A Multivariate model of orthogonal turning operation on cutting tool dynamics modeled by optimum cutting parameters using genetic algorithm

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Abstract: Turning accuracy and high productivity rates have become the key determinants and both accuracy and surface quality plays vital role. In this publication a diversified multivariate model of an orthogonal turning operation has been formulated considering a series of turning experiments. Using the obtained experimental data, the cutting dynamics has been modeled with radial basis function neural network for different work piece materials. In par with basic cutting parameters, tool overhang and tool wear were selected as inputs and static cutting edge forces, average roughness values and critical chatter length on work piece were presented as outputs. For four work materials considered in experiments, four neural networks were trained. Using these neural network models, optimum cutting parameters such as speed, depth of cut, feed and tool-overhang lengths are projected by minimizing total cutting edge force with the help of genetic algorithms.

Keywords: cutting parameters, design parameters, neural network and genetic algorithm.

I. INTRODUCTION

Turning is one of the widespread machining operations in various industries. In this process, it work-piece rotates about its own longitudinal axis on the head stock of a machine called lathe. The work-piece is supported by the chuck at one end called head stock and by a tailstock at the other. A cutting tool mounted on the tool post of the lathe is fed along the work-piece axis to remove material according to the dimensions and produce the required shape.

In this process, there are several parameters that define the cutting conditions. They are cutting speed, feed rate, and cutting depth. Cutting speed is defined as the rate at which the uncut portion of the surface of the work-piece passes along the cutting edge of the tool. Feed rate is calculated as the distance moved by the cutting tool along the longitudinal direction for each revolution made. Cutting depth is defined as the thickness of the metal that is removed along the radial direction. by the cutting tool in the longitudinal direction in each revolution. Cutting depth is the thickness of the metal removed in the radial direction. The principal surface machined is concentric with the axis of the work-piece as shown in Fig 1.1.

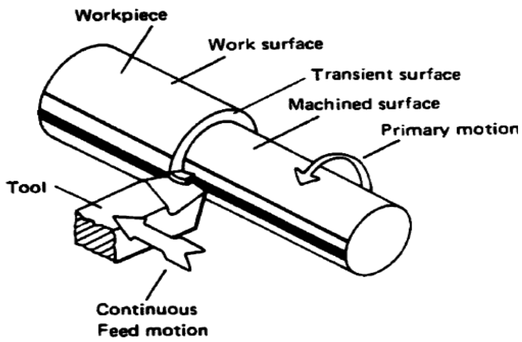

Figure 1.1: Cylindrical turning on a lathe

Turning operations are more predominantly used to more accurately and precisely produce net shapes in the manufacturing sector. Applications range from the turning of dies and molds, jet engine spares made from heat resistant alloy components, aircraft fuselage components and wing panel structures, and especially biomedical parts. The machining of small and compact structures may technically only take a few minutes compared to the overall mass production applications in industries, while complex dies, molds and aerospace structures in fact may take several more days of turning when accuracy and productivity rates become crucial determinants in the economic persistence of the manufacturing industry. Both the accuracy of dimension and surface quality of machined parts are usually influenced by the relative vibrations between the machine tool used and machine part structures, the selection of appropriate tool geometry and grade, the positioning accuracy of the tool and the work piece, and the thermal stability of the computer controlled machine tools. Process planners usually select cutting conditions such as depths of cut, spindle speeds, and feed-rates based on their accumulated experience and knowledge which has been gained earlier.

II. Experimental analysis

Further in the third study, the experimental cutting tests are performed on the 1Hp center lathe machine available at the CMTI Bangalore. To record output response parameters such as the cutting force of the components along all three directions (X.Y and Z), flank wear, surface roughness & critical chatter lengths with the process input factors.

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In this parametric study four different work piece materials are considered for the experimental analysis and their levels are given in the Table 2.1.

Table 2.1 Cutting operational parameters with various levels

Work-piece Material	Cutting Speed rate (m/min)	Feed rate (mm/rev)	Depth of cut (mm)	Tool overhang length(mm)
EN19steel	7,14, 24	0.1 (constant)	0.1,0.2,0.3,0.4,0.5, 0.6,0.7	52,56,59,63
EN9 Steel	7,14, 24	0.1(constant)	0.1,0.2,0.3,0.4,0.5, 0.6,0.7	53,56,60,63
Mild Steel	7,14, 24	0.1, 0.138, 0.175, 0.2, 0.275, 0.35, 0.5	0.1(constant)	52,55,58,61
Aluminium 6061	7,14, 24	0.1, 0.138, 0.175, 0.2, 0.275, 0.35, 0.5	0.1(constant)	54,57,59,63

The experimental cutting tests has been initiated for the few lengths of the work pieces as the tool advances its structural properties such as cutting stiffness is drastically changes. The output responses such as feed force (Fx). Radial forces (Fy), Tangential forces (Fz) and the critical lengths due to chatter are considered by varying the levels of feed(f), cutting speed(v) , depth of cut(d) and tool overhang lengths. In the present case, the tool overhang is considered as the length between the end of the cutting edge to the shank position in the tool holder. Using the meter scale the appropriate lengths has been adjusted in the tool holder. Figure 2.1 demonstrate the experimental lathe setup employed to carry out the cutting tests.

Fig.2.1 Experimental setup employed

2.1 Neural network

In comparison with the back propagation neural network models, the recent network like Radial basis function has multiple advantages during its functioning. This RBF network, contains a single hidden layer at its centre and further the training is to be provide at the output layer with a high convergence rate. The working principle and the training of the layers are briefly explained at the below section.

Radial basis network consists of three predominant layers: (i) the basic Input layer (i) Hidden layer which consists of radial basis neurons (iii) output layer which possess linear neurons. The input layer passed through a nonlinear stimulation function called radial basis function to extract the outputs from the above mentioned hidden neurons. Figure 2.2 shows the RBF model with different inputs and outputs.

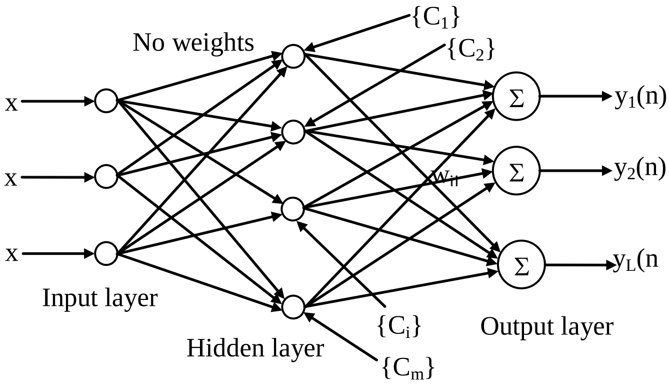

Fig.2.2. Schematic of a RBF network

An RBF can be designated as a multidimensional function that is dependent on the distance between the input vector and the center vector. The input layer comprises of neurons with a linear function that only feeds the input to the hidden layer. Further the association between the input layer and the hidden layer are not biased, that is each of the hidden neuron receives a corresponding input value which is intact. The hidden neurons are specific processing units that perform the radial basis function.

(3) Inverse multi-quadratic function: $f(r) = (r^2 + \sigma^2)^{-1/2}$

(4) Thin-plate-spline function: $f(r) = r^2 \log(r)$

(5) Piece-wise linear function: $f(r) = ½(|r+1| - |r-1|)$

(6) Cubic approximation function: $f(r) = ½(|r^3+1| - |r^3-1|)$

Here σ is a real time parameter (called scaling parameter) and r denotes the distance between the input vector X and the center vector at i^{th} hidden node C_i. The Distance is customarily measured by the Euclidean norm written as: $\|X - C_i\|$. Let the input vector at any time n be denoted by $X(n) = [x_1(n), x_2(n), \ldots\ldots x_N(n)]^T$ and let the center vector of each and every hidden neuron be denoted by C_i(for i = 1,2,…..H), where H is the neuron number of the hidden layer. Then the output is given by

$$h_i(n) = f_i(\|X(n) - C_i\|) \quad \text{(for i = 1,2,3, 4…..H)} \quad (1)$$

The association between the hidden layer and the output layer are biased. Each neuron from the output layer has a linear input-output relationship so that they perform the simple summations equations: that is, the output executed by the i^{th} neuron in the output layer at any given time n is

$$y_i(n) = \sum_{j=1}^{H} w_{ij} h_j(n) = \sum_{j=1}^{H} w_{ij} f_j(\|X(n) - C_j\|), \text{ (i = 1,2,3, …….L)} \quad (2)$$

where L is the number of neurons in output layer and w_{ij} is the connection weight between the j^{th} neuron in the hidden layer and i^{th} neuron in the output layer. At the end of processing all input sets (known as epoch or cycle), a square error is computed according to the relation:

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$$MSE = \sum_{n=1}^{M} (Y(n) - \hat{Y}(n))^2 \quad (3)$$

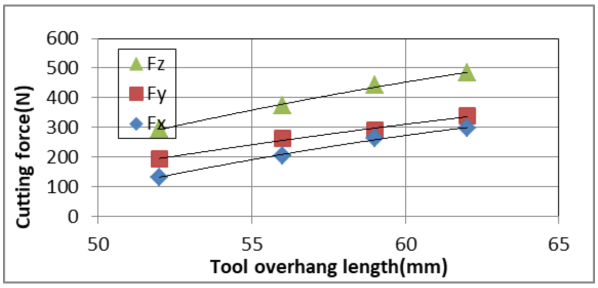
where $Y(n) = [y_1(n)\ y_2(n)\ \ldots\ldots\ y_L(n)]^T$ is the output vector and $\hat{Y}(n)$ is the corresponding desired output (target) vector and M is the total number of available training sets.

III. Results and discussions

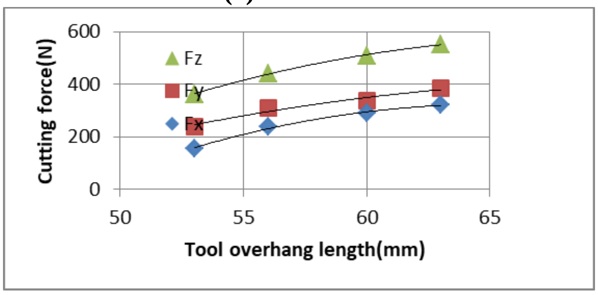
From practical point of view in the first two sets of experiments, feed is kept constant while in the last two sets of experiments depth of cut is maintained constant.

3.1 Cutting forces with variation in tool overhang lengths (TOL)

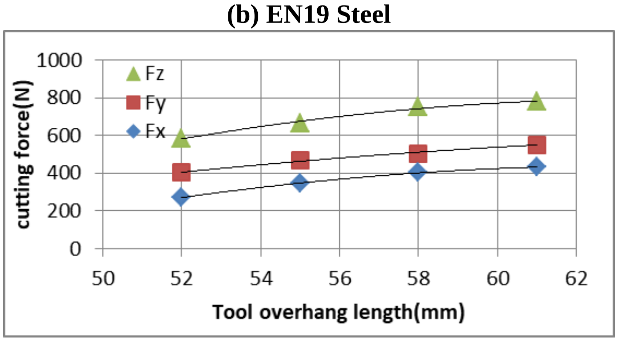
In the initial conduction of cutting experiments, cutting forces has been evaluated with the deviation in the depth of cut at different levels of tool overhang lengths. It is clearly evident that when there is an upsurge in the overhang lengths the magnitude of the cutting edge forces has been drastically improved in three cutting directions as shown in the Fig.3.1



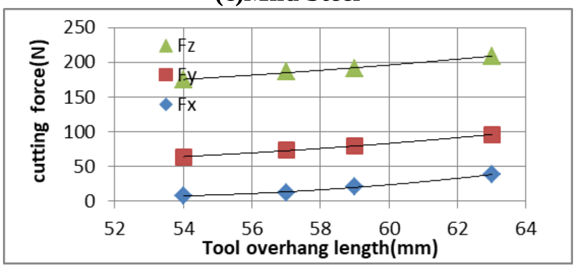
(a) EN9 Steel



(b) EN19 Steel



(c)Mild Steel

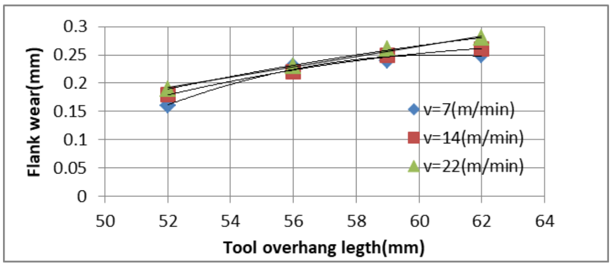


(d) Al 6061

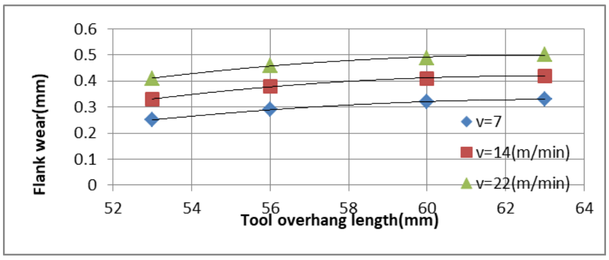
Figure: 3.1. Variation of cutting forces with different TOL

3.2 Flank wear with variation in tool overhang lengths (TOL)

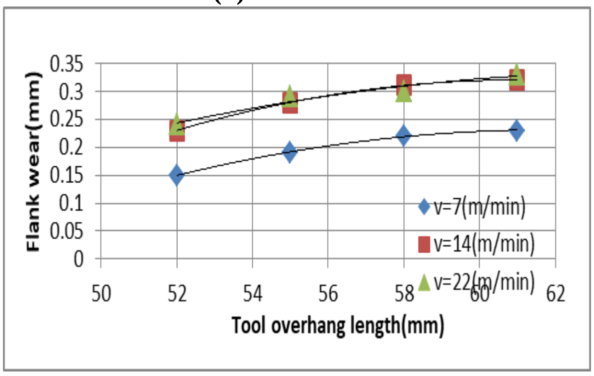
Furthermore, the Figures 3.2(a) to 3.2(d) represents the effect of tool overhang length on the flank wear. It is observed that an increment in the values of the tool overhang length, there is an increase in the flank wear for different materials.



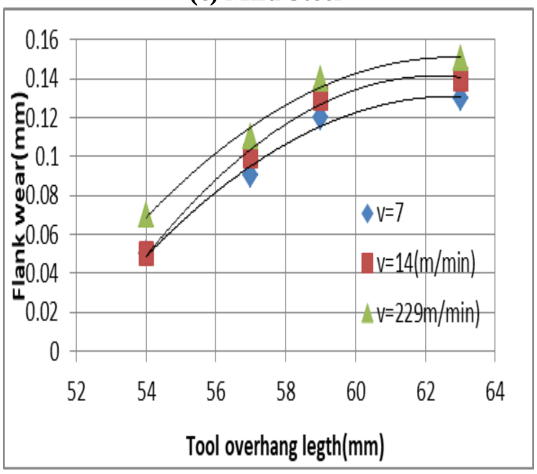
EN9 Steel



(b) EN19 Steel



(c) Mild Steel

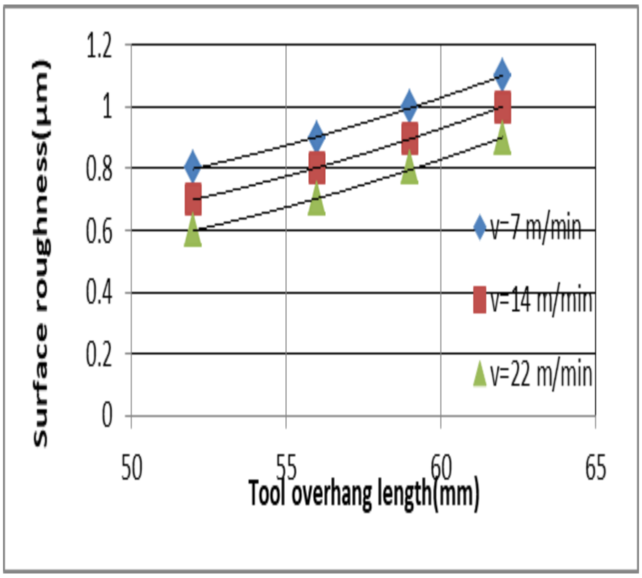


(d) Al 6061

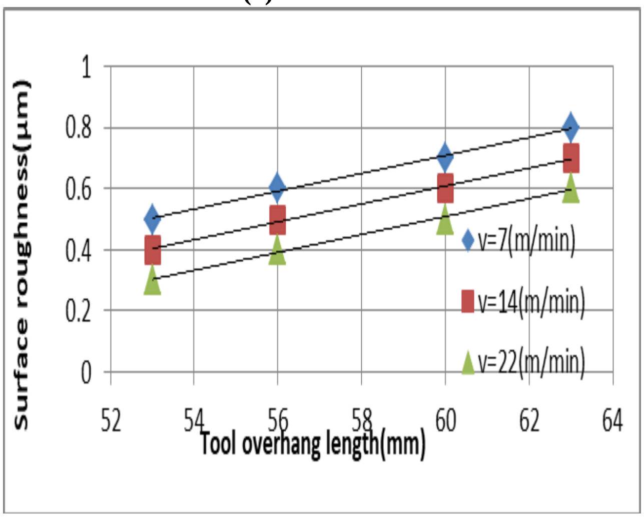
Fig 3.2(a)-(d) Flank wear with variation in tool overhang lengths (TOL)

3.3 Surface roughness with variation in tool overhang lengths (TOL)

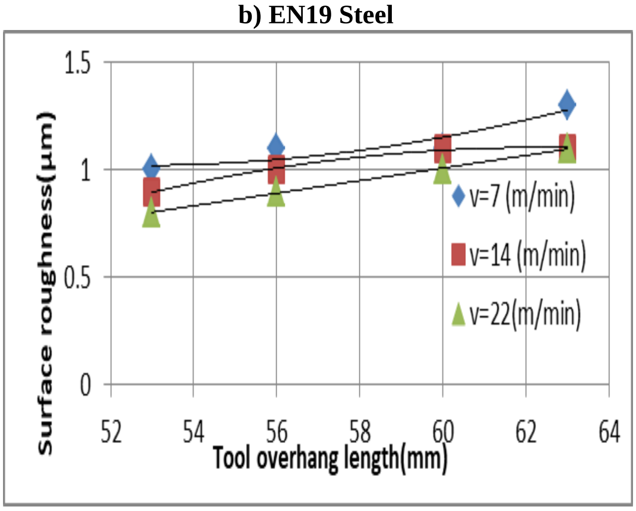
The effect of tool over hang length on the surface roughness for different materials has been analyzed. It is observed that, as the tool overhang length increases there is a reduction in the surface roughness (Ra) values as shown in Fig.3.3(a)-(d).



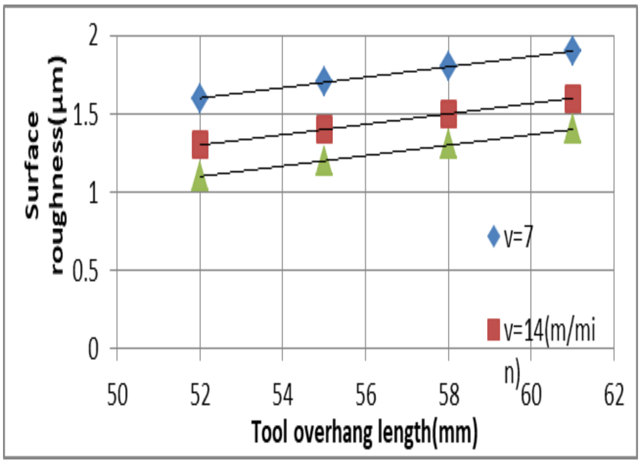
(a) EN9 Steel



b) EN19 Steel



(c) Mild Steel



(d) Al 6061

Fig. 3.3 (a)-(d) Deviation of tool overhang length with the surface roughness (Ra)

Figures 3.4 show the network training in terms of mean square error variation at every cycle. Here σ_j is selected as 1. As σ_j increases the average predictions were found to be reasonably poor for EN9 steel.

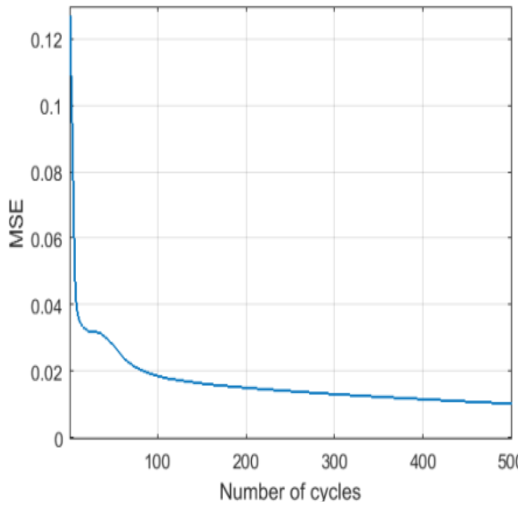


Fig. 3.4 Variation of mean square error during turning.

IV. Experimental studies

The cutting parameters such as the cutting speed, the tool feed rate and the depth of cut attained have different effects on the cutting forces, tool wear and tear and exterior surface quality and critical chatter length. Hence in order to know the simultaneous effect of tool overhang along with the standard cutting factors on cutting edge forces, surface roughness along with tool wear status, a chain of cutting experiments were carried out. These are shown for four different work materials (EN9 steel, EN19 steel, Mild steel and Aluminium 6061) in Tables 4.1 and 4.2. Tables also depict optimum machining settings predicted by GA program for the respective minimum values of cutting forces.

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Table-4.1: Output values of Genetic Algorithm Program with respect to input ranges (d=0.2mm)

Material	v(m/min)	f(mm/rev)	l(mm)	F_x(N)	F_y(N)	F_z(N)	R_a(μm)	C_c(mm)	v_o(m/min)	f_o(mm/rev)	l_o(mm)
EN19 Steel	7-14	0.1-0.4	53-57	462.6	631.5	723.6	1.46	16.23	7	0.1	56.95
	7-14	0.1-0.4	57-63	466.8	631.0	723.8	1.35	16.21	7	0.1	63.00
	7-14	0.4-0.7	53-57	542.9	810.8	923.9	2.51	14.27	7	0.4	56.90
	7-14	0.4-0.7	57-63	539.3	808.6	923.3	2.45	14.28	7	0.4	62.97
	14-22	0.1-0.4	53-57	586.4	760.1	856.7	2.12	18.07	14	0.1	57.00
	14-22	0.1-0.4	57-63	591.5	755.4	857.2	2.14	18.12	14	0.1	57.00
	14-22	0.4-0.7	53-57	595.4	801.5	964.6	3.21	13.71	14	0.4	56.89
	14-22	0.4-0.7	57-63	601.5	785.0	966.5	3.23	13.12	14	0.4	62.95
EN9 Steel	7-14	0.1-0.4	52-56	441.6	430.4	725.6	1.49	17.7	7	0.1	55.9
	7-14	0.1-0.4	56-62	489.8	513.8	912.5	1.38	14.8	7	0.1	61.9
	7-14	0.4-0.7	52-56	504.0	551.1	934.8	2.54	14.2	7	0.4	55.9
	7-14	0.4-0.7	56-62	584.0	631.8	921.3	2.49	13.0	7	0.4	62.0
	14-22	0.1-0.4	52-56	424.1	615.0	834.7	2.18	16.4	14	0.1	55.9
	14-22	0.1-0.4	56-62	430.3	623.3	788.6	2.19	16.2	14	0.1	61.2
	14-22	0.4-0.7	52-56	688.6	736.1	989.6	3.29	12.0	14	0.4	55.9
	14-22	0.4-0.7	56-62	689.9	737.8	998.7	3.28	12.2	14	0.4	61.5

Table-4.2: Output values of Genetic Algorithm Program with respect to input ranges (f=0.1 rev/mm)

Material	v (m/min)	d (mm)	l(mm)	F_x (N)	F_y (N)	F_z (N)	R_a (μm)	C_c (mm)	v_o (m/min)	d_o (mm)	l_o (mm)
Mild steel	7-14	0.1-0.3	54-57	598.6	888	1334.2	1.86	9.64	7	0.1	56.9
	7-14	0.1-0.3	57-61	597.3	889	1339.7	1.92	9.65	7	0.1	61.0
	7-14	0.3-0.5	54-57	620.2	1032	1443.2	2.96	7.73	7	0.3	56.9
	7-14	0.3-0.5	57-61	639.0	1031	1442.6	2.98	9.24	7	0.3	61.0
	14-22	0.1-0.3	54-57	773.9	1175	1556.8	3.85	8.96	14	0.1	56.9
	14-22	0.1-0.3	57-61	773.9	1178	1557.9	3.89	8.97	14	0.1	60.9
	14-22	0.3-0.5	54-57	716.7	1224	1587.3	4.67	8.57	14	0.3	56.8
	14-22	0.3-0.5	57-61	718.6	1225	1589.4	4.81	7.04	14	0.3	60.9
AL6061	7-14	0.1-0.3	54-57	164.2	236.7	392.7	0.91	12.14	7	0.1	57.0
	7-14	0.1-0.3	56-62	164.4	236.8	392.8	0.94	12.06	7	0.1	61.5
	7-14	0.3-0.5	53-56	187.2	258.4	428.1	1.13	12.36	7	0.3	55.9
	7-14	0.3-0.5	56-62	188.1	258.9	428.6	1.14	12.32	7	0.3	61.8
	14-22	0.1-0.3	53-56	208.4	313.2	466.7	1.31	10.83	14	0.1	55.6
	14-22	0.1-0.3	56-62	208.7	313.4	466.7	1.31	10.54	14	0.1	61.9
	14-22	0.3-0.5	53-56	212.4	319.8	481.2	1.68	10.85	14	0.3	55.9
	14-22	0.3-0.5	56-62	212.6	319.9	481.2	1.69	10.89	14	0.3	61.9

This chapter has illustrated the analytical and experimental results relating to orthogonal and oblique turning operations. All the results are very much coinciding with the published data available in literature. In all the three cases presented only monitoring of instability during cutting operation is considered.

V. Conclusions

In this case study, an exclusive multivariate model of an orthogonal turning operation has been articulated based on a sequence of turning experiments. Using the various experimental data for different work piece materials, the cutting dynamics is modeled with radial basis function neural network. In addition to basic cutting parameters, tool overhang and tool wear were selected as inputs and static cutting forces, average roughness values and critical chatter length on workpiece were presented as outputs. For four work materials considered in experiments, four neural networks were trained. In each case, all the 84 experimental values were summarized with few network parameters (central vectors and weights). As a next step of using these neural network models, optimum cutting parameters namely speed, feed, depth of cut and tool-overhang lengths are established by minimizing total cutting force with the help of genetic algorithms. It is found that compared to speed, feed, and depth of cut the tool overhang has profound influence on the cutting forces and critical chatter locations. The stability lobe diagrams with different tool overhang lengths (stiffness) were plotted.

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