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GREY BASED TAGUCHI APPROACH INTEGRATED WITH ENTROPY MEASUREMENT FOR OPTIMIZATION OF SURFACE ROUGHNESS AND DELAMINATION DAMAGE FACTOR DURING END MILLING OF GFRP COMPOSITES

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Abstract: The objective of this paper is to proposed to implement Grey based Taguchi method with quality loss function coupled with entropy measurement to optimize process parameters in CNC end milling of GFRP composites .End milling is the utmost process in machining division in the shop floor due to its capacity of generating complex shapes with reasonable accuracy and surface finish. However with the development of CNC milling machine, the flexibility has been incorporated along with versatility in the machining process. In order to build up a bridge between quality and productivity to obtain the same in an economic path, the present study highlights the optimization of surface roughness average of the milled slot on GFRP work piece material has been identified as quality attribute where as delamination damage factor has been treated as performance index directly related to productivity. An effort has been complete to optimize surface quality characteristic and performance index means that these multi criterions could be satisfied simultaneously up to the required level. Depending on specific importance, the precedence weight of entity of surface quality and productivity traits has been approximate by entropy measurement. Multi objectives spoke about to quality of the surface and performance index has been gathered to assess an equivalent single quality index called as grey relational grade which has been optimized finally by Taguchi technique.
Key words: CNC end milling, GFRP, Delamination damage factor, surface roughness, Grey based Taguchi method, Entropy measurement.

1. INTRODUCTION

Glass fiber reinforced polymer matrix (GFRP) composite materials offer superior properties like high specific strength and damping capacity, excellent corrosion and fatigue resistant and low coefficient of thermal expansion. Hence, they are used in automotive, aerospace, sporting goods, marine, chemical industries. In these areas, the milling of GFRP implies coping with problems that are not encountered when machining other conventional materials. End milling of GFRP composite materials may lead to widespread damage and may cause many problems arised with fiber such as delamination, breakage, pull out and micro cracking due to the non homogeneity and anisotropic nature. For this reason numerous authors in the literature has been investigated GFRP milling process and reported the factors that influence the surface quality of the finished component. Moreover, some researchers have investigated the effects of machining parameters particularly on the delamination damage behavior of GFRP composites (Babu, J. and Philip, J., 2014).

Roughness plays a key role in finding how a real surface of an object will interact with its surrounding conditions. Rough surfaces usually wear and tear more quickly and have higher friction coefficients than smooth surfaces. Roughness is frequently a common analyst of the recital of a mechanical component since in discretions on the surface may create nucleation sites for crack propagations and causes corrosion. Also roughness is usually undesirable, it is difficult and expensive to control during machining. Reducing roughness of a surface will generally exponentially increase its machinability costs. This often results in increasing component cost towards customer. However, the method in the rear side of the creation of roughness is complex and dependent on the type of machining process selection; therefore it is very difficult to calculate its value through analytical formulae. Therefore, in manufacturing sector machine operators usually apply trial and error methods to setup cutting conditions especially in end milling in order to obtain the desired surface roughness. This method is not effective and efficient because of time consuming. So it is a need for seeking a systematic approach that can help to setup milling operations and also to help in acquiring the desired surface quality. While slots formation in end milling of GFRP some defects are created between the fiber layers. These are defined as any deviation along the longitudinal or transverse directions of orientation of the fiber layers during preparing hand layup method especially in curing phase of the resin to prepare structure or component which is generally possible during the fabrication stage. Delamination comprises a stern discontinuity because they do not relocate interlaminar tangential forces and under compressive loads, they can cause rapid and disastrous buckling failure.

1.1 Motivation of the present work

Sunil Hansda et. al. (2014) adopted Taguchi method combined with utility concept approach to optimize the delamination factor and average surface roughness were taken as the measure of response characteristics for GFRP composites in drilling process. Authors are concluded based on experimental results that the spindle speed is insignificant but the feed rate is highly significant and effective than drill diameter and material thickness. Tom Sunny et. al. (2014) reported in their study the effect of speed and feed on delamination behavior of composite materials by conducting drilling experiments using Taguchi's orthogonal array and ANOVA using three different tools. The results of these experiments reveal that too low feedrate and high spindle speed can also increase the delamination damage. Chaudhari et. al. (2016) developed a Adoptive neuro fuzzy interface system (ANFIS) models to forecast delamination factor as a function of different combination of machining parameters. Yigit Karpat et. al. (2012) selected a sine function to represent the average relationship between cutting force coefficients and fiber cutting angle. In their study sine function is shown to yield good force predictions during milling of CFRP laminates. Vinod Kumar Vankanti et. al. (2014) presented in their report the optimization of drilling process parameters namely, cutting speed, feed, point angle and chisel edge width for glass fiber reinforced polymer (GFRP) composites using the application of Taguchi and ANOVA analysis. C.C. Tsao and H. Hocheng (2005) were utilized the medical equipment for the computerized tomography and C-Scan technique for measuring delamination during the drilling of CFRP composites. Theodoros Hasiotis et. al. (2011) investigated the efficiency of the ultrasonic inspection method to examine the defects in laminated composite fibrous CFRP and GFRP materials. Syed Altaf Hussain et. al. (2014) introduced an efficient optimization methodology using RSM and GA to minimize the surface roughness while turning of GFRP composites. I.S.N.V.R. Prasanth et. al. (2017) illustrated the influence and decisive analysis of milling process parameters on the surface quality of GFRP composite laminates was systematically carried out with a designed carbide end mill tool. R Vinayagamoorthy (2018) conducted a comprehensive review on major issues involved while machining of fiber reinforced plastics. In that review the author also discussed about the effect of cutting parameters and setting of optimal conditions for measured responses and also reported the different statistical techniques to enhance the machinability by some researches. F. Islam et. al. (2016) focused on prediction of framework for delamination damage in simplified manner during milling of unidirectional GFRP composites. Sreenivasulu R. (2013) also studied on end milling of GFRP composites and adopted artificial neural network (ANN) along with Taguchi's method to optimize surface roughness and delamination damage taken as responses. In his experimentation, travelling microscope was used to measure delamination damage.

The above review of literature describes that the earlier researchers concentrated on different features of modeling and simulation of surface quality during milling. Developed models gave the correlations among various cutting parameters during milling operations and surface roughness. Apart from surface quality, study on delamination damage has been found in a limited extent. Parametric optimization of milling process parameters and their responses has been reported too. But it has been identified that optimization is highlighted a single objective function. In a multi response process, it may arise the optimization of a single response may harm quality for rest of the output responses. Therefore it is advised to alter the individual objective function into correspondent single objective function; it is possible only by assigning individual response weights depending on their relative prominence. It seems that there is no particular guideline for this assignment of weights for chosen output responses and entirely depends on decision maker, so it may cause to change the optimality setting of parameters. In view of the above consideration the present investigations deals with the application of grey based Taguchi method for optimization of surface roughness and delamination damage factor during CNC end milling process with integration of entropy measurement methodology to evaluate priority of individual weights of responses based on statistical data acquired from experimental values.

2. EXPERIMENTATION

In the present work, glass fiber reinforced polymeric (GFRP) composite material was fabricated by hand layup method using 33% fiber and 66% general purpose resin with randomly oriented long fibers with size 300mmX50mmX25mm. In this investigation, the experiments were carried out on a CNC vertical machining center (KENT and ND Co. Ltd, Taiwan make) to perform 10mm rectangular slots along longitudinal direction by K10 carbide, four flute end milling cutter loaded on ATC (Automatic Tool Changer) of the CNC machine with a computer aided part programming as shown in Figure 1. Furthermore the cutting speed (rpm), the feed rate (mm/min) and depth of cut (mm) are controlled by choosing three different levels in the experiment. Each experiments was conducted as per Taguchi's L_9 orthogonal array plan which provides much reduced variance for the experiment resulting optimum setting of process control parameters. Orthogonal array provides a set of well balanced experimental settings (with less number of experimental runs) and Taguchi's signal to noise ratio (S/N), which are logarithmic function of desired output and act as objective functions in the optimization process. This methodology assists in data analysis and guess optimum results. The surface roughness was measured at five places on each slot then average of them in µm is taken by a surface analyser of Form Talysurf 50 (Taylor Hobson Co Ltd) which is shown in Figure 2. Similarly, the maximum delamination damage (W_{max}) around the rectangular slot periphery was obtained at randomly selected five points using ultrasonic C-scan setup as shown in Figure 3 after that delamination damage factor calculated using width of cut (W) has taken as diameter of the slot performed in end milling. Finally delamination damage factor (F_d) was found by relation i.e., $F_d = W_{max} / W$.

Table 1. Properties of GFRP provided by the supplier

Mechanical and Thermal Properties	Hand layup method
Tensile Modulus , [MPa]	169.75
Tensile Strength , [MPa]	60
Coefficient of linear expansion, [m/m°C]	$2x10^{-5}$
Thermal conductivity, [W/mK]	0.29
Density, [Kg/m^3]	1260

Table 2. Process control parameters and their levels

Symbol	Factors	Unit	Level 1	Level 2	Level 3
A	cutting speed	[rpm]	1000	1250	1500
B	feed rate	[mm/min]	200	300	400
C	depth of cut	[mm]	0.5	1	1.5

Fig. 1. GFRP work piece setting on CNC milling machine

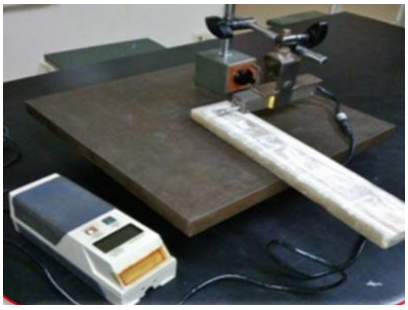

Fig. 2. Surface roughness measuring setup

2.1 Measurement of delamination damage

The ultrasonic C-Scan test was conducted on AIT-5112 setup to found the delamination damage obtained along the slots performed during end milling operation on GFRP composite work piece used in the experimentation. The workpiece was mounted in between the sender and receiver and scanned at standard incidence reflective angle through transmission mode by means of a standard broadband transducer with a frequency of 5 MHz. The measuring equipment contains a 0.025mm resolution scanner, an ultrasonic receiver of AIT-2230 type and a digitized oscilloscope used for radio frequency echo signal data acquisition. During scanning, the sender discharges ultrasonic waves while the attenuation through the receiver was recorded at each point on the machined slot and the measured information stored on the internal storage buffer and conveys this message to the CPU of the computer once the buffer is filled. A database acquisition system (DBMS) representing the internal delamination damage of the slot image was created, which permits to post-processer by selecting the suitable gate location and band width. A schematic of the ultrasonic C-Scan is shown in Figure 3. Extract the delamination damage results from images formatted in ultrasonic C-Scan were obtained from commercial software (Photo Impact 6.0) which contains a number of high-contrast images, each consisting of 200X200 pixel resolution and recorded in each scanning (sample image shown in Figure 4). The extraction of maximum delamination damage width was taken an average of five measurements along the length direction at five randomly selected points of a milled rectangular slot periphery.

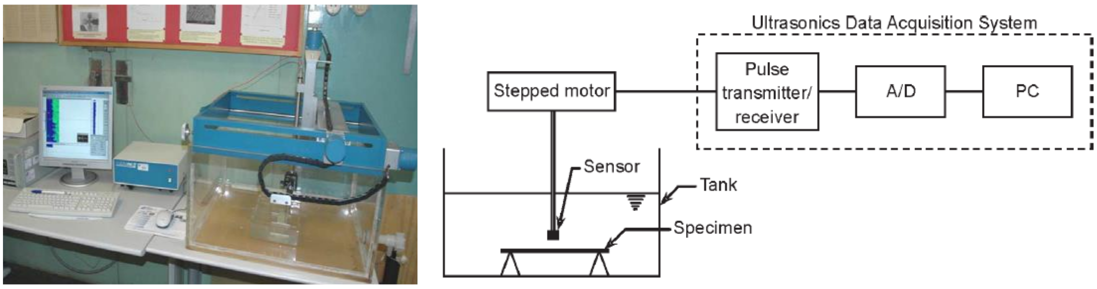

Fig. 3. Ultrasonic C-scan setup for measuring delamination damage

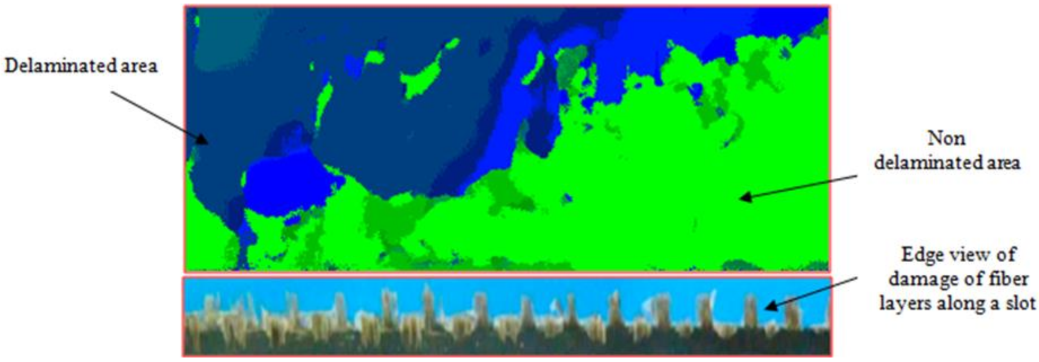

Fig. 4. Ultrasonic C-scan sample image of machined GFRP workpiece along a slot

3. GREY RELATIONAL ANALYSIS

The grey system theory can be utilized to solve the confused interrelationships among the multiple responses efficiently. In a grey system part of the information is known and some is unknown. GRA is applied in optimization of process parameters in various machining operations with multiple-responses. In the grey relational analysis, the grey relational grade is employ to show the relationship among the data sequences. If the two sequences are similar, then the value of grey relational grade is equivalent to one. The grey relational grade also represents the degree of influence that the comparability sequence could be expert over the reference sequence (experimental runs). Therefore, if a particular comparability sequence is more important than the other comparability sequences to the reference sequence, then the grey relational grade for that comparability sequence and reference order will be much more than other grey relational grades.

Table 3. Taguchi experimental plan as per L_9 orthogonal array and recorded responses

Exp.No	Machining parameters			Responses	
	Cutting Speed (A) [rpm]	Feed rate (B) [mm/min]	Depth of Cut (C) [mm]	Delamination damage Factor (F_d)	Average Surface Roughness (R_a) [µm]
1	1000	200	0.5	1.22	2.630
2	1000	300	1.0	1.85	5.306
3	1000	400	1.5	1.24	3.810
4	1250	200	1.0	1.56	5.178
5	1250	300	1.5	1.47	2.066
6	1250	400	0.5	1.68	6.192
7	1500	200	1.5	1.51	3.266
8	1500	300	1.0	1.18	8.670
9	1500	400	0.5	1.12	3.852

3.1 Data pre-processing

Data pre-processing was generally required because the range and unit of one data sequence may fluctuate from the other data sequence. Data preprocessing is also essential when the sequence disperse range is too large or when the directions of the goal in the sequence orders are dissimilar. Data pre-processing is a means of transporting the original sequence to a comparable sequence. If the target value of original order of data sequence is infinite, then it has a characteristic of the “larger is better” case. The original sequence can be normalized as follows:

$$x_i^*(k) = \frac{x_i^0(k) - \min x_i^0(k)}{\max x_i^0(k) - \min x_i^0(k)} \tag{1}$$

When the “smaller is better” case is a characteristic of the original order of sequence of data, then the original order of sequence should be normalized as follows:

$$x_i^*(k) = \frac{\left[\max x_i^0(k) - x_i^0(k)\right]}{\left[\max x_i^0(k) - \min x_i^0(k)\right]} \tag{2}$$

However, if there is a definite target value (desired value) to be achieved, the original sequence will be normalized in form:

$$x_i^*(k) = 1 - \frac{\left|x_i^0(k) - x^0\right|}{\max x_i^0(k) - x^0} \tag{3}$$

the actual order of sequence can be simply normalized by the most basic methodology, i.e. let the values of original sequence be divided by the first value of the sequence:

$$x_i^*(k) = \frac{x_i^0(k)}{x_i^0(1)} \tag{4}$$

Where, i = 1. . . m; k = 1. . . n. ‘m’ is the number of experimental data items and ‘n’ is the number of parameters, $x_i^0(k)$ denotes the original sequence, $x_i^*(k)$ the sequence after the data pre-processing, $\max x_i^0(k)$ the largest value of $x_i^0(k)$, $\min x_i^0(k)$ the smallest value of $x_i^0(k)$ and x_i^0 is the desired value.

For data pre-processing in the grey relational analysis, all the responses are taken as the “smaller is better”. All the data sequences after pre-processing using equation (2) comparability sequence are obtained from corresponding Table 4. The original (reference) sequences of each performance characteristics are transferred to comparable sequences by normalizing the experimental data. According to the Julong D. (1985) greater the normalized values of results corresponding to the better performance and the best normalized result should be equal to one and then the grey relational coefficients are found to be communicating the relationship between the ideal and the actual experimental results.

Table 4. Normalized response data (grey relational generation) and estimated quality loss data

SI, No.	Response data (normalized)		Quality loss data (estimated)	
	F_d	Ra	F_d	R_a
Ideal sequence	1.0000	1.0000	0.0000	0.0000
1	0.8631	0.9146	0.1369	0.0854
2	0.0000	0.5094	1.0000	0.4906
3	0.8356	0.7359	0.1644	0.2641
4	0.3973	0.5288	0.6027	0.4712
5	0.5205	1.0000	0.4794	0.0000
6	0.2328	0.3753	0.7671	0.6248
7	0.4657	0.8183	0.5342	0.1817
8	0.9178	0.0000	0.0822	1.0000
9	1.0000	0.7295	0.0000	0.2704

3.2 Grey relational coefficient and grey relational grade

In grey relational analysis, the measure of the relevancy between two systems or two sequences is defined as the grey relational grade. When only one sequence, $x^0(k)$, is available as the reference sequence, and all other sequences serve as comparison sequences, it is called a local grey relation measurement. After data pre-processing is carried out, the grey relation coefficient $\xi_i(k)$ for the k^{th} performance characteristics in the i^{th} experiment can be expressed as:

$$\xi_i(k) = \frac{\Delta_{\min} + \xi\Delta_{\max}}{\Delta_{0i}(k) + \xi\Delta_{\max}} \tag{5}$$

Here $\Delta_{0i} = \left\|x_0(k) - x_i(k)\right\| =$ difference of the absolute value $x_0(k)$ & $x_i(k)$; Ψ is the distinguishing coefficient $0 \le \Psi \le 1$; $\Delta_{\min} = \forall j^{\min} \in i \forall k^{\min} \left\|x_0(k) - xj(k)\right\| =$ the smallest value of Δ_{0i}; and $\Delta_{\max} = \forall j^{\max} \in i \forall k^{\max} \left\|x_0(k) - xj(k)\right\| =$largest value of Δ_{0i}. After averaging the grey relational coefficients, the grey relational grade γ_i can be computed as:

$$\gamma_i = \frac{1}{n}\sum_{k=1}^{n}\xi_i(k) \tag{6}$$

$$\gamma_i = \frac{\sum_{k=1}^{n} w_k \xi_i(k)}{\sum_{k=1}^{n} w_k} \tag{7}$$

The distinguishing coefficient ξ can be substituted into equation (5) to deduce the grey relational coefficient. If all the process parameters are of equal weightage, then ξ is 0.5. The grey relational coefficients and grade values for each experiment of the L_9 orthogonal array are calculated by applying equations (5 and 7) and depicted in Table 5.

Table 5. Grey relational coefficients of individual responses

SI. No.	Response values (normalized) for quality loss					
	Case-1		Case-2		Case-3	
	F_d	R_a	F_d	R_a	F_d	R_a
1	0.7849	0.8541	0.8455	0.7454	0.6460	0.8978
2	0.3333	0.5047	0.4286	0.3375	0.2000	0.6045
3	0.7526	0.6544	0.8202	0.4863	0.6033	0.7396
4	0.4534	0.5148	0.5544	0.3466	0.2932	0.6141
5	0.5105	1.0000	0.6100	1.0000	0.3427	1.0000
6	0.3946	0.4445	0.4943	0.2858	0.2458	0.5455
7	0.4834	0.7334	0.5840	0.5791	0.3188	0.8049
8	0.8588	0.3333	0.9012	0.2000	0.7526	0.4286
9	1.0000	0.6489	1.0000	0.4804	1.0000	0.7349

Table 6. Overall grey relational grade and predicted optimal setting

SI. No	Case-1	Case-2	Case-3
	$w_1 = w_2 = 0.5$	$w_1 = 0.75$, $w_2 = 0.25$	$w_1 = 0.25$, $w_2 = 0.75$
1	0.8195	0.7954	0.7720
2	0.4190	0.3831	0.4023
3	0.7035	0.6533	0.6714
4	0.4841	0.4505	0.4536
5	0.7552	0.8050	0.6713
6	0.4195	0.3901	0.3956
7	0.6084	0.5815	0.5618
8	0.5961	0.5506	0.5906
9	0.8245	0.7402	0.8675
Optimal setting	A3B3C3	A3B1C3	A3B3C1
Rank of factors	2(A), 3(B), 1(C)	2(A), 3(B), 1(C)	2(A), 3(B), 1(C)

Table 6 overall grey relational grades using the equation (7) for three sets of response weightage. In case 1, equal priority has been given to both delamination damage factor and average surface roughness. In case 2, 75% importance has been given to delamination damage factor and rest 25% provided for average surface roughness. Similarly in case 3, delamination damage factor assigned of 0.25 and surface roughness priority weight is 0.75.

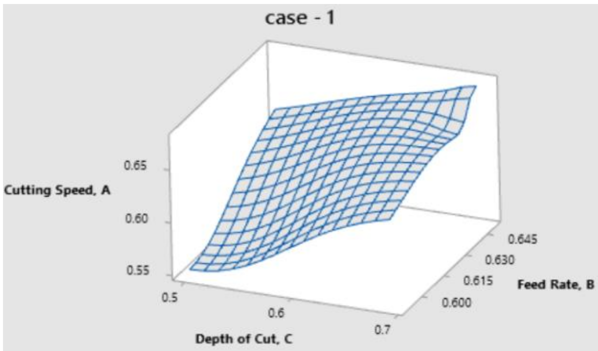

Fig. 5. Surface response plot for evaluation of optimal setting (case 1)

4. RESULTS AND DISCUSSIONS

Optimal factor setting for the aforesaid three case studies have been shown in Table 6. These have been evaluated from surface response plots obtained from Minitab@19 design expert software for all three cases and shown in Figures 5, 6 and 7 respectively. It has been observed that the optimal factorial combination is sensitive to the individual response weights. However, assignment of these weights greatly depends on the decision maker. Therefore, it seems to be a need to propose a means which can estimate the output response weights mathematically so as to evade disparity of optimal setting of input parameters due to various setting of output response priorities defined by the decision maker.

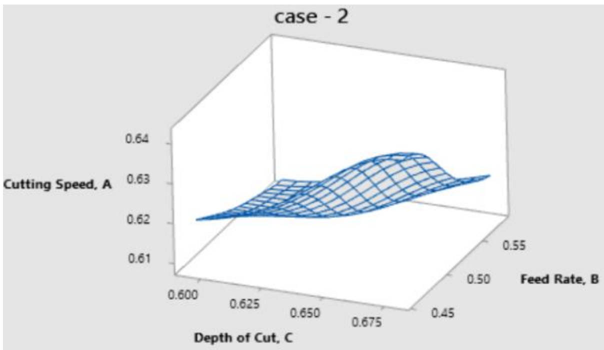

Fig. 6. Surface response plot for evaluation of optimal setting (case 2)

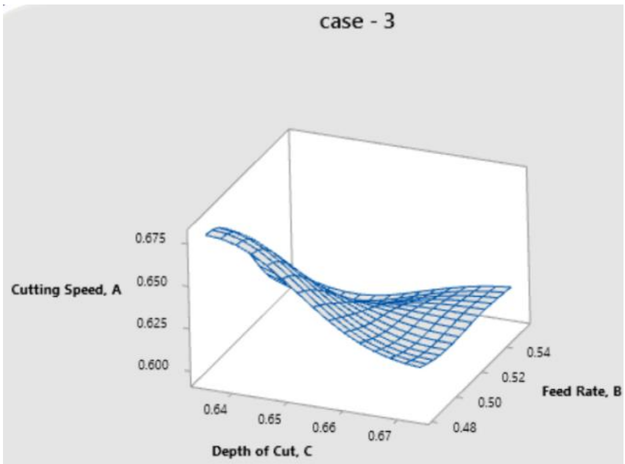

Fig. 7. Surface response plot for evaluation of optimal setting (case 3)

In sight of the above truth, the study recommends the relevance of entropy measurement method for orderly estimations and tactical assessment of individual response weights. The evaluation procedure is given in detail in further sections.

4.1 Entropy measurement technique

In theory of information, entropy is a quantitative measure of a physical system how it is disorder when subjected to external factors on it. As applying the phenomenon of this concept the weight measurement of individual factors which influence on the system. The effect of chosen attribute with a large entropy means that it has a more diversity to respond with a system which undergoes a process so the selected attribute has more significant to the response. Now days this method is used to decide the weights in grey relational analysis. According to this method, the mapping function $f_i:[0,1]\rightarrow[0,1]$ is used in entropy should convince three situations: (1) f_i (0) = 0; (2) f_i (x) = f_i (1-x) and (3) f_i (x) is monostimulantly increasing in the range $x\in(0,0.5)$, thus, the following function $w_e(x)$ can be used as the mapping function in entropy measure.

$$w_e(x) = xe^{1-x} + (1-x)e^{x} - 1 \qquad (8)$$

The greatest amount of this function occurs at x = 0.5 and the value is $(e^{0.5}-1)=0.6487$. In order to acquire the mapping result in the range [0, 1]. It is defined as new entropy function:

$$W \equiv \frac{1}{(e^{0.5}-1)}\sum_{i=1}^{m} w_e(x_i) \qquad (9)$$

Assume there is a order of sequence $\in_i=\{r_i(1), r_i(2), r_i(3), \ldots\ \ldots, r_i(n)\}$, where $r_i(j)$ is the grey relational coefficient. Also it is noticed that i = 1,2,3,4……,m; j = 1,2,3,……, n. m = total number of conducted experiments as per Taguchi's L_9 orthogonal array and n = total number of responses chosen in the experimentation.

The steps for weight calculation of each response is as follows

(a) Calculation of the sum of the grey relational coefficient in all data sequences for each response

$$D_j = \sum_{i=1}^{m} r_i(j),\ \ j = 1,2,\ldots\ldots,n \qquad (10)$$

(b) Evaluation of the normalized coefficient

$$k = \frac{1}{(e^{0.5}-1)\times m} = \frac{1}{0.6847\times m} \qquad (11)$$

(c) Calculation of the entropy of each response

$$e_j = k\sum_{i=1}^{m} w_e\left(\frac{r_i(j)}{D_j}\right), \ j = 1,2,\ldots,n \qquad (12)$$

Here, $w_e(x) = xe^{1-x} + (1-x)e^{x} - 1$

(d) Calculation of the sum of entropy

$$E = \sum_{j=1}^{n} e_j \qquad (13)$$

(e) Calculation of the weight of each response

$$w_j = \frac{1}{n-E}\cdot\frac{1}{\sum_{j=1}^{n}\frac{1}{n-E}[1-e_j]}, here,\ j = 1,2,\ldots,n \qquad (14)$$

The sum of grey relational coefficients Dj, j = 1, 2… for both delamination factor and surface roughness average, have been calculated using equation (10). These are depicted in Table 7. The value of the normalized coefficient has been calculated using equation (11). In the present case, m = 9. Therefore, the evaluated value of the normalized coefficient becomes k = 0.1713.

Table 7. Calculation of Dj (sum of grey relational coefficients)

Sum of grey relational coefficients of each responses	
Delamination damage factor	Average surface roughness
5.5715	5.6881

Table 8. Calculation of $\left(\frac{r_i(j)}{D_j}\right)$

SI.No.	$\left(\frac{r_i(j)}{D_j}\right)$	
	Delamination damage factor	Average surface roughness
1	0.1409	0.1502
2	0.0598	0.0887
3	0.1351	0.1150
4	0.0814	0.0906
5	0.0916	0.1758
6	0.0708	0.0781
7	0.0867	0.1289
8	0.1541	0.0586
9	0.1795	0.1141

The values of $\left(\frac{r_i(j)}{D_j}\right)$ and $k * w_e * \left(\frac{r_i(j)}{D_j}\right)$ for delamination damage factor and surface roughness average have been depicted in Table 8 and 9, respectively. Entropy of the responses has been calculated using equation (12); the values have been furnished in Table 10. The sum of entropy E = has been calculated using equation (13). The individual weights (Table 10) have been calculated using equation (14). It has been found that both delamination damage factor and surface roughness average are equally important $w_1 = w_2 = 0.5$. It corresponds to case 1. The overall grey relational grade has been calculated using equation (7) shown in Table 6 earlier. Hence, multi objective optimization functional task has been converted into a single objective optimization problem using the combination of Taguchi methodology and grey relational theory. Higher is the value of grey relational grade, the corresponding input factor combination is said to be close to the optimal. The optimal input factor combination as evaluated using Figure 5 is A3B3C3. After determining the optimal setting of input parameters, confirmatory test has been conducted and found satisfactory results. On optimal level of setting of parameters, experimentally attained value of overall grey relational grade became more compared to Taguchi's prediction.

Table 9. Calculation of $k * w_e * \left(\frac{r_i(j)}{D_j}\right)$

SI.No.	$k * w_e * \left(\frac{r_i(j)}{D_j}\right)$	
	Delamination damage factor	Average surface roughness
1	0.0551	0.0580
2	0.0259	0.0371
3	0.0532	0.0465
4	0.0343	0.0377
5	0.0382	0.0657
6	0.0303	0.0331
7	0.0364	0.0512
8	0.0593	0.0254
9	0.0667	0.0462

Table 10. Calculation of e_j (entropy of each quality indexes)

Entropy of each response	
Delamination damage factor	Average Surface Roughness
0.399398	**0.401029**

Table 11. Calculation of w_j (weightage value of each quality characteristics)

Response weights	
Priority value of Delamination damage factor (W_1)	Priority value of average Surface Roughness (W_2)
0.50068	**0.49932**

5. CONCLUSIONS

The earlier study deals with multi criterion optimization of CNC end milling by pertaining grey based Taguchi approach. Application of grey relation theory is suggested to alter multiple objectives into a single objective function (overall grey relational grade) to make it possible to investigate the influence of process parameters using Taguchi method. In conventional Taguchi technique not able to solve a multi objective optimization problem may not be solved especially in the case of design of experiments. So, in the present paper Taguchi method has been integrated with grey relation theory. Entropy measurement technique has been suggested to compute individual output response weights of the process according to their relative priority. The combination of entropy measurement with grey based Taguchi method was utilized in the present study proficiently implemented for continuous quality enhancement during a process not only CNC end milling but also any other conventional machining operations where multiple objectives come under consideration.

In the said above paragraphs, it has been assumed that all responses are independent i.e., uncorrelated. But in the actual practice this assumption may diverge. How to handle this situation appears truly a challenging job. There exists adequate scope to prolong a research in this particular direction. Furthermore, interaction effect of machining parameters may also be considered in future scope of work.

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