 countries of which France is a part of [20]. Such a common market aims at integrating balancing markets of different SOs in Europe to foster effective competition, transparency, ease to new entrants and increase in liquidity. Characteristics of the FCR product and rules which need to be followed when bidding for FCR are as follows [5]:

- The FCR product delivery period is 4 h on the following periods: $\{1-4, 5-8, 9-12, \dots, 21-24\}$. An offer made focuses on delivery of bid volume over a given delivery period.
- The bids submitted should be symmetric which means for a given period, the BSPs must bid same volume in both upward and downward directions.

2.2. *Contracting of* aFRR

Contracting of aFRR capacity is done through a national day ahead call for tenders where the SO specify the requirements for aFRR capacity [5].

- The aFRR product delivery period is one hour. A BSP can bid for one or more consecutive hours. The delivery period is defined over following periods: $\{1, 2, 3, 4 \dots, 23, 24\}$
- Bids can be symmetric or asymmetric. However, the procurement by SO is symmetric.
- Bids can divisible or indivisible.

2.3. *Contracting of* mFRR *and* RR

Contracting of these reserves is done through call for tenders which are (1) annually and (2)daily [4]. In this paper, we mainly focus on capacity procurement via daily tenders. The daily tenders specify the capacity requirement for the entire day D.

- For a given gate (for a day D), the bids relate to full day commitment, i.e., the delivery period for mFRR and RR product is 24 h.
- The bids can be asymmetric and indivisible.

3. Proposed model

An ESS aggregator who wants to participate in the balancing markets by placing bids for multiple services simultaneously for different time blocks of the next day can use proposed model as in Fig. 2. The optimization module discussed in Section 3 is at the heart of the proposed solution which requires the estimated inputs of markets (balancing market prices: $\hat{\mathrm{CP}}$, $\hat{\mathrm{AP}}$) and the probability of activation (π). These estimates are obtained from the sub-modules discussed in Sections 3.2 and 3.3 respectively. Additionally, it also takes in the technical information of all the ESS available with it. In this paper, we have used the terms ESS and batteries interchangeably.

3.1. *Optimization model*

Let $\mathcal{B}$ be the set of ESSs available with an aggregator. Each ESS shares its technical specifications and its availability with the aggregator. The aggregator participates in the ancillary services market and offers the aggregated capacity to the system operator by bidding for the four services. The capacity and energy prices of these services vary over time and also the activation/calling of these services depends on the system conditions. It is assumed that the aggregator is participating as a price taker and whatever quantity is offered as a service, it will be procured by the SO at the market price of the service. The aggregator earns revenue from offering these services to the SO and compensates the ESSs. In this work, we do not focus on the profit allocation methods which can be calculated with the methods discussed in literature. The idea here is to maximize the profit of an aggregator (and indirectly that of ESSs) by offering the ancillary services while modeling all the constraints of the services and ESS.

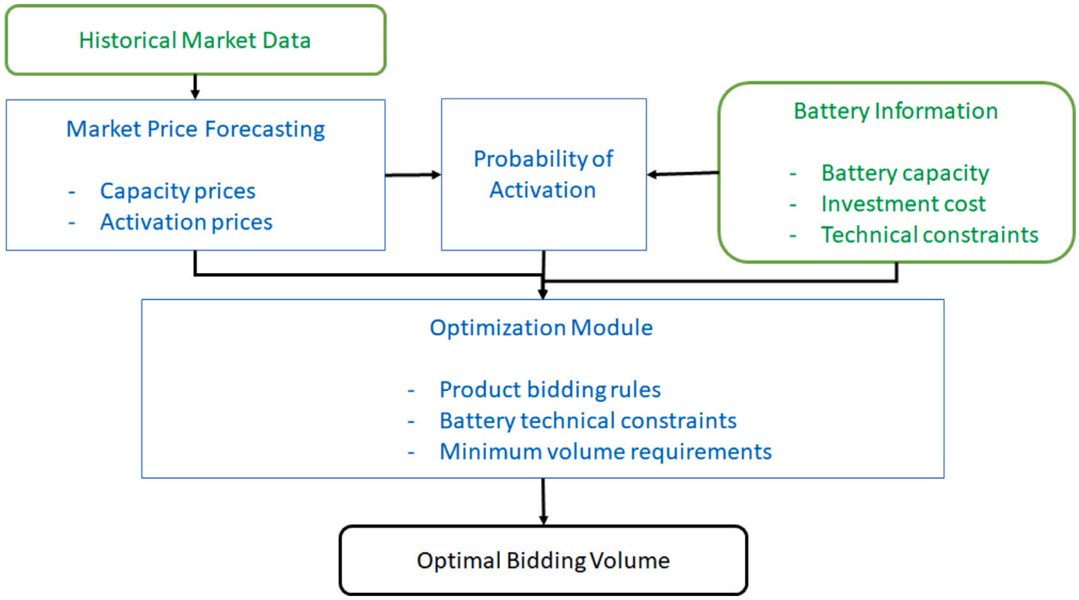


Fig. 2. Proposed model for ESS aggregator to bid in balancing market.

Objective function

The objective of the ESS aggregator is maximize its profit by optimally trading for all the ancillary services by utilizing its available capacity as indicated in (1).

$$\textbf{Obj}: \max_{\mathcal{V},\mathcal{P}^{\text{chg}},\mathcal{P}^{\text{dsg}}} \sum_{t\in\mathcal{T}}(\mathcal{R}_t^{\text{FCR}}+\mathcal{R}_t^{\text{aFRR}}+\mathcal{R}_t^{\text{mFRR}}+\mathcal{R}_t^{\text{RR}}) - \sum_{b\in\mathcal{B}} C_b^{\text{deg}} \tag{1}$$

Here, $\mathcal{V} = \{\mathsf{fcr}^{\mathsf{Up}}, \mathsf{fcr}^{\mathsf{Dn}}, \mathsf{afrr}^{\mathsf{Up}}, \mathsf{afrr}^{\mathsf{Dn}}, \mathsf{mfrr}^{\mathsf{Up}}, \mathsf{mfrr}^{\mathsf{Dn}}, \mathsf{rr}^{\mathsf{Up}}, \mathsf{rr}^{\mathsf{Dn}}\}$ is the set of decision variables corresponding to bid volumes for all the services in both the directions, $\mathcal{T}$ is the set of hours of the day over the optimization is run, $\mathcal{P}^{\text{chg}}$ and $\mathcal{P}^{\text{dsg}}$ is the set of all the charging and discharging volumes for batteries $b \in \mathcal{B}$ and hours $t \in \mathcal{T}$. Profit earned by the aggregator is the difference between the revenue from all the services and the degradation cost of ESS that provide those services. The revenue obtained from FCR is as shown in (2). The first term, $\hat{\text{CP}}_t^{\text{FCR}}(\mathsf{fcr}_t^{\mathsf{Up}} + \mathsf{fcr}_t^{\mathsf{Dn}})$, corresponds to the revenue earned from capacity markets in hour t, while the second term corresponds to the revenue earned from balancing energy markets. For each time slot t, the aggregator initially bids its volume in capacity markets for both up and down directions ($\mathsf{fcr}^{\mathsf{Up}}, \mathsf{fcr}^{\mathsf{Dn}}$). On being accepted, it is paid for being on standby with the capacity price $\hat{\text{CP}}_t^{\text{FCR}}$ for both directions. It is also paid when asked for deployment in balancing energy markets. If π_t represents the probability of a capacity bid being called to deploy, then the deployed energy could be expressed as $\pi_t^{\text{FCR}^{\text{Up}}}\mathsf{fcr}_t^{\mathsf{Up}}\Delta_t$ and $\pi_t^{\text{FCR}^{\text{Dn}}}\mathsf{fcr}_t^{\mathsf{Dn}}\Delta_t$ where Δ_t is the duration of deployment. Payment from balancing energy markets is done with their corresponding activation prices of $\hat{\text{AP}}_t^{\text{FCR}^{\text{Up}}}$ and $\hat{\text{AP}}_t^{\text{FCR}^{\text{Dn}}}$ respectively. The revenue terms for other services are calculated similarly as shown in (3)–(5).

$$\begin{aligned}\mathcal{R}_t^{\text{FCR}} &= \hat{\text{CP}}_t^{\text{FCR}}(\mathsf{fcr}_t^{\mathsf{Up}} + \mathsf{fcr}_t^{\mathsf{Dn}})\\ &\quad + \Delta_t(\hat{\text{AP}}_t^{\text{FCR}^{\text{Up}}}\pi_t^{\text{FCR}^{\text{Up}}}\mathsf{fcr}_t^{\mathsf{Up}} + \hat{\text{AP}}_t^{\text{FCR}^{\text{Dn}}}\pi_t^{\text{FCR}^{\text{Dn}}}\mathsf{fcr}_t^{\mathsf{Dn}}) \quad \forall t\in\mathcal{T}\end{aligned} \tag{2}$$

$$\begin{aligned}\mathcal{R}_t^{\text{aFRR}} &= \hat{\text{CP}}_t^{\text{aFRR}}(\mathsf{afrr}_t^{\mathsf{Up}} + \mathsf{afrr}_t^{\mathsf{Dn}})\\ &\quad + \Delta_t(\hat{\text{AP}}_t^{\text{aFRR}^{\text{Up}}}\pi_t^{\text{aFRR}^{\text{Up}}}\mathsf{afrr}_t^{\mathsf{Up}} + \hat{\text{AP}}_t^{\text{aFRR}^{\text{Dn}}}\pi_t^{\text{aFRR}^{\text{Dn}}}\mathsf{afrr}_t^{\mathsf{Dn}}) \quad \forall t\in\mathcal{T}\end{aligned} \tag{3}$$

$$\begin{aligned}\mathcal{R}_t^{\text{mFRR}} &= \hat{\text{CP}}_t^{\text{mFRR}}(\mathsf{mfrr}_t^{\mathsf{Up}} + \mathsf{mfrr}_t^{\mathsf{Dn}})\\ &\quad + \Delta_t(\hat{\text{AP}}_t^{\text{mFRR}^{\text{Up}}}\pi_t^{\text{mFRR}^{\text{Up}}}\mathsf{mfrr}_t^{\mathsf{Up}} + \hat{\text{AP}}_t^{\text{mFRR}^{\text{Dn}}}\pi_t^{\text{mFRR}^{\text{Dn}}}\mathsf{mfrr}_t^{\mathsf{Dn}}) \ \forall t\in\mathcal{T}\end{aligned} \tag{4}$$

$$\begin{aligned}\mathcal{R}_t^{\text{RR}} &= \hat{\text{CP}}_t^{\text{RR}}(\mathsf{rr}_t^{\mathsf{Up}} + \mathsf{rr}_t^{\mathsf{Dn}})\\ &\quad + \Delta_t(\hat{\text{AP}}_t^{\text{RR}^{\text{Up}}}\pi_t^{\text{RR}^{\text{Up}}}\mathsf{rr}_t^{\mathsf{Up}} + \hat{\text{AP}}_t^{\text{RR}^{\text{Dn}}}\pi_t^{\text{RR}^{\text{Dn}}}\mathsf{rr}_t^{\mathsf{Dn}}) \quad \forall t\in\mathcal{T}\end{aligned} \tag{5}$$

The volume bid for the services at time t is provided by appropriately charging ($p_{t,b}^{\text{chg}}$) and discharging ($p_{t,b}^{\text{dsg}}$) of the batteries. Continuous utilization of a battery affects its health which decreases its life. The depreciation of a battery's health is quantified through degradation cost as calculated in (6). Here γ is the linear approximation of the slope of the degradation curve with respect to time, in terms of number of life-cycles and hours of operation. C_b^{inv} is the investment of battery b while Cap_b is its capacity in kWh. Thus, the term $\gamma\frac{C_b^{\text{inv}}}{\text{Cap}_b}$ is equivalent to the degradation cost per unit energy. Including degradation cost in the objective function ensures that no battery is over exploited, i.e., all the batteries are utilized appropriately based on their capital cost and capacities.

$$C_b^{\text{deg}} = \gamma\frac{C_b^{\text{inv}}}{\text{Cap}_b}\sum_{t=1}^{T}(p_{t,b}^{\text{chg}} + p_{t,b}^{\text{dsg}})\Delta_t \quad \forall b\in\mathcal{B} \tag{6}$$

Constraints

FCR **and** aFRR **constraints:** For FCR, the entire day is divided in six blocks where each block constitutes of four hours. The set of blocks is defined as $\mathcal{T}^{\text{FCR}} = \{k_1, k_2, k_3, \dots, k_6\}$. Each k is a set of four hours such that k_1 denotes $\{t = 1\dots4\}$, k_2 denotes $\{t = 5\dots8\}$, k_3 denotes $\{t = 9\dots12\}$, …, k_6 denotes $\{t = 21\dots24\}$. It indicates that the bid volume in each slot t in any block k should be equal which is as indicated in (7). FCR product bidding has to be symmetric, $\mathsf{fcr}^{\mathsf{Up}}$ volume should be equal to $\mathsf{fcr}^{\mathsf{Dn}}$ volume at any given time slot t as in (8).

$$\mathsf{fcr}_{t_1}^{\mathsf{Up}} = \mathsf{fcr}_{t_2}^{\mathsf{Up}} \quad \forall t_1, t_2 \in k, \forall k\in\mathcal{T}^{\text{FCR}} \tag{7}$$

$$\mathsf{fcr}_t^{\mathsf{Up}} = \mathsf{fcr}_t^{\mathsf{Dn}} \quad \forall t\in\mathcal{T} \tag{8}$$

The contract interval for aFRR is one hour. The aggregator can independently bid for one or more consecutive hours. Thus, for aFRR, one block constitutes of one hour i.e. $\mathcal{T}^{\text{aFRR}} = \{k_1, k_2, k_3, \dots, k_{24}\}$ where k_1 denotes $\{t = 1\}$, k_2 denotes $\{t = 2\}$, k_3 denotes $\{t = 3\}$, …, k_{24} denotes $\{t = 24\}$. Its bidding may not be symmetric in both directions.

mFRR **and** RR **constraints:** For these two products, SO requires a bid for an entire day commitment. Thus for these products, the entire day is considered as a single block such that $\mathcal{T}^{\text{manual}} = \{k_1\}$ where k_1 denotes $\{1, 2, 3, \dots, 24\}$. Bid volume for all the time slots t for the entire day has to be the same as in (9)–(12).

$$\mathsf{mfrr}_{t_1}^{\mathsf{Up}} = \mathsf{mfrr}_{t_2}^{\mathsf{Up}} \quad \forall t_1, t_2 \in k, \forall k\in\mathcal{T}^{\text{manual}} \tag{9}$$

Table 2
Details of β variables in the formulation.

Service	k	β notation	No. of β
FCR	6	$\beta_k^{\mathrm{FCR^{Up}}}$	6
$\mathrm{aFRR^{Up}}$	24	$\beta_k^{\mathrm{aFRR^{Up}}}$	24
$\mathrm{aFRR^{Dn}}$	24	$\beta_k^{\mathrm{aFRR^{Dn}}}$	24
$\mathrm{mFRR^{Up}}$	1	$\beta^{\mathrm{mFRR^{Up}}}$	1
$\mathrm{mFRR^{Dn}}$	1	$\beta^{\mathrm{mFRR^{Dn}}}$	1
$\mathrm{RR^{Up}}$	1	$\beta^{\mathrm{RR^{Up}}}$	1
$\mathrm{RR^{Dn}}$	1	$\beta^{\mathrm{RR^{Dn}}}$	1
Total no. of β variables			58

$$\mathsf{mfrr}_{t_1}^{\mathsf{Dn}} = \mathsf{mfrr}_{t_2}^{\mathsf{Dn}} \quad \forall t_1, t_2 \in k, \forall k \in \mathcal{T}^{\text{manual}} \tag{10}$$

$$\mathsf{rr}_{t_1}^{\mathsf{Up}} = \mathsf{rr}_{t_2}^{\mathsf{Up}} \quad \forall t_1, t_2 \in k, \forall k \in \mathcal{T}^{\text{manual}} \tag{11}$$

$$\mathsf{rr}_{t_1}^{\mathsf{Dn}} = \mathsf{rr}_{t_2}^{\mathsf{Dn}} \quad \forall t_1, t_2 \in k, \forall k \in \mathcal{T}^{\text{manual}} \tag{12}$$

Minimum volume requirement: As per the bidding rules in Section 2, the minimum bidding requirement for any service is 10^3kW. For a given time slot, aggregator has a choice whether to bid or not. The aggregator has to ensure that if it bids, the volume is greater than 10^3kW. For example, when bidding for $\mathsf{fcr}_t^{\mathsf{Up}}$, it has two options - (1) do not bid i.e $\mathsf{fcr}_t^{\mathsf{Up}} = 0$kW or (2) $\mathsf{fcr}_t^{\mathsf{Up}} \geq 10^3$kW. It needs to enforce an either-or condition where first condition has an equality constraint while second condition has an inequality constraint. Such either-or condition can be implemented using binary variable β as (13)–(15).

$$\mathsf{fcr}_k^{\mathsf{Up}} \leq 0 + M\beta_k^{\mathrm{FCR^{Up}}} \quad \forall k \in \mathcal{T}^{\mathrm{FCR}} \tag{13}$$

$$\mathsf{fcr}_k^{\mathsf{Up}} \geq 0 - M\beta_k^{\mathrm{FCR^{Up}}} \quad \forall k \in \mathcal{T}^{\mathrm{FCR}} \tag{14}$$

$$\mathsf{fcr}_k^{\mathsf{Up}} \geq 1000\beta_k^{\mathrm{FCR^{Up}}} \quad \forall k \in \mathcal{T}^{\mathrm{FCR}} \tag{15}$$

Here, M is a very large number. As the bid volume $\mathsf{fcr}^{\mathsf{Up}}$ is same for all the time slots t in a block k, introducing one binary variable $\beta_k^{\mathrm{FCR^{Up}}}$ for each block is enough. Also, $\mathsf{fcr}_t^{\mathsf{Up}} = \mathsf{fcr}_t^{\mathsf{Dn}}$, so including binary variables for one direction is sufficient. Similar constraints will be applicable for all the remaining services. As we are bidding in terms of blocks for each service, the number of binary variables will be equal to its corresponding number of blocks as in Table 2.

Mapping of services and battery charging/discharging: The volume bid in all the services at time t is due to charging and discharging of the batteries. Providing down services is equivalent to charging the batteries while up services results in discharging of batteries as shown in (16) and (17) respectively.

$$\sum_{b \in \mathcal{B}} p_{t,b}^{\text{chg}} = \mathsf{fcr}_t^{\mathsf{Dn}} + \mathsf{afrr}_t^{\mathsf{Dn}} + \mathsf{mfrr}_t^{\mathsf{Dn}} + \mathsf{rr}_t^{\mathsf{Dn}} \quad \forall t \in \mathcal{T} \tag{16}$$

$$\sum_{b \in \mathcal{B}} p_{t,b}^{\text{dsg}} = \mathsf{fcr}_t^{\mathsf{Up}} + \mathsf{afrr}_t^{\mathsf{Up}} + \mathsf{mfrr}_t^{\mathsf{Up}} + \mathsf{rr}_t^{\mathsf{Up}} \quad \forall t \in \mathcal{T} \tag{17}$$

Eq. (18) and (19) limit the charging and discharging volumes of each battery b for time t within their corresponding charging/discharging rates ($P_b^{\text{chg max}}$, $P_b^{\text{dsg max}}$) based on its individual technical characteristics. The binary variable $\alpha_{t,b}$ ensures that a battery either charges or discharges (not both) for each time slot t.

$$p_{t,b}^{\text{chg}} \leq P_b^{\text{chg max}} \alpha_{t,b}, \quad \forall t \in \mathcal{T} \quad \forall b \in B \tag{18}$$

$$p_{t,b}^{\text{dsg}} \leq P_b^{\text{dsg max}} (1 - \alpha_{t,b}), \quad \forall t \in \mathcal{T} \quad \forall b \in B \tag{19}$$

As seen from the constraints (16)–(19), at any given time t the aggregator can bid for both upward and downward services. However, one battery can contribute to only one direction of service (either up or down). Thus, for a time slot t, if the aggregator is bidding for both directions, one subset of batteries is scheduled for up direction while another exclusive subset gets scheduled for down direction. There is no overlapping of batteries between these two subsets. This enables the aggregator to bid for both directions without any energy arbitrage happening between its own assets.

Battery soc constraints: Eq. (20) corresponds to the relationship between soc of each battery and its charging and discharging volumes for each time slot t. Eq. (21) limits the soc of each battery within its maximum and minimum limits as mentioned in its technical specifications.

$$soc_{t,b} = soc_{t-1,b} + (\eta^{\text{chg}} p_{t,b}^{\text{chg}} - p_{t,b}^{\text{dsg}}/\eta^{\text{dsg}})\Delta_t, \quad \forall t \in \mathcal{T} \quad \forall b \in \mathcal{B} \tag{20}$$

$$SoC_b^{\min} \leq soc_{t,b} \leq SoC_b^{\max}, \quad \forall t \in \mathcal{T} \quad \forall b \in \mathcal{B} \tag{21}$$

Non negativity constraint: All the decision variables are non-negative (22).

$$\mathsf{fcr}_t^{\mathsf{Up}}, \mathsf{fcr}_t^{\mathsf{Dn}}, \mathsf{afrr}_t^{\mathsf{Up}}, \mathsf{afrr}_t^{\mathsf{Dn}}, \mathsf{mfrr}_t^{\mathsf{Up}}, \mathsf{mfrr}_t^{\mathsf{Dn}}, \mathsf{rr}_t^{\mathsf{Up}}, \mathsf{rr}_t^{\mathsf{Dn}}, p_{t,b}^{\text{chg}}, p_{t,b}^{\text{dsg}} \geq 0 \quad \forall t \in \mathcal{T} \tag{22}$$

The proposed formulation is an MILP problem. The integer variables are introduced in two places: (1)$\alpha_{t,b}$ for the decision of state of battery — charging or discharging of battery b for each time t and (2) β for minimum volume either-or condition. The number of binary variables α depends on the size of dataset considered — number of batteries b and the number of time slots t over which the formulation is being solved. On the other hand, the number of β variables is constant as it depends on the number of blocks of each service which are already pre-defined. The optimization model has some stochastic variables. However, using Stochastic programming approach leads to a large MILP whose size will scale with the number of scenarios. Such a problem is computationally expensive and could be hard to solve within the timeframe of the decision making. We suggest an approximation method to make the model faster to help decision making in real-life scenarios where a large number of batteries are expected.

Remarks: If we compare the bidding rules of all the four services, it can be seen that aFRR is the most flexible to bid for as its block duration is only one hour and the aggregator can change its bid volume for each consecutive hour. The next flexible product is FCR where one block corresponds to four hours while the manually activated services mFRR and RR are least flexible as they require bidding commitment of same volume for the entire day. This flexibility affects the schedule creation. The final output schedule is also dependent on the capacity and activation prices as the objective is to maximize the profit. The formulation would want to bid for the most profitable service. As the bidding is done in blocks, it is intuitive that the optimization model prefers that service which has the highest average price (both capacity and activation prices) for the entire day.

3.2. Market price forecasting

The optimal bidding schedule is dependent on the market prices. As the market prices vary on a daily basis and the aggregator needs to create the bidding schedule on a day ahead basis, it needs to use the forecasted prices as actual prices are not known. Price forecasting in the proposed approach is done using the standard univariate Auto Regressive Integrated Moving Average (ARIMA) method [21]. Its equation is represented by (23).

$$y'_t = c + \phi_1 y'_{t-1} + \cdots + \phi_p y'_{t-p} + \theta_1 \epsilon_{t-1} + \cdots + \theta_q \epsilon_{t-q} + \cdots + \epsilon_t \tag{23}$$

Here, y'_t is the differenced series. The predictors of this method include the lagged terms of the value to be forecasted $(y_{t-1}, \ldots, y_{t-p})$and its lagged errors $(\epsilon_{t-1}, \ldots, \epsilon_{t-q})$. This model is characterized as model with order (p, d, q) where, p is the order of auto regressive part (lagged terms), d is the degree of first differencing and q is the order of the moving average part (error lag). The values of p and q are selected using the Auto Correlation Function (ACF) and Partial Auto Correlation Function (PACF) plots. The value of d is selected such that y'_t is a stationary series whose properties do not depend on the time at which it is observed. Once the values of p, d, q have been chosen, the values of the parameters $c, \phi_1, \ldots \phi_p, \theta_1, \ldots, \theta_q$ are calculated by minimizing the sum of residuals ϵ_t of all the historical points of the training dataset.

3.3. Probability of activation π

We assume that the total capacity of aggregator is small as compared to the balancing markets' requirements and traded volume. Hence, aggregator's bid will have no effect on the market clearing and its prices. For our case study, we assume that the aggregator acts a price taker in balancing capacity market. When participating in balancing energy markets, the aggregator wants to bid so as not to incur loss i.e. at-least recover the investment/capacity cost. For this, let us consider that the aggregator bids with a price to cover the amortized capacity cost (i.e. capacity cost of operating its assets) for each time slot t. Clearing of balancing energy markets is done based on merit order clearing — lower priced bids are called upon first for deployment. The bids that get cleared and are called for deployment are paid with the marginal clearing price (forecasted activation market price in our case). Thus the probability of activation (π) of the aggregator's reserved capacity will depend on the relative values of bid amortized cost and the forecasted market price.

Let the forecasted activation price for a service be $\hat{\mathrm{AP}}$ and the bid amortized capacity cost be bP. We have defined the upper and lower limits ζ^H and ζ^L to consider the uncertainty associated with the forecasted activation prices such that:

- If $bP \leq \zeta^L \hat{\mathrm{AP}}$, then $\pi = 1$.
  Here, as the aggregator's bid price is much less than the forecasted cleared market price, we can safely assume that its' entire capacity volume will be called upon for deployment in real time.
- If $bP \geq \zeta^H \hat{\mathrm{AP}}$, then $\pi = 0$.
  In this case, as the aggregator's bid price for balancing energy market is much higher than the forecasted market clearing price, it is safe to assume that the aggregator's capacity will not be called for deployment.
- If $\zeta^L \hat{\mathrm{AP}} \leq bP \leq \zeta^H \hat{\mathrm{AP}}$, then it can be assumed that π follows a linear function and takes a corresponding value below 0 to 1.

4. Approximation model

In a real life scenario, the aggregator will have very large number of ESS for meeting the minimum volume requirements. These ESS will be owned by different individual entities and will be distributed across various nodes of the network. Hence they have to be treated individually and cannot be grouped. As the number of ESS $\mathcal{B}$ available with the aggregator will increase, the number of binary variable $\alpha_{t,b}$ will also increase. An MILP problem is NP-hard and becomes computationally expensive to solve for large number of binary variables as the computation time grows exponentially. Hence, we propose an approximation technique which intends to give similar output but within reduced simulation time. This approximation technique is carried out in two steps:

1. **Approximated Nonlinear Programming (NLP)**: In this step, we intend to remove all the binary variables and replace them with continuous variables within the bounds of [0,1] by adding appropriate penalties in the objective function. Let $\mathbb{A}$ be the set of all the continuous $\alpha_{t,b}$ variables and $\mathbb{B}$ be the set of all continuous β variables. The objective function of this approximated NLP is as shown in (24). All the other constraints will be kept the same.

$$\max_{\mathbb{A},\mathbb{B}} \sum_{t=1}^{T} (\mathcal{R}^{\mathrm{FCR}} + \mathcal{R}^{\mathrm{aFRR}} + \mathcal{R}^{\mathrm{mFRR}} + \mathcal{R}^{\mathrm{RR}}) - \sum_{b=1}^{\mathcal{B}} C_b^{\mathrm{deg}} - \lambda_1 - \lambda_2 \tag{24}$$

$$\text{where} \quad \lambda_1 = \sigma_1 \Big(\sum_{b=1}^{\mathcal{B}} \sum_{t=1}^{T} \alpha_{t,b}(1 - \alpha_{t,b})\Big) \tag{25}$$

$$\begin{aligned}\text{and} \quad \lambda_2 = {} & \sigma_2 \Big(\sum_{k=1}^{6} \beta_k^{\mathrm{FCR^{Up}}}(1 - \beta_k^{\mathrm{FCR^{Up}}})\Big) \\ & + \Big(\sum_{k=1}^{24} \beta_k^{\mathrm{aFRR^{Up}}}(1 - \beta_k^{\mathrm{aFRR^{Up}}}) + \beta_k^{\mathrm{aFRR^{Dn}}}(1 - \beta_k^{\mathrm{aFRR^{Dn}}})\Big) \\ & + \big(\beta^{\mathrm{mFRR^{Up}}}(1 - \beta^{\mathrm{mFRR^{Up}}}) + \beta^{\mathrm{mFRR^{Dn}}}(1 - \beta^{\mathrm{mFRR^{Dn}}}\big) \\ & + \beta^{\mathrm{RR^{Up}}}(1 - \beta^{\mathrm{RR^{Up}}}) + \beta^{\mathrm{RR^{Dn}}}(1 - \beta^{\mathrm{RR^{Dn}}})\big)\end{aligned} \tag{26}$$

Eq. (25) is the penalty associated with $\alpha_{t,b}$ while (26) corresponds to penalty of β. These penalty terms are such that the variables are pushed to take values either close to 0 or 1 which indirectly mimics the function of a binary variable. σ_1 and σ_2 are the weights associated with the two penalty terms. These weights are chosen such that the penalty terms are in the same range of the revenue terms and do not overpower them or become negligible so that we get an unbiased schedule. It can be seen that the resulting formulation becomes a NLP problem with a non convex objective function and all linear constraints.

2. *Reduced* **MILP formulation**: The solution of the NLP problem in the first step gives the continuous values of the variables $\alpha_{t,b}$ and β which are not all exactly 0 or 1 but some lie between 0 and 1. We can approximate and fix the values of those variables who are very close to 0 and 1 and solve the new MILP problem with reduced number of variables (*reduced* MILP). As the contribution/number of $\alpha_{t,b}$ is much higher than the β, we only approximate for $\alpha_{t,b}$ and do not make any assumptions for β. Hence, we define a threshold with a lower limit of γ^L and a upper limit of γ^H and follow the mentioned approach:

   - For $\alpha_{t,b} \leq \gamma^L$ - round off to 0 and for $\alpha_{t,b} \geq \gamma^H$ - round off to 1. Declare these $\alpha_{t,b}$ as parameters with the approximated binary values.
   - For all the $\alpha_{t,b}$ between these two limits $[\gamma^L, \gamma^H]$, pass them as variables and solve the *reduced* MILP problem again to get new binary values of the $\alpha_{t,b}$.

   Thus for the *reduced* MILP problem, the binary variables will be (1) the $\alpha_{t,b}$ who lie within the $[\gamma^L, \gamma^H]$ (let us denote them by the set $\mathbb{A}_1$) and all the β's (set $\mathbb{B}$). The objective function for such *reduced* MILP is as in (27). By doing this, we reduce the number of binary variables and thus save a lot of computation time. The flow of the entire approximation technique is mentioned in Algorithm 1.

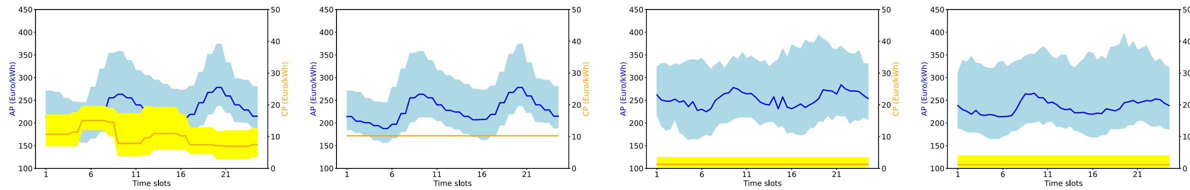
Algorithm 1 Approximation Algorithm

```
Replace binary variables α_{t,b}, β as continuous variables in the
  optimization problem.
Add penalty terms in the objective function as given by the Eqns.
  (25) and (26).
Solve The NLP optimization problem of (24).
Approximate the continuous variables α_{t,b} to be 0 or 1
  if α_{t,b} ≤ γ^L then
    α_{t,b}=0
  else if α_{t,b} ≥ γ^H then
    α_{t,b}=1
  else
    α_{t,b} ∈ {0, 1}
  end if
Solve The new MILP with reduced number of binary variables as
  in (27).
```

$$\max_{\mathbb{A}_1,\mathbb{B}} \sum_{t=1}^{T} (\mathcal{R}^{\mathrm{FCR}} + \mathcal{R}^{\mathrm{aFRR}} + \mathcal{R}^{\mathrm{mFRR}} + \mathcal{R}^{\mathrm{RR}}) - \sum_{b=1}^{\mathcal{B}} C_b^{\mathrm{deg}} \tag{27}$$

5. Experimental setup

Market details: We test the proposed trading strategy for aggregators with a real world dataset of the French balancing market. The



(a) $\mathrm{FCR}^{\mathrm{Up}}$ (b) $\mathrm{aFRR}^{\mathrm{Up}}$ (c) $\mathrm{mFRR}^{\mathrm{Up}}$ (d) $\mathrm{RR}^{\mathrm{Up}}$

Fig. 3. Spread of actual balancing market prices.

Table 3
Performance of forecasting model.

	$\mathrm{FCR}^{\mathrm{Up}}$	$\mathrm{FCR}^{\mathrm{Dn}}$	$\mathrm{aFRR}^{\mathrm{Up}}$	$\mathrm{aFRR}^{\mathrm{Dn}}$	$\mathrm{mFRR}^{\mathrm{Up}}$	$\mathrm{mFRR}^{\mathrm{Dn}}$	$\mathrm{RR}^{\mathrm{Up}}$	$\mathrm{RR}^{\mathrm{Dn}}$
MAPE	11.29	10.89	12.15	12.11	15.12	16.7	14.92	18.6

capacity and activation prices of ancillary services market are available with the RTE [7]. The capacity prices are different for each service but are the same for both the directions of a particular service. Capacity prices of services are much lower than their corresponding activation prices. Also, they have a very low variance as compared to the latter as seen in Fig. 3. Clearing of bids in capacity markets is to done to procure the requirements put forth by SO which are fairly constant. Hence a high variance is usually not seen in the cleared capacity prices. On the other hand, activation of the procured services is done to settle the real time imbalances of the system. Constantly changing quantum and direction of imbalance leads to highly varying activation prices in balancing energy markets on a daily basis as shown in Fig. 3. This variance creates a need for forecasting of prices.

Since, only time series data of prices of different services is available, no exogenous variables are considered to forecast these time series [22,23]. Use of exogeneous variables may also pose challenge in forecasting them and hence may lead to higher inaccuracy in the prediction of the target variable. The problem we considered in this paper is being solved by an aggregator who may not have access to the system data e.g., system demand, generation, network etc. to be used as exogenous variables. Activation prices are forecasted using the standard ARIMA model mentioned in Section 3.2. The Mean Absolute Percentage Error (MAPE) over the simulation period for all the services is mentioned in Table 3. Though these forecast errors seem to be on a higher side, we have observed that the forecasted price profiles have similar relative pattern as that of actual price profiles from the historical data. This results in similar choices of services with actual or forecasted prices and hence, does not affect the services selection to maximize the revenue.

Subscriber's battery dataset: The aggregator has 500 batteries of different technical specifications available with it. A distribution of battery capacities available with aggregator is shown in Fig. 4. Due to electrochemical constraints of battery, the SoC bounds of $SoC^{\min}$ and $SoC^{\max}$ are considered to be 10% and 90% of the battery capacity respectively. The charging/discharging efficiency of battery is taken to be 95%.

Aggregator assumptions: It is observed that the minimum time duration which is common for bidding blocks of all services is one hour. Thus, we have $\mathcal{T} = \{1, 2, 3, \dots, 24\}$ for this particular set-up. As the activation price used is forecasted, there is a level of uncertainty associated with it. To be within a safe bounds, we consider an error range of 25% and define $\zeta^L = 0.75$ and $\zeta^H = 1.25$ for calculation of activation probability π. Thus π follows a linear function and takes values between 0 to 1 when the bid price ranges from 0.75$\hat{\mathrm{AP}}$ to 1.25$\hat{\mathrm{AP}}$ respectively.

Techniques compared: On the described aggregator setup and market details, we study the performance of the three techniques mentioned below. All these techniques use IBM CPLEX solver [24] for MILP and NLP formulations on a laptop with 8 GB RAM.

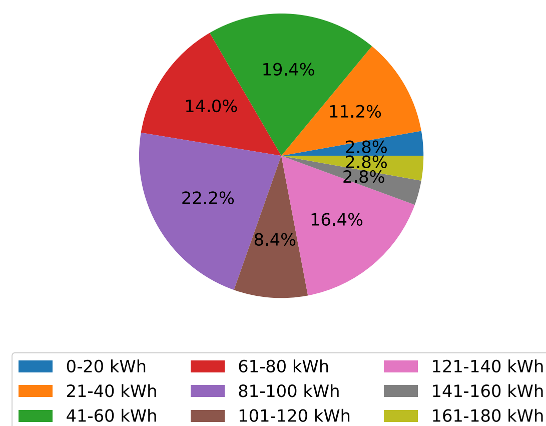
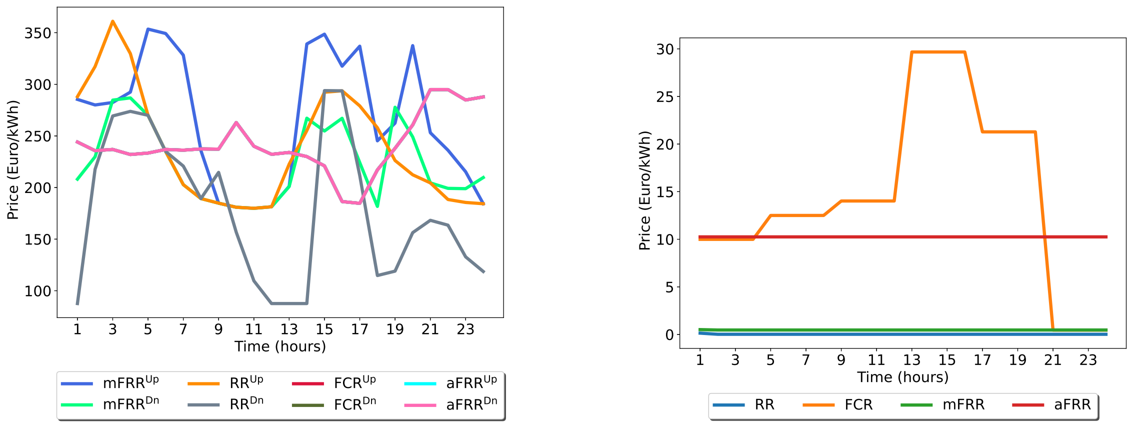


Fig. 4. Distribution of battery capacities Cap_b available with the aggregator.

1. **Baseline method**: We try to attempt to develop a simple baseline for the aggregator based on the logic of bidding for the highest price service to maximize the revenue. In this method, the aggregator first picks out two of the most profitable services of opposite directions based on their average prices over the day. These are the services for which the aggregator will bid for in the balancing markets. It then schedules its ESS assets such that the profit from those two services is maximized while the technical constraints of the assets are followed. This scheduling is done using a similar formulation discussed in Section 3.1 where the revenue terms and the bidding constraints of only selected services are active but all the battery related constraints are active. Compared to the proposed methods, this is a simpler and less complicated technique which might be preferred by the traders.
2. **Original MILP method**: This refers to the MILP formulation discussed in Section 3.1. When we simulate the setup for large number of ESS, it is found that the problem does not converge to give an optimal solution even after many hours of simulation. Hence, to get a solution within a reasonable time, we solve the original MILP with a tolerance; this tolerance is set using the option `mip gap` of the solver [25]. This mip gap tolerance sets a relative tolerance on the gap between the best integer objective and the objective of the best node remaining.
3. **Approximation method**: We introduce an approximation method specifically catered to this problem as described in Section 4. The weights σ_1 and σ_2 in the penalty terms of (25) and (26) are taken to be 0.1. The second step of approximation method is simulated for a threshold of $[\gamma^L, \gamma^H]$= [0.05,0.95] for $\alpha_{t,b}$.



(a) Activation Prices (b) Capacity prices

Fig. 5. Forecasted balancing market prices for the sample day.

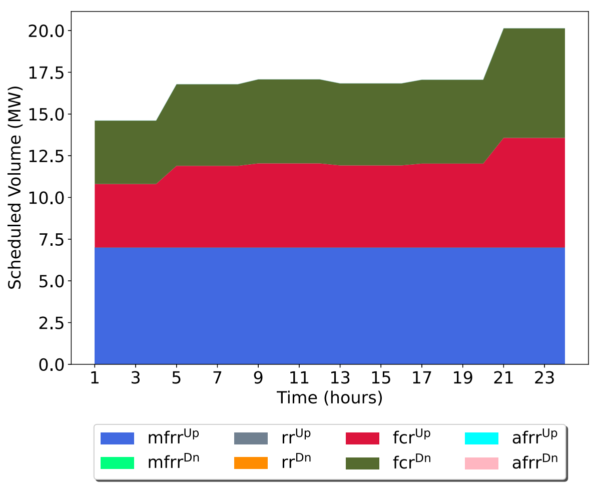


Fig. 6. Output bidding schedule from baseline method for the sample day.

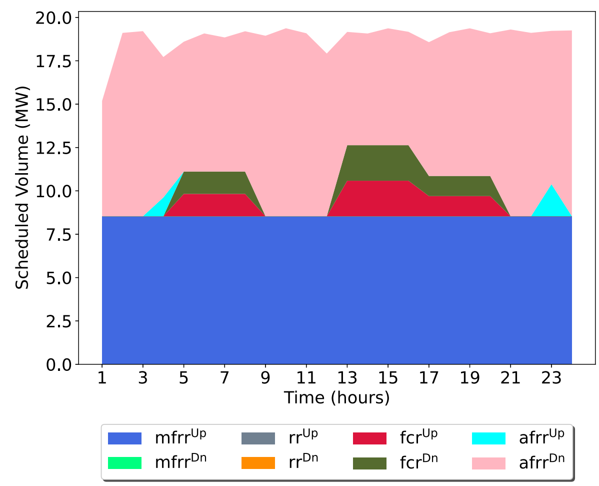


Fig. 7. Output bidding schedule from original MILP method for the sample day.

Metrics for comparison: The performance of the mentioned techniques is compared over 15 simulation days based on the following three parameters: (1) net profit earned (2) total volume scheduled for bidding in the markets and (3) total simulation time.

6. Results

The three solution techniques are tested with the French balancing market data and an ESS aggregator with a large number of batteries. The study is done over a duration of 15 days *1st April 2022–15th April 2022*. Fig. 5 shows the capacity and activation prices of different services for a sample day (*9th April 2022*).

Results of the baseline method: Based on the average price of the sample day (considering both activation and capacity prices), the highest paying service is mfrr$^{\text{Up}}$ followed by fcr$^{\text{Dn}}$. Thus for the baseline method, the aggregator schedules its capacity in these two services. As seen from the output bidding schedule of Fig. 6, the aggregator bids most of its capacity in mfrr$^{\text{Up}}$ followed by less volumes in fcr$^{\text{Up}}$ and fcr^{Dn} services. As fcr is a symmetric service, the aggregator bids equal volumes in both directions whereas a full day commitment is seen in mfrr$^{\text{Up}}$ which complies with the bidding rules.

Results of the original MILP method: The schedule obtained for the sample day from original MILP method *(mip gap = 3%)* is shown in Fig. 7. It can be seen that the aggregator bids most of its volume in two services - mfrr$^{\text{Up}}$ and afrr$^{\text{Dn}}$ followed by some lesser volume being scheduled in fcr$^{\text{Up}}$ and fcr$^{\text{Dn}}$. For mfrr$^{\text{Up}}$, there is a full day commitment of same volume whereas the committed volume changes each hour for afrr$^{\text{Dn}}$ service which is as per the bidding rules. Here we see, the combination of both — the most profitable service mfrr$^{\text{Up}}$ and the most flexible service in the opposite direction afrr$^{\text{Dn}}$ being dominantly scheduled in the output. A small volume is scheduled symmetrically for fcr in one block as it is the second highest rewarding service. It can be seen that the original method selects services based on profits and flexibility.

Results of approximation method: Now we discuss the results for the sample day using approximation method. A histogram of values of α's obtained from the first step of approximation method (approximated NLP) for the same sample day of Fig. 5 is as indicated in Fig. 8. It can be seen that almost half of the α's have values which are very close to 0 or 1. We intend to approximate these to their respective binary values and pass them as parameters in the second *reduced* MILP step of the approximation. Similar observations are made for almost all the simulation days. Hence, we have considered a tight threshold of $[\gamma^L, \gamma^H]$ = [0.05,0.95] for the second step of approximation method. The output schedule from the second *reduced* MILP step is as shown in Fig. 9. The bidding schedule obtained from the approximation method show similar allocations to the services as in the case with original MILP method. Most of the volume is scheduled for highest price service of mfrr$^{\text{Up}}$ and most flexible service of afrr^{Dn}. Here some of the volume is scheduled for fcr and afrr$^{\text{Up}}$ service as all the automatically activated

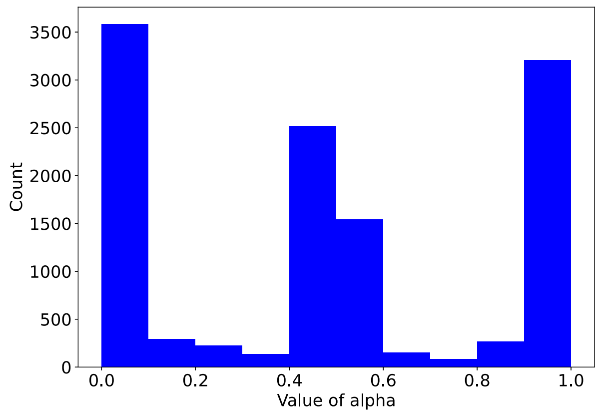


Fig. 8. Histogram of α values obtained from first step of approximation method for the sample day.

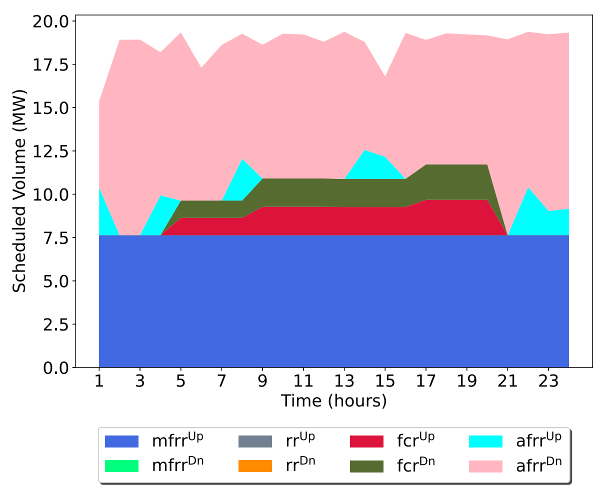


Fig. 9. Output bidding schedule from approximation method for the sample day.

services have the same activation prices. The slight difference in output volume schedules is due to approximations made in the solution technique. However, it is important to note that the total volume scheduled for bidding is almost same as that of original MILP.

Comparison of relative performance of the three techniques: Comparison of total scheduled volumes and profit earned for the mentioned techniques over the entire simulation duration is shown in Figs. 10(a) and 10(b) respectively. It can be seen that there are slight differences in output volume scheduled by all the three techniques. The average aggregated volume bid on a daily basis by the baseline method is 427 MW, by the original MILP method is 447 MW wheres the approximation method bids 434.8 MW on an average. The original MILP method gives better volume scheduling by 4.6% while the approximation method improves it by 1.8% in comparison to the baseline method. The daily average profit earned by the baseline method is 105,000 Euro, by original MILP is 125,000 Euro while by the approximation method is 123,000 Euro. In terms of profit, original MILP method improves the profit by 19.6% while the approximation method improves it by 17.8% when compared to the baseline method. It is thus evident that there is significant improvement in profit by both the proposed methods over the baseline method in spite of small differences in bid volumes. This behavior stays true to the proposed methods' objective of maximizing the profit rather than the volume. Henceforth, for brevity we will focus on analyzing the performance of the two proposed techniques of original MILP and approximation method.

Out of the two proposed techniques, original MILP performs better both in terms of profit and scheduled volumes. However, the computation time taken by these methods is different as shown in Fig. 11. It can be seen that the total time taken by the approximation method is considerably less than the time taken by the original MILP. Computation time of approximation method is almost 53% less than that of the original MILP method. This is because — in original MILP all the α's are considered as binary variables which makes the problem tedious resulting in a longer computation time. For the proposed approximation method, the first step of approximated NLP gets solved quickly as all the variables are continuous in nature. For the second step of *reduced* MILP, 56.8% of the α's close to 0 or 1 are approximated and passed as parameters and only 43.2% of α's are passed as binary variables. This decrease in the number of binary variables leads to reduction of total computation time of the method. It is to be noted that the results obtained from original MILP are with a mip gap setting of 3%. We could not get a converged optimal solution from the original MILP with a smaller mip gap. It can be said that there is a considerable saving in computation time with the approximation method when compared with original MILP with the mip gap setting of 3%. The average time taken by original MILP to solve one day is around 1988 s (33 min) while the time taken by the approximation method is 655 s (11 min) respectively. Despite the large number of variables, we believe the MILP takes only 33 min to run because a demand from the SO is large relative to the sizes of the batteries. Thus a good approximation can be obtained by allocating the batteries to the most profitable service.

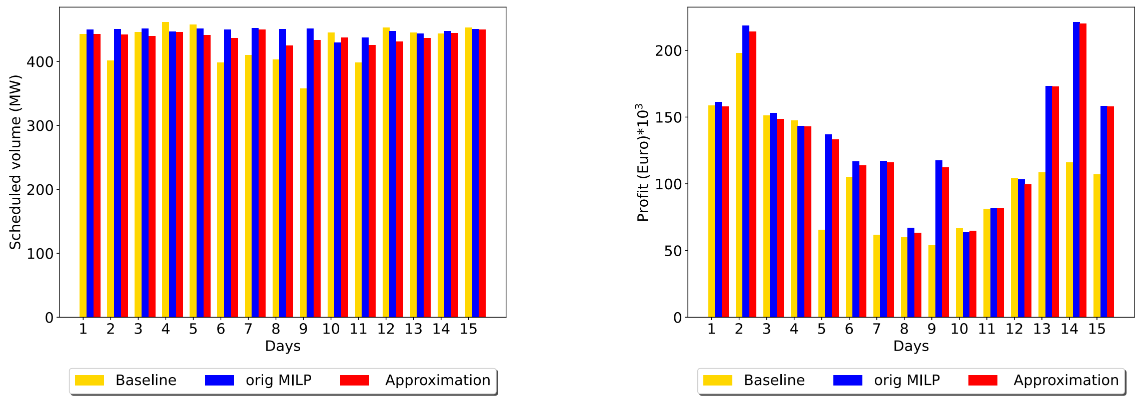
Comparison of approximation method and original MILP with increased mip gap: The average decrease in profit due to approximation method with respect to original MILP simulated with mip gap of 3% is around 1.8%. This profit performance is equivalent to simulating original MILP with an approximate mip gap of 5%. The profits obtained for both the techniques are same but there is some difference in their simulation times. The simulation time required for such a scenario is shown in Fig. 12. The average reduction in simulation time of original MILP with mip-gap of 5% is 49% which is worse than the approximation method. Thus, the approximation method gives results within less time.

Scalability: The approximation method gives us output bid schedules which are very close the results of the original MILP model while saving time. This savings in time becomes significant from scalability point of view. The time taken by the original MILP increases exponentially with increasing number of binary variables. But in case of approximation method, as the number of binary variables get significantly reduced in the second step of *reduced* MILP, the total time taken by it is considerably less when compared to the original MILP method. This is shown by the simulation time comparison of both the techniques for a larger dataset of 1000 batteries of Fig. 13.

Thus it can be said that among the three approaches, the baseline method takes least computation time but compromises on the optimal profit, the original MILP formulation gives better profit, but it may not be scalable for the real life implementations and the approximation method helps in ensuring scalability of the model with profit closer to the original formulation.

7. Conclusions

To the best of our knowledge, this is one of the first works that proposes a trading strategy across all services in a balancing market as an operation research problem. This strategy enables an ESS aggregator to bid for multiple services simultaneously while adhering to each service's bidding rules. We have also put forward an approximation method which is capable of achieving computational scalability without significantly sacrificing on the bidding performance. The proposed methods have been tested using real world data traces.



(a) Net volume scheduled for bidding

(b) Net profit earned

Fig. 10. Comparison of metrics.

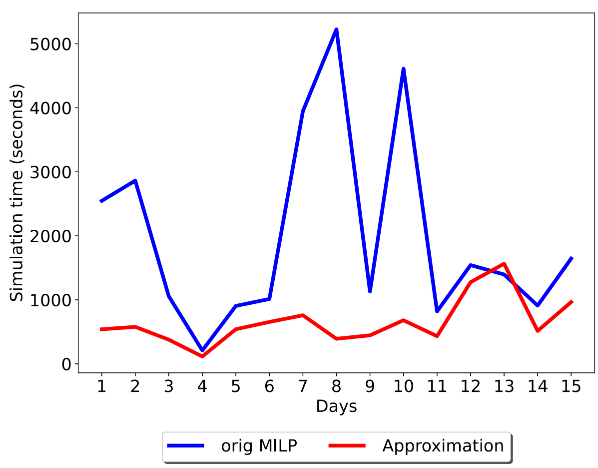


Fig. 11. Simulation time comparison.

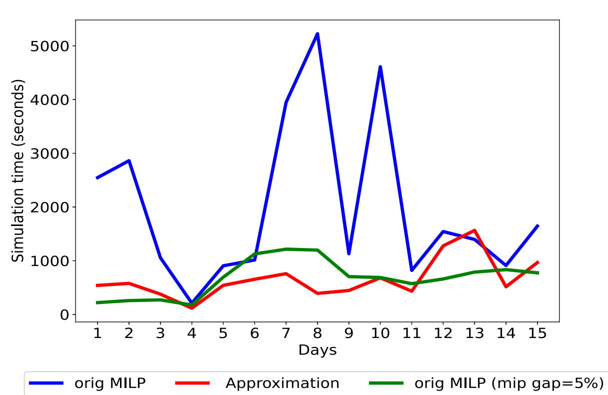


Fig. 12. Simulation time comparison of original MILP with mip gap of 5%.

Both the proposed methods perform better than the baseline method. Our approximation reduces the computation time with respect to the original MILP method by as much as 50% while giving comparable optimality. The proposed strategy can be further extended to include different DERs like roof-top solar PV, EV, demand response in the aggregator's portfolio.

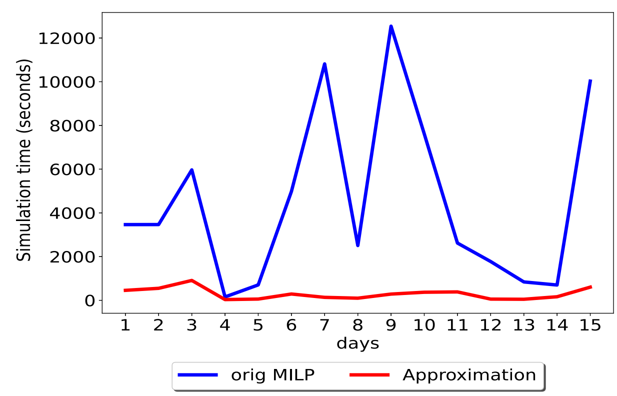


Fig. 13. Simulation time comparison for dataset of 1000 batteries.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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