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Optimization of Machining Parameters Using Fuzzy Based Principal Component Analysis during dry turning operation of Inconel 625 – A hybrid approach

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Abstract

The paper presents a hybrid approach for optimization of machining parameters during dry turning operation of Inconel 625. Inconel 625 is known to be the most difficult to cut material and processing of which is a major challenge to the manufacturing sector. Various researches have been conducted to optimize the machining parameter using utility theory, grey relational theory in combination with Taguchi method. In this paper fuzzy based Principal component function coupled with Taguchi's design of experiment is used for optimization of machining parameters for minimum surface roughness, and power consumption, and maximum material removal rate. Taguchi based design of experiment facilitates the finding of the most relevant information about the feature of the system to be optimized. L9 orthogonal array has been chosen as the design of experiment for the current study. The multiple responses are aggregated into a single multi-performance index using fuzzy based Principal component function. To avoid uncertainty, imprecision and vagueness, fuzzy system is incorporated in this research work. The fuzzy reasoning grades so obtained are optimized using the Taguchi. The optimal setting and the influence of the process parameters on the multi-performance index is determined using response table, response graph and analysis of variance. Finally, optimal cutting conditions for the minimum machinability properties were highlighted.

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Keywords: Inconel 625; Taguchi method,; Principal component analysis; Fuzzy inference system

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1. Introduction

Inconel 625 is a nickel based alloy which exhibits excellent thermo-mechanical properties. These properties enable it to withstand stringent working conditions which find numerous applications in aerospace, nuclear, chemical and petrochemical industries [1]. However, processing of which poses certain bottlenecks and are referred to as difficult to cut material [2]. Loss of surface integrity due to excessive work hardening, rapid tool wear due to uneven strong stress field by thermo-mechanical coupling influences the overall economy of the manufacturing sector [3]. Numerous researchers have addressed the problem related to surface integrity so obtained after machining operation. It was noted from the work of A. Devillez et al. [4] that a cutting speed of 60 m/min in dry machining of Inconel gave acceptable surface finish using a coated carbide insert. Surface integrity of the machined part also depends on the type of cutting insert used. A comparative study on PVD coated monolayer and multilayer inserts was done by Jindal et al [5] and it was concluded from their work that multilayer coated carbide insert TiAlN performed better than TiCN and TiN owing to its high hardness at elevated temperature (T $\geq$ 750ºC) which is supported by the fact that TiAlN forms a protective layer of Al_20_3 and also an intermediate layer comprising of Ti, Al, N and O_2 which lead to higher oxidation resistance. The results obtained by Prengel et al [6] were in conjunction with the above mentioned work.

Generally, three important indexes are required to evaluate the overall performance of the turning process. They are surface roughness, power consumption and material removal rate. In such a multi-performance problem where the responses are correlated with cutting parameters viz. cutting speed, feed rate, and depth of cut, to ensure an optimal condition for operation an efficient optimization technique should be employed. Numerous experimental studies have been carried on to study the effect of each parameter on the process and optimization of dry turning operation of Inconel alloys. Taguchi's robust design method has been extensively used for optimization of process parameters. This method uses the S/N ratio of the response instead of the response itself to decide the level of the input parameter to optimize the output response [7, 8]. This procedure is beneficiary when it is used to optimize single response, but fails to optimize multiple responses. Such multi response problems can be solved using the MRSN technique where the total loss function is computed using to summing up weighted loss functions of individual response variables and then transformed to MRSN followed by optimizing the MRSN, one of the major limitations of this method is determining the weightage for each response which is a difficult task. PCA is one such method which eliminates these problems, where the numbers of variables are reduced to few, interpretable combinations. Each of this combination corresponds to a principal component and is uncorrelated with each other. Usually in the PCA method principal components with Eigen value greater than 1 are only considered because they account too much of the variation in data and the rest of the components are neglected for the optimization. Neglecting the components with lesser significance isn't viable when anticipating high accuracy. In this study we have proposed a new method to incorporate the missing variance while evaluating the multiple performance indexes using Fuzzy logic.

2. Analysis Method

2.1 Taguchi Experiment Design: Taguchi's robust design introduced by Genichi Taguchi is pinnacle amongst the design tools available for developing an efficient manufacturing system. It is a method often relied upon to design the orthogonal array of experiments, with much less variance amongst the experiment results. This method helps in developing orthogonal array with relatively less number of experiments sufficient to analyse and optimize the process.

2.2 Grey Relational Coefficient (Quality Characteristics): Grey relational approach has been widely used in engineering systems and solving several optimization problems [9-10]. In this approach the output characteristic data is normalized ranging from zero to one, known as grey relational normalization, this step is necessary because every attribute has different units and range, and sometimes the range of sequence is too large. Next, the grey relational coefficient is calculated using the normalized values, which represents the correlation between the desired value and actual experimental value followed by calculating the overall grey relational grade by averaging the relational coefficients, but according to the method suggested in this paper doesn't necessitate the generation of overall grade.

The grey normalized value for lower the better criterion can be determined using the formula:

$$x_i(k)\frac{\max y_i(k) - y_i(k)}{\max y_i(k) - \min y_i(k)}$$

The grey normalized value for larger the better criterion can be determined using the formula:

$$x_i(k)\frac{y_i(k) - \min y_i(k)}{\max y_i(k) - \min y_i(k)}$$

Where $x_i(k)$ is the grey normalized value for the k^{th} response and min $y_i(k)$ and max $y_i(k)$ being the largest and smallest value amongst $y_i(k)$ respectively.

2.3 Principal Component Analysis: PCA initially developed by Pearson and Hotelling to interpret large data in a more meaningful and easy way by developing linear combinations of the original responses. The q principal components devised through PCA method account to most of the variation of the original p responses, where $q \leq p$. Suppose X_1, X2……$X_p$be the p response variables, using PCA the following q uncorrelated can be calculated.

$Y_1=e_{11}X_1 + e_{12}X_2 +\ldots+ e_{1p}X_p$

$Y_2=e_{21}X_1 + e_{22}X_2 +\ldots+ e_{2p}X_p$

$Y_q=e_{q1}X_1 + e_{q2}X_2 +\ldots+ e_{qp}X_p$

Where e_{q1}, $e_{q2,}e_{q3}$ …$e_{qp}$are the elements of the q^{th} Eigen vectorand $e_{q1}^2+ e_{q2}^2+\ldots+e_{qp}^2 = 1$

It is to be understood that each principal component has different amount of Accountability proportion (AP), defined as how much the component accounts to the variation in data. When these components are accumulated they increase the accountability proportion and is referred as Cumulative accountability proportion (CAP). The PCA can be performed using software like MINITAB[11], STATISTICA, SAS, etc.

PCA is an effective method to determine small number of components that account major sources of variation in a huge data set where the operation involves multiple response variables. Wire EDM is one such process and so PCA approach was chosen as an efficient method for optimisation of Wire EDM.

2.4 Fuzzy Logic: Fuzzy logic introduced by LotfiZadeh, is problem solving system methodology providing an easy way to arrive at conclusion based upon incomplete, ambiguous, noisy values. Fuzzy logic's approach is tantamount to a human making decisions, but in a faster way. A Fuzzy Logic System consists of five important parts, Fuzzifier, Membership functions, Rules, Inference System, Defuzzifier. Firstly the fuzzifier converts the gathered crisp set of input data into fuzzy data using fuzzy linguistic terms and membership functions. Using the set of rules provided an inference is made, in the form of a fuzzy data which has to be converted into crisp data set, the defuzzifier using the membership functions converts it into crisp data. The component diagram of Fuzzy logic system is shown as fig.1

3. Methodology

This study presents a hybrid method for correlated multi responses using Fuzzy logic based PCA technique. Most of the PCA based optimization techniques consider only Principal Component with Eigen value greater than 1 (which accounts to most of the variance), to evaluate the performance index. The principal components with less accountability proportion are neglected implying a lesser accuracy. To achieve more accuracy by taking every principal component into consideration we have introduced a new method based on fuzzy logic to evaluate the Multiple Performance.

Before advancing to the methodology, we have listed down the parameters and variables used in this technique.

Parameters and Variables:

$y_i(k)$ Response value of the k^{th} response under i^{th} experiment
max $y_i(k)$ Maximum response value of the k^{th} response
min $y_i(k)$ Minimum response value of the k^{th} response
$x_i(k)$ Normalized Grey value of the k^{th} response under i^{th}experiment
$\Delta_{oi}(k)$ The absolute difference between the max $x_i(k)$ and $x_i(k)$
$\Delta_{min}(k)$ The minimum value of the $\Delta_{oi}(k)$
$\Delta_{max}(k)$ The maximum value of the $\Delta_{oi}(k)$
ζ Distinguishing Coefficient
ξ Grey Relational Grade
$Z_i(p)$ Principal component score of p^{th} principal component in i^{th} experimental trial
$\alpha_{kp}$$k^{th}$ element in the p^{th} Eigen vector
PC_1 First Principal Component 1
PC_2 First Principal Component 2
PC_3 First Principal Component 3
MPI_1 Multiple Performance Index 1
MPI Multiple Performance Index(Final)

The proposed method:

Step 1: Identify the significant variables in the process environment. It is necessary to identify the variables that influence the response(s) that we are interested.

Step 2: Design a proper experiment using Taguchi Design and run the experiments.

Step 3: Normalize the k^{th} response under i^{th}experimental trail using Grey Normalization Formula:
The grey normalized value for lower the better criterion can be determined using the formula:

$$x_i(k)\frac{\max y_i(k) - y_i(k)}{\max y_i(k) - \min y_i(k)}$$

The grey normalized value for larger the better criterion can be determined using the formula:

$$x_i(k)=\frac{y_i(k) - \min y_i(k)}{\max y_i(k) - \min y_i(k)}$$

Step 4: Calculate the grey relational grade to find relationship among the series using the formula:

$$\xi(k) = \frac{\Delta_{\max} + \zeta\Delta_{\max}}{\Delta_{oi}(\mathbf{k}) + \zeta\Delta_{\max}}$$

Step 5:
(a)Conduct Principal Component Analysis on the grey relational grade of each quality characteristic and find Eigen value λ_k and corresponding Eigen vector from correlation matrix formed by the grey grades.
(b)Evaluate the principal component score of each experiment using the formula below:

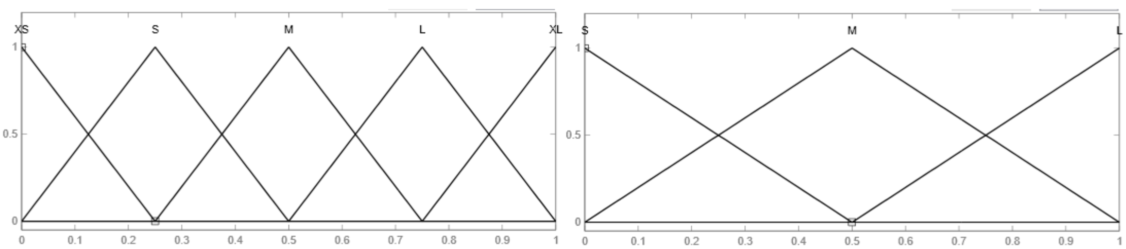
$$Z_i(p) \text{ is } \sum_{i=0}^{n} x_i(k)\ \alpha_{kp}$$

Step 6: Normalize the principal component scores of each principal component using higher the better criterion.
Step 7: Define the membership function and fuzzy rules, in this paper two input one output fuzzy logic system has been used. Such a system consists of a set of if-then control rules as stated below.

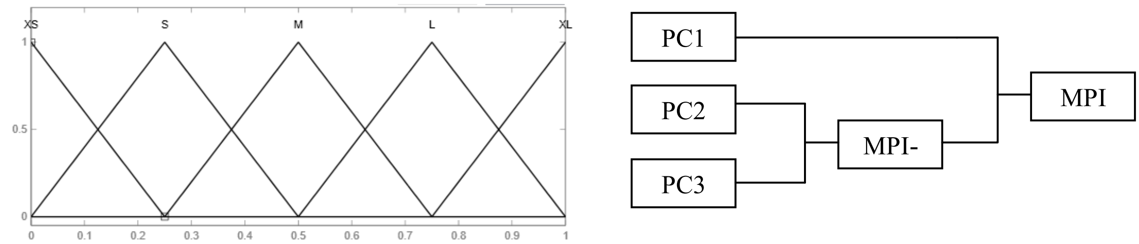
Rule 1: If f_1 is A_1 and f_2 is B_1 then f_3 is C_1 else
Rule 2: If f_1 is A_2 and f_2 is B_2 then f_3 is C_2 else
.
.

Rule m: If f_1 is A_m and f_2 is B_m then f_3 is C_m

f_1 and f_2 areinputs and f_3 is the output, A_i, B_i, $C_i$are fuzzy subsets defined by corresponding membership functions. In this method Five and Three Fuzzy subsets have been defined for the two inputs and Five subsets for the output as shown in fig (1).
Step 8: This step may vary according to the number of principal components one has to deal with, as this paper deals with three principal components the procedure has been illustrated for three PCs. Initially the principal components are classified into principal components with eigen value greater than 1 and the rest. Using the principal component scores corresponding to the components with eigen value less than 1(PC_2, PC_3) as input and obtain MPI1. Using the same rules and membership functions evaluate the final MPI using the major principal component (PC_1) and the MPI1 as input. This step is illustrated in the fig 2.
Optimal setting is then decided by the MPI value evaluated from 2 Step Fuzzy.



(a)Membership function of input 1 (b) Membership function of input 2



(c)Membership function of output

(d)Two Level Fuzzy Inference System

Fig.1

Multiple Performance Index		Input 1				
		XS	S	M	L	XL
Input 2	S	XS	XS	S	M	L
	M	XS	S	M	L	XL
	L	S	M	L	XL	XL

Table1: Fuzzy Rules

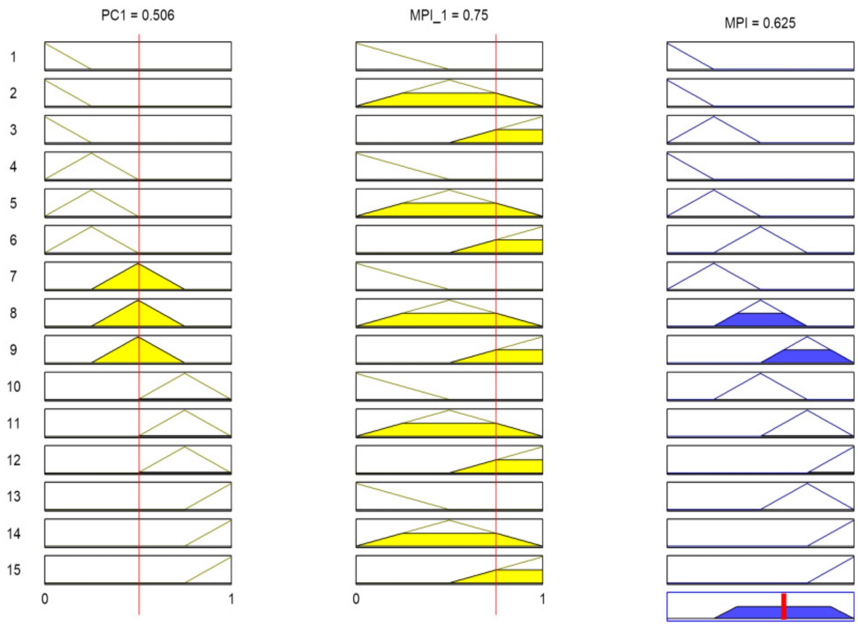


Fig 2: Membership Functions

4. Data Processing

Table2: Process parameters

Parameters	Code	Level 1	Level 2	Level 3
Cutting Speed (m/min)	A	30	50	70
Feed rate (mm/rev)	B	0.103	0.206	0.294
Depth of cut	C	0.4	0.8	1.2

Table 3:Quality characterization

S.no	Process parameters			Experimental Values			Grey Relational Coefficient		
	V	F	D	Ra	PC	MRR	RA	PC	MRR
1	30	0.103	0.4	2.785	0.2465	10.5678	0.463108	1	0.333333
2	30	0.206	0.8	2.9126	0.287	42.2712	0.442548	0.785032	0.39793
3	30	0.294	1.2	3.8543	0.537	90.4932	0.333333	0.337363	0.564251
4	50	0.103	0.8	1.3417	0.289	35.226	0.975983	0.776786	0.381501
5	50	0.206	1.2	3.062	0.3842	105.678	0.420681	0.517857	0.64977
6	50	0.294	0.4	3.237	0.4123	50.274	0.397665	0.47147	0.418398
7	70	0.103	1.2	1.6137	0.3378	140.7672	0.807459	0.618311	1
8	70	0.206	0.4	1.9503	0.313	49.3164	0.665298	0.689832	0.415838
9	70	0.294	0.8	3.4587	0.5423	73.9746	0.371888	0.333333	0.490405

Table 4: Principal Component Analysis

	$\Psi_1(PC_1)$	$\Psi_2(PC_2)$	$\Psi_3(PC_3)$
Eigen value	1.4603	1.1980	0.3417
Eigen Vector	[0.581,0.759,-0.294]	[0.573,-0.125,0.810]	[-0.578,0.639,0.508]
AP	0.487	0.399	0.114
CAP	0.487	0.886	1.000

Table 5: Evaluation of MPI

S.NO	PC			NORM PC			MPI_1	MPI
	PC1	PC2	PC3	PC1	PC2	PC3		
1	0.930	0.410	0.540	0.849	0	1	0.25	0.648
2	0.735	0.477	0.447	0.594	0.085	0.776	0.322	0.504
3	0.283	0.605	0.309	0	0.249	0.442	0.248	0.094
4	1.044	0.771	0.126	1	0.459	0	0.246	0.781
5	0.446	0.702	0.417	0.213	0.372	0.703	0.484	0.247
6	0.465	0.507	0.283	0.239	0.124	0.380	0.217	0.208
7	0.644	1.195	0.436	0.474	1	0.748	0.906	0.647
8	0.787	0.631	0.267	0.662	0.282	0.341	0.28	0.534
9	0.324	0.568	0.247	0.053	0.201	0.292	0.227	0.181

Table 6:Anova Analysis of responses

Source	DF	SS	Adj MS	F	P	%P
Surface Roughness (R_a)						
Cutting Speed (A)	2	0.6615	0.3307	2.26	0.307	11.02
Feed rate (B)	2	4.8417	2.4209	16.52	0.057	80.71
Depth of cut (C)	2	0.2019	0.1010	0.69	0.592	3.36
Error	2	0.2931	0.1466			4.88
Total	8	5.9983				
Notes: S = 0.382826 R-Sq = 95.11%						
Power Consumption (PC)						
Cutting Speed (A)	2	0.002982	0.001491	0.89	0.89	3.22
Feed rate (B)	2	0.072450	0.036225	21.73	21.73	78.31
Depth of cut (C)	2	0.013749	0.006875	4.12	4.12	14.86
Error	2	0.003334	0.001667			3.6
Total	8	0.092515				
Notes: S = 0.0408306 R-Sq = 96.40%						
Material Removal Rate (MRR)						
Cutting Speed (A)	2	2427.3	1213.7	3.95	0.202	18.78
Feed rate (B)	2	126.4	63.2	0.21	0.829	0.978
Depth of cut (C)	2	9753.5	4876.8	15.87	0.059	75.47
Error	2	614.8	307.4			4.76
Total	8	12922.0				
Notes: S = 17.5323 R-Sq = 95.24%						

Table7: Analysis of Variance for MPI

Source	DF	SS	Adj MS	F	P	%P
Multiple Performance Index						
Cutting Speed (A)	2	0.00326	0.00163	0.15	0.868	0.66
Feed rate (B)	2	0.42274	0.21137	19.63	0.048	86.02
Depth of cut (C)	2	0.04391	0.02195	2.04	0.329	8.93
Error	2	0.02153	0.01077			4.38
Total	8	0.49143				
Notes S = 0.103758 R-Sq = 95.62%						

Table8:Taguchi Analysis for MPI

Level	A	B	C
1	-10.073	-3.232	-7.619
2	-9.311	-7.849	-7.648
3	-8.026	-16.329	-12.143
Delta	2.048	13.096	4.524
Rank	3	1	2

6. Results and Discussion

This paper is an exposition of machining study of Inconel 625 with medium sharp cutting insert using a hybrid Fuzzy based principal component analysis method advocated by Taguchi. The results of the above study have elucidated below:

- The analysis has been performed using statistical analysis software (MINITAB). The ANOVA model of the hybrid approach is propitious enough to predict the influence of each input variables on surface roughness, power consumption and material removal rate with confidence level of 95.62%.
- Feed rate is determined to be the most prominent factor in the study that contributed to most of the variation. The contribution of each process variable is feed rate-68%, depth of cut-8.93%,cutting speed-0.66% ,determined using the above mentioned hybrid method.
- The optimum parameter values for the turning of Inconel 625 were found to be cutting speed 70mm/min, feed rate 0.103mm/rev and depth of cut to be 0.4mm.
- An acute improvement has been observed in the multi response optimization of machining parameters using this approach.

7. Conclusion

Table9: Comparison of confidence level of various optimization techniques

	GREY	PCA_W/O_GREY	PCA_W_GREY	PCA_FUZZY_W/O_GREY	PCA_FUZZY_W_GREY
R^2	92.54%	95.49%	94.83%	94.12%	95.62%
LEVELS	A3B1C3	A2B1C2	A2B1C2	A2B1C1	A3B1C1

The above table is a comparison of confidence level of different optimization procedures and the levels suggested by each method. The hybrid fuzzy based principal component analysis takes all the principal components into account to evaluate the performance index reducing the error. There is a substantial increase in the confidence level of this approach compared to that of grey method proving the novelty of this method. This hybrid concept is not just restricted to optimization of turning process, it can be used in optimization problems which have correlated multiple objectives. In addition, the benefit of using overall multi-performance indices (MPI), in this case hybrid fuzzy based PCA, in the Taguchi method is that the optimality of the parameters can be pledged through the monotonicity of the performance index.

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