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A comprehensive assessment of minimum quantity lubrication machining from quality, production, and sustainability perspectives

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A B S T R A C T

The article presents minimum quantity lubrication (MQL) machining of Ti-6Al-4 V in a collective framework of multiple objectives - quality (surface roughness), environmental friendliness (specific cutting energy, tool wear, and oil consumption), and production (material removal rate and tool wear). In one of the first of its kind, the proposed approach uses cutting fluid parameters (oil quantity in the oil+air mixture, air pressure, and proportion of oil at the rake and flank face) along with machining parameters in multi-objective meta-heuristic optimization. The investigation reveals that the three objectives are distinct functions of process inputs. Thus, focus on one of the objectives - quality, production, and environmental aspects - hampers the others. A reasonable balance between the three aspects can be achieved through simultaneous optimization. Precise control over cutting fluid parameters, especially the oil proportion at rake and flank face, is a major factor that helps in improving environmental friendliness and productivity. The findings of the investigation will be useful for preparing a guideline for simultaneous selection of machining and cutting fluid parameters for economic and environmental viable manufacture of quality products.

1. Introduction

Minimum quantity lubrication (MQL) has evolved as an alternative to wet machining in many tool and workpiece combination scenarios. Lower consumption of cutting fluids results in reduced occupational health hazards on the shop floor, without compromising the machined surface quality [8]. This has made MQL an environmentally friendly machining process [23]. With the constantly increasing demands of difficult-to-machine materials, such as titanium and nickel-based alloys, further improvements in this technique are required. When machining titanium alloys, heat is accumulated at the tool-workpiece interface because of lower thermal conductivity. Conventionally, machining of these alloys is done using a large amount of coolant. To successfully introduce MQL for the machining of titanium alloys, its effectiveness must be understood [4]. Several ambiguities in the MQL technique still exist, which limit its widespread use in industrial scenarios. For example, in a single-point metal cutting operation, as shown in Fig. 1, since the rake and flank faces of the tool, are most affected by heat, distributing the cutting fluid in proportion to heating at these two locations might be more beneficial compared to an individual supply at these two locations in equal proportion.

Vazquez et al. [27] have demonstrated the effectiveness of MQL in reducing tool wear and burr formation while micro milling Ti-6Al-4V alloy. These authors also found that the surface finish could be improved by adjusting the spraying direction of the MQL fluid, as well as reducing tool wear compared to conventional coolant application and dry machining. Compared to conventional flood coolant supply, localized cooling using a through-tool coolant supply has been reported more efficient in reducing the surface roughness. Specifically, focused cutting fluid can result in the more optimal usage of the cutting fluid; however, the location of the supply and the amount of oil in the aerosol are additional parameters that need to be controlled in MQL.

Recently, investigators have attempted to quantify the effects of operating parameters on the efficacy of the MQL process through process modeling and optimization. To obtain lower surface roughness, Simunovic et al. [25] used the response surface method to optimize the machining parameters of speed, feed, and depth of cut, as well as different cooling and lubricating conditions for a face-milling process. Shokoohi et al. [24] investigated the effectiveness of wet, dry, and minimum quantity cooling and lubrication machining on workpieces that were either pre-cooled or not. The power consumption and surface roughness were analyzed through regression models. Jiang et al. [10] developed an optimization model to reduce the cutting fluid consumption and process cost for a turning operation. The machining parameters (speed, feed, and depth of cut) were considered as process variables. Process cost was defined in terms of product operation cost and cutting tool cost, while the cutting fluid consumption was defined in terms of reusable cutting fluid and non-reusable cutting fluid. The multi-objective optimization model developed from this work was effective in

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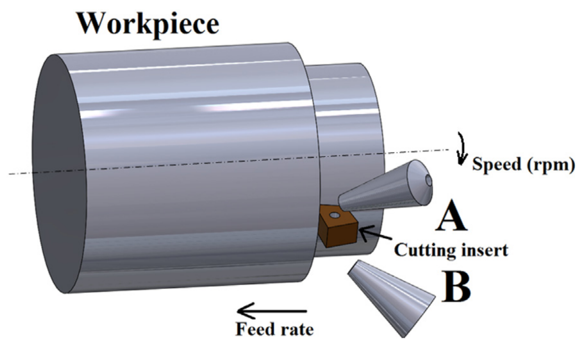

Fig. 1. Schematic representation of single point metal cutting operation with multiple nozzle (A = Nozzle at the rake face; B = Nozzle at the flank face).

reducing the consumption of cutting fluid by 17%. Pusavec et al. [14] developed predictive models for surface roughness, cutting force, and tool wear, where cutting speed, feed rate, depth of cut, and different cooling and lubrication conditions were used as input variables. Coolant was mainly focused on the rake and flank face of the tool, either individually or in combination. When the MQL aerosol was supplied at the rake and flank face simultaneously, favorable surface integrity characteristics were achieved with lower power consumption. In a subsequent study [15], the developed models were further used to optimize process parameters for better tool life, surface quality, and lower power consumption. Davoodi and Tazehkandi [3] developed a regression model to show the effect of cutting speed and undeformed chip thickness on cutting force, feed force, and tool tip temperature. These authors found that the lowest undeformed chip thickness, when accompanied by the highest cutting speed, could result in lower cutting forces and tool tip temperature for dry machining condition; the performance was comparable to that of conventional wet machining. Liu et al. [12] used a coupled response surface design to analyze the effect of cutting speed, feed rate, and depth of cut on the cutting force and surface roughness under dry, wet, and MQL conditions. The effect of feed rate was more prominent on the surface roughness and cutting force, followed by cutting speed and depth of cut. MQL showed better performance compared to dry and wet machining. Saini et al. [17] optimized the effect of cutting speed, feed rate, and approach angle on main cutting force and tool tip temperature under dry and MQL conditions. Zhang et al. [28] optimized speed, feed, depth of cut, and lubrication conditions for environmentally friendly machining austenitic stainless steel with high efficiency and less energy consumption. [2] statistically analyzed the effect of MQL, compressed air cooling, and dry cutting on surface quality generated while milling magnesium alloy.

From the analysis of literature, it is observed that process modeling and optimization investigations regarding MQL have been conducted with a limited number of machining process parameters, with primary focus on the surface finish of the machined sample (e.g., [3,5–7,9,11,12,16,18,19]). Other objectives, such as specific cutting energy [7,11,12], flank wear [5], cutting forces [3,13], material removal rate [13], and power consumption [11], are rarely optimized. Few investigations have attempted to optimize MQL process for the productivity and cutting fluid consumption [10,15]. However, an environmentally friendly machining process should have lower energy consumption, lower material usage, and cutting fluid consumption. On the other hand, from the industrial point of view, a profitable production process should maximize the production rate (maximizing the material removal rate and simultaneously minimizing the tool wear, because tool wear leads to change in tool geometry that causes a delay in production). With new developments in MQL process, such as controlled supply of cutting fluid at localized places (e.g., rake and flank) [1]; MQL parameters, such as fluid supply rate, as well as its pressure and distribution at rake and flank faces, should be included in the process model, together with machining parameters (e.g., cutting speed, tool feed rate, and depth of cut). Moreover, process models for responses of various types, which represent quality, production rate, and environmentally friendliness, need to be developed.

The broader objective of this investigation is to present the underlying dynamics of MQL from quality, production rate, and environmentally friendliness perspectives, given the latest developments in the process. The investigation seeks to develop a new process model for responses such as surface roughness, specific cutting energy, oil consumption rate, tool wear, and material removal rate, as functions of MQL parameters, in addition to conventionally investigated machining parameters. Consequently, through selection and aggregation of appropriate process models, the article develops assessment approaches of the MQL process focused on quality, production or environmental friendliness. The aim is to evaluate the inherent system trade-offs that occur when the process is optimized from the individual perspectives of quality, production or environmentally friendliness and, thus, offer a guideline for parameter selection for better utilization of the process capability.

The following section presents a mathematical formulation of the problem under consideration. A detailed experimental investigation is presented next wherein machining parameters (i.e., cutting speed, depth of cut, and tool feed rate) along with MQL parameters (i.e., the proportion of oil at rake and flank face, amount of oil rate and pressure of aerosol) are varied following a design of experiments. The process outcomes, namely, surface roughness, cutting force (used for computing specific cutting energy), material removal rate, tool wear rate, and oil consumption rate, are recorded for machining of Ti-6Al-4 V as a candidate material. Subsequently, development of process models and multi-objective optimization are presented, followed by a discussion on the results and conclusions.

2. Mathematical formulation

The MQL optimization problem under consideration is a multi-input multi-output (MIMO) system where there are n input variables (x) that affect the process responses. The quality objective y can be defined as follows:

$$\boldsymbol{y_j = f_j(x_i)} \qquad \boldsymbol{i = 1, \ldots, n \ \ and \ \ j = 1, \ldots, m} \tag{1}$$

The MIMO system can be converted in to a multi-input single-output (MISO) system through aggregation of different responses that leads to

$$\boldsymbol{Y = A\left(y_j\right) = g(x_i)} \tag{2}$$

where Y is an aggregate objective, A is an aggregation function that eventually be expressed as g, a function of input x_i. The aggregate function, known as an aggregate index, developed by Swamee and Tyagi [26] and subsequently used by [21,22]) in the optimization of manufacturing problems, is used in the present investigation. The aggregate index is given as follows:

$$\boldsymbol{Y = \left(1 - m + \sum_{j=1}^{m} s_j^{-\frac{1}{\beta}}\right)^{-\beta}} \tag{3}$$

where 'β' is a positive constant. At $\beta = 0.4$, the aggregation most satisfactorily overcomes the problem of 'ambiguity' and 'eclipsing'. s_j are sub-indices that are responses normalized between 0 and 1. If the response is expected to be 'higher-the-better', the sub-index is given as follows:

$$\boldsymbol{s_j = \frac{y_j - y_j^{min}}{y_j^{max} - y_j^{min}}} \tag{4}$$

where y_j^{max} and y_j^{min} represent the maximum and minimum value of y_j over the total domain of process parameters, respectively. For the

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