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Parametric optimization of microchannel heat exchanger using socio-inspired algorithms

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ABSTRACT

Miniaturized products and systems have emerged as game-changing innovations with huge potential in the modern period with increasing emphasis on sustainable development and green energy. Automotive, astronomical, electronics, and medical research are just a few of the industries where micro electro mechanical systems (MEMS) have found use. In addition to that, microchannel heat exchangers (MCHX) have been created in response to the growing demand for effective cooling solutions for these small systems. Optimization of these MCHX is important for improving the overall system efficiency. In this work, two popular socio-inspired evolutionary algorithms viz. teaching learning-based optimization (TLBO) and cohort intelligence (CI) are applied for optimizing three objectives such as power density, compactness factor, and heat transfer with pressure drop (HTPD) for air-water MCHX. The results obtained are significantly improved when compared with genetic algorithm (GA). Moreover, both the techniques are observed to be robust. This study investigates the use of socio-inspired artificial intelligence (AI) algorithms to support the design and optimization of heat exchangers, highlighting their potential to address complex engineering challenges more efficiently.

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1. INTRODUCTION

The pursuit of energy efficiency and sustainability has taken on extreme importance in a world where the demand for energy keeps rising and the effects of climate change come out greater and larger. Energy efficiency and sustainability have been a prominent research area to work upon. In line with the same, heat exchangers play an important role. As a result of their increased efficiency, they may use less energy, making them a more environmentally friendly option for heating, cooling, and refrigeration systems. Reduced energy use results in less influence on the environment and less greenhouse gas emissions. Moreover, waste heat from power generation, industrial operations, and exhaust gases can all be collected and used through heat exchangers. The entire energy requirement and waste can be reduced by using this recovered heat for applications such as home hot water and space heating. Apart from all the points of traditional heat exchangers, size, weight, and inefficient heat transfer are the major drawbacks.

However, from the past few decades, the demand for industrial miniaturized products is quite enhanced owing to the disruptive technologies across various domains such as aerospace, bio-medical, semiconductor and electronics, and automotive. This has resulted in the development of microchannel heat exchangers (MCHX). To meet the growing cooling requirements of small systems, MCHX have been developed. Typically, such systems have a diameter that is smaller than 1 mm in size. Furthermore, the area density is greater than 10,000 m^2/m^3. MCHX has several advantages, including a higher heat flux, a smaller size, a lighter weight, and a higher energy efficiency. This has enabled MCHX to tackle a wide range of challenging thermo-hydraulic issues that have plagued numerous academics and industries [1].

Several designs in terms of geometrical novelties to enhance the thermo-hydraulic performance of MCHX have been proposed [2]–[4]. There exist various key performance indicators (KPIs) such as heat flux, pressure drop, power density (PD), and thermal resistance. Specifically, for the micro and mini sized heat exchangers, performance criteria referred to as compactness factor (CF) has been developed [5], [6]. Some of the aforementioned criteria are to be maximized (CF, PD, heat flux) while others (thermal resistance, pressure drop) are to be minimized which are considered as objective functions in optimization problems. The heat flux, or the amount of heat produced per unit area, increases as the size of the system or product decreases. Due to its smaller size compared to traditional systems, the product or system has less space available for heat dissipation and can results in the overheating of such systems [7]. For micro devices, the standard air-cooling method was ineffective. In order to increase the rate of heat transfer, liquid cooling methods have been created [8].

Many researchers reviewed some prominent aspects of MCHX. Sur and Gulia [9] reviewed MCHX, microchannel heat sink and polymer heat exchangers and put forward their opinion on future trends of MCHX. Xiong *et al.* [10] given the opinion on future simulation and experimentation investigations on two-phase flow distribution in MCHX. Recently, many studies have been carried out on optimization of MCHX. The parameters considered usually are fin pitch, channel height, channel width, no. of channels per tube and length of MCHX [11]. The ideal geometry of a heat exchanger has been determined using multi-objective optimization [12].

The impacts of various geometrical factors, including row pitch, fin pitch, wall thickness, and channel count, on heat generation pressure drop, energy efficiency, and compactness have been studied using the response surface methodology. In order to conduct analysis, the fluent module has been used. Additionally, optimization via genetic algorithm (GA) has been done [13]. Design optimization of micro channel heat sink was achieved with evolutionary algorithms [14]. Thermo-hydraulic performance optimization of a disk-shaped and elliptical pin fin micro channel heat sink was carried [15], [16].

Generally, the solution techniques are classified in two broad verticals viz. deterministic algorithms and approximation algorithms. Deterministic techniques are based on the numerical methods and calculates the exact solution of a problem whereas the approximation algorithms are artificial intelligence (AI) based techniques which explores the search space and quickly converges to the global optimum. However, the global optimum may not be the exact solution rather essentially being the nearest point. As the problem complexity increase and problem becomes NP-hard, the deterministic methods fail to find the optimum solution in the finite time. Hence, there exists various AI based algorithms used for solving complex optimization problems.

All these methods are essentially nature inspired methods. GA [17], [18], simulated annealing (SA) [19], particle swarm optimization (PSO) [20] are some prominent examples. The methods which are based on the societal behavior are referred to as socio-inspired optimization methods. The league championship algorithm [21], soccer league competition algorithm [22], ideology algorithm [23], and teaching learning-based optimization (TLBO) [24], [25] are some of the examples of socio based methods. One such technique is cohort intelligence (CI) and its variations [26], [27] which is applied in this work. In the past, variations of CI algorithms are applied for optimizing the process parameters for advanced manufacturing processes [28]–[30].

The current work is referred to from [12] wherein the experimentation, mathematical modelling and optimization using GA of air-water MCHX have been carried out. In this work, TLBO algorithm and CI algorithms are applied for maximizing the PD, CF, and heat transfer rate combined with pressure drop. Multivariate optimization considering "Fin pitch (F_p), transversal MCHX tube row pitch (P_t), number of small channels per multiport tube (n_sc) and multiport tubes wall thickness (t_wall)" is carried out.

The structure of the paper is as follows: section 2 introduces the problem, presents the mathematical formulation and explain the algorithms used in this study. Section 3 shares the results a, long with a discussion of their implications. Finally, section 4 concludes the paper and highlights possible directions for future work.

2. PROBLEM FORMULATION AND METHODOLOGY

The objective functions are referred from [13]. Four variables are considered viz. fin pitch in mm (x_1), tube row pitch in mm (x_2), no. of small channels per tube (x_3), and tube wall thickness in mm (x_4).

- Power density: PD is defined as the ratio rate of heat transfer per unit mass to the rate of heat transfer per unit mass of referent (ref) heat exchanger. The mathematical function which is to be maximized is given in (1)

$$Max\ PD = 1 + 0.15526\,x_1 - 0.0515\,x_1^2 + 0.09588\ x_2 + 0.04586\ x_1\,x_2 - 0.02775\,x_2^2 - 0.25361\,x_3 - 0.03508\,x_1\,x_3 - 0.02608\,x_2\,x_3 + 0.09113\,x_3^2 - 0.36243\,x_4 - 0.06115\ x_1\,x_4 + 0.02007\ x_2\,x_4 + 0.09322\ x_3\,x_4 + 0.9552\,x_4^2 \quad (1)$$

– Compactness factor: CF represents rate of heat transfer per unit volume of microchannel heat exchanger. The objective function for maximization of CF is described in (2).

$$Max\ CF = 1 - 0.0114\,x_1 - 0.01435\,x_1^2 - 0.06616\ x_2 - 0.00032\,x_1\,x_2 - 0.00901\,x_2^2 - 0.26208\,x_3 - 0.00188\,x_1\,x_3 + 0.01866\,x_2\,x_3 + 0.09496\,x_3^2 - 0.089916\,x_4 + 0.03203\ x_1\,x_4 + 0.00794\ x_2\,x_4 + 0.01459\ x_3\,x_4 - 0.00094x_4^2 \quad (2)$$

– Heat transfer rate combined with pressure drop (HTPD): the third objective function combines the average rate of heat transfer per unit area with air-water side pressure drop. Moreover, to consider the effect of consumed mechanical energy, two factors viz. ventilation power and pumping power are also considered. The objective function is to be maximized and the mathematical expression is mentioned in (3).

$$Max\ HTPD = 1 + 0.02605\,x_1 - 0.00687\,x_1^2 - 0.05239\,x_2 - 0.0026\,x_1\,x_2 + 0.00227\,x_2^2 - 0.02386\,x_3 - 0.00892\,x_1\,x_3 - 0.00255\,x_2\,x_3 + 0.00758x_3^2 - 0.00111\,x_4 + 0.01235\,x_1\,x_4 + 0.000023\,x_2\,x_4 - 0.00155\,x_3\,x_4 - 0.00464\,x_4^2 \quad (3)$$

For all the objective functions discussed, the design variables are subject to lower and upper bounds, as defined in (4) to (7). These are referred to from [12].

$$1 \le x_1 \ge 2 \quad (4)$$

$$10 \le x_2 \ge 20 \quad (5)$$

$$10 \le x_3 \ge 20 \quad (6)$$

$$0.2 \le x_4 \ge 0.6 \quad (7)$$

2.1. Teaching learning-based optimization algorithm

The TLBO algorithm is a population-based, socio-inspired optimization method that draws inspiration from the dynamics of a traditional classroom. Originally introduced by researchers in [24], [31], TLBO models the way knowledge is shared and gained between a teacher and students. In this approach, each individual in the population represents a student, while the problem variables are treated as different subjects or courses being studied.

The performance of each "student" is measured by the objective function, which reflects how well they've "learned" or improved over time. The best-performing individual in the group takes on the role of the "teacher," guiding others to enhance their performance. A flowchart outlining the TLBO process is shown in Figure 1. For a more in-depth explanation and the full algorithmic flow, readers are encouraged to consult [31].

2.2. Cohort intelligence algorithm

The CI algorithm models the self-supervising behavior of candidates within a cohort, capturing their ability to improve independently over time. It draws inspiration from the natural tendency of individuals to evolve by observing and emulating the behavior and qualities of others in the group. Each candidate follows a specific behavioral pattern, which may be enhanced by adopting beneficial traits observed in peers. The pseudocode for the CI algorithm is presented in Figure 2. For detailed mathematical formulations and the algorithmic flowchart, readers are referred to the appendix of [24].

3. RESULTS AND DISCUSSION

As discussed in the introduction section, in the current work, two nature inspired optimization techniques viz. CI and TLBO are applied. The algorithms are coded in MATLAB R2021. The platform used is Windows with an Intel Core i5 processor and 4 GB RAM. Appropriate parameterization plays a crucial role while using such approximation algorithms. There exist various methods to find the optimum controlling parameters for any solution technique. Exhaustive literature review is being carried out in conjunction with several initial trials for selecting the best controlling parameters for CI and TLBO algorithms and are presented in Table 1. To check the robustness of the algorithms, each objective function is evaluated for 30 times and a standard deviation (SD) is reported.

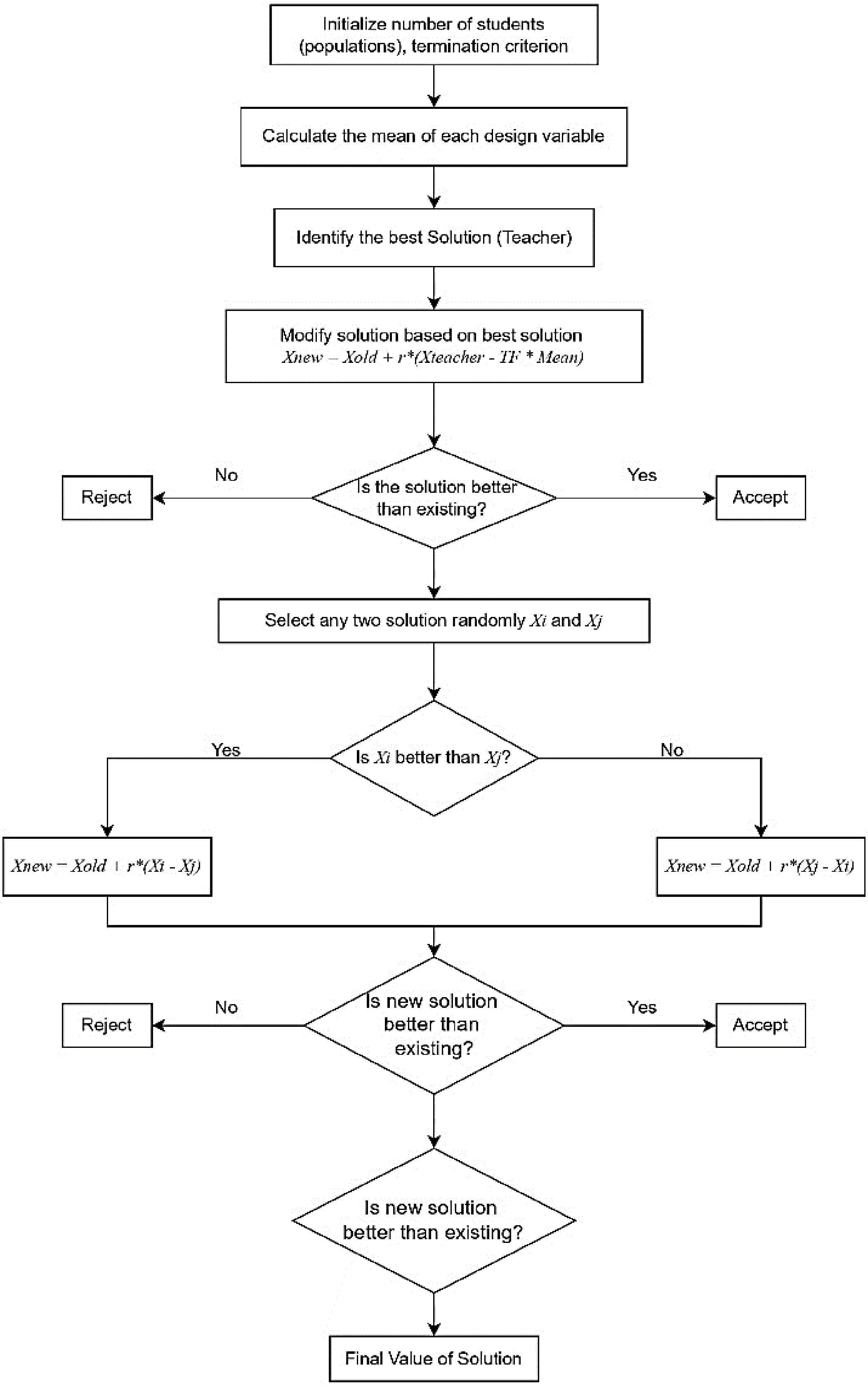

Figure 1. The flowchart of TLBO algorithm [31]

Objective function Minimize $f(x)$
Select number of candidates in the cohort c
Set interval reduction factor r
Set convergence parameter ϵ
While *(No of Learning attempts < Max Learning attempts)*
Generate the Randomize qualities of each candidate
Evaluate objective function for every candidate.
Evaluate probability associated for every candidate in the cohort
Use following strategy (RW, FBest, FBetter, or Alienation) to select behaviour to follow by each candidate.
Shrinkage of the interval for every candidate
If *(Convergence criterion met)*
Accept the current best candidate and its behaviour as a final solution
Else
Generate the Randomize qualities of each candidate as 2nd iteration
End
End

Figure 2. The pseudocode of CI algorithm

Table 1. Control parameters and stopping criteria

Solution methodology	Parameter	Stopping criteria
TLBO	Population size =100	Objective function value is less than 10^{-16}
	Generations =500	
CI	Number of candidates =5	
	Value of reduction factor = 0.99	

The solutions obtained using the TLBO and CI algorithms are summarized in Table 2. Each problem was solved 30 times, and the mean and best results are reported. The SD is also included to indicate the consistency of the solutions. For comparison, the results are evaluated against those obtained using the GA, as reported in [31]. Additionally, the table presents the optimal values of the design variables along with the corresponding objective function values.

Table 2. Solutions using TLBO and CI

Function	Variable	GA [13]	TLBO	CI
Power density	x_1	2	1	1.8491
	x_2	20	10	10.4412
	x_3	20	20	19.8620
	x_4	0.2	0.6	0.3946
	Mean solution	NA	26.5371	24.9633
	Standard-deviation	NA	0.0000	0.0000
	Best solution	27.0136	26.5371	24.9633
	Mean runtime in seconds	30	0.6832	0.0810
Compactness factor	x_1	1	1	1.8049
	x_2	10	17.2855	17.5736
	x_3	20	20	20
	x_4	0.2	0.6	0.2708
	Mean solution	NA	36.5111	36.3148
	Standard-deviation	NA	0.0000	0.0000
	Best solution	36.1386	36.5111	36.3148
	Mean runtime in seconds	30	0.6611	0.1035
HTPD	x_1	2	1	1
	x_2	10	10	10
	x_3	20	20	20
	x_4	0.6	0.2	0.3381
	Mean solution	NA	2.5824	2.5796
	Standard-deviation	NA	0.0000	0.0000
	Best solution	1.4541	2.5824	2.5796
	Mean runtime in seconds	30	0.6504	0.1123

Figure 3 shows the convergence plot for TLBO and CI algorithms. For the objective function HTPD, results of TLBO and CI algorithms are improved by 77.59% and 77.40% respectively as compared with GA solutions. The results demonstrate improvement in thermo-hydraulic performance of MCHX contributing significantly towards green system and sustainable future. For CF problem, there is marginal improvement in the results, 1.03% and 0.48% with TLBO and CI algorithm respectively. It is important to note that the SD for TLBO and CI is very minimal demonstrating the robustness. Figures 3(a) to 3(f) shows the convergence plots for TLBO and CI algorithms.

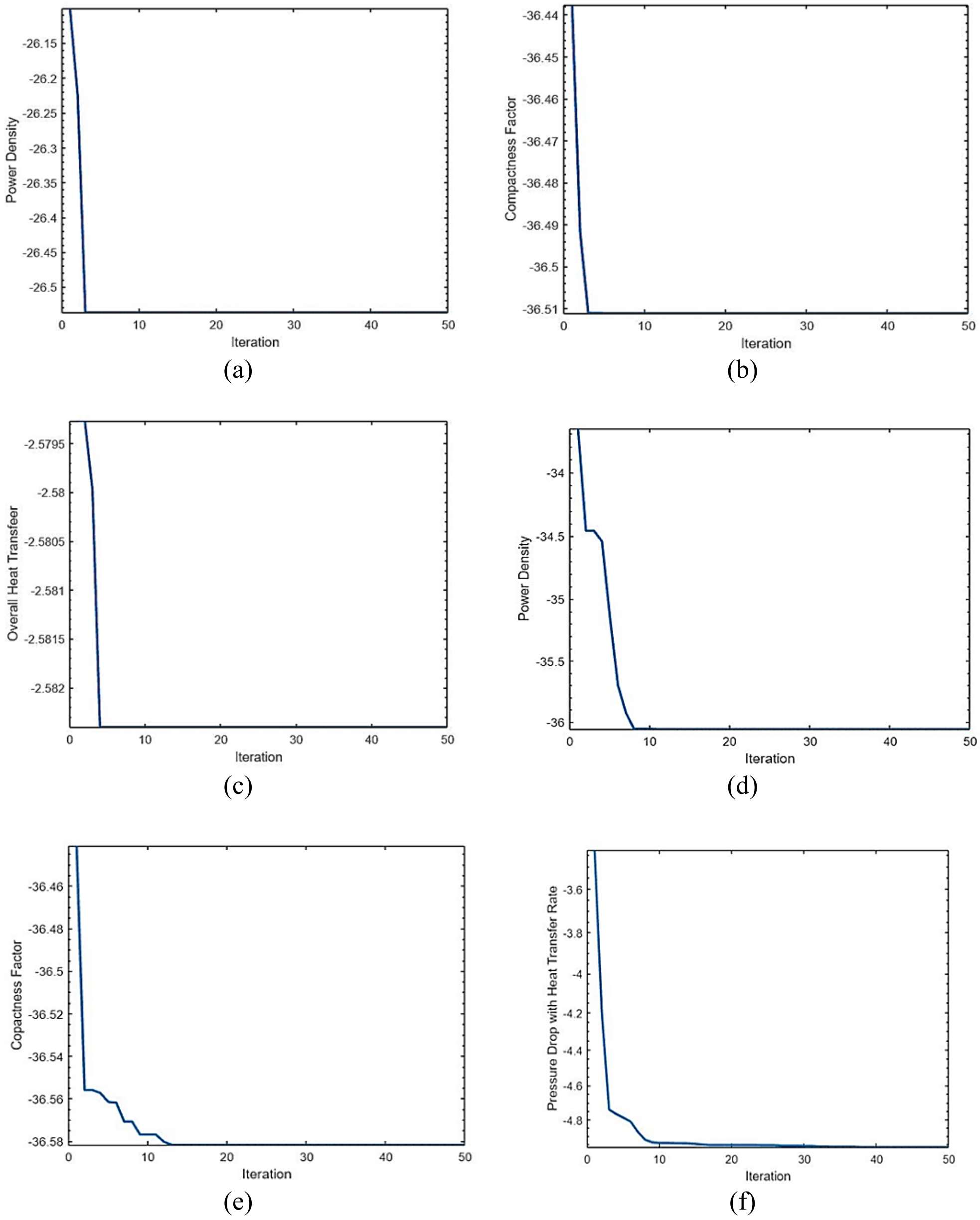

Figure 3. Convergence plots with TLBO and CI algorithm: (a) PD with TLBO, (b) CF with TLBO, (c) HTPD with TLBO, (d) PD with CI, (e) CF with CI, and (f) HTPD with CI

4. CONCLUSION

In this paper, two socio-inspired optimization methodologies referred to as TLBO and CI are applied for optimizing the air/water MCHX. Three objective functions are considered viz. PD, CF, and HTPD. All these objectives are to be maximized for improving the efficiency of MCHX. The results obtained are compared with GA. The results for HTPD problem are significantly improved (by 77.59% and 77.40%) with TLBO and CI algorithms respectively when compared with reported GA solutions. A marginal improvement of 1.03% and 0.48% is observed with TLBO and CI algorithm respectively. Furthermore, the SD validates the robustness of the algorithms. The results demonstrate the applicability of socio-inspired optimization techniques in the area of heat exchangers. In the near future, the more complex, constrained and multi-objective problems from MCHX domain could be solved with these techniques.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Vikas Gulia	✓	✓			✓	✓		✓	✓	✓				
Aniket Nargundkar	✓	✓	✓	✓		✓		✓	✓	✓				

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The authors confirm that the data supporting the findings of this study are available within the article.

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