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"A Comparative study on C45 carbon steel machining Experimental Values with an Artificial Neural Network"

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Abstract
This study examined the ways in which C45 medium carbon steel's machining characteristics were affected by a rise in trace elements such as phosphorus and sulfur. In this work, two distinct samples with specific varying percentages of sulfur and phosphorus were compared using tool inserts which are coated to study machining characteristics [variation/sample-1 S -0.006% and P-0.013% (Lesser percentage of phosphorous and sulfur) and variation/sample-2 S-0.017% and P-0.025% (phosphorous and sulfur having higher percentage)]. Using turning machine the Surface finish, cutting forces and material removal, tool tip temperature, and tool wear at flank were all examined and listed in the table for ANN evaluation with two distinct phosphorus and sulfur percentages. The 3-[9]1-1 network model was trained on a dataset of experimental values and then ANN findings are compared with the machining outcomes. This study uses 81 datasets for performance evaluation. The Levenberg-Marquardt approach is used to train the network and the findings of these methods are compared. Iteration twelve yielded the best-fit validation result for the response parameter R = 0.95, indicating near-linear association and very good correlation between the values from the experiments and the projected values. With the increase of trace minerals, like sulfur and phosphorus, better validation metrics of R=0.9848 were achieved by the sixth iteration.
Keywords: *Artificial Neural Network, Carbon steel, Tungsten Carbide and Machining*.

1. Introduction

1.1 Carbon Steel: Considering carbon steel's machining properties using various tools, the principal objective of this project is to investigate the residual (trace effects) components of phosphorus, sulfur, nitrogen, tin, arsenic, etc [1].

Figure 1.1:C45 circular bars with a diameter of 32 mm[1]

1.2 Turning Process: Turning is the technique of creating a surface of revolution by eliminating unwanted material with a one-point cutting tool. Three variables are monitored by the operator: speed V (m/min) (mm), feed f (mm/rev), and doc d. Among the most important processes utilized to create machine parts in industries including shipping, automotive, and aerospace. The three force components—the thrust force (FZ), which acts orthogonally to the feed (FX), the speed of cutting, the turning process produces the main cutting force (FY), which acts in the way of the speed of cutting, and the force acting moving toward the feed rate. The cutting mechanism, which includes chip formation, the frictional and thermal properties at the tool-chip interface, and the development of crater and flank wear at the cutting edge, may be better understood by taking into account that the relation between the cutting conditions (speed of cutting, feed, and doc), tool characteristics (tool angles, nose radius, and material), and the machining properties of the work material. Axles, drive shafts, and other components like induction-hardening pins and high-strength shafts are examples or applications of C45 steel-made parts utilized in the automobile industry that gets machined a lot [2]. In this work C45 steel samples were procured and tested by Optical Emission Spectrometry (OES) for material grade and composition to select two distinct samples of P and S with distinct percentage of trace elements.

1.2.1 **HMT lathe**

Figure 1.2.1: The HMT lathe utilized in the turning experiment [3].

1.3 Tool Inserts:

DCMT: Tool Insert

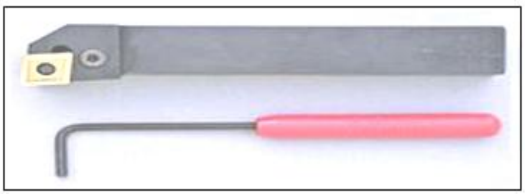

Figure 1.3.1: A tool holder with a tool inserts **Figure 1.3.2:** Insert carbide coated tool with Ti

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D stands for diamond shape; C for relief angle (7˚); M for size tolerance (mm); T for hole in center; 15 for insert width; and 04 for insert thickness [3].

1.3.1 Coated tool inserts: Usually, uncoated tungsten carbide is used as a standard to measure different carbide implants. Therefore, you can machine materials at higher rpms and increased feet of surface area per minute with a coated type carbide insert, which will increase edge breakage resistance and prolong tool life. Titanium nitride, or TiN for short, is the most common coating for carbide inserts. It has a gold finish [4]. To increase tool life and productivity, many more types of coatings are available. TiCN stands for titanium carbonitride. TiAlN, for example, is an acronym for titanium aluminum nitride. The figure 1.3.1 shows a tool holder with a tool inserts and 1.3.2 shows the clear image of Insert carbide coated tool with Ti [5].

1.4 Artificial Neural Network Implementation: A good study requires a well-trained artificial neural network.. Numerous experimental outcomes that can be trained are necessary to obtain the same. One can create a network and then evaluate it using various algorithms. The following steps can be used to outline the ANN method for material science.

- ❖ Data collection and preprocessing
- ❖ ANN training and configuration optimization and ANN performance evaluation If step 2 is not adequate, go back to step 1
- ❖ Use the trained ANN for simulation and prediction.

The primary benefits of artificial neural networks (ANNs) are their ability to easily simulate complex non-linear, multidimensional functional relationships without the need for assumptions and their direct formation from experimental data. A few of ANN's drawbacks are

- ❖ Predicted values and the training dataset should be sufficiently close.
- ❖ More datasets are needed for difficult situations.

The following parameters are regarded as input and output layers for the current investigation.

- ❖ Cutting depth, feed rate, and speed, and other input layers are examples of output layers.
- ❖ Examples of output layers include temperature, power of cutting, tool wear, surface roughness, and MRR.

The most recent Simulink MATLAB software version, R2019a, used to write ANN applications. After then, the dataset is split up into several pieces at random sections following the software's entry of the input and output details. There are a few datasets for training, a few for validation, and a few for testing [6]. Everyone is chosen at random based on the experimental results, and the procedure involves instruction and evaluation numerous times. Numerous neurons, are intricately linked processing units, make up these structures that cooperate to solve particular issues. Similar like humans, ANNs learn by doing.

1.4.1 **Uses of Neural Network:** It is feasible to use neural networks to find patterns and identify trends in because computers have a great the capacity to derive significance from complex or Uncertain data, they can find information too complicated for people or alternative computer techniques. One could consider a system of artificial intelligence that has been educated to become an "expert" in the specific field on which it's been assigned to find the data. Based on novel scenarios of interest, this specialist can then be utilized to produce "what if" answers and forecast outcomes [7].

1.4.2 **The Neuron Biological System:** There is one specific kind of brain that is the greatest fundamental component of a human brain cell it enables us to recall, reason, and integrate past experiences into every action we take. Every one of these cells can be connected to 2,000,000,000 additional neurons, they are called neurons. The fundamental parts are of four types of a natural neuron and they are one soma, second synapses, third axons, and fourth dendrites. In short, biological neuron get information from an assortment of sources, organizes it somehow, and produces the result after applying a non-linear one in general procedure to it [8]. Figure 1.4.1 illustrates the connections between the four components of a condensed biological neuron.

1.4.3 The Neuron system: A neuron is constructed far more simply to compare a real neuron, as observed in the illustration below.

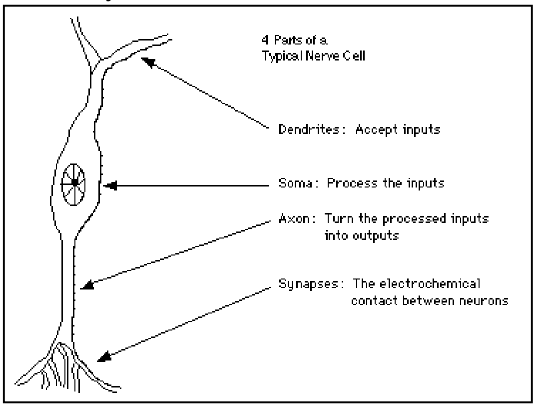


Figure 1.4.1: Nerve cell

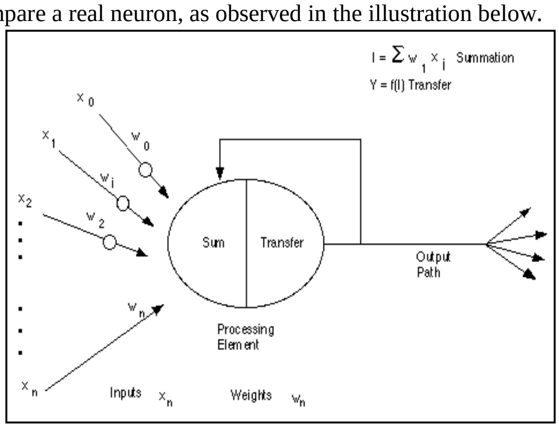


Figure 1.4.2: Network mathematical representation

As seen in Figure 1.4.2, the symbol X in mathematics stands for the network's numerous inputs. These inputs are all multiplied by the connection weight, denoted as W.
In the most basic case, an output is created by simply adding these products together and passing them via a transfer function. Even though this basic building block is employed to construct with each artificial neural network, some differences and their fundamentals may differ [10].

1.4.4. Design of Neural Network.

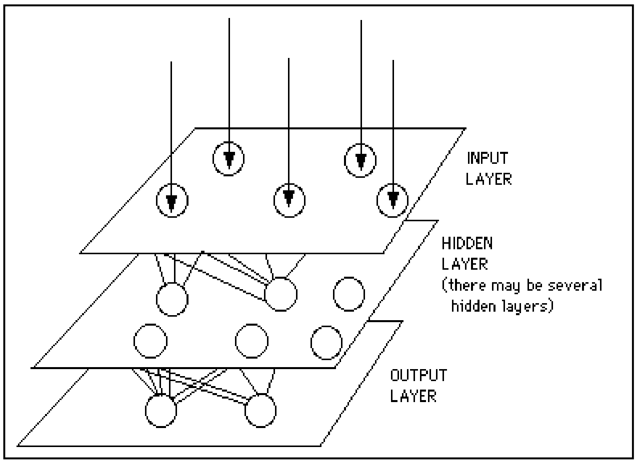
To come up with a design that is acceptable, the process of determining decisions requires the developers to undergo a trial-and-error period.

- ❖ Neurons are arranged layer by layer as part of network process.
- ❖ Choosing the type of partnership between neurons inside a layer by layer and between that layer's neurons.
- ❖ Regulating a neuron's information processing and output by allowing them to learn the proper the connection weight values from a training data set to evaluate how strongly networks are connected.
- ❖ The basic phases in the procedure for iteration of creating a network are depicted in figure 1.4.3.

Figure 1.4.3 shows the 3 layers of units, or layers of neurons, that make up artificial neural networks. In the input layer, neurons process data from the surroundings, while the result layer's neurons communicate outcome from the system user or the external environment. Each hidden layer's activity is defined via the weights on the connection between the activities of the input units in addition to as the hidden units.

MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
ISSN: 1053-7899
Vol. 36 Issue 1s, 2026, Pages: 2621-2630

Figure 1.4.3: Neural network layers



2. Training Data

2.1 Procedures:ANN's main objective is to compute predicted values and lessen the quantity of trials that researchers must perform for the purpose of obtain the desired findings. This shows the both the available experiment input and the accessible experiment output. In the current study, MATLAB R2019 is a unique modeling package, was applied.

The subsequent actions are conducted in order to predict the value.

STEP 1: Enter nftool as the command within the same prompt.

STEP 2: Once the command has been entered, it shows the application where the target and input files must be posted. The experiment's parameters, including feed rate, cut depth, and Input files are the term used to describe speed of cutting. The output files include references to the outcome of the temperature, cutting force, and tool surface wear experiments, surface roughness, and MRR.

STEP 3: Following the upload of the files for input and output, validation, and testing are conducted.

Here, it is necessary to determine the quantity of samples that will be utilized for confirmation and testing.

STEP 4: Training is the subsequent action after validation and testing. In this situation, training may be done using a different algorithm.

STEP 5: The Levenberg-Marquardt approach was employed to train the network.. At this stage, we can produce the validation check, training graph, and regression graph.

STEP 6: After training the software, it might be saved and used to make a plot that shows the error, or the distinction between the results and target values.

2.2 Experimental Data for training : From table 2.2.1 Training information on controlling process variables in Cutting C45 carbon steel with Ti coated inserts with reduced sulfur and phosphorus percentages S-0.006% P-0.013% in 1st Sample and table 2.2.2 Training information on controlling process variables in Cutting C45 carbon steel with Ti coated insert tools with a increase in percentage of sulfur and phosphorous S%-0.017 P%-0.025 Sample 2.

Table 2.2.1: Training information on controlling process variables in Cutting C45 steel with Ti coated inserts with reduced sulfur and phosphorus percentages:

Various cutting depths for Ti coated inserts (Sample-1) S-0.006% P-0.013% in Sample 1							
Input data			**Output data**				
Cutting speed(m/min)	**Feed rate (mm/min)**	**Depth of cut (mm)**	**Surface roughness (µm)**	**MRR (g/min)**	**Temperature (Deg.)**	**Tool wear (mm)**	**Cutting force (kgf)**
114	0.125	0.5	161.36	7.7	71	3.4	5
		1.0	162.59	12.2	89	4.2	9
		1.5	164.79	16.8	97	4.25	12
	0.175	0.5	190.28	13.1	89	3.1	9
		1.0	196.20	20	105	3.4	13
		1.5	183.32	26.8	142	3.3	29
	0.225	0.5	199.86	16.3	96	3.6	13
		1.0	192.94	25.6	119	4	17
		1.5	237.59	25.9	121	4.15	25
160	0.125	0.5	172.49	12.5	86	3.4	7
		1.0	150.16	15.5	90	3.96	8
		1.5	176.35	30.7	116	4.11	18
	0.175	0.5	204.43	18.5	92	3.12	8
		1.0	198.5	25.5	106	3.22	12
		1.5	239.93	43.5	132	4.02	22
	0.225	0.5	190.98	21.2	104	2.28	9
		1.0	211.11	36.8	124	3.42	17
		1.5	222.13	49	146	3.99	22
200	0.125	0.5	172.02	13.6	84	2.98	4
		1.0	180.27	20	97	3.24	7
		1.5	168.71	33.1	115	4.21	12
	0.175	0.5	191.21	12.8	80	3.28	3
		1.0	169.6	31.6	83	3.2	9
		1.5	184.64	40.2	89	3.68	12
	0.225	0.5	223.65	24.2	66	3.42	7
		1.0	233.52	33.4	87	3	10
		1.5	230.05	57.4	108	2.98	22

MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
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Vol. 36 Issue 1s, 2026, Pages: 2621-2630

Table 2.2.2: Training information on controlling process variables in Cutting C45 steel with coated inserts with a increase in percentage of sulfur and phosphorous:

Various cutting depths for Ti coated inserts (Sample-2) S%-0.017 P%-0.025 Sample 2							
Input data			Output data				
Cutting speed(m/min)	**Feed rate (mm/min)**	**Depth of cut (mm)**	**Surface roughness (µm)**	**MRR (g/min)**	**Temperature (Deg.)**	**Tool wear (mm)**	**Cutting force (kgf)**
114	0.125	0.5	191.05	9.1	71	2.64	10
		1.0	169.43	8.2	72	2.74	7
		1.5	191.54	21.4	86	2.15	28
	0.175	0.5	208.57	3.4	40	2.02	6
		1.0	221.2	11.2	74	3.77	10
		1.5	211.71	18.4	51	2.225	16
	0.225	0.5	237.29	9.9	35	1.86	7
		1.0	254.6	12.4	67	3.18	10
		1.5	218.65	13.9	61	3.48	15
160	0.125	0.5	184.52	3.9	35	2.22	3
		1.0	192.02	17	56	2	9
		1.5	183.20	32.6	62	2.21	17
	0.175	0.5	195.01	11	38	2.22	5
		1.0	218.36	18.3	52	2.22	9
		1.5	221.71	36.3	78	3.30	19
	0.225	0.5	217.90	19.6	59	1.68	8
		1.0	287.68	36.9	72	3.61	16
		1.5	247.97	52.9	84	3.75	28
200	0.125	0.5	171.72	14.9	63	2.22	4
		1.0	190.53	16.2	69	2.20	6
		1.5	182.93	36.9	90	3.2	14
	0.175	0.5	182.62	19.1	72	2.1	7
		1.0	218.88	32	78	2.5	13
		1.5	236.99	31.5	99	3.1	13
	0.225	0.5	248.42	24.2	80	2	6
		1.0	225.9	47.1	105	2.4	15

3. Findings and Discussion

3.1 Tool Inserts with Ti Coated and Different Depths for cutting (Sample-1) The ANN 3-[9]1-1 model was trained on a dataset from the experimental samples having a smaller proportion of S% and P% (S%-0.006 and P%-0.013). To train the ANN's, the Levenberg Marquardt technique [9] is employed and the anticipated these methods' values are compared. Figure 3.2 displays a plot of linear regression between the results and the suitable objective for the LM's method. The response's R-value is 0.95With the same value, the objective and the outcome will fit linearly. An overview of the pattern-finding technique's ANN outcomes is displayed in figure 3.1. A performance curve illustrating errors from validation, testing, and training is presented in Figure 3.3. The validation error rose after the 12th iteration, which had the optimal validation results. This study uses 81 datasets to gauge performance. The goal criteria are temperature, cutting force, tool wear, surface roughness, and MRR; the input variables include depth of cut, feed rate, and cutting speed. The projected value of the ANN is nearly identical to the experimental values, as seen in Figures 3.4 to 3.8.

The results of the ANN are used to order the experimental findings.

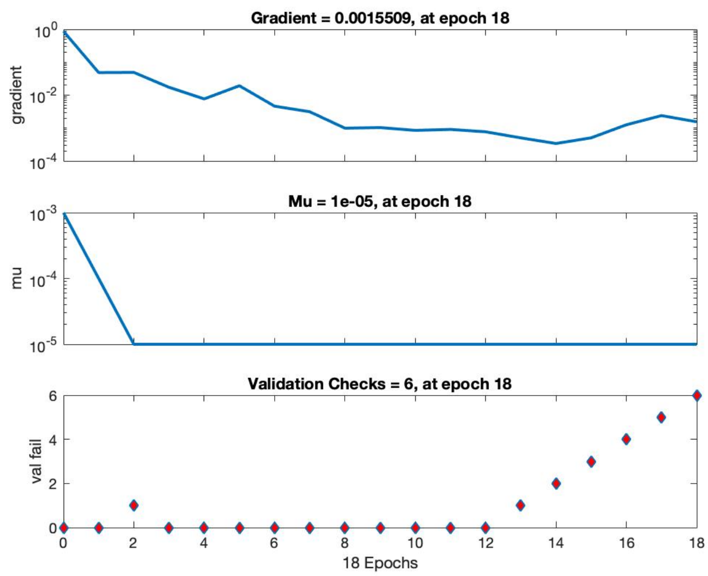

Figure 3.1: Checks for ANN Validation, Mu, and Gradient

MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
ISSN: 1053-7899
Vol. 36 Issue 1s, 2026, Pages: 2621-2630

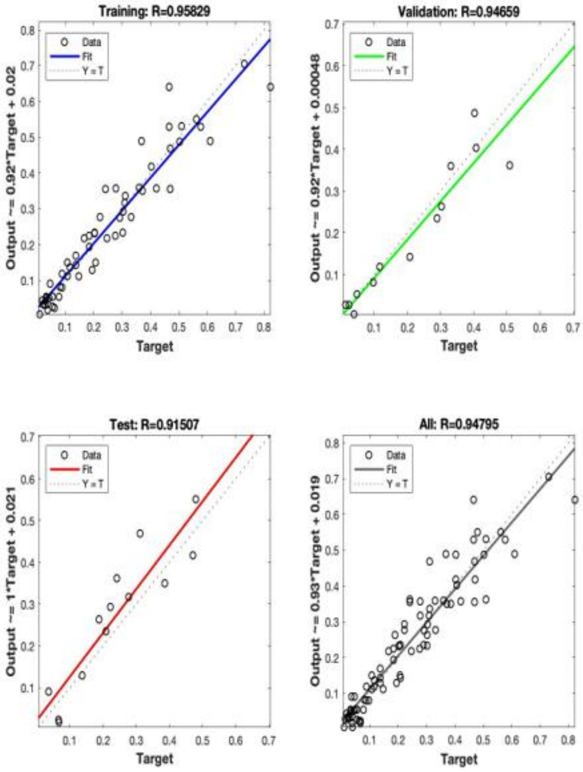

Figure 3.2: The LM algorithm's regression plot

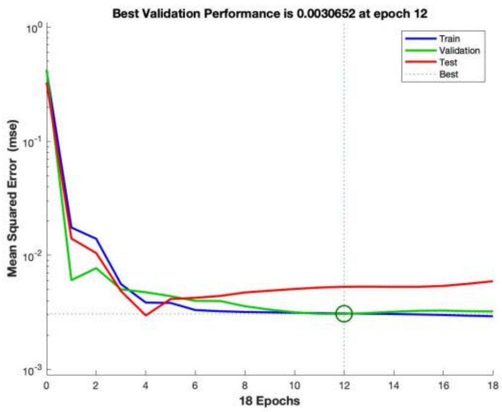

Figure 3.3: Graph of the LM algorithm's efficiency

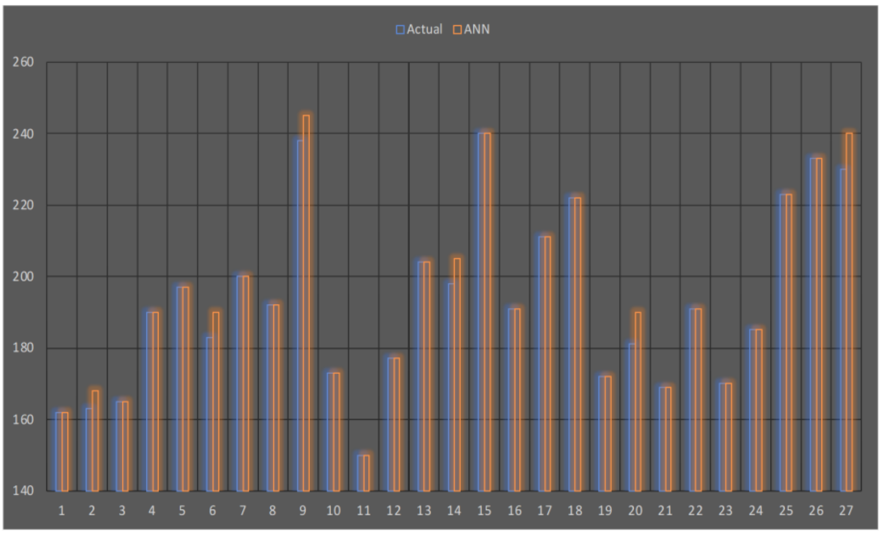

Figure 3.4: Actual surface roughness versus ANN

MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
ISSN: 1053-7899
Vol. 36 Issue 1s, 2026, Pages: 2621-2630

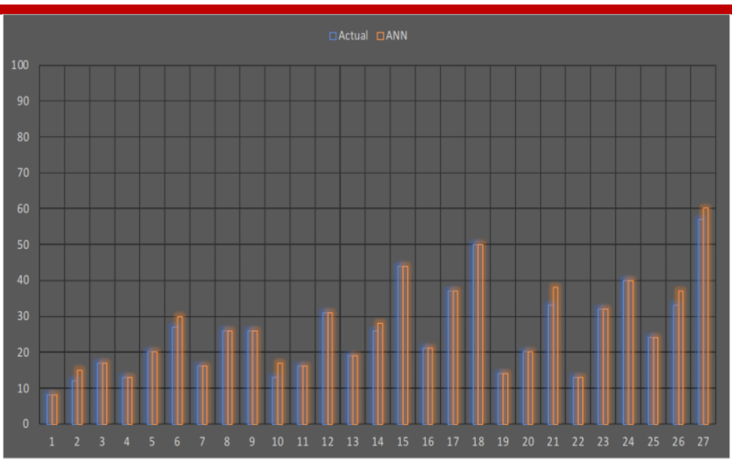

Figure 3.5: Comparing Actual with ANN-MRR

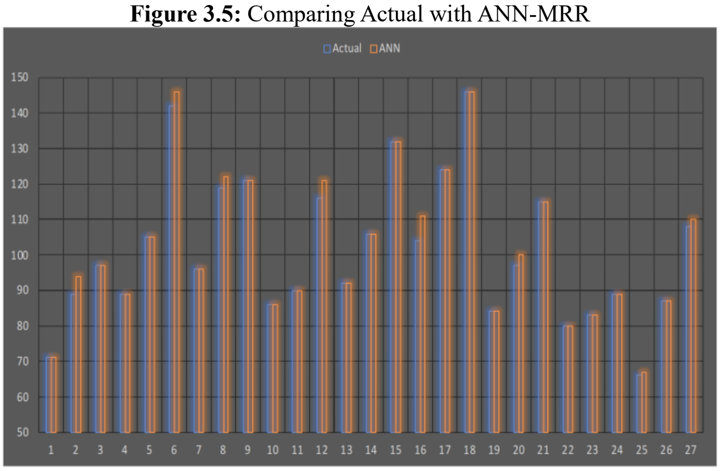

Figure 3.6: Comparing ANN with actual – Temperature

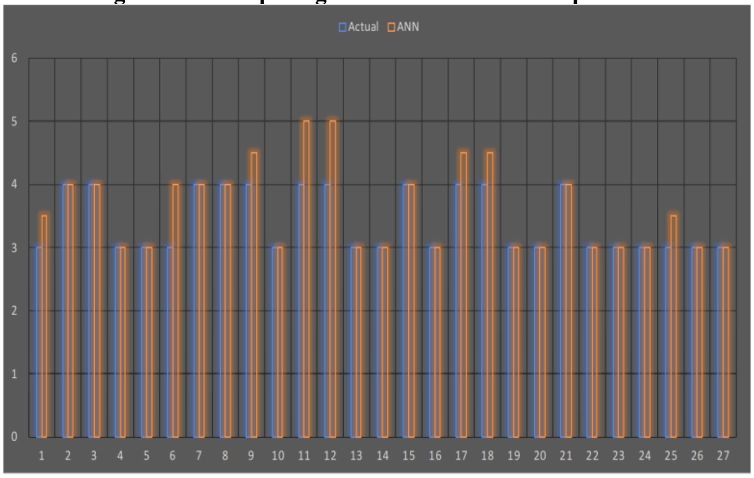

Figure 3.7: Comparing ANN with actual – Tool Wear

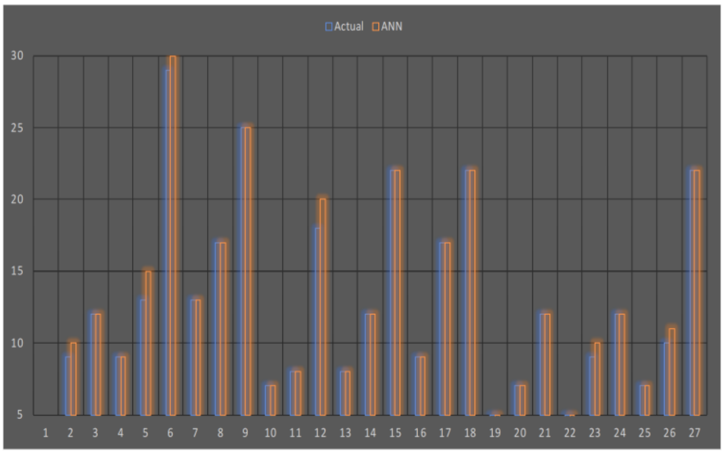

Figure 3.8: Comparing ANN with actual – cutting force

MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
ISSN: 1053-7899
Vol. 36 Issue 1s, 2026, Pages: 2621-2630

3.2 Tool Inserts with Ti Coated and Different Depths for cutting (Sample-2) More phosphorus and sulfur are present within the sample with P%-0.025 and S%-0.017. A visualization of the results using linear regression and associated objective of the LM approach is shown in Figure 3.9. The response's R score is 0.9858. With the same value, the result and the objective will fit linearly. Figure 3.10 displays the ANN findings summary, a pattern recognition tool. A performance curve displaying errors from testing, validation, and training is displayed in Figure 3.11. The optimal validation performance was attained. in the sixth repetition, at which point the validation error will increase from zero or lower. This study uses 81 datasets to evaluate performance. While surface finish or roughness are input factors, cutting speed, feed rate, and depth of cut, MRR, tool wear, temperature, and force are used as objective parameters. As seen in Figures 3.12 to 3.16 the ANN's projected value and the outcomes of the experiment are almost the same. The ANN's output is utilized to order the experimental findings.

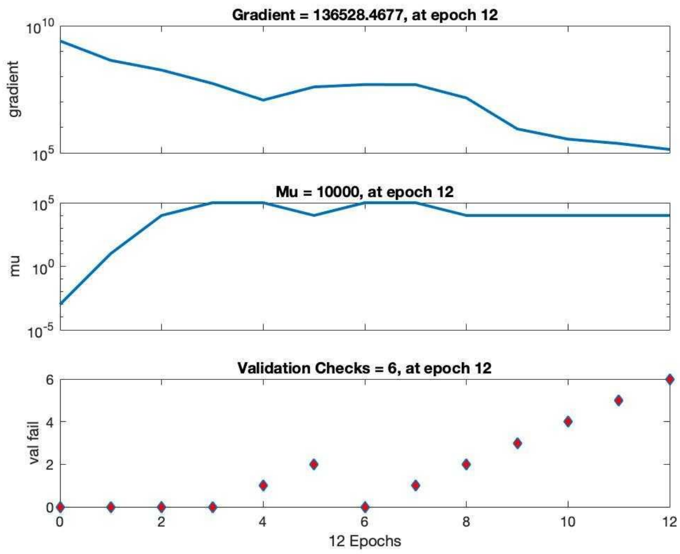

Figure 3.9: The LM algorithm's regression plot

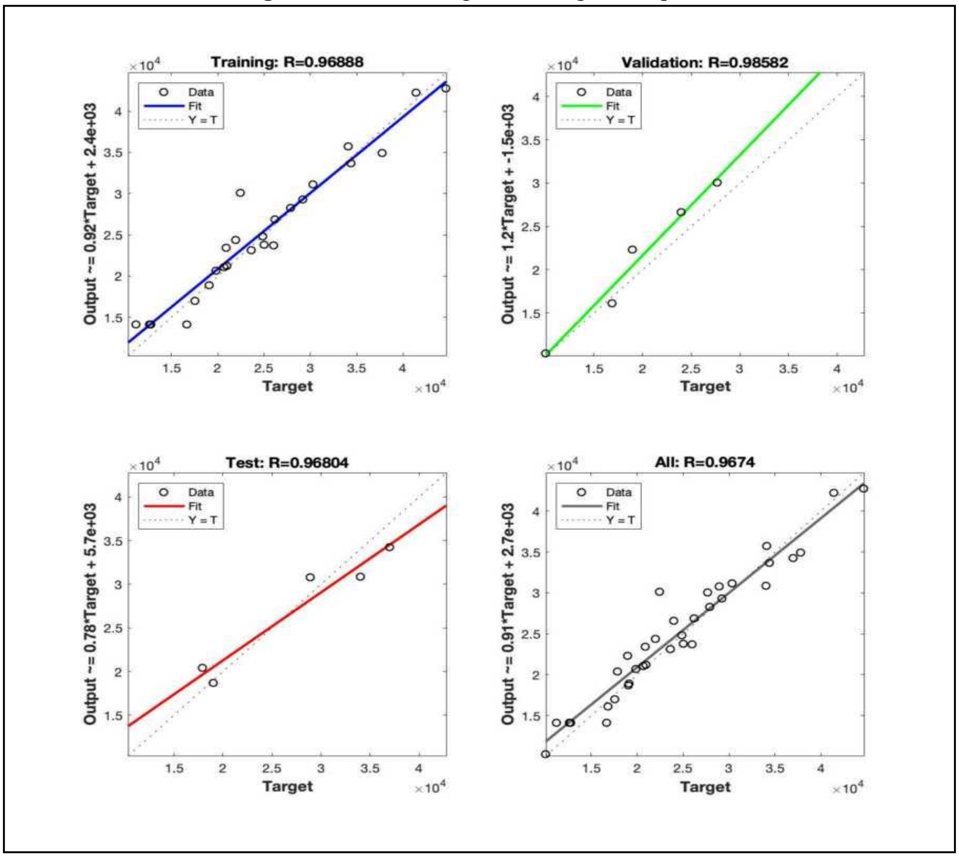

Figure 3.10: Checks for ANN Validation, Mu, and Gradient

MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
ISSN: 1053-7899
Vol. 36 Issue 1s, 2026, Pages: 2621-2630

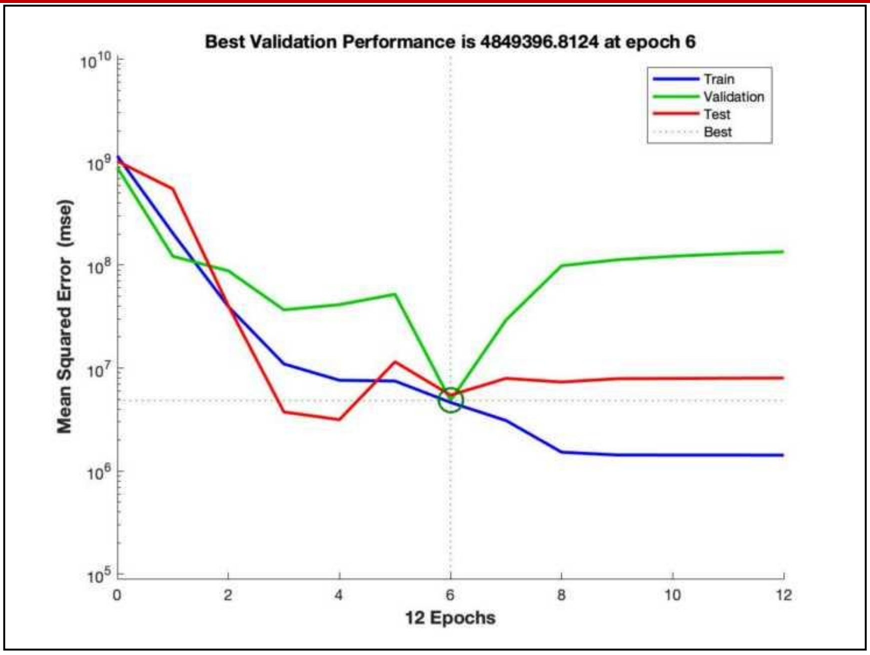

Figure 3.11: Graph of the LM algorithm's efficiency

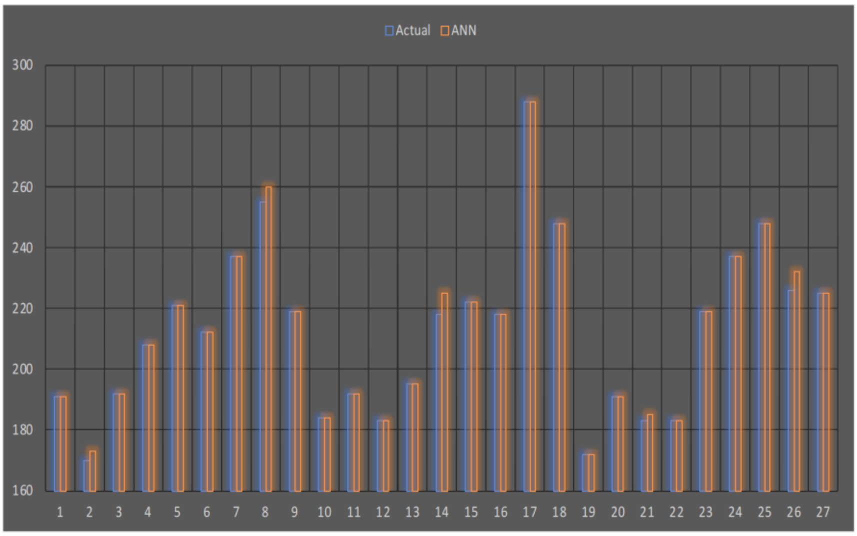

Figure 3.12: Actual Surface roughness with ANN

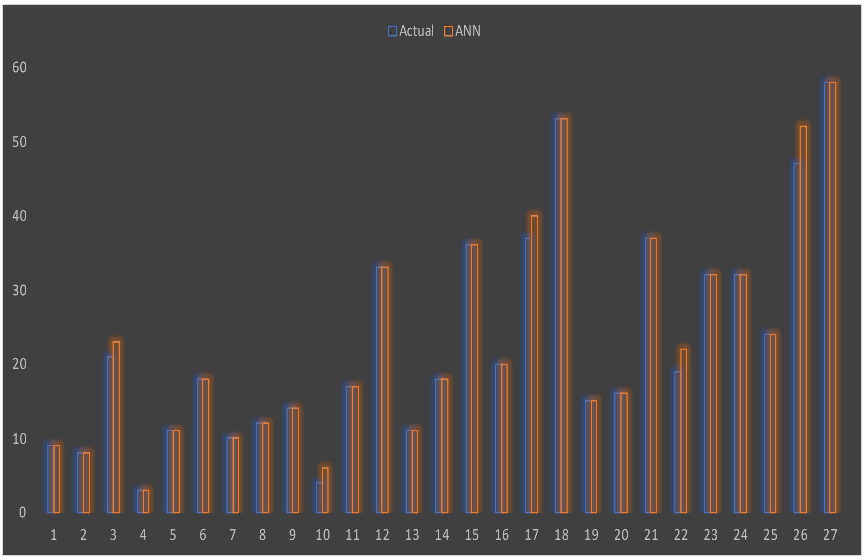

Figure 3.13: Comparing Actual with ANN-MRR

MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
ISSN: 1053-7899
Vol. 36 Issue 1s, 2026, Pages: 2621-2630

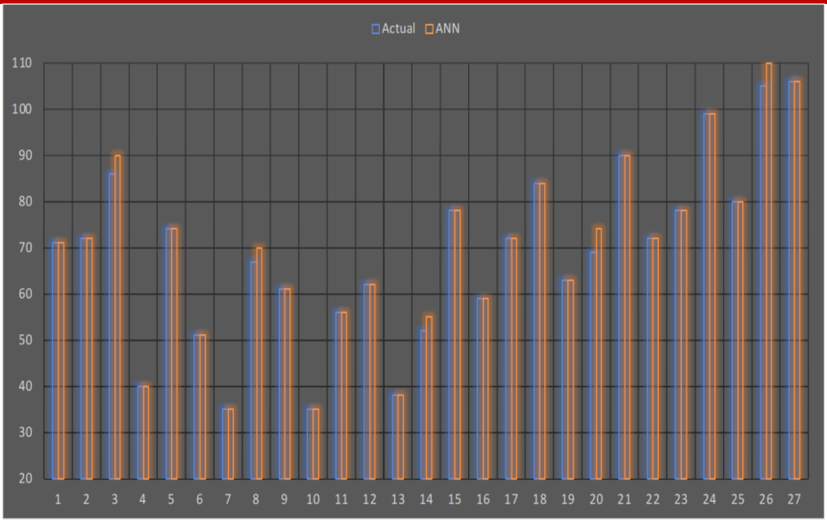

Figure 3.14: Comparing Actual with ANN- **Temperature**

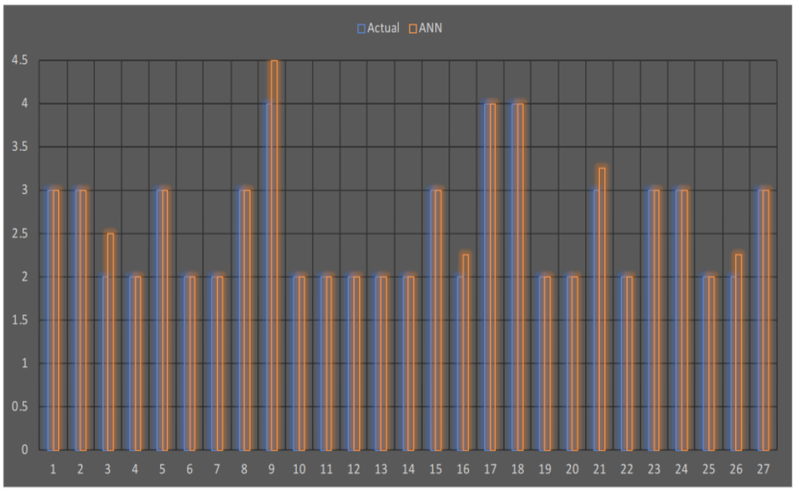

Figure 3.15: Comparing Actual with ANN– **Tool Wear**

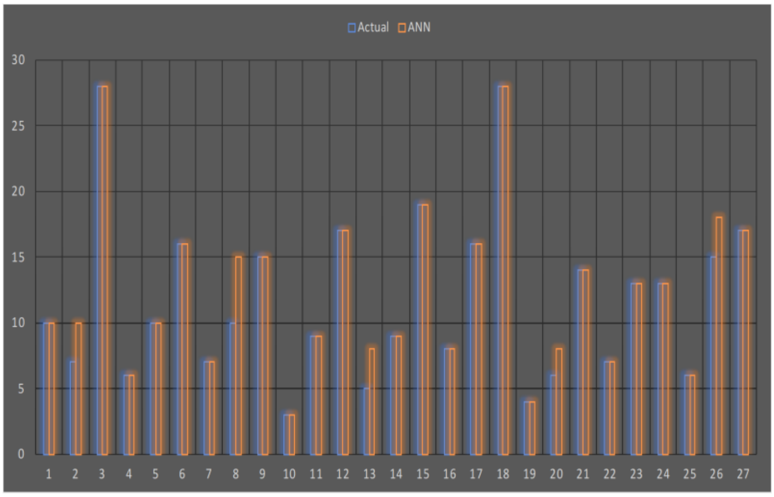

Figure 3.16: Comparing Actual with ANN – **cutting force**

4. ANN CONCLUSION

In this research, the machining parameters and the output obtained by the turning process are recorded and listed in the Table1.1 and 1.2 for two distinct percentages of sulphur and phosphorus. The value was predicted using an ANN analysis, followed by a comparison to the experimental results. The BP A neural network has been suggested. and evaluated using the 3-9-1 model and the LM approach. The LM method is utilized to predict tensile, flexural, erosive, and wear results. Because of their extensive training, the Models are quite helpful. for predicting weight reduction and other attributes.

✓ Using a Ti-coated tool to machine C45 steel for samples with a lower concentration of trace elements R= 0.95 indicates a roughly linear fit and good agreement between the experimental and predicted values, and the 12th iteration yielded the best validation. 81 datasets were used in the investigation.

✓ At the sixth iteration, samples used to machine C45 steel with higher levels of trace elements like phosphorus and sulfur produced a better validation value of R=0.9848.

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