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Heat Transfer Enhancement in Radiator using Nanofluid and Machine Learning Algorithm

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Abstract: *This research article describes a statistical analysis of heat transfer by developing an artificial neural network-based machine learning model. Automotive heat removal levels are of high importance for maximizing fuel consumption. Current radiator designs are constrained by air-side impedance, and a large front field must meet the cooling requirements. There is enormous demand for powerful engines in smaller hood areas has caused a lack of heat dissipation in the vehicle radiators. As a prediction, exceptional radiators are modest enough to understand coolness and demonstrate great sensitivity to cooling capacity. Enhancement of heat transfer coefficient continues to be an important research area in various fields of engineering ranging from microelectronics to high powered automobiles. The initial effort in the present research study is to enhance the heat transfer coefficient in a vehicle radiator using nanofluids with high thermal conductivity. The world's most abundant element 'Carbon' astoundingly exists in various structures and one such form is tube commonly known as Carbon Nanotubes (CNTs). Heat transfer enhancement in water and coolant-based systems with different concentrations of nano particles (carbon nanotubes) have been investigated from an engineering system perspective. One such system considered is a "SUZUKI (800CC) - CAR RADIATOR", cooling circuit using different nanofluids to replace the conventional engine coolant. In the present study, the effect of nano-fluid heat transfer to enhance in water and coolant-based systems with multi walled carbon nanotubes has been investigated. The improvement of heat transfer when compared to water, coolant (water + ethylene glycol 60:40) and water with MWCNTS and coolant with MWCNTS has been studied. It has been observed that there is an enhancement of heat transfer up to 30% when coolant and CNTS are used as a cooling medium. An artificial neural network model is used for regression analysis to predict the heat transfer in terms of Nusselt number and thermohydraulic efficiency, and the results showed high prediction accuracies. The artificial neural network model is robust and precise and can be used by thermal system design engineers for predicting output variables. Two different models are trained based on the features of experimental data, which provide an estimation of experimental output based on user-defined input parameters. The models are evaluated to have an accuracy of 97.00% on unknown test data. These models will help the researchers working in heat transfer enhancement-based experiments to understand and predict the output. As a result, the time and cost of the experiments will reduce.*

Keywords: Al2O3, ZnO, ANN, NN, MSE, MAE, Machine Learning, Heat Transfer, Radiator.

I. INTRODUCTION

The demand to improve the heat transfer rate from thermal equipment's for an effective cooling process is growing by the day. Even though numerous ways for increasing heat transfer rate are already accessible, such

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as incorporating machine learning algorithms (artificial neural network), employing nanofluids to make the radiator more compact and effective. Nanofluids are a type of heat transfer fluid that has designed suspension nanoparticles (1-100 nm) scattered throughout the fluid. Water, organic fluids (e.g., ethylene, Tri ethylene, and so on), motor oil, polymeric solutions, bio-fluids, and other basic fluids are commonly found in base fluids. Carbon in various configurations (e.g., carbon nanotubes, graphite, diamond), metals (e.g., copper, silver, gold), metal oxides (e.g., titania, zirconia), and functionalized nanoparticles are often used as nanoparticles. The use of nanofluids has discovered a wide range of possible uses.

Linear regression, neural networks, support vector machines and support vector regression, decision trees, and other basic machine learning algorithms are all addressed. Because of their high efficiency, machine learning methods like as ANN are being investigated by several researchers. ANN has found widespread application as a new computational model in dealing with a wide range of complex real-world issues, and its popularity stems from information processing characteristics such as learning power, high parallelism, fault tolerance, nonlinearity, noise tolerance, and generalization abilities [1].

The artificial neural network has become more and more demanding because to its simplicity, versatility, and accessibility to a wide range of training methodologies. Weighted links connect the processors of the human brain, allowing impulses to move between them. After receiving various input parameters from other neurons in line with the weights of their connections, a neuron generates output parameters. Due to the feed forward neural network's simple form and simplicity of mathematical analysis, it has become the most popular in engineering applications. In this ANN design, there is only one input layer, one hidden layer, and one output layer. Data is sent from the input nodes to the output layer nodes through the network once they have received a set of feed forward process input parameters. Nonlinear input-output transformations are performed by the nodes using sigmoid activation functions. The mathematical foundations of the training and testing procedures for the best ANN have been studied by P. Nephron [2].

An analytical method known as ANN may be used to calculate relationships between single and multiple input and output variables. Additionally, this approach may be utilized to resolve issues with simulation, modelling, control, prediction, and categorization. ANN is a "black box" model that receives inputs, transmits those inputs, and produces outputs. Utilizing ANN, investigate heat transmission. This review's objective is to outline the ANN structure, approach, and implementation issues in general heat transfer problems, as well as notable heat transfer applications using ANN, such as investigations of fluidized bed heat transfer and heat exchangers, and their related discoveries. An overview of ANN modelling to forecast the heat transfer coefficient and Nusselt number for a horizontal tube immersed in a gas-solid fluidizing bed of large particles is given in the experimental study to increase the efficiency with which ANN is used in heat transfer research. Additionally, ANN may be utilized successfully in a variety of heat transfer applications [3].

By using an ANN model, the impact of the convectors' design parameters on heat transmission and overall weight has been calculated [4]. ANN is used to transmit heat in an air cooler with traditional twisted tape inserts. The mean relative errors for the training and test sets of the best ANN structure discovered in this study were 0.457% and 0.478%, respectively [5]. In response to external inputs, a neural network (NN) may learn a highly nonlinear connection that processes information [6].

NOMENCLATURE

Re	Reynold's number
Nu	Nusselt number
m	Mass Flow Rate
D	Inner diameter of tube

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Q	Heat flow, Watts (Heat Transfer Rate)
Cp	Specific Heat Capacity
ΔT	Temperature difference
A	Area, m^2
L	Length of tube, m
K	Thermal conductivity, w/m k
H	Heat Transfer Coefficient

GREEK SYMBOLS

ρ	Density
Δ	Difference

ABBREVIATIONS

ANN	Artificial Neural Network
KNN	K-nearest neighbors
DT	Decision Tree
RF	Random Forest
NN	Neural Network
MSE	Mean Square Error
MAE	Mean Absolute Error
RMSE	Root Mean Square Error
SVM	Support Vector Machine

II. ARTIFICIAL NEURAL NETWORK STRUCTURE AND METHODOLOGY

(Artificial Neural Network Technique for Predicting Water-Alumina Nanofluid's Thermo-Physical Properties) Aluminum Oxide Nanofluids' preparation A water-Al_2O_3 nanofluid is produced after the first phase of nanoparticle manufacturing is complete and the second phase of nanoparticle dispersion in the carrier fluid. Alumina nanoparticles with a 99.5% purity were purchased from Nano Labs in India. The Scherer equation was used to calculate the average size of the obtained nanoparticles. The nanoparticle's average size was determined to be between 30-40 nm. Based on the known volume concentration of the nanofluid, nanoparticles were distributed in the base fluid in the proper ratios. The equation was used to calculate the mass of nanoparticles needed to create the requisite concentration of the nanofluid. The amount of Al_2O_3 nano powder required for the creation of various nanofluid concentrations is listed in Table.

To maintain the nanoparticles properly disseminated and from settling, sodium dodecyl sulphate (SDS) in an amount equal to one-tenth of the nanoparticle quantity was utilized as a surfactant. Overuse of surfactants is not advised as it might affect the nanofluid's thermo-physical properties. Figure 1 shows an approach that is systematic and step-by-step. Al_2O_3 nanoparticles and surfactant were first added to the base fluid after being metered out to the necessary quantity. For roughly 30 minutes, magnetic stirring was used to create a homogenous solution. To prevent agglomerations in the nanofluid, the solution was then sonicated for around 3 hours at a frequency of 20 KHz using an ultrasonic sonicator. The sonication method includes a 10-minute interval to avoid heating the nanofluid for 30 minutes while forming a homogenous solution.

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Figure 1: Magnetic Stirrer for Stirring Nanofluid.
(PES's MCOE Chemistry lab)

Table 1: Weight of the nano powder required for different volume concentration.

Sr. No.	Volume Concentration (%)	Weight of Al_2O_3 Nano Powder (gm)
1	0.05	1.9869
2	0.1	3.9739
3	0.2	7.9478
4	0.4	15.8956
5	0.6	23.8434

After that, the solution was sonicated for about 3 hours using an ultrasonic sonicator (Make: Oscar Electronics) at a frequency of 20 KHz to avoid agglomerations in the nanofluid. A break of 10 minutes is given in sonication process to prevent the heating of nanofluid above the desired temperature. Pictorial view of the magnetic stirrer and the digital balance used for stirring process and for the weighment of the nano powder and surfactant are shown in Fig1.

2.1) DEVELOPMENT OF ANN MODEL ANN

Technique was developed based on inspiration from dendrites in complex human brain system. ANN consists of many processing units fully interconnected as nodes or artificial neurons, organized in layers. There are three groups of node layers in general, namely, the input layer, one or more hidden layers, and an output layer, each of which is occupied by several nodes.

The transfer functions for the layers were tansig/ tansig/ tansig/ purelin respectively. The details of the ANN parameters are shown in Table 2.

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www.ijirid.in

Table 2: Optimum parameters of ANN for the study

ANN Parameters	Details
Neural Network	MLP
No. of hidden layers	2
No. of neurons in the input layer	5
No. of neurons in the first hidden layer	8
No. of neurons in the second hidden layer	18
No. of neurons in the output layer	1
Learning rate	0.5
No. of epochs	1000
Adaption learning function	Train 1m
Training error	0.00001

The approach is more precise since ANN has a huge number of processing units operating in parallel across the network. It also works with dynamic modelling and adaptive control, making it simple to implement any abrupt changes and controls in the system. Utilizing all of the experimentally collected thermal conductivity and viscosity measurement data, thermal conductivity datasets and viscosity datasets were produced. The supervised back propagation (BP) learning strategy, which is used to train feed-forward networks, involves shifting weights and biases layer by layer from the output layer towards the input layer. The chain rule method's neural network is trained via backpropagation. To put it simply, this technique does a backward pass after each feed-forward run through a network in order to modify the model's parameters depending on weights and biases.

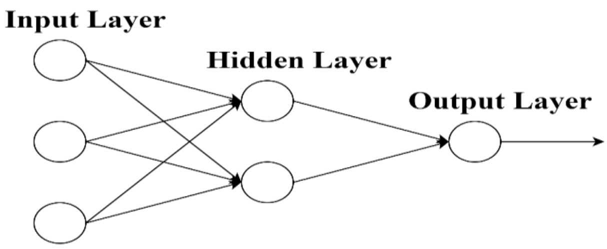

Figure 2: Feed-forward neural network model

The whole experimental data used to measure thermal conductivity and viscosity were combined to create the thermal conductivity dataset and the viscosity dataset. The datasets included 100 measurements of viscosity and thermal conductivity at various volume fractions between 0.01 percent and 0.1 percent. Seventy measures in all were used for training, thirty for testing, and one hundred for validation.

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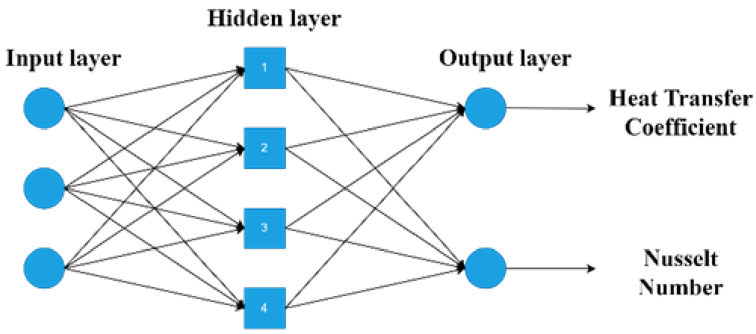

Figure 3: ANN diagram

III. EXPERIMENTAL PROCEDURE AND DATA REDUCTION

Applying the following expression, one may get the heat transfer coefficient on the air side by knowing the overall heat transfer coefficient:

$$Q = \rho_w C_{pw} V_w (T_{w\,in} - T_{w\,out}) \tag{1}$$

Where the water's density, thermal capacity, and volume flow rate are denoted by _w, Cp, and V_w, respectively. Applying the following expression, one can get the heat transfer coefficient on the air side by knowing the overall heat transfer coefficient.

$$h_a = \left(\frac{1}{U} - \frac{d_o}{h_w d_i} - \frac{d_o}{2k_c} ln \frac{d_o}{d_i}\right)^{-1} \tag{2}$$

Where h, w is the heat transfer coefficient on the water side and d_i and d_o are the inner and outer diameters of the inner heat exchanger tube, respectively.

It was discovered during the current investigations that the transition zone corresponds to the mean Reynolds number Re 4757. As a result, most expressions described in the literature would fall short of offering physically accurate values for the heat transfer coefficient in the heat exchanger's inner tube. It was discovered that the following equation fits Nu, w, on the water side:

$$Nu_w = 0.036Re^{0.8}Pr^{\frac{1}{3}}\mathrm{di}^{0.055} \tag{3}$$

Where l represents the length of the inner tube Eq. (3) proposes a Nusselt number for developing turbulent flows and it also provides accurate results for the transition region of the flow in the inner tube of the present work.

The heat transfer coefficient on the water side was derived based on the Nusselt number using the following expression:

$$h_w = \frac{k_w Nu_w}{d_i} \tag{4}$$

Where k_w denotes the thermal conductivity of water.

The heat transfer results were presented in the dimensionless form by using Nusselt number on the air side calculated as follows:

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$$Nu_a = \frac{h_a D_h}{k_a} \tag{5}$$

Where $D_h = D_i - d_o$ represents the hydraulic diameter and Di denotes the inner diameter of the outer pipe. The same hydraulic diameter was used for the calculation of the Reynolds number on the air side [4].

The selected numerical parameters for optimization were the number of neurons in the hidden layer (2-40), momentum coefficient (0.1-0.7) and step size (0.1-0.4) in the hidden layer, epoch number (100-3000) and training times (1-5). The goodness of fit of the optimal ANN to the experimental data was based on coefficient of determination (R^2), MSE and mean absolute error, (MAE) for the tested models.

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(x_{pi} - x_{di})^2}{\sum_{i=1}^{N}(x_{pi} - \bar{x})^2} \tag{6}$$

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(x_{pi} - x_{di})^2 \tag{7}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|x_{pi} - x_{di}| \tag{8}$$

x_{pi} is the network output from observation i, x_{di} is the experimental output from observation i, x is the average value of experimental output and N is the total number of data observation. A well-trained ANN model should produce small MAE, RMSE and SE with large R2 values.

IV. RESULTS AND DISCUSSIONS

Based on experimental data, an artificial neural network model was provided; 70% of the data were used for training and the remaining 30% were used for testing. By selecting values from the data at random, validation was carried out. The mean square error is calculated to determine the model's performance, and Python code is used to carry out the calculations. This model uses Machine Learning (ML) for training, random data division for validation, and mean square error calculation for performance evaluation. Table 3 contrasts several neural network regression algorithms' mean absolute error (MAE), root mean square error (RMSE), mean square error, prediction speed, and training time.

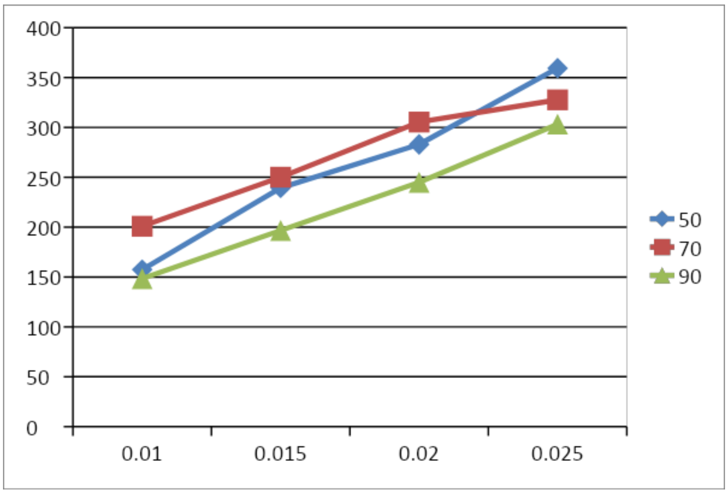

Figure 4: Q Vs Ø

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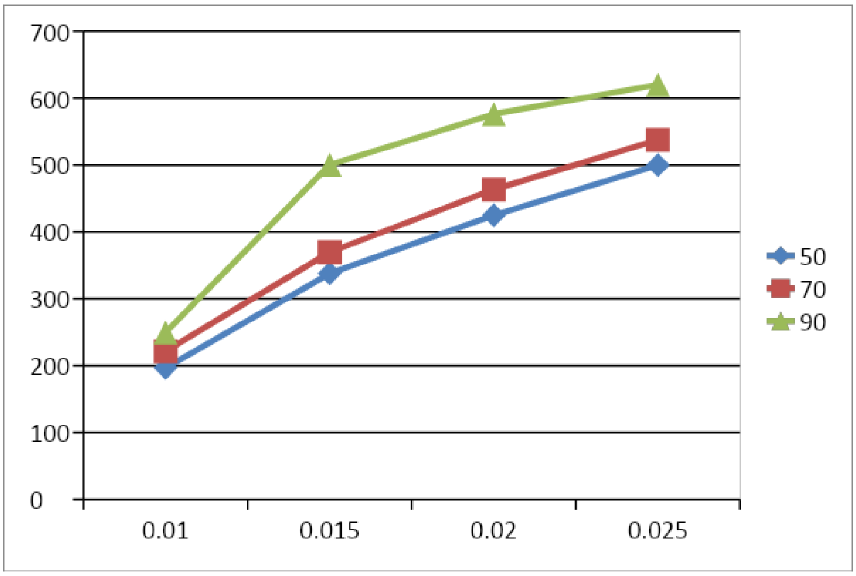

Figure 5: h Vs Ø

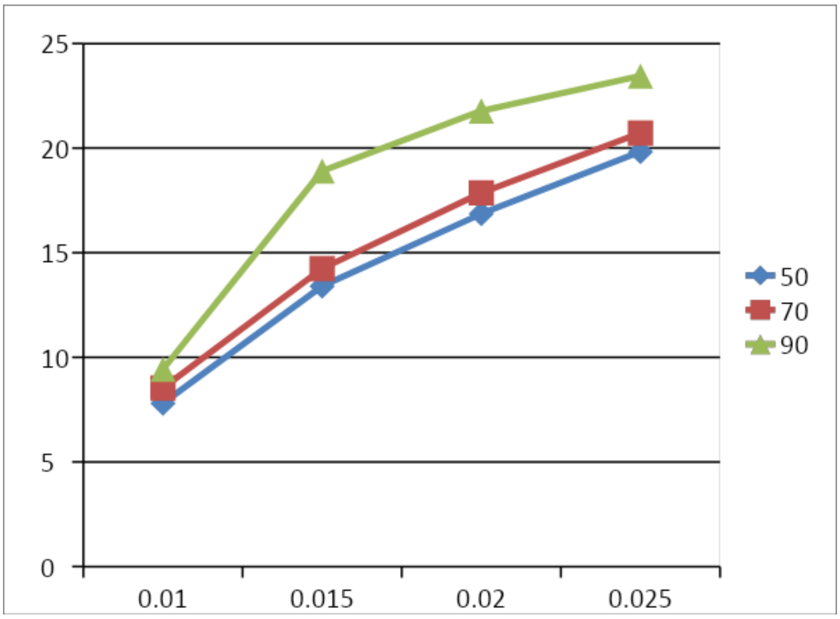

Figure 6: Nu Vs Ø

Table 3: Comparison of thermal conductivity validation of ANN using regression methods

Method	RMSE	R^2	MSE	MAE	Estimation speed (obs/s)	Time of training (s)
Decision Regression tree	6.026893	-1.9785	36.3234	5.460000	1500	5.5195
Support vector regression	3.554434	0.65239	12.6340	3.382631	1200	5.0

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V. CONCLUSION

In this research, the characteristics impacting the specific heat capacity of various nanofluids, as well as the proposed models, are discussed. Increase in the volume fraction of nanostructure for the nanofluids with conventional base fluids causes a decrease in the specific heat capacity. The specific heat capacity of nanofluids is affected by temperature, and its growing or decreasing trend with temperature is depending on the base fluid. Numerous correlations have been developed for more accurately estimating the specific heat capacity of nanofluids than analytical models. The comparison of experimental and anticipated values of the proposed ANN model revealed that there is remarkable agreement between the predicted and experimental heat transfer findings with the least error. Because of its great accuracy, the suggested ANN model provides a dependable adaptable mathematical structure for modelling and prediction of outcomes, and it can therefore be utilized to exactly reproduce the experiments. It took 5 seconds and 4 seconds, respectively, to train the datasets for thermal conductivity (K) and viscosity, respectively. The performance of the suggested model was tested using a variety of regression approaches, and it was found that among them, Support vector regression produced the best results.

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