***Keywords:*** *Machine Learning, CFD, Temperature Prediction, Pin-Fin*

## NOMENCLATURE

|  |  |
| --- | --- |
| *Wi* | Weight matrix for layer i (dimensionless) |
| *bi* | Bias vector for layer i (dimensionless) |
| *̂yi*  *yi*  *f(.)* | Predicted temperature for the ith sample (K)  Ground truth temperature for the ith sample (K)  Activation function (dimensionless) |
| **Greek Symbols** | |
| *δ* | Huber loss transition point  (smoothness parameter) |
| *LHuber*  *η* | Huber loss function used for training (K)  Learning rate for the Adam optimizer |
| **Subscripts** | |
| *A*  *src*  *tgt* | Source  Target |

## INTRODUCTION

Fin surfaces are widely used in heat dissipation processes. Though traditional research and development is going on to increase the efficiency of the fin, machine learning approach could be a good alternative to predict the heat transfer through the specific coordinates in 2d and 3d planes. Traditional systems rely on numerical analysis and finite volume analysis which are heavy computational tasks. Recently data driven approaches like Artificial Neural Networks (ANNs) gained popularity in the thermal field. In this system, we train the model with some input parameters along with targeted output, then we predict the output with some unknown data. We have taken △T(x, y, z1,2,…,6) as input parameters and then predicted the △T for other z planes.

## BODY OF THE PAPER

The

### Artificial Neural Network Model Architecture

## To predict temperature differences (∆T) at the unmeasured z-planes (z = 575 and z = 600), an artificial neural network (ANN) was trained using data from six known planes: z = 0, 100, 175, 275, 375, and 475.

Fig. 1 shows the model structure for visualisation.

* + 1. Interpolation using IDW

To align the (x, y) coordinates across all datasets, **Inverse Distance Weighting (IDW)** was applied using cKDTree for efficient neighbor search. For each target point, the temperature was interpolated from its 10 nearest neighbors, with weights inversely proportional to the square of the distance (p=2p = 2p=2). This provided a consistent temperature field over the Z = 0 plane, essential for ∆T computation.

* + 1. Temperature difference calculation

Temperature difference (ΔT) was computed with respect to the base plane (Z = 0):

This highlights the thermal variation across the z-direction and was used as the learning target for the ANN.

* + 1. ANN model for ∆T prediction

An ANN was trained to predict ∆T at deeper planes (z = 575, 600) using known data from z = 0 to 475. The model used are as follows:

Input: Scaled (x, y) and ∆T using Standard Scaler

Layers: 256 → 128 → 64 → 32 → 16 neurons, with **Swish** activation and output layer with linear activation function

Techniques: Batch normalization and 20% dropout to handle the outliers and edge cases of the dataset. The model was trained using the **Adam optimizer** with gradient clipping (clipnorm = 1.0). Two loss metrics were used given in eq. Early stopping and learning rate scheduling improved convergence and prevented overfitting.

## EQUATIONS

Euclidean distance is given by dji between jth and ith position

(1)

Wights for its k-nearest neighbour

(2)

Normalising the weights

(3)

Interpolation Ti at point j

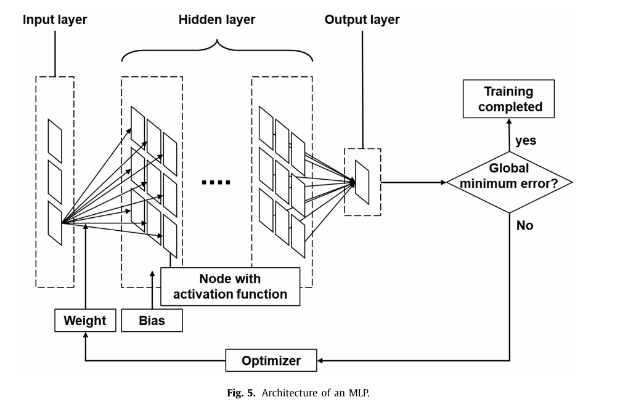
(4)

Mean absolute error formula

(5 )

Huber loss formula

## FIGURES



**Fig 1. Structure of the ANN**

Figure 1 shows the basic implementation structure of the Artificial Neural Network used along with labelled weights and biases and use of optimizer to automatically change the weights and biases to get the maximum accuracy with least error.

## TABLES

**Table 1: Distribution of loss metrics at different runtime**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Epochs** | **Huber Loss** | **MAE** | **Val Huber Loss** | **Val MAE** |
| 1 | 0.0846 | 0.1859 | 0.0321 | 0.0903 |
| 2 | 0.0481 | 0.1366 | 0.0185 | 0.0813 |
| 3 | 0.0335 | 0.1194 | 0.0192 | 0.0615 |
| 20 | 0.0162 | 0.0984 | 0.0084 | 0.0356 |
| 29 | 0.0129 | 0.0928 | 0.0044 | 0.0258 |
| 30 | 0.0126 | 0.0916 | 0.0042 | 0.0285 |

## Figure 1 shows the distribution of losses alog the training of the ANN mmodel at different epochs. The fluctuation of val huber loss and val mae suggests that there is overfitting of model due to the data. The model is reading and learning the trend instead it is not generalizing or predicting.

## REFERENCE STYLE

References should be numbered according to their first occurrence in the text and cited giving the last name of the author followed by the reference number in brackets e.g., Hilborn [3]. For papers with two authors, last names of both the authors should be mentioned, e.g., Rees and Pop [4]. For three or more authors, only the last name of the first author followed by et al. should be given, e.g., Sarkar et al. [2].

Reference to journal papers should include authors’ surnames, followed by initials, year of publication, name of the journal (abbreviated according to standard practice), volume number, and numbers of first and last pages. Reference to publications in conference proceedings should include surname(s) of author(s), followed by their initial(s), year of publication,paper/ page number, name of the conference, dates, place and country. Reference to books should include surname(s) of author(s), initial(s), year of publication, title of the book, edition of the book, place of publication, name of publisher, and pages referred to. Reference to book chapters should include: surname(s) of author(s), initial(s), year of publication, title of chapter, title of the book, edition, initial(s) and name(s) of editor(s) (if any), name of publisher,place of publication. Reference to thesis should include the surname of the author, followed by initials, the title of thesis, year of publication, the degree for which submitted, the name of university and the city and country where located. For articles by DOI, the reference should include the name(s) of author(s), followed by initial(s), year of publication, name of source, and DOI number. For online documents, the reference should include the surname(s) of author(s) followed by initial(s), year, source title, complete web address and date of accessing the site. Representative examples of different types of references are given in the next section.

## REFERENCES

*Journals*

[1] Kerschen, G. and Golinval. J.C.,2002, J. Sound Vib., 249, 849 - 865.

[2] …

*Conference Proceedings*

[3] Sarkar, S., Lore, K.G., and Sarkar, S., Proc. 2015 International Conference on Cognitive Computation:Integrating Neural and Symbolic Approaches - COCO’15. Montreal, Canada, 2015, 93–101.

[4] …

*Books*

[5] Hilborn, R.C., 2000, *Chaos and Nonlinear Dynamics*. Second Edition, New York: Oxford University Press, New York, USA.

[6] …

*Book Chapters*

[7] Rees, D.A.S. and Pop, I., 2005, Local Thermal Non-equilibrium in porous medium convection,in: Transport Phenomena in Porous Media, vol. III., Ingham, D.B. and Pop, I. (ed.), 147-174. Elsevier, Oxford, UK.

[8] …

*Theses*

[9] Zou, Y., 2007, Exploring recurrences in quasiperiodic dynamical systems. PhD thesis, University of Potsdam, Potsdam, Germany.

[10] …

*DOI documents*

[11] Slifka, M.K. and Whitton, J.L., 2000, J Mol Med. (2000) doi:10.1007/s001090000086

[12] …

*Online documents*

[13] Cartwright, J., Big stars have weather too. (IOP Publishing PhysicsWeb, 2007), http://physicsweb.org/articles/news/11/6/16/1. Accessed 26 June 2007

[14] …