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Pioneering Heat Exchanger Network Synthesis: A TOPSIS Driven Paradigm for Optimal Solutions

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ABSTRACT

Multi-Criteria Decision Making (MCDM) is a significant challenge across various domains, requiring adept resolution of conflicts arising from diverse objectives and criteria. This study proposes an innovative approach aimed at optimizing controllability, minimizing irreversibility, and maximizing overall effectiveness in control system design to address this challenge. The primary objectives of this study are to introduce a novel methodology for selecting Heat Exchanger Networks (HEN) using the well-established Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) method. Additionally, a closeness coefficient is introduced to rank alternatives networks based on their proximity to the ideal solution. Two illustrative case studies are presented to showcase the methodology's effectiveness, adaptability, and robustness in discrete multi-criteria decision-making problems, particularly in the context of HEN selection. Consistently identifying HEN configurations that fulfill controllability objectives, the methodology demonstrates its effectiveness and potential for broader applications beyond HEN optimization. The case study results affirm the adaptability and robustness of the proposed approach. In summary, this paper introduces an original and versatile approach to address the complexities of multi-criteria decision-making, specifically in the context of HEN selection. Rooted in the TOPSIS method and fortified by the closeness coefficient, the methodology holds promise for intricate decision-making processes and offers transformative possibilities for control system design. The study concludes by inviting further exploration of the proposed methodology, emphasizing its significant contribution to the field and its potential for widespread impact. Researchers and practitioners are encouraged to investigate and apply this innovative approach in diverse decision-making scenarios. The ranking results reveal that alternatives M and K is the optimum one among all the alternatives for both cases with a closeness coefficient equal to 0.651 and 0.971.

1. Introduction

The synthesis of heat exchanger networks (HENs) in the domain of chemical engineering is crucial for optimizing heat recovery and minimizing operational costs within the chemical industry, especially in the face of escalating energy expenditures and increasingly stringent environmental

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regulations [1]. However, despite their significance, recent literature on HENs is notably sparse, posing a challenge for researchers aiming to assess and compare the latest studies [2].

These methodologies can be broadly categorized into three principal paradigms: mathematical programming techniques, thermodynamic approaches, and stochastic techniques. However, it is notable that our comprehensive literature review underscores the absence of recent references, which poses a challenge to the comparative evaluation of the presented results against more contemporary studies within the field [3].

The motivation for undertaking this research stems from the recognition of persistent challenges and gaps in the existing literature. Labor-intensive manual design efforts in pinch analysis, complexity challenges in mathematical optimization techniques, and the often-overlooked impact of mass flow rate variations on heat transfer coefficients have collectively driven us to pursue a more integrated and nuanced approach. Furthermore, our proactive integration of controllability analysis aligns with our broader objective of establishing a well-structured operational framework to ensure the resilience and adaptability of control mechanisms in response to external perturbations.

This paper aims to address this research gap by advancing the field of HEN synthesis. Our research focuses on enhancing heat recovery efficiency, optimizing cost-effectiveness, and ensuring compliance with evolving energy and environmental standards in industrial processes. The research delves into controllability analysis, focusing on key parameters such as disturbance intensity and control precision, with the objective of identifying HEN configurations that exhibit robust controllability. Moreover, an exergy analysis is conducted to gain insights into exergy flows between different unit operations, shedding light on the overall performance of the plant and its subsystems. The study also explores the impact of variations in mass flow rates on heat exchanger parameters and thermal efficiency through thermal effectiveness analysis. To address the challenge of selecting the most optimal solution, a TOPSIS method is introduced. This strategy combines and normalizes parameters to generate a dependable indicator for optimizing HEN duty and overall performance.

The contributions of the proposed methodology can be arranged as follows:

- Introduces an innovative methodology that optimizes controllability, minimizes irreversibility, and maximizes overall effectiveness in control system design. The use of TOPSIS method, along with a unique closeness coefficient, sets the framework for a novel approach in addressing complex decision-making challenges.
- Demonstrates its potential for broader applications beyond HEN optimization. The illustrative case studies presented showcase its effectiveness, indicating adaptability to diverse scenarios and industries, thus contributing to the versatility of the approach.
- Establishes the adaptability and robustness of the methodology, making it a valuable solution for discrete multi-criteria decision-making problems. The methodology consistently identifies HEN configurations that fulfill controllability objectives, emphasizing its reliability in practical applications.
- Addresses a critical challenge in control system design by emphasizing controllability analysis at an early stage in the operational synthesis phase. This proactive approach facilitates the seamless integration of operational design and control systems, mitigating the need for recurrent structural modifications.
- Recognizes the transformative potential of the methodology. By unfolding its versatile capabilities, the work not only advances control system design but also holds promise for diverse applications where intricate decision-making is prevalent. This acknowledgement highlights the broader impact and significance of the proposed approach.

- Concludes with an invitation to explore the transformative possibilities offered by the methodology. This forward-looking perspective encourages further research and application, contributing to the ongoing evolution of decision-making processes in industrial settings.

The paper is designed as follows: Section 2 provides the existing literature related to different methods and techniques. The definition of each criterion and justification is presented in Section 3. Section 4 introduces TOPSIS proposed methodology. Section 5 and 6 gives the illustrative case studies, results and discussion; respectively. The managerial implications are provided in Section 7. Section 8 highlights our concluding remarks, the limitations, and future research directions.

2. Literature review

Among the methodological strategies, thermodynamic techniques, particularly pinch analysis, emerge as highly effective tools. Despite its status as one of the earliest methods in this domain, pinch analysis has undergone continual refinement, cementing its reputation as a versatile tool for optimizing industrial processes [4,5]. This method rigorously identifies the 'pinch point' within the process, enabling precision in heat exchange optimizations geared towards the reduction of energy consumption and the enhancement of process efficiency [6]. However, a significant challenge lies in the labor-intensive nature of manual design efforts, a challenge that has been partially mitigated through the development of automated software tools [7,8].

Mathematical optimization techniques, which are integral to HEN synthesis, can be delineated into two primary categories: successive and concurrent processes [9]. Successive techniques fragment the HEN synthesis problem into subsidiary components, often relying on mixed-integer linear programming (MILP) or nonlinear programming (NLP) formulations. In contrast, concurrent methodologies endeavor to attain the optimal HEN without subdividing the challenge, typically relying on mixed-integer nonlinear programming (MINLP) formulations [7]. While MINLP paradigms offer the potential for better results, they often introduce complexity challenges, particularly for larger problem scopes, necessitating the application of strategies such as the 'phase' and 'block' concepts, where the HEN is divided into preheating, heat recovery, and cooling blocks to reduce complexity [10].

The variability inherent in real-world industrial processes, with their ever-shifting operating conditions, introduces an additional layer of complexity [11]. Unfortunately, the bulk of existing research predominantly revolves around the realm of heat exchanger controller systems, frequently overlooking the substantial impact of mass flow rate variations on the overall heat transfer coefficients [12]. In response to this oversight, researchers have embarked on investigations aimed at enhancing process structures, a realm categorized into two genres: steady-state and dynamic approaches [13]. While steady-state methodologies are conceptually simpler, they may prove inadequate for scenarios marked by significant operating condition fluctuations, in contrast to dynamic approaches, which, although more intricate, are better suited to accommodate such exigencies. The choice between these paradigms' hinges on the inherent characteristics of the process and the specific objectives of the control regime [14].

The amalgamation of process design and control remains a persisting challenge, often entailing hierarchical or successive procedures that inherently involve iterative processes of considerable duration [15]. Controllability, a pivotal criterion within this context, warrants early attention during the operational synthesis phase to facilitate the seamless integration of operational design and control systems. Regrettably, controllability analysis is frequently deferred to a post-design stage, entrusted to control engineers subsequent to the establishment of the operational framework. This tendency primarily arises from the reliance on the arithmetical paradigm of operation [16].

In essence, the establishment of a well-structured operational framework assumes a central role in ensuring the effectiveness of control mechanisms in the face of external perturbations. Controllability, exergy analysis, and thermal effectiveness constitute the key pillars in this endeavor, with particular relevance in the context of HENs. This approach not only underpins the realization of elevated controllability standards but also streamlines the process control system design, thereby mitigating the need for recurrent structural modifications.

In comparison to existing studies, our research distinguishes itself in several key aspects. Firstly, we acknowledge the scarcity of recent references in the literature and aim to fill this void by presenting a comprehensive approach that integrates various strategies. Secondly, while previous research has primarily centered on pinch analysis and mathematical optimization techniques, our study adopts a more holistic approach by integrating controllability analysis early in the operational synthesis phase. This integrated approach allows us to address the challenges faced by existing methodologies in a more comprehensive and effective manner.

In summary, our research aims to not only address existing challenges and fill gaps in the literature but also to present a comprehensive and innovative approach to HEN synthesis. Through this study, we endeavor to make a substantial contribution to the field of chemical engineering, offering valuable insights that can contribute to the optimization of industrial processes in a sustainable and efficient manner.

3. Definition of criteria

The three criteria are defined as follows:

Controllability is the ability to maintain process variables close to their desired values in the face of external disturbances via manipulating input variables. Maximizing controllability enables precise regulation of process outputs through control systems. This criterion is crucial for effective integration of design and control in HEN synthesis.

Irreversibility is the inability to restore a system back to its initial state after a process has occurred. Minimizing irreversibility reduces exergy destruction and enhances the overall plant efficiency and resource utilization. This criterion provides insights into losses and performance.

Thermal effectiveness is the ratio of actual heat transfer to the maximum theoretical heat transfer in a heat exchanger. Maximizing this criterion improves heat recovery and thermal efficiency. It indicates adequate heat exchanger sizing and flow rates.

These three criteria offer a comprehensive set of parameters to optimize HEN synthesis from the perspectives of controllability, thermodynamic performance, and heat transfer effectiveness. They overcome the limitations of single-criterion approaches prevalent in literature. The multi-criteria technique provides a more reliable way to handle trade-offs between conflicting objectives in HEN design

4. Proposed Methodology

The methodology outlined in this study comprises four stages and employs the Technique for Order of Preference by Similarity to Ideal Solution TOPSIS method to select the most suitable alternative from a set of options. This selection is based on the proximity of each alternative to the Ideal Positive Solution and its distance from the Ideal Negative Solution. The TOPSIS method uses a vector approach to calculate compromise rankings by considering both the best and worst performance of each alternative. Figure 1 illustrates the typical stages involved in the TOPSIS approach adopted in this study.

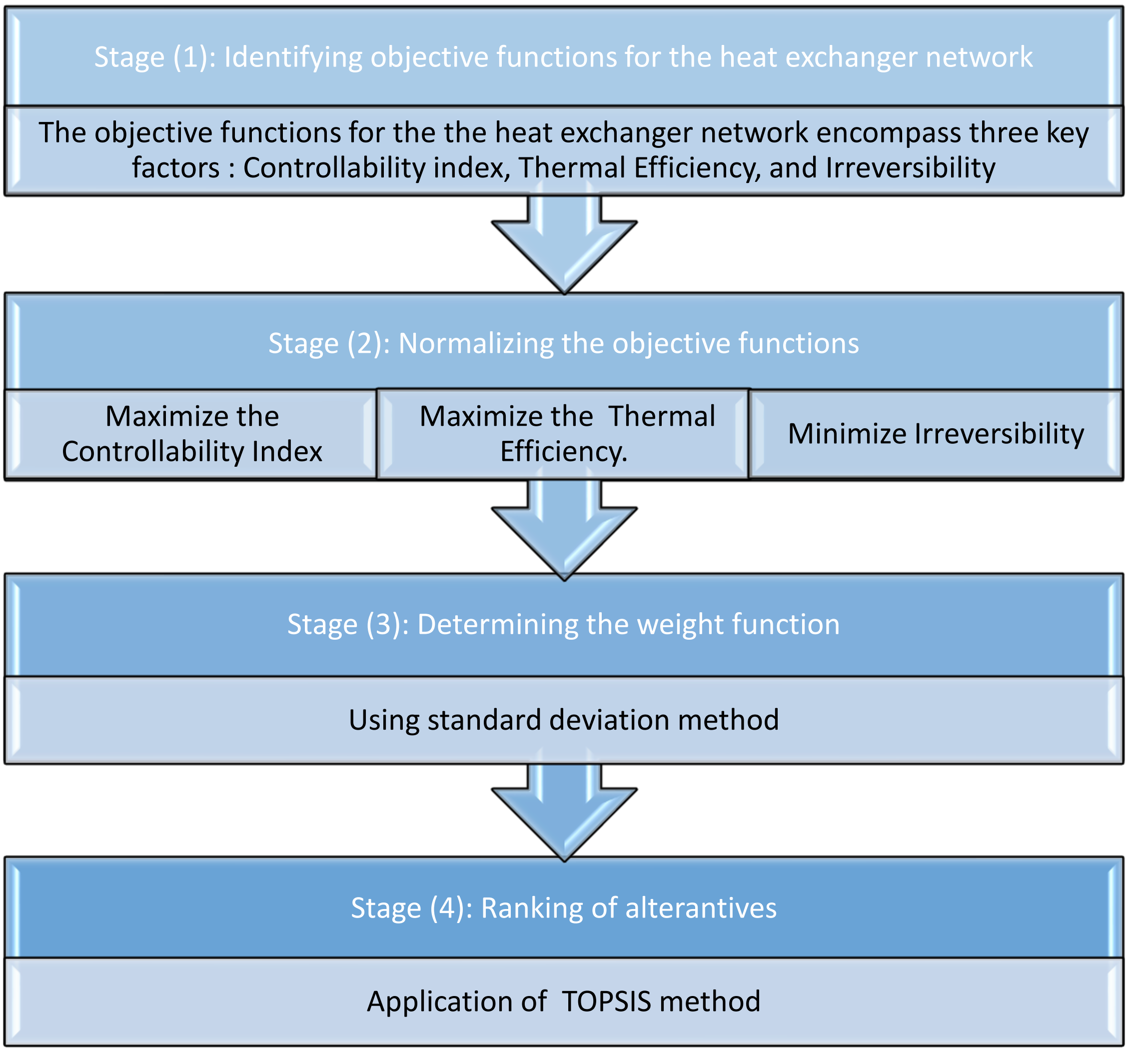

Fig.1. Flow chart of typical steps involved in the TOPSIS approach

Subsequent stages are used for optimizing and ranking alternatives in complex systems, particularly those with conflicting criteria where a compromise solution is necessary.

4.1. Stage 1: Objective Functions Identification

The first stage involves identifying and describing the objective functions, which include:

Controllability Analysis: This involves studying various parameters such as the degree of disturbance intensity, control precision, and disturbance propagation patterns to achieve a highly controllable (HEN). The controllability index value is determined, with the highest value being favored. However, a limitation of this method is the difficulty in deciding the optimum index when multiple solutions have the same highest value.

Exergy Analysis: This analysis determines the exergy flows transferred between the unit operations of the plant, providing insights into overall plant performance or subsystems performance. Exergy analysis is essential due to the irreversibility of all real processes.

Thermal Effectiveness Analysis: This analysis considers variations in mass flow rates, which affect parameters such as fouling coefficients, heat transfer coefficients, and NTU (Number of Transfer Units). These variations impact heat transfer duty and outlet temperatures, making thermal efficiency essential for each alternative.

4.1.1. Quantification of index of structural controllability

The disturbance vector, D , represents the magnitudes of disturbances in process streams, while the control precision vector, C , represents the required precision of control for each stream. The disturbance propagation matrix, R, determines the extent to which a disturbance in one stream affects another. The structural controllability index evaluates the network's sensitivity to disturbances and ease of control based on these definitions [17].
The equation can be represented in the subsequent format:

$$E_{tot} = D^T RC \tag{1}$$

$$E_{tot} = \sum_{i=1}^{N} \sum_{j=1}^{N} d_i R_i C_j \tag{2}$$

$$E_{tot.,min} = minE_{tot.} = D^T IC = \sum_{i=1}^{N} d_i C_i \tag{3}$$

$$E_{tot.,max} = maxE_{tot.} = maxD^T RC = \sum_{i=1}^{N} d_i \sum_{j=1}^{N} C_i \tag{4}$$

Now the index ISC can be defined based on $E_{tot.,max}$ and $E_{tot.,min}$ as:

$$I_{SC} = \frac{E_{tot.,max} - E_{tot.}}{E_{tot.,max} - E_{tot.,min}} \tag{5}$$

4.1.2. Exergy analysis

The term "exergy" refers to the amount of energy which can be retrieved from a thermodynamic system. Exergy analysis is a valuable tool for analyzing such systems, as it allows for the measurement of the thermodynamic irreversibility associated with a given process. Minimizing irreversibility enhances the overall plant efficiency and resource utilization. This criterion provides insights into losses and performance associated with a given process pinch.
Irreversibility = Exergy of Hot – Exergy of cold

$$Irr. = \Delta Ex_{Hot} - \Delta Ex_{Cold} \tag{6}$$

$$\Delta Ex_{Hot} = Q_H(1 - \frac{T_O}{T_{AMH}}) \tag{7}$$

$$\Delta Ex_{Cold} = Q_C(1 - \frac{T_O}{T_{AMC}}) \tag{8}$$

Where, T_o is ambient temperature and equal 290 K.

4.1.3. Thermal effectiveness analysis

Maximizing this criterion improves heat recovery and thermal efficiency. It gives an indication on adequate heat exchanger sizing and flow rates.

$$\varepsilon = \frac{Q}{Qmax} \tag{9}$$

$$Q = Cp_H(T_{H,in} - T_{H,out}) = Cp_C(T_{C,in} - T_{C,out}) \tag{10}$$

$$Q_{max} = min(Cp_H, Cp_C)(T_{H,in} - T_{C,in}) \tag{11}$$

Equation (8) provides a thermodynamic definition of ε. in heat exchangers operating under normal conditions.

$$Q_{max} = (Cp_{min})(\Delta T_{max}) \tag{12}$$

The thermal effectiveness definition can be rewritten as follows

$$\varepsilon = \frac{C_H(T_{H,in}-T_{H,Out})}{C_{min}(T_{H,in}-T_{C,in})} = \frac{C_C(T_{C,Out}-T_{C,in})}{C_{min}(T_{H,in}-T_{C,in})} \tag{13}$$

4.2. Stage 2:Objective Functions Normalization

The Multi-Criteria Decision Making (MCDM) problems are represented in a matrix format, where G_i represents alternatives and C_j represents criteria. Normalization methods for maximizing and minimizing criteria are applied to standardize the decision matrix, resulting in a matrix indicating the relative performance of alternatives [18].

$$D = \begin{array}{c} \\ G_1 \\ G_2 \\ \vdots \\ \\ G_m \end{array} \begin{array}{c} \begin{array}{ccccc} C_1 & C_2 & .. & .. & C_n \end{array} \\ \begin{bmatrix} Y_{11} & Y_{12} & .. & .. & Y_{1n} \\ Y_{21} & Y_{22} & .. & .. & Y_{2n} \\ .. & .. & .. & .. & .. \\ .. & .. & .. & .. & .. \\ Y_{m1} & Y_{m2} & .. & .. & Y_{mm} \end{bmatrix} \end{array} \tag{14}$$

The most common normalization method is;

(i) for max, we have

$$p_{ij} = \frac{Y_{ij}-min(Y_{ij})}{max\,(Y_{ij})-min(Y_{ij})}\ ,(i\epsilon m \quad , \ j\epsilon n) \tag{15}$$

(ii) for min, we have

$$p_{ij} = \frac{max(Y_{ij})-Y_{ij}}{\max\,(Y_{ij})-\min(Y_{ij})}\ ,\ (i\epsilon m \quad , \ j\epsilon n) \tag{16}$$

As a result, a standardized decision matrix *M* is acquired indicating the relative performing of the substitutions as:

$$M = \begin{bmatrix} p_{11} & p_{12} & .. & .. & p_{1n} \\ p_{21} & p_{22} & .. & .. & p_{2n} \\ .. & .. & .. & .. & .. \\ .. & .. & .. & .. & .. \\ p_{m1} & p_{m2} & .. & .. & p_{mn} \end{bmatrix} \tag{17}$$

4.3. Stage 3: Weight Function Determination

The weights of criteria are estimated using the standard deviation method, where each criterion's weight is calculated based on its variance and mean. A set of weights is assigned to each criterion, reflecting its relative importance in the decision-making process.

(i) The standard deflection method estimates the weights of purposes through:

$$W_i = \frac{\sigma_i}{\sum_k^m \sigma_k} \tag{18}$$

Where,

$$\sigma_i = \sqrt{\frac{\sum_{i=1}^m (Y_i - Y^\sim)^2}{n-1}} \tag{19}$$

And, $Y^\sim$ = mean variable

$$Y^\sim = \sum_{i=1}^m Y_i / n \tag{20}$$

(ii) A set of weights ($w_1, w_2 \ldots\ldots\ldots\ldots w_n$) and $\sum_i^n w_i = 1$, where $w_i > 0$, *(i = 1, 2… n)* is given to the corresponding criterion Y_i, where *(i = 1,2,…, n)*. The matrix $V = w_i p_{ij}$ is calculated by multiplying the elements at each column of the matrix M by their associated weights w_i, *(i = 1,…, n).*

$$V = \begin{bmatrix} w_1 p_{11} & w_2 p_{12} & .. & .. & w_n p_{1n} \\ w_1 p_{21} & w_2 p_{22} & .. & .. & w_n p_{2n} \\ \cdots & \cdots & .. & .. & \cdots \\ \cdots & \cdots & .. & .. & \cdots \\ w_1 p_{m1} & w_2 p_{m2} & .. & .. & w_n p_{mn} \end{bmatrix} \tag{21}$$

(iii) Calculate the separation measures ($\beta_i^+ and \beta_i^-$) between alternatives using the distance Minkowski Lp Metric as follow:

$$\beta_i^+ = \sqrt{\sum_{j=1}^m (V_{ij} - V_j^+)}^2, (i = 1, \ldots\ldots\ldots, n) \tag{22}$$

$$\beta_i^- = \sqrt{\sum_{j=1}^m (V_{ij} - V_j^-)}^2, (i = 1, \ldots\ldots\ldots, n) \tag{23}$$

(iv) In terms of performance evaluation of alternatives, the higher the value, the better performance.

Optimum alternative is selected according to the greater relative closeness.

$$F_i = \frac{\beta_i^-}{\beta_i^- + \beta_i^+} \tag{24}$$

where $0 \leq F_i \leq 1$.

4.4. Stage 4: Ranking of Alternatives

The alternatives are ranked based on their closeness coefficient, F_i, which is calculated using the separation measures between alternatives obtained from the Minkowski Lp Metric. The alternative with the highest F_i is considered the best compromise solution or optimal choice.

In summary, the methodology incorporates Controllability, Irreversibility, and Thermal Effectiveness as criteria to optimize HEN synthesis, addressing the limitations of single-criterion approaches. This multi-criteria technique provides a reliable way to handle trade-offs between conflicting objectives in HEN design, contributing to the field of HEN synthesis.

5. Illustrative Case Studies

5.1. Case 1

A commonplace case test is 4SP1 studied by [19]. Table 1 exhibits the disorders on the inlet/outlet temperatures and heat capability flow rates.

Table 1
Stream Data for 4SP1 HEN Synthesis problem

Stream	T_i^S (°C)	T_i^t (°C)	MCp_i (kW/°C)	$\delta T_i^{S(+)}$ (°C)	$\delta T_i^{S(-)}$ (°C)	$\delta MCp_i^{(+)}$ (kW/°C)	$\delta MCp_i^{(-)}$ (kW/°C)	δT_i^t (°C)	Q_i (kW)
H1	175	45	10	2.0	2.0	0.4	0.40	4.0	1300
H2	125	65	40	4.0	3.0	0.1	0.20	3.0	2400
C1	20	155	[20]	1.0	0.6	0.05	0.10	6.0	2700
C2	40	112	15	1.0	3.0	0.3	0.40	5.5	1080

Table 2 displays the objective functions including Index of Structural controllability (I_{SC}), irreversibility and thermal effectiveness for each alternative. The final solutions for possible alternatives are displayed in Figures 2-6.

Table 2
Objective functions of possible alternatives for Case 1

Alternatives	Index of Structural controllability (I_{SC})	Irreversibility (Irr.)	Thermal Effectiveness (ε)
K	0.615	416.066	1.736
L	0.800	402.139	1.664
M	0.800	402.008	1.670
N	0.800	402.320	1.632
O	0.615	403.083	1.992

The normalized decision matrix, the standard deviation ($\boldsymbol{\sigma_i}$), the objective weight ($\boldsymbol{\tau_i}$) and Stage 3 results of the TOPSIS method by using Eq. (14-21) are exhibited in Table 3.

In the next step, the computed values of separation measures and closeness coefficients are exhibited in Table 4. The outcomes are evaluated by using Eq. (22-24).

The optimum solution is equal to (0.6511) which corresponds to alternative M. Figure 4. represents the network chart for the final solution at the optimum minimal approach temperature.

Table 3
Normalized decision matrix, standard deviation (σ_i), objective weight (τ_i) and stage 3 results of TOPSIS method for Case 1

Normalized Decision Matrix			
Alternatives	Index of Structural controllability (I_{SC})	Irreversibility (Irr.)	Thermal Effectiveness (ε)
K	0.169421	0.205402	0.199678
L	0.220386	0.198527	0.191396
M	0.220386	0.198462	0.192086
N	0.220386	0.198616	0.187716
O	0.169421	0.198993	0.229124
Standard Deviation ($\boldsymbol{\sigma_i}$) and Objective weight ($\boldsymbol{\tau_i}$) results			
Standard Deviation ($\boldsymbol{\sigma_i}$)	0.027914	0.003027	0.016851
Objective weight ($\boldsymbol{\tau_i}$)	0.584075	0.063335	0.35259
Stage 3 Results of TOPSIS method			
Alternatives	Index of Structural controllability (I_{SC})	Irreversibility (Irr.)	Thermal Effectiveness (ε)
K	0.000000	0.000000	0.101859
L	0.584075	0.062745	0.031341
M	0.584075	0.063335	0.037218
N	0.584075	0.061929	0.000000
O	0.000000	0.058492	0.352590

Table 4
The relative closeness of possible alternatives for Case 1

Alternatives	$\boldsymbol{\beta_i^+}$	$\boldsymbol{\beta_i^-}$	$\boldsymbol{F_i = \beta_i^- / (\beta_i^- + \beta_i^+)}$
K	0.638765	0.101859	0.137532
L	0.321249	0.588271	0.646793
M	0.315372	0.588676	**0.651156**
N	0.352593	0.587349	0.624878
O	0.584095	0.357409	0.379615

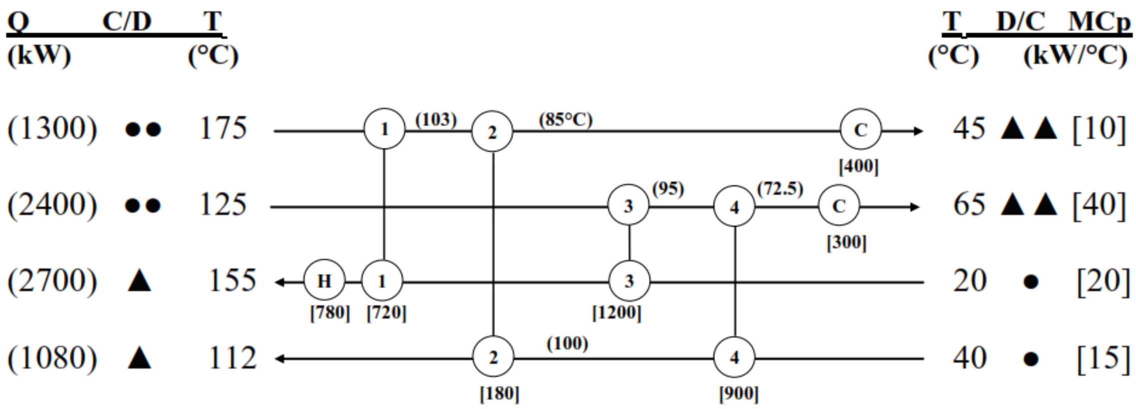

Fig. 2. Final solution of alternative (K)

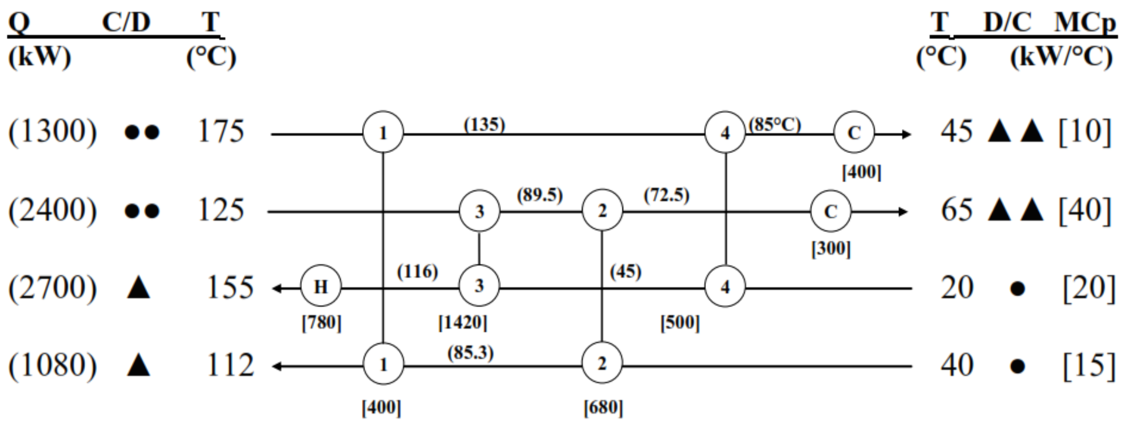

Fig. 3. Final solution of alternative (L)

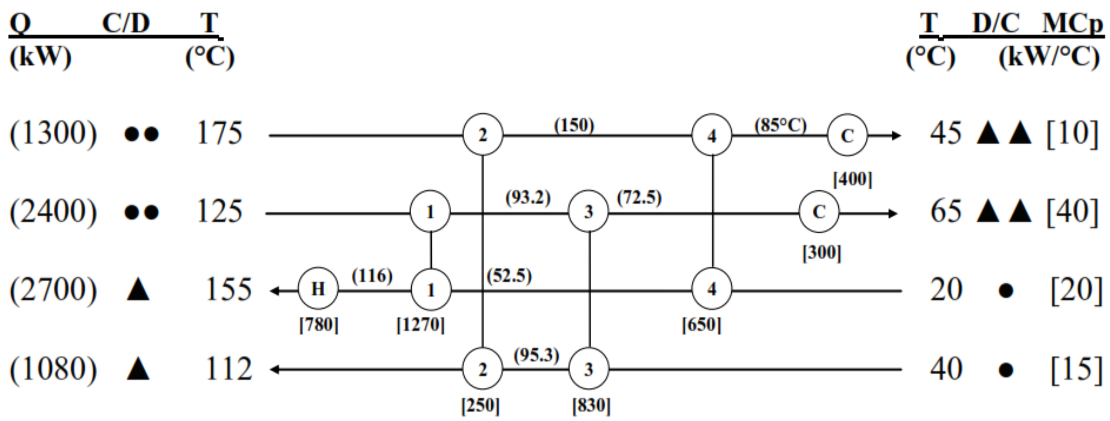

Fig. 4. Final solution of alternative (M)

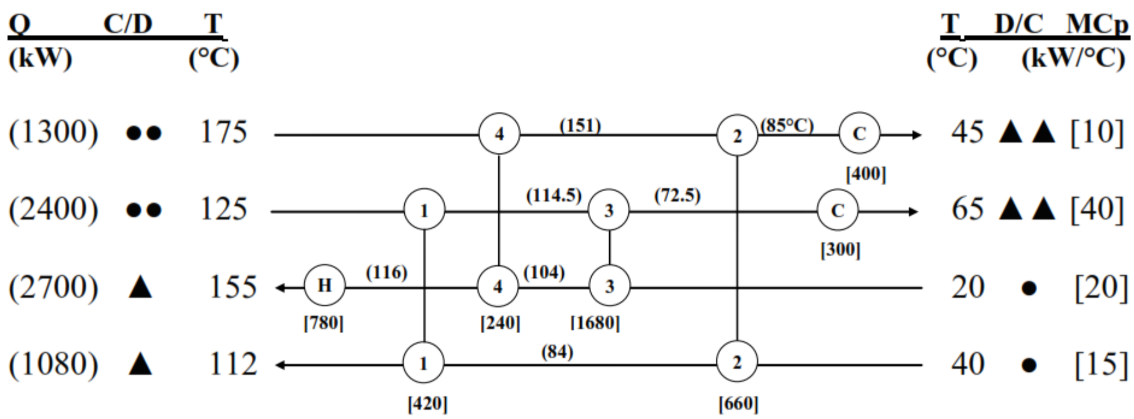

Fig. 5. Final solution of alternative (N)

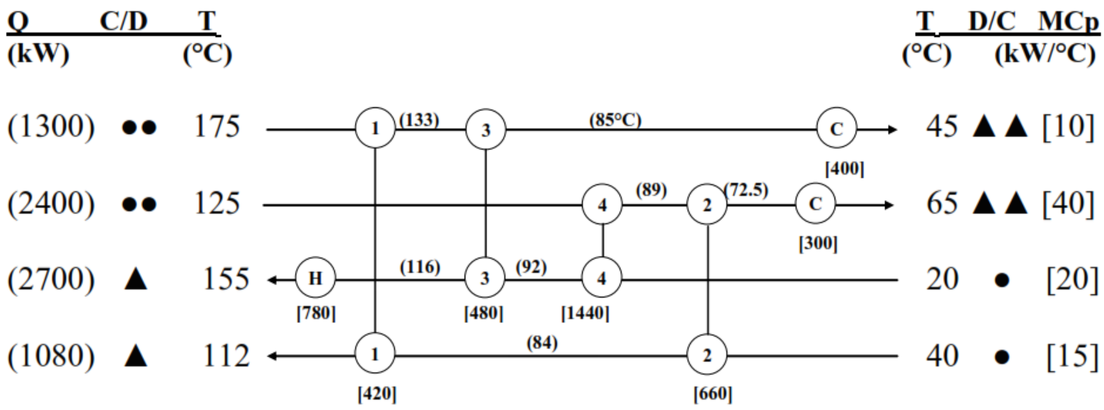

Fig. 6. Final solution of alternative (O)

5.2. Case 2

The case described and reported here is 5SP1 studied by [17,19–22]. Table 5 exhibits the disorders on the inlet/outlet temperatures and heat capability flow rates.

Table 5

Stream Data for 5SP1 HEN Synthesis problem

Stream	T_i^S (°C)	T_i^t (°C)	MCp_i (kW/°C)	$\delta T_i^{S(+)}$ (°C)	$\delta T_i^{S(-)}$ (°C)	$\delta MCp_i^{(+)}$ (kW/°C)	$\delta MCp_i^{(-)}$ (kW/°C)	δT_i^t (°C)	Q_i (kW)
H1	204.4	65.6	13.29	2.0	2.0	0.4	0.4	5.5	1884.7
H2	248.9	121.1	16.62	4.0	3.0	0.1	0.2	3.0	2124.0
C1	93.3	204.4	13.03	1.0	0.6	0.05	0.1	6.0	1447.6
C2	65.6	182.2	12.92	2.0	2.5	0.1	0.05	7.0	1506.5
C3	37.8	204.4	11.40	1.0	3.0	0.3	0.4	1.0	1899.2

Table 6 displays the objective functions including Index of Structural controllability (I_{SC}), irreversibility and thermal effectiveness for each alternative. The normalized decision matrix, the standard deviation (σ_i), the objective weight (τ_i) and Stage 3 results of the TOPSIS method are exhibited in Table 7. The final solutions for possible alternatives are displayed from Figures 7-11.

Table 6

Objective functions of possible alternatives for Case 2

Alternatives	Index of Structural controllability (I_{SC})	Irreversibility (Irr.)	Thermal Effectiveness (ε)
K	0.958	359.616	2.436
L	0.917	338.430	2.316
M	0.750	384.725	2.284
N	0.083	341.996	2.360
O	0.083	358.430	2.156

Table 7

Normalized decision matrix, standard deviation ($\boldsymbol{\sigma_i}$), objective weight ($\boldsymbol{\tau_i}$) and stage 3 results of TOPSIS method for Case 2

Normalized decision matrix			
Alternatives	Index of Structural controllability (I_{SC})	Irreversibility (Irr.)	Thermal Effectiveness (ε)
K	0.343246148	0.201669249	0.210872576
L	0.328556073	0.189788341	0.200484765
M	0.268720889	0.215750139	0.197714681
N	0.029738445	0.19178812	0.204293629
O	0.029738445	0.201004152	0.186634349
Standard Deviation (σ_i) and Objective weight (τ_i) results			
Standard Deviation (σ_i)	0.157913	0.01029	0.008955
Objective weight (τ_i)	0.891368	0.058086	0.050546
Stage 3 Results of TOPSIS method			
Alternatives	Index of Structural controllability (I_{SC})	Irreversibility (Irr.)	Thermal Effectiveness (ε)
K	0.891368	0.031504	0.050546
L	0.849601	0.058086	0.028884
M	0.679477	0.000000	0.023107
N	0.000000	0.053612	0.036827
O	0.000000	0.032992	0.000000

The separation measures and relative closeness coefficients of possible alternatives for Case 2 are presented in Table 8.

Table 8

The relative closeness coefficients of possible alternatives for Case 2

Alternatives	β_i^+	β_i^-	$F_i = \beta_i^- / (\beta_i^- + \beta_i^+)$
K	0.026582	0.893355	**0.971105**
L	0.047051	0.852074	0.947671
M	0.221415	0.679870	0.754334
N	0.891485	0.065042	0.067997
O	0.893152	0.032992	0.035623

The optimum solution is equal to (0.9711) which corresponds to alternative K. Figure 7 represents the network chart for the final solution at the optimum minimal approach temperature.

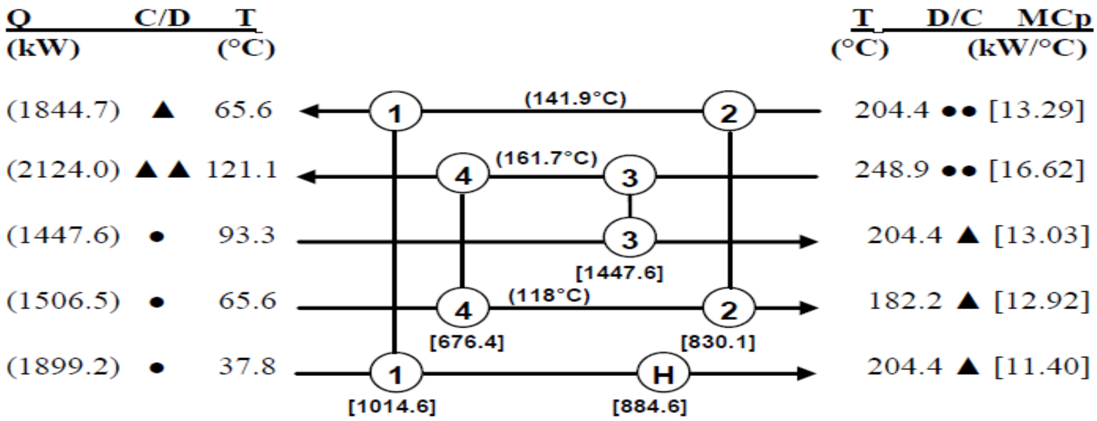

Fig. 7. Final solution of alternative (K)

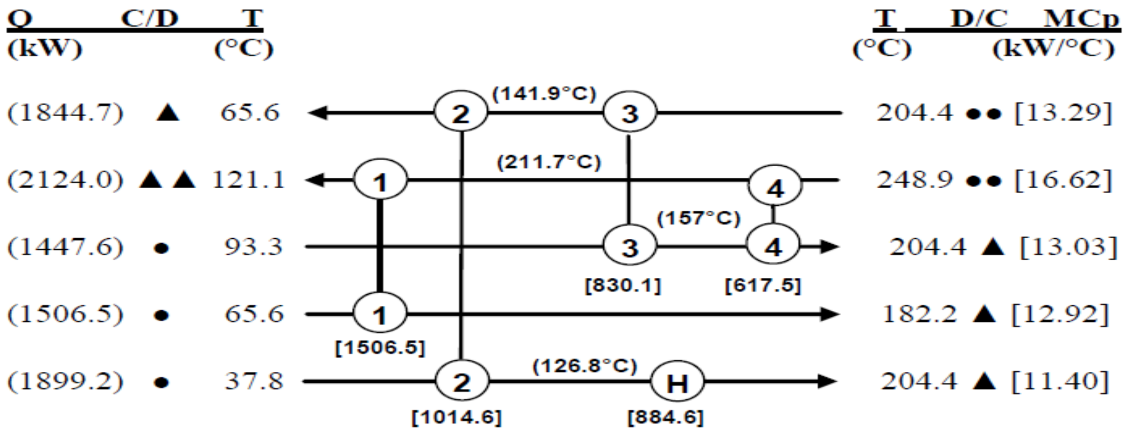

Fig. 8. Final solution of alternative (L)

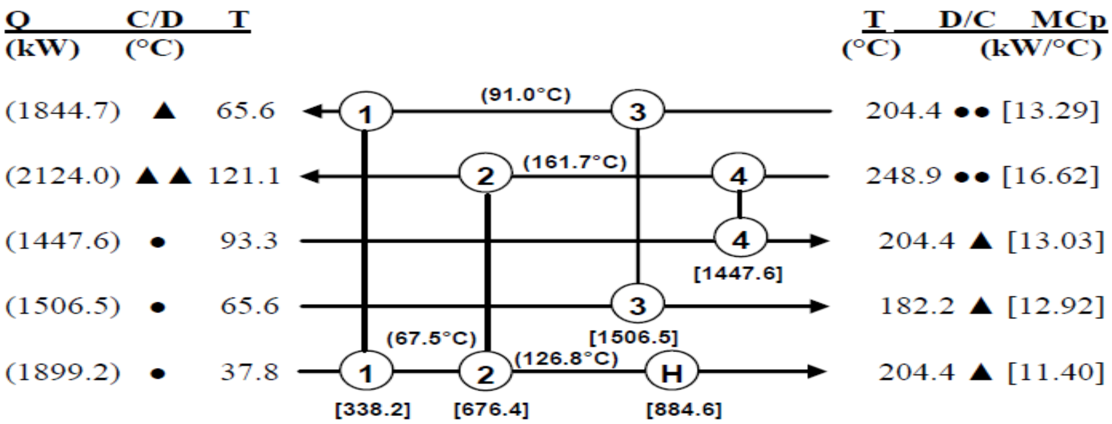

Fig. 9. Final solution of alternative (M)

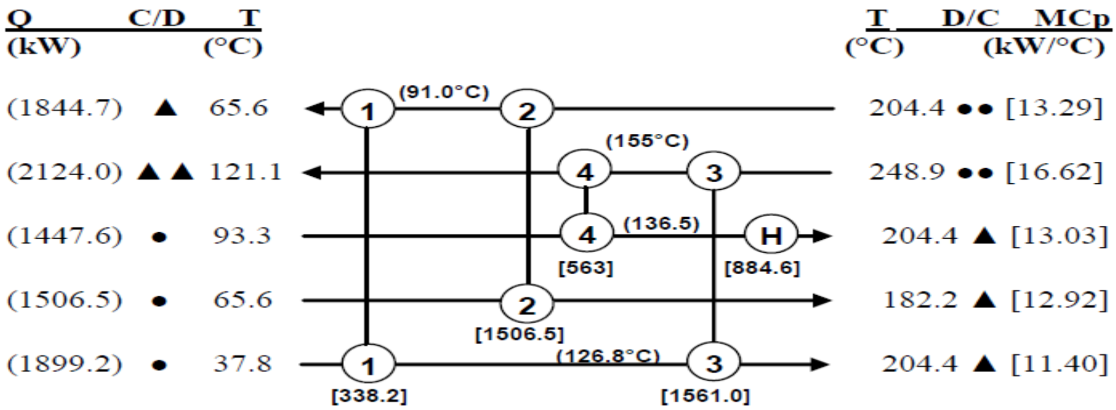

Fig. 10. Final solution of alternative (N)

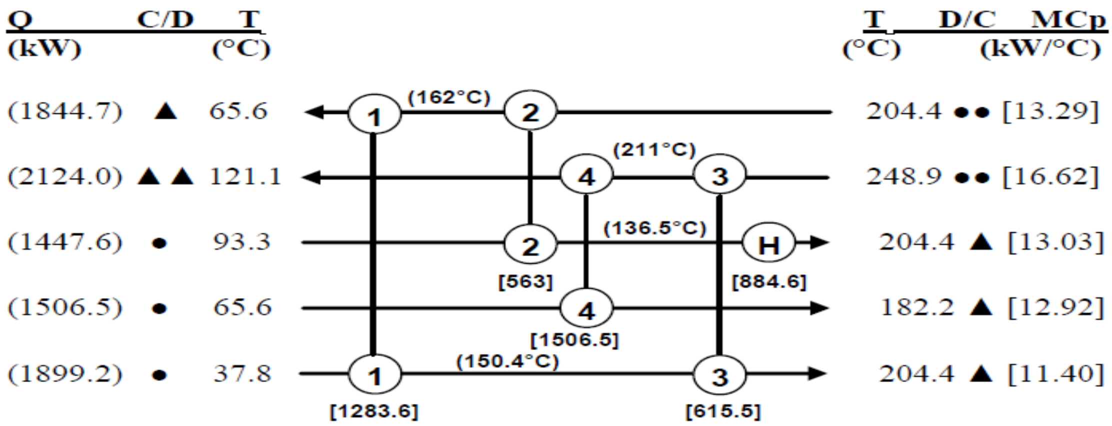

Fig. 11. Final solution of alternative (O)

6. Results and Discussion

The findings of this study demonstrate the effectiveness of the proposed multi-objective optimization model in identifying the optimal configuration for (HENs). In both cases studied, the TOPSIS method consistently identified the optimal outcome, confirming the model's ability to handle conflicting objectives successfully.

Table 9 compares the results of various studies that investigated the HEN of the H5SP1R example using different strategies, such as a dispersal strategy integrating controllability with operation design and a knowledge engineering process integrating controllability with HEN synthesis. HIDEN, an enforcement of the dispersal strategy, was also examined. Notably, alternative (K) showed a high index of structural control and closeness coefficient.

Prior methods focused only on the index of structural controllability as the decision parameter, favoring the maximum value as the optimal choice, despite its limitations when multiple solutions have equal values. In the 5SP1 case, the authors did not address this issue and relied on the highest value of (**I**$_{SC}$). Alternatives (N and O) yielded the same minimum values across the three previous approaches. In contrast, our TOPSIS paradigm, which incorporates several objectives such as irreversibility, thermal effectiveness, and the structural controllability index, yielded discrete and robust results for ranking the alternatives.

By incorporating multiple objectives and reconciling conflicting priorities, the multi-objective optimization model provides valuable insights into resource allocation. However, it is important to acknowledge that, like any analytical approach, the TOPSIS method has inherent limitations and potential drawbacks, such as its sensitivity to the normalization procedure and the assumption of equal importance for all criteria. Addressing these limitations requires implementing strategic measures, such as sensitivity analysis and incorporating weighting factors reflecting stakeholder preferences.

To further advance the field, future research should focus on exploring the scalability of the model and integrating advanced machine learning and artificial intelligence techniques to enhance its performance [23,24] . In conclusion, while the TOPSIS method serves as a valuable tool for optimizing heat exchanger networks, addressing its limitations through strategic measures will enhance its reliability and practical effectiveness in real-world applications.

Table 9
Results obtained by different methods for 5SP1 Case

Criterion		Authors			
Strategy		Distributed Strategy - Artificial intelligence (A.I) [17,19]	Distributed Strategy - Knowledge Approach (K.A) [20]	Hybrid Intelligent System (HIDEN) [21]	Present Work (TOPSIS)
MER (kW)		884.6	884.6	884.6	884.6
Decision Parameter			(I_{SC})		(F_i)
Alternatives	K	0.462	0.958	0.958	0.971
	L	0.429	0.917	0.917	0.947
	M	0.263	0.750	0.750	0.754
	N	0.172	0.083	0.083	0.067
	O	0.172	0.083	0.083	0.035

7. Managerial Implications

The managerial and practical implications of this study are significant, particularly for industries where optimizing (HENs) is critical. The proposed TOPSIS-driven methodology offers decision-makers a systematic tool to evaluate and select optimal HEN configurations tailored to their specific requirements.

By maximizing controllability, the approach facilitates tighter regulation of process variables against disturbances, enabling managers to maintain consistent output quality and operate closer to operational constraints safely. Enhanced controllability also facilitates easier integration of design and control, reducing the time and costs associated with control structure revisions.

Minimizing irreversibility helps managers improve resource efficiency and reduce exergy destruction, aligning with sustainability objectives and reducing energy expenses associated with irrecoverable heat losses. The exergy analysis also provides valuable insights into performance improvements required in different plant sections.

The thermal effectiveness analysis offers actionable input for managers regarding heat exchanger sizing and flow rates, enabling them to maximize heat recovery and minimize heating/cooling utility requirements, thereby capitalizing on waste heat availability.

The multi-criteria perspective provides managers with a robust framework to handle trade-offs between competing goals. By consolidating controllability, thermodynamic, and heat transfer parameters into a single optimization model, more reliable HEN decisions can be made, aligned with business priorities.

In summary, this research offers decision support for HEN synthesis, enabling managers to make data-driven decisions, optimize efficiency, and enhance process reliability. The practical insights can drive significant cost and performance improvements in industrial facilities.

8. Conclusion

In conclusion, this study introduces an innovative approach for optimizing (HEN) synthesis, with a primary focus on three pivotal objectives: the maximization of controllability, the minimization of irreversibility, and the maximization of overall effectiveness. Leveraging recent technological advancements and computational tools, our decision-making framework exerts a substantial influence on the selection of optimal substitutional choices, thereby profoundly shaping the resulting network configurations. The application of the TOPSIS method, while demonstrating effectiveness in systematically identifying enhanced network configurations, brings both advantages and disadvantages to the fore.

One notable advantage of TOPSIS is its capacity to offer a systematic and straightforward means of ranking alternatives based on multiple criteria. By taking into account both the similarity to the ideal solution and the similarity to the anti-ideal solution, TOPSIS provides a balanced perspective, proving particularly valuable in addressing intricate decision-making problems, such as those encountered in HEN synthesis.

However, it is essential to acknowledge the limitations of TOPSIS. The method assumes equal importance among criteria, which may not accurately reflect the varying significance of criteria in real-world scenarios. Furthermore, the sensitivity of TOPSIS to the choice of normalization methods for criteria can lead to divergent rankings based on the selected normalization technique. Additionally, TOPSIS does not inherently accommodate uncertainties in data, potentially posing challenges in situations where data precision is lacking or subject to variations.

Future direction of research can be incorporated through differential weighting of criteria based on stakeholder needs through analytic hierarchy process, integrating TOPSIS with machine learning techniques like neural networks for predictive capabilities and handling complexity. Explore opportunities to apply the TOPSIS optimization approach beyond HEN synthesis to other chemical process networks.

The model was validated by applying it to two established HEN synthesis case studies in literature, successfully identifying optimal configurations. The approach was evaluated by comparing final rankings against published results from prior techniques. Consistent identification of top alternatives was observed. Quantitative performance metrics like computation time, optimality gap, and result consistency across trials can further assess effectiveness.

In light of these considerations, while TOPSIS demonstrates its effectiveness in identifying enhanced HEN configurations, its advantages and disadvantages must be carefully weighed. Despite its limitations, our research underscores the potential utility of TOPSIS as a valuable decision support tool in the realm of HEN synthesis, providing systematic guidance for optimizing heat recovery, cost reduction, and alignment with energy and environmental regulations.

Author Contributions

Conceptualization, M.H., H.A.; methodology, M.H; investigation, M.H., H.A.; resources, M.H., H.A.; writing—original draft preparation, M.H.; writing—review and editing, M.H.; supervision, M.H; All authors have read and agreed to the published version of the manuscript.

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Conflict of interest
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Replication of results: The models as well as the optimization framework referred herein are available from the author upon request.

Appendix A
Intensity of Disruption Levels
The extent of disruption intensity is directly proportional to the deviation of output variables from their standard set points in response to input variable disturbances. Classifying the degrees of disturbance intensity at the network inlet based on the magnitude of input variable disturbances, three distinct levels can be identified, as proposed by [20]:

Level 1: Minor Disturbance	(●)
Level 2: Moderate Disturbance	(●●)
Level 3: Severe Disturbance	(●●●)

Quantifying disturbances is contingent upon the nature of the synthesis problem.

$$(\delta Qi\,) \cong \max\{\,\left| MCp_i \delta Ti^{S\,(+)} - \delta MCp_i^{(+)} (Ti_t - Ti_S) \right|, \left| MCp_i \delta Ti^{S\,(-)} - \delta MCp_i^{(-)} (Ti_t - Ti_S) \right. \quad \text{(A-1)}$$

Control Precision Levels
Heuristically, control precision levels for each output are categorized into those levels mentioned below, as outlined by [20]:

Level-1: low control precision	(▲)
Level-2: moderate control precision	(▲▲)
Level-3: high control precision	(▲▲▲)

Patterns of disturbance propagation
Disruptions have the potential to propagate across a pinch point within the network provided. The four patterns of propagation linguistically as described by [20]

Pattern-1: very severe propagation	(Through 0 or 1 process unit)
Pattern-2: severe propagation	(Through 2 process units)
Pattern-3: moderate propagation	(Through 3 process units)
Pattern-4: negligible propagation	(Through 4 or more process units)

Structural Controllability Index
Vector *D* encompasses all disturbances present within a network. Each element d_i in the *D* vector denotes a disturbance applied at the inlet of stream *i* in the network, and the vector is structured as follows:

$$D = \begin{bmatrix} d_1 \\ d_2 \\ \vdots \\ d_N \end{bmatrix} \tag{A-2}$$

Control Precision Vector C

Vector *C* delineates the necessary levels of control precision for all output variables. Each element c_j in the *C*-vector signifies the required control precision at the outlet of stream *j* within the network, and the vector is structured as follows:

$$C = \begin{bmatrix} C_1 \\ C_2 \\ \vdots \\ C_N \end{bmatrix} \tag{A-3}$$

Propagation Matrix R

A disorder diffuses across many disorder pathways impacts the stabilization of several output variables; the factor in matrix signifies a disorder that diffuses from the input *i* to the output *j* in the net; this matrix has the format of:

$$R = \begin{bmatrix} R_{1,1} & R_{1,2} \dots & R_{1,N} \\ R_{2,1} & R_{2,2} \dots & R_{2,N} \\ \vdots & \vdots & \vdots \\ R_{N,1} & R_{N,2} \dots & R_{N,N} \end{bmatrix} \tag{A-4}$$

Fuzzy Membership

As mentioned in the pre-realized diffusion style, a value can be self-specified to the R_{ij} input in matrix *R* as follows [20]:

$$R_{ij} = \begin{Bmatrix} 1.00, & pattern - 1\, propagation \\ 0.5, & pattern - 2\, propagation \\ 0.25, & pattern - 3\, propagation \\ 0.00, & pattern - 4\, propagation \end{Bmatrix}$$

Nomenclature

A.I	Artificial Intelligence
HENs	Heat Exchanger Networks
HIDEN	Hybrid Intelligent System
HTU's	Heat Transfer Units.
K.A	Knowledge Approach
MCDM	Multi-criteria Decision Making
MER	Minimum energy requirements
MILP	Mixed-Integer Linear Programming
MINLP	Mixed-Integer Nonlinear Programming
NIS	Negative ideal solution
NLP	Nonlinear Programming
PIS	Positive ideal solution
TOPSIS	Technique for Order Performance by Similarity to Ideal Solution
C^*	The thermal capacity of stream
C_h	Heat capacity of hot stream
C_c	Heat capacity of cold stream
D	Disturbance vector
d_i	Element of disturbance vector *D* of stream *i*

E_j	Effects of all patterns of disturbance of stream *j*
E_{tot}	Effects of all patterns of disturbance
Irr.	Irreversibility
I_{SC}	Index of structural controllability
N	Total number of streams
R	Disturbance propagation matrix
$R_{i,j}$	Element of disturbance propagation matrix *R*, representing disturbance propagation from the inlet of stream *i* to the outlet of stream *j*
Q_i	Heat duty of stream *i*
T_0	Ambient Temperature
T_{AM}	Logarithmic mean temperature difference
ΔT_{LMK}	Log mean temperature difference for interval K
T_{AMH}	The logarithmic mean temperature difference for hot streams
T_{AMC}	The logarithmic mean temperature difference for cold streams
ΔT_{max}	Fluid inlet temperature difference
Cp	Heat capacity flow rate of the streams
Cp_H	Heat capacity flow rate of hot streams
Cp_c	Heat capacity flow rate of cold streams
Cp_{min}	The smaller *Cp* in Cp_H and Cp_c
T	Temperature of streams
q_i	Stream duty on hot stream (*i*) in enthalpy interval K
q_j	Stream duty on cold stream (*j*) in enthalpy interval K
A	Heat exchanger area for vertical heat transfer required by interval
h_i and h_j	Film transfer coefficients for hot and cold stream including wall and fouling resistances
σ_i	Standard deviation of performance rating factor$\left(P_{1j}, P_{2j}, \dots \dots \dots P_{mj}\right)$ in the *R* matrix.
W_i	Objective weight
T_i^S	Source temperature of stream *i*
T_i^t	Target temperature of stream *i*
$\delta T_i^{S(+)}$	Deviation of the source temperature of stream *i* in the positive direction
$\delta T_i^{S(-)}$	Deviation of the source temperature of stream *i* in the negative direction
$\delta M_{Cpi}^{(+)}$	Deviation of the heat capacity flow rate of stream *i* in the positive direction
$\delta M_{Cpi}^{(-)}$	Deviation of the heat capacity flow rate of stream *i* in the negative direction
δT_i^t	Allowable deviation of target temperature of stream *i*
δQ_i	Heat duty absolute value of the deviation of stream *i*
ΔEx	Specific exergy

Superscripts

S	Source
t	Target

Subscripts

i	Stream *i*
j	Stream *j*
H	Hot streams
C	Cold streams

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