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OPTIMAL DESIGN OF CONSTRUCTAL CONDUCTIVE PATHWAYS USING MACHINE LEARNING ALGORITHMS

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Increasing the heat flux of future microchips requires implementing a reliable cooling system to reduce their operating temperatures. Researching better designs for high thermal conductivity pathways embedded into heat-generating components is also essential due to concerns about dimensions and costs. The present study investigates the Constructal design of highly conductive pathways embedded into a heat-generating piece using a numerical code based on finite element method (FEM) and an optimization process based on machine learning algorithms (MLAs). The inserted high thermal conductivity occupies a fixed volume fraction. Geometrical features of the highly conductive are considered the optimization variables, and minimization of the peak temperature is considered the optimization objective. To accomplish the optimization process, machine-learning algorithms are used and critically compared to determine the most efficient option among the considered ones. Finally, the optimal Constructal designs predicted by the machine-learning approach are compared with the optimal configurations generated by conventional methods.

Keywords: Constructal design; Machine learning; Optimization; Highly conductivity pathways; Electronic cooling.

1. INTRODUCTION

Microelectronic technology advances have enabled the miniaturization of dense electronic chip packages. However, miniaturization leads to increased heat generation and higher temperature, which can challenge microelectronic device operation. Conduction-based heat dissipation is among the prominent cooling methods for thermal management and efficient heat dissipation systems development. Bejan [1] proposed a new cooling method in 1997 using high thermal conductivity materials and tree-shaped channels, introducing the Constructal Theory fundamentals [2]. This led to further research by many researchers, including [3-5]. Combining machine learning (MLAs) with numerical analysis and data structures can accelerate analyzing and solving problems and save computational costs [6]. Many researchers have combined ML regression models and computational fluid dynamics (CFD) to conduct thermal analysis and optimize thermal systems [6]. Also, based on the Constructal Theory, researchers have applied ML methods to optimize the maximum temperature of studied cases [7]. The main objective of this study is to investigate the constructal design of highly conductive pathways embedded into a heat-generating piece using a numerical code based on finite element method (FEM) and an optimization process based on MLAs to reduce computational cost.

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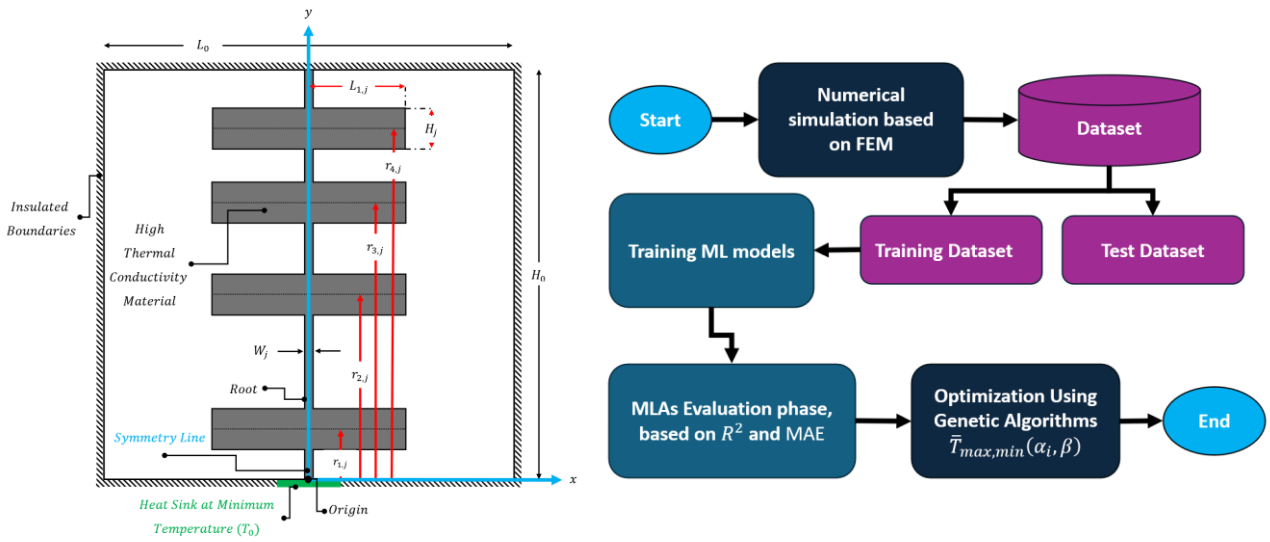
2. MATERIALS AND METHODS

Figure 1(a) depicts the 2D heat-generating medium with $N = 4$ equal high thermal conductive branches (k_h) embedded in a low thermal conductive material (k_l). The medium generates heat at a uniform rate. The heat sink at a lower constant temperature (T_0) dissipates the heat, while the other outer surfaces are insulated. Figure 1(b) shows a brief flowchart of this study's machine learning algorithm-genetic algorithm (MLA-GA) method. A numerical simulation based on FEM is initially run on studied parameters to generate a dataset for training and testing the various MLAs. Different MLAs are analysed and compared using ML evaluation metrics, including regression coefficient R^2 and mean absolute error MAE, to determine the most suitable MLA for the dataset obtained from FEM. In the following, an optimization is implemented using the genetic algorithm GA to minimize the objective function ($\bar{T}_{max,min}$) based on the selected MLA. For various heights of the branch (H_j), the decision variables comprise the distance ratio of each branch from the origin ($\alpha_i = r_{i,j}/H_0$), and the length ratio of equal branches ($\beta = L_{1,j}/W_j$) with a fixed volume fraction ($\phi = A_h/(A_h + A_l)$).

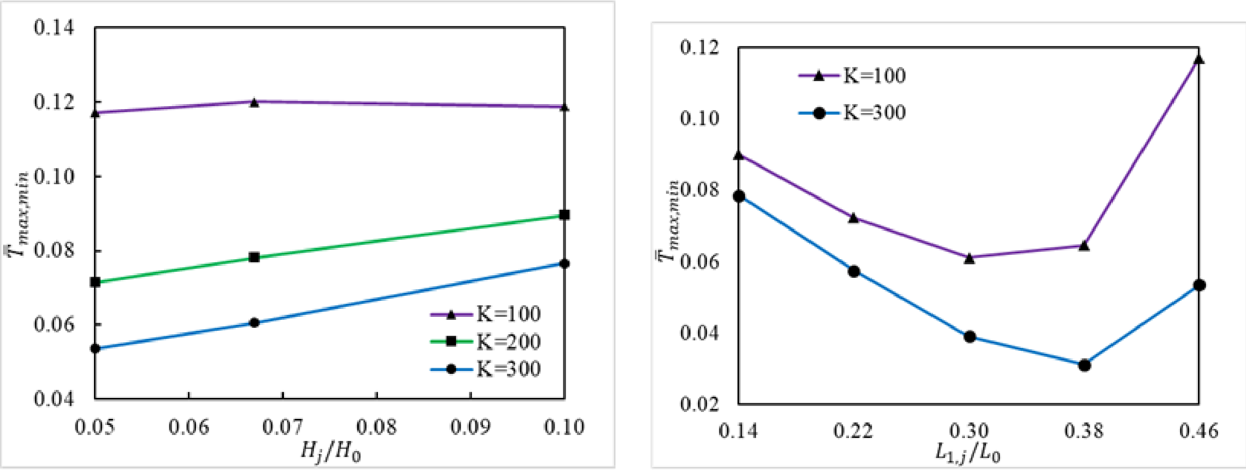


(a) (b)

Fig. 1 – (a) Schematic geometry of high conductivity pathways and coordinate system, (b) a flowchart of the methodology.

3. RESULTS

After comparing several ML models, it is found that for the present problem, the performances of Extra-trees regression model [8] are superior compared to other models. Therefore, the results in Fig. 2 and Tables 1 and 2, are based on the (complicated) function obtained by Extra-trees regression model and the GA optimization procedure that uses this function. Figure 2 illustrates (a) the effects of branch height at constant length ($L_{1,5}/L_0 = 0.46$) and (b) branch length at constant height ($H_5/H_0 = 0.05$) on $\bar{T}_{max,min}(\alpha_i, \beta)$ for various thermal conductivity ratios and, for $\phi = 0.2$.



(a) (b)

Fig. 2 – The effects of (a) branch height at constant length and (b) branch length at constant height on $\bar{T}_{max,min}(\alpha,\beta)$.

Table 1 compares the predicted $\bar{T}_{max,min}(\alpha,\beta)$ values using the ML-GA method and those from previous studies for various thermal conductivity ratios at $\phi = 0.2$ and $H_5/H_0 = 0.05$.

Table 1

Comparison between the results of this study and previous works

K_h/k_l	**Present Work**	**I-shaped [3]**	**Recursive Localization [4]**	**GA [5]**
100	0.0612	–	0.0376	–
300	0.0312	0.0840	0.0222	0.0446

Table 2 presents the $\bar{T}_{max,min}$ values obtained using both the MLA and the FEM. The predicted results by the ML-GA method closely match the FEM results, for $K_h/K_l = 200$, $H_5/H_0 = 0.05$, and $L_{1,4}/L_0 = 0.38$.

Table 2

Comparing results predicted by ML-GA method and FEM

Parameter	**ML-GA**	**FEM**	**Deviation (%)**
$\bar{T}$	0.040512	0.040500	0.03

4. DISCUSSION AND CONCLUSIONS

The study utilized the MLAs-GA method to optimize the conductive pathways based on the Constructal Theory, aiming to reduce computational costs. The Extra-trees regression ML model shows good accuracy in predicting objective function values when compared with other MLAs using evaluation metrics on the dataset obtained from FEM. Also, the validity of the MLA-GA result based on the Extra-trees regression ML model is further confirmed with FEM.

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