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# Regression Modelling and Neural Computing for Predicting the ultimate Tensile Strength of Friction Stir Welded Aerospace Aluminium Alloy

Akshansh Mishra[1], Jonathan Ve Vance[2], Shubham Maurya[3], Abhijeet Singh[4], Adarsh Tiwari[5]
[1]*Founder and Project Scientific Officer, Stir Research Technologies, Uttar Pradesh, India*
[2]*Department of Engineering Design, IIT Madras, India*
[3]*Department of Mechanical Engineering, BBD, Lucknow, Uttar Pradesh, India*
[4]*Department of Mechanical Engineering, UPES, Dehradun, India*
[5]*Department of Mechanical Engineering, Sagar Institute of Technology and Management, Barabanki, India*

***Abstract:*** ***AA7075 is an aluminum alloy that's almost as strong as steel, yet it weighs just one third as much. Unfortunately its use has been limited, due to the fact that pieces of it couldn't be securely welded together by the traditional welding process. Friction Stir Welding (FSW) process overcomes the limitations of conventional welding process. The aim of our present is to compare the predicted results of the Ultimate Tensile Strength (UTS) of Friction Stir welded similar joints through Regression modeling and Artificial Neural Network (ANN) modeling. It was observed that the linear regression algorithm is able to make more accurate predictions compared to neural network algorithm for small dataset.***
***Keywords: Artificial Neural Network; Regression Model; Friction Stir Welding; Artificial Intelligence***

## I. INTRODUCTION

The manufacturing industries have faced many challenges in cutting cost and maintaining efficiency in while developing welding based product. Welding is a very expensive manufacturing process and some of the challenges that are faced while carrying out this process are the factors that amount to porosity, undercut, deformation, cracks, incomplete penetration and fusion. To handle this problem an effective manufacturing process has been developed, called as Friction Stir Welding. The main advantage of FSW over other conventional welding process is that it doesn't melt the base metal which will further not lead to the defects formation arised due to entrapment of the gas in the weld zone. FSW is a solid state joining method which plasticize the base metal to be joined by the heat generation due to friction generated by the contact surfaces of the tool and the base metal. If we talk techanically, FSW is governed by the parameters like the tool rotational speed, traverse speed, tool tilt angle and various geometrical aspects of the tool used during the process. The major advantage that this technique has over the other conventional techniques is the ability to join the alloys which are difficult to join by conventional welding process like TIG and MIG welding. High temperature alloys like Titanium can be easily welded by FSW process. Also, lesser welding time and inducing lower heat energy meaning better efficiency are other edges that FSW has over its competitions. Now the rising issues in the manufacturing industry is that a welding process needs to be expeditious and accurate to improve performance and strength of the welding structure. Hence an optimization study and test of FSW process needs to be carried out in order to improve the industry standards. However, this optimization approach requires to measure extremely sensitive welding factors which is difficult to carry out with human intervention. So one of the most best method is to use machine deep learning approach. The deep learning techniques which can be used in FSW research domain are Artificial Neural Networks (ANNs) and Machine Vision system for determining the quality of the joints. Artificial Neural Network is primarily designed to replicate information processing of the human brain or the neural system of a human body. Neural network consists of basic elements called neurons which process the input signal from a defined system and push it to a transfer function which is differentiable so as to generate an output which works in a similar way as the brain neurons. The main question that arises now, is that why to use this system? A very logical and practical explanation would be due to the problems arising in the data management systems built by our predecessors which is incapable of handling the technological advancement and growth in the industry. The neural network can easily overcome challenges like the input data size and the incoherency of the unstructured data that is available in abundance. The neural network works on the principle of training functions that update bias values and weights, so as to reduce probability of errors. When talking about the Architecture of the neural network, it is a multi-layer network consisting of input parameter feed, output layer, and at least one training function to processes input to yield output as shown in the Figure 1.

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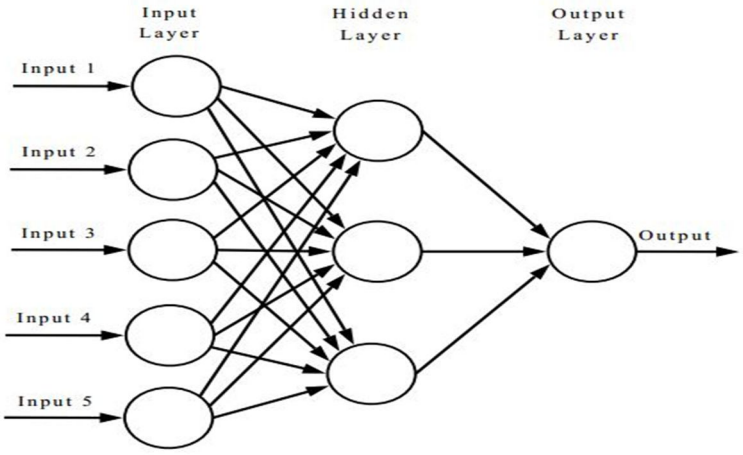


Figure 1: Schematic representation of Neural Network Architecture

Observe the Figure 2 in order to understand the mechanism of the working of Artificial Neural Network.

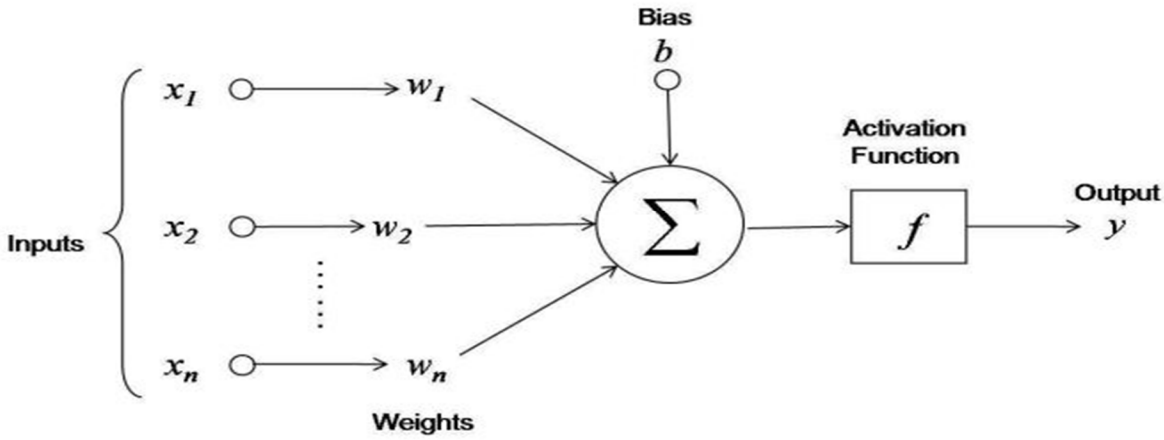


Figure 2: Block diagram of Neural Network Architecture

The datasets extracted from global sources are provided in the form of input layer, which then propagates through hidden layers where it undergoes the training function of the output. Training holds the foremost importance in the accuracy of the prediction of response. The accuracy of the network is measured by the Mean sum of Squared Error (MSE) between the measured and predicted values. The newly adjusted weight and bias value is again sent backwards for further training. Thus this continuous iterative process of training the dataset goes on through the feedback system and will stop once an acceptable error is reached.

Friction Stir Welding (FSW) process utilizes the Artificial Neural Network Technique to reduce the number of experiments and thus it also reduced the cost of the experiment. Akshansh *et al* [1] looked into the use of ANNs in the investigation of tool parameters (as well as mechanical properties of the material), for the evaluation of feedback forces which is provided by Friction Stir Welding process. It was concluded that ANNs can be used to effectively reduce cost and time, by considering the accuracy of the predictions, and that a good correlation can be observed between the predicted data obtained from the ANN and the FEM models. Chiteka *et al* [2] aimed at determining the most crucial parameters that the UTS of the material depends upon (i.e., rotational speed and welding speed), and use them to predict the UTS. It talked about the complex non-linear correlation between UTS and the input parameters, which made ANNs the obvious choice of model. It was concluded that prediction of UTS using the input parameters was accurate within acceptable errors. But the reverse, ie, prediction of input parameters from UTS was not feasible, as different combinations of input parameters produce the same UTS, and also the range of input parameters the machine can produce is also restricted. Ghetiya *et al* [3] hypothesised the use of a standard 4-8-1 ANN to predict UTS from input parameters like tool shoulder diameter, tool rotational speed, welding speed and axial force. All input and output data was normalised to within a range of 0.1 to 0.9, before

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training. The results of prediction were very close to experiment results. The overall R value for training, validation and testing was found to be bigger than 0.99 and the error was less than 3%. Gupta *et al* [4] predicted the values of tensile strength, average microhardness at weld nugget zone (WNZ) and average grain size at WNZ by ANN modeling and regression modeling. It was observed that the overall average percentage prediction error of ANN model was small as compared to regression model.

In our study we have trained our prediction model on Backward Propagation (BP) algorithm and we have used ReLu as an activation function for obtaining the output. In the Neural Network architecture the inputs can be tool rotational speed, traverse speed, tool tilt angle and geometrical parameters like tool pin diameter and too shoulder diameter. The output in the ANN architecture can be Ultimate Tensile Strength, hardness and grain size of the Friction Stir Welded joints.

## II. EXPERIMENTAL PROCEDURE

The setup for Friction Stir Welding process requires the alloys to be joined, tool which is harder than the base alloys and the fixture which is used to hold the alloy workpiece in contact throughout the joining process. AA 7075 Aluminium alloys of the dimension 250mm X 100mm X 5mm is used in this study as a base alloy. The chemical composition of AA 7075 is shown in the Table 1. H13 is used as a tool material for joining the workpiece alloys. The direction of the welding was normal to the rolling direction. The tensile testing was carried out on Universal Testing Machine (UTM). Result of the tensile testing is tabulated in the Table 2.

Table 1: Chemical composition of AA 7075 alloy

| Component | Weight % |
|---|---|
| Al | 87.1-91.4 |
| Cr | 0.18-0.28 |
| Cu | 1.2-2 |
| Fe | Max 0.5 |
| Mg | 2.1-2.9 |
| Mn | Max 0.3 |
| Si | Max 0.4 |
| Ti | Max 0.2 |
| Zn | 5.1-6.1 |

Table 2: Experimental dataset

| Factors | Uncoded welding parameters | | | | Coded welding parameters | | | | UTS |
|---|---|---|---|---|---|---|---|---|---|
| Symbol<br>Sample nos. | Rotation speed *R* (rpm) | Welding speed *W* (mm/min) | Shoulder diameter *D* (mm) | Pin diameter *P* (mm) | Rotation speed A | Welding speed B | Shoulder diameter C | Pin diameter D | $\sigma_{uts}$ (MPa) |
| 1 | 425 | 50 | 13.5 | 4.5 | −1 | −1 | −1 | −1 | 465 |
| 2 | 575 | 50 | 13.5 | 4.5 | 1 | −1 | −1 | −1 | 444 |
| 3 | 425 | 80 | 13.5 | 4.5 | −1 | 1 | −1 | −1 | 460 |
| 4 | 575 | 80 | 13.5 | 4.5 | 1 | 1 | −1 | −1 | 423 |
| 5 | 425 | 50 | 16.5 | 4.5 | −1 | −1 | 1 | −1 | 450 |
| 6 | 575 | 50 | 16.5 | 4.5 | 1 | −1 | 1 | −1 | 436 |
| 7 | 425 | 80 | 16.5 | 4.5 | −1 | 1 | 1 | −1 | 462 |
| 8 | 575 | 80 | 16.5 | 4.5 | 1 | 1 | 1 | −1 | 448 |
| 9 | 425 | 50 | 13.5 | 5.5 | −1 | −1 | −1 | 1 | 448 |
| 10 | 575 | 50 | 13.5 | 5.5 | 1 | −1 | −1 | 1 | 433 |
| 11 | 425 | 80 | 13.5 | 5.5 | −1 | 1 | −1 | 1 | 480 |
| 12 | 575 | 80 | 13.5 | 5.5 | 1 | 1 | −1 | 1 | 459.3 |
| 13 | 425 | 50 | 16.5 | 5.5 | −1 | −1 | 1 | 1 | 428 |
| 14 | 575 | 50 | 16.5 | 5.5 | 1 | −1 | 1 | 1 | 422 |
| 15 | 425 | 80 | 16.5 | 5.5 | −1 | 1 | 1 | 1 | 466 |
| 16 | 575 | 80 | 16.5 | 5.5 | 1 | 1 | 1 | 1 | 476 |
| 17 | 350 | 65 | 15 | 5 | −2 | 0 | 0 | 0 | 440.6 |
| 18 | 650 | 65 | 15 | 5 | 2 | 0 | 0 | 0 | 415 |
| 19 | 500 | 35 | 15 | 5 | 0 | −2 | 0 | 0 | 458 |
| 20 | 500 | 95 | 15 | 5 | 0 | 2 | 0 | 0 | 487 |
| 21 | 500 | 65 | 12 | 5 | 0 | 0 | −2 | 0 | 448 |
| 22 | 500 | 65 | 18 | 5 | 0 | 0 | 2 | 0 | 427 |
| 23 | 500 | 65 | 15 | 4 | 0 | 0 | 0 | −2 | 458 |
| 24 | 500 | 65 | 15 | 6 | 0 | 0 | 0 | 2 | 472 |
| 25 | 500 | 65 | 15 | 5 | 0 | 0 | 0 | 0 | 466 |
| 26 | 500 | 65 | 15 | 5 | 0 | 0 | 0 | 0 | 461.5 |
| 27 | 500 | 65 | 15 | 5 | 0 | 0 | 0 | 0 | 455 |
| 28 | 500 | 65 | 15 | 5 | 0 | 0 | 0 | 0 | 459.5 |
| 29 | 500 | 65 | 15 | 5 | 0 | 0 | 0 | 0 | 453 |
| 30 | 500 | 65 | 15 | 5 | 0 | 0 | 0 | 0 | 452 |
| 31 | 500 | 65 | 15 | 5 | 0 | 0 | 0 | 0 | 458 |
| 32 | 500 | 65 | 15 | 5 | 0 | 0 | 0 | 0 | 464 |
| 33 | 500 | 65 | 15 | 5 | 0 | 0 | 0 | 0 | 465 |
| 34 | 500 | 65 | 15 | 5 | 0 | 0 | 0 | 0 | 463 |
| 35 | 500 | 65 | 15 | 5 | 0 | 0 | 0 | 0 | 457 |
| 36 | 500 | 65 | 15 | 5 | 0 | 0 | 0 | 0 | 456 |

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The most significant inputs critical to the prediction of UTS are the rotational speed of the tool (RS) and the welding speed (WS). For best training of any machine learning algorithm, all the inputs must be scaled to the same range. We have used the "MinMaxScaler" module in the Scikit-learn library, to scale both the input fields to within the range -1 to 1.

```
from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()
df['RS'] = scaler.fit_transform(df['RS'].values.reshape(-1,1))
df['WS'] = scaler.fit_transform(df['WS'].values.reshape(-1,1))
```

Next, we have used the Leave-One-Out Cross Validation (LOOCV) method to determine the mean absolute percentage error (MAPE) of the models.

```
from sklearn.model_selection import LeaveOneOut
loo = LeaveOneOut()
for train_index, test_index in loo.split(x):
    x_train, x_test = x.iloc[train_index], x.iloc[test_index]
    y_train, y_test = y.iloc[train_index], y.iloc[test_index]
    ....
```

This splits the input and target data frames into training and testing sets, by holding out a single input and output sample as the testing set, and the remaining as the training set; and it does this sequentially such that every sample becomes the test set exactly once. Thus, if n is the number of samples, then exactly n number of models are designed. The absolute errors, in percentage, on the last (test) sample in each model are averaged out to obtain the mean absolute percentage error (MAPE), which can be used to evaluate and compare different models. The two machine learning algorithms we are testing are the 2-4-8-1 neural network model as shown in the Figure 1 and the linear regression model.

The architecture I have used is a 2-4-8-1 model, with the first layer being the input layer and the last, the output layer. I have designed it using the Sequential () model from the Keras library.

```
from keras.models import Sequential
from keras.layers.core import Dense, Activation
from keras.callbacks import ModelCheckpoint, EarlyStopping
model = Sequential()
model.add(Dense(4,input_dim=x_train.shape[1],activation='relu'))
model.add(Dense(8,activation='relu'))
model.add(Dense(1))
model.compile(loss='mean_squared_error',optimizer='adam')
monitor = EarlyStopping(monitor='val_loss',min_delta=1e-3,
                        patience=5, verbose=1, mode='auto')
checkpointer = ModelCheckpoint(filepath="best_weights.hdf5",
                               verbose=0,save_best_only=True)
model.fit(x_train,y_train,validation_data=(x_test,y_test),
          callbacks=[monitor,checkpointer],verbose=0,epochs=1000)
model.load_weights('best_weights.hdf5')
y_pred = model.predict(x_test)
```

The activation functions in each layer is the rectified linear unit (ReLu), and the loss function, the mean squared error (MSE). The optimization algorithm is the Adam optimization algorithm, which is an extension of the standard gradient descent algorithm.

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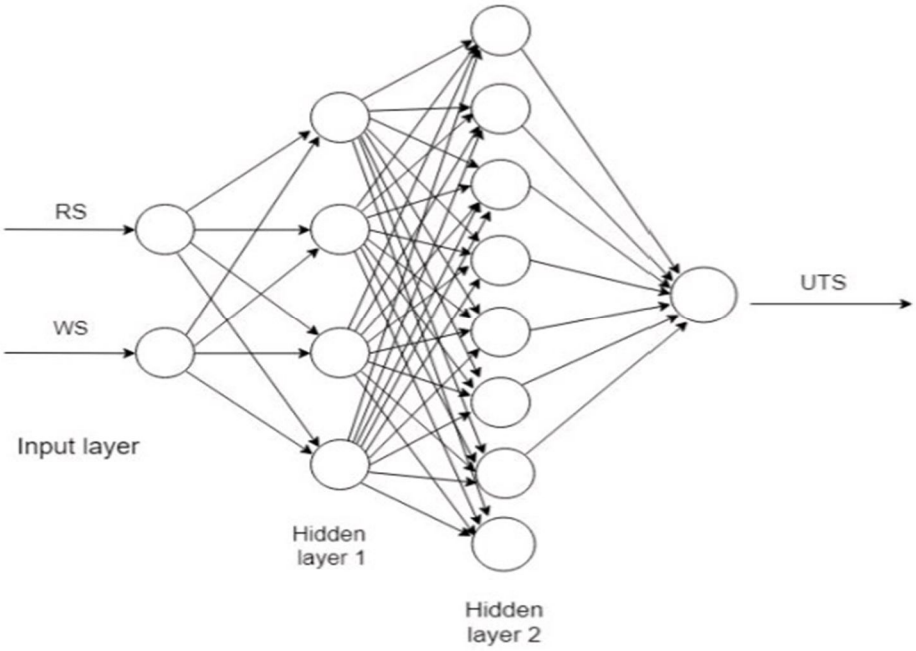


Figure 3: Neural Network architecture used in this study

The hypothesis function for linear regression is:

$y = a_0 + a_1x_1 + a_2x_2$

We have used the Linear Regression model from scikit-learn library. It uses the Ordinary Least Squares solver from scipy, to converge to the global minimum.

```
from sklearn import linear_model
regr = linear_model.LinearRegression()
regr.fit(x_train, y_train)
y_pred = regr.predict(x_test)
```

Based on the data, linear regression model seems to be able to make more accurate predictions. To test this, we have trained the neural network as well as the linear regression models on the entire dataset. Further, we have chosen 3 new samples which have not been used for training either model, and compared the predictions from both models with the experimental values.

## III. RESULTS AND DISCUSSIONS

Predicted values and experimental values for linear regression and neural network algorithms on new samples are shown in the Table 3.

Table 3: Predicted values Vs Experimental values for linear regression and neural network algorithms on new samples

| Prediction from linear regression | Prediction from neural network | Experimental (actual) value | Error (neural network) | Error (linear regression) |
|---|---|---|---|---|
| 452.46 | 441.98 | 472 | 6.36% | 4.22% |
| 436.19 | 445.41 | 444 | 0.32% | 1.75% |
| 453.98 | 432.59 | 461.5 | 6.26% | 1.62% |

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The histogram of the experimental is shown in the Figure 2.

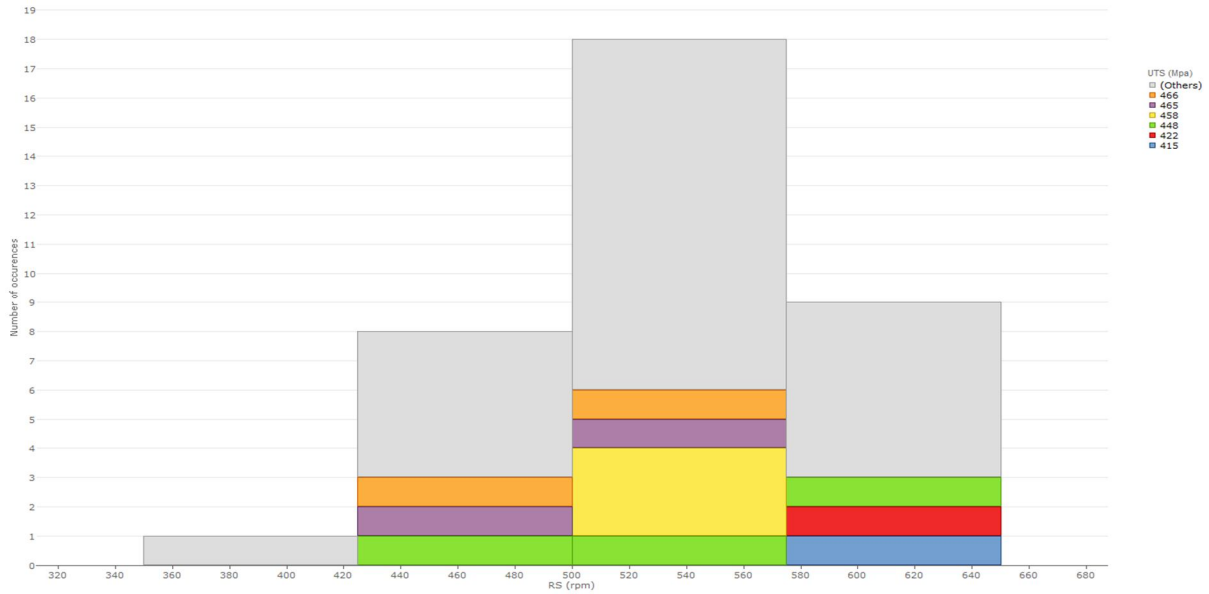


Figure 4: Histogram of experimental dataset

Histogram of the given experimental dataset is used to see the shape of the data's distribution, especially when determining whether the output of a process is distributed approximately normally. It is observed that it is the edge peak distribution which similarly looks like the normal distribution except that it has a large peak at one tail. Usually this is caused by faulty construction of the histogram, with data lumped together into a group labeled "greater than."

The time series and frequency chart of the experimental dataset is shown in the Figure 3 and Figure 4.

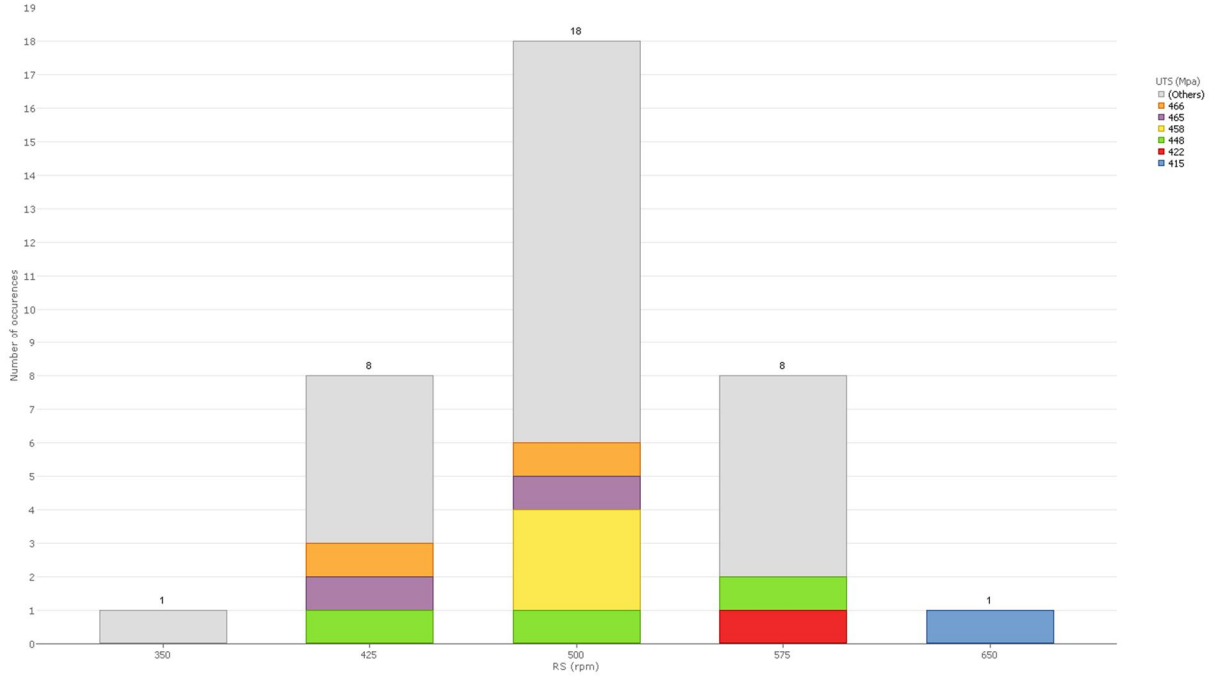


Figure 5: Time series depiction of experimental dataset

In the Figure 3 Time Series graph illustrates data points at successive intervals of time. Each point on the chart corresponds to both a time and a quantity that is being measured. In the figure UTS is measured against Rotational Speed (rpm).

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In the Figure 4 frequency table is used to display the number of occurrences of a particular value or characteristic i.e. Ultimate Tensile Strength (UTS).

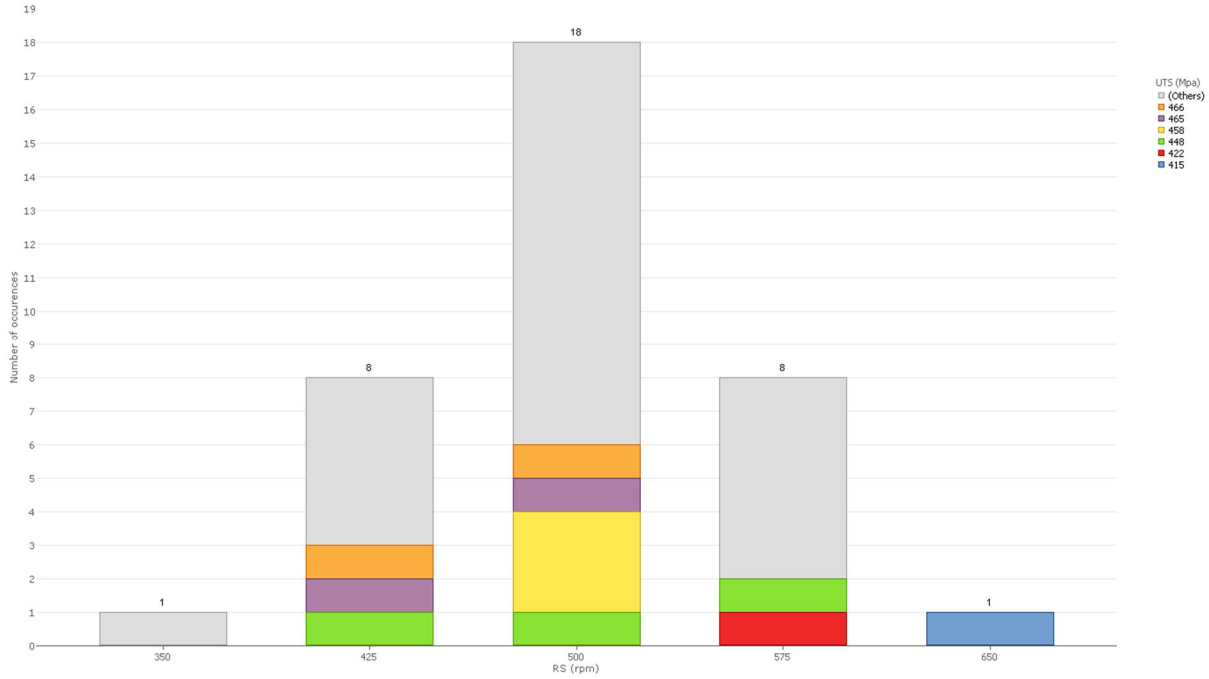


Figure 6: Frequency chart of experimental dataset

3 dimensional surface plots represent three-dimensional data, here there are three variables. One variable is dependent on the other two while the other two variables are independents. The surface map and contour map of the experimental dataset are show in the Figure 5 and Figure 6.

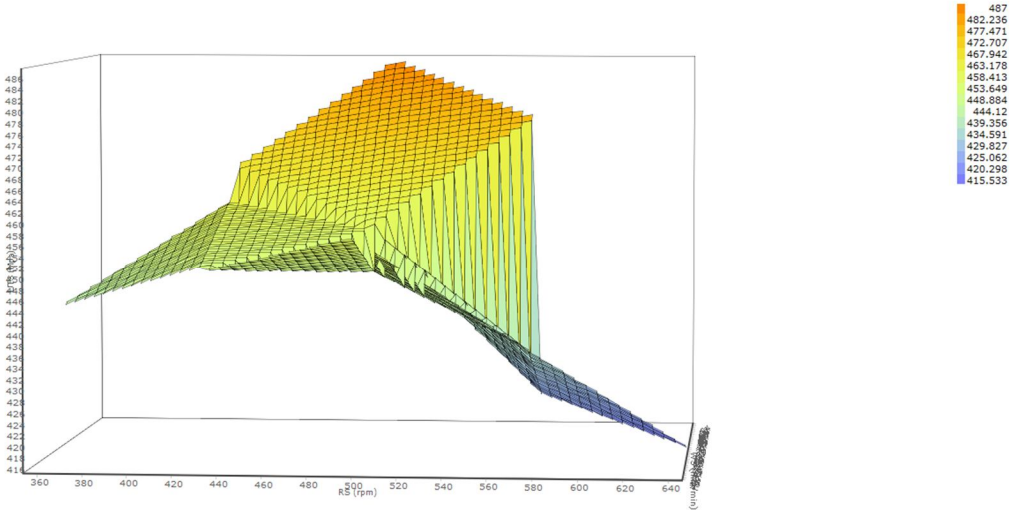


Figure 7: Surface map of the experimental dataset

From Figure 5 it is observed that the Ultimate Tensile Strength (UTS) is a dependent variable and Rotational Speed and Welding Speed are independent variables.

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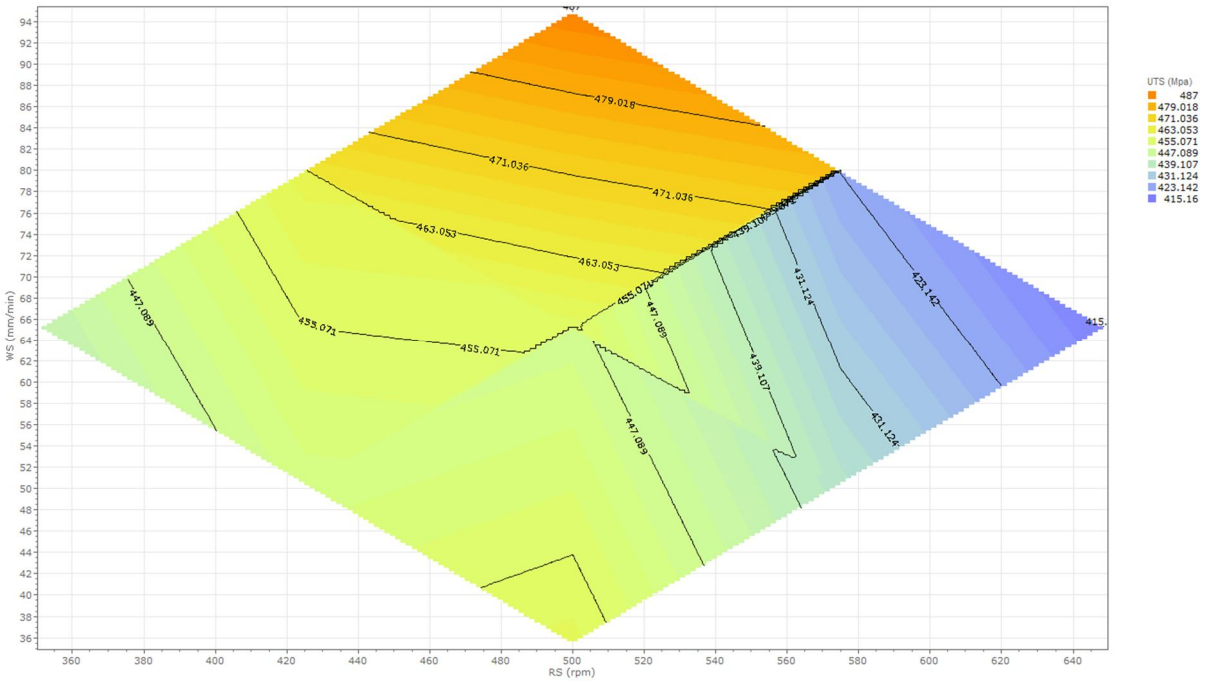


Figure 8: Contour map of the experimental dataset

Figure 6 represents the contour variation of Ultimate Tensile Strength (UTS) with the rotational speed and welding speed.
The Mean Absolute Percentage Error (MAPE) from the Leave-One-Out Cross Validation (LOOCV) method for the Artificial Neural Network model is calculated to be 7.04%. From the Leave-One-Out Cross Validation method, a mean absolute percentage error (MAPE) of only 2.55% was obtained for the Regression model.
Average error % obtained for the neural network model is 4.31% while Average error % for linear regression model is 2.52 %.

## IV. CONCLUSION

The mean absolute percentage error (MAPE) calculated on the Leave-One-Out Cross Validation (LOOCV) method gave the following values for 2-4-8-1 neural network model and a regression analysis method:
For regression analysis, MAPE is equal to 2.55% and for 2-4-8-1 neural network model and MAPE is equal to 7.04%. On running the algorithms on the new samples, we have obtained: Average error % (neural network) is equal to 4.31 % and Average error % (linear regression) is equal to 2.52 %. From the mean absolute percentage error (MAPE) values as well as the tabulated data, it is clear that linear regression algorithm is able to make more accurate predictions compared to neural network algorithm.
It can be concluded that for small dataset, predicted value obtained by the Regression analysis is more accurate than the predicted value obtained by the Artificial Neural Network. The accuracy of the predicted value obtained by the Artificial Neural Network can be improved by training the Neural Network on more dataset. Future work is required to analyse the effect of various activation functions for obtaining the output.

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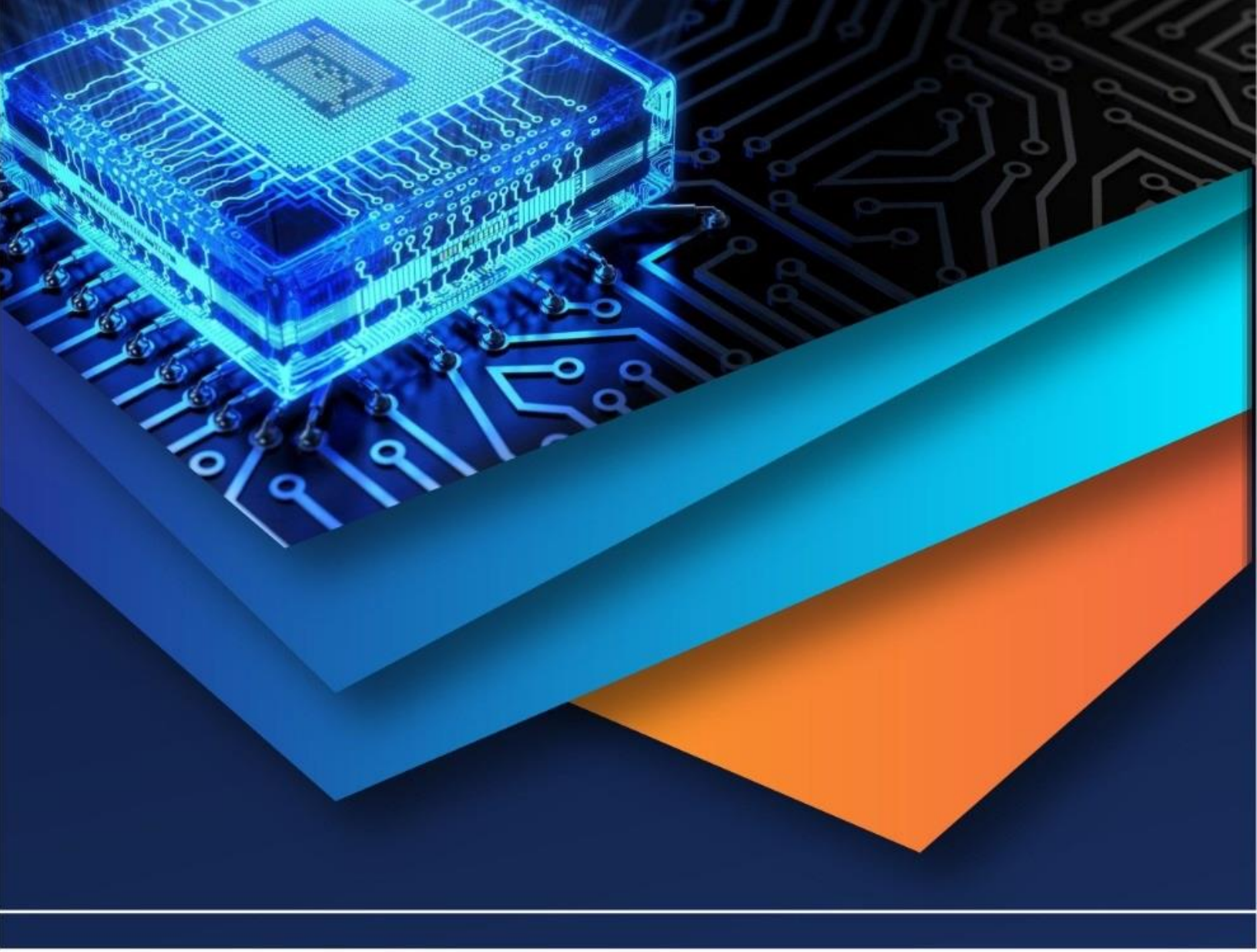

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