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Optimal Design Approaches for Cost-Effective Manufacturing and Deployment of Chemical Process Families with Economies of Numbers

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ABSTRACT

Developing methods for rapid, large-scale deployment of carbon capture systems is critical for meeting climate change goals. Optimization-based decisions can be employed at the design and manufacturing phases to minimize costs of deployment and operation. Manufacturing standardization results in significant cost savings due to economies of numbers. Building off previous work, we present a process family design approach to design a set of carbon capture systems while explicitly including economies of numbers savings within the formulation. Our formulation optimizes both the number and characteristics of the common components in the platform and simultaneously designs the resulting set of carbon capture systems. Savings from economies of numbers are explicitly included in the formulation to determine the number of components in the platform. We show and discuss the savings we gain from economies of numbers.

Keywords: Optimization, Process Design, Energy Systems, Carbon Capture, Technoeconomic Analysis

INTRODUCTION

Effectively combatting climate change relies on large-scale deployment of critical chemical process systems, such as carbon capture or water desalination. In traditional process system design approaches, engineers uniquely design each installation focused on economies of scale. However, this approach is expensive and coupled with long deployment timelines. Modular design approaches derive savings from economies of numbers by offering a catalog of small, stackable designs. However, a pure modular approach neglects the benefits of economies of scale. In this paper, we develop a rigorous, optimization-based design method, inspired by product family design literature [1], that designs a family of process variants while simultaneously optimizing a platform of unit module designs that can be shared across this set of processes. This approach seeks to exploit both economies of scale and economies of numbers to minimize costs while achieving manufacturing standardization and reduced deployment timelines.

This work builds on our optimization formulation for process family design [2] and extends it to explicitly include the benefits of economies of numbers. Economies of numbers (sometimes referred to as economies of learning) is a well-documented cost saving phenomenon [3,4]. It characterizes the manufacturing cost savings due to standardization; in particular, it is capturing the correlation between cost reduction and the number of times a particular product has been manufactured. Following an approach like that in Gazzaneo et al. (2022), we develop a costing expression that captures total manufacturing costs as a function of the number of unit modules produced.

If the platform has a small number of unit module designs, there are fewer options to share across all the process variants. Therefore, we will be manufacturing more of each of these designs and gaining increased benefits from economies of numbers. However, increasing the number of unit module designs in the platform gives each process variant more options leading to a more "optimized" design (at the cost of reducing savings due to economies of numbers). With the optimization formulation in Stinchfield et al. (2023) the number of unit module designs included in the platform must be pre-specified. In this work, by including the economies of numbers explicitly, we allow the mathematical programming formulation to determine the optimal number of unit module designs to include in the platform. We demonstrate this approach on multiple case studies, including an MEA-based carbon capture system and a water desalination process.

LITERATURE REVIEW

Modular and product family design approaches have been studied in many different industrial applications. Gonzales-Zugasti (2000) describes how a product family approach can be applied to NASA's exploratory space missions beginning with a two-stage optimization approach [9]. Simpson et. al. (2004) used a genetic algorithm for product family design optimization for the selection of parts of aircraft [11]. Pirmoradi et al. 2015 devised a two-phase platform configuration approach utilizing sensitivity analysis, metamodeling, and a black-box optimization strategy to craft a variety of universal electric motor designs [12]. In general, research focused on product family design focuses on heuristic and probabilistic-based optimization techniques, rather than employing rigorous deterministic mathematical programming algorithms.

Product family design derives significant savings from standardization of elements within a product. Manufacturing cost savings associated with standardization are due to *economies of numbers* (sometimes referred to as economies of *learning*). Increasing the number of products to be produced results in lower per unit costs, as documented by Wright et al. (1936). Specifically, the authors reported how the per unit cost of manufacturing an airplane *decreased* with respect to the number of airplanes manufactured [13]. This correlation has since been documented across many industries with different levels of cost reduction.

The effect of economies of numbers can be captured mathematically as a function of the number of units manufactured, n, and their resulting discount factor, F_n. The learning rate α captures the impact of production levels on cost as shown in (1).

$$F_n = n^{-\alpha} \tag{1}$$

Equation (1) is also referred to as the learning curve and is shown graphically in Figure 1, with an $\alpha = 0.2$.

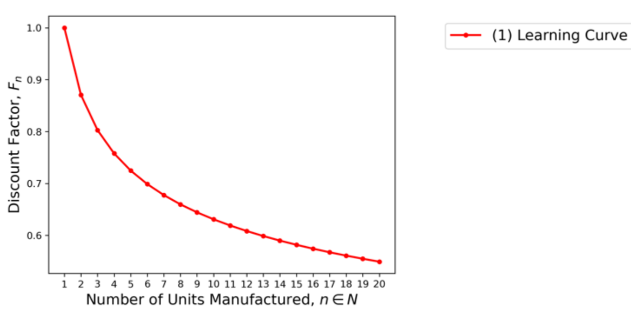

Figure 1: Example Learning Curve[13]
($\alpha = 0.2$)

Learning curves are product specific. They exhibit the general behavior shown in Figure 1 but vary significantly depending on the specific industry and unit manufactured. In practice, α is selected based on experience or data. Argot and Epple (1990) explored factors affecting this parameter, including organizational forgetting, turnover, and transfer of productivity gains, and how it can potentially reduce costs [14].

Economies of numbers has been mentioned occasionally, but favorably, in literature related to chemical and process systems engineering. Liebermann (1984) investigated this concept and used a many-shot approach to try and determine which factors affected the learning rates in a plant or chemical manufacturing context [3]. Weber et al. (2019) describe how economies of numbers apply to the chemical process industries [15]. Gazzaneo et al. (2022) proposed a novel technoeconomic framework for costing intensified modular systems in the process engineering industry [4].

This cost benefit from manufacturing standardization applies only to part of the overall process cost (e.g., labor, but not materials). Therefore, we expect these learning curves to decay towards an asymptote. Gazzaneo et al. (2022) define a piecewise function that includes a lower limit on the discount factor, as shown in (2).

$$F_n = \begin{cases} n^{-\alpha}, & if\ n^{-\alpha} \geq F_{bound} \\ F_{bound}, & if\ n^{-\alpha} < F_{bound} \end{cases} \tag{2}$$

This modified relationship is shown in Figure 2 with $\alpha = 0.2$ and $F_{bound} = 0.7$.

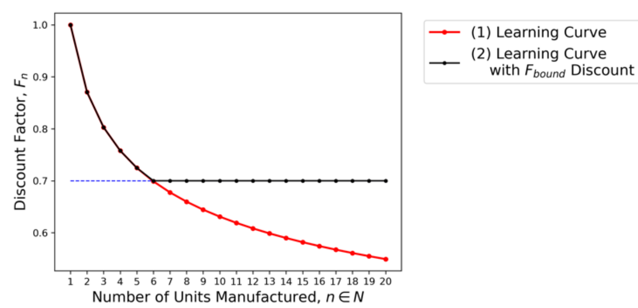

Figure 2: Example Learning Curve with Maximum Discount[4]
($\alpha = 0.2$ and $F_{bound} = 0.70$)

In this work, we use a similar economies of numbers correlation that also includes a maximum discount, F_{bound}, with a smooth transition.

PROBLEM APPROACH

In previous work, we have presented a discretization-based Mixed Integer Linear Program (MILP) to solve the process family design problem [2]. In this section, we present modifications to this formulation that include cost trade-offs associated with economies of numbers and avoid explicitly specifying the size of the platform.

Problem Description

Given a process architecture, we wish to specify the designs for a set of *process variants*. A process variant v requires customization of the process architecture to meet a set of specific requirements; the specifications are parameterized in the vector $\mathbf{r_v}$. For example, take an industrial refrigeration system that a grocery store chain wishes to deploy at 10 different stores. While the general refrigeration system architecture will be the same at each location (i.e., the units required to build the system), the design details for each store (e.g., the size and maximum cooling capacity) can be different.

The *process system architecture* refers to the flowsheet of the process system; this defines all the *unit module types* necessary to build an instance of the process. In the case of the refrigeration system example, unit module types could include the compressor, condenser, valve, and evaporator. We store this set of unit module types in the set M. Each variant v will have exactly one of each unit module type $m \in M$. The variable vector $\mathbf{d}_{v,m}$ is the *unit module type design* for each unit module type m and each variant v.

Our goal is to design and deploy multiple variants $v \in V$ in a cost optimal manner by determining the unit module type designs $\mathbf{d}_{v,m}$ and operating variables $\mathbf{o}_v$. We wish to save on engineering and manufacturing costs by optimizing a platform of common unit module designs to share across the process variants. This means there are fewer unique units to design and reduced manufacturing costs for the shared designs due to economies of numbers. We separate the unit module types M into those that are designed *commonly* (stored in the set C, and is included in the platform) and the remaining that are designed *uniquely* for each variant (stored in the set U). The sets C and U are disjoint ($C \cap U = \{\}$) while their union recovers the set M ($C \cup U = M$). The design specifications for the shared platform unit module types are captured by the corresponding variable vectors $\hat{\mathbf{d}}_{c,l}$. We index the common designs by a label $l \in L_c$ to differentiate between options (e.g., different sizes of a compressor). The collection of common designs $\hat{\mathbf{d}}_{c,l}$ for all common unit module types $c \in C$ determines the platform $\mathcal{P}$. All unique unit module types $u \in U$ are designed specifically for each variant; they do not require any standardized elements.

Problem Formulation

To determine an optimal process system design for a single variant with a set of design requirements, a traditional approach would start by building the set of equations that defines the system (i.e., physics, costing, etc.). An optimization could then be performed, parameterized with the requirements, where the designs for all unit module types $m \in M$ and operational decisions are decision variables. In most applications, this system of equations will be a nonlinear program (NLP). In our approach, we must design *multiple* systems, one for each variant $v \in V$. Additionally, the unit module designs included in the platform are optimized simultaneously. And, for each variant, the common unit module design must be selected from those in the platform. This introduces discrete decisions and leads to a Mixed-Integer Nonlinear Program (MINLP).

Success optimization of MINLPs in process systems engineering can be a challenge; oftentimes, it is an active area of research. In the process family design setting, it can quickly become impractical to directly solve the MINLP with the entire set of design, costing, and performance equations in the overall formulation. Our approach to this challenge was to develop a Mixed-Integer Linear Programming (MILP) formulation that relies on a discretized set of *candidate* designs for the common unit module types $c \in C$. For each possible combination of candidate common unit module designs and each process variant $v \in V$, we optimize the process system for the unique unit module designs, operating variables, and cost. We call this a design *alternative* for variant v. From here, we build a set of feasible and infeasible design combinations and their associated costs. These form the input data for the MILP formulation.

We select a combination of common unit module designs to assign to a particular variant using the binary decision variable $x_{v,a}$. Here, a refers to a particular design *alternative* and all feasible alternatives for a variant v are stored in the set A_v. The binary decision variables $y_{c,l,n}$ determines the designs of common unit module types to include in the platform and how the number that are manufactured. The parameter M_c sets the upper limit on the number of designs of unit module type c to include in the platform. Of course, the problem is constrained to ensure we do not select alternative a for a variant v unless we have also selected the corresponding unit module designs in the platform.

As described in the previous section, we aim to capture cost savings associated with economies of numbers within our formulation. Like Gazzaneo et al. (2022), we use a function that approaches F_{bound} as $N \to \infty$, and the smooth formulation is shown in (3).

$$F_n = F_{bound} + (1 - F_{bound}) \times n^{-\beta} \tag{3}$$

This function captures the cost reduction due to economies of numbers while accounting for fixed costs (e.g., materials) that do not decrease with increasing n. The parameter β also represents a learning rate. However, since this is only applied to a portion of the overall manufacturing costs, we use different values from α to capture similar behavior to that in Gazzaneo et al. (2022), as shown in Figure 3.

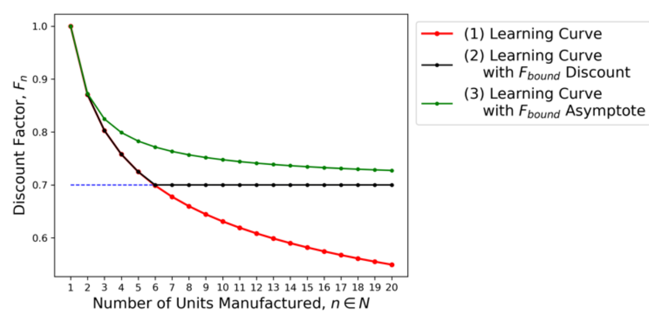

Figure 3: Learning Curve with Asymptotic Approach towards Max. Discount ($\alpha = 0.2$, $F_{bound} = 0.70, \beta = 0.8$)

We pre-compute each possible discounted unit module cost based on the number of times the unit module type could be manufactured. The base cost of each unit module type c design l is stored in $p_{c,l}$. We store the discounted costs in $\widehat{p_{c,l}}^n$, where each entry represents the cost of unit module type c for common design l if is manufactured n times. We introduce the binary variable $y_{c,l,n} \in \{0,1\}^N$ to indicate the number of manufactured units of unit module type c and common design l.

Formulation (4) describes the MILP we used to design a process family from a set of candidate common designs with discounts from economies of numbers.

$$\min_{x,y,\rho} \sum_{v\in V} w_v \sum_{a\in A_v} x_{v,a} c_{v,a} - \rho \tag{4a}$$

$$\text{s.t.} \sum_{a\in A_v} x_{v,a} = 1 \qquad \forall v \in V \tag{4b}$$

$$\sum_{l\in L_c} (1 - y_{c,l,0}) \le M_c \quad \forall c \in C \tag{4c}$$

$$x_{v,a} \le 1 - y_{c,l,0} \qquad \forall c \in C, l \in L_c, (c,l) \in Q_a \tag{4d}$$

$$\sum_{n=0}^{N} y_{c,l,n} = 1 \qquad \forall c \in C, l \in L_c \tag{4e}$$

$$\sum_{n=0}^{N} n \times y_{c,l,n} = \sum_{v\in V} \sum_{a\in A_{v,c,l}} w_v x_{v,a} \qquad \forall c \in C, l \in L_c \tag{4f}$$

$$\rho = \sum_{c\in C} \sum_{l\in L_c} \sum_{n=0}^{N} n \times y_{c,l,n} \times \left(p_{c,l} - \widehat{p_{c,l}}^{\,n}\right) \tag{4g}$$

$$0 \le x_{v,a} \le 1 \qquad \forall v \in V, a \in A_v \tag{4h}$$

$$y_{c,l,n} \in \{0,1\} \qquad \forall c \in C, l \in L_c, n \in N \tag{4i}$$

$$\rho \in \mathbb{R}^1 \tag{4j}$$

The objective (4a) minimizes the total weighted cost of all variants including the total savings from economies of numbers, contained in the variable ρ. Constraint (4b) ensures only one alternative (i.e., combination of common unit module designs) is selected for each variant. Constraint (4c) sets an upper limit of M_c on the number of common designs selected to be in the platform. Constraint (4d) ensures an alternative can only be selected if we also choose to select the required unit module designs for the platform. (4e) and (4f) constrain the binary indicator $y_{c,l,n}$ to be 1 if design l for unit module type c has been selected to be manufactured n-times and 0 otherwise. (4g) calculates the total cost savings attributed to unit module manufacturing standardization for the given process family and stores the entire discount in the variable ρ. (4h) – (4j) defines the domain for the three optimization variables. Notably, (4g) defines $x_{v,a}$ to be a continuous variable between the bounds of 0 and 1. For all case studies, $x_{v,a}$ converges to binary decision, most likely but due to similarities in the formulation to the P-Median optimization problem[16].

CASE STUDY

In this section, we describe the case study used to demonstrate our optimization approach. We chose a monoethanolamine solvent based carbon capture system simulated in Aspen Plus© as a part of the CCSI2 initiative [8]. The CCSI2 initiative focused on developing computational tools and models for accelerating the commercialization of carbon capture technologies. The flowsheet described by Morgan et al. (2022) is shown in Figure 4.

Solvent-based processes, particularly amines, are a mature class of technology for CO_2 capture from point sources of power generation and industrial processes. The solvent-based CO_2 capture process is shown schematically in Figure 4.

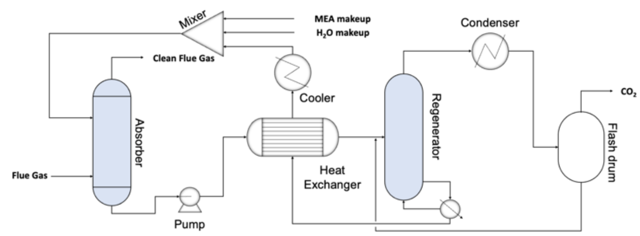

Figure 4: MEA Carbon Capture Flowsheet

As shown in Figure 4, the point source flue gas containing CO_2 enters the bottom of the absorber and is contacted countercurrently with solvent flowing down the column. The CO_2-lean solvent stream enters at the top of the column. The transfer of CO_2 from the gas to the liquid occurs through reactive absorption and the mass transfer area is generally provided by structured packing. Since the reaction of CO_2 with amine is exothermic, solvent intercooling is often included in the process design to expel the heat of absorption associated with the reaction. At one or more locations in the column, a portion of the solvent is extracted and cooled by cooling water before being returned to the column. This generally results in lowering the temperature profile in the absorber, and thus increasing the driving force for CO_2 uptake in the liquid. The flue gas with reduced CO_2 content exits the top of the absorber, and the CO_2-rich solvent exits the bottom. The rich solvent is pressurized to avoid flashing at higher temperatures required for solvent regeneration and is heated in the lean/rich heat exchanger by the lean solvent exiting the bottom of the stripper. In the stripper the CO_2 is separated from the solvent with the energy requirement for the endothermic reaction provided by the steam input to the reboiler. The stream exiting the top of the stripper primarily contains CO_2 and H_2O, the latter of which is condensed and returned to the stripper as reflux. This results in a high purity stream of CO_2 which is compressed and sent for sequestration or utilization. The lean solvent exits the bottom of the stripper and is cooled by the rich solvent in the lean/rich heat exchanger. The trim cooler, which uses cooling water, provides the residual duty required to cool the solvent prior to its return to the top of the absorber column.

This model has been adapted in this work for a process family design problem that accommodates a variety of flue gas feed conditions including a range of flowrates and CO_2 concentrations. Representing different industrial flue gas sources. We define the set of variants $v \in V$ to be different combinations of flue gas flow rates and flue gas CO_2 concentrations. This was motivated by the fact that these quantities vary significantly by carbon capture application and the design decisions depend heavily on these two quantities and they differ significantly at each potential carbon capture location, depending on capacities of plants and the source of CO_2. For this case study, we consider 7 flue gas flow rates and 9 CO_2 concentrations.

The set of unit module types for this system are all of those defined in the flowsheet, which is to say M =[absorber, pump, heat exchanger, regenerator, condenser, flash drum, cooler, mixer]. For the commonly designed absorber and regenerator (identified by orange graphically in Figure 4), we design for a specific *volume* of each column. To run simulations in Aspen Plus®, absorber and regenerator designs were specified using reported parameters from NCCC [7] as a baseline. For the absorber, we tested 6 diameters $(0.5m, 0.6m, \dots, 1.0m)$ and 8 regenerator diameters $(0.3m, 0.4m, \dots, 1.0m)$. Furthermore, to optimize the lean loading we considered 5 different CO_2 lean loading concentrations $(0.16, 0.17, 0.18, 0.19,\ 0.20)$ and selected the best lean loading for each combination of design for the absorber, regenerator, and process variant based on lowest total annualized cost. Given the 63 different process variants we wish to design, 6 absorber designs, 8 regenerator designs, and 5 CO_2 lean loadings considered this case study required 15,120 simulations. After running each simulation the results were used to calculate total annualized cost for each design alternative.

RESULTS & DISCUSSIONS

In this section, we present the results from the case study described in the previous section by employing methodology described in the Problem Approach section. We discuss key findings from the results.

We designed the process family using the optimization formulation described in (4). We do not include (4c), instead allowing the formulation to select however many of the candidate unit module designs to include in the platform. The optimization resulted in selection of four common designs for the absorber (out of six possible) and four common designs for the regenerator (out of eight possible), as shown in Figure 5.

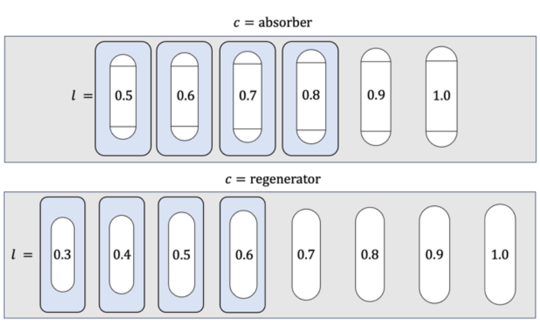

Figure 5: Carbon Capture Platform, $\mathcal{P}$

The common designs selected for the platform are identified by the blue shaded boxes. To differentiate between the designs, l corresponds to the diameter (in m.) of the design.

The design of the platform $\mathcal{P}$ is determined simultaneously with the design of the process family $\mathcal{F}$ in the optimization formulation. From the process platform constructed and shown in Figure 5, the corresponding optimal design of the process family is shown in Figure 6.

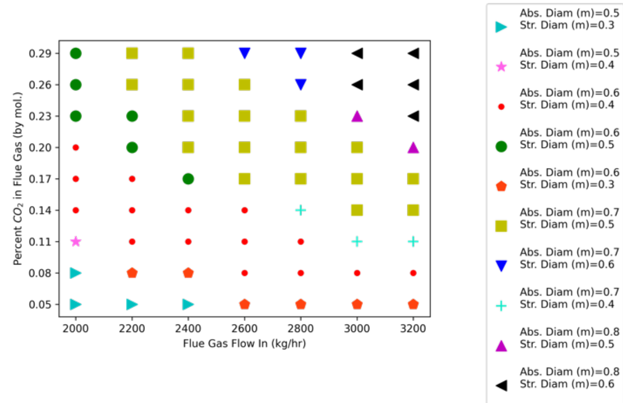

Figure 6: Carbon Capture Process Family, $\mathcal{F}$

Figure 6 describes which combination of absorber and regenerator designs offered in the platform (shown in Figure 5) are assigned to each variant $v \in V$. The x-axis corresponds to the flue gas flow rate that descibes a particular variant v; the y-axis corresponds to the percentage of CO_2 in the flue gas at variant v.

Using Gurobi©, it took under a second to solve this problem. The formulation presented in (4) for this case study resulted in 1,376 constraints, 646 continuous variables, and 896 binary variables. The objective of this optimization resulted in a total annualized cost, discounted by savings due to economies of numbers, to be $\$72.5M$. We used a learning rate $\beta = 0.8$ and a maximum discount factor of $F_{bound} = 0.7$. Savings associated with economies of numbers, captured in the value for the variable ρ, came out to be approximately $\$2.38M$ annually. The percentage of savings associated with the overall cost is approximately 3.3%. If we only consider the capital costs for this system, the percent savings is 26.8%.

To compare this approach to a more traditional method, we optimized each carbon capture variant independently. To do this for the case study presented, we selected the combination of candidate absorber and regenerator designs that minimized the cost of the variant, with no discounts due to economies of numbers or limitations on the number of common designs that could be used. In this way, we design each variant *individually* rather than as a family. The overall objective cost of this individual optimization came out to $\$74.86M$, which is over $\$2M$ more expensive than taking the process family design approach. This demonstrates the importance of considering economies of numbers in the design of chemical process systems due to the benefits it can provide.

CONCLUSIONS & FUTURE WORK

Process family design lends insight into how standardization within the process systems engineering manufacturing industry can potentially save money. In particular, the optimization approach described in this paper aims to capture and fully exploit cost savings by quantifying the impact of economies of numbers on the design of a process family. We demonstrated this approach on a carbon capture case study, motivated by the need to deploy these systems rapidly and cost-effectively to combat the effects of climate change. The results of this case study showed a decrease in total annualized cost compared to taking the discretized approach described in Stinchfield et al. (2023) and a traditional engineering approach. The optimization formulation presented in this work selected the size of the platform, rather than having to predefine the size, which further allowed the formulation to determine the optimal trade-off between standardization and customization of the system.

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REFERENCES

1. Jiao, Jianxin, Timothy W. Simpson, and Zahed Siddique. "Product family design and platform-based product development: a state-of-the-art review." Journal of Intelligent Manufacturing 18 (2007): 5-29.
2. Stinchfield, Georgia, et al. "Optimization-Based Approaches for Design of Chemical Process Families using ReLU Surrogates." In proceedings, FOCOPO/CPC 2023.
3. Lieberman, Marvin. "The Learning Curve and Pricing in the Chemical Processing Industries." RAND Journal of Economics 15 (1984): 1984-213.
4. Gazzaneo, Vitor, et al. "A techno-economic analysis framework for intensified modular systems." Journal of Advanced Manufacturing and Processing 4.3 (2022)
5. Khajavirad, Aida, Jeremy Michalek, and Timothy Simpson. "A decomposed genetic algorithm for solving the joint product family optimization problem." 48th AIAA/ASME/ASCE/AHS/ASC Structures, Structural Dynamics, and Materials Conference. 2007.
6. Bynum, Michael L., et al. *Pyomo-optimization modeling in python*. Vol. 67. Berlin/Heidelberg, Germany: Springer, 2021.
7. Morgan, J. C., A. Soares Chinen, B. Omell, D. Bhattacharyya, and A. Deshpande (2022). Carbon capture simulation for industry impact (CCSI2), v3.2.1. mea steady state model
8. Gonzalez-Zugasti, Javier P. "Models for Platform-Based Product Family Design." Massachusetts Institute of Technology, 2000.
9. Zhou, K., Du, G., and Jiao, R.J., "Personalized service product family design optimization considering crowdsourced service operations," Computers & Industrial Engineering, vol. 166, pp. 107973, 2022.
10. Simpson, T. W. and D'Souza, B. S., "Assessing variable levels of platform commonality within a product family using a multiobjective genetic algorithm," Concurrent Engineering, vol. 12, no. 2, pp. 119-129, 2004.
11. Pirmoradi, Z., Hajikolaei, K. H., and Wang. G. G., "Designing scalable product families by the radial basis function–high-dimensional model representation metamodelling technique," Engineering Optimization, vol. 47, no. 10, pp. 1423–1439, 2015.
12. Wright, T. P. "Factors Affecting the Cost of Airplanes." Journal of the Aeronautical Sciences, Vol. 3, 1936.
13. Argote, L., Epple, D., "Learning curves in manufacturing," Science, New Series, vol. 247, no. 4945, pp. 920-924, Feb. 23, 1990.
14. Weber, R. S.; Snowden-Swan, L. J. The economics of numbering up a chemical process enterprise. J. Adv. Manuf. Process. 2019, 1 (1–2), e10011.
15. ReVelle, Charles S., and Ralph W. Swain. "Central facilities location." Geographical analysis 2.1 (1970): 30-42.