



24th DAAAM International Symposium on Intelligent Manufacturing and Automation, 2013

## Tool Wear Classification using Decision Trees in Stone Drilling Applications: a Preliminary Study

Miho Klaic\*, Tomislav Staroveski, Toma Udiljak

*Faculty of Mechanical Engineering and Naval Architecture, Ivana Lucica 5, 10000 Zagreb, Croatia*

---

### Abstract

Process parameters of stone drilling with a small diameter twist drill were used to predict tool wear by means of a machine learning decision tree algorithm. The model links tool wear with features extracted from the force sensor and the main and feed drive current sensors signals recorded under different cutting conditions and different tool wear states. Signal features extracted from both the time and frequency domain were used as input parameters for construction of a decision tree which classifies the tool state into sharp or worn. The model was refined by selecting only the feature sources most important for classification. The best model achieves 90% accuracy in classification and relies only on features of the current signals, which simplifies its implementation in a CNC system for industrial applications.

© 2014 The Authors. Published by Elsevier Ltd. Open access under [CC BY-NC-ND license](https://creativecommons.org/licenses/by-nc-nd/4.0/).  
Selection and peer-review under responsibility of DAAAM International Vienna

*Keywords:* tool wear, stone drilling, tool condition monitoring, machine learning

---

### 1. Introduction

Tool wear estimation and breakage detection are generally considered to be among the most important problems in modern CNC machine tool automation. Implementation of reliable tool condition monitoring (TCM) system would allow the tool wear state information to be sent to the CNC unit in order to suggest suitable adaptive and/or corrective actions[1]. As a result, higher automation level of machine tools would be achieved with several important benefits:

---

\* Corresponding author. Tel.: +385 1 6168 439; fax: +0-000-000-0000 .  
E-mail address: [miho.klaic@fsb.hr](mailto:miho.klaic@fsb.hr)

- Downtime caused by the tool failure and possible consequent machine damage would be prevented. This is important economical factor since the downtime cost can be significant compared to the price of the cutting tool.
- Underuse or overuse of tools would be avoided by scheduling tool change in a timely manner and thus, more economic production would be possible. Due to the variations in the tool life, economical tool life cannot be achieved without means for tool wear monitoring.
- Scrap or rework of the work piece would be minimised.
- TCM is mandatory prerequisite for unmanned machining and flexible automated manufacturing.
- Optimization of machining process by adaptive control of cutting conditions would be possible (with several criteria such as maximum tool life, optimal energy consumption or maximal productivity).

For all of the above reasons, various TCM approaches have been extensively studied in the past two decades [1]. In general, TCM methods are classified in two categories: direct and indirect. With direct methods it is possible to get the accurate measurements of the tool wear by capturing actual geometric changes arising from wear, which is in industrial environment done either by using cameras for visual inspection or laser based sensors for distance and size measurements. However, due to the practical limitations of direct TCM methods, the cutting process has to be stopped as the view is obstructed by the coolant, chips and continuous contact between cutting tool and workpiece. Industrial applications of direct TCM techniques are severely limited by these difficulties and such systems are more often employed in research to support the investigations of indirect TCM approaches.

In indirect TCM approaches, the machining process is continuously monitored by a number of sensing devices such as force, vibration, acoustic emission (AE), main/feed drive current sensors and others. Sensor signals are first conditioned and processed in order to extract a number of features correlating with the tool wear. Features are then analyzed by suitable algorithms in order to estimate the degree of tool wear by empirically determined correlations. The main reason for multi sensor approach is potentially more reliable estimation of the tool condition, which might not be accomplished by using single type of sensor. Even though indirect TCM approaches are generally less accurate, they have the advantages of continuous on-line monitoring and less complicated setup. Hence they are generally considered to be more suited for industrial applications.

Due to the high nonlinearity of the cutting processes, universally applicable general purpose TCM system has not yet been devised. Instead, such solutions are tailored for specific cutting tool, workpiece material and machining operation. Most recent review of TCM approaches in general are described by Tetiat *al* [1]. A detailed review of studied and applied techniques of indirect monitoring in drilling is described by Jantunen [2]. It is concluded that only a limited number of TCM methods have been successfully developed in drilling. In addition, the majority of studies are limited in terms of cutting process parameter variation such as cutting speed, feed rate, drill diameter and material and also workpiece material.

Tool wear increases the friction between the cutting lips and surrounding workpiece material, which consequently leads to the increase of cutting forces and temperature. The distribution of heat and the gradients of pressure and stress along the cutting lips accelerate associated physical and chemical processes causing the drill to wear faster. This process gradually leads to catastrophic drill failure, occurring at the moment when drill can no longer support the cutting forces.

Cutting conditions and geometry of the twist drill varies from the chisel edge to the margin along the cutting lips. As a result, different wear patterns can be observed and used as wear criterion on the drill such as flank wear, chisel edge wear, outer corner wear, margin wear and crater wear [3]. Progressive flank wear was the dominant wear criterion in most of the research on TCM in drilling [2, 4]. Cutting edge rounding was also suggested in [5] as novel wear criterion in drilling composite materials. Outer corner wear is also often classified as predominant type of drill wear due to highest cutting speed being present on the outer corner of the cutting lips [6, 3].

Most of indirect TCM approaches in drilling are based on the measurements of torque, cutting forces, spindle and feed motor currents as well as low and high frequency vibrations and AE. Vibrations are generally considered to be very sensitive to surrounding noise inherent to the cutting process [7], even though successful attempts relying on such measurements have been reported. More common approaches are based on the cutting force and motor current measurements.

Torque and cutting forces are considered to provide good assessment of the tool condition since the cutting forces increase with the progression of tool wear [3, 8]. However, such measurements are also influenced by workpiece

hardness. Subramanian and Cook [9] report drill life to be strongly influenced by work material hardness, which may account for variations of drill life observed in industrial conditions. Therefore, torque and thrust force can be used as variables for drill wear sensing only when there is a close tolerance of the workpiece hardness, of the order of  $\pm 5$ .

By measuring main spindle and feed drive motor current it is possible to obtain indirect measurements of the torque and cutting forces as well as machine power output. The main spindle current is proportional to the resulting cutting force and torque, while the feed motor closely correlates to the thrust force. Hence, motor current based TCM approaches are quite common and have been applied in a production [1]. Main advantage of such approaches is that the machining process is not disturbed by the measuring system. In addition, current signals can be obtained from the machine tool servo drives, allowing possibilities for “sensorless” TCM [7]. However, such measurements are less accurate compared to the direct force measurements, because current signals besides the cutting process information also contain the motor and drive train dynamics, and are dependent on the inherent temperature rises in the motors, as well as the axis lubrication state [1]. Current measurements have been reported to be reliable in monitoring at medium and heavy cuts [10].

Most of the covered research on TCM in drilling is focused on metal machining applications. Much less studies of drill wear on non-homogeneous materials such as composites [11, 12] and very few studies are done for stone drilling applications.

Stone is material most commonly used in architecture and renovation of monuments. Such materials are heterogeneous, which is result of different sedimentation layers, grain sizes as well as micro and macro cracks. Hence, it is often not possible to use hardness measurements such as Vickers, Brinell, Rockwell, etc. In addition, measurements provide index data for material surface and not in the bulk of the material [13]. Hardness of such materials is thus more often estimated *in situ* by means of drilling resistance measuring systems (DRMS) in which the thrust force is measured under constant cutting conditions and deduced to material hardness. Tool wear in stone drilling is investigated for correction of hardness estimation using DRMS instruments [13-16].

The main objective of this paper was to analyze signal features that could potentially be correlated with the drill wear in stone drilling, and to develop a simple yet reliable tool wear model applicable for indirect TCM in such applications. Secondary aim was to establish the types of drill wear typical for such applications. Since no close tolerances are required in stone machining, machine tools for such applications are generally less accurate and less expensive compared to the machine tools for metalworking. Motivation for this work is found in the hypothesis that the economically justified TCM method applicable for such machinery and applications would have to be very simple, consisting of minimal number of sensors and simple algorithms which could be coded for low-end control systems hardware.

## 2. Experiential setup

Simplified version of the experimental system originally applied in [17] was used in this work. This system consists of small test bed milling machine, CNC system with an open architecture controller [18] and external measurement system used for signal recording and remote control of the CNC system (Fig. 1.).

Cutting force measurements were made using the force sensor type 9257B and the charge amplifier type 5017B manufactured by KISTER Holding AG (Switzerland). Main spindle and feed motor current measurements were made using the servo CNC servodrives type DPCANIE-015A400 manufactured by AMC Inc. (USA). Measuring signals were acquired using the NI CopactRIO external measurement system type cDAQ-9178, manufactured by National Instruments Inc. (USA). Customized measurement software developed in the LabView environment [17] was used for cutting conditions setup, storage of the acquired signals and NC drilling cycle program generation. Each measurement started by issuing the trigger signal from the CNC control system to the external measurement system. Acquired signals were processed using the MATLAB software, which is also used for the feature extraction and visualization of measured quantities. Direct measurements of the drill cutting lips were made using the industrial camera type DMK41AF02 manufactured by Imaging Source GmbH (Germany), equipped with the telecentric lenses type TC2309 manufactured by Opto Engineering S.r.l. (Italy.)

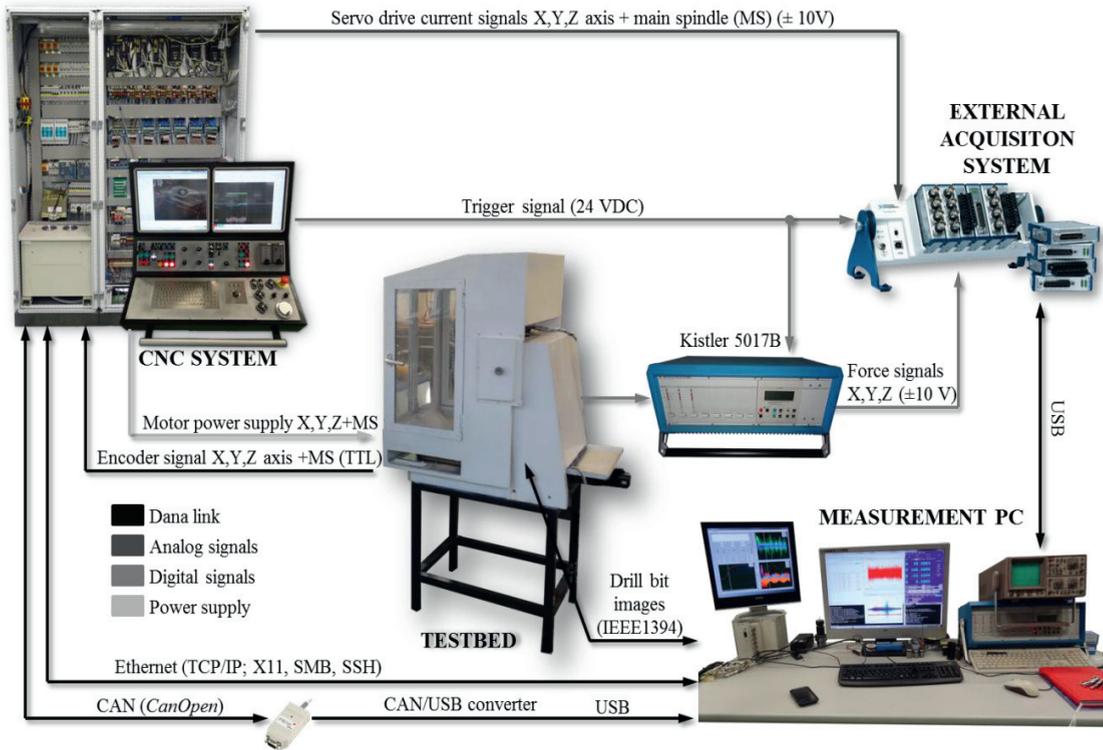


Fig.1. Schematic diagram of the experimental set-up.

In the experimental system a small diameter (5 mm) twist drill type BOSCH CYL-9 was used to drill 10 mm deep holes in *AdriaGrigioMachiato* stone samples (Fig. 2.) under different cutting conditions (Table 1.) and different tool conditions (Fig. 3.). Thrust and drift force, as well as the main and feed drive current sensors signals were synchronously recorded during each drilling cycle on external measuring system (Table 2).

Table 1. Cutting conditions used in the experiments.

Drill diameter $d_1$ (mm)	Cutting speed $v_c$ (m/min)	Feed rate $f_z$ (mm/rev).	Spindle speed $n$ ( $\text{min}^{-1}$ )	Feed velocity $v_f$ (mm/min)	Borehole depth $a_p$ (mm)	Cycle time $t_d$ (s)	Replications
5	10	0,05	636,61	31,83	10	37,7	10
	30	0,05	1909,85	95,49		12,56	
	50	0,05	3183,09	159,15		7,54	
	10	0,1	636,61	63,66		18,85	
	30	0,1	1909,85	190,98		6,28	
	50	0,1	3183,09	318,30		3,77	
	10	0,15	636,61	95,49		12,56	
	30	0,15	1909,85	286,47		4,18	
	50	0,15	3183,09	477,46		2,51	

Table 2. List of measured signals in the experimental setup. Measurement range for the force sensor is displayed with respect to the design limitations of the testbed.

Source	Signal	Range	Sampling rate
Force sensor	Cutting force component in X axis direction ( $F_x$ )	$\pm 1200$ N	1 kHz
	Cutting force component in Y axis direction ( $F_y$ )		
	Cutting force component in Z axis direction ( $F_z$ )		
Feed drives current sensors	X axis feed motor current ( $I_x$ )	$\pm 7$ A	1 kHz
	Y axis feed motor current ( $I_y$ )		
	Z axis feed motor current ( $I_z$ )		
Main spindle drive current sensor	Spindle motor current ( $I_s$ )		

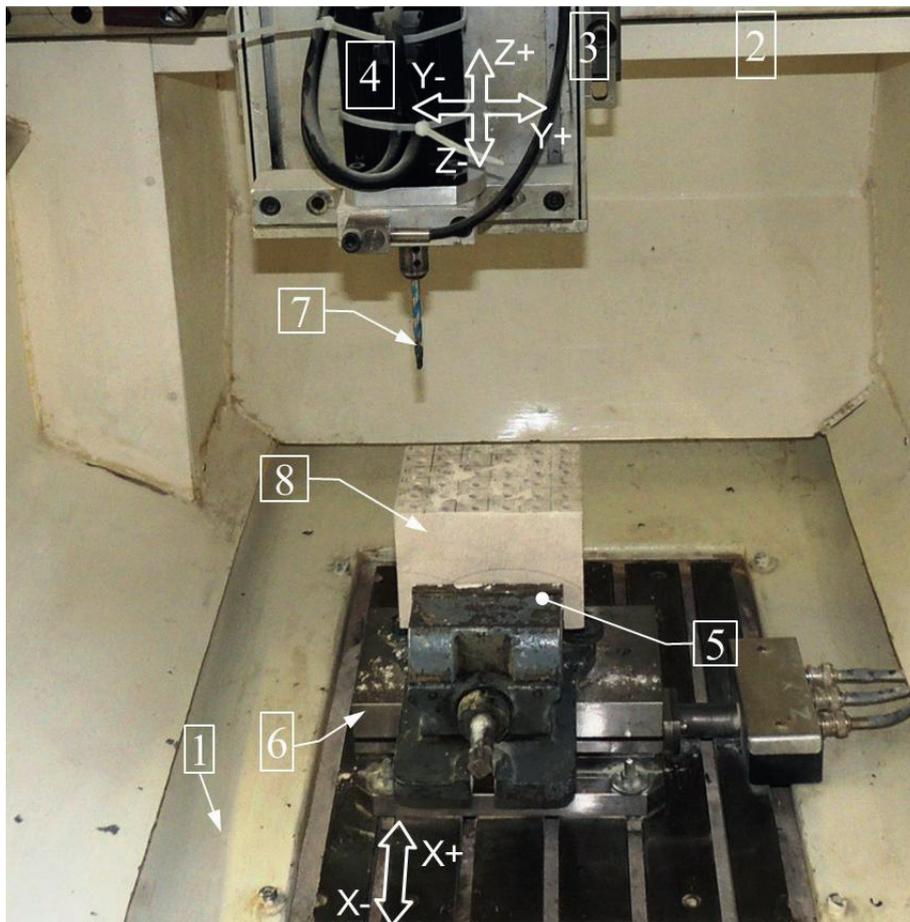


Fig. 2. Testbed machine work area and sensor placement. (1) X axis feed drive; (2) Y axis feed drive; (3) Z axis feed drive; (4) main spindle drive; (5) workpiece fixture; (6) three axis force sensor; (7) test drill; (8) sample stone workpiece.

Measurements are first taken while drilling with completely sharp drill and then repeated using the dull drill (Fig. 3.). After completing the measurements with the sharp drill, it was then used to drill a number of cycles until it completely worn out [19]. On a worn drill, flank wear and cracks were observed as dominant wear features.

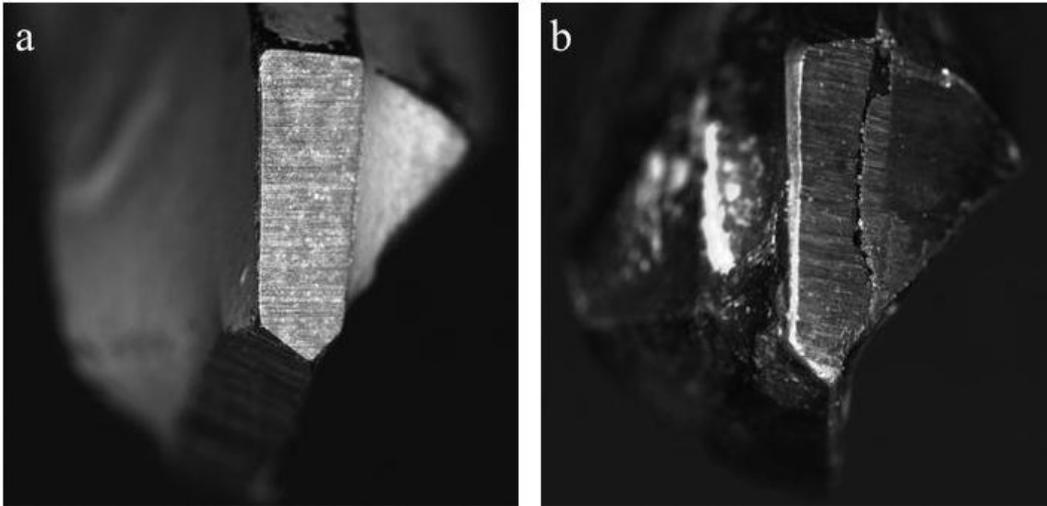


Fig. 3. (a) sharp drill bit; (b) dull drill bit.

### 3. Signal processing and feature extraction

In order to extract signal features to be potentially correlated with different tool conditions, Butterworth low-pass signal filtering was applied (500 Hz cut-off frequency), with respect to the sensors bandwidth and acquisition hardware sampling rates. For feature extraction in time domain, low-pass Butterworth filtering was applied with 2 Hz cut-off frequency. In time domain, “maximum” values of quantities were calculated on the basis of the average of 10% of peak signal measurements, while areas under curve were calculated by numerical integration of measured quantities in the drilling cycle time interval. For feature extraction in frequency domain, the power of spectral components on drill and cutting lip frequencies was calculated. Total of 11 features has been extracted from the time domain and 14 features were extracted from the frequency domain (Table 3.).

Table 3. Description and notation of features

Features extracted in time domain			Features extracted in frequency domain			
Method	Quantity	Notation	Method	Quantity	Notation	
Maximum value	Thrust force ( $F_z$ )	Max_Fz	Power of spectral components on the rotational frequency of the drill	Cutting force component in X axis direction ( $F_x$ )	SPR_Fx	
	Resultant cutting force ( $F_R$ )	Max_Fr		Cutting force component in Y axis direction ( $F_y$ )	SPR_Fy	
	Spindle motor current ( $I_s$ )	Max_Is		Cutting force component in Z axis direction ( $F_z$ )	SPR_Fz	
	Z axis feed motor current ( $I_z$ )	Max_Iz		X axis feed motor current ( $I_x$ )	SPR_Ix	
				Y axis feed motor current ( $I_y$ )	SPR_Iy	
				Z axis feed motor current ( $I_z$ )	SPR_Iz	
				Spindle motor current ( $I_s$ )	SPR_Is	
Area under curve	Thrust force ( $F_z$ )	Surf_Fz		Power of spectral components on the lip frequency of the drill	Cutting force component in X axis direction ( $F_x$ )	SPL_Fx
	Resultant cutting force ( $F_R$ )	Surf_Fr			Cutting force component in Y axis direction ( $F_y$ )	SPL_Fy
	Drift force ( $F_D$ )	Surf_Fd			Cutting force component in Z axis direction ( $F_z$ )	SPL_Fz
	Spindle motor current ( $I_s$ )	Surf_Is			X axis feed motor current ( $I_x$ )	SPL_Ix
	Z axis feed motor current ( $I_z$ )	Surf_Iz			Y axis feed motor current ( $I_y$ )	SPL_Iy
	Z axis feed motor power ( $P_z$ )	Surf_Pz			Z axis feed motor current ( $I_z$ )	SPL_Iz
	Spindle motor power ( $P_s$ )	Surf_Ps			Spindle motor current ( $I_s$ )	SPL_Is

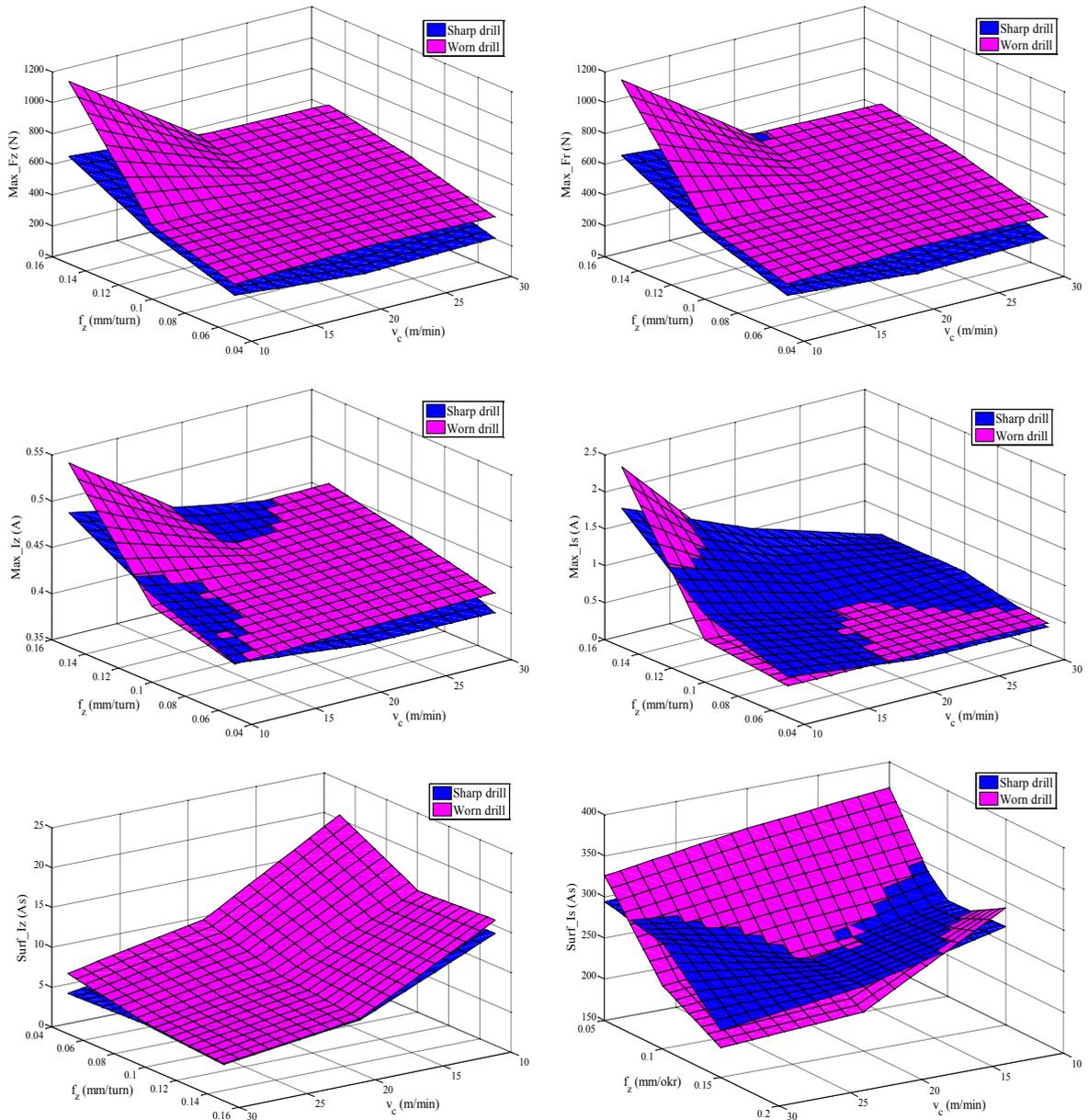


Fig. 4. Some measurement results obtained from the experiments displayed in average quantity value vs feed rate vs cutting speed. Quantities are labeled according to descriptions in Table 3.

#### 4. Tool wear model

For the analysis of the extracted features, classification model based on machine learning was used. Several models based on the implementation of C4.5 decision trees algorithm in the WEKA package [19] have been constructed with respect to the feature source signal (force sensor or current sensors) in order to establish minimal number of required sensors and features for reliable wear estimation. Models were analyzed using the RELEIF

algorithm [20] by considering relative merit and ranking of features in order to estimate their importance in predicting to tool wear. Prediction accuracy of the constructed models was assessed by tenfold cross-validation. Finally, the best model decision tree was visualized using the Graphviz software [21].

In the first model, all features values are used. Second and third model use only the features extracted from the force and current sensors respectively. Each model was constructed using all available features followed by refinement (minimization) using the RELEIF algorithm to include only the most significant features. Average rank value of 5,8 was used as feature selection threshold for minimized models. Cutting conditions were used as fixed input attributes in all models. Classification results are displayed in tables 4 and 5.

Table 4. Ranking of extracted features by the RELEIF algorithm is used to measure their relative importance for classification. Bold entries are used in minimized models

Model 1 (force + current sensor)			Model 2 (force sensor only)			Model 3 (current sensors only)		
Feature	Average merit	Average rank	Feature	Average merit	Average rank	Feature	Average merit	Average rank
<b>Max_Fz</b>	<b>0,059 ± 0,003</b>	<b>2,1 ± 1,87</b>	<b>SPL_Fy</b>	<b>0,053 ± 0,005</b>	<b>2,2 ± 1,6</b>	<b>Max_Iz</b>	<b>0,053 ± 0,004</b>	<b>1,5 ± 0,67</b>
<b>Max_Fr</b>	<b>0,059 ± 0,003</b>	<b>3,1 ± 1,87</b>	<b>SPR_Fy</b>	<b>0,05 ± 0,005</b>	<b>2,9 ± 1,92</b>	<b>Surf_Iz</b>	<b>0,052 ± 0,004</b>	<b>1,7 ± 0,46</b>
<b>Surf_Iz</b>	<b>0,058 ± 0,003</b>	<b>3,1 ± 1,76</b>	<b>Max_Fz</b>	<b>0,048 ± 0,003</b>	<b>3,3 ± 1,42</b>	<b>Surf_Pz</b>	<b>0,043 ± 0,009</b>	<b>2,9 ± 0,7</b>
<b>Surf_Fd</b>	<b>0,054 ± 0,003</b>	<b>5,6 ± 1,62</b>	<b>SPR_Fx</b>	<b>0,05 ± 0,005</b>	<b>3,7 ± 1,95</b>	<b>Max_Is</b>	<b>0,037 ± 0,004</b>	<b>3,9 ± 0,3</b>
SPR_Fy	0,053 ± 0,005	5,8 ± 2,79	<b>Max_Fr</b>	<b>0,048 ± 0,003</b>	<b>4,1 ± 1,45</b>	<b>SPL_Is</b>	<b>0,019 ± 0,003</b>	<b>5,5 ± 0,5</b>
Max_Iz	0,053 ± 0,004	6,5 ± 2,54	<b>Surf_Fd</b>	<b>0,044 ± 0,002</b>	<b>5,6 ± 0,92</b>	<b>SPR_Iz</b>	<b>0,017 ± 0,002</b>	<b>5,7 ± 0,64</b>
Surf_Fr	0,052 ± 0,002	6,6 ± 1,62	Surf_Fr	0,043 ± 0,002	6,7 ± 1	Surf_Ps	0,014 ± 0,007	6,9 ± 0,7
SPR_Fx	0,052 ± 0,005	7,0 ± 2,41	Surf_Fz	0,043 ± 0,002	7,7 ± 1	Surf_Is	0,009 ± 0,002	8,4 ± 1,02
Surf_Fz	0,052 ± 0,002	7,7 ± 1,62	SPR_Fz	0,037 ± 0,003	9,0 ± 0,77	SPL_Iz	0,006 ± 0,001	9,6 ± 1,11
SPL_Fy	0,049 ± 0,004	8,7 ± 2,15	<b>v<sub>c</sub></b>	<b>0,031 ± 0,005</b>	<b>9,8 ± 0,4</b>	SPR_Is	0,005 ± 0,001	10,2 ± 1,08
Surf_Pz	0,042 ± 0,008	10,8 ± 3,31	SPL_Fz	0,019 ± 0,001	11,0 ± 0	SPR_Ix	0,005 ± 0,002	10,5 ± 1,36
Max_Is	0,041 ± 0,004	11,7 ± 1,27	SPL_Fx	0,002 ± 0,002	12,0 ± 0	SPR_Iy	0,003 ± 0,001	11,7 ± 1,1
SPR_Fz	0,038 ± 0,003	12,3 ± 0,78	<b>f<sub>z</sub></b>	<b>-0,012 ± 0,005</b>	<b>13,0 ± 0</b>	SPL_Ix	0,002 ± 0,002	12,6 ± 1,02
Surf_Is	0,024 ± 0,003	14,2 ± 0,4				SPL_Iy	-0,003 ± 0,001	14,0 ± 0,45
SPR_Iz	0,017 ± 0,002	15,7 ± 0,9				<b>f<sub>z</sub></b>	<b>-0,01 ± 0,003</b>	<b>14,9 ± 0,3</b>
SPL_Fz	0,017 ± 0,001	15,8 ± 0,6				<b>v<sub>c</sub></b>	<b>-0,021 ± 0,003</b>	<b>16,0 ± 0</b>
SPL_Is	0,014 ± 0,003	17,3 ± 1,35						
Surf_Ps	0,015 ± 0,007	17,4 ± 1,28						
<b>v<sub>c</sub></b>	<b>0,008 ± 0,005</b>	<b>19,9 ± 2,3</b>						
SPL_Fx	0,004 ± 0,002	20,7 ± 1,55						
SPR_Iy	0,004 ± 0,001	20,8 ± 1,17						
SPR_Is	0,004 ± 0,001	21,5 ± 1,02						
SPL_Iz	0,002 ± 0,001	22,9 ± 1,22						
SPR_Ix	0,002 ± 0,002	23,1 ± 1,45						
SPL_Ix	-0,001 ± 0,002	24,7 ± 0,46						
SPL_Iy	-0,007 ± 0,002	26,1 ± 0,3						
<b>f<sub>z</sub></b>	<b>-0,013 ± 0,005</b>	<b>26,9 ± 0,3</b>						

Table 5. Classification results by machine learning using C4.5 algorithm. Success rate of classification is expressed in the percentage of correctly classified tool conditions (sharp or worn). Results are confirmed by tenfold cross validation. More reliable results are indicated by higher kappa values. The best model is marked by the bold section.

	Model 1 (force + current sensor)		Model 2 (force sensor only)		Model 3 (current sensors only)	
	Full	Minimized	Full	Minimized	Full	Minimized
Features (attributes) used	27	6	13	8	16	<b>8</b>
Correctly classified instances	88,88 %	87,77 %	86,66 %	82,22 %	87,22 %	<b>90 %</b>
Incorrectly Classified Instances	11,11 %	12,22 %	13,33 %	17,77 %	12,77 %	<b>10 %</b>
Kappa statistic	0,7778	0,7556	0,7333	0,6444	0,7444	<b>0,8</b>
Mean absolute error	0,1182	0,1362	0,1406	0,179	0,1476	<b>0,1072</b>
Root mean squared error	0,3272	0,3419	0,3485	0,4054	0,3499	<b>0,3008</b>
Relative absolute error	23,64 %	27,24 %	28,12%	35,80 %	29,51 %	<b>21,43 %</b>
Root relative squared error	65,43 %	68,38 %	69,7%	81,07 %	69,97 %	<b>60,15 %</b>
Total Number of Instances	180	180	180	180	180	<b>180</b>

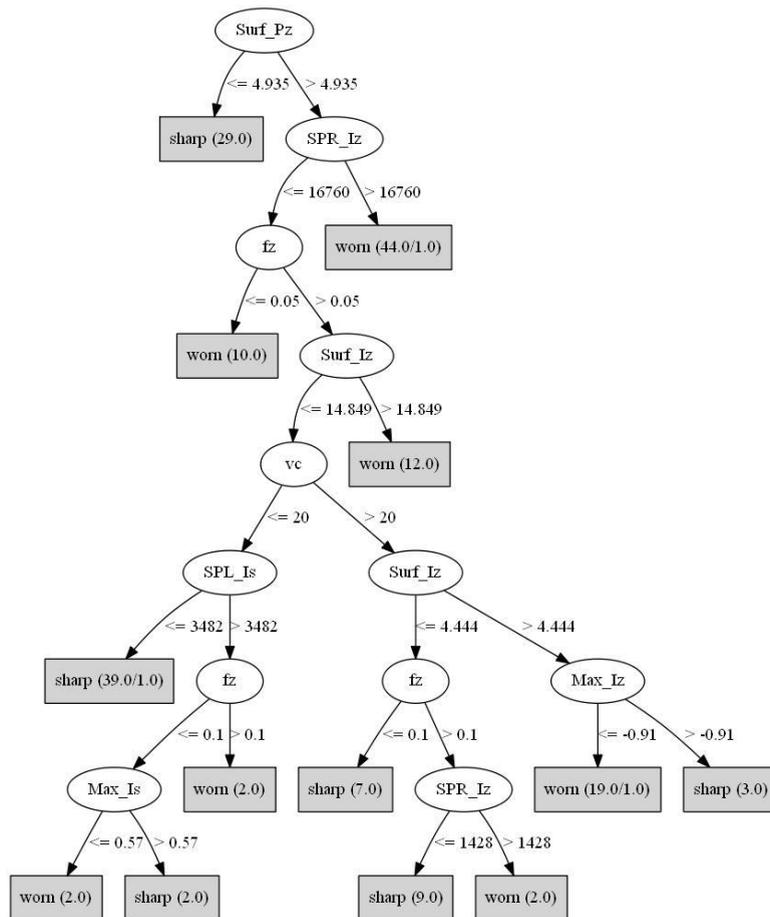


Fig. 5. Decision tree for the model 3 with best classification results (built by the C4.5 algorithm).

## 5. Conclusion

In this work a decision tree machine learning algorithm (C4.5) has been applied in stone drilling for classification of tool wear under different cutting conditions. Cutting force and motor current measurements have been taken in order to extract a number of features for classification of two different tool conditions: sharp and completely worn. Several models generated by the C4.5 algorithm have been constructed and verified in order to establish the best classification results with respect to minimal number of sensors and features necessary for reliable tool wear estimation. Most successful was the model with classification success rate of 90 %, which uses only eight features extracted from the current signals. Advantages of this model are that no additional sensors are required which may be costly and may disturb the machining process. Constructed model is also very simple to implement in the CNC control system and can be used for industrial applications.

Even though the model shows promising results, it should be noted that this is a preliminary study aimed at performing a basic classification of tool condition (completely sharp and worn). Presently, experimental data is obtained while drilling a single type of stone material with a single type of twist drill. Future experimental work will therefore be focused on the research of wider range tool wear classification. It will include different types of stone materials, different drill diameters and geometries as well as different degrees of the drill wear.

## References

- [1] R. Teti, K. Jemielniak, G. O'Donnell, D. Dornfeld, "Advanced monitoring of machining operations", *CIRP Annals - Manufacturing Technology*, Vol. 59, no. 2, pp. 717-739, 2010.
- [2] E. Jantunen, "A summary of methods applied to tool condition monitoring in drilling", *Journal of Machine Tools and Manufacture*, Vol. 42, no. 9, pp. 997-1010, 2002.
- [3] H.M. Ertunc, K.A. Loparo, "A decision fusion algorithm for tool wear condition monitoring in drilling", *International Journal of Machine Tools and Manufacture*, Vol. 41, no. 9, pp. 1347-1362, 2001.
- [4] I. Abu-Mahfouz, "Drilling wear detection and classification using vibration signals and artificial neural network", *International Journal of Machine Tools and Manufacture*, Vol. 43, no. 7, pp. 707-720, 2003.
- [5] A. Faraz, D. Biermann, K. Weinert, "Cutting edge rounding: An innovative tool wear criterion in drilling CFRP composite laminates", *International Journal of Machine Tools and Manufacture*, Vol. 49, no. 15, pp. 1185-1196, 2009.
- [6] H.M. Ertunc, K.A. Loparo, H. Ocak, "Tool wear condition monitoring in drilling operations using hidden Markov models (HMMs)", *International Journal of Machine Tools and Manufacture*, Vol. 41, no. 9, pp. 1363-1384, 2001.
- [7] L. A. Franco-Gasca, G. Herrera-Ruiz, R. Peniche-Vera, R. de J. Romero-Troncoso, W. Leal-Tafolla, "Sensorless tool failure monitoring system for drilling machines", *International Journal of Machine Tools and Manufacture*, Vol. 46, no. 3-4, pp. 381-386, 2006.
- [8] S.C. Lin, C.J. Ting, "Tool wear monitoring in drilling using force signals", *Wear*, Vol. 180, no. 1-2, pp. 53-60, 1995.
- [9] K. Subramanian, N.H. Cook, "Sensing of drill wear and prediction of drill life (I)", *Journal of Engineering for Industry, Transactions of the ASME*, Vol. 99, no. 2, pp. 295-301, 1977.
- [10] L. Xiaoli, "On-line detection of the breakage of small diameter drills using current signature wavelet transform", *International Journal of Machine Tools and Manufacture*, Vol. 39, no. 1, pp. 157-164, 1999.
- [11] X. Wang, P.Y. Kwon, C. Sturtevant, D. Kim, J. Lantrip, "Tool wear of coated drills in drilling CFRP", *Journal of Manufacturing Processes*, Vol. 15, no. 1, pp. 127-135, 2013.
- [12] D. Iliescu, D. Gehin, M.E. Gutierrez, F. Girot, "Modeling and tool wear in drilling of CFRP", *International Journal of Machine Tools and Manufacture*, Vol. 50, no. 2, pp. 204-213, 2010.
- [13] G. Exadaktylos, P. Tiano, C. Flareto, "Validation of a model of rotary drilling of rocks with the drilling force measurement system", *International Journal for Restoration of Buildings and Monuments*, Vol. 6, no. 3, pp. 307-340, 2000.
- [14] M. Pamplona, M. Kocher, R. Sneathlaga, "Halite – A new calibration material for microdrilling resistance measurements", *Journal of cultural heritage*, Vol. 11, no. 2, pp. 180-184, 2010.
- [15] J. D. Rodrigues, D. Costa, "A New Method for Data Correction in Drill Resistance Tests for the Effect of Drill Bit Wear", *International Journal for Restoration*, Vol. 10, no. 3, pp. 1-18, 2004.
- [16] M. Pamplona, M. Kocher, L. Aires-Barros, "Drilling resistance: overview and outlook", *Zeitschrift der Deutschen Gesellschaft für Geowissenschaften*, Vol. 158, no. 3, pp. 665-679, 2007.
- [17] T. Staroveski, "Wear Modelling of Medical Drill", PhD thesis, University of Zagreb, Faculty of Mechanical Engineering and Naval Architecture, Zagreb, 2013.
- [18] T. Staroveski, D. Brezak, T. Udiljak, D. Majetic, "Experimental Machine Tool for Process Monitoring and Control Systems Research", in *22nd Daaam International Symposium, Annals Of Daaam International 2011*, Vienna, 2011, pp. 0023-0024.
- [19] A. Bartulović, "Stone drilling", Diploma thesis, University of Zagreb, Faculty of Mechanical Engineering and Naval Architecture, 2013.
- [20] I.H. Witten, E. Frank, *Data Mining: Practical Machine Learning Tools and Techniques with Java Implementations*. San Francisco, CA, USA, Morgan Kaufmann, 1999.
- [21] I. Kononenko, E. Simec, M. Robnik-Sikonja, "Overcoming the Myopia of Inductive Learning Algorithms with RELIEFF", *Applied Intelligence*, Vol. 7, no. 1, pp. 39-55, 1997.
- [22] J. Ellson, E.R. Gansner, E. Koutsofios, S.C. North, G. Woodhull, "Graphviz and Dynagraph — Static and Dynamic Graph Drawing Tools", in *Graph Drawing Software*, Springer Berlin Heidelberg, 2004, ch. Mathematics and Visualization, pp. 127-148.