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Modeling the Process Parameters of Roller Burnishing using RSM and Prediction of Micro Hardness using Artificial Neural Network

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Abstract— Neural network computational techniques are a new alternative to conventional numerical modeling. This paper presents modeling using response surface methodology (RSM). Box and Wilson Central Composite Design (CCD) is used for preparing experiment matrix. The independent parameters in the experiment are speed, feed, force and number of tool passes. These variables are controlled during the burnishing process. The response parameter is micro hardness. Experimental samples are prepared using Single Roller Burnishing Tools (Carbide). Vickers micro hardness tester is used to measure micro hardness. A quadratic mathematical model is developed using RSM. An Artificial neural network (ANN) model is developed using three-layer feed-forward back-propagation. The neural network model is trained using measured values of micro hardness. The different algorithms are used to train the model. Best performance is achieved with correlation coefficient 0.9. This study concludes that an artificial neural network is the best alternative to fit the nonlinear data.

Keywords—— Burnishing , RSM, Micro Hardness, ANN

I. INTRODUCTION

The performance of the product, besides the cost and time is becoming an important aspect in today's manufacturing industries. The performance of the product is influenced by the surface alteration during the manufacturing process. The mechanical and metallurgical modifications are in the outer most surface layer of few microns. This small layer significantly affects functional performance of the product. The machined surface inherently contains irregularities or deviations from the prescribed geometrical form. "No machining techniques, however precise, will manufacture a molecularly flat surface on standard materials" [1]. Burnishing is a finishing process that is used to impart specific physical, mechanical properties on surfaces. The principle of the burnishing method relies on plastic deformation, achieved via the applying of an extremely polished ball or roller subjected to an external force on the surface of the work piece. Engineering parts area often left with residual machining marks of irregular heights and spacing. Therefore, once the applied pressure surpasses the yield strength of the material, the asperities are compressed plastically and flow into the valleys, resulting in a smooth and uniform surface texture.

The effect of burnishing process on different mechanical and metallurgical properties is studied in the past. The past investigations can be categorised in five significant groups; use of contact mechanics to develop analytical model, study of one variable at a time approach, statistical techniques using design of experiment such Taguchi orthogonal array, response surface methodology and developing first order and second order empirical relationship, finite analysis with contact mechanics, and intelligence techniques such as fuzzy logic, artificial neural network.

Different techniques for fitting the linear and nonlinear data using regression analysis is successfully used in the last few decades. But recently an artificial neural network (ANN) becoming popular to fit the nonlinear data. A neural network modeling approach is used by [2] for the prediction of surface roughness (Ra) in milling. Data is collected with the experiment based on the principles of Taguchi Design of Experiments which used for the training and checking of the networks' performance. The ANN technique for hard turning process is used by [3]. The model predicts the surface roughness and tool flank wear. The combination of design of experiment (DoE) method and ANN is used by [4].Taguchi approach with the back-propagation neural network to accomplish faster convergence during training and the desired accuracy during the recall step [5]. An artificial neural network based predictive model of average surface roughness in turning hardened EN 24T steel has been presented by [6]. Artificial neural network results [7] showed that, generated models were capable of estimation of parameters with high accuracy.

Table 2 The chemical composition of the workpiece.

Si	Cu	Fe	Zn	Mn	Mg	Pb	Al
0.349	0.070	0.367	0.057	0.067	0.40	0.064	98.54

All these studies have judged the developed models using an ANN to be enough precise, so they can be used for the machined process. Based on previous literature studies abilities of the ANN include; able to fit nonlinear data; compare to conventional modeling approach ANN is more efficient; it is easy to add a new parameter in the ANN model; ANN software toolbox is available easily, hence without prior knowledge of programming it is easy to construct the ANN.

Table 1 Burnishing experiment matrix

standard order	Speed m/min	Feed mm/rev	For ce N	Tool passes	Microha rdness HV
5	20	0.5	40	2	114
17	10	0.6	30	3	96
2	40	0.5	20	2	88
24	30	0.6	30	5	138
7	20	0.7	40	2	117
16	40	0.7	40	4	110
27	30	0.6	30	3	102
19	30	0.4	30	3	116
14	40	0.5	40	4	120
31	30	0.6	30	3	115
8	40	0.7	40	2	93
9	20	0.5	20	4	106
13	20	0.5	40	4	116
21	30	0.6	10	3	81
30	30	0.6	30	3	114
4	40	0.7	20	2	76
12	40	0.7	20	4	106
23	30	0.6	30	1	98
15	20	0.7	40	4	120
20	30	0.8	30	3	107
3	20	0.7	20	2	93
22	30	0.6	50	3	116
18	50	0.6	30	3	106
1	20	0.5	20	2	91
10	40	0.5	20	4	117
11	20	0.7	20	4	109
26	30	0.6	30	3	101
6	40	0.5	40	2	103
25	30	0.6	30	3	103
29	30	0.6	30	3	113
28	30	0.6	30	3	103

Figure 1. Burnishing process

Limitations can be summarized as; different training algorithms are available such as BP, RB etc. hence it is difficult to choose one of them; a number of neurons in hidden layer are adjusted with trial and error; variety of transfer functions and training functions are available, so it becomes difficult to choose for an application; there are different opinions about the amount of training data and testing data.

II. EXPERIMENT METHODOLOGY AND MODEL DEVELOPMENT

This work examines the effect of roller burnishing process on Aluminum (Al 63400) work piece. The optical emission spectroscope is used to verify the composition of the work piece, the results are presented in the Table 2. The raw dimensions of the round work piece are 32 mm diameter and 600 mm length. The initial turning operation is performed with speed. Initial turning conditions were defined for all work pieces as cutting speed 40 m/min, feed = 0.2 mm/rev and depth of cut 0.1 mm. The surface tester is used to quantify the surface roughness Ra value. The observed values are in the range of 1.7 to 2.18 µm. The single roller carbide-burnishing tool is used in the experiment. The experimental setup is shown in the Figure 1.The roller penetration is controlled by the spring fitted in the shank of the tool. The spring stiffness value 19.33 N/mm is measured in the laboratory. This value is used for the calculation of the force. The force is measured using the dial gauge attached to the tool.

In this work four independent parameters which can be controlled during experiments are selected. These are speed, feed, force, and number of tool passes. The response or dependent variable is microhardness. The range of controllable parameters were observed in trial experiments. After these trial experiments, the range for speed (20-50 m/min), feed (0.5-0.8 mm/rev), force (20-50 N) and a

Figure 2. Microhardness testing

number of tool passes (1-5) were selected. In this study we have to fit a polynomial of degree two. Number of independent variable and degree of polynomial suggest that there are 15 coefficients in the model. Hence number of experimental run should be more than 15. Four factors and five levels CCD were selected. The experimental runs consist of 16 factorials, eight axials, and seven center points. Design matrix of these 31 experiments is developed with Design-Expert version 7.To make system error low the design matrix is arranged in the random manner as shown in the Table 1.

A. Experimental Characterization

The microhardness testing instrument MVH-1(square based diamond indenter microscopic attachment with computer display) is used for measurement. The magnification power of the instrument is in the range of 100X -600X.The instrument is shown in the Figure 2.

In microhardness testing very small force ranging from 100-1000g is applied depending upon the material. In the current work 500g load is applied on the workpiece with the help of diamond intender. The force is kept for 10 seconds. When the force is removed the indention, mark is left on the work piece. The shape of indentation mark is a rhombus. The built-in microscope of 100X-600X used to measure the diagonals of the mark. The microhardness is depending upon the force and area of the indentation mark. The value of Vickers microhardness is calculated using the formula ($HV=1.84\ F / d^2$). Where, F= Load in kgf and d = average of the diagonals, d_1 and d_2 in mm. To minimize the experimental error, three readings were taken along the periphery of the workpiece. The average of three reading is used. The observed values are summarized in the Table 1.

B. Statistical significance of the experiments

Once the data is collected from the experiment, it is analyzed with the help of ANOVA. The regression analysis is used to build empirical model, which is generally of first order or second order. The statistical significance of the model is checked using p-value and lack of fit test. The p-value is 0.0001 which significantly less than 0.05. Lack of fit is insignificant. Hence the statistical validity of the model is verified. After testing the significance of the quadratic model, the individual and interaction effects of parameters was studied. Linear effects of speed, and feed are insignificant parameters even though their quadratic effects are significant. The "Lack of Fit F-value" of 0.60 implies the Lack of Fit is not significant relative to the pure error. There is a 77.32% chance that a "Lack of Fit F-value" this large could occur due to noise. Fitness of the quadratic model is assessed by the R^2 value. This value is in the range of 0-1. Value zero indicate no fit at all and one indicate perfect fit, which is ideal case. In the
Statistical analysis this value should be around 0.9 for best fit. In the current analysis the value is 0.899 which confirms the fitness of the model. The model can be efficiently used to predict the responses.

III. ARTIFICIAL NEURAL NETWORK

The biological neural network used by brain consists millions of neurons interconnected with neighbors. The neurons communicate with each other through electrochemical signal. ANN structure is based on the biological neural network. Biological neural network consists of cell body (soma), dendrites, axon, and synapses. The neurons are connected through synapses through which input signals are received. When sum of signal surpasses a threshold, a response is sent through axon. A neuron is an information-processing unit that is fundamental to the operation of the neural network. The input signal is received through synaptic connections. The connections have its own strength termed as weight which may be a positive or negative number. Each input is multiplied by the weight of the synaptic connection and summed together. The externally applied bias is added to this sum which gives induced local field. On this field, activation function or squashing function is applied to give the desired output. The output range within certain interval is computed by the activation function.

A. Design of ANN

Design of network consists of three important tasks, collection and preparation of the data, selection of the architecture and finally measure the performance of the network. In the neural network design process, data should be collected first, and then prepared as sample input. The

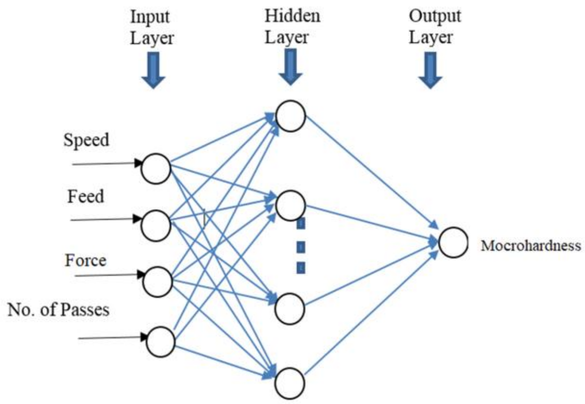

Figure 3. Schematic representation of ANN model

experimentation knowledge cannot be incorporated in the neural network; hence, accuracy is entirely depending on the data prepared to train the network. Multilayer networks can be trained to generalize well within the range of inputs for which they have been trained. It is not able to accurately extrapolate beyond the data range of experimentation. Therefore, experimentation should span the full range of input space of neural network. Experimental data is pre-processed and dived into subsets before it is used to train the data. In this study, data is used from previous experimentation done with response surface method. Dataset of 31 experiments are available to prepare neural network.

B. Collection and preparation of the data

In the experiment data units of parameters are speed in m/min, feed in mm/rev, and force in Newton. All the parameters are expressed in different units. Also, the magnitude of the absolute values (0.5 to 40) is very different. Hence pre-processing of the raw data is essential. Hence the experiment data should be normalized first. Normalization is a pre-processing technique used to rescale attribute values to fit in a specific range. Nonlinear activation functions squash the output in the range of (0, 1) or (-1, 1). Hence it is necessary to rescale the output values in actual units. The normalize data speed up computation as reported by [8]. Different techniques are used for normalization such as min-max , and z-score as reported by [9].

Typical data flow sequence is input layer-preprocessing block-first layer-hidden layers-post processing block-output layer. In the burnishing process data presented in the Tab. 2 for controllable parameters and responses is normalized using min-max formula, in the range of (-1,1).

C. Dividing the data

In an ANN the normalized data is separated into three parts, training set, validation set, and test set. The amount of data used for training, validation, and testing varies in the literature review. But several studies uses a small amount of data less than 30 and still the network presented a good performance[10]. There is no general guideline to divide the data for training, testing and validation. If training samples are more than the amount of testing samples network gives satisfactory results as suggested by [11]. The recommended ratios are 90%:5%:5%, 80%:10%:10% and 70%:15%; 15% for training, testing and validation respectively. In the current research work the ratios of 70%:15%, 15% is used which is the default style of MATLAB.

The training set consists of the input signal along with output signal. The burnishing controllable parameters are input signal and surface microhardness is output signal. From the experimental results of the burnishing process 70% data is selected randomly for training set. During the computations the synaptic weights and thresholds are adjusted, till there is discrepancy between output signal and the desired output corresponding input from the experiment results. When the discrepancy falls within an acceptable limit, the generalized solution is achieved. Validation data set do not adjust the weight of the network. It is used to avoid overfitting and stopping criteria of the training process. The test data is used to check the final performance of a developed model. The data set ideally should be independent of the training and validation set. The model is now allowed to predict with inputs from a new set of data. Therefore, the results generated will reflect the model's success/failure. This will be your real-world implementation.

D. Network architecture

The number of input nodes corresponds to the number of variables or parameters used for the study. It is recommended that one should select the minimum number of parameter which embed the unique features of the experiment/process. Statistical methods such as the design of experiment are used in the preliminary stage to select the process parameters. Four burnishing parameters are selected are speed, feed, force and number of tool passes. The number of output nodes are relatively easy to specify as it is directly related to the problem under investigation. In the current research work one-output node, is for surface microhardness.

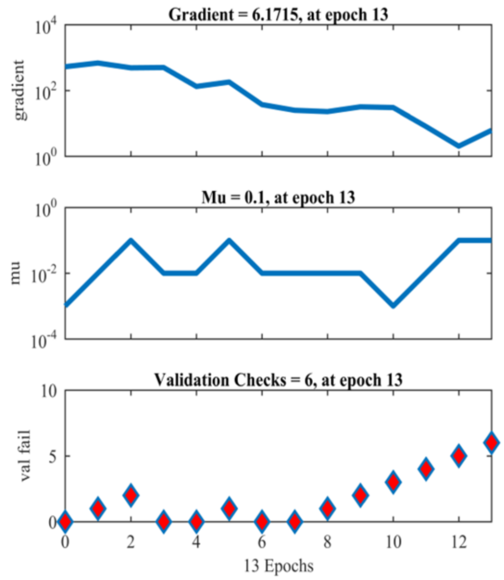

Figure 6. Training state ANN for microhardness model

Number of hidden layers selected is generally depends on the complexity of the problem. Typical range is one to four. Each layer is fully connected to the succeeding layer. Without hidden layer, ANN becomes just a statistical regression tool. Researchers are free to vary a number of hidden layers and number of neurons within it. Increasing the number of neurons in the hidden layer increases the power of the network but requires more computation and is more likely to produce overfitting. Increasing the number of layers added more complexity hence in this study number of hidden layer is kept one and number of neurons within it is varied. Guidelines for number of nodes in the hidden layer is reported by [11]. It should be n/2, 1n, 2n or 2n+1 where n is number of input nodes. In the current research work n=4 hence a number of hidden neurons are 2,4,8,9. Such type of network structure is designated as 4-j-1 meaning that it has four input neurons in input layer, j neurons in hidden layer and one neuron in output layer. The researchers have applied various structures to get the best performance. For example the work of [12] studies eight network structures, which are 3–1–1, 3–3–1, 3–6–1, 3–7–1, 3–1–1–1, 3–3–3–1, 3–6–6–1 and 3–7–7–1. [10] studies structure of 5-5-1, 5-10-1, 5-15-1 and 5-20-1. The feed-forward back-propagation model for burnishing process is developed using Neural Network Toolbox™ 7 of MATLAB. Model is of three-layer input, hidden and output is schematically represented in the Figure 3. All the neurons in the layers are connected to each other. In the input layer, there are four neurons for four independent controllable burnishing process parameters. The second layer is the hidden layer where a number of neurons are varied. A number of neurons selected are 1, 2,4,6,8 and 9. In output layer, there is one neuron. The networks 4-1-1, 4-2-1, 4-4-1, 4-6-1, 4-8-1and 4-9-1 is tested for surface microhardness.

E. Selection of activation function

The activation function also called as a transfer function determines the relationship between the input and output nodes of the neural network. The activation function introduces the nonlinearity in the neural network. Any differentiable function can be used as the activation function. However, the previous research of indicating that nature of problem decides a transfer function. In the current work mathematical model is built with RSM. Suggested model for the burnishing parameters and responses surface microhardness is quadratic relationship. Hence a nonlinear transfer function is used. Hence, among the above logistic transfer function is mostly used to train the Network. The neural network training is nothing but unconstrained nonlinear optimization problem. During training, the weights are iteratively modified to minimize the mean square error between the desired and actual output values for all output nodes over all input patterns. Many optimization methods are available to solve an unconstrained nonlinear optimization problem, hence there is various algorithms are available for neural network training. The most popular method is back-propagation algorithm, which implements a gradient steepest descent method of optimization. The back-propagation computation is derived using the chain rule of calculus. For gradient descent algorithm, a step size, which is called the

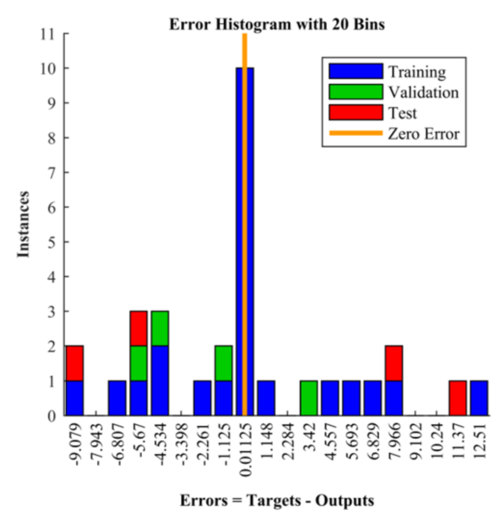

Figure 5. Histogram of ANN for microhardness model

learning rate in ANN, must be specified. Learning rate determines the magnitude of weight changes. Convergence of the algorithm depends on learning rate; the smaller learning rate tends to slow the learning process while the larger learning rate may cause the network to oscillate.

To overcome this difficulty, the concept of momentum parameter is introduced in the algorithm. Due to the momentum parameter, it is possible to use large learning rate resulting in fast convergence. As the learning rate and momentum can take any value between 0 and 1, it is impossible to find the best combination. The variation and modification results in numerous training algorithms. The training algorithm used in the current work are Levenberg-Marquardt, Bayesian Regularization, Scaled Conjugate Gradient, Variable Learning Rate Gradient Descent, and Gradient Descent. Performance of the network

F. Performance of the network

The most important measure of performance is the prediction accuracy it can achieve beyond the training data as reported by [11]. Forecasting error is used for the performance of the network. It is the difference between the desired value and the predicted value. Different forecasting methods are presented in the literature. The different method generally provides different performance, hence [13] reported that number of different methods should be used and aggregate the information to judge the performance of the network.

After training is finished network performance can be checked by the performance plot, training state plot, error histogram plot and regression plot. The performance is often measured in terms of accuracy of forecasting error, which is the difference between the actual and predicted value. The error is calculated by different techniques. The most frequently used techniques are: mean absolute deviation, sum of squared error, mean squared error and root mean squared error. There is no guideline which performance function should be used. Based on the literature review, MSE performance function is used in the current work.

To determine the best network structure, two criteria are considered. The first criterion is the consideration of the smallest value for the absolute average error value of the testing sample set to justify the network structure that gives the best prediction for the surface microhardness value. In this way, the absolute average value of MSE is calculated for each network structure. The aim is for the MSE absolute average to be as small as possible (approaching zero) to justify that the network structure has given the best prediction. The comparison of different training algorithms and variations of nodes is determined for all the network networks 4-1-1,4-2-1, 4-4-1, 4-6-1, 4-8-1and 4-9-1 and the best network found is 4-1-1 and 4-2-1 for surface microhardness. The performance of this to networks is discussed in the following section.

The performance plot Figure 4 shows the value of the performance function versus the iteration number for microhardness. It plots, training, validation and test performances. From graph, the error reduces after more epochs of training. The best validation performance is at 9 th epochs for surface microhardness. There is no increase in error on the validation data, indicates that the network does not start overfitting the training data. The best performance is taken from the epoch with the lowest validation error.

The error histogram plot Figure 5 shows the distribution of the network errors for surface microhardness and microhardness respectively. The error has uniform distribution pattern about zero. The training state plot is shown in the Figure 6. It shows the progress of other training variables, such as the gradient magnitude, the number of validation checks, etc. The regression plot Figure 7 shows a regression between network outputs and network targets.

If the training were perfect, the network outputs and the targets would be exactly equal, but the relationship is rarely perfect in practice. The three axes represent the training, validation and testing data. The dashed line in each axis

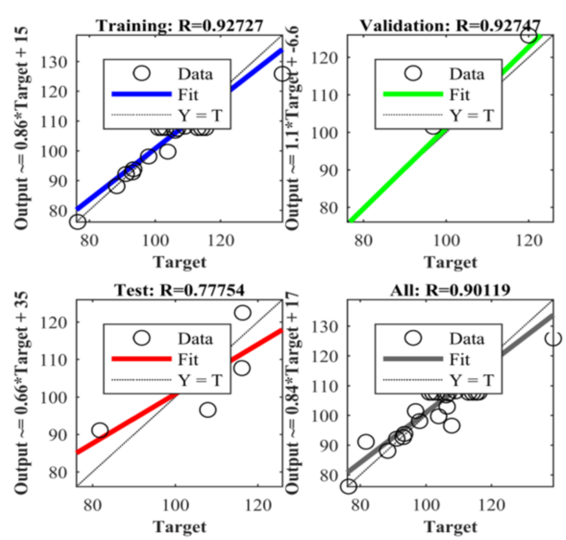

Figure 7. Regression ANN for microhardness model

represents the perfect result – outputs = targets. The solid line represents the best-fit linear regression line between outputs and targets. The R-value is an indication of the relationship between the outputs and targets.

This value is in the range of 0-1. Value zero indicate no relationship at all and one indicate perfect relationship, which is ideal case. In the ANN analysis this value should be around 0.9 for best fit. In the current analysis the value is 0.9 which confirms the fitness of the model. The network can be efficiently used to predict the responses.If the network is not sufficiently accurate, you can try initializing the network and the training again. In such a situation number of neurons in hidden layer is increased gradually which gives network more flexibility to optimize the parameters or different training function is used.

IV. CONCLUSIONS

In this research review of the burnishing process for microhardness, using ANN is discussed. An experiment was conducted using RSM with CCD. Total 31 experiments were performed. The controllable parameters are speed, feed, force and number of passes. The responses are microhardness. ANOVA is performed to check the validity of the model developed. The experimental data are used in developing an ANN.

An important issue of ANN modelling is discussed. The number of layers and number of neurons in the hidden layer is determined using trial and error method. The issue relating sample size and distribution of data for training, testing and validation are discussed.

Modifying the number of neurons in the hidden layer, with same training algorithm and the same sample size and its distribution gives different values for microhardness. The study has applied to 4-1-1, 4-2-1, 4-4-1, 4-6-1, 4-8-1and 4-9-1 network structures. The 4-1-1 and 4-2-1 structure gives the best performance for the microhardness respectively. Best performance is achieved with correlation coefficient 0.9 for the response microhardness.

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