AN ASYMPTOTIC APPROACH TO ESTIMATE THE THERMAL CONDUCTIVITY OF A SQUARE PLATE UNDER NATURAL CONVECTION

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ABSTRACT

The present work is to develop a reduced order model, using Artificial Neural Networks (ANN) based inverse technique on a transient heat transfer problem. The proposed methodology has been demonstrated on a two- dimensional heat slab to estimate the unknown parameters such as thermal conductivity (k). A 2D model of the material (Teflon) is developed and encapsulated with the fluid domain, is simulated using CFD. To minimize the influence of mesh size on the results, grid independence study is carried out. The input to the CFD model is heat flux and thermal conductivity varying between $400 \leq q \leq 600$ W/m2 and $0.1 \leq k \leq 0.6$ W/mK respectively, the output is temperature of the Teflon plate. The input-output data set from CFD simulation are used to train the ANN network, which act as a proxy model. The neural network used in this work is based on the feed forward back propagation algorithm. The optimum number of neurons required for the neural network is determined by neuron independence study. The experimental data are input to the inverse model (ANN) to estimate the thermal conductivity of the Teflon plate for an unknown heat flux. The method can be used for different applications and provides a good accuracy on the result.

Keyword: *Teflon, Levenberg-Marquardt Algorithm, Artificial Neural Network (ANN), Heat flux (q),Thermal conductivity (k), Natural convection, and Computational Fluid Dynamics (CFD).*

1. INTRODUCTION

The best performance out of the materials that we use in all aspects of our daily lives can be achieved by our ability to understand thermal conductivity. Effective testing and measurement of thermal conductivity is critical to this endeavor. There are several possibilities to measure thermal conductivity, each of them suitable for limited range of materials, depending on the thermal properties and the medium temperature. In general, there are two basic techniques of measurement steady state or non- steady state technique. When material that is analyzed, is in complete equilibrium, the steady state technique as the name suggests, performs a measurement. The disadvantage generally is that it takes a long time to attain the required equilibrium. The non-steady state techniques perform a measurement during the process of heating up. The advantage is that measurements can be made relatively quickly. To introduce Artificial Neural Network (ANN), it mimics the biological neural network inspired computational algorithm that is extensively used in machine learning and Artificial Intelligence. It is an assemblage of networks connected through an intermediate decision-making points called neurons. These neurons work exactly in the same fashion as the neurons in our brain. These networks can learn to perform tasks by considering examples without being programmed with any task specific rules. The structure of an ANN usually consists of 3 groups of neurons called layers - the input layer, the hidden layer, and the output layer. The hidden layer is the decision-making layer. There might bemultiple layers of hidden layers depending upon the complexity of the problem. This is where all the computations take place through various computational algorithms, in this case Levenberg- Marquardt algorithm is used.

2. METHODOLOGY

The first step in determining the thermal conductivity is obtaining the temperature data set, by running the CFD analysis of the model byvarying the thermal conductivity between 0.1 to 0.6. The temperature data sets obtained from the CFD for different thermal conductivity values aretaken from 'n' different points. The number of points to be considered is determined by performing a temperature point independent study.
These temperature data set, and their respective conductivity is fed into the neural network toolbox to train the artificial neural network, in this toolbox the temperature data sets are fed into the input section and their respective thermal conductivities in the output section. The training of the artificial neural network takes place using Levenberg-Marquardt algorithm. The experimental temperature values through which the conductivity is to be determined is obtained by running another CFD simulation for the thermal conductivity of value 0.25 W/m.K , which is obtained from thermal property table for Teflon. There is always error when temperatures are determined experimentally, so to introduce error into the simulated temperature data set, a uniform noise is added. This temperature data set is now fed into the trained neural network, and it provides the thermal conductivity as it output. This thermal conductivity obtained is the actual result.

2.1 Geometry Model

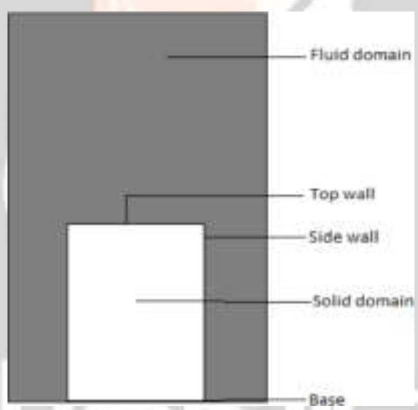

Fig -1: Geometry Model

This model consists of a 2D square for Teflon material of dimensions 50x50(mm). A fluiddomain is introduced to carefully identify the convection of heat from the solid domain andunderstand the fluid behavior, the fluid domain dimensions are 75x100(mm). For meshing purposes, grid independent theory has been studied to determine the optimum mesh sizing to reduce the computational effort. And during the study it was found that temperatures hardly changed between fine and super-fine mesh sizes and therefore decided to go with fine meshing. For the boundary conditions, the flux at the base is 500W/m^2 and the temperatures of the top and side walls are taken the same i.e., 297K. Theanalysis is done using pressure-based considerations and buoyancy is taken into consideration.

2.2 Grid Independent Study

This procedure is a good practice to follow in CFD simulations. It is to make sure that by fixing the number of grid points, the temperature attains a constant value and has reached independent state or not.
In grid independent study, we find the temperature in the result obtained at different fixed grid points, when different mesh sizing is provided and the optimum one is chosen i.e., the meshing of the lesser size if the difference is minimal. The variation between fine and super fine mesh is negligible and thus mesh with element size of 2mm is sufficient for the actual simulation.
When a model is designed, in the design modeler and proceeded to meshing of the sample, there areoften regions of high activity and regions of much less activity happening. In these respective regions, it is often necessary to mesh the regions of high activity to finer mesh sizes to get accurate values and simultaneously reduce the mesh

sizes in regions of low activity. This procedure reducesthe computational time.

Table -1: Grid Independent Study

Coarse Mesh(9mm)	Fine Mesh(2mm)	Super-Fine Mesh(0.1mm)
312.9	312.6	312.6
312.3	311.3	311.2
311.3	310.2	310.2
310.1	309.8	309.7
308.9	309.1	309.1
308	308	307.99
307.3	307.7	307.7

2.3 Artificial Neutral Network

The activation function is present in each neuron that defines the output of the neuron. The role of the activation function is to introduce non-linearity in the modelling capabilities of the network. Tan Sigmoid is the activation function adopted here.

Training of the neural network is an iterative procedure of forward propagation and back propagation by learning the values of the parameters - weights and biases. Of the simulated temperature values got from the CFD simulations, 70% of the values is used for the learning process while the rest is used for testing and validating the efficacy of the network.

The training data is passed through the network insuch a way that all the neurons apply their transformation to the information they receive from the neurons of the previous layer and sending it to the neurons of the next layer. That is, passing the input data through the network. The final layer will be reached with a result of label prediction for those input examples. To make up for the errors arising, weights are adjusted and added until good predictions are obtained.

Once this is done, back-propagation is followedto propagate this loss to each one of the parameters that make up the model of the neural network, this propagated information to update the parameters of the neural network with the gradient descent in a way that the total loss is reduced, and a better model is obtained. Iterations are continued in the previous steps untilwe consider that we have a good model.

The number of hidden layers in ANN's may range from 1 to 1000 layers of hidden layers. The network with single hidden layer is used for simpler calculations and therefore less complicated in constructing and evaluating. Hence, they are known as shallow networks and networks with large number of hidden layers are called deep learning networks.

Neuron independent study is conducted to determine the number of neurons in the hidden layer. To what extent the k value depends on the number of neurons is the primary objective. This is done using the ANN module in MATLAB. Inthis module, input the fixed temperature pointsand simultaneously input the number of neuronsto get the k value as output. From this module,the network is generated along with the deviationin the values of k. Root mean error is also found. This procedure is carried out for increasingnumber of neurons until we arrive at a number where the k values become constant. In our case, the results obtained were at 5 neurons.

Table -2: Neutron Independent Study

Number of Neutrons	Deviation	M.S.R
1	0.0064	0.9876
2	0.0026	0.9763
3	0.0019	0.9981
4	0.0028	0.9723
5	0.0007	0.9999
6	0.008	0.9872
7	0.0041	0.9828

3. RESULTS AND DISCUSSIONS

In the present work, thermal conductivity of a Teflon material has been determined using simplified model developed upon CFD simulations, thus accelerating the estimation process. At the first instance, experimental data were not available so, generated a synthetic data using CFD simulations, which mimics the actual experimentation. The input and output for the numerical experimentations are thermal conductivity and temperature data set.

Uniform noise has been added to the output temperature data so that random errors is considered during estimation procedure. To decide the number of temperature points to be taken for neural network we performed temperature point independent study. In this study a network for different number of points were created and observed how much variation does the output obtained from the network have compared to the actual value. It is observed that by increasing the number of points over 10 there isn't much change in the conductivity values. Thus, we fix the number of points as 10 for the actual experimentation and simulations.

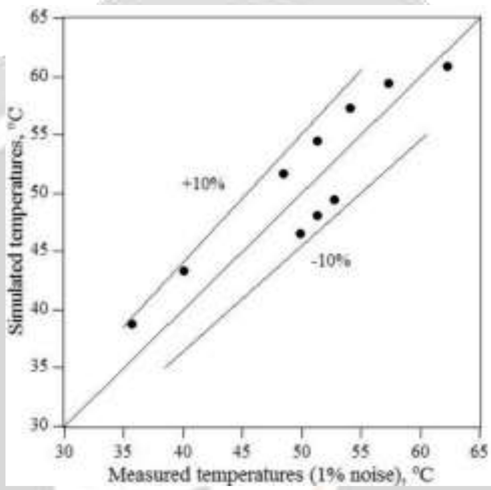

Fig -2: Parity Plot

The ANN is trained by providing the simulated temperature data set as input and their corresponding 'k' as output, using L-M method. The experimental temperatures are put into this trained network and obtain the conductivity value.

To validate the network, CFD simulation for the obtained 'k' and observe the error in the temperature values obtained through simulation and the experimental temperature values. The estimated thermal conductivity of a present problem has been validated. It is within 10% of uncertainty and the temperatures got from the experimental value of 'k' and the simulated value of 'k' is plotted as shown below to much accuracy and good agreement.

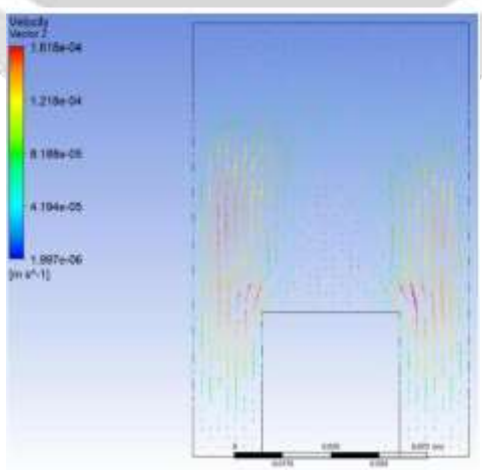

Fig -3: Velocity Contour

This simulation is modeled by taking Boussinesq Approximation into consideration. This approximation takes buoyancy into consideration because of which natural convection takes place, the temperatures slowly decrease with the height. Due to the temperature gradient present between the solid and the ambient temperature, a boundary layer is formed. This boundary layer causes the close surrounding air temperature to increase, now, this causes the density to decrease and the density at the farther points to increase. This difference in density causes the hotter air with lesser density to rise while the colder air with greater density to go below which causes a circulation of fluid, as shown in Figure 3.

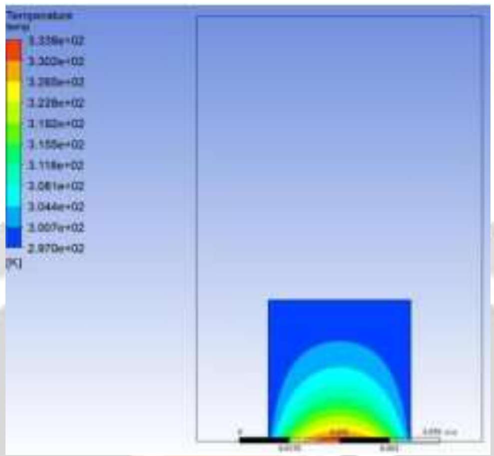

Fig -3: Temperature Contour

Once the grid independent study is conducted, to check if the trained ANN is valid or not, this step is necessary. How many temperature points needs to be selected over the grid to input them to the neural network after training it, to get the least deviation of k value is checked. The k value got as the output should be independent of the number of temperature points considered. At what temperature point k values remains fixed should be determined.

Table -3: Grid Independent Study

Number of Points	'k'
5	0.1823
7	0.2425
9	0.2468
10	0.2485
12	0.2502

Table -4: Grid Independent Study

Grid size (mm)	Temperature points	No. of Neurons	M.S.R	Literature'k'	Simulated 'k'
2	10	5	0.9999	0.25	0.26

4. CONCLUSIONS

This work proposes a simpler inverse model (Neural network) built upon limited number of the CFD simulations for a conjugate heat transfer problem, to estimate the thermal conductivity of aTeflon plate.

This approach accelerates the estimation process, thus reducing the computational effort and cost. The estimated value of 'k' was 0.26 W/m.K and it seems to be in good agreement with literature.

The inferred value of 'k' was used in the CFD model to obtain the temperatures. The simulated temperatures are compared with the experimental temperature data, and it was observed that both the data are in good agreement

(±10%). Thus, demonstrating the efficacy of the estimation procedure.

5. REFERENCES

[1]. Pradeep S Jakkareddy et al.(2022). An inversetechnique to estimate the heat flux of a slab with transient heat conduction. *Advances in Mechanical and Materials Technology*.

[2]. Ming Gao et al.(2009). Performance prediction of wet cooling tower using artificial neural network under crosswind conditions. *International Journal of Thermal Sciences.*

[3]. R Eslamloueyan et al.(2009). Estimation of thermal conductivity of pure gases by using artificial neural networks. *International Journal of Thermal Sciences.*

[4]. Zhihang Song et al.(2013). Airflow and temperature distribution optimization in data centres using artificial neural networks. *International Journal of Heat and Mass Transfer.*