A Mathematical Framework to Study the Impact of Technological Learning on Portfolio Planning

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Abstract

Technological learning leads to cost reduction in investment and operation. Different learning factors have different impacts on portfolio planning. This work develops a mathematical framework based on optimization for studying the impact of technological learning on portfolio planning. The integer programming (IP) model minimizes the investment and operation costs of the project portfolio by optimizing the selection of processes and technologies based on the nature of the learning factors considered. A case study of planning carbon capture (CC) to meet the annual capture targets while accounting for technological learning due to shared knowledge reveals that more capture facilities are deployed in the early planning periods to accelerate technological learning. The total cost of capture was reduced by $170 million when a log-linear curve with a learning rate of 0.30 was used to model the technological learning.

**Keywords**: Learning effect, Integer programming (IP), Carbon Capture (CC)

* 1. Introduction

Economic competitiveness enables a technology's deployment, while its stable commercialization also depends on technology cost reduction (Elia et al., 2021). Multiple factors drive technology cost reductions, such as investment in research and development (learning-by-researching), shared/spill-over knowledge (learning-by-copying), functionality improvement (learning-by-using), and economies-of-scale (learning-by-doing) (Upstill and Hall, 2018). Different learning curves are used to mathematically represent technology cost reductions (Anzanello and Fogliatto, 2011). Each learning factor can affect different aspects of portfolio planning, and the extent depends on the nature of the learning curve selected. For example, learning-by-using can reduce operational costs, while learning-by-copying can reduce the investment cost of a technology. The technology should be implemented as early as possible to get the utmost benefit from the former learning factor. But for the latter, deployment should be delayed to gain experience from as many other deployed projects. Thus, a strategic deployment of technologies is necessary to maximize the cost reductions from different learning factors over the planning period.

This paper introduces a multiperiod optimization model to study the effect of technological learning on the selection of processes and technologies to produce a set of products over a planning period. The model's objective is to minimize the total cost of technology deployment and operation to meet the product demands.

* 1. Mathematical Model Formulation

An optimization-based framework is developed to integrate the processes (*i**I*) and technologies (*j**J*) under a single network for planning technology deployment to produce products (*k**K*) with the available raw materials (r*R*) over a planning horizon (*t**T*). Figure 1 illustrates the overall superstructure. Based on the demand for the products *k* and the availability of materials (*Rrt*) over time *t*, the processes *Pi* are selected to produce products *Xkt* using one of the compatible and cost-effective technologies *TGj* to minimize the total cost of technology deployment and operation, while considering the cost reduction due to different learning factors along the planning horizon.

A diagram of a product

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Figure 1. Superstructure of processes and technologies selection to produce products.

* + 1. Binary Variables

The sets *i**I, j**J, k**K,* and *t**T* represent the processes, technologies, products, and planning periods. The sets *m1**M1, m2**M2, ..,mm**MM and n1**N1, n2**N2, ..,nn**NN* represent different learning effects on investment and operating costs. A binary variable *yi,j,k,t* is defined in Eq. (1) to represent the selection of a process and a compatible technology to produce product at time . Two sets of binary variables, *bmi,j,k,t,m1,..,mm* and *bni,j,k,t,n1,..,nn*, are introduced in Eqs. (2) and (3) to track learning due to different learning effects in investment and operation of the technology used to produce product *k*.

|  |  |
| --- | --- |
|  | (1) |
|  | (2) |
|  | (3) |

* + 1. Parameters

The amount of product *k* that can be produced by process *i* with technology *j* at time *t* is represented by the parameter *D'i,j,k,t*, which depends on the availability of resources. The annualized investment to implement a facility with a capacity that produces *D'i,j,k,t* amount of product *k*using technology *j* is represented by the parameter *ICi,j,k,t*. The annual operating cost is represented by the parameter *OCi,j,k,t*. The cumulative extent of cost reduction in the investment and operating costs due to different learning effects *m1,..,mm* and *n1,..,nn* at time *t* are represented by two sets of parameters, *αi,j,k,t,m1,..,mm* and *βi,j,k,t,n1,..,nn*, respectively. The demand for product *k* at time *t* is represented by *Dk,t*.

* + 1. Constraints

Equations (4) and (5) ensure process *i* uses at most one technology *j* to produce product *k,* and the same technology is used in the subsequent periods. For a technology deployed in a process (i.e., *yi,j,k,t* =1), one binary variable corresponding to each considered learning effect *M1,..,MM* and *N1,..,NN* on investment and operating costs takes a value of one, by Eqs. (6) and (7). Otherwise, the binary variables *bmi,j,k,t,m1,..,mm* and *bni,j,k,t,n1,..,nn* take a value of zero. Equation (8) ensures that the annual demand for each product (*Dk,t*) is met by producing *D'i,j,k,t* amount using the selected processes and technologies.

|  |  |
| --- | --- |
|  | (4) |
|  | (5) |
|  | (6) |
|  | (7) |
|  | (8) |

* + 1. Objective

The objective is to minimize the total cost (*TC*) of producing a set of products over the planning horizon while meeting annual demands. The cost consists of annualized investment and annual operating costs for the deployed technologies, which are computed accounting for the cost reduction due to technological learning, as given in Eq. (9).

|  |  |
| --- | --- |
|  | (9) |

Using technology *j* for process *i* to produce product *k* at time *t* leads to an investment (*ICi,j,k,t*) and an operation cost (*OCi,j,k,t*) which are added to the total project cost with the variable, *yi,j,k,t*. The parameters *αi,j,k,t,m1,..,mm* and *βi,j,k,t,n1,..,nn* represent the cumulative extent of cost reduction in the investment and operating costs due to different learning effects *m1,..,mm* and *n1,..,nn* at time *t*. The reduction extents are accounted for in the total cost with the binary variables tracking the learning, *bmi,j,k,t,m1,..,mm* and *bni,j,k,t,n1,..,nn*.

* + 1. Implementation of technological learning models

Equations (1) to (9) yield an integer programming model (IP) that optimizes the selection of processes and technologies based on technological learning and product demands over a planning period. Incorporating technological learning models into the developed multiperiod portfolio planning model is demonstrated with an example of implementing learning from shared/spill-over knowledge (learning-by-copying). The extent of this learning-by-copying on a technology to be deployed at time *t* depends on the number of processes that already use the same technology to produce the same product *k*. Let the set *m1M1={1,2,…,I'}* represent the learning effects due to shared knowledge, where *I'* represents the total number of processes in the network. The binary variable *bmi,j,k,t,m1,..,mm* tracks the technological learning extent for a process based on the number of processes already using the technology (computed using *yi,j,k,t*) with parameter, *L1m1*=*{1,2,…,I'}.* For example, for a fourth-of-a-kind process, the binary variable *bmi,j,k,t,4,..,mm* takes a value of 1 as *L14*=4, and the summation of the variable *yi,j,k,t-1* is 3. Equation (6) ensures that only one binary variable is selected per source using this technology for this learning effect. Equation (11) enforces that the same binary variable is selected at subsequent periods so that the learning extent does not change over time.

|  |  |
| --- | --- |
|  | (10) |
|  | (11) |

The implementation of the learning curve to the developed shared/spill-over knowledge-based learning model is demonstrated using two different learning curves, log-linear and S-curve (Anzanello and Fogliatto, 2011). For the log-linear curve, the cost reduction extent (*LC1j,k,m1*) for an *m1th* process that uses the technology *j* to produce *k* depends on the learning rate for the technology *LR1j,k*, as shown in Eq. (12), and it can take a value between 0 and 1. To avoid complete cost reduction due to infinite learning, the maximum cost reduction extent possible for the technology (*MRj,k*) is introduced in the model by defining the cost reduction as a piecewise function such that *LC1j,k,m1*=*MRj,k*. The S-curve initially has slow progress in learning and then a rapid ascent. The cost reduction extent for the *m1th* process depends on the learning rate, *LR2j,k*, which takes a value greater than zero, and the inflection point in the curve, *TR2j,k*, as given in Eq. (13).

|  |  |
| --- | --- |
|  | (12)  (13) |

* 1. Results and Discussion

The capabilities of the developed model are demonstrated with a case study of planning carbon capture (CC) from 20 different emission sources over a period of 20 years (discretized into 20 equal time periods). The carbon composition in the flue gas varies from 4 to 47%. The annual capture target increases biannually by 5% (from 30% to 70%). Two post-combustion capture technologies, absorption using aqueous monoethanolamine (ABS-MEA) and pressure swing adsorption using methyl viologen exchanged zeolite Y (PSA-MVY), are considered. The emission sources data and the cost models from Hasan et al. (2015) are used to construct model parameters.

Under no technological learning, the model optimizes the selection of emission sources to minimize the total capture cost while meeting the annual capture targets. ABS-MEA is preferred for sources with low carbon composition in flue gas, while PSA-MVY is cost-effective for sources with high carbon composition. The effect of cost reduction in investment on the portfolio planning decisions is analyzed by considering the technological learning from shared knowledge for PSA-MVY. Two different learning curves, log-linear and S-curve (Eqs. 12 and 13), are considered. Figure 2 shows the extent of cost reduction for the Nth-of-a-kind facility due to shared knowledge when the learning curves' parameters are varied. The maximum cost reduction extent possible is taken as 20%. The curves 1 to 3 represent the log-linear curves having learning rates (LR1) of 0.05, 0.10, and 0.30. At higher rates, the cost reduction extent reaches the maximum value from learning from fewer facilities using the technology. Curves 4 to 6 represent the S-curves having learning rates (LR2) of 1.5, 3, and 1.5 and inflection points (TR2) of 4, 4, and 6. The curves with higher learning rates and lower inflection points require learning from less number of facilities to reach the maximum cost reduction.

The models are formulated in Python V3.9.12 using PYOMO V6.4.1 and solved to an optimality gap of 1% using CPLEX V20.10 on an AMD Ryzen Threadripper PRO 3955WX 3.89 GHz processor with 16 cores and utilizing a maximum of 64 GB RAM.

A diagram of a graph

Description automatically generated

Figure 2. The extent of cost reduction due to technology learning from shared knowledge for different parameters of the log-linear curve and the S-curve.

Figure 3 shows the portfolio planning decisions for the cases when technological learning for PSA-MVY is considered and modeled using a log-linear curve with a learning rate of 0.10 and for the case not considering learning. Figures 3(a) and 3(b) show the CO2 composition in flue gas and the total CO2 emitted by the sources. The technology deployment decisions for the sources to meet annual capture targets over the planning period are shown in Figures 3(d) and 3(c) for the cases with and without learning, respectively. In the early planning periods, sources with high emissions are selected for capture. Other sources are selected to meet the higher capture targets over time. Comparing the results for the two cases in Figures 3(c) and 3(d), it can be seen that when technological learning is considered, some facilities using PSA-MVY are implemented in earlier periods to accelerate the learning for the later deployed facilities. On the other hand, some facilities are deployed in later periods to make the capture more cost-effective with technological learning. Source 2 uses ABS-MEA for capture in the case without technological learning. However, when the PSA-MVY learning is considered, PSA-MVY becomes more cost-effective than ABS-MEA for source 2 by the time of its capture facility deployment. The total capture cost decreases from $25.98B to $25.88B when the PSA-MVY investment cost decreases by the log-linear curve with a rate of 0.10.

The effect of modeling the learning with different learning curves and using different learning parameters on the planning decisions is shown in Figure 4. For the log-linear learning curve with a learning rate (LR1) of 0.05, the number of facilities using PSA-MVY at different planning periods does not change from that in the case with no learning. But as the learning rate is increased (LR1= 0.10 and LR1= 0.30), more facilities using PSA-MVY are deployed in the early planning periods to accelerate learning and to reduce the total capture cost further to $25.88B and $25.81B. For the S-curve with a high learning rate (LR2= 3) and a higher inflection point (TR2= 6), though the capture cost decreases due to technological learning, the deployment decisions remain unaffected. On the other hand, when a lower learning rate and inflection point (LR2= 1.5l; TR2= 4) is used, the deployment decisions are similar to the log-linear case with LR1=0.30, but its capture cost is still high due to its longer slow learning phase. The solution time (wall clock time) for these cases varies from 120 seconds to 15,600 seconds.

* 1. Conclusions and Future Directions

This work developed a multi-period optimization model that assists the selection of processes and technologies to produce a set of products while meeting product demands and accounting for the effect of technological learning on investment and operating costs. A case study of CC demonstrated the capability of the model to minimize the total cost of capture planning by accelerating technological learning due to shared knowledge by implementing more facilities in the early planning periods. Future work will extend the analysis to include the effect of other technological learnings, such as learning-by-doing and learning-by-researching, on portfolio planning decisions.

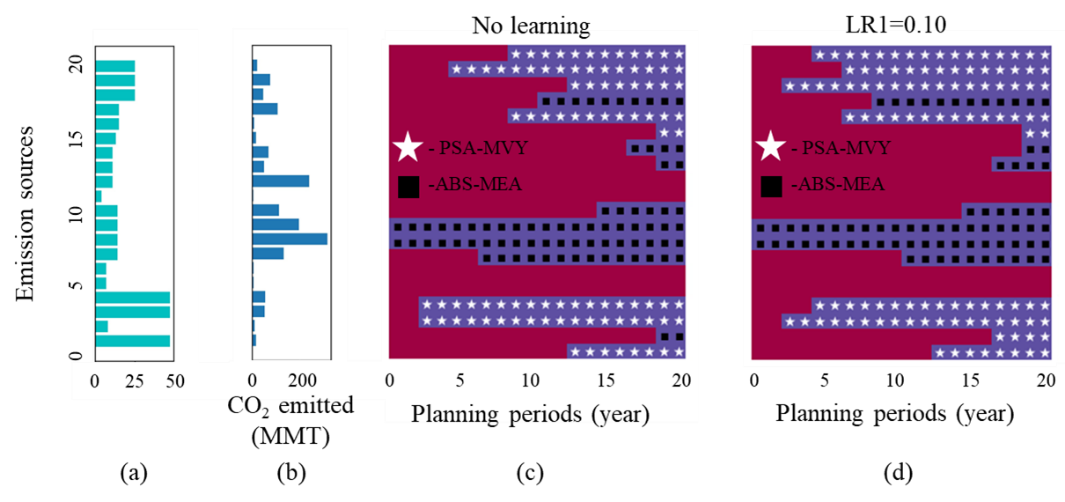


Figure 3. (a) CO2 composition of the emission sources. (b) Total CO2 emitted by the sources over the planning period. Deployment of capture technologies to the sources over the planning periods to meet the biannually increasing capture targets: (c) when technological learning is not considered, and (d) when learning due to shared knowledge for PSA-MVY is considered.

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Figure 4. No. of facilities using PSA-MVY at different planning periods when technological learning from shared knowledge is considered and modeled with log-linear (LR1) and S-curves (LR2 & TR2) for different learning parameters.

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