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Optimization-based Design of Product Families with Common Components

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Abstract

For many industries addressing varied customer needs means producing a family of products that satisfy a range of design requirements. Manufacturers seek to design this family of products while exploiting opportunities for shared components to reduce manufacturing cost and complexity. We present a mixed-integer programming formulation that determines the optimal design for each product, the number and design of shared components, and the allocation of those shared components across the products in the family. This formulation and workflow for product family design has created significant business impact on the industrial design of product families for large-scale commercial HVAC chillers in Carrier Global Corporation. We demonstrate the approach on an open case study based on a transcritical CO_2 refrigeration cycle. This case study and our industrial experience show that the formulation is computationally tractable and can significantly reduce engineering time by replacing the manual design process with an automated approach.

Keywords: product family design, discrete optimization, product manufacturing

1. Introduction

For many industries, addressing global markets and varied customer needs means producing a family of products that are able to satisfy a range of design requirements. For example, commercial chiller systems for HVAC sold in different regions of the world are subject to different operating and boundary conditions, customer cost and performance expectations, and efficiency regulations. This requires the design and manufacturing of a family of products to meet requirements of different geographical regions and customer needs. Optimizing each of the products independently results in significantly increased manufacturing cost and complexity since each design will include unique sizing for all of the sub-components, ignoring the potential for sharing these components across multiple products within the family. Therefore, manufacturers seek to design the entire family of products simultaneously, determining the optimal design for each product, the designs of

common components, and the assignment of these components to each of the products in the family. This is a highly-combinatorial problem, that is typically performed with heuristics and ad-hoc approaches, takes significant engineering time, and results in sub-optimal designs. Many industries need effective design of product families that can exploit shared components, and this is an active area of research in manufacturing where various heuristics and optimization strategies have been applied (Simpson et al. 2014). Some examples of optimization-based approaches have focused on definition and optimization of a commonality index or degree of commonality (Thonemann & Brandeau 2000) and application of genetic algorithms (Liu et al. 2011). Integer programming techniques have also been used in, for example, the integration of the supply chain with the product family design (Baud-Lavigne et al. 2016). These concepts have applicability to chemical process design. In particular, for decentralized applications where many instances of similar processes with different performance specifications are required, the benefits of well-designed product families allow for significant reduction in engineering and construction costs.

In this paper, we present an mixed-integer programming formulation for product family design with common sub-components developed in collaboration with researchers at Carrier Global Corporation. Instead of manufacturing uniquely specified (e.g., sized) components for each product, we seek to manufacture a small number of component designs and share these across multiple products. The formulation determines the cost optimal designs for each of the products, the optimal sizing for the shared components, and the allocation of these components for each of the products. This formulation and workflow for product family design has created significant business impact on the industrial design of product families for large-scale commercial HVAC chillers in Carrier Global Corporation. In one application, the product family design workflow selected common compressors for a global family of over 200 products, leading to significant direct cost savings (material and labor), indirect cost savings (prototype design, build, and test), and an order of magnitude reduction in R&D time associated with this task. This process is being used and extended within Carrier across several product lines.

We demonstrate the product family design formulation on an open case study considering a family of HVAC products based on a CO_2 refrigeration cycle described in Li & Groll (2005). The model for the system is built using the IDAES process modeling platform (Lee et al. 2021) and the product family design problem is implemented in Pyomo (Bynum et al. 2021). The approach is shown to be computationally tractable for real-world systems, with significantly reduced engineering time, replacing the manual design process with an automated, optimization-based approach.

2. Product Family Design Formulation

We assume that the set of products P and their performance requirements have already been specified (e.g., from market analysis). Product requirements may be captured as boundary conditions that must be matched exactly or as inequalities that provide bounds on the product performance. The set of components where there is opportunity for utilizing shared designs across multiple products is given by C, and the set of candidate designs for each component c is given by S_c. Our goal is to optimally design all of the products $p \in P$ while reducing the overall manufacturing costs by utilizing a (hopefully small) subset of the candidate component designs in these products.

For each product p we consider a set of design alternatives. For each alternative, we specify which candidate component designs are to be utilized in the product. For the initial set of design alternatives, we typically consider all combinations of candidate designs for each of the components (i.e., the Cartesian product of all S_c for all $c \in C$). Then, for each of these alternatives, we can perform simulations (or optimizations) and identify the alternatives that meet the required performance specifications. We define this set of all feasible alternatives for product p as A_p. The set Q_a is a tuple set that captures the specific candidate component designs used within each alternative a.

The proposed formulation for optimal design of product families with common components is shown in Equations (1-6). The binary variables z_{cs} identify which candidate designs s are selected for each component c, and x_{pa} captures which alternative is selected for product p. Equation (1) is the objective function, and the first term captures the expected cost associated with the family design where w_p is the expected sales (or sales fraction) for each product, and α_{pa} is the annualized cost if alternative a is selected for product p. The second term captures the cost required to develop the manufacturing process for each unique component selected. In many industrial examples, the cost of this manufacturing complexity is difficult to capture, and we can also constrain the number of candidate component designs selected with Equation (2).

$$\min_{x,z} \sum_{p \in P} w_p \sum_{a \in A_p} \alpha_{pa} x_{pa} + \sum_{c \in C} \sum_{s \in S_c} \beta_{cs} z_{cs} \tag{1}$$

s.t.

$$\sum_{s \in S_c} z_{cs} \leq N_c \qquad \forall\, c \in C \tag{2}$$

$$\sum_{a \in A_p} x_{pa} = 1 \qquad \forall\, p \in P \tag{3}$$

$$x_{pa} \leq z_{cs} \qquad \forall\, p \in P, a \in A_p, (c,s) \in Q_a \tag{4}$$

$$0 \leq x_{pa} \leq 1 \qquad \forall\, p \in P, a \in A_p \tag{5}$$

$$z_{cs} \in \{0,1\} \qquad \forall\, c \in C, s \in S_c. \tag{6}$$

Equation (3) ensures that only one alternative is selected for each product, and Equation (4) allows alternative a for product p only if the required components have been selected.

3. Process Case Study

For our case study, we consider the design of a family of products for commercial HVAC applications based on the transcritical CO_2 refrigeration cycle described in Li & Groll (2005). The process flow diagram is shown in Figure 1. We developed an IDAES model for this process using the standard unit model library with the exception of the ejector which required a custom model. The compressor model includes an efficiency curve to capture the drop in efficiency when it is operating away from the design flowrate. IDAES also includes a costing framework that was used to capture the equipment capital costs.

We consider two performance criteria when specifying the products P. The cooling capacity is the primary criterion determining the size of the components in the refrigeration

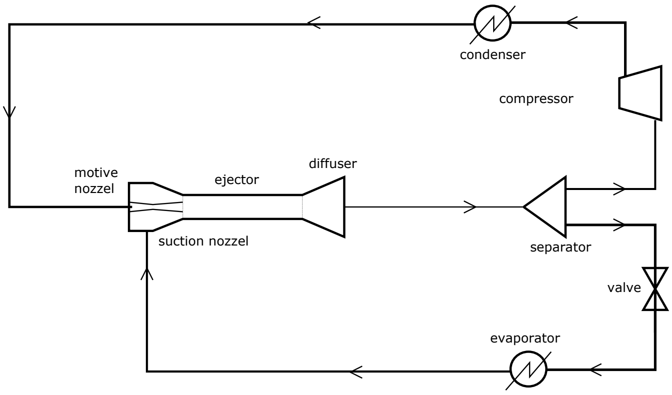

Figure 1: Process flowsheet for CO2 refrigeration cycle. This model was based on Li & Groll (2005)

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cycle and can vary significantly based on customer needs. The outside air temperature varies significantly by region, and different units are designed for different conditions.

Here, we consider capacities of CAP=$\{80, 100, 120, 140, 160, 180, 200\}$ tons of refrigeration and outside air temperature specifications of OAT=$\{28, 29, 30, 31, 32, 33, 34, 35\}$ degrees Celsius. With these specifications, we have a total of 56 different products to consider, identified as the Cartesian product of all values in CAP and OAT.

The opportunities we consider for shared components across the products include the evaporator, the condenser, and the compressor, defining C=$\{\text{Evap}, \text{Cond}, \text{Compr}\}$. We consider five sizes of evaporator labeled A through E in order of increasing size, seven sizes of condenser labeled A through G in order of increasing size, and four sizes for the compressor, labeled A through D, also in order of increasing size. This gives us a total of 140 alternatives to consider for each product defined by the Cartesian product of the different candidate components specified as, $S_{\text{Evap}} = \{\text{A}, \text{B}, \text{C}, \text{D}, \text{E}\}$, $S_{\text{Cond}} = \{\text{A}, \text{B}, \text{C}, \text{D}, \text{E}, \text{F}, \text{G}\}$, and $S_{\text{Compr}} = \{\text{A}, \text{B}, \text{C}, \text{D}\}$.

We performed simulations for each of these alternatives across all the products (with CAP and OAT specified as boundary conditions) for a total of 7840 simulations. Of these, 3708 were infeasible and not able to meet the desired performance specifications. The feasible alternatives were used to define the remaining data required in the optimization formulation along with recorded capital and operating costs from the IDAES model.

The product family design problem (1-6) was formulated in Pyomo (Bynum et al. 2021) and solved using Gurobi (Gurobi Optimization, LLC 2021). We set the maximum number of candidate components to 2 for each of the evaporator, condenser, and compressor. Gurobi was able to solve this problem in under one second. Results showing the optimal designs are illustrated in Figure 2. The figure on the left shows the solution considering capital cost only (materials and construction). In this case, the optimization selected evaporators C and D, condensers A and B, and compressors A and B for manufacturing. The colors on the figure show unique designs, and the legend on the right indicates which selected components were matched with each design. The optimization selected a larger

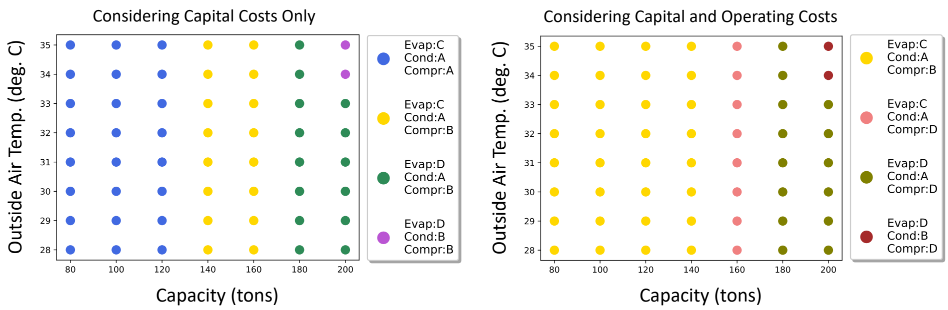

Figure 2: Optimal design of the product family with capital costs only on the left and capital plus operating costs on the right.

compressor when moving from 120 to 140 tons of capacity, and a larger evaporator when moving from 160 to 180 tons. As well, we see a change to a larger condenser for the higher outside air temperatures at the largest capacity. In this case, since we considered capital costs only, the optimization has selected the smallest compressors that are able to guarantee feasibility across the products. However, for most of these products, these compressors are operating off of their design flowrates and not achieving peak efficiency.

The figure on the right shows the optimal product family design considering both capital and operating costs. Here, we notice that the optimization did not select the smallest compressors, but has selected larger compressors so that they are operating closer to their design flowrate for improved operating efficiency.

4. Conclusion

In this paper, we have presented a formulation for optimal product family design. This formulation determines optimal designs across a set of products from a number of defined alternatives while reducing manufacturing costs by exploiting the opportunity for shared components across multiple products. This approach has been used industrially at Carrier Global Corporation with significant reduction in both costs and engineering time. The approach is also easily extended to support optimization of non-shared components by replacing the simulations with optimization problems for each of the alternatives considered.

This formulation can be efficiently solved for large data sets with commercial mixed-integer linear programming solvers. The computational bottleneck is the large number of simulations or optimizations that are required to gather the input data. It can be beneficial to use engineering knowledge to reduce the set of alternatives, and consequently, the total number of simulations that need to be performed.

It is important to note that there are a number of chemical process applications that can benefit from distributed operation of smaller, intensified, modular processes (Baldea et al. 2017). Any application that requires a large number of similar processes with variation in specific process requirements is an excellent candidate for the approaches outlined in this paper. This includes, for example, applications in water treatment, carbon capture from smaller localized sources, direct air capture, and other environmental processes. The

concepts of product family design can be utilized to shift from one-off unique designs for each application to the definition of a suite of products that span the design space while reducing manufacturing costs with shared components.

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