Coaxiality error analysis and optimization of cylindrical parts of CNC turning process

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Abstract

High precision rotary shafts with precise geometrical tolerances are generally mounted with a micron level clearance between the gears and casing during operation in industrial applications. Dynamics cyclic loads are inevitable in most of these applications which has an adverse effect on the fatigue life of the critical parts. Ensuring close dimensional tolerances and coaxiality during machining is highly desirable, as it affects the rotary characteristics in many applications. Thus, control of coaxiality error plays a vital role in rotating shafts and high precision machine tools. However, use of high precision machining would drastically increase the cost of manufacturing. Thus, a cost-effective machining process that could potentially reduce the coaxiality error is of high industrial importance. The present research efforts made an attempt to achieve minimum coaxiality error on cylindrical machined parts by optimizing parameters (cutting speed, feed rate, depth of cut and cutting tool nose radius). Experiments are planned, viz. central composite design matrix and statistical analysis determine the influence of machine parameters on coaxiality error of high-strength Al 7075 alloy by applying response surface methodology. Feed rate and depth of cut factors showed significant effect on coaxiality error. All machining parameters showed a non-linear effect on coaxiality error, which defines the strong interaction factor effects. The empirical equations derived were used to minimize coaxiality error by determining a set of machining parameters, viz. applying Big-Bang and Big Crunch and Rao (Rao-1, Rao-2 and Rao-3) algorithms. Rao algorithms outperform the Big-Bang and Big Crunch algorithm both in computation effort and solution accuracy. The results of Rao algorithms are experimentally verified, which resulted in reduced coaxiality error equal to 1.013 µm and resulted in 72.6% improvement compared to CCD experiments.

Keywords Coaxiality error · RSM · CCD · Rao algorithms · BB-BC

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1 Introduction

Many industrial applications (automotive, aerospace, energy, aviation, railway, etc.) use bearings either in pairs or multiple pairs mounted on shafts [1, 2]. High precision rotary shafts use precise geometric tolerances which are desirable for such applications [3, 4]. Shafts of the gears are supported, viz. by bearings which are likely to be present at the front and end cover of external gear machines [5]. Clearances (in microns) are given to limit the physical contact between the gears and casings during operation in a machine [6]. The dynamic cyclic load ensures relative rotational motion for roller bearings which causes vibration and results in reduced fatigue life of aeronautical parts [7]. To meet the stringent requirements to close dimensional tolerances without minimal vibrations, the clearance between the parts is to be maintained by manufacturing with minimal error [5, 6]. Manufacturing errors (caused by inappropriate machine-tool setting, machine flexibility, machine constants errors, etc.) are unavoidable in the actual machine and geometrical inaccuracies (if any) which could result in accidents, malfunctioning and failure (which affects reliability and safety) of parts during service life [8–11]. Manufacturing and assembly errors in terms of large clearance affect the load distribution, which in turn affect the fatigue life of roller bearings [7, 12]. Manufacturing errors such as coaxiality and perpendicularity were common during the service life of journal and thrust bearings [13]. Errors can be reduced by using precision machine tools, but it increases the overall manufacturing cost [14]. It was reported that geometrical errors account for 40% of total machining errors [15].

Geometrical errors in parts during service life or operation affect adversely mechanical properties and fatigue behaviour [16, 17]. Coaxiality error (for example, deviation of central threaded shaft part and axis rotation of machine tool during machining) causes cyclicity error which in turn affects the transmission [18]. Coaxiality error leads to displacement errors in the threaded shaft moving in an axial direction of nut [19]. The influence of coaxiality, perpendicularity and roundness error between the journal bearing on spindle rotation to control the fluid flow for low-speed hydrostatic rotary table possessing multiple channels were analysed to compensate error design and hydrostatic spindle assembly [20]. Lathes and grinding processes employ hydrostatic spindles with bearings, wherein geometry errors in the shaft and error motions (radial, axial and tilt) of spindle affect the coaxiality of two journals [21, 22]. The geometrical inaccuracies of bearings cause mechanical movement between the shaft and bush results in error motions [23]. The rotary characteristics of aero-engine are affected mainly by form errors (coaxiality and cylindricity errors) in low pressure turbine shafts [24]. The coaxiality error of hypoid gear drive with multi-tooth meshing results in transmission errors in helicopters and trucks [25]. The design changes are made that could optimize the gears of initial phase angles and pinion axis eccentricities resulted in reduced transmission errors. The assembly of geometrical errors, i.e. backlash, shaft misalignment in gears and mounting components (i.e. shafts, bearings and housings), causes adverse effects during the operation of a gear train [26]. The coaxiality and roundness errors affect the lubrication performance of bearings in internal combustion engines [27]. Helicopters are dynamically unstable and a suitable method to stabilize them is by maintaining coaxiality of rotors in unmanned air vehicles [28]. The influence of coaxiality error (deviation caused by loading line of action and radial line of the disc) of disc and spacer were investigated which causes splitting action results in tensile strength error leads to alter the crack initiating position [29]. Clamping and forming errors are inevitable during machining, as it alters the geometrical tolerances of high precision products [2]. Coaxiality error present in the compound gear shaft causes noise and vibration, which creates an adverse effect in the mechanical transmission system that damages parts and reduces service life [30]. The above literature confirms that coaxiality in assembly or rotating parts plays a vital role, which uses design changes for error compensation and is treated as a post-processing technique with increased cost. Improving machining accuracy with appropriate control of process variables could compensate for these errors and improve the service life of parts [31]. Therefore, cost-effective processing during the machining stage that could reduce coaxiality error with control of factors by performing analysis and optimization is of industrial relevance.

In recent years, attempts are required to reduce the geometrical deviations of parts with appropriate control of process variables that tend to increase the functionality and reliability of machined products in industrial applications [32]. The cutting parameters (CS, FR) effect during dry turning operation on macro-geometrical errors (straightness, parallelism, roundness, cylindricity and concentricity) are analysed while machining aluminium alloy (UNS A97075 alloy) [33]. FR seems to be the most dominating factor than CS on the geometrical deviation in parts. Micro-geometrical deviation (SR) are dependent on cutting parameters during turning operation [34–38]. CS, FR and DOC were the major factors that affected the surface roughness when turning aluminium alloy [38]. In addition to the above factors, NR also had major impact on the surface roughness of machined textures [37]. The macro-geometrical errors in machined parts play a significant role, if present which affects the physical–chemical properties (residual stress,
microhardness, corrosion) and mechanical behaviour (tensile and fatigue) of functional parts [33, 39]. The factors, i.e. CS and FR, affect largely on the geometrical deviations, while conducting analysis on the machined parts. In the turning process, the cutting parameters (CS and FR) effect on straightness, parallelism and roundness of aluminium alloy [39, 40]. Low and high values correspond to CS and FR and vice versa, resulted in unacceptable results [40], which indicates a strong interaction among the said parameters. The difference in percent contribution, i.e. cutting speed, possesses higher contributions for straightness and parallelism, whereas feed rate for roundness and circular run-out [39]. The above literature proven that cutting parameters showed a strong impact on micro- and macro-geometrical deviations. The nose radius is one of the important factors that strongly influence geometrical deviations but is neglected in most of the studies. Furthermore, turning process parameters behaves non-linearly on geometric deviations, and estimation of interaction factors was neglected in most of the studies. Moreover, coaxiality error is the most dominating response variable which affects the functional behaviour of machined parts which are being neglected in most studies. Therefore, stringent demand still exists to address the above shortcomings to produce better results.

Statistical methods, i.e. Taguchi method (TM) and response surface methods (RSM), are ideal tools to estimate the detailed insights (contribution of individual and interaction factor effects, derive mathematical input–output relationship useful for prediction and optimization) of a process with limited experimental trials [41–43]. TM identify the contributions of cutting parameters of boring operations that affect the coaxiality and concentricity of machined parts [44]. Taguchi method (TM) was applied to maximize the material removal rate (MRR) after minimizing the surface roughness (SR) and roundness of AA6063 T6 aluminium alloy machined parts [45]. TM limit to estimation the interaction factors that affect and determine regression equations useful for performing prediction and optimization. The cutting parameters effect on concentricity of globe plug check valve parts was determined by applying two-level full factorial design [46]. The major disadvantage of this work is the curvature effects are neglected and grey relational analysis determined optimized conditions are treated as local solutions which are far from the global solutions. Central composite design (CCD) of experiments based on RSM estimates the cutting factor (CS, DOC, NR and FR) effect of individual and interaction term and derives equations useful for prediction and optimization of MRR, SR, cylindricity and circularity errors [47]. However, coaxiality error is an important factor that affects the functional behaviour in machines and is neglected in their research efforts. Previous studies reported [43, 47, 48] that DOE with RSM is a widely accepted method to perform experimental investigation with three or more factors influencing output quality characteristics. DOE and RSM enabled researchers to investigate all the process variables simultaneously to estimate factor effects (significance test of individual and interaction variables), which offer in-depth insight into all input variables on the output responses. Furthermore, experimental errors for the developed model were estimated with a minimum set of experiments, and thereby logical conclusions are drawn. The literature review concluded that CCD is an efficient tool not only to analyse the process effects but also to derive equations useful for performing optimization.

In recent years, artificial intelligence tools (teacher learning-based optimization (TLBO), genetic algorithm, bald eagle search algorithms (BES), particle swarm optimization (PSO), Rao, JAYA) predicted better optimal conditions from regression equations derived from the RSM technique applied for sand moulding [48], squeeze casting [49, 50], turning [47], wire electric discharge machining process [51], fused deposition modelling [52] and drilling [53] processes. TLBO optimize the wire electrical discharge turning process to determine the best machining conditions for SR, roundness and cylindricity of Inconel 825 alloy [54]. PSO minimizes the coaxiality error of bevel gear relative to spline [30]. However, the control of cutting factors during the manufacturing stage was not analysed during their examination. Rao algorithms outperformed other algorithms (JAYA and PSO) for predicting better optimal conditions for the FDM process [52]. Rao algorithms showed better performance for 23 benchmark functions for solving optimization problems related to both two types (constrained and unconstrained) [55]. Thereby, Rao algorithm is a suitable tool for performing objective optimization of the turning process.

Appropriate coaxial alignments in assembled parts ensure better functional performances and offer long service life. The machined shaft parts with large coaxiality errors affect the mechanical transmission structure. To date, attempts made by distinguished researchers focussed on the post-processing step, i.e. after machining the design and structures, are changed to compensate for the manufacturing errors which increase the cost. The coaxiality error affects the functional behaviour (rotary characteristics) and service life of the parts, and control of machining parameters during machining that reduces the coaxiality error was neglected in most of the machining studies. CCD proven as an efficient tool that could detail the process insights and derive empirical regression equations with limited practical experiments, and utilizing such tool for analysing coaxiality error is neglected in literature. Artificial intelligence tools successfully optimize various manufacturing problems, and there exists a stringent demand in reducing coaxiality error during machining stage by determining appropriate set of machining parameters.
In the present work, cost-effective systematic methodology proposed to optimize during the machining stage that reduce the coaxiality error by appropriate choice of cutting parameters (CS, DOC, NR and FR). CCD experimental plans were used to conduct experiments and apply RSM for estimating factor effects (individual, curvature and interaction) and derive regression equations. Artificial intelligence-based BB-BC algorithm and Rao (Rao-1, Rao-2 and Rao-3) algorithms was applied to minimize the coaxiality error by optimizing cutting parameters in the machined parts. The performance of all four algorithms is evaluated in terms of solution accuracy and convergence rate. Experiments are conducted for the best optimized conditions and validate a model for practical utility in industries.

2 Materials and methodology

High-strength Al 7075 alloy is widely used as a workpiece material that possesses a wide range of applications in aircraft sectors [56]. High-strength materials were used in structural parts (gears, shafts, valves, building upper wing skin, stringers, missiles, keys, defence applications and stabilizers) possessing higher stresses [57–59]. Chemical composition and the properties of Al 7075 alloy used in the present work are as shown in Tables 1 and 2, respectively [60].
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![Flowchart](image)

**Fig. 2** Flowchart illustrating the experimental stages and processes

1. **Start**
2. Conduct Pilot Experiments
3. **Machining Parameters**
   - Cutting Speed
   - Feed
   - Depth of Cut
4. **Cutting Tool Geometry**
   - TNMG160404MTTT8115
   - TNMG160408MTTT8115
   - TNMG160412MTTT8115
5. **Analyze Outcomes**
6. **Identify Levels of Parameters**
7. Validation of Model
8. **Recommend Optimal Machining Parameters**
9. Future Scope

**Steps:**
- Identify Levels of Parameters
- Conduct Pilot Experiments
- Analyze Outcomes
- Conduct CCD Experiments
- Perform Analysis
- Validation of Model
- Optimization by Artificial Intelligence Tool
- Rao (Rao-1, Rao-2 & Rao-3) Algorithm
- Big-Bang Big-Crunch algorithm
- Recommend Optimal Machining Parameters

**Steps Diagram:**
- Preliminary Experimental Analysis
- Coaxiality error (μm)

**Equation:**
\[ Y = \beta_0 + \sum \beta_i X_i + \sum \beta_{ij} X_i^2 + \sum \beta_{ijk} X_i X_j + \sum \beta_{ijkl} X_i X_j X_k\]
The process has been split into four stages which are explained below:

### 2.1 Stage 1: Preliminary or pilot experimental analysis

In this stage, preliminary experiments were conducted to investigate the factors with substantial influence on the coaxiality of the cylindrical machined part. Experiments were conducted by varying the one-factor-at-a-time (OFAT) approach in a research laboratory, considering three different tool NR (0.4, 0.8 and 1.2 mm) and relief angle as tool parameters and machining parameters (CS, FR and DOC). It was noticed that tool relief angle exhibited limited influence, thus considering that factor for experimental analysis is of redundant effort. All other factors (machining parameters and nose radius) were shown to have a significant influence on coaxiality error in the cylindrical part. After identifying the appropriate influencing factors, it is necessary to find their operating levels. To estimate the non-linear relationship among the process variables, the more than two operating levels are to be chosen. For factors with more than two-level, the range of values needs to be chosen carefully. A wider range of values can yield an unviable solution, and too closer values may not yield optimum process information. Thus, preliminary experiments could help to determine the appropriate levels influencing the output response (in this case coaxiality error) keeping in view the quality of the machined part and process economics.

### 2.2 Stage 2: CCD-based RSM for data collection and statistical analysis

To collect the cutting parameters, nose radius and influencing coaxiality error data for analysis, experiments were planned and conducted as per the matrix developed according to face cantered CCD. To avoid bias and perform accurate analysis, the experiments were carried out in random order. Set of influencing factors and their levels (low, medium and high) considered for data collection and statistical analysis are presented in Table 3. Eighty-one experiments including three replicates have been conducted to obtain a total of twenty-seven treatment conditions as input data and coaxiality error as output data (refer to Table 4).

RSM performs the statistical factors analysis (full quadratic effects: linear, square and interaction) and derive mathematical non-linear regression equations expressed outputs as a non-linear function of input variables. The general form of a mathematical non-linear regression equation is given by Eq. (1).

$$
\begin{align*}
Y_{\text{output}} &= \beta_0 + \sum_{i=1}^{k} \beta_i x_i + \sum_{i=1}^{k} \beta_i x_i^2 + \sum_{i=1}^{k} \beta_i x_i x_j \\
&= \beta_0 + \sum_{i=1}^{k} \beta_i x_i + \sum_{i=1}^{k} \beta_i x_i^2 + \sum_{i=1}^{k} \beta_i x_i x_j
\end{align*}
$$

The results can be graphically interpreted in the three-dimension form of surface plots for better understanding the relations between the output parameter and the input parameters. To confirm the developed regression model, analysis of variance (ANOVA) is adapted that could check for any statistically significant differences between the means of independent influencing factors (CS, DOC, NR and FR) over the output response (coaxiality error).

### 2.3 Stage 3: Validation of model

The $R^2$ (r-squared), i.e. coefficient of determination, is a statistical measure used in a regression model that explains the proportion of variance (how much variability of one factor is caused by its relationship with other) or goodness of fit. Note that $R^2$ value varies in the ranges between 0 and 1. The $R^2$ value close to 1 signifies perfect fit which enables the model towards better predictions and 0 indicates the model fails to predict accurately the data points.

### 2.4 Stage 4: Optimization using artificial intelligence tools

Upon completion of experimental analysis and models which are validated against $R^2$ value with a better fit, the optimization task is carried out to determine the cutting parameters and nose radius for obtaining the desired output. In recent years, artificial intelligence tools are used as a computing tool to conduct optimization tasks and

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### Table 3 Details of influencing and output factors

| Influencing parameters | Units | Levels (low, medium, high) | Output parameter | Unit |
|-------------------------|-------|-----------------------------|------------------|------|
| Cutting speed ($A$)     | m/min | 94, 188, 282                | Coaxiality error | μm   |
| Cutting tool nose radius ($D$) | mm | 0.4, 0.8, 1.2 |                  |      |
| Depth of Cut ($C$)      | mm    | 0.4, 0.7, 1.0               |                  |      |
| Feed rate ($B$)         | mm/rev| 0.1, 0.15, 0.2              |                  |      |
draw conclusions for further recommendations [47–55]. An algorithm-based optimization executes iterative comparison on various solutions until optimal or satisfactory solutions could find. Present work uses Rao algorithms and BB-BC-based artificial intelligence tool to conduct optimization tasks that could optimize the entire process (by determining values of cutting parameters: CS, DOC, NR and FR) for obtaining reduced coaxiality error.

3 Results and discussion

The results and analysis of factors of pilot experiments and face-centred CCD on coaxiality error of cylindrical machined parts are discussed. Statistical analysis of variance, surface plots and non-linear regression analysis (full quadratic effects: linear, square and interaction factor effects) were carried out. The optimization task has been carried out to determine the cutting conditions that minimize the coaxiality error.

3.1 Pilot experimental trials

The outcomes of the proposed work are measured through statistical analysis. Pilot experimental trials are conducted by applying OFAT in a research laboratory. Pilot experiments are the initial set of experiments carried out to examine factors that influence coaxiality error. It was observed that machining factors influencing the coaxiality error were observed to vary in the ranges between 1.296 and 23.648 μm (refer to Fig. 3a–c). Factors and their respective values that result in coaxiality error more than 15 μm were discarded, and the optimal operating ranges of factors were fixed as shown in Table 3.

3.2 Statistical DOE and RSM

Pilot experiments set the basis for the selection of optimal factors and levels required for planning experiments as per the CCD matrix. After analysing the pilot experimental
studies with cutting parameters influence on coaxiality error, the factors and their levels are set and conducted experiments as per CCD presented in Table 4. Three replication experiments are performed for each treatment (experimental) condition, and corresponding average values of coaxiality error are recorded (refer to Table 4). In the subsequent step, the main effect curves and surface response graphs are used to explain the effect and interaction of the factors between the input parameters over desired output responses. Finally, significance and variance were analysed using the ANOVA.

3.2.1 Main effect plots

Main effect plots explain the effect of each input variable when varied with three levels to understand how a value of the input variable could favourably influence the output response. Main effect plots provide graphical illustrations of such findings. Figure 4a–d illustrates the main effect of all the input variables on coaxiality error. The coaxiality error to be reduced to a minimal value is the main objective during the machining operation. Noted that, cutting speed and cutting tool nose radius resulted in approximately the flat surface (cutting parameters varied between their three levels caused the coaxiality error to vary ~ 5 to 7 μm), which clearly define there exists no significant impact on coaxiality error (refer to Fig. 4a–d). Increased CS tends to increase the cutting temperature with a simultaneous reduction in cutting forces as a result of the thermal softening of workpiece material [61]. Furthermore, machined chips are taken out from the cutting zone at a higher cutting speed, and this phenomenon could help to reduce heat as the chips carry away heat quickly. The reduction of temperature and cutting forces render workpiece material soft and control the coaxiality error. Higher values of nose radius resulted in reduced coaxiality error, which could be due to the reduction in compressive residual stresses [62]. Low values of feed rate made the surface residual stresses more compressive which might result in higher values of coaxiality error. Conversely, beyond the optimal values of feed rate, the cutting forces increase rapidly, which hinders the control over geometrical accuracy causing higher coaxiality error [63]. Increased values of depth of cut increase the cutting forces that cause geometrical inaccuracies on the work part due to induced vibrations resulting in increased coaxiality error [64].

3.2.2 Surface plots for coaxiality error

Surface plots explain the behaviour of interaction effect of any two-input variable (after keeping the rest at mid-value) on the response, coaxiality error. They exhibit the combined effect of selected input variables. Figure 5a–f illustrates various surface plots of cutting parameters (CS, FR and DOC) and cutting tool nose radius on coaxiality error.

Figure 5a–b represents the interaction effect of CS with FR and DOC on coaxiality error. The cutting speed was found to have a negligible effect compared to FR and DOC. This can be seen from the three-dimensional (3D) plots that the resulted curve of cutting speed with a variation on coaxiality error is seen to be almost flat. Feed rate being the most dominating factor affects the coaxiality error than the other parameters (CS and DOC). The resulting surface plot was found to be in good agreement with the analysis of variance of coaxiality error presented in Table 5. Cutting speed showed negligible impact with coaxiality error while observed from the main effect plot (refer to Fig. 4), and the same had been noticed while examining the interaction effect of CS and FR (refer to Fig. 5a). It was also noticed that the middle value of the feed rate at any value of cutting speed has better control over coaxiality error. The combination of low values of CS and DOC and high values of CS and DOC resulted in lower coaxiality error (refer to Fig. 5b). Keeping low values of CS and DOC could result in the least possible cutting force, whereas at higher cutting speed, the chips possessing more heat are taken away from the cutting zone quickly results in reduced cutting forces as a result of higher temperature [61]. Similar observations are found for a combination of low values of CS and NR and high values of CS and NR with coaxiality error (refer to Fig. 5c). Higher values of cutting speed reduce the cutting forces and workpiece deflection which might be the probable reasons for minimum coaxiality error on the machined surfaces [65]. This occurred due to strong interaction factor effects (AC and AD) among themselves with coaxiality error. The results of the significance test conducted for cutting parameters interaction (AC and AD) were found significant and are found to be in good agreement with the surface plots (refer to Table 5). Figure 5d–e shows an approximately similar trend for the interaction factors of FR with a DOC and NR on coaxiality error. The middle values of FR at low and high values of NR and DOC resulted in minimum coaxiality error. This behaviour dictates the strong significant
interaction factor effects (refer to Table 5). Note that FR interaction with NR (BD) was found to have a more dominating effect than BC (FR interaction with DOC). Surface plots are consistent with results of analysis of variance test conducted for coaxiality error. The set of higher NR and lower DOC resulted in reduced values of coaxiality error (refer to Fig. 5f). The surface plots behaviour of all cutting parameters and tool nose radius on coaxiality error seems to be non-linear, and therefore the resulted square terms ($A^2$, $B^2$, $C^2$ and $D^2$) were found significant at 95% confidence level. The results of the analysis of variance were found to be in good agreement with the ANOVA.

### 3.2.3 Multiple non-linear regression

The present work employs three operating levels for all cutting parameters (CS, FR, DOC) and NR to estimate the performance in terms of non-linearity on coaxiality error of cylindrical part. Multiple regression analysis was performed to derive the coaxiality error equation (based
Fig. 5 3D surface plots representing coaxiality error with the interaction effect of (a) CS and FR, (b) CS and DOC, (c) CS and NR, (d) FR and DOC, (e) FR and NR, and (f) DOC and NR
on experimental data) as a function of cutting parameters and tool nose radius (refer to Eq. (2)).

\[
\text{Coaxiality error} = +9.21738 + 0.107803 A - 407.27722 B \\
+ 28.60404 C + 17.07372 D - 0.072101 AB \\
- 0.042988 AC - 0.031762 AD + 31.46667 BC \\
- 34.43750 BD + 8.89479 CD - 0.000115 A^2 \\
+ 1464.75556 B^2 - 21.87346 C^2 - 7.69757 D^2
\]  
(2)

The relationship of input variables with coaxiality error is tested to know their practical significance using ANOVA. Tests are carried out for the pre-set confidence level equal to 95%. This indicates the parameters with a \( p \) value less than or equal to 0.05 are said to be significant, which practically signifies those terms in regression equations do not influence much on coaxiality error. It was observed that the terms such as (A) cutting speed, (D) nose radius and interaction term namely AB (cutting speed with feed rate) were found insignificant towards coaxiality error. All square terms were found significant which clearly defines their relationships with coaxiality error could be non-linear. FR showed dominating effect followed by the DOC, CS and NR, respectively. This can be estimated based on the sum of squared values determined for the factors. Although individual terms such as CS (A) and NR (D) were found insignificant, their interaction term (AD) was found to have a significant contribution to coaxiality error. It was also clearly noticed that the lack-of-fit term for the model was found insignificant. Removing insignificant terms makes the lack-of-fit term significant. Non-contributory terms exclusive in regression equation not only reduce the prediction accuracy, but also result in imprecise input–output relationships [43].

The developed non-linear regression model is validated by conducting the coefficient of determination test. Referring to Table 6, since the \( R^2 \) value obtained is more than 40% (95.77%), it is evident that the correlation of obtained results for desired response is holding good for the experimental data collected. \( R^2 \) value close to 1 depicts the reliability and consistency of the data collected and the model established. Since the developed model has more than three independent variables with multiple regression nature, the goodness of the fit has been tested by comparing adjusted \( R^2 \). It was noticed that the adjusted \( R^2 \) value of 90.83% is in good agreement. Thus, evidencing the model has not been over-fit and seen to be statistically adequate for performing analysis and optimization.

Table 5 ANOVA test results were obtained for coaxiality error

| Source  | Sum of squares | DF | Mean square | F value | p value | Significance |
|---------|---------------|----|-------------|---------|---------|--------------|
| Model   | 131.64        | 14 | 9.40        | 19.39   | <0.0001 | Significant  |
| A-CS    | 0.5366        | 1  | 0.5366      | 1.11    | 0.3136  |              |
| B-FR    | 7.69          | 1  | 7.69        | 15.85   | 0.0018  |              |
| C-DOC   | 4.88          | 1  | 4.88        | 10.06   | 0.0080  |              |
| D-NR    | 0.0673        | 1  | 0.0673      | 0.1388  | 0.7159  |              |
| AB      | 1.84          | 1  | 1.84        | 3.79    | 0.0754  |              |
| AC      | 23.51         | 1  | 23.51       | 48.47   | <0.0001 |              |
| AD      | 22.82         | 1  | 22.82       | 47.05   | <0.0001 |              |
| BC      | 3.56          | 1  | 3.56        | 7.35    | 0.0189  |              |
| BD      | 7.59          | 1  | 7.59        | 15.65   | 0.0019  |              |
| CD      | 18.23         | 1  | 18.23       | 37.58   | <0.0001 |              |
| A^2     | 2.67          | 1  | 2.67        | 5.50    | 0.0371  |              |
| B^2     | 34.48         | 1  | 34.48       | 71.09   | <0.0001 |              |
| C^2     | 9.97          | 1  | 9.97        | 20.55   | 0.0007  |              |
| D^2     | 3.90          | 1  | 3.90        | 8.04    | 0.0150  |              |
| Residual| 5.82          | 12 | 0.4851      |         |         |              |
| Lack of fit | 4.20   | 10 | 0.4198   | 0.5173  | 0.8049  | Not significant |
| Pure error       | 1.62 | 2  | 0.8115    |         |         |              |
| Cor total       | 137.46       | 26 |            |         |         |              |

Table 6 Correlation and statistical test results for CCD model developed on coaxiality error

| Test                   | Description | Value   |
|------------------------|-------------|---------|
| Correlation test       | \( R^2 \)   | 0.9577  |
|                        | Adjusted \( R^2 \) | 0.9083 |
| Statistical significance test | Significant terms | B, C, AC, AD, BC, BD, CD, A^2, B^2, C^2, D^2 |
|                        | Insignificant terms | A, D, AB |

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3.3 Artificial intelligence optimization

Optimization of the various phenomenon, processes, designs and functional aspects requires an appropriate statistical analysis. In recent days, artificial intelligence-based algorithms use statistical regression models to derive empirical equations that perform optimizing tasks [47–50, 52, 53]. Numerous artificial intelligent algorithms (genetic algorithm, PSO, BES, TLBO, differential evolution, grey wolf optimization, JAYA and so on) are available today for researchers to conduct optimization tasks. However, the selection of artificial intelligence algorithms for optimization is dependent primarily on researchers. In the present work, Big-Bang and Big Crunch optimization and Rao algorithms are employed to perform optimization for minimum coaxiality error with a set of cutting parameters and cutting tool nose radius.

3.3.1 Rao algorithm

In recent years, researchers are searching simple metaphor-less and parameter-less algorithms to solve complex problems at reduced computation time and efforts [55, 58]. This is because algorithm-specific parameters require tuning and inappropriate tuning of parameters could result in solutions far from the desired one [47, 51]. Rao has proposed three algorithms in the name of Rao-1, Rao-2 and Rao-3 which are metaphor-less and parameter-less simple algorithms for optimization [55]. The complete insights of Rao algorithms is explained in the literature [55].

Rao algorithms function to tune only common parameters (population size and iterations) and do not tune other algorithm-specific parameter (unlike for GA, PSO, GWO, BES and so on) during a search of optimal locations. These algorithms tested on various unconstrained optimization problems comprise of uni-modal, multimodal and fixed-dimension multimodal problems [55], power flow in a power system [66], bioenergy systems [67] and additive manufacturing [52], resulted in better performances. The Rao algorithms had shown satisfactory results and therefore the proposed work intended to adapt the Rao algorithm for optimization of coaxiality error for the turning process.

3.3.2 Big-Bang-Big Crunch algorithm

Erol and Eksin are credited for developing the BB-BC algorithm, which works with two phases (Big Bang and Big Crunch) [68]. In the BB phase, N candidate solutions are distributed randomly in a search space uniformly. The values of fitness functions are estimated for each candidate solution. In BC phase, the convergence operator possesses more inputs but produces single output by computing the centre of mass. The best fitness corresponds to candidates are selected according to centre of mass. Later, computation of new candidate fitness value is done by subtracting or adding a random number around the centre of mass wherein the possibility of finding a better solution as iteration progresses. The above procedures are repeated till the set goal was met. The detailed working procedure with mathematical computations is explained in the published literature [68–70].

3.3.3 Summary results of optimization algorithms and confirmation experiments

BB-BC and Rao (Rao-1, Rao-2 and Rao-3) algorithms were applied to determine the set of optimized machining conditions (CS, FR, DOC and NR) for minimum coaxiality error. To minimize the coaxiality error the objective function (empirical equation derived based on experimental input–output) was used as presented in Eq. (2). During the optimization task, the algorithms (BB-BC, Rao-1, Rao-2 and Rao-3) search appropriate values of machining conditions subjected to variable constraints: 94–282 m/min for CS, 0.1–0.2 mm/rev for FR, 0.4 to 1 mm for DOC, and 0.4–1.2 mm for NR, such that minimum coaxiality error was ensured. All Rao algorithms produced minimum coaxiality error (0.9465 µm) for the same optimal machining conditions (CS, 282 m/min; FR, 0.1558 mm/rev; DOC, 0.4 mm; NR, 1.2 mm). However, the BB-BC algorithm produced minimal coaxiality error equal to 0.9725 µm during their optimal search (refer to Table 7). This concludes that Rao algorithms produced better solution accuracy than the BB-BC algorithm. This occurrence might be due to the drawback of the search mechanism of the BB-BC algorithm.

| Details of algorithms         | Input parameters (CS, FR, DOC and NR) | Output value (coaxiality error) |
|------------------------------|--------------------------------------|---------------------------------|
| Rao-1, Rao-2 and Rao-3       | 282 m/min; 0.1558 mm/rev; 0.4 mm; 1.2 mm | 0.9465 µm                       |
| Big Bang-Big Crunch (BB-BC)  | 281.7 m/min; 0.1573 mm/rev; 0.401 mm; 1.2 mm | 0.9725 µm                       |
| Experimental conditions (refer Fig. 6) | 282 m/min; 0.156 mm/rev; 0.4 mm; 1.2 mm | 0.963 µm + 1.180 µm + 0.897 µm = 1.013 µm |
that if all candidate in the first stage of big-bang is located in the small portion of search space, then there exists a greater probability to get trapped in local solutions [69]. Rao algorithms resulted in the optimal solutions with the population size and iteration kept equal to 100 and 10, respectively. For the same population size and iterations, the BB-BC algorithm resulted in local solutions possessing the coaxiality error equal to 1.12 µm. To improvise the solution accuracy, a large number of candidates (population size, 1000; and iteration 100) were initialized which resulted still in a local minima solution equal to coaxiality error of 0.9725 µm. Note that the computation time increases with an increased number of function evaluations (population size and iteration) for any algorithm [70]. The computation time for Rao and BB-BC algorithms are found equal to 10 s and 125 s, respectively. The experiments performed for Rao algorithms determined machining condition, wherein the average of three replicate experimental coaxiality error value was found equal to 1.013 µm (refer Fig. 6a–c). Rao algorithms were found to be an efficient tool to conduct optimization tasks for minimizing the coaxiality error.

4 Conclusions

Manufacturing errors in the machine tools can happen for many reasons. Coaxiality is one such error that would affect the machines during assembly or while performing intended work. Precision machines like aircraft, nuclear reactors and chemical plants are highly sensitive to operate. In such applications, a minor error in coaxiality could cause major malfunctioning of the entire system. In this view, the present work is focused on the various factor influencing the coaxiality of a part made of high-strength Al 7075 alloy. Cutting parameters (CS, FR, DOC and NR) operating at three-level each were considered for the study. The objective of the study is to optimize the input factors for the least possible coaxiality error during CNC turning operation. A statistical design of experiment with CCD was set for investigation, and response surface models were used to develop a mathematical model. The models are validated subjected to ANOVA tests. Main effect plots and surface plots explain graphically to illustrate the effect of individual input variable and their interaction of any two variables. Followed by artificial intelligent optimization for estimating minimum coaxiality error was carried out by applying Rao algorithms and BB-BC algorithms.

The following conclusion was drawn from the entire experimental analysis.

(i) Through main effect plots, it was clear that cutting speed and tool nose radius have no substantial influence over coaxiality error. This is evident due to the least variation in the cutting force for varied CS and NR, whereas FR and DOC are the major influencing parameters with 0.4 mm for DOC and 0.15 mm/rev for FR which were shown better response over controlling the coaxiality error.

(ii) Through surface plots, the interaction effect of input variables has proved that depth of cut is the key variable that needs to be maintained at a low value of 0.4 mm for which a higher cutting speed of 282 rpm and a higher nose radius of up to 1.2 mm are shown better control over coaxiality error. In all the cases, the feed rate has to be maintained with 0.15 mm/rev.

(iii) All input factors had shown the non-linear relationship with coaxiality error.

(iv) ANOVA analysis was conducted for the developed model, wherein the coefficient of determination $R^2$ value was found equal to 0.9577. As it can be seen, $R^2$ value is close to 1, which signifies that the model is statistically adequate (highly synchronous with the experimental results) for performing optimization tasks.

(v) From BB-BC and Rao (Rao-1, Rao-2 and Rao-3) algorithms, the coaxiality error was optimized to a minimum value. All Rao algorithms outperformed the BB-BC algorithm in determining the solution accuracy with a coaxiality error equal to 0.9465 µm. The experimental validation showed the results of the Rao algorithm determining optimal machining conditions (CS, 282 m/min; FR, 0.156 mm/rev; DOC, 0.4 mm; NR, 1.2 mm) are capable to produce coaxiality error equal to 1.013 µm.

(vi) The computation time of BB-BC and Rao algorithms are found equal to 125 s and 10 s, respectively. This clearly defines the efficiency of Rao algorithms in optimization tasks.

Availability of data and material The data used in this work can be requested by contacting the corresponding author.

Declarations

Ethics approval Not applicable

Consent to participate Not applicable
Conflict of interest The authors declare no competing interests.

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