RESEARCH ARTICLE OPEN ACCESS

Smart Prediction of Surface Finishing Quality of En-8 Work Piece by ANN Model

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ABSTRACT

Turning is a material removal process a subtractive form of machining which is used to create parts of circular or rotational form of desired geometry/shape by removing unwanted material. Accuracy of any process depends on involvement of operational variables. The operating parameters that contribute to turning process are Cutting speed, Depth of cut, Feed rate. Vibrations, tool life, tool wear, surface finish and cutting forces etc are also in direct relation with values selected for process parameters. So to improve the efficiency of process and quality of the product it is necessary to control the process parameters. We have considered surface roughness the parameters with main focus as it dictates the aesthetics and sometimes ergonomical characteristics of the product. In this work a neural network is created using feed forward back propagation technique for simulation of the process using the Matlab Neural network toolbox. So with assurance of accuracy of the predictive capabilities of the neural network it was then used for optimization.

Keywords:- Artificial Neural Network, MATLAB, MRE, MSE, Regression, Surface roughness, Turning process.

I. INTRODUCTION

Metal forming will be analysed as a method of managing metals, to develop elements, their assemblies, and their structures. It represent a large array of producing processes. concerning seventieth of the metals forming processes ar analysed by metal cutting that is additionally a kind of reductive producing. for the length of those procedures, power driven machine tools ar used to urge obviate the fabric from the present pure mathematics or form to the well-liked shapes. Cutting processes are divided into many procedures that chiefly embrace drilling, milling, grinding, and turning. Considering its pertinency and flexibility, there ought to be no confusion that turning is amongst the foremost necessary processes. the subsequent processes will be performed with success on the turning machine: Chamfering, a angle on the on the corner of the piece of work for easier sexual activity of the parts; parting, cutting the tip of the half by giving radial feed to the tool; threading, to provide either external or internal threads; boring, one purpose tool given a linear feed on the axis of rotation. the most applications would come with machine elements, shafts, engine elements like pistons, cylinders, pulleys, axles, etc.

For this model development the info has been taken from the experimental study applied on piece of work material particularly EN-8 with coated ceramic tool. The tests were carried for a length of sixtyX 60 millimeter during a Madras machine mfrs. Ltd lathe. the most objective of this paper is to hold out the experiments by choosing totally different variables and their levels, applying artificial neural network (ANN) then analyzing the results obtained victimization

multivariate analysis, Mean sq. Error(MSE) and Magnitude of Relative Error (MRE). The results obtained conclude that ANN is reliable methodology and it will be promptly applied to totally different metal cutting processes with bigger confidence.

II. THE TURNING OPERATION

Turning may be a material deduction method, a reductive kind of machining that is employed to form elements of circular or move kind of desired geometry/shape by removing superfluous material. The necessary parts of the turning method ar machine or shaping machine, piece of work material that may be a piece of a pre-shaped half, the fixture to that the fabric is connected. The fixture is tied to the turning machine and is then permissible to rotate for a large vary of speeds. the opposite finish of the piece of work is engaged with the tail stock to permit good rotation and avoid eccentric rotations. The abstract illustration of a turning machine is represented in Figure 1.

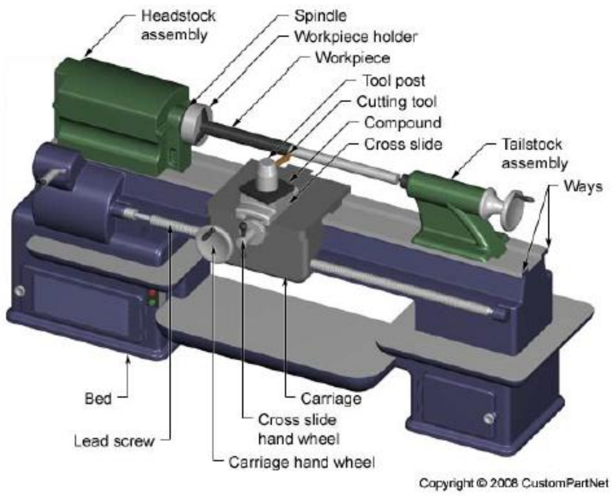

Figure 1: Representation of lathe machine

III. RELATED WORK

Lee and chen (2003) highlighted on artificial neural networks employing a sensing technique to observe the result of vibration made by the motions of the cutter and work piece throughout the cutting method developed an on-line surface recognition system [5]. Choudhury and Bartarya (2003) centered on style of experiments and also the neural network for prediction of tool wear. The input parameters were cutting speed, feed and depth of cut; flank wear, surface finish and cutting zone temperature were hand-picked as outputs [3]. Chien and Tsai (2003) developed a model for the prediction of tool flank wear followed by an improvement model for the determination of best cutting conditions in machining 17-4PH stainless-steel. The back-propagation neural network (BPN) was accustomed construct the prognostic model [2].

Ozel and Karpat (2005) studied for prediction of surface roughness and gear flank wear by utilizing the neural network model compared with regression model [8].

Kohli and Dixit (2005) projected a neural-network-based methodology with the acceleration of the radial vibration of the tool holder as feedback. For the surface roughness prediction in turning method the back-propagation formula was used for coaching the network model [4].

Pal and Chakraborty (2005) studied on development of a back propagation neural network model for prediction of surface roughness in turning operation and used steel work-pieces with high speed steel because the cutter for acting an outsized range of experiments [9].

Ozel and Karpat (2005) developed models supported feed forward neural networks in predicting accurately each surface roughness and gear flank wear in end dry laborious turning [8].

Abburi and Dixit (2006) developed a knowledge-based system for the prediction of surface roughness in turning method. Fuzzy pure mathematics and neural networks were used for this purpose [1].

Zhong et al. (2006) expected the surface roughness of turned surfaces victimization networks with seven inputs particularly tool insert grade, work piece material, tool nose radius, rake angle, depth of cut, spindle rate, and feed rate [12].

Reddy et al. (2008) adopted multiple correlation model and artificial neural network to manage surface roughness prediction model for machining of metallic element alloys by CNC turning. For judgment the potency and skill of the model in surface roughness prediction the authors used share|the share|the proportion} deviation and average percentage deviation [10].

Wang et al. (2008) studied on Hybrid Neural Network-based modeling approach integrated with Associate in Nursing analytical tool wear model and a synthetic neural network that was accustomed predict CBN tool flank wear in turning of hardened 52100 bearing steel [11].

IV. DEVELOPMENT OF ANN MODELS

A. Choice of performance criteria:

The first stage within the ANN model development method is that the selection of performance criteria, as this finds out however the model is assessed and can as a result have an effect on several of the succeeding steps like coaching and also the selection of spec. Performance criteria might embrace measures of coaching and process speed; but, the foremost usually used performance criteria are Root Mean square Error (RMSE), Mean Absolute Error (MAE), Regression ®, Magnitude of Relative Error (MRE), coefficient of correlation (CC), etc.

B. **Choice of data sets:**

At a minimum, the available data need to be divided into two subsets; one for training and the other for independent validation of the trained model. However, in general, three data sets are required; namely a training, testing and validation set. Cross-validation with an independent data set is usually engaged during training to evade overfitting. The same happens if a trial-and-error procedure is used to optimise the network architecture or to choose the network inputs or parameters of the optimisation algorithm used. Therefore, the training data are used to search for an optimal set of network weights, the testing data are used to select the finest network during development and, if cross-validation is in use, to prevent overfitting, and the validation set is used to validate or confirm the generalisability of the selected model. Therefore, to attain good generalisation of the data generating relationship, the training data should be a representative sample of the population from which the data were obtained. While it is important for each of the data subsets to be representative of the data population, the proportion of samples to be included in each of the subsets is also a vital consideration. An optimal training data set is "one that fully represents the modelling domain and has the minimum number of data pairs in training". This is so because large sets of recurring data can reduce training with only slight progress in network performance. However, due to the time and cost factors involved in data collection, in many practical cases the available data are limited. Therefore, it is again important to consider the comparative sizes of the subsets, so as to include the utmost amount of information in the training data set.

C. Data Pre-processing:

Data pre-processing involves data transformation into a format that will enable easier and more effective processing by the ANN. This may include rescaling, standardisation, de-trending, distribution, transformation and removal of outliers. The easiest and most frequently used form of pre-processing is linear transformation, which involve transforming the data such that the variables have same values. Rescaling generally refers to the scaling of data between specified upper and lower bounds. If xi is the ith raw value of variable x, the ith linearly transformed value can be obtained by rescaling according to (1):

$$\tilde{x}_i = \left(\frac{x^T_{high} - x^T_{low}}{x_{\max} - x_{\min}} \right) . x_i + \left(\frac{x^T_{low} . x_{\max} - x^T_{high} . x_{\min}}{x_{\max} - x_{\min}} \right)$$

(1)

Where in (1), xmax and xmin are the maximum and minimum values of the untransformed variable, while xThigh and xTlow are specified upper and lower bounds which become the new maximum and minimum values of the transformed data, respectively.

D. Determination of ANN inputs:

Finding out what the vital inputs are for a given problem will be one of the greatest critical factors in ANN model development, as the inputs contain the key information necessary to define the data-generating association. This can also be one of the most tricky tasks in modelling. Also the number of potentially important inputs can be great. However, the insertion of superfluous inputs is not needed, as such inputs do not give any useful information about the causal relationship, but enhance the size and difficulty of the network, making the task of extracting significant information from the data tough. On the other hand, leaving out key inputs results in a loss of important information, which can be harmful to the predictive performance of an ANN.

E. Determination of ANN architecture:

ANN architecture consists of the number of input and output nodes, the number and configuration of hidden layer nodes, the connection between the nodes and the types of activation functions used within the network. Therefore, network architecture determines model complexity. In case of fully connected feedforward Multi Layer Perceptrons (MLP), in which the input and output nodes are predetermined according to the number of input and output variables included in the model, hence finding of an suitable ANN architecture, and thus model difficulty, comes down to selecting the number and configuration of hidden layer nodes and selecting which activation functions to use on the hidden and output layers [7][6].

Activation functions are required to bring in nonlinearity into an ANN. Any nonlinear function is capable of this. However, when a gradient descent type search algorithm is used for training, the activation function must be continuous and differentiable. Sigmoidal activation functions, such as the logistic or the hyperbolic tangent (tanh), given by (2) and (3), respectively (where gin is the summed input to a node), are very much used on the hidden layer nodes. The tanh, logistic and linear activation functions are shown in Figure 2 where it can be seen that the tanh and logistic activation functions are bounded on the ranges [-1,1] and [0,1], respectively, whereas the linear function is un-restricted.

$$g(zin) = \frac{1}{1+e^{-zin}} \quad (2)$$

$$g(zin) = \frac{e^{zin} - e^{-zin}}{e^{zin} + e^{-zin}} \quad (3)$$

$$g(zin) = zin \qquad (4)$$

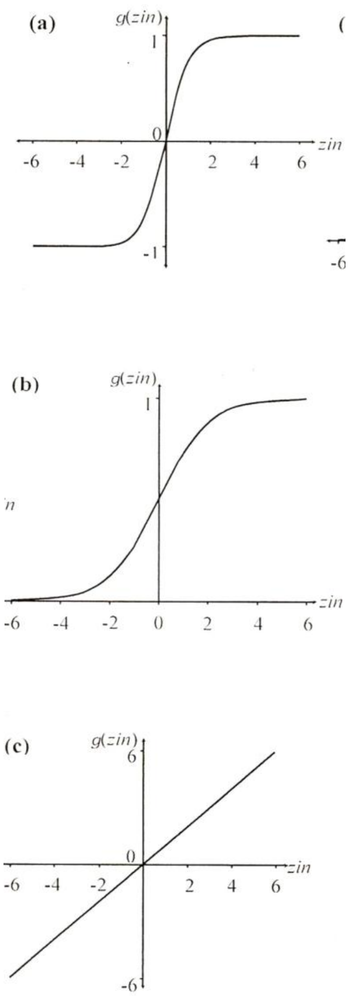

Fig. 2: Typical activation function (a) tanh, (b) logistic and (c) linear or identity

The ease in ANN architecture determination largely lies in selecting the number and configuration of hidden layer nodes, which, in turn, determine the number of weights in the model. However, this is one of the most vital and intricate tasks in designing an ANN. Usually, the number of hidden layers is fixed, next the number of nodes in each hidden layer is selected. As mentioned earlier, only one hidden layer is necessary to estimate any continuous function. Even though the above results are helpful in selecting the number of hidden layers, they do not give any guidance in selecting the number of hidden nodes. Theoretically, the best number of hidden nodes is that which results in the smallest network able to sufficiently capture the underlying association in the data. An equilibrium is required between having too few hidden nodes such that there are inadequate degrees of freedom to sufficiently capture the underlying relationship (i.e. the data are underfitted), and having too many hidden nodes such that the model fits to noise in the individual data points, rather than the general trend underlying the data as a whole (i.e. the data are overfitted) [7][6].

The most frequently used method for obtaining the number of hidden layer nodes is by trial-and error, where a number of networks are trained, while the number of hidden nodes is steadily increased or decreased until the network with the best generalisability is found.

F. ANN Training:

During training the plan is to search for values for the connection and bias weights so that the output formed by the ANN estimate the training data well. However, it is not enough to just reproduce solution in the training data set; rather, a generalized solution appropriate to all examples is necessary. ANNs, like all mathematical models, work on the supposition that there is a real function underneath a system that relates a set of K independent predictor variable xK to M dependent variables of interest yM . Therefore, the in general the aim of ANN training is to deduce an acceptable estimate of this relationship from the training data, so that the model can be used to create accurate forecast when presented with new data.

G. ANN validation:

An ANN can attain nearly perfect “in-sample” performance, which is evaluated according to the fit between the model outputs and the sample of data that it was trained on. On the other hand, before the model can be used to produce predictions or simulate data, it needs to be validated, which is usually done by evaluating its “out-of-sample” performance, or generalisability when applied to an independent set of validation data, using the performance criteria chosen. To make sure appropriate validation of the ANN model, it is very important that the validation data were not used in any way during training and model selection.

V. RESULTS AND DISCUSSIONS

This section describes the best achieved results for ANN model. Table 1 below shows the computed values of Regression and MSE values for the model considering different network structures. For the network identification used in the second column of table the first number indicates the number of neurons in the input layer, the last number indicates the number of neurons in the output layer, and the numbers in between represent neurons in the hidden layer.

From table 1, it is clear that for ANN model 3-2-1 is the best model developed with the least MSE value of 0.00913 and the best regresion values of 0.9935, and 0.9960 for training, and testing data sets respectively and overall regression value of 0.9923. The same has been depicted graphically in figure 3 given below. Further, from Table 1 it is evident that as the number of neurons in the hidden layer increases the performance of the ANN model in terms of regression as well as MSE values decreases, although there is an improvement in the training dataset regression value for 3-4-1 and 3-6-1 network models.

Table 1:- Statistical Parameters for different network structures for M1 Model

Structure No.	No. of Neurons	Regression Values	
		Training Val.	Testing Val.
1	**2**	**0.9935**	**0.9960**
2	4	0.998	0.9613
3	6	0.999	0.953
4	8	0.767	0.9103
5	10	0.977	0.227
6	15	1.000	0.765
7	20	0.618	0.028

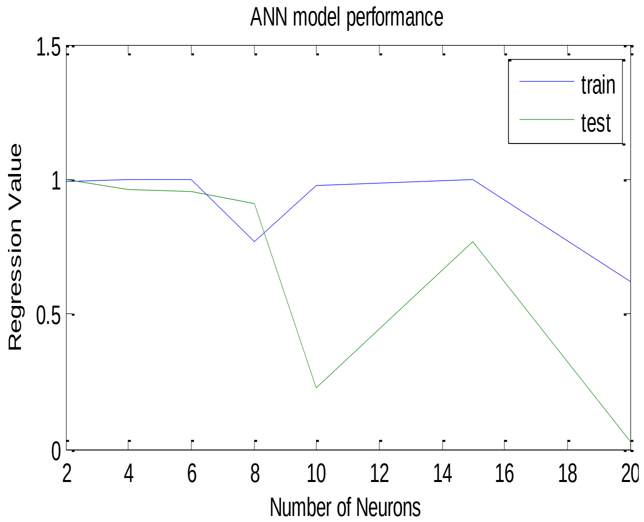

Fig 3:- Graphical representation of Regression values for ANN Model

Further from table 1 and figure 3 one can see that in general the R values for training are in general better than testing and validating datasets except for 3-2-1 model wherein testing and validating datasets have performed better.

VI. CONCLUSIONS

In this paper, applicability and capability of ANN technique for surface roughness prediction has been investigated. For this the experimental data has been procured from the earlier published paper in published in International Journal of Engineering Science and Advance Technology, Vol.2, Issue 4, 2012, pp 807-812. ANN model having variable number of neurons in the hidden layer were trained and tested using ANN technique. It is seen that in this study ANN model is very robust, characterised by fast computation and capable of handling the noisy and approximate data. In ANN model, 3-2-1 network structure was found to be the best forecasting model.

REFERENCES

[1]. Abburi N. R. and Dixit U. S., (2006), "A knowledge-based system for the prediction of surface roughness in turning process" Robotics and Computer-Integrated Manufacturing, Volume 22, pp. 363–372.

[2]. Chien W.T. and Tsai C.S., (2003), "The investigation on the prediction of tool wear and the determination of optimum cutting conditions in machining 17-4PH stainless steel", Journal of Materials Processing Technology, Volume 140, pp. 340–345.

[3]. Choudhury S. K. and Bartarya G., (2003), "Role of temperature and surface finish in predicting tool wear using neural network and design of experiments", International Journal of Machine Tools and Manufacture, Volume 43, pp. 747–753.

[4] Kohli A. and Dixit U. S., (2005),"A neural-network-based methodology for the prediction of surface roughness in a turning process", International Journal of Advanced Manufacturing Technology, Volume 25, pp.118–129.

[5] Lee S. S. and Chen J. C., (2003), "Online surface roughness recognition system using artificial neural networks system in turning operations" International Journal of Advanced Manufacturing Technology, Volume 22, pp. 498–509.

[6]. MACLEOD, C. "An Introduction to Practical Neural Networks and Genetic Algorithms for Scientists and Engineers".

[7]. MAIER, H.R., (1995), "A review of Artificial Neural Network.", Research Report no. R131. Dept. of Civil and Env. Engg. The University of Adelaide.

[8]. Ozel T. and Karpat Y., (2005), "Predictive modeling of surface roughness and tool wear in hard turning using regression and neural networks", International Journal of Machine Tools and Manufacture, Volume 45, pp. 467–479.

[9]. Pal S. K. and Chakraborty D., (2005), "Surface roughness prediction in turning using artificial neural network", Neural Computing and Application, Volume14, pp. 319–324.

[10] Reddy B. S., Padmanabhan G. and Reddy K. V. K., (2008), "Surface Roughness Prediction Techniques for CNC turning", Asian Journal of Scientific Research, Volume 1, Number 3, pp. 256-264.

[11] Wang M. Y. and Lan T. S., (2008), "Parametric Optimization on Multi-Objective Precision Turning Using Grey Relational Analysis", Information Technology Journal, Volume 7, pp.1072-1076.

[12] Zhong Z. W., Khoo L. P. and Han S. T., (2006), "Prediction of surface roughness of turned surfaces using neural networks", International Journal of Advance Manufacturing Technology, Volume 28, pp. 688–693.