Dealing with uncertainty and disruptive events in generation expansion optimization models

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Overview

Generation expansion models are used in setting up scenario projections for the electric power sector. Typically these models minimize the total discounted cost of building and operating power plants over a timespan of, e.g., 50 years in order to cover a certain demand.

Since we cannot make clear predictions of the state of the investment climate years ahead in the future, it is important to take uncertainty into account in the decision making process and hence, in generation expansion models. One method that can incorporate uncertainty in long-term investment planning is stochastic programming. Stochastic programming has been applied to many areas of study including generation expansion optimization. Studies considering long-term uncertainties in stochastic fuel prices (Schröder, 2014), demand growth (López et al., 2007) and policy measures (Kanudia & Shukla, 1998) have been conducted extensively. More recently, multiscale multihorizon stochastic programming methods have been applied to capture both long-term uncertainty and short-term (operational) uncertainty (Kaut et al., 2014).

The stochastic programming method is founded on the assumption that the uncertain parameters can be described by a corresponding probability distribution. After all, a suitable scenario tree has to be composed in order to capture the parameter's uncertain behavior. However, capturing every possible parameter outcome in a scenario tree is difficult when the time horizon is spanning decades. Short-term uncertainties such as hour-to-hour price variations, RES power production and load fluctuations can be represented easily by a probability distribution, since the causes of these fluctuations are more or less known. To put this differently, these fluctuations are *known unknowns*; this is the reason why we are able to make probability distributions. However, once we start composing scenarios for the coming years, there are factors that cannot be foreseen. We do not know what these factors are; history just teaches us that disruptive events happen and that those events are governing the way in which prices, demands and policies evolve. These 'shocks' can take the form of sudden fuel price changes, technology breakthroughs or drastic policy measures. Since we have no idea about the causality of these events before they actually happen, it is very difficult to take them into account in scenario based representations of uncertainties used in stochastic programming.

Acknowledging the fact that disruptive events cannot be easily anticipated quantitatively by probability distributions, the question that arises is how well stochastic programming performs in generation expansion models when such a disruptive event occur. As such, we seek for a novel modeling methodology that provides more robust solutions towards shocks.

Methods

In this paper, the aim is to assess and improve the performance of a stochastic programming optimization under shock occurrence. In a first step, we make an assessment of the performance of stochastic optimization based on a comparison between three investment paradigms.

- The first paradigm is one where the investment decisions are based on the results of a stochastic optimization. Suppose the stochastic optimization is performed based on a scenario tree as presented in Figure 1. In every time step investments are made taking into account each of the scenarios with their corresponding probabilities. Assume now that a shock occurs at a time step. The investments in the previous time steps are fixed and cannot be modified. With these fixed investments we solve the deterministic optimization for only the shock scenario. In this way, we are able to examine how investments based on stochastic optimization recover from a shock.
- Second, we solve the deterministic shock scenario for the case where the initial investments are based on the results of the average deterministic optimization (i.e. the values of the parameters at each stage are the probability weighted average of the stochastic optimization).
- For the last paradigm it is assumed that perfect information about the shock is available. In this way the shock scenario is anticipated completely and the investments in all stages can be chosen freely.

A comparison between these three cases indicates the performance of a stochastic programming optimization under shock occurrence respective to a deterministic average optimization and a perfect information optimization. A sufficient number of experiments is performed in order to reach general conclusions on this topic

In a second step, we seek to improve the stochastic programming optimization in order to better cope with the occurrence of shocks. This is done by investigating the impact of the scenario tree structure on the robustness of the achieved solution. The introduction of low probability, extreme scenarios into the scenario tree might result in a capacity mix that is more robust and less prone to parameter variations. This more robust capacity mix intuitively will consist of a large number of different technologies, which will have an impact on the value of the objective function. The difference in optimality compared to the case with the original scenario tree is expressed as the *cost of robustness*.

Results

The model, which minimizes total system costs, is run for the Belgian system (i.e. demand and renewable generation characteristics). Furthermore, we make use of a greenfield setting where no existing units are in place. As a mere illustration of uncertainty and its high impact on model outcome.
Figure 2 shows the dependency of the installed capacity on the gas price used in the model. It can be seen that input parameters have a substantial impact on the results and that uncertainty treatment is an important issue to be addressed in generation expansion models.
Results on the performance of stochastic programming under the occurrence of shocks are fully presented in the final contribution.

Conclusions

In the final contribution, conclusions are drawn regarding the performance of a capacity expansion planning using stochastic programming compared to a deterministic optimization.
Furthermore, the findings regarding the effect of scenario tree structure on the robustness of the investment decisions will be discussed. Expanding the scenario tree with extreme scenarios is expected to improve the robustness of the resulting capacity mix, which would contain a large number of different technologies.

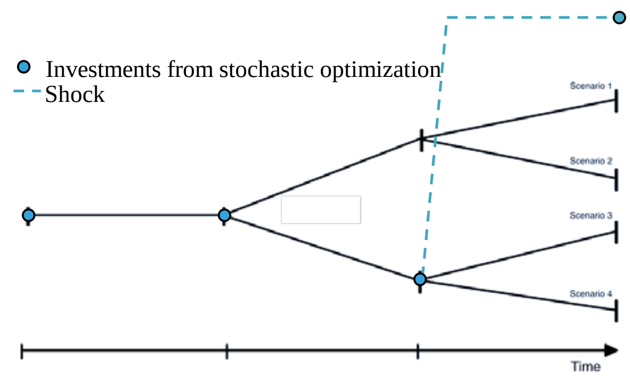

Figure 1: Scenario tree with a shock occurring at a specific stage. The blue dots indicate the investment decisions that are made in accordance with the stochastic programming results up to the point where the shock occurs.

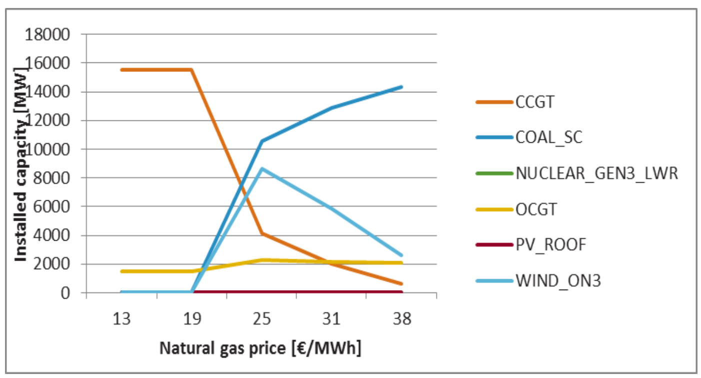

Figure 2: The sensitivity of the generation mix with respect to the price of natural gas used in the optimization of a generation expansion model.

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