Proceedings of the 14th International Symposium on Process Systems Engineering – PSE 2021+
June 19–23, 2022, Kyoto, Japan
http://dx.doi.org/10.1016/B978-0-323-85159-6.50203-7

Capacity Planning for Sustainable Process Systems with Uncertain Endogenous Technology Learning

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Abstract

The development and deployment of renewable technologies are key to achieving decarbonization. Optimal capacity expansion requires complex decision making that accounts for future cost reduction with increased deployment, which is also termed technology learning. Having a perfect foresight over the technology cost reduction, however, is highly unlikely. This has motivated us to develop a capacity planning model that incorporates such uncertainty. To this end, we apply a multistage stochastic programming approach with endogenous uncertainty, which results in a mixed-integer linear programming (MILP) formulation. The proposed model is applied to a case study on power capacity expansion planning, highlighting the differences in expansion decisions for low- and high-learning scenarios, which indicates the importance of stochastic optimization.

Keywords: stochastic optimization, endogenous uncertainty, technology learning

1. Introduction

Over the past few decades, the unfavorable shift in global climatic conditions has driven us to focus on renewable technology development to lower carbon emissions. The increasing energy demand has further aggravated the need for alternatives to traditional fossil energy sources. However, in addition to developing new technologies, making them economical as fast as possible remains a challenging task. In general, the cost of a technology is a function of several interrelated factors, including pricing and the number of competitors, government regulations and policies, the scale of production, and demand. The reduction in the cost of a new technology due to these factors is often termed technology learning.

Of all the stated, the scale of production constitutes a major driving force for cost reduction in new technologies. The reduction in cost as a function of installed capacity is often expressed using learning curves. Learning curves have often been used as a tool to estimate the time for a new technology to become cost-competitive. For example, Rubin et al. (2007) utilize learning curves for cost projection of power plants equipped with carbon capture and storage technology.

A less considered aspect is utilizing learning curves to make optimal capacity expansion decisions for driving down the cost of a plant or a technology in the least possible time. Most of the literature on optimization concerning learning curves assumes that they can be constructed deterministically. For example, Heuberger et al. (2017) present a power capacity expansion formulation assuming fixed learning curves for various power generation and storage technologies. However, the lack of reliable historical data, the dependence of learning on the decisions made in real time, and the influence of other external factors make it very difficult to predict the learning curves. Therefore, decisions obtained based on deterministic learning curves may be severely sub-optimal.

To increase the practical relevance of capacity expansion models, our work incorporates uncertainty in technology learning curves. Uncertainty in learning rates has been accounted for, if at all, using methods such as sensitivity analysis and Monte Carlo simulation (Kim et al., 2012). Even though such methods provide valuable insights, their inability to account for non-anticipativity constraints demands a more rigorous optimization framework. For this reason, we explore the feasibility of stochastic programming in incorporating uncertain learning curves for multiperiod capacity expansion problems.

Uncertainty is generally classified as either exogenous or endogenous. The uncertainty not affected by decisions is termed exogenous, whereas decision-dependent uncertainty is termed endogenous. Endogenous uncertainty is further classified as type-1 and type-2. Type-1 uncertainty arises when decisions alter the probability distribution of the uncertain parameters (Peeta et al., 2010), whereas type-2 uncertainty affects the timing of the realization of the uncertain parameters (Goel and Grossmann, 2006). In a capacity expansion problem with an uncertain learning curve, the uncertainty in expansion cost resolves only when the capacity is actually increased; thus, the uncertainty here classifies as type-2 endogenous. In this work, we develop a multistage stochastic programming model for capacity planning with uncertain endogenous technology learning and apply it to a power expansion case study.

2. Stochastic programming model

To capture the interconnectivity of technologies, model their simultaneous availability to satisfy product demand, and optimize their selection for capacity expansion and operations, we consider a general process network comprising process and resource nodes as illustrated in Figure 1. Processes and resources are denoted by square and circular nodes, respectively. The arcs in the network denote the directed flow of resources. Process nodes can represent chemical and manufacturing processes or, generally, technologies. Resource $j \in \mathcal{J}$ from a process $k \in \mathcal{K}$ can either serve as an input resource to process $k' \in \mathcal{K} \backslash \{k\}$, be discharged from the process network, or be purchased from outside the network.

The goal is to determine optimal capacity expansion decisions during the planning horizon $\mathcal{T}$, and devise optimal operational decisions in each scheduling horizon $\mathcal{H}_t$ based on each process's installed capacity, demand of resources, and all the involved costs. Uncertainty in technology learning curves is accommodated by considering different possible scenarios (combination of learning curves for multiple uncertain technologies).

2.1. *Capacity expansion constraints*

Based on the process network in Figure 1, we define binary variable x_{kits} that equals 1 if process k undergoes capacity expansion to (at least) the permissible point $i \in \mathcal{I}_k$ in time period $t \in \mathcal{T}$ of scenario $s \in \mathcal{S}$. We further define the variables C_{kts} and Δ_{kts} such that they represent the cumulative installed capacity and additional capacity installed of

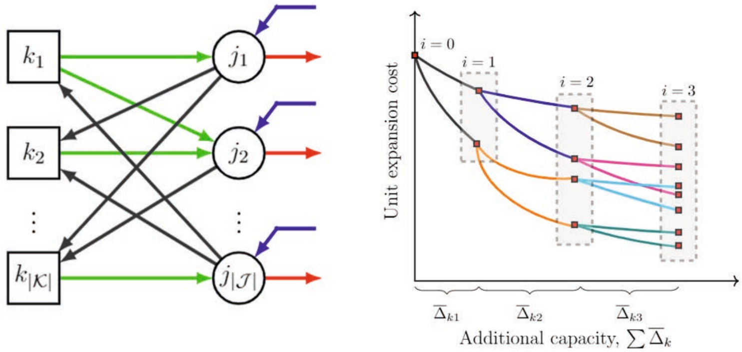

Figure 1: A general process network and an illustrative uncertain learning curve. Each discrete expansion point i acts as a source of uncertainty. In this case, we have two, four, and eight possible unit expansion costs at $i = 1, 2,$ and, 3 respectively.

a process k in time period t of scenario s, respectively. Then, the following constraints control the timing and extent of capacity expansion for each technology:

$$C_{k0s} = \overline{C}_{k0} \qquad \forall k \in \mathcal{K}, \forall s \in \mathcal{S} \quad \text{(1a)}$$
$$C_{kts} = C_{k,t-1,s} + \Delta_{kts} \qquad \forall k \in \mathcal{K}, t \in \mathcal{T}, \forall s \in \mathcal{S} \quad \text{(1b)}$$
$$\Delta_{kts} = \sum_{i \in \mathcal{I}_k} x_{kit} \overline{\Delta}_{ki} \qquad \forall k \in \mathcal{K}, t \in \mathcal{T}, \forall s \in \mathcal{S} \quad \text{(1c)}$$
$$\Delta_{kts} \leq b_{kt} \qquad \forall k \in \mathcal{K}, t \in \mathcal{T}, \forall s \in \mathcal{S} \quad \text{(1d)}$$
$$x_{kits} \leq \sum_{\tau=1}^{t} x_{k,i-1,\tau s} \qquad \forall k \in \mathcal{K}, i \in \mathcal{I}_k \backslash \{1\}, t \in \mathcal{T}, \forall s \in \mathcal{S} \quad \text{(1e)}$$
$$\sum_{\tau=1}^{t} x_{ki\tau s} \leq 1 \qquad \forall k \in \mathcal{K}, i \in \mathcal{I}_k, t \in \mathcal{T}, \forall s \in \mathcal{S} \quad \text{(1f)}$$
$$g(Q_{hts}, C_{kts}) \leq 0 \qquad \forall k \in \mathcal{K}, h \in \mathcal{H}_t, t \in \mathcal{T}, \forall s \in \mathcal{S} \quad \text{(1g)}$$
$$x_{kits} \in \{0,1\} \qquad \forall k \in \mathcal{K}, i \in \mathcal{I}_k, t \in \mathcal{T}, \forall s \in \mathcal{S} \quad \text{(1h)}$$
$$C_{kts}, \Delta_{kts} \geq 0 \qquad \forall k \in \mathcal{K}, t \in \mathcal{T}, \forall s \in \mathcal{S} \quad \text{(1i)}$$
$$Q_{hts} \in \mathbb{R}^{|\mathcal{J}||\mathcal{K}|} \times \mathbb{Z}^{|\mathcal{K}|} \qquad \forall t \in \mathcal{T}, h \in \mathcal{H}_t, \forall s \in \mathcal{S} \quad \text{(1j)}$$

where $\overline{C}_{k0}$ denotes the initial installed capacity of process k. The incremental capacity for process k from point $i-1$ to i is denoted by $\overline{\Delta}_{ki}$. Constraints (1a)-(1c) together represent the capacity balance. Constraints (1d) limit the capacity expansion of a process k by the available budget b_{kt} in time period t. Constraints (1e) ensure that we move in the positive direction on the learning curve in a sequential fashion, i.e., we can only install additional capacity corresponding to point i if we have already installed the additional capacity corresponding to point $i-1$. Constraints (1f) imply that investment at any point $i \in \mathcal{I}_k$ cannot be made more than once in any time period. Constraints (1g) are a condensed representation of all the operational constraints, including production scheduling, inventory management, scheduling startup/shutdown of units, limiting emissions and storage, to name a few. Operational decision variables Q_{hts} can be both continuous and discrete and are constrained by the installed capacities of the processes in the network.

2.2. *Non-anticipativity constraints*

Non-anticipativity constraints (NACs) ensure the equality of decisions for all pairs of indistinguishable scenarios at any point in time during the planning horizon. Mathematically, NACs are represented as follows:

$$x_{ki1s} = x_{ki1,s+1} \quad \forall k \in \mathcal{K}, i \in \mathcal{I}_k, s \in \mathcal{S}, s < |\mathcal{S}| \tag{2a}$$

$$\begin{bmatrix} Z_t^{s,s'} \\ x_{ki,t+1,s} = x_{ki,t+1,s'} \quad \forall k \in \mathcal{K}, i \in \mathcal{I}_k \end{bmatrix} \vee \left[\neg Z_t^{s,s'} \right] \quad \forall (s,s') \in \mathcal{P}', t \in \mathcal{T} \setminus \{T\} \tag{2b}$$

$$Z_t^{s,s'} \iff \bigwedge_{(r,i) \in \mathcal{D}(s,s')} \left[\bigwedge_{\tau=1}^{t} (\neg x_{ri\tau s}) \right] \quad \forall (s,s') \in \mathcal{P}', t \in \mathcal{T} \setminus \{T\} \tag{2c}$$

$$Z_t^{s,s'} \in \{\texttt{true}, \texttt{false}\} \quad \forall (s,s') \in \mathcal{P}', t \in \mathcal{T} \setminus \{T\} \tag{2d}$$

where $\mathcal{D}(s,s')$ is the set containing sources of endogenous uncertainty (expansion points in our case) that distinguish scenario s from s'. The Boolean variable $Z^t_{s,s'}$ is true if uncertainty has not been realized in any of the uncertain parameters that belong to the set $\mathcal{D}(s,s')$. Further, $\mathcal{P}'$ denotes the minimum or reduced set of scenario pairs that is sufficient to express all the NACs. The details on the disjunction and logic-based formulation of NACs for endogenous uncertainty problems can be found in Goel and Grossmann (2006). Also, we refer the reader to Hooshmand and MirHassani (2016) for redundant NAC removal strategies in case of endogenous uncertainty and an arbitrary scenario set.

2.3. *Objective function*

The objective is to minimize the expected net cost over the entire planning horizon; thus, the overall stochastic optimization problem can be summarized as follows:

$$\begin{aligned} \min \quad & \sum_{s \in \mathcal{S}} p_s \sum_{t \in \mathcal{T}} \alpha_t \Bigg[\sum_{k \in \mathcal{K}} \sum_{i \in \mathcal{I}_k} \left(\int_{\Phi_{k,i-1}}^{\Phi_{ki}} f_{ks}(\Phi_k) \mathrm{d}\Phi_k \right) x_{kits} + \\ & \qquad \sum_{h \in \mathcal{H}_t} \sum_{k \in \mathcal{K}} \sum_{j \in \mathcal{J}} u_{jkhts}(Q_{hts}, C_{kts}) \Bigg] \\ \text{s.t.} \quad & \text{Eqs. (1a) - (1j), (2a) - (2d)} \end{aligned}$$

where p_s denotes the probability of scenario s and α_t denotes the discount factor for time period t. The learning curve for process k is encoded in the model as $f_k(\Phi_k)$ and $\Phi_{ki} := \sum_{i'=1}^{i} \overline{\Delta}_{ki}$. Note that we make no assumptions on the form of the learning curve since the integral term (expansion cost on increasing capacity from point $i-1$ to i) is a parameter that can be pre-calculated. The cost function u captures all operating costs including the cost of specific modes of operation, utilizing storage, purchasing and discharging resources, tax on emissions, etc.

3. Industrial case study

The proposed framework is applied to a capacity expansion case study for a network of power generation technologies. Specifically, we consider seven technologies and categorize them into one of the following three categories – conventional (no cost reduction), deterministic (known learning curve), and uncertain technology (uncertain learning curve). Nuclear, coal, combined cycle gas turbine (CCGT), and open cycle gas turbine (OCGT) are considered conventional, onshore wind and solar are assumed to be deterministic, and offshore wind is assumed to have an uncertain learning curve. The model and data for this case study are partially adapted from Heuberger et al. (2017). The planning problem was modeled using JuMP v0.21.10 in Julia v1.6.3 and was solved using Gurobi v9.1.2. The model was solved to optimality (0.01% tolerance) in 3,150 s.

The planning horizon spans eight 5-year time periods from 2015 to 2055. The capacity expansion decisions are made at the start of each of these time periods. Figure 2 illustrates the eight possible learning curves for offshore wind technology and the eventual scenario tree based on the expansion decisions made. The scenario tree indicates that the offshore wind capacity increases by 2.5 GW at $t = 1$; however, as expected, we do not see any further expansion for the low-learning case (high-cost scenarios). On the contrary, for the high-learning case (low-cost scenarios), at $t = 2$, the capacity further expands by 5.8 GW, resulting in four scenario tree nodes. Thus, stochastic programming adapts its decisions to the future expansion cost, generating practically viable solutions in the process.

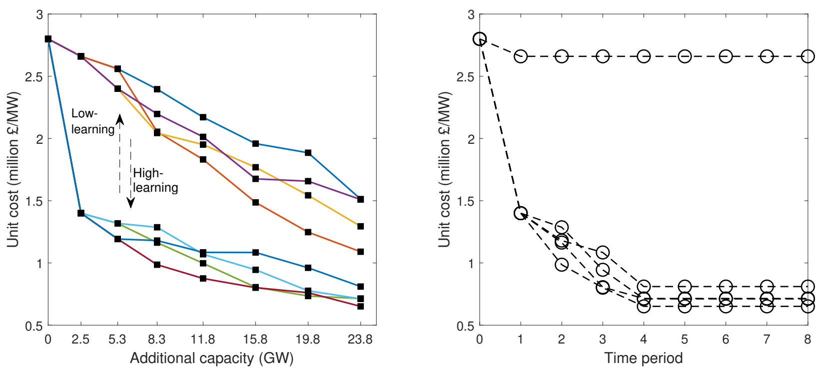

Figure 2: The possible learning curves considered for offshore wind are illustrated on the left. Scenario tree (right) reveals expansion decisions for offshore wind.

Next, Figure 3 illustrates the distribution of capacity for all technologies throughout the planning horizon. Clearly, in comparison to the high-learning scenario, the low-learning scenario does not favor offshore wind expansion. This reduced capacity expansion in offshore wind is compensated by expansions of conventional technologies such as nuclear and OCGT. Note that the expansions are governed not only by the expansion cost but also by the expansion budget, lifetime of each technology, and the time-varying power generation capacity. The proposed stochastic programming model effectively integrates the above factors with the uncertain cost to generate the optimal capacity distribution.

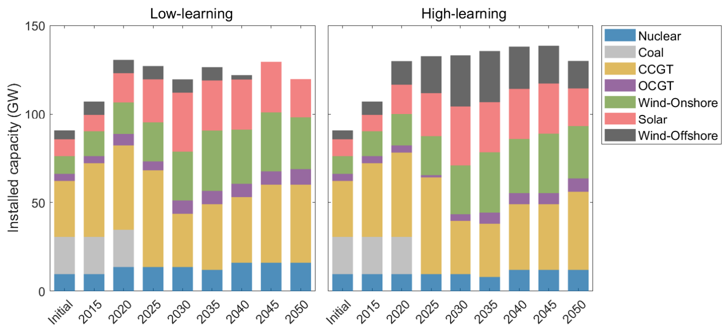

Figure 3: Capacity distribution of power generation technologies under low- and high-learning scenarios.

4. Conclusions

In this work, we proposed a rigorous optimization framework for a general process network that can be utilized to model energy systems containing both renewable and non-renewable technologies. We utilize stochastic programming to account for the long-neglected aspect of uncertainty in technology learning curves. The case study on power capacity expansion showcases the adaptability of stochastic programming in providing decisions optimal to individual scenarios. The difference in decisions also indicates that any solution obtained through a deterministic model, which essentially is a single scenario case, would often be sub-optimal for any perturbation in the assumed deterministic learning curves.

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