Smart prediction of surface micro-hardness after milling based on fuzzy inference model

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Abstract. The lack of comprehending and control of the micro-hardness of the machined surface is an important obstacle to the use of the milling process. In order to optimize the machining process by milling, this work has focused on the problem of micro-hardness changing of machined surfaces by milling, which has been the subject of several scientific works. A fuzzy inference model was developed to study the influence of cutting conditions (cutting speed, feed per tooth and depth of cut) on the micro-hardness of machined surfaces by milling. The predicted values, obtained by fuzzy model, are compatible with the experimental values, with an average error percentage of 0.63%.

1. Introduction

During the last decades, many experiments have been carried out to investigate the milling conditions that affect the variation of microhardness of milled surfaces. These experiments are extremely difficult and require a lot of time and material. And here is a small bibliographic search for some scientific works that have studied the microhardness of milled surfaces:

A.L. Mantle et al. [1] studied the surface integrity of a high speed milled gamma titanium aluminide, they found that the microhardness evaluation of the subsurface indicated a hardened layer to a depth of 300 μm.

W. Bouzid Sai et al. [2] studied the influence of machining by finishing milling on surface characteristics, two different materials were used in their study, the carbon steel (CS) and the duplex stainless steel (DSS). For carbon steel samples the maximum value of microhardness is higher and penetrates deeper into the surface layer with the increasing of feed. This is due to an increase in both chip thickness and tool chip contact length. Hence, cutting temperature and cutting forces change in the same direction as the feed. In addition, they noticed also that, microhardness is high at high cutting speeds which confirms that temperatures reach higher levels. No major changes of surface layer depth are noted. They consider that to improve wear and fatigue material resistance, the cutting speed must be high.

Xiaoh Wang [3] did an intelligent prediction of surface micro-hardness after milling based on smooth support vector regression, but he didn't show the results of the predicted microhardness obtained by his model and he didn't specify the accuracy of his model compared to the experimental values of the microhardness.
A. Ginting et al. [4] in their study Surface integrity of dry machined titanium alloys, they found that the microhardness is altered down to 350 μm beneath the machined surface. The first 50 μm is the soft subsurface with microhardness value 8% less than the bulk material hardness caused by thermal softening in the ageing process. Down to 200 μm is the hard subsurface with microhardness value 8% harder than the bulk material hardness caused by the cyclic internal workhardening and then it gradually decreased to the bulk material hardness.

Du Jin et al. [5] investigated the damage of the machined surface and subsurface in orthogonal milling of FGH95 superalloy, they concluded that the machined surface microhardness is higher than the bulk material demonstrates the appearance of work hardening during hard machining of FGH95. And also, higher cutting speeds mean higher surface microhardness.

F. Wang et al. [6] studied the effects of cutting conditions on microhardness and microstructure in high-speed milling of H13 tool steel, they concluded that the subsurface microhardness is less high than that on the machined surface. The predominant factor determining the machined surface hardness would be the severe plastic deformation induced by mechanical load. Furthermore, the hardness of machined surface decreases with the increase of cutting speed and feed per tooth due to thermal softening effects.

P. Muñoz-Escalona et al. [7] in their study influence of cutting environments on surface integrity and power consumption of austenitic stainless steel, they found that the specimen machined in a cryogenic environment achieved higher values of hardness in subsurface compared to specimen machined in a dry environment. They reported that this is probably due to strain hardness during the cutting process been more noticeable in the cryogenic environment due to the decrease of the cutting temperature. In the case of the dry environment the increase of temperature probably helped to soften the material easing the removal of material. And they noticed also when the cutting speed or the feed per tooth changed there were no noticeable changes on microhardness, however all the specimens' hardness started to stabilize at 100 μm from the machined surface.

Yang Houchuan et al. [8] investigated the influence of cutting speed and tool wear on the surface integrity of the titanium alloy Ti-1023 during milling, they concluded that the Hardening can occur when machining Ti-1023. The depth of hardening decreases with the increase in cutting speed. The effect of tool wear on hardening is significant. When VB ranges from 0 to 0.2 mm, the depth of hardening increases from 35 to 55 μm. Then, at VB=0.35 mm, the depth of hardening reaches 130 μm. And also softening regions appear on the subsurface after a certain degree of tool wear, and when tool wear increases, the softening regions are more pronounced.

H. Hassanpour et al. [9] In their research, hard milling of 4340 alloy steel using MQL system is investigated and the effects of this process on microhardness are determined by applying RSM design of experiment method (DOE). The analysis of variance showed that quadratic polynomial models estimate the surface microhardness correctly and the average estimated error was 1.18% and the maximum error of the model was 5%. And they found that all hard-milling parameters had an increasing effect on microhardness. Also, feed rate with 73.1%, cutting speed with 14.4% and axial depth of cut with only 5.1% affected microhardness.

W. Akhtar et al. [10] studied the effect of machining parameters on surface integrity in high speed milling of super alloy GH4169/Inconel 718, they used to type of cutting insert, the cemented carbide inserts and whisker reinforced coated ceramic inserts. They found that the work hardening of the work piece surface took place in all the cutting experiments whether for carbide inserts or ceramic inserts, resulting in increased hardness of the machined surface as compared to the bulk material. However, due to wet cutting conditions employed for carbide tools as compared to dry condition for ceramic tools, carbide tools always resulted in comparatively greater surface hardness. However, the difference in the maximum surface hardness value obtained for both types of the tools was not big.

H. Zheng et al. [11] studied the effect of ball milling treatment on the microstructure and microhardness of Nb-25Cr alloy, they found that the microstructure refinement becomes much more significant as ball milling duration is extended, and the microhardness is obviously improved after ball
milling and that is related to decreased grain size. And an abrupt drop in hardness was observed in the 48h treated sample due to the emergence of cracks on the surface of the Nb-25Cr alloy.

J. C. Pereira et al. [12] in their study the surface integrity of AISI 1010 and AISI 4340 steels subjected to face milling, they reported that the cutting fluid possesses a beneficial influence on surface integrity, i.e. it slightly reduced residual stresses and microhardness values. And they concluded also that the microhardness distribution beneath the surface of AISI 1010 steel was not altered by changes in any of the investigated parameters, as well as by alterations in the axial depth of cut and the use cutting fluid. And also, they stated that higher microhardness values near the surface of AISI 4340 steel is generated due the increasing of cutting speed and feed per tooth.

Y. Zhenchao et al. [13] in their research the effect of milling parameters on surface integrity in high-speed milling of ultrahigh strength steel, they concluded that Surface microhardness decreases with milling speed and feed per tooth, but increases with milling depth.

W. huang et al. [14] in their comparison of surface integrity and fatigue performance for hardened steel ball-end milled with different milling speeds, they found that the fatigue life for milled samples raise at least 83% compared with that of polished samples. This is due to the high surface residual compressive stress and the enhanced microhardness. Moreover, excessive surface strain hardening will increase surface brittleness (which can accelerate the crack propagation ratio) which is detrimental to fatigue resistance. Different cutting speed causes a difference in degree of strain hardening because of the discrepancy in thermomechanical coupling field.

I. Mathoř et al. [15] investigated the effect of milling parameters on microhardness and microstructure during dry and flood milling of Ti-6Al-4V, they found that the use of flood milling generated a maximum value of microhardness compared to the use of dry milling.

This bibliographic study show that some prediction methods have been developed to solve the problem of the changing in the microhardness of machined surfaces by milling and this for their ability to model different phenomena.

However, the progress on the use of Numerical Approaches to predict the microhardness of machined surfaces still lagging behind the other advances in the industry.

This is why we propose in this work to use the fuzzy logic approach to predict the microhardness and to study the effect of cutting parameters on the microhardness of surfaces machined by milling.

2. Experimental database

The aim of our work is to make a smart prediction of the microhardness of surfaces after milling, so we will create our own model using one of the artificial intelligence methods which is fuzzy logic based on an experimental database, which includes the variation of the micro-hardness according to the cutting parameters (cutting speed, feed per tooth and depth of cut) on which we will develop our model on MATLAB.

The table 1 presents the experimental values of the variation of the microhardness (in HV) as a function of the cutting parameters (cutting speed \( V_c \), feed per tooth \( f_z \) and depth of cut \( a_p \)).

The microhardness measurement of the surface of the milled steel AISI 1060 was done by the Vickers method with HV3 using the Ultrasonic Portable Hardness Tester ‘Ultramatic 2 HV400’.
| $f_z$ (mm/tooth) | $V'_m$ (m/min) | 0.25 | 0.5 | 0.75 |
|-----------------|-----------------|------|-----|------|
| 100             | 125.6           | 117.4| 129.6|
| 150             | 133.4           | 132.8| 136.4|
| 200             | 126.4           | 142.4| 130  |
| 250             | 120.2           | 130.6| 128.6|
| 300             | 122             | 128.6| 125.4|
| 0.09            | 0.09            |      |      |      |
| 100             | 130.6           | 127.4| 132.2|
| 150             | 134.6           | 137.4| 141.2|
| 200             | 117.4           | 138.2| 130.3|
| 250             | 114.8           | 131.4| 126.6|
| 300             | 125.2           | 122.2| 127.8|
| 0.12            | 0.12            |      |      |      |
| 100             | 131.6           | 130.2| 130.2|
| 150             | 134.6           | 147.4| 136.4|
| 200             | 116.8           | 130.4| 131.6|
| 250             | 128.4           | 121.6| 125.6|
| 300             | 126.2           | 127.6| 127.6|
| 0.15            | 0.15            |      |      |      |
| 100             | 125             | 140.8| 138.4|
| 150             | 137.2           | 123.4| 132.8|
| 200             | 131.4           | 136.4| 124.4|
| 250             | 123             | 125.4| 123.8|
| 300             | 137.2           | 135.4| 122  |
| 0.18            | 0.18            |      |      |      |

3. Fuzzy modelling

3.1. Fuzzy variables
The table 2 represents the limit values of the input and output parameters, for the fuzzy model used, it is to define the universe (Domain) of discourse associated with this study.

| Parameter            | MIN value | MAX value |
|----------------------|-----------|-----------|
| $a_p$ (mm)           | 0.25      | 0.75      |
| $f_z$ (mm/tooth)     | 0.09      | 0.18      |
| $V'_m$ (m/min)       | 100       | 300       |
| $H$ (HV)             | 114.8     | 147.4     |

3.2. Fuzzy system
The input (cutting parameters) and output (microhardness) variables of the fuzzy system used for the prediction of the microhardness during milling of AISI 1060 steel are shown in the figure 1.
3.3. Definition of linguistic variables
In this part we will define all the linguistic variables associated with each parameter used from the experimental basis used as shown in the figures 2, 3 and 4.

![Figure 1. Input and output of the fuzzy system.](image)

![Figure 2. Linguistic variables for depth of cut.](image)

![Figure 3. Linguistic variables for feed per tooth.](image)

![Figure 4. Linguistic variables for the cutting speed.](image)

We will represent the experimental values of the output parameter which is the microhardness for all the experimental tests in the form of a scatter plot in order to define the linguistic variables associated with the microhardness. This representation allows us to divide the universe of discourse into a set of intervals, the purpose of which is to minimize the number of intervals as shown in the figures 5 and 6.
3.4. *Membership functions*

In this study we will use three types of membership function, the Triangular, Trapezoidal and Gaussian function as shown in the figures 7, 8 and 9.
Figure 7. Triangular membership functions.

Figure 8. Trapezoidal membership functions.

Figure 9. Gaussian membership functions.
3.5. The fuzzy rules
The sixty fuzzy rules, in table 3, were established according to the experimental conditions. Each rule takes the following form:

If \( a_p \) (linguistic variable) and \( f_z \) (linguistic variable) and \( V_c \) (linguistic variable) then \( H \) (linguistic variable).

The set of fuzzy rules developed are grouped together in the table 3.

| \( a_p \) | \( f_z \) | \( V_c \) | The Microhardness |
| --- | --- | --- | --- |
| TP | G | B | J |
| P | L | L | N |
| M | G | Q | J |
| G | C | J | I |
| TG | E | I | G |
| TP | J | I | K |
| P | L | N | P |
| M | B | N | J |
| G | A | K | H |
| TG | F | E | I |
| TP | K | J | J |
| P | L | R | N |
| M | A | J | K |
| G | I | D | G |
| TG | G | I | I |
| TP | F | P | O |
| P | N | F | L |
| M | K | N | F |
| G | E | G | F |
| TG | N | M | E |

4. Results and discussion

4.1. Results
Now we are going to transform the linguistic values from the fuzzy model to numerical values, it is the defuzzification which represents the last step. The figure 10 represents the superposition of the values of the experimental microhardness and the values of the microhardness obtained with the three membership functions (Triangular, Trapezoidal and Gaussian):
Figure 10 shows the superposition between the predicted surface microhardness values and the experimental values.

We notice a similarity between the microhardness values using the three types of membership functions, and we notice that the Triangular and Trapezoidal membership functions are almost identical, so to make the choice between the three type of the membership functions: Triangular, Trapezoidal and Gaussian, we propose to use the standard deviation in order to define the values closest to the experimental results.

To calculate the standard deviation, the formula 1 is used:

\[ \sigma = \left( \frac{1}{N} \sum_{i=1}^{N} (H_{\text{pred}} - H_{\text{exp}})^2 \right)^{1/2} \]  

(1)

\( H_{\text{exp}} \): The experimental microhardness.

\( H_{\text{pred}} \): The predicted microhardness.

In our case \( N = 60 \) Tests.

- The standard deviation for the Triangular-type membership function is 1.0113.
- The standard deviation for the Trapezoidal-type membership function is 1.0030.
- The standard deviation for the Gaussian-type membership function is 1.9492.

We notice from the standard deviation that the results of the Trapezoidal membership function are closest to the experimental results compared to the results of the Triangular and Gaussian membership functions.

4.3. Study of the accuracy and error of the fuzzy system

To calculate the percentage error of the 60 tests, the formula 2 is used:
\[ e_i = \frac{1}{N} \sum_{i=1}^{N} \left[ \frac{H_{\text{exp}} - H_{\text{pred}}}{H_{\text{exp}}} \right] \times 100 \]  

(2)

\[ H_{\text{exp}}: \text{The experimental microhardness.} \]

\[ H_{\text{pred}}: \text{The predicted microhardness (Trapezoidal).} \]

In our case \( N = 60 \) Tests.

\[ e_i: \text{Error rate} \]

To calculate the percentage of the accuracy of the 60 tests, the formula (3) is used:

\[ A = \frac{1}{N} \sum_{i=1}^{N} \left[ 1 - \frac{|H_{\text{exp}} - H_{\text{pred}}|}{H_{\text{exp}}} \right] \times 100 \]  

(3)

\[ H_{\text{exp}}: \text{The experimental microhardness.} \]

\[ H_{\text{pred}}: \text{The predicted microhardness (Trapezoidal).} \]

In our case \( N = 60 \) Tests.

\[ A: \text{Accuracy} \]

All results are grouped together in the table 4.

**Table 4.** The fuzzy system results.

| Tests | Cutting parameters | Microhardness results | Error % | Accuracy % |
|-------|--------------------|-----------------------|---------|------------|
|       | \( V_c \) | \( f_z \) | \( a_p \) | \( H_{\text{exp}} \) | \( H_{\text{pred}} \) |         |         |
| 1     | 300    | 0.09    | 0.5     | 128.6  | 128      | 0.47    | 99.53   |
| 2     | 150    | 0.09    | 0.25    | 133.4  | 133      | 0.30    | 99.70   |
| 3     | 100    | 0.09    | 0.25    | 125.6  | 125      | 0.48    | 99.52   |
| 4     | 100    | 0.12    | 0.5     | 127.4  | 128      | 0.47    | 99.53   |
| 5     | 250    | 0.09    | 0.25    | 120.2  | 119      | 1.00    | 99.00   |
| 6     | 250    | 0.09    | 0.5     | 130.6  | 129      | 1.23    | 98.77   |
| 7     | 300    | 0.12    | 0.25    | 125.2  | 123      | 1.76    | 98.24   |
| 8     | 200    | 0.15    | 0.25    | 116.8  | 115      | 1.54    | 98.46   |
| 9     | 250    | 0.12    | 0.25    | 114.8  | 115      | 0.17    | 99.83   |
| 10    | 150    | 0.15    | 0.25    | 134.6  | 133      | 1.19    | 98.81   |
| 11    | 300    | 0.18    | 0.25    | 137.2  | 136      | 0.87    | 99.13   |
| 12    | 250    | 0.12    | 0.5     | 131.4  | 131      | 0.30    | 99.70   |
| 13    | 100    | 0.09    | 0.5     | 117.4  | 117      | 0.34    | 99.66   |
| 14    | 300    | 0.18    | 0.5     | 135.4  | 135      | 0.30    | 99.70   |
| 15    | 150    | 0.12    | 0.25    | 134.6  | 133      | 1.19    | 98.81   |
| 16    | 100    | 0.15    | 0.25    | 131.6  | 131      | 0.46    | 99.54   |
| 17    | 200    | 0.18    | 0.5     | 136.4  | 136      | 0.29    | 99.71   |
| 18    | 250    | 0.15    | 0.5     | 121.6  | 120      | 1.32    | 98.68   |
| 19    | 300    | 0.12    | 0.5     | 122.2  | 122      | 0.16    | 99.84   |
| 20    | 150    | 0.09    | 0.5     | 132.8  | 133      | 0.15    | 99.85   |
| 21    | 300    | 0.15    | 0.25    | 126.2  | 125      | 0.95    | 99.05   |
| 22    | 250    | 0.18    | 0.25    | 123    | 122      | 0.81    | 99.19   |
| 23    | 150    | 0.15    | 0.5     | 147.4  | 146      | 0.95    | 99.05   |
| 24    | 150    | 0.12    | 0.5     | 137.4  | 136      | 1.02    | 98.98   |
| 25    | 200    | 0.12    | 0.25    | 117.4  | 117      | 0.34    | 99.66   |
The average error rate is 0.63% and the average accuracy is 99.37%, that’s mean that our prediction model based on fuzzy logic works correctly and with high accuracy and can be used as a solution to predict microhardness before starting milling provided that we respect a very specific range of parameters (defined by the universe of discourse) when using this model.

4.4. Graphical representation of results
Figure 11 shows the functions obtained using fuzzy logic simulation as follows:
• The surface (a) represents the variation of the surface microhardness as a function of the feed per tooth and the depth of cut for a cutting speed 100 m / min.
• The surface (b) represents the variation of the surface microhardness as a function of the depth of cut and the cutting speed for a feed per tooth 0.09 mm / tooth.
• The surface (c) represents the variation of the surface microhardness as a function of the feed per tooth and the cutting speed for a depth of cut 0.75 mm.

Figure 11. Variation of the predicted micro-hardness with the fuzzy logic model as a function of the cutting parameters.

Figure 11 illustrates the influence of cutting parameters on the microhardness of machined surfaces during milling operations.

From the figure 11 (a) it can be seen that the value of the microhardness becomes maximum for maximum values of the feed per tooth and average values of the depth of cut (0.5 mm). While the minimum values of microhardness are obtained for minimum values of feed per tooth and average values of depth of cut.

On the other hand, a higher feed per tooth leads to an increase in the microhardness of the machined surfaces.

From the figure 11 (b) it can be seen that the value of the microhardness becomes minimum for minimum values of cutting speed and average values of the depth of cut (0.5 mm) and also for maximum values of cutting speed and minimum values of the depth of cut. While the maximum values of microhardness are obtained for average values of cutting speed (200 m / min) and average values of depth of cut.

On the other hand, a higher cutting speed leads to a decrease in the microhardness of the machined surfaces regardless of the depth of cut.
From Figure 11 (c) it can be seen that the value of the microhardness becomes maximum for an average value of feed per tooth (0.12 mm / tooth) and a low value of cutting speed (150 m / min). While the minimum values of microhardness are obtained for maximum values of feed per tooth and cutting speed.

On the other hand, a higher cutting speed results in a decrease in the microhardness of the machined surfaces regardless of the feed per tooth.

5. Conclusion
In this work an approach based on fuzzy logic was carried out in order to predict the effects of cutting conditions on the micro-hardness of surfaces machined by milling. The main results of this work can be summarized as follows:

- The micro-hardness of the machined surface is much higher than that of the raw material.
- The severe plastic deformation induced by a mechanical load (the effect of the cutting tool), which varies according to the cutting parameters, is the predominant factor determining the microhardness of the machined surface by milling.
- The microhardness of the milled surface decreases with the increasing of cutting speed and Depth of cut due to the thermal softening effects.
- The change in micro-hardness results from the changes in microstructure due to the effects of the mechanical-thermal coupling.
- Work hardening induced by plastic deformation of the surface should be the predominant factor in the micro-hardness of the milled surface.
- The fuzzy model, developed during this study, makes it possible to predict the micro-hardness of surfaces machined by milling.
- The study of the fuzzy model efficiency was confirmed by the analysis of the error / accuracy ratio.
- The predicted values are in good agreement with the experimental values, with an average percentage error of 0.63% for the micro-hardness calculation of surfaces machined by milling.
- The approach based on fuzzy logic can be used also to predict other phenomena of milling process like cutting temperature and roughness.

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