SYNTHSEP and DOMES: why a bottom-up approach outperforms superstructures in optimizing complex energy systems

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Abstract:

Optimizing the configuration of energy systems generally involves three levels of analysis, commonly referred to as Synthesis, Design, and Operation (SDO). Synthesis defines the system topology through the selection of components and their interconnections. Design concerns the sizing of these components and the definition of operating parameters at design conditions, while Operation addresses their dynamic scheduling over time. Although Design and Operation are often treated jointly, Synthesis is rarely included due to the combinatorial complexity associated with exploring multiple component combinations. The most common strategy to incorporate Synthesis optimization is a top-down approach, in which the designer defines a superstructure embedding all possible system configurations, while the optimization model identifies the optimal solution by removing non-contributing elements. However, this approach strongly depends on designer's expertise, which effectively determines the search space of the optimization problem. In contrast, bottom-up approaches start from elementary components and progressively combine them through intelligent rules to generate feasible system configurations. This paradigm reduces dependence on designer's expertise and enables a broader exploration of the search space. This paper highlights the potential of the bottom-up approach by analysing and comparing two methods: SYNTHSEP, for the generation of innovative power cycle configurations, and DOMES, for SDO optimization of distributed multi-energy systems including energy networks. This paper shows that a common approach based on smart evolutionary rules enables bottom-up optimization to outperform traditional top-down approaches across different spatial scales, either by finding solutions closer to the global optimum or by enabling the resolution of highly complex optimization problems.

Keywords:

Bottom-Up Methods; Evolutionary Algorithms; Problem Decomposition; SDO Optimization; Synthesis.

1. Introduction

With the increasing need to decarbonize the economy, the design of innovative and highly integrated energy systems is becoming progressively more relevant, both at the single-plant level and at the distributed or multi-energy system (MES) level. However, higher degrees of integration also lead to increased system complexity, thereby requiring dedicated optimization tools to support the design process. Approaches based solely on engineering experience and rules of thumb are generally unable to capture the numerous interactions and interdependencies among the large number of decision variables and constraints involved.

In general, the comprehensive optimization of an energy system, either at the single-plant or MES level, involves three layers of analysis, namely Synthesis, Design, and Operation (SDO) [1]:

- Synthesis consists in selecting the system components and defining their interconnections;
- Design refers to determining component sizes and the physical properties of working fluids at nominal conditions;
- Operation concerns the scheduling and management of components over the system lifetime.

The synthesis problem, which defines the system topology, is typically formulated using binary decision variables. Design decisions are generally represented by continuous variables (e.g., turbine inlet temperature and pressure in a power cycle, or the rated electrical capacity of a cogeneration unit in a MES), subject to upper and lower bounds imposed by spatial, technological, legislative, and other constraints. Operation

decisions can be represented by either continuous or binary variables. Continuous variables describe the value of design parameters under different operating conditions (e.g., turbine inlet temperature or power output during off-design operation), whereas binary variables account for discontinuities in operation (e.g., unit commitment constraints such as minimum load thresholds).

Among the three layers, the synthesis problem is the most critical in the SDO optimization framework, as it entails high computational complexity due to the need to consider all possible, or at least all meaningful, combinations of system components. These combinations are governed by binary synthesis variables, whose number may lead to a combinatorial explosion of the search space. Therefore, solving the complete SDO problem requires advanced optimization methodologies.

Beyond heuristic design strategies, which were widely adopted in earlier studies, particularly for single power plants, one common approach to synthesis optimization is based on superstructures. In this approach, all candidate components and their possible interconnections are embedded within a comprehensive superstructure (see, for example, Elsido, et al. [2] for single-plant optimization and Wirtz, et al. [3] for MES optimization). The optimizer selects the optimal configuration by activating or deactivating components and connections through binary variables. However, this approach inherently restricts the search space according to the designer's prior knowledge used to construct the superstructure, potentially excluding the global optimum from the feasible solution set [4]. This constitutes a top-down approach, in which a general superstructure is specified a priori and subsequently reduced to the configuration that best satisfies the objectives and constraints of the problem.

An alternative, less common approach to synthesis optimization is based on evolutionary procedures (also referred to as expert systems), which mimic human reasoning or natural evolution in constructing system layouts [5, 6]. This approach follows a bottom-up paradigm, whereby elementary components are combined according to predefined rules to generate the final system configuration. Bottom-up approaches are particularly suited for identifying innovative configurations, as they do not rely on predefined superstructures or prior design assumptions. However, their application in SDO optimization of energy systems, both at the single-plant and MES levels, remains limited due to two major challenges. First, the global optimum must be included within the feasible solution space, which requires the development of algorithms capable of systematically exploring all admissible configurations. Second, the resulting optimization problem must remain computationally tractable while ensuring sufficient accuracy, which necessitates the use of efficient solution strategies and advanced algorithmic implementations.

At the single-plant level, Lazzaretto, et al. [7] introduced the superstructure-free SYNTHSEP method for the optimal synthesis and design of thermodynamic cycles. SYNTHSEP represents the first bottom-up optimization method in this domain. It is based on the combination of elementary thermodynamic cycles composed of fundamental processes, from which more complex and efficient configurations can be derived. The methodology was initially developed for subcritical systems (e.g., Organic Rankine Cycles [8], vapor-compression refrigeration cycles [9]), and was subsequently extended to transcritical and supercritical systems (e.g., supercritical CO2 (SCO2) cycles [10]). SYNTHSEP has demonstrated superior performance compared to superstructure-based methods, as it enables the identification of novel cycle layouts achieving higher efficiencies than those reported in the literature.

At the MES level, Voll, et al. [11] proposed a superstructure-free method for the SDO optimization of distributed energy systems. Their approach relies on a set of rules that iteratively modify an initial configuration by replacing selected subsystems. However, as acknowledged by the authors, these rules are still influenced by prior experience, thus partially inheriting the limitations of superstructure-based approaches. Moreover, the method is limited to energy conversion and storage technologies and does not explicitly account for energy networks, which are essential components of integrated systems. More recently, Dal Cin, et al. [12] introduced the DOMES method for the complete SDO optimization of MES including multiple energy networks. This approach combines elementary conversion and storage technologies with network branches to generate the system topology, while simultaneously optimizing design and operation. The combination process is governed by a rigorous set of rules that ensures full exploration of the solution space while preventing the generation of infeasible or inherently suboptimal configurations. Compared to previous approaches, DOMES enables the integrated optimization of energy systems and networks with high accuracy and within acceptable computational times.

The objective of this paper is to investigate why bottom-up methods outperform top-down methods in the SDO optimization of energy systems, both at the single-plant level, considering SYNTHSEP, and at the MES level, considering DOMES. The transition from top-down to bottom-up optimization represents a fundamental paradigm shift, opening new avenues for managing increasingly complex energy systems. As the number of components and their interactions increases, the probability of capturing the globally optimal system configuration within a predefined superstructure becomes negligible. Conversely, the combinatorial space of elementary components is virtually unbounded, implying that, given infinite time, the global optimum could in principle be reached. However, practical time constraints render the use of smart algorithms and intelligent rules essential to efficiently guide the search toward optimal configurations, as this paper seeks to demonstrate by identifying the common features and core structure underlying the two methods considered.

2. Methodology

The SDO optimization of an energy system can, in general, be formulated as follows:

Find $\boldsymbol{S}, \boldsymbol{D}, \boldsymbol{O}(t)$ that minimizes $f\left(\boldsymbol{S}, \boldsymbol{D}, \boldsymbol{O}(t)\right)$

$$\text{with } \boldsymbol{S} = \begin{Bmatrix} s_1 \\ s_2 \\ \vdots \\ s_n \end{Bmatrix}, \boldsymbol{D} = \begin{Bmatrix} d_1 \\ d_2 \\ \vdots \\ d_m \end{Bmatrix}, \boldsymbol{O}(t) = \begin{Bmatrix} o_1(t) \\ o_2(t) \\ \vdots \\ o_l(t) \end{Bmatrix}, \tag{1}$$

subject to $g_j\left(\boldsymbol{S}, \boldsymbol{D}, \boldsymbol{O}(t)\right) \leq 0,\ j = 1,2,\dots,p$ and $l_j\left(\boldsymbol{S}, \boldsymbol{D}, \boldsymbol{O}(t)\right) = 0,\ j = 1,2,\dots,q,$

where $\boldsymbol{S}$, $\boldsymbol{D}$, and $\boldsymbol{O}(t)$ denote the sets of synthesis, design, and operation decision variables, respectively; $f\left(\boldsymbol{S}, \boldsymbol{D}, \boldsymbol{O}(t)\right)$ is the objective function; and $g_j\left(\boldsymbol{S}, \boldsymbol{D}, \boldsymbol{O}(t)\right)$ and $l_j\left(\boldsymbol{S}, \boldsymbol{D}, \boldsymbol{O}(t)\right)$ represent the inequality and equality constraints. The variable t denotes time, accounting for the dynamic nature of the operation variables.

The objective function and constraints are generally nonlinear, thus leading to a mixed-integer nonlinear programming (MINLP) formulation [13]. However, under specific assumptions, these relationships can be linearized without significant loss of accuracy, resulting in a mixed-integer linear programming (MILP) problem [14]. Constraints are typically defined at each level of analysis. Synthesis constraints describe, for example, the feasible locations for component installation and the admissible interconnections among components. Design constraints limit the size of installed components based on spatial availability, technological options, and market availability, and bound the nominal values of physical properties according to technical specifications, safety requirements, and regulatory limits. Operational constraints primarily describe component performance, including characteristic equations and off-design behavior, while enforcing mass, energy, and power balances. The objective function may include one or multiple criteria, such as the minimization of economic cost or maximization of profit, the maximization of energy or exergy efficiency, and the minimization of environmental impact, including CO_2 emissions. In the following, the SYNTHSEP and DOMES methods are presented within this general framework.

2.1. The SYNTHSEP method

The SYNTHSEP method has been developed for the optimization of thermodynamic cycles, with the aim of determining the optimal cycle topology, intensive thermodynamic variables, and extensive quantities (e.g., mass flow rates, mechanical power, and heat transfer rates). The method is based on the following key principles:

- Any cycle topology can be obtained through the (partial) combination, or superimposition, of Elementary Cycles (ECs), each composed of four fundamental processes: compression, heating, expansion, and cooling. Figure 1 illustrates different types of single EC, while Figure 2 provides all possible configurations obtained by combining two ECs;
- By imposing appropriate constraints derived from Pinch Analysis, it is possible to decouple the synthesis of the cycle layout from the design of the heat exchanger network (HEN) responsible for internal and external heat transfer processes.

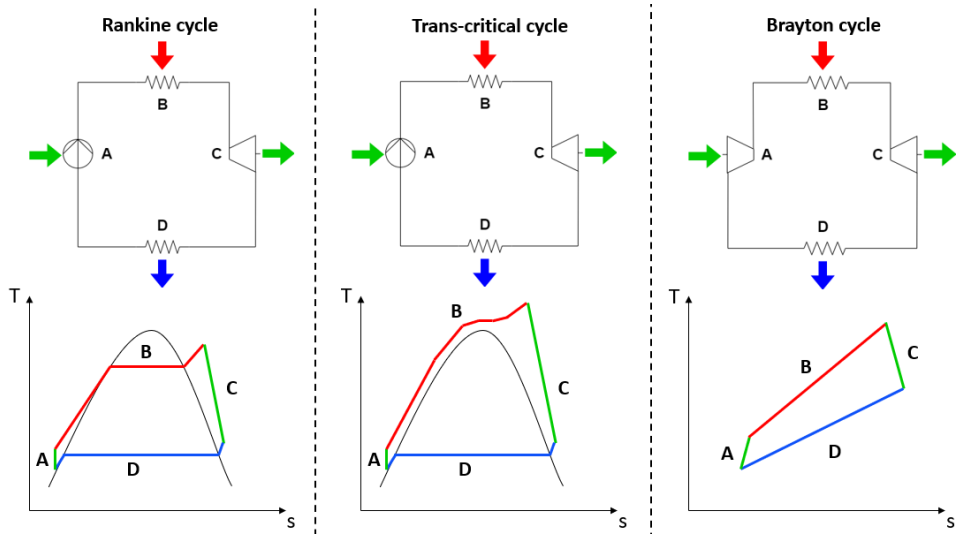

Figure. 1. *Different types of Elementary Cycles.*

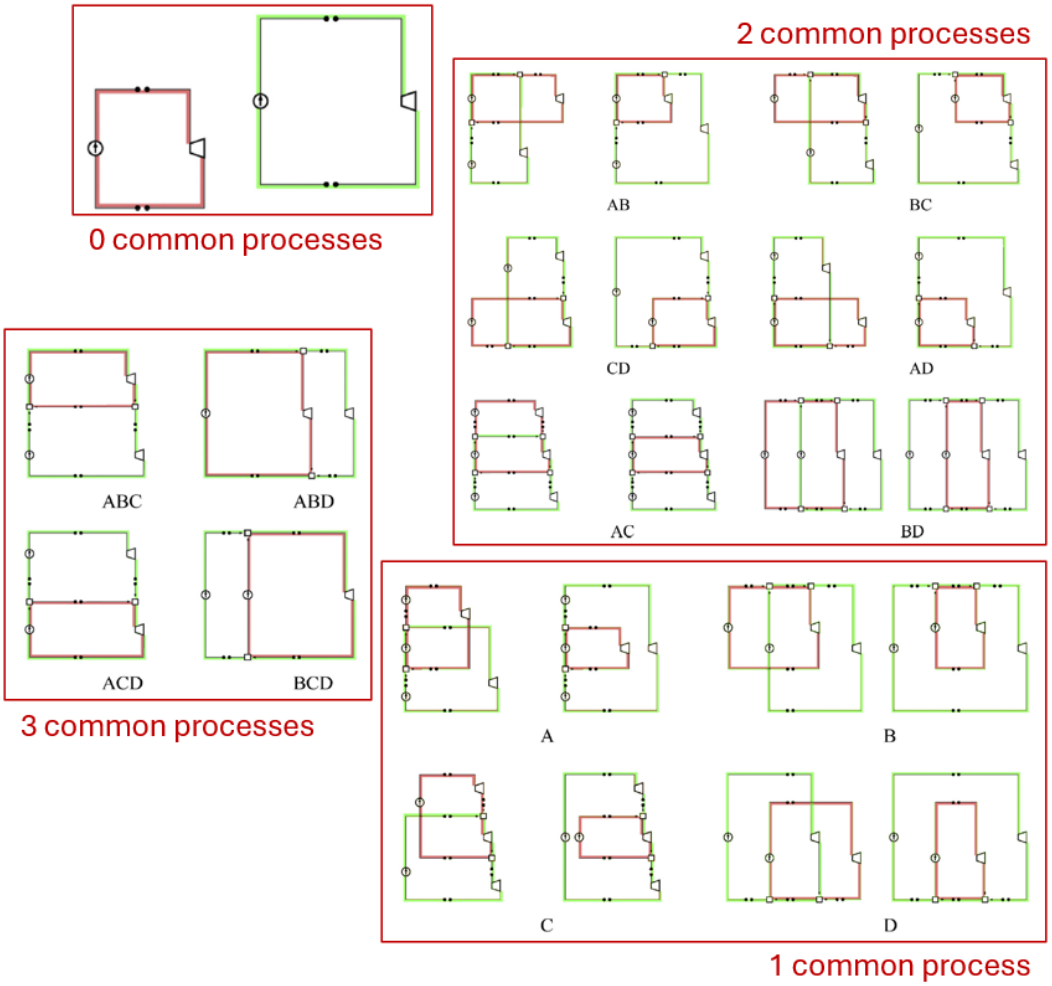

Figure. 2. *All possible combinations of two Elementary Cycles.*

Elementary Cycles are combined by sharing, at least partially, one or more fundamental processes. The bottom-up nature of the SYNTHSEP method ensures that all admissible combinations of ECs are included in the search space of the optimization problem, which is therefore not restricted a priori, unlike in superstructure-based approaches.

The heat transfer section is treated as a “black box” following the HEATSEP method [15], which represents a precursor of SYNTHSEP for thermodynamic cycles of given topology. The feasibility of heat exchange processes is enforced throughout the optimization by means of a constraint that ensures the absence of

cumulative heat deficits in the thermal cascade, as defined by the Problem Table in Pinch Analysis. This formulation enables the decoupling of the synthesis–design optimization of the thermodynamic cycle, addressed by SYNTHSEP, from the HEN design problem, which lies outside its scope. Nevertheless, a feasible HEN can always be derived a posteriori (e.g., by applying standard Pinch Analysis rules).

The configuration of a thermodynamic cycle obtained by combining two or more ECs, together with the associated thermodynamic decision variables, is referred to as a Basic Configuration. The basic configuration is fully defined by:

- The number of combined ECs, n_C, which is an integer ($n_C \geq 1$);
- The fundamental processes shared by two or more ECs, identified by a list of binary variables of length n_C for each type of elemental process (compression, heating, expansion and cooling), which determine the system topology;
- Six normalized thermodynamic variables for each EC, namely: pressure and specific enthalpy at the compression inlet, pressure and specific enthalpy at the expansion inlet, and two auxiliary enthalpy variables required to model isothermal mixing and splitting among multiple ECs.

A key feature of the SYNTHSEP method is the separation between the optimization of intensive variables and system topology (i.e., $\boldsymbol{D}$ and $\boldsymbol{S}$, respectively) and the optimization of extensive variables, namely the mass flow rates of the ECs, $\dot{\boldsymbol{m}}$. To this end, a two-level iterative evolutionary algorithm is employed (see Figure 3).

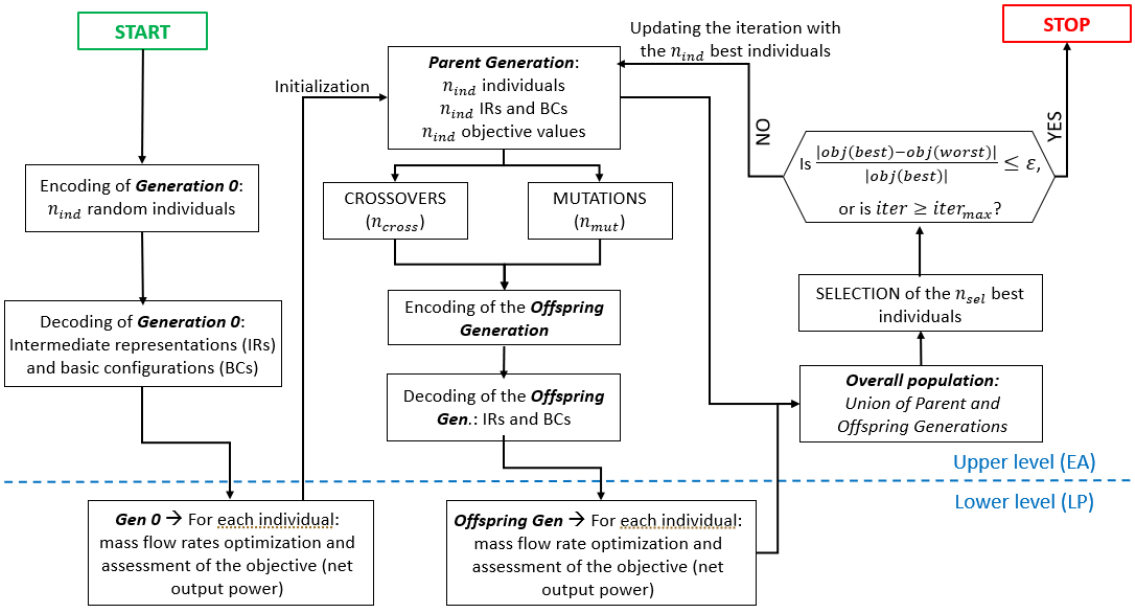

Figure. 3. *Flowchart of the SYNTHSEP algorithm.*

The upper level determines the set of variables $\boldsymbol{S}$ and $\boldsymbol{D}$, while the lower level receives these values and solves the following optimization problem:

Find $\dot{\boldsymbol{m}}$ that minimizes $f(\boldsymbol{S}, \boldsymbol{D}, \dot{\boldsymbol{m}}, T^*)$

$$\text{with } \dot{\boldsymbol{m}} = \begin{Bmatrix} \dot{m}_{EC,1} \\ \dot{m}_{EC,2} \\ \vdots \\ \dot{m}_{EC,l} \end{Bmatrix}, \text{ subject to } \sum_i \dot{m}_{EC,i}^{HS} \Delta h_{HS}(T^*) - \dot{m}_{EC,i}^{CS} \Delta h_{CS}(T^*) \geq 0 \; \forall \, T^* \in PT, \tag{2}$$

where the superscripts HS and CS denote the sets of hot and cold streams in the Problem Table (PT) and T^* represents a temperature level in the thermal cascade. Satisfying Equation (2) guarantees the feasibility of the overall heat exchange process and ensures the existence of at least one corresponding HEN. It is worth noting that the constraint in Equation (2) is linear with respect to the mass flow rates. As a result, the lower-level problem can be efficiently solved using Linear Programming (LP) techniques.

A key aspect contributing to the computational efficiency of the SYNTHSEP method is that the evolutionary algorithm is not purely stochastic. Conversely, the generation of new candidate configurations is guided by a

structured set of rules, which prevent the creation of infeasible solutions and resolve inconsistencies arising from the combination of different topologies, pressure levels, and enthalpy values. This significantly reduces the number of configurations to be evaluated, thereby accelerating the optimization process.

2.2. The DOMES method

The objective of the DOMES method is to determine the optimal location, type, size, and operation of energy conversion and storage units required to meet the energy demand of end users within a MES, together with the topology and capacity of the energy networks supplying them.

The overall optimization framework is formulated as a MILP problem. This choice is motivated by the need to maintain computational tractability in large-scale applications, as the inclusion of nonlinear relationships would significantly increase the computational burden. However, as discussed previously, the large number of binary variables involved in the synthesis and operation stages may still lead to a combinatorial explosion, even within a MILP formulation.

To address this issue, the DOMES method decomposes the complete SDO problem into two hierarchical levels, coordinated by an evolutionary algorithm, as illustrated in Figure 4:

- Upper level (synthesis): all binary variables associated with the synthesis problem are determined at this stage, including the inclusion or exclusion of energy conversion and storage units at specific nodes, as well as the presence or absence of network connections between nodes. The output of the upper level is a set of candidate system configurations, each corresponding to a specific topology, which are passed to the lower level;
- Lower level (design and operation): for each candidate configuration generated at the upper level, the sizing and operation of the selected components and network connections are optimized through a MILP formulation. This decomposition enables the solution of multiple MILP problems, each characterized by a limited number of binary operational variables (further reduced through time series aggregation), which can be solved in parallel. As a result, the overall computational effort is significantly reduced. At this stage, all model constraints are enforced, including energy balances and performance relationships of energy conversion and storage technologies based on their characteristic equations.

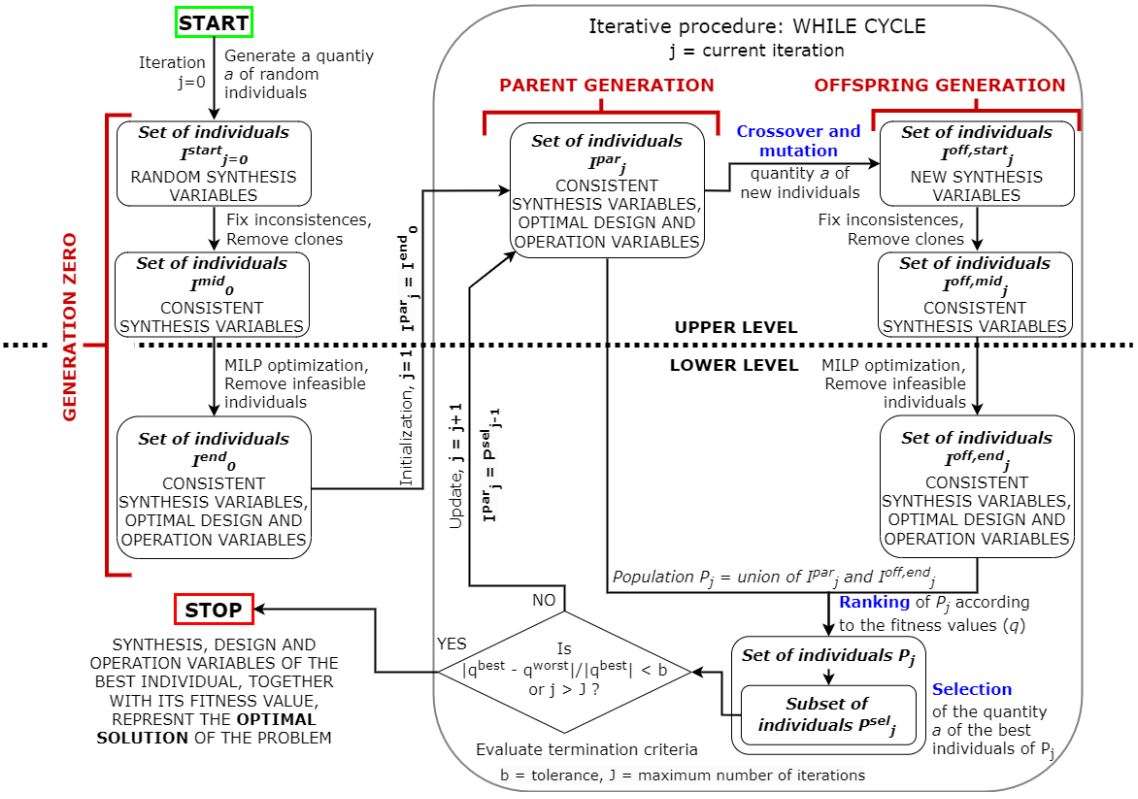

Figure. 4. *Flowchart of the DOMES algorithm.*

Similarly to the SYNTHSEP method, computational efficiency is enhanced through a structured set of rules that guide the evolutionary algorithm. These rules prevent the generation of inconsistent system configurations

that would lead to infeasible or inherently suboptimal solutions. As a result, the search process is effectively restricted to the most promising regions of the solution space, thereby accelerating convergence toward the global optimum. Figure 5 shows an example of these consistency rules applied to a district heating network included in a MES, which, in DOMES, is represented as a multi-nodal system.

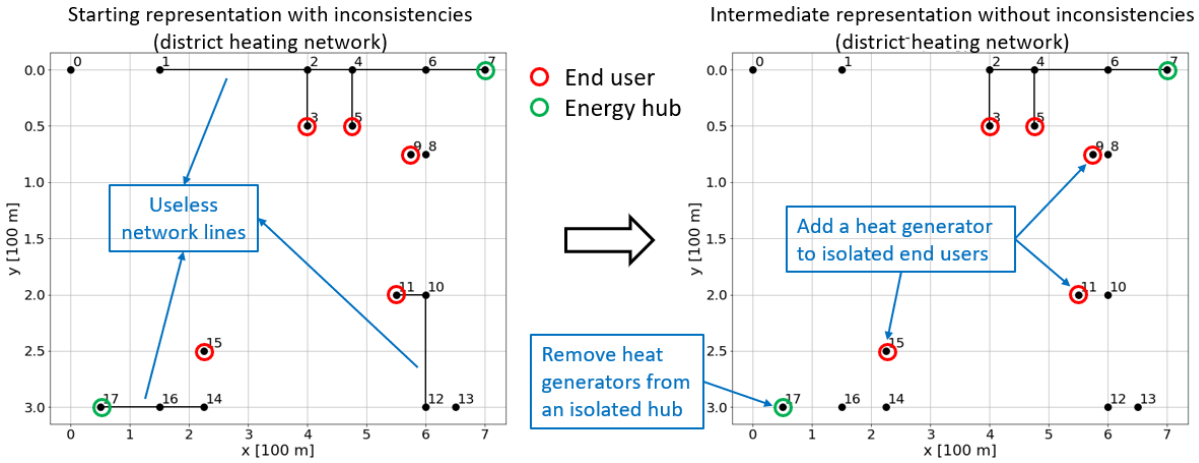

Figure. 5. *DOMES consistency rules applied to a district heating network.*

2.3. Common features between the SYNTHSEP and DOMES methods

Although the SYNTHSEP and DOMES methods are applied at different spatial scales and address distinct optimization problems, namely, the design of thermodynamic cycle configurations and the SDO optimization of MESs, respectively, they share several fundamental features.

First, both methods exhibit a clear bottom-up structure. No predefined superstructure is required to generate the final system configuration. Conversely, the system evolves through the recombination of elementary components, guided by a set of consistency rules. In the SYNTHSEP method, these elements are represented by elementary cycles, whereas in the DOMES method they consist of individual energy conversion and storage technologies, as well as network connections.

Second, both approaches exploit a structural, or conceptual, decomposition of the overall optimization problem to reduce computational complexity. In both cases, this decomposition is managed by an evolutionary algorithm that addresses the combinatorial nature of the synthesis problem. As a result, the search for the system topology is confined to the upper level, while multiple lower-level subproblems, characterized by a reduced number of binary decision variables, can be solved efficiently and in parallel using conventional optimization techniques. In particular, the lower-level problem in SYNTHSEP reduces to a linear programming (LP) formulation, as the only decision variables are the mass flow rates of the elementary cycles. In contrast, the lower-level problem in DOMES is formulated as a MILP, due to the presence of residual binary variables associated with operational decisions (e.g., unit commitment constraints such as on/off states of components).

Finally, in both methods the size of the search space is effectively reduced through the application of consistency rules that guide the evolutionary process. These rules prevent the generation of infeasible or inherently suboptimal configurations, thereby focusing the search on the most promising regions of the solution space. This leads, on the one hand, to a significant reduction in computational time and, on the other hand, to the ability to address larger-scale optimization problems (i.e., involving a higher number of components) while maintaining satisfactory solution accuracy.

3. Results

This section provides a concise overview of representative applications of the SYNTHSEP and DOMES methods, with the aim of highlighting the advantages of bottom-up optimization approaches over top-down, superstructure-based methods in terms of solution accuracy and computational efficiency.

3.1. The SYNTHSEP method for the optimization of SCO2 power cycles

The SYNTHSEP method is applied here to the design of SCO2 power cycles for waste heat recovery in industrial applications [10]. The inlet temperature of the waste heat stream, $T_{WH,in}$, is varied within the range of 200–700°C. The waste heat stream is assumed to have a constant thermal capacity flow rate of 10 kW/K, while the ambient temperature, T_{amb}, is fixed at 30°C. A minimum temperature difference of 10°C is imposed for all heat transfer processes. The isentropic efficiencies of the compression and expansion processes are assumed to be constant and equal to 0.66 and 0.81, respectively. The objective of the optimization problem is the maximization of the net power output extracted from the waste heat source.

Figure 6 presents the optimal SCO_2 cycle layouts obtained at three representative temperature levels of the waste heat stream, namely 200°C, 500°C, and 700°C. In these layouts, heat exchange processes are represented through so-called thermal cuts, which correspond to enthalpy variations along the streams. It should be noted, however, that the SYNTHSEP method ensures the thermodynamic feasibility of these heat exchange processes, guaranteeing through Pinch Analysis theory that at least one corresponding HEN can be realized.

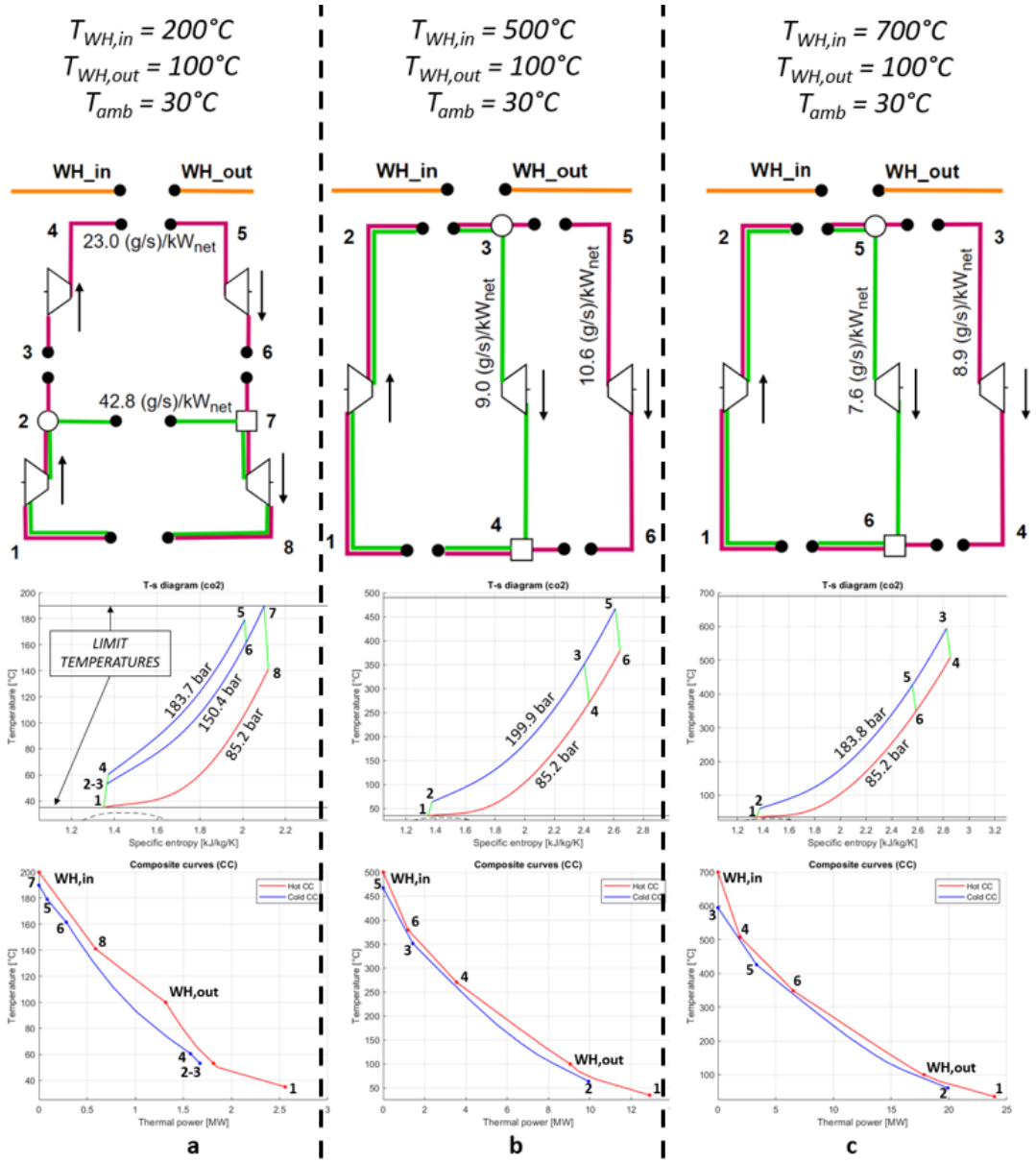

Figure. 6. *Optimal layout, T-s diagram and Composite Curves of the SCO2 cycles obtained for an inlet temperature of the waste heat stream of a) 200°C, b) 500°C, c) 700°C.*

The results highlight a significant evolution of the optimal cycle configuration as the temperature level increases. At low temperatures, the optimal solution corresponds to a two-pressure-level configuration. As the temperature increases, the optimal layout transitions toward a parallel-expansion configuration, which allows for an improved matching of the hot and cold composite curves and, consequently, a more effective heat recovery.

Table 1 compares the cycle efficiencies obtained with the SYNTHSEP method with those reported by Carraro, et al. [16] as well as with the best-performing configurations identified in their literature review under the same boundary conditions. The study by Carraro, et al. [16] is selected as a benchmark because it first identifies the most efficient SCO2 cycle layouts available in the literature and subsequently enhances their performance through improved internal heat recovery using the HEATSEP method. At lower temperature levels, the improvements achieved by SYNTHSEP are marginal (e.g., + 0.1% in cycle efficiency at 300°C). In contrast, at higher temperatures, the performance gains become more significant. At 700°C, the SYNTHSEP method achieves a cycle efficiency of 30.2%, corresponding to an absolute improvement of 1.5% compared to the best values reported in the literature.

Table 1. *Optimal SCO2 cycle efficiencies compared to the literature[1].*

Inlet temperature of the heat source, °C	Cycle efficiency, %		
	Literature best[2]	Carraro, et al. [16]	SYNTHSEP
300	14.8	14.9	14.9
500	23.2	23.2	24.0
700	28.7	28.7	30.2

[1] Comparison at equal boundary conditions: outlet temperature of the waste heat source equal to 100°C, ambient temperature equal to 30°C, compression and expansion isentropic efficiencies equal to 0.66 and 0.81, respectively.
[2] The best efficiency values of the literature are taken from the review available in [16].

3.2. The DOMES method for the optimization of urban energy systems

This section aims to highlight the problem simplification and the associated reduction in computational time enabled by the DOMES method when applied to urban energy systems of increasing complexity (i.e., with an increasing number of nodes). To this end, we analyse the results of the simplified test-case MES presented by Dal Cin, et al. [17].

The system represents a residential neighborhood located in Padova, Italy, including photovoltaic systems, heat pumps, combined heat and power units, gas boilers, thermal and electrical storage systems, as well as the potential implementation of a district heating network and an electrical microgrid. The test case is structured into nine “blocks” (from block A to block I), which are progressively added starting from block A. The SDO problem is solved for each of the nine resulting system configurations, in order to assess the performance of the DOMES method. Figure 7a illustrates the overall layout of the test case, where the nine blocks are distinguished by different colors, while Figure 7b provides a detailed view of block A. Each block includes at least two residential end users equipped with distributed photovoltaic systems, heat pumps, and storage units, as well as an energy hub that may host a combined heat and power unit. In addition, each block is connected to the main power grid through an interface node for electricity exchange. The lines shown in the figures represent the admissible paths for energy networks, enabling local energy exchange.

Figure 8 compares the performance of the DOMES method with that of a conventional superstructure-based MILP approach as the system size increases from the single block A to the full nine-block configuration [17]. As expected, the computational time increases with the size of the problem. However, this increase is exponential for the superstructure-based approach, whereas it is approximately linear for the DOMES method (Figure 8a). As a result, DOMES is able to solve the optimization problem for the full configuration (block I) within a time limit of 24 hours, while the superstructure-based approach exceeds this limit already at block D (a machine with an Intel(R) Core(TM) i9-12900K 3.20 GHz processor and 64 Gb RAM has been used).

At the same time, the loss in optimality associated with the DOMES method remains negligible. As shown in Figure 8b, the maximum relative deviation with respect to the superstructure-based solution remains below 1.5%. It should be noted that, in this case, the superstructure is complete; therefore, the corresponding MILP

formulation guarantees global optimality, making it a suitable benchmark for assessing the accuracy of the DOMES approach.

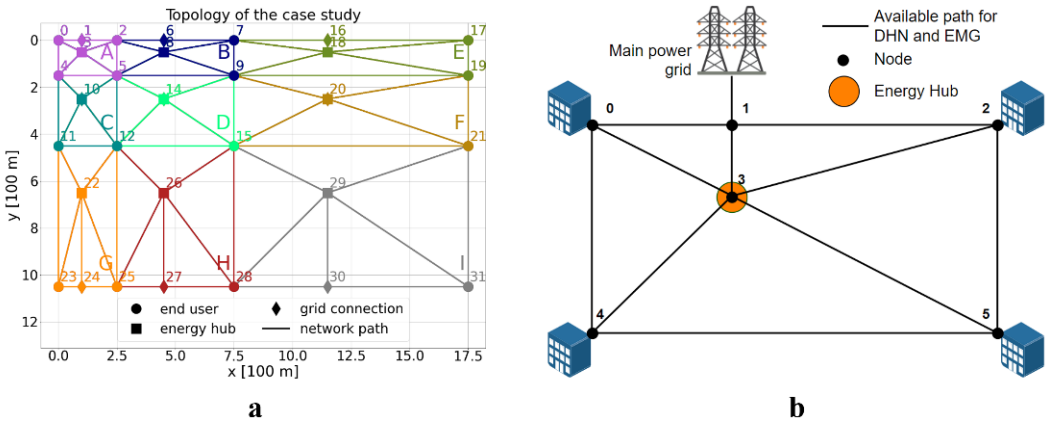

Figure. 7. *Modular urban MES a) and elementary block b) considered for DOMES application.*

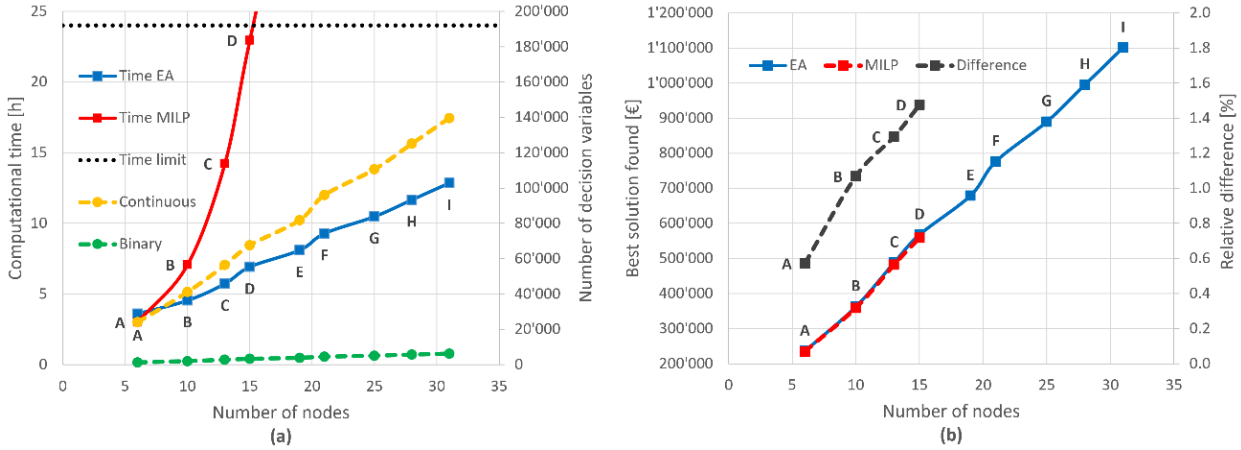

Figure. 8. *Comparison between DOMES (refer to EA in the figure) and the superstructure-based MILP method (refer to MILP in the figure) in terms of a) computational time and b) optimality.*

3.3. Discussion

The considered application examples highlight the twofold advantage of bottom-up optimization methods over top-down, superstructure-based methods. First, bottom-up methods enable a substantial reduction in the computational time required to solve the optimization problem. As demonstrated by the DOMES application, the two-level decomposition governed by an evolutionary algorithm significantly simplifies the overall problem structure. In particular, the combinatorial complexity associated with binary synthesis variables is handled at the upper level, while multiple lower-level subproblems, characterized by a limited or null number of binary variables, can be solved efficiently using MILP or LP techniques and in parallel. As a result, bottom-up approaches are capable of addressing optimization problems of significantly higher complexity under the same computational resource and time constraints. Second, bottom-up approaches ensure that the global optimum is included within the search space and can be approximated with high accuracy. The application of the SYNTHSEP method shows that bottom-up approaches can achieve solutions that are closer to the global optimum than those obtained with superstructure-based methods commonly adopted in the literature (see, e.g., Ma, et al. [18]), indicating that the global optimum may not be contained within the predefined superstructure. Even in cases where the superstructure is complete and guarantees global optimality, the loss of accuracy associated with bottom-up approaches remains negligible, as demonstrated by the DOMES application.

The key enabler of efficient bottom-up optimization lies in the structured set of rules that guide the evolutionary algorithm throughout the iterative solution process. These rules play a crucial role in reducing the effective size of the search space by systematically excluding infeasible and inherently suboptimal configurations, thereby limiting the number of candidate solutions to be evaluated.

However, this aspect also represents a limitation of bottom-up approaches. The effectiveness of the method strongly depends on the definition of problem-specific consistency rules, which must be carefully derived from the underlying physical and structural characteristics of the system under study. Consequently, these rules need to be developed ad hoc for each class of application, as exemplified by the differences between the SYNTHSEP and DOMES methodologies.

4. Conclusions

This paper has analyzed the advantages of bottom-up optimization methods over superstructure-based, top-down approaches for the synthesis, design, and operation (SDO) optimization of energy systems across different spatial scales, ranging from single power plants to multi-energy systems (MESs). The analysis has been carried out through two representative methods, namely SYNTHSEP and DOMES. The former is applied to the synthesis of innovative thermodynamic cycle configurations, while the latter addresses the integrated optimization of urban MESs including multiple energy networks.

The results show that the bottom-up approach can significantly reduce computational complexity, thereby enabling the solution of optimization problems characterized by a larger number of decision variables and constraints, which would be otherwise impossible to solve within reasonable computational time using conventional top-down methods based on superstructures. At the same time, bottom-up methods ensure a more effective exploration of the solution space, increasing the likelihood of identifying configurations close to the global optimum. This is achieved by combining a broad coverage of admissible configurations with the systematic exclusion of inherently suboptimal regions of the search space.

In general, the following key features can be identified as enabling factors for efficient bottom-up optimization:

- Identification of elementary components and processes: the problem is structured in terms of fundamental building blocks that can be combined to generate complex system configurations;
- Problem decomposition: the optimization problem is divided into hierarchical levels, with most binary decision variables handled at the upper level, while multiple lower-level subproblems, characterized by reduced combinatorial complexity, are solved efficiently and in parallel using linear optimization techniques;
- Use of evolutionary algorithms: iterative procedures are employed to coordinate the interaction between the different levels, guiding the search toward the global optimum;
- Definition of smart consistency rules: a structured set of problem-specific rules governs the combination of elementary components, ensuring that the global optimum is included within the search space while filtering out infeasible and inherently suboptimal configurations. This substantially improves computational efficiency by reducing the number of candidate solutions that must be evaluated.

Overall, the bottom-up approach to the optimization of energy systems represents a paradigm shift compared to conventional superstructure-based methods, particularly in applications characterized by high combinatorial complexity. This new perspective expands the frontiers of what can be considered a tractable optimization problem, enabling the analysis of systems with an increasing number of components and interactions, and the exploration of wider system boundaries.

Nomenclature

HEN	Heat Exchanger Network
LP	Linear Programming
MES	Multi-Energy System
MILP	Mixed Integer Linear Programming
SCO2	Supercritical Carbon Dioxide
SDO	Synthesis, Design, Operation

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