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# A review on superstructure optimization approaches in process system engineering

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## Keywords:

Process systems engineering  
Superstructure optimization  
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## A B S T R A C T

In this paper, we survey the main superstructure-based approaches in process system engineering, with a particular emphasis on the existing literature for automated superstructure generation. We examine both classical and more recent representations in terms of generality, ease of use, and tractability. We also discuss the implications that different representations may have on strategies for algebraic modeling and optimization. We then review the state-of-the-art in software implementations to support synthesis. Finally, we examine the use of evolutionary—recently referred to as superstructure-free—approaches, in which algorithmic procedures dynamically generate and evaluate candidate process structures.

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## 1. Introduction

Conceptual process design is a central pillar of chemical engineering, concerning the definition, simulation, optimization, and control of chemical processes. This design task involves the synthesis of complex chemical processes through the integration of simpler unit blocks characterized by physical and chemical properties. Methodological developments in process synthesis has been addressed by the Process Systems Engineering (PSE) community (Klatt and Marquardt, 2009; Cremaschi, 2015; Grossmann and Harjunkoski, 2019), which has developed powerful mathematical optimization and simulation tools to address chemical process design and control problems. In particular, Mixed-Integer Nonlinear Programming (MINLP) and Generalized Disjunctive Programming (GDP) techniques are well-suited to problems involving selection among discrete process alternatives with nonlinear process phenomena (Grossmann, 1989; Grossmann et al., 2000; Grossmann, 2002; Trespacios and Grossmann, 2014; Chen and Grossmann, 2019).

Two main approaches exist for conceptual process design: hierarchical decomposition (Douglas, 1985; Sirola and Rudd, 1971) and superstructure synthesis (Umeda et al., 1972; Chen and Grossmann, 2017), with superstructure synthesis preferred for its systematic evaluation of a large space of structural alternatives

(Saif et al., 2009; Barnicki and Sirola, 2004; Westerberg, 2004). Hierarchical decomposition involves a sequential procedure in which the process design is progressively defined in stages (or levels). At each level, specific decisions are made based on engineering judgement and rules-of-thumb, starting with broader decisions of the greatest consequence. For detailed reviews on hierarchical decomposition approaches see the works of Dimian (2003) and Goh and Ng (2015). However, interactions between decisions at different detail levels (e.g. separation design and heat integration) are difficult to capture with hierarchical decomposition (Duran and Grossmann, 1986b; Lang et al., 1988). In contrast, superstructure synthesis attempts to solve the simultaneous design problem as a mathematical programming problem. Hybrid approaches combining ideas from both hierarchical decomposition and mathematical programming have also been studied by Daichendt and Grossmann (1997) and more recently by Zhang et al. (2016). Targeting techniques are also available, which identify *a priori* characteristics of advantageous structures by analyzing physical properties of the chemical system; these have been applied to great effect in heat exchanger networks (Linnhoff and Hindmarsh, 1983; Hohman, 1971), and in heat and water integration (Klemeš and Kravanja, 2013). The composite curves diagram in pinch analysis (Linnhoff and Hindmarsh, 1983) and the attainable region-based methods, introduced by Horn (1964) and popularized by Glasser et al. (1987), are among the most notable targeting techniques, used in the design of heat exchanger networks and reaction-separation systems. More recent contributions by Feinberg and Ellison (2001) and Frumkin and Doherty (2018) extend ideas of the latter beyond their geometric origins.

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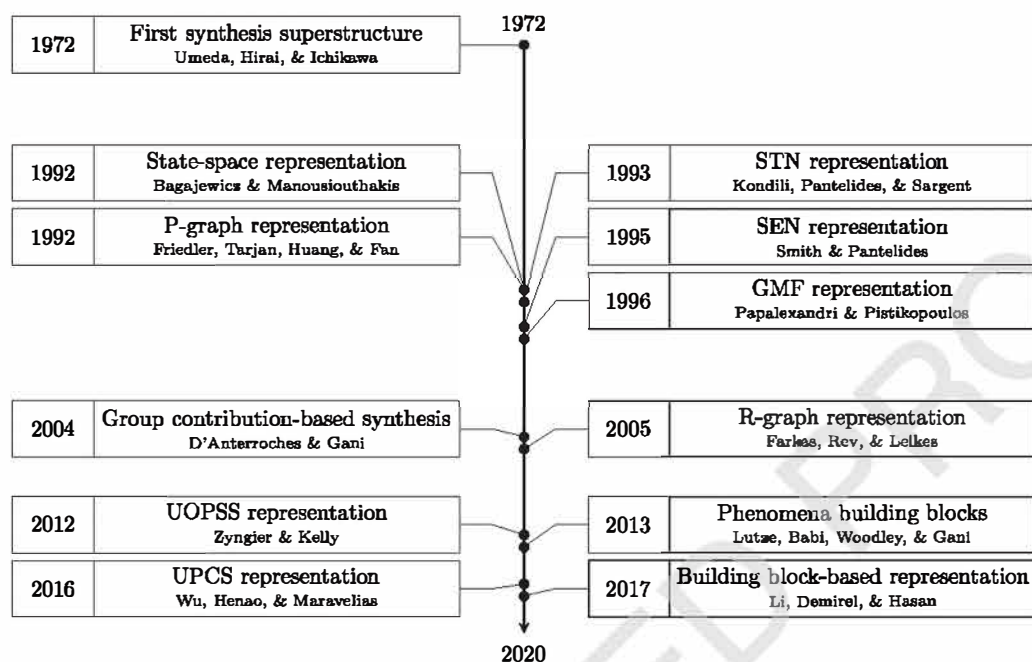


Fig. 1. Abbreviated timeline of superstructure synthesis representations.

53 Superstructure-based process synthesis, introduced in  
54 Umeda et al. (1972), involves three main sequential steps: (i)  
55 the postulation of a superstructure, which encapsulates the set  
56 of all feasible alternative process structures; (ii) the translation  
57 of the superstructure into a mathematical programming model;  
58 and (iii) the computation of an optimal structure by solving the  
59 mathematical optimization model. The approach gained traction  
60 first in subsystems (Sargent and Gaminibandara, 1976; Grossmann  
61 and Sargent, 1976), then in general flowsheet design (Kocis and  
62 Grossmann, 1989). Early reviews in the area can be found by  
63 Nishida et al. (1981), Westerberg (1991), and Bagajewicz and  
64 Manousiouthakis (1992).

65 An inherent limitation of superstructure-based approaches is  
66 the need to define an initial superstructure to capture all the de-  
67 sired alternatives. A poorly-constructed superstructure may omit  
68 several feasible or optimal process flowsheets. Moreover, the choice  
69 of representation may impact tractability of the resulting opti-  
70 mization formulation (Yeomans and Grossmann, 1999). In re-  
71 sponse, the community has developed two main approaches: (a)  
72 automated superstructure generation methods, and (b) evolution-  
73 ary “superstructure-free” approaches. In automated superstructure  
74 generation, the superstructure is constructed from a set of alterna-  
75 tives via deterministic algorithmic procedures; on the contrary, in  
76 the superstructure-free approach, candidate structures are dynam-  
77 ically generated during the search process.

78 In this paper, we provide a critical review of the state-of-the-  
79 art in superstructure based synthesis, with a focus on the methods  
80 and tools available to generate appropriate superstructure repre-  
81 sentations. We then compare these approaches to superstructure-  
82 free design strategies. The rest of the paper is organized as fol-  
83 lows. In Section 2, we survey the representations and algorithmic  
84 procedures proposed in the literature to automate the generation  
85 of the superstructure of a given process. We also describe algori-  
86 thmic post-processing procedures proposed to reduce the complexity  
87 or the redundancy of superstructure representations, and to trans-  
88 late the superstructure into a mathematical programming formu-  
89 lation. In Section 3, we discuss implications of the superstructure  
90 representation on modeling and solution strategies. In Section 4,  
91 we review current software implementations for process synthesis.

92 Then, in Section 5, we briefly summarize superstructure-free ap-  
93 proaches. Methodological conclusions and final remarks follow in  
94 Section 6.

## 95 2. Superstructure representations

96 In this section we present the different techniques proposed  
97 in the literature to generate and optimize the superstructure of a  
98 given chemical process. Selection of the appropriate superstructure  
99 representation is a necessary prerequisite in automated superstruc-  
100 ture generation. Over the years, several representations and gener-  
101 ation approaches have been proposed in literature (see Fig. 1);  
102 these can be divided into two classes: the traditional approaches  
103 proposed in the 1990s, and newer representations developed after  
104 the turn of the millennium. The traditional approaches involve net-  
105 work or graph representations in which the chemical process is di-  
106 vided into stages (or states) and tasks. These interlinked states and  
107 tasks describe the progressive transformation of the inputs (or raw  
108 materials) into the desired outputs (or final products) by means  
109 of sequential operations (or functions). Computer-aided generation  
110 of alternatives in these approaches can be done with means-ends  
111 analysis (Siirola et al., 1971).

112 In recent years, new challenges and opportunities—detailed in  
113 the following review papers—have spurred renewed interest in  
114 process design, leading to the development of several new super-  
115 structure representations. There have been efforts to design more  
116 sustainable processes (Martín and Adams II, 2019) for the circular  
117 economy (Avraamidou et al., 2020). Interest in process intensifica-  
118 tion renewed interest in representations able to capture selection  
119 and integration of physical and chemical phenomena, in contrast to  
120 traditional equipment-oriented superstructures (Sitter et al., 2019;  
121 Tula et al., 2019a; Tian et al., 2018a). At the same time, equipment  
122 size reductions from process intensification have led to interest in  
123 modular process units (Baldea et al., 2017), with applications in the  
124 oil and gas industry (Tsay et al., 2018). New superstructures that  
125 aim to simplify solution strategies and software platforms to sup-  
126 port the use of these new representations have also arisen (Mitsos  
127 et al., 2018; Tula et al., 2019b). Finally, Ryu et al. (2020) explic-  
128 itly examines the interactions needed to synthesize a process em-

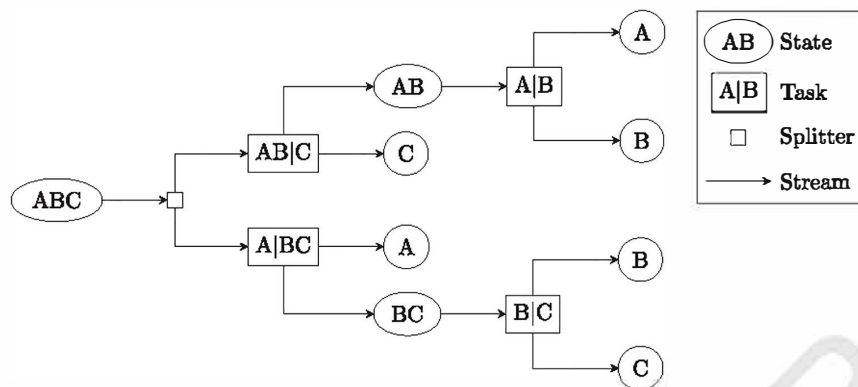


Fig. 2. State-Task Network (STN) superstructure for a 3 component sharp split distillation sequence.

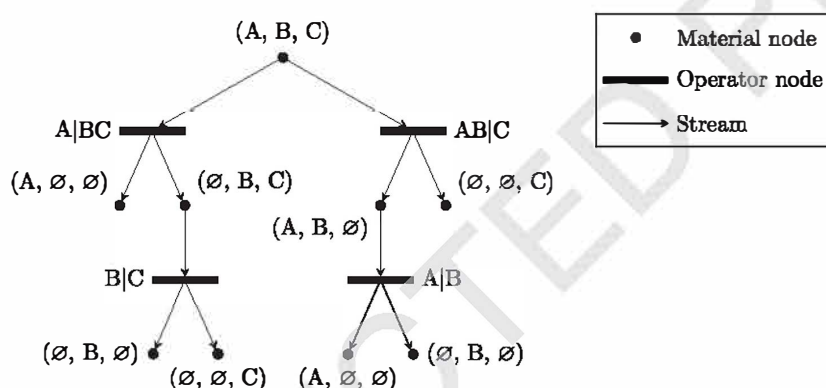


Fig. 3. P-graph network superstructure (PNS) for a 3 component sharp split distillation sequence.

129 bedding multiple different representations. In the following sections, we elaborate on both traditional and new representations  
 130 that build on its ideas. As previously introduced, the STN can be  
 131 constructed by taking into account all of the tasks needed to convert a process through means-ends analysis (Siirola et al., 1971),  
 132 and connecting them via associated intermediate states.  
 133

### 134 2.1. State-task network representation

135 The state-task network (STN) representation (see Fig. 2) was  
 136 first introduced in Kondili et al. (1993) for multi-product/multi-  
 137 purpose scheduling problems, and extended to process flowsheet  
 138 design by Yeomans and Grossmann (1999), in which the repre-  
 139 sentation is applied to the synthesis of distillation sequences with  
 140 and without heat integration. The STN representation consists of  
 141 a directed graph with two main classes of nodes: states and tasks.  
 142 States, as their name implies, represent a physical or compositional  
 143 state of the feeds, intermediates, or products. The transition be-  
 144 tween these states is accomplished through processing tasks. A su-  
 145 perstructure task can be conditional or common to all the alterna-  
 146 tive structures; this distinction is only made when the superstruc-  
 147 ture is translated into a mathematical programming formulation.

148 For conceptual design, the processing tasks also need to be as-  
 149 sociated with equipment selection. Due to its origins as a multi-  
 150 product scheduling representation, the STN supports variable task-  
 151 equipment (VTE) assignment, in addition to the more traditional  
 152 one task-one equipment (OTOE) assignment. In VTE, a single piece  
 153 of equipment may perform multiple different processing tasks (e.g.  
 154 batch reactors that perform both reaction and mixing tasks), and  
 155 the final equipment-task assignment is given by the optimization  
 156 result. However, OTOE is far more common in overall flowsheet de-  
 157 sign, with each task associated *a priori* to a piece of equipment. In  
 158 that way, the superstructure more closely resembles a process flow  
 159 diagram with conditional flow paths. The STN-OTOE representation

is still commonly used today, and has inspired new representations  
 that build on its ideas. As previously introduced, the STN can be  
 constructed by taking into account all of the tasks needed to convert a process through means-ends analysis (Siirola et al., 1971),  
 and connecting them via associated intermediate states.

### 165 2.2. P-Graph representation

166 The process graph (P-graph) concept first appeared in  
 167 Friedler et al. (1992a). As such, it is a contemporary to the  
 168 STN, with many similarities between the two representations. The  
 169 P-graph is a bipartite graph (see Fig. 3), whose vertices consist of  
 170 material (M-type) and operating unit (O-type) nodes. An operating  
 171 unit accepts one or multiple input materials, and produces one  
 172 or more outputs. P-graph material nodes correspond to STN state  
 173 nodes; P-graph operating units, to STN tasks.

174 Drawing upon ideas from graph theory,  
 175 Friedler et al. (1992b) show that combinatorially feasible pro-  
 176 cess structures are subgraphs of the P-graph that satisfy the  
 177 following system of axioms.

**Axiom S1.** Every final product of the process is represented by a  
 M-type vertex in the graph.

**Axiom S2.** A M-type vertex represents a raw material, if and only  
 if it has no incoming incident arcs.

**Axiom S3.** Every operating unit defined in the synthesis problem  
 corresponds to an O-type vertex in the graph.

**Axiom S4.** There exists at least one path from each operation unit  
 node to a node representing a final product.

**Axiom S5.** Every material node should represent an input or an  
 output to/from at least one operating unit node.

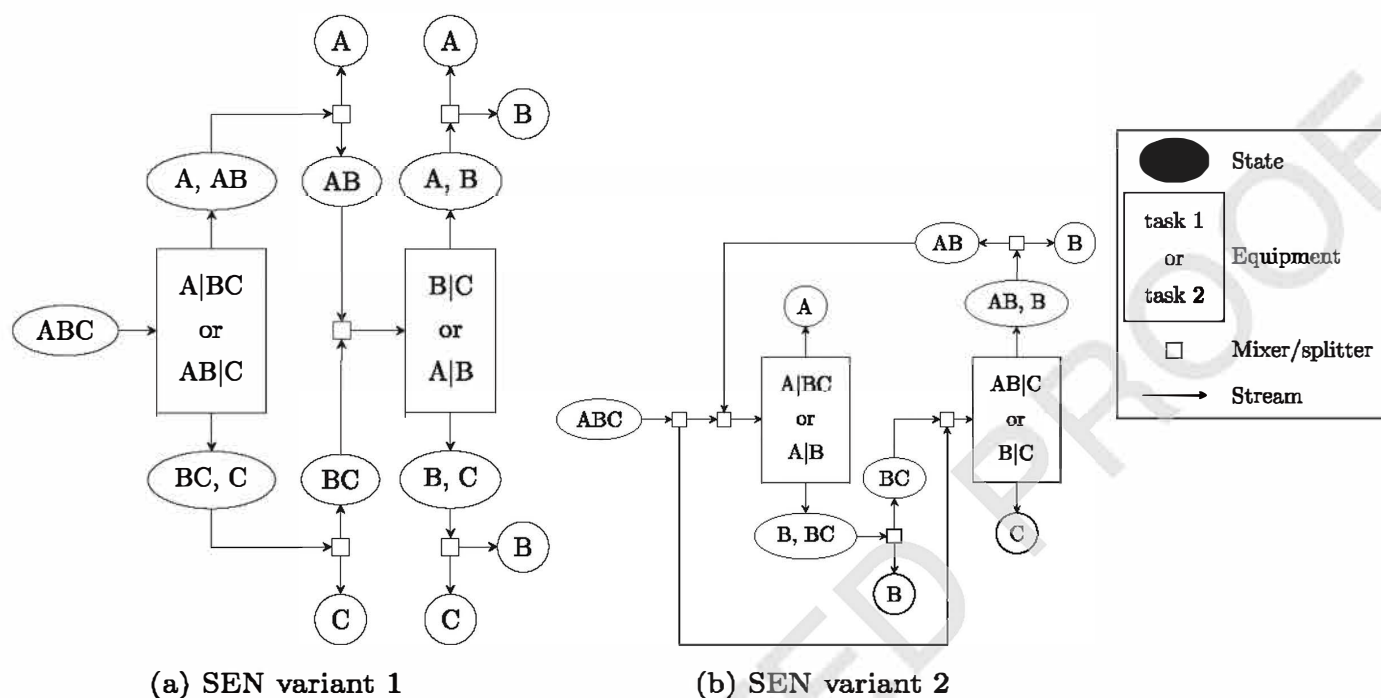


Fig. 4. State-Equipment Network (SEN) superstructure for a 3 component sharp split distillation sequence.

188 **Axiom S1** ensures that all desired products appear in the super-  
 189 structure, while **Axiom S2** defines which nodes are the raw materi-  
 190 al input nodes. **Axiom S3** ensures that all considered operating  
 191 units appear in the graph. **Axiom S4** requires that each operating  
 192 unit be connected to at least one final product, i.e. there are no  
 193 irrelevant operations. Finally, **Axiom S5** enforces that every materi-  
 194 al node is connected to at least one operating unit node, i.e. there  
 195 are no irrelevant materials. The set of structures described by these  
 196 axioms is closed under union, and the superstructure corresponds to  
 197 the union of all the structures.

198 The P-graph methodology distinguishes itself among early super-  
 199 structure representations by providing a systematic algorithm  
 200 for generating the P-graph (Friedler et al., 1993). The computa-  
 201 tional complexity of this algorithm is polynomial in the number  
 202 of the materials and in the maximal degree of its vertices  
 203 (Friedler et al., 1993). An accelerated branch-and-bound (ABB)  
 204 strategy was also developed to exploit the P-graph representa-  
 205 tion by restricting the search to combinatorially feasible structures  
 206 and solving the relaxations at branched nodes in reduced space  
 207 (Friedler et al., 1996). It is noteworthy that contemporary to this,  
 208 the same motivations guided development of the logic-based outer  
 209 approximation algorithm for Generalized Disjunctive Programming  
 210 (Türkay and Grossmann, 1996) (see also Section 3.3). Connections  
 211 between the P-graph representation and GDP formulations were  
 212 subsequently explored in Brendel et al. (2000).

213 The mathematical rigor unpinning the P-graph methodology is  
 214 a key advantage of the approach; however, its closed implementa-  
 215 tion and complex notation limit its accessibility to a chemical en-  
 216 gineering audience. For more detail, recent reviews on the P-graph  
 217 approach may be found by Lam (2013) and Friedler et al. (2019).

### 218 2.3. State-equipment network representation

219 In the state-equipment network (SEN) representation (see  
 220 Fig. 4), introduced by Smith and Pantelides (1995), the superstruc-  
 221 ture nodes are states and equipment, with task assignment to the  
 222 equipment determined as an optimization result. For some prob-  
 223 lem classes, e.g. distillation sequence design, SEN requires fewer

operator (equipment/task) nodes than the equivalent STN repre-  
 224 sentation. For a three-component system with sharp separations, 225  
 226 the SEN requires two equipment nodes versus four task nodes for  
 227 the STN; for a four-component system, the ratio is four to 10 for  
 228 the SEN and STN, respectively. However, with the SEN, the combi-  
 229 natorial complexity is found in the equipment interconnections,  
 230 so it is more effective when the equipment selection is known *a*  
 231 *priori* (Yeomans and Grossmann, 1999), as in distillation sequences  
 232 and reactor selection (Ramapriya et al., 2018).

233 Note that multiple logically-equivalent SEN variants may be  
 234 possible with differing assignment of potential tasks to the equip-  
 235 ment, as seen in Section 2.3 for a distillation sequence superstruc-  
 236 ture. Variant 1 (Fig. 4a) has a more intuitive flow pattern, with the  
 237 first separation taking place in the first column, and the second  
 238 separation taking place in the second column. Variant 2 (Fig. 4b)  
 239 groups the tasks by the split taking place, with the A|B separation  
 240 in the first column, and the B|C separation in the second column.  
 241 As a result, variant 2 potentially has less physical property vari-  
 242 ation between discrete task selections at either the condenser or  
 243 reboiler end of the column, with a high concentration of the same  
 244 pure component. This could improve computational performance  
 245 in optimization algorithms. The relative merits of these two vari-  
 246 ants remains an open question.

247 Related to both the STN and SEN is the Resource-Task Network  
 248 (RTN) representation, introduced by Pantelides (1994), in which  
 249 the resource nodes can refer to material states (as in the STN)  
 250 and/or equipment (as in the SEN). The RTN is more common in  
 251 process scheduling applications, but can be useful in simultane-  
 252 ous scheduling and design problems. We omit a detailed discussion  
 253 here and refer the interested reader to recent reviews on schedul-  
 254 ing formulations (Harjunkoski et al., 2014; Brunaud et al., 2020).

255 The recent Processing Step-Interval Network, proposed by  
 256 Bertran et al. (2016), can also be seen as an extension of the  
 257 STN/SEN, with influence from early heat exchanger network mod-  
 258 els (Yee and Grossmann, 1990). The representation adds structure  
 259 and nuance to the states through the use of processing intervals.  
 260 An example of its use can be found in Garg et al. (2019) for the  
 261 production bio-succinic acid.

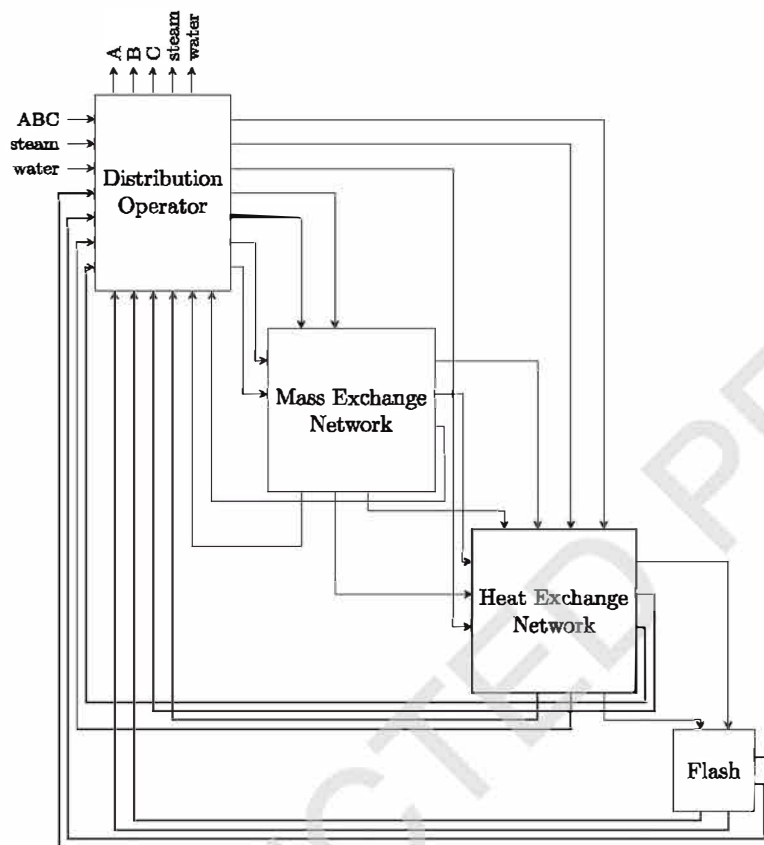


Fig. 5. State-Space Representation (SSR) superstructure for a 3 component sharp split distillation sequence. Boxes represent state-space operators. Arrows represent state variables that are inputs to or outputs from their respective operators.

#### 2.4. State-space representation

The state-space representation (SSR) was adapted from the concept of “state space” in system theory (Zadeh and Desoer, 1979). In the state-space approach, the design problem is posed as identification of the properties of the input-state-output relations between input and output variables (Bagajewicz and Manousiouthakis, 1992). The input/output variables are defined by the process engineer, while the input-state-output relations between variables yield a given structure. For process synthesis, the structure involves sequential applications of two classes of functions, namely (a) mixing and splitting of streams in the distribution network, and (b) unit operations which determine the process operator.

The SSR was motivated by the ability to easily generate complex distillation configurations such as Petlyuk columns. In Bagajewicz and Manousiouthakis (1992), the SSR for a distillation network is introduced as the integration of heat- and mass-exchanger operations. The state space approach was further extended by Wilson and Manousiouthakis (2000), which explores the limits of discretization of the design space. Another similarly-motivated extension was recently developed by Liesche et al. (2019).

The SSR is characterized by matrix operations involving the state variables. The numerical structure of these matrix operators ultimately translates to a physical process structure. Visualization of the SSR (see Fig. 5) involves abstract boxes representing the operators, interconnected by the state variables serving as inputs to or outputs from these operators. The mathematical convenience of the matrix-operator interpretation has gained the SSR significant popularity in process integration (mass/heat/work exchange) appli-

cations (see Table A.2). In Saif et al. (2009), a comprehensive survey on the applications of the SSR methodology to optimization of membrane and hybrid membrane process systems for wastewater treatment is presented.

The SSR is a very general representation, but given its abstractness and lack of supporting software tools, it has seen limited uptake outside of its proven area of process integration (Fig. 6).

#### 2.5. R-graph representation

Farkas et al. (2005b,c) adapt the SEN-OTOE to create the R-graph representation, in which nodes correspond to the inlet and outlet ports of each candidate process unit. The inlet ports function as multi-stream mixers, while the outlet ports correspond to splitters. Directed edges between the ports represent process streams, which always originate from an outlet port and end at an inlet port. The R-graph representation also features source and sink units, corresponding to raw materials and products, respectively. The source unit only has an outlet port, while the sink unit only has an inlet port. By definition, all R-graph nodes must be connected to another node in the graph.

The R-graph is motivated by modeling concerns that may arise in the traditional STN or SEN approach. First is the problem of multiplicity and redundancy, whereby a superstructure encodes multiple equivalent solutions, needlessly increasing the computational cost of the search algorithm. These redundant structures are easily created when unit bypasses are possible. In addition, no unique algebraic description is generally available for a given superstructure. Simple algebraic transformations can give rise to an infinite number of mathematical programming formulations that all yield the same engineering solution.

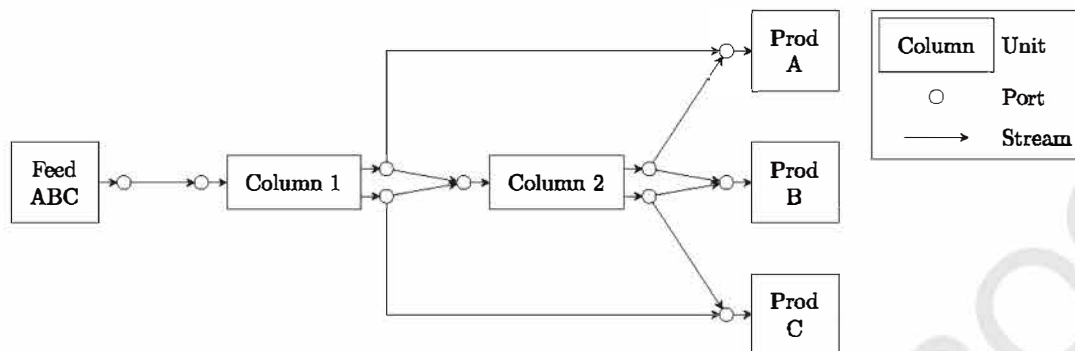


Fig. 6. R-graph superstructure for a 3 component sharp split distillation sequence.

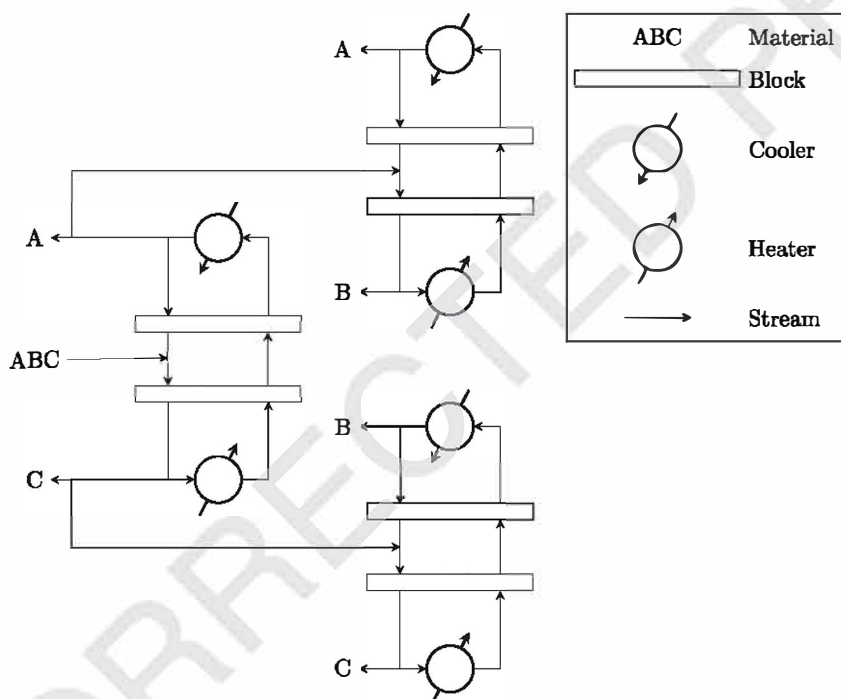


Fig. 7. GMF superstructure for a 3 component sharp split distillation sequence.

321 Farkas et al. (2005b) address superstructure multiplicity by  
 322 proposing techniques to consider only R-graphs that are non-  
 323 isomorphic. They then introduce the “basic” GDP (BGDP) model  
 324 in the spirit of the GDP formulation in Yeomans and Gross-  
 325 mann (1999), but exploiting the R-graph to avoid introduc-  
 326 ing additional logical relations that would be required to de-  
 327 fine certain substructures. Kocis and Grossmann (1988) and  
 328 Sztikai et al. (2002) perform a computational analysis on litera-  
 329 ture synthesis problems, demonstrating the procedures to build  
 330 the BGDP and various mathematical representations (Farkas et al.,  
 331 2005c). The methodology is then applied to distillation column de-  
 332 sign and optimization by Farkas et al. (2005a).

333 As with the P-graph approach, the R-graph exploits mathemat-  
 334 ical properties of graphs to improve solution strategy performance.  
 335 Here, the R-graph also takes advantage of logical representability  
 336 benefits conferred by GDP modeling. However, no software tools  
 337 exist to support the R-graph approach, and the modern-day bene-  
 338 fits of BGDP over a traditional GDP are an open question given the  
 339 prevalence of linear preprocessing for logical relations (Fig. 8).

#### 340 2.6. Generalized modular framework representation

341 The generalized modular framework (GMF) representation was  
 342 introduced by Papalexandri and Pistikopoulos (1996) to simplify

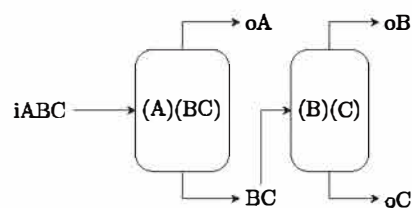


Fig. 8. Group contribution based flowsheet for 3 component sharp split distillation sequence.

343 superstructure generation with an aim to identify advantageous  
 344 structural alternatives without needing to explicitly pre-postulate  
 345 them, much like the state-space representation. GMF was also first  
 346 developed with a focus on mass and heat exchange networks, with  
 347 a later distillation sequencing example by Proios et al. (2005) (see  
 348 Fig. 7). GMF is one of the first major representations to explicitly  
 349 facilitate design of reactive separation systems (Papalexandri and  
 350 Pistikopoulos, 1996). The reaction-separation superstructure intro-  
 351 duced by Linke and Kokossis (2003) can be seen as an extension  
 352 based around similar ideas. More recently, GMF has also been ex-  
 353 tended to explore operability issues of design (Tian et al., 2018b).

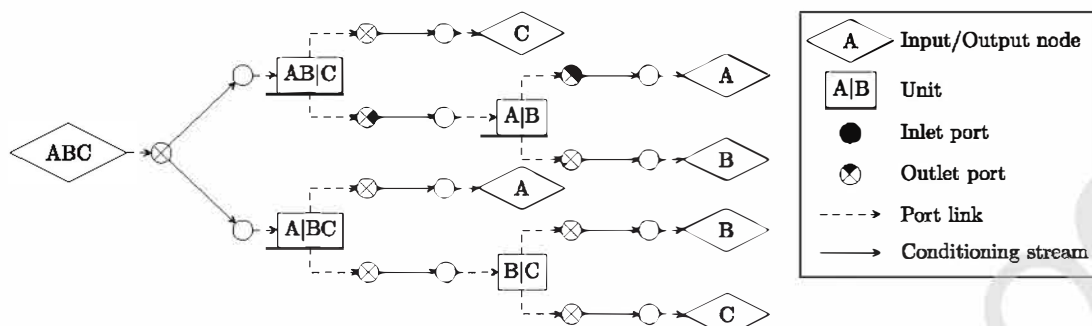


Fig. 9. UPCS representation for a 3 component sharp split distillation sequence.

## 354 2.7. Group contribution based methodology

355 The group contribution based process flowsheet synthesis  
 356 approach is detailed by d'Anterrosches and Gani (2004,  
 357 2005), drawing inspiration from group contribution methods  
 358 in thermodynamic property prediction for molecular design  
 359 (Fredenslund, 2012). In property prediction, a function is developed  
 360 relating the contribution of different molecular groups (atoms with  
 361 different bonding relationships) to the value of a physical property  
 362 of interest. For molecular design, this prediction function is used to  
 363 determine the optimal molecular groups that constitute a potentially  
 364 novel molecule. Applied to flowsheet synthesis, a group can  
 365 be represented by a process unit or a set of units, with the goal to  
 366 determine which collection of process units contribute to give the  
 367 best flowsheet performance. The approach, computer-aided flowsheet  
 368 design (CAFD), is illustrated for the design of a distillation  
 369 column by d'Anterrosches and Gani (2005).

370 As with molecular design, a difficulty of this method is obtaining  
 371 parameters for the prediction function that determines the  
 372 contribution of various potential process groups to an overall design  
 373 objective, and their ability to satisfy process specifications.  
 374 However, if parameters are found that give accurate predictions,  
 375 evaluation of different process alternatives is generally computationally  
 376 inexpensive. Tula et al. (2014, 2015) present a recent  
 377 overview of the CAFD framework (Fig. 9).

## 378 2.8. Phenomena-building block approach

379 In the early 2010s, renewed interest in process integration  
 380 and nontraditional process units led to the development of the  
 381 phenomena-building block (PBB) approach by Lutze et al. (2013),  
 382 extending phenomena-centric ideas promoted by Hauan and  
 383 Lien (1998). As with earlier strategies like the state-space and GMF  
 384 representations, PBB allows for a broader design space that can  
 385 automatically generate processes with novel combinations of chemical  
 386 and physical phenomena taking place within process units. A  
 387 major challenge with approaches that attempt to propose novel  
 388 equipment is the selection of an appropriate optimization objective  
 389 function. As a proxy, many methods use thermodynamic insights,  
 390 seeking to minimize either energy or exergy use in the process.  
 391 Kuhlmann and Skiborowski (2016) propose use of development  
 392 of an PBB equipment database as one solution to this challenge.  
 393 Other strategies avoid this problem entirely by proposing screening  
 394 rules that leave a tractable set of promising candidate flowsheets  
 395 to evaluate (Holtbruegge et al., 2014). However, these screening  
 396 rules may require simplifying assumptions about the process  
 397 to be made, and may prematurely exclude advantageous process  
 398 structures.

## 2.9. Unit, port, conditioning stream representation

399

The unit, port, conditioning stream (UPCS) representation was  
 introduced by Wu et al. (2016), consisting of three elements: (a)  
 units, which can be general process units, source units, or sink  
 units; (b) ports, which correspond to unit inlets and outlets, and  
 serve as multi-stream mixers and splitters; and (c) conditioning  
 streams, which link outlet and inlet ports, while also handling temperature  
 and pressure change operations.

The UPCS representation is heavily influenced by ideas in the  
 STN, the P-graph, the R-graph, and the more recent unit operation-  
 port-state (UOPSS) superstructure (Zyngier and Kelly, 2012). The  
 UPCS thus continues the tradition of drawing inspiration from the  
 process scheduling literature (Kelly, 2004; 2005).

As in the P-graph method, Wu et al. (2016) describe an algorithm  
 to generate a UPCS superstructure. First, the set of considered process  
 units are selected based on knowledge of the applicable reaction and  
 separation tasks. Next, inlet and outlet ports are defined for each  
 unit, and streams are created to connect each outlet port to all inlet  
 ports. From this fully-connected starting point, the authors describe  
 four rules to prune invalid and unnecessary connections, based on the  
 set of "minimal" and "feasible" components for each port. Minimal  
 components are those that must be present at an inlet or outlet port.  
 For example, a reactor  $A + B \rightarrow C$  would be ineffective without  
 components A or B, so those would be considered minimal components  
 for the reactor inlet port. Feasible components are those that may  
 be present at a given port. All minimal components are also feasible,  
 but a reactor inert I may be considered feasible but not minimal.

**Rule 1.** All minimal components for outlet ports should be feasible  
 for connected inlet ports.

**Rule 2.** All minimal components for inlet ports should be feasible  
 in at least one connected outlet port.

**Rule 3.** All outlet ports connected to a reactor inlet port must contain  
 at least one feasible component that is minimal for the reactor inlet.

**Rule 4.** All minimal components for a separator inlet port must be  
 feasible in connected outlet ports.

Rule 1 ensures that inlet ports do not receive infeasible components  
 from connections to outlet ports. Rule 2 ensures that each inlet port  
 receives its necessary components. Rule 3 reduces the number of  
 streams connected to a reactor inlet. It is worth noting that in some  
 systems, inerts may be important to the reaction controllability, so  
 care should be given to which components are deemed feasible versus  
 minimal. Rule 4 avoids unnecessary mixing and separation by  
 preventing, among other possibilities, a pure component at a  
 separator outlet from being immediately remixed into the separator  
 inlet.



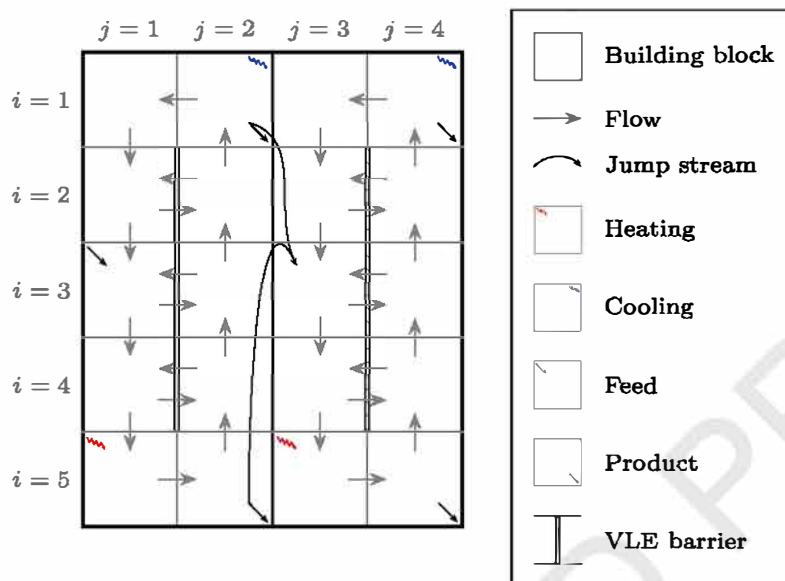


Fig. 10. Building block-based superstructure for a 3 component sharp split distillation sequence.

446 By shifting temperature and pressure change complexity to the  
 447 streams, UPCS generates visually simpler superstructures than the  
 448 STN-OTOE. Use of ports also reduces bypass redundancy, as with  
 449 the R-graph representation. However, even after screening with the  
 450 described connectivity rules, automated superstructure generation  
 451 techniques often produce many more interconnections than are ac-  
 452 tive in the final solution. As a result, the authors also introduce  
 453 simplification strategies that reduce the number of conditioning  
 454 streams that must be considered. These simplifications are made  
 455 based on engineering judgement and restrict the generality of the  
 456 strategy. However, they reflect real optimization tradeoffs between  
 457 the generality of a superstructure representation, the fidelity of  
 458 the physical property calculations, and the computational tractabil-  
 459 ity of its solution. By distinguishing between minimal and feasible  
 460 components, the UPCS provides more chemical engineering nuance  
 461 than the P-graph, while also providing a general algorithm for gen-  
 462 erating its representation.

#### 463 2.10. Building block-based superstructure

464 The building block-based superstructure (BBS) (Demirel et al.,  
 465 2017) is the most recent contribution that attempts to provide  
 466 a very general representation, capable of capturing aspects of  
 467 novel equipment design. The representation consists of a two-  
 468 dimensional grid of blocks, pictured in Fig. 10. Each block rep-  
 469 resents a control volume, capable of admitting flow across its  
 470 boundaries to/from its adjacent blocks. Flow across these bound-  
 471 aries can be fully restricted, semi-restricted (to represent mem-  
 472 brane/separation systems), or fully open. Each block admits raw  
 473 material feed into and product withdrawal from the control vol-  
 474 ume, as well as chemical reactions. Each block also admits tem-  
 475 perature and pressure change operations. The control volume of  
 476 each block is assumed to be well-mixed, with uniform composi-  
 477 tion, temperature, and pressure in its exit streams.

478 Unlike the graph-based representations, the BBS approach  
 479 prioritizes generality and graphical accessibility over solution  
 480 tractability. By allowing a broad range of operations in each grid  
 481 cell, the BBS permits the representation of diverse equipment de-  
 482 signs without the need to explicitly postulate alternatives, includ-  
 483 ing novel combinations of phenomena that may lead to new equip-  
 484 ment designs. Moreover, the two-dimensional grid layout facili-  
 485 tates an elegant visualization of the optimal structure. Discretiza-

tion in the spatial domain for plug flow reactors and membranes  
 can also be represented as a series of linked grid blocks. However,  
 the structure of the BBS creates a difficult mathematical program-  
 ming problem.

The BBS therefore challenges the state-of-the-art in modeling  
 and solution techniques. To tackle tractability considerations, two  
 main avenues of investigation have arisen: new solution techni-  
 ques tailored to the block-grid structure and the careful appli-  
 cation of problem-specific engineering expertise. Symmetry is a  
 prominent feature of the BBS, due to the versatility of its blocks.  
 Each block in the BBS is identical, except the boundary blocks,  
 which have fewer interconnections. Li et al. (2018) therefore pro-  
 pose symmetry-breaking constraints to reduce the resulting combi-  
 natorial redundancy. Iterative strategies that explore partitions of  
 the feasible region in a “frame-by-frame” manner have also been  
 proposed (Li et al., 2018). However, as with most problems, spe-  
 cialized process knowledge can be a much more powerful tool.  
 By carefully applying domain restrictions, e.g. pre-specifying flow  
 directions, block boundaries, raw material/product block identi-  
 ties, reaction blocks, etc., the problem can be made much more  
 tractable. To aid in this, Li et al. (2018) proposes the use of “jump  
 streams” to connect arbitrary blocks with each other, avoiding the  
 need for specifying empty blocks to accomplish the desired connec-  
 tivity. An example of their use can be seen in Fig. 10, where the  
 distillate and bottoms of the first column are connected to the feed  
 of the second column. Engineering knowledge also plays a role in  
 superstructure generation. In general, it is an open question how  
 many rows and columns should be postulated in the initial su-  
 perstructure. For the special case of distillation sequence design,  
 the number of BBS rows should correspond to the number of col-  
 umn trays to be considered. In this example, the BBS representa-  
 tion, pre-specified for the three component sharp split distillation  
 sequence design, resembles the SEN variant 1 (see Fig. 4a). How-  
 ever, successive restrictions of the design space based on engineer-  
 ing knowledge can compromise solution novelty—a central feature  
 of the BBS representation—and so these restrictions should be ap-  
 proached carefully. Ultimately, the BBS provides an initial start-  
 ing point for approaching the central tradeoff in superstructure-  
 based synthesis (between generality, model fidelity, and tractabil-  
 ity) that emphasizes the former two factors, and the solution strat-  
 egy should be tailored accordingly.

### 527 3. Modeling and solution strategies

528 This paper is focused primarily on discussing different super-  
529 structures, but we will briefly touch on the modeling and solution  
530 strategies here, because they can often be a factor in selection of  
531 the representation. The classic approach involves posing a math-  
532 ematical programming formulation as a large-scale mixed-integer  
533 nonlinear programming (MINLP) problem (Grossmann et al., 2000).  
534 Discrete decision variables capture structural alternatives; continu-  
535 ous variables, the process conditions (e.g. temperatures, flowrates,  
536 pressures, and equipment sizes). This formulation, expressed  
537 within an algebraic modeling platform, would then be sent to a  
538 numerical solver to obtain optimal values of the decision variables.

539 In general, process design is a computationally difficult prob-  
540 lem, with nonconvex functions involved describing the process  
541 units and their interconnections. These complications can lead to  
542 intractable formulations, which modelers often address by impos-  
543 ing simplifying assumptions (e.g. ideal thermodynamics and linear  
544 approximations) or tailored restrictions of the search space.  
545 Grossmann and Santibanez (1980) address the use of linear ap-  
546 proximations in superstructure optimization problems. In addition,  
547 more general advanced strategies have been developed to effec-  
548 tively model and solve this difficult class of problems. In the fol-  
549 lowing subsections, we present several themes common among  
550 these strategies: logic-based modeling, surrogate models, and de-  
551 composition algorithms.

#### 552 3.1. Logic-based modeling

553 Process design problems offer significant mathematical struc-  
554 ture in the discrete domain, a feature exploited by the graph-based  
555 superstructures (P-graph, R-graph, UPCS). Likewise, the struc-  
556 tural relationships described by a superstructure can be encoded  
557 through logic-based modeling. Generalized Disjunctive Program-  
558 ming (GDP) (Raman and Grossmann, 1994) offers an intuitive way  
559 to express the logical-OR (disjunctive) relationship between differ-  
560 ent process alternatives, while also capturing the connection be-  
561 tween these logical clauses and the algebraic relations that de-  
562 scribe each respective alternative (Chen and Grossmann, 2019).  
563 GDP also allows imposition of logical statements; for example, that  
564 selection of a cheaper reactor necessitates feed pretreatment.

565 GDP is an extension of disjunctive programming from the op-  
566 erations research community (Balas, 2018) to allow for nonlinear  
567 algebraic relationships. Therefore, it unlocks a suite of solution  
568 strategies that may be applied to the synthesis problem, including  
569 systematic reformulations to different MINLP representations that  
570 may yield improved computational performance (Trespalcios and  
571 Grossmann, 2014). GDP modeling also preserves logical structure  
572 for tailored decomposition algorithms (see Section 3.3).

#### 573 3.2. Surrogate models

574 In process design, many process unit alternatives may fea-  
575 ture complex first-principle models describing transport, thermo-  
576 dynamic, and/or kinetic relationships that are relevant to the prob-  
577 lem, but too computationally expensive to include directly in the  
578 optimization formulation. In this case, surrogate models (or meta-  
579 models) play a key role—replacing these expensive models with a  
580 more tractable approximation that is trained with simulated data  
581 from the model, or with experimental measurements (Cozad et al.,  
582 2014). Standard optimization algorithms can then be applied us-  
583 ing the surrogate models, as in Mencarelli et al. (2019), or trust  
584 region-based methods can be used (Eason and Biegler, 2016). If the  
585 surrogate does not provide derivative information, then derivative-  
586 free “black box” algorithms may be necessary (Rios and Sahinidis,  
587 2013).

Different classes of surrogates can be used, ranging from lin- 588  
ear surrogates to Gaussian processes to artificial neural networks 589  
(ANNs). In Super-O, piecewise linear representations of different 590  
process segments can be used as the building blocks of a super- 591  
structure optimization (Bertran et al., 2016). Henao and Maravelias 592  
(2010, 2011) introduce a surrogate-based superstructure framework 593  
based on the STN-OTOE approach. Fahmi and Cremaschi (2012) in- 594  
tegrate GDP and ANNs—the trained ANN surrogates are substituted 595  
in place of the first-principle models in a GDP formulation. Kriging 596  
interpolators have also been used (Davis and Ierapetritou, 2015; 597  
Caballero and Grossmann, 2008). Recently, Schweidtmann and Mit- 598  
sos (2019) introduced a framework for global optimization of su- 599  
perstructure synthesis problems with ANNs. 600

Note that in this work, we do not touch on training and par- 601  
ameter estimation concerns associated with using surrogate mod- 602  
els. Instead, we refer the reader to a recent review paper in the 603  
area of surrogate modeling for process design (McBride and Sund- 604  
macher, 2019). 605

#### 606 3.3. Decomposition algorithms

Decomposition algorithms that partition a problem into multi- 607  
ple tractable subproblems are commonly used to tackle large-scale 608  
optimization challenges. Classic examples of this include the Outer 609  
Approximation (OA) (Duran and Grossmann, 1986a) and General- 610  
ized Benders Decomposition (GBD) (Geoffrion, 1972) algorithms, 611  
which separate the design problem into a master problem that 612  
solves a linear approximation of the full space problem and a sub- 613  
problem that evaluates a fixed flowsheet configuration taking into 614  
account the nonlinear relationships. At each iteration, the solution 615  
of the master problem proposes a new realization of the discrete 616  
variables for the subproblem, and the nonlinear subproblem so- 617  
lution, if feasible, gives new candidate solution points. The sub- 618  
problem solution also gives new variable values at which to add 619  
linearizations to augment the master problem; OA and GBD differ 620  
in the generation of these linearizations. Termination occurs when 621  
the solution of the master problem converges with the solution of 622  
the subproblem. 623

This two-level decomposition between discrete flowsheet se- 624  
lection and detailed evaluation remains the most common theme 625  
among decomposition strategies for process design. Kocis and 626  
Grossmann (1989) present a specialized MINLP decomposition ap- 627  
proach for synthesis based on Lagrangean decomposition. The dis- 628  
crete elements of an MINLP for process synthesis usually de- 629  
scribe logical relationships between superstructure alternatives. 630  
With GDP, decomposition may be applied directly on this logi- 631  
cal layer. The logic-based outer approximation (LOA) algorithm 632  
(Türkay and Grossmann, 1996) exploits this structure to solve 633  
the nonlinear subproblems in reduced space, avoiding zero-flow 634  
numerical challenges present in MINLP formulations. Logic-based 635  
branch and bound (LBB) (Lee and Grossmann, 2000) does the same 636  
to solve node relaxations in reduced space, as with the ABB strat- 637  
egy for P-graph (Friedler et al., 1996). 638

Note that strategies presented in this section differ from hi- 639  
erarchical decomposition (Douglas, 1985) in that the decomposi- 640  
tion takes place within an computational solution framework with 641  
mathematical guarantees on convergence to optimality. In particu- 642  
lar, LBB and a global optimization extension to LOA, GLOA (Lee and 643  
Grossmann, 2001), offer convergence guarantees to within an  $\epsilon$  tol- 644  
erance. The other discussed decomposition strategies assume con- 645  
vexity, yielding a numerical heuristic for nonconvex chemical pro- 646  
cess flowsheet problems. Hybrid strategies have also been pro- 647  
posed in which physical insights are used as rules of thumb to 648  
screen the solution space before applying a mathematical program- 649  
ming algorithm (Bommareddy et al., 2011). 650

#### 651 4. Software implementations

652 Well-established commercial software tools exist for process  
653 simulation, but not yet for process synthesis (Tula et al., 2018).  
654 As a result, standard industrial practice for synthesis remains ei-  
655 ther trial-and-error using simulators, guided by engineering intu-  
656 ition or an expert system package, or the development of special  
657 purpose implementations in algebraic modeling systems. However,  
658 to provide general capabilities for systematic superstructure syn-  
659 thesis, new tool sets are needed.

660 To be successful, our community needs software tools to ac-  
661 commodate two classes of users: general users who wish to tackle  
662 an understood problem, and advanced users whose design chal-  
663 lenges lead them to push the state-of-the-art. The former desire a  
664 tool with an accessible interface that will consistently deliver re-  
665 liable answers for their analyses. The latter, frequently academics  
666 or researchers at national labs and major corporations, demand all  
667 of the above in addition to the ability to adapt or extend the tool  
668 for unknown or unforeseen challenges. The needs of general users  
669 limits technology transfer from academia into industry. Academic  
670 software rarely benefits from the funding required to create an e-  
671legant user interface. Moreover, the finesse required to reproduce  
672 academic results often necessitates hiring a student from the rel-  
673 evant research group. On the other hand, without investing in ad-  
674 vanced functionality and flexibility for advanced users, innovation  
675 in the tool will eventually stagnate, and these users may opt to  
676 develop a more capable alternative. Developers must balance these  
677 issues among other considerations when choosing where to devote  
678 limited resources.

679 Actively developed synthesis software packages include Pro-  
680 CAFD (Tula et al., 2017), P-Graph Studio (Friedler et al., 2019),  
681 MIPSYN (Kravanja and Grossmann, 1990), SYNOPSIS (Tian et al.,  
682 2018b), and Pyosyn (Chen et al., 2019), all of which find their roots  
683 in academia. ProCAFD is the most sophisticated of these tools in  
684 its support of general users, with a graphical user interface and  
685 the ability to automatically generate process alternatives from a  
686 set of raw materials, products, and reactions. It builds upon pre-  
687 existing work in the ICAS (Gani et al., 1997) tool set. P-Graph Stu-  
688 dio also features a graphical interface; however, it is less adapted  
689 to chemical engineering use, requiring more user input to set up  
690 the problem. MIPSYN, on the other hand, has a simple graphical  
691 interface, but includes a notion of chemical engineering unit mod-  
692 els to aid the user. MIPSYN poses synthesis problems as MINLP  
693 or reformulations of GDP models (Ropotar and Kravanja, 2009),  
694 which are solved via an integration with the GAMS algebraic mod-  
695 eling platform (Brook et al., 1988). SYNOPSIS and Pyosyn are both  
696 newer synthesis frameworks, created as part of two Department  
697 of Energy projects: RAPID (Bielenberg and Palou-Rivera, 2019) and  
698 IDAES (Miller et al., 2018), respectively. SYNOPSIS is built upon the  
699 GMF superstructure representation, though the tool itself has not  
700 yet been publicly released. As with MIPSYN, an integration with  
701 GAMS allows solution of the resulting MINLP models. Pyosyn, on  
702 the other hand, does not prescribe a choice of superstructure, in-  
703 stead focusing on support for high level modeling representations  
704 and solution strategies. Pyosyn supports GDP modeling with the  
705 open-source Pyomo.GDP (Chen et al., 2018) library, which also en-  
706 ables a suite of solution schemes (Chen and Grossmann, 2019).  
707 Specialized chemical engineering support is provided by the IDAES  
708 unit model library (Lee et al., 2018), with network representation  
709 capabilities using Pyomo.Network.

710 Most of the described tools have a closed-source code base,  
711 with some providing free academic licenses upon request. This has  
712 the advantage of protecting intellectual property and generating a  
713 revenue stream to fund continued research, general user-oriented  
714 features such as improved graphical interfaces, and customer sup-  
715 port. However, the community must also support open platforms

716 that allow for prototyping of new innovations and integration of  
717 these tools with existing capabilities; otherwise, it risks stagnation  
718 as in the process simulation domain.

#### 719 5. Superstructure-free approaches

720 Given the challenges of properly generating and solving the su-  
721 perstructure synthesis problem, evolutionary "superstructure-free"  
722 approaches have been a longstanding fixture of chemical engineer-  
723 ing practice (Nishida et al., 1981). Boonstra et al. (2016) discuss  
724 the distinction between superstructure-based and superstructure-free  
725 approaches. Superstructure-free approaches also tend to adopt a  
726 two-level decomposition approach, separating the discrete topolog-  
727 ical decision and the detailed flowsheet evaluation, as detailed in  
728 Section 3.3. However, instead of a mathematical programming ap-  
729 proach to propose flowsheets from the combinatorial search space,  
730 an evolutionary algorithm dynamically generates alternative struc-  
731 tures, which are then evaluated by an optimization algorithm.  
732 Preuss et al. (2014) compare use of an evolutionary algorithm for  
733 the upper level and a purely MILP-based approach.

734 Voll et al. (2012) describe a two-phase hybrid proce-  
735 dure, combining an evolutionary algorithm and a determinis-  
736 tic optimization phase for the energy supply system problem.  
737 Neveux (2018) present a similar approach: a structure is generated  
738 according to the following mutation rules: (i) block addition be-  
739 tween two existing blocks, (ii) block removal, and (iii) permutation  
740 of two streams. An NLP is then solved to evaluate the performance  
741 of the structure generated. Machine learning has also been pro-  
742 posed as a flowsheet identification technique (Zhang et al., 2019).

743 Superstructure-free approaches avoid the need for integer vari-  
744 ables to model the on/off state of a unit. This often expedites the  
745 rate at which new candidate flowsheets are generated. However,  
746 rigorous lower-bounding guarantees to assert mathematical opti-  
747 mality without exhaustive enumeration are lost. In applications for  
748 which these mathematical lower bounds are unimportant or out-  
749 weighed by other considerations, superstructure-free approaches  
750 can be a valuable search heuristic.

#### 751 6. Conclusions

752 Process design is a central challenge of chemical engineering,  
753 for which superstructure optimization is a powerful analysis tool.  
754 When selecting the correct superstructure representation for a  
755 given design problem, the relevant factors are generality, ease of  
756 use, and tractability. The representation must capture the relevant  
757 choices in processing unit or phenomenological alternatives, clearly  
758 represent the space of options, and support formulation of a math-  
759 ematical programming problem that is amenable to available opti-  
760 mization strategies. In this review, we present the main contribu-  
761 tions that led to development of the existing representations, and  
762 offer the reader our perspective on their relative strengths with re-  
763 spect to different criteria. We discuss algorithms that exist for au-  
764 tomated generation of both the process alternatives as well as their  
765 superstructure representation. We also discuss implications that a  
766 choice of representation can have on the modeling and solution  
767 phases of superstructure-based synthesis.

768 Finally, we highlight the central tradeoff that exists in tack-  
769 ling superstructure optimization problems: between the generality  
770 of the representation, the fidelity of the process unit/phenomena  
771 models, and the tractability of solution strategies. The systematic  
772 and integrated analysis of alternative structures is the key advan-  
773 tage of the superstructure-based approaches; however, they often  
774 yield large-scale non-convex mathematical programming formula-  
775 tions, which are difficult to solve. We highlight various model-  
776 ing and optimization strategies that aim to overcome this chal-  
777 lenge. In some cases, authors have chosen to pursue evolution-

**Table 1**  
Acronyms.

| Acronyms (alphabetical order) |  |
|-------------------------------|--|
| ANN                           | Artificial neural network                |
| BGDP                          | Basic generalized disjunctive problem    |
| CAFD                          | Computer aided flowsheet design          |
| CAMD                          | Computer aided molecular design          |
| GDP                           | Generalized disjunctive programming      |
| GMF                           | Generalized modular framework            |
| MINLP                         | Mixed integer nonlinear programming      |
| NLP                           | Nonlinear problem                        |
| OTOE                          | One task-one equipment                   |
| PBB                           | Phenomena building blocks                |
| PSE                           | Process system engineering               |
| SEN                           | State equipment network                  |
| SSR                           | State-space representation               |
| STN                           | State-task network                       |
| UOPSS                         | Unit-operation-port-state superstructure |
| UOSS                          | Unit-operation-stock superstructure      |
| UPCS                          | Unit, port, conditioning stream          |
| VTE                           | Variable task-equipment                  |

778 ary “superstructure-free” approaches in which alternative process  
779 structures are dynamically generated and evaluated from a base  
780 case flowsheet. This may lead to faster search speeds in the dis-  
781 crete design space, at the expense of losing finite time mathemat-  
782 ical convergence guarantees.

### 783 Author Statement

784 The students Luca Mencarelli and Qi Chen did most of the work  
785 while Prof. Grossmann and Dr. Alexandre Pagot supervised it and  
786 gave feedback as well as suggestions for improvement

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### 792 Declaration of Competing Interest

793 The authors declare that they have no known competing finan-  
794 cial interests or personal relationships that could have appeared to  
795 influence the work reported in this paper.

### 796 Appendix A. Superstructure synthesis case studies

797 Table A.2 summarizes literature case studies that have been ex-  
798 amined with each representation. We denote with “\*” those exam-  
799 ples involving solution of an MINLP or nonlinear GDP, “•” those in-  
800 volving solution of an MILP (including linear approximation of an  
801 MINLP), and “–” where the problem was solved by other means.

**Table A.2**

Superstructure design examples and case studies.

- Pierce and Realf (1996): multi-chip module scheduling and design
- \* Caballero and Grossmann (2001): 5 hydrocarbon distillation sequence
- Tao et al. (2003): azeotropic separation design
- \* Ahadi-Oskui et al. (2006): cogeneration power plant, 32 alternatives
- Montolio-Rodríguez et al. (2007): acetic acid production

(continued on next page)

**Table A.2 (continued)**

|             |   |
|-------------|---|
| STN         | <ul style="list-style-type: none"> <li>• Karuppiah et al. (2008): corn-based ethanol plant synthesis</li> <li>• Drobež et al. (2009): biogas process design</li> <li>* Henao and Maravelias (2011): plant subsystems using surrogate models (amine scrubbing, malic anhydride)</li> <li>• Martín and Grossmann (2013): biorefinery optimization</li> <li>• Wang et al. (2014): thermal power plant design – Halim and Srinivasan (2006): waste minimization</li> <li>• Liu et al. (2006): process retrofit downstream bioprocessing</li> <li>• Voll et al. (2013): distributed energy system design (linearized MINLP)</li> <li>• Vance et al. (2013): sustainable energy supply chain, 21 structures</li> <li>• Heckl et al. (2015): multi-period design for corn processing</li> <li>• Ong et al. (2017): biorefinery design (linearized MINLP)</li> <li>• Edeleva and Stennikov (2018): energy systems optimization</li> <li>• How et al. (2018): biomass supply chain network design</li> </ul> |
| P-Graph     | <ul style="list-style-type: none"> <li>• Aviso and Tan (2018): polygeneration</li> <li>• Éles et al. (2018): plant energy supply</li> <li>• Chin et al. (2019): heat-integrated water network (linearized NLP)</li> <li>• Bartos and Bertok (2019): production line balancing – Xu et al. (2015): downstream bioprocess design</li> <li>• Several other examples exist with a similar modeling and solution approach: automotive ammonia production, biomass networks, benzaldehyde production, carbon capture storage, reaction pathway identification, enterprise wide supply, steam supply, and heat integration. We refer interested readers to the recent review paper of Friedler et al. (2019).</li> <li>* Smith and Pantelides (1995): ethylbenzene production – Dünnebiere and Pantelides (1999): thermally linked distillation columns</li> <li>– Linke and Kokossis (2007): extension for Denbigh reaction systems</li> </ul>  |
| SEN         | <ul style="list-style-type: none"> <li>* Nie et al. (2012): scheduling and dynamic optimization of batch processes</li> <li>* Moreno-Benito et al. (2016): batch process development with dynamics</li> <li>* Cui et al. (2017): coal-based methanol distillation sequence</li> <li>• Madenoor Ramapriya et al. (2018): biorefinery design</li> <li>• Bagajewicz et al. (2002): water treatment network, 8 process units</li> <li>• Dong et al. (2008): integrated heat and water network design, 3 process units</li> <li>• Liao et al. (2010): hydrogen distribution network retrofit, moderate size</li> <li>* Zhou et al. (2012b): water allocation with heat integration</li> </ul>  |
| State-Space | <ul style="list-style-type: none"> <li>* Zhou et al. (2012a): hydrogen distribution network design for hydrotreating</li> <li>* Saif and Elkamel (2013): membrane network design</li> <li>* Hong et al. (2016): heat-integrated water network, 15 process units</li> <li>– Pichardo and Manousiouthakis (2017): hydrogen production from natural gas</li> <li>• Böcking et al. (2019): membrane network design with experimental validation</li> </ul>  |
| R-graph     | <ul style="list-style-type: none"> <li>• Emhamed et al. (2007): desalination facility location</li> <li>• Proios et al. (2005): 4 component heat-integrated distillation sequence design</li> <li>• Alqusane et al. (2006): reactive adsorption column design</li> </ul>  |
| GMF         | <ul style="list-style-type: none"> <li>• Damartzis et al. (2016): amine-based CO<sub>2</sub> capture process design</li> <li>• Tian et al. (2018c): heat exchanger network synthesis with safety and operability</li> <li>* Tian et al. (2020): methyl tert-butyl ether (MTBE) reactive distillation</li> </ul>   |

(continued on next page)

Table A.2 (continued)

|                |   |
|----------------|---|
| Process Group  | <ul style="list-style-type: none"> <li>– Tula et al. (2015): hydrodealkylation of toluene</li> <li>– Lucay et al. (2015): mineral concentration</li> <li>* Kuhlmann and Skiborowski (2017): ethanol dehydration</li> <li>– Kuhlmann et al. (2018): transesterification of propylene carbonate</li> </ul>    |
| PBB            | <ul style="list-style-type: none"> <li>– Garg et al. (2019): bio-succinic acid production</li> <li>* Kuhlmann et al. (2019): ethyl tert-butyl ether (ETBE) production</li> <li>* Wu et al. (2017): bio-process design (25 binaries)</li> <li>* Fasahati et al. (2019): cyanobacteria biorefinery</li> </ul> |
| UPCS           | <ul style="list-style-type: none"> <li>* Peng et al. (2019): concentrated solar power plant design</li> <li>* Ng et al. (2019): lignocellulosic biorefinery design</li> <li>• Matsunami et al. (2020): solid drug manufacturing</li> <li>* Li et al. (2018): process integration</li> </ul>                 |
| Building Block | <ul style="list-style-type: none"> <li>• Li et al. (2018): fuel gas network synthesis—4 headers, 5 sinks</li> </ul>   |

802 The references in the table below are curated from the list of arti-  
803 cles citing each representation's source publication, as identified by  
804 their respective publishers. See Table 1 for definition of acronyms.

### 805 Supplementary material

806 Supplementary material associated with this article can be  
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