Systems & Control Transactions

Research Article - Peer Reviewed Conference Proceeding
ESCAPE 35 - European Symposium on Computer Aided Process Engineering
Ghent, Belgium. 6-9 July 2025
Jan F.M. Van Impe, Grégoire Léonard, Satyajeet S. Bhonsale, Monika E. Polańska, Filip Logist (Eds.)

PSE PRESS

Optimization Of Heat Exchangers Through an Enhanced Metaheuristic Strategy: The Success-Based Optimization Algorithm

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ABSTRACT

The optimization of shell-and-tube heat exchangers (STHEs) is critical for improving energy efficiency, reducing operational costs, and mitigating environmental impacts in industrial applications. This study evaluates the performance of the Success-Based Optimization Algorithm (SBOA), a novel metaheuristic strategy inspired by behavioral patterns in success perception, against seven established algorithms—Cuckoo Search, Differential Evolution (DE), Grey Wolf Optimization (GWO), Jaya Algorithm, Particle Swarm Optimization, Teaching-Learning Based Optimization, and Whale Optimization Algorithm—for minimizing the total annual cost (TAC) of STHE designs. Using the Bell-Delaware method, the optimization framework incorporates eleven decision variables, including geometric and operational parameters, subject to thermo-hydraulic constraints. A penalty function method enforces feasibility by dynamically adjusting constraint weights. Statistical analysis of 30 independent runs reveals that DE achieves the lowest mean TAC (6,090 USD/year) with minimal variability (SD = 22.57), while GWO attains the best median TAC (6,076 USD/year). Although SBOA identifies competitive solutions (minimum TAC = 6,074 USD/year), its high standard deviation (270.66) underscores inconsistency in convergence.

Keywords: metaheuristic optimization, Success-Based Optimization algorithm, shell-and-tube heat exchangers, Bell-Delaware method.

INTRODUCTION

The optimization of shell-and-tube heat exchangers (STHEs) plays a significant role in enhancing energy efficiency, reducing operational costs, and minimizing environmental impacts across various industries, including petrochemicals, power generation, and HVAC systems. STHEs are favored for handling high pressures and temperatures while maintaining an effective balance between heat transfer area and spatial footprint. However, designing an optimal STHE involves managing a set of thermo-hydraulic equations and multiple decision variables, such as tube diameter, baffle spacing, deflector configuration, and the number of tube passes [1, 2].

Traditional deterministic optimization methods, including MINLP and algorithms like BARON and DICOPT, have been widely employed to address these design challenges. These methods rely on mathematical programming and gradient-based techniques to provide precise solutions with rapid convergence for convex problems. Despite their effectiveness, deterministic approaches encounter limitations when applied to real-world scenarios characterized by non-linearity, multiple local optima, and mixed discrete-continuous variables. Additionally, the dependency on explicit mathematical models difficult their applicability when utilizing commercial simulators like Aspen Plus® or HYSYS®, which do not always offer direct mathematical formulations of the design problems.

Although this study employs an explicit model based on established thermo-hydraulic equations (e.g., Bell–Delaware method, pressure-drop correlations), the complexity arises from (a) mixed discrete-continuous decision variables and (b) non-convex behavior that can lead to multiple local optima. While deterministic solvers, in principle, handle nonlinear mixed-integer problems, preliminary attempts indicated considerable computational effort and occasional convergence to suboptimal solutions, depending on initial guesses.

Metaheuristic optimization algorithms present an alternative approach capable of handling the inherent complexities of STHE design. Algorithms such as Genetic Algorithms (GAs), Particle Swarm Optimization (PSO), Grey Wolf Optimization (GWO), and Differential Evolution (DE) have been applied to optimize STHE configurations by balancing exploration and exploitation within complex, high-dimensional search spaces [3]. These algorithms effectively avoid local optima and adapt to various problem landscapes without the need for gradient information, making them suitable for practical optimization tasks where traditional methods fall short.

The wide variety of metaheuristic algorithms introduces opportunities and challenges in selecting the most appropriate method for specific STHE optimization problems. The NFL Theorem's [4] implications extend to practical engineering challenges, where algorithm performance hinges on problem-specific features such as dimensionality, constraint types, and the balance between discrete and continuous variables. Recent advances in metaheuristics have introduced hybrid and adaptive strategies to address these challenges, yet a systematic comparison of their efficacy in STHE optimization remains underexplored. This study bridges this gap by rigorously testing SBOA, a behaviorally inspired algorithm, against seven benchmark methods. By integrating dynamic sub-populations and probabilistic exploration-exploitation mechanisms, SBOA aims to balance global search capabilities with local refinement—a critical requirement for complex STHE design problems.

This study focuses on applying and comparing the performance of the Success-Based Optimization Algorithm (SBOA) with several established metaheuristic algorithms—Cuckoo Search (CS), Differential Evolution (DE), Grey Wolf Optimization (GWO), Jaya Algorithm (JAYA), Particle Swarm Optimization (PSO), Teaching-Learning Based Optimization (TLBO), and Whale Optimization Algorithm (WOA)—in the optimization of STHE designs. The research aims to identify effective strategies for minimizing the total annual cost (TAC) while adhering to operative and geometrical constraints. The comparative analysis seeks to provide insights into the strengths and limitations of each algorithm, thereby assisting practitioners in selecting the most suitable optimization tool for their specific heat exchanger design needs.

METODOLOGY

The Success-Based Optimization Algorithm

The SBOA was developed with initial inspiration drawn from psychological studies on human perceptions of success and failure [5]. According to Frieze and Weiner [6], an individual's success in performing an activity is influenced by personal ability, applied effort, task difficulty, and luck. Building on these insights, SBOA integrates behavioral patterns that prioritize successful solutions while maintaining diversity within the population to prevent premature convergence.

SBOA begins by generating an initial population of candidate solutions. Each candidate solution $x_{i,j}$ is represented within a matrix X of size $\mathrm{n} \times \mathrm{m}$, where n is the number of candidate solutions and m is the number of decision variables. The initial candidate solutions are generated randomly within the defined lower (lb) and upper (ub) bounds for each decision variable using the equation 1.

$$x_{i,j} = lb_j + \mathrm{rand}(0,1) \cdot (ub_j - lb_j), \quad i = 1, \dots, n; \quad j = 1, \dots, m \tag{1}$$

Each candidate solution is evaluated using the objective function f_{obj}, resulting in a fitness vector F, shown in equation 2.

$$\mathrm{F} = \left[f_{\mathrm{obj}}(X_1), f_{\mathrm{obj}}(X_2), \dots, f_{\mathrm{obj}}(X_n)\right] \tag{2}$$

The SBOA utilizes two sub-populations of influence, spA and spB, to guide the search process.

- Sub-population *spA***:** This sub-population consists of the top three candidate solutions based on fitness, shown in equation 3.

$$spA = \begin{bmatrix} x_{spA1,1}, & \cdots & x_{spA1,j}, & \cdots & x_{spA1,m} \\ x_{spA2,1}, & \cdots & x_{spA2,j}, & \cdots & x_{spA2,m} \\ x_{spA3,1}, & \cdots & x_{spA3,j}, & \cdots & x_{spA3,m} \end{bmatrix} \tag{3}$$

- Sub-population *spB*: The composition of *spB* varies dynamically. Initially, it includes candidates ranked between the best solution and those near the population mean. As the algorithm progresses and diversity decreases, a fixed number of individuals are assigned to *spB* to maintain exploration capabilities.

A probability criterion $r \leq C_{p1}$ determines whether new candidate solutions are influenced by *spA* or *spB*, where r is a random number between 0 and 1.

When $r \leq 1C_{p1}$, new candidate solutions are generated using *spA* as in equation 4:

$$G_j = spA_{1,j} + D_1 \cdot (2r2_j - 1) \cdot |(2r3_j - j) \cdot (spA_{\text{rand},j} - X_{i,j})| \quad (4)$$

Here, D_1 decreases linearly from 1 to 0 over the iterations, facilitating the transition from exploration to exploitation. The new candidate solution GG replaces the current solution X_i only if $f_{obj}(G) \leq f_{obj}(X_i)$.

When $r > 1C_{p1}$, the updating process leverages *spB* to enhance exploration. Two strategies are employed based on another probability criterion $r \leq 1C_{p2}$, if it is satisfied equation 5 is used, otherwise equation 6 is employed.

$$X_{i,j}^{t+1} = X_{i,j}^{t} + D_2 \cdot (2r4_j - 1) \cdot (2r5_j) \cdot (spB_{\text{rand},j} - X_{i,j}^{t}) \quad (5)$$

$$X_{i,j}^{t+1} = X_{i,j}^{t} + D_2 \cdot (2r4_j - 1) \cdot (2r5_j) \cdot (spB_{\text{avg},j} - X_{i,j}^{t}) \quad (6)$$

In both cases, D_2 decreases linearly from 1 to 0, promoting finer search as iterations proceed.

Application to STHE Optimization

The SBOA was applied to optimize the design of shell-and-tube heat exchangers using the Bell-Delaware method. The optimization problem involves eleven decision variables:

Continuous Variables:

- Shell Internal Diameter (D_s).
- Outer Tube Diameter (d_o).
- Central Baffle Spacing ($L_{b,c}$).
- Inlet and Outlet Baffle Spacing ($L_{b,i}, L_{b,i}$).
- Diametral Gap between Shell and Baffles (δ_{sb}).
- Diametral Gap between Tubes and Baffles (δ_{tb}).
- Outer Diameter of Tube Bundle (D_{otl}).

Discrete Variables:

- Tube Pitch (P_t):
- Tube Layout Angle (TL)
- Baffle Cut Percentage (B_c)
- Number of Tube Passes (N_p)

The objective is to minimize the Total Annual Cost (TAC), which comprises the annualized fixed cost (C_{fix}) and the operating cost (C_{op}), as shown in equation 7.

$$TAC = C_{\text{fix}} + C_{\text{op}} \quad (7)$$

The optimization problem is subject to constraints ensuring operational and geometrical feasibility, including limits on pressure drops, fluid velocities, and tube length, as described in equations 8-13.

$$\min_x \quad \text{TAC}(x) \quad (8)$$

subject to:

$$\Delta P_t \leq \Delta P_{\max,t} \quad (9)$$

$$\Delta P_s \leq \Delta P_{\max,s} \quad (10)$$

$$v_{\min,t} \leq v_t \leq v_{\max,t} \quad (11)$$

$$\frac{L}{D_s} \leq 15 \quad (12)$$

$$lb_i \leq x_i \leq ub_i \quad (13)$$

Where ΔP_t and ΔP_s are the pressure drops on the tube and shell sides, v_t is the fluid velocity in the tubes, L is the tube length, D_s is the shell diameter, lb_i and ub_i are the lower and upper bounds for the decision variables, and x is the vector containing the eleven decision variables shown in Tables 1 and 2, where their limits and allowed values are displayed.

Table 1. Limits for continuous design variables.

Design Variable	Symbol	Lower Limit	Upper Limit
Shell Internal Diameter	D_s	300 mm	1,500 mm
Outer Tube Diameter	d_o	6.35 mm	50.8 mm
Central Baffle Spacing	$L_{b,c}$	$0.2D_s$	$0.55D_s$
Inlet and Outlet Baffle Spacing	$L_{b,i}, L_{b,o}$	$L_{b,c}$	$1.6L_{b,c}$
Diametral Gap between Shell and Baffles	δ_{sb}	$0.01D_s$	$0.1D_s$
Diametral Gap between Tubes and Baffles	δ_{tb}	$0.01d_o$	$0.1d_o$
Outer Diameter of Tube Bundle	D_{otl}	$0.8(D_s - \delta_{sb})$	$0.95(D_s - \delta_{sb})$

Table 2. Allowed values for discrete design variables.

Design Variable	Symbol	Allowed Values
Tube Pitch	P_t	$1.25d_o, 1.5d_o$
Tube Layout Angle	TL	$30°, 45°, 90°$
Baffle Cut Percentage	B_c	25%, 30%, 40%, 45%
Number of Tube Passes	N_p	1, 2, 4

To manage constraints during the optimization process, a penalty function method is applied. This approach incorporates penalty terms into the objective function to account for any constraint violations. The modified objective function is expressed as equation 14.

$$\begin{aligned} min \quad \mathrm{TAC}(x) &+ \lambda_1\, max\left(0, \Delta P_t - \Delta P_{\max,t}\right) \\ &+ \lambda_2\, max\left(0, \Delta P_s - \Delta P_{\max,s}\right) \\ &+ \lambda_3\, max\left(0, v_t - v_{\max,t}\right) \\ &+ \lambda_3\, max\left(0, v_{\min,t} - v_t\right) \\ &+ \lambda_4\, max\left(0, \frac{L}{D_s} - 15\right) \end{aligned} \quad (14)$$

To handle the constraints (Eqs. 9–13), it was implemented a dynamic penalty approach. The penalty coefficients (λ) initially take moderate values and increase linearly up to 50,000 over the course of the iterations. This strategy allows exploration in the early stages, while ensuring that near the final steps all constraints are strictly enforced. Although penalty methods may cause steep cost surfaces, we mitigated potential numerical issues by careful parameter tuning and by gradually escalating the penalty values until the stablished value.

Table 3. Parameter setting for optimization algorithms.

CS	DE	GWO	JAYA
Yang and Deb [7[	Storn [8]	Mirjalili et al. [9]	Rao [10]
n = 50	n = 50	n = 50	n = 50
$\alpha = 1$	$C_r = 0.7$		
$p_a = 0.25$	$F = 0.6$		
PSO	**TLBO**	**WOA**	
Kennedy and Eberhart [11]	Rao et al. [12]	Mirjalili and Lewis [13]	
n = 50	n = 50	n = 50	
w - linearly decreasing from 0.9 to 0.2			
$v_{max} = 6$			
$c_1 = 2$			
$c_2 = 2$			

Several optimization algorithms were included in this comparison to evaluate their effectiveness in solving the presented problem. The participating algorithms are Cuckoo Search (CS), Differential Evolution (DE), Grey Wolf Optimization (GWO), Jaya Algorithm (JAYA), Particle Swarm Optimization (PSO), Teaching-Learning Based Optimization (TLBO), and Whale Optimization Algorithm (WOA). For each algorithm, 30 independent experiments were conducted, each comprising 100 iterations with 50 candidate solutions per iteration. This rigorous experimental framework ensures the statistical validity and reliability of the comparative results. The parameters used for the different employed optimization algorithms are reported in Table 3.

Case studies

The case study involves distilled water located on the shell side with a mass flow rate of 22.07 kg/s. The inlet and outlet temperatures for the distilled water are 33.9°C and 29.4°C, respectively. The cold fluid is hard water situated on the tube side, exhibiting a mass flow rate of 35.31 kg/s with inlet and outlet temperatures of 23.9°C and 26.7°C, respectively.

Carbon steel is utilized as the construction material for both the shell and the tubes. The correction factors applied for calculating the installation cost are Cm=1.7, Ct=1.0, and Cp=1.0.

RESULTS

Table 4 displays the statistical outcomes for the third case study's TAC. GW achieves a consistently small standard deviation (SD) across multiple experiments, indicating uniform solutions. Although DE only manages to reduce its SD after iteration 35, it ultimately attains a stable convergence with the lowest mean TAC and smallest SD overall. The SBOA finds the best solution in at least one experiment, but the final SD remains high. This outcome suggests a lack of consistency among the solutions generated by SBOA, similar to the performance observed in PSO and TLBO. GWO's median TAC is slightly lower than DE's, whereas SBO's median is 6,154 USD/year, indicating that at least half of SBO's solutions deviate considerably from its best result.

Table 4. Statistical Results for Case Study

	CS	DE	GWO	JA
Median	6213.14	6079.54	6076.45	6392.31
Mean	6214.27	6090.73	6115.13	6385.67
SD	97.25	22.57	109.93	194.52
Minimum	6080.67	6074.89	6075.18	6107.79
	PSO	**SBOA**	**TLBO**	**WOA**
Median	6225.49	6154.87	6284.85	6859.73
Mean	6246.88	6273.03	6343.07	6871.36
SD	165.56	270.66	193.23	467.50
Minimum	6077.77	6074.83	6153.98	6228.60

Comparisons indicate that GWO records the lowest median TAC, while DE provides the smallest average TAC and standard deviation. SBOA's single best solution is on par with the top-performing algorithms, but its overall variability is notable.

The SBOA-derived design (Table 5) features a compact shell diameter (0.30 m) and high tube count (900), achieving a heat transfer area of 42 m². The 90° tube arrangement and single-pass configuration minimize pressure drops (14,100 Pa tube-side, 5,180 Pa shell-side), aligning with efficiency goals. However, the 18 baffles and narrow central spacing (0.113 m) may pose maintenance challenges, underscoring the trade-offs between cost minimization and practicality.

Table 5. Values for the different variables for the best STHE design found.

Variable	Value
Shell diameter (m)	0.3000
Outer tube diameter (mm)	6.3500
Number of tubes	900
Heat transfer area (m²)	42.0000
Tube length (m)	2.3400
Tube pitch (mm)	7.9400
Tube arrangement angle (°)	90
Number of tube passes	1
Central baffle spacing (m)	0.1130
End baffle spacing (m)	0.1810
Baffle cut (%)	45
Baffle-tube diametrical gap (mm)	0.0635
Baffle-shell diametrical gap (mm)	3.0000
Bundle outer diameter (m)	0.2750
Number of baffles	18
Tube velocity (m/s)	1.8300
L/D ratio	7.8000
Tube-side pressure drop (Pa)	14100.0
Shell-side pressure drop (Pa)	5180.0
Shell mass flow rate (kg/s)	22.1000
Tube mass flow rate (kg/s)	35.5000

The dynamic penalty coefficients effectively enforced constraints, with final designs satisfying all pressure drop and velocity limits. However, the aggressive penalty escalation (to 50,000) risks overshadowing the primary objective in early iterations, potentially discarding promising infeasible solutions. Future work could explore adaptive penalty strategies that weigh constraint violations relative to TAC reductions.

A one-way ANOVA (Table 6) was done to compare the mean cost across eight different optimization algorithms. The results indicate a statistically significant difference among these means, as shown by the relatively large F-value (29.8160) and the very small p-value (7.010874×10^{-33}). In other words, the variation in cost between the algorithm groups is unlikely to be due to chance alone, and we can reject the null hypothesis that all algorithms have the same mean cost. This finding suggests that at least one of the algorithms demonstrates a different average performance compared to the others.

Table 6. One-way ANOVA analysis.

	Sum of Squares	df	F-value	p-value
Algorithm	$4.4402\text{X}10^{+6}$	8.0	29.81	$7.0108\ \text{X}10^{-3}$
Residual	$4.8585\ \text{X}10^{+6}$	261.0	-	-

Table 7 shows the average runtime for each algorithm per experiment. DE requires only 0.2987 seconds on average, while GWO and JAYA follow closely, also maintaining sub-second times. SBOA takes slightly longer. The runtime differences may be attributed to the simpler operator structure of DE, which involves fewer internal loops and parameters compared to algorithms like SBO (which employs dual sub-populations). All tested methods remain computationally feasible in practical engineering contexts according to the computational time.

Table 7. Computational time per experiment.

	CS	DE	GWO	JA
Time (s)	0.7795	0.2987	0.3423	0.3044
	PSO	**SBOA**	**TLBO**	**WOA**
Time (s)	0.3261	0.5205	0.7926	0.4523

CONCLUSION

This study underscores the effectiveness of metaheuristic algorithms in optimizing STHE, with DE and GWO as particularly robust options for minimizing total annual cost under operational constraints. DE is distinguished by its consistency and computational efficiency, making it well-suited for routine optimization tasks, while GWO excels in searching in complex, non-linear search spaces due to its hierarchical search mechanism. The SBOA also demonstrates significant potential, achieving competitive solutions in terms of cost minimization. However, its performance exhibits higher variability across independent runs compared to DE and GWO, which may require additional refinement for applications demanding strict reproducibility.

The selection of an appropriate algorithm remains a critical consideration, as highlighted by the No-Free-Lunch Theorem, which asserts that no single method outperforms others across all problem types. DE's strength lies in its ability to handle mixed-variable problems through a balanced mutation-recombination process, while GWO's structured approach effectively avoids local optima. SBOA, inspired by behavioral patterns in success perception, introduces a unique dual-subpopulation strategy that balances exploration and exploitation. Although this approach yields highly competitive solutions in certain runs, its variability suggests that further tuning or hybridization with deterministic methods could enhance its consistency.

In terms of constraint management, the dynamic penalty functions employed in this study effectively enforce feasibility by progressively increasing penalty weights. This approach ensures that final solutions adhere to operational and geometric constraints, though the aggressive scaling of penalties in early iterations may occasionally hinder the exploration of promising regions in the search space. Future work could explore adaptive penalty strategies that more flexibly balance constraint satisfaction and objective optimization.

From a practical perspective, the optimal designs generated by SBOA, such as its compact shell diameter and high tube count, demonstrate its ability to identify cost-effective configurations. However, certain design features, like the narrow baffle spacing, may pose maintenance challenges, underscoring the need to balance cost savings with operational practicality.

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