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EXPERIMENTAL INVESTIGATION TO OPTIMIZE PARAMETERS OF REVERSE ENGINEERING TECHNOLOGY FOR RECONSTRUCTING FREE FORM SURFACES

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ABSTRACT

Reverse engineering technique is the process of duplicating an existing component by capturing the physical geometry of the components. In this work the influence of the various reverse engineering process parameters on the deviation (surface accuracy), process time, memory, defects and curvature deviations surfaced have been analyzed to reconstruct freeform surface with reverse engineering technology. The parameters considered are the noise levels, number of points and number of triangles. The effects of these input parameters on the responses have been critically analyzed using Taguchi method. The proposed approach was carried out on a model with freeform surface which was modelled in CAD software and machined on CNC machine.
The CAD models of the selected part are developed based upon combination of parameters given by Taguchi L9 orthogonal array design for point cloud obtained from portable non-contact CMM. It has been found that that the final responses of reverse engineering process for freeform surfaces depends significantly on number of input points of point cloud data, number of triangles in polygon model and noise reduction level.

Key words: *Reverse Engineering, Free Form Surfaces, Taguchi Method, Parameters, and Optimized Condition*.

I. INTRODUCTION

Engineering can typically be defined as “the application of scientific and mathematical principles to practical ends such as the design, manufacture, and operation of efficient and economical structures, machines, processes, and systems”[1]. This category of engineering is generally referred to as Forward Engineering. An emerging yet promising engineering concept is utilizing forward engineering in a reverse way. This method is referred to as Reverse Engineering. Several organizations defined reverse engineering in different ways in their respective perspectives. The society of manufacturing engineers(SME) states reverse engineering as the practice of “starting with finished product or process and working backward in a logical fashion to discover the underlying new technology”(Francis, 1988) [2] .Reverse engineering is the negation of forward engineering. Existing product is input to reverse engineering and subsequently a CAD model is created for modification or reproduction to the design aspect of the product. It can also be termed as the process of duplicating an existing component by capturing the component's physical dimensions. Reverse engineering is considered in order to redesign the system for better maintainability or to produce a copy of a system without having the design from which it was originally produced. The evolution of computer vision applications in the recent past added the advantages of rapid processing, accuracy and reliability in the Reverse Engineering processes. In medical, manufacturing, research and military applications there is a regular demand for reconstruction of scenes and objects, and this rapid prototyping becomes possible through the use of CAD model designs for inspection purposes. The ultimate aim of reverse engineering any product is to finally generate its 3-dimensional CAD which is free from noise, defects and holes. This needs a stable image acquisition system that can acquire data with high level of accuracy in a sufficient time frame. Reverse engineering system uses range and intensity images of objects as the inputs. The output of any reverse engineering system is 3D reconstruction of geometric primitives. Designing in CAD will be very challenging when products are more organic in shape. In those cases there is no guarantee that the CAD representation can replicate the freeform model exactly. Reverse engineering eliminates this problem as the physical model is the source of information for the CAD model

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II. SURFACE RECONSTRUCTION

2.1. Part selection

The selected part for this study is machined on CNC milling machine which is modeled on CAD package Fig.1. This part has freeform surfaces with sharp edges and is smooth enough to acquire a good point cloud data. The selected part with point cloud data acquisition setup is illustrated in Fig.2

Figure 1 Selected part

2.2 Point cloud data acquisition

The selected part is digitized using the portable laser scan arm. The portable flexible scan arm has a measuring range up to 6 feet and can scan up to 19,200 points/s with accuracy up to 35 microns. Acquired point cloud data is cleaned through the available tools viz. delete outliers and select disconnected components. Fig.2. Shows process of reverse engineering from digitization stage to CAD modelling stage.

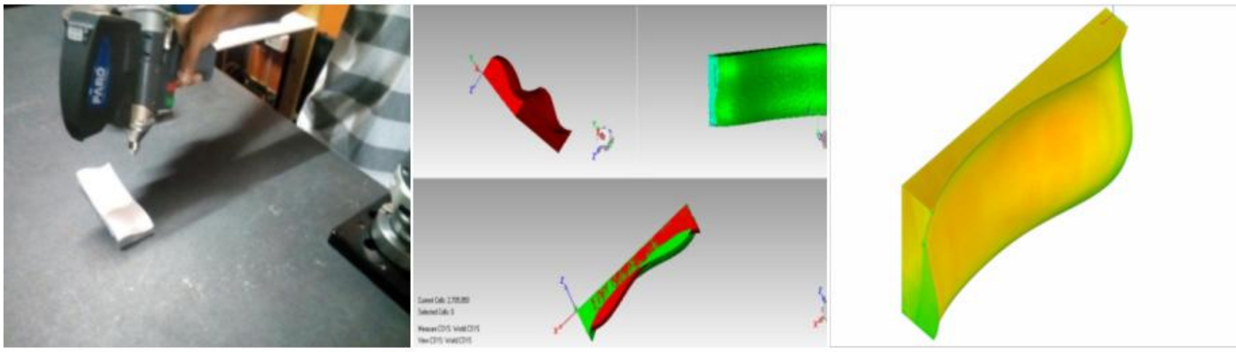

Figure 2 Reverse engineering process

III. TAGUCHI EXPERIMENT

To study the effects of various process parameters on the response, many statistical techniques is used. In the present investigation Taguchi method of experimental design is undertaken for the optimization of responses and trial runs are conducted for the range of the parameters. In this study three parameters namely noise reduction level, number of points and triangle count have been taken and the Table.1 shows those parameters with their levels. For conducting experiments L9 OA of Taguchi is employed and is presented in Table.2

Table 1 Process parameters

S. No	Parameter	Notation	Low (1)	Medium (2)	High (3)
1	Noise reduction	A	1	2	3
2	Number points (%)	B	33	66	100
3	Triangle Count (%)	C	33	66	100

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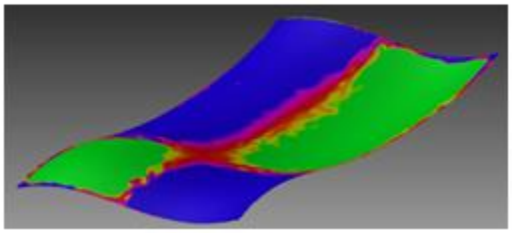
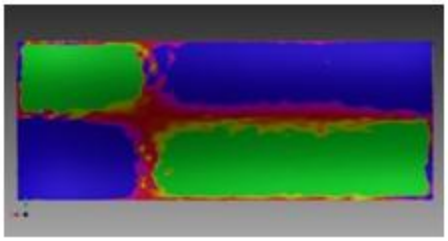
Table 2 L9 Orthogonal Array

Runs	A	B	C
1	1	1	1
2	1	2	2
3	1	3	3
4	2	1	2
5	2	2	3
6	2	3	1
7	3	1	3
8	3	2	1
9	3	3	2

The reverse engineering process is performed according to the design matrix and responses are observed. In this investigation the responses viz. deviation, memory, process time, defects and curvature deviations are observed and analyzed for their optimization. The offset distance between predefined points on actual surface and corresponding points on reverse engineered model is measured by contact based CMM. Root mean square (RMS) values of measured points are taken to calculate deviation. While stop clock experiment has Intel® core (TM) i34160 3.60GHz RAM 4GB 64-bit OS. Similarly memory and defects are noted from reverse engineered model while the curvature deviation is founded by comparing Gaussian curvature of reverse engineered model with the original CAD model as is illustrated in Fig.3



a) Gaussian curvature RE surface model



b) Top view of Test Image

Figure 3 Curvature Analysis

IV. RESULTS AND ANALYSIS

The experimentation is performed randomly to avoid the bias and the responses are observed. The measured responses of the reverse engineered point cloud data are presented in Table.3.

Table.4.1: Taguchi Results of the point cloud data

Run	Deviation (mm)	Memory (MB)	Time (Sec)	Defects	Curvature Deviation (%)
1	0.020122	28.90	160.89	843	63.10
2	0.026419	115.00	775.70	1122	57.30
3	0.019641	258.00	1274.70	1856	62.90
4	0.019641	57.80	276.10	473	58.02
5	0.021602	173.00	493.67	937	58.09
6	0.020562	86.50	425.01	841	62.50
7	0.020517	86.90	289.94	691	58.60
8	0.030295	57.60	282.60	340	57.25
9	0.026872	173.00	566.00	670	62.12

4.1. Taguchi Deviation analysis

The S/N ratio for the response deviation is computed and is presented in Table 4.2. The S/N ratio for each level of parameter is computed and presented in Table 4.2. The S/N ratio for each level and its overall means for each of the responses are taken and plotted on S/N ratio graph given in Fig.4.1.

Table.4.2: S/N ratio for deviation

S.No	Response	Parameter	S/N Ratio			Total Mean	Contribution %
			Low	Medium	High		
1	Deviation	Noise reduction level	13.21	13.73	11.85	12.93	35.98
		No. of points	13.94	11.75	13.10		44.38
		No. of triangles	12.68	12.37	13.73		19.04

These S/N ratios for the response are plotted at their levels of the Input parameters given in Fig 4.1. It is found that the deviation is effected largely by the parameter number of points and least by triangle count and moderately by the parameter noise reduction.

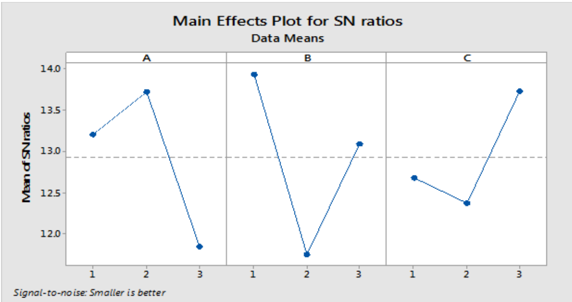


Fig.4.1 S/N ratio graphs for Deviation

Table.4.3. Optimal Deviation Condition-Taguchi

S.No	Response	Optimal Condition for Parameters		
		A	B	C
1	Deviation	Medium	Low	High

Table.4.4: ANOVA Computations for deviation

Source	DF	Adj SS	Adj MS	F-Value
A	2	0.004485	0.002242	62.09
B	2	0.005531	0.002766	76.58
C	2	0.002373	0.001187	32.86
ERROR	2	0.000072	0.000036	
TOTAL	8	0.012462		

Optimum condition for achieving the minimum deviation is obtained when the noise reduction is at middle level while number of points and triangle count at the low and high level respectively the condition is compiled in Table 4.3.

Taguchi Curvature Deviation Analysis

The S/N ratio for the response is computed and these are plotted for the input parameters the S/N ratios are given in Table 4.5 and the graphs are presented in Fig 4.2.

Table.4.5 S/N ratio for the curvature deviation

S.No	Response	Parameter	S/N Ratio			Total Mean	Contribution %
			Low	Medium	High		
1	Curvature deviation	Noise reduction level	-35.71	-35.54	-35.46	-35.56	10.62
		No. of points	-35.54	-35.20	-35.92		69.49
		No. of triangles	-35.69	-35.43	-35.54		9.31

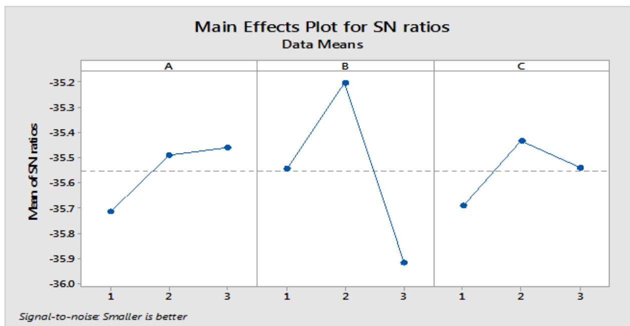


Fig.4.2 S/N ratio graphs for Curvature Deviation

Table.4.6. Optimal curvature deviation Condition-Taguchi

S.No	Response	Optimal Condition for Parameters		
		A	B	C
1	Curvature Deviation	High	Medium	Medium

Table 4.7 ANOVA Computations for curvature deviation

Source	DF	Adj SS	Adj MS	F-Value
A	2	5.646	2.823	1.00
B	2	36.931	18.466	6.57
C	2	4.946	2.473	0.88
ERROR	2	5.620	2.810	
TOTAL	8	53.144		

The variation in curvature deviation is caused majorly by the parameter no of points and almost equally by the remaining two other input parameters. The optimum condition for the minimum curvature deviation is obtained when the noise reduction is at its high level and the other parameters are at their middle level.

Taguchi memory analysis

The memory is influenced almost equally by the parameters no of points and triangle count and an insignificant effect is caused by the parameter noise reduction

Table.4.8: S/N ratio for the memory

S.No	Response	Parameter	S/N Ratio			Total Mean	Contribution %
			Low	Medium	High		
1	Memory	Noise reduction	-39.55	-39.58	-39.58	-39.57	3.71

		level					
		No. of points	-34.41	-40.39	-43.91		46.09
		No. of triangles	-34.39	-40.40	-43.92		46.36

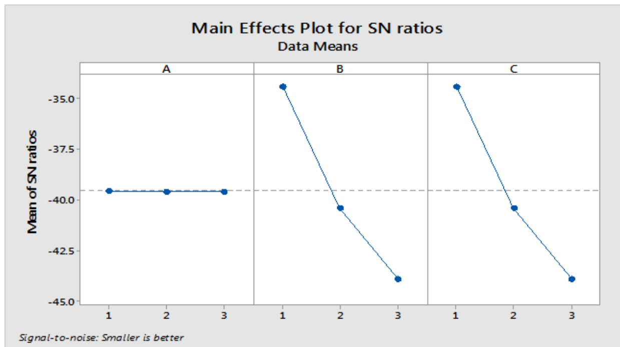


Fig.4.3 S/N ratio graphs for Memory

Table.4.9. Optimal memory Condition-Taguchi

S.No	**Response**	**Optimal Condition for Parameters**		
		A	**B**	**C**
2	Memory	Medium	Low	Low

Table 4.10 ANOVA Computations for Memory

Source	**DF**	**Adj SS**	**Adj MS**	**F-Value**
A	2	1587	793.4	0.97
B	2	19711	9855.6	12.06
C	2	19826	9913.0	12.13
ERROR	2	1634	817.2	
TOTAL	8	42758		

The S/N graph plotted is plotted by identifying the optimum condition it is found that the noise reduction at medium level and the other parameters were at their low level resulted in optimal condition.

Taguchi Defects analysis

The noise reduction parameter has contribute to the extent of 51.99% in causing the defects to occur while the triangle count influenced by 26.31% and the no of points influenced to the extent of 21.05%.

Table.4.14: S/N ratio for the Defects

S.No	**Response**	**Parameter**	**S/N Ratio**			**Total Mean**	**Contribution %**
			Low	**Medium**	**High**		
1	Defects	Noise reduction level	-61.63	-57.14	-54.65	-57.81	51.99
		No. of points	-56.27	-57.02	-60.13		21.05
		No. of triangles	-55.88	-57.01	-60.53		26.31

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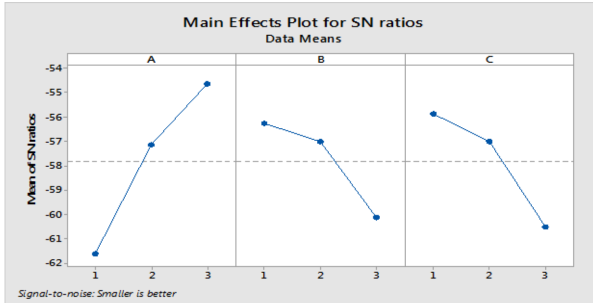

Fig.4.5 S/N ratio graphs Defects

Table.4.15. Optimal Condition-Taguchi

S.No	**Response**	**Optimal Condition for Parameters**		
		A	**B**	**C**
1	Defects	High	Low	Low

Table 4.16 ANOVA Computations for Defects

Source	**DF**	**Adj SS**	**Adj MS**	**F-Value**
A	2	806867	403433	80.86
B	2	326699	163349	32.74
C	2	408405	204202	40.93
ERROR	2	9978	4989	
TOTAL	8	1551948		

The minimum number of defected can be obtained when the noise reduction is at its highest level while the other parameters no of points triangle count are at their low level.

4.2. Taguchi analysis for all responses.

Table.4.17 Optimal Condition-Taguchi

S.No	**Response**	**Optimal Condition for Parameters**		
		A	**B**	**C**
1	Deviation	Medium	Low	High
2	Memory	Medium	Low	Low
3	Time	High	Low	Low
4	Defects	High	Low	Low
5	Curvature Deviation	High	Medium	Medium

The optimal condition is to have minimum of all the responses and is consolidated by having the high S/N ratio obtained from the parameters chosen Fig.4.1. The optimal condition as per Taguchi analysis given in Table.4.3
The curvature deviation and defects are in the least magnitude when the parameter triangle count is at low level while the memory and time are least when all the parameters are at the low level. It is found that the noise reduction parameter has contribution from 3.71 to 51.99 percent for achievement of all the responses, the parameter number of points contributed in the range 21.05 to 69.49 percent while the triangle count has accounted from 9.31 to 46.36 percent. For memory and curvature deviation responses very little effect is there from the parameter noise reduction level; however, this parameter is imparting large number of defects. All the responses are consistently and almost constantly affected by the second parameter number of points. The time of reconstructing and consequently the defects, curvature deviations are very high when the parameter number of points is at the highest level. It is found the majority of responses are optimized with noise reduction at high level, number of points at low level and triangle count at low level

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4.3 Modified Taguchi analysis

Taguchi method is designed effectively to study single quality characteristic, but for optimizing the process parameters for multiple quality characteristics simultaneously, modified Taguchi method would serve better [62][63]. The S/N ratios of all responses are added together by giving a weight age of 20% i.e. 1/5 to each and the weighted response is computed which is presented in Table.4.18.The weighted response S/N graph is plotted against the parameter levels as shown in Fig 4.6.

Table.4.18: Weighted Responses-Taguchi

S,No	Response	Parameter	S/N Ratio			Total Mean
			Low	Medium	High	
1	Weighted	A	-35.67	-34.06	-33.79	-34.53
		B	-31.94	-34.88	-36.69	
		C	-32.37	-35.11	-36.27	

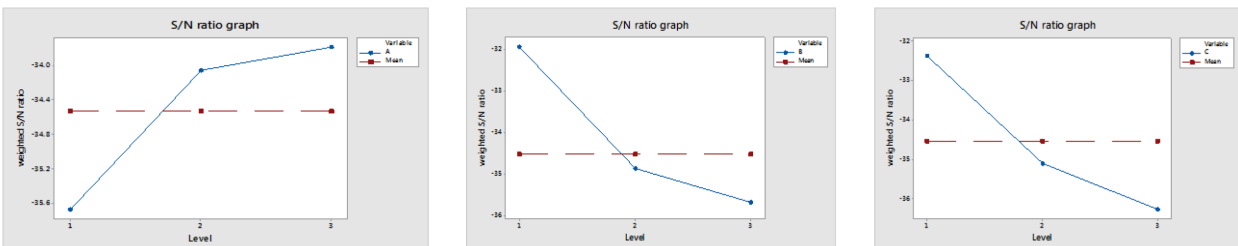

Fig.4.6 S/N ratio graphs for modified Taguchi analysis

V. CONFIRMATION EXPERIMENT

It is found the optimal condition is arrived by the Taguchi and modified Taguchi analyses with a specific combination of the parameters and levels. By employing these conditions, a new experiment is designed and conducted. It has yielded the responses as given in Table.4.19. These responses are the lowest and improved to a large extent by using the Taguchi method.

Table.4.19 Results of confirmation experiments

S.No	Input Parameters			Deviation (mm)	Memory (MB)	Process Time (sec)	Defects	Curvature Deviation (%)
1	High	Low	Low	0.019641	28.90	160.89	340	57.25

VI. CONCLUSIONS

- For deviation analysis a single point cloud is made for the object which is scanned multiple times and later merged.
- Noise reduction is done for removing outliers in the generation of better freeform surface.
- Wrapping process made the surface smooth while dealing with unorganized points
- Curvature deviation is better estimated by curve-D algorithm.
- The curvature deviation is 57.25% with 340 defects which are least in their magnitude when the parameters triangle count is at the low level and noise reduction is at the high level in the Taguchi analysis.
- The memory (28.9mb) and process time(167.89 secs) are least when the noise reduction, number of points and triangle count are at their lowest level while employing with Taguchi method.

- The optimal condition for curvature deviation by Taguchi method has been found when the noise reduction is at its high level(3) and the other parameters number of points (66%) and triangle count(66%) are at their medium level.
- The optimal condition for deviation by Taguchi method is found when the triangle count is at its high level(100%), noise reduction is at medium level(2) and number of points is at its low level(33%).
- The overall optimal conditions for all the responses namely deviation, memory, time, defects and curvature deviation are 0.0196mm,28.9MB,160.89secs,340 and 57.25% respectively These are found when the noise reduction is at its high level(3) and the other parameters are at their low level(33% each).
- Response surface methodology (RSM) have been applied for various sample sizes considering the factors noise reduction level, triangle count and smoothing levels for their quantitative effects on the responses. The minimum deviation is almost constant irrespective of sample size and the maximum deviation has reduced with increase of sample size. The perturbation in the deviation is noticed with independent with noise reduction level. The deviation is predominantly operated by smoothing levels and mildly by the parameter triangle count.
- The maximum deviation is 0.0621 mm with 20% sample size and found to be reduced to 0.0302 mm with 100% sample size
- The curvature deviation is lowest (54.4%) with medium samples and increased with small and large samples to the extent of 63.3%.The curvature deviation is importantly governed by the parameter smoothing levels and to a lesser degree by the parameter triangle count.
- The memory size has increased with the increase of sample size. It has occupied highest memory (28.7MB) when the parameter triangle count is taken at high level(100%). The other parameters did not play any major role in the response memory.
- The number of defects obtained are independent of sample size but solely dependent upon the parameter smoothing levels only. Highest number of defects(134) is resulted when the smoothing levels parameter is at its lowest level(0).
- Process time increased with the sample size similar to the response memory. The process time is lowest(5.21 secs) when the noise reduction levels is at its low level(0) in small samples while it has increased(22.66) with smoothing level in large samples(100% sample size).

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