Experiment with the Multivolt Drop Technique to Predict the Physical Properties of Al6061 using Artificial Neural Network

Kanikicharla Jaya Sudheer Kumar, B. Chandra Mohana Reddy

Abstract: ***According to this study, because of its light weight, high specific strength, and stiffness at high temperatures, Al6061 is the most appropriate material in the transportation business. The major goal of this research is to evaluate the physical properties of Al6061, such as thermal conductivity and electrical resistivity, by experimental investigation utilizing the multivolt drop approach. As Artificial Intelligence techniques become more widespread, they are being used to forecast material properties in engineering research. So, the second goal of this research is to employ Artificial Neural Networks to build a prediction model with fewer errors by utilizing experimental data. It will reduce the situation of direct observations throughout a wide range of temperatures where the physical properties of Al6061 are significant. As a consequence, it was discovered that the enhanced optimum ANN has significant mechanical properties that impact prediction. The anticipated results in electrical resistivity and thermal conductivity had Root Mean Squared Errors of 0.99966 and 0.99401, respectively, with R-Square average values of 0.820105. Various tests and ANN methodologies were used to validate and compare the suggested results. The comparison of predicted values with multivolt drop experimental results demonstrated that the projected ANN model provided efficient Al6061 accuracy qualities.***

Keywords: Al6061 metal matrix, Thermal conductivity, Electrical resistivity, Artificial Neural Network, Multivolt drop technique

I. INTRODUCTION

An artificial neural network (ANN) model is utilized in this article to evaluate the thermal conductivity ratio of Al 6061. Heat transfer plays an important role in several applications; the thermal conductivity of aluminum may be predicted using materials with high thermal conductivity. Thermal conductivity has a linear relationship with temperature in the examined range [1]. The increase in thermal composite conductivity as Al particle size decreases might be due to more stable thermal conductive channels for smaller Al particles. Furthermore, when the composites are heated, heat tends to travel through the Al particles, allowing an electric charge to flow to the lowest resistance. Furthermore, because electric charge flows where resistance is lowest, heat tends to flow through the Al particles when composites are heated. The relationship between soil electrical resistivity and geotechnical properties is a significant engineering challenge. The goal of the study is to develop a method for predicting the electrical resistivity of soil [2]-[3]. Depending on the substance, electrical resistivity varies widely, starting at about 10-6 in metals and reaching 1016 in polyethylene. The ANN model produces the most accurate prediction values. Because the effective thermal conductivity in the research area was empirical [4], the layered thermal conductivity was calculated using trained ANN models. ANNs use heat and nanoparticle quantity percent as inputs, and the output is thermal conductivity and electrical resistivity [5]. The best ANN architecture was found by altering the number of neurons in the hidden layer and calculating the ANN's performance for each neuron number. The optimal ANN model developed predicts experimental data with reasonable agreement in mean absolute percent error.

1.1 Research Gap

Reviewing previous efforts made by various authors in the description of the properties of the Al6061 alloy, we can see that considerably less study has been done in estimating the thermal conductivity and electrical resistivity of the specific metal matrix. Although prior research has been able to describe the varied properties of the Al6061 alloy that has been implanted with other materials such as Si, Br, and so on, This research primarily focuses on the prediction and comparison of Al6061's thermal conductivity and electrical resistivity using an Artificial Neural Network (ANN), as well as comparing the end findings with the material's other attributes.

1.2 Research Objectives

1. The thermal conductivity and electrical resistivity of Al6061 were investigated using multivolt experimental techniques.
2. Create a prediction model for Al6061 alloy using MATLAB software (ANN using the Levenberg-Marquardt method and hybrid activation function swish and mish).
3. Validate the anticipated output using multiple ways to determine accuracy and dependability using an ANN model (hybrid activation function swish, mish).

1.3 Framework

The experiment has been carried out to collect data during the heat treatment process in order to determine the physical properties of Al 6061, such as thermal conductivity and electrical resistivity.

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The apparatus used to test Al6061 was a heat treatment method. The experimental data was loaded into an ANN, which would then be assessed for its ability to predict physical characteristics. To predict values, it was assessed and compare the experimentally computed data.

II. LITERATURE REVIEW

[6] It was investigated changing the electric and thermal properties of aluminum components by electrodepositing multi-walled carbon nanotubes (MWCNTs) on them (EDP). The pattern coated with 0.05 mg/mL of MWCNTs exhibits a 36 percent increase in heat conductivity and a 9.6 percent increase in electrical conductivity, according to the data. [7] In order to assess the impact of FSW parameters on the microstructure and electrical properties of the metal matrix, he looked at frictional steer welding (FSW) of Al6061-T6 with natural Cu plates. It was found that the quickest traverse speed (60 mm/min) produced the lowest resistivity values, while the slowest traverse speed (20 mm/min) produced the highest electric resistivity values.

In [8] proposed the effect of graphite and silicon carbide reinforcement in the Al6061 matrix to examine how the mechanical properties of the metal matrix were altered. They discovered that the stiffness of composites increased significantly with the addition of SiC_p, up to a maximum of 15%, and that the inclusion of SiCp with a low weight percentage resulted in an increase in tensile energy and a decrease in percent elongation. [9] Used an ultrasonic non-destructive approach to assess the mechanical, electrical, and physical properties of SiC-reinforced Al6061 composites. According to this study, when compared to un-reinforced Al alloy, the ductility is reduced by 20.8 percent, and the bulk density and porosity are also increased, while the electrical conductivity is reduced. In the paper [10] conducted studies to determine how the mechanical, tribological, and physical aspects of composites reinforced with titanium dioxide relate to one another (TiO_2). Greater TiO_2 content in the matrix was demonstrated to cause mechanical Al6061-TiO_2 composites to expand greatly, losing their tribological and ductility capabilities.

In [11] suggested the Dual Heat Treatment (DHT) in Al6061-T6 alloy using genetic rules set (GA) and ANN techniques. The simulation results show a 41 percent increase in heat conductivity and electrical conductivity with a reduced floor roughness of 1.78975 m. In the research [12] used ANN to create an arithmetic simulation model for the Al6061 investigation of thermal conductivity alloy. Based on the results of mathematical calculations, a chart of thermal conductivity variation, which is required for the implications of the chemical composition of Al6061-T6 alloy, has been provided, which has over mechanical residences and elaboration temperature.

To evaluate the impact of tool diameter, spindle speed, and feed charge on the outer roughness of the hole, he carried out an exploratory study using Minitab 16 software [13]. According to the results of the analysis, the spindle speed and tool diameter are the parameters that have the most influence on the floor roughness. At [14] conducted research to forecast the wear resistance of Al6061 alloy by reinforcing it with 2, 4, and 6 wt. percent Vanadium pentoxide (V_2O_5) and silicon carbide (SiC) ANN powder to increase the powder's wear resistance. According to the results, with a regression coefficient of 0.999, it was established that the greater wt. percent reinforcement of V_2O_5 increased when compared to the wear resistance of aluminum to SiC. [15] A technique for evaluating the surface roughness accuracy value in CNC milling was developed using an Artificial Neural Network in Al6061 alloy. According to the aforementioned study, the ANN model is 98.35 percent accurate in predicting floor roughness in Al6061 alloy.

The ANN provides a method for calculating the ideal neuron number, as well as the ANN performance and correlation coefficient approaches shown in [16] to be capable of forecasting nanofluid behavior, though the fitting technique made fewer errors. The ANN strategy outperformed other methods in forecasting nanofluid thermal conductivity based on the amount of nanoparticles and temperature. The fitting approach entails determining the method's correlation coefficient after fitting a surface to the experimental data points, and then comparing the absolute error value for both procedures.

An artificial neural network was used to forecast the thermal conductivity ratio values. Two hidden layers with five neurons each make up the greatest artificial neural network architecture [17]. When the experimental thermal conductivity ratio is compared to the artificial neural network outputs, the correlation demonstrates the artificial neural network's high capacity and accuracy in forecasting thermal conductivity ratio data. According to the sensitivity investigation, the hybrid's sensitivity to nanofluid's thermal conductivity grew as solid amount and hotness fractions increased.

An approach for creating experimental data points is provided in order to pick the best ANN in terms of performance. Three different states were investigated, including ANN, experimental, and fitting approaches, and their errors in knf prediction were investigated. At the same time, comparing methodologies for calculating the knf is an important subject [18]. A novel technique for forecasting the knf using ANNs can make a substantial contribution to defining the most desirable performance and obtaining the best and most accurate state.

Thermal conductivity data is required for computer simulation and mathematical modelling of heat transport processes. Several gases' thermal conductivity had accumulated over time. Exact experimental thermal conductivity measurement of gases, on the other hand, is a time-consuming and challenging technique, especially at extremely high and/or extremely low temperatures. In this context, [19] used conventional data to build feed-forward ANN models to predict monatomic gases' thermal conductivity of 119 at atmospheric pressure throughout a wide range of temperatures. Trial and error resulted in a single hidden layer with seven NN neurons. According to the the findings of the outcome tests, the created ANN model can correctly predict thermal conductivity.

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Techniques for Prediction: ANNs are frequently deployed and used. The ability of ANN to solve complex non-linear problems is its primary advantage. A number of parameters impact the thermodynamic and physical characteristics of nanofluids, including base fluid type, particle size and shape, temperature, volume concentration, and Nano-particle volume concentration. Traditional models cannot predict thermophysical parameters properly; however, ANN approaches are well suited for accurate prediction at the present moment to predict thermal conductivity in various situations [20]. As a consequence, a Multilayer Perceptron model was used to anticipate thermal conductivity over a wide range of base fluids, concentrations, and temperatures.

Due to its better electrical and thermal qualities, aluminium is the second most widely used metal. A significant subset of an important class of technological materials. All raw overhead electrical transmission cables are composed of aluminium alloys. Researchers and manufacturers have greatly enhanced the tensile strength and conductivity of overhead wires [21]. They have also been creating designs and automating processes to extend service life and operating temperatures. The thermal and electrical conductivities of the materials used in broadcast lines must be understood.

Low alloying Due to their high electric conductivity and excellent properties, aluminium alloys are increasingly being used to construct overhead power transmission lines. Research [22] showed the combination of boron treatment and grain refinement to be an effective strategy for enhancing the electrical conductivity and mechanical characteristics of the alloys. Aluminium is always utilised as a replacement for copper in the production of electrical conductors. Aluminium is widely used in electrical engineering to transfer enormous amounts of electricity from hydraulic systems, thermal power plants, and nuclear power plants to major consumer regions. Aluminium used in the wire and cable industry must have excellent mechanical properties, as well as good conductivity, corrosion resistance, and heat resistance.

2.1 Research Significance

The mentioned literature reviews provide a severely restricted analysis of Al6061. The quest for low-cost, lightweight, and strong materials has fueled the development of hybrid reinforced composites made from low-cost Al6061. Several researchers have attempted composite fabrication using reinforcement [23],[24], [24], [25] but only a few have used ANN to predict electrical resistance, thermal conductivity, hardness, and tensile strength of composites using hybrid reinforcements. The study's originality is that it casts the AA6061/Al2O3/SiC composites using multivolt drop methods and calculates the required parameters for optimizing the composites' attributes. The thermal conductivity and electrical resistivity of AA6061/Al2O3/SiC composites were studied. Finally, using the experimental data as input variables, the ANN was used to anticipate the thermal conductivity and electrical resistivity of the composites. The use of ANN can minimize testing time and the expense of tests.

III. MATERIALS AND METHODOLOGY

The physical framework and the ANN-based computational model used in this current system for calculating the physical properties of Al6061, such as thermal conductivity and electrical resistivity, have been researched and assessed. The experiment used non-steady state approaches for time-dependent observations. The physical testing experimental study was carried out utilizing Millivolt drop method approaches, which included the measurement of thermal conductivity and electrical resistivity characteristics. The final prediction has been made in ANN based on the validation of experimental data and valuation. The suggested physical and computational system model is depicted in Figure 1.

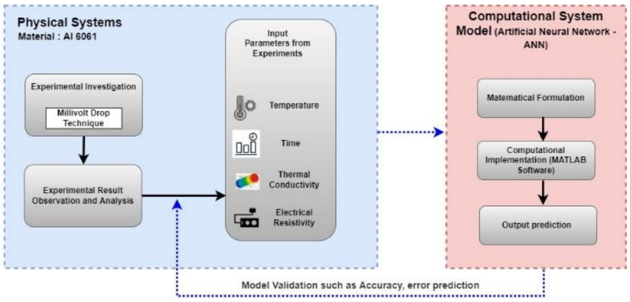

Figure 1 Block diagram of proposed method for physical properties

3.1 Materials

To properly investigate and comprehend the material characteristics, the Al6061 wrought aluminum matrix alloy, which is often used in the transportation sector, was chosen. Another reason to use this wrought aluminum alloy is because of its numerous properties such as strength, high erosion resistance, chemical and thermal stability, high melting point, bearing capacity, weldability, and so on. Al6061 is used in a variety of applications including subsonic aircraft, construction boats, rail coaches, crane and roof, automobile engines, bridges and military bridges, and chimneys due to its high specific strength and stiffness at higher temperatures and reduced weight. Table 1 includes physical, chemical composition, and other information as well as mechanical qualities.

Table 1 Al6061 - Chemical Composition and other properties

Chemical Composition (mass fraction %)	Physical Properties	Mechanical Properties
Magnesium (Mg) – (0.80-1.20)	Thermal Conductivity – 166 W/m.K	Tensile Strength – 260 Min MPa
Iron (Fe) – (<0.70)		
Chromium (Cr) _ (0.04-0.35)	Electrical Resistivity – 0.040 * $10^{-6}\Omega$.m	
Titanium (Ti) – (<0.15)		Hardness –95 HB
Silicon (Si) – (0.40.0.80)	Modulus of Elasticity – 70 GPa	
Manganese (Mn) – (0.0-0.15)	Thermal Expansion – 23.4 * 10^{-6} /K	Stress – 24 Min MPa
Zinc (Zn) – (<0.25)		
Aluminum (Al) – (95.8-98.6)	Density – 2.70 g/cm^3	
Copper (Cu) – (0.15-0.40)	*Melting point – 650 ^{0}C*	

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3.2 Experimental Procedure

Computational methodologies and physical system investigations were employed in this suggested scheme to forecast the superior thermal conductivity and electrical resistivity of Al6061.

3.3 Multivolt-drop method for Electrical conductivity And Temperature Measurement

The millivolt drop technique method employing an electrodeposition procedure is the most simple and precise way for measuring physical characteristics Figure 2. The matrix metal Al6061 sample was collected and joined with the metallic points on both corners using this procedure. This results in a current flow in the metal, which is submerged in an aluminum container. Millimeters were used to measure the associated voltage drop. For the thermal behavior of the metal Al6061, a current of 10 amps is now applied. The heat was generated using a DC power source. The measurement was made every 8 seconds for a total of 292 seconds using a digital thermocouple, and the voltage was 50V with measurements every 3V for electrical conductivity. The experiment was carried out at room temperature.

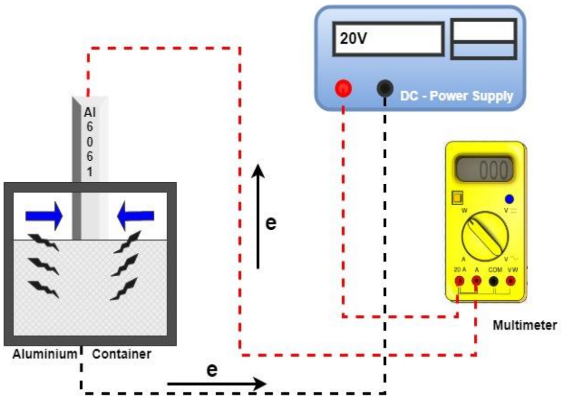

Figure 2 Multivolt drop technique for thermal conductivity and electrical resistivity analysis

The experimental values are used to manually calculate thermal conductivity and electrical resistance using scientific methods. At constant potential, the current flowing through the conductor Al6061 and the electrical conductivity are computed as follows:

$$\sigma = \frac{n\,e^2\tau}{m^*}\Omega^{-1}\mathrm{m}^{-1} \qquad (1)$$

Where, τ – Relaxation time, n – number of electrons, m^* - effective mass of electron

The thermal conductivity was determined using different temperatures. With regard to a temperature gradient, the heat transmitted to Al6061 per unit area is:

$$Q = K\,\frac{dx}{dt} \qquad (2)$$

$$Q = \frac{K\,(T_1 - T_2)}{2\lambda} \qquad (3)$$

$$K = \frac{Q}{A\frac{dx}{dt}}\ \mathrm{Wm^{-1}k^{-1}} \qquad (4)$$

The relationship between electrical conductivity and thermal conductivity is defined using the Wiedemann-Franz Law as follows:

$$\frac{K}{\sigma T} = \frac{3}{2}\frac{K_B^2}{e^2} \quad \text{(From the kinetic energy of an electron)} \qquad (5)$$

$$\frac{K}{\sigma T} = L \qquad (6)$$

Where L is Lorentz number (L=2.44 * 10^{-8} $\mathrm{W\Omega K^{-2}}$)

Electrical resistivity is inversely proportional to conductivity and it is calculated by,

$$\rho = \frac{TL}{K} \qquad (7)$$

3.2.2 Artificial Neural Network (ANN)

Several artificial intelligence techniques have been employed in the field of material science to make various types of assessments or predictions about the characteristics and performance of commercial components and materials. The artificial neural network (ANN) is a mathematical model based on the natural activity of neurons and the architecture of the human nervous system [26], [27]. Perceptron's are the essential components of a multi-layer neural network that forms an ANN that is arranged hierarchically based on layers [28]. Neurons are made up of layers that are not connected to one another and whose input data originates from the same source (the outside or another layer) and that delivers their information to the same destination (another layer or the outside).

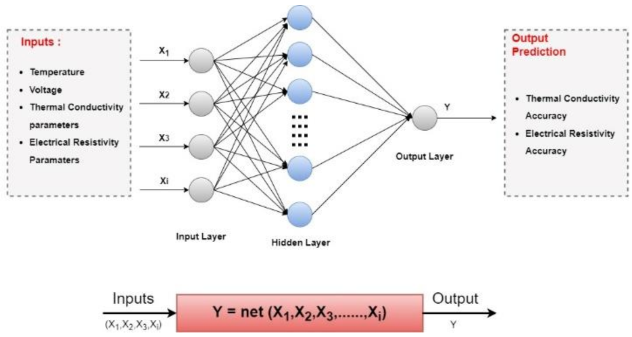

Figure 3 Typical Artificial Neural Network Architecture

The standard ANN architecture is seen in Figure 3. An ANN contains three layers: an input, a hidden layer, and an output layer. The network's nodes and neurons are defined by the input and output layers. The relationship between the input and output layers of a neural network is defined by the hidden layer, which employs several types of neurons. The following equation describes the input data to the network's hidden layer:

$$X_{hidden,k} = \sum_{l=1}^{n} W_{lk}u_l + \theta_k \qquad (8)$$

The error function was derived from the output layer and results. During validation, training, and testing, it defines the actual and anticipated values. It may be stated as follows:

$$Errors = \sum_{l=1}^{N}(Y_l - t_l)^2 \qquad (9)$$

Where, W_{lk} is weight coefficient between input and hidden neurons, u_l is input value, θ_k is hidden neuron biases and N is number of datasets in ANN model. ANN is a supervised learning approach that may be used to train on a labelled input dataset to learn a nonlinear function.

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It can do classifications and regressions. [29] This can, in certain instances, outperform traditional programming. However, neural systems have various drawbacks, the most significant of which is that they often disclose complicated computation involving thousands of operations [30]. In the case that it is possible to detect which input variables exist in small networks, it is critical in decision making via simulating synaptic weights [31]. Figure 4 depicts the general ANN Network model. The development of an ANN model may be separated into three major steps:

- Defining the problem's inputs and outputs.
- Using the weights and biases of the input, hidden, and output layers to train the network
- Evaluating network performance by comparing expected and actual values.

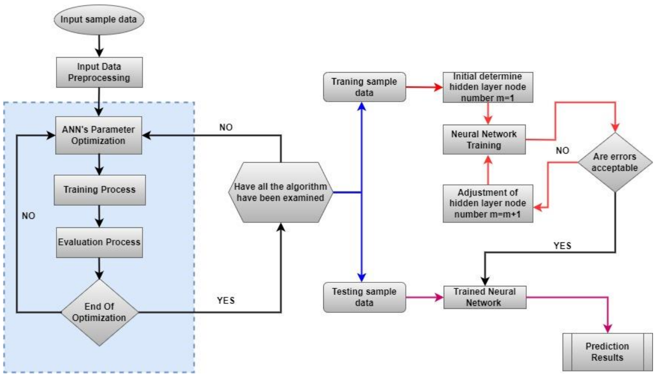

Figure 4 ANN architecture of proposed system model

IV. RESULTS AND DISCUSSIONS

4.1 Physical experimental system result

In this analysis, the aim set for the Multi-volt drop technique is to display the accurate thermal conductivity qualities and electrical conductivity of Al6061, and MATLAB software is utilised for prediction and output curve fitting. The conclusion of the inquiry is conducted in accordance with the Wiedemann-Franz Law. The experiments were carried out at various voltages, temperatures, and times. The principal effective analysis plot is used to investigate the influence of each electrical and thermal limitation, such as conductance. The experiment's output has been analysed, and the derived findings have been used for curve fitting.

Data is often presented in tabular form from the acquired results. However, making it depict patterns through graphic illustration is a divergence from the trends. Curve fitting is therefore employed exclusively for creating curves using data and mathematical calculations. It should be similar to the actual data series. Curve fitting is used to create a functional relationship between the parameter values and the observed dataset. The quality of the curve fit determines the precision of the curve fit.

General curve fitting equations:

$$log_{10}y = a + b(log_{10}T) + c\,(log_{10}T)^2 + d\,(log_{10}T)^3 + e\,(log_{10}T)^4 \quad (10)$$

It can be solved as follows:

$$y = 10^{a+b(log_{10}T)+c(log_{10}T)^2+d(log_{10}T)^3+e(log_{10}T)^4} \quad (11)$$

Where, a, b, c, d, e are coefficients, T is the temperature, y is the property to solve for.

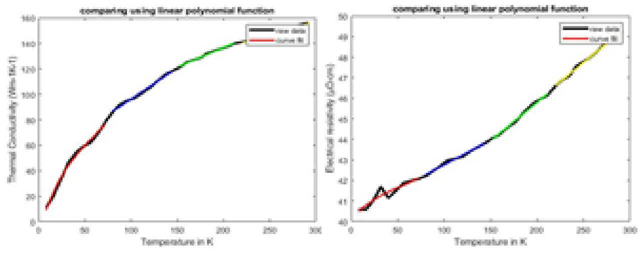

Figure 5 Thermal conductivity and Electrical resistivity curve fitting of Al6061

The thermal and electrical properties of Al6061 as a function of temperature are depicted in Figure 5. The presence of electrons is responsible for the heat conductivity Q of the metal matrix Al6061. It is proportional to electrical conductivity but inversely proportional to electrical resistance and thermal conductivity. As can be seen, the thermal conductivity and electrical resistivity of the metal matrix Al6061 are related to temperature fluctuations.

In order to assess the quality, two numbers are used to calculate the curve fitting criteria: Root Mean Squared Error (RMSE) and R-Square.

Root Mean Squared Error (RMSE):

It is standard fit error of the regression from the standard deviation of data.

$$RMSE = \sqrt{\frac{SSE}{n}} \quad (12)$$

Where, $SSE = \sum_{i=1}^{n} Err\,(i)^2$ and n = total number of data points, SSE = Sum of Squared Error, SSR = Sum of Squares of the Regression

$$SSR = \sum_{i=1}^{n}(f(x(i)) - Mean)^2 \quad (13)$$

$$SST = SSR + SSE \quad (14)$$

R- Square:

This will assess the successful curve fit from the data variance, also known as the relationship between actual and predicted response levels. When the R-Square value is greater, the fit is better.

$$R^2 = \frac{SSR}{SST} \quad (15)$$

Table 2 RMSE and R2 value - Based on the parameters (Thermal Conductivity & Electrical Resistivity)

Prediction Model – Linear and Cubical Polynomial Function	Thermal Conductivity	Electrical Resistivity
Root Mean Squared Error (RMSE)	Linear data – 0.965154 Cubic data – 0.999993	Linear data – 0.9933889 Cubic data – 0.999391
R-Square (R^2)	Linear data – 3.022370 Cubic data – 0.029564	Linear data – 0.084667 Cubic data – 0.029564

The R-square and Root Mean Squared Error from the projected linear and cubical polynomial functions are predicted in Table 2. The average RMSE in thermal conductivity is 0.9825735, while the average RMSE in electrical resistivity is 0.9963899, with R2 values of 1.525967 and 0.114243, respectively.

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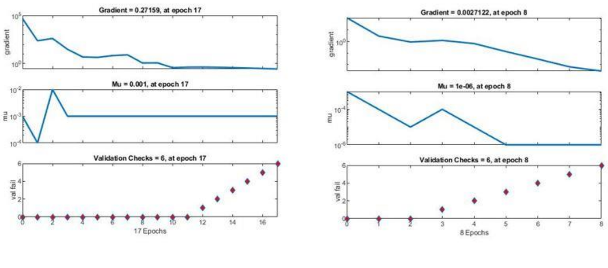
It demonstrates that the thermal conductivity and electrical resistivity values of the prediction investigational result model are well characterized across a wide range of values.

4.2 Artificial Neural Network Result Analysis – Prediction Model

The experimental findings serve as the dataset for ANN modelling. Eighty percent of the data was used for training, while the remaining twenty percent was used for testing. Before training the dataset, the input and output dataset were normalized. Choosing the proper input parameters is crucial when using ANN models to anticipate tensile strength and hardness. The factors that impact the thermal conductivity and electrical resistivity of Al6061 are tested using the multivolt drop approach. Based on experimental results, a total of four input factors were found, all of which are regarded as essential. The usual multi-layer feedforward back propagation hierarchical neural networks were created using the MATLAB Neural Network Toolbox. The NN is made up of three layers: the input layer, which contains the input data set; the system layer; and the output layer, which serves as the brain and displays the system's results. The Levenberg-Marquardt algorithm was used to train the network. The network was built with one hidden layer and 37 neurons. The average error (MSE) has been used to evaluate the network's performance. The thermal conductivity and electrical resistivity of Al 6061 composites were trained, and their performance was evaluated using the correlation coefficient and percentage of prediction error. Actual Value - Predicted Value) /Predicted Value) * 100 Further hybrid activation functions have been applied in the neural networks of swish and mish to promote faster learning and better performance.

4.2.1 Thermal Conductivity and Electrical Resistivity:

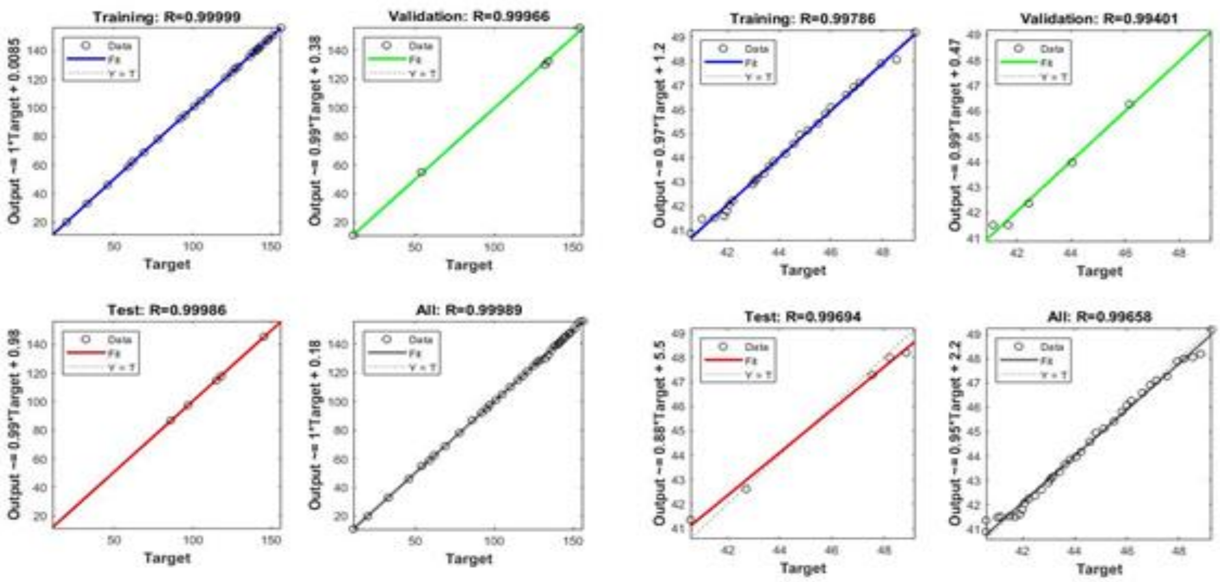
To reduce the MSE, a neural network with one hidden layer and 37 hidden neurons was chosen. Figures 6 – 9 show the performance of the thermal conductivity and electrical resistivity networks after training using the Levenberg-Marquardt algorithm.



(a) Thermal Conductivity (b) Electrical Resistivity

Figure 6 Training state of the network

Figure 7 shows that the average regression value of R is close to one (0.9996 for thermal conductivity and 0.99401 for electrical resistivity), indicating that the projected output using ANN is closely related to the actual data. Individually, training, testing, and validation may all benefit from this.



a) Thermal Conductivity b) Electrical Resistivity

Figure 7 Performance of Network

Figure 7 depicts the network's performance, which is measured in epochs, or the number of times the network needs to repeat itself to reach generality. After two training cycles, the ANN had reached a stable state. Figure 9 depicts the error curves for training, testing, and validation. The graph depicts the decrease in error across the network' sepochs, or iterations, during training, validation, and testing. There was no progress in generalization by the 17th century. The highest performance was attained during the 11th epoch, when the MSE for thermal conductivity was determined to be 2.2261 throughout training and validation. At the eighth epoch, there was no improvement in electrical resistivity generalization. The best performance was attained at the 2nd epoch, with the MSE throughout training and validation being 0.039846.

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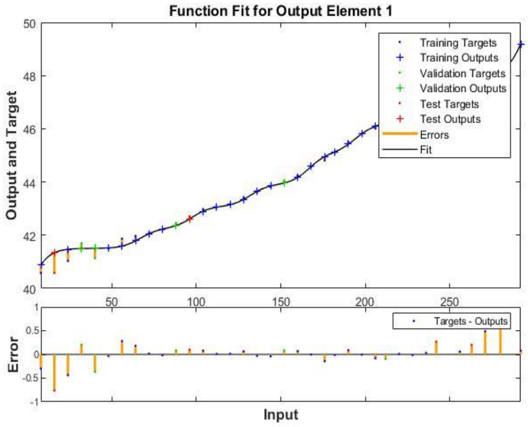
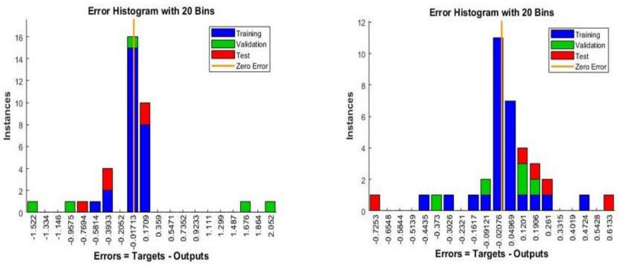


Figure 8 Function fit for given input and output



(a) Thermal Conductivity

(b) Electrical Resistivity

Figure 9 Error Histogram

The function fit of the projected output curve is shown in Figure 8. The quality of fit is definitely above the threshold, and inaccuracy is fairly low.

4.3 Validation of proposed method

The suggested innovative method, the Levenberg-Marquardt algorithm, as well as the hybrid activation functions swish and mish, employed in our model, were verified against the existing model. [32]developed an ANN model using a back-propagation algorithm to predict the hardness of an aluminum alloy, and [34-44] used friction stir processing in conjunction with an ANN model and a response surface methodology model to predict micro hardness and wear properties. According to the comparative results, our new technique provides superior performance and a faster learning prediction model.

Table 3 Existing and proposed ANN method in physical and mechanical properties of Al6061 for database [32].

AUTHOR	[32]		
	Experimental value	**Existing**	**Proposed**
Actual	137	0.672955	92.85
	92	0.389937	97.85
	146	0.729559	91.35
Predicted	137	132.6247	92.85
	92	89.73639	97.85
	146	147.305	91.35
Error	137	0.031936	2.05E-07
	92	0.024604	-8.46E-07
	146	0.008893	2.69E-07

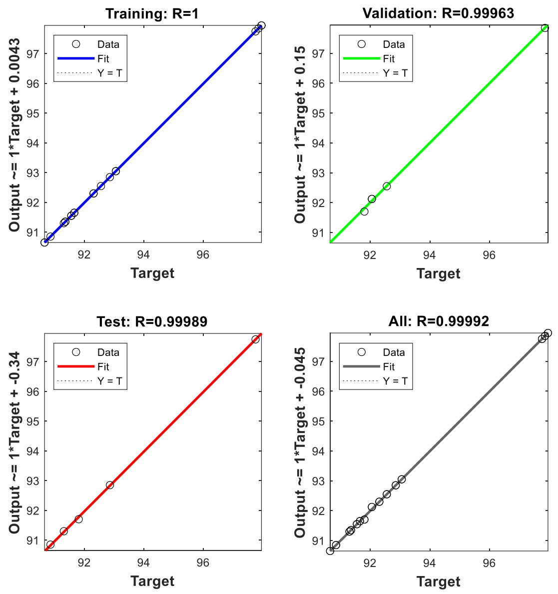


Figure 10 Performance of network - our proposed model for database Suleiman, 2018

Table 4 Existing and proposed ANN method in physical and mechanical properties of Al6061 for database [33].

AUTHOR	[33]				
	Experimental value	**Existing**		**Proposed**	
		Hardness	**Weight loss**	**Hardness**	**Weight loss**
Predicted	153 155 158 162 155 161 167 172 158	153.95	4.186	153	4.195908
		154.57	4.087	156.0994	4.159234
		158.01	3.999	157.8739	3.958624
		161.97	3.818	162.2036	3.864282
		156.89	4.106	157.1228	4.105722
		161.15	3.850	166.3108	3.86535
		166.89	3.788	167.147	3.804271
		172.09	3.719	172.6261	3.729104
		157.98	3.952	155.3617	3.954909

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Error	153	0.62	0.805	-2.47E-06	0.024092
	155	0.27	0.171	-1.09942	-0.07923
	158	0.006	0.025	0.126149	0.041376
	162	0.01	0.052	-0.20356	-0.04428
	155	1.21	0.097	-2.12278	0.004278
	161	0.09	0.025	-5.31083	-0.01535
	167	0.06	0.052	-0.14695	-0.01427
	172	0.05	0.026	-0.62614	-0.00491
	158	0.01	0.05	2.638319	-0.00491

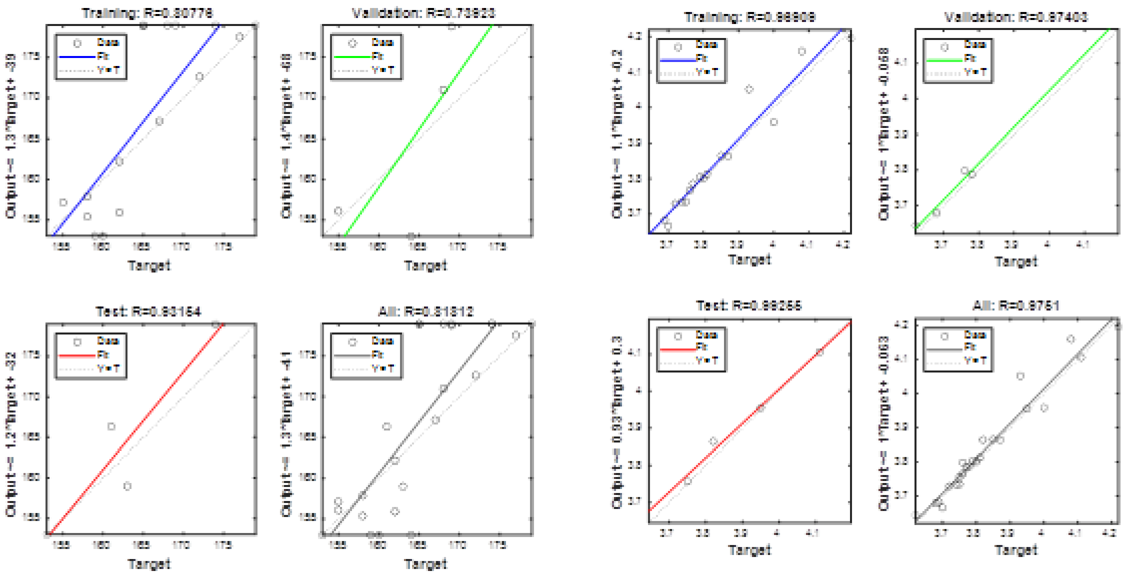

Figure 11 Performance of network (Hardness and Weight loss) - our proposed model for database (Khojastehnezhad 2021)

Because it contains strong training data of experimental and anticipated results, our suggested trained model predicts with less error. Furthermore, it will forecast future unknown values with greater accuracy, with an R value close to 1. For testing data with regard to prediction of thermal conductivity and electrical resistivity, the constructed ANN model using the Levenberg-Marquardt algorithm and hybrid activation function swish and mish has a low MSE and a high regression value near to 0.996835. The proposed hybrid activation function algorithm has been evaluated and tested with existing dataset and the accuracy level is increased and the error value decreased. The evaluation result has shown in Table 3 - Table 4 table 3 and 4. The network performance is shown in Figure 10 - Figure 11.

Table 5 Existing and proposed ANN method in physical and mechanical properties of Al6061.

AUTHOR	Material	Results
[34]	Al6061-T6	166Wm-1k-1.
[35]	Al 6061 - EDM (Electric Discharge Machining)	0 and 4%
[36]	Polycrystal diamond and Al6061	85.19%
[13]	Al6061	9.54%
[37]	Al6061	0.000809 and 0.710
[11]	Al6061-T6	1.78975 µm
[38]	Al6061-T6	316 mm min21
[39]	Al6061	3% to 4%
[12]	Al6061	R2 1=0.9872 and R2 2=0.9878
[14]	Al6061	0.8394%
[40]	Al6061	25.13 m/min
[41]	Al6061-T6	97.4, 96.6 and 98.5%
[36]	Al6061	90.62%
[42]	Al6061	7.74% and 4.58%
[43]	Al6061-10	1.51
[15]	Al6061	98.35%
[44]	Al6061-MWCNT	0.987
Our Proposed Method	**Al6061 – Electrical Resistivity & Thermal Conductivity**	**Regression value is 0.996835 Curve fitting RMSE and R^2 is 0.9894817 and 0.820105**

It displays the experimental and anticipated findings, as well as the expected error percent from the optimum ANN model of previous research and our new technique. Table 5 shows how the comparison and validation demonstrate the effective modifications and accuracy in the suggested experimental data and ANN technique model.

V. CONCLUSIONS

The metal Al6061 physical characteristics were effectively conducted using a multivolt drop method experiment at various temperature ranges.

The voltage, temperature, applied power, conductivity, and resistivity factors are all taken into account. The following are the results of the experimental study and the ANN prediction:

1. For thermal conductivity and electrical resistivity, the Root Mean Squared Error of linear and cubical polynomial functions is 0.965154, 0.999993, and 0.9933889, 0.999391, respectively. 3.022370, 0.029564, and 0.084667, 0.029576 are the R-Square values, respectively. The results show that the experimental data curve fitting is of good quality; thus, as the temperature rises, so do the electrical resistance and thermal conductivity.

2. The Levenberg-Marquardt approach, in conjunction with a hybrid activation function, was utilized to optimize the built ANN model, which effectively computed electrical resistivity and thermal conductivity with a minimal percentage error and accuracy of 0.99966 and 0.99401, respectively.

Data Availability: Data available on only reasonable request

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