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TOOL WEAR MONITORING UNDER PRACTICAL CONDITIONS

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***Summary**. Several works have been presented about tool wear monitoring systems (TWMS) using Artificial Neural Networks(ANN), fed with measurements from sensors. They show good results for detecting whether the tool is fresh or worn. In most of these works the tests were carried out for one type of tool (usually uncoated and with a flat rake face) artificially worn, one type of workpiece material and under a narrow range of cutting conditions. Although these results are important, they cannot be accepted as being good in practical situations, where coated tools with chip breakers and different materials are frequently used. The present work reports the results of research to build a TWMS for two types of tools and two different materials. During the tests for data acquisition the tools were continually used in a turning operation. Before interruptions to observe the stage of wear of the tool, measurements of force and acceleration were undertaken. The data obtained were used to train and to test the ANNs. The results suggest that for a TWMS to work successfully in practical situations, it must have a characteristic design different from those developed to be used for one type of tool and one type of material.*

***Keywords:** Tool wear monitoring, Tool monitoring, Tool wear*

1. INTRODUCTION

Motivated by the lack of a reliable tool wear monitoring system to predict the amount of wear of a tool at any time for different combinations of tool and material, research has been carried out by a number of workers aiming to provide information that could be used to produce such a system.

The works reported by Lee et al. (1989), Yao et al. (1990), Sokolowski et al. (1992) and Lister (1993) showed results of measurements of force and/or vibration of cutting tools during tool wear tests using uncoated tools with flat rake surfaces. The values of the signals and the amount of wear of the tools were correlated. Although these results are important, they cannot be accepted as being good for tools used in practical situations, where coated tools with chip breakers are mainly used.

The results of tool wear tests with coated tools and their correlation to the force and vibration of the cutting tool were reported by Karapanev et al. (1980) and by Bonifacio et al. (1994) respectively.

The static and dynamic behaviour of the tools were reported by Lister (1993) and Dan et al. (1990) as being useful as a source of information about tool wear.

Rangwala et al. (1987) described the use of Artificial Neural Networks (ANNs) for integration of signals from sensors for detection of tool wear states. Since then several authors have presented papers about different ways of using ANNs for tool wear monitoring. A literature review about these works can be found in Dimla et al. (1997).

Das et al. (1996) built a multiple feed forward ANN 5-3-1 to estimate the flank wear when fed with the three components of the cutting force, the cutting speed and the feed rate. The cutting tests in this work were carried out using uncoated P30 tools and low carbon steel SAE 1025. The average flank wear and the output of the ANN presented good correlation. According to the authors the result of the ANN was not so good when machining at high speed and high feed rate. In their opinion it may have been due to unstable built-up-edge formation, mild vibration or random chip breaking, that were observed, in certain cases, during the cutting tests.

Dimla et al. built a multiple feed forward ANN 12-20-1 to estimate the flank wear when fed with the energy from the three components (in the cutting, feed and depth directions) of the force, the energy from the three components of the acceleration, three components of the static cutting force, the cutting speed, the feed rate and the depth of cut. The output of the ANN was {1} for a worn tool and {0} for a sharp tool. This work was carried out using a P15 coated tool and a P25 uncoated tool, and work piece material SAE 4340. A second set of data were obtained from cutting tests undertaken with P10 and P40 tools and SAE 1040 steel. The main conclusions of this work were:

- The ANNs are sensitive to the tool insert type;
- Best results where found for ANN tested with data from cutting tests with SAE 4340 work piece material when P15 coated tool, harder than the P25 uncoated tool, was used. For cutting tests with SAE 1040 the highest success rate was achieved when the softer P40 tool data was used to test the ANN trained with data from tests with the P10 tool. Based on these results in their opinion the sensitivity of the ANNs to the tool material is rather inconclusive.

In the present work the authors show part of the results of research to built a Tool Wear Monitoring System based on measurements of force and acceleration, processed by a multiple feed forward ANN trained by backpropagation. It is expected that such a system will have presented in its output the amount of tool life used so far, at any time during turning operations, for different combinations of tools and workpiece materials. Several cutting tests with two different materials and two types of coated tools were carried out for data acquisition.

2. EXPERIMENTAL SET-UP

The cutting tests for data acquisition consisted of orthogonal turning operations on bars with a diameter of 100mm and a length of 600mm. During these tests signals of three components of force (cutting force(Pc), feed force (Pa) and depth force (Pp)) and acceleration (cutting (Ac), feed (Aa) and depth (Ap)) were sampled at different stages of the test. Next the tests were interrupted for observation and measurements of the main types of tool wear using a microscope. When it was relevant, a photograph of the tool was taken. In some cases, the profile of its rake face was made with a surface finish measuring instrument by means of the set up presented in “Fig. 1”. Materials, tools and cutting parameters used in the tests are shown in “Table 1”.

Usually the cutting parameters suggested by tool manufacturers, for a tool life of 15 minutes, are highly conservative, so when they are adopted the tool lasts 4 to 5 times longer.

Table 1. Materials, tools and cutting parameters used in the tests.

FAMILY OF TESTS	TEST	v (m/min)	a (mm/rev)	p (mm)	TYPE OF TOOL	WORK PIECE MATERIAL
T	T1	280	0.30	2.0	P25 CNMG432*	SAE 1040
	T2	190	0.50	3.0		
	T3	230	0.50	3.0		
	T4	250	0.37	1.0		
	T5	270	0.37	2.0		
	T6	250	0.37	2.0		
TT	TT1	290	0.37	2.0	K15 CNMA432**	
	TT2	310	0.37	2.0		
	TT3	310	0.50	1.0		
	TT4	330	0.50	1.0		
U	U1	330	0.30	2.0	P25 CNMG432*	SAE 1021
	U2	250	0.30	3.0		
	U3	320	0.30	2.0		
	U4	250	0.50	2.0		

* Iscar ic656 - coated and grooved (with chip breaker on the rake face) tool.
** Iscar ic428 - coated tool.

The cutting parameters were selected for this work aimed to have a real tool life of 15 minutes. In some tests the cutting parameters were chosen so as to cause a tool life different from 15 minutes, to obtain data to train and to test the ANNs not only for normal, but also for softer and harder cutting conditions. The criteria adopted for the end of tool's life, and therefore to stop the tests, were loss of the coating in the rake face for tests with SAE 1040 steel and the size of the notch for the tests with SAE 1021 steel.

The equipments used during the cutting tests were: accelerometers Bruel & Kjaer 4332 & 4334; charge amplifiers Kistler 5006 and 5001; digital tachometer ONO SOKKI HT-331; dynamometer Kistler 9263; input/output board Amplicon PC-30 PGH; lathe Dean Smith & Grace type 18 Centre Lathe, fitted with 20hp variable speed drive; personal computer Opus 486-33mhz; and surface finish measuring instrument Taylor Hobson Talysurf 10.

3. MAIN RESULTS OF THE TESTS FOR DATA ACQUISITION

3.1 Characteristics of tests with the steel SAE 1040 Steel Workpiece material

The main types of wear observed during the tests were flank wear on both flanks, notch on the main flank and crater. During these tests correlation between the progression of the wear and the increase of the three components of the static force were observed. On the other hand the progression of the tool wear and the trends of the acceleration could not be easily correlated.

The progression of the main types of tool wear were fairly continuous which probably contributed to the continuity of the graphs of the components of the static force.

3.2 Characteristics of the cutting tests with steel SAE 1021 Steel Workpiece material

The main types of wear observed during the tests were notch wear, wear of the coating on the rake face and flank wear. The graph of "Fig. 2" displays the progression of the static force in the cutting direction during a tool wear test typical for this material. In these cases, the progress of the tool wear can be divided in the following phases:

In the first phase, it was observed that workpiece material adhered in the groove of the tool.

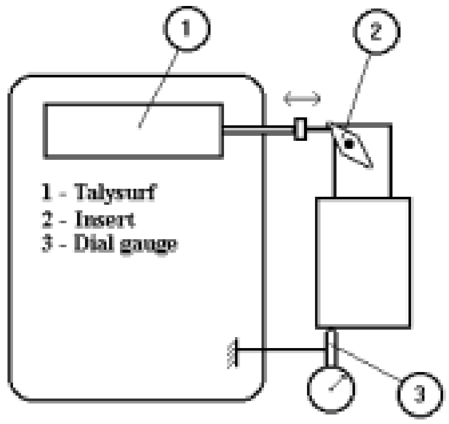


Figure 1– Set up used to record the of the tool on paper.

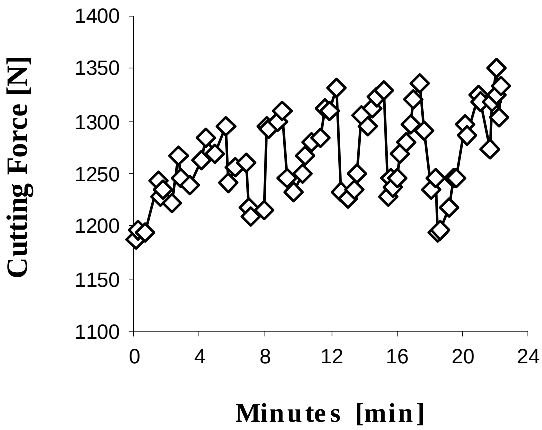


Figure 2 – Graph of the values of static force profile in the cutting direction measured during test U1.

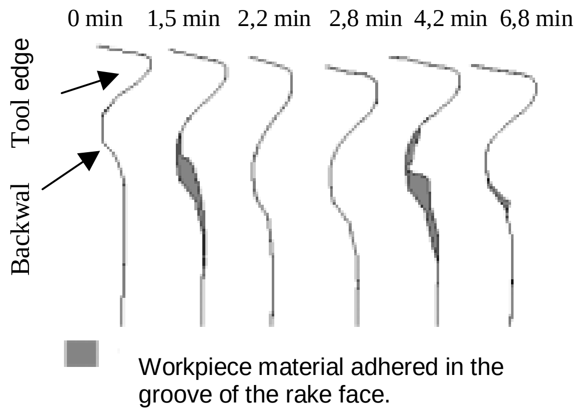


Figure 3 – Profile of the tool recorded at different stages of the U1 test.

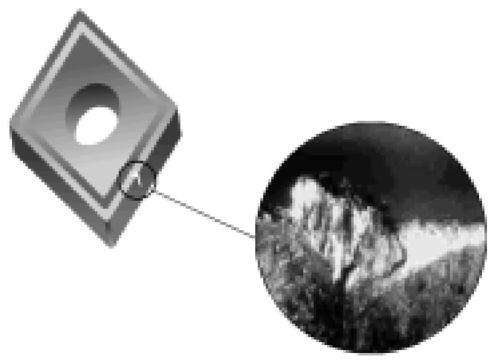


Figure 4 – Work piece material adhered in the notch.

In the second phase, cycles were observed in which the workpiece material built up in the back wall inside of the groove of the rake face of the tool, and was then removed by the chip. In "Fig. 3" the profile of the rake face of the tool at different stages of the cutting tests can be observed, where the adhered material is represented by the grey colour. During this phase, the components of the static force, mainly in the cutting and feed direction, have had cycles of increase followed by small decrease. The values of the forces observed after each cycle, were greater than in the previous one.

In the fourth phase a scratched area beneath the notch was observed, as if it was its continuation. This may suggest that the material adhered on the notch was pulled down against the surface of the flank. In this phase cycles of gradual increase and sudden decrease of the force components were still observed, but in each cycle the amplitude of the sudden decrease of the force components were smaller and its maximum values were greater than the ones observed in the previous cycle.

4. EXPERIMENTS WITH ANNs FOR ESTIMATION OF THE PERCENTAGE OF THE TOOL LIFE USED SO FAR AT STAGES OF ITS LIFE

In these experiments, the ANNs were trained to display in its output the percentage of the life of the tool used so far when fed with three components of the force and/or the RMS of the three components of the acceleration. “Table 2” shows the structure, the parameters used as input and the tests used in the training section of each ANN. Data from tests with both materials and with coated and grooved tools were used to train and to test the ANNs, while data from tests with flat tools were only used to test the ANNs. The values of Mean Relative Error (MRE) suggested by Masters (1993) to measure the prediction error of ANNs, were adopted in this work to evaluate the performance of the ANNs.) The value of MRE is calculated by “Eq. (1)” where “Oi” is the value estimated by the ANN, “Ti” is the value expected for this estimation (target) and n the number of values estimated during each test of the ANN.

$$MRE = 1/n \Sigma \, ABS\,[[Ti - Oi] / Ti]] \text{ for } i=0 \text{ to } i=n-1 \tag{1}$$

Table 2. Characteristics of the ANNs trained for these experiments

ANN	STRUCTURE of the ANN*	INPUT	TESTS USED IN THE TRAINING SECTION
1A	6x5x1	Pc, Pa, Pp, Ac, Aa & Ap	T1 &T2
1B	3x4x1	3 comp. of static force only	T1 & T2
1C	3x4x1	3 RMS of comp. of acceleration only	T1 & T2
2	6x5x1	Pc, Pa, Pp, Ac, Aa & Ap	T1, T2, T3, T4, T5 & T6
3	6x5x1	Pc, Pa, Pp, Ac, Aa & Ap	U1, U2, U3 & U4

* I (number of input neurons) x H (number of hidden neurons) x O (number of output neurons)

4.1 Experiments with ANNs for data from tests of the “T” family

“Figure 5” shows the graphs of percentage of tool life used so far againist time predicted by ANNs 1A, 1B, 1C and ANN2 fed with data from T1 and T2 tests.

It can be observed in “Table 3” that the MSE for the ANN 1A tested for data from “T1” and “T2” tests are 0,218 and 0,161 respectively. The small values of MSE for the estimations of the ANN 2, that was trained with data from all tests of the “T” family, suggests that the ANN displays superior performance when trained with data from tests undertaken with different cutting parameters. It can be concluded from the comparisons between the MSE of the values predicted by ANNs 1B and 1C for tests “T1” and “T2” that the values of force are more effective in providing information about the tool wear state than the values of acceleration.

Table 3. Values of Mean Relative Error (MRE) between the percentage of the tool life predicted by ANNs 1, 1B, 1C and 2, and the real percentage of the tool life.

TESTS	MSE between the percentage of the tool life predicted by the ANNs and the percentage of the real tool life.			
	ANN 1A	ANN 1B	ANN 1C	ANN 2
T1	0,218	0,213	0,395	0.147
T2	0,161	0,123	3,07	0.142
T3	0,538	-	-	0.122
T4	1,23	-	-	0.271
T5	1,25	-	-	0.337
T6	0.991	-	-	0.185

Table 4. Correlation between the percentage of the tool life predicted by the ANNs, for data from tests of all families, and time.

ANN	Correlation between the percentage of the tool life predicted by the ANNs and time.													
	T1	T2	T3	T4	T5	T6	TT1	TT2	TT3	TT4	U1	U2	U3	U4
1A	0.97	0,99	0,97	0,94	0,92	0,96	-	-	-	-	-	-	-	-
1B	0,99	0,99	-	-	-	-	-	-	-	-	-	-	-	-
1C	0,82	0,90	-	-	-	-	-	-	-	-	-	-	-	-
2	0,98	0,98	0,99	0,92	0,99	0,99	0,82	0,86	0,35	0,81	0,24	0,43	0,55	0,26
3	-	-	-	-	-	-	-	-	-	-	0,54	0,53	0,30	0,86

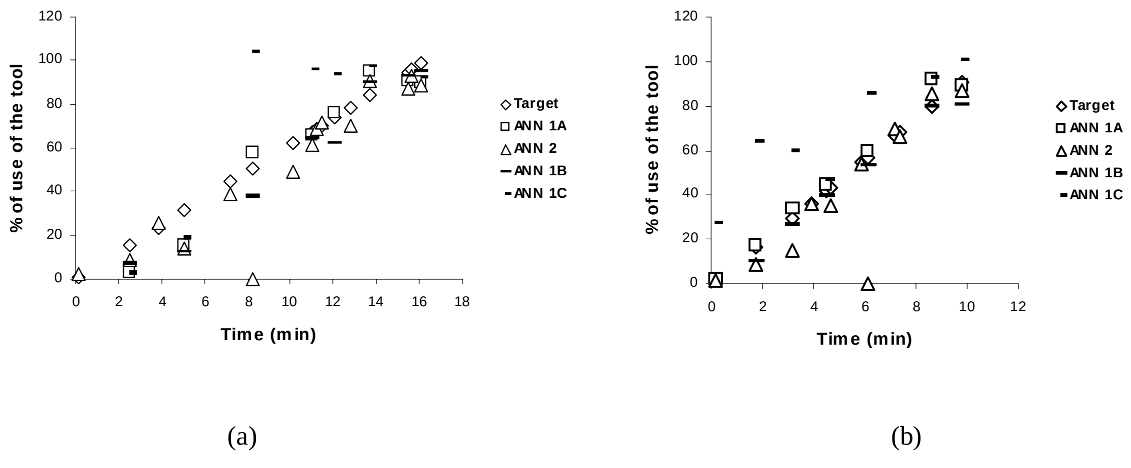
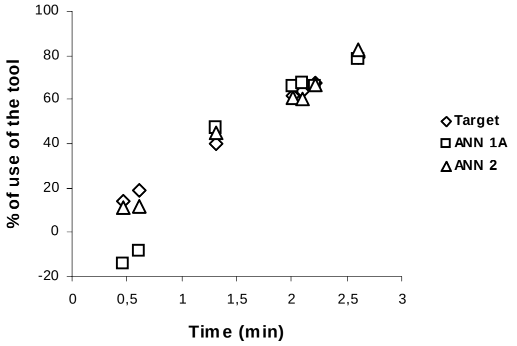
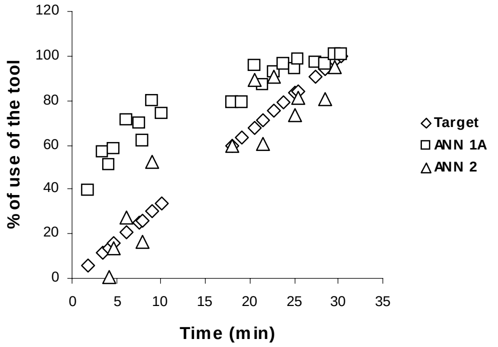


Figure 5 - Graphs showing percentage of use of the tool estimated by four ANNs x time, tested for data from tests: (a) T1 and (b) T2.

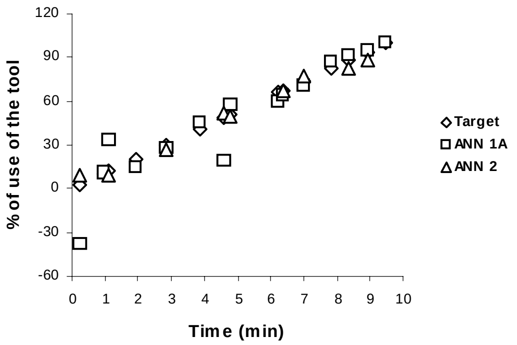
The performance of the ANN 1A was tested for data from tests T3 to T6, that were not used in its training section. The values of the MRE calculated for this experiment indicate poor results. The results from ANN 1A for data from tests “T3” and “T5”, shown in “Fig. 6” (a) and (c), could be considered acceptable, excepted for a few points that were far from the target, which could be caused by errors in their measurements. On the other hand, the high values of correlation of the estimations of ANN 1A with time indicate that the performance of a ANN could be improved if data from tests “T3” to “T6” were included in the training section. This hypothesis appears to be acceptable taking into account the small values of MSE calculated for the results from ANN 2 when it was tested for data from tests “T3” to “T6”.



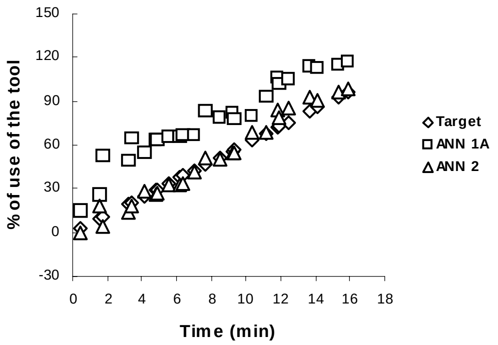
(a)



(b)



(c)



(d)

Figure 6 - Graphs showing percentage of use of the tool estimated by ANN 1 and ANN 2 x time, tested for data from tests: (a) T3; (b) T4; (c) T5; (d) T6.

4.2 Experiments with ANNs for data from tests of the “TT” family

“Figure 7” shows the graphs of ANN 2 tested for data from the “TT” family, that were not used in its training section. Although the values of MSE calculated for this experiment were extremely high, the results showed adequate correlation with time (see “Tab.4”) except for tests with data from test “TT3”.

The superior results of the tests with data from tests “TT1” and “TT2” were probably due to the rate of wear caused by high temperatures and high stresses generated by their harder cutting conditions compared with the ones in tests “TT3” and “TT4”.

Taking into account that the progress of the wear of the rake and the flank faces of the tools were continuous during the “TT” tests and that the estimations of the ANN 2 for these tests showed correlation with time, better results could be expected from an ANN trained with data from these tests, in the same way that better results were found with ANN 2 than with ANN 1 when they were tested for data from tests “T3” to “T6”.

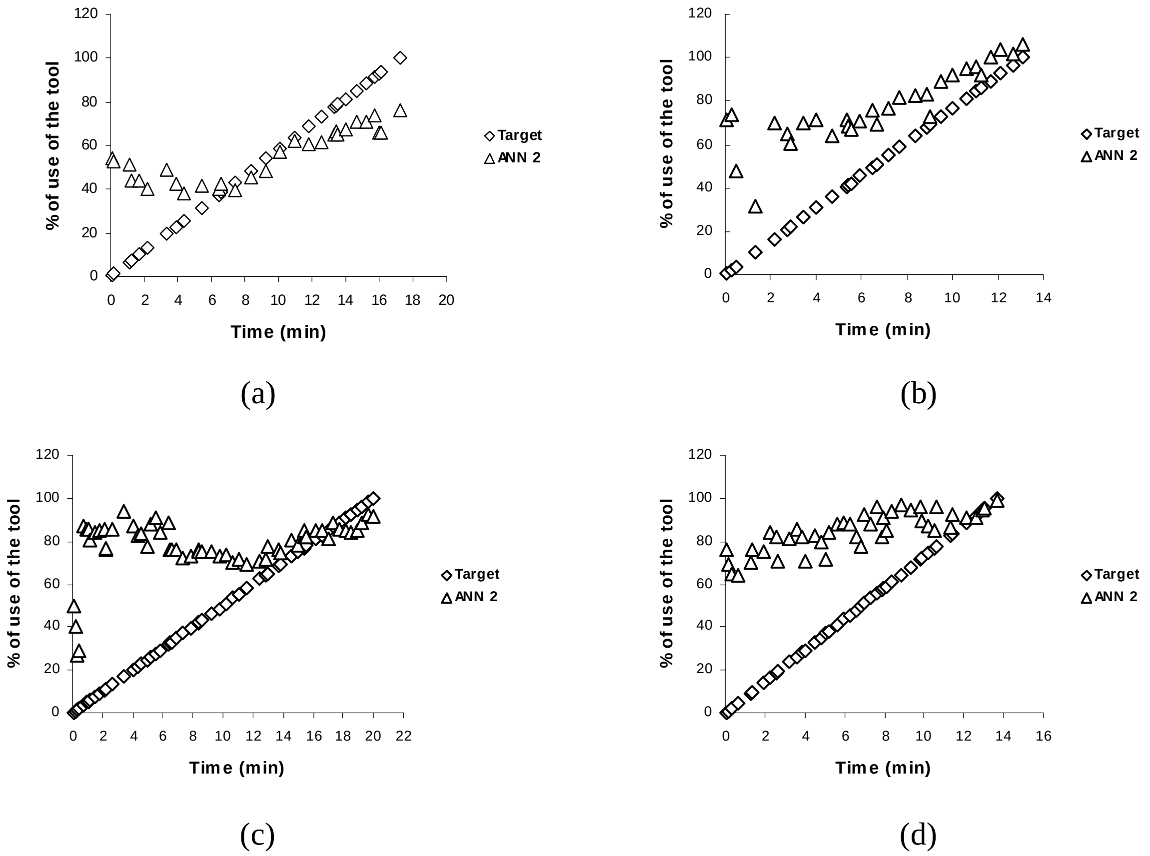


Figure 7 - Graphs percentage of use of the tool estimated by ANN 2 x time, tested for data from tests: (a) TT1; (b) TT2; (c) TT3 and (d) TT4.

4.3 Experiments with ANNs for data from tests of the “U” family

“Figure 8” shows the graphs of the ANN 2 and ANN 3 tested for data from the “U” family. Poor results were obtained from ANN 2 with high values of MSE and low correlation with time. ANN3 was trained with data from “U” tests aiming to improve the estimations of percentage of use of the tool. Huge values of MSE were still observed and almost no improvements of the correlation with time were observed except when ANN 3 was tested with data from test U4.

The poor results of this experiments could be caused by cycles of adhesion and removal of the work piece material, described in section 3.2, which were reflected in the values of the force components. During these cycles, the same values of force were measured at different stages of the cutting test, which appears to be the main problem to obtain acceptable estimations of the tool wear state from a ANN trained with values of force and acceleration only.

5. CONCLUSION

Best results were obtained from ANNs trained and tested with data from all tests with workpiece material SAE 1040 and P25 coated and grooved tools ("T" family). ANN 1 trained with data from only two tests did not show satisfactory results when tested for data from other tests.

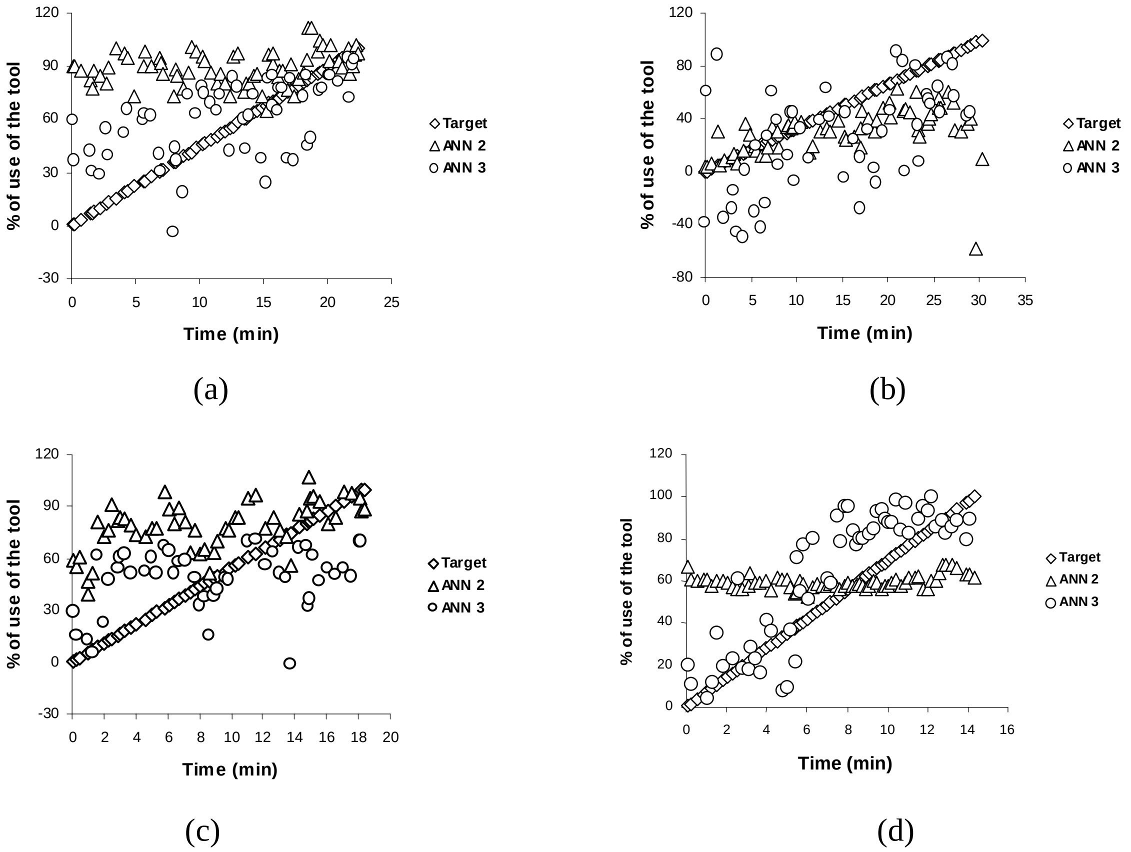


Figure 8 - Graphs showing percentage of use of the tool estimated by ANN 2 and ANN 3 x time, tested for data from tests: (a) U1; (b) U2; (c) U3 and (d) U4.

It appears that the success of the ANNs trained with data from the tests with workpiece material SAE 1040 were due to the continuous progression of the wear of the rake face of the tool. It indicates that satisfactory results could also be obtained for ANNs trained to monitor cutting tests with other hard steels.

ANN 1B trained only with components of static force presented better estimations than ANN 1C trained with only the RMS of acceleration components.

The ANNs show sensitivity to the type of tool, as was also observed by Dimla et al. (1997), but it appears that their performance could be improved if data from tests with different types of tools were used in the training section.

The ANNs trained with data from cutting tests with SAE 1040 steel (ANN 2) presented poor results when tested for data from cutting tests undertaken with SAE 1021 and with the same type of tool. There was almost no improvement in the results from a ANNs trained with data from these tests with SAE 1021 steel. These poor results could be explained by the discontinuous character of the progress of the components of the static force during these tests. The characteristics of these tests could explain the problems of Das et al. (1996) during their research.

It seems that to have a reliable ANN, able to cope with the characteristics of the cutting tests with a ductile material like SAE 1021, it must be built to detect the type of tool wear mechanism dominant at any time of the tool wear test.

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