Surface roughness modelling in finish face milling under MQL and dry cutting conditions

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ABSTRACT: The effect of lubrication-cooling condition on surface roughness in finish face milling operations has been widely investigated. Different cutting speeds and lubrication cooling conditions (dry, wet and MQL), in finish face milling of AISI 420 B stainless steel, have been considered. The evolution of the surface finish and tool wear with cutting time have been monitored. Analytical and artificial neural network-models, able to predict the surface roughness under different machining conditions, have been proposed.

Key words: Dry cutting, MQL, Finish face milling, Modelling, Surface roughness

1 INTRODUCTION

The reduced utilization of cooling lubricants, in order to improve environmental protection, safety of machining processes and to decrease time and costs related to the number of machining operations, can be pursued performing machining processes with the MQL (minimum quantity of lubricant) technique or without any cutting fluid (dry cutting) [1]. Such approaches can allow the obtaining of the product specifications, in terms of surface roughness and dimensional accuracy, by the shortening conventional process cycles (i.e. avoiding grinding). The effect of the lubrication-cooling condition on the surface quality of the machined part strongly depends on the type of machining operation to be performed (e.g. turning, milling, etc.), as well as on the process parameters to be used. In particular, in face milling operations cutting takes place with high frequency tooth impacts, depending on the cutting speed, and discontinuously due to the presence of several teeth; for such reasons dry and MQL face milling can be performed over a wide field of workpiece materials [2-4], once that the proper cutting materials and tool coatings, with improved performances, and machining parameters are considered [4-7].

A very useful tool for industrial finish machining applications is represented by the availability of models able to predict surface roughness (Ra) as a function of lubrication cooling technique, cutting parameters, etc. In this way, the knowledge of the surface roughness levels can be used in the design stage of machining operations. A review of predictive models and related approaches has been reported in [8,9], also under dry machining [10]. Among them statistical (MRA) and artificial neural network (ANN) modelling approaches are the most used.

In this framework, the present work aims at building predictive models of surface roughness including, among the input parameters, also the lubrication cooling condition. The present paper represents the first step of such investigation and focuses on the study in depth of the effect of different lubrication-cooling conditions and cutting speed on the surface roughness in finish face milling operations. The machining tests have been performed at different cutting conditions on AISI 420B stainless steel. Analytical and non analytical models, relating surface roughness with process parameters and lubrication cooling condition, are proposed.

2 EXPERIMENTAL AND MODELLING

2.1 Experimental

Finish face milling tests were performed on blocks (width:32 mm; length along the feed direction: 345 mm; height: 130 mm) of 420B stainless steel under wet, dry and MQL conditions. The tests under MQL condition were performed using a system based on the use of a pneumatic pump delivering a minimal quantity of lubricant (20 ml/h) along a capillary tube fitted inside length of the air line to the nozzle head. At this point the lubricant droplet is introduced into the air stream and transported to the cutting edge. The tool holder was characterised by a diameter (THD) of 63 mm. Five inserts in cemented carbide (R245 12 T3 E-ML) [11] with two layer coatings (TiN and TiAlN) were mounted on the tool holder with the axial rake angle of 23° [7]. The milling experiments were carried out with only one tooth–workpiece contact each time.

The cutting parameters were selected by considering that finish face milling can be used as an operation alternative to grinding. Therefore, according to the tool manufacturer recommendations [11], cutting speed (Vc) was varied between 120 and 180 m/min. A depth of cut of 0.2 mm and a feed of 0.14 mm/tooth was used. The effect of the feed variation was not taken into account for its negligible effect on surface roughness, due to the geometry of the insert used [11]. The wear criterion and the approach followed for tool wear and surface roughness evaluation are reported in [7].

2.2 Modelling approach

The surface roughness Ra was modelled using the multiple regression analysis (MRA) and artificial neural network (ANN) approaches. In both the cases, the surface roughness Ra was related to the cutting speed (Vc), cutting time (t) and lubrication cooling condition. When the MRA approach is concerned a second (polynomial) order regression model was used according to the following formulation:

$$R_a = a_0 + a_1 t + a_2 V_c + a_3 LC + a_4 t^2 + a_5 V_c^{\,2} + a_6 LC^2 + \\ + a_7 V_c t + a_8 LCt + a_9 V_c LC \qquad (1)$$

where, *LC* represents a constant value which takes into account the lubrication cooling condition and the coefficients a_i ($i=1,..9$) represent the regression coefficients. The values of such coefficient are summarised in table 1.

Concerning the ANN-based approach, a multi-layer feed forward artificial neural network, using the back-propagation algorithm, was built. Nine inputs were used: V_c, t, LC, V_c^2, t^2, LC^2, $V_c t$, LCt, $V_c LC$. The output of the ANN was the Ra value. Different network configurations were considered; the final one consisted of one hidden layer with nine hidden neurons. The topology and training parameters for the developed artificial neural network-based models are shown in table 2.

Table1. Regression coefficients.

Coefficient	Value
a_0	1.056
a_1	5.65E-04
a_2	-1.04E-02
a_3	3.23E-02
a_4	1.41E-05
a_5	3.12E-05
a_6	1.00
a_7	2.21E-06
a_8	-1.23E-02
a_9	6.9E-05

Table2. Topology and training parameters for ANN.

Number of input nodes	9
Number of output nodes	1 (Ra)
Number of hidden layers	1
Number of hidden nodes	9
Activation function input-hidden layers	Sigmoid
Activation function output-hidden layers	Linear
Distribution of weights	Gaussian
Momentum coefficient	0.1
Learning coefficient	0.9

3 RESULTS AND DISCUSSION

3.1 Experimental

The surface roughness, plotted vs. time under different conditions, in terms of cutting speed and lubrication-cooling technique, is reported in Figure 1. For each cutting speed investigated, Ra tends to decrease with increasing cutting time under wet cutting, as shown by other authors [3], whilst a slight increase can be detected under dry cutting. When the MQL condition is considered, it can be observed that the Ra vs. cutting time curves assume values similar to, or lower than, those obtained under wet cutting. Moreover, the VB values detected under MQL condition are slightly lower than those observed under wet and dry conditions, especially at the highest cutting speed investigated.

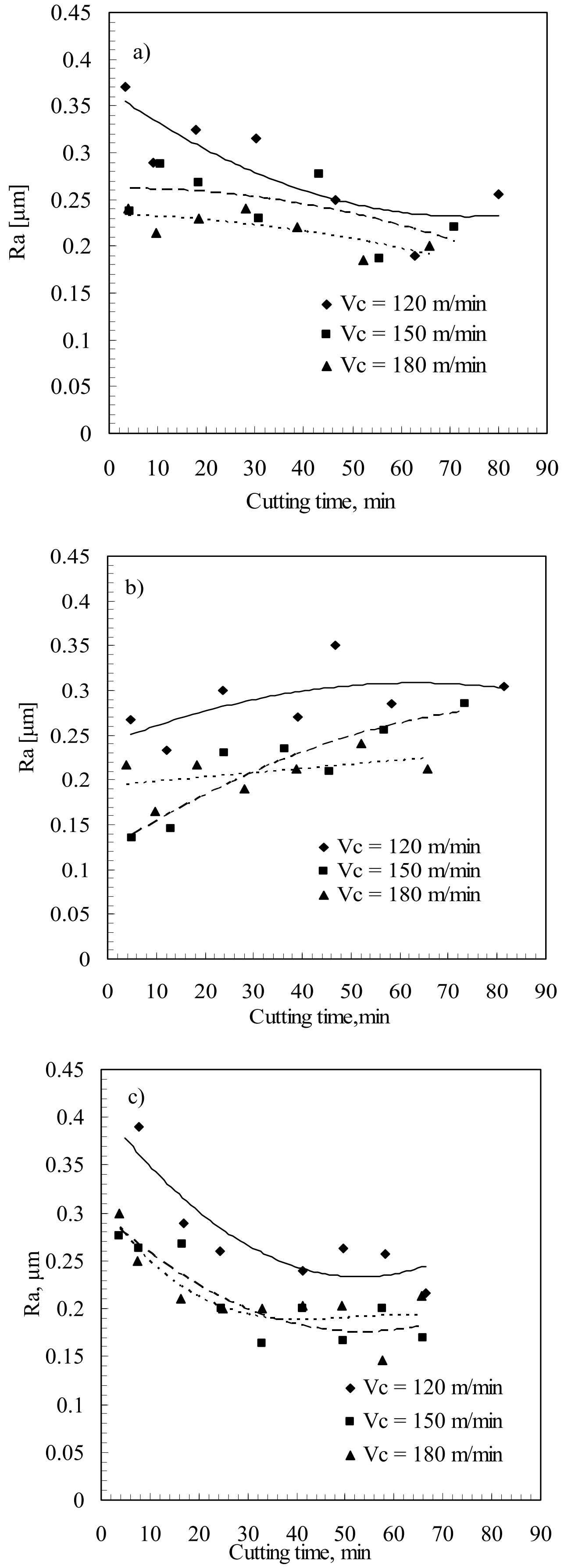

Fig. 1. Surface roughness vs. cutting time under wet (a), dry (b) and MQL condition (c) at Vc=120, 150 and 180 m/min.

As shown by the authors in a previous work [7] and by other researchers [3] the mean tool-chip interface temperature detected under dry cutting is higher than that observed under wet machining.This could be responsible for the increase in VB but, on the other hand, also for the workpiece material softening. In the experimental conditions of the present investigation, the latter effect should prevail on the former, at least at lowest cutting speed investigated.
The interesting results obtained under MQL conditions, in terms of Ra and VB, can be attributed to the beneficial effect of the aerosol that produces a cooling of the insert allowing at the same time the material softening due to temperature increase in the deforming zone, however, such aspect needs to be further investigated.

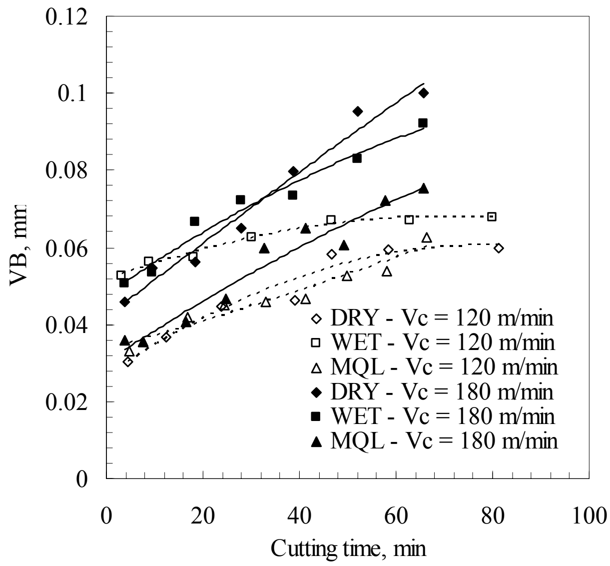

Fig. 2. VB vs. cutting time, under wet, dry and MQL condition at Vc=120 and 180 m/min.

3.2 Modelling

The effectiveness of both the modelling approaches in predicting Ra has been checked using surface roughness vs. cutting time curves not used in the building of the model. Figure 3 shows the comparison between experimental Ra vs. cutting time curve, obtained at 150 m/min under wet condition, and the ones predicted using MRA and ANN models.
Both the MRA and ANN models, under the experimental and modelling conditions of the present investigation, allow to predict Ra vs. cutting time curves, when the lubrication cooling condition is considered as a input variable.

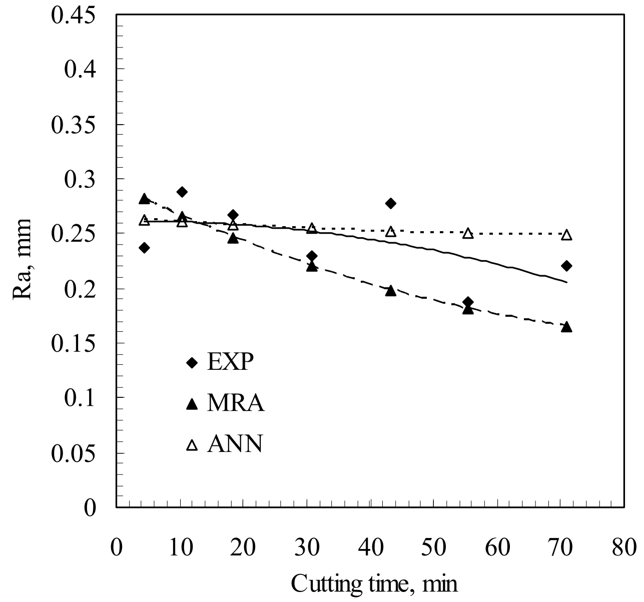

Fig. 3. Comparison between experimental Ra vs. cutting time curve obtained at 150 m/min – wet and those predicted by MRA and ANN.

4 CONCLUSION

Machining tests have been performed under different cutting conditions on AISI 420B stainless steel. MRA and ANN models, relating surface roughness with parameters and lubrication cooling condition, have been proposed.

The MQL lubrication cooling technique provides, under the experimental conditions of the present research, very low values of Ra and VB, especially at higher cutting speeds. When the modelling stage is concerned, both the MRA and ANN models can be used in predicting Ra values. Of course, the prediction capability of both the models can be improved with increasing the number of the experimental curves to be used in the building stage and in the validation one.

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