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Basant Singh Sikarwar
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Preface

This book combines cutting-edge research articles on fluid and thermal engineering from the 2nd Biennial International Symposium on "Fluids and Thermal Engineering" (FLUTE-2023) which was organized by the Department of Mechanical Engineering from 20 to 21 July 2023 at Amity University Noida Campus, sponsored by DRDO. The symposium's central theme revolved around "Scientific and Technological Advances in Materials for Energy Storage and Conversions". The symposium provided a platform for researchers, academicians, and industry experts from around the world to converge and exchange their knowledge and insights in the field of fluids and thermal engineering. The focus of the symposium was on the latest advancements and innovations related to materials used in energy storage and conversion technologies.

The Symposium hosted almost 150 participants to exchange scientific ideas. During two days of the symposium, researchers from academics and industries presented the most recent cutting-edge discoveries, conducted various scientific brainstorming sessions, and exchanged views on practical problems in thermal engineering. This symposium also provided a scope to establish a network for collaboration between academia and industry. The primary emphasis was on the recent developments and innovations in various fields of mechanical engineering through plenary and keynote lectures. It was supported by IIT Guwahati, IIT Hyderabad, DRDO & Budapest University of Technology & Economics, Hungary.

In particular, this volume discusses different topics of fluid and thermal engineering in 59 chapters, such as heat transfer enhancement and heat transfer equipment, multiphase transport and phase change, solar energy and its application, alternative fuels, refrigeration, and air conditioning, numerical methods in fluid mechanics and heat transfer, multimode heat transfer and micro and nanoscale transport. The contents of this book will be helpful for researchers as well as industry professionals.

This book indulges the fluid and thermal science engineering aspects, mainly will serve as a reference guide for researchers and practitioners, and is expected to foster better communication and closer cooperation between academia and industry partners.

We would like to acknowledge all the participants who have contributed to this volume. We also deeply express our gratitude for the generous and constant support provided by Amity University, Noida and our sponsor DRDO. Thanks to the publishers and every staff of the department and institute who have directly or indirectly helped to accomplish this goal. We also profoundly express our gratitude for the generous support provided by Amity University Noida. We would also like to express our gratitude to the Founder and President of Amity University, Dr. Ashok K. Chauhan, for providing all kinds of support. This book is not complete without his blessings.

Noida, India
December 2023

Dr. Basant Singh Sikarwar
Dr. Sanjeev Kumar Sharma

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About the Editors

Dr. Basant Singh Sikarwar is a Postdoc from Iowa State University USA, Ph.D. from Indian Institute of Technology Kanpur, India, and M.Tech. Indian Institute of Technology Roorkee, India. His research experience is quite diversified in many aspects of thermo-fluids research with an emphasis on phase change phenomena and the formation of interfaces. The subject is poised for growth because of several engineering applications such as optimization of cooling techniques, thermal management of engineering systems, drop evaporation dynamics, boiling, water harvesting from moist air, dropwise condensation, and thermal energy storage. During his Ph.D., he developed a Finite Volume-based CFD solver, and his research group has been using this CFD solver for his research in thermal and fluid engineering. He published 75+ SCI/Scopus-indexed journals and 100+ Scopus-indexed conference manuscripts. He completed one research-funded project of the Science Engineering Research Board (SERB), India, and three research-funded projects are going on in his lab. He chaired many conferences and is a member of the editorial board of many journals and book series. He supervised four Ph.D. students, and four Ph.D. are going to his lab. Currently, He is a Professor and Heading the Department of Mechanical Engineering at Amity University Noida, India. In addition, he is an Assistant Director at the Amity directorate of Engineering, Technology, and Innovation (ADETI) and a member of the task force, Amity Institute of Defence Technology. Dr. Sikarwar has delivered many guest lectures at National/International conferences and workshops. He has also been the author/co-author of two books and the inventor of 10 Indian patents.

Dr. Sanjeev Kumar Sharma completed Ph.D. (Thermal Engineering) from Indian Institute of Technology IIT(ISM) Dhanbad. He did his M.Tech. (Energy Management) from IIT Delhi in 2008 and B.Tech. (Mechanical Engineering) from G. B. Pant University of Agriculture & Technology, Pant Nagar in 2003. For the last eighteen years, he has been involved in experimental and theoretical study of many aspects of novel desalination techniques, food-energy-water nexus, boiling and condensation. During his Ph.D. he developed a novel desalination device to fulfill the requirement of potable water. He published more than 30 SCI/Scopus-indexed journals and conference articles on novel desalination techniques, food-energy-water nexus, boiling and condensation.

Optimization of Three-Stage Heat Exchanger Design Using Modified Differential Evolution Algorithm

I. R. Gawai and D. I. Lalwani

Abstract The size plays a decisive part in the selection of a heat exchanger. A heat exchanger with a smaller size with equal or higher thermal performance is always desirable. In this paper, the amended differential evolution algorithm (ADEA) is modified (modified-ADEA), and utilized to optimize a three-stage heat exchanger (TSHE) design problem. Also, a novel penalty assignment method is introduced which assigns a penalty based on the degree of constraint violation and total constraints violated by the individual. The three-stage heat exchanger is optimized to obtain the same performance with minimum heat transfer area. The optimized solution is compared with the optimum solution reported by algorithms ADEA, BA, HS, and GA. The modified ADEA found the best optimum results among the compared algorithms.

Keyword Design optimization · Three-stage heat exchanger design · DE · Evolutionary algorithms

Nomenclature

Cp	Specific heat, kl
CR	Crossover probability
Ct	Constraint tolerance
F	Scaling or Mutation factor
fx	Objective function
fxchild	Objective function of child
fxparent	Objective function of parent
G	Generations (in flowchart)
gx	Constraint function
J	Number of inequality constraints

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K	Number of equality constraints
Lb	Lower bound
M	Mutant individual
NP	Number of individuals in population
Sc	Scaled function
Tr	Trial vector
Ub	Upper bound
V	Mutant individual
w	Weight function
W	Flow rate
X	Individual in the population
x	Decision variable
U	Overall heat transfer coefficient

Abbreviations

ADEA	Amended Differential evolution algorithm
BA	Bat Algorithm
CHE	Compact heat exchanger
DE	Differential Evolution
EA	Evolutionary algorithms
GA	Genetic Algorithm
HS	Harmony Search
HVAC	Heating, Ventilation, and air conditioning
NFE	Number of function evaluation
NOC	Total number of constraints
NOCV	Number of constraints violated
PS	Population size
RPDoE	Random population using design of experiment
SD	Standard Deviation

Greek Symbols

λ	Lambda constant
ψ	Combined function
Σ	Sigma

Subscript

D	Dimension
g	Generation
i	Individual number in population
j	Inequality constraint number
min	Minimum value
max	Maximum value
k	Equality constraint number

1 Introduction

For the past couple of decades, evolutionary algorithms (EAs) are used for the optimization of numerous problems. Darwin's theory of evolution, 'survival of the fittest', inspired the optimization process in EAs [1]. Such an optimization approach makes EAs a good choice for optimizing complex real-life problems [2]. One of the members of EAs is the differential evolution (DE) algorithm [3]. DE algorithm optimizes a population of *NP* individuals (solutions), which are made up of real number vectors of dimension D. In every generation g, each parent individual or a solution X_i, where i changes from 1 to *NP*, is mutated using a suitable mutation strategy to form a mutant individual, V_i. A recombination or crossover operation is carried out between V_i and X_i a to yield a child individual or trial vector, Tr_i. The comparison of child and parent individuals is conducted, and better individual is selected. The Eq. (1) shows the general form of a single objective optimization problem.

$$\begin{aligned} \text{Maximize/Minimize} \quad & f(X) \\ \text{Subject to} \quad & g_j(X) \le 0 \quad j = 1, 2, \ldots, J \\ & h_k(X) = 0 \quad k = 1, 2, \ldots, K \\ & X_i^{(Lb)} \le X_i \le X_i^{(Ub)} \quad i = 1, 2, \ldots, NP \end{aligned} \tag{1}$$

where J and K are the number of inequality constraints and equality constraints, respectively. *NP* is the total number of individuals in the population. ${X_i}^{(Ub)}$ and ${X_i}^{(Lb)}$ are the bounds on variables that together form a decision variable space or search space. An individual X_i is a vector of D number of decision variables, i.e., $X_i = [x_1, x_2, \ldots, x_D]_i$. The portion of search space where all the $(J + K)$ constraints are satisfied, is referred to as the feasible space.

The optimum solution is the best possible solution to a given problem within a feasible space of constraints. To reach an optimum solution, DE relies mainly on the mutation strategy and control parameters' selection. The control parameters, namely, scaling factor and crossover probability, change according to a problem. Finding the best value of control parameters for every problem is laborious and not advisable. Takahama and Sakai [4] suggested using a range of control parameter values and the solution's or the individual's rank. A balanced approach to exploration and exploitation is achieved by using a range of values and providing a parameter value according to an individual's rank. An algorithm was proposed by Rana and Lalwani [5] which incorporates the ranking method of Takahama and Sakai [4], along with a few other changes in the differential evolution algorithm. The altered version of DE was called as amended differential evolution algorithm (ADEA). ADEA uses the concept of design of experiment to uniformly distribute the randomly generated initial population (RPDoE). It was found that the initial population has a significant impact on the number of function evaluations (*NFE*s) to reach optimum [6]. In the mutation strategy, DE/rand/1 was used but two mutant individuals were created instead of one. After mutation, the mutant is checked if it lies within variable bounds. If the mutant goes out of bound, then in DE the mutant is replaced with a random individual within an individual but in ADEA, a mutant is replaced by the best individual in the current generation. Also, 'sigma-' (Σ) constraint handling technique was used for the optimization of constrained optimization problems. In $\Sigma(x)$, the sum of constraint violation is given in the selection procedure, the emphasis was put on the value of constraint violation along with the objective function value.

In a heat exchanger high 'area density' is desired. The area density can be expressed as the heat transfer area over heat exchanger volume. The higher area density leads to a reduced weight and volume. Because of these traits, together with their great heat transmission efficiency, a heat exchanger with high area density is preferred in many industrial applications, as they require less material and space. The compactness of a heat exchanger holds great importance in applications, where space constraints are vital [7]. Such heat exchangers with high area density are used in numerous applications, like, to increase the efficiency of HVAC systems [8], agricultural applications like paddy drying [9], in automotive industries to improve the performance of thermoelectric generators [10], and in energy recovery system in aerospace industry [11]. Due to its complex design process, the optimization of TSHE is an ideal problem to solve using evolutionary algorithms.

In the present work, a few modifications were made in ADEA. For many problems, the sum of constraint violations may not be enough penalty to reach the optimum in given *NFE*s. Hence, in the proposed algorithm the value of penalty is based on the number of constraints violated by an individual. The feasibility and infeasibility of parent and child individuals are taken into account in the selection procedure. A TSHE design problem is optimized using the proposed algorithm.

The following structure is adopted for the paper: Sect. 2 provides an explanation of the proposed algorithm. Section 3 introduces the TSHE problem. The solution to the TSHE and the ensuing discussion are presented in Sect. 4. Lastly, Sect. 5 encompasses the conclusion of the paper.

2 Proposed Algorithm

Rana and Lalwani [5] modified DE to solve constrained optimization problems. The design of the experiment method was used to generate a random population. A range of parameters, scale or mutation factor (F) and crossover probability (CR), was introduced and an individual was assigned the parameter values according to their rank in the population. A mutation strategy, which creates two mutant individuals, was implemented. The selection process was based on objective function value, and constraints were violated. Finally, a penalty method was employed that relies on the degree of constraint violation.

Figure 1 shows the flowchart of the ADEA algorithm.

The current study considers two amendments from ADEA, which are the constraint handling method and selection procedure.

2.1 Novel Weighted Constraint Handling Method

In the Σ-constraint handling method, the combined function, ψ, is created by taking a sum of the objective function value and the sum of violations by the respective individual. Therefore, an individual with the highest sum of violations will rank last in the sorted list of combined functions, ψ. But a situation may arise where for an individual a single constraint violation value could be bigger than another individual who is violating multiple constraints. This situation is shown below.

	gx1	gx2	gx3	gx4	Σ
Individual 1	0	0	40	0	40
Individual 2	7	3	20	5	35

In the above example, gx1-to-gx4 represents four constraints. Both individuals are violating constraints. *Individual 1* violates only one constraint gx3, whereas *individual 2* violates all four constraints. The Σ-constraint handling method would rank *individual 2* above *individual 1*, as Σ of *individual 1* is larger than *individual 2*, but one can see from the above example, *individual 2* needs to satisfy all the constraints and *individual 1* has to satisfy only one constraint to achieve feasibility. Hence, the selection of *individual 2* over *individual 1* could delay the convergence at optimum and require more function evaluations. To avoid such a situation, a novel weighted constraint handling method is proposed in this study. The flowchart given in Fig. 2 illustrates the steps of evaluating a penalty using the weighted sum method.

The steps to evaluate novel weighted penalty are as follows:

Step 1: Evaluate objective function value $f\left(X_i^G\right)$ and constraint function value $g\left(X_i^G\right)$.

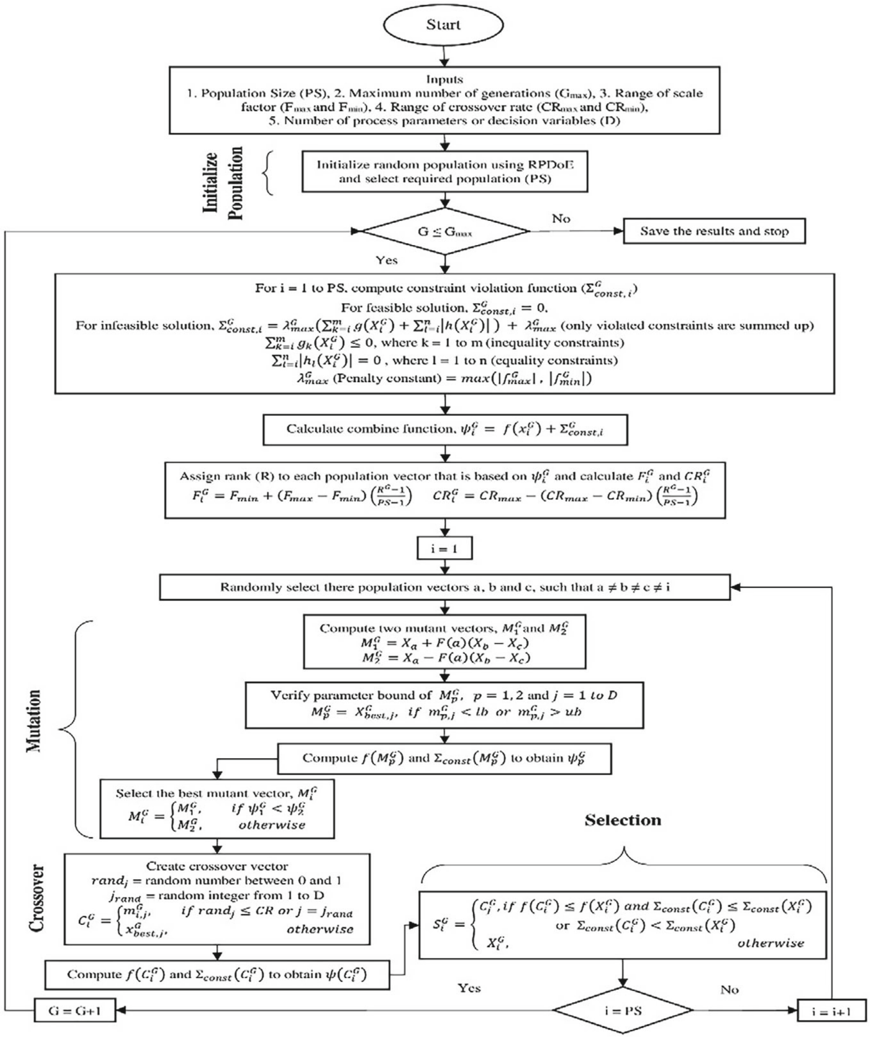

Fig. 1 Flowchart for ADEA algorithm [5]

Step 2: Zero the violations which are less than constraint tolerance, Ct, $(g\left(x_{i,j}^{G}\right) \leq Ct) = 0$. The value of Ct in the current study is taken as 10^{-6}.

Step 3: Scaling the violations: Divide each constraint $g(x)_{i,k}$ with the maximum value of respective constraint $\max\left(g(x)_k\right)$

Step 4: Take the sum of scaled violations for each individual and multiply it by the number of constraints violated (NOCV) by the same individual.

Step 5: Take a ratio of a number of constraints violated by an individual (NOCV) to the total number of constraints (NOC) and add the ratio to the multiplication

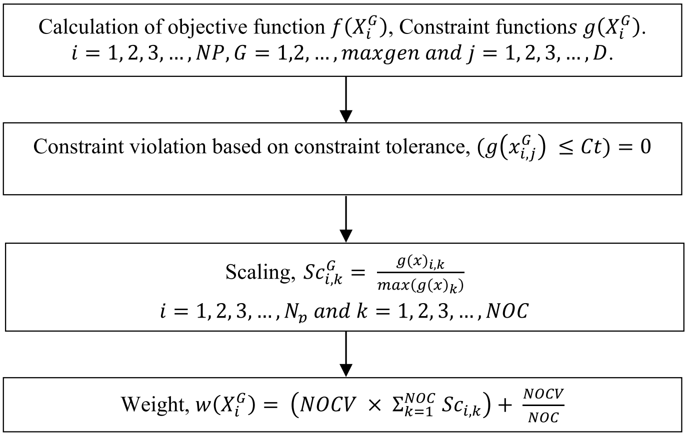

Fig. 2 Novel weighted constraint handling method

of the sum of scaled violation and NOCV. The obtained answer is the final weight.

Weight,

$$w\left(X_i^G\right) = \left(NOCV \times \sum_{k=1}^{NOC} Sc_{i,k}\right) + \frac{NOCV}{NOC}$$

The weight is used to form a combined function. The combined function can be evaluated using Eq. 2.

$$\psi_i^G = fx_i^G + w_i^G * \lambda + \lambda, \quad i = 1, 2, \ldots, NP, G = 1, 2, \ldots, maxgen \tag{2}$$

where λ is the maximum absolute value of fx_i^G. The λ is added to only infeasible individuals.

The sorting in the algorithm is carried out using the combined function, ψ. The novel weighted penalty puts more emphasis on the number of constraints violated by an individual. The scaling step brings the amount of violation between 0 and 1. The scaling helps in the cases where the difference between the values of violations is very large, such as the violation of one constraint is in decimals but the violation of other constraint is in hundreds or thousands. This difference is mitigated using scaled values. By using scale, an individual gets affected by the respective constraint violations of the entire population. Such an approach reduces the *NFE*s by directing the convergence toward the optimum solution. The following example calculates the combined function for four arbitrary individuals. The λ in this example is 60.

Table 1 demonstrates the novel weighted constraint handling method on four arbitrary individuals. According to Σ constraint handling method, individual 4 ranked the highest. However, individual 4 violated two constraints and individual 3 has violated only one constraint. The novel weighted constraint handling technique values the number of violated constraints more. Hence, individual 1 will rank highest even though, individuals 3 and 4 have lower constraint violation value. It can be seen from Table 1 that individuals 3 and 4 violate the same number of constraints, but the amount of violations of individual 3 is more than individual 4. Hence, the proposed constraint handling method ranked individual 4 higher than individual 3. The example shown in Table 1 represents the capability of the proposed method, to distinguish between the individuals with same number of constraint violations.

2.2 Selection

In the selection procedure of the unconstrained optimization algorithm, an individual with a better objective function value is selected. Whereas, in a constrained optimization algorithm, the penalty method is employed to remove the infeasible individuals. In the selection strategy of the current study, the combined function is compared. The selection procedure is depicted in Table 2. When both child and parent are feasible, i.e., all the constraints are satisfied, then an individual with objective function value nearer to optimum is selected, because the penalty method won't be applied to any of the individuals. In the scenario where one individual is feasible while the other is infeasible, the feasible individual is chosen. However, if both individuals are infeasible, their combined function value, ψ, is compared, and the better one is selected.

The selection procedure for a minimization problem is shown below in Table 2.

3 Heat Exchanger Design

The problem of heat exchanger design involves a set of eight decision variables and six inequality constraints. Also, none of the constraints are redundant which makes the optimization process very challenging.

The problem statement is given as follows [12], a fluid with a specified flow rate, W and specific heat, C_p, undergoes heating by passing through a sequence of three heat exchangers in series, taking it from initial temperature of T_0 to a final temperature of T_3. Each heat exchanger (or stage) of the process involves heating the cold fluid by means of hot fluid having identical W and C_p as the cold fluid. The hot fluid's temperatures upon entering the heat exchangers (t_{11}, t_{21} and t_{31}) and overall het transfer coefficients of the heat exchangers (U_1, U_2, U_3) are all constant and known values.

$$f(A_1, A_2, A_3, T_1, T_2, t_{12}, t_{22}, t_{32}) = f(x_1, x_2, x_3, x_4, x_5, x_6, x_7, x_8)$$

Table 1 Application of novel weighted constraint handling method

	fx	$gx1$	$gx2$	$gx3$	$gx4$	Σ	scgx1	scgx2	scgx3	scgx4	Σscgx	NOCV	$\frac{NOCV}{NOC}$	Wt	ψ
Ind 1	30	0	0	40	0	40	0	0	0	1	1	1	0.25	1.25	165
Ind 2	40	5	5	20	5	35	0.33	0.25	1	1	2.583	4	1	11.332	779.92
Ind 3	50	10	20	0	0	30	0.66	1	0	0	1.66	2	0.5	3.82	339.2
Ind 4	60	15	10	0	0	25	1	0.5	0	0	1.5	2	0.5	3.5	330

Table 2 Selection procedure

Child individual	Parent individual	Selection (minimization)
Feasible	Feasible	min(fxchild, fxparent)
Feasible	Infeasible	fxchild
Infeasible	Feasible	fxparent
Infeasible	Infeasible	$\min(\psi_{\text{child}}, \psi_{\text{parent}})$

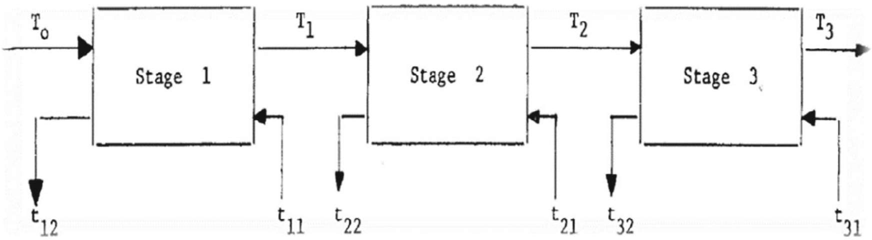

Fig. 3 Three stage Heat exchanger system (TSHE) [12]

The objective is to minimize the overall heat transfer surface area while maintaining the same thermal performance (Fig. 3).

Minimize, total heat transfer area,

$$f(x) = x_1 + x_2 + x_3.$$

Subject to constraints,

$$\begin{aligned}
g_1(X) &= x_4 + x_6 - t_{11} - T_0 \le 0,\\
g_2(X) &= x_5 + x_7 - t_{21} - x_4 \le 0,\\
g_3(X) &= T_3 + x_8 - t_{31} - x_5 \le 0,\\
g_4(X) &= x_4 + \hat{U}_1 x_1 T_0 - T_0 - \hat{U}_1 x_1 x_6 \le 0,\\
g_5(X) &= x_5 + \hat{U}_2 x_2 x_4 - x_4 - \hat{U}_2 x_2 x_7 \le 0,\\
g_6(X) &= T_3 + \hat{U}_3 x_3 x_5 - x_5 - \hat{U}_3 x_3 x_8 \le 0.
\end{aligned}$$

where

$$\hat{U}_i = \frac{U_i}{WC_p}, \quad i = 1, 2, 3.$$

$$T_0 = 100\,°\text{F},\ T_3 = 500\,°\text{F},\ WC_p = 10^5\ \text{Btu/(h °F)}$$

The parameter bounds are given in Table 3.

Table 3 Values of t_{i1} and U_i

i	t_{i1} (°F)	U_i (Btu/(h ft^2 °F))
1	300	120
2	400	80
3	600	40

$$100 \leq x_1 \leq 10000;$$
$$1000 \leq x_2, x_3 \leq 10000;$$
$$10 \leq x_4, x_5, x_6, x_7, x_8 \leq 1000.$$

4 Result and Discussion

Table 4 reports the optimum decision variables obtained using modified ADEA, along with its respective constraint function values and optimum function value. Table 5 provides the comparison between the best, mean, standard deviation (SD), and worst results obtained in this study and the findings of other researchers. The decision variables are evaluated up to seven decimal places. Table 4 shows that modified ADEA provides the optimum value of the objective function (7049.2358) and satisfies all the constraint values that are below the constraint tolerance, 10^{-6}.

Table 5 lists the results of the proposed algorithm and other researchers. The researchers who used GA to solve the TSHE problem did not achieve a minimum solution. Amirjanov [15] obtained the highest standard deviation. The standard deviation shows the degree of consistency in the results. The lowest SD is shown by Patel et al. [18]. The proposed algorithm showed a satisfactory level of consistency in the results. Although, the ADEA obtained the best mean and worst results, the minimum, i.e., optimum, result is scored by modified ADEA.

Table 4 Results of heat exchanger design using modified ADEA

Decision variables	Modified-ADEA	Constraints	
x_1	579.3426823	g_1	9.97E-07
x_2	1359.863785	g_2	9.99E-07
x_3	5110.029312	g_3	9.98E-07
x_4	182.0208693	g_4	−0.00037
x_5	295.5986239	g_5	−0.00061
x_6	217.9795295	g_6	−0.00093
x_7	286.4226450	$\boldsymbol{F}(\boldsymbol{x})$	7049.2358
x_8	395.5987237		

Table 5 Heat exchanger design results comparison

Author(s)	Best	Mean	Worst	SD
Deb (GA) [13]	7060.221	–	–	–
Jaberupour and Khorram (HS) [14]	7051.3012	–	–	–
Amirjanov (GA) [15]	7054.316	7372.613	8835.655	1000
Chootinan and Chen (GA) [16]	7049.2607	7049.5659	7051.6857	0.57
Yang (BA) [17]	7049.248	7049.2484	7049.3307	0.00523
Patel et al. (ADEA) [18]	7049.2480	**7049.2480**	**7049.2480**	**1.423E−7**
Modified-ADEA	**7049.2358**	7049.4792	7051.0946	0.4739

'–': data not available, 'SD': standard deviation, 'HA': Harmony search, 'GA': genetic algorithm, 'BA': Bat Algorithm

5 Conclusions

The conclusions of the current paper are listed below:

- A TSHE problem is successfully optimized using modified ADEA.
- A novel constraint handling technique is introduced, which considers the degree of constraint violation and constraints violated.
- A selection method based on the feasibility of the individual is used.
- The proposed algorithm. Modified ADEA outperformed ADEA, GA, BA, and HS algorithm.
- The modified ADEA was able to achieve 7049.2358, slightly better than other algorithms.

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Numerical Investigation of Cavitating Base MHKF-180s and Modified MHKF-180s Hydrofoils

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Abstract In this study, the hydrodynamic performance of 2D MHKF-180s hydrofoil (without dimple) and modified MHKF-180s hydrofoil (with dimple) is computationally analyzed. The investigation is conducted at a fixed angle of attack (α) of 2° using the Realizable $k-\epsilon$ turbulence model and the Zwart-Gerber-Belamri (ZGB) cavitation model. The main objective is to investigate the effect of a dimple placed at 40% of the chord length for supercavitating condition and non-cavitating condition. The simulations are performed at a constant Reynolds number, Re = 1.3 $\times$ 10^6 using Ansys Fluent. The hydrodynamic performance is evaluated based on various parameters, including lift coefficient (C_l), drag coefficient (C_d), lift-to-drag ratio (l/d), pressure coefficient (C_p), vapor volume fraction, pressure variation, and turbulent kinetic energy. It was concluded that the dimple has no influence on supercavitating behavior. However, in the non-cavitating scenario, the sharp edge of the dimple leads to the formation of a small vapor cavity, resulting in a decrease in the lift coefficient and an increase in the drag coefficient.

Keyword Realizable $k-\epsilon$ · Modified hydrofoil · Cavitation · MHKF-180s

1 Introduction

A hydrofoil is a kind of foil that possesses a wing-shaped structure which is used for lifting a boat above the water surface. These foils function by redirecting the flow in a downward direction, which generates an upward force known as lift. These foils have various applications in both commercial and military industries. When hydrofoils operate at high velocities; they create a sudden decrease in pressure surrounding their surfaces, giving rise to a phenomenon called cavitation. Cavitation occurs when the fluid pressure falls below the vapor pressure, leading to the generation of tiny bubbles or cavities. These bubbles can implode and potentially damage nearby objects. To

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investigate this phenomenon, researchers utilize a dimensionless parameter called the cavitation number (σ). Cavitation has both positive and negative effects, depending on the circumstances. For instance, in pumps, cavitation restricts fluid flow and reduces efficiency, whereas in the case of torpedoes, cavitation aids in achieving high speeds in water.

Over the past few years, researchers have conducted many experimental and computational investigations to examine the behavior of fluid undergoing cavitation in different scenarios. These studies are focused on modifying various hydrofoils such as NACA0015, NACA4415, NACA4311, and so on [1–3]. For instance, Binci et al. [4] studied the flow field in dimpled surfaces using both numerical and experimental approaches. They found that the dimple causes the reduction of drag and laminar separation bubble (LSB). Kumar et al. [5] assessed the unsteady cavitating flow over a semi-circular dimple on NACA4412. They discovered that under partial cavitation and at a lower angle of attack, the base hydrofoil outperforms the modified but at a higher angle of attack, the modified outperforms the base hydrofoil. Similarly, Wang et al. [6] studied the active cavitation suppression on a dimple NACA66 MOD. They discovered that the jet could achieve a cavitation suppression effect of 69.35% ensuring the range of hydrodynamic performance does not exceed 5%. Krishnan and Roy [7] computationally explored the aerodynamic performance of modified NACA0012 for low Re. They discovered that the flow separation effect was less dominant in modified aerofoil and was pushed toward the leading edge of the modified aerofoil. Lewthwaite and Amaechi [8] computationally explored the modification effect using various shapes on 2D NACA0017. They concluded that the dimple delayed the separation point which led to an increase in the aerodynamic performance. Similarly, Livya et al. [9] numerically studied the aerodynamic effect by using dimples on aircraft wings. They discovered that dimple creates turbulence which leads to a delay of flow separation which increases the stall angle. Chalia and Bharti [10] analyzed the improvement of aircraft performance by using vortex generators and dimples over the airfoil surface. They found that the overall performance of dimples is better as compared to aerofoil modified with a vortex generator. Sharmin et al. [11] analyzed the effects of geometric surface modifications through dimples and static extended trailing edges on NACA0012 aerofoil. They concluded that the dimple cavity creates a laminar to turbulent transition (i.e., flow separation delay happens) which was further accelerated by the flap at the optimum angle of attack. Sowmyashree et al. [12] numerically studied the effect of semi-circular dimples on the aerodynamic performance of NACA2412 aerofoil. They concluded that the inward dimple provided better aerodynamic efficiency than outward dimple and unmodified aerofoil. Stolzman and Manoharan [13] computationally investigated the effect of dimple on NACA aerofoil. It was concluded that at higher AOA, dimple positioned anywhere along the chord increases performance, but at low AOA, dimples placed further near the trailing edge were found favorable. Venkatesan et al. [14] computationally and experimentally investigated the aerodynamics performance of dimpled NACA2412. They found that after taking multiple dimples (plain, square, elliptical, triangular, and rectangular), the square dimple results outperformed other dimples.