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Multi-objective optimization of CNC turning parameters using genetic algorithm and performance evaluation of nanocomposite coated carbide inserts

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Inconel 600 is a super alloy known for its properties like low thermal conductivity and work hardening. The work hardening property of this alloy makes it harder and harder during successive passes of the tool during machining. Therefore, machining of this type of material demands innovation in tool material, selection of proper combination of parameters and their levels for economical machining. Coated carbide tool inserts are most widely used for machining Inconel alloys. These inserts are coated with special materials by PVD or CVD technique to reduce flank wear, improve surface finish of machined components and increase the material removal rate (MRR). In this work carbide insert coated with nanocomposite coatings like AlTiN and TiAlSiN commercially known as Hyperlox and HSN^2 were used and their performance during machining of Inconel 600 was studied. As improper selection of process parameter influences on the quality of products and productivity, it is important to identify the optimum combination of input process parameters. Most of the time the influence of the input process parameters on the output parameters like MRR, surface roughness and flank wear is studied independently. Information obtained through single objective optimization may not be sufficient because industries desire to optimize all the output parameters, simultaneously. Multi-objective optimization is the only solution to satisfy the requirements of industries and genetic algorithm based multi-objective optimization is adopted in this work in order to get the optimum combination of input process parameters to obtain maximum material removal rate, minimum surface roughness and minimum flank wear simultaneously.

1. Introduction

Inconel 600 is a nickel-based super alloy which is most widely used in applications where high strength and resistance to high temperature are required. It is a solution strengthened nickel based austenitic alloy (Zhang et al., 2014). The versatility of this alloy has led to its use in aerospace industries for making jet engines and aircraft turbines due to high yield strength, corrosion resistance and excellent fatigue resistance. The other applications of Inconel alloys include manufacturing of internal combustion engine parts, components of space vehicles, heat exchangers and parts used in petrochemical industries (Yadav et al., 2015). The presence of nickel in the alloy gives it corrosion resistance against most of the organic and inorganic chemicals used in the working environment (Del Prete et al., 2013). Machining of such

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novel materials can be done efficiently with tools which possess special characteristics. Coating carbide tool inserts with harder chemicals like AlTiN and TiAlSiN by Physical Vapour Deposition (PVD) or Chemical Vapour Deposition (CVD) technique will give the tool its strength and hardness. Therefore, they are being widely used for machining of aerospace alloys like Inconel 600. Conventional experimental design of combination of input parameters to conduct experiments has many complexities. The number of experiments to be conducted for the selected number of parameters will have an exponential relation. Taguchi's design eliminates the need for unnecessary experiments. It is also well known for its robustness (Ross, 2015).

The response or output parameters of machining like material removal rate (MRR), surface roughness and flank wear are a few important characteristics to be studied while machining a material. Surface roughness plays important role in improving corrosion resistance, fatigue strength, precision assembly of parts and tribological properties, whereas flank wear rate influences the tool life, surface finish, MRR and dimensional accuracy of machined components. Therefore, surface roughness, flank wear and MRR are taken as the parameters of interest in the study. Improper selection of machining parameters and their levels cause premature wear of cutting tools and also greatly affects the surface quality of the work material and MRR. In order to obtain the desired level of output parameters and to balance between the cost and quality of manufacturing the best combination of input parameters need to be identified. Artificial intelligence techniques like Genetic Algorithm (GA), Artificial Neural Network (ANN), Fuzzy Logic (FL) and Particle Swarm Optimization (PSO) are used to obtain the proper combination of input parameters (Sardinas et al., 2006). Genetic algorithm is a most widely used Artificial Intelligence technique for optimization. It has several advantages, including faster convergence rate to near global optima, and the ability to improve global optimum because of its specialized operators like crossover and mutation. Rather than selecting an individual in a close neighbourhood and getting trapped in local optima, these operators select random individuals (Pham & Karaboga, 2009). The literature review reveals that most of the studies conducted on this material, were towards optimization of a single objective (Das et al., 2015). But, industry demands innovation in manufacturing processes and procedure where importance is distributed amongst various conflicting objectives like surface roughness, tool wear and material removal rate. Solving of multiple single objective problems of a process into a multi-objective problem was accomplished by Samanta and Chakraborty (2011). With this background multi-objective optimization of machining parameters to achieve minimum surface roughness, minimum flank wear of tool and maximum MRR is performed in this work.

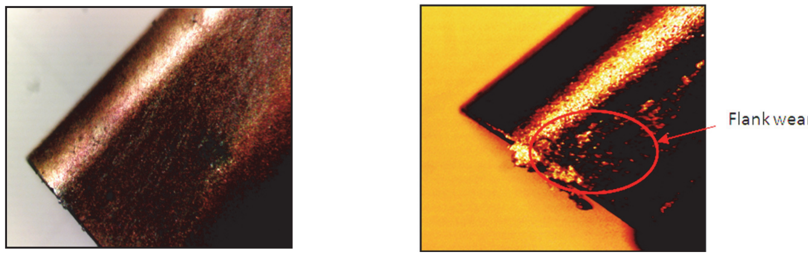
2. Experimental procedure

2.1 Material and Methods

The material used for experimentation was Inconel 600 rods of diameter 50 mm and length 200 mm. The experiments were carried out in Galaxy Midas-6 CNC turning centre. Carbide tool inserts coated with AlTiN supernitride of nanocomposite structure called Hyperlox® and TiAlSiN with 3-layer nanocomposite structure called HSN$^{2®}$ with maximum application temperature of 1100ºC were used for turning the work material. All the four cutting edges of each insert were used for machining. No coolant was used while machining the work material as it may neutralise the influence of coating materials on the response parameters like surface roughness (R_a), flank wear (V_B) and material removal rate (MRR). Surface roughness of the machined work material was measured using Mitutoyo SJ-210 surface roughness tester. The cut off length used for the measurement of surface roughness was 0.8 mm. Flank wear of the tool was measured using Mitutoyo Tool maker's microscope with camera setup. The image of the tool insert was taken before and after each experimental trial in order to measure the tool wear by image processing technique using ImageJ software. Typical image of the tool insert obtained before and after each experiment is shown in Fig. 1. The MRR obtained for each combination of process parameters during experimentation was calculated with the help of the standard formula given in Eq. (1) and therefore the MRR remained the same for the two types of tool inserts (Sardinas et al., 2006).

$$MRR = v_s \times f \times d, \tag{1}$$

where, v_s is the peripheral velocity of the spindle in mm/min, f is the tool feed rate in mm/rev and d is the depth of cut in mm.



(a) (b)

Fig.1. Tool insert (a) before machining and (b) after machining

2.2 Experimental Design

Three input process parameters which were proved to have a direct relationship with the output response parameters were chosen in this study based on literature review.

Table 1
Input parameters and their levels

Factors	Unit	Symbols	Levels		
			1	2	3
Spindle speed	rpm	v	1500	2000	2500
Depth of cut	mm	d	0.25	0.5	0.75
Tool feed rate	mm/rev	f	0.1	0.15	0.2

Table 2
The L_{27} orthogonal array of input parameters and the output parameters obtained through experimentation

Trial No.	Levels of input parameters			Surface roughness and flank wear for different type of tool inserts				Material removal rate MRR (mm³/min)
				Hyperlox		HSN²		
	v	d	f	Surface roughness R_a (µm)	Flank wear V_B (mm)	Surface roughness R_a (µm)	Flank wear V_B (mm)	
1	1	1	1	0.676	0.0381	0.588	0.0373	3858.26
2	1	1	2	0.756	0.0545	1.002	0.0565	5787
3	1	1	3	1.980	0.0227	1.886	0.0235	7716
4	1	2	1	0.876	0.0445	0.858	0.0454	5144
5	1	2	2	1.128	0.0876	1.106	0.0882	7716
6	1	2	3	1.912	0.0754	1.746	0.0754	10288
7	1	3	1	0.348	0.0442	0.734	0.0429	6430
8	1	3	2	1.010	0.0591	1.028	0.0587	9645
9	1	3	3	1.716	0.1123	1.758	0.1129	12860
10	2	1	1	0.860	0.0421	0.726	0.0435	7539
11	2	1	2	0.908	0.0480	1.028	0.0484	11308.5
12	2	1	3	2.144	0.0723	2.444	0.0735	15078
13	2	2	1	0.972	0.0500	1.372	0.0513	10052
14	2	2	2	1.584	0.0186	1.184	0.0180	15078
15	2	2	3	2.102	0.0254	1.708	0.0261	20104
16	2	3	1	0.420	0.0356	0.622	0.0350	12565
17	2	3	2	1.086	0.0431	1.090	0.0433	18847
18	2	3	3	1.904	0.0156	1.746	0.0152	25130
19	3	1	1	1.374	0.0222	0.764	0.0219	10867.5
20	3	1	2	1.356	0.0072	1.150	0.0059	16301.25
21	3	1	3	2.096	0.0061	2.904	0.0066	21735
22	3	2	1	0.732	0.0123	1.350	0.0132	14490
23	3	2	2	1.400	0.0875	1.602	0.0881	21735
24	3	2	3	2.124	0.0143	1.792	0.0148	28980
25	3	3	1	0.530	0.0721	0.636	0.0731	18102.5
26	3	3	2	0.966	0.0265	1.044	0.0269	27168.75
27	3	3	3	1.726	0.0058	1.768	0.0063	36225

They are spindle speed, tool feed rate and depth of cut. The combination of input process parameters for conducting the experiments were formulated using Taguchi's orthogonal array to eliminate the conventional full factorial design (Wu & Hamada, 2011) of experiments. The three factors and three levels of each of these parameters chosen are shown in Table 1 which is based on the capability of the machine and the cutting tool. In order to bring out the relationship between the input and response parameters, Taguchi's L_{27} orthogonal array was used due to its higher resolution factor when compared to other orthogonal arrays. Experiments were conducted with each of the coated carbide tool inserts. The L_{27} orthogonal array used for experimentation and the values of the output parameters obtained through experimentation is shown in Table 2.

3. Results and discussion

3.1. Surface Roughness (R_a)

The measured values of surface roughness (R_a) were analyzed using MINITAB15 software. Regression equations obtained for surface roughness for Hyperlox and HSN^2 tool inserts are given in Eqs. (2-3).

$$R_a(\text{Hyperlox}) = 3.15 + 0.86 \times v + 0.00301 \times d - 123.2 \times f + 7.00 \times v^2 + 473 \times f^2 - 0.00428 \times v \times d + 25.0 \times v \times f + 0.0433 \times d \times f - 0.00250 \times v^2 \times d - 20.7 \times v^2 \times f + 0.00820 \times v \times d \times f - 78 \times v \times f^2 - 0.1713 \times d \times f^2 \tag{2}$$

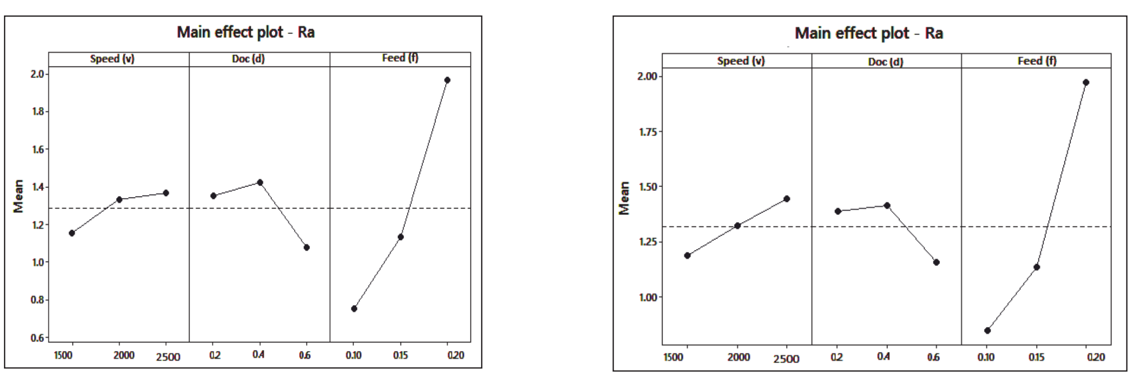
$$R_a(HSN^2) = - 13.44 - 2.5 \times v + 0.01790 \times d + 34.1 \times f - 3.20 \times v^2 + 356 \times f^2 + 0.00510 \times v \times d + 4.6 \times v \times f - 0.0948 \times d \times f + 0.00041 \times v^2 \times d + 15.1 \times v^2 \times f - 0.0147 \times v \times d \times f + 43 \times v \times f^2 - 0.1341 \times d \times f^2 \tag{3}$$

A low value of the predicted r-square shown in Table 3 indicates that the regression equation obtained can be used only for estimating the R_a value within the bounds of the input parameters. It cannot be used to predict the value of R_a outside the bounds of the machining parameters selected for experimentation.

Table 3
The model summary table for surface roughness (R_a)

Regression model	Tool coating used	r-square	r-square (predicted)
R_a	Hyperlox	98.08%	32.24%
	HSN^2	98.37%	18.62%

The main effects plot for surface roughness is shown in Fig. 2. It shows that surface roughness is predominantly influenced by feed (Asiltürk & Akkuş, 2011). The increase in feed value increases the surface roughness and vice versa (Das et al., 2015; Asiltürk & Akkuş, 2011; Aslan et al., 2007). The effect of input process parameters on surface roughness is found to be the same in both the tool inserts.



(a) (b)

Fig.2. Main effects plot for surface roughness of (a) Hyperlox tool insert and (b) HSN^2 tool insert

Analysis of variance (ANOVA) was performed with a confidence level of 95% to find the parameters influencing surface roughness and the result are shown in Table 4. Tool feed rate is the most influencing parameter as seen from the P-value (zero) for both the tool inserts in Table 4. Lower value of the tool feed rate reduces the number of peaks and valleys reducing surface roughness.

Table 4
ANOVA table showing the significance of input process parameters on surface roughness (R_a) in terms of P-value

Source	Degree of freedom	Sum of Squares	Mean square	F-Value	P-Value
Hyperlox tool insert					
v	2	0.2301	0.11505	3.10	0.067
f	2	6.9319	3.46593	93.32	0
d	2	0.5998	0.29991	1.08	0.603
Error	20	0.7428	0.03714		
Total	26	8.5045			
HSN^2 tool insert					
v	2	0.3545	0.17727	2.04	0.156
f	2	6.1203	3.06014	35.21	0
d	2	0.2952	0.14760	1.70	0.208
Error	20	1.7383	0.08692		
Total	26	8.5084			

3.2. Flank Wear Analysis

Analysis of variance for flank wear was performed for a confidence level of 95%. Regression equation obtained for flank wear of the Hyperlox tool insert is given in Eq. 4 and that of HSN^2 is given in Eq. (5).

$$V_B\ (\text{Hyperlox}) = -0.086 + 0.87 \times v - 0.87 \times f - 1.68 \times v^2 - 6.3 \times f^2 - 0.00041 \times v \times d + 5.18 \times v \times f + 0.00136 \times d \times f + 0.000814 \times v^2 \times f - 0.00267 \times v \times d \times f - 5.9 \times v \times f^2 + 0.0029 \times d \times f^2 \tag{4}$$

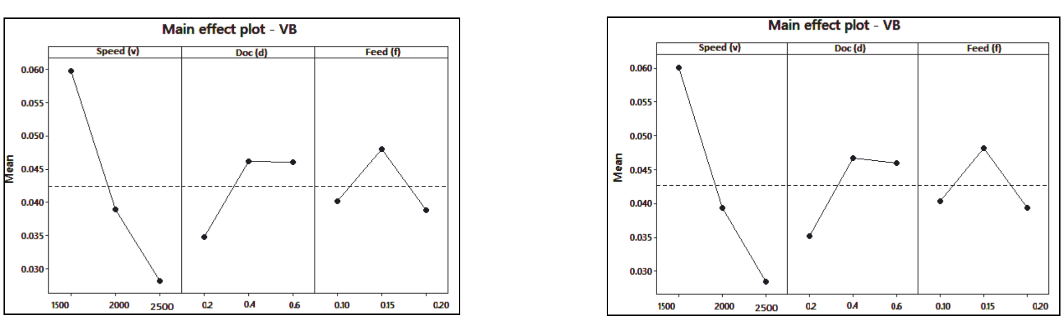
$$V_B\ (HSN^2) = -0.13 + 0.93 \times v + 0.000028 \times d - 0.59 \times f - 1.73 \times v^2 - 6.6 \times f^2 - 0.00042 \times v \times d + 4.81 \times v \times f + 0.00120 \times d \times f + 0.000834 \times v^2 \times d + 0.95 \times v^2 \times f - 0.00271 \times v \times d \times f - 4.9 \times v \times f^2 + 0.0029 \times d \times f^2 \tag{5}$$

The r-square value for flank wear is given in Table 5. The lower values of predicted r-square indicate that the regression equation obtained from the experiment cannot be used beyond the limits of bounds of the parameters used in this study.

Table 5
The model summary table for flank wear (V_B)

Regression model	Tool coating used	r-square	r-square (predicted)
V_B	Hyperlox	80.96%	20.88%
	HSN^2	79.73%	23.4%

Fig. 3a and Fig. 3b shows that the flank wear increases in inverse proportion with spindle speed (Aslan et al., 2007) for both the tools. This is because when the spindle speed is reduced, cutting force is also reduced favoring the formation of serrated chips. The serrated chips in turn increases the flank wear.



(a) (b)

Fig. 3. Main effects plot for flank wear (a) Hyperlox tool insert and (b) HSN^2 tool insert

Table 6
ANOVA table showing the significance of input process parameters on flank wear V_B

Source	Degrees of freedom	Sum of squares	Mean square	F-Value	P-Value
		Hyperlox tool insert			
v	2	0.004647	0.002323	3.45	0.045
f	2	0.000442	0.000221	0.30	0.745
d	2	0.000767	0.000383	0.52	0.603
Error	20	0.014775	0.000739		
Total	26	0.020630			
		HSN^2 tool insert			
v	2	0.000747	0.000374	3.25	0.040
f	2	0.000422	0.000211	0.28	0.760
d	2	0.004628	0.002314	0.49	0.618
Error	20	0.015178	0.000759		
Total	26	0.020975			

The results of analysis of variance (ANOVA) are shown in Table 6. The spindle speed (***v***) is the most influential input process parameter as evident from the P-value (0.045 and 0.04) given in Table 6 which is below 0.05.

3.3. Volumetric Material Removal Rate Analysis

As the volumetric material removal rate was calculated using the conventional formula given in Eq.1, it is high when all the parameters are at their highest value as shown in Fig. 4. Regression equation obtained for MRR when using Hyperlox and HSN^2 tool inserts for machining are given in Eq. (6).

$$\text{MRR (Hyperlox and HSN}^2\text{)} = -28860 + 28036 \times v + 7.42 \times d + 98964 \times f \tag{6}$$

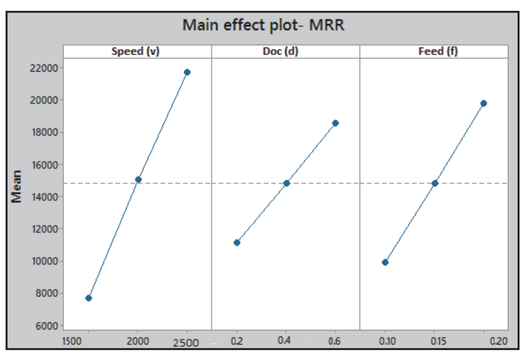


Fig. 4. Main effects plot for volumetric material removal rate when machining the work material with the Hyperlox and HSN^2 tool inserts.

Table 7
ANOVA table showing the significance of input process parameters on the volumetric material removal rate (MRR)

Source	Degree of freedom	Sum of Squares	Mean square	F-Value	P-Value
		Hyperlox tool insert			
v	2	884999388	442499694	71.61	0
f	2	247774133	123887067	20.05	0
d	2	440725685	220362843	35.66	0
Error	20	123588588	6179429		
Total	26	1697087795			
		HSN^2 tool insert			
v	2	884999388	442499694	71.61	0
f	2	247774133	123887067	20.05	0
d	2	440725685	220362843	35.66	0
Error	20	123588588	6179429		
Total	26	1697087795			

As the conventional formula is used to calculate the theoretical volumetric MRR, the r-square values obtained for the regression equation is equal to 100 percent for both the tool inserts and the regression equation for MRR remains the same for both the tool inserts. The results of analysis of variance (ANOVA) are shown in Table 7. Since the P-value of all the parameters are equal to zero, all the three parameters equally influence the MRR.

4. Multi-objective optimization using genetic algorithm

Genetic Algorithm (GA) is a directed search, global optimization algorithm that provides the initial solution with a set of initial population. The initial population is taken from the bounds of input parameters and the initial solution of R_a, V_B and MRR are found. With this initial solution, the algorithm will then iterate to find the second generation and it will continue the iteration till the stopping criterion is reached. The initial population may be a set of randomly generated numbers or may be a set of probable solutions in case where much knowledge is already gained about the process. In this work the initial population chosen is within the limits of bounds of parameters. This will reduce the computation time for the optimization problem (Pham et al., 2000)**.** Genetic algorithm optimizes the given problem using operators like selection, crossover, mutation and inversion. In this work multi-objective optimization with GA is done using the multi-objective optimization toolbox of MATLAB software.

The various functions used in the multi-objective optimization toolbox are shown in Table 8. A function is created to code the regression equation of surface roughness, tool wear and material removal rate and to combine them to form the multi-objective equation. A code is developed and this function is then saved as m-file and called in the multi-objective optimization tool box for the purpose of optimization.

Table 8
Functions used in Matlab multi-objective optimization tool box

Functions	Fed input	Definition
Fitness function	@ga_hyperlox	It is the name of the function created for the purpose of multi-objective optimization.
Number of variables	3	It is the total number of parameters under consideration for study or the number of variables in the function definition
Bounds	Lower Bound [1500 0.25 0.1] Upper Bound [2500 0.75 0.2]	These are the values of lower and upper most values of speed, depth of cut and feed respectively.

The initial population for each type of the coated tool was changed in every iteration. The stopping criteria obtained by changing the initial population is checked every time. The convergence plot and the stopping criteria of 100% is achieved for an initial population of 36 for Hyperlox and for an initial population of 32 for HSN^2 tool inserts.

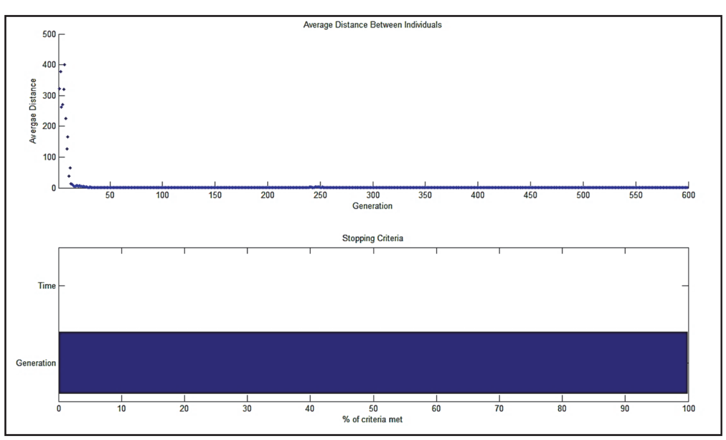


Fig.5. The convergence plot and the percentage of stopping criteria met

The convergence plot and the percentage of stopping criterion obtained are shown in Fig. 5. GA continue the iteration till the stopping criterion of 100% is reached. At the end of the iterations the algorithm generates a population of individuals that are optimal. These optimal output parameters differ by a small value because the average distance between the individuals is close to zero. The solution of an optimum combination of input parameters and the corresponding output parameters provided by GA for the two different tool inserts is shown in Table 9 and in Fig. 6. It shows that the Hyperlox tool insert has superior performance than HSN^2 tool insert. It is due to the higher hardness of AlTiN of the coating (Bouzakis et al., 2007), that imparts wear resistance. The solution provided by GA was validated through confirmation experiments which showed an average of 85% conformance with the results.

Table 9

Optimum combination of input parameters and output parameters obtained using genetic algorithm based multi-objective optimization approach

Type of tool coating	Input Parameters			Output parameters		
	Speed (rpm)	Feed (mm/rev)	Depth of cut (mm)	Surface roughness R_a(µm)	Tool wear V_B (mm)	MRR (mm^3/min)
Hyperlox	2456.63	0.11	0.75	1.894	0.15814	29432.86
HSN^2	2344.78	0.1011	0.75	2.673078	0.202382	29358

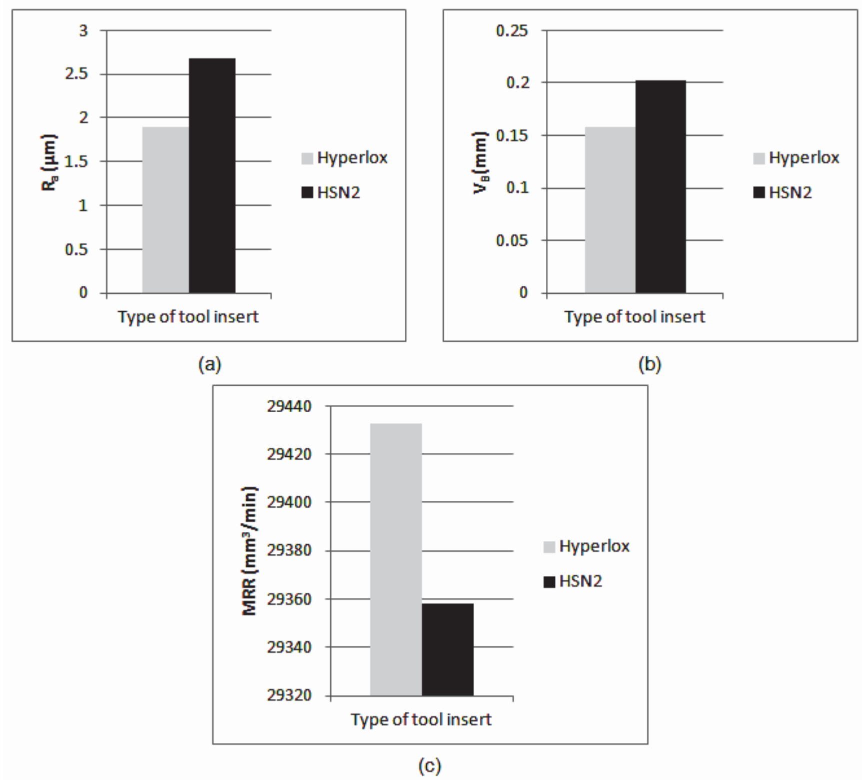


Fig. 6. Comparison of performance of Hyperlox and HSN^2 tool inserts on (a) Surface roughness (R_a) (b) Flank wear (V_B) and (c) Volumetric MRR

5. Conclusion

Thus, machining of Inconel 600 was successfully carried out and regression equations were obtained for surface roughness(R_a), volumetric MRR and tool wear (V_B). These equations were converted into a multi-objective equation and was solved using genetic algorithm based multi-objective optimization toolbox in MATLAB. An optimum combination of input parameters and the corresponding optimum solution for R_a, MRR and V_B were obtained. The performance of both the tools for machining Inconel 600 was compared and the following conclusions are drawn:

(1) Optimum combination of process parameters given by the GA tool box for Hyperlox tool insert is spindle speed 2456.63 rpm, tool feed rate 0.11 mm/rev and depth of cut 0.75 mm. The optimum combination of process parameters and for HSN^2 tool insert is spindle speed 2344.78 rpm, tool feed rate 0.1011mm/rev and depth of cut 0.75 mm. The solution given by GA after solving the multi-objective equation shows maximum spindle speed and depth of cut within their bounds as the MRR is to be maximized whereas the tool feed is minimum as the surface roughness R_a and tool wear V_B are to be minimized.

(2) P-value conveys the weight of evidence against a hypothesis. Higher the value of P, higher is the probability that the hypothesis is wrong. For 95% confidence level the P-value must not be more than 0.05 (Douglas C. Montgomery, 2003). The results show that the feed rate is statistically significant for surface roughness in both the tool inserts due to the lower value of P. All the input process parameters considered in this study are statistically significant for MRR due to lower values of P (zero). The input process parameters considered in this study are not statistically significant for tool wear due to high values of P. It is because other factors like tool nose radius, vibration and chatter in the machine tool are not considered as input parameters (Das et al., 2015).

(3) The results of optimization obtained shows that the Hyperlox tool insert is superior in performance than the HSN^2 tool insert. The Hyperlox tool insert is capable of yielding 29% lower value of surface roughness, 22% lower value of tool wear and 0.2% higher value of MRR than the HSN^2tool insert.

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