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Application of Artificial Neural Network in Minimizing Defects of Rotary Shouldered Connections: A Case Study

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ABSTRACT

The aim of this paper is to minimize defects of rotary shouldered connections in a Manufacturing Company using artificial neural network. To achieve this, simple linear regression was carried out, the data obtained was used to train the neural network. The regression obtained using the simple linear regression and ANN was 0.1764 and 0.42665. Also, from the analysis, the mean square error of the artificial neural network was 0.00860542, when compared to the mean square error (8.6953) from the data of the simple linear regression shows a closer value to the line of best fit. The gradient of the artificial neural network is observed to be 2.1092e^{-13} at epoch 6 during training, 1e^{-9} during testing at epoch 6 and 0 upon validation check at epoch 6. The results when compared, showed that the artificial neural network minimized the defects up to 47.65%. It was recommended that further study should incorporate a larger dataset as it will improve the accuracy of the model.

KEYWORDS: Artificial Neural Network, Simple Linear Regression, Error Histogram, Best Validation Performance, Training State

1. INTRODUCTION

Great concerns have been in the mind of researchers on the continuous defects of manufactured products; therefore, increase the level of work load among manufacturing company, to determine the extent of defects and how it can be reduced to a barest minimum. Lilly *et al.* (2015), stated that the purpose of a manufacturing company is to construct and sell artefact products to satisfy an existing or created demand, thereby:

i. Make profit
ii. Achieve a high return on investment,
iii. Provide employment in the community by supplying commodities needed by society.

These objectives are often only of secondary importance, the main objective being to perpetuate the business. For this, the manufacturer should have service or products which can be sold with sufficient profit to finance the current and future business.

Yonatan *et al.* (2013) asserts that a happy customer is more preferable to a loyal customer, because a happy customer is satisfied while a loyal customer, regardless of the service obtained still returns for more service. The existence of many companies on the market is conditioned with a number of satisfied customers. Customers are key factor of the existence and company development on the market. Customer satisfaction is often associated with the customer gratification. Products or service that are source of satisfaction provide the desirable value to their customers, at least in a sufficient degree. According to Grzegorz and Jolanta (2011), Standard ISO 10004 specifies that satisfaction is a judgment or an opinion expressed by the customer and reflects the gap between the customers vision of the expected products and customer perception of the delivered product.

Hairulliza *et al.* (2014) opined that quality can be defined as fulfilling specification or customers requirement without any defect, as such a product is said to be high quality if it is functioning as expected and reliable. According to Annisa (2019), ISO 8402-1986 defines quality as the totality of features and characteristics of a product or service that bears the ability to satisfy stated or implemented need. Yonatan *et al.* (2013) further opined that improvement in quality of product is pertinent for a company in order to survive and to grow in competitive market.

Laurent and Hermel (2004) in Latif (2016) opined that there is a linkage between quality and profit. It is considered a competition source of the organization leading to customer satisfaction, increasing loyalty, elevating the organization profit on short and long term.

According to Latif (2016), satisfaction is the impression of reward received by the customer after making the sacrifice of purchasing a product. As such, satisfaction is a positive impression from the customer side towards the consumed product, this impression is found by comparing the customer expectation with the actual product performance. Satisfaction was further described as a psychological state following the purchase of a product translated by a temporary feeling resulting from the difference between the customer expectations and the actual realization, being parallel with the previous time with the service.

Defects in production process are results of production of parts or assembly which do not meet customers' demands, standard requirement and specification (Murco & Sanin, 2018). These defects may occur due to single cause or a combination of causes. Correct identification of the root causes of the defect is difficult because of the involvement of various factors which may include technical factors like process design, and process flow (Suraj *et al.* 2015)

Sileshi and Ajit (2016) carried out an analysis on the reduction of defect rate of final products through statistical process control tools using an ammunition cartridge at a cartridge production factory, which include pareto analysis, cause and effect diagrams, attributes p-control charts, and capability analysis/percentage (87.53%). The Pareto analysis revealed that there was high number of defect rate per month for ET-tools (968), height out of standard (107), overweight (62), dispersion failure (39), speed failure (0), and underweight (15). The P-control analysis showed that most of the defects per month reduced as ET-tools (405), overweight (50), dispersion failure (10), and underweight (5). Appropriate recommendations were made in line with the root cause of the defects.

Suraj *et al.* (2015) applied the six-sigma method to reduce defects and improve quality on green sand-casting process. The DMAIC (Define-Measure-Analyze-Improve-Control) methodology was utilized along with the taguchi method to minimize the defects. Tools such as project charter, process map, and cause-and-effect diagrams were utilized. The correlation of defects, with the mould hardness, green strength, and pouring rate were determined using Design of Experiments (DOE) and Analysis of Variance (ANOVA). The experimental results showed that casting defects of the molding process declined by 5.6 %.

Lim and Ria (2015) adopted the seven tools method to reduce the rate of defective products in a food field company. It was observed that the company's production processes were outside the tolerance limits. It was recommended that a quality control technique that could monitor the effect of the two main factors (i.e man and machine) be employed.

Arturo *et al*. (2018) applied the Plan-Do-Check-Act (PDCA) cycle to reduce defects in a manufacturing industry. It was observed that due to increase in demand on the product, several defects were detected in the welding process of electronic boards. The Lean Manufacturing process was adopted: Pareto Charts and flow charts were used for analysis. A reduction in defects of the electronic boards was observed. The percentage of defects for the model 595310-001-00 decreased by 65%. Similarly, the defects for the model 595407-XXX-00 were reduced by 79%, whereas the defects of the model 595481-00X-00 decreased by 77%

Atigre *et al.* (2017) applied the 8D methodology for minimizing the defects in manufacturing process. It involved the deployment of an 8 disciplinary approach, (8 steps), that were followed by the quality improvement team for solving problems related to defects as well as process improvement, after which the effectiveness was analyzed. The steps involved in the 8Ds included; from the cross-functional team (D1); describe the problem (D2); contain the problem (D3); identify the root causes (D4); address the corrective actions (D5); implementation of corrective actions (D6); prevent the reoccurrence of the problem (D7); congratulate the team (D8). The result showed that total rejection for coupling disc part was minimized from 37.95% to 6.57%. The case study was a 150 9001:2000 certified.

Abigo *et al*. (2019) applied Artificial Neural Network in the optimization of soap production with Patrich Global Enterprise as case study. The Neural network training was done using a data set of linear programming problems. An objective function of two variables and three constraint equations was adopted. This trained Neural Network was used to optimize soap production profit for two different kinds of soap, bathing and laundry soaps. The Neural Network structure consisted of eleven inputs and four outputs with a neural structure of two hidden layers and fifty neurons. The training algorithm used was feed-forward back propagation with a Bayesian Regularization error. The Neural Network results when compared with traditional simplex method of optimization, proved to be 98% accurate. The maximum projected profit was up to 91% increase from #30,625 to #58,500 in a month.

According to Nimbale and Ghute (2016) control chart techniques have been utilized in industries to track a process in quality improvement. In many manufacturing industries Shewhart X chart and Tukey’s charts are used to monitor single observation data. The uses of Artificial Neural Network (ANN) model have recently been recommended as Statistical Quality control (SQC) tool. Neural network scheme was developed for monitoring process mean. The performance of X chart, Tukey’s chart and ANN model was evaluated by Average Run Length (ARL) using the simulation under normal and non-normal distributions. The ARL comparison between traditional X chart, Tukey’s chart and ANN model showed that ANN is effective.

2 MATERIALS AND METHODS

The data for this work was obtained from the quality control records of a Manufacturing Company. The Company is a local content company founded in 2002. It is basically an oil servicing company that renders services ranging from machining, fabrication, installation, commissioning, decommissioning to logistics. Mechanical Systems Limited is a Manufacturing company that is certified with API SPEC SCI, 6A and 7-1, and ISO 9001. The data obtained consisted of units produced and their corresponding defective units of rotary shouldered connections. The defective units were determined using Non-destructive test and liquid penetrant test. Simple linear regression and Artificial Neural Network was used to analyze the data obtained from the case study, upon which comparison of the results obtained was carried out. Furthermore, Ishikawa diagram was used to determine the various causes of the defects.

2.1 Analytical Model

According to Wahua (2010), the Simple Linear Regression model is as expressed in Equation (1)

$$\hat{Y} = \alpha + \beta X \tag{1}$$

where

α= Equation parameters for linear regression

β= Equation parameters for linear regression

From Equation (1), to determine α Equation (2) is utilized

$$\alpha = M_Y \beta M_x \tag{2}$$

where β is determined as

$$\beta = \frac{X - M_X}{Y - M_Y} \tag{3}$$

$$Mx = \frac{\sum X}{n} \tag{4}$$

$$M_Y = \frac{\sum Y}{n} \tag{5}$$

where

M_x = Mean of X values

M_Y = Mean of Y values

X = Unit produced

Y = Defective units

n = Number of parameters

Furthermore, the mean squared error can be calculated as

$$MSE = \frac{(\boldsymbol{Y} - \hat{Y})^{\mathbf{2}}}{n} \tag{6}$$

where

MSE = Mean squared error

$(Y - \hat{Y})^2$ = Square of deviate.

$$M_\beta = \frac{\sum \beta_s}{n} \tag{7}$$

where

M_β = Mean value of the regression coefficients

$\sum \beta_s$ = Sum of the regression coefficients.

2.2 Datasets for Artificial Neural Network

For training and testing purposes for our model, the data is broken down into three distinct datasets. These datasets consist of the following:

i. Training set
ii. Validation set
iii. Test set

Training set
Training set is the set of data used to train the model. During each epoch, the model was trained over and over again on this same data in the training set, and it will continue to learn about the features of this data. The model makes predictions based on what it's learned about the training data, it consists of 70% of the dataset. During the training process, the model will be classifying the output for each input in the training set. After this classification occurs, the loss will then be calculated, and the weights in the model will be adjusted. Also, during the next iteration, it will classify the same input again.

Test set
The test set is a set of data that is used to test the model after the model has already been trained. The test set is separate from both the training set and validation set. After the model has been trained and validated using the training and validation sets, the model is then used to predict the output of the unlabeled data in the test set. The test set provides a final check that the model is generalizing well before deploying the model to production. The test set consist of 15% of the data.

Validation set

The validation set is a set of data, separate from the training set, that is used to validate the model during training. This validation process helps give information that may assist with adjusting the parameters during fine tuning. The model was trained on the data in the training set with each epoch during training and was simultaneously validated on the data in the validation set. During training, the model classifies each input from the validation set as well. It was doing this classification based only on what the artificial network has learned about the data it's being trained on in the training set. The data in the validation set is separate from the data in the training set. So, when the model is validating on this data, this data does not consist of samples that the model already is familiar with from training. The validation set consists of 15% of our data set.

2.3 Dataset for Training, Testing, and Validation

A data set was used in training the neural network to be able to adjust and predict solutions in the format of a linear regression problem. Table 1 shows the dataset used for the training, testing, and validation.

Tables 1: Dataset for Training, Testing, and Validation

X_1	Y_1	X_2	Y_2	X_3	Y_3	X_4	Y_4	X_5	Y_5
10	6	25	8	25	4	13	6	17	7
16	10	33	13	27	6	17	10	19	5
13	5	31	5	32	12	25	4	33	5
11	7	43	13	22	7	20	11	26	8
19	5	27	4	31	6	26	4	37	11
20	8	33	8	20	4	22	10	23	4
26	11	41	13	45	19	19	5	31	13
23	7	25	10	38	8	26	10	25	7
24	8	29	5	41	13	24	7	42	8
20	11	48	6	30	11	33	5	0	0
35	16	37	12	14	6	41	11	0	0
31	9	25	5	29	12	37	9	0	0

where

X_1 = Units produced for 2016
Y_1 = Defective units for 2016
X_2 = Units produced for 2017
Y_2 = Defective units for 2017
X_3 = Units produced for 2018
Y_3 = Defective units for 2018
X_4 = Units produced for 2019
Y_4 = Defective units for 2019
X_5 = Units produced for 2020
Y_5 = Defective units for 2020

2.4 Architecture of the Artificial Neural Network

The Multilayer perceptron of the Artificial Neural Network used in this work is seen in Figure 1. It shows the feedforward network consisting of layers of neurons, with an input layer, an output layer, and a hidden layer all interlinked.

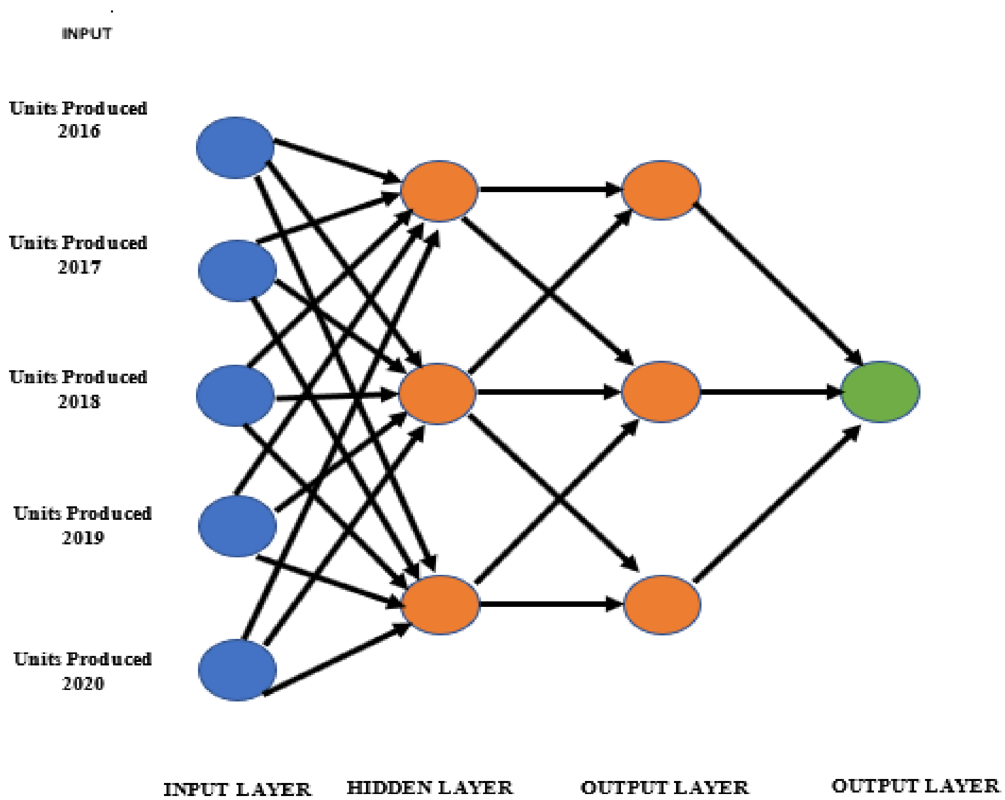

Figure 1: Architecture of the Neural Network

2.5 Training of Artificial Neural Network

During the course of setting up the neural network for training, the data was arranged into input and output variables. The number of neurons used was twelve (12), it enabled the weight (w) and the bias (b) of each neuron to be adjusted to suit the best size of the network. Figure 2 shows the structure of the artificial neural network with the input and output variable

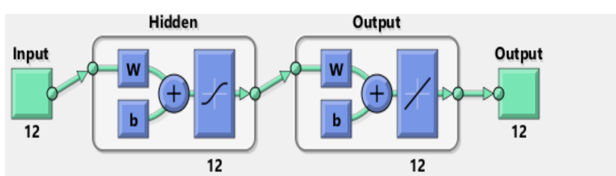

Figure 2: Structure of the Artificial Neural Network with the Input and Output Variable

3. RESULTS AND DISCUSSION

3.1 Simple Linear Regression Analysis of Defective Rotary Shouldered Connections

The result obtained from the simple linear analysis carried out on the defects on Rotary Shouldered Connections during machining from quality control records (as shown in Table 1) of the Manufacturing Company are given below

From Equation (3), the values of β have been obtained

$$\beta = \frac{795.2278}{4507.5092}$$

$= 0.1764$

From Equation (2), α was calculated and is presented in Equation (8)

$$\alpha = 8.2982 - (0.1764 \times 27.2807)$$

$= 3.4859$

From Equation (1), the linear regression model becomes

$$\hat{Y} = 3.4859 + 0.1764X \quad (8)$$

From Equation (7), the mean squared error is calculated as

$$\frac{495.63366}{57}$$

$= 8.6953$

From the simple linear regression analysis carried out, the results showed a regression coefficient of 0.1764, a regression constant of 3.4859, and a mean squared error 8.6953.

3.2 Analysis Artificial Neural Network Results

From Figure 2, the artificial neural network best validation performance is observed to be 49.0927 at epoch 3.

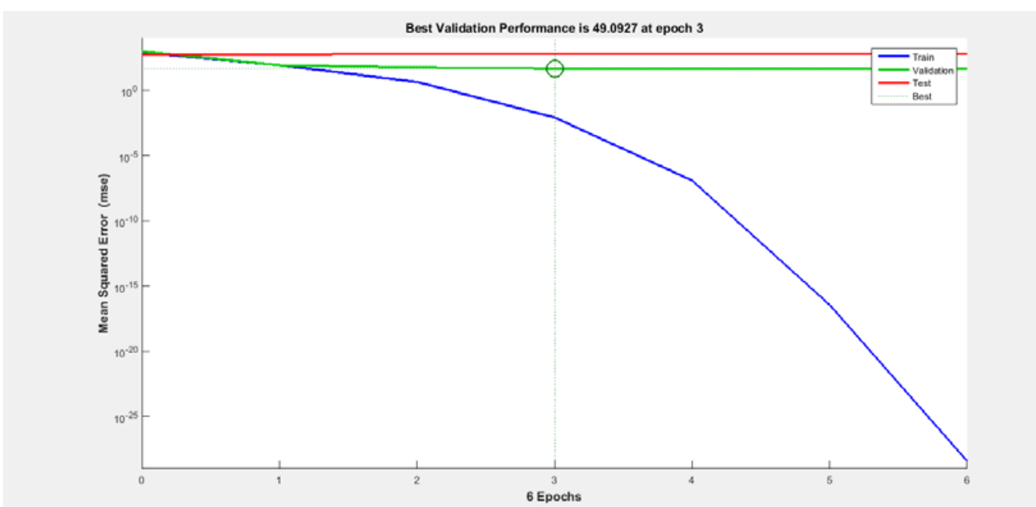

Figure 2: Neural Network Best Validation Performance (Combined Dataset)

The regression models readily allow inference on the significance of explanatory variables and expected predictive capability. From Figure 4.22, the regression of the artificial neural network during is 0.99995, -0.29869 during testing and -0.69351 during validation. The average regression of the combined dataset is observed to be -0.42665 which is a moderate regression coefficient value (Patrick *et al.* 2018). The adaptation of regression in Artificial Neural Network helps to increase the prediction therefore making the system linear (Kuang, *et al.* 2021; Aasi & Mishra, 2021 and Mas & Ahlfeld, 2007).

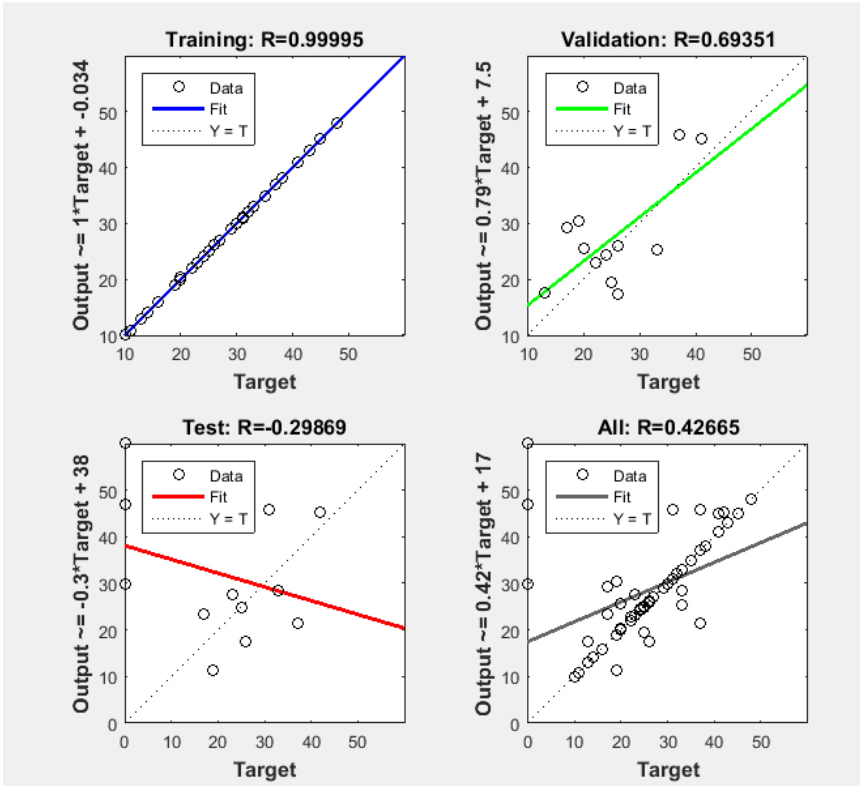

Figure 3: Neural Network Regression

From the histogram error in Figure 4, the total error range is divided into 20 smaller bins. At the mid of the plot, we have a bin corresponding to the error of -1.457e^{-16} and the height of that bin for training dataset lies between 45 and 45. It was also observed that the errors were high during the training process but then reduced significantly during testing. The result show that the more the bins the better the prediction which is line with the study of Heinrich (2021), if too few bins are chosen, the rank histogram is likely to miss miscalibrations; if too many are chosen, even perfectly calibrated forecast systems can yield rank histograms that do not appear uniform, thereby improving on the performance of the model (Rahman, *et al.* 2021).

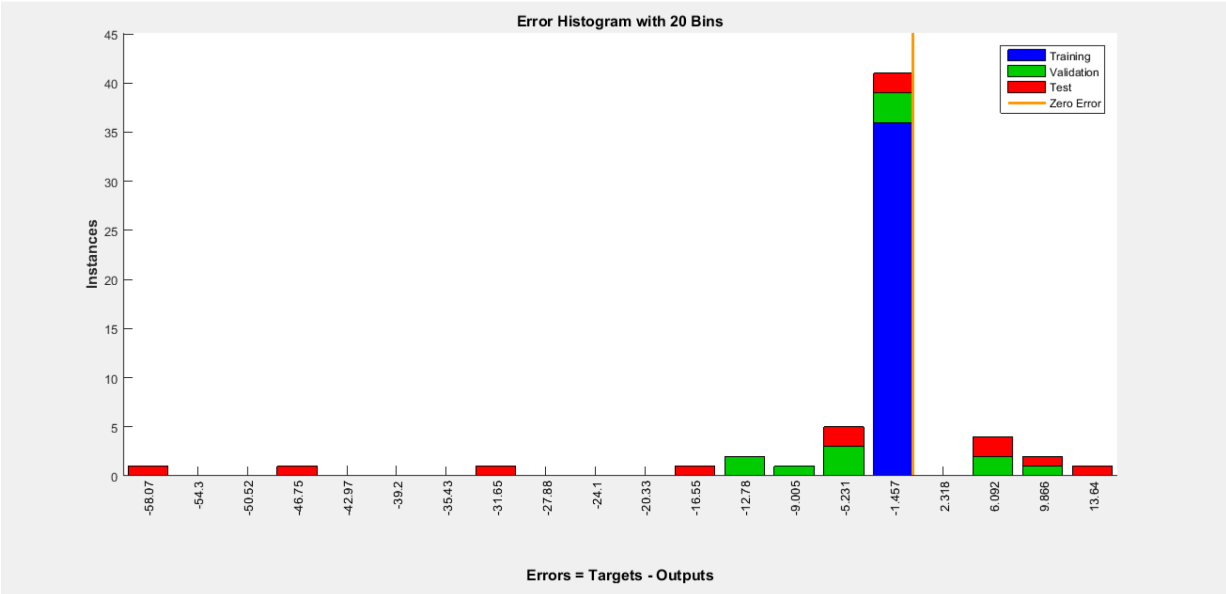

Figure 4: Neural Network Error Histogram

Based on the data, Artificial Neural Network training state was deployed to learn the dataset for the prediction. From Figure 5, the gradient of the artificial neural network is observed to be 2.1092e^{-13} at epoch 6 during training, 1e^{-9} during testing at epoch sting at epoch 6 and 0 upon validation check at epoch 6. The output obtained on the dataset depicts that the result obtained is line with the following work on Novák & Lehký (2006) that an efficiency training of a dataset helps to prepare the dataset for effective prediction.

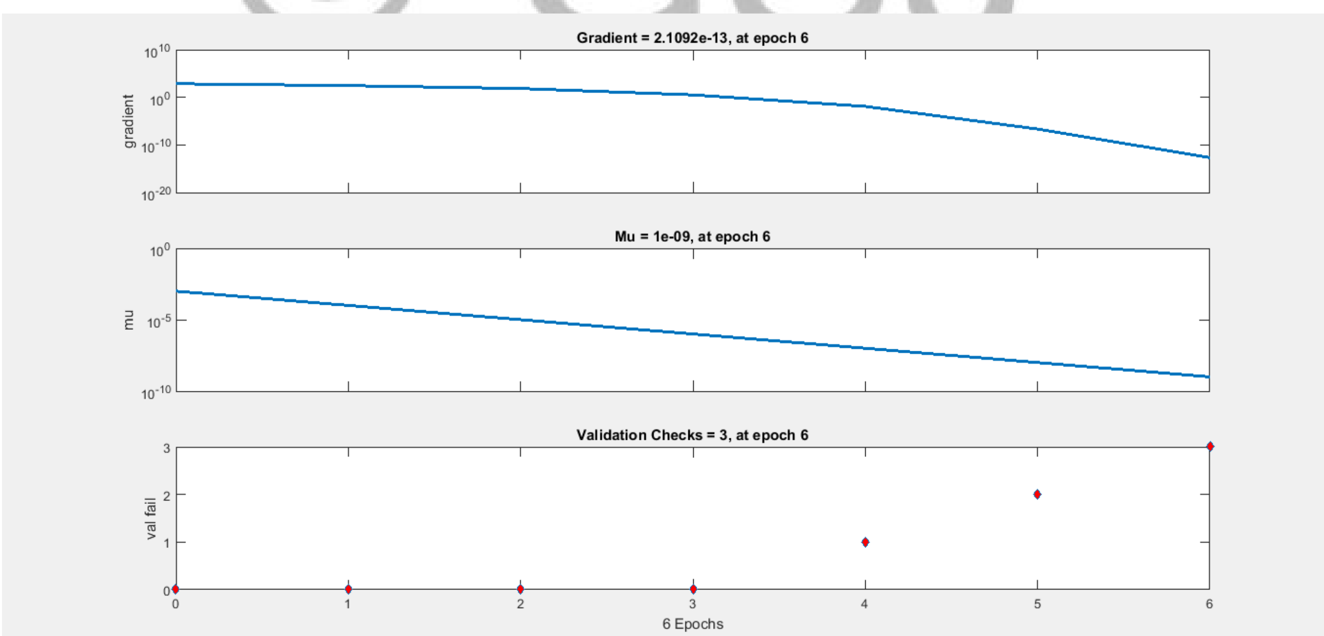

Figure 5: Neural Network Training State (Combined Dataset)

3.3 Comparison of the Simple Linear Regression and Artificial Neural Network Results

To ascertain the difference between the simple linear regression result and the artificial neural network result, the regression coefficient of the Simple Linear Regression is compared to that of the artificial neural network. The regression obtained using the simple linear regression and ANN was 0.1764 and 0.42665.

Hence, the percentage difference can be calculated as

$$\frac{0.1764}{0.42665} \times 100$$

$$= 0.4134 \times 100$$

= 41.34%

As such, it can be said that artificial neural network has been able to minimize the defects of the rotary shouldered connections up to 41.34%.

Also, from the analysis, the mean square error of the artificial neural network is 0.00860542, when compared to the mean square error (8.6953) from the data of the simple linear regression, shows a closer value to the line of best fit. Furthermore, the mean square obtained when ANN was applied to the data were minimal to that of statistical, which shows that the ANN was an improve tool for prediction because it makes use of hybridized method for optimization, which is in line with the study of Quiza *et al.* (2007), that Artificial Neural Network model produce a better and accurate prediction for Rotary Shouldered Connections.

4. CONCLUSION

From the analysis carried out on minimizing the defects of rotary shouldered connections, the simple linear regression approach gave a regression coefficient of 0.1764, while the artificial neural network gave a regression coefficient of 0.42665. Also, the artificial neural network gave a mean square error of 0.00860542 which is closer to the line of best fit when compared to that of simple linear regression which is 6.73386.

In comparison of the two approaches, it is noted that the effectiveness of artificial network in minimizing defects cannot be overemphasized, as it has been seen to be able to minimize the defects of the rotary shouldered connections up to 41.34%.

From the detailed analysis carried out, it is recommended that:

i. Further study should incorporate a larger dataset as it will improve the accuracy of the model.
ii. The result be compared with that of other machining learning tools such as Random Forest and Support Vector Machine.

This research has shown that control of defects in production process can be achieved by the application of artificial neural network and Ishikawa diagram which enumerates the causes of the defects. The introduction of ANN shows that it can enhance production with less minimal error.

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