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ORIGINAL ARTICLE

Performance analysis and optimization in turning of ASTM A36 through process capability index

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Abstract Organizations now a days acquaint process capability index (C_{pi}) to appraise the quality of their items with an aim to improve quality and cut down the operating costs which enhance the productivity and help them to stay competitive. In this paper process capability study is performed for turning operation, keeping in mind the end goal to check the process performance within specific limits. Three process input like spindle speed, feed and depth of cut has been chosen for process capability study in plain turning operation following Taguchi's L_{27} orthogonal array. Process capability index was evaluated for two machining attributes frequency of tool vibration and average surface roughness. Single response optimization was executed for these two machining qualities to explore the input settings, which could optimize turning process ability. Optimum parameter settings for frequency of tool vibration and average surface roughness were found to be spindle speed: 240 rpm, feed: 0.16 mm/rev, depth of cut: 0.2 mm. and spindle speed: 240 rpm, feed: 0.16 mm/rev, depth of cut: 0.1 mm. respectively.

1. Introduction

The quality of an item is measured as far as total loss to the society because of functional variety and side effects. More loss means lower quality. This loss happens because of the failure of the item to convey the desired performance and because of destructive side effects of it including its expenses. It is impractical to reach zero loss or perfect quality condition, yet utilizing robust design engineering technique we can enhance the quality of an item by minimizing the impact of the reasons for variation without eradicate of the causes. This is accomplished by optimizing the item and process design to make the execution insignificantly sensitive to causes of variation.

Based on the customer's needs and associated costs it is necessary for the supplier to set realistic cost and effective part specifications. Within the given tolerance limits capability studies can assess how well a process is capable of producing components. A viable quality administration framework ought to guarantee the nature of the parts in view of taking suitable corrective activities. If we know the capability of our process,

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we can choose the most convenient process among competing processes to fulfil the customer expectation. Process capability analysis helps to summarize process capability in terms of essential metrics and also helps to forecast the extent to which the machining process will be able to hold customer requirements or tolerances. It is an inherent quantitative measurement of a process to fulfil the requirements of the product (Kane, 1986; Kotz and Johnson, 1993; Montgomery, 2007; Wu et al., 2009).

Statistical quality control is an important concept for industrial managers to understand. Process Capability is the capacity of the procedure to understand a characteristic that will fulfil the prerequisites for that characteristic. As of late, process capability investigation has assumed a critical part in guaranteeing nature of fabricated items. The process capability index is generally utilized in industrial process as a part of modern procedure to monitor the product as per the specification limits. This kind of capability index is valuable to decrease the variety in the product.

Turning, primitive machining processes in the manufacturing industry, is a basic material removal process which is carried out on a lathe. Lathe has the ability to turn the work-piece in a desired shape with the help of cutting tool at a feed, given rotational speed and at a predefined depth of cut. Researchers have attempted several approaches to identify multiple process parameter settings that can increase quality, at higher productivity levels; require the turning process to be executed more efficiently. So it is utmost important to identify optimal parameter settings using a process capability index to improve tool life, lessen cutting force, reduce chip thickness and increase surface accuracy in turning process.

Process capability index is outline insights which quantify the real or the potential execution of procedure attributes with respect to the objective and particular points of confinement. It has been the most regularly utilized index as a part of the practice since it gives limits on the procedure division of defectives. It is an important conception under statistical process control which portray the strength of a process to produce components within tolerance limits.

As of late, to know whether the process can meet the requirements a statistical quality control approach known as Process Capability Analysis (C_{pi}) has been introduced. C_{pi} plays a significant part in persuade quality of manufactured products. Several modern businesses these days recommend the process capability index and utilize it as a management tool for measuring products quality (Chen et al., 2015). Higher the index, very less chance that the item will be outside the specifications. As noted by numerous quality control practitioners and researchers, Process Capability Index is yield-based and is not dependent on target (Pearn, 1998). It is a competent tool which continuously improved quality, productivity and also helps in taking administrative decisions (Rajvanshi and Belokar, 2012) and can measure the internal potential of a process. Capability index (C_{pi}) demonstrates that within the range specified by the design limits how well a produced part can fit (Abdolshah, 2013).

Using Taguchi's quality loss function Antony (2001) figures out the important factors that effect turning operation and also finds out the optimal settings. Pawade and Joshi (2011) used Taguchi grey relational analysis to optimize different input parameters for high speed turning and shows that feed rate display strong effect on surface roughness and cutting forces. Through desirability function Abhang and Hameedullah (2015) optimized tool wear and surface roughness when they turn EN-31 steel. Tungsten carbide inserts were used to studied controllable parameters like cutting velocity, tool nose radius, and concentrations of solid–liquid lubricants, feed rate and depth of cut. Shihab et al. (2014) examined turning parameter effect on surface roughness and micro-hardness in CNC hard turning and found that sequence wise feed rate, depth of cut and cutting speed were the most effective parameters on surface integrity. Suresh et al. (2014) find out the machining parameters' optimal level of turning process using grey-fuzzy algorithm for Al–SiC–Gr hybrid composites. They took feed rate, cutting speed and mass fraction of SiC–Gr as process parameters for their L_{27} orthogonal array. Jana et al. (2010) turn mild steel in CNC turning and using RSM method find out that feed, depth of cut and cutting speed are the significant factor for high MRR and low surface roughness. Cabrera et al. (2011) also used cutting speed, depth of cut and feed rate as input parameters in turning of reinforced PEEK CF30 and also used Grey Taguchi approach to optimize cutting force and surface roughness. Bhagora and Shah (2015) used input parameters like cutting speed, cutting depth, tool nose radius and feed rate in turning of ASTM A242 TYPE-2 ALLOYS STEEL. They used artificial neural network and Regression analysis to optimize surface roughness.

Few researchers used different gradient-free method to optimize different machining parameters in machining operations. Martin et al. (2009) used genetic algorithm to find out optimal tuning to maximize the tool's working life and the material removal rate for a network controlled high-performance drilling process. Sardiñas et al. (2006) used genetic algorithm to optimize tool life and operation time for turning operation taking into account cutting depth, feed and speed as cutting parameters. Haber et al. (2002) introduced knowledge-based system Fuzzy Logic Controllers and Fuzzy Models for process supervision, control and its application to the machining processes.

From these literature overview, it can be seen that as far as process effectiveness, quality of output or economy concern, there has been a basic absence of experimental studies on process capability of turning process. Extensive work has been carried out using Process Capability investigation on different steps of managerial process (Amiri et al., 2012; Aslam et al., 2013; Basu et al., 2014) and also in machining processes like WEDM (Chalisgaonkar and Kumar, 2014), grinding (Kumar et al., 2012), casting (Singh and Singh, 2013) but very few works have been done on Turning (Erameh et al., 2016; Kahraman et al., 2012).

Surface roughness plays an essential part to figure out how an actual item relates with its surroundings and also an important predictor of mechanical items performance. It also has considerable effect on machined part's properties like fatigue and wear resistance etc. Tool vibration effects surface roughness as well as the final design of the work-piece. So frequency of tool vibration is an important criteria we have to consider during turning in lathe. Thus, the motivation behind this paper is to concentrate on the assessment and advancement of process capability index of turning operation for two essential quality attributes; frequency of tool vibration and average surface roughness. Based on the researcher's work (Antony, 2001; Cabrera et al., 2011; Khan and Maity, 2016; Parida and Maity, 2016) three essential input parameters like spindle speed, feed and depth of cut has been chosen for this experimental work. Thus, the results can be utilised by the engineers willing to identify an optimal solution of turning operation of ASTM A36 Mild Steel bar.

2. Materials and methods

Plain turning experiments were performed on a heavy duty Panther Lathe Machine. Manufactured by- Gujarat Lathe Manufacturing Co. Pvt. Ltd, India Model-2050/4 (Centre Height: 254 mm.; No. of Spindle Speed: 8; Range of Spindle Speed: 30–1235 rpm; Feed Range: 40 mm/rev.). The work piece material was ASTM A36 Mild Steel bar of 24 mm. diameter and 300 mm. length. Table 1 shows the material composition of ASTM A36. Square shaped cemented carbide cutting tool insert was used for all the experiments. To minimize the experiments turning operations were carried out following L_{27} Orthogonal Array (by the help of MINITAB 16 Statistical Software) taking three prevalent input parameters spindle speed, feed and depth of cut were taken as input criterion. Machining parameters which were considered for experiments are shown in Table 2. Frequency of tool vibration was measured using analyser Picoscope 2202. It was mounted some distance from the tool tip to measure vibrations in the cutting speed direction. This position was as close as possible to the tool tip, but at a sufficient distance to prevent metal chips from the job surface during turning. After the experiments average surface roughness of all machined surfaces was measured utilizing Mar Surf PS1 Surface Roughness Tester. The surface roughness was measured at five different locations on the machined surface and average value of surface roughness has been taken for further examination.

3. Methodology

Process capability indicates an execution measure of the machine operation which turned out to be exceptionally famous in evaluating the capacity of manufacturing procedures henceforth deciding the machine tool achievement. More endeavours have been given to uses and studies of process capability index. A process capability index is a numerical synopsis that analyses the behaviour of an item or procedure characteristic in designing details.

3.1. Assessment of process capability

Following three steps are followed to find out the process capability of attributes criterion. In this work frequency of tool vibration and average surface roughness are two attributes.

1st Step. Computation of mean ($\overline{X}$): Computation of mean is ascertained for every trial run by using following equation.

$$\overline{X} = \sum_{i=1}^{N} \frac{x_i}{N} \tag{1}$$

Here,

X_i = response parameter value for *i*-th replicate trial.
N = number of replicates.

2nd Step. Computation of standard deviation (σ): Following equation was used to compute Standard deviation (σ).

$$\sigma = \sqrt{\frac{\sum_{i=1}^{N} \left(x_i - \overline{X}\right)^2}{N}} \tag{2}$$

Here,

x_i = Response parameter value for i-th replicates of a distinct trial.
$\overline{X}$ = Mean of the N replicates for the trial.

3rd Step. Process capability index (C_{pi}): following equation was used to calculate process capability index (C_{pi}) for each experimental run.

$$C_{pi} = \min\left\{\frac{[\overline{X}] - LSL}{3\sigma}, \frac{USL - [\overline{X}]}{3\sigma}\right\} \tag{3}$$

Here,
USL = upper specification limit for individual attributes.
LSL = lower specification limit for individual attributes.

USL and LSL actually are a destination value. Specification limits are typically provided from outside which depends on production necessities, market prerequisites). It can either be one-sided or two-sided.

3.2. Single response optimization

In mid-1980s Taguchi introduced signal-to-noise (S/N) ratio to reduce variation and to optimize design parameters. S/N ratio is the most critical and valuable parameter when analysed with respect to the target and variety in contrasting of two arrangements of tests. In this research, to find out quality characteristics evaluation index, objective parameters are converted into S/N ratio. To achieve robust process performance, a higher value of S/N ratio is desirable. There are three sorts of signal-to-noise ratio depending on the attribute characteristics which are smaller-the best, larger-the-best and nominal-the-best. To diminish alteration of response parameters like frequency of tool vibration and average surface roughness within specification limits our main focus is to maximize process capability index (C_{pi}). To find out the S/N ratio in smaller is the best criterion we have to follow the following equation:

$$S/N_{cpi} = -10\log_{10}\left[\frac{1}{\mathrm{n}}\sum_{i=1}^{n}\frac{1}{y_{ij}^2}\right] \tag{4}$$

Table 1 Chemical composition of ASTM A36 Mild steel.

Material	C	Mn	Cu	Si	S	P	Fe
Percentage (%)	0.15	1.03	0.20	0.22	0.022	0.030	Balance

Here

y_{ij} = Response value of a characteristic in ith replicate of the jth trial.
n = total number of trials.

4. Results and discussions

To find out the process capability of two attributes known as frequency of tool vibration and average surface roughness in our turning operation, we took two trials for each set of experiments following Taguchi's L_{27} which is shown in Table 3. After that the mean value ($\overline{X}$) of each experiment was found out using equation 1. Standard deviation (σ) for each experiment were found out using Eq. (2). Following that process capability index (C_{pi}) for two attributes were observed using Eq. (3) and represent in tabulated form in Table 4. For process capability analysis following specification limits were selected.

USL for frequency of tool vibration = 420 Hz,
LSL for frequency of tool vibration = 260 Hz,
USL for surface roughness = 7.0 μm,
LSL for surface roughness = 0.0 μm.

To maximize process capability index (C_{pi}) following Eq. (4) S/N ratio was ascertained in smaller is the best criterion. Figs. 1 and 2 represent the S/N ratio plots for C_{pi} (frequency of tool vibration) and C_{pi} (average surface roughness) respectively. Table 5 shows optimum parameter settings for both the outputs.

4.1. Confirmation experiments

At the concluding stage Taguchi's parametric design is to forecast and certify the enhancement of the performance characteristics with the preferred optimum parameter setting. Using the optimum level of process parameters the predicted values of the S/N ratio ($\hat{\gamma}$) can be calculated as:

Table 2 Input parameters with their limits.

Parameter	Denotation	Level		
		Low	Medium	High
Spindle speed (rpm)	A	160	240	400
Feed (mm/rev)	B	0.08	0.16	0.32
Depth of cut (mm)	C	0.1	0.15	0.2

Table 3 Experimental design and collected response data.

Exp. No.	Spindle speed (rpm)	Feed (mm/rev)	Depth of cut (mm)	Frequency of tool vibration f (Hz)		Average surface roughness R_a (μm)	
				1st Trail	2nd Trail	1st Trail	2nd Trail
1	160	0.08	0.15	270.7	271.2	1.97	2.24
2	160	0.08	0.2	281.1	280.7	2.01	2.11
3	160	0.32	0.15	325	311.8	6.84	6.72
4	160	0.32	0.1	322.9	321.6	6.16	6.25
5	160	0.16	0.1	295	295.7	2.58	2.67
6	400	0.32	0.15	395	395.8	5.46	5.72
7	240	0.16	0.1	326.5	322	2.38	2.47
8	400	0.16	0.15	362	360.2	1.68	1.85
9	160	0.16	0.2	310	308.6	3.02	3.21
10	400	0.16	0.1	347	344.6	2.29	2.43
11	240	0.16	0.15	337.7	340.1	2.20	2.31
12	400	0.08	0.2	355	356.7	1.66	1.75
13	240	0.32	0.1	350	351.8	6.01	6.23
14	240	0.08	0.1	297	295.9	1.59	1.48
15	240	0.08	0.15	321	322.8	1.80	1.72
16	160	0.08	0.1	263.2	262.8	1.88	1.97
17	240	0.08	0.2	325.7	324.8	1.82	1.65
18	160	0.32	0.2	345.8	344.1	6.72	6.39
19	400	0.08	0.15	342.2	340.8	1.54	1.68
20	160	0.16	0.15	302.7	301.5	3.42	3.22
21	400	0.16	0.2	383.8	384.5	2.60	2.41
22	240	0.32	0.15	371.8	370.8	5.84	5.62
23	400	0.32	0.1	376	374.4	5.82	5.58
24	240	0.32	0.2	374.7	373.8	6.28	6.08
25	400	0.32	0.2	401	401.4	5.89	5.65
26	240	0.16	0.2	352.6	353.8	2.84	2.71
27	400	0.08	0.1	322.2	320.8	1.38	1.52

Table 4 Evaluation of process capability index (C_{pi}).

Exp. No	$\bar{X}$ (Frequency)	σ (Frequency)	C_{pi} (Frequency)	$\bar{X}$ (Roughness)	σ (Roughness)	C_{pi} (Roughness)
1	270.95	0.25	14.60	2.105	0.135	5.20
2	280.9	0.2	34.83	2.06	0.05	13.73
3	318.4	6.6	2.95	6.78	0.06	1.22
4	322.25	0.65	31.92	6.205	0.045	5.89
5	295.35	0.35	33.67	2.625	0.045	19.44
6	395.4	0.4	20.50	5.59	0.13	3.62
7	324.25	2.25	9.52	2.425	0.045	17.96
8	361.1	0.9	21.81	1.765	0.085	6.92
9	309.3	0.7	23.48	3.115	0.095	10.93
10	345.8	1.2	20.61	2.36	0.07	11.24
11	338.9	1.2	21.92	2.255	0.055	13.67
12	355.85	0.85	25.16	1.705	0.045	12.63
13	350.9	0.9	25.59	6.12	0.11	2.67
14	296.45	0.55	22.09	1.535	0.055	9.30
15	321.9	0.9	22.93	1.76	0.04	14.67
16	263	0.2	5.00	1.925	0.045	14.26
17	325.25	0.45	48.33	1.735	0.085	6.80
18	344.95	0.85	29.43	6.555	0.165	0.90
19	341.5	0.7	37.38	1.61	0.07	7.67
20	302.1	0.6	23.39	3.32	0.1	11.07
21	384.15	0.35	34.14	2.505	0.095	8.79
22	371.3	0.5	32.47	5.73	0.11	3.85
23	375.2	0.8	18.67	5.7	0.12	3.61
24	374.25	0.45	33.89	6.18	0.1	2.73
25	401.2	0.2	31.33	5.77	0.12	3.42
26	353.2	0.6	37.11	2.775	0.065	14.23
27	321.5	0.7	29.29	1.45	0.07	6.90

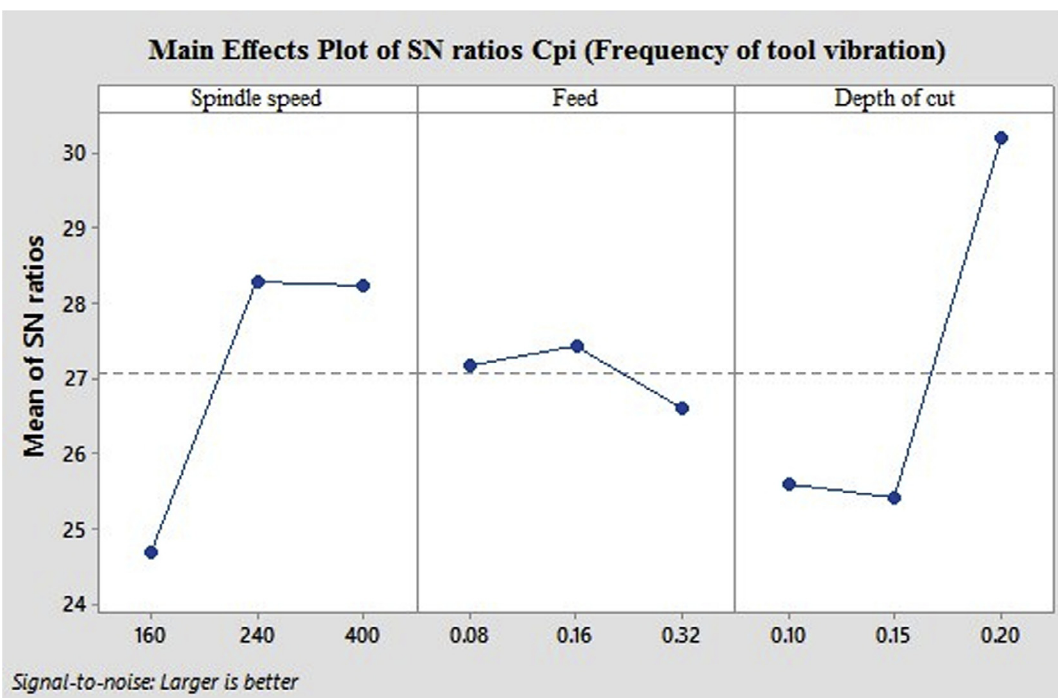

Figure 1 S/N ratio plot for C_{pi} (Frequency of tool vibration).

$$\hat{\gamma} = \gamma_m + \sum_{i=0}^{p} (\bar{\gamma}_j - \gamma_m) \tag{5}$$

Here

γ_m = mean value of S/N ratio of total experimental runs.

$\bar{\gamma}_j$ = S/N ratio corresponding to the optimum factor level.

p = number of factors.

Table 6 shows confirmation test results which were conducted in optimum conditions. Predicted machining performance and actual machining performance were compared and satisfactory reconciliation was retrieved between these two performances which validate the result. The advancement of the C_{pi} (frequency of tool vibration) and C_{pi} (average sur-

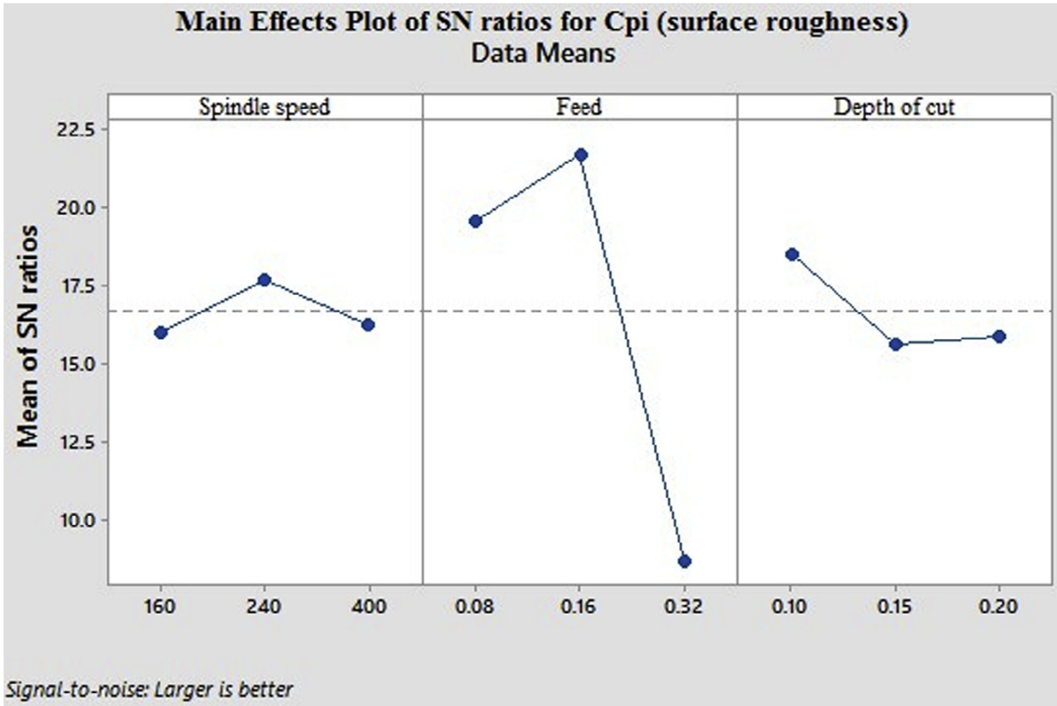

Figure 2 S/N ratio plot for C_{pi} (Average surface roughness).

Table 5 Optimal parameter settings for single response.

Response characteristics	Optimal parametric setting
Frequency of tool vibration, f (Hz)	Spindle speed: 240 rpm, feed:0.16 mm/rev, depth of cut:0.2 mm
Average surface roughness, R_a (μm)	Spindle speed: 240 rpm, feed:0.16 mm/rev, depth of cut:0.1 mm

Table 6 Conformation results.

Process parameter condition	C_{pi} (frequency)-process parameter setting	C_{pi} (roughness)-process parameter setting
Initial level	14.60 – A:160 rpm, B:0.08 mm/rev, C:0.15 mm	5.20 – A:160 rpm, B:0.08 mm/rev, C:0.15 mm
Predicted optimum condition	37.11 – A:240 rpm, B:0.16 mm/rev, C:0.2 mm	17.96 – A:240 rpm, B:0.16 mm/rev, C:0.1 mm
Experimental	39.33 – A:240 rpm, B:0.16 mm/rev, C:0.2 mm	18.76 – A:240 rpm, B:0.16 mm/rev, C:0.1 mm

face roughness) from the starting parametric setting was examined to be 24.73 and 13.56 respectively. Consequently the machining performance is enhanced significantly at optimum conditions.

5. Conclusions

In this experimental study, process capability index has been researched for turning of ASTM A36 mild steel. On the ground of investigation results the accompanying conclusions might be drawn:

(1) Process Capability Analysis is the most convenient approach to measure the capacity of a process. Though it has some limitations which prevent a deep and flexible analysis because of the crisp movement and specification limits still it is broadly utilized as a part of industrial process to monitor the product according to the specification limits which is helpful to reduce the variation in the product.
(2) Optimum process parameter settings for process capability index (C_{pi}) of frequency of tool vibration were found to be spindle speed: 240 rpm, feed: 0.16 mm/rev, depth of cut: 0.2 mm. For average surface roughness, the optimal setting is Spindle speed: 240 rpm, feed: 0.16 mm/rev, depth of cut: 0.1 mm.
(3) From the present study, with the proposed optimal parameters it is possible to increase the efficiency of machining process and decrease production cost in an automated manufacturing environment.
(4) Confirmation test results confirmed that the determined optimum condition of turning parameters fulfils the certain requirements.
(5) The research findings from the process capability analysis will provide effective guidelines and the results would be a good technical database for the aerospace, automobile and military applications in fabrication and machining aspects.

This work may be extended further by considering some other performance characteristics of turning operation such as cutting tool life, dimensional deviation, cutting temperature, etc. The Process capability index technique presented in this study might also be applied for the different conventional machining process like milling, drilling, forming etc. as well as different non-conventional process like EDM, USM, LBM etc.

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