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RESEARCH ARTICLE

Operational Planning Strategies to Mitigate Price Uncertainty in Day-Ahead Market for a Battery Energy System

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ABSTRACT As renewable energy sources become more prevalent, effective grid balancing becomes crucial due to their inherent uncertainty. Battery Energy Storage Systems (BESS) can enhance grid reliability and efficiency by complementing these variable sources. However, to encourage investments in BESS, market participation must be economically viable for owners. Energy arbitrage is one of the main revenue streams for BESS allowing them to buy electricity when prices are low and sell it when they become higher, thus optimizing the revenues. However, in energy markets such as the Day-Ahead market (DA), the BESS owners submit their bids/offers one day before delivery, without perfect foresight of the future rates. This uncertainty poses a challenge that limits the energy provision capabilities and can incur a loss of profit due to the imperfect price forecast. Tailored strategies are then needed to mitigate those uncertainties and minimize the profit loss. This article proposes different operational planning strategies for a BESS participating in DA. Specific interest is attached to the explainability of the proposed methods to assure high profits while reducing the model's complexity and computational time. The proposed strategies include 1) price forecast and scenario generation, using Geometric Brownian Motion (GBM) based either on a single-point forecast or historical data; 2) optimization process; and 3) choice of a single BESS bidding and operating schedule that is ultimately applied in real-time. Two baselines are introduced, one relying on a back-casting method, and a second based on traditional stochastic optimization. Several studies have neglected to thoroughly assess the bidding strategies by evaluating the profit against the actual prices. Hence, this study assesses the performance of the proposed methods and the baselines relative to the profit obtained in an ideal scenario with a perfect forecast in the French market over 2021.

INDEX TERMS Bidding strategy, energy markets, energy storage, price uncertainty, optimization.

I. INTRODUCTION

Renewable energy sources, especially wind, and solar energy, are expected to play a significant role in the world energy mix in the coming years [1]. The European Commission has projected an increase in the share of renewable energy in the final energy consumption of the European Union (EU) from 18.9 % in 2018 to 32 % by 2030 [1]. However, renewable generation volatility challenges grid operations to maintain stability and ensure a reliable power supply to consumers. Energy storage systems have emerged as a solution to tackle these emerging challenges while bringing more flexibility to the system [2]. As a result, both energy storage suppliers, and renewable energy producers have increased market prospects. Thus, the global installed energy storage industry is expected to reach 741 GW/1,890 GWh by 2030, with batteries accounting for 79 % of the total installed capacity [3].

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A. ABBREVIATIONS AND ACRONYMS

Abbreviations:

ESS	Energy storage system.
BESS	Battery Energy storage system.
MILP	Mixed integer linear programming.
DA	Day Ahead market.
ID	Intra Day market.
SOC	State of charge.
GBM	Geometric Brownian Motion.
AIC	Akaike Information Criteria.
SARIMA	Seasonal Auto Regressive Integrated Moving Average.

Indices and time sets

s	Scenario index for DA prices.
t	Time Index.
S	Set of considered scenarios.
T	Set of one day time steps.

Parameters:

π_t^{da}	Actual energy prices in DA (€/MWh).
$\hat{\pi}_t^{da}$	Day before energy prices in DA (€/MWh).
$\tilde{\pi}_t^{da}$	Forecasted energy prices in DA (€/MWh).
$\acute{\pi}_t$	Generated price scenario by Methods A, B.
dt^{da}	Time resolution for DA market (1 h).
P_{max}	Battery power capacity (MW).
E_{cap}	Battery Energy capacity (MWh).
$\eta^-_, \eta^+$	Charging and discharging efficiency (%).
soc_{max}, soc_{min}	Maximum and Minimum values for the state of charge (%).
ρ_s	Probability of occurrence for scenario s.

Variables:

$p_t^{+/-}$	Discharging / charging ESS powers (MW).
$p_t^{da+/-}$	Discharging / charging DA powers (MW).
u_t	Binary variable, if discharging = 1, if charging = 0.
soc_t	Battery state of charge (%).

B. RELATED WORK

Battery energy storage systems (BESS) are one of the envisioned technologies for wider storage adoption and can effectively participate in various markets as energy arbitrage, reserve, and balancing markets [4]. Due to the flexibility in the storage sizing, the operation horizon can align with the trading resolutions of these markets [5]. The optimal energy arbitrage typically consists of buying energy during off-peak hours at a lower price and selling it during peak hours at a higher price. Higher revenues can be expected with BESS able to generate high revenues by participating in both Day-Ahead (DA) and Intraday (ID) energy markets [6]. Like all energy markets (and pool markets in general) bids are submitted before the actual prices are known. Thus, bidding decisions and control schedules are typically taken based on price prediction (e.g. on a day-ahead basis) [7]. To address this, researchers have developed operational planning techniques that account for the uncertainty in energy or reserve prices.

In the context of BESS participating in the DA market, the bidding strategies usually consist of three main steps i) price forecast and price scenarios generation, ii) optimization process, and iii) evaluation of selected BESS schedule. The following section provides the related literature review for each of those steps.

1) PRICE FORECAST AND SCENARIO GENERATION

Several approaches have been presented in the literature to predict energy prices. One of the simplest assumptions is back-casting, which uses historical prices from the day before to schedule BESS operation for the next day [1] – i.e. somewhat equivalent to a simple persistent model. Furthermore, the authors in [2] added a random noise around the persistent profile to introduce some volatility/uncertainty. The standard deviation of this added noise displays a fixed value or increases noise with time [3] – to account for the increasing error for multi-step-ahead predictions. In [4] and [5], one price profile was forecasted using the Auto Regression Integrated Moving Average model (ARIMA) before different potential scenarios were generated using the Monte Carlo simulation. This process considered the inter-temporal relation between the hourly prices using the covariance matrix [6]. In [7], price uncertainty was modeled by a normal distribution probability density function (PDF) [8] and a Gaussian distribution was assumed with a 20 % standard deviation. Dedicated statistical models have been also used for price forecasting, as in [9] where a unified unit commitment and economic dispatch model used a stochastic process for forecasting and decision-making.

2) OPTIMIZATION PROCESS

After generating the prices, an optimization-based problem is formulated to reach the optimal BESS schedule that can be used in the bidding process. Various optimization techniques are typically implemented to output the scheduling of a BESS in energy markets: deterministic, stochastic optimization, and robust optimization are the most commonly used techniques. The optimization's output schedules can be bids in quantity (i.e. energy/ power over time) or bids in both quantity and prices. Indeed, in the case of large-scale assets (i.e. significant market power), market prices can be impacted by individual bids [10]. In reference [11], the authors investigated the optimal bidding for high-capacity participants in the Day-Ahead (DA) market, examining how BESS size and placement affect market prices and owners' profits. However, when dealing with small-scale BESS, such as the 10 MW BESS as in this paper context, market influence is relatively limited. In such a case, the BESS owner can be considered as a price taker, exclusively submitting quantity bids that are presumed to be consistently accepted.

In deterministic optimization, the market participant does not account for uncertainty and assumes a perfect forecast of the prices. This formulation of the problem is usually used to evaluate the benefits of a certain market and calculate the maximum theoretical profits [12]. Price uncertainty can be integrated with deterministic optimization using backcasting, where the market participant assumes low volatility of prices and uses one price profile from historical data to bid for the following day as investigated in [2]. The results showed that backcasting is suitable for DA bidding where 93% of the maximum profits could be achieved considering PJM market data of 2017. On the other hand, products with more volatile prices in the intraday market failed to achieve reasonable results using the same technique [3].

The second optimization technique is stochastic optimization, where the objective function is formulated to consider multiple potential scenarios along with their probabilities of occurrence [13]. The authors in [14] presented a multi-scenario optimization problem that focuses on the bidding of a price-taker BESS in joint energy and reserve markets with price uncertainty. Similarly, in [15], stochastic optimization was used for bidding in day-ahead and real-time price dynamics. Adaptive stochastic optimization has been introduced also to solve day ahead MILP deterministic models in [16]. A two-step stochastic unit commitment with wind power forecast uncertainty was used to schedule the battery storage in power system operation with renewable resources [17]. The authors in [18] proposed another stochastic programming framework to optimize energy and reserve quantity bids for storage units, considering the inherent market price volatility due to renewable availability. Moreover, a multi-stage stochastic optimization has been used in [24] and [25] to optimize the bids of a wind-PV-battery hybrid system in multiple markets that included day-ahead, intraday, and balance markets.

On the other hand, robust optimization does not necessarily require a wide range of scenarios and can only consider a boundary of possible changes in prices - e.g. minimum and maximum expected changes [20]. Despite the feasibility of the solutions over any realization of prices, it is a conservative approach that can limit the profits of energy arbitrage. As a result, robust optimization is mostly proposed for real-time energy markets [21]. The work in [7] introduces an innovative hybrid approach for stochastic and robust optimization techniques. The method allows the BESS owner to optimally bid in both DA and ID markets. Stochastic programming is employed to account for the uncertainties inherent in DA prices, while a robust optimization approach ensures conservative decision-making within the ID, particularly in light of its highly volatile price dynamics. Indeed, robust optimization stands as an optimal choice for real-time energy markets, giving the participants the flexibility to adjust their risk exposure. As the energy prices in real-time markets are more volatile, the risks of profitability and competitiveness increase.

TABLE 1. Comparison of related bibliography.

Ref	Storage technology	Uncertainty management in DA	Assessment Evaluation
[2]	BESS	Back casting	Yes
[4]	BESS	stochastic	No
[7]	BESS	stochastic	No
[13]	CAES	robust	No
[22]	CAES	robust	Yes
[18]	BESS	stochastic	No
[23]	BESS	probabilistic scenarios	No
This work	BESS	stochastic	Yes

3) EVALUATION OF THE SELECTED SCHEDULE

For a rigorous validation of any operational strategy, it is imperative to implement an assessment phase once the BESS schedule/bidding is settled. This evaluation relies on the computation of the actual revenues generated by the chosen operational schedule while considering the actual DA prices. Simultaneously, the maximum theoretical revenues can be computed through a deterministic optimization based on a perfect forecast (once the actual DA prices are known). Then, an error percentage is assigned to each bidding strategy, whose performances can then be assessed in terms of precision with the optimum. It is important to note that such an evaluation phase is oftentimes neglected in the literature. Ultimately, many related studies do not evaluate a specific BESS schedule once the optimization process they propose is performed. As an example, in the case of stochastic optimization performances are somewhat evaluated offline where they merely calculate the total expected profit but there is not a single schedule that is ultimately decided and evaluated [13], [18], [22], [25].

Table 1 summarizes some of the reviewed studies to mitigate uncertainty in DA prices for storage participation in energy markets. In a study by authors [2], an evaluation step was presented, but it relied on outdated data from 2016, making it incongruent with current energy price dynamics. Conversely, studies by [22] proposed a max-min formulation for DA bidding in worst-case scenarios, comparing it to the perfect case, yet the simulations were limited to Compressed Air Energy Storage (CAES) and did not extend to BESS. In [7], DA revenues resulting from different scenarios in stochastic optimization were only compared internally, lacking a specific reference. Similarly, [13] compared stochastic optimization results against robust optimization under different risk levels but omitted consideration of an optimal case for comparison.

In [23], authors factored probabilistic scenarios into revenue calculations for the DA market. Nevertheless, the primary objective was to assess BESS participation in energy markets and evaluate the impact of stacking services, accounting for battery degradation. Authors in [4] compared the performance of quantity price bids to that of quantity bids alone. However, the absence of a perfect forecast case as a baseline hinders the evaluation of how both methods perform in the real market. Stochastic simulations in [18] scrutinized the influence of BESS location, size, and efficiency on profits. Despite introducing and comparing three bidding strategies in real-time markets, there was no consideration of a perfect forecast case for comparison.

C. SCOPE OF STUDY AND CONTRIBUTION

The aforementioned works introduced several methods to mitigate price uncertainty when operating in the DA market. However, while some studies propose complex approaches for price forecasting, their practical application and expected results in an operational context are often not thoroughly considered. Additionally, the methods for generating price scenarios either depend on complex models requiring advanced statistical knowledge or overly simplistic approaches that add random noise to historical data. These methods often result in unrealistic price spikes that do not accurately reflect the evolution of DA market energy prices.

More importantly, the expected profits are not systematically analyzed against actual prices while applying a given BESS schedule Many studies, such as those in [13], [18], [22], and [25] calculate the total expected profit, but without selecting a single BESS operating schedule, applying it, and assessing the profit with regards to actual prices.

In this context, this paper proposes end-to-end self-explanatory operational planning strategies for a BESS involved in the DA market – i.e. prices forecast and scenarios generation, optimization for market bidding, and schedule selection followed by an evaluation that considers actual prices. The goal is to as close as possible to the maximum theoretical profits (i.e. obtained with a perfect forecast) while limiting the complexity of the models so that they can be rapidly implemented in industry. For the price scenario generation, two methods based on Geometric Brownian Motion (GBM) are implemented. GBM is a well-known method in stock forecasting, but not widely used in energy price forecasts. We adapt the stochastic process of GBM to capture the intertemporal relations between the hourly prices with no need to calculate probability density function or calculate covariance matrix as usually done in most statistical methods. Simple backcasting will be used as a baseline to compare the efficacy of the methods proposed (i.e. optimize the BESS schedule based on the prices observed the day before delivery). The study proposes five strategies to select the BESS bidding schedule from the generated price scenarios. Conventional stochastic optimization using Sample Average Approximation (SAA) is considered as a second baseline for the optimization techniques. An evaluation step is finally introduced where we compare the five strategies against the two baselines and a perfect forecast case. All the methods are assessed in terms of precision with the theoretical maximum revenue. The work aims to mitigate uncertainties in DA prices using explainable methods that can be used promptly and without the need for a great amount of historical data. The work also evaluates the need for a price forecast, where we show that adapting GBM to generate price scenarios from historical provides superior performances than more complex statistical approaches. The main contributions of this paper can be then summarized as:

- Complete operational planning for a BESS, including the forecast, the optimization, and the choice of a single operating schedule.
- A framework to generate day-ahead energy price predictions using Geometric Brownian Motion (GBM) based either on a single-point forecast or historical data.
- A sensitivity analysis of the revenue to the quality of forecasts, the prediction scenarios, and the control of the BESS.

The rest of the paper is organized as follows. Section II presents the strategy to bid under uncertainty in the DA market. It proposes two methods for generating price scenarios in addition to the deterministic and stochastic modeling of BESS operation in DA. Furthermore, it presents five strategies to select the optimum operation schedule for the battery. Section III displays the simulation and results. Furthermore, a sensitivity analysis between the forecast quality and the number of considered price scenarios is presented. Section IV concludes the paper and discusses the ongoing investigations.

II. THE BIDDING STRATEGY

The technical road map presented in Fig. 1 depicts the overall planning strategy with the different methods investigated, especially for the forecasting part with profile generation and the choice of the BESS schedule.

A. DESCRIPTION OF THE DAY AHEAD (DA) MARKET

DA enables the different market actors as generators (producers), consumers, retailers (suppliers), and traders to buy and sell energy daily. It aims at providing an initial operating schedule for the TSO to meet the predicted demand for the next day. DA market has then a horizon of 24 hours and a resolution of one hour in all European countries except in the United Kingdom, where the resolution is 30 min [24]. The energy trade is done in power exchange markets, where the bids are submitted before noon on day d-1 for the energy trade of day d. BESS can trade in the DA market to perform an arbitrage taking advantage of the energy price variations along the day. Hence, the BESS optimizes its operation to charge at the lowest possible prices and then to discharge at peak prices. The remuneration of these energy products is based on quantity (in €/MWh). The average price for DA energy products has increased from 51 €/MWh in 2018 up to 110 €/MWh in 2021 and yet increasing due energy crisis as deducted from the French market data [25]. This shows the potential of achieving energy arbitrage in the coming years. Optimization models are needed to decide the optimal dispatch schedule to maximize the profits. It is assumed that the BESS owner submits offers at high prices and bids

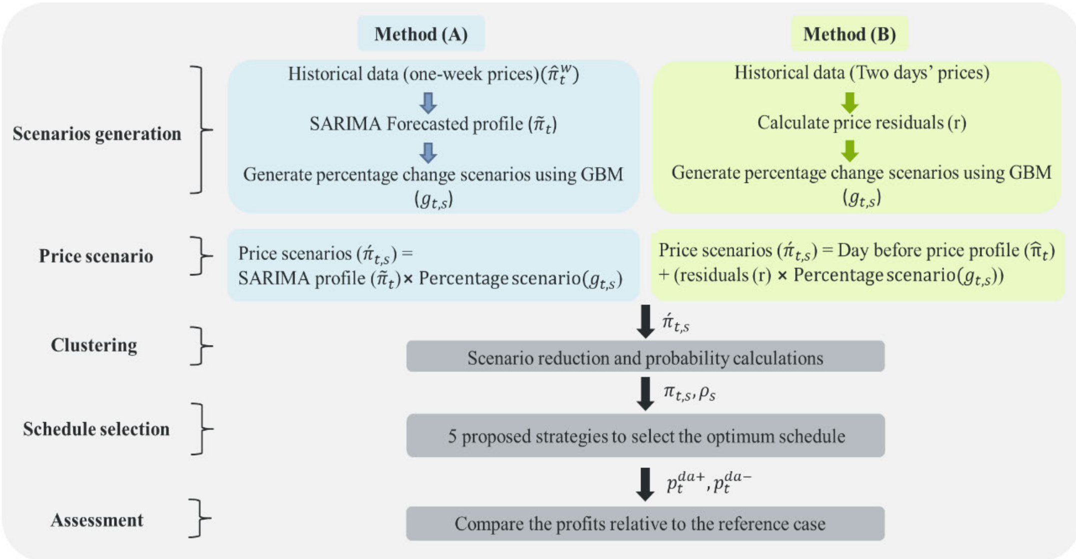

FIGURE 1. Framework of two stochastic operational planning methods of a BESS bidding on the day-ahead energy market.

at zero prices to ensure getting selected in the clearing process. In the scope of this paper, the BESS is considered a price taker where we only consider small-medium scale batteries. As a result, the BESS bids/offers are assumed to not affect the market clearing prices [26]. A mixed integer linear programming (MILP) model is proposed in the coming sections to simulate the BESS participation in the DA market.

B. SCENARIO GENERATION

1) METHOD(A) - SARIMA AND GBM

In the first method to generate Day ahead (DA) price scenarios, a Seasonal Auto Regressive Integrated Moving Average (SARIMA) model is used to generate a single-point forecast for each day (i.e. single profile). The model uses a combination of three elements: seasonality, trend, and residuals to create a forecast for future values of the time series [27]. Seasonality is used to capture the recurring patterns of the price that repeat at fixed intervals as hourly and daily. The trend accounts for non-seasonal differences and represents the long-term direction and movement of the time series. The residuals are used to estimate the unpredictable error [27]. As an example, Fig. 2 illustrates such a decomposition for prices over a week.

The prices one week before the day of delivery were given as input for the regression model to predict the following day. The process involves a stepwise search procedure and cross-validation to find the most optimal set of hyperparameters for the SARIMA model. A grid search is conducted across all possible combinations of parameters and the combination with the minimum Akaike Information Criteria (AIC) score is selected [28]. This cross-validation for the fitted parameters (p, d, q) and $(P, D, Q, m)_s$ was done automatically using the auto_arima package in Python [29]. The details are outside the scope of this paper.

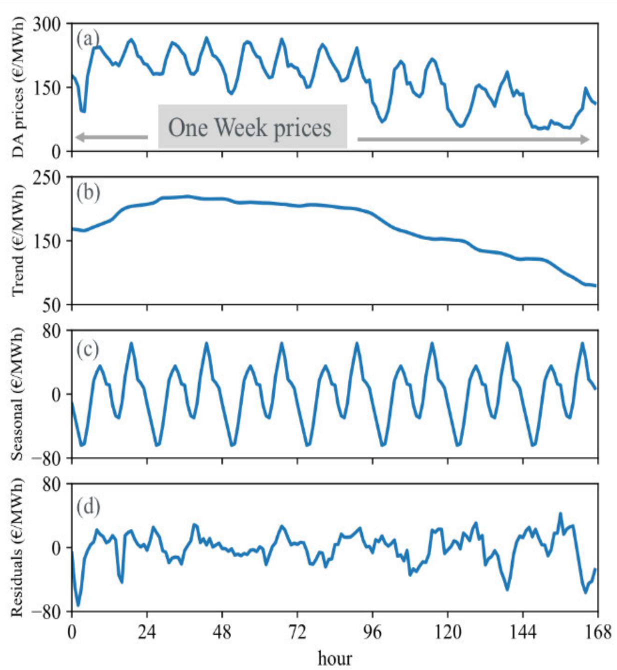

FIGURE 2. Decomposition of one-week historical prices in DA. a) One-week historical prices, b) Trend component, c) Seasonality component, d) Residuals component.

In the second step, Geometric Brownian Motion (GBM) is used to generate multiple scenarios around the SARIMA profile. GBM is a mathematical model typically used to describe the behavior of financial products over time. It is a continuous stochastic process that assumes that the logarithmic returns of an asset follow a normal distribution with constant drift and volatility [30]. In the context of energy prices, the mean represents the expected price level, and the volatility measures the uncertainty (or the risk) associated

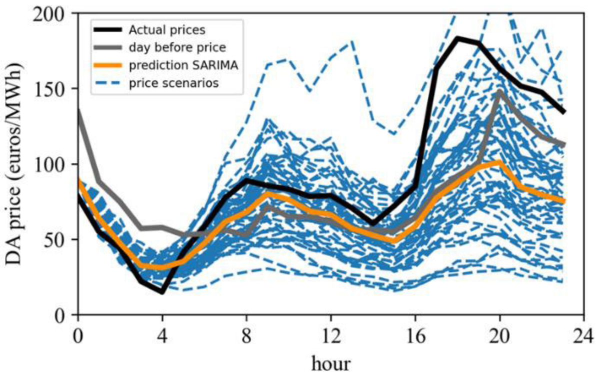

FIGURE 3. Generating 50 price scenarios using Method (A) (Day = 304).

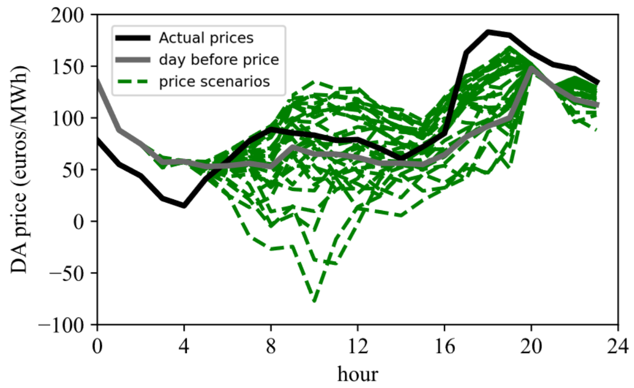

FIGURE 4. Generating 50 price scenarios using Method (B) (Day = 304).

with future price movements [31]. Hence, the forecasted scenarios can capture the continuously compounded growth rate and better model the underlying dynamics of asset prices [32]. Since the log return is additive over time, the log of the entire period can be calculated by summing all the individual time intervals. Thus, the drift μ and volatility σ can be calculated as follows in (1) and (2), where N is the number of data points ($\hat{\pi}_t^w$) is the price of one week of historical data, and t is an hourly time step. A price scenario ($\acute{\pi}_t$) is generated by multiplying a percentage profile (g_t) by the forecasted single-point profile ($\tilde{\pi}_t$) as shown in (3). Each percentage profile follows the stochastic formulation (4),where g_t is the percentage at time step t, g_0 is the initial point (100 %), and w_t is the random change from the wiener process (assumed to follow a Gaussian normal distribution). The percentage change is limited between (60 % - 140 %) of the one-point forecasted profile. Finally, the process are repeated to generate 500 price scenarios ($\acute{\pi}_{t,s}$) by creating multiple percentage scenario ($g_{t,s}$), an example of 50 scenarios is shown in Fig. 3.

$$\mu = \frac{1}{N} \times \sum_{t=0}^{t=168} \log\left(\frac{\hat{\pi}_t^w}{\hat{\pi}_{t-1}^w}\right) \tag{1}$$

$$\sigma = \sqrt{\frac{1}{N} \times \sum_{t=0}^{t=168} \left(\log\left(\frac{\hat{\pi}_t^w}{\hat{\pi}_{t-1}^w}\right) - \mu\right)^2} \tag{2}$$

$$\pi'_{t,s} = \tilde{\pi}_t \times g_{t,s} \tag{3}$$

$$g_t = g_0 \times e^{(\mu - \frac{\sigma^2}{2})t + \sigma \times w_t} \tag{4}$$

2) METHOD(B) - PRICE RESIDUALS

The second method to generate price scenarios does not rely on a specific forecast technique for the sake of simplicity. Instead, it considers the changes in historical prices over the two days before the delivery time. The price residuals (r) (i.e. errors with actual values observed) are calculated as the difference in the prices between these two successive days before the delivery day. Then, percentage scenarios (g_t) are multiplied by the residuals (r) to generate price scenarios as shown in (5). Compared to Method(A), the drift and volatility of the GBM are selected based on the log-returns of the historical price residuals. An example of generated price scenarios for one day is presented in Fig. 4. The dependence on historical data is visible over the first four hours, where all price scenarios display values close to the observations the day before – i.e. the price residuals at these hours were zeros.

$$\pi'_{t,s} = \hat{\pi}_t + \left(r \times g_{t,s}\right) \tag{5}$$

3) SCENARIO REDUCTION

To reduce the computational time of the optimization phase and to assure that the selected scenarios are representative of all possible cases, a conventional clustering is implemented on the profiles generated ($\acute{\pi}_{t,s}$) – with both methods (A) and (B). The clustering is based on the Euclidian distance between the scenarios using the K-mean algorithm [12]. The weights of the representative scenarios ($\rho_{t,s}$) are calculated based on the size of each cluster. The significance of the cluster depends on the ratio between the number of scenarios in each cluster compared to the total number of scenarios. An example of 10 reduced scenarios ($\pi_{t,s}$) for one day is presented in Fig. 5.

C. OPTIMIZATION PROCESS

1) BASELINE 1: DETERMINISTIC FORMULATION

The day ahead market (DA) has a resolution of one hour and a horizon of 24 hours, where the bids are submitted at noon of the day before delivery. The market bids are submitted as energy products in quantities of (MWh) and the remuneration for suppliers is in (€/MWh) [25]. The objective function (6) models the BESS operation in the DA market, where t ∈ T is a temporal set representing one day at a resolution of one hour (dt). The BESS model considers energy storage capacity (E_{cap}), maximum charging and discharging rates (p_{max}), charging and discharging efficiencies, battery state of charge's limits (soc_{min} and soc_{max}), and initial and final charge states. This deterministic formulation optimizes the BESS operation based on one price profile that can be either a perfect forecast profile (π_t^{da}) or a historical price profile ($\hat{\pi}_t^{da}$)

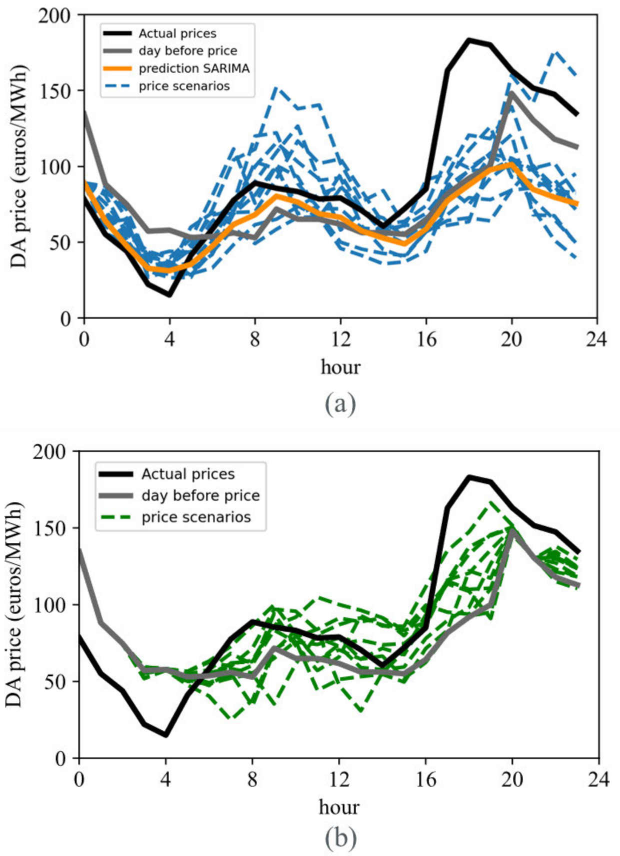

FIGURE 5. **Reduced 10 price scenarios (Day= 304). a) Method (A), b) Method (B).**

to represent the first baseline.

$$\max_{p_t^{da,-},p_t^{da,+}} r = \sum_{t\in T} \pi_t \times \left(p_t^{da,+} - p_t^{da,-}\right) \times dt \tag{6}$$

$$0 \leq p_t^{da,+} \leq p_{max} \times u_t \tag{7}$$

$$0 \leq p_t^{da,-} \leq p_{max} \times (1 - u_t) \tag{8}$$

$$soc_t = soc_{t-1} + \left(p_t^{da,-} / \eta^- - p_t^{da,+} \times \eta^+\right) \times dt \times \left(100/ E_{cap}\right) \tag{9}$$

$$soc_{\min} \leq soc_t \leq soc_{\max} \tag{10}$$

$$soc_{t=T} = soc_{t=0} \tag{11}$$

Constraints (7) and (8) define the limit of the DA discharging and charging powers to the BESS capacity. A binary variable ut is introduced to avoid potential simultaneous charging and discharging - the binary variable denotes the discharging mode. The state of charge of the battery (soc) is updated every time step, where charging and discharging efficiencies (η-, η+) are introduced. The (soc) is limited by (10) between predefined maximum and minimum state of charge levels. Equation (11) guarantees that the soc of the battery at the end of the day is equal to the one at the beginning of the day.

2) BASELINE 2: STOCHASTIC OPTIMIZATION USING SAA

In this traditional technique, the BESS schedule is obtained by running the stochastic optimization problem in (12) using the Sample Average Approximation (SAA) [4]. In which the expected value of the objective function is calculated over a finite set of price scenarios to represent the uncertainty. As expressed in (12), the formulation maximizes the expected profits over all the price scenarios (πt,s) taking into consideration their probability of occurrence (ρs). The BESS constraints (7) – (11) are aggregated along all the investigated scenarios (i.e. set S) in the stochastic operation. The result of this stochastic strategy is a single operating schedule for the battery that presents the optimal solution for the weighted average price profile of all price scenarios. The expected profit of this schedule is calculated using the actual prices on the day of delivery.

$$\max_{p_t^{da-},p_t^{da+}} r = \sum_{t\in T}\sum_{s\in S} \rho_s \times \pi_{t,s} \times \left(p_t^{da+} - p_t^{da-}\right) \times dt \tag{12}$$

In this section, we propose five strategies to generate the optimal BESS bidding schedule. The optimization is scenario-based, where the deterministic objective function is solved for all generated price scenarios resulting in a set of possible schedules. In practice, only one schedule profile shall be considered as the actual bidding quantities. Each strategy then includes a selection process for the optimal bidding schedule. The DA revenues are then calculated using the selected schedule and the actual prices of the DA market to be compared with the perfect forecast case.

3) S1: MOST PROBABLE PRICE SCENARIO

This strategy selects the most probable price scenario ($\bar{\pi}_t$) (maximum probability of occurrence) among all generated scenarios, as shown in (13). Then it solves the deterministic optimization, which is presented in (6), using this selected price profile.

$$\bar{\pi}_t = \left\{\pi_{t,s} \middle| \rho_s = \max\left(\rho_s\right)\right\} \forall t \in T, \forall s \in S \tag{13}$$

$$\max_{p_t^{da-},p_t^{da+}} r = \sum_{t\in T} \bar{\pi}_t \times \left(p_t^{da+} - p_t^{da-}\right) \times dt \tag{14}$$

4) S2: AVERAGE OF ALL BESS SCHEDULES

The second strategy solves the deterministic optimization problem in (6) once for each scenario with the usage of the corresponding price profile ($\pi_{t,s}$). The result of this iterative process is a set of possible schedules ($p_{t,s}^{da+}$, $p_{t,s}^{da-}$). The optimal schedule is then selected as the average of the resulting schedules, as shown in (15).

$$p_t^{da+}, p_t^{da-} = \left\{ \sum_s \frac{\left(p_{t,s}^{da+}, p_{t,s}^{da-}\right)}{s} \forall t \in T, \forall s \in S \right\} \tag{15}$$

The following three strategies use the same iterative optimization problem as discussed in S2. That results in generating a set of solutions for the BESS schedules

($p_{t,s}^{da+}$, $p_{t,s}^{da-}$). The possible solutions are evaluated based on different price profiles to select the optimum schedule. A yield function (y) is introduced to calculate the yield of each schedule (it is a KPI for evaluation only, not an actual DA profit). The BESS schedule which achieves the maximum yield is selected as the optimal one as shown in (16). In each strategy, the price profiles used to calculate this yield function are identified.

$$p_t^{da+}, p_t^{da-} = \left\{ p_{t,s}^{da+}, p_{t,s}^{da-} \middle| y_s = \max(y_s) \right\} \tag{16}$$

5) S3: PRICE SCENARIO-BASED STRATEGY

This strategy calculates the yield of each schedule using the corresponding price scenario ($\pi_{t,s}$), as shown in (17).

$$y_s = \pi_{t,s} \times \left(p_{t,s}^{da+} - p_{t,s}^{da-} \right) \tag{17}$$

6) S4: SARIMA PROFILE-BASED STRATEGY

In this strategy, all the schedules are evaluated using one price profile, which is the SARIMA forecasted price profile that day ($\tilde{\pi}_t$) as shown in (18).

$$y_s = \tilde{\pi}_t \times \left(p_{t,s}^{da+} - p_{t,s}^{da-} \right) \tag{18}$$

7) S5: MOVING MONTHLY AVERAGE PROFILE-BASED STRATEGY

This strategy proposes the monthly moving average prices (π_t^m) to evaluate the BESS schedules. Historical data are used to calculate (π_t^m) for each day and it is used to evaluate the yield of each scenario as shown in (19).

$$y_s = \pi_t^m \times \left(p_{t,s}^{da+} - p_{t,s}^{da-} \right) \tag{19}$$

III. OBTAINED RESULTS

Once the optimal BESS schedule is selected, the actual DA revenues can be calculated daily from the realized price profiles. Ultimately, the performances of the proposed strategies can then be compared with the two introduced baselines, and assessed to compare the optimal case with a perfect forecast (precisions to the optimum expressed in %).

Simulations are performed over two months of historical data in 2021 for the French electricity market which was collected from RTE and Entso-e 2021 databases [25]. The considered BESS is a 10 MW/10 MWh storage with $\eta^- = \eta^+ = 0.9$, $soc_{min} = 0.2$, $soc_{max} = 0.9$, and $\mathrm{soc}_0 = \mathrm{soc}_\mathrm{T} = 0.5$.

A. TWO MONTHS SIMULATIONS

1) RESULTS WITH METHOD (A)

At first, Method (A) is considered to generate price scenarios for each day over two months (November – December). The clustering phase is applied for every daily prediction with reduced numbers of scenarios - 10, 20, and 50 scenarios. Table 2 displays the obtained results, where the reference back-casting approach leads to a significant error of 49.3% (precision to optimum with perfect foresight). The results

TABLE 2. Simulation results for Method (A) over two months.

Optimization Methodology	Revenues €	Error %
Deterministic with Perfect forecast	31,592	--
Deterministic with Back casting	16,021	49.3
Stochastic method (A) – 10 price scenarios		
Baseline - stochastic	19,324	38.9
S1	17,988	43.1
S2	18,899	40.2
S3	19,383	38.6
S4	19,314	38.8
S5	21,537	31.8
Stochastic method (A) – 50 price scenarios		
Baseline - stochastic	19,086	39.5
S1	19,568	38.0
S2	18,781	40.6
S3	20,566	34.8
S4	19,370	38.6
S5	22,593	28.4

demonstrate the proposed planning produces superior results compared to the reference for all investigated strategies to select the BESS schedule. Analysis reveals that S5, which employs a monthly moving average of energy prices to evaluate the schedules, yields the optimal selection of BESS schedules. S3 is the second-best option, with performance improving as the number of considered scenarios increases. Alternatively, using S4 achieves the same level of error without being dependent on the number of scenarios. Notably, the first three strategies exhibit a similar range of errors over all scenarios considered. Finally, it can be concluded that three out of the five proposed strategies (S3, S4, S5) overperform the traditional strategy introduced in the literature with the weighted average of all price scenarios (Baseline).

A sample of the results in terms of daily profits is presented over 15 days in Fig. 6, where 50 scenarios are considered. The results show that usage of Method (A) with S5 always shows similar or better performance compared to the Baseline case except on the first day (n=0). The analysis reveals that this high error in revenues is due to the high error in the price forecast. An example is (n = 0, 11) where the forecast error exceeded 30 %. That opens the door to wondering about the impact of price forecast on the expected revenues that could be achieved by the proposed bidding strategy (see Section II-C for further details).

2) RESULTS WITH METHOD (B)

Table 3 displays the results obtained with Method (B) to generate the price profile scenarios. The results from the first three strategies to select the BESS schedule do not significantly improve the revenue compared to the reference case - error in the range of 44% - 47%. As observed with Method (A), S5 appears to be the most performant with around 35 % error with the optimum. More importantly, the results in Table 3 demonstrate that the overall performance of Method (B) is inferior to Method (A). The minimum error

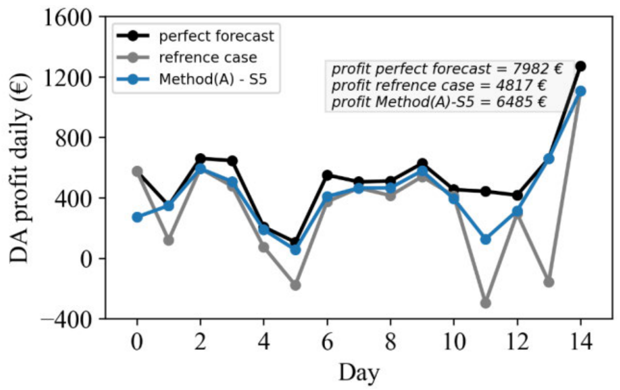

FIGURE 6. Stochastic results for Method (A) over 15 days – using 50 scenarios.

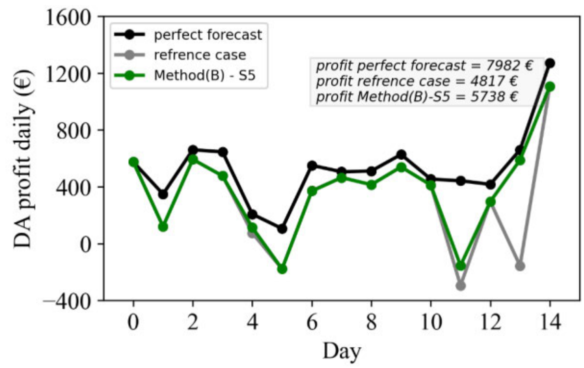

FIGURE 7. Stochastic results for Method (B) over 15 days – using 50 scenarios.

TABLE 3. Simulation results for Method (B) over two months.

Optimization Methodology	Revenues €	Error %
Deterministic with Perfect forecast	31,592	--
Deterministic with Back casting	16,021	49.3
Stochastic method (B) – 10 price scenarios		
Baseline - stochastic	17,467	44.7
S1	17,596	44.3
S2	16,853	46.6
S3	17,509	44.5
S4	19,301	38.9
S5	19,496	38.2
Stochastic method (B) – 50 price scenarios		
Baseline - stochastic	17,299	45.2
S1	17,046	46.0
S2	16,609	47.4
S3	15,557	50.7
S4	20,241	35.9
S5	20,375	35.5

reached is 35 % compared to the 28 % that could be reached using Method (A).

It can also be noticed that the effect of increasing the number of considered scenarios has a more significant impact on Method (B). A sample of the results is presented over 15 days Fig. 7, where 50 scenarios are considered. The results show that S6 always has a similar or better performance than the reference case. On the other hand, Method (B) has more points with a similar performance to the reference case compared to Method (A). This is due to the dependency on historical data, where both the reference case and Method (B) depend on the prices of the previous day.

B. ONE-DAY EXAMPLE

For illustrative purposes over one day, Fig. 8 .a, displays the optimal charging (-) and discharging (+) quantity bids for the DA using a perfect forecast case, while the results of the reference backcasting are displayed in Fig. 8.b. For the selected day, back casting results in a 91 % error as the charging/discharging process does not occur in the right time slots due to errors in price profiles. On the other hand, the scenarios generated from the SARIMA forecasted profile

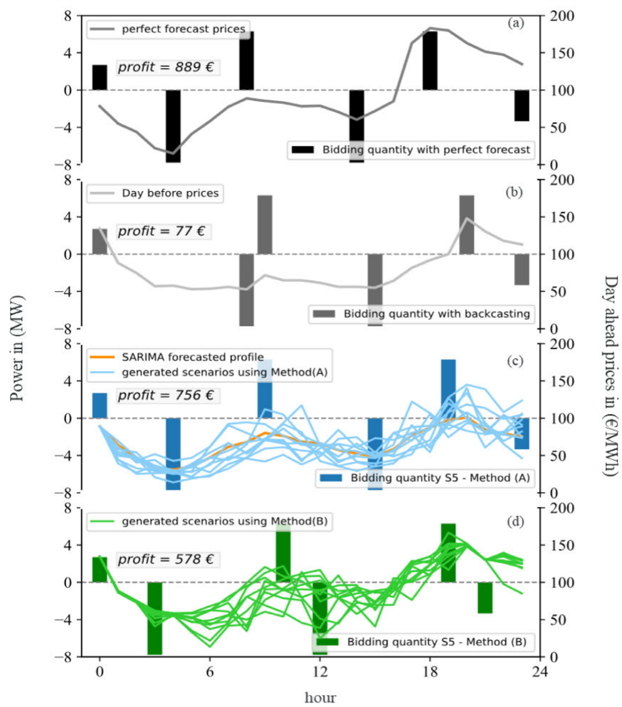

FIGURE 8. One-day BESS schedule (a) with the perfect forecast, (b) with back casting, (c) Method (A)-S5, (d) Method (B)-S5.

(presented in orange Fig. 8.c) could better identify the peaks on and off for the energy prices of the following days compared to the prices of the day before. That gave the BESS owner the possibility to optimize the bidding quantities at the right hours. As shown in Fig. 8, Method (A), using 10 scenarios, enhances the error in revenues by 76 % and reduces it to only 15 % error (756 €compared to the optimal result of 889 €). On the other hand, Method (B) shows less performance with an error of 35 % (578 €compared to the optimal result of 889€).

C. SENSITIVITY ANALYSIS ON THE FORECAST QUALITY

The analysis reveals that the accuracy of the SARIMA forecast varies in the range of 5 % to 45 %. Furthermore, the previous results showed that the number of considered

TABLE 4. Simulation results for Method (B) over two weeks.

#N	Optimization Methodology	Revenues €	Error %
	Deterministic with Perfect forecast	7,674	--
	Deterministic with Back casting	4,399	42.7
	Stochastic method (B)		
10	S5	4,608	44.3
20	S5	4,979	38.2
50	S5	4,784	33.0
100	S5	5,057	30.7

TABLE 5. Sensitivity analysis for forecast quality and number of scenarios.

Forecast error %	0 –10	10 – 20	20 – 30	30 – 40
# N	Error in revenues using highest profit scenario %			
10	20.1	38.4	47.4	53.9
20	20.4	31.4	36.5	49.9
50	22.9	29.8	36.9	44.3
100	23.8	25.4	33.7	35.8

scenarios has an impact on the profits. Hence, in this section, a sensitivity analysis on the impact of the forecast quality is performed over two weeks while considering the best strategy to select the BESS schedule (i.e. S5). It should be noted that Method (B) is not dependent on any forecast, as it only uses historical prices to generate scenarios. Thus, for Method (B) the only sensitivity is the number of considered scenarios. The results in Table 4 indicate that the error is drastically reduced by 14% when considering 100 scenarios compared to only 10 scenarios. It also is noted that considering a low number of scenarios (10 in this case) can result in worse results than the reference case.

In this sensitivity analysis, only S5 is used with Method (A) to select the BESS schedule over the two weeks. The forecast quality of the price profiles was classified into ranges of 0 - 10 %, 10 – 20 %, 20 – 30 %, and 30 – 40 %. for a different number of scenarios. The results of the sensitivity analysis, in Table 5, indicate a strong correlation between the price forecast errors and the revenues. In scenarios with low forecast error (0-10%), the revenue error was relatively low, and the results were notably improved by 22% compared to the reference case.

Furthermore, the results show that low error could be reached by only considering a low number of scenarios which decreases the computational time. On the contrary, for forecast errors ranging from 10 to 40 %, it was necessary to consider a high number of scenarios to outperform the reference case. As an example, in the case of high forecast errors (30 - 40 %), the performance only exceeded the reference case when considering 100 scenarios. The study emphasizes the importance of selecting the proper number of scenarios according to the available forecast quality as the results vary over a wide range of revenue errors (minimum = 20 % – maximum = 53 %). It can be concluded that in situations where the forecast error exceeded 20 %, the study suggests relying only on historical prices by using Method (B) to generate price scenarios. With forecast error higher than 20 %, Method (A) could not exceed the performance of Method (B) even with a greater number of scenarios.

IV. DISCUSSION

The proposed methods aim to maximize the profits of the BESS by performing energy arbitrage while mitigating the uncertainty of the energy prices in the DA market. However, in the case of considering a BESS as a part of a microgrid that includes intermittent sources and loads, the objective of the BESS will aim to minimize the total operating cost [21]. The bidding problem will then be more challenging due to the multiple sources of uncertainty, including the power output of renewables, load variation, and DA prices.

The provision of other ancillary services, such as the Frequency Containment Reserve (FCR) could be also considered. The operational planning for FCR will be adapted according to the structure of the market, where the revenues depend more on the reserve (€/MW) rather than the activated energy (€/MWh). Hence, the uncertainty of energy prices will not affect the profits in such a market. On the other hand, the uncertainty of the frequency measurements will affect the BESS activation schedule, which may lead to huge penalties in case the BESS does not have enough energy at the time of activation. In future studies, management strategies are proposed to control the state of charge level of the BESS while participating in the FCR market to maximize profits.

V. CONCLUSION

The bidding strategy includes price forecasting, price scenario generation, and a stochastic optimization process before five strategies are compared against traditional stochastic optimization to select the best BESS schedule. Two methods are proposed to generate price scenarios using Geometric Brownian Motion (GBM) - Method (A) involves forecasting one-point price profiles using SARIMA and Method (B) depends on the price residuals between each two successive days (no forecast needed). A reference case has been also introduced by using back-casting, where the prices of the day before are used to bid for the next day. Finally, all methods are compared to the optimum case with a perfect forecast.

The simulation results indicate that both methods outperform the reference case. Moreover, the results show that Method (A) (average of 28 % error) exceeds Method (B) (average of 35 % error) compared to the reference case (49 % error). On the other hand, Method (B) requires less computational time and less data as no forecast is needed. Finally, a sensitivity analysis over two weeks demonstrates that the performance of stochastic optimization using Method (A) is dependent on the accuracy of the forecast In cases where the forecast accuracy is over 80 %, it is recommended to employ Method (A), achieving low errors of revenues around 20 % compared to 42 % in the reference case. Alternatively, Method (B) is preferable with only 30 %. The analysis also revealed that considering a high number of scenarios is more critical for Method (B) which is a tradeoff between computational time and complexity as no forecast is required. The proposed strategy can provide a guide for BESS operators dealing with a third party to get the price forecast.

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