Section A-Research paper
ISSN 2063-5346

Optimum design parameters of spiral plate Heat exchanger using Tangent search algorithm.

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doi: 10.48047/ecb/2023.12.si6.369

Abstract

Spiral plate heat exchangers are anticipated to be energy-effective because of their widespread application throughout the petrochemical, pharmaceutical, and food production sectors. Given these constraints, the focus of this study is on optimizing heat exchanger performance. The objective function is to maximize the heat transfer efficiency of a spiral plate heat exchanger. The mathematical formulation of the issue takes into account the plate sizes, plate distances, and plate thicknesses. All are subject to the heat obligations, pressure drop constraints, and technical constraints of such setups. The Tangent search algorithm (TSA) is being researched as a potential new optimization method. The Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and Whale optimization were all investigated for comparison purposes. According to the findings, the TSA produced the most accurate result in the least amount of time.

Key words: Spiral plate heat exchanger, Tangent search method, Genetic Algorithm, Kruskal-Wallis analysis

INTRODUCTION

Heat exchangers may be found virtually everywhere in the industrial world since they are one of the most important components of nearly all chemical processes. These are the instruments that make it possible for heat to be transferred between two or more fluids[1]. There are three possible configurations for the transfer of heat: liquid-liquid, liquid-gas, and gas-gas. Heat exchangers can be utilized to either cool a fluid that is already hot or warm a fluid that is already cold, or they can do both simultaneously. Heat exchangers have a wide range of uses and can be found in places such as power plants, refineries, petrochemical industries, process industries, food and drug industries, and companies that deal with heating and air conditioning[2]. The processing of very viscous fluids flows with a high solid content, and flows that combine solid and liquid phases are some of the most common applications for spiral heat exchangers[3].

One of the costliest problems that can arise with heat exchangers is the need for cleaning after fouling, which can result in lost time as well as resources. As an illustration, the expenditures associated with fouling in the industries of the United States can reach up to 5 billion dollars annually.

The Spiral Plate Heat Exchanger (SPHE) holds a unique position of prominence among the several kinds of heat exchangers that are utilized in industrial settings for the purposes of heating and cooling fluids[4]. The structure of an SPHE is depicted in Figure 1; it is made up of two sheets that are rolled around a central rod, which results in the formation of two independent concentric channels. Further, it is possible to improve the velocity and heat transfer behavior by selecting a distance between the heat transfer surfaces that ranges from 5 to 50 mm. This kind of heat exchanger typically has a heat capacity that can reach up to 1 megawatt and a heat transfer surface area that can cover up to few hundred square meters in a single unit[5].

There is access to both the concurrent and the countercurrent trends that the flows take. The core of the heat exchanger is almost always where the hot fluid begins its journey, and it leaves through the outermost ring[6]. Because cold fluid can enter the system from either the center or the periphery, the choice that is made will result in either concurrent or countercurrent flows, depending on the situation. It cannot be denied that a countercurrent configuration provides superior performance in terms of heat transfer.

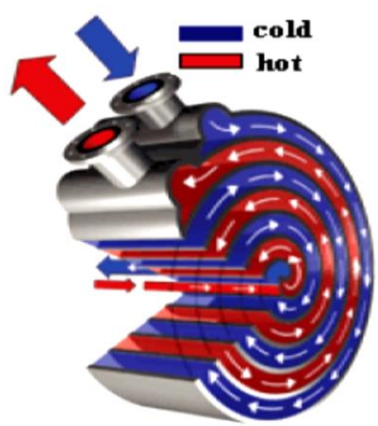

Fig. 1 Illustration of a Spiral Heat Exchanger[7]

Heat exchanger design is an extremely complicated mathematical and computer challenge since it involves the integration of several variables that rely on various values and ranges (depending on the mathematical formulation used). The physical model is organized by the variables that define the model, and hence various modern design methodologies use computer simulations to test the design in a virtual setting. The work [8] in stands out among the methods proposed in the specialized literature because it presents a sizing method whose objective function is to reduce the maximum allowable pressure to obtain the smallest possible spiral plate heat exchangers while still respecting a previously established heat transfer coefficient. The appropriate heat exchanger size is determined in [9] using a combination of traditional methods and simulations. Due to the nonlinear nature of the design of these components, optimization approaches and procedures have been developed and have shown to be useful in finding solutions to this kind of issue. These [10] includes, but is not limited to, heuristic and metaheuristic methods, linear and nonlinear approaches, and commercial optimization software. Many mathematical formulations in various research domains have been solved using these methods in recent years.

To cut down on production costs, the authors[10] used the multi-objective non-dominated sorting genetic algorithm (NSGA-II) to optimize the heat transfer and pumping power of a tube and shell heat exchanger. Using the NSGA-II, they were able to provide a precise and fast answer that satisfies the requirements of pressure drop and heat duty. The cost of manufacturing and running a shell and tube heat exchanger is reduced by almost 5% with a low computing cost using a Particle Swarm Optimization (PSO) method in [11]. The programme takes into account a set of limitations imposed by pressure drops and heat duty. In [12], a Wind Turbine Optimization (WTO) algorithm is examined to see whether it may reduce the expenses of running and building a spiral plate heat exchanger. There would therefore be an annual cost savings of 19.3 percent. The authors of [13] suggest using a multi-objective optimization approach to get the size of a small-scale model of a thermoacoustic refrigerator; their design challenge included interdependent factors such as the ideal stack size and plate spacing. The General Algebraic Modelling System (GAMS) was used to design and solve their nonlinear mathematical model, and an optimum Pareto front was used to choose the best solution to the issue. Another study by the same group of researchers, [14] optimized the stack's size to maximize efficiency, minimize heat loss, and maintain a constant output power. In order to determine the answer to the issue within the given limitations, they additionally used GAMS and Pareto's solution model. Adsorption is used to lower the overall hardness, alkalinity, and chemical demand for oxygen in a wastewater treatment facility, as described by authors [15].The procedure was controlled by the amount of adsorbent used and the duration and velocity of mixing. Responsive Surface Methodology (RSM) and GAMS were utilized to solve the mathematical model of the issue. On the other hand, GAMS offered a single optimum solution of greater quality than those produced by RMS, proving that GAMS is the quickest and most efficient approach.

1.1 Main novelties and contributions

According to the author's understanding and the analysis of the relevant literature, a number of methodologies have been employed to identify the design parameters of spiral heat exchanger. The purpose of this study is to develop a new approach for design parameter identification. Tangent search algorithm (TSA) has been used to extract the unknown key design parameters of a spiral heat exchanger in order to evaluate the steady-state under diverse operating conditions. The ability to switch between $-\infty$ and ∞, as well as the function's periodicity, provide a decent balance between exploration and intensification, making this a useful function for finding optimal search spaces. The proposed method has some significant distinctions from prior methods. The TSA algorithm provides a rapid convergence rate and avoids the issue of local optimums, while providing superior outcome in the exploitation and exploration stages.

PROBLEM FORMULATION AND MATHEMATICAL DESIGN

The analytical issue is the design of a counter-flow spiral plate heat exchanger, and the corresponding mathematical model was created using [16]. The first step in any process is to determine the system's heat duty (Q) using the equation (1).

$$Q = \left[\dot{m}C_p(T_o - T_i)\right]_h = \left[\dot{m}C_p(T_i - T_o)\right]_c \qquad (1)$$

where $\dot{m}$ is the mass flow rate, C_p is the specific heat of the fluid, T_i and T_o are the fluid input and outlet temperatures. The heated fluid will be denoted by the subindex h, and the cold fluid by the subindex c. Similarly, Q may be determined by using Eq. (2).

$$Q = UA\Delta T_{LMTD} \qquad (2)$$

where U is the overall heat transfer coefficient, which is defined in Eq. (3).

$$U = \left(\frac{1}{h_h} + \frac{t}{k_p} + \frac{1}{h_c} + R_f\right)^{-1} \qquad (3)$$

where h_h, and h_c are the convective heat transfer coefficients of the hot and cold fluid, respectively; k_p, the thermal conductivity of the exchange wall; t, its thickness; and R_f, the fouling factor.

Also

$$\Delta T_{LMTD} = \frac{(T_{hi} - T_{co}) - (T_{ho} - T_{ci})}{ln\left(\frac{T_{hi} - T_{co}}{T_{ho} - T_{ci}}\right)} \qquad (4)$$

And

$$A = 2 * l * h \qquad (5)$$

Where A is the heat transfer area and l and h is the total length and the height of the exchanger respectively.

The average diameter of the spiral is described (R_m) in Eq. (6) and given by the maximum and minimum diameter of the spiral.

$$R_m = \frac{R_{min}+R_{max}}{2} \tag{6}$$

The average hydraulic diameter (D_h) is defined by Eq. (7), where S is the spacing of the channels through which the fluid will circulate. This hydraulic diameter is approximately two times the spacing of the channel.

$$D_h = \frac{4(flow\ area)}{(wetted\ perimeter)} = \frac{2hS}{h+S} \tag{7}$$

Equation (8) represents Nusselt number correlation proposed by Minton [15] for the spiral plate heat exchangers. From the calculated Nusselt number, the convective heat transfer coefficient is calculated.

$$Nu = \frac{hD_h}{k} = 0.0239\left(1+5.54\frac{D_h}{R_m}\right)Re^{0.806}Pr^{0.268} \tag{8}$$

Where Re is the Reynold's number $\left(Re = \frac{\dot{m}D_h}{hS\mu}\right)$ and Pr is the Prandtl number $\left(Pr = \frac{Cp\mu}{k}\right)$.

Pressure drop (ΔP) is determined in accordance with Darcy–Weisbach's expression, as in Eq. (9),

$$\Delta P = 0.000850\rho(LV^2) \tag{9}$$

The outer diameter of the spiral is determined by Eq. (13), where C is the diameter of the core.

$$D_s = (1.28L(S_h+S_c+2t)+C^2)^{1/2} \tag{10}$$

The set of constraints of the problem is given by Eqs. (11) and (12), which limit the pressure drop based on the calculation of Eq. (9), being compared to the ΔP_{max} (6.894 kPa) and the required heat expressed in Eq. (1), which is compared to the calculation of Eq. (2).

$$\Delta P_{h,c} - \Delta P_{max} = 0 \tag{11}$$
$$Q - UA\Delta T_{LMTD} = 0 \tag{12}$$

Such restrictions are required to confine the problem and prevent infeasible solutions because, as each limitation is penalized, the search space is constrained and the algorithm is forced to give a feasible solution.

The objective function F, is defined as

$$Objective\ function, F = U + (P_1 + P_2) \tag{13}$$

Where P_1 = *maxima of* $(0, \Delta P_{h,c} - \Delta P_{max})$ *and* P_2 = *maxima of* $(0, Q - UA\Delta T_{LM})$

Subject to constraints

$0.5 \leq h(m) \leq 1.5;\ 10 \leq l(m) \leq 20; 0.005 \leq S(m) \leq 0.032\ and\ \ 0.0032 \leq t(m) \leq 0.008;$

TANGENT SEARCH ALGORITHM

The fundamental building block of the Tangent Search Algorithm (TSA)[17] is the tangent function, a very elementary mathematical operation. The ability to switch between -∞ and ∞, as well as the function's periodicity, provide a decent balance between exploration and intensification, making this a useful function for finding optimal search spaces. In the TSA algorithm, all motion equations are driven by a global step of the type "step*tan(θ)", where the tangent function fulfills the role of flight function as in the classical flight function; for convenience, we refer to this as tangent flight.

The majority of optimization algorithms, whether derivative-based or derivative-free, use the following like descent equation:

$$X^{i+1} = X^i + step * d \tag{14}$$

Where *step* is the amount of a move and *d* is the direction of the motion, the distinction resides in how step is computed. The derivative-based approaches employ Gradient or Hessian information to calculate this step, while the free derivative methods, such as metaheuristics, use a stochastic step to converge to global optima. A good algorithm is one with a good step-size, where a large value favors exploration and a small value favors exploitation. An effective optimization algorithm should have a better balance between intensification and exploration. Too much intensification causes the algorithm to converge too fast to a local minimum, while too much exploration causes the process to be too sluggish and diverge sometimes. TSA consists of three major components to achieve this objective: intensification, exploration, and escape local minima components.

The objective of the exploration phase is to thoroughly investigate the search space and identify the most promising possibilities. Although the intensification component is intended to steer the search process toward the best existing solution in the population, the expansion component is used to expand the search space. In order to prevent being stuck in a local minimum, the escape local minima process is performed at each iteration to a random search agent (solution).

Figure 2 depicts the suggested population-based metaheuristics flowchart.

Section A-Research paper
ISSN 2063-5346

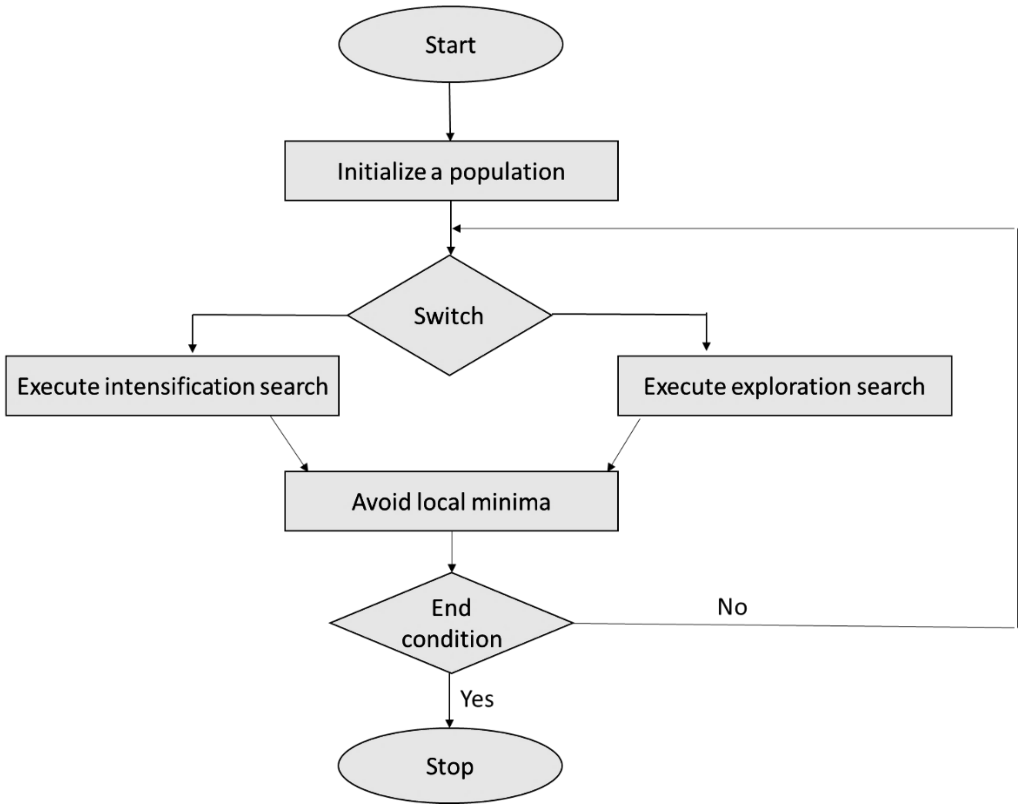

Fig. 2 Flow chart of Tangent search algorithm[17]

Initialize a population

Similar to other population-based optimization techniques, TSA generates a random beginning population inside the solution space's borders. The initial solution is equally dispersed over the search space and is calculated using the following equation:

$$X_o = lb + (ub - lb) * rand(D) \tag{15}$$

where lb and ub are the problem's lower and upper bounds, rand produces uniformly distributed random numbers in the range [0, 1], and D is the problem's size.

Intensification search

In the intensification search, TSA first does a random local walk led by the following equation (Eq. 3), and then replaces some variables of the found solution with the values of the corresponding variable in the current optimum solution using Equation 4. The fraction of replacement variables is 20% for issues with dimensions more than 4, and 50% for problems with dimension less than or equal to 4.

$$X_i{}^{f+1} = X_i{}^f + sep * \tan(\theta) * (X_i{}^f - optS_i{}^f) \tag{16}$$

$$X_i{}^{f+1} = optS_i{}^f ; if\ varaible\ i\ is\ selected \tag{17}$$

Thus, the produced solution ${X_i}^{f+1}$has a similarity percentage of less than 50% with the best existing solution, which helps to improve the present solution locally.

Each obtained solution X is replaced by the following equation if its values overflow the bounded conditions.

$X(X < lb) = rand * (ub - lb) + lb \; or \; X(X > lb) = rand * (ub - lb) + lb$
(18)

Exploration search

In contrast to local search approaches, the metaheuristics-based population has a high exploratory capacity due to the global random walk. In this technique, TSA creates a global random walk using a product of variable step size and tangent flight. The tangent function aids in effectively exploring the search space. Indeed, θ close to pi/2 will make the tangent value larger, and the resulting solution will be distant from the present solution, but θ close to 0 will give the tangent function small values, and the resulting solution will be close to the existing solution. Thus, the following exploratory search equation combines the global and local random walks.

${X_i}^{f+1} = {X_i}^{f} + step * \tan(\theta)$ (19)

Parameters explanation

P_{switch}, P_{esc}, and step, θ are the primary parameters utilized to emphasis exploitation and exploration search in TSA's search algorithm. The switching parameter P_{switch} [0,1] controls the balance between local and global random walks; the second parameter, P_{esc}[0,1], controls the probability of escape procedure. In descent techniques, the parameter step serves as the step-size parameter, directing and emphasizing the exploitation and exploration of the search space. TSA employs a variable step-size in order to effectively converge to the optimal solution and prevent accuracy loss.

Initially, TSA uses a high step-size, but as the search process progresses, the step-size lowers nonlinearly with each iteration. This size-adaptive activity aids TSA in striking a balance between exploration and exploitation. In addition to having a significant effect on the step-size, the tangent flight imparts oscillatory and periodic behavior. TSA employs a nonlinear decreasing technique for the adaptive step size based on the logarithmic function to modify the exploitation and intensification search processes. The logarithm function is a slow function that aids in the maintenance of a close convergence.

RESULTS AND DISCUSSION

To assess the efficacy of the Tangent search algorithm, other meta heuristic algorithms such as Particle Swarm optimization, Grey wolf optimization, Whale optimization algorithm, Ant colony optimization and Artificial bee colony optimization were also studied and compared. To obtain a fair comparison, each algorithm was conducted 20 times independently, with a maximum of 1000 iterations. Algorithms are executed in MATLAB R2021a and works-on Intel Core i7 with 5GHz CPU and 16GB RAM. Table 1 shows the parameters of the competing algorithms (default settings).

Table 1 Operational criterion of all studied algorithms

Algorithms	operational criterion
Particle Swarm optimization (PSO)[18]	Population (Swarm) size = 100; weight, w = 1; Personal learning coefficient, c1 = 1.5; Global learning coefficient, c2 = 2.0; Maximum iterations =1000;
Grey wolf optimization (GWO)[19]	Wolves number = 100; Coefficient set (default) 2.0; Maximum iterations =1000;
Whale optimization algorithm (WOA)[20]	Whales number = 100; a = -1 to -2 (default); Maximum iterations =1000;
Ant colony optimization (ACO)[21]	Ant Number (population size) = 100; Intensification factor, q = 0.5; Distance deviation ratio, zeta = 1; Maximum iterations =1000;
Artificial bee colony optimization (ABC)[22]	Colony size (population size) = 100; Acceleration coefficient, a = 1; Maximum iterations =1000;
Tangent search algorithm (TSA)[17]	P_{switch} = 0.3 & the probability of the escape Procedure is P_{esc} = 0.8.

Table 2 shows the values of the properties used in this study as reported in Minton's work.

Table 2 Operational parameters[6]

parameters	Hot stream	Cold stream
Mass flow *m* (kg / s)	0.784	0.747
Inlet temperature T_i (K)	473.15	333.15
Outlet temperature T_o (K)	393.15	423.55
Density ρ (kg/m^3)	843	843
Specific heat *Cp* (J/kg K)	2973	2763
Viscosity μ (Pa s)	0.0034	0.008
Thermal conductivity *k* (W/m K)	0.348	0.322

Fouling resistance R_f (m^2K / W)	1.0567x10^{-4}
Thermal conductivity k_p (W/m K)	14.53
Maximum pressure drop ΔP_{max} (kPa)	6.894

Table 3 represents the optimum design parameters obtained by different algorithms. On comparison its clearly visible that the parameters obtained by the Tangent search algorithm are in close agreement with the report work of Minton's study. In terms of computational time, TSA demonstrates the shortest calculation time to optimize the design parameters, which is 0.18sec, which is much shorter than applying any other metaheuristic algorithm.

Table 3 Optimum design values obtained by different algorithms

Variables	Minton's design[6]	PSO	GA	WOA	ACO	ABC	TSA
h (m)	0.61	0.592	0.607	0.522	0.557	0.544	0.511
l (m)	12.74	12.821	12.87	12.75	14.75	13.01	14.22
S (m)	0.0063	0.00573	0.00585	0.00627	0.00623	0.00644	0.0063
t (m)	0.0032	0.00319	0.00313	0.00389	0.00317	0.0032	0.00322
Computational time (s)	----	0.45	0.56	0.77	0.63	0.53	0.28

Further, figure 3 compares both the overall heat transfer coefficient as well the heat duty obtained by different algorithms. The results indicated that the proposed algorithm TSA, obtained the best feasible solution among different algorithms studied, with optimum overall heat transfer coefficient (260.04 W/m^2 K), which is 18.2% more than the original calculations. This is because the original design didn't use an optimization technique or method to figure out the size of the exchanger. TSA also meets the heat duty because its configuration transfers 192.22 kW of heat and the pressure drops of the hot and cold fluids reach 1.5 kPa and 1.3 kPa, respectively, which is well with the maximum permissible limits. These results also show that TSA is a quick and effective way to find an optimal solution that meets all the problem's constraints and requirements at a least computational timing.

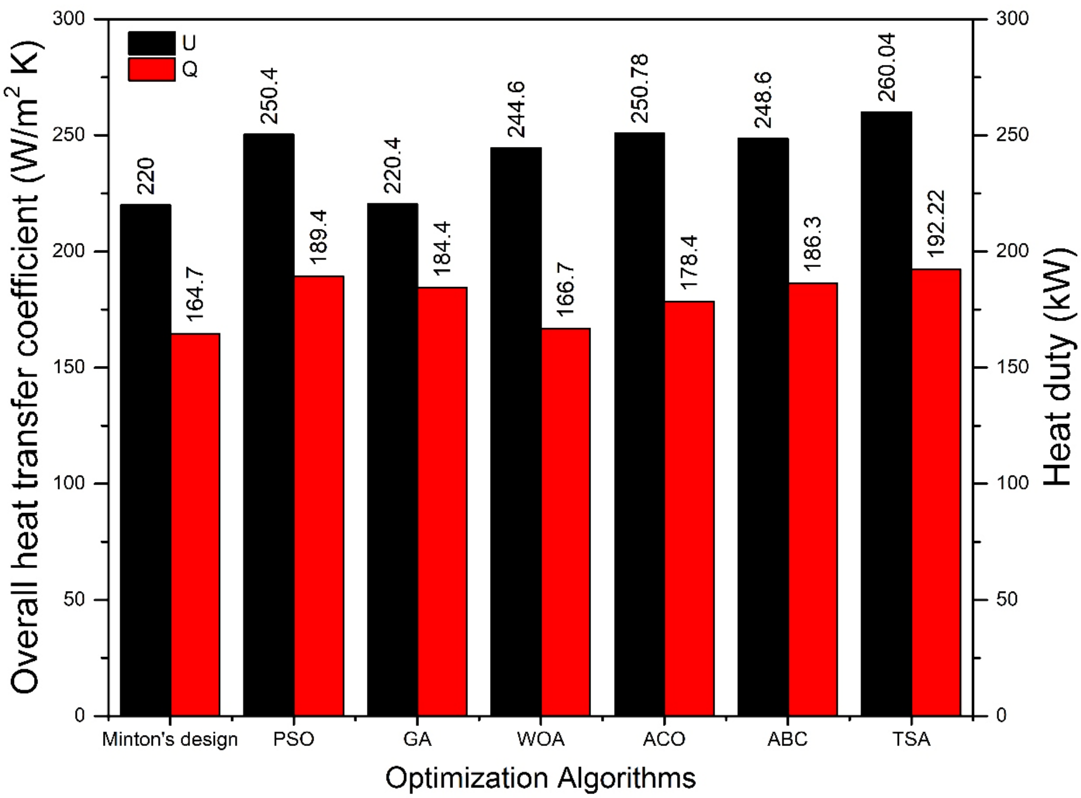

Fig. 3 Overall heat transfer coefficient and heat duty for different algorithms

Non-parametric statistical tests[23], such as the Wilcoxon rank sum test and the Kruskal-Wallis analysis of variance (ANOVA), are used to determine the significance level of all studied methods. Table 4 displays the 5% p-values derived from the Wilcoxon test. This test demonstrates that TSA's significance with other algorithms is less than 0.05. The Kruskal Wallis ANOVA test of TSA with other algorithms is shown in Table 5. Chi-square displays probability values. Figure 4 depicts a Kruskal-Wallis ANOVA comparison of the mean ranking of TSA and other algorithms. This demonstrates the superior ranking of TSA based on the improved accuracy and repeatability of the results. Based on the foregoing validation, it can be concluded that TSA facilitates the achievement of the required optimization solution.

Table 4 Wilcoxon rank sum test ($p \leqslant 0.05$)

Compared Algorithms	p-values
TSA vs PSO	2.15E-18
TSA vs GA	2.11E-20
TSA vs WOA	1.33E-14
TSA vs ACO	5.85E-22
TSA vs ABC	2.05E-21

Table 5 Kruskal Wallis ANOVA test

Sources	SS (sum of squares)	*Df* (Degree of freedom)	MS (Mean square)	Chi-square	Prob>Chi-square
Columns	1.07E+07	4	42645.2	147.89	1.65E-24
Error	2.39E+07	294	9103.3	--	--
Total	2.06E+07	399	--	--	--

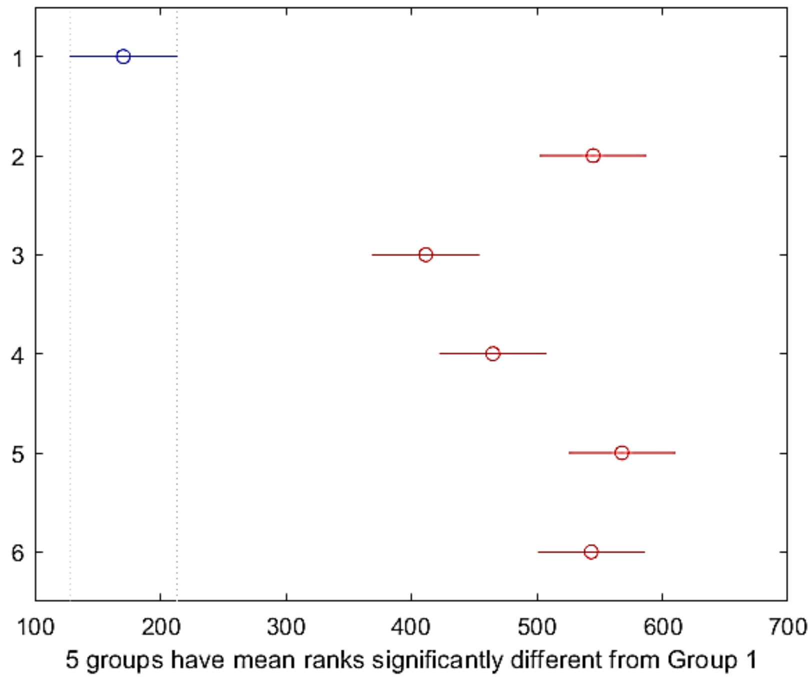

Fig. 4 Multi Comparison of mean ranking using Kruskal Wallis ANOVA test

CONCLUSION

Due to the extensive number of system variables and characteristics, the challenge of sizing heat exchangers is a laborious one. Finding an acceptable, cost-effective, and efficient design requires many hours of manual iteration. Hence, designers should use optimization methods to change input parameters and the fluid's characteristics in order to efficiently tackle each unique challenge.

This study advocated the use of Tangent search algorithm, which proved to be a rapid and effective optimization technique for addressing nonlinear problems of this sort. It presented a unique solution and yielded the best results when compared to other algorithms.

Maximizing the total heat transfer coefficient increases the exchanger's efficiency and permits a higher heat transfer rate; consequently, a smaller transfer area is required. To define the exchanger and its construction characteristics, future work will incorporate a model that integrates the cost of the exchanger (including its useful life forecast).

Section A-Research paper
ISSN 2063-5346

Authors' contributions: Entire work done in manuscript i.e., conception and design; drafting of the manuscript is carried out by Amanpreet Sandhu and simulation results and critically analyzing from intellectual content writing is carried out by Parminder Singh.

Funding: The author declares that there was no sponsorship, nor any sort of funding required for this work.

Availability of data and materials: All data generated or analyzed during this study are included in this article.

Acknowledgement: The authors declares that there was no sponsorship, nor any sort of funding required for this work.

Nomenclature

$\dot{m}$	Mass flow rate (kg/s)
C_p	Specific heat (J/kg.K)
T	Temperature
U	Overall heat transfer coefficient (Wm^2.K)
A	Heat transfer area
h	Height of the spiral heat exchanger
k	Thermal conductivity (W/mK)
R_f	Fouling factor
l	Length of the spiral heat exchanger
S	Spacing spacing of the channels
ΔP	Pressure drop
Re	Reynold's number
Pr	Prandtl number
D_s	outer diameter of the spiral
$\mathbf{C}$	diameter of the core

Greek Symbols

μ	Viscosity of the fluid
ρ	Density of the fluid
i	Inlet stream
o	Outlet stream
c	Cold stream

Abbreviations

LMTD	Log mean temperature difference
TSA	Tangent search algorithm
GA	Genetic algorithm
PSO	Particle swarm optimization
WOA	Whale optimization algorithm

ABC Artificial bee colony optimization

ACO Ant colony optimization

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