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NEURAL NETWORK APPROACH FOR CUTTING PARAMETER SELECTION IN MILLING

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***Abstract**: This paper proposes a predictive open-loop control approach to maintain effective speed regulation during end-milling operation. The process is analyzed analytically using two-degree of freedom model and the time domain and frequency domain data are used to construct a chatter prediction neural network model. Sixty training sets are prepared with and without chatter conditions. A neural network controller is proposed for tracking the overall response within chatter limits. The effectiveness of prediction network and controller is illustrated with an example.*
***Keywords**: End-milling; Analytical Modeling; Neural network; Feedback control; Chatter stability.*

1. INTRODUCTION

In modern industry the objective is to manufacture low cost and high quality products in short time. Automated and flexible manufacturing systems are employed for that purpose along with CNC machines that are capable of achieving high accuracy and short processing time. Self-excited vibrations occurring in machine tools have become serious hurdle for these objectives. Undesired relative vibrations between tool and work piece affect the quality of machined surface and material removal rate. If the modal parameters of the machine tool are identified and cutting forces are known, it is possible to predict these vibrations or design a technology to avoid instability during cutting.

Traditionally, stable conditions are visualized by stability charts (Altintas, 2000) which depict the maximum chatter-free chip width as a function of spindle speeds. In operations like peripheral end milling, stability may also be determined by the time domain simulation, where the tool displacements are obtained by numerical integration of equations of motion within the plane of cut. Onset of chatter (instability) can be predicted by monitoring the power spectrum of the displacement of a tool. When chatter starts, a sharp spike develops around the natural frequency of the system (Braun, 1975). Hence the most common approach to chatter detection is to investigate the spectral density of a process signal and develop a threshold value that indicates chatter. As tooth passing frequency contains significant energy, the process signal must be filtered when this tooth passing frequency is close to a dominant structural frequency. In normal conditions cutting forces can be approximated by a low frequency (corresponding to the tooth passing frequency) sinusoidal function. Hence histogram of cutting force signal takes the shape of bowl. When chatter occurs, several high frequency components (corresponding to tool vibration frequency and machine tool vibration frequency) also appear in cutting forces. As a result histogram changes to a bell shape.

To attain a desired quality of machined surface and improve the material removal rates, it is thus necessary to predict the regions of instability in machining and control such states online to a maximum possible extent by changing the operating parameters appropriately. Many authors have proposed various approaches for identifying the chatter conditions. In order to avoid storage of a large database of response at every operating condition, many chatter prediction algorithms employ expert system approach for modeling the chatter. In this regard, neural networks and fuzzy systems have an important role in monitoring the machining process. Artificial neural network models have gained more attention and are used in new application areas each day. Neural networks as data processing systems can predict the unknown signature upon proper training. Especially the unified chatter data is amenable to process through neural networks. In this regard, a chatter development prediction procedure is proposed for cylindrical turning using multilayer neural networks (Tansel et al. 1991). Later the use of self-organization neural network model has been described (Gradisek et al., 1996) to predict the optimal cutting depths in orthogonal cutting system. These works have not considered chatter directly although they are based on the fact that nonlinear dependency of the cutting force on cutting velocity could cause chaotic vibrations in the cutting tool. In another paper (Du, 1999), an approach of monitoring engineering processes, in particular tool conditioning in machining processes is proposed using Artificial Intelligence (AI) approach from a set of sensor signals. Chatter prediction in boring operations using Fuzzy ARTMAP has been attempted in another work (Wang & Fee, 2001). Here the network subsequently controls the operating parameters based on the predicted chatter. In another paper, (Hino et al., 2006) Fuzzy neural network model is used to predict the chatter in end-milling process. The data for neural network is developed from wavelet analysis of force signals. More recently (Yoon & Kim, 2007) radial basis function neural network is employed to predict the stability lobe diagram in milling using FFT and time series spectrum analysis data.

The chatter suppression approaches can be categorized into passive and active methods. Usually passive methods suppress chatter by using energy absorbing dampers or by changing the cutting conditions to reduce the energy generated during machining. Practically passive methods are not effective. Active approach regulates the feed and spindle speeds using the stability zones. A fuzzy approach of online chatter suppression in end-milling is a basis for presentation in another paper (Liang et al., 2004). Another article on chatter suppression (Chiou et al., 2003) described active control or alteration of the machine tool structure without changing the cutting conditions. This has capability to suppress the mode coupling mechanism and alleviates regenerative effects.

Present work focuses on intelligent monitoring of chatter states using probabilistic neural network (PNN) model. The model is constructed from a data derived from time-domain and power spectrum of cutting force signals in planar ending milling operation. The milling tool is analytically modeled as a two-degree of freedom system and time-domain solutions are obtained by solving the delay differential equations. FFT signals and power spectrum data of the cutting forces at various operating conditions are derived using a MATLAB program. At constant angle of immersion, feed-rate, spindle speed and axial depth of cut are varied simultaneously. Stability lobe diagram is obtained conventionally and is used to check the stable regions obtained from time-domain simulations. A simple control strategy is proposed using radial basis function (RBF) neural network controller to set the spindle speeds for eliminating the unstable conditions. Section-2 presents analytical modeling employed in present work for deriving unstable cutting conditions. Section-3 gives brief introduction to methodology and neural networks. The results of the analysis are shown in section-4.

2. ANALYTICAL MODELING

Mechanics of end-milling process plays an important role in high-speed machining. Fig.1 shows the geometry of cutting tool. For effective milling process, it requires consideration of material removal rates and surface roughness throughout the machining.

During the milling process, chatter vibrations can occur at certain combinations of axial depth-of-cut and spindle speed. This undesired phenomenon may be due to either physical mechanisms like friction, thermodynamics, mode-coupling or caused by the regeneration of waviness of the surface of work piece. This so called regenerative effect is the most widely recognized cause of instability in cutting processes.

A simple model of the cutting forces is one which expresses the tangential cutting forces to be proportional with the instantaneous chip thickness. Hence

$$F_t = K_t\, b\, h(t) \tag{1}$$

where K_t is the specific cutting force, b is the axial depth of cut and h(t) is the instantaneous chip thickness. K_t is generally provided from cutting tests representing the material strength and tool shape. The radial force is expressed in terms of tangential force as:

$$F_r = K_r\, F_t \tag{2}$$

Where K_r is a proportionality constant.

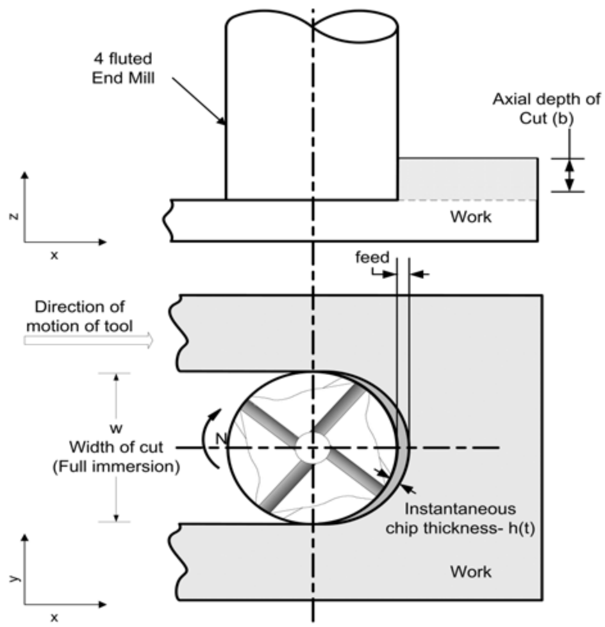

Fig.1 Geometry in End-milling process

The critical parameter in eqn. (1) is the chip thickness because it changes not only with the geometry of cutting tool and cutting parameters, but also with the uneven surface left by the previous passes of the cutting tool. Hence, after determining the chip-thickness for an uncut fresh surface, this thickness must be compared with the undulations left by the cutting tool during previous passes at the same position to obtain the instantaneous thickness of the material to be removed. This variation due to surface waviness from previous passes is known as the surface regeneration mechanism. The dynamic model of the planar milling cutter used in the present study is assumed to be a system with one mode of vibration in each direction X and Y and feed direction is along the X-axis. The system under consideration is shown in Fig. 2, where X-Y coordinate system is fixed with respect to the machine tool structure and its axes are aligned with the principal modes of oscillation.

The process of feeding in Y-axis can be represented by swapping the modal parameters in the X and Y directions. The milling cutter has Z teeth which are assumed to be equally spaced. The dynamics of the milling system can be given by the differential equations as:

$$m_x \ddot{x} + c_x \dot{x} + k_x x = \sum_{j=0}^{Z-1} F_{xj} = F_x(t) \tag{3}$$

$$m_y \ddot{y} + c_y \dot{y} + k_y y = \sum_{j=0}^{Z-1} F_{yj} = F_y(t) \quad (4)$$

where m, c and k are mass, damping and stiffness of the machine tool structure in modes X and Y respectively, F_{xj} and F_{yj} are the components of cutting force that act on j^{th} tooth, which are obtained by projecting radial and tangential forces in these two vibration modes. In order to express these forces in terms of the instantaneous geometry of the chip, the rotating coordinate system u_i-v_i is used.

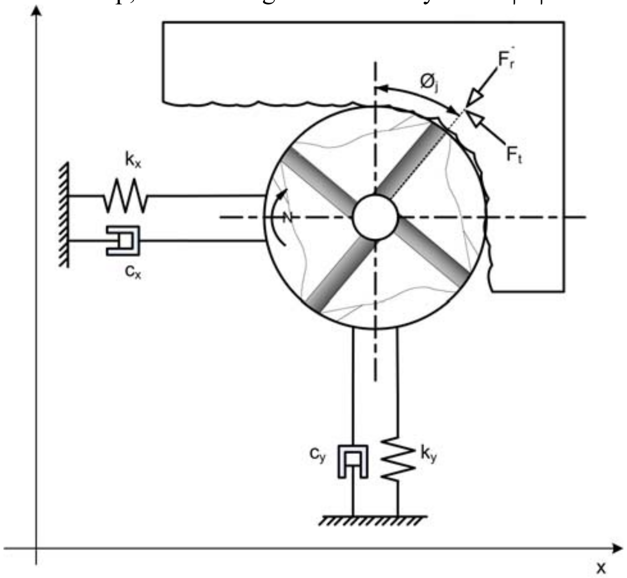

Fig.2 Milling Model with 2-DOF

Referring to this system, any tooth of the milling cutter can be viewed as a single-point cutting tool of a lathe, thus machining theory of turning can be employed. For tooth number (j) which is at the instantaneous angular immersion ϕ_j measured clockwise from the negative Y-axis at a particular instant, the tangential, radial and axial milling force components (F_{tj}, F_{rj} and $F_{aj)}$ on it can be calculated from the corresponding chip-load, cutting condition, tool geometry by using single-point cutting mechanics. The cutting forces on tooth number (j) can be expressed in terms of fixed coordinate system X and Y as follows:

$$F_x(t) = \sum_{j=0}^{Z-1} F_{xj} = \sum_{j=0}^{Z-1} (F_{tj} \cos\phi_j + F_{rj} \sin\phi_j) \quad (5)$$

$$F_y(t) = \sum_{j=0}^{Z-1} F_{yj} = \sum_{j=0}^{Z-1} (-F_{tj} \sin\phi_j + F_{rj} \cos\phi_j) \quad (6)$$

Here ϕ_j varies with time as $\phi_j(t)=\Omega t$, where Ω is spindle speed.

For milling process, the size of the cut taken by each tooth will depend on the deformed chip thickness and the depth of cut (or width of cut). The undeformed chip thickness is therefore a fundamental variable of the cutting process, which can be altered by a number of practical variables such as the diameter of cutter, feed per tooth (feed rate), etc. In dynamic milling process, these cutting forces excite the structure in the feed and normal directions, causing displacements x and y respectively. Since the chip thickness is measured in radial direction, the dynamic displacements are carried to rotating tooth number (j) in the radial direction (chip thickness direction), which can be expressed as:

$$v_j = x \sin\phi_j + y \cos\phi_j \quad (7)$$

The resulting instantaneous chip thickness therefore consists of static part $f_t \sin\phi_j$ and dynamic component caused by the vibrations of the tool at the present and previous tooth periods, which can be referred to as modulation v_j and v_j^0 respectively. v_j^0 is usually modulated by the previous tooth (j-1). The outer modulation is given by

$$v_j^0 = \min\{vj_{-1}(t-T),\ v_{j-2}(t-2T) + h_{sj},\ v_{j-3}(t-3T) + 2h_{sj} \ldots\} \quad (8)$$

where $T=2\pi/(Z\Omega)$ is period between successive tooth engagements. The total chip load can be obtained by adding the nominal chip thickness to the present deflection modulation v_j and preceding deflection modulation v_j^0 which can be expressed as:

$$h(\phi_j) = [f_t \sin\phi_j + (v_j^0 - v_j)]\, g(\phi_j) \quad (9)$$

where $g(\phi_j)$ is a unit step function which defines whether the tooth is in cut or out of cut. If ϕ_{st} and ϕ_{ex} represent the start and exit immersion angles of cutter to and from the cut respectively, then

$$g(\phi_j) \quad = 1 \text{ if } \phi_{st} \le \phi \le \phi_{ex}$$
$$= 0 \text{ if } \phi_j < \le \phi_{st} \text{ or } \phi_j > \le \phi_{ex} \quad (10)$$

For an end milling cutter, in up-milling $\phi_{st}=0$ and ϕ_{ex} depends on the radial depth of cut, whereas for down-milling ϕ_{ex} is always equal to π. When $h(\phi_j)>0$, it means that the cutting tooth number (j) is in contact with the arc being machined and the cutting force component on it can be determined in terms of this chip load. If $h(\phi_j)<0$, it means that this tooth is out of cut and the force on it must actually be set to zero. This expresses the basic nonlinearity of dynamic cutting process.

In the dynamic chip load regeneration mechanism the static component of the chip thickness ($f_t \sin\phi_j$) is dropped from the expression as it does not contribute to the dynamic behavior of the system. Equations (5) and (6) can be rearranged and written in matrix form as:

$$\begin{Bmatrix} F_x \\ F_y \end{Bmatrix} = \frac{1}{2} b K_t [A(t)] \begin{Bmatrix} \Delta x(t) \\ \Delta y(t) \end{Bmatrix} \quad (11)$$

where [A(t)] is a matrix of time varying dynamic milling force coefficients considering the effect of all the teeth (Altintas, 2000) and $\Delta x(t)$ and $\Delta y(t)$ are variations of displacements in x and y directions with time and angular velocity defined as:

$$\begin{Bmatrix} \Delta x(t) \\ \Delta y(t) \end{Bmatrix} = \begin{Bmatrix} x(t) - x(t-T) \\ y(t) - y(t-T) \end{Bmatrix} \quad (12)$$

Here $T=\dfrac{2\pi}{Z\Omega}$ is called tooth passing period. By taking Fourier transforms of eqn.(11) and defining chatter frequency ω_c the following equation can be written in frequency domain:

$$\{F\}e^{i\omega_c t}=\frac{1}{2}bK_t\left[1-e^{-i\omega_c T}\right][A_o]\phi(i\omega_c)\{F\}e^{i\omega_c t} \tag{13}$$

Solving the characteristic equation and finding complex eigenvalues, it is possible to express the critical depth of cut, corresponding speeds and chatter frequencies as

$$b_{lim}=-\frac{2\pi\lambda_R}{NK_t}(1+\kappa^2) \tag{14}$$

$$\Omega=\frac{60}{NT} \tag{15}$$

$$\omega_c T=(2k+1)\pi-2\tan^{-1}\kappa \tag{16}$$

Where $\kappa = \lambda_I/\lambda_R$ is ratio of imaginary to real parts of complex eigenvalue. Thus the transfer function of the machine tool system is identified and the dynamic cutting coefficients are evaluated from the derived equation for a specified cutter and radial immersion angle of cut. Stability lobe diagram (SLD) in terms of depths of cut and spindle speeds are obtained by sweeping the chatter (excitation) frequencies around the natural frequencies of the system. These plots give the stable operating conditions (a_{lim}, N) to avoid chatter oscillation of the system.

3. PRESENT METHODOLOGY

In the present approach, the results of time-domain simulation in terms of x and y displacements and corresponding forces are used to obtain the Fourier coefficients and the power spectra. By observing the time-domain plots of chatter oscillations, the characteristics of frequency domain plots are defined for two conditions: 'with chatter' and 'without chatter'. This is considered as input vector for chatter prediction neural network model. If there is a peak mode in power spectrum, then it is defined as a condition for chatter. With this criterion for chatter state in each cutting condition, simulated experimental data is obtained and verified using the stability lobe diagram. After arranging the data, the output vector is classified. By providing the correct set of weights in the architecture of neural network with input and output vectors, the complete learning is accomplished by reiterations. After identifying the chatter state, a controller network is trained with RBF algorithm to supply chatter free conditions of spindle speed and feed data. The approach is shown in flowchart (Fig. 3).

3.1 Neural network for chatter prediction

Probabilistic neural network is a direct continuation of the work on Bayes classifiers (Specht, 1990). Because of ease of training and sound statistical foundation in Bayesian estimation theory, PNN has become an effective tool for solving many classification problems. PNN learns to approximate the probability density functions of the training examples. The PNN architecture used is shown in Fig. 4.

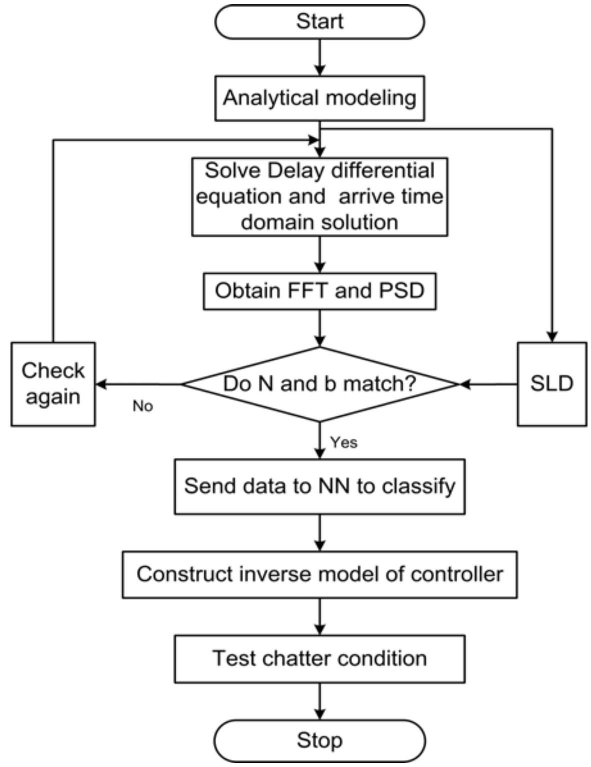

Fig. 3: Flowchart of methodology

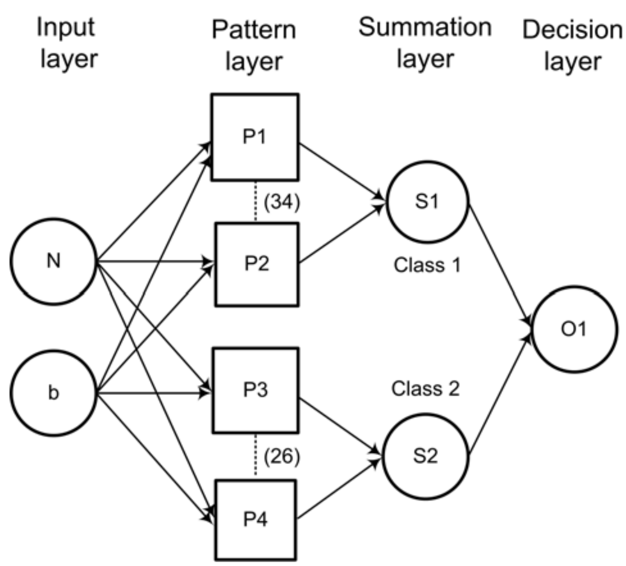

Fig. 4: Probabilistic Neural Network

It consists of nodes in three layers after the inputs:

(1) Pattern layer, where there is one pattern node for each training example. Each pattern node forms a product of the weight vector (w_{ji}) and the given example for classification (X_i), where the weights entering a node are from a particular example. The output of the j^{th} neuron in pattern layer is given by:

$$\phi_j = \exp\left\{\frac{-(X_i - w_{ji})^T (X_i - w_{ji})}{2\sigma^2}\right\} \qquad (17)$$

where σ is smoothing parameter. As the training data set becomes larger, the network size may grow proportionally. Thus one of the outstanding issues associated with PNN is determining network size. However, in this paper, this issue is not addressed because the training samples are of manageable size. (2) Summation layer, where each summation node receives the outputs from pattern nodes associated with a given class. (3) Decision layer with nodes as binary neurons that produce the classification decision. The only factor that needs to be selected for training is the smoothing factor.

3.2 Chatter control strategy

After predicting the existence of chatter, it is necessary to implement a controller to maintain correct operating conditions. Once chatter occurs, a high pitched sound can be heard and large intensity at a certain specific frequency other than the spindle speed and tooth passing frequency will appear in power-spectrum. This frequency is referred to as 'chatter frequency (f_c)'. This frequency can be obtained from FFT spectrum and depends on the spindle-speed at one particular depth of cut. In the present context, the open-loop control strategy is employed using an inversely trained neural network with chatter frequency and corresponding amplitude from FFT data as input and change of speed as output. The process dynamics (system) receives the desired speed for a depth of cut to overcome the chatter. Fig.5 shows the control strategy employed in the problem.

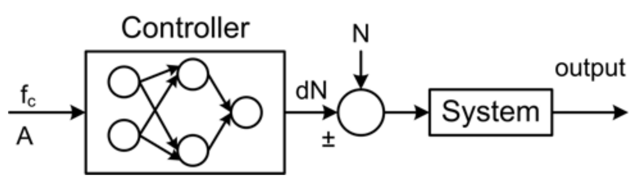

Fig. 5: Open-loop neural network controller

4. RESULTS AND DISCUSSION

Using the time-domain model for chatter in milling, a computer program is developed in MATLAB to solve the delay differential equations. Response in terms of x and y displacements and the corresponding cutting forces are obtained. The end mill is represented by two orthogonal modes having the properties shown in Table-1. (Tlusty et al., 2000).

Table-1 Machining Conditions

Mode	Frequency (Hz)	Damping (%)	Stiffness (N/m)
X	665	1.59	7e7
Y	795	1.84	1e8

Using this system, the time and frequency domain simulations for straight cutter and full-immersion up-milling operation at different values of depth of cut are carried out. The cutting conditions are entry-angle 0^o, exit-angle 180^o and feed per tooth 0.1 mm (kept constant throughout). Figures 6 and 7 show the output results of the program in 6 revolutions.

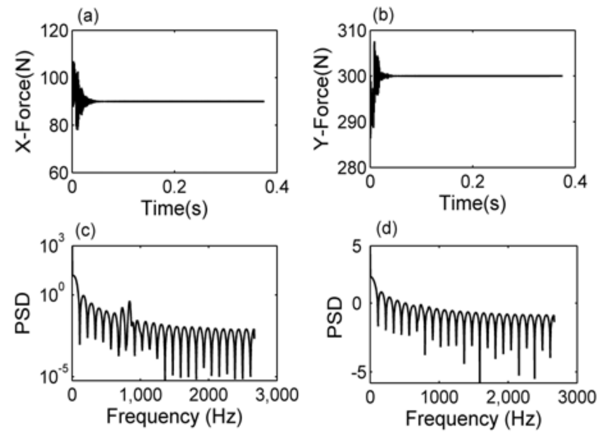

Fig. 6: Simulation of a stable cut in milling (N=1000 rpm & b=1 mm)

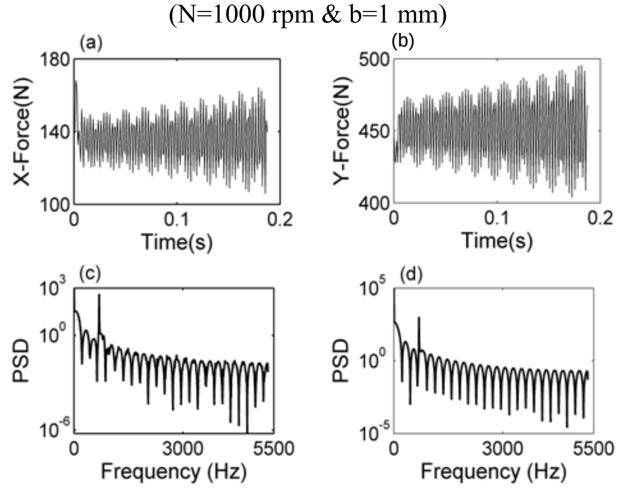

Fig. 7: Simulation of an unstable cut in milling (N=2000 rpm & b=1.5 mm)

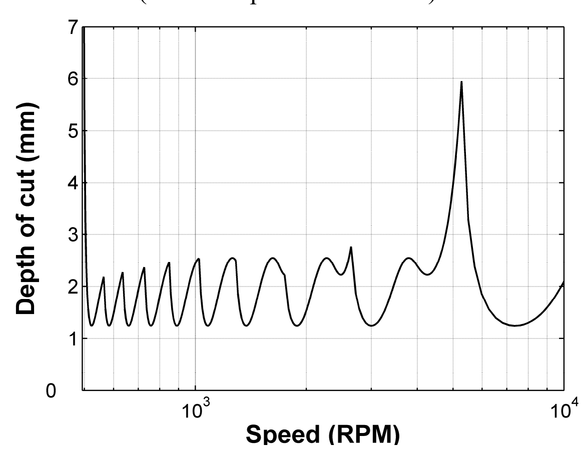

Fig. 8: Stability lobe diagram of the system described above.

For preparing neural network data, 34 chatter cases and 26 non-chatter cases are considered. Chatter state is identified from time-domain signal and compared for correctness using SLD. Fig. 9 shows the input data for classification neural network considered.

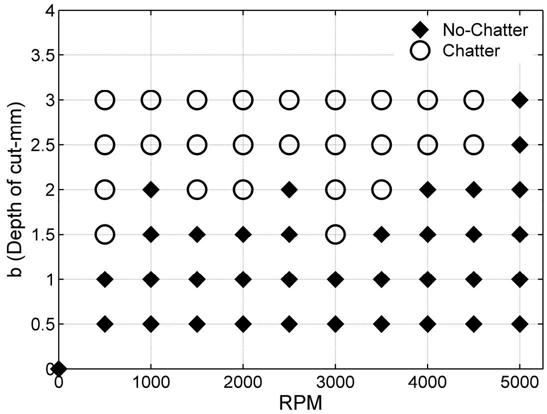

Fig. 9: Classification data for neural network

PNN is trained with different values of b and N and corresponding state of chatter. Fig. 10 shows the output classification pattern of some of the trained as well as untrained instances. On conducting various trials, it is found that the percentage accuracy of classification is very good with a smoothing factor=1.0.

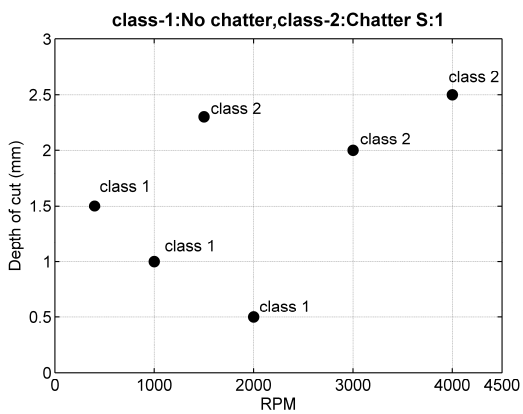

Fig.10: Output classification by PNN

For training the controller network, chatter data is collected in terms of chatter frequency (at an axial depth of cut) as input and corresponding deviation in operating speed (from the nearby non-chatter speed) as output. A radial basis function neural network (2-2-1) is employed (Rao & Srinivas, 2001) for training the data at a depth of cut=2 mm. Fig. 11 shows the training data employed.

The control network predicts the chatter-free speeds for unknown chatter conditions also. The network is tested for various values of chatter conditions. Fig. 12 shows the outputs of system in terms of $F_y(t)$ with and without controller.

In all the cases, it is found that the network predicts effectively the required speeds to avoid the chatter.

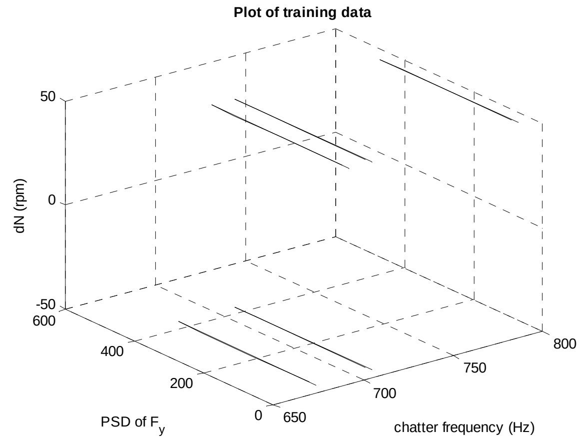

Fig.11: Training data employed for RBF network

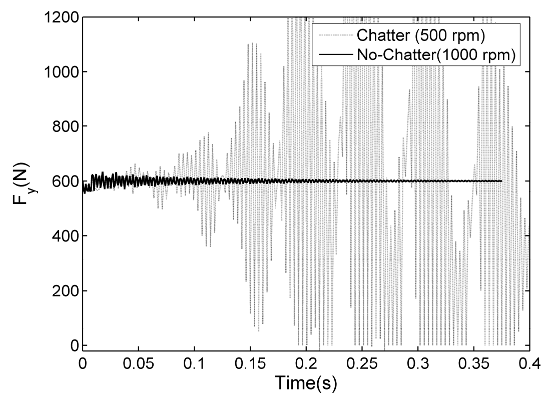

Fig. 12: Output of the system

5. CONCLUSIONS

A unified methodology has been presented in this paper to predict the better operating conditions with reference to chatter. Conventional 2-DOF system has been employed to model the end-milling process. The data has been used to train a classifier network. Cutting force spectra were employed to train the controller neural network. The system outputs with this open-loop controller were found to be very encouraging. Total time taken for predicting the chatter and control is 5 seconds on a 500 MHz Pentium processor. This gives a scope for implementing the controller in multi-dimensional space.

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