Application of Multiple Back-Propagation ANN for Predicting Finish Surface Roughness Produced by Vereco CNC Cylindrical Grinding Machine

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***Abstract*— Large industrial operations, such as those in manufacturing, marine, and oil & gas, rely on cylindrical grinding as one of their most critical machining processes. One of the difficulties encountered throughout the cylindrical grinding process is anticipating the workpiece's exact surface roughness after the process. Due to the process's inability to predict the exact surface roughness, the processing time and quality produced are difficult to control. Several independent variables that are immediately quantifiable are used to build a data set for the training procedure in this study. Predicting the ultimate surface roughness generated by the cylindrical grinding process is critical for optimizing production time, quality, efficiency, and customer satisfaction. An artificial neural network with multiple backpropagation algorithms is applied. Through the learning process, the best combination of learning is obtained, namely: a learning rate of 0.057 and a momentum of 0.434 with one hidden layer in which there are 10 hidden nodes. This combination is believed to be the best training combination to produce the minimum error between the target and the true value. The root mean squared error of the test calculation was 0.0436 with a prediction accuracy of 95.64%. This set of experiment results produces predictive results through the validation process and succeeds in predicting the finish surface roughness with promising results (accuracy in the range of 94.683-97.661%).**

Keywords—*surface roughness, Artificial Neural Network, multiple backpropagation, production quality, customer satisfaction*.

I. Introduction

Cylindrical grinding processes using a grinding machine exist to support large companies including manufacturers and maritime companies in reconditioning their large engines or engine parts. This is not a simple process that can be done by anyone, only a highly trained experienced operator can operate the machine. The reconditioned parts of this machine must be treated with high precision, in order to achieve the specific results demanded by the customer. An important factor to be maintained or improved to the quality of the process that should be considered is the surface roughness of the workpiece. The quality produced by the cylindrical grinding process greatly affects the results of the surface microscopic conditions of the workpiece.

Surface roughness is widely used as a quality measure by customers that relate to the specification of mechanical products [1]. The quality features must be influenced by several parameters to attain the desired level of surface roughness [2]. The most common strategy involves selection process parameters and applying various methodologies that can predict surface roughness. Benardos and Vosniakos [1] showed in their review that several approaches could be used for predicting surface roughness. Among them are Classification, Machining theory-based, Experimental investigation, Design of Experiments, and Artificial Intelligence approaches. Those approaches have exhibited advantages and disadvantages but given the trend of today's technology, the most promising seems to be the Machine Learning approach.

Numerous researches have been conducted on the cylindrical grinding process, but mostly related to the Design of Experiments and Machine Learning approach. Several of them include optimization of machining parameters [3], using the Taguchi method for predicting surface roughness [4] [5] [6], using Artificial Neural Network (ANN) for predicting surface roughness of AISI H13 Steel with minimal cutting fluid [7], single point incremental forming of AA3003-O alloy application by ANN [8], decision tree as one method available in data mining also introduced [9], while Li et.al. discussed several machine learning algorithm for predicting surface roughness in extrusion-based additive manufacturing [10].

Lin et.al. reported that vibration signals combined with a deep learning predictive model could be applied to predict the surface roughness [11], response surface methodology (RSM), and ANN was used for optimized prediction [12]. A more advanced technique is introduced by Alajmi & Almeshal by ANFIS-QPSO that combines the strengths of fuzzy systems and evolutionary optimization [13], Kong et.al proposed Bayesian linear regression [14], while Abu-Mahfouz et.al introduced clustering techniques [15], and Pan et.al. discussed that in the era of digitalization, new insights into methodologies for predicting ground surface roughness are tied to Industry 4.0, where enhanced machining theory, experiment design and artificial intelligence have affected many elements of various fields [16].

The machine tested in this research is the Vereco RG 700 CNC Cylindrical Grinding Machine. The workpiece that is normally reconditioned by this grinding machine is usually very large, for example, the crankshaft of a ship's engine belonging to a cargo ship company. Apart from the crankshaft, large engine or engine parts such as cooling rolls, calendar rolls, and drum blocks are also possible to be reconditioned on this machine as long as their dimensions are within the maximum limits. Experiments need to be carried out to determine the relationship between the grinding process variables and the surface roughness of the workpiece.

When the study was conducted, this Vereco RG 700 CNC Cylinder Grinding Machine is the only machine in Indonesia that can repair large parts with a length capacity of more than nine meters. Therefore this machine has a strict lead time every day to complete parts reconditioning work. If there is a rework, the schedule that has been set will be completely reset and the customer cannot accept the delay. The worst case is that customers ask for penalties for lateness, and there have been about 70% defects for almost every month.

The factor that always violates the schedule is the surface roughness produced at the end of the process that does not meet the specifications requested by the customer. The final machining process of components requires the use of a cylindrical grinding process, which produces smooth surfaces with tight tolerances. As a result, a numerical model is needed to calculate the final surface roughness of the cylindrical grinding process. Numerical models would not only anticipate the completed workpiece surface roughness, but they can also help the company enhance the finish's quality and speed up operations.

The purpose of this research is to apply the artificial neural network (ANN) approach with the Multiple Backpropagation training methods to predict final surface roughness produced by a Vereco RG 700 CNC cylindrical grinding machine. It is believed that the ANN would allow for the determination of the optimal value for related variables in order to predict final surface roughness.

II. Methods

ANN can be used as a predictive method because it has the characteristics of finding patterns which are numerical combinations [17]. This method can detect patterns of interconnection in a constantly changing environment. In prediction, a function that describes a time series process is defined. The function is obtained by matching past data. Past data values are represented as function values. Function model of ANN which describes the past data structure. The function describes the dependence of the current data value on the previous data. The application of ANN for prediction takes a small amount of time to conduct because of its characteristics, namely that the learning process must be carried out first. Experiments need to be carried out to determine the best results for the number of hidden layers, the specified learning rate, and the selection of learning techniques on the planned network.

A. Identification of Research Variables

It was determined through interviews with the machine operators and managers of a related department that the traverse feed, depth of cut, wheel speed, and workpiece hardness were the most critical factors. Unfortunately, determining the magnitude of these variables from the document archive is challenging since the number of variables generated will vary across restoration procedures.

B. Data Collection

The design of experiment approach is used to acquire the data. Traverse feed, depth of cut, wheel speed, material hardness, grinding wheel grit size, and surface roughness are the process variables in this study. The surface roughness is the dependent variable, and the grinding process will result in a value for that variable. The obtained roughness value will then become the target value in training the neural network.

C. Data Analysis

The selection of the ANN model parameter is very important in the development of an effective ANN model. Several contributing factors influence the efficacy of the ANN model, as follows:

1) Data for ANN Model

The data are obtained on-site with several supervisions from the management of the company. The experiment is conducted during the working hour with the expectation of obtaining the direct connections between several factors which have direct contact with the workpiece and the surface roughness produced from the cylindrical grinding process.

2) Architecture

A neural network will be built to conduct the ANN calculation. The input independent variables are represented by five input nodes, which are as follows: traverse feed, depth of cut, wheel speed, material hardness, and grinding wheel grit size. Once this calculation is completed, the training process is carried out using various combinations of the number of hidden layers, the number of neurons in each hidden layer, the learning rate and momentum of the system.

The architecture of the network is the feed-forward multilayer perceptron. This architecture is chosen considering the other variable that might exist other than the five independent variables set in this study. The feed-forward structure is chosen to see the direct implication or effect of each layer with the other. If a feedback structure is used, it might create an unbalanced condition in the network.

Backpropagation is an ANN with a supervised learning method that is widely used by researchers around the world in building a numerical model. This method is commonly used in a multi-layer network with the aim to minimize errors in the output produced by the network during the training process.

3) Activation Function

The activation function chosen in this study is the unipolar sigmoid function. This activation function is chosen because this function has the most similarity in replicating how the brain processes the information. The output generated by this function has the value of a sigmoid, which means:

$$Sig(f(x)) = \frac{1}{(1+e^{-f(x)})} \tag{1}$$

Where the *f(x)* is the summation of all the input values multiplied by each synaptic weight and added with the bias value, and *e* is the constant and is approximately equal to 2.72.

4) ANN Training Algorithm

The training of the network will use the backpropagation method. It is a supervised training method and the most used training method in several fields of studies. This training method is chosen to adjust the parameter of this study which has the target value. Where there are target values in a neural network, a supervised learning method is used. In this training method, the system adjusts continuously the synaptic weights to minimize the error of the comparison between the result generated by the network and the target results.

In this study, the complete numerical model will be generated using the help of the ANN training tool: Multiple Back-Propagation Version 2.2.2. The training is conducted by considering the training parameter chosen initially and will be repeated using another combination of training parameters until the desired result with minimum mean squared error is obtained.

5) *Number of Iterations*

The number of iterations in this study is set whether to optimize the mean squared error resulting from the training or to minimize the training time. A balanced quality between that intent has to be achieved in order to produce maximum training quality and minimize the time required in experimenting. The iterations in this study are limited to 35,000 epochs to limit the training process duration.

6) *Weight Initialization*

The initialization of synaptic weights in this study uses a uniform random limit between [-1;1]. This method is chosen because this is the simplest method in initializing the synaptic weights and is believed to be able to minimize the training process time.

It is conducted continuously in order to obtain the best model in achieving the lowest mean squared error. The mean squared error is the result of the comparison between the target values obtained from the experiment and the result generated by the network.

7) *Training Process*

To conduct the training process, several combinations of training variables have to be set. In this study, the number of the hidden layer is limited to only two-layer, the learning rate and momentum are initially set to 0.1 with the ability to update their value automatically by the software.

After training combinations are set, the training is conducted on all the combinations. The results of each training process will be observed and the best result will be chosen to be tested again. The best result from the 1st training process will be tested again using different sets of combinations to see if there is any better result generated by the 2nd training process. One best result obtained from two training processes will be analyzed and the weights generated by the network will be recorded.

Using the best training combination, a prediction using a new set of data will be conducted to see if the training combination can be applied for predicting the finish surface roughness.

8) *Analysis*

After the ANN implementation results are obtained, then the quantitative analysis is carried out. The major variables influencing the research object are examined one by one and linked to the problems that arise. The investigation will assess whether or not this method is capable of predicting the final surface roughness produced by the cylindrical grinding process.

III. RESULTS AND DISCUSSION

A. *Data Collection*

In this study, five independent variables and one dependent variable were considered as the factors that most influenced the final surface roughness value resulting from the cylindrical milling process. The five parameters are as follows: traverse feed rate (X_1), depth of cut (X_2), wheel speed (X_3), surface hardness value (X_4), and wheel grit size (X_5), with the target surface roughness represented by (Y). As indicated in Table I, four independent variables have three levels and one independent variable has only one level.

TABLE I. PARAMETERS OF THE EXPERIMENT

Variable	Level 1	Level 2	Level 3	Unit
Traverse Feed Rate (V_t)	100	150	200	mm/min
Depth of Cut (DoC)	0.005	0.010	0.015	mm/rev
Wheel Speed (V_w)	300	400	500	RPM
Hardness (HRC)	50	55	60	HRC
Wheel Grit Size (MESH)	80	80	80	MESH

1) *Traverse feed*

Traverse feed is generated by the motor attached to the headstock in order to move the headstock in the z-axis direction. The speed is determined by the motor capacity and the gearbox capacity of the headstock. It is also determining the result obtained from the machining process. If the feed is too slow, indeed it will produce better results in the process but it cost a huge amount of time. On the other hand, if the feed is too fast, the result produced by the process will be worse, even though the processing time will be shorter. The worse result in this process is regarded to the higher roughness value. Usually, customers require smooth finish surface roughness, especially plastic companies.

2) *Depth of Cut*

The depth of cut of a grinding wheel determines the processing time and the finish surface roughness produced. It is the cutting range of a grinding wheel to the workpiece in one revolution. One revolution is when the headstock moves from the [0;0] coordinate to the other end of the work-piece or when the headstock reaches the end of the work-piece and returns to the [0;0] position. It can be set according to the operator. Normally in a cylindrical grinding process, the depth of cut is set between 0.005 mm and 0.02 mm. It is possible to set the depth of cut less than 0.005 mm or higher than 0.02 mm. However, if the depth of cut is too low, the process will need an unbelievably long process time in finishing the process. It almost does not touch the surface of the workpiece if the depth of cut is set around 0.001 mm or 0.002 mm per revolution. On the other hand, if the depth of cut is too much, the workpiece will rattle during the process, which will cause chatter marks along the surface of the workpiece.

3) *Wheel Speed*

Grinding wheel rotational speed is determined by the mechanical speed reducer pulley attached between the grinding wheel shaft and the motor. The size of the pulley is determined by the machine producer in order to achieve maximum and safe rotational speed.

The calculation of the pulley ratio gives us an image of how it is used to reduce the rotation generated by a motor. The calculation indicates that each one rotation generated by the motor, makes the target pulley moves 0.625 rotation. In this case, the motor can produce 800 rotations per minute. Theoretically, it can rotate the wheel up to 500 RPM, but the capacity of the motor is decreased due to its aging process.

4) *Material Hardness*

The company where the experiment is conducted provides hard chromium plating which has the hardness of HRC 50-65. The high hardness level of the plating is due to the precise mixture ratio between the Chromium Acid (Cr3+), Sulfuric Acid (H2SO4), and the Catalyst which is the secret ingredient of the mixture.

With four factors having three-level and one factor having one level, then the numbers of experiment combinations are the multiplication of the levels of each independent variable which is $3^4 \times 1^1 = 81$. According to the design of experiments methods, these 81 experiments should be conducted to compile the best combination.

B. *Experimental Data*

Each roughness (Ra) value measured is an average of eight separated positions in each roll segment. Fig. 1 exhibits the surface roughness obtained from the 81 experiments.

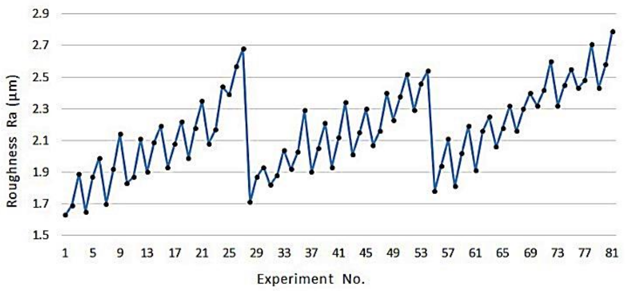

Fig. 1. Surface roughness value obtained experimentally

These 81 experiments will be used as a training data set to generate weights for the ANN architecture and a target value. A network will be generated through the process and it will be set as the guidance to predict finish surface roughness produced by considering the mentioned four independent variables. In this learning process, 71 of the data was used for the training process and 10 of the data was used for the testing process. Five data will be applied for validation.

C. *Neural Network Data Training*

The parameters of the ANN training are chosen limitedly random with the hope of finding the best variable combination to obtain the best ANN training performance. Initially, the following parameters were used to determine the best ANN architecture for this case, namely:

1) *Iterations:*

35,000 iterations for each training process. In this experiment to define *the* best ANN architecture, the training process is limited to 35,000 epochs to limit the training time required for each training combination. With that limit, it is hoped that the best combination of the number of neurons in hidden layers could be found through the training process.

2) *Hidden layer:*

In this experiment, the hidden layer is restricted to two hidden layers to prevent the training process from taking an excessive amount of time, which would be unnecessary and perhaps could be done in further experiments.

3) *Neurons:*

The experiment attempts to find the best combination of architecture. Starting with a combination of one hidden layer with 2 hidden nodes without a second hidden layer, ending with a combination of a first hidden layer with 10 hidden nodes and a second hidden layer with 8 hidden nodes. It is assumed that even numbers, with a difference of one node, are sufficient to eliminate similar results generated by the training process produces more various results.

4) *Learning rate and momentum:*

The initial learning rate and momentum are set to be 0.1 to give space for them to adjust according to the need in the training process. The software will automatically adjust the learning rate and momentum as it trains the data until it reached the desired results.

5) *Weights:*

The initial weights are set using uniform random between -1 and +1. The weights will also update automatically in the software until it produces desired results.

The training process is conducted using software of Multiple Back-propagation versions 2.2.2. As described in the previous Section C, the parameters are tested using several combinations of several neurons in two hidden layers as shown in Table II.

TABLE II. ANN TRAINING PARAMETER

Para meter	Variable	Level 1	Level 2	Level 3	Level 4	Level 5
A	Hidden neurons in 1st hidden layer	2	4	6	8	10
B	Hidden neurons in 2nd hidden layer	0	2	4	6	8

The combination of Parameter A and Parameter B generates 25 combinations of training combinations. There is no exact evidence on setting a perfect combination between those variables. Ref [18] proved that through multiple alternatives used to analyze a data set, NN with one hidden layer outperformed a linear network with no hidden layer. Based on that information, it is assumed that a numerical model with hidden layers tends to produce a result in high accuracy compared to the one without a hidden layer.

The software was first to set to initiate the experiment until it reaches the 35,000 epochs of iterations, hoping that it could distinct the architecture combinations based on the RMSE and accuracies generated. The experiment shows that, with 35,000 epochs of iterations, the lowest RMSE of and the highest testing accuracy was produced by the combination number 21 (1 hidden layer with 10 nodes). The training and testing RMSEs were 0.0311 and 0.0573 respectively. The training and testing accuracies were 71% and 94.27% respectively. Fig. 2, indicates the testing accuracies of each combination.

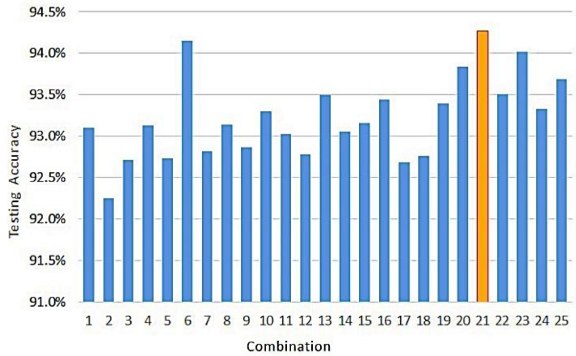

Fig. 2. Testing accuracy obtained from the training

The accuracy of training varies from 15% to 95% during the training process. Because the specified condition is that the software conduct training until it reached 35,000 epoch, the software stops carrying out the training process once it reaches the specified epochs. Therefore, the training process may be considered complete by the software even though the training accuracy is lower than the testing accuracy, which is imperfect and unsatisfactory.

Therefore, the observation made throughout the experiment, indicates that there was a finding in the process. The finding was that the RMSE generated was inconsistent. Occasionally, it generates the lowest RMSE during the training before the process is completed in 35,000 epochs of iterations, which caused the possibility that the RMSE could increase again during the training process's completion, as the software was configured to always complete the training process when it reaches 35,000 epochs of iterations. That means that this experiment did not succeed to generate the highest accuracy possible.

Therefore, the experiment must be repeated entirely with a different set of rules. This time, the software was configured to find the lowest RMSE throughout the process regardless of the iterations. That means that whenever the RMSE reaches its lowest and starts to rise again, it will stop the process and record the last data.

Indeed, the experiment with the new set of rules shows that the best RMSE and accuracy were possible to be obtained without necessarily requiring the training process to continue until it reached the 35,000 epochs of iterations. The training with this new set of rules also shows that combination number 21 still produces the best results, which concluded that the optimal architecture for this study was one hidden layer with 10 nodes inside the layer. Fig. 3 illustrates the architecture design.

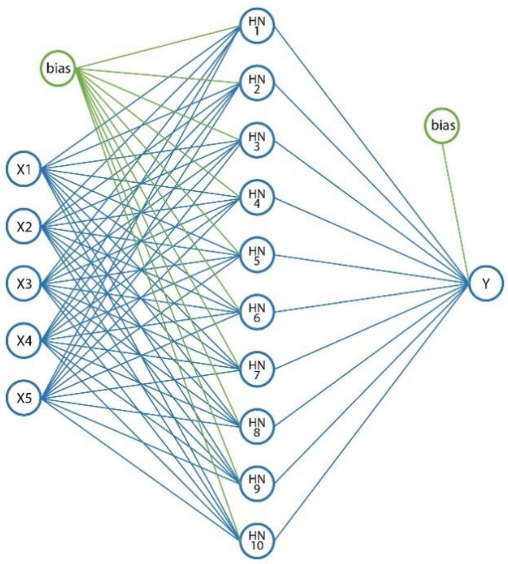

Fig. 3. Training network

However, what differentiated was that the training process was able to achieve better RMSE and accuracy with just 28,026 epochs of iterations, suggesting that a larger number of training epochs does not necessarily generate better results. Table III denotes the parameters recorded from the training process.

TABLE III. TRAINING EXPERIMENT USING 1 HIDDEN LAYER (10 HIDDEN NODES)

Variables		28,026 EPOCHS					Accuracy (%)	
Nodes HL 1	***Init. Weight***	***LR***	***MO***	***TR RMSE***	***TS RMSE***	***Time (min)***	***Training***	***Testing***
10	[-1;1]	0.057	0.434	0.0314	0.0436	28	96.86%	95.64%

The 28,026 epochs of iterations were succeeded in producing better training and testing accuracy of 96.86% and 95.64% respectively, also it recorded the lowest training and testing RMSE of 0.0314 and 0.0436 respectively. Unfortunately, the software did not provide a visualized comparison between the outputs of the neural network with the training data used. Fig. 4 exhibits a graph showing the training update for the training combination of 1 hidden layer and 10 hidden nodes. The black curve represents Traning and the red curve represents Testing. While the horizontal axis is the number of iterations and the vertical axis is RMSE.

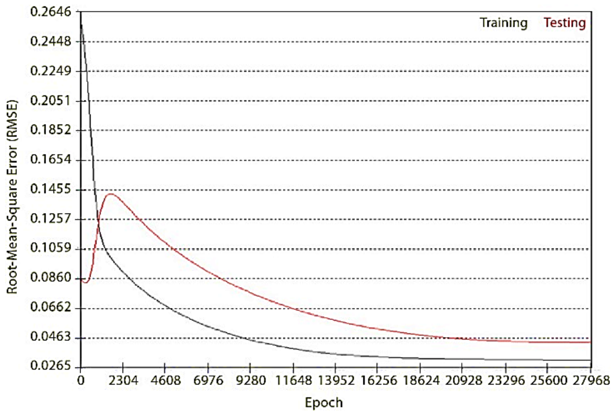

Fig. 4. Graph of training error update with 1 hidden layer and 10 hidden node

The RMSE and the weights generated on the final training and testing process are represented by Table IV and Table V. The weights will be used to predict surface roughness with the same variables, but with different values.

TABLE IV. WEIGHTS GENERATED FROM THE TRAINING PROCESS (1)

To the 1st HL	**From the input layer**					
	bias	***1st neuron***	***2nd neuron***	***3rd neuron***	***4th neuron***	***5th neuron***
1st neuron	-0.33784	-0.23359	0.21538	-0.10618	0.60300	-0.01251
2nd neuron	-0.47269	-0.09951	0.20746	0.56550	0.99864	0.68311
3rd neuron	-0.79575	0.64427	-0.46350	-0.29495	-0.45988	0.31561
4th neuron	0.04860	0.82896	0.89794	-0.43126	-0.43525	-0.33721
5th neuron	-0.80480	-0.98096	-1.02759	-0.02840	-0.07982	0.88776
6th neuron	0.14669	-0.13642	-0.81335	-0.00551	-1.28705	0.05464
7th neuron	0.08290	0.20186	0.80586	0.16451	0.72762	-0.72809
8th neuron	-0.77433	0.64776	0.94602	1.15013	-0.28043	-0.13613
9th neuron	0.86860	0.52458	-0.34193	-0.94177	-0.98548	-0.49564
10th neuron	0.27022	-0.35270	0.27674	0.78162	-0.25211	-0.09557

TABLE V. WEIGHTS GENERATED FROM THE TRAINING PROCESS (2)

To the output layer	Bias	From the 1st hidden layer				
		1st neuron	*2nd neuron*	*3rd neuron*	*4th neuron*	*5th neuron*
1st neuron	0.189	-0.399	0.843	0.226	0.583	-1.049
		6th neuron	*7th neuron*	*8th neuron*	*9th neuron*	*10th neuron*
		-1.602	0.955	1.164	-0.564	0.280

D. Validation

The data obtained from the ANN training has to be validated. The validation is required to be conducted to see if it can be used to predict the finish surface roughness. The followings are the prediction parameter used to validate the study and the variables are randomized between the maximum and the minimum number used in the experiment. Then the data is calculated using the weights generated by the 5-10-1 network, which produced the best accuracy. The roughness results generated are shown in Table VI.

TABLE VI. VALIDATION

No	Vt	Doc	Vw	HRC	MESH	Ra Predicted	Ra Actual	Accuracy (%)
1	166	0.013	364	54	105	2.51692	2.64	95.338%
2	110	0.008	408	59	116	2.39069	2.27	94.683%
3	111	0.006	416	57	113	2.34470	2.23	94.857%
4	162	0.007	368	51	74	2.43371	2.51	96.961%
5	133	0.011	449	52	114	2.47082	2.53	97.661%

The validation shows that utilizing the neural weights derived from prior data could predict surface roughness produced by a cylindrical grinding machine with an accuracy of 94.683-97.661 percent. This result concludes that the ANN approach could be utilized to forecast surface roughness of finished surfaces generated by grinding using the Vereco CNC Cylindrical Grinding Machine. The ANN weights will still be utilized in the future to estimate the roughness of cylindrical grinding on Vereco CNC machines. This calculating method is intended to boost corporate productivity and quality.

IV. CONCLUSION

This study has shown that the analysis of the error between the target value and the actual value obtained shows that the ANN approach with Backpropagation learning can predict finish surface roughness. The data set's training produces the following optimum learning combinations: Learning Rate (0.057), Momentum (0.434), Hidden Layer (1 layer), and Hidden Nodes (10 nodes). The optimum training combination generates an error of (0.314) and testing RMSE of (0.0436). The process accuracy was as follows: training accuracy (96.86%) and testing accuracy (95.64%). Predicting the final surface roughness with high accuracy (94.683-97.661%) may be achieved by using the best weights from the learning process.

To enhance the network's training outcomes, additional influencing independent factors, degrees of independent variables, and training combinations should be included. It is expected that the network will create better weights with fewer mistakes as more influencing independent variables, levels, and training combinations are added. In this study, the predictive capabilities of the ANN technique were effectively applied to heavy machinery operations, particularly cylindrical grinding on Vereco CNC machines.

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