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Modelling Neural Networks for prefiguration of the tensile strength of Friction Stir Welded Pure Copper joints

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ABSTRACT: Artificial Neural Network (ANN) possesses a remarkable ability to extract connotation from different set of data structures. It is inspired from the mimicking of the working of biological nervous system. ANN learning abilities are more like us because they learn by examples. In this research paper prefiguration of the tensile strength of Friction Stir Welded pure copper alloys is performed. The Quasi- Newton algorithm method is used for training the neural networks. The results showed that the traverse speed is most important variable which contributes 101.3% to the output i.e. tensile strength. The accuracy of 95.71% is obtained between the actual tensile strength and predicted tensile strength.
Keywords: Artificial Neural Network; Friction Stir Welding; Tensile Strength; Quasi – Newton Algorithm

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I. INTRODUCTION

ANN is a new type of structuralized model which stores information of the objects by means of the topological structures. This distributed holographic information storage instructs ANN the properties of error tolerance, error prevention, association and parallel operation. By the models of ANN which is a self- learning and non- linear mapping abilities are also obtained [1]. ANNs can be also described as the biologically inspired simulations that are performed on computer to do a certain specific set of tasks like clustering, classification, pattern recognition etc.

ANN consists of three layers i.e. Input layer, Output layer and the Hidden layer. The input layer consists of the artificial neurons which receives input from the outside world. This is the only stage where the actual learning on the network takes place. The hidden layers are incorporated between the input layers and output layers. The only job of hidden layer is to transform the input into something meaningful that the output layer unit can use in some way. The output layer consists of those artificial neurons which respond to the information that is fed into the system. It should be noted that the each of the hidden layers is individually connected to the neurons in its input layer and also to its output layer.

E. Malekiet al [2] used ANN technique to model the Friction Stir Welding effects on the mechanical properties of 7075-T6Aluminum alloy. He used thirty AA7075-T6 Aluminum alloy specimens to train the neural network. The neural networks developed were based on back propagation (BP) algorithm. He considered tool rotational speed, welding speed, axial force, shoulder diameter, pin diameter and tool hardness as inputs of the ANNs while yiels strength, tensile strength, notch tensile strength and hardness of the welding zone were considered as outputs of the neural networks. He concluded that if the networks are adjusted carefully then ANN can be used for modelling of Friction Stir Welding effective parameters.

Brahma Rajuet al [3] predicted the tensile strength of Friction Stir Welded joints of AA6061-T6 alloy by using ANN. He used three types of neural network architectures i.e. Back Propagation Neural Network (BPNN), Radial Basis Function Network (RBFN) and Generalized Regression Neural Network (GRNN). The results obtained indicated that the there was a good agreement between the experimental values and predicted values.

Dehabadiet al [4] investigated the ANN for predicting the Vickers microhardness of Friction Stir Welded AA6061 alloys. Mean absolute percentage error (MAPE) for train and test data sets did not exceeded 5.4% and 7.48%.

H. Okuyucu et al. [16] developed an artificial neural network (ANN) model for the analysis and simulation of the correlation between the friction stir welding (FSW) parameters of aluminium (Al) plates and mechanical properties.

The input parameters of the model consist of weld speed and tool rotation speed (TRS). The outputs of the ANN model include property parameters namely: tensile strength, yield strength, elongation, hardness of weld metal and hardness of heat effected zone (HAZ). Good performance of the ANN model was achieved. The model can be used to calculate mechanical properties of welded Al plates as functions of weld & tool rotation speeds. The combined influence of weld speed and TRS on the mechanical properties of welded Al plates was simulated. A comparison was made between measured and calculated data. The calculated results were in good agreement with measured data. The aim of the paper was to show the possibility of the use of neural networks for the calculation of the mechanical properties of welded Al plates using FSW method. Results showed that, the networks can be used as an alternative in these systems.

L Fratini and G Buffa [17] studied the continuous dynamic re-crystallisation phenomena occurring in the FSW of Al alloys. A good agreement with the experimental results was obtained using the ANN model. In regard to ANNs, it noted that ANNs perform better than the other techniques, especially RSM when highly non-linear behaviour is the case. Also, this technique can build an efficient model using a small number of experiments; however the technique accuracy would be better when a larger number of experiments are used to develop a model.

In our present work ANN architectures were trained on Quasi Newton algorithm for predicting the tensile strength of Friction Stir Welded pure copper joints.

¶ EXPERIMENTAL PROCEDURE

The base metal used in this research was pure copper with dimensions 150 mm X 100 mm X 6mm. The plates to be joined were mounted on the fixture and Friction Stir Welding process was carried out by using H13 tool steel. The tensile specimens of the given dimensions were prepared as shown in the Figure 1. The tensile testing was carried out on Universal testing machine whose results are tabulated in the Table 1.

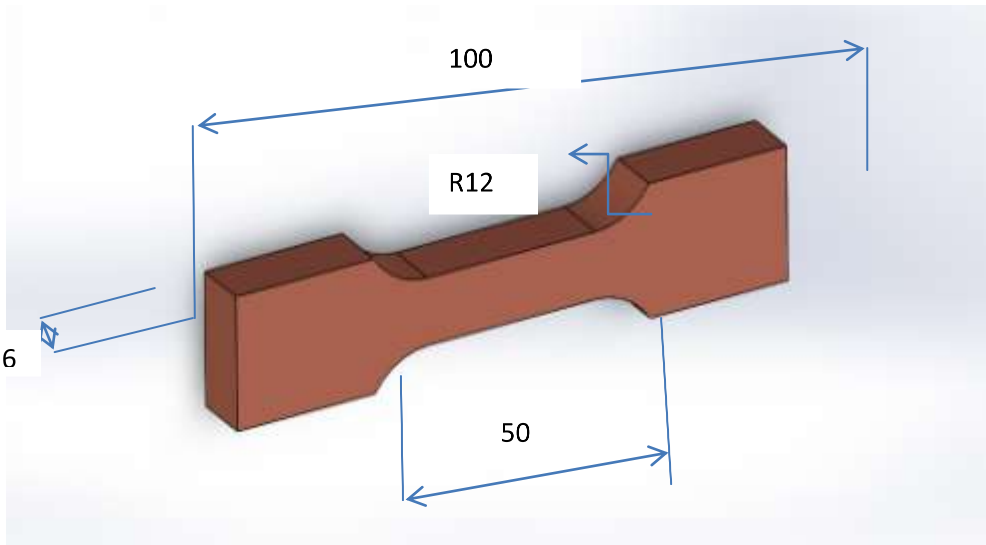


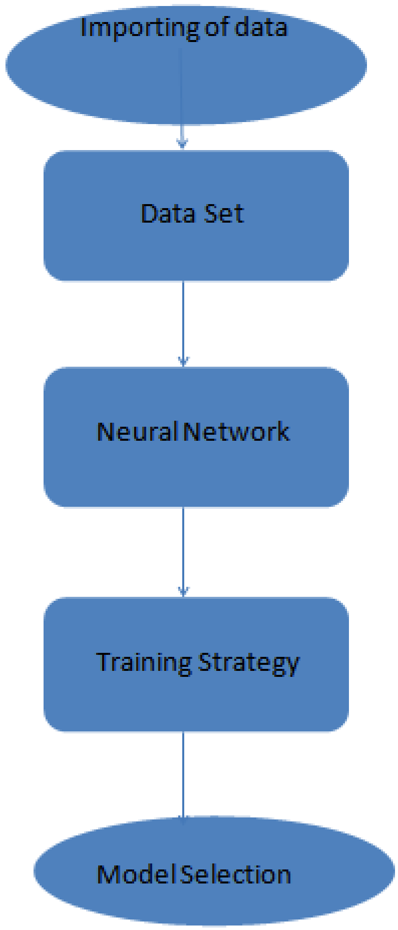
Figure 1: Design of tensile test specimen. All dimensions are in mm.

Rotational Speed in RPM	Traverse Speed (mm/min)	Tensile Strength (MPa)
1000	25	82
1000	55	62
1000	40	65
1000	10	92
2500	10	104
2500	40	77
2500	25	89
2500	55	67
4000	10	110
4000	40	82
4000	55	74
4000	25	103

Table 1: Tensile Strength at given tool rotational speed and tool traverse speed

In the present work we have used Neural Designer software for training and testing the Neural Networks. The first eleven data were trained and the tensile strength at the tool rotational speed of 4000 rpm and traverse speed of 25 mm/min was calculated by using Quasi Newton algorithm.

The various processes which were involved are shown in the form of flow chart.



II. RESULTS AND DISCUSSIONS

3.1 Data Set

The data set contains the information for creating the predictive model. It comprises a data matrix in which columns represent variables and rows represent instances. Variables in a data set can be of three types: The inputs will be the independent variables; the targets will be the dependent variables; the unused variables will neither be used as inputs nor as targets. Additionally, instances can be: Training instances, which are used to construct the model; selection instances, which are used for selecting the optimal order; testing instances, which are used to validate the functioning of the model; unused instances, which are not used at all.

The next table shows a preview of the data matrix contained in the imported file Stir Research.xlsx. Here, the number of variables is 3, and the number of instances is 11.

Rotational Speed in RPM	Traverse Speed (mm/min)	Tensile Strength (MPa)
1000	25	82
1000	55	62
1000	40	65
1000	10	92
2500	10	104
2500	40	77
2500	25	89
2500	55	67
4000	10	110
4000	40	82
4000	55	74

Table 2: Imported data matrix

The following table depicts the names, units, descriptions and uses of all the variables in the data set. The numbers of inputs, targets and unused variables here are 2, 1, and 0, respectively.

Name	Use
Rotational Speed (RPM)	Input
Traverse Speed (mm/min)	Input
Tensile Strength (MPa)	Target

Table 3: Variables Table

The next chart illustrates the variables use. It depicts the numbers of inputs (2), targets (1) and unused variables (0).

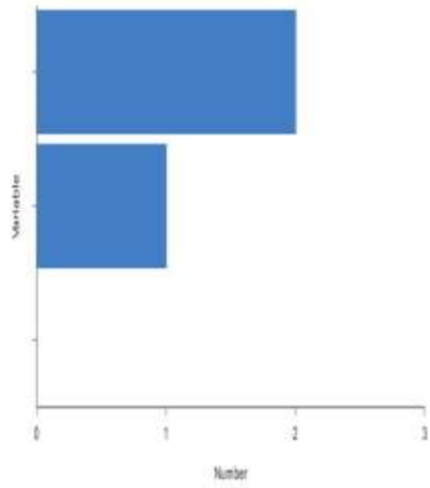


Figure 2: Variables bar charts

The following pie chart details the uses of all the instances in the data set. The total number of instances is 11. The number of training instances is 7 (63.6%), the number of selection instances is 2 (18.2%), the number of testing instances is 2 (18.2%), and the number of unused instances is 0 (0%).

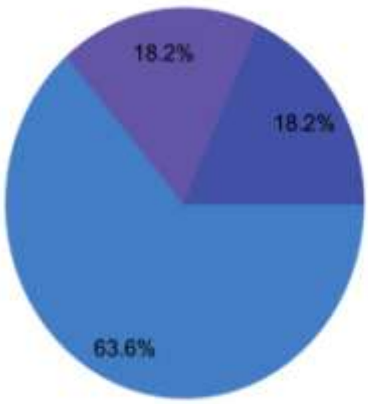


Figure 3: Instances Pie Chart

Basic statistics are very valuable information when designing a model, since they might alert to the presence of spurious data. It is a must to check for the correctness of the most important statistical measures of every single variable.The table 4 below shows the minimums, maximums, means and standard deviations of all the variables in the data set.

	Minimum	**Maximum**	**Mean**	**Deviation**
Rotational Speed	1000	4000	2363.64	1246.81
Traverse Speed	10	55	33.1818	18.2034
Tensile Strength	62	110	82.1818	15.5552

Table 4: Data Statistics Results

Histograms show how the data is distributed over its entire range. In approximation problems, a uniform distribution for all the variables is, in general, desirable. If the data is very irregularly distributed, then the model will probably be of bad quality.The following chart shows the histogram for the variable Rotational speed (rpm). The abscissa represents the centers of the containers, and the ordinate their corresponding frequencies. The minimum frequency is 0%, which corresponds to the bins with centers 1450, 1750, 2050, 2350, 2950, 3250 and 3550. The maximum frequency is 36.3636%, which corresponds to the bins with centers 1150 and 2650.

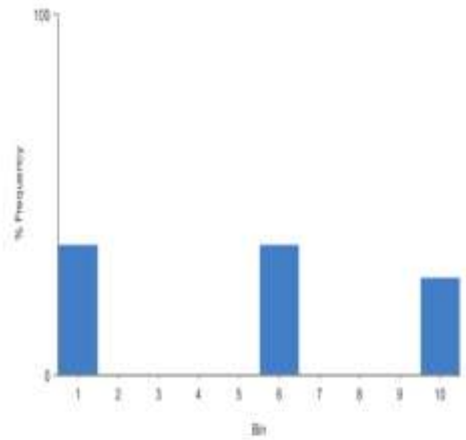


Figure 4: Rotational Speed (RPM) distribution Chart

The following chart shows the histogram for the variable Traverse Speed. The abscissa represents the centers of the containers, and the ordinate their corresponding frequencies. The minimum frequency is 0%, which corresponds to the bins with centers 16.75, 21.25, 30.25, 34.75, 43.75 and 48.25. The maximum frequency is 27.2727%, which corresponds to the bins with centers 12.25, 39.25 and 52.75.

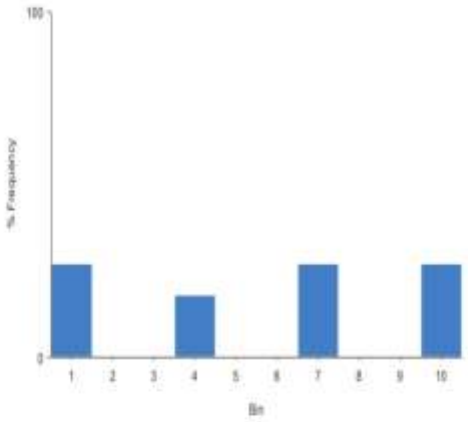


Figure 5: Traverse Speed (mm/min) distribution chart

The following chart shows the histogram for the variable Tensile Strength. The abscissa represents the centers of the containers, and the ordinate their corresponding frequencies. The minimum frequency is 0%, which corresponds to the bin with center 98. The maximum frequency is 18.1818%, which corresponds to the bins with centers 64.4 and 83.6.

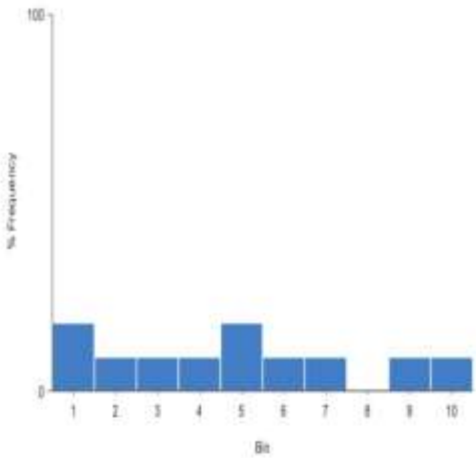


Figure 6: Tensile Strength (MPa) distribution Chart

Box plots display information about the minimum, maximum, first quartile, second quartile or median and third quartile of every variable in the data set. They consist of two parts: a box and two whiskers. The length of the box represents the interquartile range (IQR), which is the distance between the third quartile and the first quartile. The middle half of the data falls inside the interquartile range. The whisker below the box shows the minimum of the variable while the whisker above the box shows the maximum of the variable. Within the box, it will also be drawn a line which represents the median of the variable. Box plots also provide information about the shape of the data. If most of the data are concentrated between the median and the maximum, the distribution is skewed right, if most of the data are concentrated between the median and the minimum, it is said that the distribution is skewed left and if there is the same number of values at the both sides of the median, the distribution is said to be symmetric.The following chart shows the box plot for the variable Rotational speed (rpm). The minimum of the variable is 1000, the first quartile is 1000, the second quartile or median is 2500, the third quartile is 4000 and the maximum is 4000.

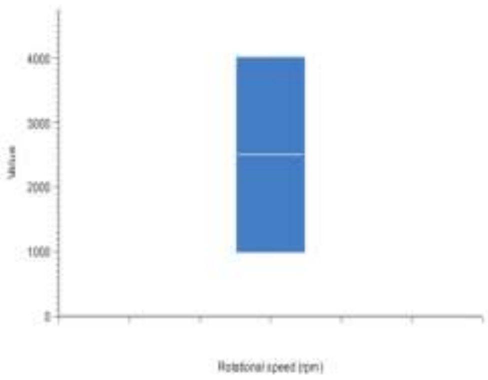


Figure 7: Rotational speed (rpm) box plot

The following chart shows the box plot for the variable Traverse Speed. The minimum of the variable is 10, the first quartile is 10, the second quartile or median is 40, the third quartile is 55 and the maximum is 55.

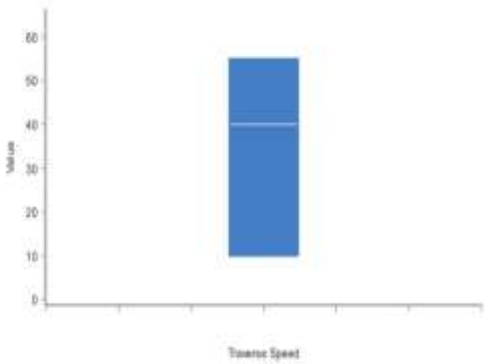


Figure 8: Traverse Speed (mm/min) box plot

The following chart shows the box plot for the variable Tensile Strength. The minimum of the variable is 62, the first quartile is 67, the second quartile or median is 82, the third quartile is 92 and the maximum is 110.

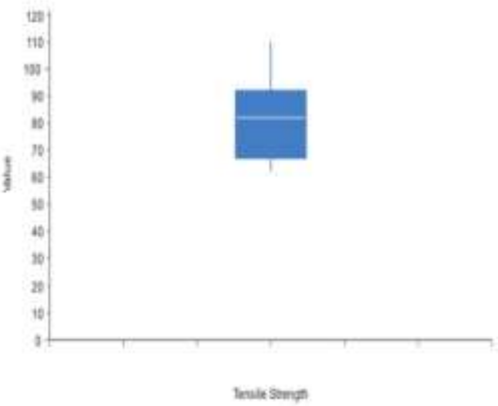


Figure 9: Tensile Strength (MPa) box plot

Target balancing task balances the distribution of targets in a data set for function regression. It unuses a given percentage of the instances whose values belong to the most populated bins. After this process, the distribution of the data will be more uniform and, in consequence, the resulting model will probably be of better quality.

The percentage of unused instances has been 10%, which corresponds to 1 instances. The following chart shows the histogram for the target variable Tensile Strength. The abscissa represents the centers of the containers, and the ordinate their corresponding frequencies. The minimum frequency is 0, which corresponds to the bins with centers 71.8, 85.3 and 98.8. The maximum frequency is 2, which corresponds to the bins with centers 67.3, 76.3 and 80.8.

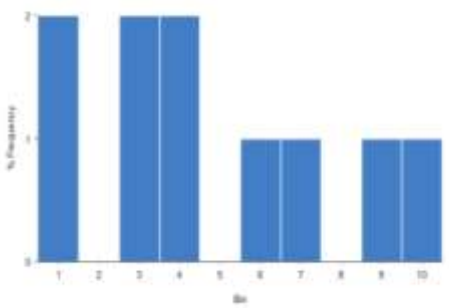


Figure 10: Tensile Strength Histogram

Scatter Plot task plots graphs of all target versus all input variables. That charts might help to see the dependencies of the targets with the inputs.The following chart shows the scatter plot for the input Rotational speed (rpm) and the target Tensile Strength.

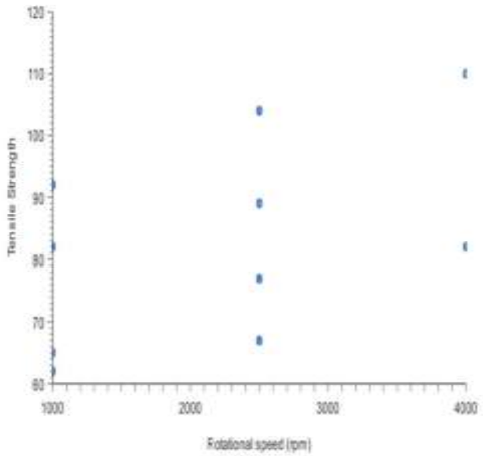


Figure 11: Tensile Strength (MPa) scatter chart vs Rotational speed (rpm)

The following chart shows the scatter plot for the input Traverse Speed and the target Tensile Strength.

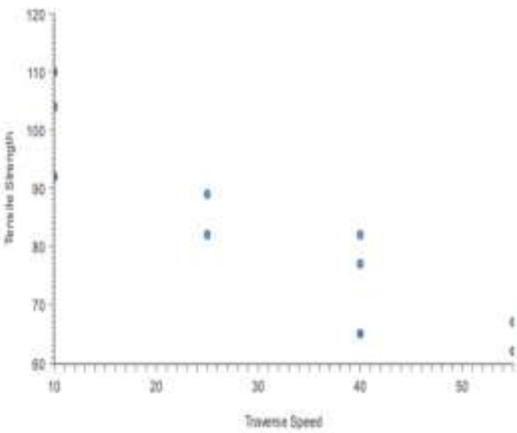


Figure 12: Tensile Strength (MPa) scatter chart vs Traverse Speed (mm/min)

Correlation Matrix task calculates the absolute values of the linear correlations among all inputs. The correlation is a numerical value between 0 and 1 that expresses the strength of the relationship between two variables. When it is close to 1 it indicates a strong relationship, and a value close to 0 indicates that there is no relationship.The following table shows the absolute value of the correlations between all input variables. The minimal correlation is 0.231869 between the variables Rotational speed and Traverse Speed. The maximal correlation is 0.231869 between the variables Rotational speed and Traverse Speed.

	Rotational Speed	Traverse Speed
Rotational Speed	1	0.232
Traverse Speed		1

Table 5: Correlation Matrix

It might be interesting to look for linear dependencies between single input and single target variables. This task calculates the absolute values of the correlation coefficient between all inputs and all targets. Correlations close to 1 mean that a single target is linearly correlated with a single input. Correlations close to 0 mean that there is not a linear relationship between an input and a target variables. Note that, in general, the targets depend on many inputs simultaneously.The following table shows the absolute value of the linear correlations between all input and target variables. The maximum correlation (0.895744) is yield between the input variable Traverse Speed and the target variable Tensile Strength.

	Tensile Strength
Traverse Speed	-0.896
Rotational Speed	0.365

Table 6: Tensile Strength linear correlations

The next chart illustrates the dependency of the target Tensile Strength with all the input variables.

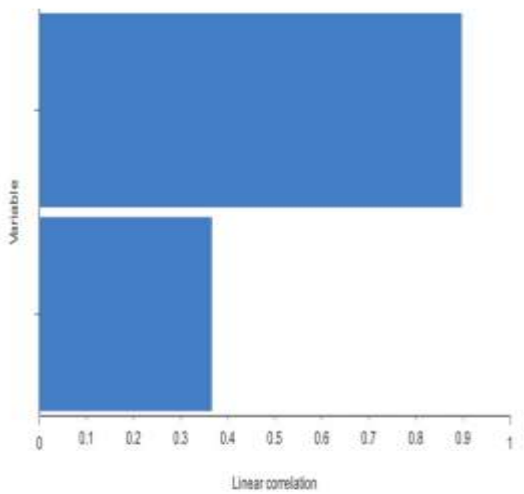


Figure 13: Tensile Strength bars chart

When designing a predictive model, the general practice is to first divide the data into three subsets. The first subset is the training set, which is used for constructing different candidate models. The second subset is the selection set, which is used to select the model exhibiting the best properties. The third subset is the testing set, which it is used for validating the final model. The following table shows the uses of all the instances in the data set. Note that the instances are arranged in rows of 10. The total number of instances is 11. The numbers of training, selection, testing and unused instances are 6, 2, 2 and 1, respectively.

	1	2	3	4	5	6	7	8	9	10
0	Train	Unused	Train	Train	Train	Sel.	Test	Test	Train	Sel.
10	Train									

Table 7: Instances Table

The following pie chart details the uses of all the instances in the data set. There are 6 instances for training (54.5%), 2 instances for selection (18.2%), 2 instances for testing (18.2%) and 1 unused instances (9.09%).

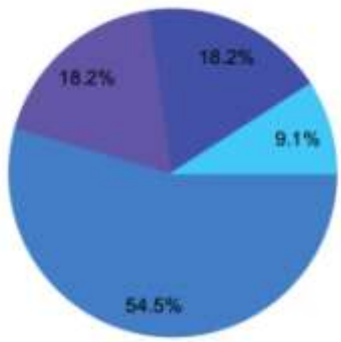


Figure 14: Instances pie chart

Principal components analysis allows to identify underlying patterns in a data set so it can be expressed in terms of other data set of lower dimension without much loss of information. The resulting data set should be able to explain most of the variance of the original data set by making a variable reduction. The final variables will be named principal components. Since this process is not reversible, it will be only applied to the input variables. The next table shows in the first column the relative explained variance for every of the principal components and in the second column the cumulative explained variance. The number of principal components of the resulting data set depends on the minimum value of the cumulative variance that it is desired the final data set had.

	Relative Variance	Cumulative Variance
1	61.7761	61.7761
2	38.2239	100

Table 8: Principal Components Results

The next chart shows the cumulative explained variance for the principal components. The x-axis represents each of the principal components and the y-axis depicts the cumulative explained variance. As it can be seen, the total explained variance for all the principal components is 100% but if the number of chosen principal components decreases also makes it the total explained variance.

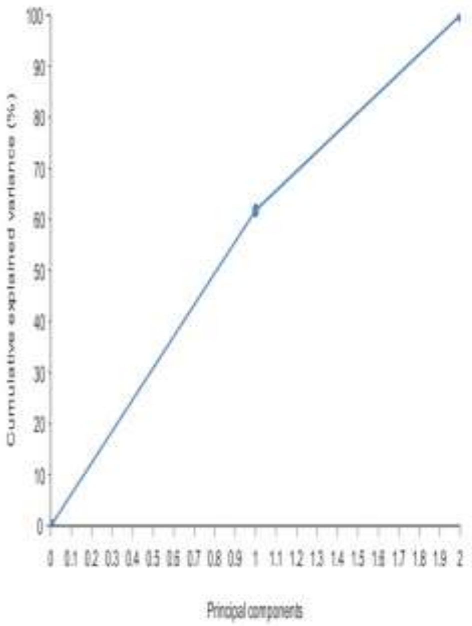


Figure 15: Explained Variance Chart

3.2 Neural Network

The neural network represents the predictive model. In Neural Designer neural networks allow deep architectures, which are a class of universal approximator.The number of inputs is 2. The next table depicts some basic information about them, including the name and the units.

	Name	Units
1	Rotational Speed	RPM
2	Traverse Speed	mm/min

Table 9: Inputs in Neural Network

The size of the scaling layer is 2, the number of inputs. The scaling method for this layer is the Minimum-Maximum. The following table shows the values which are used for scaling the inputs, which include the minimum, maximum, mean and standard deviation.

	Minimum	Maximum	Mean	Deviation
Rotational Speed	1e+003	4e+003	2.36e+003	1.25e+003
Traverse Speed	10	55	33.2	18.2

Table 10: Scaling layer values for inputs

The number of layers in the neural network is 2. The following table depicts the size of each layer and its corresponding activation function. The architecture of this neural network can be written as 2:3:1.

	Inputs Number	Neurons Number	Activation Function
1	2	3	Hyperbolic Tangent
2	3	1	Linear

Table 11: Size of each layer and their activation function

The following table shows the statistics of the parameters of the neural network. The total number of parameters is 13.

	Minimum	Maximum	Mean	Standard Devi.
Statistics	-1.19	1.41	0.103	0.786

Table 12: Statistical Parameters of the neural network

The size of the unscaling layer is 1, the number of outputs. The unscaling method for this layer is the minimum and maximum. The following table shows the values which are used for scaling the inputs, which include the minimum, maximum, mean and standard deviation.

	Minimum	Maximum	Mean	Deviation
Tensile Strength	65	110	84.2	14.8

Table 13: Values for scaling the inputs

A graphical representation of the network architecture is depicted next. It contains a scaling layer, a neural network and an unscaling layer. The yellow circles represent scaling neurons, the green circles the principal components, the blue circles perceptron neurons and the red circles unscaling neurons. The number of inputs is 2, the number of principal components is 2, and the number of outputs is 1. The complexity, represented by the numbers of hidden neurons, is 3.

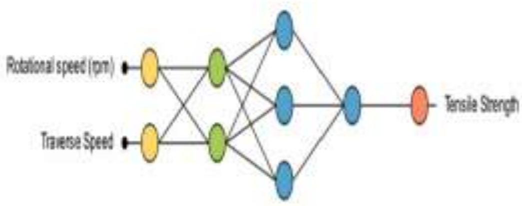


Figure 16: Neural Network architecture for predicting tensile strength

The loss index plays an important role in the use of a neural network. It defines the task the neural network is required to do, and provides a measure of the quality of the representation that it is required to learn. The choice of a suitable loss index depends on the particular application.The normalized squared error is used here as the error method. It divides the squared error between the outputs from the neural network and the targets in the data set by a normalization coefficient. If the normalized squared error has a value of unity then the neural network is predicting the data 'in the mean', while a value of zero means perfect prediction of the data.The neural parameters norm is used as the regularization method. It is applied to control the complexity of the neural network by reducing the value of the parameters. The following table shows the weight of this regularization term in the loss expression.

	Value
Natural Parameters norm weight	0.001

Table 14: Weight of the regularization term

The procedure used to carry out the learning process is called training (or learning) strategy. The training strategy is applied to the neural network in order to obtain the best possible loss.The quasi-Newton method is used here as training algorithm. It is based on Newton's method, but does not require calculation of second derivatives. Instead, the quasi-Newton method computes an approximation of the inverse Hessian at each iteration of the algorithm, by only using gradient information.

	Description	Value
Inverse Hessian approximation method	Method used to obtain a suitable training rate.	BFGS
Training rate method	Method used to calculate the step for the quasi-Newton training direction.	BrentMethod
Training rate tolerance	Maximum interval length for the training rate.	0.001
Minimum parameters increment norm	Norm of the parameters increment vector at which training stops.	1e-009
Minimum loss increase	Minimum loss improvement between two successive iterations.	1e-012
Performance goal	Goal value for the loss.	1e-012
Gradient norm goal	Goal value for the norm of the objective function gradient.	0.001
Maximum selection loss increases	Maximum number of iterations at which the selection loss increases.	100
Maximum iterations number	Maximum number of iterations to perform the training.	1000
Maximum time	Maximum training time.	3600
Reserve parameters norm history	Plot a graph with the parameters norm of each iteration.	false
Reserve loss history	Plot a graph with the loss of each iteration.	true
Reserve selection loss history	Plot a graph with the selection loss of each iteration.	true
Reserve gradient norm history	Plot a graph with the gradient norm of each iteration.	false

The following plot shows the losses in each iteration. The initial value of the training loss is 1.24264, and the final value after 96 iterations is 0.0834866. The initial value of the selection loss is 63.1754, and the final value after 96 iterations is 3224.15.

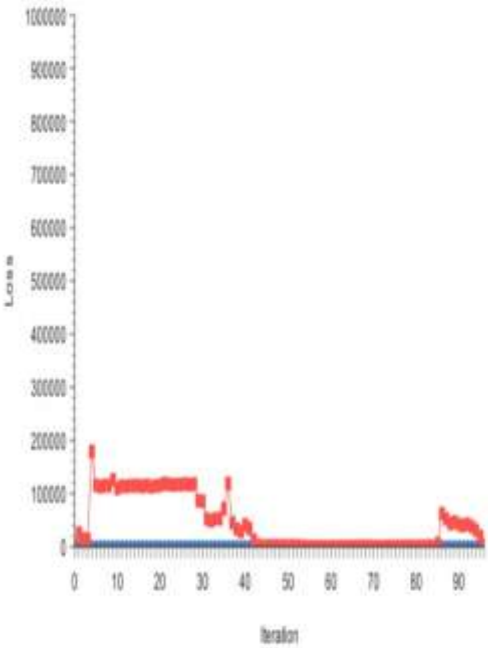


Figure 17: Loss in each iteration

The next table shows the training results by the quasi-Newton method. They include some final states from the neural network, the loss functional and the training algorithm.

	Value
Final parameters norm	80.5
Final loss	0.0835
Final selection loss	3.22e+003
Final gradient norm	0.000873
Iterations number	96
Elapsed time	00:00
Stopping criterion	Gradient norm goal

Table 15: Quasi Newton Method Results

3.3 Model Selection

Model selection is applied to find a neural network with a topology that optimizes the loss on new data. There are two different types of algorithms for model selection: Order selection algorithms and input selection algorithms. Order selection algorithms are used to find the optimal number of hidden neurons in the network. Inputs selection algorithms are responsible for finding the optimal subset of input variables.

The inputs selection algorithm chosen for this application is growing inputs. With this method, the inputs are added progressively based on their correlations with the targets.

	Description	Value
Trials number	Number of trials for each neural network.	1
Tolerance	Tolerance for the selection loss in the trainings of the algorithm.	0.01
Selection loss goal	Goal value for the selection loss.	0
Maximum selection failures	Maximum number of iterations at which the selection loss increases.	1
Maximum inputs number	Maximum number of inputs in the neural network.	2
Minimum correlation	Minimum value for the correlations to be considered.	0
Maximum correlation	Maximum value for the correlations to be considered.	1
Maximum iterations number	Maximum number of iterations to perform the algorithm.	100
Maximum time	Maximum time for the inputs selection algorithm.	3600
Plot training loss history	Plot a graph with the training losses of each iteration.	true
Plot selection loss history	Plot a graph with the selection losses of each iteration.	true

Inputs importance task calculates the selection loss when removing one input at a time. This shows which input have more influence in the outputs.The next table shows the importance of each input. If the importance takes a value greater than 1 for an input, it means that the selection error without that input is greater than with it. In the case that the importance is lower than 1, the selection error is lower without using that input. Finally, if the importance is 1, there is no difference between using the current input and not using it. The most important variable is Traverse Speed, that gets a contribution of 101.3% to the outputs.

	Contribution
Rotational Speed	0.823
Traverse Speed	1.013

Table 16: Importance of each input

The best selection is achieved by using a model whose complexity is the most appropriate to produce an adequate fit of the data. The order selection algorithm is responsible of finding the optimal number of neurons in the network.Incremental order is used here as order selection algorithm in the model selection.The next chart shows the loss history for the different subsets during the incremental order selection process. The blue line represents the training loss and the red line symbolizes the selection loss.

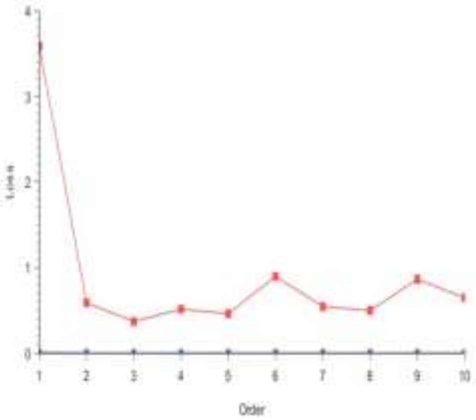


Figure 18: Incremental order loss plot

A standard method to test the loss of a model is to perform a linear regression analysis between the scaled neural network outputs and the corresponding targets for an independent testing subset. This analysis leads to 3 parameters for each output variable. The first two parameters, a and b, correspond to the y-intercept and the slope of the best linear regression relating scaled outputs and targets. The third parameter, R2, is the correlation coefficient between the scaled outputs and the targets. If we had a perfect fit (outputs exactly equal to targets), the slope would be 1, and the y-intercept would be 0. If the correlation coefficient is equal to 1, then there is a perfect correlation between the outputs from the neural network and the targets in the testing subset.The next chart illustrates the linear regression for the scaled output Tensile Strength. The predicted values are plotted versus the actual ones as squares. The coloured line indicates the best linear fit. The grey line would indicate a perfect fit.

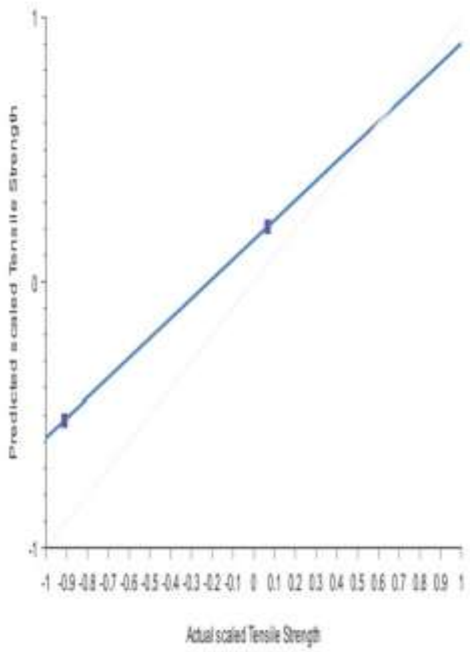


Figure 19: Tensile Strength linear regression chart

Testing error task measures all the losses of the model. it takes in account every used instance and evaluate the model for each use.The next table shows all the errors of the data for each use of them.

	Training	Selection	Testing
Sum squared error	943.666	452.014	88.1451
Mean squared error	157.278	226.007	44.0725
Root mean squared error	12.541	15.0335	6.63871
Normalized squared error	0.622129	36.1611	0.364236
Minkowski error	241.861	107.563	31.9359

Table 17: Errors table

The error data statistics measure the minimums, maximums, means and standard deviations of the errors between the neural network and the testing instances in the data set. They provide a valuable tool for testing the quality of a model.The table below shows the minimums, maximums, means and standard deviations of the absolute, relative and percentage errors of the neural network for the testing data.

	Minimum	Maximum	Mean	Deviation
Absolute error	3.18972	8.83011	6.00991	3.98835
Relative error	0.0708827	0.196225	0.133554	0.0886301
Percentage error	7.08827	19.6225	13.3554	8.86301

Table 18: Tensile strength error data statistics

A neural network produces a set of outputs for each set of inputs applied. The outputs depend, in turn, on the values of the parameters.The next table shows the input values and their corresponding output values. The input variables are Rotational speed and Traverse Speed; and the output variable is Tensile Strength.

	Value
Rotational Speed (rpm)	4000
Traverse Speed (mm/min)	25
Tensile Strength (MPa)	107.97

Table 19: Predicted Tensile Strength at given inputs

The next plot shows the output Tensile Strength as a function of the input Rotational speed (rpm). The x and y axes are defined by the range of the variables Rotational speed (rpm) and Tensile Strength, respectively.

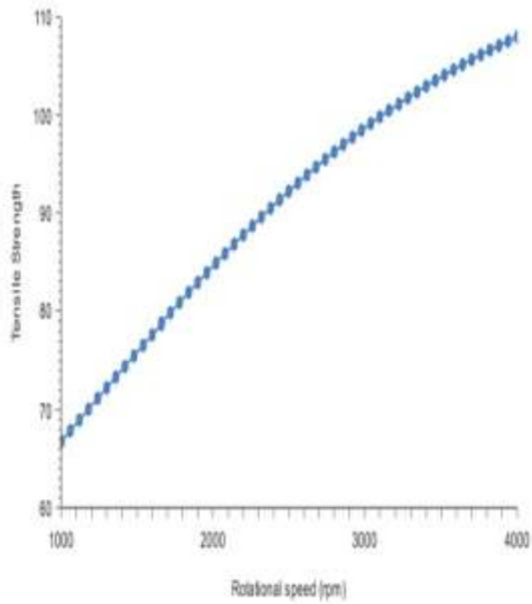


Figure 20: Tensile Strength against Rotational speed (rpm) directional line chart

The next plot shows the output Tensile Strength as a function of the input Traverse Speed. The x and y axes are defined by the range of the variables Traverse Speed and Tensile Strength, respectively.

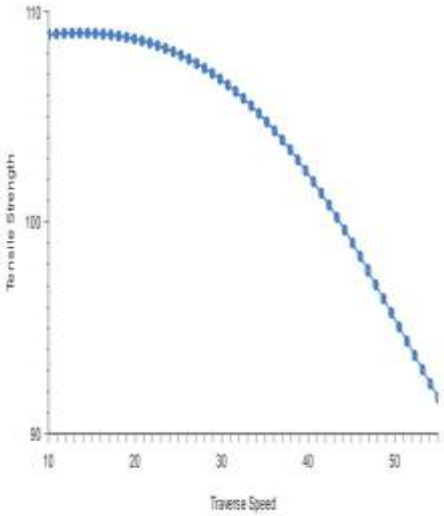


Figure 21: Tensile Strength against Traverse Speed directional line chart

III. CONCLUSION

The actual tensile strength calculated at the rotational speed of 4000 rpm and 25 mm/ min traverse speed is 103 MPa while predicted tensile strength from Neural Network architecture is 107.97 MPa. So the accuracy for predicting the tensile strength using the neural network architecture is 95.17%. It can be also concluded that Neural Network architecture can be used to reduce cost and time of the experiment.

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