Pool Trading for Hybrid Wind-Solar Power Producers

David Könen, Daniel Piersig, Laura Poreschack, Moritz Wegener

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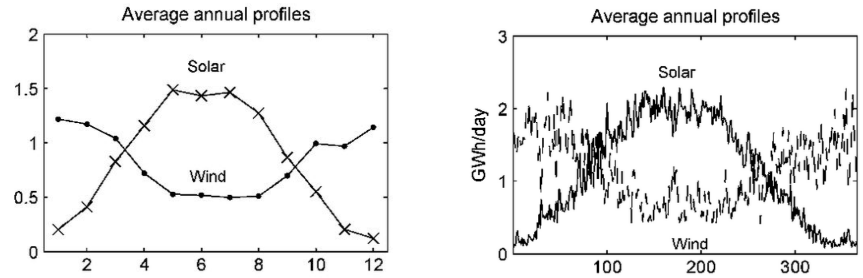
1 Introduction

Renewable energies are currently advancing and gaining an increasing share of the energy production. On the one hand, this is induced by the desire to decrease the carbon footprint and on the other hand, the population is facing a decreasing availability of fossil fuels like natural gas, coal and oil. The advantage of renewable energies is that apart from not requiring fuel, which induces zero fuel costs, it is emission-free and therefore supported by the government. However, these energy sources are also non-dispatchable and have the major disadvantage of uncertainty. Conejo et al. [3] considered the case of a wind power producer. Due to the uncertainty, the wind power producer must rely on the energy traded on the balancing market. Therefore, he solved an optimisation problem to maximise the expected profits from trading on the day-ahead market and the adjustment market while also minimising the costs incurred in the balancing market caused by energy deviations.

In addition to the uncertainty, the wind power producer also faces a substantial fluctuation in production throughout the year, caused by the strong dependence on wind availability over different months in a year. Considering a wind power producer in Europe, wind availability is much higher in the winter than summer months, see, e.g. [5].

For this case study, we consider the case of an energy producer producing both wind power as well as solar energy. Several studies have been carried out to see how both resources' production variability can be decreased by exploiting the anti-correlation of wind speed and solar irradiance. Coker et al. [1] considered a region in south-west Britain to assess the variability of wind, solar and tidal current energy resources. Santos-Alamillos et al. [4] aimed at finding the optimal spatial distribution of wind and solar farms across the Southern Iberian Peninsula to minimise the resulting net variability. Bett et al. [2] analysed daily data for Great Britain and found evidence for an overall anticorrelation between wind speed and solar irradiance. As a side product, they also discovered that solar variability is significantly higher than wind variability and that both variabilities are higher in winter than in summer. Inspired by these results, we wish to set up a pool trading model for an energy producer offering energy produced from both solar and wind power plants. This setting of a hybrid wind-solar power producer overcomes the strong fluctuation in production throughout the year due to the strong over year anti-correlation of wind speed and solar irradiance, see figure 2. In addition to the anti-correlation between wind speed and solar irradiance over the whole year, there is also an anti-correlation between both over the day, even if it is much smaller. We will exploit this anti-correlation over the day and include it into the forecast for wind and solar power production. Therefore, we will apply the forecast for wind power production for a time t in dependence on the previous times' wind speeds and previous times' solar irradiance to improve the forecast precision possibly.

Brauchen wir (a) und (b) und warum ist die y-Achsen Beschriftung nur rechts?



(a) (b)

Figure 1: The average annual profiles of solar irradiance and wind speed [5]

To solve the decision problem, the hybrid energy producer has to face, we will solve a scenario-based multi-stage optimization problem. For generating wind and solar power scenarios, we will use a time-series-based approach. With the generated data, we consider two cases. First, we look at a situation where we do not have an adjustment market. Second, we add an adjustment market to our situation. We compare the revenue of a hybrid producer with the sum of the revenues of a solar and a wind power producer. Our results show that the more risk averse a producer is, the more profitable it is to produce in a hybrid scheme. This effect can be observed in both market situations. We conclude that this profitability stems from the anit-correlation of the two weather conditions as a decrease in availability of solar irradiance is most likely to be compensated by an increase of wind speed and vice versa. This gives more planning security and therefore a higher expected profit. Moreover, the decrease in planning insecurity also explains why more risk averse producers profit more from a hybrid production scheme.

2 Decision framework

In the introduction we mentioned the three major trading places for energy, namely the day-ahead, the adjustment and the balancing market. All three of these are cleared in a single auction process, however at different times of the day.

· The day-ahead market is cleared at a given time period t^D of day $d-1$.

- The adjustment market is cleared at time period t^A of day $d-1$. Please note that time period t^A takes place *after* time period t^D.
- The balancing market ensures the real-time balancing between the generation of and demand for energy by balancing out differences between the real-time operation and the last energy program settled on in the previous markets. Therefore, it is cleared just before each time period of day d.

There are three major decisions the hybrid energy producer has to face. First, he has to submit an offering curve to the day-ahead market for day d. The day-ahead market for day d is closed at 10 am of day $d-1$. Then, he has to modify the submitted energy offers in the adjustment market depending on how the wind and solar power forecast updates change. The adjustment market for day d is closed at 11.45 pm of day $d-1$. Finally, he needs to balance out his energy deviations by trading in the balancing market for each time period of day d. From now on, we assume hourly periods. This means that the balancing market for the time period 6.00-7.00 am of day d closes at 5.50 am of day d.

The producer faces several factors that influence his short-term decision making process. It is inevitable to account for the imbalance costs, i.e. the costs entailed by deviations in the energy production. Apart from that, he is influenced by all sorts of mechanisms through which energy deviations are priced in the balancing market and the beneficial impact of an adjustment market clearing after the clearance of the day-ahead market. Energy deviations are not unusual for producers of non-dispatchable energy sources as windspeed and solar irradiance exert a high variability. As soon as a producer deviates from his agreed-upon amount of energy he has traded on the market before, he has to sell its surplus or buy his generation deficit at an *imbalance price*. We denote the price for positive energy deviations, i.e. higher production than planned, by λ_t^+, and the price for negative energy deviations by λ_t^-. We denote the price for positive energy deviations, i.e. higher production than planned, by λ_t^+, and the price for negative energy deviations by λ_t^-.

Let δ_t be the system imbalance for time t, that means if $\delta_t < 0$ there is an negative system imbalance and otherwise a generation excess or balance ($\delta_t = 0$) in the power system. Then λ_t^+ and λ_t^- are given by

$$\lambda_t^+ = \begin{cases} \lambda_t^D & \text{if } \delta_t < 0 \\ \min(\lambda_t^D, \lambda_t^{DN}) & \text{if } \delta_t \geq 0. \end{cases} \qquad \lambda_t^- = \begin{cases} \max(\lambda_t^D, \lambda_t^{UP}) & \text{if } \delta_t < 0 \\ \lambda_t^D & \text{if } \delta_t \geq 0. \end{cases}$$

where we write λ_t^D for the day-ahead market price, λ_t^{UP} for the price of the upward energy that may needs to be added and λ_t^{DN} for the price of the downward energy that may have to be discharged from the system.

The producer offers an amount E_t^D of energy at the day-ahead market, while his plant produces an amount E_t, which is most probably not equal to the amount offered at the day-ahead market. We denote the total deviation by

$$\Delta_t = E_t - E_t^D = d_t \left(P_t - P_t^D \right)$$

indicating the timespan by d_t and the actual resp. offered amount of power by P_t resp. P_t^D. Here, the total power produced in time t is given by the sum of the produced solar power P_t^S and wind power P_t^W, i.e.

$$P_t = P_t^S + P_t^W.$$

Similary it holds $\overline{P}_\tau = \overline{P}_\tau^S + \overline{P}_\tau^W$. In this decision framework, we assume that the hybrid power producer can only offer a total energy amount and cannot offer price differences between the produced solar and wind energy.

We define the imbalances price ratios by

$$r_t^+ = \frac{\lambda_t^+}{\lambda_t^D} \quad \text{and} \quad r_t^- = \frac{\lambda_t^-}{\lambda_t^D}.$$

Given these ratios, we can define the imbalance cost C_t for time t as

$$C_t = \begin{cases} \lambda_t^D \left(1 - r_t^+\right) \Delta_t & \text{if } \Delta_t \geq 0 \\ -\lambda_t^D \left(r_t^- - 1\right) \Delta_t & \text{if } \Delta_t < 0. \end{cases}$$

Then we can formulate the revenue R_t in terms of the maximum level of revenue, which could be realised in a situation free of wind and irradiance uncertainty, and the imbalance cost, i.e.

$$R_t = \lambda_t^D E_t - C_t.$$

Given this formulatuion, it is easy to deduce that maximising the revenue is equivalent to minimising the imbalance costs.

2.1 Uncertainty Characterization

We face four major sources of uncertainty. The most essential source of uncertainty is the weather, which influences both the wind and solar power generation. Apart from that, we have uncertainty concerning the market characteristics like day-ahead market price, adjustment market price and the prices for imbalance.

To deal with these uncertainties in order to solve the decision problem the hybrid power producer has to solve, we consider a scenario-based multi-stage optimization problem. For this purpose, we consider N_T periods of the market horizon, N_D scenarios for day-ahead prices, and N_A scenarios for the adjustment market prices. Thus, we have several realisations of day-ahead and adjustment market prices, which we summarise in

$$\lambda^D = \left\{ \lambda_t^D \quad | \quad t \in \{1, .., N_T\} \right\}$$
$$\lambda^A = \left\{ \lambda_t^A \quad | \quad t \in \{1, .., N_A\} \right\}.$$

We also have N_P scenarios for wind and solar power production, which splits up in N_{P_1} scenarios for the power production during the time interval between the closures of the day-ahead and adjustment market and N_{P_2} scenarios for the wind and solar power production for the time intevall during the market horizon. Similarily to the realisations of day-ahead and marekt price we summmarize the different realisations for wind and solar power production with

$$\begin{aligned}
\overline{P}^W &= \left\{ \overline{P}^W_\tau \quad | \quad \tau \in \{1, \dots, N_{T_1}\} \right\} \\
\overline{P}^S &= \left\{ \overline{P}^S_\tau \quad | \quad \tau \in \{1, \dots, N_{T_1}\} \right\} \\
P^W &= \left\{ P^W_t \quad | \quad t \in \{1, \dots, N_T\} \right\} \\
P^S &= \left\{ P^S_t \quad | \quad t \in \{1, \dots, N_T\} \right\}
\end{aligned}$$

where N_{T_1} is the number of periods during the time lapse between day-ahead and adjustment market-clearing process.

The hybrid power producer has to adhere the following sequence of decisions. First, he designs an offer strategy for the day-ahead market and submits his selling offers for each period of the market horizon. Second, once the day-ahead market price is known for each time period, he has to decide on the amount of energy that he wishes to sell or buy from the adjustment market. As soon as the adjustment market prices are known as well as the imbalance prices and the generated wind and solar power, the producer knows his level of imbalance and can compute the resulting costs for the latter.

2.2 A Hybrid Wind Solar Pool Trading Model Formulation

We set up a maximisation model for the hybrid wind-solar power producer. As already discussed previously, the producer has to decide on the amount of energy offered on the day-ahead resp. adjustment market for each timeperiod t and each scenario ω, denoted by $P^D_{t\omega}$ resp. $P^A_{t\omega}$. We split up the total deviation Δ_t into a positive and a negative deviation Δ^+_t resp. Δ^-_t such that

$$\Delta_t = \Delta^+_t - \Delta^-_t,$$

which we also have to include as one of the constraints. Thus, we wish to maximise the profit given by the sum of the revenues on the respective markets and possible imbalance costs. As we also aspire to consider the risk aversion of the producer, we include a conditional-value-at-risk term. For this, we need a weighting factor, denoted by β, the confidence level α, an auxiliary variable ζ and the continuous non-negative variable η, which is defined as the maximum of the auxiliary variable minus the revenue. We also have to include this definition as a constraint in our maximisation model.

The first block of constraints restricts the amount of energy we offer on both markets. First, we cannot offer more energy on the day-ahead market than the maximum amount of energy we can produce in both plants, denoted by $P_{\max}$. In each scenario and for every timeperiod, the total amount of energy offered, $P^O_{t\omega}$, comprises the amount of energy we offer on the day-ahead and the adjustment market and can, again, not exceed the maximum amount of energy we can produce. The latter comprises the maximum amount of solar energy we can produce, expressed by the parameter $P_{\max}^{S}$, and the maximum amount of wind energy we can produce, denoted by $P_{\max}^{W}$. Moreover, in any scenario, each source's amount of energy cannot exceed the respective maximum production amount.

The second block of constraints considers possible deviations. First, we define the total deviation as the difference between the actually produced and the initially offered amount of energy, multiplied by the duration of the time period. Apart from that, we split up the total deviation in terms of the positive, i.e. excess energy, and negative, i.e. energy deficit, deviation. On the one hand, the positive deviation cannot exceed what was actually produced in that scenario. This would happen if the producer didn't offer anything on either market, but then produced something non-zero. On the other hand, the negative deviation cannot be larger than $P_{\max}$, in which case the producer would offer all its capacity on the market, but actually produces nothing.

The offering curve conditions induce the third block of constraints. The first constraint ensures that offering curves are non-decreasing, which is a realistic and valid assumption to make on the energy market. Herefore we define the matrix O to sort the day-ahead prices associated with each period in an increasinglx manner for each scenario ω. Therefore, element $O(t, \omega)$ represents the position of the day-ahead price $\lambda_{t\omega}^{\mathrm{D}}$ over all scenarios $\omega \in \Omega$. Here identical day-ahead prices are associated with equal values in the matrix O^{D}, i.e., if $\lambda_{t\omega}^{\mathrm{D}} = \lambda_{t\omega'}^{\mathrm{D}}$ then $O^{\mathrm{D}}(t, \omega) = O^{\mathrm{D}}(t, \omega')$.

Moreover, the producer can only submit one offering curve no matter which imbalance price realises. We call this assumption the "non-anticipativity" constraint. This condition has to hold for the offering curve on the day-ahead market and the adjustment market. However, the amount of energy offered on the adjustment market might change with the day-ahead market price realisation and the wind and solar power forecasts, which are more precise the closer you get to the point of energy delivery. Conejo et al. refer to this as the "certainty gain effect", cf. [3]. When formulating the mathematical model, one has to differ between the time periods between the closure of the day-ahead market and the adjustment market and the time periods between the adjustment market's closure and delivery. This is only of relevance for the constraints concerning the non-anticipativity constraints. Therefore, we use the t as the overall timeperiod index and τ for the timeperiods between the closure of the day-ahead and the adjustment market.

The final block of constraints evolves around the conditional-value-at-risk measures, which are introduced in a more detailed way in Chapter 4 of [3].

Combining the explained objective with all these constraints gives the mathematical model below, which we shall translate into Julia as found in the provided notebook.

$$\begin{gathered}\text{Maximize}_{\,P_{t\omega}^{\mathrm{D}},\forall t,\forall\omega;P_{t\omega}^{\mathrm{A}},\forall t,\forall\omega;\Delta_{t\omega}^{+},\forall t,\forall\omega;\Delta_{t\omega}^{-},\forall t,\forall\omega;\eta_{\omega},\forall\omega;\zeta} \\ (1-\beta)\sum_{\omega=1}^{N_\Omega}\sum_{t=1}^{N_\mathrm{T}}\pi_\omega\left[\lambda_{t\omega}^{\mathrm{D}}P_{t\omega}^{\mathrm{D}}d_t+\lambda_{t\omega}^{\mathrm{A}}P_{t\omega}^{\mathrm{A}}d_t+\lambda_{t\omega}^{\mathrm{D}}r_{t\omega}^{+}\Delta_{t\omega}^{+}-\lambda_{t\omega}^{\mathrm{D}}r_{t\omega}^{-}\Delta_{t\omega}^{-}\right] \\ +\beta\left(\zeta-\frac{1}{1-\alpha}\sum_{\omega=1}^{N_\Omega}\pi_\omega\eta_\omega\right)\end{gathered} \tag{1}$$

$$
\begin{aligned}
0 \leq P_{t\omega}^{\mathrm{D}} &\leq P_{\max}, && \forall t, \forall \omega && (2)\\
P_{t\omega}^{\mathrm{O}} &= P_{t\omega}^{\mathrm{D}} + P_{t\omega}^{\mathrm{A}}, && \forall t, \forall \omega && (3)\\
0 \leq P_{t\omega}^{\mathrm{O}} &\leq P_{\max}, && \forall t, \forall \omega && (4)\\
P_{t\omega} &= P_{t\omega}^{S} + P_{t\omega}^{W}, && \forall t, \forall \omega && (5)\\
P_{\max} &= P_{\max}^{S} + P_{\max}^{W}, && && (6)
\end{aligned}
$$

$$
\begin{aligned}
\Delta_{t\omega} &= d_t \left(P_{t\omega} - P_{t\omega}^{\mathrm{O}} \right), && \forall t, \forall \omega && (7)\\
\Delta_{t\omega} &= \Delta_{t\omega}^{+} - \Delta_{t\omega}^{-}, && \forall t, \forall \omega && (8)\\
0 \leq \Delta_{t\omega}^{+} &\leq P_{t\omega} d_t, && \forall t, \forall \omega && (9)\\
0 \leq \Delta_{t\omega}^{-} &\leq P_{\max} d_t, && \forall t, \forall \omega && (10)
\end{aligned}
$$

$$
\begin{aligned}
P_{t\omega}^{\mathrm{D}} - P_{t\omega'}^{\mathrm{D}} &\leq 0, && \forall t, \forall \omega, \omega' : O\left(\lambda_{t\omega}^{\mathrm{D}}\right) + 1 = O\left(\lambda_{t\omega'}^{\mathrm{D}}\right) && (11)\\
P_{t\omega}^{\mathrm{D}} &= P_{t\omega'}^{\mathrm{D}}, && \forall t, \forall \omega, \omega' : \lambda_{t\omega'}^{\mathrm{D}} = \lambda_{t\omega}^{\mathrm{D}} && (12)\\
P_{t\omega}^{\mathrm{A}} &= P_{t\omega'}^{\mathrm{A}}, && \forall t, \forall \omega, \omega' : \left(\lambda_{t\omega'}^{\mathrm{D}} = \lambda_{t\omega}^{\mathrm{D}} \forall t\right) && \\
& && \text{and } \left(\overline{P}_{\tau\omega'} = \overline{P}_{\tau\omega}, \forall \tau = 1, 2, \ldots, N_{\mathrm{T}_1}\right) && (13)
\end{aligned}
$$

$$
-\sum_{t=1}^{N_{\mathrm{T}}} \left[\lambda_{t\omega}^{\mathrm{D}} P_{t\omega}^{\mathrm{D}} d_t + \lambda_{t\omega}^{\mathrm{A}} P_{t\omega}^{\mathrm{A}} d_t + \lambda_{t\omega}^{\mathrm{D}} \left(r_{t\omega}^{+} \Delta_{t\omega}^{+} - r_{t\omega}^{-} \Delta_{t\omega}^{-} \right) \right] + \zeta - \eta_{\omega} \leq 0, \forall \omega \qquad (14)
$$

$$
\eta_{\omega} \geq 0, \quad \forall \omega \qquad (15)
$$

3 Case Study

3.1 Scenario Generation

As already mentioned in subsection **??** our model has to account for variations with respect to solar and wind power generation in between the clearance of the day-ahead and adjustment market $\overline{P}^{W}$,$\overline{P}^{S}$ and during the market horizon P^{W}, P^{S} as well as the prices at the day-ahead and adjustment market λ^{D}, λ^{A} and the imbalance price ratios r^{+},r^{-}. Market prices are assumed to be independent of power generation. However, interdependencies within the sets of $\left\{\overline{P}^{W}, P^{W}, \overline{P}^{S}, P^{S}\right\}$ and $\left\{\lambda^{D}, \lambda^{A}, r^{+}, r^{-}\right\}$ respectively can not be neglected.

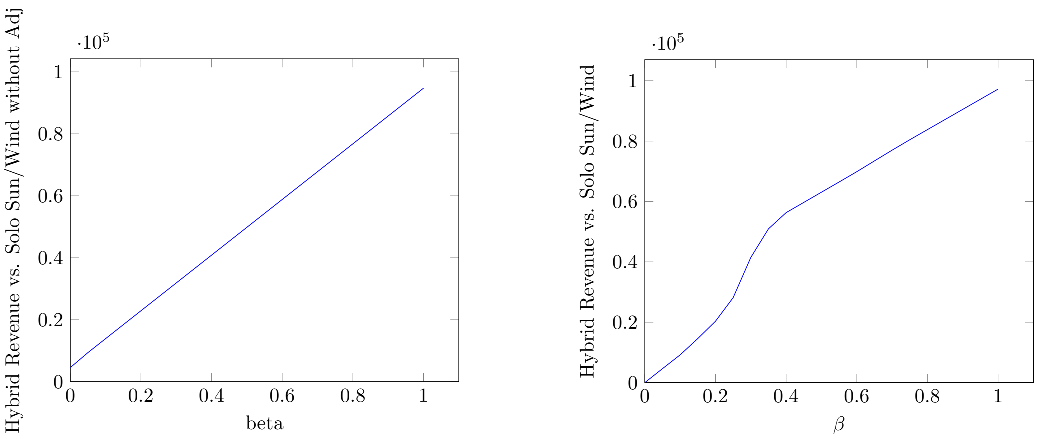
Without loss of generality, we limit our analysis to a single time period 12:00 PM - 13:00 PM. Furthermore, for the sake of simplicity, we utilize the market scenario of page 220 [3]. With respect to power generation our goal is to model an even split between solar and wind energy on an average day. To do so, we analyze historical data from the 50Hertz control area in Germany (https://data.open-power-system-data.org/time_series/). The data set supplies hourly power generation from 01. January 2015 to 01. October 2020. As mentioned before, solar and wind power generation is strongly dependent on the weather and hence exibits strong seasonal effects. While such seasonal effects have interesting economical implications on their own, they should not drive the variance of power generation in our scenarios. In other words, making use of scenarios that best represent the market for a variety of seasons would exaggerate the spread in power generation and hence not represent the energy market at any day throughout the analyzed period. Furthermore, in the data set, the average power generation from wind is 216% higher than the solar power generation. To mitigate the skewness towards wind energy and the seasonal effects, we first normalize the average power generation of both supply streams to $5.000MW$. Second, we subtract the 30-day moving average and reapply the overall average ($\sim 5.000MW$). To account for the negative correlation between solar and wind power generation, we fit both supply streams to ARMA models of the form $y_t = \mu + \phi\left(y_{t-1} - \mu\right) + \varepsilon_t + \theta\varepsilon_{t-1}$ and compute the variance-covariance Matrix G of ε^S and ε^W, where ε^S $\left(\varepsilon^W\right)$ refers to the residual vector of the solar (wind) energy ARMA model. The stochastic processes for solar and wind energy supply can hence be described as follows:

$$\overline{P}^W = \mu^W + \epsilon_1^W \tag{16}$$
$$\overline{P}^S = \mu^S + \epsilon_1^S \tag{17}$$
$$P^S = \mu^S + \phi^S\left(\overline{P}^S - \mu^S\right) + \epsilon_2^S + \theta^S\epsilon_1^S \tag{18}$$
$$P^W = \mu^W + \phi^W\left(\overline{P}^W - \mu^W\right) + \epsilon_2^W + \theta^W\epsilon_1^W. \tag{19}$$

Note again, that ε^S and ε^W refer to the residual vectors from the fitted ARMA models while $\left(\epsilon_1^S, \epsilon_1^W\right)$ and $\left(\epsilon_2^S, \epsilon_2^W\right)$ correspond to two independent realizations of the same random variable distributed according to a multivariate normal distribution with variance-covariance matrix G and mean $\overline{\varepsilon}^S$, $\overline{\varepsilon}^W$. Here $\overline{\varepsilon}^S$ $\left(\overline{\varepsilon}^W\right)$ refers to the average of the residual vector ε^S $\left(\varepsilon^W\right)$. ϕ^S, ϕ^W, θ^S, θ^W refer to the parameter results of the fitted ARMA models and μ^S $\left(\mu^W\right)$ refers to the mean of the normalized historical data set for solar (wind) energy. For $\left(\epsilon_1^S, \epsilon_1^W\right)$ and $\left(\epsilon_2^S, \epsilon_2^W\right)$ respectively we generate 1.000 realizations and cluster down to 4 branches based on euclidean distance, resulting in a total of 16 scenarios for power generation. Matching each power generation scenario with each of the eight price scenarios we get a total of 128 scenarios.

3.2 Results

Considering different values for risk aversion, we wish to compare a hybrid producer's revenue with the sum of two single energy producers' revenues, i.e. the sum of the revenues of a solar only producer and a wind power only producer. The way we modelled the problem, it was possible to simply neglect one energy source by setting the respective parameters to zero. Consequently, we could use the sam emodel for all three producers. Apart from that, we optimised the revenue once for the situation with an adjustment market and once for the situation without an adjustment market. The results are summarised in the figures below.



(a) (b)

Figure 2: Revenue

We plotted the difference in the revenue of the hybrid producer and the sum of both single producers' revenues on the vertical axis. We presented the risk aversion factor β on the horizontal axis. Overall, we see that the hybrid model is more advantageous for risk-averse producers. The more risk-averse a producer is, the more profitable it is to offer solar and wind power collectively. One striking difference is that the curve on the right starts in the origin while the curve on the left does not. If we have an adjustment market and are not risk-averse, it does not matter whether one producer offers both energies or two producers offer one energy each. The reason is that a risk-seeking producer offers everything on the day-ahead market and plans on buying back the deficit on the adjustment market. This is due to him expecting a lower price on the adjustment market than on the day-ahead market for our given data. On the other hand, if we do not have an adjustment market, we can exploit the anti-correlation. Thus, the variance of the produced amount of energy decreases and therefore, the hybrid producer can offer more energy for a given day-ahead price. Hence, it is more profitable to produce both collectively.

Apart from that, we observe a linear growth behaviour in a market system without an adjustment market. When adding the adjustment market to the system, we notice a slight bump. At some value for the risk aversion factor β, the producer is not brave enough anymore to trade on arbitrage since he would face losses in specific scenarios.

4 Conclusion

References

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