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Multiperiod Heat Exchanger Network Synthesis With Pinch-Based Strategies and Metaheuristics

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Heat exchanger networks (HENs) are a widely studied subject. These systems may undergo important variations in their operating conditions. Such uncertainties lead networks to require some degrees of flexibility. An efficient approach to address such uncertainties is the development of multiperiod solutions. However, these are difficult to develop since one must synthesize a network that is simultaneously feasible under a given number of conditions. This work presents a method based on pinch insights and a hybrid meta-heuristic. It employs the "spaghetti" network concept as initial estimations for single-period networks, which are refined and merged in a single solution that is able to operate under multiple period conditions. The merged solution is refined as well with a multiperiod HEN model, and a final multiperiod network is achieved. The method was able to outperform previous literature regarding total annual costs (TAC) for the multiperiod HEN developed. The case study approached is one of the largest multiperiod cases for HEN synthesis in the literature (15 streams, 4 periods). The obtained solution has TAC 3.5% lower than the literature solutions.

Keywords: optimization, multiperiod heat exchanger network, meta-heuristic, pinch analysis (PA), heat integration

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INTRODUCTION

Efficient synthesis of energy recovery systems is a subject of main concern in the industrial area. Mitigating energy consumption is fundamental for a more sustainable future. Process engineers and academics in the area keep searching for better solutions regarding energy integration in industrial plants. Prominent pioneer studies regarding methodologies for efficient synthesis of energy recovery systems in industrial plants, namely, the synthesis of heat exchanger networks (HEN) date back to the late 70's. By that time, pinch technology arose as a set of techniques that could methodologically find fundamental aspects in an energy recovery project, such as the energy targets to be achieved in an efficient design. The pioneering work for pinch technology was published by Linnhoff and Flower (1978), where an algorithmic thermodynamically oriented procedure could produce a problem table containing process stream energy requirements and lead to minimum energy targets. These techniques could be easily applied computationally with well-established algorithms. The work of Linnhoff and Hindmarsh (1983) presented an extended understanding of the pinch method, presenting physical insight and graphical basis for following works. Later on, pinch-based techniques were developed that could approach different aspects in HENs such as minimum heat exchange surface estimation, making possible the prediction of both capital and operating costs in a network (Townsend and Linnhoff, 1984; Linnhoff and Ahmad, 1990).

In those works, the proposal was to take advantage of the enthalpy or temperature interval concept to estimate minimum area required for heat recovery within these intervals. From this area estimation, it was also possible to calculate approximate capital cost for the minimum energy requirement network. Pinch technology, later called pinch analysis, has evolved since and became one of the most well-accepted bases for solving energy-related problems in the industry. The interested reader is referred to a comprehensive review study on pinch-based techniques and new directions for these methods, conducted by Klemeš et al. (2018). HEN synthesis techniques are a mature academic subject, and numerous methodologies have arisen since pinch first appeared. Some are extensions of pinch or use some of its insights in other platforms. In special, the first methods based on mathematical programming formulated pinch algorithmic procedures as optimization problems, such as in the sequential techniques developed by Floudas et al. (1986), which could lead to a final HEN configuration by solving sequentially optimization models for minimum energy targets, minimum units, and minimum capital costs. Other methods are purely optimization-based, involving the one-step synthesis of HEN by deriving and solving to minimal costs a mathematical model (in general, a mixed-integer non-linear programming, MINLP, model) from a pre-conceived superstructure. This is the case of the hyperstructure model of Floudas and Ciric (1989), a broad model that comprised several piping and matching options such as stream splits, crossflow, and multiple sequential units in stream branches. Due to this broadness, the model proved challenging to be solved to optimality. On the other hand, another MINLP model was developed by Yee and Grossmann (1990), derived from the so-called stagewise superstructure (SWS). It was structurally much simpler, with stream splits limited to a single unit per branch, and utilities were placed exclusively at the end of streams. However, the derived model could be solved much more easily to near optimal solutions.

Mathematical models such as those cited have been employed as basis for several studies in the following years, undergoing adaptations and having different solution techniques being applied to. Deterministic solution techniques have been applied with considerable success in the original works, especially with solvers such as those present in GAMS platform. The recent advances in deterministic algorithms include the TransHEN/HENSyn method (Nemet et al., 2018), which uses a sequential approach based on finding promising matches for building a promising superstructure and then optimizing it. The scheme was able to find good solutions for large-scale cases, including a 173-streams problem. An extension of that method was later proposed by Caballero et al. (2021), which could find better solutions for several literature benchmark cases. Another trend regarding solution approaches for HEN synthesis involves the use of metaheuristics for solving optimization models. Despite their stochastic nature and impossibility of ensuring global optimality, these methods can be applied in several tries, and it has been demonstrated that they have good probabilities of finding near-optimal solutions for large-scale cases. Metaheuristic-based techniques in HEN synthesis may be used alone or in hybridization, especially in two levels. This involves using one method for the combinatory part of the problem (match definition) and another one for continuous variable optimization (heat duties and stream split flowrates). Advances can be cited here such as the hybrid technique based on simulated annealing (SA) and particle swarm optimization (PSO), generating another algorithm called rocket fireworks optimization (RFO) in the SA-RFO hybridization (Pavão et al., 2017a), and the methods based on random walk (Xiao et al., 2021).

The developments cited so far involve, in general, the synthesis and optimization of HEN under their nominal conditions without involving any uncertainties that may happen during the plant operation. These may appear, for instance, as variations in flowrates due to efficiency drop in separation processes, catalyst degradation leading to smaller amount of a desired output, lower quality feed, seasonal temperature changes, etc. These changes may also be predictable with accuracy in flexible plants that need to be flexible for producing more than one product. In either case, plant data must be retrieved for a given amount of time, and a multiperiod model can be derived considering a finite set with, for instance, different inlet/outlet temperatures or heat capacity flowrates. A weighting value is associated with each identified scenario of operating conditions, representing its probability of occurrence or an accurate duration prediction. The set generates a single problem whose solution must be feasible for operation under the conditions of each of those periods. However, this creates a complicating aspect under the optimization point of view. Problems become much more constrained and computationally burdening, so that these conditions can be considered by a single solution. In other words, a given heat exchanger must have enough heat exchange surface for performing its heat exchange task in all periods, despite the required surface is different in each period. Thus, the maximum area among those required values in each exchanger must be considered for predicting capital costs. Mathematically, this involves a discontinuity for considering such a maximum value.

Some works that presented methodologies for dealing with such uncertainties are worth citing. Floudas and Grossmann extended the techniques developed for single-period networks for dealing with the flexibility issue (Floudas and Grossmann, 1986, 1987). Later, Aaltola (2002) and Verheyen and Zhang (2006) developed similar approaches based on the stagewise superstructure (Yee and Grossmann, 1990). However, those models differ regarding capital costs calculation. Instead of using the discontinuous *max* function for calculating area according to the maximum required value, Aaltola (2002) considered an average value, which made the model considerably easier to be solved, although less accurate. Verheyen and Zhang (2006) were able to overcome such an issue. They were able to consider maximum areas in heat exchange units by considering

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Abbreviations: CC, Capital costs; CU, Cold utility; GAMS, General Algebraic Modeling System; HEN, Heat exchanger network; HRAT, Heat recovery approach temperature; HU, Hot utility; MER, Minimum energy requirement; MINLP, Mixed-integer non-linear programming; NLP, Non-linear programming; OC, Operating costs; PSO, Particle swarm optimization; RFO, Rocket fireworks optimization; SA, Simulated annealing; SWS, Stagewise superstructure; TAC, Total annual costs.

additional inequalities in the formulation and avoided the use of the *max* function. Escobar et al. (2014) used the SWS with a heuristic Lagrangean approach for the model solution. They tested case studies with nominal conditions and under different numbers of scenarios. Isafiade et al. (2015) employed a superstructure based on temperature intervals that slightly differ from the SWS concept, since in the latter intervals are strictly structural and do not depend on temperatures. Miranda et al. (2017) presented an improved version of the model presented by Floudas and Grossmann (1987) regarding their by-passes. Pavão et al. (2018a) employed a metaheuristic approach to solve the multiperiod HEN synthesis problem and were able to point out that the metaheuristics could be advantageous for the use with this problem as well. An interesting structural improvement for multiperiod HEN problems is the timesharing mechanism concept developed by Jiang and Chang (2015). In this proposal, heat exchangers can perform different tasks (i.e., have different matches) in different periods. This reduces considerably the heat exchange surface requirements and consequently total annual costs. However, authors also point out that additional piping structure must be considered, which could make implementation complex in practice. The services of each unit are determined with a simple algorithmic procedure. The timesharing mechanisms were employed later by Miranda et al. (2016) with different deterministic solution techniques and better solutions than those then published were found. Oliveira et al. (2017) applied Jiang and Chang's (2015) concept to a biorefinery heat integration and were able to greatly reduce energetic expenses. An additional post-optimization step to the algorithmic procedure of Jiang and Chang (2015) was later proposed by Pavão et al. (2018b). Heat exchanger surfaces were recurrently re-optimized whereas their tasks were reorganized, which greatly reduced TAC. Recent efforts by Elsido et al. (2021) propose using multiperiod models to HEN also with the integration of thermodynamic cycles and thermal storages. The interested reader is also referred to the comprehensive review on multiperiod HEN presented by Kang and Liu (2018).

It is worth noting that multiperiod models are a prominent branch of uncertainty studies in process engineering. In general, due to the large number of energy balances that need to be carried out in HEN models, the number of scenarios to be considered needs to be limited to make the optimization procedure computationally viable [e.g., four extreme cases, as proposed by Marselle et al. (1982)]. A more complete analysis could be considered by assuming statistical distributions for temperature or flowrate conditions (e.g., normal or log-normal distributions). These distributions can be discretized, and final design costs also result in distributions whose values are uncertain. Although computationally burdening, this certainly constitutes matter for future investigation. One can attempt to reduce average costs, variance, or other uncertainty metrics. This sort of uncertainty analysis was applied to HEN synthesis considering utility costs as uncertain (Pavão et al., 2017b, 2018c). These parameters are used only in operating costs calculation and represent a much smaller computational load even with a large number of scenarios (around 1,000 scenarios are considered in the cited works).

As previously mentioned, solving the multiperiod HEN synthesis problem is computationally burdening. Depending on the approached case, computing times may be of up to days. Hence, developing techniques that improve these times and may also lead to a better solution is fundamental. This is the main aim of the present work. The hybrid metaheuristic method of Pavão et al. (2018a) used a trivial solution as initial guess. A trivial solution for HEN synthesis is actually a solution with no heat recovery, in which all heat demanded by cold streams is provided by hot utilities and excess heat in hot streams is removed by cold utilities. The solutions found by the method of Pavão et al. (2018a) were promising, but for large-scale cases, it took a long time to find good solutions. In this work, a pinch-based strategy is proposed to find a promising solution in a quick manner, which can then be evolved by the aforementioned hybrid metaheuristic method. It is expected that solutions for large-scale cases are found faster and have lower costs.

METHODOLOGY

The first step of the methodology consists in applying two fundamental steps of pinch analysis for each period conditions separately. **Figure 1** presents a flow diagram that can be followed throughout the present explanation. Energy targets (Linnhoff and Flower, 1978) and minimal area targets (Townsend and Linnhoff, 1984; Linnhoff and Ahmad, 1990) are found, and an optimal value for the heat recovery approach temperature (HRAT) is obtained. This is a base parameter in pinch analysis, which determines the "degree" of heat integration. The smaller this value is, the smaller the utility requirements are, but, on the other hand, more heat exchange surface must be employed. This is why it is important to find an optimal value for HRAT. HRAT optimization *via* the methods proposed by Townsend and Linnhoff (1984) and Linnhoff and Ahmad (1990) finds an estimated value for heat exchange surface in optimal networks by finding minimum areas required in a given number of enthalpy intervals and distributing total area equally among a predicted number of units. Minimal area for a given value of HRAT is found by assuming vertical matching only within each enthalpy interval individually. This involves depleting energy needs at each interval among the streams present in that interval only. Performing vertical heat exchange in all enthalpy intervals results in a minimum energy requirement (MER) network, but a large number of stream splits and heat exchange units are necessary to complete such task, which is why this type of network is often called a "spaghetti" design and is, in general, unpractical. Moreover, minimal area is exactly predicted only for cases with equal heat transfer coefficients for all streams. However, when these values differ but are in similar orders of magnitude, minimum area estimation is still satisfactory using an averaging technique with these coefficients [refer to mathematical derivation in Linnhoff and Ahmad (1990)]. Although the complex "spaghetti" is mostly useless *per se*, its usefulness comes from the fact that one can estimate the total area required in one of those designs without having to effectually synthesize the detailed HEN structure. By predicting total area

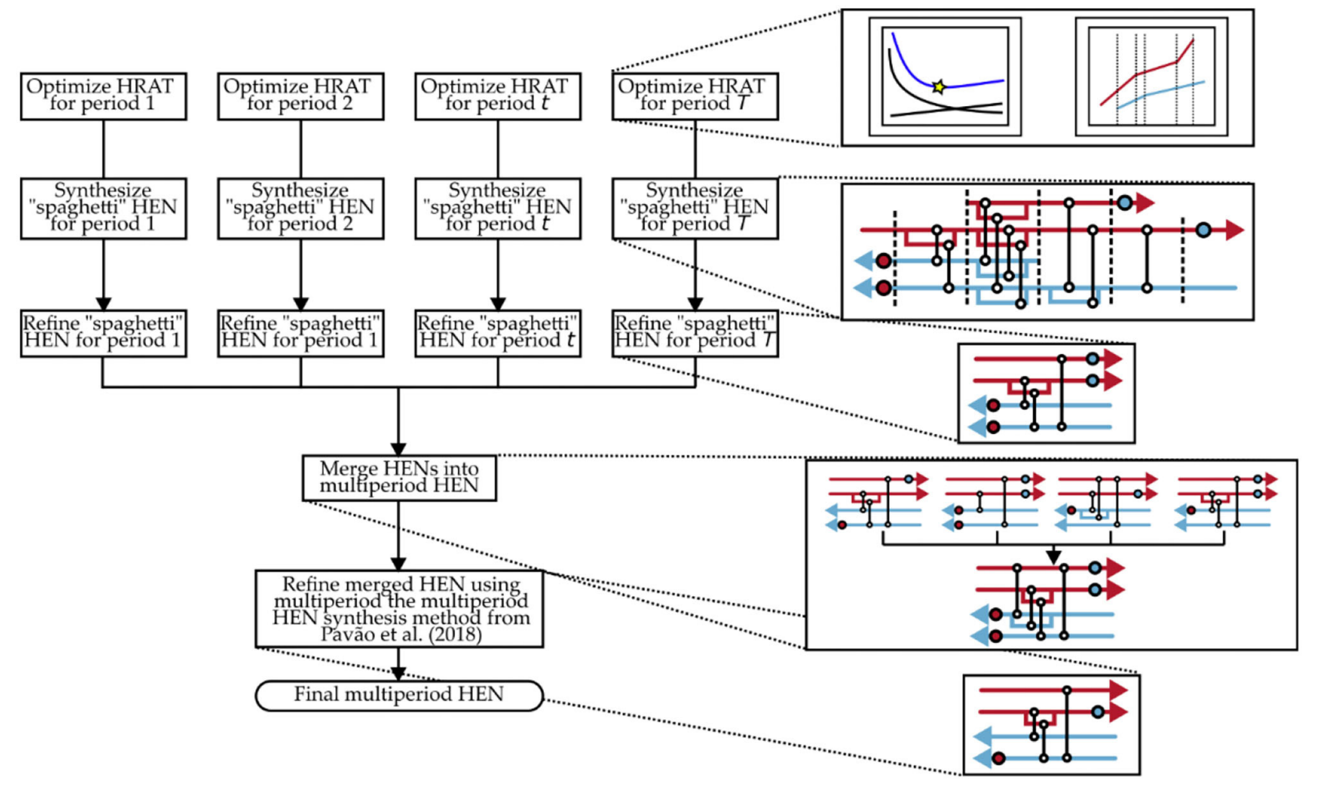

FIGURE 1 | Methodology flow diagram.

required in a spaghetti solution, one can distribute that value throughout a coherent number of hypothetical units and find a good estimation for final HEN costs (yearly capital + operating costs in general within ± 5% of a final detailed solution).

After optimal HRATs are found for all periods, it is possible to generate a "spaghetti" structure for each period data using the respective HRAT value. These structures serve as a promising initial guess for the next optimization-based step of the methodology. Each of these guesses are input for the application of the simulated annealing—rocket fireworks optimization [SA-RFO (Pavão et al., 2017a)] for single-period HEN. They are promising guesses since spaghetti solutions are maximum energy recovery (MER) solutions, but due to the large number of units, they are likely to have large heat exchange surface. With spaghetti solutions as initial guesses, SA-RFO efficiently finds good individual solutions for each period.

In the final step of the methodology, the individual period solutions are merged into a single multiperiod solution. Note that, until this step, all previous steps can be executed in parallel. In our implementation, we simply compile several instances of the program that is executed prior to merging under the different conditions of each period. Depending on the number of possible threads in a machine and the problem size, more than one optimization run for each period can be conducted for a single period. Then, from the reports return, we perform a simple manual check of solutions' quality prior to merging (which is also manually done). The merged solution serves as initial guess for the multiperiod version of SA-RFO (Pavão et al., 2018a). Both single and multiperiod versions of SA-RFO use, as basis HEN superstructure, the SWS developed by Yee and Grossmann's (1990), which is well studied in the process synthesis literature.

Simulated annealing—rocket fireworks optimization is a two-level meta-heuristic solution approach developed for HEN synthesis. It uses SA for defining HEN structure whereas continuous decision variables (heat loads, stream split fractions) are optimized with RFO. The method is summarized as follows.

1. Begin with a trivial HEN structure (only hot/cold utilities are used for heating/cooling process streams without heat recovery);
2. Add/remove a random heat exchanger;
   2.1 Apply RFO to heat loads/stream split fractions associated to existing heat exchangers with the objective of minimizing total annual costs;
      2.1.1 RFO begins with a continuous SA (CSA) step: moves are performed to heat loads or stream split fractions of random units present in the current structure;
      2.2.2 Several random solutions are generated (forming a swarm), and the continuous SA solution, which is a promising one, is incorporated to this swarm for guidance.

To these solutions, particle swarm optimization (PSO) is applied for refinement.

2.2 Return results to the outer level (SA);

3 Apply SA acceptance rules for the new solution;

4. Apply SA termination rules; if the termination rules are satisfied, return the final best solution, otherwise, return to step 2.

It should be noted that SA-RFO is slightly different depending on the model it is applied to. Some minor adjustments are performed, so that RFO performs search in a multiperiod model. Each move in the aforementioned scheme, in item 2.1.1, is randomly executed to a variable in a given unit. If the multiperiod model is being considered, a random period is selected as well. Regarding item 2.1.2, PSO solutions must be generated and altered regarding its decision variables for all periods as well. Hence, processing time is approximately multiplied by at least the number of periods present.

Mathematical Models

This section briefly presents the main equations from each mathematical model employed here. Since HRAT optimization has a single decision variable (HRAT itself), it is carried out by a simple sensitivity analysis procedure varying its value with 0.001 steps from 1 to 50 K. This sensitivity analysis provides HEN total annual costs within the evaluated range, and the optimal value can be identified by observing the recorded results. Minimum area calculation steps are presented in depth in the previous literature (Townsend and Linnhoff, 1984; Linnhoff and Ahmad, 1990). This implementation was made algorithmically in the present work in C++ language following steps proposed in the aforementioned works. However, the interested reader is also referred to the work of Colberg and Morari (1990), who presented a non-linear programming (NLP) model that finds optimal HRAT.

The model used both for single and multiperiod HEN synthesis is derived from the classical SWS of Yee and Grossmann's (1990) and does not consider its original non-isothermal mixing constraint, making the model broader. In-depth derivations based on such a superstructure can be found in the original paper (with isothermal mixing consideration) and in several other works in the literature. The format used here, regarding its nomenclature and mathematical arrangement, is in accordance with those derived in Pavão et al., 2017a, 2018a, where isothermal mixing was not considered. The full models can be found in those works. Here, for elucidative

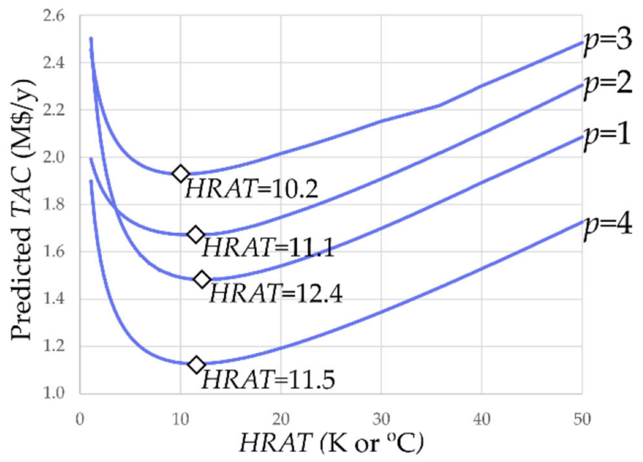

FIGURE 2 | Identification of optimal HRAT for each period conditions.

TABLE 1 | Case study stream data.

Stream	Tin (°C)				Tout (°C)	F (kW/°C)				h (kW/(m^{2}K))
Period	**1**	**2**	**3**	**4**	**All**	**1**	**2**	**3**	**4**	**All**
H1	180	170	170	190	75	30	31.5	28.5	31.5	2
H2	280	270	270	290	120	60	63	57	63	1
H3	180	170	170	190	75	30	31.5	28.5	31.5	2
H4	140	130	130	150	40	30	31.5	28.5	31.5	1
H5	220	210	210	230	120	50	52.5	47.5	52.5	1
H6	180	170	170	190	55	35	36.75	33.25	36.75	2
H7	200	190	190	210	60	30	31.5	28.5	31.5	0.4
H8	120	110	110	130	40	100	105	95	105	0.5
C1	40	50	30	50	230	20	21	21	19	1
C2	100	110	90	110	220	60	63	63	57	1
C3	40	50	30	50	190	35	36.75	36.75	33.25	2
C4	50	60	40	60	190	30	31.5	31.5	28.5	2
C5	50	60	40	60	250	60	63	63	57	2
C6	90	100	80	100	190	50	52.5	52.5	47.5	1
C7	160	170	150	170	250	60	63	63	57	3

Area costs = 8000 + 500·$A^{0.75}$; HUCosts (325–325°C) = 80 $/(kWyr); CUCosts (25–40°C) = 10 $/(kWyr).

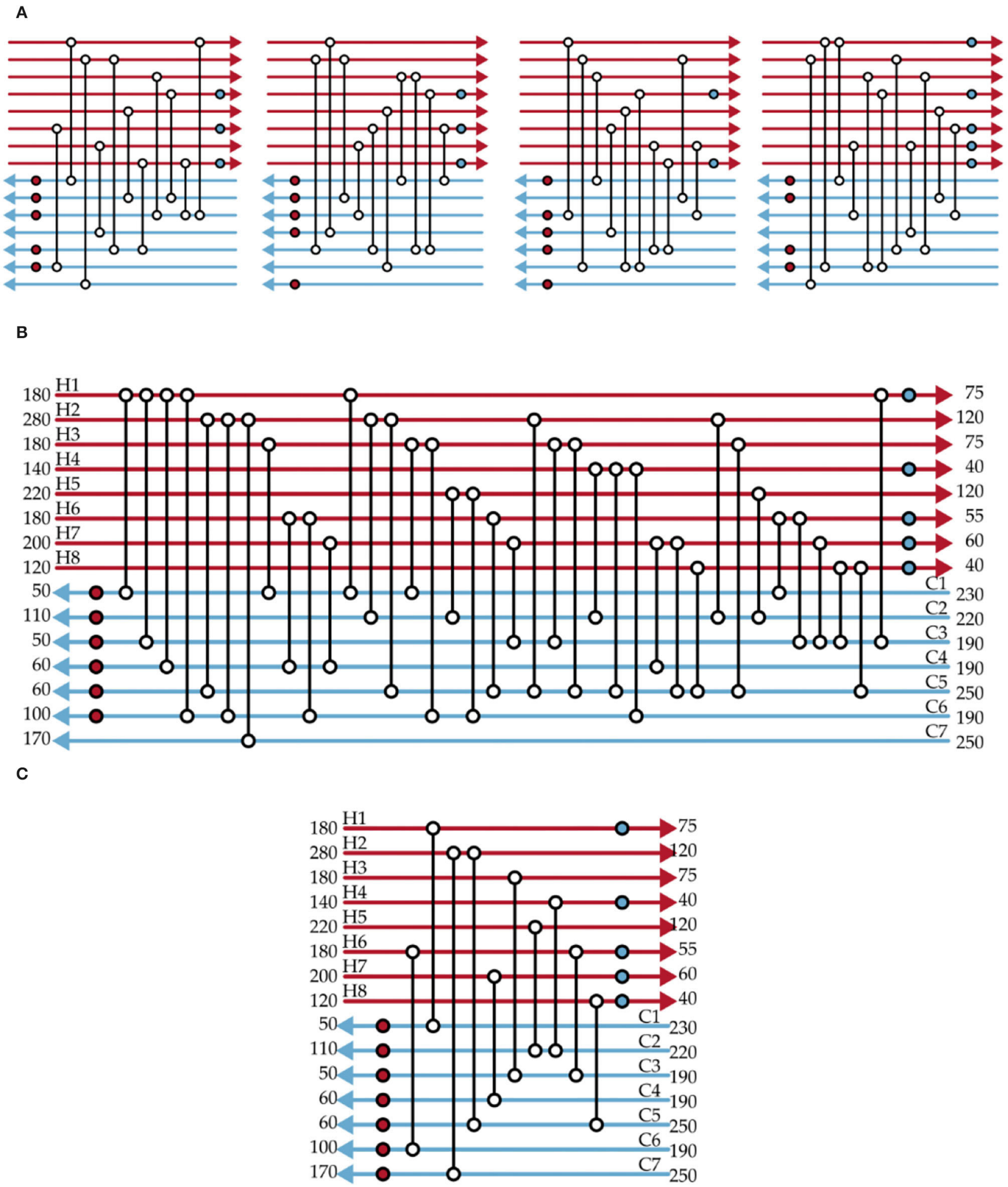

FIGURE 3 | Topologies for period individual solutions, merged solution, and final solution. **(A)** individual refined topologies for periods 1–4. **(B)** Multiperiod HEN topology merged from individual single-period refined solutions. **(C)** Refined multiperiod HEN topology.

TABLE 2 | Individual period solutions data.

Period	Units	Area (m^2)	HU (kW)	CU (kW)	TAC ($/y)
1 (spaghetti)	122	4,130.6	9,587.2	7,212.2	2,577,712
1 (refined)	19	4,864.0	9,919.8	7,544.8	1,556,690
2 (spaghetti)	128	4,003.9	11,893.5	8,874.8	2,791,765
2 (refined)	18	4,029.4	12,579.4	9,560.7	1,715,079
3 (spaghetti)	134	3,781.4	16,121.0	2,804.7	3,132,770
3 (refined)	17	3,397.4	17,387.2	4,071.0	1,979,150
4 (spaghetti)	143	4,363.4	4,177.7	12,794.0	2,433,048
4 (refined)	20	4,119.7	5,073.3	13,689.6	1,181,395

TABLE 3 | Comparison of the multiperiod HEN to the results reported in the literature.

	Units	Area (m^2)	CC ($/y)	OC ($/y)	TAC ($/y)
Escobar et al. (2014)	18	–	–	–	1,978,054
Pavão et al. (2018a)	24	3,810	661,240	1,132,635	1,793,875
This work (merged)	50	13,672	1,993,037	996,180	2,989,217
This work (refined)	22	4,380	692,219	1,110,170	1,729,389

purposes, we present heat exchange area calculation and the model for total annual cost minimization for both single (Equations 1, 2) and multiperiod (Equations 3, 4) situations. Differences between single and multiperiod models must be pointed out. By comparing Equations 1 and 3, it can be noted that the areas used for capital cost calculations are distinct. In Equation 1, costs are calculated as functions of area by a simple capital cost correlation, widely used in the literature and that has three parameters, B, C, and β that depend mainly on structural factors of a given type of heat exchanger. The subscripts in that equation regard hot and cold streams (i and j), and stages (k), whereas variables are $A_{i,j,k}$ (which stands for the area of a i–j stream match at stage (k), Acu_i (area for a cooler placed at the end of a hot stream (i), and Ahu_j (area for a heater placed at the end of a cold stream j). In Equation 3, the presence of a new subscript (t) is observed, which refers to the period being considered. Parameters or variables with such a subscript refer to their conditions at specific periods. Another observed aspect is the presence of *max* functions. For a given heat exchanger, different heat exchange surface values may be required according to the operating period. Thus, *max* functions are used to assure that the greatest of these values is used for capital cost calculations, so that the heat exchanger is implemented feasibly for the worst-case scenario.

In Equation 2, operating cost calculation is based simply on the total requirements of hot and cold utilities multiplied by a respective operating cost factor, and then, these are summed up to capital costs for TAC calculation. In Equation 4, these utility-related costs are weighted among periods *via* the D_t parameter which, in general, stands for the period typical duration or probability of occurrence.

$$AreaCC = \sum_{i \in NH} \sum_{j \in NC} \sum_{k \in NS} z_{i,j,k} \cdot \left(B + C \cdot A_{i,j,k}^{\beta}\right) + \sum_{i \in NH} zcu_i \cdot \left(B + C \cdot Acu_i^{\beta}\right) + \sum_{j \in NC} zhu_j \cdot \left(B + C \cdot Ahu_j^{\beta}\right) \quad (1)$$

$$\begin{array}{lll} (SP\_HEN) & min & \{TAC = AreaCC + HUCosts \cdot TotalHU + CUCosts \cdot TotalCU\} \\ & s.t. & SWS - related\ equations\ (as\ in\ Pavãoet\ al.,\ 2017a) \end{array} \quad (2)$$

$$AreaCC = \sum_{i \in NH} \sum_{j \in NC} \sum_{k \in NS} z_{i,j,k} \cdot \left(B + C \cdot \left(\max_{t \in NP}\left(A_{i,j,k,t}\right)\right)^{\beta}\right) + \sum_{i \in NH} zcu_i \cdot \left(B + C \cdot \left(\max_{t \in NP}\left(Acu_{i,t}\right)\right)^{\beta}\right) + \sum_{j \in NC} zhu_j \cdot \left(B + C \cdot \left(\max_{t \in NP}\left(Ahu_{j,t}\right)\right)^{\beta}\right) \quad (3)$$

$$\begin{array}{lll} (MP\_HEN) & min & \left\{ \begin{array}{c} TAC = AreaCC + \\ HUCosts\left(\sum_{t \in NP} D_t \cdot TotalHU_t\right) + CUCosts\left(\sum_{t \in NP} D_t \cdot TotalCU_t\right) \end{array} \right\} \\ & s.t. & SWS - related\ equations\ (as\ in\ Pavãoet\ al.,\ 2018a) \end{array} \quad (4)$$

CASE STUDY

Given the difficulties in solving multiperiod HEN models, in general, small and medium ones (around 4–8 streams) are approached. To validate the methodology presented here, the application to a large-scale case study is proposed. The problem has 15 streams (eight hot and seven cold) and was proposed by Escobar et al. (2014). The authors used a well-studied large-scale HEN benchmark case (Björk and Pettersson,

TABLE 4 | Heat duties, required areas, and area/maximum area ratios for all matches in all periods.

Match (*i,j,k*)	**(6, 6, 1)**	**(1, 1, 2)**	**(2, 7, 4)**	**(2, 5, 7)**	**(7, 4, 7)**	**(3, 3, 8)**	**(5, 2, 8)**	**(4, 2, 9)**	**(6, 3, 9)**	**(8, 5, 9)**	**(1, CU, –)**	**(4, CU, –)**	**(6, CU, –)**	**(7, CU, –)**	**(8, CU, –)**	**(HU, 1, –)**	**(HU, 2, –)**	**(HU, 3, –)**	**(HU, 4, –)**	**(HU, 5, –)**	**(HU, 6, –)**	**(HU, 7, –)**
Period 1	($p = 1$)																					
Heat duty (kW)	2,982.8	2,631.4	4,266.6	5,333.4	3,723.7	3,150.0	5,000.0	817.9	974.2	3,356.8	518.6	2,182.1	418.0	476.3	4,643.2	1,168.6	1,382.1	1,125.8	476.3	3,309.8	2,017.2	1,133.4
Area	323.5	164.3	116.4	569.2	431.7	237.1	771.4	87.3	36.2	357.2	15.2	119.3	22.0	47.0	500.8	14.4	17.9	7.5	3.3	33.1	19.6	11.2
A/Amax %	95.7	91.1	94.6	100.0	99.2	95.3	92.8	91.6	100.0	83.2	56.6	82.1	41.1	56.8	81.2	81.7	49.4	54.6	49.3	71.5	73.0	54.9
Period 2	($p = 2$)																					
Heat duty (kW)	2,434.6	2,359.8	3,553.0	5,897.0	3,364.7	2,992.5	4,725.0	278.9	680.2	2,616.1	632.7	2,556.1	1,111.4	730.3	4,733.9	1,420.2	1,926.1	1,472.3	730.3	3,456.9	2,290.4	1,487.0
Area	338.2	167.9	108.6	478.8	435.4	248.8	822.8	42.1	19.3	427.3	18.1	130.5	44.9	65.6	519.5	16.9	24.1	9.5	5.0	34.6	22.1	14.4
A/Amax %	100.0	93.1	88.3	84.1	100.0	100.0	99.0	44.2	53.4	99.6	67.2	89.8	83.8	79.2	84.2	96.3	66.9	69.7	73.7	74.8	82.0	70.2
Period 3	($p = 3$)																					
Heat duty (kW)	2,891.9	2,707.5	4,046.3	4,503.7	3,705.0	2,707.5	4,275.0	835.2	931.8	3,603.1	0.0	1,729.8	0.0	0.0	3,046.9	1,492.5	3,079.8	2,240.7	1,020.0	5,123.2	2,883.1	2,253.7
Area	332.7	167.9	103.1	256.0	432.6	93.3	325.4	95.4	35.4	429.2	0.0	105.8	0.0	0.0	406.9	17.6	36.1	13.7	6.8	46.3	26.9	20.5
A/Amax %	98.4	93.1	83.8	45.0	99.3	37.5	39.1	100.0	98.0	100.0	0.0%	72.8%	0.0%	0.0	65.9	100.0	100.0	100.0	100.0	100.0	100.0	100.0%
Period 4	($p = 4$)																					
Heat duty (kW)	3,052.1	2,569.9	4,352.3	6,357.7	3,705.0	3,622.5	5,775.0	0.0	432.7	2,119.2	1,052.6	3,465.0	1,476.5	1,020.0	7,330.8	850.1	495.0	599.8	0.0	2,353.1	1,222.9	207.7
Area	318.9	180.4	123.0	562.3	432.6	244.7	831.4	0.0	9.7	130.1	26.9	145.3	53.6	82.8	617.0	11.0	6.8	4.2	0.0	25.0	12.4	2.3
A/Amax %	94.3	100.0	100.0	98.8	99.3	98.3	100.0	0.0	26.9	30.3	100.0	100.0	100.0	100.0	100.0	62.5	18.8	30.4	0.0	54.0	46.3	11.0

2003) and reformulated it for considering not only its nominal conditions, but also uncertainties of 10 K in inlet temperatures and 5% in heat capacity flowrates that were modeled as a set of four equal duration periods. This is in line with the proposal of Marselle et al. (1982) for the design of resilient plants that may undergo some typical variations in their stream supply conditions, namely, apart from nominal conditions (scenario 1), there are three extreme scenarios with minimum ΔT/maximum area requirement (scenario 2), maximum heating requirement (scenario 3), and maximum cooling requirement (scenario 4). Those authors employed a heuristic Lagrangean method to solve the formulated model. **Table 1** summarizes the assumed conditions.

According to the method proposed, HRAT optimization is first applied. **Figure 2** presents the plots of predicted TAC as a function of HRAT at each period. In the figure, the identified value of optimal HRAT in each period is shown.

The "spaghetti" solution for each period is then synthesized and used as initial guess for refinement with SA-RFO. These solutions have minimum energy requirements, as proposed in the pinch method. However, the large number of heat exchange units makes them, in general, unpractical. In **Figure 3A**, the refined solution topologies for each period are presented. **Table 2** presents number of units, total heat exchange area, hot and cold utility requirements, and TAC for spaghetti and refined solutions for each period being considered. It is worth noting how large can be the number of units in spaghetti solutions. In this large-scale case, it varies from 122 to 143, which is an unpractical value. However, when refined, these numbers are reduced to nearly 20, a much more coherent value. It is also interesting to point out that in some cases, total area increases when the network is refined. For example, in period 1, it is initially 4,130.6 m^2, which is increased to 4,864.0 m^2 in the refined solution. However, the huge number of small units in the initial solution contributes much to TAC due to fixed capital cost per unit and the behavior of the capital cost function (which grows faster in small values due to the β exponent being lower than 1.0). The 19 units in the refined solutions are larger regarding total surface, and total fixed costs are smaller. In all cases, utility requirements slightly increase in refined solutions.

In the next step, these solutions are merged. The merged topology is presented in **Figure 3B**. The number of units is considerably large, and the multiperiod SA-RFO version is applied. The merged HEN has a large TAC due to the large number of units, which lead to large heat exchange area. **Figure 3C** presents the topology of the final multiperiod HEN. It has a much smaller number of units and a much lower TAC.

Table 3 presents a comparison to the literature in terms of number of units, total heat exchange area, capital costs (CC), operating costs (OC), and TAC. It can be noted that the present method is able to outperform solutions from Escobar et al. (2014) as well as from our previous methodology (Pavão et al., 2018a), where SA-RFO did not have an initialization procedure. In those works, the initial guess was simply a network with no heat recovery among process streams—all heat was provided/removed by utilities. Moreover, in the method by Pavão et al. (2018a), the computing time was of 20 h and 2 min and the method was developed to run serially, whereas the present work took 5 hand 44 min for the whole procedure, and it could be performed with parallel processing at single-period HEN synthesis. The reduction was considerable, since algorithms were run in computers with similar performances. In this work, all runs were carried out on a computer with an Intel® Core™ i7-8750H CPU @ 2.20 GHz and 8.00 MB of RAM, vs. the Intel® Core™ i5-4690 CPU @ 3.5 GHz and 8.00 MB of RAM from Pavão et al. (2018a). These central processing units (CPUs) have similar performances for single-thread tasks, with advantage for the present one for parallel computing (PASSMARK, 2022). The program was written in C++ language in Microsoft Visual Studio 2019. The detailed data for the found solution including heat duties and areas for all heat exchangers can be found in **Table 4**. A design aspect worth noting in these results is the high ratio between required and available area in all periods, especially for the larger units. This ratio ($A/Amax$) provides a good way of evaluating overdesign in flexible units. In a heat exchanger that is overdesigned for a given task, part of the material streams by-pass such a piece of equipment to be mixed downstream, so that heat load is as determined. The closer $A/Amax$ is to 100%, the lower is the amount of "extra" area needed. Some units are notable under that characteristic. The largest unit, for match (5, 2, 8), whose area is of 831.4 m^2 has an average $A/Amax$ ratio of 83%. Other large units such as that for match (7, 4, 7) (435.4 m^2) and match (6, 6, 1) (338.2 m^2) have notable average $A/Amax$ ratios of 99.4 and 97.1%. This means those units design is adequate for use in all periods with few bypassing requirements.

CONCLUSIONS

A method for the synthesis of multiperiod heat exchanger network synthesis was developed. It is based on a pinch-based method for proposing an initial multiperiod solution that had minimal energy requirements and was applied to a large-scale case study. The initial multiperiod solution was refined with a two-level hybrid meta-heuristic method. The final solution of the large-scale case outperformed other previous literature solutions. It was observed that, despite the large number of units, the TAC is notably lower than in previous work. Future investigation regarding possible piping or controllability issues due to the large number of units can be performed. Moreover, thorough optimization robustness tests can be run to different case sizes for inferring metaheuristic algorithm applications to even larger cases. The initialization procedure also reduced total time required for this computationally burdening case study. Hence, it can be concluded that the proposed method can handle large-scale cases efficiently and exploration of pinch-based techniques embedded with metaheuristic may be interesting alternatives to the majorly used deterministic methods.

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

AUTHOR CONTRIBUTIONS

LP was responsible for conception, model and computational codes development, case studies, and writing. CC was responsible for conception, writing, model development, and case studies. MR was responsible for conception, model development, case studies, supervision, and founding. All authors contributed to the article and approved the submitted version.

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The handling editor AI is currently organizing a Research Topic with the author MR.

NOMENCLATURE

A	Heat exchanger area [m^2]
Amax	Maximum area requirement among all periods for a unit [m^2]
Acu	Cooler area [m^2]
Ahu	Heater area [m^2]
AreaCC	Area-related capital costs [$/y]
B	Fixed costs parameter [$/y]
C	Capital costs factor [$\$\cdot y^{-1}\cdot m^{-2\beta}$]
CUCosts	Cold utility cost factor [$/kWy]
D	Period yearly duration or probability of occurrence [-]
F	Heat capacitance flowrate [kW/°C]
h	Convective heat transfer coefficient [$kW/(m^2K)$]
HRAT	Heat recovery approach temperature [K]
HUCosts	Hot utility cost factor [$/kWy]
i	Hot stream index [-]
j	Cold stream index [-]
k	Stage index [-]
max	Function that returns maximum value in a vector [-]
NC	Cold streams set [-]
NH	Hot streams set [-]
NP	Periods set [-]
NS	Stages set [-]
t	Period index [-]
TAC	Total annual costs [$/y]
Tin	General stream supply temperature [°C]
Tout	General stream target temperature [°C]
TotalCU	Total cold utility requirement [kW]
TotalHU	Total hot utility requirement [kW]
z	Binary variable for heat exchanger existence [-]
zcu	Binary variable for cooler existence [-]
zhu	Binary variable for heater existence [-]
β	Capital cost exponent [-]