Towards Financial Risk Management for Intermittent Renewable Generation with Battery Storage

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Abstract

As levelized costs of electricity for many renewable generation sources are continuing to fall and as feed-in tariffs are consequently being phased out, financial risk hedging for intermittent renewable generators takes a central stage. Battery storage as complementary capacity can support renewable generators regarding a more stable supply of electricity. In this study, we take first steps in modelling battery storage options as service products that are provided by battery storage operators to renewable generation operators. We model the situation theoretically, develop corresponding hedging strategies and apply the models to a fictional solar PV plant. The results show that battery storage options can reduce the risk for intermittent renewable generators and that the options can be financially beneficial for both the battery storage and the renewable capacity operator.

1. Introduction

Around the globe, the decarbonization of electricity generation through renewable energy sources is at the heart of efforts to mitigate the effects of climate change. Decreasing costs of intermittent renewable generation capacity as well as subsidy schemes lead to a substantial expansion of photovoltaic and wind generation capacity. The intermittent nature of weather dependent generation causes uncertainty that complicates the electricity system operation. Shorter ramping times are required from conventional thermal power plants to react to changes in renewable generation and forecasting techniques for intermittent renewable generation need to be improved [1]. However, the intermittent nature of renewable energy generation also affects the operators of the renewable capacity. The uncertain generation coupled with uncertain market prices causes high financial risk for renewable generators. Even if they enter power purchasing agreements or are being compensated through a feed-in tariff they still face a considerable quantity risk [2].

Feed-in tariffs are usually limited to some time period over which they are paid to generators. In Germany, the first renewable installations lose their feed-in tariff in the beginning of 2021. In their brief, the authors of [3] find that risk hedging will soon take a center stage for renewable generation. This moves risk assessment and management to the top of the agenda for renewable generators. Renewable generators face two types of risk: Quantity and price risk. A similar perspective on price and quantity risk is described in [4] for load serving entities. The authors also describe some correlation between the two risks. A higher demand in terms of quantity is positively correlated with high prices and vice versa. This is similarly true for renewable generation but with inverse correlation. Higher renewable generation from intermittent resources leads to lower electricity prices as their marginal cost of production is zero. Therefore, higher generation is inversely correlated with the market price. This is a dilemma for renewable generators even though it allows for some natural hedging because lower quantities are supported by higher prices and lower prices are associated with higher generation. However, as the relationship is not strictly linear, renewable generators face considerable market risks [2].

The intermittency of renewable generation can be complemented with battery storage capacity to increase the controllability in regards to the system but also the profit of renewable generators. A battery storage can be used to shift the income of excessive generation to times with lower generation and higher prices. This way, renewable generators are less vulnerable to temporarily low market prices. However, battery storage capacity

URI: https://hdl.handle.net/10125/71017
978-0-9981331-4-0
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is expensive and it is not profitable to keep a battery charged over several days only to discharge in times of low generation. This way the battery capacity is idle for a substantial time horizon and can therefore not turn any profit. Consequently, renewable generators need battery storage service providers that agree to charge their batteries at certain times and discharge them for the renewable generator when needed, while simultaneously optimizing their own profits in between. The storage operators are thus providing a service for renewable generators that needs to be fairly priced. In this paper, we model this situation and the fair pricing of such an instrument. We then introduce several heuristic strategies for renewable generators which intend to reduce their price and quantity risk. We assess the effect and the pricing for these strategies in a case study. We also discuss whether this service is financially viable given the price of battery storage or other storage capacity. We thus provide three contributions with this paper: We model the use of battery storage for renewable risk hedging as a form of option and provide a fair pricing mechanism. We develop heuristic strategies for renewable generator risk hedging through the use of battery storage and finally we assess the use of these strategies in a case study and determine a fair market price.

2. Related work

Risk hedging strategies have a long tradition in energy market research (e.g., [5, 6, 7]). Options as a specific hedging instrument and their effects are described in [8], for example. One of the first considerations of combined price and quantity risk is presented in [4] for load serving entities that need to supply varying demand from a wholesale market with varying prices at fixed retail rates. In [9], the authors use a copula approach to assess joint generation and price risk for a wind turbine in Denmark. They find that an independent consideration of the two risks leads to an underestimation of the total risk for the wind turbine. The case risk hedging for renewable generators has recently attracted more attention. In [2], the authors find that the intermittent generation by the growing renewable generation capacities further increases the price and quantity related risks of operators. They conclude that unhedged renewable portfolios carry a significant amount of risk and that plain vanilla forwards provide poor hedging opportunities. However, they are the only liquid market alternative for risk hedging on the electricity market. In [4], the authors develop a hedging strategy but state themselves that the results are purely hypothetical as options are not actively traded on electricity markets. The authors of [10] describe risk reduction strategy for renewable generators through the diversification over different technologies and locations to reduce the dependence on local weather phenomena. In [11], the authors describe the interplay between forward and spot trading and the effects of different trading strategies for renewable generators.

Another approach is the short-term risk hedging through multi-period trading on the day-ahead and intraday market which has been considered by [12] for solar and [13] for wind park operators. Both studies include imbalance prices to model penalties for deviations from production forecasts and thus consider a short-term hedging problem for daily deviations. The authors of [14] consider the dynamic sizing of storage capacities in order to compensate wind production forecast deviations, again focusing on short-term deviations from production forecasts in order to avoid imbalance penalties. The authors of [15] link a solar plant and a natural gas generation unit that do not have to be located in physical proximity into a virtual generator that is able to provide stable electricity production. Solar and gas swaps are introduced as financial instruments to mitigate the price- and quantity related risk of both operating entities.

The joint operation of a renewable power plant and a connected storage has been addressed in numerous publications, however, often not in regards to risk reduction. For example, the authors of [16] investigate the optimal operation of a co-located photovoltaic and storage system in order to maintain a systems voltage limits. The authors of [17] develop a strategy for a photovoltaic plant with an integrated storage system to optimally participate in the electricity market. Control strategies to enhance grid integration and to smoothen short-time production deviations from large solar plants using battery storage systems have been designed by [18]. The authors of [19] assess hydrogen production as storage option for renewable generation but find that it is not economical to re-convert the hydrogen to power. One closely related study is [20]. The authors are evaluating the use of options as hedging instruments for renewable generation and compare it to the use of a pumped hydro power plant. However, the authors hedge the deviation from a forecasted generation instead of a deviation from long-term financial expectations of generation. They are also assuming known electricity prices which they formulate as possible future work. We address both limitations in this study.

As shown, previous studies usually focus on an integrated renewable energy and storage system that is jointly installed and operated. This approach significantly increases the investment costs that an operator faces in advance. For the case of risk hedging with battery storage, the authors of [14] find that the best results can be achieved through dynamic sizing of the storage unit, i.e., the utilization of different storage capacities each day. The authors suggest that the storage should operate "as an independent market entity, where each producer may rent the necessary daily storage capacity for hedging the risk". Following these results, we consider the utilization of a battery storage unit as a service provider. We investigate the potential of a solar plant operator to protect herself against quantity and price risk through a service agreement with a storage provider that allows the charging of the battery storage at one point in time and the discharging at another freely chosen point in time within the agreed duration period of the contract. In the course of this paper, we describe the general features of risk hedging strategies for the solar plant operator and demonstrate an exemplary strategy on the example of a simulated solar plant. Besides the description of the storage strategy, the main contribution is the evaluation of the possibility of using battery storage capacity as a service for risk hedging purposes for renewable generators in the form of battery storage options.

3. Theoretical considerations

In this section, we begin by describing the problem analytically. We model the risk of renewable generators and introduce the use of a battery storage for risk reduction. Assume that q_t is the actual generation of a renewable generator at time t and Q_t is the random variable of the generation at time t. Furthermore, assume that $\tilde{Q}_t$ is the distribution of that generation. We use the same nomenclature for the price at any given time with p_t as the actual market price, P_t is the random variable of the price and $\tilde{P}_t$ is the corresponding distribution. The random profit of a renewable generator with marginal generation cost of zero is then given as follows.

$$\Pi_t = Q_t \cdot P_t \tag{1}$$

From this, we can calculate the expected profit for any given time. This leads to the following equation. As higher renewable infeed leads to lower wholesale electricity prices, the covariance in this equation serves as a natural hedging as it is negative between prices and renewable quantities. However, while this association is true on a global level, it is not necessarily true for individual renewable power plants.

$$\mathbb{E}(\Pi_t) = \mathbb{E}(Q_t) \cdot \mathbb{E}(P_t) + Cov(Q_t, P_t) \tag{2}$$

To assess the associated risk, we need to consider the variance of the profit. It is described in the following formula.

$$\begin{aligned} Var(\Pi_t) = Var(Q_t \cdot P_t) = Cov(Q_t^2, P_t^2) + \\ (Var(Q_t) \cdot \mathbb{E}^2(Q_t)) \cdot (Var(P_t) \cdot \mathbb{E}^2(P_t)) - \\ (Cov(Q_t, P_t) + \mathbb{E}(Q_t)\mathbb{E}(P_t))^2 \end{aligned} \tag{3}$$

The joint variance increases with the individual variances and the expected values. It can be reduced through a negative covariance between the prices and generation quantities but it depends on the individual mechanics.

A renewable generator that wants to reduce the uncertainties of its profits is not necessarily interested in reducing the risk of individual time steps but would rather try to guarantee a stable stream of profits over periods of time, such as days or weeks. Therefore, in this paper, we consider the differences in profit relative to an average day in the respective month. As renewable generation varies greatly over the seasons, it is reasonable to assume that a renewable generator would have different profit expectations for a day in July and December. However, even in December, a renewable generator might achieve an average, above average or below average day. Being able to hedge against below average days is an argument towards investors for lower interest rate payments and thus an important tool for renewable generators. It is important to define the risk measure that renewable generators are trying to minimize. One obvious choice is the reduction of the variance. A renewable generator has the following objective in regards to the reduction of the variance with m being a particular month, n being the number of considered days for that month and d_m being a particular day in that month.

$$min(\bar{\pi}^m - \pi^{d_m})^2 = min(\frac{1}{n}\sum_{j=1}^{n}\sum_{t=1}^{24}\pi_t^m - \sum_{t=1}^{24}\pi_t^{d_m})^2 \tag{4}$$

Other measures that we consider in this study are the Value at Risk (VaR) and the Conditional Value at Risk (CVaR) [21]. The VaR for a certain confidence level α is the α-quantile of the distribution function of the loss function X for a certain portfolio. The CVaR is the integral over the interval [0,α] of the inverse distribution function of losses. Assume that the losses of a renewable generator for a day in a specific month are distributed according to $F(\pi^m)$. Then the VaR to the level of α is defined as $VaR^m(X) = min(x|F_X(x) \geq \alpha)$ and the CVaR is defined as $CVaR^m = \frac{1}{\alpha} \cdot \int_0^{\alpha} VaR^m(X)$.

The VaR for $\alpha = 0.05$ thus corresponds to the lowest of the 5% largest losses. The CVaR is the average of the 5% largest losses and is therefore always higher than the VaR, but is a more robust measure of risk. The VaR and the CVaR are better measures to model the risk of a renewable generator than the variance as they describe negative deviations from the mean rather than also punishing positive deviations. Consequently, they have been used as risk measures by the authors of the studies presented in [12, 13].

We now introduce the battery storage as a risk hedging instrument. The action of charging and discharging a battery storage can only be described over a time horizon. Therefore, we propose a time period T that is associated to each battery storage option equivalent to the life of a regular financial option. The renewable generator has to choose this period when charging the battery storage, which influences the option pricing. We can then differentiate between battery storage options that can be exercised at any time during the period (American battery storage options) or which can only be exercised at the end of the period (European battery storage options). We will describe the impact on the option price later in this section. In the case of American battery storage options, the renewable generator also needs to decide on when to exercise the option. She can develop a strategy with a specific time to exercise or try to optimize the time to exercise over the lifetime of the battery storage option. It is of course important to discuss when such decisions need to be communicated to the battery storage operator so that she can optimize her load schedule around these decisions of the renewable generator. This detailed definition of the financial product is subject to future work. The profit of the renewable generator with battery storage π^{bst} over a time horizon T with the charging decisions s_t is then given by the following equation.

$$\pi_T^{bst} = \sum_{t=1}^{T} (q_t - s_t) \cdot p_t \tag{5}$$

Therefore, a risk neutral renewable generator is willing to pay the difference between the profit with and without the use of storage ($\pi_T^{bst} - \pi_T$). However, risk averse renewable generators can use this strategy to reduce their VaR and CVaR and might therefore be willing to pay a premium.

To price the service from a storage perspective, we ignore the cycling costs for the moment and focus on the opportunity costs of the battery storage. The renewable generator charges the battery storage for free but then reserves the right to sell the charged energy at any moment within the battery storage option period (American) or at the end of the period (European). To price the American form of the option, we first define $\hat{p}_{T,t_0} = max_{t \in T}(p_t)$ as the maximum price within the option period T that starts at t_0. This price can also be expressed as a random variable $\hat{P}_T$ that has a distribution $\tilde{\hat{P}}_{t_0,T}$ depending on the time period T and the starting time t_0. This is easier for the European battery storage option because we only need to consider the distribution of the price at the end of the option period at t_1 for which we have already defined a probability distribution as $\tilde{P}_{t_1}$. The pricing of the according options then depends on the risk propensity of the battery storage. Assuming a risk neutral battery storage and ignoring cyclic aging and fixed costs, then a fair price p^o for the American battery storage option is calculated as follows.

$$p^o = (\mathbb{E}(\hat{P}_T) - p_{t_0}) \cdot s_{t_0} \tag{6}$$

It is the difference between the expected maximal price over the option period and the current price multiplied with the charged quantity. The calculation for the European battery storage option is equivalent. If a storage provider is more or less risk averse then the pricing changes. However, for a battery storage provider, providing such a service also reduces risks. By receiving a fixed premium she is less dependent on price volatility and has a secure income. Therefore, the pricing of such battery storage options also depends on the preferences of the involved parties. In the following, we describe these theoretical considerations along a case study for a fictional solar PV power plant.

4. Data analysis

In order to investigate the presented theory of risk hedging of the revenues of an operator of a renewable energy generation plant, we implement and evaluate the concept by means of a case study. We select the case of a solar PV plant operator, mainly for one apparent reason: Since the price risk is increased by the feed-in from renewable energies, in the case of a wind park it might be necessary to bridge long periods of time to avoid the price risk, since periods of high wind feed-in can continue over several days or weeks. A negative influence on electricity prices can also be observed during periods of high feed-in from solar generation, but naturally only for a few hours each day. This means that a solar PV plant operator can avoid her price risk by a short-term shift of production from the midday hours into the evening. In the case of a solar PV plant operator, the results for a delimited period of time are more robust and can be interpreted more generally. For our analysis, we use the German price, load and generation data for the years from 2015 to 2019 which is publicly available

[22]. We use the years 2015 to 2018 as training data to create a risk hedging storage strategy for a solar PV plant operator and subsequently test it for the months from May to September of 2019. We deliberately only take the summer months into account, as this is when the price effects from feed-in of solar PV generation are most pronounced and the most significant results can therefore be expected.

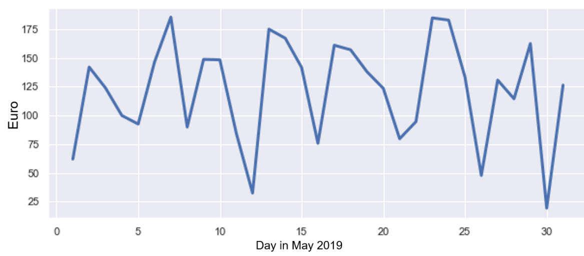

Figure 1. Daily revenues of a 1 MW solar plant

$$\pi^{d_m} = \sum_{t \in d_m} max(0, p_t) \cdot q_t \tag{7}$$

The analysis of the training data set shows the effects of quantity- and price-related risks. Daily revenues of a solar PV plant operator who directly markets her generation on the day-ahead-market fluctuate significantly. This is illustrated for the period of one month in Figure 1 using the example of a fictional 1 MW solar plant. Revenues are calculated according to Equation 7, where for each hour t in a day, the respective solar generation q_t and price on the day-ahead-market p_t are multiplied and then added. We assume that in hours with negative prices, generation is curtailed instead of sold, thus the revenue in hours with negative prices is zero. To investigate the influence of prices and daily production on the daily revenues, we plot these dependencies in in Fig. 2. The daily production is calculated as $q^{d_m} = \sum_{t\, in\, d_m} q_t$ and the realized average price for the solar generation as $P^{solar} = \pi^{d_m}/Q^{d_m}$. It can be seen that both the daily production quantity and the price that is realized per MWh have a positive effect on the daily income. The graphs show this dependency for all days in the months May to September of the training data set (2015 - 2018), whereas the generation is scaled down to 1 MW of installed capacity.

In order to hedge the price and quantity risk of a solar PV plant operator, we therefore create storage utilization strategies that are specifically targeted to counteract the respective cause of losses in revenues. We assess the risk of the solar PV plant operator using the risk

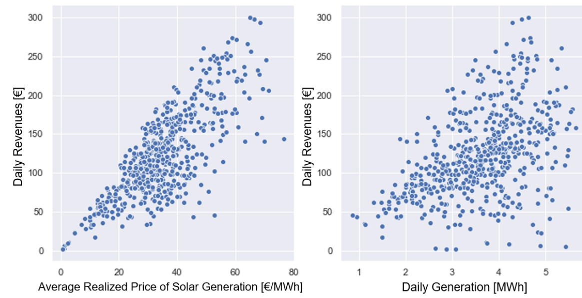

Figure 2. Influence of generation quantity and realized price on daily income

measure CVaR described in the previous section. This measure penalises downward deviations in revenues, i.e., losses compared to the expected daily revenue, while above-average revenues are not considered.The strategies developed, which are presented in the following section, are therefore aimed at specifically preventing downward deviations in profits caused by quantity or price fluctuations.

5. Storage strategies to mitigate price and quantity risk of a solar PV plant operator

On a given day, the storage operator faces the decision of how much of the electricity forecast for the next day to sell directly on the day-ahead-market and how much to charge or discharge at a given time during the next day. We stipulate that the operator must inform the storage service provider about these charging and discharging decisions in advance, so that the storage operator has enough time to plan her operation schedule accordingly. To address the revenue fluctuations associated with price and quantity uncertainties of a solar PV plant operator, we employ strategies for the storage service utilization specifically targeted at counteracting each of the two risks of negative deviations of next day's prices and production quantities. For the determination of benchmarks and decision rules, we analyze generation, load and price data from the years 2015 - 2018 and apply the derived rules to the months of May to September 2019 to test and evaluate the storage strategies. As the quantity and price risks differ with regard to the time horizon concerned, we develop two strategies to address each of the risks separately first and then later examine the effects of the individual and combined strategies. Whereas losses due to price drops can be mitigated by shifting generation within one day from low price hours to later occurring high price hours, quantity-related losses can only be compensated by shifting generation from days with above average production to days with low production.

5.1. Price risk strategy

The main risk of price-related losses consists of periods of high feed-in from renewable energy sources, as these have marginal production costs of zero and thus negatively affect prices on the day-ahead market. This is particularly noticeable at times of high wind feed-in, but also during the summer, when solar feed-in is at its peak, prices are systematically lower around midday than in the morning or evening hours. If additional influences, such as a high wind speeds occur simultaneously, periods with negative prices can occur.

A solar PV plant operator can circumvent the price risk through a short-term utilization of the storage service. If significantly lower prices are expected on the following day, solar production can be shifted from the hours of high generation into the evening hours, thus avoiding significant price drops even with little and short-term storage usage. The *price risk* storage strategy for a solar plant operator, which is intended to reduce downward deviations from the expected revenue that are caused by price drops, consists of shifting generation from the midday hours, which are high in solar generation, to the evening hours during which higher prices occur due to declining feed-in from solar PV. To this end, we train a decision tree on the data for the years 2015 to 2018, which takes the respective national load-, wind- and solar generation forecasts for the following day as input, as well as the respective month and day of the week. On this basis, the decision tree predicts whether the prices in the five hours of the following day with the highest generation fall below the 25% quantile of a month's historic electricity prices during 2015 to 2018. If the algorithm predicts such a price drop for the next day, the price hedging strategy is triggered. For each of the hours t in the charging period CP, a share $a \,\epsilon\, [0, 1]$ of the generation forecast is stored (Equation 8). The entire stored electricity of the midday hours is then discharged in equal parts in the hours of the discharging period DP in the evening hours (Equation 9), where N_{DP} is the number of hours in the discharging period. The *price risk* strategy does not postpone the sales of the generator beyond one day.

Figure 3. Implementation of decision tree to trigger the price risk strategy

$$charge_t = a \cdot q_t \quad \forall\, t \,\in\, CP \tag{8}$$

$$discharge_t = \frac{\sum_{t \in CP} \;\; a \cdot q_t}{N_{DP}} \tag{9}$$

5.2. Quantity risk strategy

The short-term quantity-related risk is expressed by the fact that the total generation on some days falls short of the average for a month, usually due to weather influences that are only predictable in the short-term future. Shifting production within one day is therefore not sufficient to protect the solar PV plant operator against these quantity associated deviations from the expected revenues. Instead, in order to counteract the quantity risk, the operator can request discharging of stored electricity from the storage service provider on days of low production to increase the daily production. In order to do so, she must preventively store surplus generation on days with above-average generation in order to build up credit with the storage service provider. The *quantity risk* strategy thus includes decision rules for such charging and discharging events. Based on the generation data from 2015 to 2018, the average daily generation is calculated for each month. This serves as a benchmark for the expected generation $\mathbb{E}(Q_{d_m})$ on a typical day d in a given month m. Based on her risk aversion, the storage operator then chooses a factor $l \,\epsilon\, [0, 1]$ that triggers a discharging event. If the generation forecast for the next day Q_{d+1} falls below this threshold (e.g., $0.8 \cdot \mathbb{E}(Q_{d_m})$), a discharging event is requested in the amount of the forecast deficit, if the operator has enough credit with the storage service provider. Credit can be built up by charging electricity to the storage and is treated as described in the previous section in the same way as an American option. When a charging event is commissioned, the solar PV plant operator determines a time horizon T for the option, within which she can retrieve, i.e., discharge, the credit at any time. However, as with all charging and discharging events, she must announce the discharging of electricity in advance. In order to make sure that sufficient credit is available with the storage service provider to cover a discharge event when it occurs, the solar PV plant operator has to built up credit in advance on days with excess generation. For the *quantity risk* strategy, the operator may decide on a planning horizon T, i.e., how long in advance a shortfall should should be planned for. The longer this period is chosen, the more likely it is that all discharge events can be covered but this security may come with a higher price for the storage service as the battery storage service provider faces larger uncertainties. The charging events of the *quantity risk* strategy are triggered as follows: For each month, we calculate the expected generation deficit that is faced by the operator for a given threshold l and a planning horizon T, based on the years 2015 to 2018. On each day, the solar PV plant operator decides whether electricity should be charged to the storage the next day based on two conditions. (1) A charging event is only requested when the generation forecast for the next day is above a month's expected daily generation and only this excess will be stored and (2) a charging event is only requested if the existing credit with the storage service provider is below the expected quantity deficits over the planning period T. When electricity is stored, the solar PV plant operator has the option of discharging this credit at any given time within the planning horizon. Note that credit with the storage service provider may expire if the requested number of days of the option elapses without a discharging event. In that case, the solar PV plant operator will request a discharging event on the last day of validity of the option in any case. In case of a discharging event, the credit with a shorter remaining option lifetime is always requested first. Figure 4 shows an exemplary set of consecutive days and the respective daily generation (blue lines) to illustrate the benchmarks for charging and discharging events. The corresponding algorithms that determine the amount of generation to be charge or discharged in each hour t when an event is triggered are displayed in Figure 5. For both the *price* and *quantity risk*, the strategy s is then defined as $s_t = charge_t - discharge_t$.

When combining the two strategies, it can make a difference in which order they are employed. If, for example, the *price risk* strategy is commissioned first, it is possible that generation has already been stored, which is then no longer available to use for the *quantity risk* strategy. We therefore deploy and investigate four different storage strategies for the solar PV plant operator: *price risk only*, *quantity risk only*, *price risk first, then quantity* and *quantity risk first, then price*.

6. Evaluation

We apply the strategies presented in the previous section to the price, load and renewable generation data in Germany during the months May to September 2019. For the design and evaluation of a storage strategy for a fictional solar PV plant operator, we scale the generation to 1 MW of installed capacity. Based on the historical training data from 2015 to 2018, we train the decision tree that decides when the price strategy is applied and determine the parameters that are required for each strategy. For the *price risk* strategy, we set the charging period CP to the fixed hours between 11 a.m. and 4 p.m. and the discharging period DP to be between 6 p.m. and 11 p.m. for each day when that the *price risk* strategy is triggered. We set the share a that is to be charged during each hour in the charging period to be 1, thus all generation is charged and then later discharged. For the *quantity risk* strategy, we set the parameter l to 0.8, thus a discharging event is commissioned whenever the generation forecast for the next day is below $0.8 \cdot \mathbb{E}(Q^{d_m})$. The planning horizon T and accordingly the time period for the battery option that is chosen when charging the storage is set to four days. For the *price risk* strategy, the battery option is analogous to a European option since the time of discharging is specified to be at the end of a one day period.

Fig. 6 shows a section of the resulting storage strategies based on the selected parameters, where positive values are charging events and negative values indicate discharging events. In this section, it can be seen that the two strategies do not overlap and can

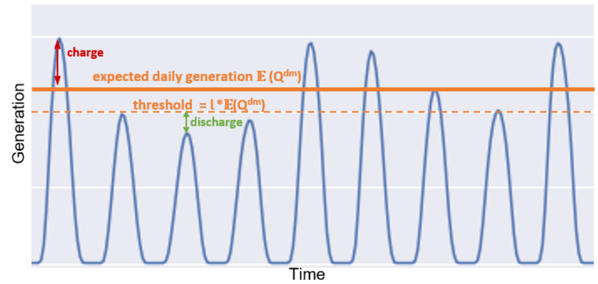

Figure 4. Schematic illustration of a charging and a discharging event in the quantity risk strategy

charging event

while excessGen > 0:
for t in CH:
$charge_t$ = min($generation_t$, excessGen)
excessGen = excessGen - $charge_t$

excessGen = Q_{d+1} - $\mathbb{E}(Q^{dm})$ CH = historically cheap hours in ascending order

discharging event

while deficitGen > 0:
for t in EH:
$discharge_t$ = min(deficit, remainingCredit)
deficitGen = deficitGen - $discharge_t$

deficitGen = l * $\mathbb{E}(Q^{dm})$ - Q_{d+1} EH = historically expensive evening hours in descending order

Figure 5. Algorithm for charging and discharging events

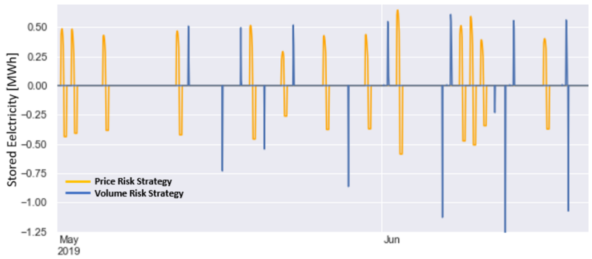

Figure 6. Extract of the resulting storage strategies

therefore easily be combined. In general, only very few overlaps occurred throughout the testing period, so that the strategies *quantity risk first, price second* and *price risk first, quantity second* only differ slightly. This indicates that the solar PV plant operator can address both the quantity and price risk through the utilization of a storage service without the two objectives getting in each others way. In the next paragraphs, we analyse the implications of the resulting strategies for the solar PV plant operator as well as the storage service provider in terms of revenues and risk hedging.

6.1. Solar PV plant operator

The CVaR serves as risk measure for the revenues of the solar PV plant operator. This measure penalises ”losses” in terms of negative deviations from the average daily revenue. In order to obtain comparable values, we use the average revenues without storage utilization to measure the downward deviations and to determine the CVaR. Our results in Fig. 7 show that the CVaR can be reduced substantially through the utilization of the storage service. Especially the strategies that involve the *price risk* strategy improve the CVaR in all months under consideration. In fact, only the *quantity risk* strategy by itself is not suitable to reduce the CVaR in all but one month. The combination of the two strategies yields the best CVaR in three out of five months and ties with the *price risk* strategy in the other two months.

A closer look at the amount of electricity stored in Fig. 9 in the respective strategies could provide an explanation for the findings. The *quantity risk* strategy uses the storage service for a comparatively small quantity of stored electricity. This could indicate that the parameters for the *quantity risk* strategy have been chosen too conservatively. For example, the threshold l for a discharging event could have been set higher. However, Fig. 8 also suggests that the quantity may not have the same importance as the price for the largest deviations from the average revenues. In May, the three largest deviations (on days 12, 26 and 30) can be reduced with the *price risk* strategy, which is expressed in the positive effect on the CVaR. The *quantity risk* strategy only affects the fifth largest deviation (day 16), which is not reflected in the CVaR with $\alpha = 0.05$. In summary, we find that the CVaR can be improved substantially with the proposed strategies based on decision heuristics from the four years prior to the testing period. This is a promising finding for future work considering the utilization of a storage as a service to hedge price and quantity related risks of renewable generation operators. We expect that with more data and a more granular strategy design, even better results can be achieved.

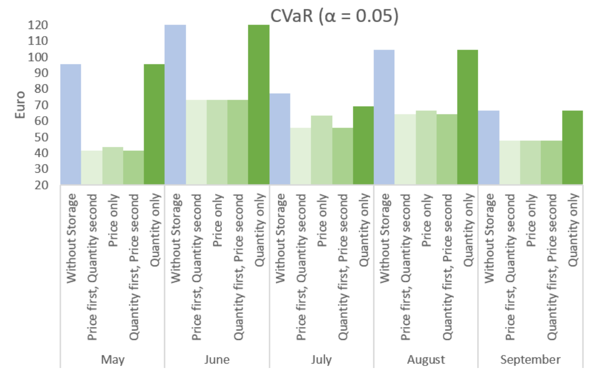

Figure 7. Negative deviations from average daily revenue

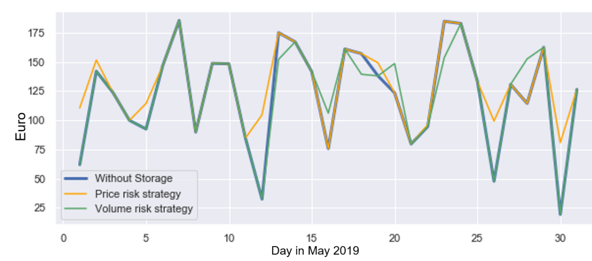

Figure 8. Impact of storage strategies on revenues

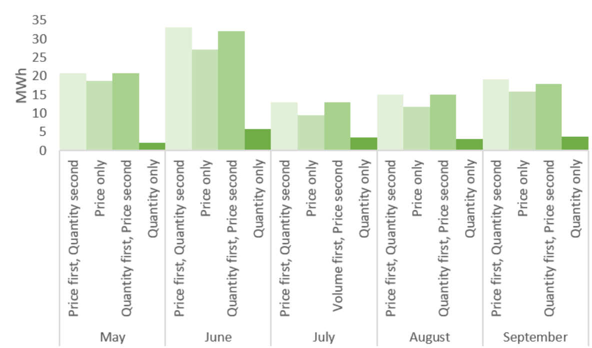

Figure 9. Quantity of stored electricity

6.2. Storage service provider

In this subsection, we evaluate the necessary payments to the storage operator for him to accept providing the battery storage options for the above described strategies. To do so, we are optimizing the storage operation assuming perfect foresight of the price development with and without the storage hedging strategy of the PV solar plant operator interfering with the storage strategy. The difference between the results gives us the opportunity costs for the battery storage operator. The storage operator solves the following optimization problem.

$$\max \quad \sum_{t=1}^{T} -s_t \cdot p_t \tag{10}$$

$$\text{s.t.} \quad S_t = S_{t-1} + s_{t-1} + s_{t-1}^{solar} \forall t \in T \backslash \{0\} \tag{11}$$

$$|s_t| \leq s \tag{12}$$

$$0 \leq S_t \leq S \tag{13}$$

$$S_0 = 0 \tag{14}$$

S	Storage capacity
S_t	State of charge at time t
s	Storage charging power
s_t	Charging decision of storage at time t
s_t^{solar}	Charging decision of solar PV at time t
p_t	Price at time t

During the considered period and with a parametrization of $s = 2MW$ and $S = 4MWh$ the storage can achieve a profit of 22,618 Euros without interference of a strategy. Including the *price risk* strategy, the storage profit decreases to 20,486 Euros. For the *quantity risk* strategy, the profit decreases slightly to 22,304 Euros. Finally, for the combined strategy the profit is 20,270 Euros. Another important consideration is the throughput. An increasing throughput can lead to more cyclic aging which would lead to more costs for the battery storage. The throughput without the provision of battery storage options is 1,436 MWh, with the *price risk* strategy it is only 1,429 MWh, with the *quantity risk* strategy it is 1,434 MWh and with the combined strategy it is 1,429 MWh. Therefore, the impact of cyclic aging in regards to battery storage option provision is negligible. Finally, to give an indication of the cost per MWh of the battery storage option we can divide the lost profit for the battery storage by the throughput caused by the renewable generator. Thus, the cost is 25.7 Euros per MWh for the *price risk* strategy, 15.2 Euros per MWh for the *quantity risk* strategy and 23.2 Euros per MWh for the combined strategy. It is therefore in the range of storage costs but further cost decreases for battery storage or increasing price volatility are necessary to make it profitable.

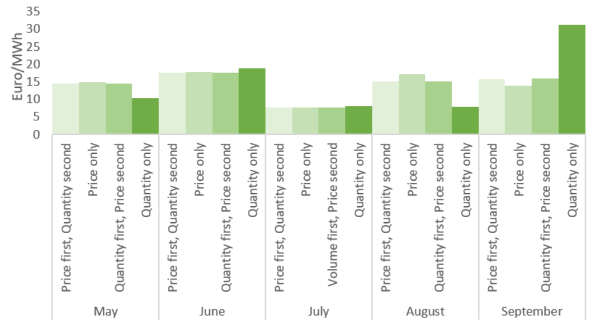

Figure 10. Revenues from storage utilization

7. Discussion

In the presented case study, we show that both the solar PV plant operator and the storage operator can benefit from the proposed constellation. Future storage costs are difficult to estimate due to the large number of technologies and dynamic price developments. However, the assessment of the opportunity costs of the storage service provider showed that the optimal strategy of the service provider actually yields less cycles when including the strategy of the solar PV plant operator and therefore marginal cyclic costs of zero could be assumed. Fig. 10 shows the revenues that the solar PV plant operator realizes through the utilization of the storage service. The values are in the range of the compensation that the storage service provider needs to request for her service as determined in the previous section. As we argued in Section 3, the solar PV plant operator might even be willing to pay a premium for the ability to decrease her risks in revenue streams in order to provide a stable investment plan. Likewise, the storage service provider may have incentives to adjust the demanded compensation according to her risk aversion and operational goals. Future research should further look into the extent to which the revenues of the solar PV plant operator justify the reimbursements for the storage service provision and the cyclic costs of storage utilization as well as the pricing of the service provided by the storage operator. However, it should be noted that electricity price spreads are likely to increase in the future as installed renewable capacities increase, thereby increasing the potential revenues from storage usage as well.

In our model, we assume that a storage is accessible as a service on demand. This is not a feasible use case for a storage facility under current regulation in many countries, mainly because of the fees charged for the charging and discharging processes. However, we assume that, in a system increasingly based on renewable energy sources, more flexibility solutions will be necessary and thus the usage of storage facilities will be promoted more strongly in the course of this development. In particular, the deployment of storage to balance intermittent generation, as presented in this study, can make a significant contribution to integrating the increasing feed-in from renewable energies into the energy system and is thus an important contribution to the stability of the energy supply.

8. Conclusion

In this paper, we make several contributions towards the financial risk management for intermittent renewable energy generation through the utilization of a battery storage service. We provide a theoretical model for the risk assessment of a renewable plant operator and the pricing of the storage service. We then develop heuristic storage strategies for a solar PV plant operator to mitigate price and quantity related negative deviations in profits. In a case study, we can show first promising results, which indicate that the use of battery storage similarly to an option as a financial instrument can provide a feasible contribution to the risk hedging objectives of the solar PV plant operator. We furthermore determine the pricing of the storage service and conclude that the proposed constellation can be beneficial for both the solar operator and the battery storage service provider.

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