# Parametric Optimization Using The Particle Swarm Optimization (PSO) Technique for Minimizing Tool Wear While Milling Inconel 718 Alloy Assisted by Minimum Quantity Lubrication (MQL)

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***Abstract*— In today's industrial scenario, the high cost involved in manufacturing is the major concern apart from the environmental factors. With the manufacturing cost reaching sky high levels, the use of a suitable optimization technique has become one major requirement while designing any manufacturing process. The current study involves a series of milling experiments on Inconel 718 alloy. Minimum quantity lubrication has been used as the cooling technique alongside the flood and the dry conditions. The combined objective functions were generated using ANOVA. Particle swarm optimization (PSO) technique was used to optimize the input parameters i.e. the cutting speed (Vc), cutting feed (F) and the depth of cut (ae) in order to minimize the tool wear (Vbmax). A series of validation experiments were performed and the PSO technique proved to be a highly effective method in predicting the tool wear (Vbmax), also allowing a simultaneous comparison amongst the cooling methods, thus, suggesting MQL to be a better cooling technique when compared to the dry and the flood cooling.**

***Keywords*— particle swarm optimization; Inconel 718; lubrication; surface roughness; depth of cut; MQL; tool wear***

## I. INTRODUCTION AND LITERATURE SURVEY

With the increasing economical and ecological pressures, the manufacturing industry seeks for newer technologies and materials for cooling of the cutting zone. New international manufacturing standards have been set up. The industries signing up for such standards will have to make certain necessary amendments in their production procedures. Air, water, land, raw material etc have to be taken into account [1–5]. Inconel 718 is a well known difficult to machine nickel based super alloy that has found a very wide application in various industries like aircraft and nuclear industry. This alloy has a property to retain its properties at very high temperatures as well. But it is these properties that cause huge difficulties in the machining process of inconel 718 like poor surface finish or short tool life. Also, the the high speed machining is not possible while machining this alloy because of the exceptional hardness and thus resulting in a very low productivity. One possible solution to this problem of a short tool life is using proper cooling techniques to control the heat generation at the work tool interface and in turn improve the tool life. The flood cooling is the basic technique used for cooling since decades to reduce the interface temperature while the MQL (minimum quantity lubrication) also known as near dry machining in the process that involves the utilization of a very low quantity of a coolant or a lubricant mixed with a carrier gas.

A fair amount of literature is available in the field of machining of inconel 718 alloy over the past two decades. Jawaid et al (2001), conducted experiments regarding the face milling if inconel 718 where the effect of cutting speed and feed on the tool wear were investigated by using a PVD TiN coated and uncoated tungsten carbide inserts. It was concluded that the uncoated inserts performed better at lower speeds while the coated inserts gave a better performance at higher speeds [6]. Sharman et al (2001), worked in the area of tool life using TiAlN and CrN coated tungsten carbide ball end milling cutters. Although the cutting speeds were maintained at 150 m /min but the longest tool life was obtained at 90 m/min with TiAlN coatings, thus explaining the crucialness of the choice of coating to influence the tool life [7]. Li et al (2006), conducted experiments to study the tool wear propagations and cutting force variations in the end milling of inconel 718. They found that the initial flank wear was the main factor in effecting the tool life. The analysis on cutting forces performed showed that the thermal effects were the main reasons for the peak force variation within a single pass [8]. Krain et al (2007) tried to optimize the tool life and productivity while milling of inconel 718. The study consisted of evaluated the feed rate, tool material, geometry and the radial depth of cut on the tool life. They concluded that no particular geometry or tool material gave overall optimal result, rather specific combinations gave specific results [9]. Yazid et al (2012) studied the surface integrity of inconel 718 while turning it with PVD coated carbide tool and cooling was performed with MQL. It was shown that severe deformations took place in the microstructure while performing the machining and the results proved that MQL improved the surface integrity [10]. Shokrani et al (2012) on the other hand used liquid nitrogen as a coolant while studying its effect on the surface roughness of inconel 718 while machining using PVD TiAlNcoated solid carbide end mills. The results indicated a reduction in 30-40 % Ra and Rz respectively [11]. Kasim et al (2013) investigated the tool wear by using a ball type end mill. A PVD coated tool was used and the cutting parameters were varied. It was pointed out that the dominant wear was near the nose and also a maximum temperature of 521 deg. Celsius was recorded which was far lower than the critical temperature of 650 deg. Celsius [12]. Ucun et al (2013) studied the effect of coating material on the tool wear in comination with the MQL process. It was shown that AlTiN, AlTiN+AlCrN and AlCrN displayed better performances compared to TiAlN+Wc/c [13]. Aramcharoan and Chuan (2014) carried on the cryogenic milling of Inconel 718 alloy. Responses in terms of tool wear and cutting forces were evaluated. It was shown that the use of a cryogenic fluid in conparison to the conventional cooling techniques lead to lesser tool wear and cutting forces [14]. Sharma et al (2014) conducted a very detailed study on the machining of various materials including tutanium, aluminum, steel, inconel etc. It was clearly concluded that the cooling techniques do play an important role in effecting the tool life while milling inconel alloys [15]. Thus, from the detailed study it is very much evident that MQL an effective technique for cooling inconel 718 alloy while milling.

(a) Particle swarm optimization (PSO)

This optimization technique possesses a very simple concept and is easliy implementable in a few lines of a computer code. It was initially developed by James Kennedy and Russel Eberheart in 1995 [16]. It combines the characterestics of noth evolution strategies (ES) and generic algorithms (GA). It easily takes care of continuous optimization problems unlike the generic algorithms. The basic concept of this technique lies in the examination of the movements of a group of natural creatures like birds and reconfiguring the created model into a computer. These groups of creatures or birds often behave like a swarm. Thus, the movement of each agent or creature inside a swarm may be modelled using simple vectors. These flocks of birds (also called intelligent agents or particles) are set across the search space in a random way and several iterations are conducted for these randomly moving particles. Each particle updates its current location during an iteration with a certain velocity on the basis of *pbest* i.e. the best searched position of that particle and *gbest* i.e. the best particle position in the entire population. In case the particle best location in a progressive iteration surpasses the global best, the *pbest* location automatically gets replaced by the *gbest* location on the basis of the equation:

$$v_i^{k+1} = w.v_i^k + c1.R1.(pbest_i - x_i^k) + c2.R2.(gbest - x_i^k) \quad (1)$$

Where, = ‘i$^{th}$’ particle velocity at ‘k$^{th}$’ iteration; w= inertia weight; c1, c2= learning rates; R1, R2= random numbers between 0 & 1; $pbest_i$ = *pbest* location of ‘i$^{th}$’ particle; gbest= gbest location of swarm; $x_i^K$= $[x_{i1}^K, x_{i2}^K, x_{i3}^K, x_{i4}^K, ..., x_{iN}^K]$, ‘i$^{th}$’ particle current position at ‘k$^{th}$’ iteration in N-Dimensional search space

After calculation of velocity, the next position of ‘i$^{th}$’ particle is calculated as given below:

$$x_i^{k+1} = x_i^k + v_i^{k+1} \quad (2)$$

Inertia weight can be selected to be any arbitrary value or following equation could be used to determine the inertia weight used in the (1) equation:

$$w = w_{max} - \frac{[(w_{max} - w_{min}) * iter_{curr}]}{iter_{total}} \quad (3)$$

Where,

$w_{max}$ = maximum inertia weight; $w_{min}$ = minimum inertia weight; $iter_{curr}$ = current iteration; $iter_{total}$ = total number of iteration

Also there needs to be an upper limit set on the maximum velocity obtained by the particles. This is obtained by the step:

If ( $v_i^k$ >($x_{ulim}$- $x_i^k$ ) and $v_i^k$ <($x_{llim}$- $x_i^k$ )), then, $v_i^k$ =-0.5* $v_i^k$

This criterion assists in controlling the speed of the particles by giving them velocity in the opposite direction, thus keeping the search space within desirable limits [17]. Zhou et al (2006) made use of neural networks trained by PSO and BP algorithms for predicting the diameter errors in the boring process. It was concluded that PSO trained neural networks led to a better optimization of the process when compared to the BP algorithm [18]. In another rare effort, Zuperl et al (2007) implemented the PSO technique on the milling process to optimize speed and feed. Cutting force was taken as the output parameter. It was noticed that PSO gave good results by reducing the machining time and improving the material removal rate [19]. Majumdar (2013), also applied PSO technique to the EDM process. Confirmation experimentation was performed and the usefulness of the results was validated [20]. Yusup et al (2012) made an exhaustive study on the use of PSO in the various metal cutting operations in the recent years. It was concluded that PSO is a highly effective technique for optimizing the parameters in the various machining operations. Machining costs and surface roughness have been the commonly calculated responses in most of the studies [21]. It is very much clear from the literature that the PSO technique has time and again proven its utility in optimizing the process parameters for the optimal results. A few studies in the field of machining have also been recorded where PSO technique has been utilized. Not much literature is available where the milling of Inconel 718 has been optimized using the PSO technique and that too when MQL plays along. So, it opens up a broad area for the following study to explore and that too in reducing the tool wear using the PSO technique.

## II. EXPERIMENTAL SETUP AND PROCEDURE

Fig. 1. (a) Cutting tool inserts (b) MQL setup (c) Tool maker's microscope (d) Experimental setup

### (a) Experimental materials and setup

The present study made use of Inconel 718 alloy in the form of cylindrical bars of diameter 123 mm and height 100 mm. The workpiece hardness was maintained at 33 HRC. The experiments were performed on a brigeport high speed milling machine (BMC 1500). The cutting tool inserts used for performing the experiments were ISCAR IC830 as shown in fig. 1 (a). The MQL setup used was NOGA minicool model with a distance 25 mm and the jet angle of $30^0$ as shown in fig. 1 (b). The oil used up in the experimentation was the Rhenus FU 60 water soluble oil. The tool wear was measured on a Mitutoyo tool maker's microscope as shown in fig. 1 (c). The complete experimental setup has been shown in the fig. 1 (d).

### (b) Experimental parameters

The experiments were carried out in a single path double pass system. The response was calculated on the basis of the second pass in each case. The cutting speed ($V_c$), feed ($f_z$) and depth of cut ($a_e$) were taken as the input parameters while the maximum tool wear ($V_{bmax}$) was taken as the response parameter. Maximum tool wear was chosen instead of average tool wear as the wear recorded was highly non uniform. So, in order to avoid any misleading results, ($V_{bmax}$) was chosen instead of ($V_{bavg}$).

A total of 13 experiments were performed under dry, flood and MQL condition. Table 1 shows the machining parameters.

Table I. Machining parameters

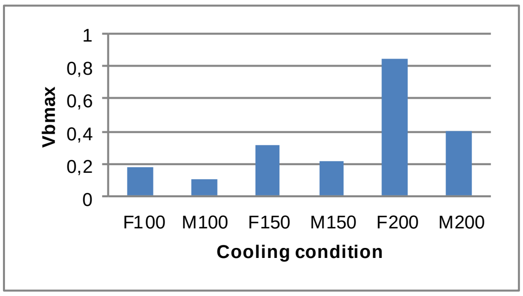
| | | | |
|---|---|---|---|
| Speed ($V_c$) (m/min) | 100 | 150 | 200 |
| Feed ($f_z$) (mm/tooth) | 0.10 | | 0.15 |
| D.O.C ($a_e$) (mm) | 0.5 | | 1.0 |
| Cooling cond. | MQL | Flood | Dry |
| Flow rate MQL (ml/hr) | 30 | | |
| Air pressure (bars) | 6 | | |
| Lubricant conc. (%) | 5 | | |
| Tool | PVD TiAlN coated carbide | | |
| Material | Inconel 718 | | |

## III. RESULTS AND DISCUSSIONS

Figure 2(a) indicates the effects of cutting speed ($V_c$) on tool wear ($V_{bmax}$) under flood and MQL cooling conditions. For flood cooling experiments the tool wear increased in the pattern 0.18, 0.32 and 0.85 mm at speeds 100, 150 and 200 m/min respectively, seeing a decrease of 78% in speed from 200m/min to 100 m/min. For the MQL experiments the readings obtained were 0.10, 0.21 and 0.40 mm seeing a decrease of 75% in speed from 200 m/min to 100 m/min. Thus it can be concluded that for both the processes i.e. flood and MQL individually, the tool wear ($V_{bmax}$) increases by nearly same values and increases noticeably as the speed is increased. Moreover, on comparing flood and MQL readings at each level, it can be seen that MQL reduces the tool wear( $V_{bmax}$) by as much as 40% and it goes to as high as 53% reduction in tool wear ($V_{bmax}$) at 200 m/min. Thus, it can be concluded that cutting speed plays a vital role in effecting the tool wear on both individual a well as relative basis. MQL leads to much lower tool wear as compared to the flood cooling, and its effect becomes more and more dominant as the cutting speed($V_c$) is increased.

Figure 2(b) shows the effect of feed ($f_z$) on the tool wear ($V_{bmax}$). At constant cutting speed ($V_c$) 150= m/min and depth of cut (ae)= 0.5mm, the results obtained show a similar pattern as seen in case of the cutting speed. At feed ($f_z$)= 0.1 mm/tooth a 34% reduction in tool wear ($V_{bmax}$) can be seen when using MQL as compared to the flood method, while at feed ($f_z$)= 0.15 mm/tooth a 39% reduction can be seen. Thus, a 50% increase in the feed ($f_z$) only leads to a 5% relative increase which is insignificant. Also, the increase in feed does not effect the results for the processes individually which can be clearly seen from the figure. Thus, it may be concluded that feed ($f_z$) does not play an important role both individually as well as relatively when comparing flood and MQL cooling. On similar lines figure 2(c) shows the effect of depth of cut (ae) on the tool wear ($V_{bmax}$) as the other two cases. Taking constant cutting speed (vc) 150= m/min and feed ($f_z$)= 0.15 mm/tooth, at depth of cut (ae)= 0.5 mm a 39% decrease in the tool wear ($V_{bmax}$) can be seen, whereas at feed ($f_z$)= 1mm 41% increase can be noted. Thus by increasing the depth of cut (ae) by 100% only a 2% increase can be obtained. This accounts for its insignificance when comparing both the process on relative terms. On the other hand, when the effects of an increase in the depth of cut (ae) are evaluated on both the processes individually, 31% and 28% increase in tool wear can be seen for both flood and MQL respectively. Thus, it would be wise to conclude that depth of cut (ae) is a significant parameter when studying the processes on individual basis. On relative basis, it is not of much significance. From Fig 2(d) it is very clear that

MQL cooling is far more effective in reducing the tool wear ($V_{bmax}$) with its effect becoming more and more effective at higher speeds.



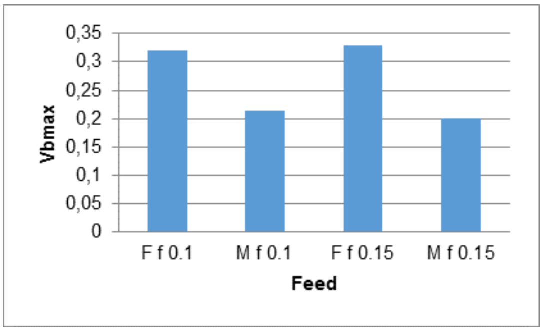

F100: Flood at 100 vc; M100: MQL at 100 vc

F150: Flood at 150 vc; M150: MQL at 150 vc

F200: Flood at 200 vc; M200: MQL at 200 vc

At fz=0.1 and ae=0.5

Fig. 2(a) Effect of vc on Vbmax

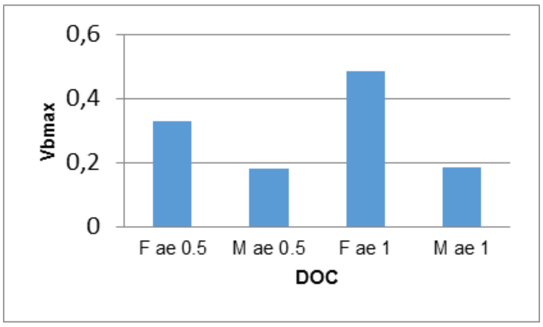



Ff 0.1: Flood at feed(fz)=0.1;Mf 0.1:MQL at feed(fz)=0.1

Ff0.15: Flood at feed(fz)=0.15;Mf 0.15:MQL at feed(fz)=0.15

vc= 150 m/min and ae=0.5 mm

Fig. 2(b) Effect of fz on Vbmax




F ae0.5=Flood at 0.5 doc; M ae0.5= MQL at 0.5 doc

F ae1= Flood at 1 doc; M ae1= MQL at 1 doc

At vc=150 m/min and fz=0.15 mm/tooth

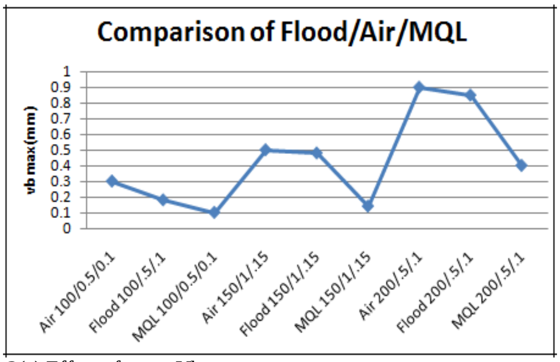



Fig. 2(c) Effect of ae on Vbmax

Fig. 2(d) Comparison of Flood, Air and MQL

(a) Analysis and optimization

Checking the model accuracy: ANOVA was brought into use for checking the model accuracy. Table 2 shows the ANOVA table. As per this technique, a P value lesser than 0.05 gives a signifiacnt model, whereas, a greater than 0.05 value signifies an insignificant model. In the present model, p-value for tool wear ($V_{bmax}$) came out to be lesser than 0.05. Hence, the model is considered to be adequate. Further the values of calculated $R^2$ and adjusted $R^2$ came out to be over 80% and 70% respectively, further justifying the adequacy and significance of the regression model.

Table II. ANOVA analysis of tool wear

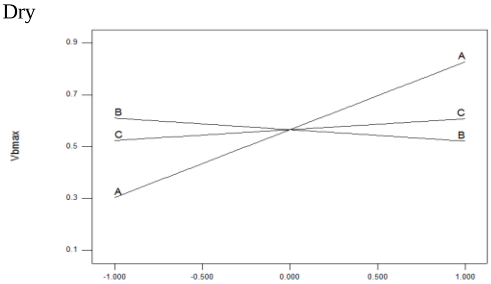
| Source | sum of Square | DF | Mean Square | F Value | Prob> F | |
|---|---|---|---|---|---|---|
| Model | 0.64 | 5 | 0.13 | 11.66 | 0.0027 | Sig. |
| A | 0.41 | 1 | 0.41 | 37.69 | 0.0005 | |
| B | 0.012 | 1 | 0.012 | 1.11 | 0.3276 | |
| C | 7.87E-003 | 1 | 7.87E-003 | 0.72 | 0.4235 | |
| D | 0.19 | 2 | 0.97 | 8.89 | 0.0120 | |
| S.D | 0.10 | | R-Squared | | 0.8936 | |
| Mean | 0.39 | | Adj R-Squared | | 0.8177 | |
| C.V | 26.88 | | Pred R-Squared | | 0.6804 | |
| PRESS | 0.23 | | Adeq Precision | | 11.772 | |

Developing the predictive mathematical model of the combined objective (C.O.) equations: The statistical technique of regression analysis was utilized to develop the predictive equations for tool wear with the help of design expert software. Separate equations were obtained for dry, flood and MQL conditions respectively. Table 3 shows the predictive equations obtained for the three cooling conditions. The figure 3 shows the perturbation analysis for the tool wear ($V_{bmax}$) at $V_c$=150 m/min; $f_z$= 0.13 mm/tooth and $a_e$= 0.75 mm. It can be clearly seen that the tool wear values are minimum for MQL, when compared to the dry and flood techniques. It is also clear from the graphs that speed (Vc) plays the most vital role in effecting the tool wear (Vbmax). Feed (fz) and DOC (ae) are relatively insignificant.

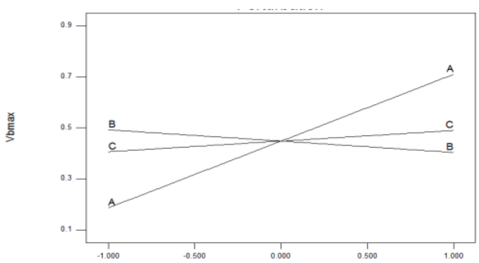
Table III. Equations for tool wear in actual factors

| Cooling condition | Equation |
|---|---|
| Dry | $V_{bmax} = -0.122 + 5.23E\text{-}003 * V_C - 1.77 * f_Z + 0.16 * a_e$ |
| Flood | $V_{bmax} = -0.239 + 5.23E\text{-}003 * V_C - 1.77 * f_Z + 0.16 * a_e$ |
| MQL | $V_{bmax} = -0.433 + 5.23E\text{-}003 * V_C - 1.77 * f_Z + 0.16 * a_e$ |

(a) Dry




(b) Flood




(c) MQL

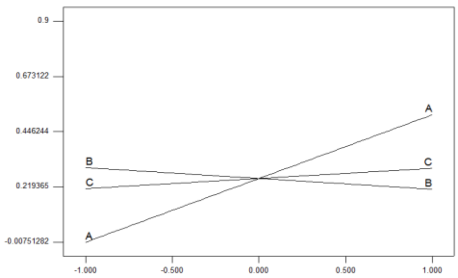



Fig. 3 Perturbation graphs for tool wear

Optimization using PSO technique: The cutting speed ($V_c$), feed ($f_z$) and depth of cut ($a_e$) were taken as the particles in PSO. The algorithm followed for PSO was as follows:

**Step 1:** The cutting speed, feed and depth of cut were randonly selected in between their minimum and maximum values.

**Step 2:** The particle velocities generated were chosen randomly between the maximum and the minimum values of the prticles.

**Step 3:** Then, the objective function values were calculated for the particles and the *pbest* and *gbest* values were assigned.

**Step 4:** Equation 1 was used then, to calculate the new velocities.

**Step 5:** Equation 2 was used next, to update the positions of all the particles.

**Step 6:** The objective function values were again calculated for the new particle positions. The new and better *pbest* and *gbest* values were also obtained.

**Step 7:** Repeated iterations were performed until the termination was made.

The equations obtained in table 3 were then employed with PSO through MATLAB. The table 4 shows the parameters of PSO used for the optimization in this case. The cutting speed ($V_c$), feed ($f_z$) and depth of cut ($a_e$) were taken as the particles or the intelligent agents. The particle population was taken to be 50. Learning factors c1 and c2 were taken to be equal where c1max=c2max=1.7 and c1min=c2min=0.5. The inertia weight factor w=0.7. Al these factors collectively play a very effective role in getting the excellent convergence characterestics of PSO as shown in figure 4. The increase in the number of particles helps in a more efficient exploration of the search space. Table 5 shows the predicted results obtained for dry, flood and MQL techniques. The results clearly show that the MQL technique is much more efficient and time saving. A 40% increase in the $V_c$, 25% in $f_z$ and 80% in $a_e$ only increases the tool wear by 17%, thus saving time and cost. The obtained results were confirmed experimentally and a very low percentage of error was recorded in the experimental results when compared to the predicted results.

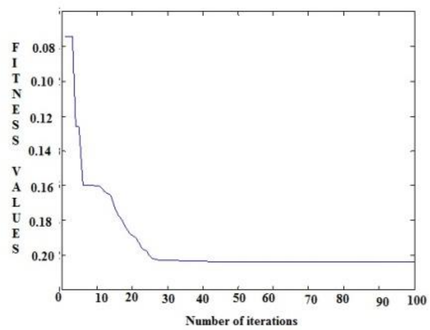



Figure 4. Convergence characteristics

Table IV. Parameters of PSO

| | |
|---|---|
| Number of variables | 3 |
| Number of particles | 50 |
| Number of iterations | 100 |
| Inertia weight, W | 0.7 |
| Learning Rate | |
| C1max=C2max | 1.7 |
| C1min=C2min | 0.5 |
| C1=C2=Cmin+R*(Cmax-Cmin) | Where R = current iteration/total iterations |
| $x_{ulim}$ | [100 0.1 0.5] |
| $x_{llim}$ | [200 0.15 1.0] |

Table V. Predicted results (PSO)

| No. | Speed $V_c$(m/min.) | Feed F(mm/rev.) | Cooling Condition | DOC (ae)(mm) | Tool wear (Vbmax) PSO |
|---|---|---|---|---|---|
| 1 | 100 | 0.12 | Dry | 0.5 | 0.172 |
| 2 | 120 | 0.13 | Flood | 0.7 | 0.189 |
| 3 | 140 | 0.15 | MQL | 0.9 | 0.202 |

Table VI. Confirmation tests

| No. | Speed $V_c$(m/min.) | Feed F(mm/rev.) | DOC (ae)(mm) | Pred. $V_{bmax}$ | Exp. $V_{bmax}$ | Error |
|---|---|---|---|---|---|---|
| 1 | 140 | 0.15 | 0.5 | 0.202 | 0.214 | 6% |
| 2 | 140 | 0.15 | 0.7 | 0.202 | 0.210 | 4% |
| 3 | 140 | 0.15 | 0.9 | 0.202 | 0.213 | 5.5% |

## IV. CONCLUSIONS

The study leads to many vital points that may be very useful for the future research work in the field of cooling techniques. The main conclusions that can be drawn from the work are:

1. MQL leads to better results when compared to the other two processes, with its effect becoming more and more commanding at higher cutting speed (vc) values
2. Cutting Speed (vc) plays the most vital role in effecting the tool wear (Vbmax) both individually for each process as well as comparatively.
3. The effect of cutting speed gets more and more dominant as the speed increases, reducing the tool wear by as high as 53% in case of MQL, when compared to flood cooling.
4. Feed (fz) plays an insignificant role in effecting the tool wear both individually as well as comparatively. A 50% increase in feed only leads to a 5% relative increase in the tool wear when comparing flood and MQL cooling, which is insignificant.
5. Depth of cut (ae) plays an important role when studying the processes individually leading to a 31% and 28% increase in the tool wear values for flood and MQL cooling, when doubled. But on comparing both the processes it plays a negligible role as a 100% increase in the depth of cut(ae) only leads to a 2% relative increase in the tool wear(Vbmax).
6. The input parameters were optimized using the PSO technique for optimization. Confirmation experiments were performed giving very low errors when compared to the experimental results. Thus, confirming the effectiveness of the technique.

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