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Prediction and optimization of surface roughness in minimum quantity coolant lubrication applied turning of high hardness steel

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A B S T R A C T

Dry machining is accredited as sustainable manufacturing; however, in case of machining a high hardness steel, an elevated temperature and eventual alteration of machined surface entail thermal pacification. As such, the minimum quantity coolant lubrication (MQCL) bridges the improved productivity with sustainability in machining. Likewise, the prediction and optimization of machining characteristics uphold sustainability by conserving resources. In this regard, this study presents the modeling and investigation of average surface roughness parameter (R_a) with respect to spindle speed (N), feed rate (f), depth of cut (a_p) and time (t) gap between MQCL pulsing in turning ~ 60 R_c steel. The least-square support vector machine (LS-SVM) method for the prediction and the interior point method (IPM) for the optimization have been employed. The devised LS-SVM model predicted R_a with 4.96% MAPE; while, IPM exhibited improvement in R_a at optimum $N = 259$ rpm, $f = 0.18$ mm/rev, $a_p = 0.25$ mm and MQCL impingement within the smallest time interval possible. Moreover, the obtained results revealed that the augmented feed due to enhanced straining and wider peak-to-peak distance increased R_a while 1 s interval based pulsing reduced R_a owing to increased lubrication and cooling.

1. Introduction

Hardened steel has its usability in some of the critical engineering applications such as the jet engine mounting, camshaft and landing gears, railroad component, high strength bearing and high pressure nozzles [1]. For these applications the demanded hardness is 40–60 Rockwell hardness C scale (R_c). Even, the required hardness can go up to 65 R_c if the material is used in making the tools and dies wherein the parts endure extensive pressure during application [2]. However, the precision machining of these high hardness materials faces difficulties in preparing within certain dimensional accuracies and keeping the minimum surface roughness.

Adversities such as the elevated cutting temperature, non-uniform dimension, increased cutting force, and aggravated tool wear necessitate the use of cutting fluid in providing the sufficient lubrication and bringing down the temperature [3]. The traditional application of cutting fluid in excess amount induces an extra-cost, reduces productivity, harms the environment and negatively afflict the operator's health by producing airborne mist and smoke [4]. Other coolant application techniques like high pressure coolant although is able to favorably turn the outcomes towards the higher productivity, still the adversities regarding the excess cutting fluid remains dominant [1,5]. Application of cryogenic cooling has been proved to solve these mutually opposing problems [6]; however, the complexity regarding the setup, cost and availability of cryogenic medium hinder its practical implementation.

In this regard, the appropriate solution seems the use of trivial amount of cutting fluid as minimum quantity coolant lubrication (MQCL), also called the minimum quantity lubrication (MQL) [7,8]. In addition, the increased pressure from the government, law enforcement and environmental agencies compels the manufacturers to adopt MQCL as an alternative sustainable cooling and lubrication (C/L) technique [9]. Yet in this situation, the biggest question regarding productivity and cost remain as concerns. As consequence, to judge the acceptability of MQCL, not only in respect of environmental sustainability but also with respect to profitability, researches have been carried out vis-à-vis different aspects of MQCL while machining various materials. For instance, Cakir et al. [10] investigated the influence of speed, feed and MQCL flow rate on the average surface roughness parameter in turning aluminum alloy. Then, Hadad and Sadeghi [11] included the nozzle

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Table 1
Parameters of heat treatment for 60 R_c.

Austenitizing		Quenching		Tempering	
Temperature (°C)	Time (min)	Temperature (°C)	Medium	Temperature (°C)	Time (min)
900	90	25	Bluta oil	135	120

position in their study besides the cutting speed, feed rate, depth of cut in turning AISI 4340 steel under MQCL. Sarikaya and Gullu [12] determined the effect of cutting conditions (dry, wet, MQCL) on the surface roughness parameters in turning of AISI 1050 steel. Sharma et al. [13] investigated the performance improvement of MQCL by using nanofluid suspension in machining AISI D2 steel. Shokoohi et al. [14] investigated the newly formulated cutting fluid, impinged as MQCL, in respect of surface roughness, power consumption and chip formation. Apart from turning, the MQCL implemented studies have been performed for other machining operations wherein good results have been found [15,16].

The productivity directly depends on the surface quality. Since the products with unacceptable surface quality are categorized as 'defective' and thereby these are not eligible to be put into application yet have consumed resources. Furthermore, the tribological characteristic, fatigue strength, corrosion, and wear behavior of a machined part depend on the surface quality [17,18] and thereby drew the attention of industrial personnel as well as researchers. Among different parameters of surface finish, the arithmetic average surface roughness (R_a) is widely used and accepted in different industries around the world to define the adequacy of a machined surface [1,19] and therefore, it is studied in this work.

Most of the works in literature have defined the relation of surface roughness with the cutting speed, feed rate and depth of cut. In addition, some works have considered the tool geometry and flow rate of the MQCL. The flow rate of fluid has been found to influence the machining performance as insufficient amount of fluid may not be able to eliminate the hurdles of dry cutting and over use of fluid can cause performance deterioration and environmental degradation [20,21]. In this regard, the flow rate which is defined in this study by the time pulse has been counted as one of the inputs.

Apart from the experimental investigation, the performance modeling of machining responses by using conventional statistical methods as well as artificial intelligence (AI) has been reported by many researchers with certain novelty either in the machining processes, materials, methods, cutting conditions, or in the adopted techniques. For instance, Sarikaya and Gullu [12] in one study employed Taguchi method and response surface method in optimization models of MQCL assisted turning of steel; wherein in another study they [22] optimized multiple performance characteristics by using grey relation based Taguchi technique in turning of difficult-to-cut material under MQCL. Camposeco-Negrete [23] optimized the energy consumption and material removal rate besides the surface roughness by using the RSM in turning. Besides, the prediction model of surface roughness was developed by using ANN [24]; the prediction of R_a by using support vector regression (SVR) was presented by [25] for turning of stainless steel. In comparison of conventional and AI technique, the AI has been reported to provide higher accuracy due to its capability of generating relationship between the inputs and outputs which are unable to be defined by the conventional techniques [26].

From the literature study, it is observable that many studies have been performed regarding the MQCL assisted machining. At the same time, different models have been presented wherein the cutting speed, feed rate and depth of cut were explored. However, very few models have considered the flow rate as the investigating and modeling variable specially in machining of high hardness steel (~60 R_c) which suggest the necessity of more studies in this field. To fill this shortage of studies, in this work, the average surface roughness parameter (R_a) has been studied alongside developing the predictive model by employing the support vector regression method and the optimization model by using the genetic algorithm technique. To accomplish these objectives, the accounted control factors were the cutting speed, feed rate, depth of cut and the time gap between the pulsing (i.e. flow rate of MQCL).

2. Experimental conditions

The machined material in this study was hardened and tempered high carbon steel possessing hardness 60 R_c. A cylindrical bar of length 300 mm and diameter 100 mm has been used. The heat treatment of the workpiece was performed in three consecutive stages: austenitizing, quenching, tempering. The austenitizing and tempering were performed in an induction furnace at different times and temperatures while quenching was accomplished by soaking the material into Bluta oil (grade 27). The obtained hardness was accepted within a tolerance of ± 2 R_c. The parameters of heat treatment are listed in Table 1.

The machining was performed in a center lathe (Model: CS6266B, Max W/P length: 1000 mm, China) by using uncoated carbide insert with ISO specification SNMM 120408. The tool insert was held by PSBNR 2525M12 tool holder. This cutting tool had a rake angle of 0°, cutting edge angle of 90° and squared shape insert with single sided chip breaker. After each machining run the arithmetic average surface roughness (R_a) was measured by using a roughness tester (SRG-4500). The impinged cutting fluid was VG-68 grade straight cut cutting oil mixed with water as ratio of 1:9.

The spindle speed (N), feed rate (f), depth of cut (a_p) and the time interval between the pulses (t) were taken as the input variables for investigation and subsequent modeling. Each of the variables was further divided into three levels as: spindle speed, N = 210–260–320 rpm; feed rate, f = 0.18–0.22–0.25 mm/rev; time interval, t = 1–3-5 s, expect for the depth of cut which has been divided into two levels a_p = 0.25–0.5 mm. These factors were arranged by following the full factorial design of experiment (DOE) to collect 54 sets of experimental surface roughness. In each set, the surface roughness values were measured at three different locations (approximately 120° apart) from which the mean was recorded and used for successive predictive and optimization modeling. Note that the prediction model of R_a is developed by using the Support vector machine and the optimization is carried out by the Interior point method. The methodology is shown in Fig. 1.

3. Support vector regression

The support vector machine (SVM) [27] is a supervised and statistical learning theory proposed by Vladimir Vapnik for solving multidimensional function estimation problems. SVM manipulates some set of labeled training data and generates input-output mapping functions (i.e. classification function, regression function). Input data is transformed to a high-dimensional feature space by utilizing non-linear kernel functions in case of classification problems. According to classes which have been previously mapped into high-dimensional feature space a separating hyper-plane is created which maximizes the margin between two data points. The margin is determined by constructing two parallel hyper-planes on each side of the separating margin. The larger the margin the better the generalization error of the classifier is

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