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Strategies for Combined Operation of PV/Storage Systems Integrated to Electricity Markets

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Abstract—The increasing share of photovoltaic (PV) power in the global energy mix presents a great challenge to power grid operators. In particular, PV powers intermittency caused by varying weather conditions can cause mismatches between energy production and expectation. Battery Energy Storage Systems (BESS) are often put forward as a good technological solution to these problems, as they are able to mitigate PV power forecast errors. However, the investment cost for such systems is high, which makes their use in operational contexts difficult. In this paper, we compare several strategies to manage a PV power plant coupled with a BESS in a market environment. They are obtained by stochastic optimization using a Model Predictive Control (MPC) approach. This paper proposes an approach that takes into account the ageing of the BESS, both at the day-ahead level and in the real-time control of the BESS, by modeling the cost associated with BESS usage. As a result, the BESS arbitrates between compensating forecast errors and preserving its own life expectancy, based on both PV production and price scenarios derived from probabilistic forecasts. A sensitivity analysis is also carried out to provide guidelines on the optimal sizing of the BESS capacity, depending on market characteristics and BESS prospective costs.

Index Terms—photovoltaics, solar power integration, storage systems, electricity markets

I. INTRODUCTION

The significant share of PV power employed in several countries causes discrepancies between expected and actual energy production. This is a major issue for Transmission System Operators (TSO), which have to ensure that energy production and demand always match. Most countries apply policies whereby the risk is borne by the PV plant operators, which pay the TSO for any discrepancies between their day-ahead forecast production and the real one.

BESS units are viewed as a very good solution to deal with these problems, thanks to their ability to compensate for errors in the forecasts. However, these systems are costly and their actual financial benefit is difficult to quantify in the long term, which makes PV plant operators reluctant to install them. Thus, it is very important to define strategies that ensure the optimal operation of a PV/BESS system, so that the benefit of installing a storage system is maximized. Two strategies are required: one for the day-ahead level when bids are submitted to the electricity market, and one for the real-time control of the BESS.

Several papers propose bidding strategies at the day-ahead level for standalone large-scale BESS [1], [2]. The optimal

offering strategy is largely dependent on market design. The standard method for real-time control of PV/BESS is Model Predictive Control (MPC). This consists in optimizing the control of the BESS on a receding horizon, in order to take into account the forecast future state of the system when optimizing the next time step. Different loss functions can be optimized on the receding horizon. In most cases, the optimized function is either the producers profit [3], [4] or the total energy imbalance [5]. Some authors also propose an MPC approach to bid on intra-day market sessions [6], [7].

However, several important points are often neglected in the literature. The first element is the ageing cost of a BESS. It is mentioned in [4] where constraints are defined to improve the life expectancy of the BESS, and in [7] where the MPC loss function is penalized by the total amount of energy flowing in and out of the BESS. At the day-ahead level, [1] considers ageing with a finer modeling. While few papers consider the uncertainty of renewable energy forecasts, [2] and [8] model this uncertainty using production scenarios.

Here, we compare several strategies to manage a PV power plant coupled with a BESS in a dual-price market environment, both at day-ahead and intra-day levels. These strategies take into account inherent uncertainties in PV generation through production scenarios derived from probabilistic forecasts and scenario reduction. The strategies are obtained by stochastic optimization using an MPC approach. In this paper, we propose to use a loss function that considers a fine modeling of the ageing cost of the BESS at each level. This allows the BESS to arbitrate between generating profit and preserving its own life expectancy in day-ahead and real-time. A closed-form solution to the market penalties minimization problem at the real-time level is also proposed as a benchmark for the MPC approach.

In section II, the different strategies for controlling the PV/BESS system at the day-ahead level and in real-time are presented. Section III presents the test case of the study, and finally section IV presents the results and draws the conclusions of the paper.

II. METHODS

A. Day-ahead Offering Strategy

Two methods are proposed for the day-ahead offering. The first method is used when the BESS only participates in the

real-time control of the plant. The second one is used when the BESS participates at both levels.

Both methods rely on the formulation of the revenue in a dual-price electricity market. In that setup, imbalances are settled at a different price depending on their sign. The revenue of a PV/BESS participant for a given market time unit is:

$$R(S) = S\pi + (P - S)\pi_R \quad (1)$$

Where P is the energy production of the participant in MWh, S is the energy sold at the day-ahead level in MWh, π is the spot price in €/MWh and π_R is the balancing price in €/MWh i.e. the price that any participant has to pay for its deviations from its day-ahead schedule. This price is dependent on the sign of the imbalance, which means $\pi_R = \pi_+$ if $P > S$, π_- otherwise. The S bids can be separated between the part coming from the stochastic PV production S_{PV} and the part coming from the deterministic BESS planning S_{BESS} . Similarly, the production is separated between its stochastic part P_{PV} and the energy coming from the BESS P_{BESS} . Since the BESS is controllable, it is assumed that $P_{BESS} = S_{BESS}$. 1 can be rewritten as follows:

$$R(S_{PV}, S_{BESS}) = P_{PV}\pi + (P_{PV} - S_{PV})(\pi - \pi_R) + S_{BESS}\pi - C_{BESS}(S_{BESS}) \quad (2)$$

C_{BESS} is the usage cost of the BESS obtained with the rainflow counting algorithm [9]. The ageing of the BESS can be divided in two components, i.e. the cycling ageing caused by the cycling ageing of the BESS, and its calendar ageing, which is the degradation caused by time. In the remainder of the paper, we will focus on the cycling ageing of the BESS and consider its calendar ageing as a given lifetime. The end of life of the BESS is defined as the minimum lifetime given by the cycling and calendar ageing.

When the BESS is not used at the day-ahead level, all of the terms that depend on the battery are null, reducing the revenue to equation 1. In these conditions, it has been proven that the optimal bid B^* that minimizes the penalties for the producer is given by [10]:

$$B^* = F^{-1} \left(\frac{\pi - \pi^+}{\pi^- - \pi^+} \right) \quad (3)$$

Where F is a forecast Cumulative Distribution Function (CDF) of the energy production of the plant. The application of this strategy for a PV power plant thus requires a probabilistic PV power forecasting model, and a forecasting model of the spot and regulation prices.

When the BESS is used at both the day-ahead and the real-time level, the entire formulation of the revenue from 2 is optimized. Since there is no constraint between S_{PV} and S_{BESS} , the optimization problem is separable. We must then solve the two problems:

$$S_{PV}^* = \underset{s \in \mathbb{R}}{\operatorname{argmax}} (P_{PV}\pi + (P_{PV} - s)(\pi - \pi_R)) \quad (4)$$

Without constraints, and

$$S_{BESS}^* = \underset{s \in \mathbb{R}}{\operatorname{argmax}} (S\pi - C_{BESS}(S)) \quad (5)$$

Under the constraints:

$$-\eta_{Dis}S \leq P_{PV} \quad (6)$$

$$-\frac{(Cap - E_{BESS})}{\eta_{Ch}} \leq S \leq E_{BESS} * \eta_{Dis} \quad (7)$$

Where Cap is the total capacity of the BESS, E_{BESS} is the energy remaining in the BESS at the time considered, and η_{Dis} , η_{Ch} are respectively the efficiencies of the BESS for the discharge and the charge. The first constraint ensures that the BESS is only charged from the PV plant and not from the grid, and the second constraint ensures that the BESS cannot contain more energy than its capacity, or less than 0.

The first subproblem is the same as the problem of the participation without a BESS, so the solution from 3 is used.

For the second problem, we can identify the temporal part of the problem from the second constraint. One of the essential characteristics of PV power forecasts is the positive correlation between the forecast errors and consecutive timesteps. In other words, if a forecast error is positive (resp. negative) for a given timestep, the forecast error for the following timestep is also very likely to be positive (resp. negative). This is a problem for BESSs, because since a BESS can compensate forecast errors, a significant error present on several consecutive scenarios would quickly either charge the BESS to its maximum or discharge it to its minimum, depending on the sign of the error. Due to the temporal correlation of the errors, this worst case scenario is much more likely than the consecutive distributions might suggest, if they were considered independent.

To account for this temporal correlation, and to model the uncertainty of the forecasts, a large number of PV production scenarios are generated following [11]. Then, the scenarios are reduced using a Partition Around Medoids (PAM) algorithm, and the optimal day-ahead planning is computed by maximizing the median of the daily revenue using equation 2 summed over the whole day. The energy remaining in the BESS is tracked to ensure that the second constraint is respected. Several risk levels are compared with the benchmark strategy where the BESS is not considered at the day-ahead level.

Then the first method (the BESS only participates in the real-time control of the plant) consists in bidding the solution of the first subproblem using equation 3 with a forecast CDF of the PV power and a deterministic forecast of the regulation prices. This method is referred to as method DA0. When the BESS participates in the bidding process, the two subproblems are solved. This second method is referred to as method DA1.

B. Real-time Control

For the real-time control, two methods are defined.

The first one minimizes the term arising from imbalances between the bids and the PV/BESS production. Since we are

in real time, the bids are already submitted and the market has been cleared. Thus, the spot prices π are known and the sole design variable is the BESS output P_{BESS} . The BESS is allowed to deviate from its planning S_{BESS} to compensate deviations coming from the PV power forecast error, thus we do not have $P_{BESS} = S_{BESS}$ anymore. In this case, the revenue for the next time step writes:

$$R(P_{BESS}) = P_{PV}\pi - (P_{PV} + P_{BESS} - S)(\pi - \pi_R) + P_{BESS}\pi - C_{BESS}(P_{BESS}) \quad (8)$$

For the first method, we focus on reducing the penalties, so we neglect the term $P_{BESS}\pi$ and the BESS usage costs $C_{BESS}(P_{BESS})$. The first neglected term represents a profit that can be obtained from the difference in spot prices during the day. However, this profit is supposed to have been taken care of at the day-ahead level. Besides, this profit alternates between positive and negative values depending on the charge or discharge of the BESS. Its impact should then be reduced when summed over several timesteps. On the other hand, the penalty term $(P_{PV} + P_{BESS} - S)(\pi - \pi_R)$ is always positive. Finally, neglecting the BESS usage costs allows us to propose a closed form solution to the revenue maximization problem.

The expectation of the penalty term Pen for the next time step writes:

$$\mathbb{E}(Pen) = \int_0^{P_n} (p + P_{BESS} - S)(\pi - \pi_R)f_{PV}(p)dp \quad (9)$$

Where P_n is the maximum amount of energy that the plant can produce on a given time step, and f_{PV} is the Probability Distribution Function (PDF) of the PV power. Since π_R is dependent on the sign of the imbalance, the expectation of the penalty term must be rewritten:

$$\mathbb{E}(Pen) = \int_0^{S-P_{BESS}} (p + P_{BESS} - S)(\pi - \pi_-)f_{PV}(p)dp + \int_{S-P_{BESS}}^{P_n} (p + P_{BESS} - S)(\pi - \pi_+)f_{PV}(p)dp \quad (10)$$

On the French electricity market, the prices are defined so that imbalances that support the grid imbalance at the national level are not penalized. That is:

$$\pi_+ = \pi, \pi_- > \pi \text{ if the grid is short of energy} \quad (11)$$

$$\pi_+ < \pi, \pi_- = \pi \text{ if the grid contains excess energy} \quad (12)$$

We suppose that we have an estimation of the probability p_G for the grid to be short on the national level. We can then substitute the forecast regulation prices π_+, π_- by random variables π_{pos}, π_{neg} modeled by a sum of Dirac distributions:

$$\pi_{pos}(x) = p_G\delta(x - \pi) + (1 - p_G)\delta(x - \pi_+) \quad (13)$$

$$\pi_{neg}(x) = p_G\delta(x - \pi_-) + (1 - p_G)\delta(x - \pi) \quad (14)$$

Which gives:

$$\mathbb{E}(Pen) = p_G(\pi - \pi_-) \int_0^{S-P_{BESS}} (p + P_{BESS} - S)f_{PV}(p)dp + (1 - p_G)(\pi - \pi_+) \int_{S-P_{BESS}}^{P_n} (p + P_{BESS} - S)f_{PV}(p)dp \quad (15)$$

Using the variable change $x = P_{PV} - S$, we get:

$$\mathbb{E}(Pen) = p_G(\pi - \pi_-) \int_0^{-P_{BESS}} (x + P_{BESS})f_{PV}(x + S)dx + (1 - p_G)(\pi - \pi_+) \int_{-P_{BESS}}^{P_n-S} (x + P_{BESS})f_{PV}(x + S)dx \quad (16)$$

Finally, using the Leibniz rule for differentiating under the integral sign, we obtain:

$$\frac{d\mathbb{E}(Pen)}{dP_{BESS}} = p_G(\pi - \pi_-)F_{PV}(S - P_{BESS}) + (1 - p_G)(\pi - \pi_+)(1 - F_{PV}(S - P_{BESS})) \quad (17)$$

The second derivative is:

$$\frac{d^2\mathbb{E}(Pen)}{dP_{BESS}^2} = -p_G(\pi - \pi_-)f_{PV}(S - P_{BESS}) + (1 - p_G)(\pi - \pi_+)f_{PV}(S - P_{BESS}) \quad (18)$$

This second derivative is always positive by definition of the regulation prices. Thus, when equaling the first derivative to 0, we find the minimum:

$$P_{BESS}^* = S - F_{PV}^{-1} \left(\frac{1}{1 + \frac{p_G}{1 - p_G} \frac{\pi_- - \pi}{\pi - \pi_+}} \right) \quad (19)$$

The first method is then to compute a forecast distribution of the PV power, deterministic forecasts of the regulation prices, and the probability that the system will be short, and to inject them into this optimal solution. Although the solution is in closed form, the BESS constraints prevent the use of this solution more than one time step ahead, and the BESS usage cost is neglected. This is referred to as method RT1.

The second method is very similar to the offering strategy including the BESS, using a Model Predictive Control (MPC). This means that the whole revenue formulation from 8 is maximized over the N next time steps, then the first time step of the optimization result is used as the command for the BESS. This allows taking into account the future forecast

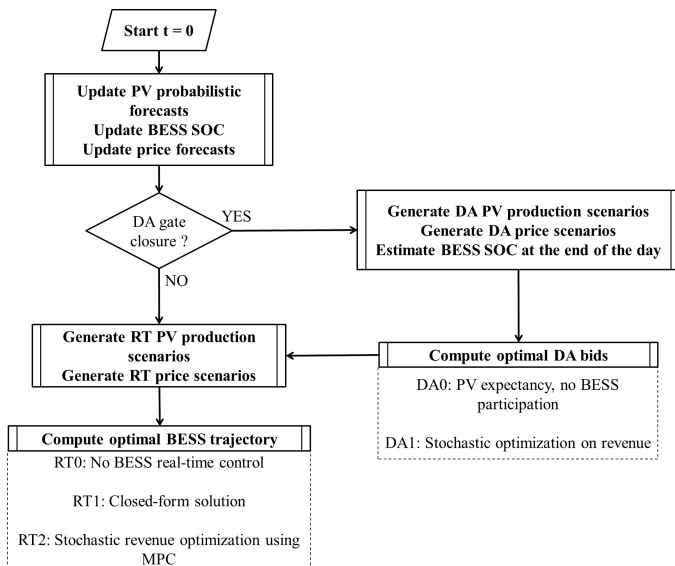


Fig. 1. Flowchart of the control algorithm

state of the system in the real-time control. Besides, two more differences exist with the offering strategy including BESS.

The first one is that since we are in a real-time setting, the spot prices and bids are known, as for the first real-time strategy. As a result, the sole design variable is the BESS command. The second difference is that we introduce a new constraint to the real-time optimization:

$$S_{BESS} \leq E_{BESS} \quad (20)$$

This constraint ensures that the day-ahead BESS planning is not violated, and mitigates the antagonist effect of using the BESS in real time when a day-ahead schedule has already been set. This second method is referred to as RT2.

III. TEST CASE

A simulation of the control of the PV/BESS is performed for a large PV plant located in France for a whole year (June 2016 to June 2017). It is located at longitude 1.20569, latitude 43.56022 and has an installed power of 6 876 kWp. Several storage sizings are evaluated.

The entire control is carried out taking an MPC approach. For each time step, the PV power and market quantities forecasts are updated based on the inputs known at the time. Then, if the day-ahead market closes for the considered time step, bids are submitted for the next day using one of the two methods from section II-A. The command for the next time step is obtained using one of the two methods from II-B. Then, the process goes to the next time step, updates the BESS State Of Charge (SOC), the PV power and market quantities forecast, and continues the algorithm until the final time step. A flowchart of the algorithm is represented on figure III.

PV power forecasts are obtained from an Analog Ensemble model [12] using Numerical Weather Prediction (NWP) from

TABLE I
EVALUATED STRATEGIES

Strategy	DA control	RT control
S0 (benchmark)	DA0	RT0
S1	DA0	RT1
S2	DA0	RT2
S3	DA1	RT1
S4	DA1	RT2

the European Center for Medium-range Weather Forecasting (ECMWF), along with in situ measurements and satellite data to improve short-term forecasts. Spot price forecasts are obtained using a Support Vector Regression (SVR), using forecasts of national electricity demand provided by the French TSO along with the month, hour and day of the week. Regulation prices are obtained by a k-nearest neighbor approach conditioned by the spot price forecast.

The BESS considered in the test case is a Lithium-Ion storage system. Ageing parameters for the rainflow counting algorithm are taken from [13] and [14]. Regarding costs, prospective values for the year 2030 from [14] are used in the base case, that is a 200 €/kWh investment cost, although the sensitivity to this parameter is studied in section IV-B.

Different combinations of day-ahead and real-time methods are evaluated. The sensitivity of the results to the installed capacity of the BESS and its investment costs is studied, providing guidelines on the sizing of the BESS for such applications. The different method combinations tested are summarized in I.

IV. RESULTS

A. Test Case Results

The results of the study are shown on table IV.

It is clear from the results that all of the strategies contribute to reducing the imbalance of the plant. The more storage capacity is available, the greater the reduction of the imbalances, except for strategy S3. For this strategy, the day-ahead method is in opposition with the real-time method, since there is no constraint to ensure that the day-ahead storage planning remains feasible when performing the real-time control. The higher the storage capacity, the more errors can be compensated, but the more the BESS is used in real-time. It seems that an equilibrium for this strategy exists at a storage capacity of around 25 % of the installed power, because the imbalance is lowered until this capacity is reached, and then increases again.

The strategies S2 and S4, which use the second method for the real-time control of the PV/BESS, provide a lower diminution of penalties than strategies S1 and S3, compared to the imbalance diminution. Thus, the second real-time control method seems to be less able to compensate critical errors, which generate significant penalties. However, since the usage cost of the batteries is included in the second real-time method, the battery life loss is significantly lower for strategies S2 and S4. Still, even if this usage cost is decreased, the BESS life

TABLE II
EVALUATION RESULTS

	Storage capacity = 10 % of installed power over an hour			
	S1	S2	S3	S4
Error reduction (%)	3.27	3.93	3.81	3.61
Penalties reduction (%)	3.67	3.56	3.94	2.21
Average energy price improvement (%)	0.16	0.11	0.16	0.025
BESS life loss (%)	1.78	1.08	2.39	1.32
	Storage capacity = 25 % of installed power over an hour			
	S1	S2	S3	S4
Error reduction (%)	6.26	6.80	7.00	5.73
Penalties reduction (%)	8.56	6.30	7.14	4.74
Average energy price improvement (%)	0.40	0.21	0.27	0.12
BESS life loss (%)	0.96	0.69	1.51	0.84
	Storage capacity = 50 % of installed power over an hour			
	S1	S2	S3	S4
Error reduction (%)	9.64	5.92	0.62	7.05
Penalties reduction (%)	13.2	8.61	3.22	5.82
Average energy price improvement (%)	0.60	0.46	0.15	0.30
BESS life loss (%)	0.64	0.23	0.87	0.54

loss is only a few percent. In the worst case, (strategy S3, 10 % of the installed power as storage capacity), the battery loses 2.39 % of its life expectancy. Counting only the cycle ageing, the BESS would last 40 years, which is longer than the typical 10-20 years life expectancy of batteries due to calendar ageing [15].

Ultimately, we deduce that it is not interesting to focus on the cycle ageing since it is low compared to the calendar ageing. Besides, using the BESS in a day-ahead setting does not significantly improve revenue. This is because the typical gap between the spot prices on a given day that can be used for generating profit in a day-ahead setting is much smaller than the gap between regulation prices and spot prices that is used to generate profit in a real-time setting. Thus, the most relevant strategy is strategy S1, which proposes a day-ahead schedule without considering storage capacity, then uses the storage to minimize penalties in real time with the optimal control proposed in II-B.

However, even for strategy S1, which focuses only on minimizing the imbalances, the energy price improvement is low compared to the penalty reduction. This can be explained by both the efficiency of the BESS, which dissipates an amount of energy proportional to the cycling, and the small gap between spot prices and regulation prices compared to other electricity markets [16]. These two effects are studied in the sensitivity analysis of the results in section IV-B.

B. Sensitivity Analysis

As shown by the results, strategy S1 seems to be the most relevant for a PV/BESS participating in an electricity market. Since it does not rely on storage parameters, a sensitivity analysis has been performed on various parameters on the study that does not change the PV/BESS control.

Two parameters are studied: the spread between the spot and regulation prices, and the round-trip efficiency $\eta = \eta_{Ch}\eta_{Dis}$ of the BESS. The energy price improvement over S0 is plotted for several values of these parameters on Fig. 2, all other parameters from the test case being equal. The numbers along

the lines show the value of the parameter for the given line. For the price spread, the number indicates the multiplication factor between the real spread and the one used to produce the results, that is for the line with number 3, the spread used to produce the results is three times larger than the real one.

As expected, the average energy price improvement increases with the gap between spot and regulation prices, and with the round-trip efficiency of the BESS. It appears that the price improvement is impacted more by the gap than by the efficiency. As the round-trip efficiency increases, the marginal improvement it makes to the energy price goes down. Besides, it cannot increase above 1. In contrast, the marginal increase from a price spread increase is steady.

Finally, Fig. 3 plots the minimal BESS size for which the PV/BESS is profitable, that is the minimal size for which the BESS pays back its investment cost before its end of life. The price spread is also considered, as the optimal BESS size is computed for several spread multiplication factors. With a unitary multiplication factor (that is, with real data from the test case), the required storage capacity is quite high even for low prospective costs. However, when the spread increases, the required capacity becomes affordable.

V. CONCLUSION

In this paper, several strategies have been studied for the participation of a PV power plant coupled with a BESS in a dual-price electricity market. The key findings are the following:

- Due to the frequent small cycling of the battery, the cycling ageing is low compared to the calendar ageing of a Lithium-Ion battery. Besides, because of a greater gap between the spot and regulation prices than between the spot prices at different instants of the day, it is more profitable to use the BESS only for compensating forecast errors.
- A BESS contributes efficiently to reducing a plants imbalance and penalties. However, because of the energy

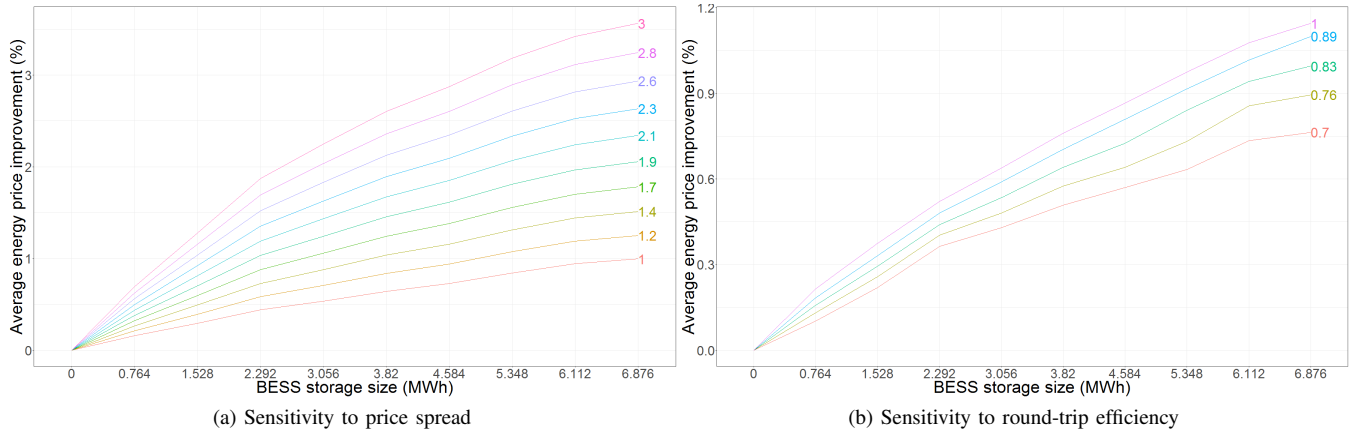


Fig. 2. Sensitivity analysis

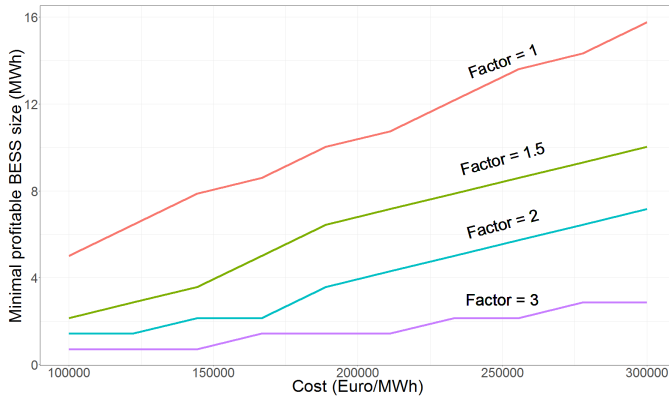


Fig. 3. Minimal profitable BESS size

dissipated by the batteries and the relatively low penalties for solar power, the improvement in the average energy price is limited.

- A sensitivity analysis reveals that the cause of a low energy price improvement is mainly the small gap between spot prices and regulation prices. Increasing this gap generates much greater revenue than reducing the dissipated energy.
- The optimal sizing of the BESS is dependent on the BESS investment costs and round-trip efficiency. In any case, the investment is quite high because, to be profitable, the storage capacity must always be in the same order of magnitude as the installed power of the plant over an hour.

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