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Finned Heat Sink Optimization Method with the Use of Computational Intelligence

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Abstract. With the technological advancements of recent years, electrical and electronic equipment has become increasingly faster, incorporating new functions while drastically reducing in size. This has led to higher power densities and heat fluxes in their components. To maintain the operating temperature of such equipment within acceptable limits - without compromising safety or reliability - the use of finned heat sinks is essential. In this context, the present work conducts a theoretical and numerical optimization analysis on the impact of geometric variables - such as fin height, width, and number -on the thermal performance of finned heat sinks used in the cooling of electrical and electronic devices. For this analysis, a straight-fin heat sink configuration was validated using experimental data available in the literature. The Generalized Subset Design (GSD) method, a Design of Experiments (DOE) approach, was employed to select simulation scenarios efficiently and reduce computational cost. All cases were simulated using commercial Computational Fluid Dynamics (CFD) software. The resulting data was used to train Machine Learning (ML) models developed in Python, an open-source programming language. The selected ML models included decision tree regressors, support vector regressors, multilayer perceptrons, and a neural network developed from scratch using Keras. A theoretical analysis of each variable was performed, and its impacts on the key thermal performance metrics were presented graphically. It was observed that both the number and width of the fins have an intermediate optimal value within the tested range, indicating non-linear behavior. The trained ML models were applied to identify behavior patterns for each geometric variable and to estimate their effect on the thermal performance of finned heat sinks.

Keywords: Computational intelligence, Electronic cooling, Design of experiment

1 Introduction

Heat evacuation of electronic devices are often managed by the association of fins and forced convection. As the system spends energy with a fan to maintain the maximum temperature levels below the specifications, the overall efficiency is decreased. Thus, in these projects, there is the optimization challenge of maintaining the electronic devices within the specification temperature levels at the minimum energy consumption.

In [1], heat sinks with planar fins were numerically analyzed and compared with the results of [2], [3] and [4]. The authors verified that there is a high sensibility of the temperature field in respect to the incoming flow pattern and geometrical configuration of the heat sink. Indeed, fins efficiency are related to the air velocity magnitude, material and fabrication methods, the interface between the fin and the heat source and the fin geometrical parameters as the number of fins, their thickness, length and width [5].

Although planar fins are widely spread in different applications, [2] studied the influence of the fin cross section geometry, maintaining all the remaining geometrical features constant. Their numerical models considered triangular, square pentagonal hexagonal and circular cross section geometries. The triangular cross section led to lower efficiency due the flow recirculation areas generated in this setup.

In order to study the relevant heat sink parameters, different methodologies have been tested. For instance, in [6], neural networks theory is exploited in different applications, such as food classification, systems patterns, electrical energy disturbances analysis and even vehicles bake lights optimizers. As well as neural networks, linear regression has also been used in the solution of problems in different fields. As discussed in [7], this method can be used in the events description, inferences and in the prediction of a specific variable. The later is the main goal of the creation of machine learning models, thus, linear regression is often used in association with tree decision models, Support Vector Machines (SVMs) and perceptron of multiple layers. Different models are available in Python libraries, as the tensorFlow2 and Scikit-Learn libraries, which are exploited in [8].

In addition to machine learning, heat sinks were studied using Design of Experiment (DOE) methodology to filter the number of experiments due the high number of possible variables used as input. In [4], the authors compared the the complete factorial method with the Taguchi method using experimental data. The factorial method required 27 experimental runs whereas the Taguchi method achieved the same result with 9 runs. The disadvantage of the Taguchi method was that is was not able to couple the results with a mathematical model like linear regression because it delivers the treated final parameters directly whereas the factorial method delivers the raw results which can be further exploited with a mathematical model.

Considering the presented literature synthesis, the present work objective is to evaluate different fins configurations through machine learning models constructed with Computational Fluid dynamics (CFD) results from a DOE study.

2 Methodology

The proposed methodology consists of a CFD model, the use of DOE to filter the number of possible simulations and then the use of machine learning techniques to build up the mathematical model that represents the thermal behavior of a heat sink.

2.1 CFD model

The CFD models were built using Fluent® v2021 R1, which is based on the finite volume method [9]. The numerical domain, illustrated in Fig. 1, was built to represent the test section of the experimental results of [1] for validation. Accordingly, as boundary conditions, there was imposed the no slip boundary conditions at the test section walls, prescribed velocity at the inlet and constant pressure gradient at the outlet. The velocity at the inlet generates a Reynolds Number of 10063. Regarding the seleted numerical models, it was set the second order upwind for the advective terms treatment, the Pressure-based Coupled Solver for the pressure-velocity coupling, the Least Squares Cell Based for the gradients estimate and the RNG k-epsilon turbulence model.

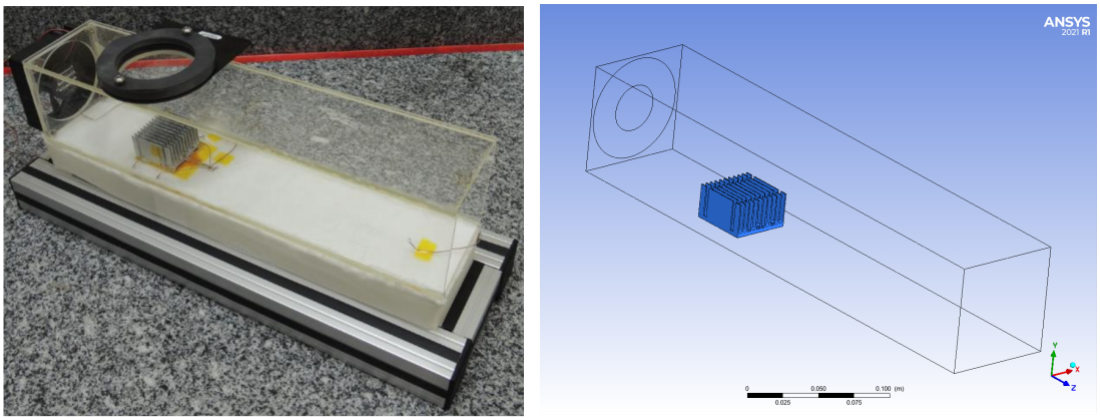


Figure 1. Numerical domain and boundary conditions

2.2 Design of experiments

The selected heat sink design variables were the fin height, between 25 and 35 mm, the fin thickness, between 1 and 3 mm, and the number of fins, between 5 and 11. Considering 3 reference values for each design variable to sweep the research domain, there are 18 experiments to run. Using the pyDOE2 library, more precisely, the Generalized Subset Design (GSD) technique, the total number of experiments was reduced to 9. The simulated cases are presented in Table 1.

Table 1. Desing variables combinations through DOE/GSD

Case	Height [mm]	Thickness [mm]	Number of fins
A	25	1	11
B	25	2	5
C	25	2	8
D	25	3	11
E	25	3	5
F	35	1	8
G	35	2	11
H	35	2	5
I	35	3	8

2.3 Trainning the preditive models

The results of the selected experiments presented in Table 1 were used to create a database to train the predictive models. Five steps were followed: import data, cleaning data, feature scaling, creation of training groups, and model validation. In order to validate the model, 3 additional cases, excluded from the DOE analysis, were simulated. They are presented in Table 2. The selected algorithms from the Scikit-Lear python library [10] were: decision tree regressor; random forest regressor, linear regressor, multiple layer perceptron and support vector regression. The Keras library, part of TensorFlow [11] was also used to test and build neural networks.

Table 2. Additional cases for model validation

Case	Height [mm]	Thickness [mm]	Number of fins
J	25	1	8
K	25	2	5
L	35	3	11

All these algorithms were used to construct a model, so that, by varying the heat sink height, thickness, and number of fins, the model should predict the maximum temperature, the Nusselt number, and its thermal resistance. To evaluate the best algorithm for each result, the R-square criterion was used.

3 Results

3.1 CFD validation and main results

The domain discretization was tested with models from 43.261 cells to models with 5.281.132 cells. The results became stable from the mesh with 764.841 cells on. The mesh selected to simulate the 9 cases had 2.119.745 cells and is illustrated in Fig. 2. The validation for different Reynolds numbers was performed comparing with experimental data from [1]. The discrepancies were below 7.8 %, as illustrated in Fig. 3.

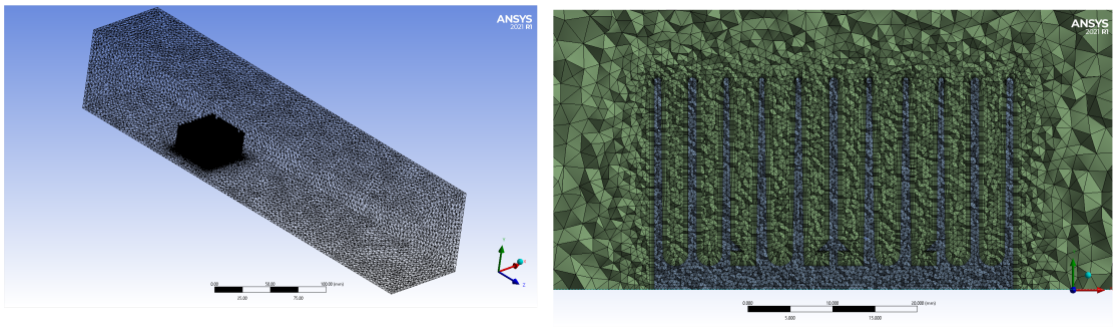


Figure 2. Numerical domain discretization

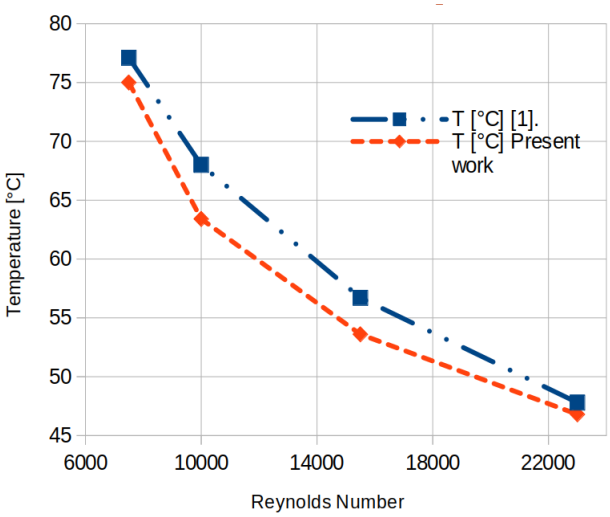


Figure 3. CFD validation with experimental data

From the CFD simulations it was obtained the data presented in Table 3. It can be drawn that as the fins' height increases, the maximum temperature decreases as well as the Nusselt number and the thermal resistance. Regarding the fins' thickness, the minimum temperature is reached for the thickness of 2 mm. As the thickness increases, the Nusselt number decreases and the thermal resistance increases. The last parameter, the number of fins, the simulations demonstrate that the minimum temperature, the minimum thermal resistance and the maximum Nusselt number is reached with 8 fins.

3.2 Constructed models using computational intelligence

The results of cases J, K and L, which were not used to train the models were compared with the results of the exploited models.

For the maximum temperature, the best results were obtained with the techniques Random Forrest Regressor (RFR), artificial neural network (Keras). The RFR result was obtained with 3000 estimates using the absolut error as the evaluation criterion. The Keras results were obtained with 2 hidden layers with 1536 neurons each. The Adam optimizer was selected and the mean quadratic error was select to measure the discrepancy. The results are presented in Table 4. The RFR algorithm delivered the results with lower discrepancy.

The Nusselt number, by the other hand, had the best predictions with the Decision Tree Regressor (DTR) and Keras. Their results are summerized in Table 4. The DTR algorithm was run with its default values. The Keras algorithm was ru with 2 hidden layers with 256 neurons each. The Adam optimizer was selected and the mean quadratic error was select to measure the discrepancy. The DTR provided better results in average than the Keras algorithm.

Table 3. Results from the CFD

Case	Tmax [°C]	Nusselt Number [adimensional]	Thermal resistance [°C/W]
A	67.7	78.6	1.64
B	126.9	102.0	2.60
C	72.7	91.6	1.98
D	162.9	31.1	4.16
E	94.9	89.0	2.87
F	61.2	96.9	1.42
G	63.0	61.8	1.56
H	77.4	93.3	2.10
I	63.3	76.9	1.59
J	76.3	98.3	1.95
K	98.8	89.6	2.99
L	94.7	31.5	2.90

Table 4. Maximum temperature estimate

Case	CFD	RFR ($\Delta Temperatura$)	Keras ($\Delta Temperatura$)
J	76,30	85,45 (11,99%)	87,17 (14,25%)
K	98,76	98,26 (0,51%)	105,09 (6,41%)
L	94,70	95,42 (0,76%)	89,05 (5,97%)

Table 5. Nusselt number estimate

Case	CFD	DTR ($\Delta Nusselt$)	Keras ($\Delta Nusselt$)
J	98,34	102,00 (3,72%)	95,08 (3,32%)
K	89,62	93,30 (4,11%)	99,61 (11,15%)
L	31,47	31,00 (1,49%)	42,23 (34,19%)

The thermal resistance estimate, at last, had the best predictions with the RFR, SVR and Keras. Their results are presented in Table 6. The RFR algorithm was run with 5000 estimates. The SVR was run with sigmode and C kernel with the regularization parameter equals 3. The Keras algorithm was ru with 2 hidden layers with 1280 neurons each. The Adam optimizer was selected and the mean quadratic error was select to measure the discrepancy. The best results depends on each case and there is not one algorithm ideal for any point.

Table 6. Thermal resistance estimate

Case	CFD	RFR (ΔRt)	SVR (ΔRt)	Keras (ΔRt)
J	1,95	1,94 (0,37%)	1,55 (20,54%)	2.00 (2,56%)
K	2,99	2,39 (20,18%)	2,53 (15,45%)	2.63 (12,04%)
L	2,90	2,61 (9,92%)	2,84 (1,97%)	2.46 (15,17%)

4 Conclusions

In the present work is presented a methodology to employ machine learning in the optimization of a finned sink heat. The most promissing algorithms identified are the Random Forest Regressor, Decision Tree Regressor, Keras and Support Vector Machine. The maximum temperature, average Nusselt Number and average thermal resistance were modeled and the tests performed demosntrated discrepancie below 12 %. Some additional test shall be executed to enhance the presented results.

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