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A COMPARATIVE STUDY OF EVOLUTIONARY AND SEARCH ALGORITHMS FOR OPTIMIZATION OF HEAT EXCHANGER WITH MICROCHANNEL COIL

Summary

In this paper a comparative study of several algorithms for the optimization of heat exchanger with microchannel coil has been done. Multivariate optimizations have included three geometrical parameters of heat exchanger which, as predicted, significantly influence hydrodynamic behavior of the system. Data set used for the optimizations have been numerically acquired and experimentally validated. The air/water side numerical model of heat exchanger composed of flat tubes with rectangular shapes has been used. Objective function that combines the heat transfer rate and the pressure drops of air and water has been developed and employed for the optimization procedures. The optimization has been performed by means of two evolutionary algorithms (Genetic Algorithm and Simulated Annealing) and Pattern Search Algorithm. The comparison of obtained results has been accomplished along with the results analysis and final conclusions.

Key words: *optimization, genetic algorithm, simulated annealing, pattern search, heat exchanger*

1. Introduction

Rapid growth of compact heat exchangers with high compactness ratio [1] has led to the heat exchangers with flat tubes, commercially known as heat exchangers with microchannel coil (MCHX). MCHX are operating through the reduced space, weight, support, energy requirements and cost for desired thermal performance. Nowadays, they are widely used in many ways in number of various applications, such as chillers, residential AC, condensing units, etc. MCHX are designed to maximize contact area both on the water and air side. The air and water velocity, temperature, choice of material, geometrical characteristics of fin surface/pipes are just some of the factors that affect heat exchanger performance [2]. Optimal values of design parameters can be achieved in many ways such as: numerical simulations, experimental investigations, analysis of selected factor/s influence on heat performance, etc.

In this paper multivariate optimization of a heat exchanger with microchannel coil has been done. Multivariate optimization included three geometric parameters that are proved to influence hydrodynamic behaviour of the system. In addition, one operating condition was added, which means a total of four independent variables for certain design.

Genetic algorithms [3] are the type of optimization algorithms that are utilized to find optimal solution(s) to a given computational problem that maximizes or minimizes a particular function [4]. These algorithms are far more powerful and efficient than random search and exhaustive search algorithms, yet require no extra information about the given problem. This feature allows them to find solutions to the problems that other optimization methods cannot handle due to a lack of continuity, derivatives, linearity, or other features [5].

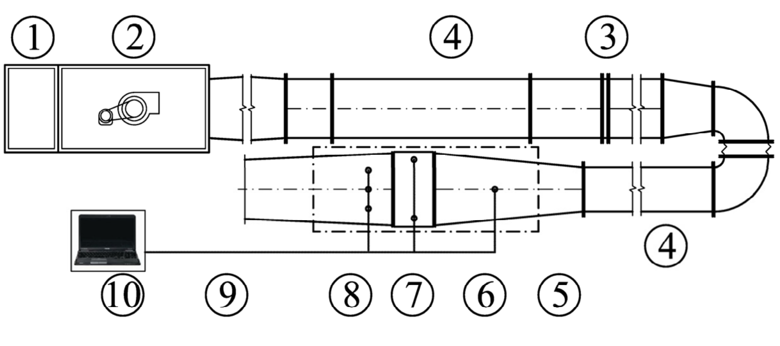
An objective function has been developed, employed for an optimization procedure and subjected to the results of numerical simulation. Experimentally validated numerical model was employed to predict the heat transfer rate and the pressure drops of air and water for each design point. The heat transfer and fluid flow simulations were performed using commercial fluid flow and a heat transfer solver FLUENT. The data used in this article has been acquired from experimental and numerical analysis of heat transfer and fluid flow in compact heat exchangers. A detailed mathematical approach and complete description of experimental apparatus can be found in several papers [6-8].

2. Background of data sets adopted for optimization

In accordance with the heat exchangers used for the experiments, numerical 3D models of adequate geometry were developed. A good agreement between experimental and numerical results was attained. A short description of the used data background follows.

2.1 Experimental set-up

The wind tunnel, available at the Faculty of Engineering, University of Rijeka, Croatia, was used for the measuring of working media temperatures and mass flow rates of several heat exchangers with microchannel coil (Figure 1). The air and distilled water were used as working fluids.



1 air inlet
2 air handling unit
3 orifice
4 air settling ducts
5 measuring station
6 air inlet temperature sensors
7 microchannel coil with water in/out temp. sensors
8 air outlet temperature sensors
9 air outlet
10 data acquisition system

Fig. 1 Schematic view of the wind tunnel [6]

The main components of the system were heat exchangers with microchannel coil (MCHX), two water flow loops, air supply unit, instrumentations and data acquisition systems. The hot/cold water loop was divided in two separate loops. First one with the water connected to water/water heat pump with capacity of 50 kW and second water loop separated with the plate heat exchanger. Second loop was built due to possible creation of lime scale in microchannels and was filled with distilled water. The lime scale is extremely dangerous for the channels with hydraulic diameter smaller than 1 mm and could cause undesired obstructions on the water side of heat exchanger. The open circuit wind tunnel system was used to suck the air from laboratory or from the open air over the air handling unit with the capability of air preheating. The National Instruments SCXI data acquisition, automation and control module system was used. The connection to personal computer was accomplished by National Instruments DAQCard. All virtual instruments were developed in LabView.

2.2 Mathematical and numerical approach

The air/water model has been used [9]. Due to the limitations of computer resources, only the portion of heat exchanger able to describe flows of air and water was taken into account. Two symmetry planes were assumed in the z-direction, perpendicular to the fin surface so that flat tubes are divided in two identical parts. A schematic view of the computational domain has been shown in Figure 2.

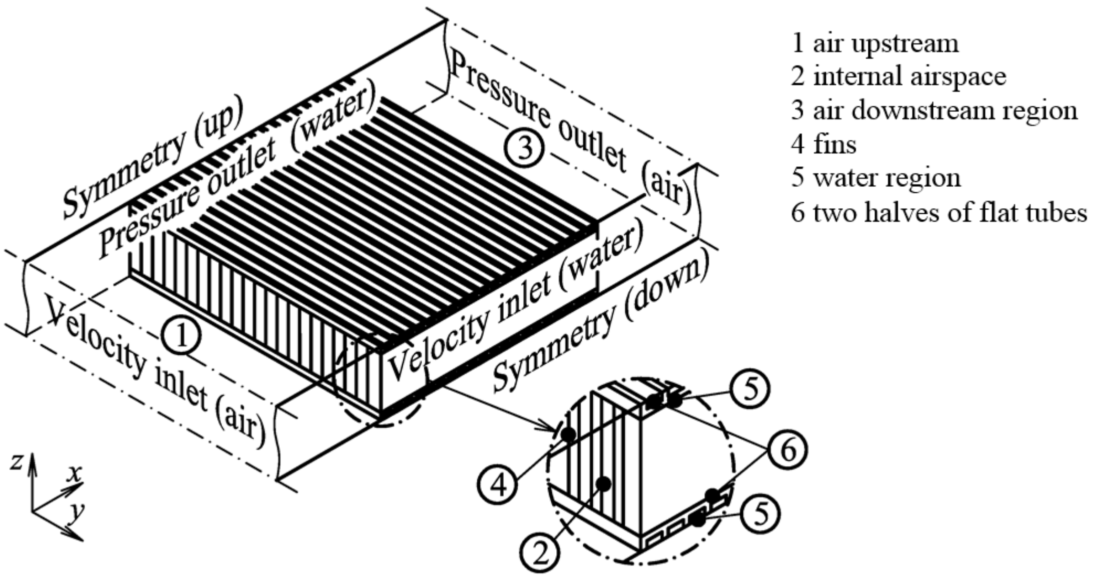


Fig. 2 Schematic view of computational domain [8]

The upstream and downstream regions have not been presented in proportional dimensions. The computational domain consists of six volume groups. A total length of computational domain has been extended 9 times from actual internal airspace. The upstream region has been extended 2.5 times to ensure inlet uniformity and the downstream region has been extended 6 times in order to prevent flow recirculation.

2.3 Comparison between Experimental and Numerical Results

The comparison between results acquired by numerical model and experimental results has been accomplished for the same ranges of air and water temperatures and the velocities used in experimental investigation. The series of numerical calculations have been done in order to analyse heat transfer and fluid flow. Due to limited paper length, the results of comparisons have been shown only for one parameter setup given in Figure 3 and Table 1, accompanied with the measured and numerically obtained water and air temperatures.

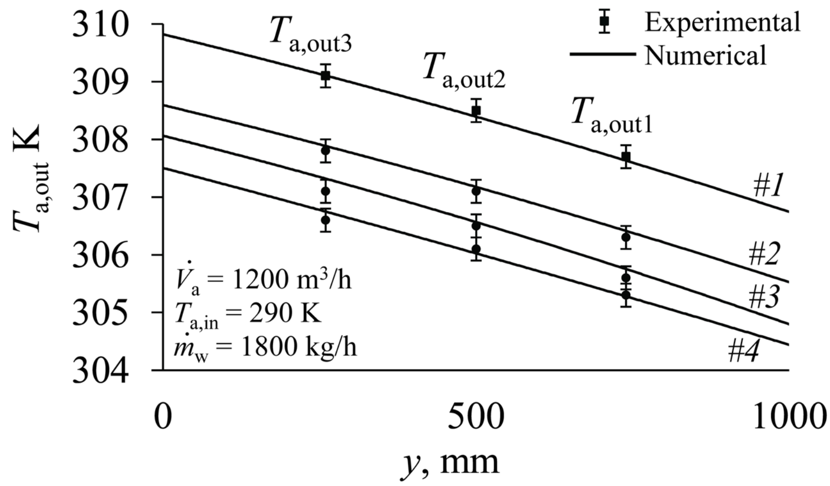


Fig. 3 Comparison of numerical and experimental results [6]

The setups (inlet air and inlet water temperatures and velocities) have been chosen with the care by considering the operational conditions of similar compact heat exchangers used in the practice. Error bars in Figure 3 have been given with the fixed value of ±0.15 K according to maximum obtained standard deviation of air outlet temperatures.

Table 1 Comparison of numerical and experimental results for water side temperatures [6]

No.	$T_{w,in}$ [K]	Experimental $T_{w,out}$ [K]	Numerical $T_{w,out}$ [K]
#1	310.0	306.6	306.8
#2	308.6	305.7	305.6
#3	308.1	304.6	304.5
#4	307.5	304.5	304.3

It is obvious that numerical simulation results coincide well with experimental data and that the deviations are within an acceptable range. The temperature differences are smaller than ±0.5 K for all valid measurements, what can be taken as the assertion of measurement methodology validity as well as the proof of used numerical simulation validity.

3. Quest for optimal design

The schematic view of reference heat exchanger with microchannel coil has been shown in Figure 4. The heat exchanger is made from multiport extruded tubes and fins placed in between.

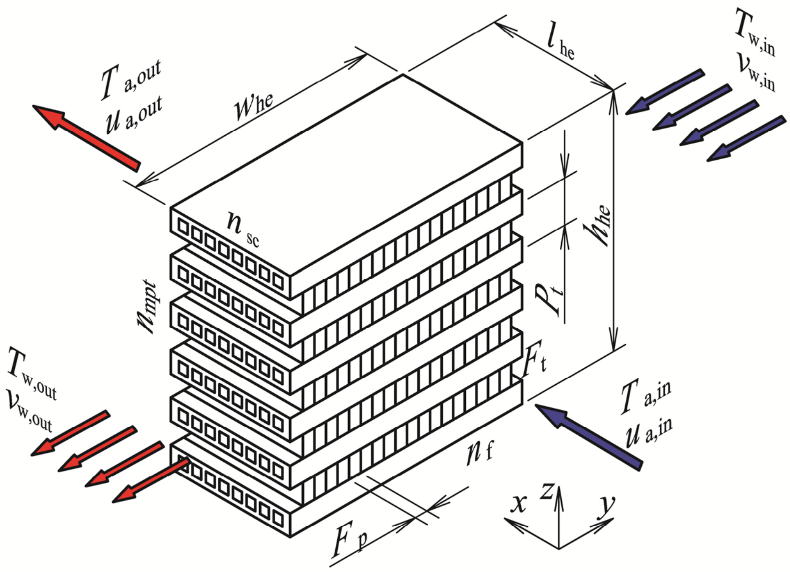


Fig. 4 Schematic view of referent heat exchanger

For the considered optimization procedure four input parameters were selected: transversal MCHX tube row pitch (P_t), fin pitch (F_p), the number of small channels per multiport tube (n_{sc}) and inlet water velocity ($v_{w,in}$). The first three are geometrical parameters, with addition of fourth that describes one operating condition. Input parameters were defined after a detailed examination of the papers that contain the analysis and/or optimizations of heat exchanger with different geometrical shapes and different operating conditions. All selected geometrical parameters were set according to the heat exchanger used for laboratory experiments. The selected input parameters used in the optimization process are shown in Table 2 along with its adequate ranges: the highest, the lowest and the reference value. The reference value of each parameter was set in the middle of domain. The last row of the same table shows the value of heat transfer surface area compared to total volume of heat exchanger (compactness).

Table 2 Ranges of selected input parameters

Selected input parameter		Minimum	Referent	Maximum
Transversal MCHX tube row pitch, P_t	x_1	5	10	15
Fin pitch, F_p	x_2	1	1.5	2
Number of small channels per tube, n_{sc}	x_3	20	25	30
Water inlet velocity, $v_{w,in}$	x_4	0.4	0.8	1.2
Compactness of MCHX, m^2/m^3		1830	1360	1290

3.1 Prescribed set of design points using Box-Behnken technique

For design problems that involve computation-intensive analysis or simulation processes, the approximation models are usually introduced to reduce the computation time. Numerical procedure for one combination of parameters (one design point), with satisfactory level of convergence, takes from 30 minutes to 2 hours. In this paper Box-Behnken method was used to reduce the number of required design points. The first step is normalization of selected input parameters with taking into account parameters range. In this way, the selected input parameter is reduced to three sizes: minimum, medium and maximum. The normalization is carried out according to the following expression:

$$X_{\mathrm{i}} = \frac{2\left(x_{\mathrm{i}} - x_{\mathrm{i,ref}}\right)}{x_{i,\max} - x_{i,\min}} \tag{1}$$

The design of experiments technique allows the designer to extract as much information as possible from the limited number of cases. The number of possible combinations of four variable parameters, coded on three level full factorial design gives total of $3^4 = 81$ design points. For the same number of variables, Box-Behnken method needs only 27 design points. In this way the significant savings in the necessary computing resources are achieved with minor influence on the precision of the results. A full set of prescribed design test points can be found in [8].

4. Multivariate optimization of a MCHX

4.1 Definition of objective function

To optimize the heat exchanger performance, a function that incorporates the enhancement of heat transfer is formulated. By use of a Design of Experiments Technique (DOE), the series of numerical simulations are performed for the prescribed set of design points in order to construct the function for the measured quantity over the design space.

$$f(x_1, x_2, x_3, x_4) = Q_{\mathrm{he}} \tag{2}$$

Therefore, to maximize the performance of MCHX, the developed objective function should be maximized. The coefficients of quadratic models for the objective function are shown in Table 3.

Table 3 Values of quadratic model for eq. (2), R^2 = 93.95%

	1	x_1	x_2	x_3	x_4
1	2541.71				
x_1	-80.229	34.6707			
x_2	-725.25	-42.605	194.438		
x_3	10.5854	-17.851	37.1311	-79.509	
x_4	386.68	8.13631	-135.8	-237.68	-120.93

The coefficient of determination (R^2) is found to be greater than 0.9 that proves accurate prediction of object function by the function model and justifies its use for further investigation.

The optimization is conducted by using three optimization methods: genetic algorithm simulated annealing, and pattern search. All used optimization methods are programmed in software *MatLab*. The objective function is of polynomial form with the defined appropriate coefficients (a_0 to a_{44}). All coefficients are stored in a 5x5 matrix (K.mat) which are then called by the optimization code for defining the objective function. Simultaneously, the upper and lower limits (x_low and x_high) of optimization parameters (x_1 to x_4) are developed as shown in the code snippet:

```
function z=fun_cilja(x)
%funkcija cilja
load('K.mat')
x_low=[22,3,1.5,200]';x_high=[36,12,10,1000]';
X=zeros(4,1);
x1=x(1); x2=x(2); x3=x(3); x4=x(4);
a0 = K(1,1); a1 = K(2,1); a2 = K(3,1); a3 = K(4,1); a4 = K(5,1);
a11 = K(2,2); a12 = K(3,2); a13 = K(4,2); a14 = K(5,2); a22 = K(3,3);
a23 = K(4,3); a24=K(5,3);a33=K(4,4);a34=K(5,4);a44=K(5,5);
z=a0+a1.*x1+a2.*x2+a3.*x3+a4.*x4+a11.*(x1.^2)+a22.*(x2.^2)+a33.*(x3.^2
)+
a44.*(x4.^2)+a12.*x1.*x2+a13.*x1.*x3+a14.*x1.*x4+a23.*x2.*x3
+a24.*x2.*x4+a34.*x3.*x4;
end
```

4.2 Genetic algorithm

Genetic algorithms are a type of optimization algorithm, aimed to find the optimal solution(s) to a given computational problem that maximizes or minimizes a particular function. Genetic algorithms represent one branch of the study field called evolutionary computation because they imitate the biological processes of reproduction and natural selection to solve for the `fittest' solutions. Like in evolution, many of a genetic algorithm's processes are random, however this optimization technique allows one to set the level of randomization and the level of control.

The optimization presented in this paper with genetic algorithm is carried out using the software package *MatLab* with the following parameters:

Population type:	Double vector
Population size:	500
Creation function:	Constraint dependant
Fitness scaling function:	Rank
Selection function:	Stochastic uniform
Reproduction elite count:	2
Reproduction crossover fraction:	0.8
Mutation function:	Constraint dependent
Crossover function:	Scattered
Migration direction:	Forward
Migration fraction/interval:	0.2/20
Constraint initial penalty:	10
Constraint penalty factor:	100
Stopping criteria:	
Generations:	100
Stall generations:	50
Function tolerance:	$1 \cdot 10^{-6}$
Nonlinear tolerance:	$1 \cdot 10^{-6}$

The pseudo code with the following steps can be used to show the operating principle of genetic algorithm:

1. Define the initial population of candidate solutions,
2. Assess the fitness of population members (individuals),
3. Repeat for every generation until the final criterion is satisfied such as the time limit, reached level of fitness among the population, etc.):
    a. Pick best fitting individuals for reproduction,
    b. Create new individuals by crossing or mutation,
    c. Assess the fitness of newly created individuals,
    d. Replace bad fitting individuals with new ones.

4.3 Simulated annealing

Simulated annealing is a global optimization tool often used in applied mathematics for finding the approximation of global optima of some function in a large search space. The inspiration and analogy of this optimization method lies in the heat treatment of metals, where the controlled cooling of heated metal is used to achieve large crystals in the metal's structure. The large crystals are achieved by letting the atoms in the crystal 'settle' to their lower energy level by themselves, thus the longer the time to cool the greater the probability for the atoms to find their lowest (optimal) position. This analogy is used for the optimization, where the initial assumed values of parameters of the objective function are gradually replaced by better values using the iterative method by which each value is validated in regard to its energy level and fitness function. After more and more iterations, the algorithm finds the values of parameters which are getting closer to the objective function's optimum (minimal value) by changing each parameter iteratively and lowering their energy level. The settings used for the algorithm are:

Start point (x_1, x_2, x_3, x_4):	10, 10, 10, 10
Max. iterations:	10000
Max. function evaluations:	12000
Function tolerance:	$1\cdot10^{-6}$
Annealing function:	Fast annealing
Reannealing interval:	100
Temperature update function:	Exponential temperature function
Initial temperature:	100

4.4 Pattern search

This method is a classical example of a search method also called the Hooke-Jeeves method. This search algorithm is continually sampling the space of solution parameters, testing the local direction of increase and continuing the search in that direction. Basically the method is evaluating the value of objective function $F(x)$ in regard to value of x. Assuming that the component x_1 of vector X is increased for some arbitrary step size s, we get the function $F(x_1 + s, x_2, \dots, x_n)$, and logically if the value of this function is $F(x_1 + s, x_2, \dots, x_n) > F(x)$, then the direction of search is successful and we set the first value $x^1 = (x_1 + s, x_2, \dots, x_n)^T$. If the previous assessment is not the case, then we analyze if the function $F(x_1 - s, x_2, \dots, x_n) > F(x)$, if this is true, then we set $x^1 = (x_1 - s, x_2, \dots, x_n)^T$. If none of these cases are true, then we set $x^1 = x$, after which the algorithm continues to define the value of x^2 by the analogy. The algorithm continues until the value of $x = x^n$ which means maximum is found, and if the value of s (step size) has become sufficiently small. The settings for the algorithm are as follows:

Start point (x_1, x_2, x_3, x_4):	10, 10, 10, 10
Poll method:	GPS Positive basis 2N
Polling order:	Consecutive
Mesh initial size:	1.0
Max. size:	Unconstrained
Expansion factor:	2.0
Contraction factor:	0.5
Initial penalty:	10
Penalty factor:	100
Bind tolerance:	$1\cdot10^{-3}$
Max iterations:	400
Max function evaluations:	8000
Function tolerance:	$1\cdot10^{-6}$

4.5 Results of optimization

Three optimization algorithms were run on a standard PC (i5 processor, 4 Gb RAM) and all three were executed in minimal computational time of 10-30 s. The genetic algorithm has executed the fastest achieving results after only 51 iterations. The pattern search algorithm finished after 68 iterations and the slowest execution was demonstrated by the simulated annealing algorithm which took 2496 iterations to achieve the optimal values. The results of optimizations for four variables (x_1 to x_4) are displayed in Table 4. All optimal values result in maximum heat exchanger's performance of approximately 3000 W. The values of distance between tubes (x_1) and the fin pitch (x_2) were left unconstrained while the value of number of small channels (x_3) was limited to the integers. The results from all three algorithms show very similar results which confirm the calculated optimum. The reason for slight discrepancy in values of x_1 and x_2 lies in the fact that those values were not constrained to the integers but floating values. For practical engineering, the results for those parameters can be rounded off to x_1 = 12.5 mm, and x_2 = 1 mm. Other two variables reached their maximum values and confirmed the thermodynamically sound assumption that the heat transfer augments with higher flow speed of fluid (x_4 = 1.2 m/s) and greater number of channels in the heat exchanger (x_3 = 24).

Table 4 Results of optimization for four variables (x_1 to x_4).

	Genetic algorithm	Simulated annealing	Pattern search
x_1	12.386	12.682	12.482
x_2	1.1	0.96	1
x_3	24	24	24
x_4	1.2	1.2	1.2

5. Conclusion

The main goal of presented work was to carry out a comparative study of several algorithms for the optimization of a heat exchanger with microchannel coil. The Box-Behnken technique has been employed to reduce the number of needed design points. Experimentally validated numerical simulations of heat exchanger with microchannel coil have been done for the prescribed set of design points. The developed objective function accounted for the influence of transversal MCHX tube row pitch, the fin pitch and the number of small channels per tube for various inlet water velocities. The defined objective function was the subject of optimization by three optimization methods: genetic algorithm, simulated annealing and pattern search. All three algorithms resulted in similar results which confirm the expected optimal values of parameters. The performed optimization pointed to optimal values at maximal velocity of 1.2 m/s (x_1 = 12.5 mm, x_2 = 1 mm and x_3 = 24). At low inlet water velocity, the improvements of thermodynamic and hydraulic properties were around 10%, compared to the referent heat exchanger. At medium speed, they were approximately 30% and for maximum value of water velocity, the acquired improvements were 45%. The compactness of heat exchanger with optimal values is 1950 m^2/m^3. Compared to the reference heat exchanger, this is 43% higher compactness, and 7% more compared with the heat exchanger with values on the upper limit domain. The presented study shows the huge potential and practical importance of various optimization techniques synergy with CFD modelling and experimental measurements in the design process of heat exchangers, which results in maximum performance and compactness while achieving savings in construction material.

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