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# Assessment of machinability of inconel 718: A comparative study of CVD & PVD coated tools

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This paper highlights the parametric appraisal in turning of inconel 718 using fuzzy inference system coupled with imperialistic competitive algorithm (ICA) approach. The machining variables such as spindle speed, feed rate and depth of cut have been taken into consideration to analyse their effect on evaluation characteristics viz. material removal rate (MRR), flank wear and surface roughness. Fuzzy inference system (FIS) has been used to integrate aforementioned evaluation characteristics into a single response known as multi performance characteristic index (MPCI) to address the issue of impreciseness and uncertainties involved in decision making. Mathematical models have also been proposed for MPCI using non-linear regression analysis which acts as an objective function in ICA. ICA is new meta-heuristic based on social political theory which is used to obtain global optimal parametric combination in machining of Inconel 718. The results indicate that single layer (single coating: AlTiN) physical vapour deposition (PVD) coated tool is more efficient as compared to multi-layered (four coatings: TiN, TiCN, $Al_2O_3$ and TiN) chemical vapour deposition (CVD) coated tool.

**Keywords:** Flank wear, Fuzzy inference system, Imperialistic competitive algorithm, Material removal rate, Surface roughness

## 1 Introduction

Inconel 718 is an oxidation and corrosion-resistant material well suited for service in extreme environment subjected to high pressure, temperature and dynamic conditions. Inconel 718 is an extensively used material in gas turbine engines, steam turbines, nuclear power plants, chemical and petrochemical equipment and aerospace and missile applications due to its excellence properties like strength at elevated temperature, excellent corrosion resistance and workability. In fact, it is difficult to machine Inconel 718 due to rapid work hardening. Its low thermal conductivity obstructs transfer of heat produced during machining to the tool, subsequently increases tool tip temperature and causes excessive tool wear. Hence, it is essential for manufacturers to study the machinability aspects of Inconel 718. Devillez *et al.*[1] have studied the behaviour of coated carbide tools at high cutting speeds in dry machining during orthogonal cutting. Cutting and feed forces are measured and tool wear mechanisms analysed for various cutting conditions. The performance of coated tool is compared and classified in order to select the tool and optimal cutting conditions. Arunachalam *et al.*[2] have developed a set of guidelines which will assist the selection of the appropriate cutting tools and conditions for generating favourable compressive residual stresses. They have specially dealt with residual stresses and surface integrity when machining (facing) age hardened Inconel 718 using two grades of coated carbide cutting tools specifically developed for machining heat resistant super alloys (HRSA). The effect of insert shape, cutting edge preparation, type of insert and nose radius of insert on both residual stresses and surface finish is studied at optimum cutting condition. Umbrello[3] has investigated the effect of cutting speed and feed on the surface integrity during dry machining of Inconel 718 alloy using coated tools. In particular, the influence of the cutting conditions on surface roughness, affected layer, micro-hardness, grain size, and microstructural alteration has been investigated. Costes *et al.*[4] have investigated to find the wear mechanisms and optimal tool grade during finishing operations of Inconel 718. They have found good result in a low CBN content with a ceramic binder and small grains. They have also checked wear mechanisms on the rake and flank faces. Fan *et al.*[5] have studied the effect of tool material, tool shape and cutting parameters on the surface quality.

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Furthermore, they have also observed the tool wear and machined surface morphology, the effect of built-up edge (BUE), chip side flow and tool wear on surface quality in dry machining Inconel 718. Thakur *et al.*[6] have attempted to study and analyse the machining characteristics considering the relationship between cutting force, tool-chip contact length, cutting temperature and its relationship with thermal loading, chip microstructure and tool life during turning of Inconel 718 using tungsten carbide (K20) insert. Homami *et al.*[7] have studied to understand the complicated relationships between the cutting conditions and the process parameters in turning from both the modelling and optimization points of view. They carried out statistical analysis for identifying the significant factors of the cutting process, artificial neural networks (ANNs) for modelling the system and genetic algorithm (GA) for optimization of the cutting parameters. Pusavec *et al.*[8] have examined the surface integrity characteristics of machined surface for different combinations of cooling/lubrication during turning of Inconel 718. The residual stresses on the machined surface and sub-surface, surface hardness and surface roughness among the significant characteristics have been studied. Jafarian *et al.*[9] have proposed the optimal machining parameters including cutting speed, feed rate and depth of cut for improving surface integrity in terms of residual stress and surface roughness in finish turning of Inconel 718. The process was modelled by ANN and GA. Then, the genetically optimized neural network system (GONNS) technique is used to find optimal machining parameters for minimizing the tensile residual stress. Amini *et al.*[10] have investigated the effect of cutting speed, feed rate and depth of cut on surface roughness and tangential cutting force during high speed turning Inconel 718 by ceramic and carbide cutting tools. Zhou *et al.*[11] have studied on surface quality generated under high speed finish turning conditions of age-hardened Inconel 718. The study also focusses on surface roughness, metallographic analysis of surface layer and surface damages produced by machining with coated and uncoated cubic boron nitride (CBN) tools. Chinchanikar and Choudhury[12] have investigated the dry cutting performance to obtain the limiting cutting conditions of well-known PVD applied single-layer TiAlN and CVD applied multi-layer TiCN/$Al_2O_3$/TiN coated carbide inserts during high-speed machining of hardened AISI 4340 steel.

Kaveh and Talatahari[13] have proposed a novel population based optimization algorithm inspired by the imperialistic competition called as imperialist competitive algorithm (ICA) for optimization of skeletal structures. This algorithm also starts with an initial population like other evolutionary algorithms. Population individuals called countries are of two types i.e. colonies and imperialists and that all together form some empires. Teimouri *et al.*[14] have used the imperialistic competitive algorithm (ICA) for multi-responses optimization of ultrasonic machining (USM) process using neuro-fuzzy inference system (ANFIS) coupled with ICA. Lian *et al.*[15] have applied ICA in process planning. Yousefi *et al.*[16] have used imperialist competitive algorithm (ICA) for optimization of a cross-flow plate fin heat exchanger with main objectives of minimization of total weight and total annual cost. Further, numerical results of ICA are compared with genetic algorithm results. Enayatifar *et al.*[17] have developed a new evolutionary algorithm for multi-objectives based on imperialist competitive algorithm (ICA). Bashiri and Bagheri[18] have proposed a new multi-response imperialist competitive algorithm (MRICA) in machining applications and compared with multi-objective genetic algorithm (MOGA). Niknam *et al.*[19] have presented an efficient hybrid evolutionary optimization algorithm based on combined modified imperialist competitive algorithm (MICA) and K-means (K) known as K-MICA for clustering of data. K-MICA algorithm is tested on several data sets and its performance is compared with ant colony optimization (ACO), particle swarm optimization (PSO), simulated annealing (SA), genetic algorithm, tabu search (TS), honey bee mating optimization (HBMO). Sabour *et al.*[20] have proposed an imperialist competitive ant colony optimization (ICACO) for optimizing the truss structures. It is observed that ICACO is able to accelerate the convergence rate effectively compared to other algorithms. Talatahari *et al.*[21] have established superiority of a novel chaotic improved imperialist competitive algorithm (CICA) over other algorithms at least for the benchmark functions. Ahmadi *et al.*[22] have presented a new ICA-ANN model for oil rate prediction of wells. Duan and Huang[23] have applied ICA in optimal path planning of unmanned combat aerial vehicle (UCAV). Idoumghar *et al.*[24] have proposed a new hybrid imperialist competitive algorithm (ICA)-particle swarm optimization (PSO) algorithm to solve single objective and multi-objective problems.

Thirumalai and Senthilkumaar[25] have applied technique for order preference by similarity to ideal solution (TOPSIS) for selecting best parameter setting out of a large number of non-dominated solutions during high-speed machining of Inconel 718 using carbide cutting tool for reduce the uncertainty in choosing the best solution. Sardinas *et al.*[26] have presented a multi-objective optimization technique based on genetic algorithms to optimize the cutting parameters such as cutting depth, feed and speed for two conflicting objectives like tool life and operation time in turning process. Yang and Natarajan[27] have attempted to solve multi-objective optimization problem (minimization of tool wear and maximization of metal removal rate) subjected to the temperature and surface roughness constraints using multi-objective differential evolution (MODE) algorithm and non-dominated sorting genetic algorithm (NSGA-II) in turning of EN24 steel using tungsten carbide tool. Karpat and Ozel[28] have presented dynamic-neighbourhood particle swarm optimization (DN-PSO) methodology for multi-objective optimization in turning process. Ranganathan and Senthilvelan[29] have used grey relational analysis based on Taguchi technique for optimization of multiple response characteristics (surface roughness, tool life and metal removal rate) in hot turning of stainless steel (type 316) using tungsten carbide tool. Umer *et al.*[30] have used multi-objective genetic algorithm (MOGA-II) optimization for oblique turning operations while machining AISI H13 tool steel using polycrystalline cubic boron nitride cutting tool. Bharti *et al.*[31] have used non-dominated sorting genetic algorithm to optimize electric discharge machining (EDM) process using Inconel 718 as work piece and copper as tool electrode. Khamel *et al.*[32] have investigated the effect of process parameters (cutting speed, feed rate and depth of cut) on performance characteristics (tool life, surface roughness and cutting forces) in finish hard turning of AISI 52100 bearing steel with cubic boron nitride (CBN) tool using composite desirability function associated with the response surface methodology quadratic models.

Bose *et al.*[33] have applied fuzzy logic based Taguchi analysis to optimize the performance parameters such as brake specific energy consumption, volumetric efficiency and brake thermal efficiency in hydrogen injection system for diesel engine. Shabgard *et al.*[34] have applied a fuzzy-based algorithm for prediction of material removal rate (MRR), tool wear ratio (TWR), and surface roughness ($R_z$ and $R_k$) in electrical discharge machining (EDM) and ultrasonic-assisted EDM (US/EDM) processes. Krishnamoorthy *et al.*[35] have used grey fuzzy optimization method to optimize the drilling parameters for multiple output performance characteristics such as thrust force, torque, entry delamination, exit delamination and eccentricity of the holes during drilling of carbon fibre reinforced plastic (CFRP) composites. Analysis of variance (ANOVA) is used to find the most influential factor in drilling of CFRP composites. Majumder[36] has described the application of a hybrid approach using fuzzy logic and particle swarm optimization (PSO) for optimizing the process parameters such as pulse current, pulse-on-time and pulse-off-time for output responses like material removal rate and electrode wear ratio (EWR) during the electric discharge machining of AISI 316LN stainless steel. Abhishek *et al.*[37] have studied the effect of process parameters such as cutting speed, feed and depth of cut on MRR and surface roughness in turining of Nylon 6 using high speed steel cutting tool. Hanafi *et al.*[38] have applied fuzzy models to optimize process parameters (cutting speed, feed rate and depth of cut) for multiple performance measures (cutting force, cutting power and specific cutting pressure) during turning of reinforced poly ether ether ketone (PEEK) composite using titanium nitrite (TiN) coated cutting tools.

Turning of extremely hard and wear-resistant materials having hardness in the range of 45-70 HRC is a challenging task for the tool makers[39-41]. The materials considered as workpiece for hard machining include hardened alloy steels, case-hardened steels, nitrided iron parts, tool and die steels, super alloys, chrome-coated hard steels and various heat treated powder metallurgical parts[40,42]. The primary prerequisites for any cutting tool for machining of such difficult to cut materials are high hot hardness, chemical stability and high toughness[40]. The tool wear plays pivotal role in defining the tool life of a cutting tool as it influences various machinability characteristics such as machining forces, cutting temperature, chip morphology, production capacity and time during machining process[40,43]. Hard machining suffers from high tool wear due to generation of high temperature causing thermal deterioration of the tool properties[40, 44]. To address these issues, turning of hard material like Inconel 718 is performed using single layer (single coating:

AlTiN) PVD coated tool and multi-layered (four coatings: TiN, TiCN, $Al_2O_3$ and TiN) CVD coated tool at several spindle speeds, depth of cut and feed rate under dry cutting condition. The experimental study has been performed to understand the effect of process parameters such as spindle speed, depth of cut and feed rate on the performance measures such as material removal rate, flank wear and surface finish. The multiple performance measures are converted into a single equivalent performance measure known as multiple performance characteristic index (MPCI). Statically valid non-linear regression models relating MPCI with process parameters have been developed. Now-a-days, evolutionary techniques are used to determine the global optimal solution. Most commonly evolutionary techniques are genetic algorithm, simulated annealing etc. but these methods take more time to find out optimal solution. Here, ICA has been implemented for generating optimal solution as it requires less number of iterations. This paper basically highlights the parametric appraisal in machining of Inconel 718 using fuzzy inference system (FIS) with ICA methodology. The results show that single layer PVD coated tool is more efficient as compared to multi-layered CVD coated tool.

### 1.1 Fuzzy inference system

The main idea of the fuzzy set theory is quite intuitive and natural. Instead of determining the exact boundary as in an ordinary set, a fuzzy set allows no sharply defined boundaries because of the generalization of a characteristic function to a membership function. This technique, being part of decisional systems based on knowledge (Knowledge Based Processing), is widely applied in the field of manufacturing systems[33-38]. Fuzzy inference is the process of formulating the mapping from a given input to an output using fuzzy logic. The mapping then provides a basis from which decisions can be made. The process of fuzzy inference involves fuzzification of crisp input by defining membership function, fuzzy logic operators and if-then rules. Block diagram of a typical fuzzy logic system is presented in Fig. 1. As outlined in Fig. 1, a fuzzy rule based system consists of four parts: fuzzifier, knowledge base, inference engine and defuzzifier. These four parts are described below:

- Fuzzifier: The real world input to the fuzzy system is applied to the fuzzzifier. In fuzzy literature, this input is called crisp input since it contains precise information about the specific information about the parameter. The fuzzifier converts this precise quantity to the form of imprecise quantity like 'low', 'medium', 'high' etc. with a degree of belongingness to it. Typically, the value of degree of belongingness ranges from 0 to 1.
- Knowledge base: The main part of the fuzzy system is the knowledge base in which both rule base and database are jointly referred. The database defines the membership functions of the fuzzy sets used in the fuzzy rules whereas the rule base contains a number of fuzzy if-then rules.
- Inference engine: The inference system or the decision-making unit performs the inference operations on the rules. It handles the way in which the rules are combined.
- Defuzzifier: The output generated by the inference block is always fuzzy in nature. A real world system will always require the output of the fuzzy system to the crisp or in the form of real world input. The job of the defuzzifier is to receive the fuzzy input and provide real world output. In operation, it works opposite to the input block.

In general, two most popular fuzzy inference systems are available: Mamdani fuzzy model and Sugeno fuzzy model. The selection depends on the fuzzy reasoning and formulation of fuzzy IF-THEN rules. Mamdani fuzzy model is based on the collections of IF-THEN rules with both fuzzy antecedent and consequent predicts. The benefit of

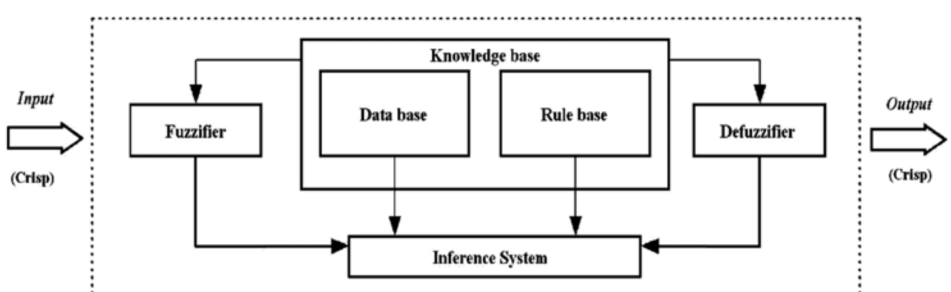


Fig. 1 — Fuzzy inference system.

this model is that the rule base is generally provided by an expert and hence to a certain degree, it is translucent to explanation and study. Because of its easeness, Mamdani model is most commonly used technique for solving many real world problems.

A fuzzy set $\tilde{A}$ is represented by trapezoidal fuzzy number which is defined by the quadruplet (a, b, c, d). Membership function $\mu_A(x)$ is defined as:

$$\mu_A(x) \begin{rcases} = 0, & x < a, \\ = \dfrac{(x-a)}{(b-a)}, & a \le x \le b \\ = 1, & b \le x \le c \\ = \dfrac{(d-x)}{(d-c)}, & c \le x \le d \\ = 1, & x > d \end{rcases} \quad \dots (2)$$

If b=c, the function is called triangular membership function. The triangular fuzzy number is used because of mathematical convenience.

The Mamdani implication method is employed for the rules definition.

For a rule $R_i$ : If $x_1$ is $A_{1i}$ and $x_2$ is $A_{2i}$……$x_s$ is $A_{si}$ then $y_i$ is $C_i$, i = 1,2,….,M

where M is total number of fuzzy rule, $x_j$ (j=1,2,…,s) are input variables, $y_i$ are the output variables, and $A_{ji}$ and $C_i$ are fuzzy sets modeled by membership functions $\mu_{A_{ji}}(x_j)$ and $\mu_{C_i}(y_i)$ respectively. The aggregated output for the M rules is:

$$\mu_{C_i}(y_i) = \max[\min\{\mu_{A_{1i}}(x_1), \mu_{A_{1i}}(x_2), \dots\dots, \mu_{A_{1i}}(x_S)\}], \quad i = 1, 2, \dots\dots\dots, M \quad \dots (2)$$

Using a defuzzification method, fuzzy values can be combined into one single crisp output value. The center of gravity, one of the most popular methods for defuzzifying fuzzy output functions, is employed. The formula to find the centroid of the combined outputs $\hat{y}_i$ is given by:

$$\hat{y}_i = \frac{\int y_i\, \mu_{C_i}(y_i)\, dy}{\int \mu_{C_i}(y_i)\, dy} \quad \dots (3)$$

**1.2 Imperialistic competitive algorithm**

The recently introduced ICA uses the socio-political process of imperialism and imperialistic competition as a source of inspiration[13]. ICA is meta-heuristic algorithm that initiates with a random number of populations namely countries, some of which are selected to be the imperialists and the remaining countries are colonized by these imperialists who collectively form an empire[18-24]. The representatives of this algorithm are called 'countries'. There are two types of countries; some of the best countries are selected to be the 'imperialist' states and the remaining countries form the 'colonies' of these imperialists. All the colonies of initial countries are divided among the imperialists based on their 'power'. The power of each country is inversely proportional to its cost. The imperialist states together with their colonies form some 'empires'. After initial formation of empires, the colonies in each empire start moving toward their relevant imperialist country. This movement is a simple model of assimilation policy which was followed by some of the imperialist states. The total power of an empire depends on both the power of the imperialist country and the power of its colonies. This fact is modelled by defining the total power of an empire as the power of the imperialist country plus a percentage of mean power of its colonies.

Then, the imperialistic competition begins among all the empires. Any empire that is unable to succeed in this competition or cannot increase its power (or at least prevent losing its power) will be eliminated from the competition. The imperialistic competition will gradually result in an increase in the power of the powerful empires and a decrease in the power of weaker ones. Weak empires will lose their power and ultimately they will collapse. The movement of colonies toward their relevant imperialist states along with competition among empires and also the collapse mechanism will cause all the countries to converge to a state in which there exists just one empire in the world and all the other countries are colonies of that empire. In this ideal new world, colonies will have the same position and power as the imperialist.

Each country is formed of an array of variable values and the related cost of a country is found by assessment of the cost function $f_{cost}$ of the corresponding variables considering the related objective function. Total number of initial countries is set to $N_{country}$ and the number of the most powerful countries to form the empires is taken as $N_{imp}$. The remaining $N_{col}$ of the initial countries will be the colonies each of which belongs to an empire. To form the initial empires, the colonies are divided among imperialists based on their power. To fulfil this aim, the normalized cost of an imperialist is defined as follows:

$$C_n = f_{cost}^{(imp,n)} - \max_i \{f_{cost}^{(imp,i)}\} \quad \text{... (4)}$$

where $f_{cost}^{(imp,n)}$ cost is the cost of the $n^{th}$ imperialist and $C_n$ is its normalized cost. The initial colonies are divided among empires based on their power or normalized cost and for the $n^{th}$ empire it will be as follows:

$$N.C_n = \text{Round}\left|\frac{C_n}{\sum_{i=1}^{N_{imp}} C_i}\right|.N_{col} \quad \text{... (5)}$$

where $N.C_n$ is the initial number of the colonies associated to the $n^{th}$ empire which are selected randomly among the colonies. These colonies along with the $n^{th}$ imperialist form the $n^{th}$ empire.

In the ICA, the assimilation policy is modelled by moving all the colonies toward the imperialist. This movement is shown in Fig. 2 in which a colony moves toward the imperialist by a random value that is uniformly distributed between 0 and $\beta \times d$.

$$\{x\}_{new} = \{x\}_{old} + U(0, \beta \times d) \times \{V_1\} \quad \text{... (6)}$$

where $\beta$ is a assimilation coefficient (taken as 2) and d is the distance between colony and imperialist. $\{V_1\}$ is a vector which its start point is the previous location of the colony and its direction is toward the imperialist locations. The length of this vector is set to unity.

In ICA, to increase the searching around the imperialist, a random amount of deviation is added to the direction of movement. Fig. 2 presents the new direction which is obtained by deviating the previous location of the country as great as $\theta$ which is a random number with uniform distribution. If the new position of a colony is better than that of the corresponding imperialist (considering the cost function), the imperialist and the colony change their positions and the new location with the lower cost becomes the imperialist.

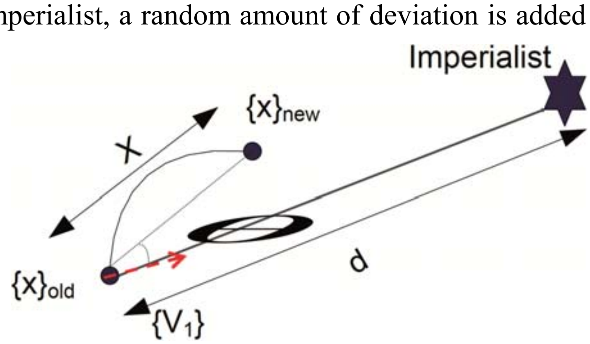

Fig. 2 — Movement of colonies to its new location.

Imperialistic competition is another strategy utilized in the ICA methodology. All empires try to take the possession of colonies of other empires and control them. The imperialistic competition gradually reduces the power of weaker empires and increases the power of more powerful ones. The imperialistic competition is modelled by just picking some of the weakest colonies of the weakest empires and making a competition among all empires to possess these colonies. Based on their total power, in this competition, each of empires will have a possibility of taking possession of the mentioned colonies.

Total power of an empire is affected by the power of imperialist country and the colonies of an empire as

$$TC_n = f_{cost}^{(imp,n)} + \xi.\frac{\sum_{i=1}^{N.C_n} f_{cost}^{(col,i)}}{NC_n} \quad \text{... (7)}$$

where $TC_n$ is the total cost of the $n^{th}$ empire and $\xi$ is a positive number (taken as 0.1).

Similar to equation 7, the normalized total cost is defined as:

$$NTC_n = TC_n - \max_i\{TC_i\} \quad \text{... (8)}$$

where $NTC_n$ is the normalized total cost of the $n^{th}$ empire. Having the normalized total cost, the possession probability of each empire is evaluated by

$$p_n = \left|\frac{NTC_n}{\sum_{i=1}^{N_{imp}} NTC_i}\right| \quad \text{... (9)}$$

When an empire loses all its colonies, it is assumed to be collapsed. In this model implementation where the powerless empires collapse in the imperialistic competition, the corresponding colonies will be divided among the other empires. Moving colonies toward imperialists are continued and imperialistic competition and implementations are performed during the search process. When the number of iterations reaches a pre-defined value, the search process is stopped. The proposed methodology includes conducting the experiments using design of experiment (DOE) approach, developing a fuzzy inference system for converting multiple machining parameters into MPCI, developing mathematical models and searching best parametric condition using ICA algorithm for maximization of MPCI. All the steps involved in the methodology is described with the help of a flow chart illustrated in Fig. 3.

## 2 Experimental Details

A series of experiments has been carried out in CNC lathe (Model No. Sprint 16 TC manufactured by: Batliboi Ltd. Surat, India) to assess the behaviour of machining parameters (spindle speed, feed rate and depth of cut) on the material removal rate and flank wear. The details of lathe specifications are shown in Table 1. A bar of Inconel 718 having diameter 30 mm, length 150 mm and tensile strength of 1100 MPa has been used as work piece material possessing composition in mass percentage of 50-55 Ni, 17-21 Cr, 2.8-3.3 Mo, 4.75-5.5 Nb, 0.35 Mn, 0.2-0.8 Cu, 0.65-1.15 Al, 1 Co, 0.3 Ti, 0.35 Si, 0.08 C, 0.015 S, 0.015 P, 0.006 B, and balance Fe. Here, first chemical vapour deposition (CVD) coated tool of CNMG 431_KC9225 manufactured by Kennametal (four coatings: TiN, TiCN, $Al_2O_3$, TiN) having tool signature (10-10-7-7-5-5-0.4) and second PVD coated CNMG 431_KC5010 manufactured by Kennametal

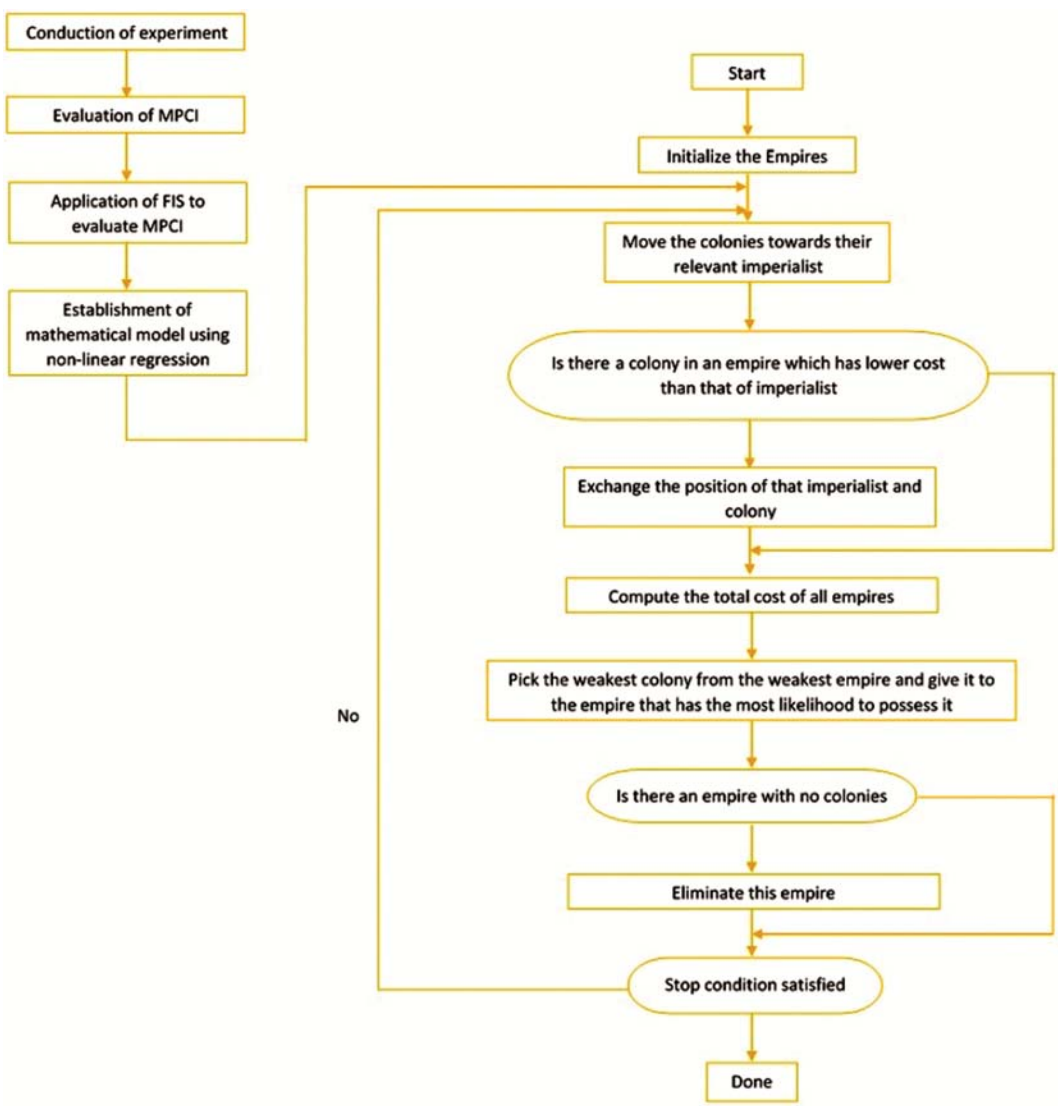


Fig. 3 — Flow chart of proposed methodology using ICA.

Table 1 — Details of CNC turning lathe.

| Details | Unit | Description |
|---|---|---|
| Swing over bed | mm | 400 |
| Turning diameter | mm | 225 |
| Turning length | mm | 300 |
| Spindle speed | RPM | 50-5000 |
| Spindle motor | KW | 5.5/7.5 |
| Z axis stroke | mm | 325 |
| X axis stroke | mm | 125 |
| Maximum no. tools in turret | NOs. | 8 |
| Rapid transverse | m/min. | 20 |

Table 2 — Process parameters and their levels (both CVD and PVD coated tool).

| Sl. No. | Factors | Symbols | Unit | Level 1 | Level 2 | Level 3 | Level 4 |
|---|---|---|---|---|---|---|---|
| 1 | Spindle speed | N | RPM | 400 | 600 | 800 | 1000 |
| 2 | Depth of cut | d | mm | 0.4 | 0.6 | 0.8 | 1 |
| 3 | Feed rate | f | mm/rev | 0.08 | 0.12 | 0.16 | 0.20 |

Table 3 — Experimental data (with CVD coated tool).

| Sl. No. | Process parameters | | | Experimental results | | |
|---|---|---|---|---|---|---|
| | N | d | f | MRR ($mm^3$/sec) | Flank wear (µm) | Surface roughness (µm) |
| 1 | 400 | 0.4 | 0.08 | 22.31 | 206.12 | 1.23 |
| 2 | 400 | 0.6 | 0.12 | 28.71 | 222.34 | 1.34 |
| 3 | 400 | 0.8 | 0.16 | 32.32 | 246.43 | 1.37 |
| 4 | 400 | 1 | 0.2 | 37.33 | 291.21 | 1.42 |
| 5 | 600 | 0.4 | 0.12 | 27.89 | 229.46 | 1.67 |
| 6 | 600 | 0.6 | 0.08 | 34.63 | 245.62 | 1.58 |
| 7 | 600 | 0.8 | 0.2 | 38.89 | 270.25 | 1.73 |
| 8 | 600 | 1 | 0.16 | 49.56 | 309.54 | 1.87 |
| 9 | 800 | 0.4 | 0.16 | 38.86 | 238.68 | 1.66 |
| 10 | 800 | 0.6 | 0.2 | 45.62 | 254.61 | 1.56 |
| 11 | 800 | 0.8 | 0.08 | 54.83 | 280.23 | 1.732 |
| 12 | 800 | 1 | 0.12 | 67.75 | 315.92 | 1.92 |
| 13 | 1000 | 0.4 | 0.2 | 41.82 | 290.85 | 1.87 |
| 14 | 1000 | 0.6 | 0.16 | 53.67 | 323.49 | 1.96 |
| 15 | 1000 | 0.8 | 0.12 | 63.41 | 345.63 | 2.07 |
| 16 | 1000 | 1 | 0.08 | 76.56 | 370.76 | 2.19 |

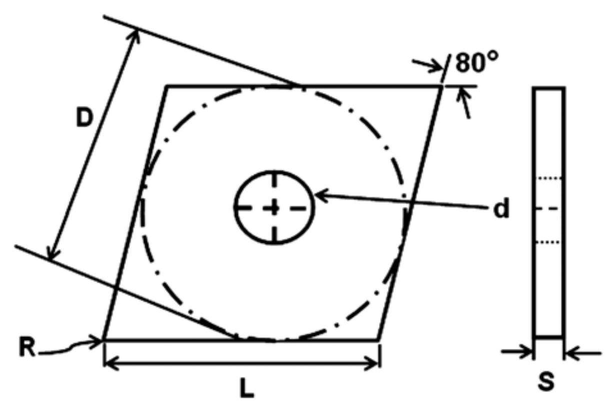


Fig. 4 — Tool dimensions.

(single coating: AlTiN) having tool signature (6-6-0-0-5-5-0.4) are used as tool materials. Base material of both coated tool is tungsten carbide (WC). PCLNL2525M12 tool holder is used for both tool insert.

Fig. 4 shows the dimensions of both tool CNMG 431: D = 12.70 mm, S = 4.76 mm, R = 0.4 mm, L = 12.90 mm, d = 5.16 mm. where, D = Theoretical diameter of the insert inscribed circle, S = Thickness of the tool insert, R = Nose radius of tool insert, L = Cutting edge length, d = Inner hole diameter.

Table 2 presents different levels of process parameters such as spindle speed, feed rate and depth of cut for turning of Inconel 718. A schematic layout for experimentation is highly required for reduction of experimental time and cost. Therefore, Taguchi method is used to design the experimental layout to examine the effect of the machining parameters with less number of experimental runs. In the present study, three process parameters have been varied into four different levels. So, the possible combination of experiments is $4^3$ (64). Hence, Taguchi method is adopted to reduce the number of experiments by utilizing the orthogonal array concept. Therefore, $L_{16}$ orthogonal array has been chosen for experimentation shown in Table 3. During experimentation, work piece is cut for a length of 60 mm in each run.

Flank wear is caused due to relative motion between the cutting tool and the work piece or the cutting tool and chip on machining area during turning. Flank wear is measured experimentally by optical microscope (SteREO Discovery V20 manufactured by Carl Zeiss MicroImaging Inc. having eyepiece magnification: 10X and objective magnification: 2.5X to 100X) as shown in Fig. 5 (a), Fig. 5 (b) Fig. 5 (c) and Fig. 5 (d). Maximum damage length of flank face has been considered for assessing the flank wear of tool insert. Experimental data of material removal rate, flank wear and surface roughness for CVD and PVD coated tool are listed in Table 3 and Table 4 respectively.

As material removal rate (MRR) and flank wear have dominant effect on economics of the machining operations, estimation of these machining characteristics is important and necessary in metal cutting for maintaining both productivity and quality.

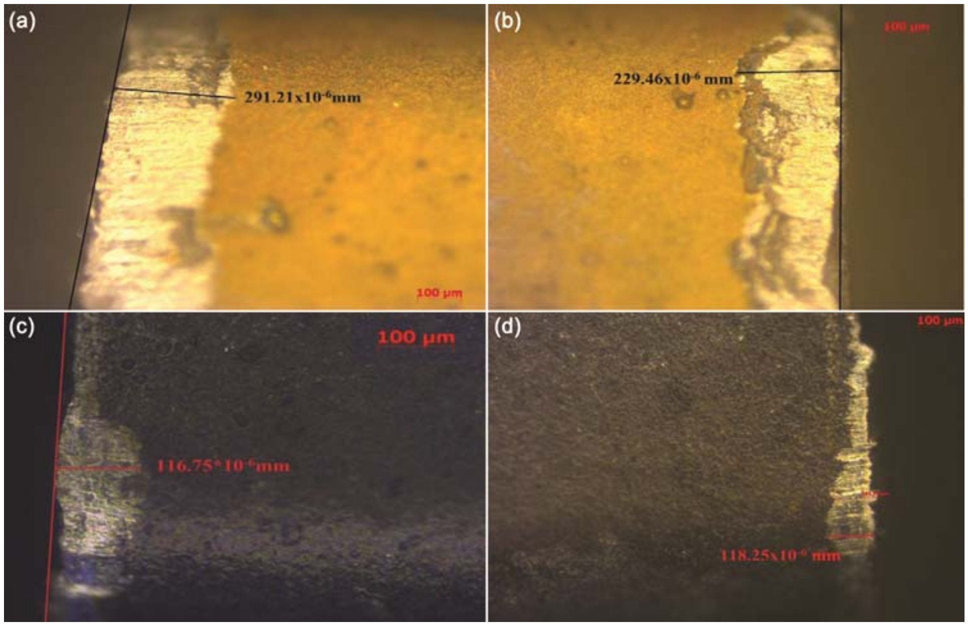


Fig. 5 — Flank wear for CVD coated tool for (a) Spindle speed 400 RPM, depth of cut 1 mm & feed rate 0.2 mm/rev, (b) Spindle speed 600 RPM, depth of cut 0.4 mm & feed rate 0.12 mm/rev, (c) Flank wear for PVD coated tool for spindle speed 400 RPM, depth of cut 0.8 mm & feed rate 0.16 mm/rev and (d) Flank wear for PVD coated tool for spindle speed 800 RPM, depth of cut 0.8 mm & feed rate 0.08 mm/rev.

Table 4 — Experimental data (with PVD coated tool).

| Sl. No. | Process parameters | | | Experimental results | | |
|---|---|---|---|---|---|---|
| | N | d | f | MRR ($mm^3$/sec) | Flank wear (μm) | Surface Roughness (μm) |
| 1 | 400 | 0.4 | 0.08 | 17.65 | 101.130 | 1.597 |
| 2 | 400 | 0.6 | 0.12 | 22.65 | 105.745 | 1.256 |
| 3 | 400 | 0.8 | 0.16 | 47.03 | 116.750 | 1.519 |
| 4 | 400 | 1 | 0.2 | 47.64 | 98.3350 | 1.815 |
| 5 | 600 | 0.4 | 0.12 | 18.34 | 96.2200 | 1.022 |
| 6 | 600 | 0.6 | 0.08 | 16.67 | 108.470 | 1.758 |
| 7 | 600 | 0.8 | 0.2 | 58.82 | 102.285 | 1.542 |
| 8 | 600 | 1 | 0.16 | 48.02 | 101.975 | 1.554 |
| 9 | 800 | 0.4 | 0.16 | 30.96 | 99.7430 | 1.227 |
| 10 | 800 | 0.6 | 0.2 | 37.95 | 96.9850 | 1.874 |
| 11 | 800 | 0.8 | 0.08 | 33.14 | 118.250 | 1.635 |
| 12 | 800 | 1 | 0.12 | 35.29 | 101.860 | 1.224 |
| 13 | 1000 | 0.4 | 0.2 | 45.25 | 99.420 | 1.315 |
| 14 | 1000 | 0.6 | 0.16 | 42.74 | 115.570 | 1.385 |
| 15 | 1000 | 0.8 | 0.12 | 41.47 | 116.360 | 1.078 |
| 16 | 1000 | 1 | 0.08 | 36.11 | 106.840 | 1.469 |

Material removal rate is defined as volume of work piece material that can be removed per time unit.

$$MRR = \frac{(V_i - V_f)}{t_m} \quad \ldots (10)$$

where, $V_i$ = initial volume of work-piece, $V_f$ = final volume of work-piece and $t_m$ = machining time. Surface roughness is another important index which is caused to action of cutting tool on work-piece. Surface roughness tester SJ-210 (Make: Mitutoyo) having a stylus which skids over machined surface to measure the roughness.

## 3 Results and Discussion

### 3.1 CVD coated tool

Experimental data are collected as per experimental plan of Taguchi's $L_{16}$ orthogonal array. Lower-the-better (LB) criterion is used for flank wear and surface roughness whereas higher-the-better (HB) criterion is used for MRR. Analysis of variance (ANOVA) is a method of partitioning observed variance into components of different explanatory variables to identify significance of each parameter. Table 5, Table 6 and Table 7 present the ANOVA table for material removal rate, flank wear and surface roughness respectively. It is to be noted that spindle speed and depth of cut are significant factors influencing on flank wear at significance level 0.05. Similarly, the factors like spindle speed, depth of cut and feed rate are significant factors influencing on MRR at significance level 0.05. For surface roughness, spindle speed, depth of cut and feed rate are significant factors at the significant level 0.05. The optimal parametric setting can be obtained from the factorial plots. Fig. 6 (a) indicates that spindle speed, depth of cut and feed rate should be maintained at 1000 RPM, 1 mm and 0.08 mm/rev respectively to maximize MRR. Similarly, Fig. 6 (b) reveals that spindle speed, depth of cut and feed rate should be maintained at 400 RPM, 0.4 mm and 0.08 mm/rev respectively to minimize the flank wear and Fig. 6 (c) indicates that spindle speed, depth of cut and feed rate should be maintained at 400 RPM, 0.4 mm and 0.20 mm/rev respectively to minimize surface roughness.

### 3.2 PVD coated tool

Experimental data are collected as per experimental plan of Taguchi's $L_{16}$ orthogonal array. Lower-the-better (LB) criterion is used for flank wear and surface roughness whereas higher-the-better (HB) criterion is used for MRR. Table 8, Table 9 and Table 10 present the ANOVA table for MRR, flank wear and surface roughness respectively. It is to be noted that spindle speed, depth of cut and feed rate are significant factors influencing on MRR at significance level 0.05. For flank wear and surface roughness, all the factors (spindle speed, depth of cut and feed rate) are significant. The optimal parametric setting can be obtained from the factorial plots. Fig. 7 (a) reveals that spindle speed, depth of cut and feed rate should be maintained at 1000 RPM, 0.8 mm and 0.20 mm/rev respectively to maximize MRR. Similarly, Fig. 7 (b) indicates that spindle speed, depth of cut and feed rate should be maintained at 600 RPM, 0.4 mm and 0.20 mm/rev respectively to minimize flank wear and Fig. 7 (c) indicates that spindle speed, depth of cut and feed rate should be maintained at 1000 RPM, 0.4 mm and 0.12 mm/rev respectively to minimize surface roughness.

Micrographs of the tool after turning with CVD and PVD coated tool are observed in scanning electron microscope (JEOL JSM 6480LV). The micrographs are shown for process parameters setting

Table 5 — ANOVA for material removal rate (R-square 99.2%).

| Source | Degree of freedom | Sum of squares | Adjusted S S | Adjusted M S | F- Value | P-Value |
|---|---|---|---|---|---|---|
| N | 3 | 2040.58 | 2040.58 | 680.193 | 140.61 | 0.000 |
| d | 3 | 1354.18 | 1354.18 | 451.392 | 93.31 | 0.000 |
| f | 3 | 104.83 | 104.83 | 34.944 | 7.22 | 0.020 |
| Residual Error | 6 | 29.03 | 29.03 | 4.838 | | |
| Total | 15 | 3528.61 | | | | |

Table 6 — ANOVA for flank wear (R-square 99.5%).

| Source | Degree of freedom | Sum of squares | Adjusted S S | Adjusted M S | F- Value | P-Value |
|---|---|---|---|---|---|---|
| N | 3 | 18222.7 | 18222.7 | 6074.22 | 204.40 | 0.000 |
| d | 3 | 14405.3 | 14405.3 | 4801.78 | 161.58 | 0.000 |
| f | 3 | 34.9 | 34.9 | 11.62 | 0.39 | 0.764 |
| Residual Error | 6 | 178.3 | 178.3 | 29.72 | | |
| Total | 15 | 32841.2 | | | | |

Table 7 — ANOVA for surface roughness (R-square 99.3%).

| Source | Degree of freedom | Sum of squares | Adjusted S S | Adjusted M S | F- Value | P-Value |
|---|---|---|---|---|---|---|
| N | 3 | 0.93630 | 0.93630 | 0.312099 | 253.26 | 0.000 |
| d | 3 | 0.15918 | 0.15918 | 0.053059 | 43.06 | 0.000 |
| f | 3 | 0.02411 | 0.02411 | 0.008036 | 6.52 | 0.026 |
| Residual Error | 6 | 0.00739 | 0.00739 | 0.001232 | | |
| Total | 15 | 1.12698 | | | | |

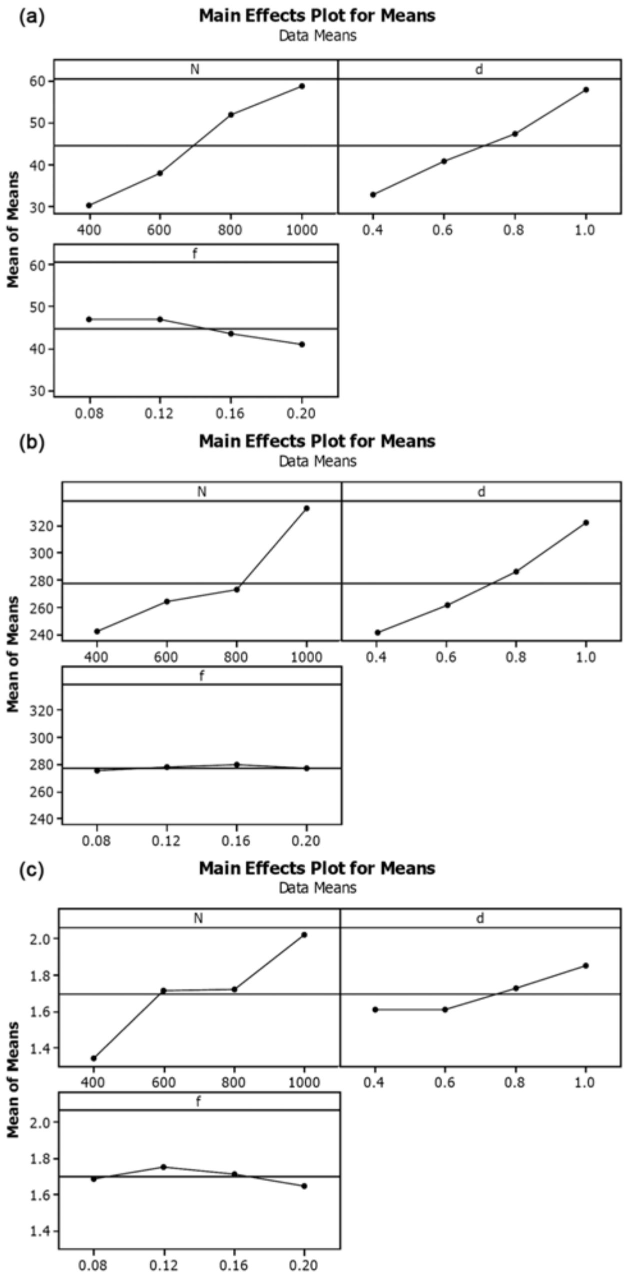


Fig. 6 — Main effect plot for (a) MRR, (b) flank wear and (c) surface roughness.

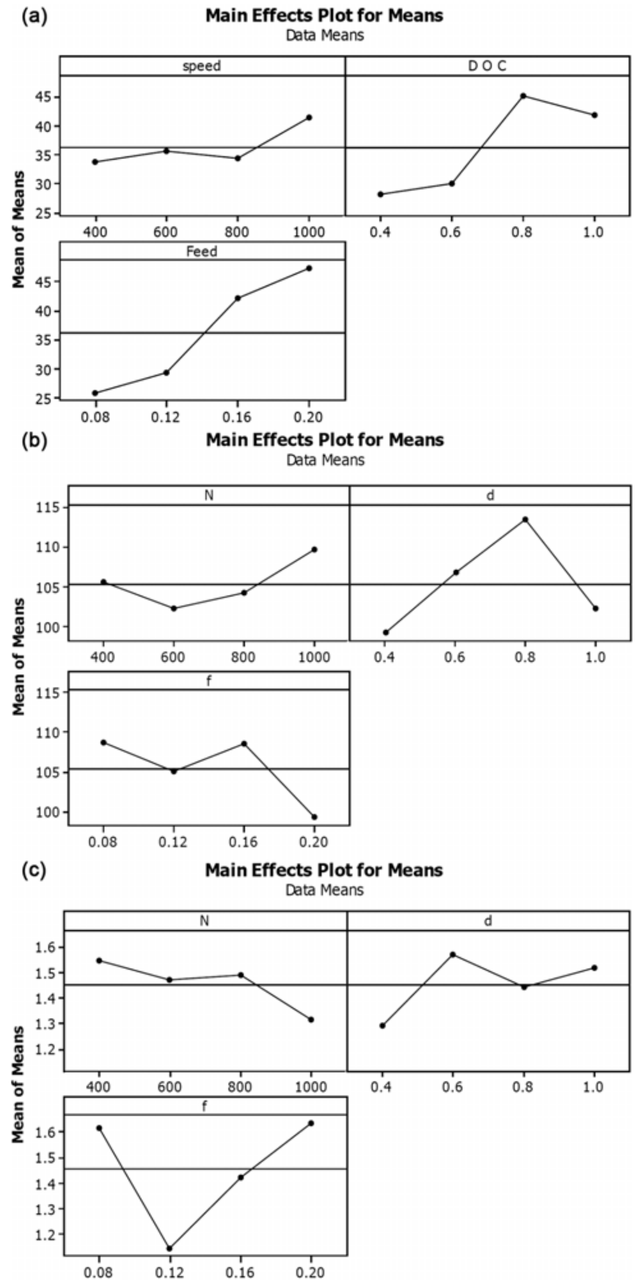


Fig. 7 — (a) Mean effect Plot for (a) MRR, (b) flank wear and (c) surface roughness.

of spindle speed of 600 RPM, depth of cut of 1mm and feed rate of 0.16 mm/rev for CVD coated tool and spindle speed of 400 RPM, depth of cut of 0.4 mm and feed rate of 0.08 mm/rev for PVD coated tool in Fig. 8 (a) and Fig. 8 (b), respectively. Flank wear is the main wear in the turning operation. The high flank wear is observed when spindle speed = 1000 RPM, depth of cut = 1 mm and feed rate = 0.08 mm in turning with CVD coated tool but in case of PVD coated tool high flank wear is observed when spindle speed = 800 RPM, depth of cut = 0.8 mm and feed rate = 0.08 mm.

### 3.3 Optimization with fuzzy inference system coupled with ICA

The methodology used for the optimization is fuzzy inference system coupled with imperialistic competitive algorithm (ICA). Fuzzy inference system has been utilized to convert multiple performance characteristics (MRR, flank wear and surface roughness) into single objective characteristics i.e.

Table 8 — Analysis of variance for means MRR (R-square 97.5%).

| Source | Degree of freedom | Sum of squares | Adjusted SS | Adjusted MS | F- Value | P-Value |
|---|---|---|---|---|---|---|
| N | 3 | 148.08 | 148.08 | 49.359 | 5.17 | 0.042 |
| d | 3 | 861.09 | 861.09 | 287.031 | 30.09 | 0.001 |
| f | 3 | 1254.39 | 1254.39 | 418.131 | 43.84 | 0.000 |
| Residual Error | 6 | 57.23 | 57.23 | 9.539 | | |
| Total | 15 | 2320.79 | | | | |

Table 9 — Analysis of variance for means flank wear (R-square 94.6%).

| Source | Degree of freedom | Sum of squares | Adjusted SS | Adjusted MS | F- Value | P-Value |
|---|---|---|---|---|---|---|
| N | 3 | 114.50 | 114.50 | 38.167 | 4.95 | 0.046 |
| d | 3 | 460.36 | 460.36 | 153.452 | 19.92 | 0.002 |
| f | 3 | 232.98 | 232.98 | 77.661 | 10.08 | 0.009 |
| Residual Error | 6 | 46.22 | 46.22 | 7.703 | | |
| Total | 15 | 854.06 | | | | |

Table 10 — Analysis of variance for means surface roughness (R-square 94.7%).

| Source | Degree of freedom | Sum of squares | Adjusted SS | AdjustedMS | F- Value | P-Value |
|---|---|---|---|---|---|---|
| N | 3 | 0.12143 | 0.12143 | 0.040477 | 4.76 | 0.040 |
| d | 3 | 0.17504 | 0.17504 | 0.058345 | 6.87 | 0.023 |
| f | 3 | 0.62280 | 0.62280 | 0.207600 | 24.43 | 0.001 |
| Residual Error | 6 | 0.05099 | 0.05099 | 0.008498 | | |
| Total | 15 | 0.97025 | | | | |

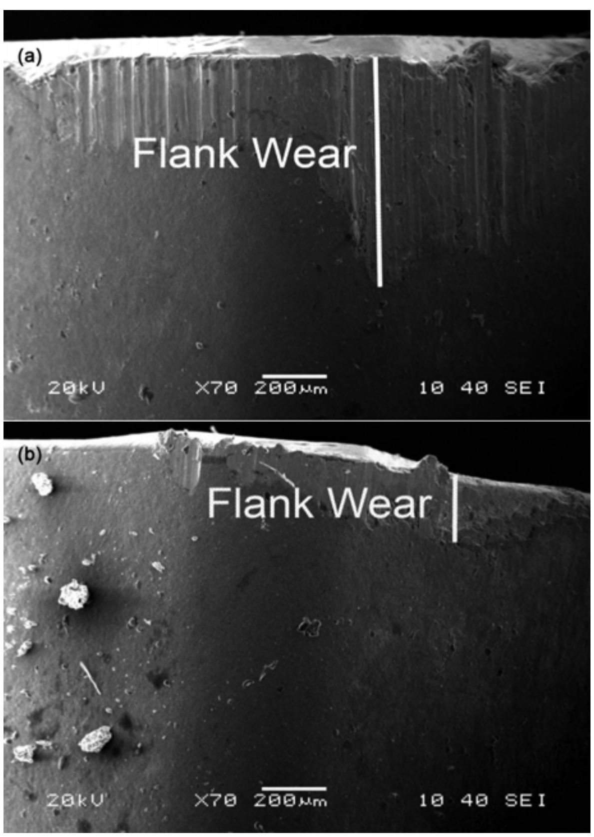


Fig. 8 — (a) Flank wear of CVD coated WC insert spindle speed of 600 RPM, depth of cut of 1 mm and feed rate of 0.16 mm and (b) Flank wear of PVD coated WC insert at spindle speed of 400 RPM, depth of cut of 0.4 mm and feed rate of 0.08 mm.

Multi Performance Characteristic Index (MPCI). Then, non-linear mathematical model has been developed as function of process parameters. Finally, this model has been fed as objective function for ICA to generate the optimal machining condition.

Initially, all the output responses (i.e. MRR, Flank wear and surface roughness) have been normalized within the range 0 to 1 (where 0 denotes as worst value and 1 denotes best value) (Table 11 and Table 12). The formulae for normalization are given as follows[37]:

For surface roughness and flank wear (Smaller-the-better criterion):

$$y_{ij} = \frac{x_{ij} - \max x_{ij}}{\min x_{ij} - \max x_{ij}} \quad \text{... (11)}$$

For, MRR (Higher-the-better criterion):

$$y_{ij} = \frac{x_{ij} - \min x_{ij}}{\max x_{ij} - \min x_{ij}} \quad \text{... (12)}$$

where $x_{ij}$ is experimental value, $\max x_{ij}$ is the maximum value and $\min x_{ij}$ is minimum observed value.

In fuzzy inference system (Fig. 9), individual normalized values of each response (for MRR, flank wear and average surface roughness) have been served as input variable. Aforementioned input responses have been expressed using three linguistic

Table 11— Normalize value of responses and MPCI (CVD Coated tool).

| Sl. No. | N-MRR | N-FW | N-SR | MPCI |
|---|---|---|---|---|
| 1 | 0 | 1 | 1 | 0.5 |
| 2 | 0.117972 | 0.901482 | 0.885417 | 0.502 |
| 3 | 0.184516 | 0.755163 | 0.854167 | 0.516 |
| 4 | 0.276866 | 0.483175 | 0.802083 | 0.525 |
| 5 | 0.102857 | 0.858236 | 0.541667 | 0.352 |
| 6 | 0.227097 | 0.760083 | 0.635417 | 0.454 |
| 7 | 0.305622 | 0.610483 | 0.479167 | 0.397 |
| 8 | 0.502304 | 0.371842 | 0.333333 | 0.411 |
| 9 | 0.305069 | 0.802235 | 0.552083 | 0.433 |
| 10 | 0.429677 | 0.705479 | 0.65625 | 0.543 |
| 11 | 0.599447 | 0.549866 | 0.477083 | 0.544 |
| 12 | 0.837604 | 0.33309 | 0.28125 | 0.54 |
| 13 | 0.359631 | 0.485362 | 0.333333 | 0.395 |
| 14 | 0.578065 | 0.287111 | 0.239583 | 0.425 |
| 15 | 0.757604 | 0.152636 | 0.125 | 0.456 |
| 16 | 1 | 0 | 0 | 0.5 |

Table 12 — Normalize value of responses and MPCI (PVD coated tool).

| Sl No. | Nr-MRR | Nr-FW | Nr-SR | MPCI |
|---|---|---|---|---|
| 1 | 0.02325 | 0.777122 | 0.325117 | 0.252 |
| 2 | 0.141874 | 0.567635 | 0.725352 | 0.453 |
| 3 | 0.720285 | 0.068089 | 0.416667 | 0.558 |
| 4 | 0.734757 | 0.903995 | 0.069249 | 0.556 |
| 5 | 0.03962 | 1 | 1 | 0.527 |
| 6 | 0 | 0.44394 | 0.13615 | 0.178 |
| 7 | 1 | 0.724694 | 0.389671 | 0.675 |
| 8 | 0.743772 | 0.738765 | 0.375587 | 0.545 |
| 9 | 0.339027 | 0.840082 | 0.75939 | 0.534 |
| 10 | 0.504864 | 0.965275 | 0 | 0.48 |
| 11 | 0.390747 | 0 | 0.280516 | 0.379 |
| 12 | 0.441756 | 0.743985 | 0.762911 | 0.587 |
| 13 | 0.678055 | 0.854744 | 0.656103 | 0.612 |
| 14 | 0.618505 | 0.121652 | 0.573944 | 0.574 |
| 15 | 0.588375 | 0.085792 | 0.934272 | 0.712 |
| 16 | 0.46121 | 0.51793 | 0.475352 | 0.473 |

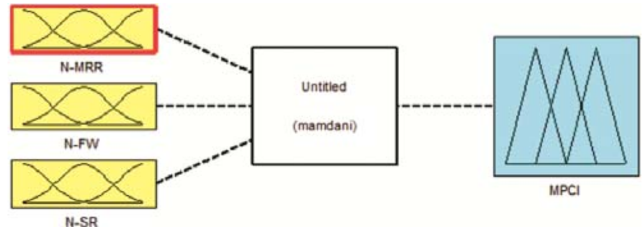


Fig. 9 — Schematic diagram of fuzzy model.

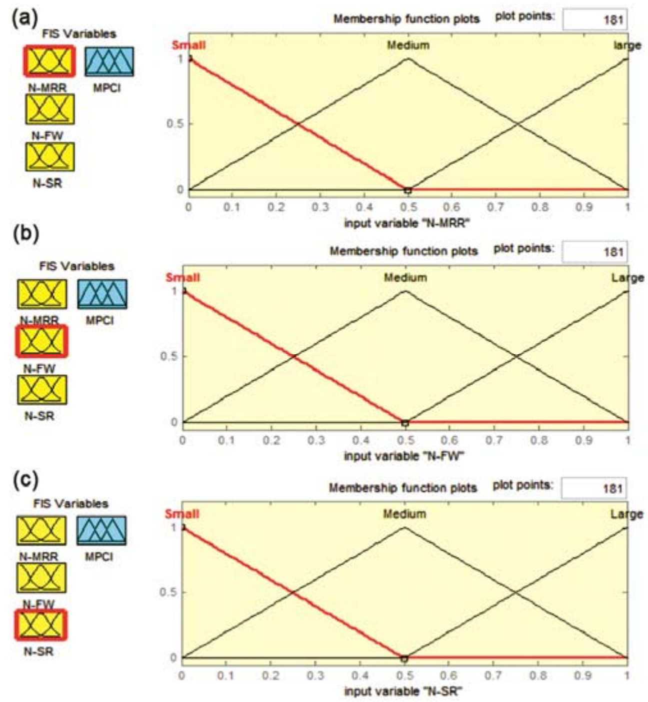


Fig. 10 — Membership function for (a) N-MRR, (b) N-FW (Flank wear) and (c) N-SR (surface roughness).

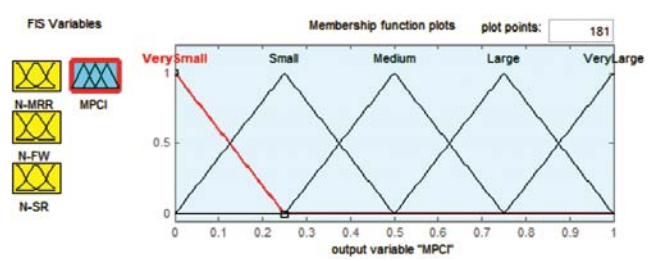


Fig. 11 — Membership function for MPCI.

variables viz. “small”, “medium” “large” as presented in Figs. 10 (a)-10 (c) whereas output factor (MPCI) has been expressed using five linguistic variables viz. “very small”, “small”, “medium”, “large”, “very large” as shown in Fig. 11.

In this work, the fuzzy set comprises for each input variable and output variable as a symmetric triangular membership function. Twenty-seven fuzzy rules (Table 13) have been explored for fuzzy reasoning (Fig. 12 (a), Fig. 12 (b)). Fuzzy logic converts linguistic inputs into linguistic output. Linguistic output is again converted to numeric values (MPCI) by defuzzification method. Numeric values of MPCIs have been tabulated in Table 11 and Table 12.

Nonlinear regression is a mathematical method for finding a nonlinear model of the relationship between dependent and independent variables. The proposed mathematical model between the independent parameters and dependent variable is presented in the following form.

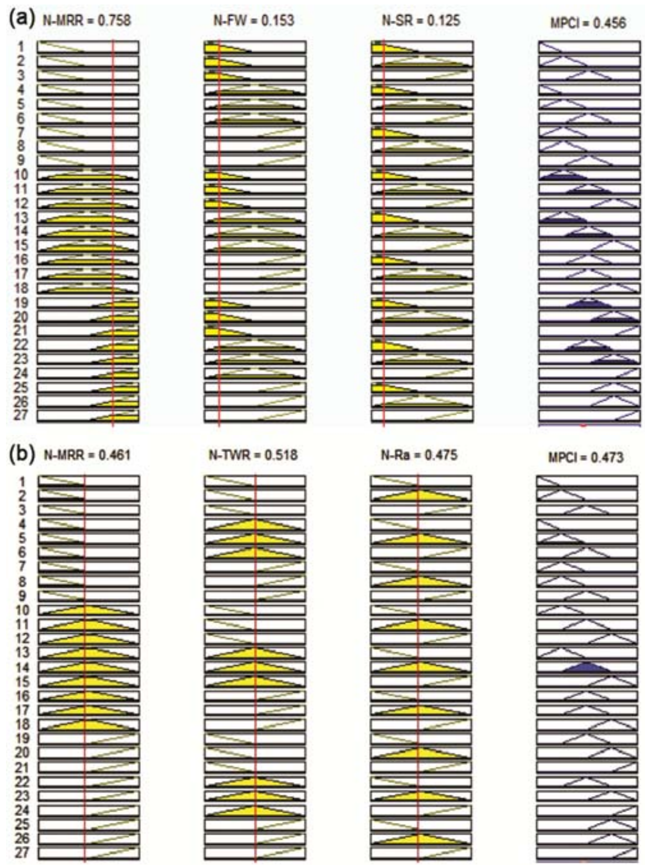


Fig. 12 — Evaluation of MPCI with fuzzy rule base (a) CVD coated tool and (b) PVD coated tool.

$$\mathrm{MPCI} = C \times N^{x_1} \times d^{x_2} \times f^{x_3} \quad \text{... (13)}$$

where C indicates a constant, N is the spindle speed, d is the depth of cut and f is the feed. $x_1$, $x_2$, and $x_3$ are estimated exponents of the regression model. Statistical software (SYSTAT 7.0) is used to estimate the parameters in nonlinear models using the Gauss-Newton nonlinear least-squares algorithm. The empirical relations between the multi performance characteristics index (MPCI) and the machining parameters are given below (Eq. 14 and Eq. 15).

MPCI empirical model for CVD coated tool (R-Square = 98.9%)

$$\mathrm{MPCI} = 0.687 \times N^{(-0.081)} \times d^{(0.164)} \times f^{(-0.102)} \quad \text{... (14)}$$

MPCI empirical model for PVD coated tool (R-Square = 97.4%)

$$\mathrm{MPCI} = 0.226 \times N^{(0.297)} \times d^{(0.257)} \times f^{(0.561)} \quad \text{... (15)}$$

Table 13 — Fuzzy rule.

| Sl. No. | MRR | Flank Wear | Sourface Roughness | MPCI |
|---|---|---|---|---|
| 1 | Small | Small | Small | Very small |
| 2 | Small | Small | Medium | Small |
| 3 | Small | Small | Large | Medium |
| 4 | Small | Medium | Small | Very small |
| 5 | Small | Medium | Medium | Small |
| 6 | Small | Medium | Large | Medium |
| 7 | Small | Large | Small | Small |
| 8 | Small | Large | Medium | Small |
| 9 | Small | Large | Large | Medium |
| 10 | Medium | Small | Small | Small |
| 11 | Medium | Small | Medium | Medium |
| 12 | Medium | Small | Large | Large |
| 13 | Medium | Medium | Small | Small |
| 14 | Medium | Medium | Medium | Medium |
| 15 | Medium | Medium | Large | Large |
| 16 | Medium | Large | Small | Medium |
| 17 | Medium | Large | Medium | Medium |
| 18 | Medium | Large | Large | Large |
| 19 | Large | Small | Small | Medium |
| 20 | Large | Small | Medium | Large |
| 21 | Large | Small | Large | Very large |
| 22 | Large | Medium | Small | Medium |
| 23 | Large | Medium | Medium | Large |
| 24 | Large | Medium | Large | Very large |
| 25 | Large | Large | Small | Large |
| 26 | Large | Large | Medium | Large |
| 27 | Large | Large | Large | Very large |

Aforesaid mathematical model are treated as objective function for ICA. Initial parameters setting for ICA as follows:

**Set up parameters for implementation of ICA**

1. Initial point [0, 0, 0]
2. Initial population

a. Number of countries 80
b. Number of imperialist 8

3. Assimilation coefficient, $\beta = 2$
4. A coefficient used to calculate total cost of empire, $\xi = 0.1$
5. Number of decades as stop condition = 1000

Finally, ICA has been implemented to find global optimal which are tabulated in Table 14 and the convergence plots are shown in Fig. 13 (a) and Fig. 13 (b).

**3.4 Comparison between CVD and PVD coated tool**

Performance of PVD and CVD coated tool is shown in Fig. 14 (a) to Fig. 14 (c). From the below

Table 14 — Optimal value of MPCI.

| Sl. No. | Tool coating | Spidle speed (RPM) | Depth of cut (mm) | Feed (mm/rev) | Fitness value |
|---|---|---|---|---|---|
| 1 | CVD | 400 | 1 | 0.08 | 0.5471 |
| 2 | PVD | 1000 | 1 | 0.2 | 0.7664 |

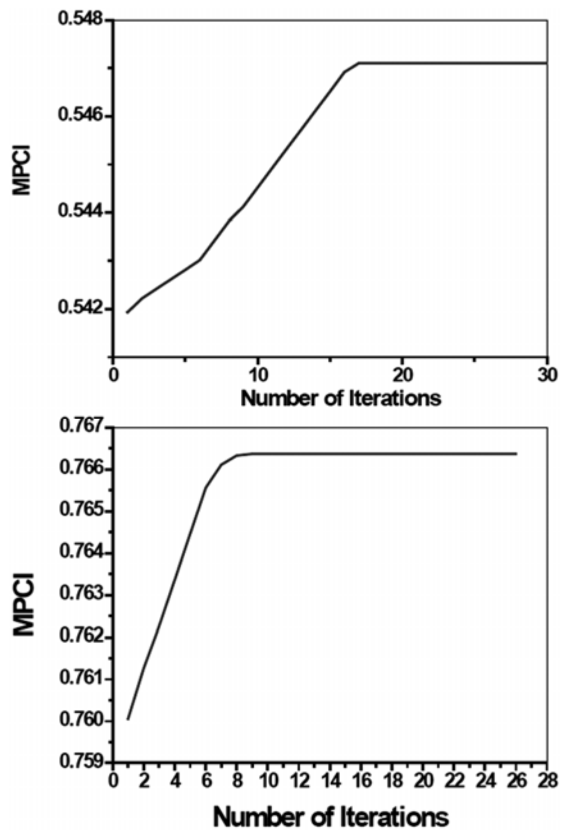


Fig. 13 — Convergence curve for MPCI (a) CVD coated tool and (b) PVD coated tool.

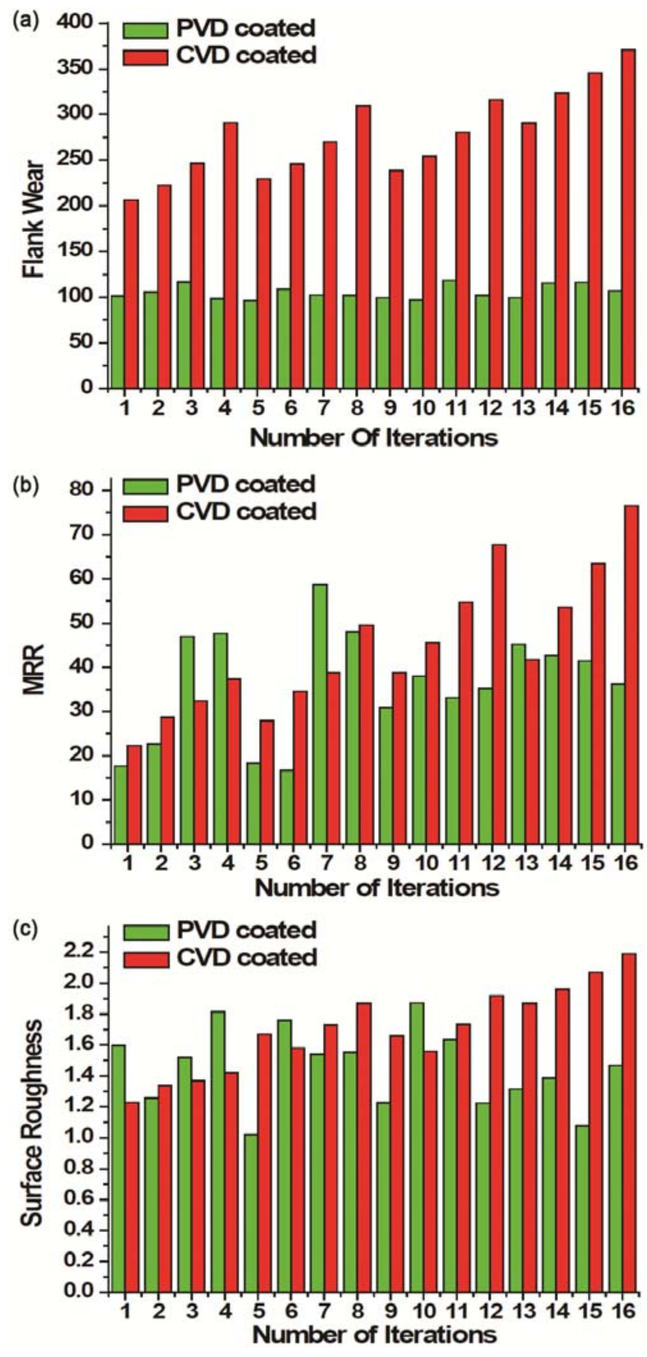


Fig. 14 — Comparison graph for (a) flank wear, (b) MRR and (c) surface roughness.

figures, it is observed that performance of PVD coated tool in case of flank wear and surface roughness is more efficient than CVD coated tool whereas in case of MRR CVD coated tool provides better result. The minimum value of flank wear for PVD coated tool and CVD coated tool is 96.22 µm and 206.12 µm respectively, the minimum value of surface roughness for PVD and CVD coated tool is 1.022 µm and 1.2 µm respectively and maximum value of MRR for PVD and CVD coated tool is 58.82 $mm^3$/sec and 76.56 $mm^3$/sec respectively. The results indicate that turning of Inconel 718 using PVD coated tool possess good surface finish with less flank wear. The result indicates that the performance of single layered (AlTiN) PVD coated tool is better than multi layered (TiN, $Al_2O_3$, TiCN, TiN) CVD coated tool[12].

## 4 Conclusions

The present work focused on parametric appraisal to evaluate optimal setup in dry turning of Inconel 718 by using fuzzy integrated with ICA approach. The multi objective optimization, which is based on fuzzy logic approach, increases the flexibility on selecting the optimal machining parameters for turning of Inconel 718. Simultaneously considering surface quality, material removal rate and flank wear status as optimization objectives. Mathematical relationship established between machining parameters and output responses in the form of non-linear regression models. ICA not only to efficiently perform the global exploration for rapidly attaining the feasible solution space but also effectively helps to reach optimal setup or near to optimal setup. The proposed methodology provides better result with less computational time and effort.

In this study, Inconel 718 has been machined under dry condition using PVD coated and CVD coated tool cutting tools. Multi objective optimization is used to obtain optimal process parameters. Fuzzy inference system coupled with ICA is used for obtain optimal process parameters. The work also highlighted the performance characteristics comparison between PVD coated tool and CVD coated tool. The following conclusions can be drawn from this study.

(i) PVD (single layer coating: AlTiN) coated tool is more efficient as compared to CVD (four layers coating: TiN, $Al_2O_3$, TiCN, TiN) coated tool in case of flank wear.

(ii) Fuzzy inference system (FIS) coupled with ICA is suitable for finding the optimal process parameters.

(iii) The optimal setting of process parameters for CVD coated tool is spindle speed 400 RPM, depth of cut 1mm and feed rate 0.08 mm/rev and for PVD coated tool is spindle speed 1000 RPM, depth of cut 1 mm and feed rate 0.2 mm/rev.

## References

1 Devillez A, Schneider F, Dominiak S, Dudzinski D & Larrouquer D, *Wear,* 262 (2007) 931.
2 Arunachalam R M, Mannan M A & Spowage A C, *Int J Mach Tools Manuf,* 44 (2004) 1481.
3 Umbrello D, *Int J Adv Manuf Technol*, 69 (2013) 2183.
4 Costes J P, Guillet Y, Poulachon G & Dessoly M, *Int J Mach Tools Manuf*, 47 (2007) 1081.
5 Fan Y, Hao Z P, Zheng M, Sun F L & Yang S C, *Int J Adv Manuf Technol*, 69 (2013) 2659.
6 Thakur D G, Ramamoorthy B & Vijayaraghavan L, *Mater Manuf Process*, 24 (2009) 497.
7 Homami R M, Tehrani A F, Mirzadeh H, Movahedi B & Azimifar F, *Int J Adv Manuf Technol*, 70 (2014) 1205.
8 Pusavec F, Hamdi H, Kopac J & Jawahir I S, *J Mater Process Technol*, 211 (2011) 273.
9 Jafarian F, Amirabadi H & Fattahi M, *Int J of Adv Manuf Technol*, 71 (2014) 817.
10 Amini S, Fatemi M H & Atefi R, *Arab J Sci Eng*, 39 (2013) 2323.
11 Zhou J, Bushlya V, Avdovic P & Stahl J E, *Int J Adv Manuf Technol,* 58 (2012) 141.
12 Chinchanikar S & Choudhury S K, *J Mech Sci Technol*, 27 (2013) 1451.
13 Kaveh A & Talatahari S, *Comput Struct*, 88 (2010) 1220.
14 Teimouri R, Baseri H & Moharami R, *J Intell Manuf*, 26 (2015) 745.
15 Lian K, Zhang C, Shao X & Gao L, *Int J Adv Manuf Technol,* 59 (2012) 815.
16 Yousefi M, Darus A N & Mohammadi H, *Int J Heat Mass Transf*, 55 (2012) 3178.
17 Enayatifar R, Yousefi M, Abdullah A H & Darus A N, *Appl Mathe Comput,* 219 (2013) 8829.
18 Bashiri M & Bagheri M, *Int J Ind Eng Prod Res,* 24 (2013) 229.
19 Niknam T, Fard E T, Pourjafarian N & Rousta A, *Eng Appl Artifl Intell*, 24 (2011) 306.
20 Sabour M H, Eskandar H & Salehi P, *World Appl Sci J,* 12 (2011) 94.
21 Talatahari S, Azar B F, Sheikholeslami R & Gandomi A H, *Commun Nonlinear Sci Numer Simulat*, 17 (2012) 1312.
22 Ahmadi M A, Ebadi M, Shokrollahi A & Majidic S M J, *Appl Soft Comput*, 13 (2013) 1085.
23 Duan H & Huang L, *Neurocomputing*, 125 (2014) 166.
24 Idoumghar L, Cherin N, Siarry P, Roche R & Miraoui A, *Appl Mathe Comput,* 219 (2013) 11149.
25 Thirumalai R & Senthilkumaar J S, *J Mech Sci Technol*, 27 (2013) 1109.
26 Sardinas R Q, Santana M R & Brindis E A, *Eng Appl Artif Intell*, 19 (2006) 127.
27 Yang S H & Natarajan U, *Int J Adv Manuf Technol*, 49 (2010) 773.
28 Karpat Y & Ozel T, *Int J of Adv Manuf Technol*, 35 (2007) 234.
29 Ranganathan S & Senthilvelan T, *Int J Adv Manuf Technol*, 56 (2011) 455.
30 Umer U, Qudeiri J A, Hussein H A M, Khan A A & Al-ahmari A R, *Int J Adv Manuf Technol*, 71 (2014) 593.
31 Bharti P S, Maheshwari S & Sharma C, *J Mech Sci Technol*, 26 (2012) 1875.
32 Khamel S, Ouelaa N & Bouacha K, *J Mech Sci Technol*, 26 (2012) 3605.
33 Bose P K, Deb M, Banerjee R & Majumder A, *Energy*, 63 (2013) 375.
34 Shabgard M R, Badamchizadeh M A, Ranjbary G & Amini K, *J Manuf Syste*, 32 (2013) 32.
35 Krishnamoorthy A, Boopathy S R, Palanikumar K & Davim J P, *Measurement,* 45 (2012) 1286.
36 Majumder A, *J of Mech Sci Technol*, 27 (2013) 2143.
37 Abhishek K, Datta S, Mahapatra S S, Mandal G & Majumdar G, *J Manufac Technol Manage,* 24 (2013) 929.

38 Hanafi I & Khamlichi A, Cabrera F M, Lopez P J N & Jabbouri A, *Measurement*, 45 (2013) 1424.

39 Sobiyi K, Sigalas I, Akdogan G & Turan Y, *Int J Adv Manuf Technol*, 77 (2015) 861.

40 Kumar C S & Patel S K, *Surface Coat Technol*, 309 (2017) 266.

41 Guo Y B & Liu C R, *J Manuf Sci Eng*, 124 (2002) 1.

42 Aslan E, Camuşcu N & Birgören B, *Mater Des*, 28 (2007) 1618.

43 Thakur A & Gangopadhyay S, *Tribology Int*, 102 (2016) 198.

44 Kim D M, Bajpai V, Kim B H & Park, *Int J Adv Manuf Technol*, 78 (2015) 1393.