Stochastic Optimisation of Energy Procurement by a large Customer with PV-system

Project Report

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Abstract

Integrating large energy consumers in the the transition towards renewable energy source is essential for a successfull energy transition. This paper takes the perspective of a large energy customer that wants to optimise its energy procurement by using energy from three different options. It can use bilateral contracts for different time horizons, purchase energy hourly on the day-ahead market or use its own energy production. On its way to becoming an environmentally friendly company, the manufacturer uses a PV system instead of operating for example its own gas turbines. Due to the following exchange of controllable energy production with stochastic renewable solar energy generation, risk handling becomes an important factor in minimising the electricity procurement cost. The proposed modeling and scenario generation approach emphasizes the importance of knowing the newly added risk in power procurement, where self-production cannot be managed when pool prices are high and solar irradiance is low. Therefore general guidelines for large electricity consumer can be given. Possible approaches for future extensions are sketched out.

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1 Introduction

The transformation of the electricity sector with unstable prices tangles not only regulators and households, but also energy consumers. They need to meet their demand for cheap and stable green energy. Unlike in the past, consumers can easily participate in the provision of renewable energy sources through PV systems. Especially for large companies, it is a good opportunity to invest in a PV system that can be installed on unused roof space and provide free electricity after installation (wirtschaftszeit, 2022). Compared to the gas turbines installed in the past, they are also not dependent on external factors such as gas prices, which can be a decisive advantage these days. Germany's rescheduled energy transition from gas to even more wind and PV power generation is exacerbating this trend. Renewable production additionally offers the possibility of a market advantage for customers, as in the case of *CelestiAL*, an aluminum that is commercially produced with the power of the sun and specifically advertised with this property (ega, 2022).

This paper takes the perspective of a large energy customer that wants to optimise its energy procurement by using energy from three different options. It can use bilateral contracts for different time horizons, either monthly or weekly. In addition, energy can be purchased hourly on the day-ahead market. On its way to becoming an environmentally friendly company, the manufacturer uses a PV system instead of operating its own gas turbines. This allows the customer to use the stochastic power generation of their own PV system to meet its energy needs.

We are optimising energy procurement for 2021, as the current gas price situation could be a good pointer for the future. Therefore we divide the year in four exemplary periods in which the PV production differs significantly. These periods are the German seasons, summer, winter, spring and autumn. We performed our optimisation on four weeks in the spring. Each day consists of three hourly periods, divided according to the expected solar production. This approach results in a total of 84 periods per season, further described in section 2.1. To cover the uncertainty included in the price and PV generation, stochastic processes are used, which are characterized using scenarios. As the consumer not focuses only on the expected value of cost, the risk weighting parameter β is used to simulate different risk aversion profiles, which are evaluated in an sensitivity analysis in section 4.1.2.

The rest of this report is structured as follows. In Section 2, our assumptions and the model are discussed. Section 3 describes the data used for our optimisation and in Section 4, the results are presented and discussed. Section 5 concludes.

2 Model

This section elaborates the model specifications used to optimise the contract strategy of the energy consumer. Section 2.1 describes the model assumptions, and Section 2.2 sketches out the stochastic program and its solution.

2.1 Assumptions

The structure of the model is based on Chapter 9 of Conejo, Carrión, and Morales (2010), which optimize the energy purchase behavior of an energy consumer with a self-prodcution facility to meet a portion of its electricity needs. They suggested a co-generation facility as an example of the self-prodcution facility. The large energy consumer considered in this paper is the is also active in the electricity market and has its own energy production. Initially, bilateral contracts are concluded on a monthly and weekly basis. Thereafter, for each period, demand is covered by additional purchases or sales on the day-ahead market. At this point, the solar power generation for this period is known. In contrast to Conejo et al. (2010), the stochastic properties of the PV plant come into play at this point, since the output of the PV plant cannot be controlled by the consumer.

We consider a medium-term planning horizon, which is one month. For this purpose, we divide the year 2021 into the four seasons of spring, summer, fall, and winter, which correlate with solar generations, as shown in the 3 section of Figure 2. At regular intervals, the consumer makes bilateral contract decisions for future power supply, and throughout the planning horizon, the consumer decides on his pool participation, taking into account the actual generation of the PV system. Without loss of generality, we focus in the following on a planning horizon of four weeks, with each day of the planning horizon divided into three eight-hour periods, morning, noon, and evening, for the sake of manageability. This division is due to the distribution of PV production. It represents a reasonable compromise between solution accuracy and computational effort. The resulting time span is four weeks, yielding 84 periods, with the pool price created in each eight-hour period through the scenario generation process described in more detail in Section 3. The consumer's electricity demand is secondary to the optimization because it does not contain uncertainty. Therefore, a weekly demand pattern with higher demand in the midday hours is used. The resulting stochastic framework is a multilevel problem since it includes more than two stages.

Since we assume a time horizon of one month, energy can be purchased on bilateral contracts for a maximum duration of one month. The price points of the contracts are set using the pool price data for the entsoe (2022) where scenario generation process, further described in section 3 is used. Although realized contract prices depend on actual pool market prices, there is less uncertainty due to their bilateral calculation. In this case, half of the realized price is made up of the negotiated contract price and half of the actual pool price. Here, the realized price is lower when the pool price is higher, but higher when the pool prices are lower. The bilateral contracts represent a first-stage or here-and-now decision, as it is made before the realization of the stochastic process. A non-anticipativity constraint ensures that the decision on the bilateral treaty cannot depend on the realization of the scenario. This constraint forces the same electricity to be purchased for each same scenario stage, regardless of the actual scenario realized.

Trading on the pool market is conducted via the day-ahead market, and we assume that we achieve average product prices for short-term day-ahead trading. The oversupply and undersupply caused by the uncertainty of solar radiation must be sold or bought on the day ahead market so that the demand is exactly met. Trading with the pool is therefore a second-stage or wait-and-see decision, since decisions are made only after the actual realization of the stochastic process is known. These decisions depend on each realization vector of the stochastic process.

The actual data used for optimisation comes from entsoe (2022), which publishes pool prices in the day-ahead market on an hourly basis. Since we want to analyze the overall behavior of a large consumer located in Germany, we did not select a specific region. Therefore, we also used PV generation data from entsoe (2022), which publishes the current solar power generation in Germany every quarter hour. Taking the perspective of a large energy consumer, we assume that the PV system size is 0.027% of the total production in Germany, resulting in a peak generation of 100MW per hour or 800MW per eight-hour period. This seems like a very high value, but since we are trying to replace the current gas turbines, it might be reasonable, especially if we take into account the 1013 MW installed by the aluminum producers mentioned in the introduction (ega, 2022). The aggregate solar generation per hour is then combined in the scenario generation process, where the actual solar generation used in a given pool price scenario ω is the corresponding solar generation for that eight-hour period. This establishes part of the dependency, since the pool price is the price for a given hour in that time period, but the solar power generation is the sum over all hours in that time period. The whole process is described in more detail in the 3 section.

We have only considered variable costs in this model because we are trying to compare the behavior of a large energy consumer with that of a gas turbine owner whose main cost drivers are variable costs. Since a gas turbine also has fixed costs, these are not considered here.

2.2 Model

The model used to solve the stochastic optimisation is shown and described below. The structure of the model is based on Chapter 9 of Conejo et al. (2010), but has been adapted to the characteristics of a PV plant. An additional time dimension, the week, is included in the Julia model because it simplifies the implementation of the non-anticipation constraint. An overview over all used variables and parameters can be found in Appendix A.1. The underlying scenario generation and usage is explained in more detail in 3.1. The exact values used for the parameters are explained further in section 3.2.

$$Minimise_{P^B;E^P,\forall\omega}$$
$$\sum_{\omega=1}^{\Omega^\lambda}\pi_\omega\sum_{t=1}^{T}(\sum_{b\in Bt}\lambda^B_{bt\omega}P^B_{b\omega}d_t+\sum_{h=1}^{H}\lambda^P_{t\omega h}E^P_{t\omega h})+\beta(\zeta+\frac{1}{1-\alpha})\sum_{\omega=1}^{\Omega^\lambda}\pi_\omega\eta_\omega \quad (1a)$$

$$\lambda^B_{bt\omega}=\frac{\lambda^B_b+\lambda^P_{t\omega h}}{2} \quad (1b)$$

$$P^{B,Min}_{b\omega}s_b\omega\leq P^B_{b\omega}\leq P^{B,Max}_{b\omega}s_b\omega,\forall b,\forall\omega \quad (1c)$$
$$E^D_t=E^S_{t\omega}+E^P_{t\omega}+\sum_{b\in Bt}P^B_{b\omega}d_t,\forall\omega\forall t \quad (1d)$$
$$E^P_{t\omega}=E^S_{t\omega},\forall\omega\forall t \quad (1e)$$
$$P^B_{b\omega}=P^B_{b\omega+1},\forall b,w=(1\dots\Omega-1)if A_{wK_b}=1 \quad (1f)$$
$$\eta_\omega\geq\sum_{t=1}^{T}(\sum_{b\in Bt}\lambda^B_{bt\omega}P^B_{b\omega}d_t+\sum_{h=1}^{H}\lambda^P_{t\omega h}E^P_{t\omega h})-\zeta,\forall\omega \quad (1g)$$
$$0\leq\eta_\omega,\forall\omega \quad (1h)$$
$$(1i)$$

The *objective* (1a) minimizes the cost of meeting electricity demand by purchasing energy through bilateral contracts P^B and the day-ahead market E^P for all periods t and scenarios ω. The cost of buying in bilateral contracts $\lambda^B_{bt\omega}$ for a given period t and scenario ω is defined in the expression (1b) as the sum for buying at the price of the contract λ^B plus the realized price in the day-ahead market λ^P divided by two. The resulting price values are then weighted by the probability of occurrence π in the objective function (1a). The second part of the objective function controls the risk by using the *Conditional Value-at-Risk* (CVar) multiplied by the weighting factor β, which allows to control the degree of risk aversion of the energy consumer. For this, the two auxiliary variables ζ and η are used, which limit the probability of high costs in unfavorable scenarios. In this way, the expected value of the costs is smaller than the (1-α) quantile.

The energy consumer's purchase behavior is restricted by four constraints. The first constraint, the *bilateral purchase bound* (1c) limits the amount of energy available for a given contract P^B with a minimum and a maximum value for power purchase. The amount of energy available for trading in the day-ahead market E^P is limited by the consumer's 1d minus the already contracted energy P^B and the actual PV production E^S. Only self-produced energy E^S can be sold in the pool, so no arbitrage trading is possible (1e). The *non anticipativity* (1f) ensures that once a contract P^B is made, the same value of the purchased energy is used in all subsequent scenarios ω. The *risk constraint* (1g) levels the auxiliary risk variables ζ and η with the cost of bilateral contracts concluded P^B and trading in the day-ahead market E^P and is required for the calculation of CVaR. The model concludes with the condition *Non-Negativity* (1h), which ensures that only positive values apply to these variables.

3 Data

This section presents the data used for the optimization problem. Section 3.1 describes the sources of the real data used here and the procedure used to generate scenarios from it. Section 3.2 then explains which parameter values were used in the baseline specification of our optimisation.

3.1 Data

Price data for the day-ahead market and the actual solar generation for the period between 01/01/2021 and 12/31/2021 in Germany comes from entsoe (2022). As expected, the actual solar irradiance follows a seasonal pattern with peak values in summer and lower values in winter, as shown in Figure 2. The assumption for the distinction between four seasons from Section 2.1 is therefore valid. The bilateral contract design is based on Chapter 9 of Conejo et al. (2010), but adjusted so that when the risk aversion parameter β equals zero, few or no contracts are signed, depending on the scenario sampling.

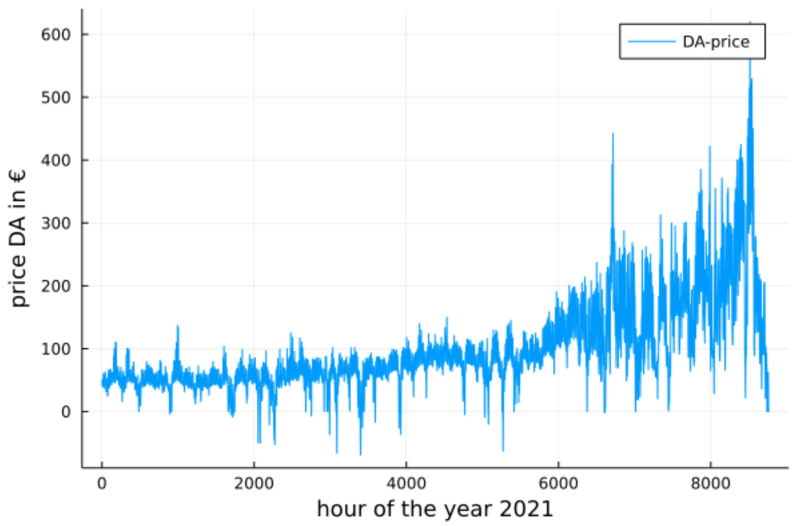

Figure 1: Day-ahead Prices in the considered time period

There appears to be a data issue where solar data is missing for 45 minutes at 2am in the period 28/03/2021. Since this occurs during the night time when there is no solar radiation, we have filled the gaps with a value of zero. In the price data set, the same hour is missing, so we added the sum of the surrounding values divided by two, since these are the nighttime hours when there is less variation.

The central element of the presented optimization are the scenarios and their creation, as they determine the validity of the model. The method used is *sampling from the data set*, which is inspired by Kaut (2021) and critically discussed in section 4.2.

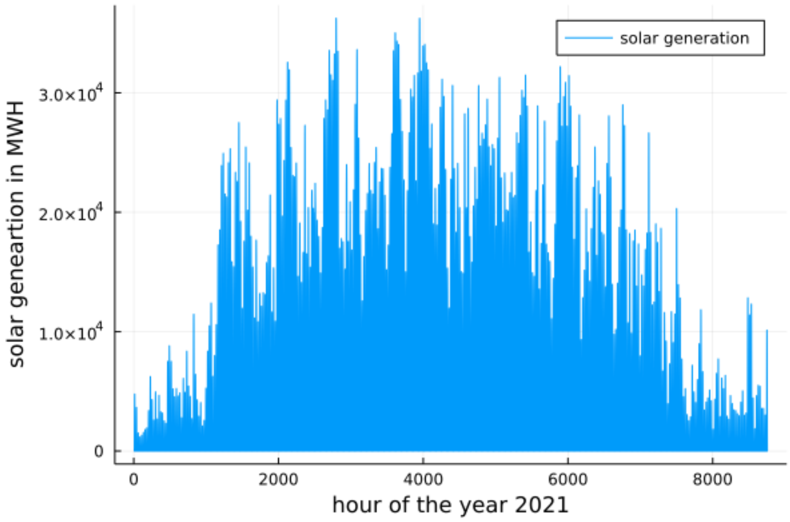

Figure 2: Solar Generation in MW in the considered time period

Since the time periods are structured in eight-hour blocks, as described in section 2.1, a sample of 616 is drawn for each block of hours. The number 616 is chosen to satisfy the need for unique prices for the scenario tree, since 1848 different prices are used in the tree (616×3). The generated tree has a 4×3×2×2 scenario structure, i.e. 4 branches descend from the root node, 3 branches descend from each node of the second stage, etc. The same procedure is used for the actual solar power generation in MW. In each stage of the tree corresponding to one of the four underlying weeks, the structure is filled with S_K different values, i.e., in the first period t_1, which is a *morning*, four different price and solar generation values are used for all corresponding 21 periods of the first week. Therefore, for each price, 12 scenarios, for each of the 21 periods are the same. In the next phase, which refers to the second week, each of the 12 equal price scenarios is divided so that 4 periods of the phase are equal and so on. The corresponding algorithm is included in the Julia code in the section *scenario creation*. The resulting tree consists of 48 different price and solar scenarios for ω, all of which differ in the final stage of the tree.

Figure 3 shows the generated day-ahead price scenarios for ω_1 in the spring season, with the time period considered. The eight-hourly repeating time pattern caused by the division into morning, noon and evening can be seen. The same pattern occurs in the solar power generation scenarios, where the generation peaks occur in the noon period, as expected.

3.2 Parameters

We choose a α level of 0.95, which results when maximizing the objective function, in optimizing the values of the 5% scenarios with the lowest profit. In combination with the β weighting parameter for risk-aversion, we can control the risk behaviour of the wind producer. For the sensitivity analysis 4.1.2, we choose different values for β. In this way, we can simulate different risk behaviours, including the risk neutral case where

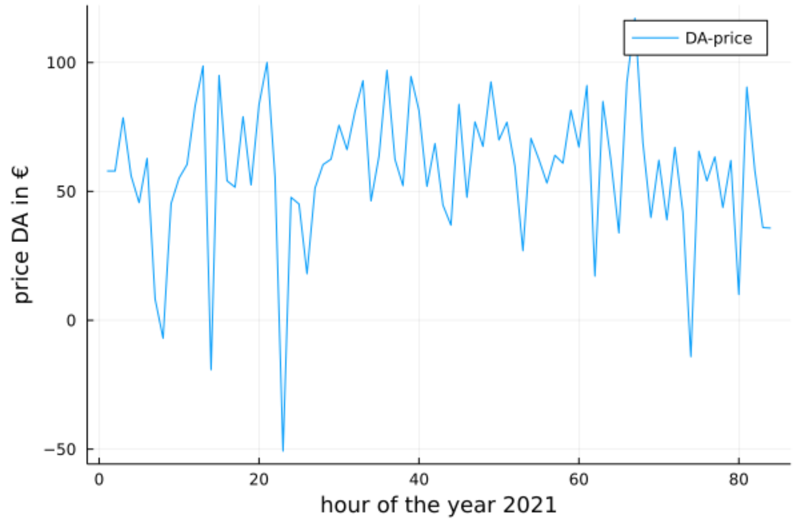

Figure 3: Day-ahead price scenarios for ω_1 in the considered time period

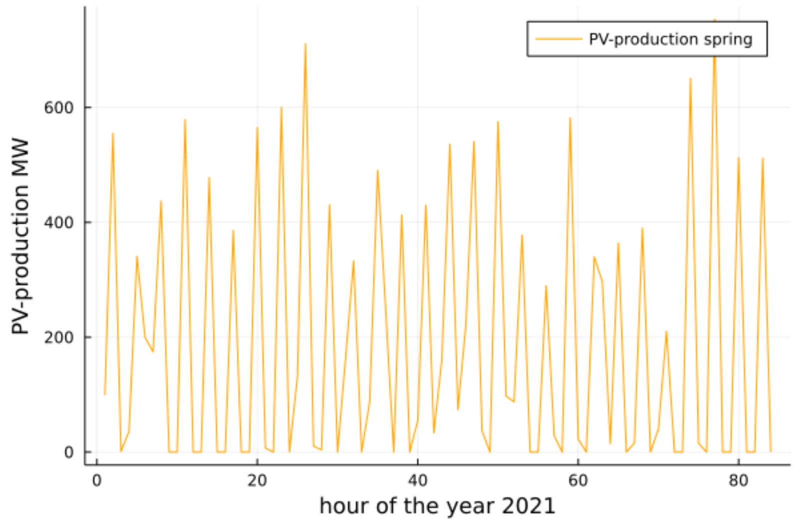

Figure 4: Solar generation scenarios for ω_1 in MW in the considered time period

the value β is 0 and therefore risk is not considered. The probability of occurrence π of a scenario ω is calculated by $\frac{1}{\Omega}$ where Ω is the number of all scenarios.

4 Discussion

Below, Section 4.1 presents the baseline results of the optimisation as well as some sensitivity analyses, and Section 4.2 discusses shortcomings of our approach and potential for future extensions.

4.1 Results

4.1.1 Baseline Results

In the results, we focus on the ω_1 and ω_16 scenarios, as they differ in each stage of the tree due to the underlying structure, as can be seen in Figure 5 and Figure 6. The total cost of fully meeting demand is 9688020 euros when β is zero and no risk is considered. Therefore, the consumer buys electricity in the day-ahead market when it is cheaper than the bilateral contracts. As can be seen in Figure 5, contract seven is chosen only in scenario ω_1.

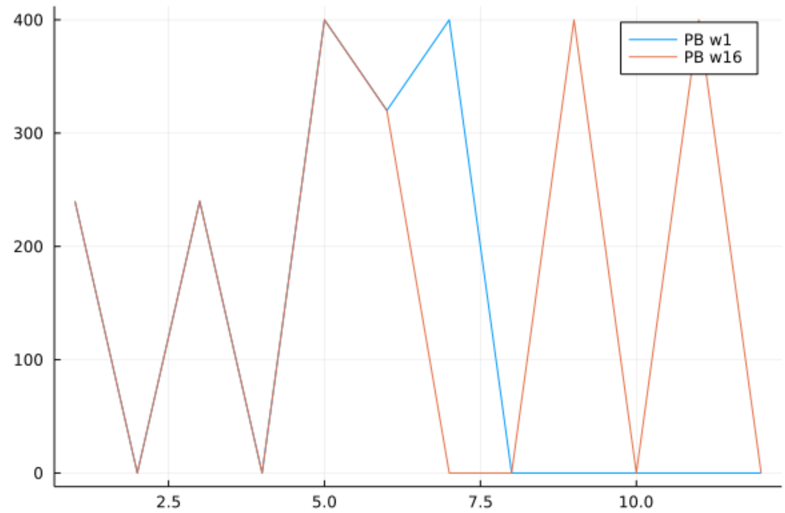

Figure 5: Power purchased from bilateral contracts in ω_1 and ω_2

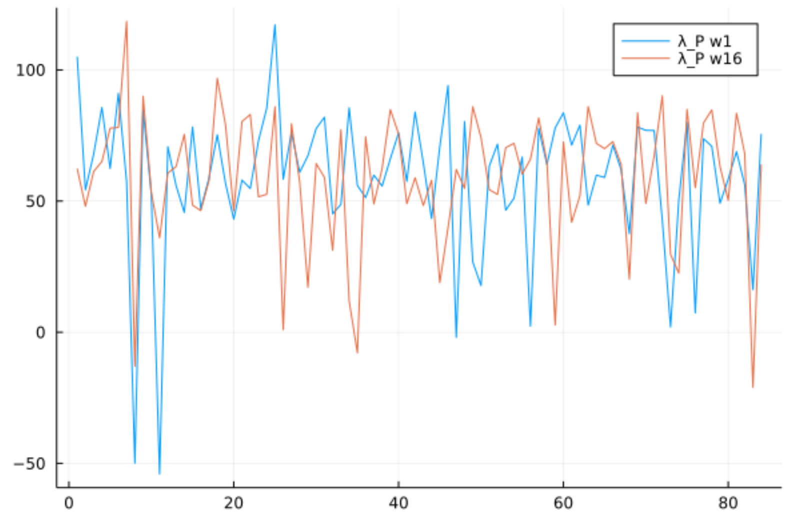

Figure 6: Day-ahead prices in ω_1 and ω_2

4.1.2 Sensitivity Analysis

In our baseline specification, the large energy consumer was risk neutral. This fact should play a role in procurement behavior. For certain scenarios, we found that the energy consumer did not behave as expected. For the scenario tree analyzed in this chapter with a higher value of β equal to five, the expected cost reduces to a value of 6078128 euros, caused by the negative price value seen in Figure 5, which reduces the CvaR as the bilateral contract decision remains the same. This behavior strongly suggests a need for improvement in the design of dynamic contracts that change according to the chosen pricing scenarios. As described in section 4.2, the use of realistic contract data seems necessary. In addition, we found that the underlying structure has problems in dealing with negative prices, as they affect the CvaR in an undesirable way.

This behavior was not observed in other scenario trees. As expected, when β is increased by the value of five, the large consumer increases the energy purchased in biletral contracts. The same expected behavior occurred when using the scenarios designed by Conejo et al. (2010). The sensitivity analysis is with these limitations in scenario generation and the construction of bileteral contracts only insufficiently feasible, but the core statement remains. Due to the strong uncertainties in both prices and PV power generation, it is essential to perform a risk assessment and analysis to ensure supply at low cost.

4.2 Shortcomings and Potential Extensions

Focusing on the overall behavior results in several shortcomings. We have only considered the spring season, which offers a good compromise between high and low solar generation. Especially the winter with its high prices, which today seem to be a good indicator for future years, is worthwhile to investigate further. Since bilateral contracts and consumer demand are not currently based on real data, because this model focuses on aggregate behavior, they appear necessary for this high-price situation. A possible extension could be to focus on a specific consumer with their demand patterns and the usable contracts they can enter into. This could usefully incorporate the period-specific contracts used by Conejo et al. (2010). Therefore, precise statements could be made, but they may not be generalizable.

Currently, the underlying scenarios are the key determinant of consumer behavior. Since they are modeled in a very simplified way in this paper, further research is needed on implementations with more complex scenarios as described in Kaut (2021). TThe actual implementation depends heavily on the sample size. Since the sample size is 616 per hour to fill the scenario tree and the data set size for the hourly period is 736, overfitting is likely. However, a very precise representation of the period under consideration is also possible, as shown by the comparison between Figure 7 and Figure 8 for the morning period. With the rolling observation period for morning, noon, and evening, the time-dependent price and especially solar generation patterns are included, as shown in Figure 3 and Figure 4. The resulting tree structure includes a total of 1848 different prices and solar irradiance values, resulting in 48 leaves with different prices for the last 21 periods. Thus, 48 different scenario time series are created, each consisting of a price with the corresponding solar generation value. At each specific node in the tree, a single hourly value from the sample is taken in the spring season, representing the eight-hour period for the price. For the same hourly single value from the sample, solar generation multiplied by eight is also taken (the length of the eight-hour period). This approach has weaknesses with respect to extreme values due to the combined formation of price and solar generation. Further research with a more precise method for creating scenarios seems necessary. Conejo et al. (2010) used the ARIMA model for their implementation, which has the weakness of not properly representing the underlying trend and seasonality. The use of a SARIMA model seems to be a suitable solution, since it can handle in particular such time-dependent data with seasonal effects.

With the growing share of PV generation, the price dependency to solar radiation is increased. Therefore, further research on this relationship seems necessary, especially in this particular setting where the consumer fully relies on PV. For this purpose, various extensions of the customer's own production and storage facilities are possible. Consumers could divide their own green power production by using wind turbines, since their production is not linked to solar irradiation and therefore a greater distribution of risk is possible. In addition, with the use of electricity storage, excess production could be used to skip high pool prices when self-production is not available. Therefore, load scheduling or purchasing at high pool prices is no longer necessary (energie-und-management, 2022). For large companies in particular, this could provide an opportunity to pair their employees' e-vehicles for use as energy storage devices as they remain stationary at company-wide charging stations during working hours. M. T. Kahlen (2018) presented a strategy for an EV fleet owner to use its EV vehicle batteries as a way to trade in energy markets, similar to what large energy consumers might do with connected EVs. These and other storage options expand the possibilities for arbitrage trading, in which energy is bought or produced more cheaply and then sold more expensively to the grid.

5 Conclusion

Integrating large energy consumers in the the transition towards renewable energy source is essential for a success full energy transition. Due to the following exchange of controllable energy production with stochastic renewable wind or solar energy generation, risk handling becomes an important factor in minimising the electricity procurement cost. The proposed modeling and scenario generation approach emphasizes the importance of knowing the newly added risk in power procurement, where self-production cannot be managed when pool prices are high and solar irradiance is low. Therefore general guidelines for large electricity consumer can be given, even though there is still room for improvement and extensions.

A Appendix

A.1 List of all Variables and Parameters

A.1.1 Indices and Numbers

t Index of time periods running from 1 to T.
ω Index of scenarios running from 1 to Ω

A.1.2 Constants

α Per unit confidence level.
β Risk-aversion weighting parameter.
π Probability of occurrence for scenarios.

A.1.3 Decision Variables

P^B Amount of energy purchased in bilateral contract.
E^P Amount of energy purchased in the day ahead market.
η Auxiliary variable in scenarios ω used to compute the *Conditional Value-at-Risk* (CVaR).
ζ Auxiliary variable used to compute the CVaR.

A.1.4 Variables

E^D Demand of the consumer.
E^S Energy supply through the PV system.
λ_b^B Price for power purchase in a contract.
$\lambda_{bt\omega}^B$ Actual price for power purchase in a contract.
λ^P Price for power purchase in the day ahead market.

A.2 Additional Figures

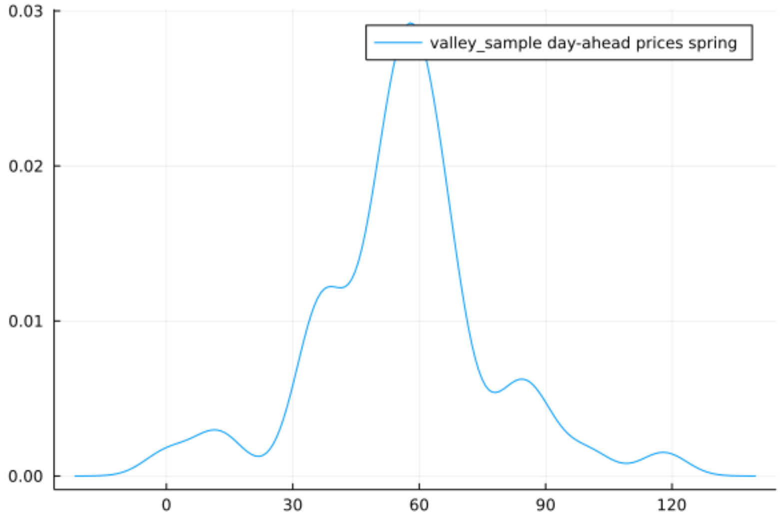

Figure 7: Price sample distribution for the morning period in season spring

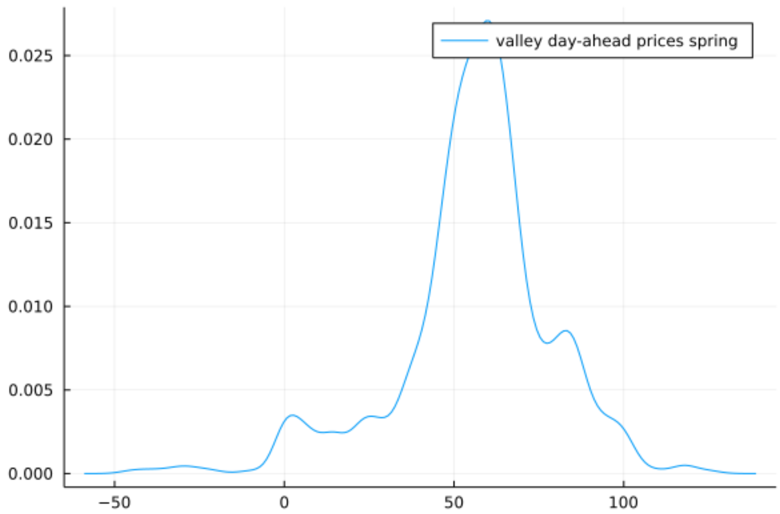

Figure 8: Prices distribution for the morning period in season spring

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