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Research Article

Adaptive symbiotic organisms search technique for cost optimization of shell and tube heat exchanger

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ABSTRACT

Nature inspired meta heuristics like swarm intelligence (SI), Artificial neural networks (ANN), evolutionary computing (EC) etc. have been used by researchers to solve single and multi-objective optimization problems of different fields. This work uses a novel α-SOS (Adaptive symbiotic organisms search) algorithm for cost optimization of shell and tube heat exchanger. This algorithm is implemented for cost optimization of two benchmark STHX problem which are used by several researchers. Validation of the results is presented by comparing the geometric, flow and operational parameters of the same design problems when solved using particle swarm optimization (PSO), Alpha tuned elephant herding optimization technique (α-EHO) and Gravitation search algorithm (GSA). Result indicates a 4.73% and 11.3% reduction in cost for both the case study respectively when compared to same problems solved using PSO. Although when comparing with α-EHO, results does not indicate any substantial difference. Furthermore, operational, and geometric dimensions are also calculated. This algorithm can be eventually applied to real world design engineering problems.

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INTRODUCTION

Researchers have been using several methods of optimization for system design purpose. These include several mathematical techniques like linear programming, non-linear programming, stochastic programming etc. Moreover, use of evolutionary algorithms has gained significant interest in the recent scenario owing to ease of mathematical formulations and readily available computer language packages. The purpose of optimization is to achieve the best design relative to criteria and constraints. One can say that any output of a design problem has always scope of improvement provided better techniques are employed for its optimization purpose. Moreover, the current manufacturing scenario demands productivity in design and developments owing to severe competition. This requires substantial efforts by the research community and engineers to develop or to validate different optimization methods for their design problems. In this article, a state-of-the-art optimization technique named "Symbiotic organisms search" or SOS is modified using adaptive tuning factor and the same is being tested on two benchmark shell and tube heat exchanger optimization problems which is

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being used by most of the researchers to test and validate their proposed algorithms.

Most of the proposed algorithms are tested on design problems of researcher's choice. Normally, a researcher proposes the algorithm by testing the same on a given problem. In most scenarios, these algorithms are not tested or validated on other nonlinear problems of different fields. The drawbacks of a particular optimization method can only be known if the method is applied on highly dynamic and nonlinear problem. This demands the use of proposed algorithms on several set of problems which can further validate the efficacy of the said technique. In this research an algorithm named "symbiotic organism search" which was primarily used to optimize a truss structure is applied on a STHX design problem. The output validates the functionality of algorithm in two different design fields thereby confirming its application in real world design engineering problems.

Widespread use of Shell and tube heat exchanger (STHX) is found in process industries. Several possible design combinations of geometric dimensions are possible to facilitate the heat transfer duty for given application. Moreover, there are many constraints in design corresponding to area, length of tube, diameter of tube etc. because of readily available material for manufacturing and stipulated design codes. However, without optimization, the geometrical output of the STHX design problem may not prove cost effective as different better combinations of the geometrical parameters might be more economically sustainable. Henceforth, a designer must check all possible combinations of such parameters keeping the heat duty in mind.

Ultimately the goal is to incur the least manufacturing and operational cost which are primarily dependent on the surface area and pressure drop encountered in the heat exchanger [1,2]. Several methods are used by researchers for objective function optimization of their respective design problems. Swarm based intelligent algorithms have been effectively proven to be providing most optimum results in design optimization field. In this work, a novel Adaptive symbiotic organism search (α-SOS) technique is used for cost optimization of two benchmark STHX design problems. The parameters obtained are validated by comparing with that of the results obtained using PSO, α-EHO and GSA for the same problems.

The results prove the efficacy of the said technique. Moreover, the result obtained using α-EHO is the output of the work done by the current researcher. Thus, validating the current obtained results. Many algorithms are used by researchers for STHX design optimization which is further mentioned here.

Different evolutionary algorithms have been used by researchers to solve the benchmark problems considered in this study. PSO technique was used by Patel and Rao [14] to optimize the overall cost of STHX. The results of the PSO technique are compared with α-SOS which is utilized in this paper. Cuckoo search algorithm was applied to same problem by Asadi et al. [1] for optimization of the total annual cost. Initial version of the same algorithm namely SOS (Symbiotic Organisms Search) and α-Elephant herding Optimization (EHO) was used by Makadia and Sankhavara [2,16] for solving the STHX design problem. [3-6] used Global sensitivity analysis (GSA), Imperialist Competitive Algorithm (ICA), Artificial Bee Colony (ABC) and Bio Geography based optimization (BBO) respectively for STHX problem. Mohanty [18,22] used gravitational search technique and firefly algorithm for solving STHX design problem. Hanafi et al. [19] used water cycle algorithm for STHX design. Rao and Saroj [20] used Jaya Algorithm for optimum design of heat exchanger considering maintenance aspects. Lemos et al. [21] and Nakao et al. [23] presented a novel STHX design considering fouling phenomenon. Lahiri and Khalfe [25] used the Ant Colony optimization for solution of STHX design. Nonetheless, the most widely used Genetic Algorithm (GA) and its subsequent alterations have been proven to be effective in solution of heat exchanger design optimization problems. Rao and Majethia [26] used Rao algorithm for design optimization of STHX. Contrary to other algorithms, Rao algorithm uses best and worst solution for finding optimal solution. Moreover, variation in Rao algorithm named SAMP Rao is also studied. Sai and Rao [27] used non dominated sorting genetic algorithm-2 and PSO for STHX design. The hybridization of algorithms is used for improving the exploration and exploitation capability. The NSGA-2 has better search capability and PSO is further applied on the results of NSGA-2 which prevents occurrence of local optima. Montano et al. [28] performed design optimization using univariate marginal distribution algorithm. However, the use of UMD did not provide better results as compared to other metaheuristics. Rao and Saroj [29] used elitist Jaya algorithm which doesn't require any algorithm specific parameters for solution purpose. Daneshparvar and Beigzadeh [30] used hybrid technique of computational fluid dynamics and genetic algorithm for multi objective optimization of helical baffles in STHX. The main geometric parameters considered were baffle pitch and angle. Caputo et al. [31] presented a review on selection of the best design methodology for optimization of STHX. Work done in the area deduces that some of the objective function led to a solution which may led to impractical design configurations. This review provided a base to researchers to choose the best method for given objective function optimization. Nia et al. [32] used simulated annealing for tube arrangement optimization of a tubular heat exchanger which can be eventually used for STHX design optimization. Mudhsh et al. [33] used fire hawk optimizer for modelling of thermo hydraulic behaviour of helical heat exchanger. The methodology can be simply applied to STHX design. Moreover, Nadi et al. [35] performed multi objective optimization of K-type shell and tube heat exchanger using particle swarm optimization. Six decision variables and two objective functions of cost and heat transfer rate where analyzed. Each method has its own algorithm specific parameters suggested by researchers. Furthermore, the modifications in the basic algorithms to improve its exploration and exploitation capabilities have also been proven in many design problems.

METHODOLOGY

Thermal Design of STHX

The thermal design involves computation of the shell side and tube side heat transfer coefficients. Corelations suggested by bell Delaware [7] and Kern [11] are used for computing the thermal parameters. The symbol for the parameter and its corresponding meaning are represented in nomenclature section. The step-by-step procedure adopted to calculate the parameters is mentioned below:

Step 1: Estimate the tube side and shell side heat transfer coefficients based on Reynolds number and friction factor. The adopted method is Kerns method.

Step 2: Estimate the overall heat transfer coefficient based on fundamental equations. Use appropriate fouling factors.

Step 3: Based on overall heat transfer coefficient and correction factors estimate the surface area of heat exchanger using LMTD method.

Step 4: Find the corresponding pressure drop on tube side and shell side.

Step 5: Estimate the initial cost based on area.

Step 5: Estimate the total operating cost based on pressure drop.

Step 6: The overall cost is the summation of initial cost and operating cost.

Tube Side Heat Transfer Coefficient

Individual heat transfer coefficients are determined from the thermal design of STHX proposed by Kern [11]. The surface area of the heat exchanger is then calculated based on overall heat transfer coefficients which is based on individual heat transfer coefficients. The initial manufacturing cost of the STHX is based on the surface area. Several geometric combinations are possible, thus, arising the need of optimization of process and geometric parameters. Moreover, it is also necessary to compute the pressure drop which governs the pumping power and thereby the operational costs. Based on the literature, the mathematical model for calculating the above parameters is presented.

The schematic diagram of STHX with primary geometric parameters is represented in Figure 1. Here D_s is the shell internal diameter, B is the baffle spacing and L_t is the tube length.

Depending upon the flow Reynolds number (Re), the tube side heat transfer coefficient (h_t) is estimated from equations 3 and 4 [7,8]. The friction coefficient f is the function of flow Reynold's number and pipe roughness which is estimated from literature data and given by Colebrook white equation [10]. The corresponding equations are 1 and 2. d is the corresponding tube diameter and L is the tube length. e is the surface roughness of the tube material and P_r is the Prandtl number. k is the thermal conductivity of tube material.

$$\frac{1}{\sqrt{f}} = 1.14 - 2\log_{10}\left(\frac{e}{d} + \frac{9.35}{\mathrm{Re}\sqrt{f}}\right) \textit{for}\ \mathrm{Re} > 4000 \tag{1}$$

$$f = \frac{64}{\mathrm{Re}}\ \text{For laminar flow} \tag{2}$$

$$h_t = \frac{k_t}{d_i}\left[3.657 + \frac{0.0677\left\{\mathrm{R}_{et}\,\mathrm{P}_{rt}\left(d_i/L\right)\right\}^{1.33}}{1 + 0.1\mathrm{P}_{rt}\left\{\mathrm{R}_{et}\left(d_i/L\right)\right\}^{0.3}}\right]_{\text{For Re} < 2300} \tag{3}$$

$$h_t = \frac{k_t}{d_i}\left[\frac{\left(f_t/8\right)\left(\mathrm{R}_{et} - 1000\right)\mathrm{P}_{rt}}{1 + 12.7\left(f_t/8\right)^{1/2}\left(\mathrm{P}_{rt}^{2/3} - 1\right)}\left(1 + \frac{d_i}{L}\right)^{0.67}\right]_{\text{For } 2300 < \text{Re} < 10000} \tag{4}$$

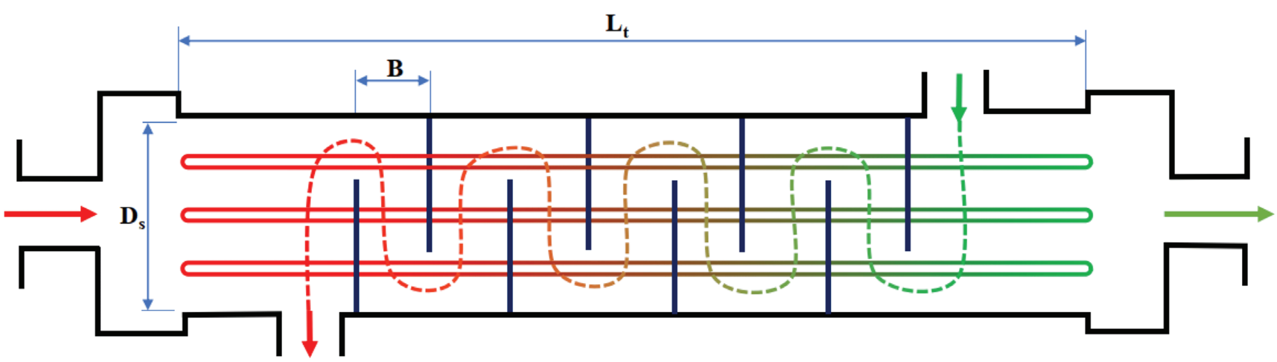

Figure 1. Schematic layout of STHX with primary geometric parameters [From Alazwari and Safaei [34], with permission from MDPI].

Whereas for Re > 10000, the heat transfer coefficient is given by equation 5:

$$h_t = 0.027\frac{k_t}{d_i}\mathrm{R_{et}}^{0.8}\,\mathrm{P_{rt}}^{1/3}\left(\frac{\mu_t}{\mu_{tw}}\right)^{0.14} \tag{5}$$

Here, K_t and f_t are the tube material thermal conductivity and friction factor respectively and μ is the dynamic viscosity with corresponding subscripts [9,10].

Shell Side Heat Transfer Coefficient

Kern [11] suggested equation 6 for computations of heat transfer coefficients at shell side.

$$h_s = 0.36\frac{k_t}{D_e}\mathrm{R_{es}}^{0.55}\,\mathrm{P_{rs}}^{1/3}\left(\frac{\mu_s}{\mu_{sw}}\right)^{0.14} \tag{6}$$

Where μ represents the fluid dynamic viscosity at wall temperature and mean fluid temperature for tube side and shell side and D_e is the shell equivalent diameter.

Overall Heat Transfer Coefficient

The overall heat transfer coefficient U is based on individual side coefficients and is given by equation 7. The corresponding fouling factors are incorporated appropriately based on values suggested in the literature. R in the below equation is fouling factor with corresponding subscripts of tube side and shell side.

$$U = \frac{1}{\frac{1}{h_s} + R_{fs} + \left(\frac{d_o}{d_i}\right)\left(R_{ft} + \frac{1}{h_t}\right)} \tag{7}$$

Surface Area of the Heat Exchanger

Using general design terminology of STHX, the surface area is computed using the Logarithmic mean temperature difference (LMTD) method. Based on the geometry appropriate correction factor F is computed and used for estimating the overall surface area which is given by equation 8. This is the overall surface area based on which the pipe length and diameter can be estimated along with the number of pipe turns. Here A is the overall surface area and Q is the heat duty.

$$A = \frac{Q}{UF\Delta T_{lm}} \tag{8}$$

Frictional Pressure Loss on Individual Sides

Kern [11] and Sinnott [12] suggested equation 9 and 10 for estimating the tube side pressure drop.

$$\Delta \mathrm{P_t} = \frac{\rho_t v_t^2}{2}\left[\frac{L}{d_i}f_t + P\right]n \tag{9}$$

Kern [11] used 4 as the value of P which is retained in present work for the sake of result comparison. However, researchers have proposed different values of P. ρ_t is the fluid density and v_t is the fluid velocity inside the pipe, whereas L is the pipe length and d_i is the internal diameter of tube. f_t is the tube side friction factor and n is the number of tubes passes.

Serna-González et al. [7] used equation 10 for estimating pressure drop in shell side flow which is suggested by Bell-Delaware method. Here B is the baffle spacing and D_s is the shell diameter. D_e is the equivalent diameter. ρ_s and v_s are the shell side fluid density and fluid velocity respectively. L is the tube length and f_s is the friction factor.

$$\Delta \mathrm{P_s} = \mathrm{f_s}\left(\frac{\rho_s v_s^2}{2}\right)\left(\frac{L}{B}\right)\left(\frac{D_s}{D_e}\right) \tag{10}$$

Cost Functions for STHX

The initial cost, discounted operating cost and the yearly running cost are to be considered for estimation of total cost which is to be minimized and the objective function. Caputo et al. [9] suggested equation 11 for overall cost of the heat exchanger comprising of the initial cost and the discounted running cost.

$$C_T = C_I + C_{doc} \tag{11}$$

Here, C_{doc} is the discounted operating cost and C_I is the initial capital investment, which is dependent on heat exchanger overall surface area, thus the comprising parameters of the total cost C_T. Moreover, Taal et al. [13] suggested equation 12 for estimation of the initial cost of the heat exchanger.

$$C_I = a_1 + a_2 A^{a_3} \tag{12}$$

Here a_1, a_2 and a_3 are numerical constants whose value is taken from Taal et al. [13] and A is the surface area.

The pumping power influences the discounted operating cost for which equation 13 is given by Caputo et al. [9].

$$C_{doc} = \sum_{j=1}^{n_y}\frac{c_o}{(1+i)^j} \tag{13}$$

Here n_y is life of equipment in years and i is the annual inflation considered as 10%. Operating cost is given by equation 14 [9].

$$C_o = P_1 C_e H \tag{14}$$

Where P_1 is the corresponding pumping power and given by equation 15 [9]. C_e is the electricity cost and H is the number of hours of operation of heat exchanger considered annually.

$$P_1 = \frac{1}{\eta}\left(\frac{m_t}{\rho_t}\Delta P_t + \frac{m_s}{\rho_s}\Delta P_s\right) \quad (15)$$

Where, m_t and m_s are the fluid mass flow rate at tube side and shell side. ρ is the fluid density with corresponding subscripts and ΔP is the pressure drop and h is the pump efficiency. The corresponding pressure drop is calculated from equation 9 and 10.

Adaptive Symbiotic Organisms Search Technique

SOS algorithm is a novel technique which relies on the principle of adaptation. It comprises of three phases i.e., Mutualism, Commensalism and Parasitism. In Mutualism phase the organisms survives mutually benefiting each other. In Commensalism phase either of the one organism will benefit from the other and the latter will remain unaffected whereas in parasitism phase only one organism will benefit thereby causing harm to other. The benefit factor in the basic SOS is either one or two which means that either the organism will benefit or will remain unaffected during interaction. Like all nature inspired algorithms SOS also randomly generates initial population. Furthermore, the population gets updated through above mentioned phases only if the function value is better than previous iteration. The initially set termination criterion decides the iteration. The flow of calculations of the algorithm is represented below [15].

Mutualism phase

Initially X_i and X_j are organisms which will interact with each other. In mutualism phase, both the organism will benefit each other mutually. Mathematical representation is given as represented in equation 16,17 and 18 [2]:

$$X_{inew} = X_i + random\ (0,1) \times (X_{best} - mutual\ vector \times BF_1) \quad (16)$$

$$X_{jnew} = X_j + random\ (0,1) \times (X_{best} - mutual\ vector \times BF_2) \quad (17)$$

$$Mutual\ vector = (X_i + X_j)/2 \quad (18)$$

As mentioned earlier the benefit factor (BF) is either chosen as 1 or 2 indicating full or partial benefit to the organism.

$(X_{best} - mutual\ vector \times BF_1)$ represents the effort to achieve the target. X_{best} is the highest degree of adaption. The solution of the function is only accepted if it yields better result before interaction.

Commensalism phase

As mentioned, only one organism will benefit, and it will have no effect on other. Same organism are again passed through interaction but only one organism will be benefited whereas other will be unaffected. Henceforth X_i will have new fitness value provided it is better before interaction. The computation will be carried out as given by equation 19.

$$X_{inew} = X_i + random\ (-1,1) \times (X_{best} - X_j) \quad (19)$$

Parasitism phase

One organism will be benefited and other will face harm in this phase. It's like lion hunting a dear for survival. Here, X_i will behave as an artificial parasite vector. Parasites are normally considered as doing harm to others for their own benefit. The host of X_i organism is X_j. X_i tries to replace X_j provided it has a better function output. Furthermore, if one organism, say X_j, remains unaffected from X_i, it will lead to its survival and thereby eliminating X_i from the population.

SOS with Adaptive Benefit Factor

The novelty introduced here is the inclusion of an adaptive benefit factors in the basic SOS algorithm hence the name Adaptive SOS. Adaptive benefit factor is introduced in the basic SOS algorithm to enhance the search capability of the technique. Adaptive benefit factors (ABF1 and ABF2) as defined by Equations 20 and 21 [15] are incorporated. A more hybrid approach of the same algorithm with variable neighbourhood search was used to solve the travelling salesman problem and global optimization [17,24].

$$ABF_1 = F\ (X_i)\ /\ F\ (X_{best})\ if\ X_{best} \neq 0 \quad (20)$$

$$ABF_2 = F(X_k)\ /\ F\ (X_{best})\ if\ X_{best} \neq 0 \quad (21)$$

Using adaptive benefit factor gives the name adaptive symbiotic organisms search. The search capability of the algorithm represents the large and small changes in the variables. Adaptive benefit factor strengthens the exploration capability thereby bringing the organism to the best position. Moreover, simple SOS might converge to a local optimum solution if the organism is already near to the best solution. Therefore, an adaptive algorithm specific factor enhances and balances the exploration and exploitation capabilities. The coding of current work is done using MATLAB 2014 a.

Solution of Benchmark Design Problem

Case studies for design optimization of STHX are taken from Kern [11] and Sinnott [12]. These design problems are solved by most researchers, henceforth, the comparisons and validations of the results can be made. The first case study is Methanol Brackish water STHX with 4.34 MW heat duty having one shell and two tube passes. The results obtained using adaptive SOS are compared with results using PSO technique, α-EHO technique and GSA technique [14,16,18]. The second case study is Kerosene Crude oil STHX with 1.44 MW heat duty with one shell pass and four tube pass configuration. Figure 2 and Table 1 are for case study 1 and Figure 3 and Table 2 are for case study 2.

The geometric limits of the design variables of Shell diameter (D_s), tube outer diameter (d_o) and baffle spacing (B) are taken as below which is suggested by TEMA (Tubular Exchanger Manufacturers Association). The convergence criteria are chosen based on the geometric constraints and 100 iterations are chosen for analysis purpose. However, it is observed that convergence is attained within 40 iterations in benchmark problem 1 and within 20 iterations in benchmark problem 2 which is evident from Figures 2 and 3.

The geometric bounds are:

$0.1 \le D_s \le 1.5$

$0.015 \le d_o \le 0.051$ and

$0.05 \le B \le 0.5$

All requisite dimensions are in meters (m).

Figure 2 is the convergence curve for case study 1. From Figure 2 it is evident that at the beginning of first iteration the total cost is tentative to be 5.3K whereas when the algorithm converges it goes to 5.0K. This convergence is attained within the 40th iteration. The subsequent iterations do not show any change in cost. Hence it can be deduced that the algorithm converges at an earlier stage. Table 1 is the result of the geometric and cost parameter obtained after applying adaptive symbiotic organism search to the design problem. It is evident from the result table that a reduction of 4.73% is observed in the total cost as compared to particle swarm optimization (PSO) technique. Corresponding reduction in shell diameter is 3.7% and a significant 29.24% decrease in tube length. However, there is no evidence of significant change in tube outer diameter. A negligible increase in the tube side heat transfer coefficient is also observed. There is decrease in Reynolds number of shell side fluid flow and small increase in the heat transfer coefficient. The overall surface area of STHX is reduced by 2.9% as compared to area obtained using PSO owing to rise in overall heat transfer coefficient. The running cost is reduced to marginal extent owing to decrease

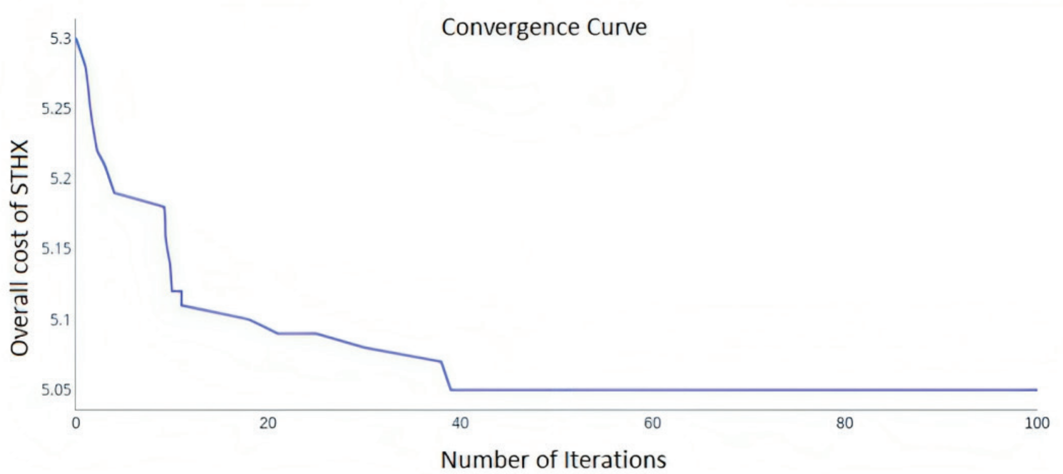

Figure 2. Cost convergence for case study 1 (Methanol Brackish water heat exchanger of 4.34 MW heat duty).

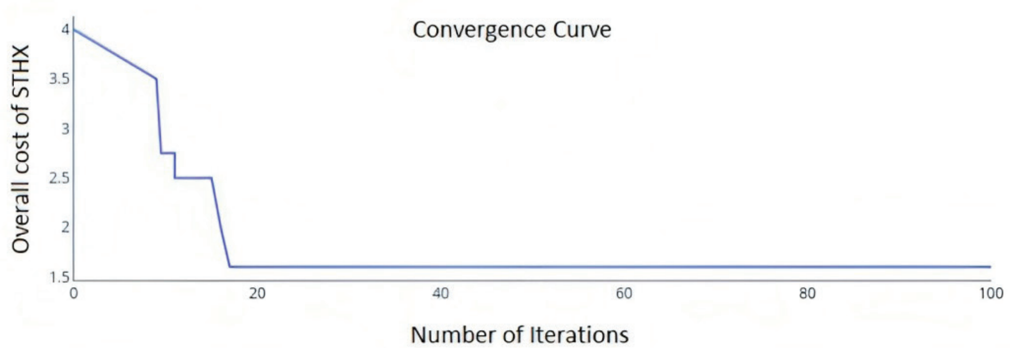

Figure 3. Cost convergence for case study 2 (Kerosene crude oil heat exchanger of 1.44 MW heat duty).

Table 1. Geometric, cost, flow, and thermal parameters for case study 1 (Methanol Brackish water heat exchanger of 4.34 MW heat duty)

Parameter	PSO	Adaptive SOS (current work)	α- EHO	GSA	Parameter	PSO	Adaptive SOS (Current work)	α- EHO	GSA
L (m)	3.115	**2.204**	2.855	2.783	Re_s	12678	**8639**	12813	10662
d_o (m)	0.015	**0.014**	0.015	0.015	Pr_s	5.1	**5.1**	5.1	5.1
B (m)	0.424	**0.48**	0.395	0.486	h_s (W/m²K)	1950.8	**2219.2**	2142	2060
D_s (m)	0.81	**0.78**	0.77	0.842	f_s	0.349	**0.34**	0.34	0.358
N_t	1658	**2960**	1698	1806	ΔP_s (Pa)	20551	**15774**	22456	12458
v_t (m/s)	0.67	**0.69**	0.66	0.678	U (W/m²K)	713.9	**784**	758	732.6
Re_t	10503	**9677**	10156	10118	A (m²)	243.2	**236.1**	216	236.9
Pr_t	5.7	**5.7**	5.7	5.7	C_I (€)	46453	**45048**	40556	45439
h_t (w/m²K)	3721	**3941**	3653	4029	C_o (€/yr)	1038.7	**1001**	1076	813.2
f_t	0.0311	**0.03**	0.03	0.031	C_{doc}(€)	6778.2	**6258**	6645	4673
d_e (m)	0.0107	**0.01**	0.01	0.0107	C_{total} (€)	53231	**50713**	46115	50112
v_s (m/s)	0.53	**0.49**	0.69	0.453	ΔP_t (Pa)	4171	**5854**	4166	4501

Table 2. Geometric, cost, flow, and thermal parameters for case study 2 (Kerosene crude oil heat exchanger of 1.44 MW heat duty)

Parameter	PSO	Adaptive SOS (Current work)	α- EHO	GSA	Parameter	PSO	Adaptive SOS (Current work)	α- EHO	GSA
L (m)	1.56	**1.39**	1.48	1.317	Re_s	15844	**14947**	15111	15004
d_o (m)	0.015	**0.012**	0.013	0.015	Pr_s	7.5	**7.5**	7.5	7.5
B (m)	0.11	**0.13**	0.11	0.11	h_s (W/m²K)	1288	**1537**	1482	1512
D_s (m)	0.63	**0.46**	0.51	0.62	f_s	0.337	**0.336**	0.336	0.34
N_t	646	**702**	681	718	ΔP_s (Pa)	21745	**23145**	22054	17962
v_t (m/s)	0.93	**1.25**	1.01	0.75	U (W/m²K)	409.3	**503**	461	348
Re_t	3283	**3091**	3217	3102	A (m²)	47.5	**43.2**	46	54.98
Pr_t	55.2	**55.1**	55.2	55.2	C_I (€)	16707	**15987**	16112	17639
h_t (w/m²K)	1205	**1414**	1316	1488	C_o (€/yr)	523.3	**611**	571	290.1
f_t	0.044	**0.06**	0.051	0.046	C_{doc}(€)	3215.6	**3487**	3396	1642
d_e (m)	0.0149	**0.014**	0.014	0.0148	C_{total} (€)	19922	**17670**	17993	19281
v_s (m/s)	0.495	**0.6**	0.515	0.476	ΔP_t (Pa)	16926	**18012**	17450	8449

in shell side pressure drop. The overall heat transfer coefficient using Adaptive SOS technique is the highest among all three methods. It is observed to be 784 W/m²K which is almost 9% higher as compared to that obtained using PSO.

Figure 3 is the convergence curve for case study 2. As shown in Figure 3, there is a substantial decrease in cost observed from 4K to 1.5K from first iteration to 20th iteration. The algorithm converges at the 20th iteration which is evident from the figure. Table 2 is the result of the geometric and cost parameter obtained after applying adaptive symbiotic organism search to the design problem of case study 2. A significant reduction of 11.3% in overall cost of STHX is observed when the problem is solved using adaptive symbiotic organism search technique as compared to PSO [14]. 26.98% reduction in shell diameter and 10.89% reduction in tube length is observed eventually. Corresponding reduction of 9.05% in overall area is observed using the adaptive SOS technique. The overall heat transfer coefficient is observed to be higher by 18% as compared to the results obtained using PSO technique [14]. Furthermore, the results are also compared with the results of the same problem solved using α-EHO technique and GSA technique [16,18]. As shown in graph, Figures 2 and 3 Y axis has a scale of 0.05 and 0.5 respectively and the number is multiplied by a factor of 10^5 which indicates the highest cost and the lowest cost after applying the said technique.

It is proved that using adaptive symbiotic organisms search technique is of great advantage for STHX design problems. The design problem can be further validated by extending the work using other nature inspired meta-heuristics. However, the suggested method may not yield superior results as compared to other metaheuristics and applied to different field problems. It all depends on the design constraints and convergence criteria which after inclusion of adaptive benefit factor may converge to local optimum. Although, providing the results which may not be optimum. Henceforth, it is required to check the method on other design problem which are highly nonlinear and dynamic in nature.

CONCLUSION

- Two benchmark STHX design problem solved using α-SOS indicates that the algorithm is efficient as far as exploration and exploitation abilities are concerned and results are better as compared to PSO.
- The surface area decreases by 2.9% as compared to results obtained using PSO for case study 1 and by significant 9.05% for case study 2.
- Owing to this reduction in surface area the overall costs reduce by a significant 4.73% for case study 1 and 11.3% for case study 2 in comparison with PSO proving the effectiveness of the said technique.
- Moreover, α-SOS has limited algorithm specific parameters which make it easier in application and implementation.
- The algorithm is unique in terms of use of adaptive benefit factor which enhances the performance in every iteration providing realistic results.
- In addition, the geometric parameters obtained are very much coherent with the reduced area and cost.
- The work can be extended by solving the problem using other algorithms and modified versions of the same. This will help to validate the efficacy of the techniques used in design optimization problems.
- Furthermore, such techniques need to be tested on highly complex and dynamic systems which would be eventually applied in actual design problems.

NOMENCLATURE

f	Friction factor
e	Pipe roughness (m)
d	diameter of tube (m)
R_e	Reynolds No.
h	Heat transfer coefficient (W/m^{2}K)
k_t	Tube material thermal conductivity (W/mK)
P_r	Prandtl No.
L	Length of tube (m)
μ	Viscosity at mean fluid (t_w) and corresponding wall temperature (t) (Pa s)
D_e	Equivalent shell diameter (m)
R	Fouling factor (m^2 K/W)
A	Surface area (m^2)
Q	Heat transfer rate (MW)
F	Geometry based correction factor for LMTD
U	Overall heat transfer coefficient (W/m^{2}K)
ΔT_{lm}	Logarithmic mean temperature difference
ΔP	Friction pressure loss (Pa)
ρ	Fluid density (kg/m^3)
v	Fluid velocity (m/s)
n	No. of tube passes
C_T	Total cost
C_I	Initial capital investment (€)
C_{doc}	Discounted operating cost (€)
C_o	Yearly running cost (€/yr)
n_y	Equipment life in years
C_e	Energy price (€/KWh)
P_1	Pumping Power (W)
H	Working hours
η	Pump Efficiency
m	flow rate (kg/s)
D_s	Shell diameter (m)
B	Baffle spacing (m)
STHX	Shell and tube heat exchanger
PSO	Particle Swarm Optimization
α-EHO	Alpha tuning elephant herding optimization
GSA	Gravitation search algorithm

Subscripts

s	Shell side
t	Tube side
i	Internal tube side
o	Outer tube side

AUTHORSHIP CONTRIBUTIONS

Authors equally contributed to this work.

DATA AVAILABILITY STATEMENT

The authors confirm that the data that supports the findings of this study are available within the article. Raw data that support the finding of this study are available from the corresponding author, upon reasonable request.

CONFLICT OF INTEREST

The author declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

ETHICS

There are no ethical issues with the publication of this manuscript.

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APPENDIX

FLOW CHART FOR ALGORITHM

```
Step I: Define the problem, minimize F(x), initialize the optimization parameters,
and set termination criterion ('FEmax', or 'gmax'); where F(x) is the objective
function and 'x' is the design vector. Organisms of the ecosystem are considered to
be a part of the population (i=1,2,…,n).

Step II: Initialize the randomly generated population within its upper and lower
bounds and evaluate it.

Step III: Identify the best solution of the ecosystem.

Step IV: begin the optimization loop.
FE=0
for g = 1 to gmax do
        for i = 1 to n do /* update the population /*
Step V: The mutualism phase:
       BF1 = 1 + round [rand] /* rand ϵ [0,1] /*
       BF2 = 1 + round [rand]
       MV = (xi+xk)/2 /* 'K' is a randomly selected population of the ecosystem, k ≠ i /*
       if f(xbest) ≠ 0 then
         ABF1 = f(xi)/f(xbest)
         xi' = xi + rand * (xbest − MV * ABF1)
       else
         xi' = xi + rand * (xbest − MV * BF1)
       end if
         xk' = xk + rand * (xbest − MV * BF2)
       if f(Xbest) ≠ 0 then
              ABF1 = f(xi)/f(xbest)
              ABF2 = f(xk)/f(xbest)
xi' = xi + rand * (xbest − MV * ABF1)
xk' = xk + rand * (xbest − MV * ABF2)
         Else
                 xi' = xi + rand * (xbest − MV * BF1)
       xk' = xk + rand * (xbest − MV * BF2)
              end if
       end if
       FE = FE + 2 /*
       /* the organisms are updated only if their new functional value is fitter
       than existing /*
         if F(xi')< F(xi) then
                 xi = xi'
         end if
            F(xk')< F(xk) then
                 xk = xk'
         end if
       end if

Step VI: The commensalism phase:

        xi' = xi + rand(−1,1) * (xbest − xk) /* 'k' is a randomly selected population of the
              ecosystem, k ≠ i /*
         FE = FE + 1
       /* the organism is updated only if its new functional value is fitter than
       existing /*
       if F(xi')< F(xi) then
         xi = xi'
       end if

Step VII: The parasitism phase:
       Parasite_Vector /* Parasite vector is a fusion of design variables of the
       organism 'i' and randomly generated design variables within its bound /* /*
       If parasite vector is fitter than the organism 'k', parasite will kill
       organism 'k' and acquire its position in the ecosystem. /*
       if F(parasite vector) < F(xk)then /* 'k' is a randomly selected population of
       the ecosystem, k ≠ i /*
              xk = parasite vector
         end if

Step VIII: Termination criterion (FE ≤ FEmax or g ≤ gmax): Repeat the procedure from
step III until the termination criterion is satisfied.
       if FE ≥ FEmax then
              break optimization loop.
       end if
       end for /* population loop end /*
       end for /* optimization loop end /*
```