

Quantifying the impact of demand uncertainty in long-term energy system optimization models

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Overview

Generation expansion models used for energy system planning purposes typically minimize the total discounted cost of operating and investing in the system over a long time horizon. This time horizon, makes it difficult to construct reliable projections of crucial input parameters for these models. It is therefore important to take uncertainties into account in energy system planning. In the case of the electric power sector, the projection of future (peak) demand drives the amount of capacity investments necessary to ensure the adequacy of the system. Since this electricity demand is uncertain, the investments made should also take into account this future uncertainty and the possible associated implications on overall system costs.

The technologies in which one can invest to cover the peak demand are characterized by different operating costs. Depending on the likelihood of running the to-be-installed capacity, a different technology mix may be more cost-optimal. Furthermore, an optimal amount of expected load shedding may exist so that the total installed capacity does not necessarily cover the entire demand in all circumstances. In other words, there is a trade-off between investing in additional capacity and the expected rate of load shedding, which depends on the value of lost load (VOLL). Ideally, a planning model takes into account an estimation of the expected operational cost due to demand uncertainty. This estimation should include (i) the trade-off between the operational costs among the different technologies and (ii) the cost of load shedding.

A common strategy used to assess demand uncertainty in expansion planning is to incorporate a planning reserve margin (Mai et. al., 2013). This is a margin imposed on, e.g., the peak demand projection so that the future system is more robust to possible demand increases and hence, to ensure system adequacy. However, the margin size is typically determined by exogeneous estimates without considering the uncertainty at hand. An endogenous estimation of the expected operational cost is therefore not possible. The expected operating cost associated with running the installed peak capacity is not taken into account, which prohibits an optimal mix of technologies to cover the uncertain peak demand. Furthermore, the trade-off between additional investments and load shedding is not included in the optimization. In fact, by design, one needs to perform this trade-off ex-ante when deciding upon the planning reserve margin. In this contribution, we seek to quantify the impact of incorporating demand uncertainty in a long-term planning model. Leveraging stochastic programming, an estimation of the expected operational cost is included in the optimization by considering several demand scenarios.

Methods

Stochastic programming is a widely used method in optimization under uncertainty. In the context of expansion planning, the objective is to minimize the total expected system cost over a set of scenarios, representing the considered uncertainties (Figure 1). The aim is to decide on a single set of first-stage investments common to all scenarios, given that future demand is still unknown. In this way, an estimation of the expected operational cost is included in the optimization.

To quantify the impact of demand uncertainty in long-term planning models, we compare the first-stage investment decisions of a stochastic optimization with the investment decisions made by a deterministic equivalent that imposes a planning reserve margin on the average demand. The comparison is made for different values of the planning reserve margin and the uncertainty range (UR) in the stochastic optimization. An important parameter to consider in the stochastic case is the value of lost load, since this determines the trade-off between investing and load shedding. As a result, a stochastic optimization with a high VOLL highlights the effect of properly considering expected operational costs among the technologies, while a lower VOLL increases the importance of the trade-off between additional investments and load shedding.

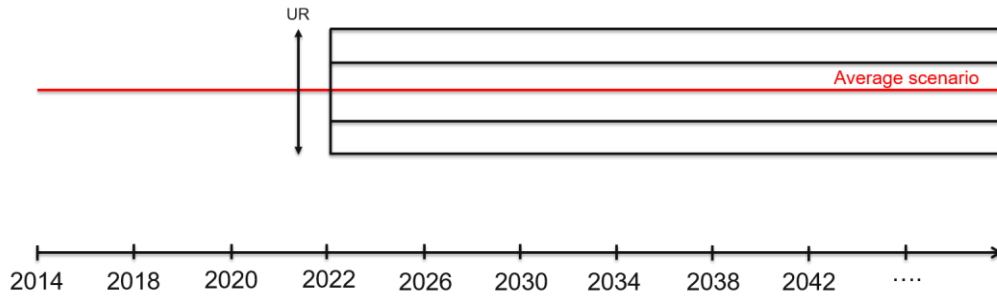


Figure 1: Scenario tree representation of possible (peak) demand evolutions in a stochastic long-term planning model. In this case, it is assumed that (peak) demand can increase or decrease by the uncertainty range (UR) with respect to the average scenario. Investment decisions in the first stage are taken considering the possibility of every second-stage development.

Results

Figure 2 shows the difference between investment decisions of a stochastic optimization with a varying uncertainty range and a deterministic optimization with an equivalent planning reserve margin. The deterministic case appears to favour the technology with the lowest investment cost (OCGT), which is in line with expectations since the expected operating costs of these investments are ignored. Furthermore, the stochastic case with a very high VOLL (∞) results in a shift from coal/OCGT towards CCGT when the uncertainty range is sufficiently large. As the UR increases, a higher demand increase becomes more probable and the operational costs in these scenarios becomes increasingly important. It is therefore beneficial to increase CCGT capacity at the expense of OCGT capacity since the increase in fixed costs is overcompensated by the decrease in expected operational costs. Similarly, a substantial demand decrease (as compared to the average scenario) becomes more probable as well. As a result, there are limited possibilities for the baseload technology to recover its fixed costs. The high fixed costs of coal are no longer justified by its low operational costs and again the generation mix shifts towards CCGT technologies.

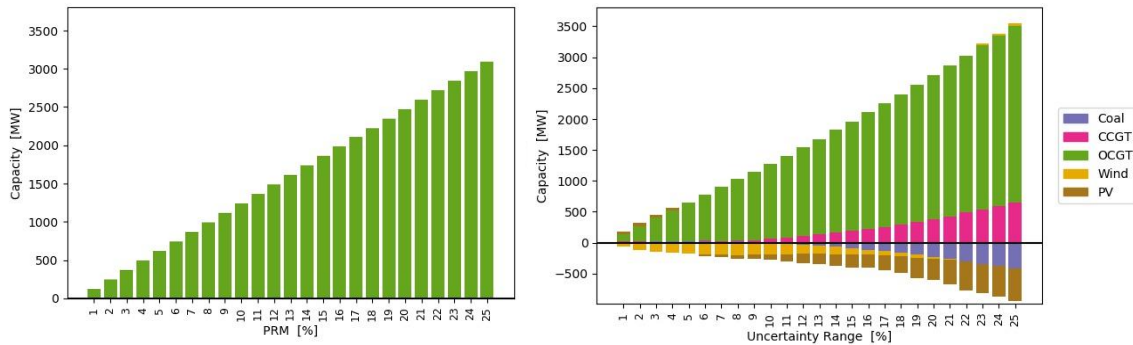


Figure 2: Investment decisions obtained by a deterministic optimization using a planning reserve margin (left) and a stochastic optimization ($VOLL = \infty$) (right).

Conclusions

Results indicate that an imposed planning reserve margin in a deterministic planning model does not consider the possible operation costs of the installed capacity used to satisfy this margin. Therefore, the lowest investment cost technology is preferred. In contrast, a stochastic planning model is able to make an estimation of the expected operational cost, which is reflected in different investment decisions. Preliminary results indicate that more mid-merit technologies emerge at the expense of base-load technologies and peak-load technologies. Future work entails allowing load shedding to be part of the optimal investment strategy. In doing so, the impact of the trade-off between additional investments and load shedding can be quantified.

References

Mai, T., Drury, E., Eurek, K., Bodington, N., Lopez, A., & Perry, A. (2013). *Resource planning model: an integrated resource planning and dispatch tool for regional electric systems* (No. NREL/TP-6A20-56723). National Renewable Energy Lab.(NREL), Golden, CO (United States).