Optimisation of Cogeneration Systems in a Competitive Market Environment

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Dealing with uncertainty in CHP planning

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1 Introduction

Within the OSCOGEN project various approaches have been proposed to analyse decision making for CHP operation under uncertainties. At the last project meeting in Ljubljana, two alternatives have particularly been put forward:

1. Stochastic optimisation,
2. Treating power plants as options in finance models.

In fact, the two methods are not as far from each other as might seem at first sight. *Stochastic optimisation* is an approach which has been put forward and developed further in the world of financial mathematics (see particularly the work of /Frauendorfer 1992; Frauendorfer 1996/). On the other hand, power plants are certainly *not simple options* - "plain vanilla" in finance terms - and standard approaches like binomial (or trinomial) trees and Monte Carlo simulations can not be used readily for valuing them. In fact, the following characteristics make power plants particular options

A. Dependency on *various underlyings* (fuel price, electricity price, heat demand),
B. *Interdependency between* different *decisions* on power plant operation (constraints like minimum operation time, minimum stop time, maximum gradients),
C. *Impossibility of storing* electricity (at larger scale).

Point A can be overcome for conventional power plants by treating them as *swap options* (options which allow to hedge between two commodity prices). But this is no longer true for Combined Heat and Power Plants, where we have at least three underlyings. Point C obliges to model power plants as a *sequence of options*, one option for every delivery time considered. Point B then implies, that the decision making on the various options cannot be separated. This leads to what is known in option theory as *path dependency* of option values.

Decision interdependency is however not equivalent to path dependency. In the case of decision interdependency, the value of the option (power plant) at time t_2 not only depends on the price at time t_1 but also on whether and how the power plant was operating at time t_1. Therefore valuing power plants as options in a finance context also requires performing some calculus on the optimal operation sequence of power plants.

Therefore, the two following alternatives emerge for determining the *optimal combination of power plant operation and trading activities*:

1. Stochastic optimisation of the combined portfolio
2. (Other) Finance methods with embedded generation optimisation

The two alternatives are sketched in the following, providing particularly some further explanations on the latter alternative.

2 Stochastic optimisation of the combined portfolio

2.1 Theory

Stochastic Optimisation is used when one or several parameters of a model (e.g. prices, demand) are stochastic and cannot be forecasted very well. Knowing the distribution of the parameter(s) one can derive with the help of stochastic programming the optimal decisions. Optimal means, that the expected value of the goal function will be maximised.

Deterministic linear models look like that:

$$\begin{aligned} \min \quad & c^T z \\ s.t. \quad & Az = b \\ & x \geq 0 \end{aligned}$$

When a parameter is uncertain it is sensible only to finalise those decisions that cannot postponed further. Decisions that can wait will be made in the future when one has better information. In the context of stochastic optimisation, the decision *z* is partitioned into *x* and *y,* where *x* is decided now and *y* will depend on the future development.

Furthermore, since *y* depends on the future, *y* is denoted as y_S where the label *s* denotes the dependence of the value on the observed future scenario *s*. The future scenario is observed with a probability of p_S then the stochastic model can be written as

$$\begin{aligned} \min \quad & c^T x + \sum_s p_s d_s^T y_s \\ s.t. \quad & Ax = b \\ & x \geq 0 \\ & T_s x + W_s y_s = r_s \quad \forall s \in S \\ & y_s \geq 0 \quad \forall s \in S \end{aligned}$$

This is the model formulation for a two stage model, where information is revealed only once in the future. When information is revealed multiple times, one can recursively define a multi-stage model.

2.2 Advantages and disadvantages of stochastic programming

Stochastic optimisation takes into account all the possible realisations of the stochastic parameter(s), when deriving the optimal decision and does not consider the scenarios independently as the approach of scenario analyses does (compare Fig 2.1). The model formulation for stochastic programming is complex but one can benefit when the distribution of the uncertain parameters can be determined.

It can be shown, that if all random values are replaced by their expected values that the expected value of the goal function of the deterministic model is higher than the expected value of the stochastic optimisation model. For a maximisation problem this means that the expected profit can be increase by using stochastic optimisation.

Further stochastic optimisation allows to define a minimum profit which has to be reached independently of the scenario, which will eventuate.

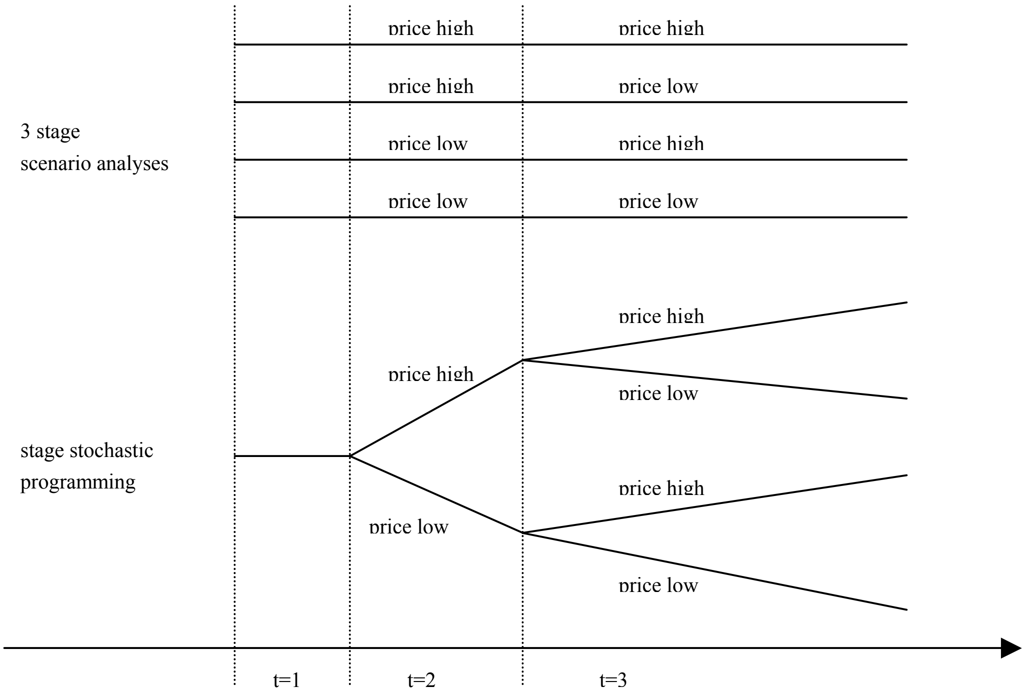

Fig. 2.1: Difference between stochastic optimisation and stochastic programming

The optimal decision at the first time step depends on the possible realisation of the uncertain parameter at the following time steps. (e.g. the decision to start-up a power plant at time step 1 depends on the possible realisation of the stochastic LPX-spot markt price process at time step 2 and time step 3). If the variance of the parameter increases, this will affect the optimal decisions, even if the expected value of this parameter remains the same.

2.3 Scenario creation

Stochastic optimisation models can be extended in a number of ways. One of the most common is to include more stages. With a multistage problem, one makes a decision now, waits for some uncertainty to be resolved, and then makes another decision based on what's happened. As the models increase very fast we have to reduce the number of scenarios.

Different approaches exists here, one of them is barycentric approximation, which creates scenarios with the help of barycenters, that represent all possible scenarios very well.

Further approaches for scenario selection will be studied the next months.

3 Finance methods with embedded generation optimisation

The basic idea of this approach is to use a series of deterministic optimisation runs for the generation portfolio to derive the so-called Greeks[1] for the generation portfolio. Then these Greeks, notably Delta Δ and Gamma Γ, can be used to determine the optimal combined portfolio using classical finance methods, e. g. applying Delta hedging. To illustrate this approach further, let us look at how the Greeks are usually defined in Finance:

$$\Delta_i = \frac{\partial V}{\partial x_i}$$

$$\Gamma_{ij} = \frac{\partial^2 V}{\partial x_i \partial x_j}$$

Δ_i is hence the first derivative of the value V of a portfolio (or portfolio component) with respect to an underlying x_i, whereas Γ_{ij} is the (possibly mixed) second derivative. In the case of a power plant system, we should approximate the Greeks through finite differences:

$$\Delta_i = \frac{V(x_{i,1}) - V(x_{i,0})}{x_{i,1} - x_{i,0}}$$

$$\Gamma_{ij} = \frac{V(x_{i,1}, x_{j,1}) - V(x_{i,1}, x_{j,0}) - V(x_{i,0}, x_{j,1}) + V(x_{i,0}, x_{j,0})}{(x_{i,1} - x_{i,0})(x_{j,1} - x_{j,0})}$$

Different choices for the co-ordinates $x_{i,1}$, $x_{i,0}$, $x_{j,1}$, $x_{j,0}$ of the evaluation points are possible, corresponding to forward, central or backward differences. For each evaluation point the deterministic power plantoptimisation model has to be . One plausible choice could be $x_{i,0} = \mathrm{E}[x_i]$, $x_{i,1} = \mathrm{E}[x_i]+\sigma[x_i]$ and similarly for x_j. However, here further thinking and numerical simulation is required. The calculation of Γ follows the same lines as for Δ, yet it can be considerably simplified, if only few mixed derivatives have to be considered. Therefore, a reduction of intertemporal interdependencies would be highly desirable.

In the case of the BEWAG longterm-model, the interconnections between various months mostly stem from the take-or-pay (fuel) contracts. It should therefore be checked, whether these contracts can be addressed by finance methods instead of incorporating them into the optimisation model. Then, independent optimisation models for the various months could be run.

4 Conclusions

The two proposed methodologies are not as different as could have been thought at first sight. Both require an optimisation model for the power plant operation. Also, both require good descriptions of the stochastic processes for the underlying variables. In both cases, judicious simplifications are also necessary to obtain valid results. Which method will provide better results, is difficult to tell without carrying out detailed simulation runs. Therefore, it is proposed to continue developing both methodologies, mutually benefiting thereby from the variety in approaches.