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OPTIMIZATION OF MICROCHANNEL HEAT EXCHANGERS USING GENETIC ALGORITHMS

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Abstract. *Optimizing heat exchangers is a crucial engineering challenge in industrial processes and energy production. Microchannel heat exchangers have been developed to increase thermal efficiency in cooling systems, allowing for better heat dissipation in a reduced space. However, optimizing these heat exchangers can be complex due to the large number of variables involved in the process. Genetic Algorithms (GA) are one approach to optimizing microchannel heat exchangers, based on the concept of natural selection and biological evolution, and capable of finding optimal solutions to complex problems through selection and reproduction processes. In this study, the thickness of the base (H_{base}), top (H_{top}) and channels walls (W_{wall}), and channel width ($W_{channel}$) and height ($H_{channel}$) were optimized for constant flowrate and heat flux. The minimization of the pressure drop (Δp), maximization of the mean outlet fluid temperature ($\bar{T}_{out}$), minimization of entropy generation (S_{gen}) and combinations of these metrics were compared as objective functions in this study. To assess the impact of the GA functional parameters, we established three population sizes (50, 100, and 200), three mutation rates (0.5%, 1%, and 2%), three elitism rates (3, 5 or 10 individuals per generation) and 300 generations. The best solution for each multi-objective function investigated was plotted on merit charts that compared thermal gains and mechanical losses respectively through Nusselt number and friction factor analyses. The results showed that if the objective is to minimize generated entropy, the channel presents the smallest possible width to minimize the total heat resistance, as the entropy generation due to heat transfer is greater than the one due to fluid friction. Conversely, if the objective is to minimize the pressure drop, the channel has the largest possible width.*

Keywords: *Optimization, Genetic Algorithm, Microchannel Heat Sink, Nusselt Number, Friction Factor*

1. INTRODUCTION

The intrinsic irreversibility of heat transfer makes the development of high efficiency heat exchangers a longstanding research area. With the increase in computational capacity, it was possible to achieve high efficiencies with the use of optimization methods to evaluate the non-linear objective functions. Optimization is the set of mathematical methods that identifies the inputs (decision variables) of a function that maximizes or minimizes its value (Baños et al, 2011). Instead of using traditional approaches, recent years efforts have employed heuristic and meta-heuristic approaches to solve, in a simple and general way, these heat exchangers optimization problems. One differentiation of these meta-heuristics methods is between the trajectory-based and the population-based ones (Baños et al, 2011). The trajectory-based uses a single solution during the search process of the optimized solution with specific procedures to avoid local optima, as the simulated annealing and hill climbing algorithms. On the other hand, the population-based algorithms use a population of solutions that evolve a number of generations searching for the optimized solution, like the genetic algorithm based on evolutionary biology, and particle swarm optimization, based on social behavior with the movement of organisms (Baños et al, 2011).

Since the pioneering work of Tuckerman and Pease, 1981, the continuous research and development of these ultra compact heat exchangers based on mini and micro channels was boosted by the higher demand for these microsystems with the microelectronics industry. Several studies have been conducted on micro channel heat exchangers (MCHE), with straight rectangular patterns being the most employed due to their favorable thermo-hydraulic characteristics and low manufacturing costs (Ahmed, et al., 2018; Alihosseini, et al., 2020). The geometric parameters of MCHE play a crucial role in its performance, and the height-width ratio of the channel cross-section has been found to predominantly affect thermal and flow resistances. Hence, geometric parameters have been used as optimization parameters in several studies focusing on improving their thermal and hydraulic performance.

Foli et al. (2006) combined CFD with optimization approaches to maximize heat transfer while considering design constraints. They used analytical and genetic algorithm-based methods, finding a trade-off between heat transfer and pressure drop. Halelfadl et al. (2014) optimized thermal resistance and pumping power in microchannel heat sinks using NGSA-II, showing improved performance with carbon nanotube-based nanofluids. Li, Zhu and He (2019) optimized channel dimensions based on the field synergy principle, while Glazar, Trp and Lenic, (2020) investigated the effects of various parameters on microchannel heat exchangers using response surface methodology.

Besides the utilization of the thermal resistances (or heat transfer rate) and pressure drop, other objective functions were proposed in the literature, with the entropy generation through heat transfer and friction being able to assess both the heat transfer capabilities and mechanical losses (Chen and Chen, 2013; Yin and Ooka, 2015). In addition to the entropy generation, Chen and Chen (2013) proposed the material cost as the multi objective functions of their genetic algorithm with 1D correlations for plate-fin heat sinks optimization. In contrast to using CFD analysis to evaluate the best geometry proposed by the optimization algorithm, as in Chen and Chen (2013), Yin and Ooka (2015) developed an optimization algorithm coupled with a CFD solver for determining the best combination of height, pitch, thickness and length of the fins for a plate-fin heat exchanger.

More complex geometries were also evaluated with genetic algorithms for double-layered microchannel (Kulkarni et al, 2016), wavy fin-and-elliptical tube heat exchangers (Damavandi et al, 2017) and double-layered microchannel heat sink with semi-porous-ribs (Wang et al, 2020). The use of CFD analysis is fundamental for the evaluation of more complex geometries, with no correlations available or more complex fluid-dynamics phenomena that requires more precise solutions. To reduce the numerical solutions needed, Kulkarni *et al.* (2016) also used surrogate modeling (Response Surface Approximation model) for the evaluation of the objective functions.

With the rise on fuel prices and urgency of reducing emissions the reuse of waste heat from power plants on secondary processes emerged as a fast and readily available approach to increase the global energetic and exergetic efficiencies of processes. These policogeneration plants, firstly developed with high exergy waste heat in mind from the combustion of fuels, biomass and/or process residues, are now being introduced in solar photovoltaic systems with low exergy heat available (Chandrasekar and Senthilkumar, 2021). The efficiency decay of photovoltaic cells by increasing the operational temperature, with maximum working temperature without permanent damage to the cell being approximately 110 °C for multijunction cells (Abo-Zahhad et al, 2020), requires an appropriate heat sink. Combined with the small dimensions of the high concentration photovoltaic cells, MCHE are ideal to cooling these devices (Ali, et al., 2020) and/or reuse the waste heat that would be lost to the environment, creating a low exergy cogeneration solar power plant.

In this work, a geometric optimization study of microchannel heat exchangers is carried out aiming at heat recovery in a photovoltaic energy system with CPV solar concentration, through the application of genetic algorithms. For this purpose, the minimization of head loss, entropy generated, and the maximization of the average fluid outlet temperature are used as objective functions.

2. METHODOLOGY

The numerical domain and optimization conditions used in this study are described next, depicting the geometric simplifications and constraints for the optimization procedure. The numerical solution and boundary conditions are detailed as well as the optimization procedure developed for this study and the distinct sets of objective functions evaluated.

2.1 Optimization Conditions

The optimization of a microchannel heat exchanger for thermal recovery on a commercial high concentration photovoltaic cell (Azur Space 3C42 multijunction), available at the Laboratory of Nano and Microfluidics and Microsystems (LabMEMS – COPPE/UFRJ), is geometrically bounded by the interface area of the cell to reduce the total thermal resistance of the heat exchanger. The system has a concentration of 820x of the solar irradiance and maximum electrical efficiency of 38.5%, corresponding to an estimated thermal loss of 35W. With the upper restrictions on the length (L) and width (W) of the microchannels region of both 23 mm, as indicated in Figure 1, the set of parameters to be optimized consists of the height of the channel ($H_{channel}$), width of the channel ($W_{channel}$) and thickness of the base

(H_{base}) and wall (W_{wall}). For the height of the microchannel region (H), it is considered as being constant and equal to 5 mm, thus determining H_{top} and bounding the domain for the optimization algorithm.

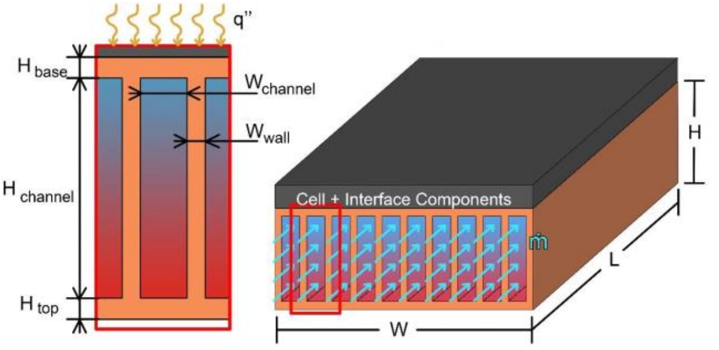


Figure 1. Representation of the area of the photovoltaic cell and domain of the (micro)channel region.

Due to the fabrication capabilities, the change of the decision parameters is not continuous, with a step of 50×10^{-6} m. Also, the lower limit for the set of parameters is 600×10^{-6} m for the channel width and height, and 200×10^{-6} m for the wall width and base height, as described in Table 1. It is noticeable the permissible dimensions in the range of micro to minichannels.

Table 1. Lower and upper limits of the set of decision parameters.

Decision Parameter	**Lower Limit**	**Upper Limit**
Channel Height ($H_{channel}$)	600×10^{-6} m	4.2×10^{-3} m(1)
Channel Width ($W_{channel}$)	600×10^{-6} m	5.0×10^{-3} m
Wall Thickness (W_{wall})	200×10^{-6} m	5.0×10^{-3} m
Base Thickness (H_{base})	200×10^{-6} m	4.2×10^{-3} m(1)

(1) with the restriction of $H_{base} + H_{channel} + H_{top} = 5 \times 10^{-3}$ m

2.2 Numerical solution methodology

Considering the symmetric velocity and temperature profiles at the rectangular microchannels of interest in this study and represented in Figure 2.a, the numerical domain to simulate the conjugate heat transfer is reduced to half of a single channel, as in Figure 2.b, and considering a uniformity on the flow distribution among different channels, as in the study of Qu and Mudawar (2002). This simplification is crucial to enable the optimization procedure based on the genetic algorithm, where hundreds (or even thousands) of high-fidelity numerical simulations are required. The body of the heat exchanger is made of aluminum (density of 2700 kg/m³, thermal conductivity of 200 W/m.K and specific heat capacity of 900 J/kg.K) and the fluid is liquid water, without phase change and considering constant thermophysical properties due to the low temperature difference along the system (density of 997 kg/m³, dynamic viscosity of 9.59×10^{-4} Pa.s and specific heat capacity of 4181 J/kg.K). This hypothesis will be further investigated to evaluate the impact on the optimization solution.

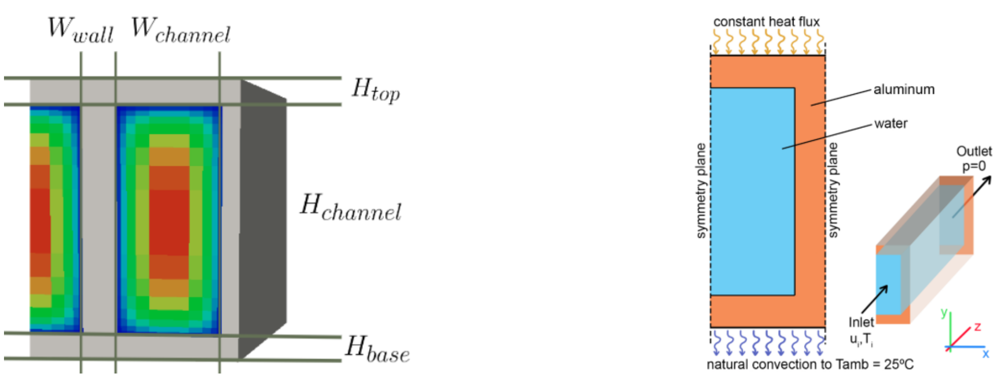
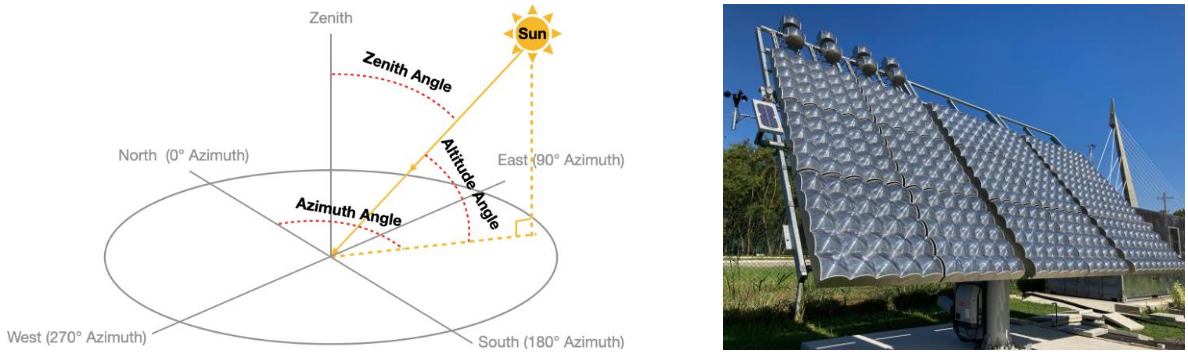


Figure 2. Representation of the (a) numerical domain of the channels and of the (b) reduced geometry with boundary conditions.

As it can be seen in Figure 2.b, the inlet consists of a temperature of 323.15 K and uniform velocity profile, determined as to provide a total flow rate $\dot{m}$ of 40 g/min divided by 2 (half of the channel) and by the number of microchannels, which is obtained with the width of the channel, thickness of the walls and total width of the microchannels region. At both sides there are conditions of symmetry for temperature and velocity at the fluid domain and temperature only for the solid domain, as indicated in Figure 2.b. The top face has an uniform heat flux of 5.472 W/cm², which represents the thermal loss of the Azur Space 3C42 multijunction photovoltaic cell distributed in the area of contact with the microchannel region considered. The bottom face has a condition of natural convection in air at 298.15 K of a plate with inclination of 25.84º with respect to the vertical plane, which represents the mean annual solar zenith angle, as in Fig. 3a, of Rio de Janeiro – RJ, Brazil, location of the LabMEMS High Concentration Photovoltaic system (Fig. 3b). Also, the bottom face has an emissivity of 0.3 to account for radiation losses. The walls have a no-slip condition for the velocity and at the outlet the pressure is equal to the atmospheric pressure at sea level, 101325 Pa.



(a) (b)

Figure 3. Representation (a) of the zenith angle ("Schematic depicting the solar zenith angle, solar altitude angle and solar azimuth angle" licensed in Zhang et al, 2021 under CC BY 4.0) and (b) image of the LabMEMS High Concentration Photovoltaic system.

Each geometry proposed by the genetic algorithm is numerically solved through the open-source software OpenFOAM to evaluate the objective functions, feedbacking the optimization algorithm. The solver uses a finite volume discretization to obtain an accurate description of the temperature and velocity fields in the fluid and solid domains with the multi-region solver *chtMultiRegionFoam*. Due to the temperatures and flow rate of the heat exchanger considered, the fluid flow is considered incompressible and laminar.

$$\boldsymbol{\nabla} \cdot \boldsymbol{U} = 0, \tag{1}$$

$$\rho_f \boldsymbol{\nabla} \cdot (\boldsymbol{U}\boldsymbol{U}) = -\boldsymbol{\nabla} p + \rho_f \boldsymbol{g} + \boldsymbol{\nabla} \cdot \left(\mu_f \boldsymbol{\nabla} \boldsymbol{U}\right), \tag{2}$$

$$\rho_f c_{p,f} \boldsymbol{\nabla} \cdot (\boldsymbol{U} T) = \boldsymbol{\nabla} \cdot \left(k_f \boldsymbol{\nabla} T\right), \tag{3}$$

$$\boldsymbol{\nabla} \cdot (k_s T) = 0 ,$$

The OpenFOAM software solves the continuity (Eq. (1)) and momentum conservation (Eq. (2)) equations for the fluid domain, and energy conservation equation for the fluid (Eq. (3)) and solid (Eq. (4)) domains, considering a steady state regime. Where $\boldsymbol{U}$ is the velocity field of the fluid in m/s, p is the pressure of the fluid in Pa, ρ_f is the density of the fluid, $\boldsymbol{g}$ is the acceleration of gravity in m/s², μ_f is the dynamic viscosity in Pa.s, $c_{p,f}$ is the specific heat capacity of the fluid in J/kg.K, k_f is the thermal conductivity of the fluid in W/m.K, T is the temperature in K and k_s is the solid thermal conductivity in W/m.K.

2.3 Optimization Procedure

The optimization procedure developed in the programming language Python for this study is based on Genetic Algorithms, a heuristic optimization method based on evolutionary biology, where individuals of a population evolve through generations with mating and mutations on its genes (Lambora and Chopra, 2019). The genetic algorithm mimics this process by preserving the predefined size of a population of individuals described by its genes (decision variables, here H_{base}, H_{top}, $H_{channel}$, $W_{channel}$, and W_{wall}) through generations (iterations) until its predefined maximum generations. At each generation, all individuals are evaluated through the numerical simulations performed on

OpenFOAM, and each one is sorted based on the value of an objective function. Then, for the next generation a new set of individuals are created based on mating of individuals where its genes are generated randomly crossing the genes of its parents and with a probability of mutation related to the hyperparameter mutation probability. Also, at each generation (iteration i) the best individuals are introduced to an elite group that can mate with the individuals of the next generation (iteration $i+1$). This is described in the flowchart presented in Figure 3.

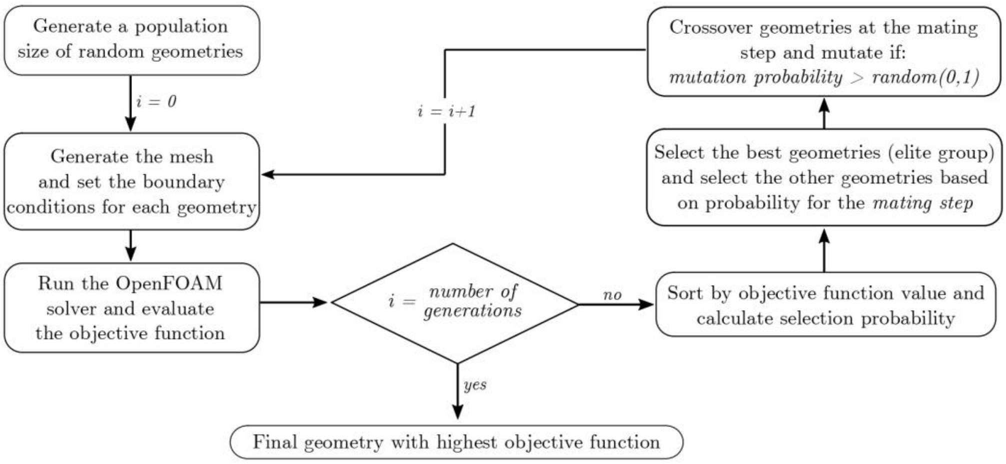


Figure 3. Flowchart of the optimization iterative procedure (iteration i) that couples the genetic algorithm with the OpenFOAM software.

2.4 Objective Functions

As recognized in various studies available in the open literature, the objective functions used to optimize heat exchangers have a great influence on the geometric decision parameters. With the objective to reuse the waste heat in secondary processes, like desalination, space heating and heat-driven cooling, the mean outlet temperature is of great relevance due to the requirements of the secondary process of interest. The mean outlet temperature $\bar{T}_{out}$ is computed considering the mass flow rate and temperature at each i of the n cells of the outlet face, with the surface area A_i, temperature T_i and normal velocity u_i, as in,

$$\bar{T}_{out} = \frac{\sum_i^n A_i u_i \rho_i T_i}{\sum_{i=1}^n A_i u_i \rho_i} = \frac{\sum_i^n A_i u_i \rho_i T_i}{\dot{m}_{channel}}, \tag{5}$$

Likewise, the reduction of the pressure drop in the system, being the difference between the inlet and outlet pressures on the channel, directly impacts the pumping power needed and can improve the global efficiency,

$$\Delta p = p_{in} - p_{out}, \tag{6}$$

Also, the entropy generation through heat transfer and friction can relate both parameters and should be evaluated, as proposed in the literature (Yin and Ooka, 2015). The evaluation of the entropy generation is made on each cell at the numerical domain, as in Equation (7), and then integrated to obtain the entropy generated in the solid and fluid domains in W/K.

$$S_{gen} = \frac{k}{T^2}\left[\left(\frac{\partial T}{\partial x}\right)^2 + \left(\frac{\partial T}{\partial y}\right)^2 + \left(\frac{\partial T}{\partial z}\right)^2\right] + \frac{\mu}{T}\left[2\left(\frac{\partial u}{\partial x}\right)^2 + \left(\frac{\partial u}{\partial y}\right)^2 + \left(\frac{\partial u}{\partial z}\right)^2 + \left(\frac{\partial u}{\partial x} + \frac{\partial u}{\partial y} + \frac{\partial u}{\partial z}\right)^2\right], \tag{7}$$

Besides these 3 objective functions, the increase in the exergy transfer to the fluid is relevant for reuse of the heat in secondary processes as it directly impacts the usefulness of the fluid flow for these purposes. Only depending on the mean outlet temperature $\bar{T}_{out}$, given that liquid water is treated as an incompressible fluid, the exergy transfer at the outlet $\dot{E}_{x,out}$ is evaluated as indicated below.

$$\dot{E}_{x,out} = \dot{m} c_p \left[(\bar{T}_{out} - T_{amb}) - T_{amb} \ln\left(\frac{\bar{T}_{out}}{T_{amb}}\right)\right], \tag{8}$$

Due to the dependency only on $\bar{T}_{out}$, it can be noticed on Equation (8) that the maximization of $\bar{T}_{out}$ implicates also in the maximization of $\dot{E}_{x,out}$. For this reason, the maximization of the exergy transfer was not considered as an independent objective function in this study.

To improve the efficiency of the micro heat exchanger, there is the objective of minimization of entropy generation and pressure drop, and maximization of the mean outlet temperature of the fluid. Due to the interest in evaluating multi objective functions, $\bar{T}_{out}$, Δp and S_{gen} undergoes a normalization procedure which makes all maximization problems having the same order of magnitude,

$$F_{\bar{T}_{out}} = \frac{\left|(\bar{T}_{out}-T_{ref})/2\right|+(\bar{T}_{out}-T_{ref})/2}{(T_{max}-T_{ref})}, \tag{9}$$

$$F_{\Delta p} = \frac{\left|\left(\Delta p^{-1}-\Delta p_{ref}^{-1}\right)/2\right|+(\Delta p^{-1}-\Delta p_{ref}^{-1})/2}{\left(\Delta p_{min}^{-1}-\Delta p_{ref}^{-1}\right)}, \tag{10}$$

$$F_{S_{gen}} = \frac{\left|\left(S_{total}^{-1}-S_{ref}^{-1}\right)/2\right|+\left(S_{total}^{-1}-S_{ref}^{-1}\right)/2}{\left(S_{min}^{-1}-S_{ref}^{-1}\right)}, \tag{11}$$

The normalized objective functions are indicated in Equation (9) for $\bar{T}_{out}$, Equation (10) for Δp and Equation (11) for S_{gen}, with reference values being set to 341 K for T_{max}, 336.5 K for T_{ref}, 0.365 Pa for Δp_{min}, 21.5 Pa for Δp_{ref}, 7.29×10^{-6} W/K for S_{min} and 4.7×10^{-4} W/K for S_{ref}. Then, the maximization of multi objective functions can be performed with the sum of the normalized objective functions $F_{\bar{T}_{out}}$, $F_{\Delta p}$ and $F_{S_{gen}}$. For the present study, the 7 objective functions investigated are described in Table 2, and the results of the functions used will be evaluated and compared.

Table 2. Objective functions investigated in the present study.

Combined parameters	**(Multi) objective functions**
$\bar{T}_{out}$	max $(F_{\bar{T}_{out}})$
S_{gen}	max $(F_{S_{gen}})$
Δp	max $(F_{\Delta p})$
$\bar{T}_{out}$ and Δp	max $(F_{\bar{T}_{out}} + F_{\Delta p})$
$\bar{T}_{out}$ and S_{gen}	max $(F_{\bar{T}_{out}} + F_{S_{gen}})$
Δp and S_{gen}	max $(F_{\Delta p} + F_{S_{gen}})$
$\bar{T}_{out}$, Δp and S_{gen}	max $(F_{\bar{T}_{out}} + F_{\Delta p} + F_{S_{gen}})$

2.5 Parameters Used in the Genetic Algorithm

As described earlier, the genetic algorithm is a heuristic method to find extremal points based on the evolutionary biology, with population number, generations, mutation rate and number of elite individuals per generation as hyperparameters to be determined. This hyperparameter tuning is fundamental for heuristic optimization methods to obtain the global extremal point and accelerate the solution. The values adopted for these hyperparameters are described in Table 3, where it can be noticed the constant number of generations of 300, which determines the end of the numerical simulations of new geometries.

Table 3. Global hyperparameters adopted in the genetic algorithm.

Hyperparameter	**Values**
Population size	50, 100 or 200 individuals
Elite group	3, 5 or 10 individuals per generation
Mutation probability	0.5%, 1% or 2%
Number of generations	300

3. MESH CONVERGENCE AND VALIDATION OF THE NUMERICAL METHODOLOGY

Before the beginning of the simulations required by the optimization algorithm it is crucial to perform a mesh convergence study to ensure the solutions are independent of the mesh. The mesh used in the present study is a structured grid with hexahedral elements constructed by the OpenFOAM mesh builder *blockMesh*. Then, after the mesh convergence study, it is possible to validate the numerical solution with experimental data available in the literature (Das and Hiremath, 2022).

3.1 Mesh Convergence Study

For the mesh convergence analysis three output parameters are evaluated: the mean temperature of the fluid at the outlet port $\bar{T}_{out}$, the mean temperature of the microchannel base surface $\bar{T}_{base}$ and the pressure drop Δp in the microchannel. The intermediate mesh M3, with 15, 31 and 100 cells respectively in the directions x, y and z, has the number of cells uniformly changed in the three directions with a growth factor on the cell numbers of 0.5 (M1), 0.75 (M2), 1.5 (M4) and 2 (M5). The number of cells and cell distribution on the domains are presented in Figure 4 for the 5 meshes evaluated, ranging from 3432 (M1) to 211200 (M5) cells. It is possible to observe the refinement on the fluid-solid interface to be able to capture the velocity and temperature gradients on these regions.

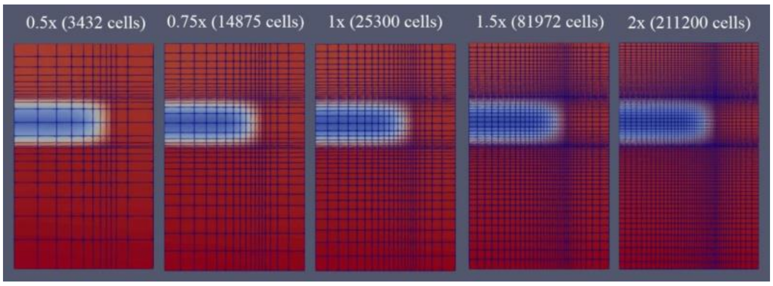


Figure 4. Representation of the 5 meshes evaluated on the mesh convergence study.

The results of $\bar{T}_{out}$, $\bar{T}_{base}$ and Δp of the numerical solution for the 5 meshes evaluated are described in Figure 5, where it is possible to observe the asymptotic variation on the output parameters with the total number of cells. With errors, relative to the mesh M5, of 0.05%, 0.27% and 2.19% for $\bar{T}_{out}$, $\bar{T}_{base}$ and Δp, respectively, the mesh M3 is used as the reference mesh for all simulations in the optimization algorithm.

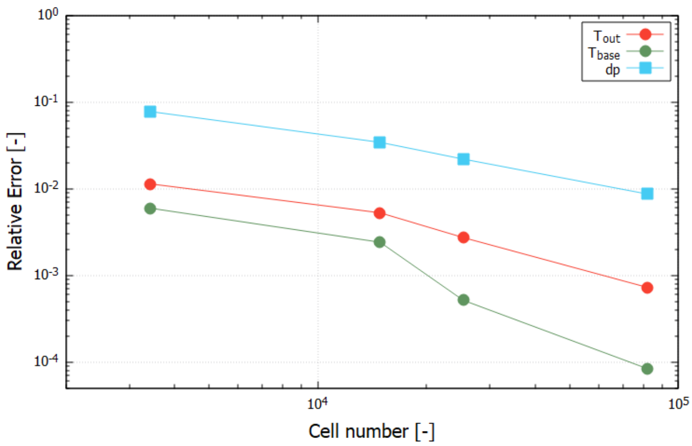


Figure 5. Mesh convergence results for the relative error with respect to the mesh M5.

3.2 Validation of the Numerical Methodology

To validate the numerical methodology the study of Das and Hiremath (2022) is used to compare the average friction factor f_{ave} and average Nusselt number Nu_{ave}, evaluating the pressure drop and heat transfer of a rectangular cross-section straight microchannel with channel height and width of 550×10^{-6} m. The length of the channel is equal to 50×10^{-3} m and the heat flux is constant and equal to 5 W/cm². In this study, there is negligible thermal losses through convection and radiation, and the fluid at the inlet has a temperature of 300 K and uniform velocity.

The results, indicated in Figure 6, show a good agreement on the average friction factor and Nusselt number at the range of Reynolds number evaluated. This good agreement enables a high accuracy solution to be used in the optimization procedure.

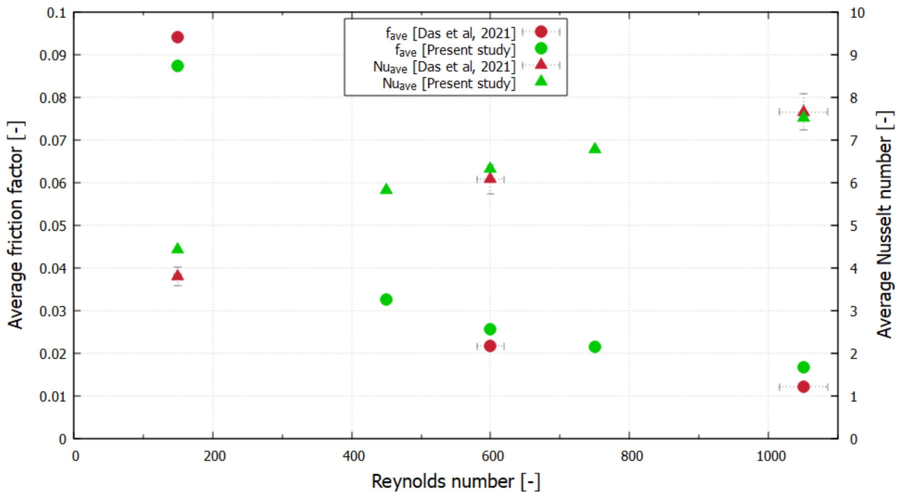


Figure 6. Results obtained for the average friction factor (f_{ave}) and average Nusselt number (Nu_{ave}) at various Reynolds numbers, for the rectangular channel with height and width of 0.55 mm of Das et al (2021).

4. RESULTS AND DISCUSSION

The evaluation of the thousands of simulations in the present study was only possible due to the simplifications of the numerical domain, as in the uniform distribution of the flow among the different microchannels and the use of symmetry conditions in the domain, both supported by experimental results available in the literature (Lee et al, 2005; Yin and Ooka, 2015). The evaluation of distinct objective and multi objective functions can facilitate the evaluation of distinct optimized conditions and enable a better decision on the final heat exchanger design.

The results of the best geometry at each objective function evaluated are described in Table 4, with the decision variables ($W_{channel}$, $H_{channel}$, W_{wall}, H_{base} and H_{top}), parameters of interest ($\bar{T}_{out}$, Δp and S_{gen}, the number of channels at the geometric restrictions considered and the hyperparameters set (population size, mutation probability and number of elite individuals) that resulted in the best geometry. Individually evaluating the 3 objective functions ($F_{\bar{T}_{out}}$, $F_{\Delta p}$ and $F_{S_{gen}}$), it is possible to note that the minimization of Δp provides the lower number of channels and consequently a higher hydraulic diameter, which is a direct result of the reduction on the friction between the fluid and the channel walls. Also, the minimization of the entropy generated provided the microchannels with the highest aspect ratio, being a result of the dependency of the temperature and velocity gradients, as in Equation (7). The minimization of the entropy generation results in the minimization of total heat resistance, which provides larger heat transfer surface area per channel and larger number of channels due to the greater values of the entropy generation by heat transfer than by friction of the fluid (Chen and Chen, 2013). Also, with an ambient temperature T_{amb} of 298.15 K, it is possible to evaluate the exergy transfer $\dot{E}_{x,out}$ using Equation (8), noticing the direct relationship with the data of $\bar{T}_{out} - T_{in}$ as expected.

Table 4. Results of the decision variables for the best geometry at the hyperparameters combinations for each objective function used in this study.

	(Multi) Objective Functions						
Parameter	$F_{\bar{T}_{out}}$	$F_{S_{gen}}$	$F_{\Delta p}$	$F_{\bar{T}_{out}} + F_{\Delta p}$	$F_{\bar{T}_{out}} + F_{S_{gen}}$	$F_{S_{gen}} + F_{\Delta p}$	$F_{\bar{T}_{out}} + F_{S_{gen}} + F_{\Delta p}$
$W_{channel}$ [mm]	0.80	0.60	5.00	4.35	0.60	5.00	0.60
$H_{channel}$ [mm]	0.60	4.20	4.20	4.20	4.20	4.20	4.20
W_{wall} [mm]	0.20	0.20	0.50	0.25	0.25	0.75	0.25
H_{base} [mm]	0.60	0.20	0.20	0.20	0.20	0.20	0.20
H_{top} [mm]	3.80	0.60	0.60	0.60	0.60	0.60	0.60
$\bar{T}_{out} - T_{in}$ [K]	10.30	9.66	10.18	10.20	10.26	10.18	10.26
Δp [Pa]	81.512	7.629	0.269	0.299	7.635	0.269	7.635
S_{gen} [10^{-6} W/K]	31.4	7.29	510	405	7.98	556	7.98
$\dot{E}_{x,out}$ [W]	5.41	5.22	5.37	5.38	5.39	5.37	5.39
Pop. Size [-]	200	200	200	200	200	100	100
Mut. Probab. [%]	0.5	2	1	2	2	2	1
Elite Individ. [-]	3	3	3	10	3	3	5
Channels	23	28	4	5	27	4	27

Evaluating the results of the 7 objective functions, it can be observed that the mean outlet temperature of the fluid, $\overline{T}_{out}$, is very similar at the 7 best geometries obtained, with values between 332.81 K and 333.45 K. With this perception, possible through the use of various combinations of the 3 objective functions, the selection of the optimized geometry can be made with process optimization methods, where an increase in the global efficiency could be possible with the reduction on the pressure drop provided by the set of objective functions with $F_{\Delta p}$. It is interesting to observe that the best geometry was achieved mostly with larger populations, and none occurred with the population size of 50 individuals. This is also true for the mutation probability, with the best geometries being obtained with higher mutation probabilities. Besides that, the maximization of $\overline{T}_{out}$ provides the geometry with the highest pressure drop between all cases. Also, analyzing the exergy transfer at the fluid outlet, it can be observed that the small variation of $\overline{T}_{out}$ indeed reflects in the exergy values, which ranges between 5.22 W/K and 5.41 W/K.

To compare the distinct geometries obtained at the 7 objective functions, it is presented the Figures of Merit of the mean Nusselt number Nu, mean friction factor f and mean outlet temperature of the fluid $\overline{T}_{out}$ in Figure 7.a, Figure 7.b and Figure 7.c, respectively. The evaluation of the mean Nusselt number with mean friction factor relates the effects of thermal gains and mechanical losses (pressure drop) on heat exchangers, normally with opposed responses regarding the channel geometry. It can be observed that the Nusselt numbers are similar in every objective function, with exception of $\overline{T}_{out}$. Also, when the pressure drop is minimized, solely or combined with S_{gen} or $\overline{T}_{out}$, the friction factor has lower values. When evaluating the mean outlet temperature of the fluid, it is evident that the proximity of the values obtained for $\overline{T}_{out}$ can be used to pursue other benefits in using an optimization based on the pressure drop, that greatly decreases the pumping power that would be needed.

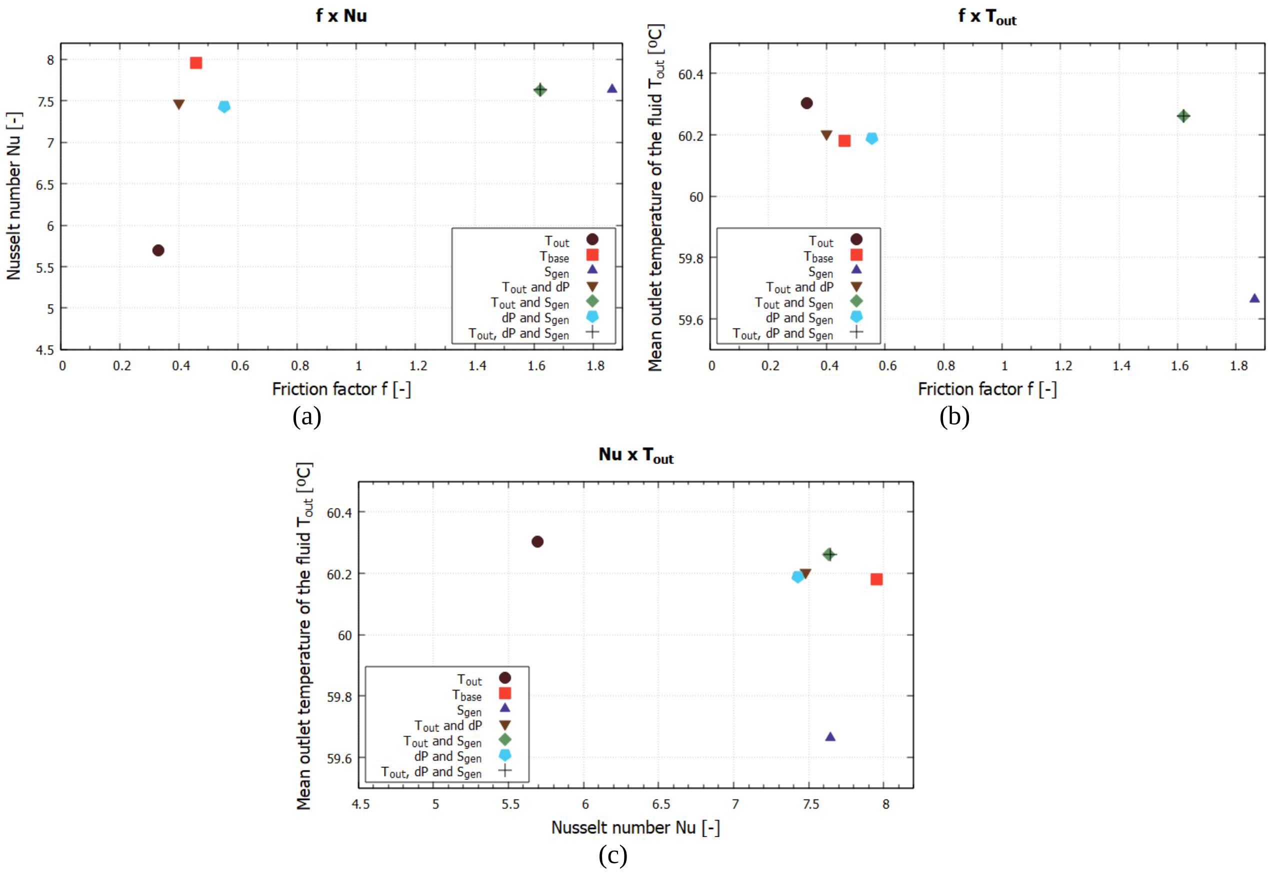


Figure 7. Figures of Merit for the results for each objective function used for the (a) friction factor and Nusselt number, (b) friction factor and $\overline{T}_{out}$ and (c) Nusselt number and $\overline{T}_{out}$.

5. CONCLUSIONS

In this study, an optimization procedure using genetic algorithm, written in the programming language Python, coupled with computational fluid-dynamics solutions, provided by the open-source software OpenFOAM, is developed to obtain the best set of microchannel geometric parameters that maximizes an objective function.

The evaluation of 3 distinct objective functions (minimization of pressure drop Δp, minimization of generated entropy S_{gen} and maximization of the mean fluid outlet temperature $\overline{T}_{out}$) and its combinations enabled the observation of a small variation on the outlet temperature of the fluid. With this observation, it can be assessed that at similar outlet temperatures for the fluid, which corresponds to similar exergies for the single-phase considered, the decision of geometries that have minimum pressure drop can decrease the pumping power needed, thus enhancing the global efficiency of the process.

The figures of merit enabled the visualization of the heat transfer capabilities together with the pressure drop of the channel proposed, making possible to evaluate the similarity in the Nusselt numbers as in the mean outlet temperature of the fluid. These similar values clearly indicate the necessity to evaluate various objective functions in optimization problems. With the best geometries proposed at each function used, a better decision can be made after comparing the results related with energetic and exergetic efficiencies of the whole process. The development of a fast and precise optimization algorithm will further allow the optimization of more complex non-straight geometries, where the complexity grows with number of parameters needed to describe each geometry.

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