Chatter recognition by monitoring the power consumption via an artificial neural network

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Chatter is a common problem in the machining process. It significantly limits the machining productivity, adversely affects the surface quality, and accelerates the premature failure of cutting tools and damages the machine tool components. In flexible machining systems the working conditions might change frequently and this may lead to increase possibility of bringing machining processes into unstable status, and hence resulting in chatter. Cutting forces and cutting power variations during stable and unstable cutting gain increasing attention as a chatter prediction method, due to its simplicity and effectiveness. Experimental results indicate an augmentation in the machining stability and improvement in the product quality, with the use of the forces and power variations method. In most researches the machining chatter is modeled as linear differential - difference equation with single regenerative effects. In reality, when chatter occurs, the amplitude of self-excited vibration increases until some non-linear effect limits any further increment. The stability analyses of linear models provide information only about the chatter threshold, but give no information about the system behaviors with instable cutting. However, the information of chatter, after stability limit has been exceeded, is of importance and is meaningful for understanding the mechanisms of chatter suppression by the forces and power variations method. When chatter starts valuable and reasonable variations occur in the cutting forces and cutting power. Based on the measured power variations and by using a good design and trained neural net work, it has been observed that there is high correlation between force and power variations on one side and possibility of chatter occurrence on the other side where it gives a useful tool for chatter recognition.

يعد الاهتزاز بين أداة القطع والشغلة, وهو ما يعرف بالاصطكاك, من أهم مشاكل عمليات التشغيل وقطع المعادن و أكثرها شيوعا. وهى تؤثر سلبا على حجم ومعدل إنتاجية عمليات التشغيل وعلى جودة الأسطح المشغلة وتعجل من تآكل أداة القطع وسرعة تدمير أجزاء الماكينات. ومما هو جدير بالذكر أن منظومات التشغيل الحديثة تتطلب تغيير مستمر وسريع لشروط القطع وهو ما يسبب عدم استقرار عمليات القطع وظهور الاصطكاك. إن التغير في قيمة ومعدل قوى القطع وكذلك القدرة المستهلكة أثناء القطع المستقر وغير المستقر يساعد بوضوح وسهولة ويسر على التنبؤ بالاصطكاك. وتوضح التجارب العملية المعتمدة على قياس ومراقبة قوى وقدرة القطع استقرار عمليات القطع وتحسن جودة الأسطح المشغلة. وقد لوحظ بوضوح تغير قيمة ومعدل قوى وقدرة القطع عند نهاية القطع المستقر وبداية القطع الغير مستقر, وهو ما يعرف بمدخل الاستقرار. واعتمادا على هذه الظاهرة فقد تم قياس هذا التغير عند ظروف قطع عديدة واستخدام هذه القياسات في برنامج شبكة عصبية مصممة جيدا ومدربة بدقة. وقد أظهرت النتائج تطابقا واضحا وكاملا بين التغير في قيمة ومعدل قوى وقدرة القطع من جهة واحتمال حدوث الاصطكاك من جهة أخرى.

Keywords: Self induced vibration, Stability in turning, Chatter recognition, Cutting power, Cutting force, Neural network

1. Introduction

Chatter, the self excited vibration, is a violent relative vibration between tool and workpiece of the cutting processes. It affects work surface finish, machining accuracy, tool life, cutting forces and cutting power. One of the important characteristics of chatter is that it draws its excitation energy from the cutting process itself and hence from the machine drives [1-3].

When the dynamic component of cutting force is just sufficient to maintain the vibration between the tool and workpiece, the machine is on the threshold of stability. If the relative vibration dies away the cutting process is stable. Conversely, if the vibrations build up the process is unstable.

The object of the theoretical approach is how to predict the cutting conditions at the limit of threshold of stability where the vibration [4-7], once initiated between the tool and workpiece, maintains itself at its original amplitude.

Chatter can be detected by monitoring the power spectrum of the machine vibration during the cutting operation. When chatter starts, a sharp spike develops around the natural frequency. The use of an Artificial Neutral Network (ANN) is proposed to shorten the development time and to increase the computational speed dramatically. ANN was developed to simulate the learning capabilities. A general ANN system can be used for many applications after it is trained on real process or simulated data. This work is aiming to introduce a new procedure to predict chatter development, and also to build a base of a new method for chatter control.

2. Neural network structure and solution methodology

Artificial neural networks ANN are one of the most effective tools in the field of recognition [8]. Neural Networks NN are typically organized in layers. Layers are made up of a number of interconnected nodes having an activation function. Patterns are presented to the network via the input layer, which communicates to one or more hidden layer, where the actual processing is done via a system of weighted connections. The hidden layers then link to an output layer where the answer is output.

The design issues in neural networks are complex and are the major concerns of system developers [9], the neural network design consists of neurons in various layers and connections among neurons. Fig. 1 exhibits neural network structure, and illustrates four common ANN topology [10]. In each panel of the figure, the arrows denoted the direction of information flow.

Most neural networks take numeric input and produce numeric output. The transfer function of a unit is typically chosen so that it can accept input in any range, and produces output in a strictly limited range. Although the input can be in any range, there is a saturation effect so that the unit is only sensitive to input within a fairly limited range.

In the current work, neural network functions are:

$$R = f(L3W * f(L2W * f(L1W * f(*f(IW * X + b1) +b2) + b3)) + b4). \quad (1)$$

$$\text{Output} = \left(\frac{R+1}{2}\right) * \text{Max Val.} \quad (2)$$

The main activation function is as:

$$AI = (2/(1+e^{-2neti}))-1. \quad (3)$$

The choice of activation function may significantly influence the applicability of a training algorithm. Several researchers recommended the use of sigmoid in recognition [9]. In this aspect, the cited structure is adapted for the case under consideration. This structure is one input layer, two hidden layers and one output layer. The following structure configurations are the most commonly used [10], fig. 2.

Training algorithms are categorized as supervised and unsupervised. In the current work the supervised training is applied. Once the network has been trained to recognize structure in the data, it can be used as a visualization tool to examine the data. The Generalized Delta Rule (GDR) is a product - learning for a feed forward, multiple-layer, structured neural network that used gradient decent to achieve training or learning by error correction. Network weights are adjusted to minimize an error based on a measure of difference between desired and actual feed forward network output. Desired input/output behavior is given in the training set. The process can be summarized as in the following flow chart fig. 3.

Once ANN is trained to a satisfactory level it may be used as an analytical tool on some other data, fig. 4.

3. Chatter recognition using ANN

The procedures required to learn and recognize the chatter to the ANN system are including the following steps. First step is to

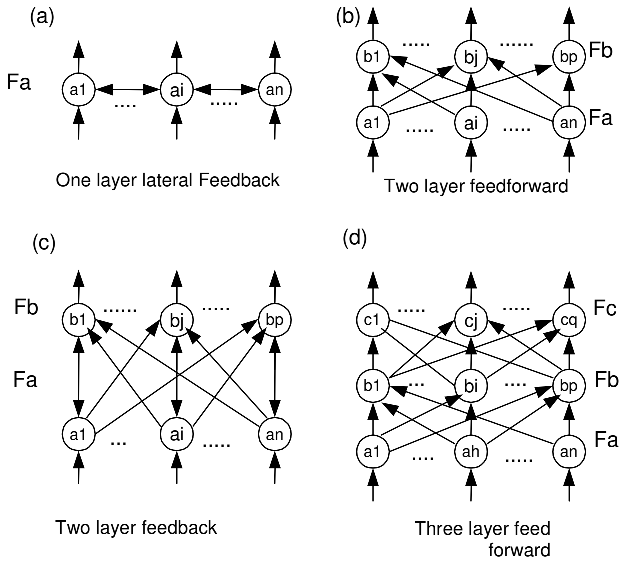


Fig. 1. Common ANS topologies.

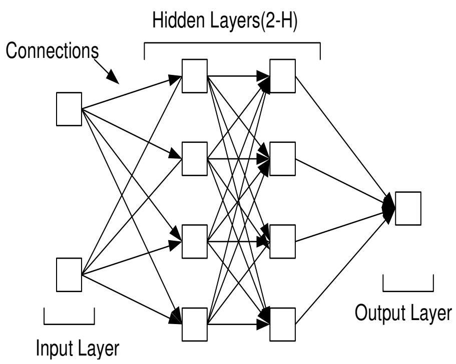


Fig. 2. Conventional neural network.

create the neural model according to the required number of inputs, number of outputs and number of hidden layers. Inter the real data based upon experiments as a training data. About 400 sets of the cutting process variable data are used. The input values contents width of cut, cutting speed, feed, natural frequency, vibration levels, cutting forces, and cutting power. The output items used were the chatter occurrences for each set of cutting process variable. Enter these data for the training output in the form of chatter occurrence or not. Then start to apply the training algorithm and the rate of learning. Therefore the output is an estimation of chatter occurrence or not.

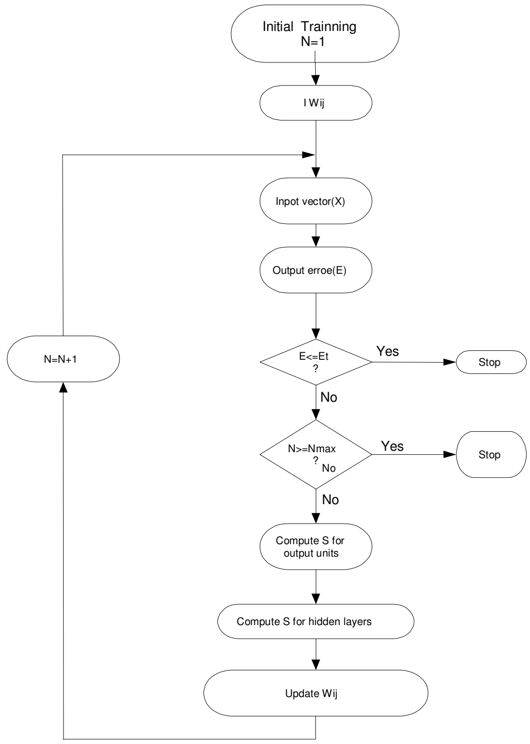


Fig. 3. Overall GDR procedure.

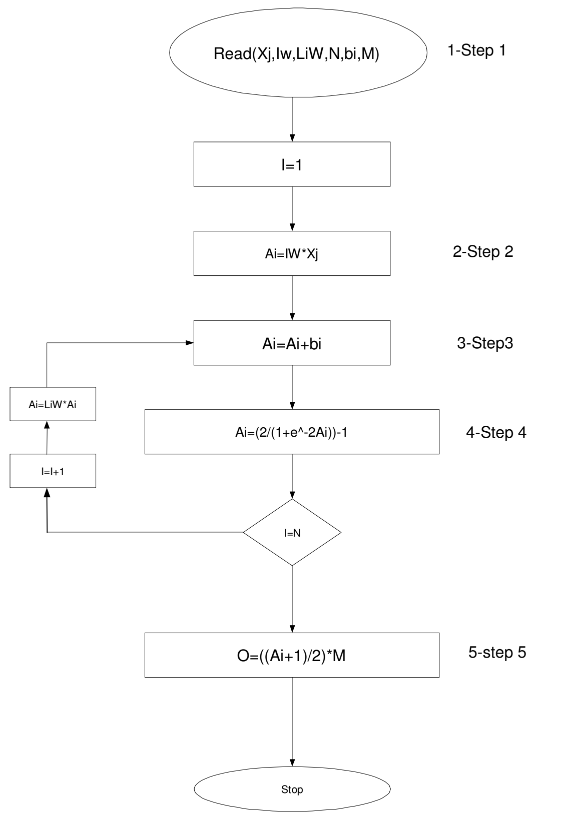


Fig. 4. Procedures for neural network mechanism.

4. Experimental work

To detect the self-excited vibration (chatter) and its relation with cutting process variables, a lot of experimental data should be obtained. The cutting tests were carried by plunge turning processes on a medium size center lathe machine; fig. 5-a shows the test rig. High speed steel tool and low carbon steel workpiece were used. The cutting conditions were chosen to cover stable and unstable cutting regions. A dual channel signal analyzer, Type 2032 B&K, used to measure and analyze the vibration signal of the machine-workpiece set during the cutting. An impact hammers, Type 8208 B&K, and force transducer 8200 B&K were used with the above analyzer to find the machine set natural frequency. The hard copies were printed through a PC computer. The cutting forces were measured, in the radial and tangential directions, by 3-components Kisller dynamometer, Type 9257A. A single phase wattmeter was used to measure the motor power related to the cutting processes. The experimental determinations of stable and unstable cut were obtained by increasing width of cut from 1 mm up to 6 mm. The machine speed range was up to 1000 rpm and feed rate of 0.08 mm/rev. where the workpiece initial diameter was 50 mm. samples of cutting conditions and results are shown in table 1.

5. Natural frequency

The natural frequency of the turning machine set is important for detection the chatter occurrences [11]. So that, first step in the experimental work is the natural frequency test for process set, machine- workpiece-tool and clamping. The procedure for this test is started by clamp the workpiece on the machine, while the machine power off. Impact the machine with the impact hammer, as shown in fig. 5-b, and measure the response vibration, for average of four impacts, by an accelerometer. The output result of this test, as frequency spectrum and pulse spectrum gives the natural frequency of the machine set.

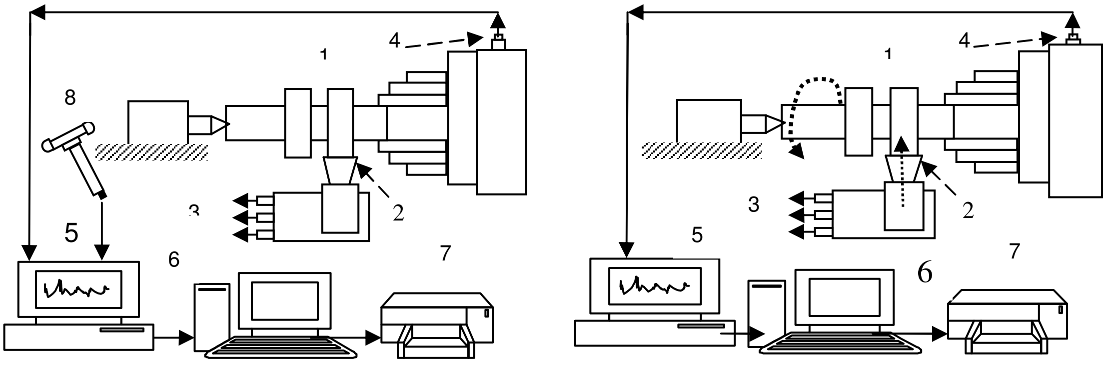
6. Results

The effects of variations of the cutting process parameters on the occurrences of chatter were used to give stable and unstable cutting regions. The levels of vibrations were measured at these regions. The threshold of stability is the start of the sudden increase of vibration levels. The frequency spectra and time domain of vibration levels were measured and analyzed for these regions. The relation of vibration level and width of cut was determined from these spectra, as shown in fig. 6, known as Threshold of Stability. Sample of measured spectra are shown in fig. 7. The frequency spectra help to watch the growing up of the vibration level at natural frequency of the machine set. The stable and unstable regions of cut are shown in the stability lobe diagram, fig. 8.

The radial and tangential cutting forces were measured for all regions of cut. The measured forces increased linearly with increase of width of cut during the stable region. For unstable region, cutting forces were smaller than the expected values (the same trend of stable cut). Also its rate of increase is less than the rate of increase in stable cutting. These changes may be due to decrease in the friction between chip and tool face. Also decrease of formation built up-edge due vibration between tool and workpiece reduce cutting forces [12]. Fig. 9 shows sample of these cutting forces relations, main cutting force (F_c) and radial cutting force (F_r). The relation between cutting power consumption and width of cut, for stable cutting, is linear. The power consumption for unstable cutting has the same trend of increase, as the stable region, but with higher values (more than 30 %) and higher rate. These increases are due to the absorption of power to produce the chatter vibrations, as shown in fig. 10.

7. Experimental verifications

Experimental studies are now conducted, again, for cutting forces and cutting power to verify the stability analysis prediction using the above ANN system. The cutting conditions of this experimental should be covered stable and unstable cutting regions. The same



(5-a) (5-a)

Fig. 5. Experimental test rig, 1) Workpiece, 2) Tool, 3) Dynamometer, 4) Accelerometer, 5) Dual channel analyzer, 6) Computer, 7) Printer, and 8) Hammer.

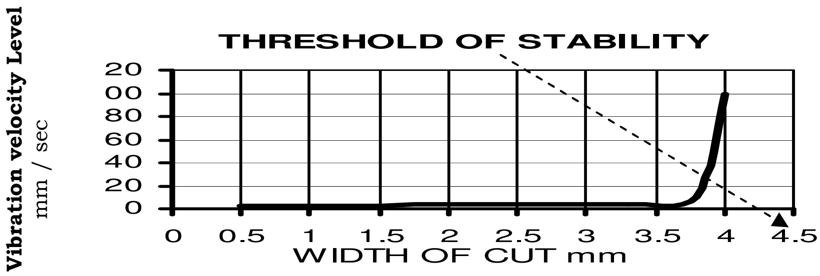


Fig. 6. Threshold of stability

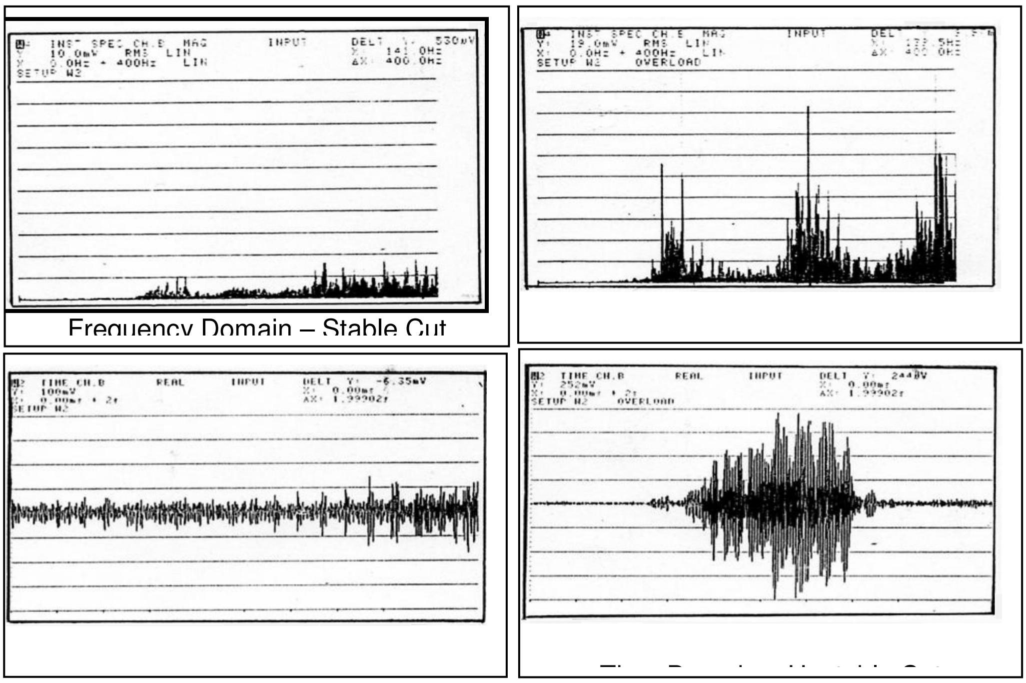


Fig. 7. Measured vibration spectra.

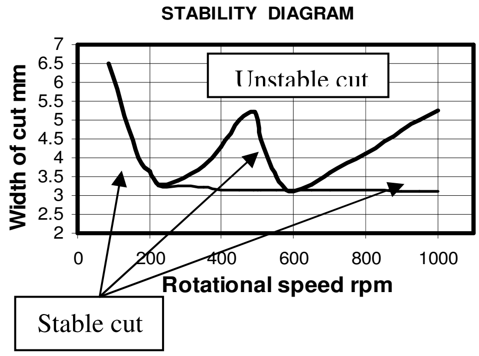


Fig. 8. Stability diagram.

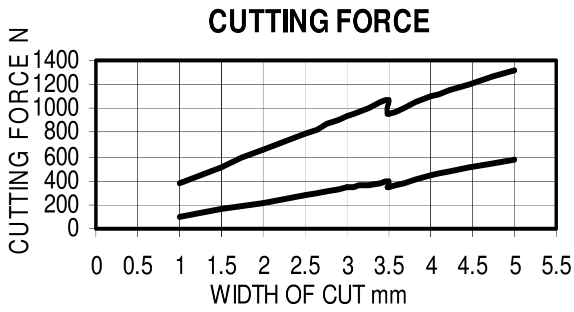


Fig. 9. Cutting force F_c > F_r.

Table 1
Experimental results

Cutting speed m/min (rpm)	Width of cut mm	Chatter (S: Stable C: chatter)	Vibration level mm/sec rms	Main cutting force F_c (N)	Thrust cutting force F_t (N)	F_c to width ratio	F_t to width ratio	Predictive power for chatter	Measured cutting power watt	% increase of power due to chatter	Measured to predictive power ratio	Compatibility With ANN System
	2	S	4	544	256	272	128	--	420	0	1	
	2.5	S	4.2	680	320	272	128	--	550	0	1	100%
	3	S	4.3	816	384	272	128	--	670	0	1	
	3.3	S	5.3	898	422	272	128	--	750	0	1	
61.6	3.5	C	15.5	952	280	174	80	810	1094	35	1.35	
(280)	3.8	C	72	1034	304	174	80	880	1276	45	1.45	
	4	C	80	1088	320	174	80	920	1380	50	1.5	
	4.5	C	84	1170	360	174	80	1040	1680	65	1.6	100%
	5	C	89	1360	400	174	80	1160	1972	70	1.7	
	2	S	4.6	440	220	220	110	--	1250	0	1	
	2.5	S	5.5	550	275	220	110	--	1430	0	1	
	2.7	S	7	590	300	220	110	--	1510	0	1	100%
143	3	S	8.4	660	330	220	110	--	1610	0	1	
(650)	3.3	C	30	429	165	130	50	1730	2336	35	1.35	
	3.8	C	84	494	190	130	50	1850	2500	35	1.35	
	4	C	110	520	200	130	50	1970	2660	35	1.35	
	4.5	C	125	585	220	130	50	2250	3150	40	1.4	100%
	5	C	140	650	250	130	50	2530	3542	40	1.4	
	6	C	170	780	300	130	50	2700	3780	40	1.4	

procedures as the above experimental work were considered in these cuttings. Table 1 shows samples of cutting conditions, at cutting speeds 61.6 and 143 m/min. These data present the learning data used for ANN system and the verification data, in gray rows, which check the compatibility of the experimental data with the prediction of the ANN system.

Verification experiments covered the range of 30 cutting speeds, from 5.5 up to 220 m/min. The total number of verification cutting was 40 sets of data. Some of these data are shown in fig. 11. A hundred per cent compatibility of the experimental data and the ANN system prediction data are obtained and verified.

8. Discussion and conclusions

A well trained ANN system has been successfully to recognize and differentiate between stable and unstable regions of cut by measuring the variation of cutting forces and cutting power related to the cutting process variables. To verify the degree of accuracy of this technique, additional measured values were fed to the system. The output of these

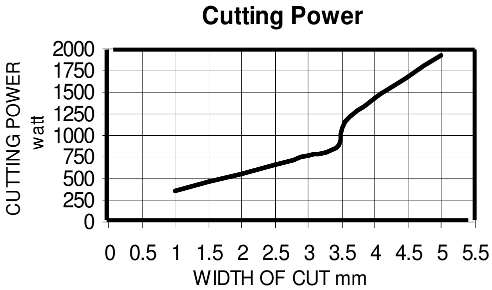


Fig. 10. Stability diagram.

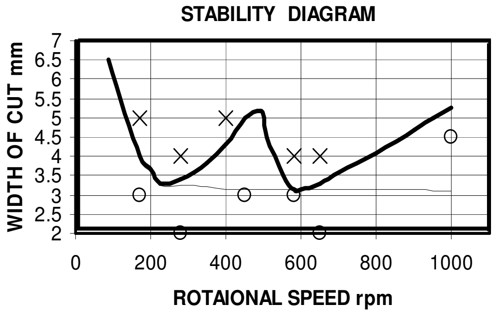


Fig. 11. Experimental verification (x: unstable cut, chatter) (o: stable cut)

inputs, occurrences of chatter or not, were plotted on the stability lobe diagram, fig. 11. The results show high correlation between the suggested predictor methodology and the experimental measurements.

It can be concluded that chatter occurrences can be recognized by measuring the variations in cutting forces and cutting power.

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