Figure 1: CNC turning machine that can make measurements with a vibration sensor and a dynamometer

Training neural networks for machining applications

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Machining is one of the most important techniques in modern-day manufacturing, and it continually evolves. One vital raw material category in machining is the nickel-based super-alloy. More recently, nickel-based super-alloys have become more widespread, especially in the aviation sector, industrial gas turbines, space applications, engines, nuclear reactors, submarines, steam production facilities, petrochemical devices, heat-resistant applications, and many more.

Each of these sectors uses machining tools, which are subject to many forces that lead to excessive vibrations which can cause deterioration and damage as well as affect processing stability and quality. To develop a stable processing strategy, it is necessary to have tool and machine vibration models to analyse the forces at play and identify the right solutions to mitigate those negative forces or avoid them entirely.

Relying on studies

In the machine industry, tool wear and surface roughness are important in determining cutting conditions. Studies have shown that determining the exact best values for, say material and tool lubrication, under various cutting conditions enables a more economical and efficient cutting process.

To reduce its speed and the effects of surface roughness on the cutting tool, the cutting process is performed under high pressure. One of the reasons for applying pressure is to reduce fractures on the cutting edge and the workpiece, and hence reduce vibrations. Increasing the pressure of the cooling water allows faster cutting speeds.

Predicting dimensional changes in cutting tools during the cutting process is especially important for understanding the machine's functionality and the lifespan of the tools. Variables such as cutting speed, depth and feed rate play an important role in predicting vibrations. Anova variance analysis testing can also be used to determine the effects of various cutting parameters.

Increased vibrations on the cutting tool are indicative of an increase in surface roughness. It is possible to say that during the cutting process of aluminium, light steel and PVC materials, cutting depth has minimum effect on tool vibration, whilst cutting force has maximum effect.

The system used for determining cutting force and vibration

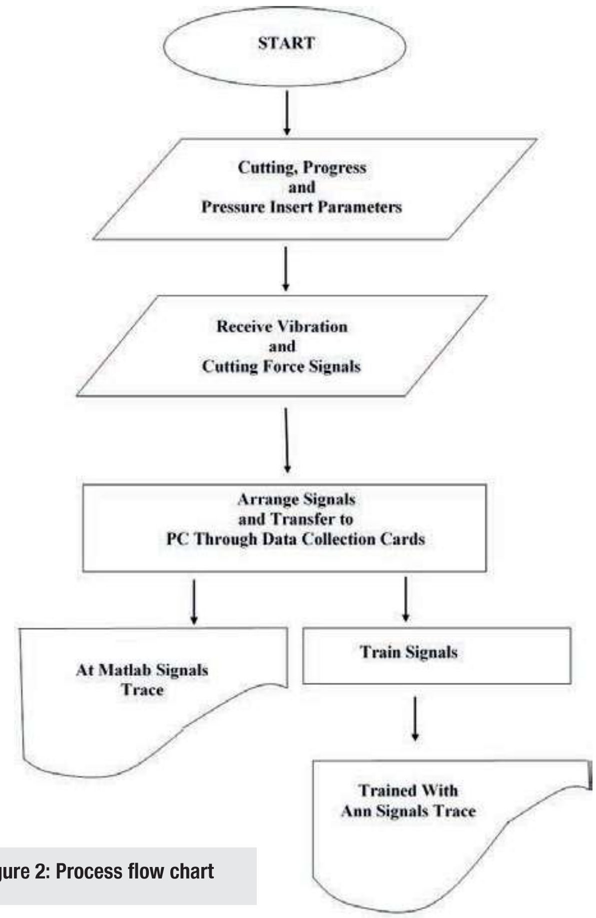

Figure 2: Process flow chart

during cutting under high cooling-liquid pressure is shown in Figure 1. Inconel 718 super alloy material was subjected to the turning process under various water pressure values. Cutting forces (progressive and tangential) were measured with a dynamometer, whilst displacement was measured with a vibration meter. Surface roughness and tool wear values were determined based on experiment parameters. Using experimental data, the cutting parameters (cutting speed, feed rate, cutting depth) and material properties – which together constitute the vibration-related factors – were collected in a database. Data was first taken into the Labview program, after which training was performed in Matlab on an artificial neural network (ANN). This enabled us to prepare vibration graphs to show tool wear, surface roughness and cutting forces according to different input values.

The flow chart of the process is shown in Figure 2.

Modelling of surface roughness mechanism is a complex process that relies on chip removal. For this reason, determining the roughness value analytically can be difficult. Equation 1, introduced by Boothroyd and Knight in 1989, determines the average surface roughness (R_a):

$$R_a = \frac{1000\,f^2}{32\,r} \tag{1}$$

Wear is defined as material loss on the contact surfaces between the cutting tool and the workpiece. In metal cutting processes, tool wear is defined as possible losses of processed products or used tools.

The ANN architecture

ANNs are information-processing systems developed from mathematical models of biological neural networks, which display a learned performance. ANNs are trained by pairing output values with corresponding input values.

Training an ANN to obtain target outputs requires a great number of inputs and steps, as well as numerous output sets for the relevant inputs. These data sets are called “training” and “test” sets. After the learning process, the test process is performed using the test inputs, to check the results of the designed network. The mechanism that enables the arrangement of weights in the network (to generate the desired inputs from the ANN during training) is called the “learning algorithm”.

There are many ANN architectures described in literature. In our project we used the multi-layered Feed-Forward Backpropagation algorithm, which is suitable for engineering applications, per Neşeli et al. 2009.

Figure 3 shows how surface roughness and tool wear predictions are performed in an established system, by using an

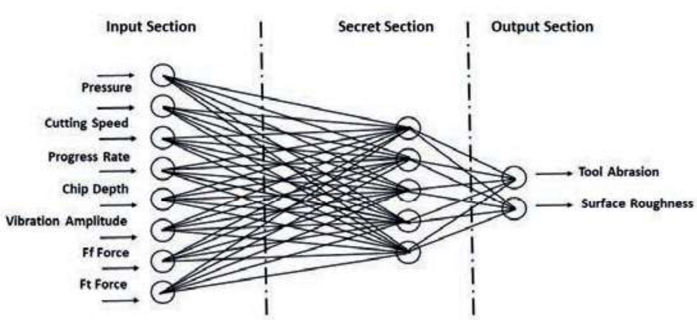

Figure 3: ANN network structure

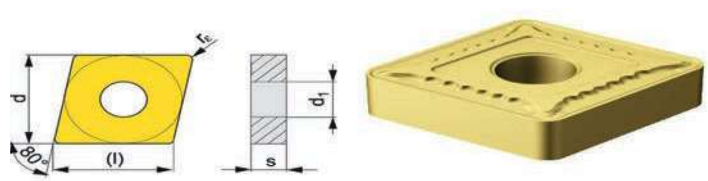

Figure 4: The cutter used in the study

Presentation (ISO)	Class	D	L	S	R
CNMG 120408-MR4	CP250	12.7	12.9	4.76	0.8

Table 1: Dimensions of the cutter in Figure 4

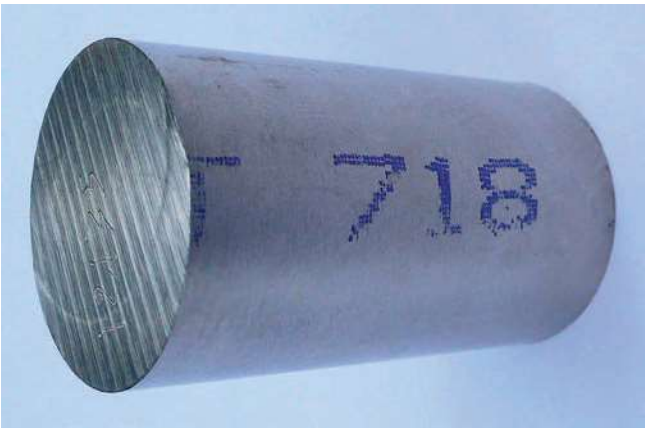

Figure 5: The Inconel 718 super-alloy used in the experiments

ANN with 13 different input parameters.

Materials

We used the SECO Jet Stream as our cutting tool, because it responds to the maximum pressure of 350 bar that we applied in this study; see Figure 4 and Table 1.

We used Inconel 718 material as the workpiece; see Figure 5. Its chemical composition is shown in Table 2, with its mechanical properties in Table 3.

The 353B31 PCB piezoelectric sensor was used to detect the vibrations; see Figure 6. The aim of using this model was to determine the suitable vibration sensitivity.

We used the 9757 dynamometer from Kistler to measure the cutting forces. Surface roughness was determined using a diamond-edged Hommel Werke T 500 tester, which takes measurements with 0.01µm sensitivity.

DAQ 6062E data collection card (Figure 7) was used to process the data from the vibration sensor and dynamometer. Its features include a 16-bit over 70 signals.

Cutting speed was 50m/s, with cutting depth of 0.25mm; the cooling liquid pressure was 6, 100 and 300bar; see Table 5.

Ni	Cr	Co	Mo	Nb+Ta	Mn	C	SI	Ti	Al	Fe
53.37	18.37	0.23	3.04	5.34	0.08	0.04	0.08	0.98	0.5	17.8

Table 2: Chemical composition of Inconel 718 super-alloy (% weight)

Tensile Strength (MPa)	Yield Strength (MPa)	Elastic Module (GPa)	Hardness (HR_c)	Density (g/cm^3)	Melting Point (°C)	Heat conductivity (W/mK)
1310	1110	206	52	8.19	1300	11.2

Table 3: Mechanical properties of the Inconel 718 super-alloy

Performance	Value
Sensitivity (±5%)	5.1mV/(m/s²)
Measurement range	±981m/s²pk
Frequency range (±5%)	1-5000Hz
Frequency range (±10%)	0.7-8000Hz
Frequency range (±3%)	0.35-15000Hz
Resonance Frequency	≥ 30kHz
Environmental	
Overload Limit	±98000m/s²pk
Working temperature	-54/+121°C
Electrical	
Excitation Voltage	18-30VDC
Excitation Current	2-20mA
Output Resistance	≤ 100 Ohm
Output Voltage	8-12VDC
Discharge period	0.5-2s

Table 4: Chemical composition of Inconel 718 (% weight)

Figure 6: PCB 353B31 vibration sensor

Figure 7: Data collection card

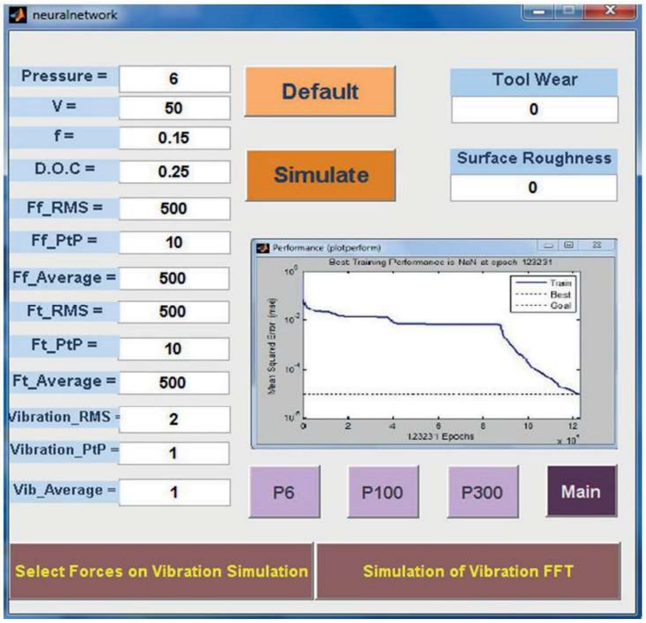

Figure 8: Artificial neural network and the prediction of tool wear and surface roughness

Figure 9: Results screen for tool wear and surface roughness

The program

During ANN training, it was possible to predict vibration wear and surface roughness based on our previously-trained network using 13 different parameters (cooling water high pressure, breaking speed, breaking depth, progress speed, force RMS, average force, peak-value force, vibration RMS, vibration average, vibration peak value, and others). The program's interface is shown in Figure 8.

Tool wear and surface roughness results are provided to the user in a separate window; see Figure 9.

In addition, with the aid of the program, we determined the time intervals and frequencies at which vibrations occurred, effectively predicting future ones; see Figures 10 and 11. As can be seen from these figures, the actual and predicted signals are very similar to one another, indicating a high degree of success of the training used for this program.

The graph on the frequency plane for the same signal is shown in Figure 11. This approach enables examination of signals on the time and frequency planes based on the Fourier series functions. Equation 2 determines the Fourier transform, F(ω), of a signal obtained on a complex exponential display; Equation 3 determines $e^{j\omega t}$:

$$F(\omega) = \int f(t)\, e^{-j\omega t}\, dt \qquad (2)$$

$$e^{j\omega t} = Cos\,(\omega t) + j\, Sin\,(\omega t) \qquad (3)$$

ANN in projects

In this study we developed an interface in Matlab by using an ANN on data obtained from the cutting workpiece made of the Inconel 718 super-alloy, at different pressures of cooling liquid, which was shown to be capable of making surface roughness and tool wear predictions according to 13 different input parameters.

The reliability of the data trained with an ANN was tested using the regression curve method. Tool wear and surface roughness estimations were found 96% and 97% reliable, respectively. The regression curves of the predictions are shown in Figure 12.

Using this interface, surface roughness and tool wear can be determined without using any physical measurements methods, saving considerable time. Furthermore, using another interface developed with the ANN method, it was possible to use cutting forces as inputs to predict the frequencies at which vibrations occurred during tests. This, again, allowed us to determine the

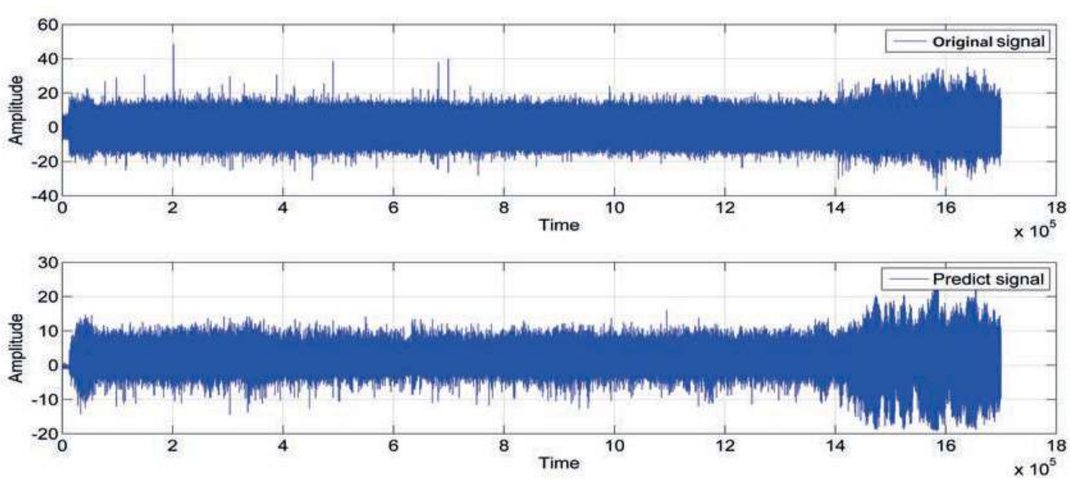

Figure 10: The determined signal on the vibration time plane based on the force signal, with ANN

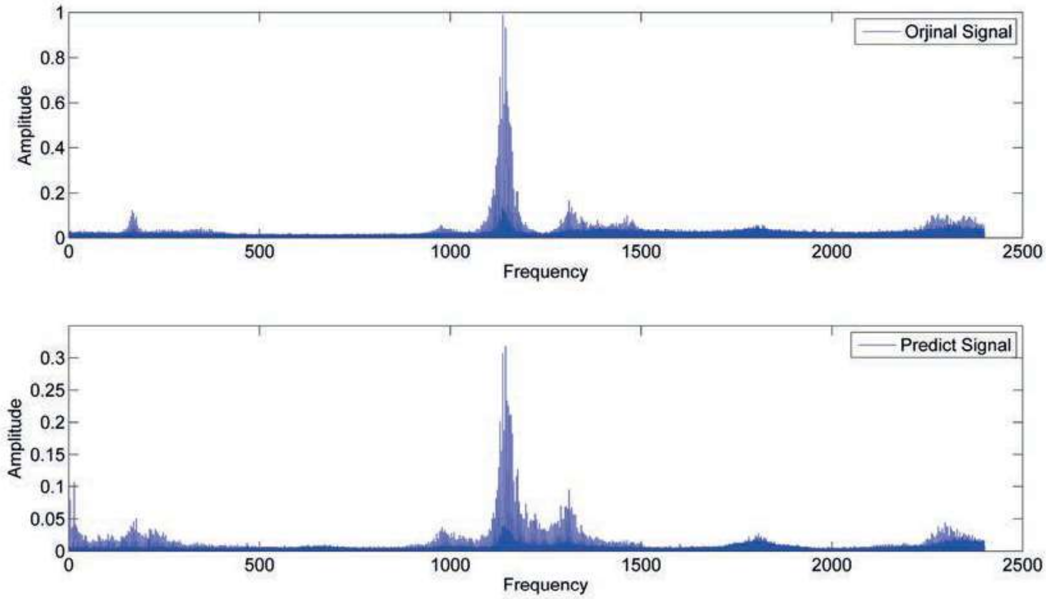

Figure 11: The signal on the vibration time plane determined based on the force signal, using ANN

frequency range of vibrations without a vibration sensor. It was understood from Figure 11 that the vibration predictions were very close to the actual values.

Tools like these could be effectively used to identify the most suitable cutting parameters to minimise vibrations during the cutting process. EW

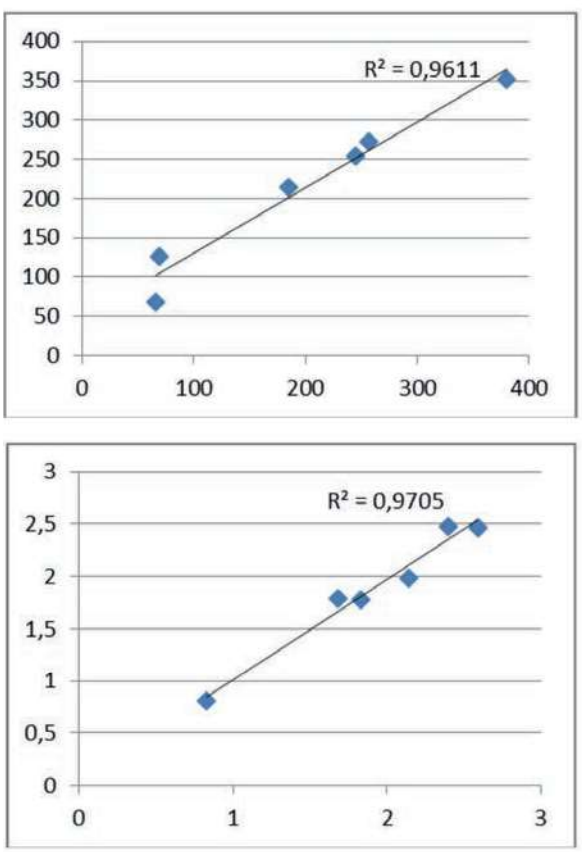

Figure 12: Tool wear and surface roughness regression curves

Test number	Pressure	Cutting Speed (m/min)	Progress speed (mm/turn)	Cutting depth
1	6	50	0.15	2.5
2	6	50	0.15	2.5
3	6	50	0.15	2.5
4	6	50	0.15	2.5
5	6	50	0.15	2.5
6	6	50	0.15	2.5
7	6	50	0.15	2.5
8	6	50	0.15	2.5
9	6	50	0.15	2.5
10	6	50	0.15	2.5
11	6	50	0.15	2.5
12	6	50	0.15	2.5
13	6	50	0.15	2.5
14	6	50	0.15	2.5
15	6	50	0.15	2.5
1	100	50	0.15	2.5
2	100	50	0.15	2.5
3	100	50	0.15	2.5
4	100	50	0.15	2.5
5	100	50	0.15	2.5
6	100	50	0.15	2.5
7	100	50	0.15	2.5
8	100	50	0.15	2.5
9	100	50	0.15	2.5
10	100	50	0.15	2.5
11	100	50	0.15	2.5
12	100	50	0.15	2.5
1	300	50	0.15	2.5
2	300	50	0.15	2.5
3	300	50	0.15	2.5
4	300	50	0.15	2.5
5	300	50	0.15	2.5
6	300	50	0.15	2.5
7	300	50	0.15	2.5

Table 5: The main parameters