An Integrated Fuzzy-MOORA Method for the Selection of Optimal Parametric Combination in Turing of Commercially Pure Titanium

Akhtar Khan, Kalipada Maity and Durwesh Jhodkar

Abstract This chapter explores the application of a hybrid approach namely multi-objective optimization based on ratio analysis (MOORA) in fuzzy context to obtain the best parametric combination during machining of commercially pure titanium (CP-Ti) Grade 2 with uncoated carbide inserts in dry cutting environment. A series of experiment was performed by adopting Taguchi based L_{27} orthogonal array. Cutting speed, feed rate, and depth of cut were selected as three process variables whereas cutting force, surface roughness and flank wear were selected as three major quality attributes to be minimized. The minimization was exploited using fuzzy embedded MOORA method and hence an optimal parametric combination was attained. The results of the investigation clearly revealed that, the fuzzy coupled with MOORA method, was capable enough in acquiring the best parametric setting during turning operation under specified cutting conditions.

Keywords Fuzzy logic · MOORA · Flank wear · Optimization · Surface roughness · Titanium

1 Introduction

The present era is well-known for the creation and development of a large number of structural materials. Among these materials, titanium and its alloys are identified as more promising owing to their inherent properties. Titanium alloys are more

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attracting than that of other similar materials due to their unique characteristics such as superior corrosion resistance, highest strength-to-weight ratio, exceptional tissue-inertness and sustainability of these properties even at elevated temperatures [1–3]. Therefore, these alloys are most widely used in aerospace, chemical processing, marine, automobile and medical industries [4, 5]. Consequently, the aforementioned applications necessitate a substantial machining. Regrettably, titanium alloys are characterized as 'hard-to-cut' type materials owing to their poor thermal conductivity and high chemical affinity [6–8]. Poor thermal conductivity restricts heat dissipation from the primary cutting zone which in turn leads to excessive temperature gradient and hence to rapid tool wear at its pre-mature stages. Similarly, high chemical affinity of these alloys contributes in localizing the heat and hence a remarkable adhesion between tool and work materials which strongly curtails the tool life. The afore-discussed consequences may possibly lead to high production cost, high energy requirement in association with compromising dimensional accuracy [9]. These challenges can be addressed by selecting an appropriate cutting tool materials as well as a suitable combination of machining variables. However, a sufficiently enormous variety of cutting tool materials are now available, carbide inserts were recognized as the most suitable for machining titanium and its alloys [10, 11]. Therefore, commercially available uncoated carbide inserts were used for the machining of the selected work material during this investigation.

Selection of an appropriated combination of cutting variables is of paramount importance while machining "hard-to-cut" materials like titanium and its alloys. In machining of such alloys, an appreciable tool life, superior surface finish and relatively lower values of the cutting forces are acknowledged as the most noticeable manufacturing desires. To meet these requirements, adoption of optimization methods becomes essential to confirm high productivity without compromising the quality. In the past few decades, several experimental investigations have been reported exhibiting the application potential of different optimization techniques for optimizing turning parameters in order to achieve quality products. Lalwani et al. [12] studied the influence of various turning variables viz. cutting speed, feed rate and depth of cut, on two distinct cut qualities (i.e. cutting force and surface roughness) while turning MDN 250 steel with ceramic inserts. Aouici et al. [13], developed response surface methodology (RSM)-based quadratic models for the prediction of various turning responses such as surface roughness and cutting force, during turning of AISI H11 steel using CBN (Cubic boron nitride) inserts. Asiltürk and Neşeli [14] and Hashmi et al. [15], in their experimental investigations also developed RSM-based empirical models for the prediction of two different surface roughness characteristics viz. arithmetic mean roughness (R_a) and maximum peak-to-valley height (R_z). The results of both the investigations indicated that the suggested quadratic models were effective enough in predicting cut qualities and can be used to estimate the machining characteristics of other machining processes too. Similarly, Tebassi et al. [16] advised two different prediction models for estimating cutting force and surface roughness during machining of nickel based super alloy Inconel 718. They suggested RSM-based quadratic model and artificial neural network (ANN)-based model. In the current investigation, they compare the estimation efficiency of both the models and noticed that, ANN model was around 10.1% more precise in estimating cutting force (F_c) and 24.83% precise in estimating average roughness or arithmetic mean roughness (R_a), in comparison to the quadratic model counterpart. Furthermore, ANN model was also signified as an effective prediction tool for predicting cutting force, tool wear and surface roughness during turning operation [17]. Abburi and Dixit [18], recommended ANN coupled with fuzzy set theory to estimate the surface roughness during turning operation. Similarly, Basheer et al. [19], also used ANN model for predicting various output characteristics while precision machining of metal matrix composites (MMCs). The above mentioned studies were performed in dry cutting environment. In contrast, some researchers have reported the effectiveness of employing cooling media such minimum quantity lubrication (MQL) in order to attain improved machinability of different titanium and nickel-based super alloys [20–23]. These investigations highlighted the technical hitches and the benefits of MQL approach in a real time manufacturing system.

In addition to the afore discussed machining approaches, optimization techniques and prediction models, an extensive work has been found in which researchers have used various multi-criteria decision making (MCDM)-based approaches to solve turning problems consisting of multiple process variables and attributes. These methods include Analytical hierarchy process (AHP), Analytical network process (ANP), Fuzzy logic, multi-objective optimization based on ratio analysis (MOORA) method and Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) method etc. [24–28]. Apart from this, some hybrid and innovative techniques viz. Fuzzy-TOPSIS, Fuzzy-MOORA, and ANP-TOPSIS were also reported in order to confirm better solution of a specific problem [29]. The aforesaid approaches were found to be more precise in attaining the best alternative among a set of feasible alternatives. From the above literature survey it is clear that, an extensive work has been dedicated to the utilization of several MCDM-based approaches in solving a wide range of problems. However, turning parameters of CP-Ti grade 2 and their vagueness has not been studied and reported adequately so far. This might be contributed to the uncertain behavior of turning responses and vague information about the interaction between turning variables. Thus, the aforesaid situation leads an unclear solution. Therefore, selection of a suitable and effective methodology to solve MCDM-based problems is a great challenge to the researchers as well as the industries dealing with such situations. Keeping in mind, the vagueness and uncertainty of turning parameters, a fuzzy embedded MOORA method has been introduced in this study. The concepts of fuzzy set theory have been implemented to determine the best parametric combination while machining CP-Ti grade 2. The relationship between turning input and the selected output, were described with the help of fuzzy linguistic variables. In addition, a fuzzy control rule was developed for each of the selected attribute by adopting seven different linguistic grades. Thus, an optimal combination of process variables was attained and reported.

2 Multi-objective Optimization Based on Ratio Analysis (MOORA)

The MOORA method is a newly introduced approach having a substantial potential in dealing with a wide range of problems comprising of multiple as well as conflicting attributes. This method was developed and proposed by two European (Vilnius; Lithuania) researchers Brauers and Zavadskas in the year 2006. Basically, this method comprises of two distinct elements viz. the ratio system and the reference point approach. The first element is used to determine the overall performance of each alternative. This can be done by calculating the difference between the summations of the corresponding normalized values related to each criteria. On the other hand, the reference point approach helps in indicating the best or optimal combination of the alternatives.

The MOORA method can be understood deeply and clearly with the help of the following steps:

Step 1: Initially a decision matrix is constructed which represents all the selected responses and the corresponding set of input variables.

$$X = \begin{bmatrix} x_{11} & x_{12} & \dots & x_{1n} \\ x_{21} & x_{22} & \dots & x_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ x_{m1} & x_{m2} & \dots & x_{mn} \end{bmatrix} \quad (1)$$

here, x_{ij} denotes the selected outcomes of the ith alternative on jth attribute, whereas m and n represents the number of alternatives (a set of input variables) and number of attributes (machining response) respectively.

Step 2: Normalization of the data sets observed in step number 1 and thus establishing a ratio system.

$$x_{ij}^* = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \quad (j = 1, 2, \dots, n) \quad (2)$$

here, x_{ij}^* denotes the normalized value of the ith alternative on jth attribute. This is a dimensionless quantity that lies between 0 and 1.

Step 3: In the next step, the overall assessment value is calculated by adding/subtracting the normalized values corresponding to each alternative. All the beneficial (higher-is-better) type performance characteristics are added whereas non-beneficial (lower-is-better are subtracted in order to obtain the overall assessment value.

$$y_i = \sum_{j=1}^{g} x_{ij}^* - \sum_{j=g+1}^{n} x_{ij}^* \quad (3)$$

here, g denotes the number of attributes related to beneficial criterion whereas $(n - g)$ is the number of attributes corresponding to non-beneficial criterion. y_i represents the overall assessment value of the ith alternative with respect to all alternatives.

Many a times, it was perceived that some of the attributes are of paramount importance when compared to the others. In such situations, weight criteria or factor can be multiplied with the same. After incorporation of weighting parameter the above equation can be written as below:

$$y_i = \sum_{j=1}^{g} w_j x_{ij}^* - \sum_{j=g+1}^{n} w_j x_{ij}^* \quad (4)$$

where, w_j is the weight of jth attribute.

Step 4: Assign ranking to overall assessment value y_i in descending order. The highest value of the y_i represents the best alternative, while the lowest value of y_i represents the worst.

3 An Introduction to Fuzzy Set Theory

A multi-criteria decision making (MCDM)—based problem has been identified as one of the difficult problems associated with real time manufacturing systems, due to the involvement of several uncertain situations. Therefore, to acquire an acceptable solution from this kind of problems has always been a challenging task to meet, for the researchers. In this situation, fuzzy set theory plays a key role in dealing with the ambiguity of the process and offers better results [30]. A fuzzy set theory, allows the decision maker to express their opinions in terms of specified linguistic variables. These linguistic variables can be converted into different fuzzy numbers with the help of fuzzy membership functions. In this way, MCDM-based problems can be solved easily and effectively. Consequently, fuzzy set theory has been identified as a significant as well as efficient tool for explaining human activities inclusive of vague and uncertain information.

Fuzzy inference system (FIS) is a well-recognized computing tool for handling linguistic knowledge and numerical data together. In general, FIS utilizes the concepts of fuzzy reasoning, fuzzy rules (If-then) and fuzzy set theory to deal with a wide range of problems viz. decision making, automatic control, robotics, classification of data and pattern recognition etc. This might be contributed to its effectiveness in mapping of any prescribed input to an output by using the aforesaid approaches. An FIS consists of four distinct elements such as fuzzifier, inference engine, knowledge base and defuzzifier. Initially, the crisp input is converted in terms of predefined linguistic variable by utilizing the membership function kept in the fuzzy knowledge base. This can be performed with the help of the first element i.e. fuzzifier and hence this process is termed as fuzzification. Secondly, the fuzzy input is converted to the

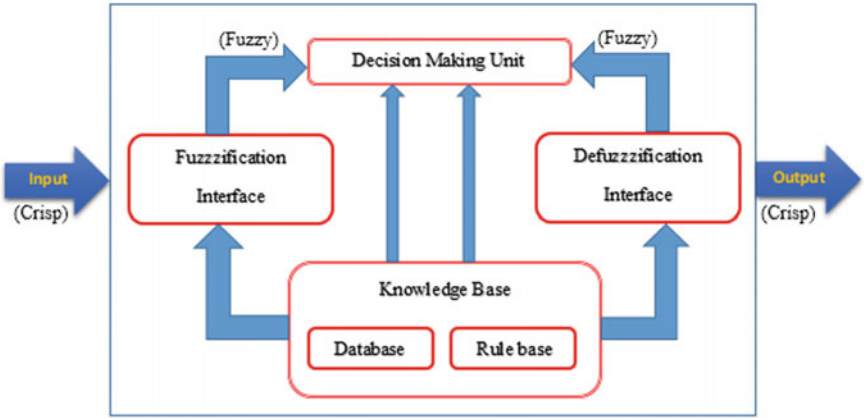

Fig. 1 The architecture of fuzzy—interface system

fuzzy output by adopting fuzzy rules (If-then) inside the inference engine. Finally, the last element i.e. defuzzified is engaged to convert these fuzzy output to a crisp value. The architecture of a fuzzy inference system is represented in Fig. 1.

Fuzzy number: A fuzzy number, is a subset of real numbers which denotes the development of the idea within a specified confidence interval [30]. For example, let A be the classical set of objects, whose elements are represented by *X*. The crisp value of a prescribed statement is characterized by means of a membership function and can be represented by a curve indicating the membership values lying in the range of 0 and 1.

$$\mu_A(X) = \begin{cases} 1, & if\ X \in A \\ 0, & Otherwise \end{cases} \tag{5}$$

Here, {0, 1} is known as the evaluation set and it is permissible to be represented in a real interval [0, 1] for the continuous mapping membership function. Moreover, assortment of a suitable membership function is of utmost significance in the fuzzification process. These membership functions are typically created by means of amply of elementary functions such as linear, quadratic and cubic polynomial curves, Gaussian distribution function, sigmoid curve etc. Conversely, the modest membership function can be created expending straight lines. In this category, the triangular membership function is recognized as the simplest one, which can be described with the help of a center-based triplet tactic. A triangular membership function can be constructed by keeping and equal and identical distance between the lowest and the highest points attached to the adjacent center. As a result of this, for each input value there will not be fuzzy sets greater than two. Similarly, the addition of their membership degrees always remains unity. Figure 2 explains the schematic representation of a triangular fuzzy membership function. For a clear understanding of fuzzy set theory and fuzzy numbers, some important definitions are enumerated below:

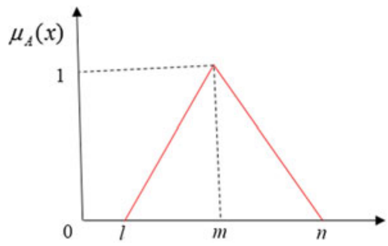

Fig. 2 A triangular fuzzy membership function

Definition 1: A fuzzy set $\tilde{A}$ in a universe of discourse X is described by a membership function $\mu_{\tilde{A}}(x)$ which is characterized as the grade of membership of x in $\tilde{A}$.

Definition 2: The triangular fuzzy numbers (TFNs) can be exemplified as $\tilde{A} = (a_1, a_2, a_3)$, and the membership function of the fuzzy number $\tilde{A}$ can be designated as below (Eq. 6):

$$\mu_{\tilde{A}}(x) = \begin{cases} 0 & x < 1, \\ \frac{x-a_1}{a_2-a_1} & a_1 \leq x \leq a_2, \\ \frac{a_3-x}{a_3-a_2} & a_2 \leq x \leq a_3, \\ 0 & x > a_3 \end{cases} \tag{6}$$

Definition 3: The fuzzy sum and fuzzy subtraction of two different TFNs are also triangular fuzzy numbers. But, the multiplication of two different TFNs is only an approximate TFN. For example, if there are two triangular fuzzy numbers $\tilde{A} = (a_1, a_2, a_3)$ and $\tilde{B} = (b_1, b_2, b_3)$, and a positive real number $r = (r, r, r)$, then the various algebraic operations between these two TFNs can be described as below:

$$\tilde{A}(+)\tilde{B} = (a_1 + a_2, b_1 + b_2, c_1 + c_2) \tag{7}$$

$$\tilde{A}(-)\tilde{B} = (a_1 - a_2, b_1 - b_2, c_1 - c_2) \tag{8}$$

$$\tilde{A}(\times)\tilde{B} = (a_1 a_2, b_1 b_2, c_1 c_2) \tag{9}$$

$$\tilde{A}(/)\tilde{B} = (a_1/b_1, a_2/b_2, a_3/b_3) \tag{10}$$

$$\tilde{A}(\times)r = (a_1 r, a_2 r, a_3 r) \tag{11}$$

Definition 4: The defuzzified value $m(\tilde{A})$ of a triangular fuzzy number $\tilde{A} = (a_1, a_2, a_3)$, can be calculated using Eq. (12):

$$m(\tilde{A}) = \frac{a_1 + a_2 + a_3}{3} \tag{12}$$

Definition 5: The distance between these two TFNs $\tilde{A} = (a_1, a_2, a_3)$ and $\tilde{B} = (b_1, b_2, b_3)$, can be calculated using Eq. (13):

$$d(\tilde{A}, \tilde{B}) = \sqrt{\frac{1}{3}(a_1 - b_1)^2 + (a_2 - b_2)^2 + (a_3 - b_3)^2} \tag{13}$$

Definition 6: The best non-fuzzy performance (BNP) value cab be computed by employing center of area (COA) method, as described in Eq. (14):

$$BNP_i = \frac{[(c - a) + (b - a)]}{3} + a, \forall_i \tag{14}$$

4 Fuzzy Embedded MOORA Method

The concept of fuzzy set theory in combination with MOORA method, was accomplished to estimate an optimal parametric combination in order to confirm better machinability of the selected work material. The hybridization of the two approaches attracted the attention of several researchers in the direction of the decision science community. Therefore, in the present work, an attempt has been made to exhibit the application potential of Fuzzy-MOORA method in solving an MCDM-based problem. The proposed hybrid approach offers a set of linguistic variables to express the opinions of decision makers. These variables were further utilized to construct fuzzy decision matrix and normalized fuzzy decision matrix. In the next step, weighted normalized matrix was acquired by adopting a suitable weightage for each of the selected response. Further, crisp values for weighted normalized fuzzy decision matrix was obtained, by calculating the best non-fuzzy performance value corresponding to each alternative. At the end, overall assessment values were computed and ranking was done by arranging them in descending order. The recommended hybrid approach consists of the following steps:

Step 1: Formation of fuzzy decision matrix using the adopted fuzzy triangular number illustrating all the alternatives (in rows) and attributes (in columns).

$$\tilde{X} = \begin{bmatrix} \left[x_{11}^l, x_{11}^m, x_{11}^n\right] & \left[x_{12}^l, x_{12}^m, x_{12}^n\right] & \left[x_{1n}^l, x_{1n}^m, x_{1n}^n\right] \\ \vdots & \vdots & \vdots \\ \left[x_{m1}^l, x_{m1}^m, x_{m1}^n\right] & x_{m2}^l, x_{m2}^m, x_{m2}^n & x_{mn}^l, x_{mn}^m, x_{mn}^n \end{bmatrix} \tag{15}$$

Step 2: Calculate the normalized fuzzy decision matrix using Eqs. (16–18).

$$x_{ij}^{l*} = \frac{x_{ij}^l}{\sqrt{\sum_{i=1}^m \left[\left(x_{ij}^l\right)^2 + \left(x_{ij}^m\right)^2 + \left(x_{ij}^n\right)^2\right]}} \tag{16}$$

$$x_{ij}^{m*} = \frac{x_{ij}^{m}}{\sqrt{\sum_{i=1}^{m}\left[\left(x_{ij}^{l}\right)^2 + \left(x_{ij}^{m}\right)^2 + \left(x_{ij}^{n}\right)^2\right]}} \quad (17)$$

$$x_{ij}^{n*} = \frac{x_{ij}^{n}}{\sqrt{\sum_{i=1}^{m}\left[\left(x_{ij}^{l}\right)^2 + \left(x_{ij}^{m}\right)^2 + \left(x_{ij}^{n}\right)^2\right]}} \quad (18)$$

Step 3: Estimate the weighted normalized fuzzy decision matrix using Eqs. (19–21).

$$V_{ij}^{m} = w_j x_{ij}^{m*} \quad (19)$$

$$V_{ij}^{l} = w_j x_{ij}^{l*} \quad (20)$$

$$V_{ij}^{n} = w_j x_{ij}^{n*} \quad (21)$$

here, w_j represents the weight criteria of each attribute.

Step 4: Convert the overall fuzzy assessment value ($\tilde{y}_i$) into a non-fuzzy value (crisp). The best non-fuzzy performance (BNP) can be calculated using Eq. (22).

$$BNP_i(y_i) = \frac{\left(y_i^n - y_i^l\right) + \left(y_i^m - y_i^l\right)}{3} + y_i^l \quad (22)$$

where $\tilde{y}_i = \left(y_i^l, y_i^m, y_i^n\right)$.

Step 5: Determine the overall fuzzy assessment value using Eq. (23).

$$\tilde{y}_i = \tilde{V}_{ij}^{+} - \tilde{V}_{ij}^{-} \quad (23)$$

here, $\tilde{V}_{ij}^{+}$ is the overall assessment value of beneficial criterion whereas $\tilde{V}_{ij}^{-}$ denotes the overall assessment value of non-beneficial criterion.

Step 6: Rank the above values by arranging them in descending order. The highest value exhibits the best alternative whereas the lowest value indicates the worst alternative.

5 Experimental Case Study

5.1 Work and Tool Materials

A cylindrical bar of commercially pure titanium (CP-Ti) was selected as the work material having diameter 50 mm and length 500 mm. The chemical composition

Table 1 Chemical composition of work material

Element	C	N	O	Fe	H	Ti
Wt. (%)	0.08–0.1	0.03	0.25	0.30	0.015	Balance

Table 2 Tool insert geometry

Parameter	
Insert shape	Square
Insert clearance angle	0°
Tolerance	±0.002
Cutting edge length	12 mm
Insert thickness	04 mm
Nose radius	0.8 mm
Holder style	PSBN
Shank height	20 mm
Shank width	20 mm
Tool length	125 mm

of the workpiece is listed in Table 1. A square shaped, ISO designated (SNMG 120408; Grade K313) cutting inserts were used for the machining of the selected work part. These inserts were rigidly mounted on a tool holder (ISO designation: PSBNR 2020K12). The geometry details of the cutting insert and tool holder are listed in Table 2.

5.2 *Domain of the Investigation*

The present investigation exploited Taguchi based orthogonal array design (L_{27}) to execute a series of experiment. These arrays were observed to be helpful in optimizing various quality characteristics and offering the best alternative amongst several alternatives. In the current investigation, an orthogonal array comprising of three factors and three levels is adopted as shown in Table 3. The allocation of the selected process variables was done according to the linear graph depicted in Fig. 3. Table 4, represents the experimental layout along with the measured outcomes.

5.3 *Experimental Procedure*

The selected round bar of the work material was turned on a heavy duty lathe (Model: NH-26; Manufacturer: HMT, India). A series of experiment was conducted as per

Table 3 Input variables with their levels

S. no.	Input variable	Unit	Levels		
			Level 1	Level 2	Level 3
1	Cutting speed (*v*)	m/min	30	60	90
2	Feed rate (*f*)	mm/rev	0.08	0.12	0.16
3	Depth of cut (*d*)	mm	0.2	0.4	0.6

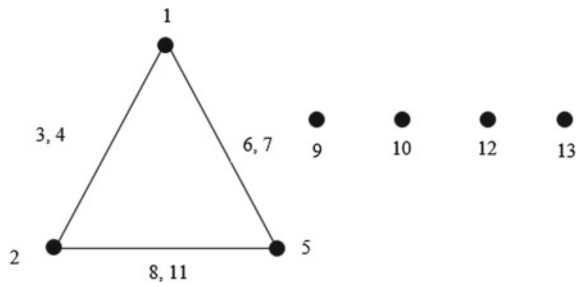

Fig. 3 Linear graph of proposed L_{27} orthogonal array

the list given in Table 4. Machining length was kept fixed as 250 mm and a new and sharp cutting edge was used for each experimental run. Figure 4 illustrates the experimental setup of the current investigation. Three distinct quality characteristics of turning operation viz. cutting force (F_c), surface roughness (R_a) and flank wear (VB) were examined and measured after completion of each trial. Cutting force was measured using a three dimensional (3D) piezoelectric dynamometer (Manufacturer: Kistler Instrument Corporation). The values of F_c were recorded at three different locations (roughly 80 mm apart) throughout the cutting length and the average value was noted. A roughness testing device (Model: Surtronic 3+ , Manufacturer: Taylor Hobson) was used to measure the roughness parameter R_a of the machined surface. The measurements of R_a values were performed at six different locations (roughly 60° apart) around the circumference of the turned part. Similarly, wear on the flank surfaces of each cutting insert was examined and measured with the help of an optical microscope (Model: Axio Cam ER_c 5s, Manufacturer: Carl Zeiss). To confirm a better measurement accuracy, wear height at the flank surfaces of each cutting tool insert was recorded at three different locations and the average value was calculated for consideration.

Table 4 Outcomes of the experimentation

Run	Input variables			Responses		
	Speed	Feed	DOC	F_c (N)	R_a (μm)	VB (mm)
1	30	0.08	0.2	67.574	1.015	0.082
2	30	0.08	0.4	115.7	1.225	0.1
3	30	0.08	0.6	99.749	1.453	0.223
4	30	0.12	0.2	135.755	1.295	0.104
5	30	0.12	0.4	110.796	1.195	0.087
6	30	0.12	0.6	78.62	1.497	0.232
7	30	0.16	0.2	126.747	1.87	0.099
8	30	0.16	0.4	78.37	1.595	0.099
9	30	0.16	0.6	96.794	1.942	0.166
10	60	0.08	0.2	76.921	1.215	0.193
11	60	0.08	0.4	117.233	1.24	0.241
12	60	0.08	0.6	101.344	1.328	0.225
13	60	0.12	0.2	138.554	1.549	0.157
14	60	0.12	0.4	113	1.517	0.093
15	60	0.12	0.6	68.873	1.413	0.23
16	60	0.16	0.2	129.407	1.597	0.145
17	60	0.16	0.4	79.994	1.995	0.11
18	60	0.16	0.6	98.058	1.721	0.196
19	90	0.08	0.2	77.93	1.337	0.11
20	90	0.08	0.4	119.074	1.402	0.124
21	90	0.08	0.6	102.799	1.395	0.282
22	90	0.12	0.2	139.544	1.696	0.142
23	90	0.12	0.4	114.067	1.338	0.217
24	90	0.12	0.6	70.667	1.114	0.23
25	90	0.16	0.2	130.199	1.566	0.225
26	90	0.16	0.4	84.638	1.64	0.239
27	90	0.16	0.6	100.175	1.509	0.253

5.4 *Estimation of Optimal Parametric Combination Using Fuzzy-MOORA Method*

In the current investigation, fuzzy coupled with MOORA method was exploited to acquire the best parametric combination of input variables during machining of CP-Ti Grade 2 using uncoated carbide inserts in dry cutting environment. The main attention was given to minimize the cutting force and tool wear in combination with an appreciable surface finish. These performance characteristics are identified as

Fig. 4 Experimental setup

Table 5 Linguistic variables used for each criteria

Linguistic variable	Triangular fuzzy numbers (TFNs)
Very low (VL)	(0, 0, 0.1)
Low (L)	(0, 0.1, 0.3)
Medium low (ML)	(0.1, 0.3, 0.5)
Medium (M)	(0.3, 0.5, 0.7)
Medium high (MH)	(0.5, 0.7, 0.9)
High (H)	(0.7, 0.9, 1.0)
Very high (VH)	(0.9, 1.0, 1.0)

of paramount importance which significantly affect the production rate as well as the production cost, to a great extent. In this situation, acquiring and adopting the best parametric combination, become a challenging task. This also contributed to the vagueness of machining characteristics and the interaction effects among the selected process variables. Therefore, the proposed fuzzy set theory, uses linguistic terms such as very good, average, poor, very poor etc. for an effective assessment of the afore mentioned machining characteristics. Furthermore, the relative weights of each machining characteristic are also explained with the help of aforesaid fuzzy linguistic variables.

During this investigation, each alternative or experimental trail was primarily described in terms of specified linguistic variables as shown in Table 5. This was done to determine the relative weights of the selected output criterion viz. F_c, R_a and VB respectively, as listed in Table 6.

Secondly, valuation of all the available alternatives was accomplished based on the linguistic variables illustrated in Table 7. During this valuation, seven dissimilar fuzzy linguistic variables viz. very poor, poor, medium poor, fair, medium good, very good etc. were occupied. Table 8 represents the results of the assessment process.

Table 6 Relative weights of each criteria

Criteria	Decision maker	Fuzzy numbers
F_c	H	(0.7, 0.9, 1.0)
R_a	H	(0.7, 0.9, 1.0)
VB	VH	(0.9, 1.0, 1.0)

Table 7 Linguistic variables used for each alternative

Linguistic variable	Triangular fuzzy numbers (TFNs)
Very poor (VP)	(0, 0, 1)
Poor (P)	(0, 1, 3)
Medium poor (MP)	(1, 3, 5)
Fair (F)	(3, 5, 7)
Medium good (MG)	(5, 7, 9)
Good (G)	(7, 9, 10)
Very good (VG)	(9, 10, 10)

Further, formation of fuzzy decision matrix was done by converting the data sets attained after the aforesaid assessment process, into a suitable triangular fuzzy numbers. The results of the conversion process are depicted in Table 9.

Normalization of the data sets illustrated in fuzzy decision matrix (Table 9), was executed using Eqs. (16–18) and the outcomes are shown in Table 10. In the next step, the relevant weights of each machining criterion were multiplied with their corresponding values to attain weighted normalized fuzzy decision matrix as illustrated in Table 11.

The data sets listed in Table 11, were further converted into crisp values using Eq. (22) and depicted in Table 12. At the end, overall assessment values were calculated using Eq. (23) and listed in Table 13.

Finally, preference ranking was given to each alternative after arranging the overall assessment values in descending order, as exhibited in Table 13. By visualizing this table, it is clearly seen that, experiment number 1 is the best alternative offering minimum cutting force and tool wear along with appreciable surface quality. In contrast, experiment number 25, is signified as the worst alternative. Thus, an adequate machinability of the selected work material lies at lower range of machining variables. At lower, cutting speed, feed rate and depth of cut, machinability of the work part was observed to be better when compared to the higher ranges of machining variables counterpart. This might be contributed to the lower machining zone temperature at lower cutting speed, feed and depth of cut. Machining of titanium alloys at lower cutting speeds, does not raise the cutting zone temperature significantly whereas this temperature may be greater at high cutting speeds. High speed machining causes rapid growth in the cutting temperature which in turn introduces strain hardening and thermal softening phenomenon. This also results in a remarkable plastic deformation of the work part and curtails the machinability to a great extent. Therefore, lower range of the process variables are strongly recommended for

Table 8 Results of the assessment

Alternative	Responses			Fuzzy linguistic variables		
	F_c (N)	R_a (μm)	VB(mm)	F_c	R_a	VB
1	67.574	1.015	0.082	VG	VG	VG
2	115.7	1.225	0.1	MP	G	VG
3	99.749	1.453	0.223	F	F	MP
4	135.755	1.295	0.104	VP	MG	VG
5	110.796	1.195	0.087	MP	G	VG
6	78.62	1.497	0.232	G	F	P
7	126.747	1.87	0.099	VP	VP	VG
8	78.37	1.595	0.099	G	MP	VG
9	96.794	1.942	0.166	F	VP	MG
10	76.921	1.215	0.193	G	G	F
11	117.233	1.24	0.241	P	G	P
12	101.344	1.328	0.225	F	MG	MP
13	138.554	1.549	0.157	VP	F	MG
14	113	1.517	0.093	MP	F	VG
15	68.873	1.413	0.23	VG	MG	P
16	129.407	1.597	0.145	VP	MP	MG
17	79.994	1.995	0.11	G	VP	VG
18	98.058	1.721	0.196	F	P	F
19	77.93	1.337	0.11	G	MG	VG
20	119.074	1.402	0.124	P	MG	G
21	102.799	1.395	0.282	F	MG	VP
22	139.544	1.696	0.142	VP	MP	MG
23	114.067	1.338	0.217	MP	MG	MP
24	70.667	1.114	0.23	VG	VG	P
25	130.199	1.566	0.225	VP	F	MP
26	84.638	1.64	0.239	G	MP	P
27	100.175	1.509	0.253	F	F	P

machining titanium and its alloys, which is also witnessed during this investigation. However, this might be limited to the selected range of machining parameters and cutting conditions.

Table 9 Fuzzy decision matrix

Alternative	Responses		
	F_c	R_a	VB
1	9, 10, 10	9, 10, 10	9, 10, 10
2	1, 3, 5	7, 9, 10	9, 10, 10
3	3, 5, 7	3, 5, 7	1, 3, 5
4	0, 0, 1	5, 7, 9	9, 10, 10
5	1, 3, 5	7, 9, 10	9, 10, 10
6	7, 9, 10	3, 5, 7	0, 1, 3
7	0, 0, 1	0, 0, 1	9, 10, 10
8	7, 9, 10	1, 3, 5	9, 10, 10
9	3, 5, 7	0, 0, 1	5, 7, 9
10	7, 9, 10	7, 9, 10	3, 5, 7
11	0, 1, 3	7, 9, 10	0, 1, 3
12	3, 5, 7	5, 7, 9	1, 3, 5
13	0, 0, 1	3, 5, 7	5, 7, 9
14	1, 3, 5	3, 5, 7	9, 10, 10
15	9, 10, 10	5, 7, 9	0, 1, 3
16	0, 0, 1	1, 3, 5	5, 7, 9
17	7, 9, 10	0, 0, 1	9, 10, 10
18	3, 5, 7	0, 1, 3	3, 5, 7
19	7, 9, 10	5, 7, 9	9, 10, 10
20	0, 1, 3	5, 7, 9	7, 9, 10
21	3, 5, 7	5, 7, 9	0, 0, 1
22	0, 0, 1	1, 3, 5	5, 7, 9
23	1, 3, 5	5, 7, 9	1, 3, 5
24	9, 10, 10	9, 10, 10	0, 1, 3
25	0, 0, 1	3, 5, 7	1, 3, 5
26	7, 9, 10	1, 3, 5	0, 1, 3
27	3, 5, 7	3, 5, 7	0, 1, 3

6 Conclusions

In this chapter, an efficient and effective hybrid method has been projected to solve machining problems having multiple cut qualities under fuzzy environment. Selection of the best alternative in order to confirm better machinability of the selected work material, was done with the help of fuzzy embedded MOORA method. Thus in the present investigation a new MCDM approach, MOORA under fuzzy environment has been applied to deal with both quantitative and qualitative machining criteria. The following conclusions may be drawn after completion of current investigation:

Table 10 Normalized fuzzy decision matrix

Alternative	Responses		
	F_c	R_a	VB
1	0.9, 1.0, 1.0	0.9, 1.0, 1.0	0.9, 1.0, 1.0
2	0.1, 0.3, 0.5	0.7, 0.9, 1.0	0.9, 1.0, 1.0
3	0.3, 0.5, 0.7	0.3, 0.5, 0.7	0.1, 0.3, 0.5
4	0, 0, 0.1	0.5, 0.7, 0.9	0.9, 1.0, 1.0
5	0.1, 0.3, 0.5	0.7, 0.9, 1.0	0.9, 1.0, 1.0
6	0.7, 0.9, 1.0	0.3, 0.5, 0.7	0, 0.1, 0.3
7	0, 0, 0.1	0, 0, 0.1	0.9, 1.0, 1.0
8	0.7, 0.9, 1.0	0.1, 0.3, 0.5	0.9, 1.0, 1.0
9	0.3, 0.5, 0.7	0, 0, 0.1	0.5, 0.7, 0.9
10	0.7, 0.9, 1.0	0.7, 0.9, 1.0	0.3, 0.5, 0.7
11	0, 0.1, 0.3	0.7, 0.9, 1.0	0, 0.1, 0.3
12	0.3, 0.5, 0.7	0.5, 0.7, 0.9	0.1, 0.3, 0.5
13	0, 0, 0.1	0.3, 0.5, 0.7	0.5, 0.7, 0.9
14	0.1, 0.3, 0.5	0.3, 0.5, 0.7	0.9, 1.0, 1.0
15	0.9, 1.0, 1.0	0.5, 0.7, 0.9	0, 0.1, 0.3
16	0, 0, 0.1	0.1, 0.3, 0.5	0.5, 0.7, 0.9
17	0.7, 0.9, 1.0	0, 0, 0.1	0.9, 1.0, 1.0
18	0.3, 0.5, 0.7	0, 0.1, 0.3	0.3, 0.5, 0.7
19	0.7, 0.9, 1.0	0.5, 0.7, 0.9	0.9, 1.0, 1.0
20	0, 0.1, 0.3	0.5, 0.7, 0.9	0.7, 0.9, 1.0
21	0.3, 0.5, 0.7	0.5, 0.7, 0.9	0, 0, 0.1
22	0, 0, 0.1	0.1, 0.3, 0.5	0.5, 0.7, 0.9
23	0.1, 0.3, 0.5	0.5, 0.7, 0.9	0.1, 0.3, 0.5
24	0.9, 1.0, 1.0	0.9, 1.0, 1.0	0, 0.1, 0.3
25	0, 0, 0.1	0.3, 0.5, 0.7	0.1, 0.3, 0.5
26	0.7, 0.9, 1.0	0.1, 0.3, 0.5	0, 0.1, 0.3
27	0.3, 0.5, 0.7	0.3, 0.5, 0.7	0, 0.1, 0.3

- The best parametric combination to attain minimum cutting force, tool wear and surface roughness, was apparent at cutting speed 30 m/min, feed rate 0.08 mm/rev and depth of cut 0.2 mm, which was observed in experiment number 1.
- Lower surface roughness, cutting force and tool wear could be expected at moderate cutting speed, feed rate and depth of cut while machining CP-Ti grade 2 with uncoated carbide inserts under dry cutting environment.
- The proposed methodology was experienced systematic, easily understandable, and robust and can be implemented to solve similar types of problems associated in real time manufacturing systems.

Table 11 Weighted normalized fuzzy decision matrix

Alternative	Responses		
	F_c	R_a	VB
1	0.63, 0.9, 1.0	0.63, 0.9, 1.0	0.81, 1.0, 1.0
2	0.7, 0.27, 0.5	0.49, 0.81, 1.0	0.81, 1.0, 1.0
3	0.21, 0.45, 0.7	0.21, 0.45, 0.7	0.9, 0.3, 0.5
4	0, 0, 0.1	0.35, 0.63, 0.9	0.81, 1.0, 1.0
5	0.7, 0.27, 0.5	0.49, 0.81, 1.0	0.81, 1.0, 1.0
6	0.49, 0.81, 1.0	0.21, 0.45, 0.7	0, 0.1, 0.3
7	0, 0, 0.1	0, 0, 0.1	0.81, 1.0, 1.0
8	0.49, 0.81, 1.0	0.07, 0.27, 0.5	0.81, 1.0, 1.0
9	0.21, 0.45, 0.7	0, 0, 0.1	0.45, 0.7, 0.9
10	0.49, 0.81, 1.0	0.49, 0.81, 1.0	0.27, 0.5, 0.7
11	0, 0.09, 0.3	0.49, 0.81, 1.0	0, 0.1, 0.3
12	0.21, 0.45, 0.7	0.35, 0.63, 0.9	0.9, 0.3, 0.5
13	0, 0, 0.1	0.21, 0.45, 0.7	0.45, 0.7, 0.9
14	0.7, 0.27, 0.5	0.21, 0.45, 0.7	0.81, 1.0, 1.0
15	0.63, 0.9, 1.0	0.35, 0.63, 0.9	0, 0.1, 0.3
16	0, 0, 0.1	0.07, 0.27, 0.5	0.45, 0.7, 0.9
17	0.49, 0.81, 1.0	0, 0, 0.1	0.81, 1.0, 1.0
18	0.21, 0.45, 0.7	0, 0.09, 0.3	0.27, 0.5, 0.7
19	0.49, 0.81, 1.0	0.35, 0.63, 0.9	0.81, 1.0, 1.0
20	0, 0.09, 0.3	0.35, 0.63, 0.9	0.63, 0.9, 1.0
21	0.21, 0.45, 0.7	0.35, 0.63, 0.9	0, 0, 0.1
22	0, 0, 0.1	0.07, 0.27, 0.5	0.45, 0.7, 0.9
23	0.7, 0.27, 0.5	0.35, 0.63, 0.9	0.9, 0.3, 0.5
24	0.63, 0.9, 1.0	0.63, 0.9, 1.0	0, 0.1, 0.3
25	0, 0, 0.1	0.21, 0.45, 0.7	0.9, 0.3, 0.5
26	0.49, 0.81, 1.0	0.07, 0.27, 0.5	0, 0.1, 0.3
27	0.21, 0.45, 0.7	0.21, 0.45, 0.7	0, 0.1, 0.3

- The unification of fuzzy-MOORA, using the concepts of fuzzy set theory, was perceived to be a competent and acceptable effort in attaining the best parametric combination to confirm high productivity without compromising the quality. However, this might be limited to the selected range of process variables.

Table 12 Crisp values for weighted normalized fuzzy decision matrix

Alternative	Responses		
	F_c	R_a	VB
1	0.843	0.843	0.937
2	0.490	0.767	0.937
3	0.453	0.453	0.567
4	0.033	0.627	0.937
5	0.490	0.767	0.937
6	0.767	0.453	0.133
7	0.033	0.033	0.937
8	0.767	0.280	0.937
9	0.453	0.033	0.683
10	0.767	0.767	0.490
11	0.130	0.767	0.133
12	0.453	0.627	0.567
13	0.033	0.453	0.683
14	0.490	0.453	0.937
15	0.843	0.627	0.133
16	0.033	0.280	0.683
17	0.767	0.033	0.937
18	0.453	0.130	0.490
19	0.767	0.627	0.937
20	0.130	0.627	0.843
21	0.453	0.627	0.033
22	0.033	0.280	0.683
23	0.490	0.627	0.567
24	0.843	0.843	0.133
25	0.033	0.290	0.567
26	0.767	0.280	0.133
27	0.453	0.453	0.133

Table 13 Overall assessment value

Alternative	Responses			y_i	Rank
	F_c	R_a	VB		
1	0.843	0.843	0.937	2.623	1
2	0.49	0.767	0.937	2.194	3
3	0.453	0.453	0.567	1.473	15
4	0.033	0.627	0.937	1.597	14
5	0.49	0.767	0.937	2.194	3
6	0.767	0.453	0.133	1.353	16
7	0.033	0.033	0.937	1.003	24
8	0.767	0.28	0.937	1.984	6
9	0.453	0.033	0.683	1.169	18
10	0.767	0.767	0.49	2.024	5
11	0.13	0.767	0.133	1.03	23
12	0.453	0.627	0.567	1.647	11
13	0.033	0.453	0.683	1.169	18
14	0.49	0.453	0.937	1.88	7
15	0.843	0.627	0.133	1.603	12
16	0.033	0.28	0.683	0.996	25
17	0.767	0.033	0.937	1.737	9
18	0.453	0.13	0.49	1.073	21
19	0.767	0.627	0.937	2.331	2
20	0.13	0.627	0.843	1.6	13
21	0.453	0.627	0.033	1.113	20
22	0.033	0.28	0.683	0.996	25
23	0.49	0.627	0.567	1.684	10
24	0.843	0.843	0.133	1.819	8
25	0.033	0.29	0.567	0.89	27
26	0.767	0.28	0.133	1.18	17
27	0.453	0.453	0.133	1.039	22

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