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Determination of Thermal Properties of Ass 304 and Prediction of Thermal Conductivity Using Artificial Neural Networks

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Abstract: *In the present era there is an immense use of Austenitic stainless steels, Extra deep drawn steel and Ni-super alloys. Mainly we find their applications in automobile industries, aircrafts, house-hold appliances etc. In the proposed project, thermal properties like thermal conductivity, heat capacity and radiation shape factor of austenitic stainless steel (deformed material), extra deep drawn steel and nickel super alloy (tools) will be calculated. These experiments are conducted from 100 o C to 400oC to calculate these thermal properties. In the proposed project also predicts the thermal conductivity of the above mentioned materials using Artificial neural networks. Better agreement of predicted effective thermal conductivity values are obtained by using artificial neural networks with the experimental results. All the experiments are carried out in the research lab at GRIET.*

I. Introduction

Stainless steels are iron- based alloys containing more than 10.5% Chromium. Stainless steel does not readily corrode, rust or stain with water as ordinary steel does. There are different grades and surface finishes of stainless steel to suit the environment the alloy must endure. Stainless steel is used where both the properties of steel and corrosion resistance are required. Stainless steel differs from carbon steel by the amount of chromium present. Unprotected Carbon steel rusts readily when exposed to air and moisture. This iron oxide film (the rust) is active and accelerates corrosion by forming more iron oxide; and because of the greater volume of the iron oxide, this tends to flake and fall away. Stainless steels contains sufficient chromium to form a passive film. The chromium in steel reacts naturally with oxygen in the air to create a passive chromium-oxide (Cr_2O_3) film on the surface of the steel. (The term passive, simplified, means the surface no longer reacts chemically to its surrounding environment). It is this passive film to which stainless steel owe their superior corrosion resistance. Even though this layer is thin , it does raise the level of friction between the tool and the work piece , which leads to galling and wearing of the tool surface.

1.1 Austenitic Stainless Steel 304

Type 304 stainless steel is the variation of the base 18-8 grade, with higher and low carbon content. The lower carbon content minimizes chromium carbide precipitate due to welding and susceptibility to intergranual corrosion. In some instances Type 304 can be used in the “as-welded” condition.
The chemical composition of ASS 304 is as follows:

ELEMENTS	CONTENT
C	0-0.08%
Mn	0-2.0%
Si	0-1%
P	0-0.05%
S	0-0.02%
Cr	17.5-19.5%
Ni	8-10.5%
Fe	Balance

The typical properties of ASS 304 are as follows:

PROPERTY	VALUES
Density	8.03g/cm^3
Melting point	1399-1454^{o}C
Co-efficient of expansion	16.9 μm/m^{o}C (0-100^{o}C)
Modulus of elasticity	193*10^{3}MPa
Thermal conductivity	16.2 W/mK at 100^{o}C
Specific heat	0.50 KJ/kgK at (0-100^{o}C)

The properties under investigation are:
- Thermal conductivity
- Heat capacity
- Radiation shape factor

1.2 Thermal Conductivity

Conduction is a process of heat transfer through solids. When as temperature gradients exists in a body, experience has shown that there is a transfer of heat from the high temperature region to low temperature region.

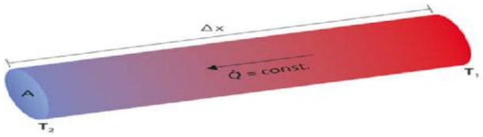


Fig 1.1: Schematic describing the concept of thermal conductivity with T1 > T2

The heat transfer rate per unit area is proportional to temperature gradient given by:

$$\mathbf{Q}/\text{ A } \alpha\ \Delta\mathbf{T}/\Delta\mathbf{X}$$

Where Q is the heat transfer rate (watts). 'A' is the area of heat transfer(m2). ΔT/ΔX is the temperature gradient in the direction of heat flow(^{O}c/m).
When the proportionality constant is inserted, we get

$$\mathbf{Q/A = - k\ \Delta T/\Delta X}$$

The positive constant 'k' is called the coefficient of thermal conductivity of the material. The negative sign indicates that heat transfer takes place in the direction of decreasing temperature. Coefficient of thermal conductivity has the units w/mk. In any conduction heat transfer problem, it is essential to have knowledge of coefficient of thermal conductivity of the material involved in heat transfer process. Although it is fairly constant in narrow temperature range, it varies over a wide temperature range. Metals, which are good conductors of heat, have high values of 'k', insulating materials have low values of 'k'.

1.3 Heat Capacity:

The amount of heat energy needed to change the temperature of a substance depends on:
(a) what the substance is;
(b) how much of it is being heated;
(c) what rise in temperature occurs.

The heat energy needed to raise the temperature of an object by 1 K is called the heat capacity of the object. However, a rather more useful quantity is the heat energy needed for 1kg only.

The specific heat capacity of a substance is the heat needed to raise the temperature of 1 kg of substance by I K. Specific heat capacity is given C. The units for C are J/(Kg K). In mathematical terms the heat capacity C is expressed as fallows

$$\mathbf{C = \Delta Q/\Delta T = dQ/dT\ [J/deg]}$$

Where dQ is the energy required to produce a dT temperature change.Ordinarily,heat capacity s specified per mole of material (e.g., J/mol-K, or cal/mol-K).

1.4 Radiation Shape Factor:

Also called shape factors or view factor. Radiation exchange between two or more surfaces depends strongly on the surface geometries and orientations, as well as on their radiative properties and temperature. To compute radiation exchange between any two surfaces, we must first introduce the concept of a view factor.

II. Experimentation

2.1 Experimental Setup:

The experimental setup consists of following equipment. A detailed description of each of the above equipment is given below

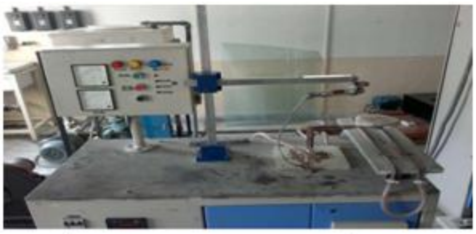


Fig: 2.1 Induction Heater Furnance Set Up

Now the insulated austenitic stainless steel 304 material is mounted on the heater as shown in the figure[3.4]. At this instant the voltage and current are measured and allow the work piece to get heat so that the required temperature can be obtained. By using non contact type pyrometer the temperature at different points marked on the material can be known. This pyrometer is made to focus unto the bottom most point as there will be maximum temperature. When the temperature is reached to 100^{o}C heater is stopped and the readings of temperature at different locations are noted. Now again heater is started, voltage and current values are noted and again allow the work piece to get heat so that it can reach up to temperature 150oC. When the temperature is reached at 150C in the same procedure readings are taken by using pyrometer. The same procedure is adopted for temperatures 100oC, to 400^{o}C at an interval of 5^{0}C. But there will be some heat lost through convection because of lack of insulation at some places like top and bottom but the values obtained through calculation are nearer to the actual values.

Fig 2.2.: Induction furnace used for heating the equipment.

Fig 2.3: Insulating material ASS 304 mounted on heater

Fig 2.4: Measuring temperature by pyrometer.

III. Artificial Neural Networks

Artificial Neural Networks (ANNs) are non – linear mapping structures based on the function of the human brain. They are powerful tools for modeling, especially when the underlying data relationship is unknown. ANNs can identify and learn correlated patterns between input data sets and corresponding target values. After training, ANNs can be used to predict the outcome of new independent input data. The networks imitate the learning process of the human brain and can process problems involving non-linear and complex data even if the data are imprecise and noisy. Neural network has great capacity in predictive modeling. A neural network is a computational structure that is inspired by observed process in natural networks of biological neurons in the brain. It consists of simple computational units called neurons, which are highly inter-connected. They are parallel computational models comprised of densely interconnected adaptive processing units. These networks are fengtine-grained parallel implementations of non-linear static or dynamic systems. A very important feature of these networks is their adaptive nature, where "learning by example" replaces "programming" in solving problems. This feature makes such computational models very appealing in application domains where one has little or incomplete understanding of the problem to 39 be solved but where training data is readily available. Neural networks are now being increasingly recognized in the area of classification and prediction, where regression model and other related statistical techniques have traditionally been employed.

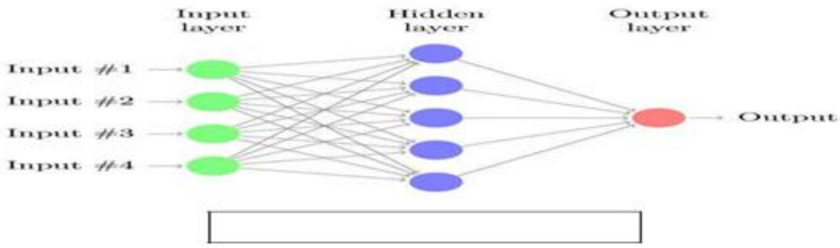


Fig 3.1 structure of neural network

The use of computational neural network (NN) as an artificial intelligence method has rapidly increased over the past 10 years in many different science and technology fields. Some of them are: chemical science, molecular structure design and polymer properties prediction, weld deposits structures and properties prediction, as a function of a very large number of variables (Cook [1]), process control etc. After learning the basic relationships between input factors and the output, the NN becomes able to generate output Fig 4.1 structure of neural network 40 variables, based only on input factors. This method is very suitable for predicting material properties in case when some of the relevant influence factors are unknown, as well as for solving many complex phenomena for which physical models do not exist.

3.1 Classification Of Neural Network

The artificial neural networks can be categorized on the basis of two major criteria: (i) based on learning rules, and (ii) the connections between processing elements. Based on learning rules, artificial neural networks can be divided into supervised and unsupervised networks. In supervised learning, the network is presented by a historical set of inputs and desired outputs. The actual output of the network is compared with the desired output and an error's calculated. This error is used to adjust the connection weights between the inputs and the outputs to reduce error between the historical outputs and those predicted by the artificial neural network. In unsupervised learning, the network is only presented with the input stimuli and there are no desired outputs. The network itself adjusts the connection weights according to the input values. Based on connections between processing elements, artificial neural networks can be divided into feed forward and feedback networks. In feed forward networks, the connections between the processing elements are in the forward direction only, whereas, in feedback networks, connections between processing elements are in both the forward and backward directions. Sometimes feed forward network is called multilayer perceptron (MLP). It is generally trained with the back propagation or error algorithm, learning vector quantization, and radial basis function. A 44 multilayer feed forward network learns by back propagation, in which error that propagates back is called feed forward back propagation. In this project, the feed forward back propagation network has been used with the training function mentioned above.

3.2 Designing The Artificial Neural Network

The temperature values and thermal conductivity of four materials (ASS304&316, EDD steel and Inconel alloy) are input parameters to predict the effective thermal conductivity of these materials mentioned above. Proper selection of the input parameters plays a key role in the artificial neural network approach and can be of help to reach a satisfactory predictive quality. The neural network model is a two layer feed forward neural network (Demuth and Beale, 2003), which is the most widely applied neural network. Each layer has different numbers of neural elements, and is fully connected to the succeeding layer through the connection weights.

Networks with different neurons in the input layer and two neuron in the output layer have been designed. MATLAB R2013a software is used for neural network programming in this study. In order to obtain the desired answer, five networks of feed forward back propagation are utilized. The training process used by these networks is iterative. When the minimum error between desired and predicted values has been obtained, the training process is 45 considered successful. The increasing method is used for selection layers and neurons for evaluation of various topologies. When the network is trapped in the local minimum, new neurons are gradually added to the network. This method has more practical potential to detect the optimum size of the network. The increasing method has some advantages as follows: (i) The network complexity gradually increases with increasing neurons, (ii) The optimum size of the network is always obtained by adjustments, and (iii) monitoring and evaluation of local minimum are carried out during the training process. Two threshold functions are used to reach the optimized (Rumelhart et al., 1986).

3.3 ANN Programming

The following are the steps involved in the sequential order for programming the artificial neural networks-

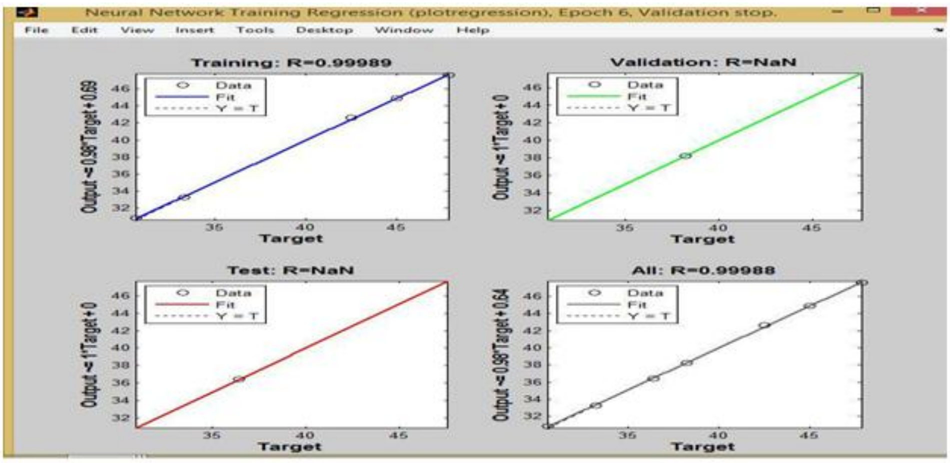
1. Matlab
2. Importing data in Matlab
3. NN tool box & importing data in nn tools
4. Create network
5. Train the network
6. Training plots (performance, training state, regression)
7. Export network to Matlab workspace

IV. Results And Discussions

The thermal properties of Austenitic stainless steel 304 & 316, Inconel-600 and Extra deep drawing quality steel found out using the set-up as presented in Chapter 3 are presented in tables 5.1, 5.2, 5.3 and 5.4. It can be observed that by increasing the temperature of all the materials there is a consistent increase in thermal conductivity and heat capacity of materials. It is also observed from these tables that by increasing the temperature thermal properties of EDD multiply more than the Inconel-600 material. Probably that is one of the reason that the material can retain strength at elevated temperature and the energy loss from the material is minimum. This makes the material suitable for turbine blades.

Table 5.1 Thermal properties of ASS 304

Temperature (^0C)	100	150	200	250	300	350	400
Thermal conductivity(W/mK)	30.589	33.24	36.41	38.2	42.48	44.98	47.79
Specific heat (KJ/KgK)	0.500	0.517	0.532	0.54	0.557	0.566	0.574
Heat Capacity (KJ)	34.27	46.69	53.37	64.9	69.71	70.22	76.40



Plot 5.1 Regression plot of ASS 304

V. Conclusion

Artificial neural networks with FEED FORWARD - BACK propagation can predict the coefficient of thermal conductivity of steels very successfully. The coefficient can be determined at different elevated temperatures. The average error in predicting the coefficient of thermal conductivity for steels & Ni-super alloy increased with increasing temperature, both in the learning and testing data set of the artificial neural network . The advantage of the artificial neural network over regression models is its ability to learn, which enables the artificial neural network to approximate the coefficient of thermal conductivity in much wider ranges of independent variables than the regression models. The approximation accuracy of the artificial neural network can be increased by higher data homogeneity in both the learning and testing data sets as well as by a wider data range in the learning data set

References

[1]. M. J. Peet1∗ , H. S. Hasan2 and H. K. D. H. Bhadeshia1Published in the International Journal of Heat and Mass TransferVol. 54 (2011) page 2602-2608 doi:10.1016/j.ijheatmasstransfer.2011.01.025.

[2]. O. Altun a,*, Y. Erhan Boke b, A. Kalemtas (Problems for determining the thermal conductivity of TBCs by laser-flash method).

[3]. Sidney.H.Avner; Introduction to Physical Metallurgy (New York: Mc Graw Hill 1964)

[4]. Khaleel Ahmed, J. Krishnan Post weld heat treatment-case study BARC newsletter, centre for Design and Manufacture. Bhabha Atomic Research Centre.

[5]. Ravi Kumar D. formability analysis of extra-deep drawing steel. Journal of Material process and Technology 2002; 130-131:31-41.