46755 – Assignment 2

Deadline: May 13, 2024 (23:59pm)

April 14, 2024

Step 1

In lectures 8 and 9, you learn about offering strategy of price-taker renewables. Please consider a wind farm with the nominal (installed) capacity of 200 MW. We are interested to formulate and solve an offering strategy problem for this farm. This problem determines her participation strategy in the day-ahead market (in terms of her hourly production quantities). Note that her offer price is zero. We consider a time framework of 24 hours. Please also note that we discard reserve and intra-day markets, and consider day-ahead and balancing markets only.

Sources of uncertainty: Please consider three sources of uncertainty, namely:

1. Hourly wind power production in the next day
2. Hourly day-ahead market prices in the next day
3. The power system need in the balancing stage in every hour, i.e., the system has either a power supply deficit or excess.

We will generate scenarios to model these three sources of uncertainty. For simplicity, we assume there is no correlation among these three sources of of uncertainty.

Scenario generation for wind power production forecast: Potential references are as following:
Reference 1: You can get wind data from the FINGRID website (Finnish TSO) or the ELIA website (Belgian TSO), and normalize them for a 150-MW wind farm. Although they report "aggregate" wind data, you can assume they are data for an individual farm. The wind profile during a day can be seen as a scenario. For example, wind profile on March 1 can be seen as scenario 1. This profile on March 2 can be seen as the second scenario, and so on.
Reference 2: `https://sites.google.com/site/datasmopf/wind-scenarios`
Reference 3: `https://www.renewables.ninja`

Scenario generation for day-ahead price forecast: Using a similar strategy, you can generate price scenarios for 24 hours from the Nord Pool website. For example, you can assume the wind farm is located in DK1, and use the corresponding hourly day-ahead market prices.

Scenario generation for the power system need (excess or deficit): You can generate a series of 24 random binary (two-state) variables, e.g., using a bernoulli distribution, indicating in every hour of the next day, whether the system in the balancing stage will have a deficit in power supply or an excess.

Final scenarios: To model three sources of uncertainty, please consider at least 1,200 scenarios. Discarding the potential correlation between these three sources of uncertainty, the total number of scenarios is equal to the number of scenarios for uncertain source 1 times the number of scenarios for uncertain source 2 times the number of scenarios for uncertain source 3. For example, if we consider 20 wind power scenarios, 20 day-ahead price scenarios, and 3 power system need scenarios, this results in 20*20*3 = 1200 scenarios.

Out of these scenarios, we will arbitrarily select at least 250 scenarios (the so-called *in-sample* or *seen* scenarios) and will use them in Steps 1.1 to 1.4 for decision making, i.e., the determination of the optimal quantity offer in the day-ahead stage. The rest of scenarios (the so-called *out-of-sample* or *unseen* scenarios) will be used later in Steps 1.5 and 1.6 for an ex-post analysis. We can assume all scenarios are equiprobable. In other words, in case we consider 250 in-sample scenarios, the probability of each scenario is 0.004.

Note 1: Under a **one-price** balancing scheme, we can generate corresponding balancing price forecasts, based on scenarios generated for day-ahead prices and for the power system need. Recall that Energinet has switched to this scheme since November 2021. The balancing price is higher (lower) than the day-ahead price if the power system has a power supply deficit (excess) in the balancing stage. Similar to the lecture, let's assume *balancing price = coefficient * day-ahead price*, and use coefficients 0.9 and 1.2 to generate balancing prices.

Note 2: Unlike Note 1, we cannot generate balancing price scenarios *a priori* if the balancing stage uses a **two-price** scheme. Recall that the balancing price will be equal to the day-ahead price if the underlying wind farm provides a positive imbalance, i.e., helps the system to cope with the system imbalances. Before determining the optimal quantity offer in the day-ahead stage, we will not be able to quantify the imbalance (whether it will be positive or negative) and therefore cannot identify whether the wind farm provides a positive imbalance or not.

Please complete the following five items:

1.1 **Offering strategy under a one-price balancing scheme:** Formulate and solve the stochastic offering strategy problem accounting for a one-price balancing scheme and in-sample scenarios. Determine the optimal hourly production quantities that the wind farm should offer in the day-ahead market. Report the expected profit. Please also illustrate the profit distribution over scenarios.

1.2 **Offering strategy under a two-price balancing scheme:** This step is similar to Step 1.1, but reformulate it for a two-price balancing scheme. Please note that we should modify the model in a way that it endogenously identifies in every hour whether the wind farm provides a positive imbalance, and if so, then the corresponding hourly balancing price should be equal to the day-ahead price in that hour. Any remarkable difference between results of Steps 1.1 and 1.2?

1.3 **Risk analysis:** For fixed coefficients of 0.9 and 1.2 and given value of $\alpha = 0.90$, formulate and solve the risk-averse offering strategy problem of wind farm under both one- and two-price balancing schemes. Recall that the objective function is in the form of [(expected profit) + (β * CVaR)]. Gradually increase the value of β, starting from zero. For each value of β, save the values obtained for the expected profit and for the CVaR, and plot a 2-dimension figure (expected profit versus CVaR). Note that the CVaR value does not include β. Please interpret this figure. In addition, please explain how the offering strategy of wind farm and her profit volatility over scenarios are changing by increasing

β.

1.4 **Out-of-sample simulation:** Given in-sample (seen) scenarios, in Step 1.3, we have obtained optimal hourly quantity offer of the wind farm in the day-ahead stage. Let's indicate it by $p_t^{\mathrm{DA}\star}$ for every hour t. Now imagine the wind farm has already submitted hourly offers $p_t^{\mathrm{DA}\star}$ in the day-ahead stage and earned x euro and we are now in the balancing stage, where uncertainties are being realized. Suppose the realization is based on the first out-of-sample (unseen) scenario. Calculate how much the wind farm should be paid or pay under this realization — let's call it y_1. Note that we do not need any optimization for this stage. Calculate the same for all unseen scenarios, i.e., y_1 to y_{950}, assuming we have 950 out-of-sample scenarios. Now, calculate the *average out-of-sample profit*, i.e., x plus average of y over 950 unseen scenarios. Please report it and check how different it is with respect to the in-sample expected profit we have already achieved in Step 1.3 (i.e., the optimal value of the objective function). How different are the probability distributions of profit in in-sample and out-of-sample analyses? If in-sample and out-of-sample profits (in expectation and their distribution) are significantly different (or indifferent), what does it imply?

1.5 **Cross validation:** Are the results of Step 1.4 very sensitive to the selection of in-sample and out-of-sample scenarios (the same number of scenarios but different scenarios)? For example, arbitrarily choose another 250 in-sample scenarios out of original 1200 scenarios. Please try to find a "good" number of arbitrarily selected in-sample scenarios (which might be different than 250), under which we get similar in-sample and out-of-sample profits. Any recommendation for scenario generation, decision-making, ex-post analyses, etc?

Step 2

In lecture 10, you learn about offering strategy of stochastic assets in ancillary service markets. For example, we consider a stochastic flexible load which could be either a large energy consumer or an aggregator of small-scale loads, e.g., electric vehicles, whose minimum and maximum energy consumption is 0 kW and 500 kW, respectively. Without loss of generality, we consider the FCR-D UP market in DK2 with hourly bids as the target market for the flexible load to sell its flexibility — we assume there is no minimum bid size requirement. The load can offer this service owed to its ability to reduce its consumption level very quickly. Please consider a single hour with a minute-level resolution.

Data generation for future stochastic load: Please randomly generate 200 consumption load profiles such that, under each profile, load for every minute is not less than 200 kW, not beyond 500 kW, and the difference of consumption load between two subsequent minutes is not more than 25 kW. Please note that these limits do not represent any technical constraints, but used for stochastic data generation purposes only. We will use 50 out of 200 profiles for in-sample decision making (i.e., reserve capacity bidding to the FCR-D UP market, in kW), and the remaining 150 profiles for the out-of-sample analysis. The probability for every in-sample profile is identical.

Please complete the following three items:

2.1 **In-sample decision making: Offering strategy under P90 rule:** Given P90 rule of Energinet, please determine the optimal reserve capacity bid (in kW) of the stochastic load in the FCR-D UP market for the hour in question. For that, please use both **ALSO-X** and **CVaR** techniques, which may give different results.

2.2 **Out-of-sample analysis:** Using 150 testing profiles, please check whether P90 rule is fulfilled for both solution techniques used. This step does not need solving any optimization. You can compare the optimal reserve bid obtained in Step 2.1 with the power consumption under the given testing profile. For example, if the stochastic load bids 300 kW to the FCR-D UP market for the given hour while its consumption under a certain profile in a certain minute is 280 kW, this shows there is a reserve shortfall of 20 kW for that minute.

2.3 **Energinet perspective:** Please take the perspective of Energinet and explore by varying the P90 rule (e.g., by varying the allowed frequency of reserve shortfall between 80% and 100%), how the optimal reserve bid (in-sample analysis using ALSO-X) and expected reserve shortfall (out-of-sample analysis) change. Do you observe any trade-off?