Optimizing the Boring Parameters on CNC Machine using IS 2062 E250 Steel Plates: Taguchi-Pareto-Box Behnken Design and Taguchi-ABC-Box Behnken Design Perspectives

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Abstract. *Due to outstanding properties such as enhanced surface roughness, fatigue strength, hardness and specific heat, the IS 2062 E250 plate has retained its competitive choice as a boring material in the automobile and aerospace industries. Unfortunately, sparse literature exists to distinguish the several boring process parameters with potential varying importance. Consequently, two novel methods are presented based on the Taguchi-Pareto-Box Behnken design (TP-BBD) and Taguchi-ABC-Box Behnken design (TABC-BBD) methods to optimize and select the process parameters. The signal to noise (SN) ratios for experimental trials was rearranged in descending order and cumulative SN ratios were computed to allow the application of the Pareto principle and the ABC methods. These outputs are fed into the Box Behnken design approach with analysis of variance conducted to reveal the linearity and significance of the parameters. Based on the process parameters considered, the response optimisation of the SN ratios for the TP-BBD method shows that the optimal setting for speed, feed, depth of cut and nose radius are 1090.91 rpm, 0.06 mm/rev, 1.2 mm, 0.606061 mm. However, for the TABC-BBD method, the response optimisation results are 800 rpm, 0.06 mm/rev, 1 mm and 0.606061 mm for speed, feed, depth of cut and nose radius, respectively. For both methods, the contour and surface plots of the SN ratios from the analysis show the range at which various parameters in the boring operation would be significant for the model.*

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1. Introduction

Every day, several tonnages of materials are bored for major sub-assemblies but wastes are generated, which could be reduced by deploying optimisation and parametric selection methods [1], [2], [3], [4], [5], [6], [7], [8]. However, in the current industrial practice, the bored hole should conventionally be of high dimensional accuracy and great surface finish [6], [9], [10]. But, the problem of surface roughness often emerges when the cutting parameters are not properly selected in bored holes and can lead to defects in components [11]. Besides, when the cutting parameters in a boring operation are not optimally selected, the surface roughness and production time are usually high leading to low quality and low productivity. For example, if the speed parameter is optimized, the rate of production would be very high leading to increased productivity [12]. This problem warrants a solution of economic importance and sustainability dimensions. Unfortunately, as of today, a dearth of literature exists on the optimisation of process parameters of the IS 2062 E250 steel plates and the further classification of the parameters according to their importance.

Further, most of the reports are focused on the optimal parametric determination alone while the significant interactions among the parameters are less studied. In the present article, the Taguchi-Pareto-Box Behnken design approach and the Taguchi-ABC-Box Behnken design method are introduced as novel approaches to optimize the cutting parameters in the boring operation on a CNC machine using the IS 2062 E250 steel plates. The proposed approaches are extensions of the Taguchi method [13], which give additional information on the prioritization of parameters and their interactions. These additional provisions aid high-quality surface roughness in the boring operation and with this, quality and productivity are increased. Thus, by introducing the Taguchi-Pareto-Box Behnken design approach and the Taguchi-ABC-Box Behnken method, this paper seeks to optimize the cutting parameters in the boring operation to reduce surface roughness, improving quality and performance.

Besides, to bridge the gap analysed earlier, this investigation examines the attributes of boring operation of the IS 2062 E250 steel plate, integrates them into two mathematical methods of Taguchi-Pareto Box Behnken design and Taguchi-ABC Box Behnken design, and develops two optimisation cum selection methods for the parametric optimisation of boring operations for the IS

2062 E250 steel plates. The principal novelties and contributions of this article are as follows. First, two efficient methodical developments are established for the boring operation of the IS 2062 E250 steel plates. Second, two main optimisation methods are introduced in search for the optimal solution and definition of ranks cum selection of the best parameter in the boring process. This is achieved through the two different mechanisms. In the first mechanism, the Pareto principle is introduced to the Taguchi method where the 80-20 rule is established for the experimental trials to rapidly acquire the preferred experimental runs upon which reliable boring activities may be planned and implemented. It then employs the Box-Behnken design to further optimize and establish interactions through plots and interpretations. The second mechanism substitutes the ABC classification scheme for the Pareto principle based on 0-69%, 70-79% and 80-100% cut off rules and employs the Box-Behnken design to study the interactions of the parameters. However, the next novelty and contribution of the article are that the IS 2062 E250 steel plates are used as a case investigation to verify the supremacy and effective attributes of the two proposed methods.

2. Literature review

The current study aims to present a novel approach used in predicting the most significant parameter and the most optimal parameter to achieve optimal surface roughness in a boring operation on a CNC machine tool, the novel approach is a combination of various methods that would include Taguchi method, design of experiment response surface methodology (Box Behnken design) approach, the Pareto principle, and the ABC principle. While they have been much research on determining the most significant and optimal parameter values to achieve optimum surface roughness in a boring operation, using various methods, very few researchers have employed the Pareto principle and also ABC principle in this regard.

Boring operations are the backbones and the most delicate finishing activity in component development; boring process could jeopardize all the efforts put into the component development in commercial activities (i.e. grinding, drilling and turning the workpiece material). This makes the need for optimisation of process parameters and response in the boring operation compelling. This research aims to analyse the characteristics of the optimisation of process parameters in the boring operation by using the combined Taguchi Pareto and Box Behnken design response surface methodology on one side and Taguchi ABC with Box Behnken design response surface methodology on the other side because of the increasing importance of optimisation in this domain of manufacturing. This section details the ideas regarding material types, machines tools, boring process input parameters and the quantitative data in boring research. To obtain results, the present authors have utilized journals papers and a research gap has been identified. Below are the various aspects that the literature on the boring operations has been segmented.

2.1 Material Types used in Boring

In the literature, many researchers have worked on various materials ranging from various types and grades of steel to types and grades of aluminium in determining the optimal and the most significant parameter in their boring operation on various machine tools for example, Abiola and Oke [7]; Patel and Deshpande [14], Vohra [1], Singh and Prakash [4], Nugroho et al. [15] all worked on various types and grades of steel on the subject matter. Abiola and Oke [7] claimed that the depth of cut is the most significant parameter in the boring process of IS 2062 E250 steel plate having the largest weight of 1 while the speed is the least important parameter with a weight of 0 by the novel entropy-decision tree-VIKOR approach to support their claim. Patel and Deshpande [14] declared that the speed, nose radius and feed are the most significant parameter in boring operation, with percentage contributions of 74.92, 11.09 and 11.12, respectively, and the optimized parameters are speed of 1400 rpm, feed of 0.6 mm/rev, depth of cut of 1.4 mm and nose radius of 0.8 mm. The IS: 2062 steel was used and the Taguchi method and ANOVA procedure were applied.

The model developed predicted the surface roughness of IS 2062 steel. Vohra et al. [1] asserted that increase in the depth of cut influences the material removal rate but increases surface roughness. They also stated that if there is an increase in cutting speed the material removal rate is increased and the surface roughness is decreased simultaneously when the work piece material is steel pipe. Their argument was backed up by employing the Taguchi method and ANOVA. All the parameter were conflicting, hence optimization of the parameter for better output was achieved. Singh and Prakash [4] stated that all cutting parameter is somehow related to one another and are conflicting. Hence, the need to optimize the parameters for increased performance. Their declaration was supported by using gray relational analysis and Taguchi method to optimize cutting parameters for optimal material removal rate and surface roughness of steel pipe (SS-304) in a boring operation. In the two approaches used, the feed rate and the depth of cut were in complete agreement.

Nugroho et al. [15] declared that the most significant factor that contributes to surface roughness is the insert radius, followed by the feed rate and depth of cut while damper position is the least significant factor in the turning process of medium carbon steel AISI 1050 on a CNC machine. The assertion was supported by using full factorial and ANOVA method for the parameter optimization. The regression model developed shows that there is a relationship between the surface roughness and the cutting parameter in considered.

Also, Nayak and Sodhi [16], Sukhdeve and Ganguly [17], Kumar et al. [5], and Abdulrazaq et al. [18] worked on various types and grades of aluminium and its alloys on the subject matter. Nayak and Sodhi [16] maintained that when the optimal parameter are set as speed 2004.54 rpm, feed rate of 95.10 mm/min and depth of cut to be 0.67mm, then there is 100% possibility that there would be a material removal rate (MRR) of 62.98 mm^3/sec and a surface roughness (Ra) of 0.2882 for Al6061 using the analysis of regression and response surface methodology. The optimal selected parameters produce optimal surface finish for the Al6061 material. Sukhdeve and Ganguly [17] asserted that the optimum parametric settings from the gray relational analysis were validated using genetic algorithm. This validates the mathematical regression model from experimental data from Taguchi analysis when the material used is AISI 1040 on a jig boring machine. The mathematical model from the Taguchi method can be validated using the presented method. Kumar et al. [5] maintained that using the gray relational analysis, support vector machine, response surface methodology the gray relational grade could be predicted and machining parameters could be optimized when AISI 4340 material is considered in a boring operation. These can be verified by confirmation experiment.

Abdulrazaq et al. [18] argued that high feed rate produces high material removal rate and good surface roughness while high spindle speed gives good surface roughness. They declared that there was little effect on material removal rate for 7024 Al-alloy material in a turning operation on a CNC machine using Taguchi method. Of all, only a few researchers worked on E250 B0 steel material [7], [14]. Hence, the choice of material in the current study was guided by the sparse information and potentials for development in the area. Furthermore, knowledge of material types during the boring operation could be effectively used to evaluate the relative degrees of optimized values obtained by each material group and aid the understanding of the optimal process parameters of the boring process when machining the IS 2062 E250 steel plates.

2.2 Machine Tools used in Boring

The machine tool used widely in the literature is various models of CNC machines. For example, in the works of Abiola and Oke [7], Nayak & Sodhi [16], Kumar et al. [19], Patel & Deshpande [14], Abdullah et al. [20] and Vohra et al. [1], various models of CNC machine was employed in collating experimental data. Other researchers like Sukhdeve & Ganguly [17] as well as Vivek and Ramesh [21] used jig boring machines and conventional lathe machines in collating experimental data respectively. Vivek and Ramesh [21] declared that the optimum parameters for the boring of E31 steel material on a lathe machine are 517.45 rpm for speed, 0.06 mm/rev for feed rate, and 0.87 mm for depth of cut using the response surface methodology to support their claim. When parameters are properly selected in a boring process, optimal surface finish is achieved. Going by the trend in the literature the machine tool employed in the current studies is the E Batilbio CNC Sprint 20TC. Hence, information on machine tools utilized during boring could be extremely useful to make boring operations attainable at optimal values to achieve optimality for boring IS 2062 E250 plates.

2.3 Responses in the Boring Process

Throughout the literature, the output parameters taken into account in determining the optimal parameters in a boring operation are surface roughness, material removal rate, tool wear, workpiece vibration, the vibration amplitude of boring bar, roughness maximum, concentricity, coaxiality, cutting force, tangential force, bore diameter and vertical reaction force. Surface roughness was considered as the only output in Abiola and Oke [7], Suresh & Diwakar [22], Nayak & Sodhi [16], Balamurugamohanraj et al. [23] and Munawar et al. [24] while multiple outputs were considered in Vivek and Ramesh [21], Sukhdeve & Ganguly [17], Satish et al. [25], Rao & Murthy [26]. However, for in-depth studies and analysis, surface roughness was the only output parameter considered in the current study. It could be concluded that the grouping of boring operation characteristics according to responses obtained is achieved according to the demands for optimal operations performance during boring that promotes sustainability in machining operations.

2.4 Boring Process Input Parameters

Most authors in the literature are in almost complete agreement as to the input parameter considered in the boring operation to determine the optimal surface roughness and other output response. Abiola and Oke [7], Patel and Deshpande [14], considered spindle speed, feed rate, depth of cut and nose radius as the input parameter considered in the boring operation for optimum surface roughness. Other authors such as Yuvaraju and Nanda [10], Patil and Jadhav [27], Ramu et al. [28], Sonar et al. [29] and Panchal [6] considered only speed, feed and depth of cut as the input parameters in their work. However, Thomas et al. [30] and Munawar et al. [24] employed input parameters like rake angle, tool length, workpiece length, type of boring bar, in addition to the basic speed, feed, depth of cut and nose radius.

In Patil and Jadhav [27], the authors asserted that PTFE gives better results compares to other viscoelastic material such as PVC and rubber. The experiment was conducted on an EN8 workpiece material. Furthermore, the surface roughness value is seen to decreases when a PTFE damper is installed on the boring tool and when Taguchi method is used to optimize the parameters. Ramu et al. [28] argued that depth of cut is the most important parameter to be considered in relation to surface roughness and material removal rate, using gray relational grade. However, the asserted that speed and feed ranked second and third, respectively, when stainless steel 316 is used in the turning operation in the experiment. Sonar et al. [29] declared that the generated equation generated through the regression analysis can be used to predict surface roughness and material removal rate. However, the Taguchi method was used to obtain the optimal solution for the turning process of Al6061 T6 on a CNC machine. Using the generated model the best decision on optimal parameter was reached. Panchal [6] maintained that the most significant parameter when the material is not hardened is the feed and depth of cut. While when the material is hardened, the feed is the most significant. However, the least significant is the speed and depth of cut on surface roughness. The work piece used is EN-36 on a CNC machine and this claim was supported by application of BBD (RSM) in obtaining the optimal parameters in both instances. The author claimed that this procedure helps in reducing the machining time, cost and tool wear rate. In the case of Thomas et al. [30], the authors claimed that analysis of variance revealed the best surface roughness condition achieved at a low feed rate. They asserted that depth of cut has no significant effect on surface roughness, The analysis of variance that they reported revealed that the best surface roughness condition is achieved at a low feed rate (less than 0.35 mnt/rev), a large tool nose radius (1.59 mm) and a high cutting speed (265 m/min and above). Their results also show that the depth of cut has not a significant effect on surface roughness. Munawar et al. [24] stated that high feed rate and low cutting speed would produce the lowest surface roughness in the boring process of AISI 1018 steel on CNC machine when Taguchi and ANOVA is adopted.

Thus, being motivated by the literature, in the current study, the input parameters considered are speed, feed, depth of cut, and nose radius due to the impact they have on the chosen output parameter. Furthermore, Vivek and Ramesh [21], Nayak and Sodhi [16], Patel and Deshpande [14], Satish et al. [25], Rao and Murthy [26] and Kumar et al. [3] gave specific values of each input parameter as the optimal values to achieve the optimum various output like the surface roughness. In a boring process, when the input parameters are properly selected by the various methods, better surface roughness is achievable [16], [19], [21]. Also, Vohra et al. [1] and Singh and Prakash [4] argued that the cutting parameter is somewhat related to one another and that they are clashing or incompatible, which results in the need for optimization for better output. Most manufacturing organization aims to produce high-quality products at minimum costs, which can be achieved only when machining parameters are optimized [16], [31]. It could be concluded from the finding that responses are one of the aspects of boring operations parametric analysis and optimisation that promotes an excellent performance of the boring operation when properly defined.

2.5 Quantitative Data in Boring Research

In boring operations, quantitative data may refer to a form of research whose intent is to quantify the gathering and examination of experimental or numerical data from a theoretical perspective. Quantitative data has been linked to a deductive method based on theoretical tests. Often, the purpose of navigating through the quantitative lens is to establish the frequency at which some defined characteristics exist. Parameters are easily conceptualized that is the key representatives of the input of the system and they are routes to observing the larger data set from the population of data from which a few experiments are extracted. Data in the literature are generally quantitative and various authors have employed different approaches in analyzing these data. For example, authors like Suresh and Diwakar [22], Patel and Deshpande [14], Kumar et al. [19], Dave et al. [32] and Abdulrazaq et al. [18] are a few of the authors that employed ANOVA in determining the most significant parameter in a boring operation for optimum surface roughness. For example, Kumar et al. [19] argued that when the optimized cutting condition obtained from DOE full factorial and ANOVA analysis and the non optimized cutting conditions were compared based on their effect on surface roughness, the optimized parameter reduced surface roughness by 49.83%. Using this method, with increased cutting speed and feed the surface rough is decrease drastically.

Dave et al. [32] asserted that the material removal rate is mostly influenced by the depth of cut while the insert influenced the surface roughness more, when the material are grade EN material in a turning operation using Taguchi method. When this method is employed increase in machine utilization and decrease in production cost is achieved. However, Abiola and Oke [7] used the entropy-decision tree-VIKOR approach in determining the ranking of parameters in the boring operation for optimum surface roughness. Suresh and Diwakar [22], Vivek and Ramesh [21], Nayak and Sodhi [16], Patel & Deshpande [14], Kumar et al. [19] and Rao & Murthy [26] are just but few of the authors that used Taguchi method and DOE's response surface methodology in determining the optimal parameters values in boring operation for high-quality surface roughness. Sukhdeve & Ganguly [17], Kumar et al. [5], Batwara & Verma [31], Saini & Pradhan [33], Ramu et al. [28], Yang et al. [34] and Rao & Murthy [26] employed other methods like support vector machine method, full factorial design, grey relational analysis, artificial neural network, and genetic algorithm. However, of all the methods used by various authors, none used the Pareto principle, the ABC principle and other evolutionary optimization approach apart from the genetic algorithm, which was used by Sukhdeve & Ganguly [17] only. The present work introduces a combination of the Taguchi method, ABC principle, Pareto principle, DOE’s response surface methodology (Box Behnken design approach) to the optimization of boring parameters of IS 2062 E250 steel plates which makes it unique from those used in the literature under review. Hence, the quantitative data may be an effective avenue to monitoring the performance of boring operations in the boring of the IS 2062 E250 plates.

2.6 Research Finding Pointers

The findings made by various analyses of various authors suggest a particular machining parameter to be the most significant in the boring operation others say otherwise for example in the works of Abiola and Oke [7] and Ramu et al. [28] agree that the most significant parameter in the boring operation on a CNC machine tool is the depth of cut, while in the works of Patel & Deshpande [14], Nugroho et al. [15] and Saini & Pradhan [33], depth of cut is not the most significant factor in the boring operation, probably owing to the difference in materials used by various authors in their various works. Hence, research finding pointers may be effective indicators of the progress made by the boring operation in achieving the performance goals of the process of boring IS 2062 E250 plates.

To further explore the literature, a summary of important studies are provided in Table 1.

Author(s)	Working material used	Machining operation /machine tool	Choice output	Choice input parameters	Method(s) used	Findings	Conclusion
Abiola and Oke [7]	E250 B0 steel material	Boring/ CNC machine	Surface roughness	Speed, feed, nose radius, depth of cut	Entropy-decision tree-VIKOR approach	Depth of cut exceeds others in performance while all other parameters exceed speed in performance to enhance surface roughness	The analysis is useful for the preparation of the annual budget for boring operation in a factory
Suresh & Diwakar [22]	Twinning induced plasticity steels	Turning/CNC machine	Surface roughness	Rate of material removal, feed, speed, depth of cut	Taguchi, ANOVA, and response surface methodology	The optimal condition of each input and output parameters were established	The optimization of process parameters is tedious and should be done with utmost attention
Vivek & Ramesh [21]	EN 31	Boring/Lathe machine	Surface roughness	Speed, feed, depth of cut	Response surface methodology	The optimum parameter was obtained and confirmation experiments were carried out to validate the optimum settings	Proper selection of parameters produces a better surface finish
Nayak & Sodhi [16]	Al 6061	Boring/CNC machine	Surface roughness	Depth of cut, feed rate, cutting speed and surface	Regression analysis, response surface methodology	The optimum parameter was established	Optimum selection of parameters produces a good surface finish
Sukhdeve & Ganguly [17]	AISI 1040	Jig boring machine	Vertical reaction force, surface roughness, material removal rate	Speed, depth of cut, cutting speed	Taguchi, grey relational analysis, genetic algorithm	The optimum parametric settings from the grey relational analysis were validated using a genetic algorithm, which validates the regression model from experimental data from Taguchi analysis	
Patel & Deshpande [14]	IS: 2062 steel	Turning/CNC machine		Speed, depth of cut, nose radius. Feed	Taguchi and ANOVA	Speed, nose radius and feed are the largely considerable parameters in the boring process	The developed model could be used to predict surface roughness
Kumar et al. [9]	Engine crankcase tappet bore	Boring/CNC machine	bore diameter	Cutting speed, feed rate, cutting allowance	DOE, RSM AND ANOVA	When cutting speed and feed increased, bore deviation decreased	40% decrease in bore deviation was recorded with an increase in cutting speed and feed
Kumar et al. [5] ·	AISI 4340	Boring	Surface roughness, tool wear, cutting force, tangential force, tool vibration	Cutting speed, depth of cut, feed rate	Gray relational analysis, support vector machine, response surface methodology	Grey relational grades were predicted and machining parameters were optimized	A confirmation experiment was conducted to validate the predicted GRG and optimized parameter
Abdullah et al. [20]	Aluminium alloy 6061, mild steel and carbon steel.	Boring/CNC machine	Concentricity and coaxiality	Cutting speed, feed rate and depth of cut	Taguchi	In concentricity, the type of material had the highest percentage contribution value (51.469%), followed by the feed rate (41.812%), depth of cut and cutting speed were not that significant with 4.841% and 1.879%, respectively. In coaxiality, material type is the largely considerable factor that influences coaxiality with 76.899% influence. Other factors are almost insignificant, cutting speed contributes 12.443%, feed rate contributes 9.862% and depth of cut contributes 0.796%.	The optimum condition for concentricity was by using the carbon steel, depth of cut of 0.2 mm, feed rate of 0.4 mm/rev and cutting speed of 560 mm/min. The optimum condition for coaxiality was by using aluminium Alloy, depth of cut of 0.2 mm, feed rate of 0.1 mm/rev and cutting speed of 750 mm/min.

Table 1 Summary of literature review for the boring operation of steel plates

Abdulrazaq et al. [18]	7024 Al-alloy	Turning/CNC milling machine	Surface roughness, the material removal rate	feed rate, spindle speed	Taguchi and ANOVA	High feed rate produces high material removal rate and good surface roughness and high spindle speed also give good surface roughness with little effect on material removal rate	High spindle speed give better surface roughness
Dave et al. [32]	grades of EN materials	Turning/CNC	material removal rate, surface roughness	depth of cut	Taguchi method	The material removal rate is mostly influenced by the depth of cut while the insert influenced the surface roughness more	An increase in machine utilization and decrease in production cost is achieved
Kumar et al. [9]	Engine crankcase tappet bore	Boring/CNC machine	surface roughness	Cutting speed, feed rate, cutting allowance	DOE Full factorial and ANOVA analysis	With increased cutting speed and feed the surface roughness decreased drastically	Optimized parameters reduced the surface roughness by 49.83%
Vohra et al. [1]	Steel pipes	Boring/CNC machine	Material removal rate and surface roughness	speed, feed and depth of cut	Taguchi method and Anova	The optimum value of each parameter was established	An increase in the depth of cut influences the material removal rate but increases surface roughness. With cutting speed growth, the material removal rate increased and the surface rough decreased correspondingly.
Batwara & Verma [31]		Turning/CNC Machine	Material removal rate, surface roughness	Depth of cut, feed rate, speed	Artificial neural network and response surface methodology	To obtain the accuracy of components, optimizing the machining parameters is very valuable. It also has a great influence on cost-effectiveness, material removal rate and surface roughness	Model equations for predicting material removal rate and surface roughness were formulated. It has an accuracy of 90% in predicting the responses
Singh & Prakash [4]	Steel pipe (SS-304)	Boring/CNC machine	Surface roughness, material removal rate	Feed, speed, depth of cut and	Taguchi method	The SN ratio was used to optimize the cutting combination of the parameters. All cutting parameters are related to one another and are conflicting.	The optimum cutting parameter in reducing the surface roughness was determined,
Nugroho et al. [15]	Medium carbon steel (AISI 1050)	Turning /CNC machine	Surface roughness	Damper position, feed rate, depth of cut, insert nose radius	DOE Full factorial and ANOVA analysis	The largely considerable factor to surface roughness is the insert radius, then feed rate and depth of cut, while damper position was the slightest considerable factor.	The result from this study validates previous researches that the factors considered influence the surface roughness of components
Kumar et al. [3]	410 stainless steel	Boring/Lathe machine	material removal rate, surface roughness	Speed, depth of cut	Taguchi and ANOVA	To increase quality and reduce cost, the material removal rate should be optimized, the optimum process parameter for the effective and efficient operation was determined	The optimum combination of process parameters improves the performance of machining processed
Saini & Pradhan [33]	Aluminium alloy 8011	Turning/CNC machine	material removal rate and surface roughness	Cutting speed, feed, depth of cut	Taguchi-Fuzzy	The largely considerable factor on the surface roughness and the material removal rate, followed by the depth of cut and the cutting speed	In this study, the feed was established as the largely considerable parameter that influences surface roughness
Panchal [6]	EN-36 (with hardening and without hardening) material	CNC machine	surface roughness	Speed, feed, depth of cut	BBD(RSM)	The largely considerable parameter of the material without hardening is the feed and depth of cut while for the hardened material the feed is the largely considerable but the slightest considerable is the speed and depth of cut on surface roughness	This analysis helps in reducing machining time, cost and tool wear rate
Sonar et al. [29]	Aluminium Alloy(Al6061 T6)	Turning/CNC machine	material removal rate	depth of cut, feed rate, speed	Taguchi	Optimum machining parameters were determined. The generated polynomial regression model could the used to predict surface roughness and material removal rate	With support from the regression model, the best decision on parameters could be reached
Ramu et al. [28]	stainless steel (316)	Turning/CNC	material removal rate, surface roughness	feed, speed, depth of cut	Taguchi-ANOVA-Gray relational analysis, grey relational grade	The best optimal combination of parameters from ANOVA shows that feed is the most important parameter affecting surface roughness, followed by speed and depth of cut.	Depth of cut is the most considerable parameter regarding surface roughness and material removal rate with the grey relational grade, while speed and feed ranked second and third

Table 1 Summary of literature review for the boring operation of steel plates (Cont'd)

Yang et al. [34]	aluminium alloy 6061T6	Boring/CNC machine	Roughness average, roughness maximum, roundness	Feed rate, cutting speed	Gray relational analysis, ANOVA	Feed rate mostly influences roughness average and roughness maximum, while the cutting speed is the most important factor in roundness	The feed rate is the largely considerable factor in a CNC boring operation
Muhammad et al. [35]	AISI 1018 steel	Boring/CNC machine	Surface roughness	Rake angle, depth of cut, speed, nose radius, feed rate	Taguchi, ANOVA	ANOVA was used to identify the largely considerable factors affecting surface roughness, S/N ratio was used to find the optimal cutting combination of the parameters	Tools with a positive rake angle and small nose radius produce a lower surface nose radius in the boring operation. Also, high feed rate and low cutting speed produced the lowest surface roughness
Patil & Jadhav [27]	EN8 material workpiece with and without viscoelastic material damper	Boring/CNC machine	surface roughness	Spindle speed, feed rate and depth of cut	Taguchi	PTFE gives the better result as compared to other viscoelastic material PVC and Rubber	The surface roughness value decreases due to installation of PTFE damper on the boring tool.
Thomas et al. [30]	Mild carbon steel	Boring	Surface roughness	Cutting speed, feed rate, depth of cut, tool nose radius, tool length and type of boring bar	ANOVA	The variance analysis showed the superior surface roughness situation at a low feed rate of less than 0.35 mm/rev, a huge tool nose radius of 1.59 mm and an elevated cutting speed of 265 m/min and over. Depth of cut has no considerable influence on surface roughness.	Influence of developed edge structure on surface roughness can be reduced by enhancing the depth of cut and intensifying the tool vibration
Yuvaraju & Nanda [10]	Glass fibre reinforced epoxy and glass fibre reinforced polyester	Boring	Vibration amplitude of boring bar and surface roughness of the workpiece	Speed, feed and depth of cut	Response surface methodology, ANOVA, Box Behnken	There is a reduction in surface roughness as well as vibration amplitude with an increase in the number of composites plates placed under the tool	Surface roughness is reduced, as well as the vibration amplitude

Table 1 Summary of literature review for the boring operation of steel plates (Cont'd)

2.7 Research Gap

The review performed above targeted the existing literature on boring process optimisation and has provided an understanding of the idea regarding the process industry. The review provided an effective route to examine an aspect of optimisation of boring operations and parametric prioritization has been ignored in a majority of studies. Moreover, the Taguchi Pareto and Taguchi ABC perspectives in combination with Box Behnken design for interaction analysis for the specific application of automobile panel and an illustration using the AA1100 sheets are absent in the literature but introducing this idea could introduce a high-performance threshold and improved planning in the boring industry. Consequently, the absence of such a study could jeopardize the profitability of the process despite having sufficient boring operations resource to prosecute all the available boring jobs. From the literature, it was established that researchers adopt optimisation methods to enhance the performance of the boring system. However, prioritization of the parameters while optimizing them was not considered. Also, the interactions of the parameters in a concurrent optimisation cum prioritization process were not recommended. Furthermore, no methods were adopted to prove that interaction prevails while processing automotive panels, particularly using the AA1100 sheets

3. Methods

3.1 Materials and Experimentation

To choose the IS 2062 E250 plate used in experimentation by Patel and Deshpande [14], the attraction includes its chemical and mechanical compositions, which make the material for wide-ranging applications in the industry. First, the standard information on the chemical and mechanical properties of the IS 2062 E250 plate was obtained from the website of Ashtapad Overseas, a prominent plate supplier in India. While the IS 2062 E250 Br is taken as a broad steel plate group, the obtained information emphasizes three different grades with changes in nomenclature as A, B and C, descended by the E250 ginned description as E250- Gr A, E250-Gr C. Although any of these could be suitable for the experimentation, perhaps Patel and Deshpande [14] were guided by cost and/or availability of the product for supplies at the period of requests for experimentation thus, the E250-GrB, fully described as IS 2062 E2050 Gr B plates were chosen by the authors. The plate consists of the element carbon, magnesium, sulphur, phosphorus, silicon and the C.E values while the element Nb+V+Ti is completely missing in it but is available in other categories of steel plates such as the E-300 (0.25max), E-350 (0.25 max) and E-450 Gr – E (0.25 max), among others.

By compositions, a maximum of 0.045% of sulphur and phosphorus are present in the chosen IS2062 E250 Gr B plates for experimentation. This chosen sample also contains a maximum value of 0.40% silicon. Other values of elements contain a maximum of 0.22% of carbon while a maximum of 1.50% is reported for magnesium. Also, the guide of plates chosen has a C.E. value of 0.41% as the maximum threshold. For the chosen IS2062 E250 Gr-B plates, six principal mechanical properties are of interest to the user and these include the bend test (min), yield stress (<20mm), (>40mm), yield stress (20-40mm), tensile strength (MIN, MPA), % derogation at gauge length 5.65 (square root of so). The yield stress at (<20mm), (20-40 mm) and (>40mm) are given as 250,240 and 230 units, respectively. However, the elongation in percentage at the gauge length 5.65 multiplied by a square root is obtained for the IS 2062 E250 Gr-B plates as 23 minutes. The bend test result is 3t, where t is the thickness of the plate. Beyond these mechanical tests, the density of the plates is 7.85 g/cm^3. Additional information includes the gauge width and length, width per sheet and weight per profit. The gauge width and length is mage ranging, for example, 7(0.1874) x 48 x 120mm represents the gauge width and length whose weight per square feet is 7.871.

Apart from the materials utilized in the boring operation, which includes the IS 2062 E250 Gr-B plates, which are classified as pre and experimental aids, other types of materials such as the software used aided in analyzing the results after the experiments. In the present study, the two software materials used are the Minitab 18 version 2020 and Microsoft Office Excel 2007. The Minitab 18 version 2020 aided in running the Box Behnken design model. Thus was actualized by creating the box Behnken design and introducing the response. Then the analysis was run after which the parameters were optimized. The authors plotted the contour plots and surface plots using the Minitab 18 also. The second software used is Microsoft Office Excel 2007, which was used in generating the signal to noise responses through the Taguchi method. Initially, in Minitab 18 version 2020, the Taguchi orthogonal array design was generated and this was introduced to Microsoft Excel to obtain the signal to noise ratios that were used in the Minitab 18 version 2020 software. Then the process of interpretation in obtaining the response commenced.

Furthermore, the Batliboi make CNC turning centre (Sprint 20 TC) was used for experimentation by Patel and Deshpande [14] whose data is used to validate the methods proposed in this work. Moreover, the chemical vapour deposition (CVD) of Ti (C, N) + Al_2O_3 coated cemented carbide inserts of 0.8 and 1.2 mm as nose radius were engaged in the experiments. Besides, the cutting inserts are the CNMG 12 04 08 PF & CNMG 12 04 12 PF (Sandvik, made), while the tool material is of the CVD coated cemented carbide and the tool holder is specified as MCLNL 25 25 M 12 [14]. Next, the cutting parameters in the boring operation are explained regarding speed, feed and depth of cut. These essential boring parameters are hugely involved in the experiment analysed in the present study and they determine the surface integrity of the material being machined. These cutting parameters concurrently proceed in three motions, stimulating the spread of the cutting tool to the IS 2062 E250 Gr-B plates down the planned path, leading to a completed surface with specified tolerance, size and shape. The cutting sped is the comparative velocity between the workpiece's surface and the tool, measured in surface metres per minute (m/min). But the feed rate is the distance travelled by the tool in a revolution of the workpiece, measured in millimeters per revolution. However, the depth of cut is the sum of the metal quantity subtracted from the IS 2062 E250 Gr-B plates in each pass that the cutting tool makes on the material. This may be computed as the product of the diameter and a coefficient.

3.2 Taguchi-Pareto-Box Behnken Design and Taguchi-Pareto-Box Behnken Design Method

This method is a combination of two methods, namely Taguchi Pareto and Box Behnken method represented in Fig. 1. Also, the Taguchi-ABC Box Behnken method is represented in Fig. 1.

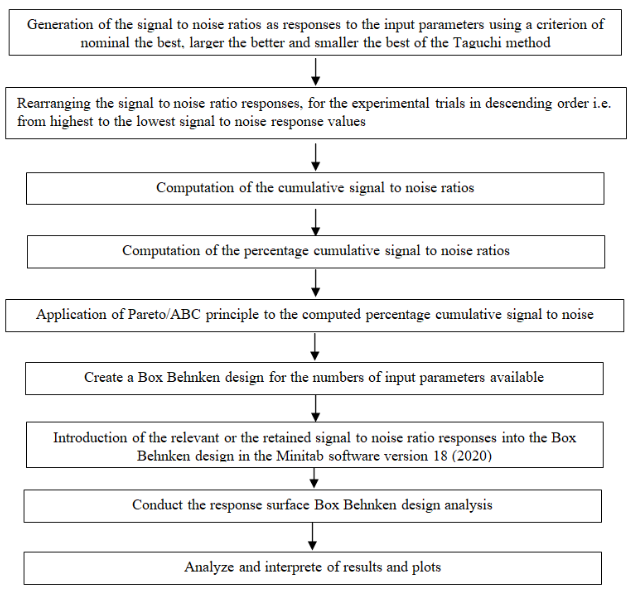


Fig. 1 Taguchi-Pareto-Box/Taguchi-ABC- Behnken Design Flow chart

3.3 Procedure for Implementing TP-BBD Method

Step 1: Generate the signal to noise rations as, responses to the input parameters using one of the critical of nominal the best, larger better, and smaller the better.

Step 2: Apply the Pareto principle of 80-20 rule whereby 80% of the SN ratios by value are cut off from the 100% total value. This may be part of all the experimental trials number. Note that the SNRs will be revised according to their value from each experimental trial. In this case, the SNR having the higher value attached to the certain experimental trial are positioned first, for instance assuming there are 27 experimental trials with, the corresponding SNRs which could be over depending on experimental data, suppose out of the 27 experimental trials, experiment trials 17, 5, 12, having corresponding values of 50, 48, 46, dB as their SNR signal to noise ratios. Besides, let us assume that the signal to noise ratio of all other experimental trials are less than 46, accordingly, as a re-arrangement is sort, the new profile of the experimental trial and the corresponding signal to noise ratio would be as follows; experimental trials 17 with a corresponding signal to noise ratio of 50 dB will be positioned first, experimental trial 5, have a corresponding signal to noise ratio of 48 dB will be next second. Furthermore, experimental trials 12, having an SNR of 46 dB will be positioned third following these are the other signal to noise ratios that would be arranged according to the strength of the value. In other words, we will have a rearranged 27 entries of the experimental trial, starting with experimental trial 17 and discarding other experimental trial that is considered to have the least SNR. Then, the analysis of the 80-20 rule of Pareto on the data will entail having the re-arranged SNR. Described in cumulative form and a cut off of 80% set at 80 % Cumulative column is 50 dB. This is relevant to experiment trial 17 by moving to the next experimental trial 5, cumulative is obtained as 98dB. Next, if we consider the cumulative base on experimental trial 12. The cumulative will be 144dB. The procedure will follow until the last item of the experimental trial with the appropriate SNR is added. Now looking at the column of the cumulative value of SNR a cut of 8% is sort on a near value.

Step 3: Establish the new set of responses and their corresponding experimental trials while discarding the old one. In this case, only those values that are by the computed 80% value of paid to would be shown.

Step 4: The responses that are retailed will be introduced into the Box Behnken design there is a need to event a new design based on the number of factors that are for the present problem. This will entail using the Minitab version 18 and year 2000. Here the Stat menu is clicked, while the DOE submenu is pointed to. Then the choice of response surface is made, furthermore, the "Create response surface design" is made the next phase within this step is to choose the two designs, which is the Box Behnken option. At the same time, there is a need to select the "number of contention factors" while the "numbers of categorical factors" remain fixed as zero. On the same dialogue box, there is a need to click on "Display available design" this option leads to the choice of the available response surface designs of which Box Behnken (Unblocked) is chosen. Arrange the columns there are opportunities to choose the numbers to experiment to use based on the numbers of factors. For example, if the choice of four factors is made there are opportunities to pick up only 27 experiments. This is clicked on and the ok button is activated. Next, the design button is clicked on without adjusting any of the items under the "designs", the ok button is clicked on. Next, the factor button is clicked on here, the actual names of the factors are inserted and lowest and highest bounds are described then, the ok button is clicked on the next phase is to go to the options button notice that "Randomize run" and "store design in sheet" have been ticked by default. In particular, "randomize runs" may have to be unticked, then ok is clicked on. Next, the result button is clicked on. What is to be done is to select the "summary and design table" and click on Ok. The next phase is to click on Ok. The outcome is a display of the summary and design table.

Step 5: Introduce the retained Pareto responses into the generated Box Behnken design.

Step 6: Analyze response surface design: This is obtained after having introduced the retained SNR's. the activation of the "Analyses response surface design" menu Stat by revisiting the Stat, DOE, response surface path to obtain it after clicking on the "Analyze response surface", menu, the response shown is selected by clicking on select then, click on the term and maintain the default setting and click on ok then click on the options button and maintain the default then click on ok. Click on the stepwise button and maintain the default and click on ok. Then click on the graph button, under graph click on "four in one" then click on ok, then click on result button and maintain the default. Then click ok then go to the storage button and click on the main ok button. This plot the various graphs of the Pareto chart of standardized effect as well as the residual plots for the SNR.

Step 7: Analyze and interprete the result

Step 8: Create the contain plots and surface plots. This is obtained by clicking on Stat, DOE, response surface and contour plots. Then click on contain plots. By following the same process surface plots are obtained as you click on the surface plot.

Step 9: Introduce the response optimize: the procedure involves clicking on Stat, DOE, response surface, the response optimizer and finally clicking on it.

Step 10: Report on results and discuss the results

3.4 Procedure for Implementing TABC-BBD Method

Step 1: Apply step 1 of the procedure for implementing the TP-BBD method of the current study

Step 2: Application of the ABC principle, in which the signal to noise ratio values is segmented into three regions namely A, B, and C based on their percentage cumulative values. This is done by first rearranging the signal to noise ratio in descending order i.e. from the highest to the lowest. Note that the rearrangement is done such that the experimental trials and their corresponding orthogonal arrays are also rearranged simultaneously together with the signal to noise ratios. That is to further say that, the various experimental trials positions and the corresponding orthogonal arrays would change position accordingly to the rearrangement. After this rearrangement, it would be observed that the largest signal to noise ratio gains the first position in the list, while the smallest signal to noise ratio would maintain the last position in the rearrangement. For an instant, assuming there are 16 experimental trials in the design, out of which we have experimental trials 4, 8, and 15 with a corresponding signal to noise ratio of 48dB, 120dB, and 94dB respectively and assuming 94dB is the largest signal to noise ratio in the experiment. Rearranging would give 8, 15, 4 experimental trials, corresponding to 120dB, 94dB, 48dB signal to noise ratios in the rearranged form giving a new data profile. Therefore, we would have a rearranged 16 experimental trials with experimental trials 8 having the highest signal to noise ratio taking the first position and some other experimental trial numbers with the least signal to noise ratio taking the last position. Applying the ABC principle would require the computation of cumulative signal to noise ratio and percentage cumulative signal to noise ratio. For example, the first rearranged signal to noise ratio would represent the first cumulative signal to noise ratio i.e. experimental trial 8 with a corresponding signal to noise ratio of 120dB is the first cumulative signal to noise ratio, the second cumulative signal to noise ratio is obtained by adding the first cumulative signal to noise ratio to the second prearranged signal to noise ratio i.e. 120dB is added to 94dB of experimental trial 15 giving 214 dB as the second cumulative signal to noise ratio. The third cumulative signal to noise ratio is also computed by adding the second cumulative signal to noise ratio to the third rearranged signal to noise ratio i.e. 214dB is added to 48 dB of experimental trial 4 giving 262 dB as the third cumulative signal to noise ratio. This procedure would be followed till the cumulative signal to noise ratio of the last experimental trial corresponding to the last signal to noise ratio is computed. This is then followed by the computation of the percentage signal to noise ratio. To compute the percentage signal to noise ratio the rearranged signal to noise ratio for all experimental trials is summed to obtain a total rearranged signal to noise ratio, then each cumulative signal to noise ratio is divided by the total rearranged signal to noise ratio, multiplied by 100. In other words, assuming the total rearranged signal to noise ratio is 2000 dB, the first percentage cumulative signal to noise ratio is computed as 120 dB divided 2000 dB giving 0.06 multiplied by 100 gives 6%, this represents the first percentage cumulative signal to noise ratio. This procedure is followed till the last percentage cumulative signal to noise ratio is computed. Now observing the percentage cumulative signal to noise ratio, we classify it into A, B, and C classes using 0 to 65% for class A, 66% to 79% for class B and 80% to 100% for class C, as applicable to the ABC principle.

Step 3: Execute step 4 to step 9 of the procedure for implementing the TP-BBD method of the current study for each of the ABC classifications i.e. A class or region, B class or region and C class or region.

4. Results and Discussion

The IS 2062 E250 steel plates experience substantial usage due to their associated outstanding attributes. Some applications such as automobiles and aerospace are the top subscribers of the IS 2062 E250 steel plates, particularly where toughness is a prerequisite for the long lifespan of the application. Moreover, boring is a manufacturing operation that may be used to hold various plates rigidly. Unfortunately, as the boring operation is initiated on the IS 2062 E250 steel plates, some damages that are detrimental to the surface roughness of the steel plates are induced on the joined plates. But these damages ought to be minimized to enhance the surface roughness of the bored IS 2062 E250 steel plates. Consequently, a comprehensive treatment of the boring operation involving the IS 2062 E250 steel plates may be the best research pursuit to achieve the goal of enhanced surface roughness stated earlier. Thus, in the present investigation, the boring process parameters in the operation of the IS 2062 E250 are analyzed to understand the effect of the damage on the bored holes in joints of steel plates such that an adequate choice of these parameters are made in a manner to minimize the damage encountered while drilling.

Furthermore, in this article, the IS 2062 E250 steel plates are bored and the experimental data reported in an earlier study, referred to by Abiola and Oke [7] was utilized for the evaluation of two novel methods of Taguchi-Pareto-Box Behnken design and Taguchi-ABC-Box Behnken design. The authors' credit for the experiment (from the literature) [14], conducted the experiments on the computerized numeric controlled machine while establishing diverse levels for the factors, namely speed, feed, depth of cut and nose radius. In this section, the results are presented and discussed under two broad leadings according to the methods applied in this study and are as follows.

4.1 Taguchi-Pareto Box Behnken Design

To obtain Taguchi-Pareto Box Behnken design, the starting, point is the establishment of the Taguchi method on the use of the experimental data. Then the Taguchi approach was further analyzed using the Pareto principle and subsequently followed by the Box-Behnken design approach to complete the method as the Taguchi-Pareto-Box Behnken design method. In this method, the response of the Box Behnken response surface design approach was obtained from the response of the Pareto approach. Besides, to apply the Pareto principle, the signal-to-noise ratio for the sixteen experimental trials was re-arranged from the highest signal-noise ratio to the lowest signal-noise ratio to the lowest signal-noise ratio. The rearrangement also applies to the orthogonal arrays simultaneously of each experimental trial. Consider Table 1 whereupon re-arrangement the cumulative of the signal-noise ratio was computed. For instance, in the experimental trial 1, the signal-noise ratio i.e. -52.0-4121098 is taken as the first cumulative of the signal-noise ratio but the second cumulative of the signal-to-noise ratio is computed by adding the first commutative of the signal-to-noise ratio to the second re-arranged experimental trial of the signal-noise ratio. For instance, -52.041212098 is, the first cumulative of the signal-noise ratio and the second re-arranged signal-noise ratio is -52.04121319. These two items are added as -5204121098 + (-52.04121319) to obtain -104.08.24242 to give the second re-arranged experimental trial signal-noise ratio. The third cumulative signal-noise ratio is also computed by adding the second cumulative signal-noise ratio to the third re-arranged signal-noise ratio to obtain -156.1236394. Besides, the same procedure is then applied to the 4th to 16thexperimental trials signal-noise ratio to compute the cumulative values respectively (Table 2).

Next, the computation of the percentage cumulative signal-noise ratio is actualized, which is computed by dividing all the cumulative signal-noise ratios by the total re-arranged signal-noise ratios previously calculated as -873.9424883. The value is then multiplied by 100. In the case of the first experimental trial, a result of 6% is obtained from -52.04121098 ÷ (-873.9424883) x 100. This gives the first percentages cumulative signal-noise ratio.
Furthermore, by applying the Pareto principle and keeping in mind that a higher signal-noise ratio is desirable in the study; the experimental trials of percentage cumulative signal-noise ratio of 80%-100% are the cutoff of the experiment by Pareto principles because they possess a lower signal-to-noise ratio, which is not desirable by the study. The procedure involves retaining experimental trials with a percentage cumulative signal-noise ratio of 1%-79%, Table 2.

	Orthogonal array				**Factors (interpreted)**				**SN ratio processing**		
Expt. trials	**S**	**F**	**DC**	**NR**	**S**	**F**	**DoC**	**NR**	**Re-arranged SN ratio**	**Cumulative of re-arranged SN ratio**	**Percentage cumulative (%)**
1	1	1	1	1	800	0.06	1.00	0.80	-52.04121098	-52.04121098	6
3	1	3	3	3	800	0.10	1.40	0	-52.04121319	-104.0824242	12
4	1	4	4	4	800	0.12	1.50	0	-52.04121519	-52.04121519	18
2	1	2	2	2	800	0.08	1.25	1.20	-52.04122024	-52.04122024	24
6	2	2	1	4	1000	0.08	1.00	0	-53.97940446	-53.97940446	30
5	2	1	2	3	1000	0.06	1.25	0	-53.97940689	-53.97940689	36
7	2	3	4	1	1000	0.10	1.50	0.80	-53.97941268	-53.97941268	42
8	2	4	3	2	1000	0.12	1.40	1.20	-53.97941492	-53.97941492	49
9	3	1	3	4	1200	0.06	1.40	0	-55.56303093	-55.56303093	55
12	3	4	2	1	1200	0.12	1.25	0.80	-55.56303169	-55.56303169	61
10	3	2	4	3	1200	0.08	1.50	0	-55.56303181	-55.56303181	68
11	3	3	1	2	1200	0.10	1.00	1.20	-55.5630324	-55.5630324	74
16	4	4	1	3	1400	0.12	1.00	0	-56.90196305	-56.90196305	80
15	4	3	2	4	1400	0.10	1.25	0	-56.90196428	-56.90196428	87
14	4	2	3	1	1400	0.08	1.40	0.80	-56.90196658	-56.90196658	93
13	4	1	4	2	1400	0.06	1.50	1.20	-56.90196898	-56.90196898	100

Note: Key: S – speed, F – feed, DoC – depth of cut, NR – nose radius, SN ratio – signal-to-noise ratio; experimental trial numbers 1, 3, 4, 2, 6, 5, 7, 8, 9, 12, 10 and 11 are retained while 16,15,14 and 13 are cut-out

Table 2 Re-arranged S/N ratio and computations of % cumulative

From now onwards, the Box Behnken design method is then introduced as the next phase of computation in the validation of the Taguchi-Pareto-Box Behnken design method. To actualize this goal, the Minitab 18 software was used. This software aided in generating the response surface from the Box Behnken design using four factors and default of 3-level design. The design summary from the Minitab 18 software entails 1 replicate, 27 base runs, 27 total runs, 1 base block and 1 total block for 4 factors. From the design, it was observed that the total number of runs is 27. However, introducing the eleven retained signal-noise ratios from the Pareto approach into the Box Behnken design in the Minitab 18 software to analyse the response surface design was not directly feasible since the number of runs needs to be equal to the number of responses. Thus by following previous works the method used was adopted to overcome this limitation.

The adopted approach was to repeat the responses of the experimental trials 1 to 4 for experimental trials 13 to 16 since they share the same attributes and are from the same data set. Furthermore, experimental trials 5-8 was taken as the experimental trial 17-20 based on the justification given in the preceding sentences. Besides, the same approach was adopted for experimental trials 21-24, which repeats the experimental trials 13-15 was also repeated for experimental trials 25-27. However, upon the completion of the responses, the analysis was conducted and the outputs of the analysis are given in Tables 3 to 6.

Source	**Df**	**AdjSS**	**AdjMS**	**F-value**	***p*-value**
Modal	14	50.6253	3.6161	3.14	0.027
Linear	4	0.2179	0.0545	0.05	0.995
Speed	1	0.0363	0.0363	0.03	0.862
Feed	1	0.0363	0.0363	0.03	0.862
Depth of cut	1	0.0000	0.0000	0.00	1.000
Nose radius	1	0.1453	0.1453	0.13	0.729
Square	4	50.1895	12.5474	10.89	0.001
Speed x Speed	1	4.6876	4.6876	4.07	0.067
Feed x Feed	1	0.0053	0.0053	0.00	0.947
Depth of cut x Depth of cut	1	0.0213	0.0213	0.02	0.894
Nose radius x Nose radius	1	41.2457	41.2457	35.81	0.000
2-way Interaction	6	0.2179	0.2179	0.03	1.000
Speed x Feed	1	0.0000	0.0000	0.00	1.000
Speed x Depth of Cut	1	0.0000	0.0000	0.00	1.000
Speed x Nose radius	1	0.1089	0.1089	0.09	0.764
Feed x depth of cut	1	0.0000	0.0000	0.00	1.000
Feed x Nose radius		0.1089	0.1089	0.09	0.764
Depth of Cut x Nose radius	1	0.0000	0.0000	0.00	1.000
Error	12	13.8227	1.1519		
Lack of Fit	10	13.8227	1.3823	3.11693E	0.000
Pure Error	2	0.0000	0.0000		
Total	26	64.4479			

Table 3 Box Behnken Analysis

Response	Goal	Lower	Target	Upper	Weight	Important
S/N Ratio	Maximum	-56.2231	-52.0412		1	1

Table 4 Analysis of variances

Solution	Speed	Feed	Depth of cut	Nose radius	S/N ratio fit	Composite desirability
1	1090.91	0.06	1.2	0.606061	-51.9335	1

Table 5 Response optimization - S/N ratio Parameter

Variable	Setting
Speed	1096.97
Feed	0.06
Depth of cut	1.2
Nose radius	0.606061

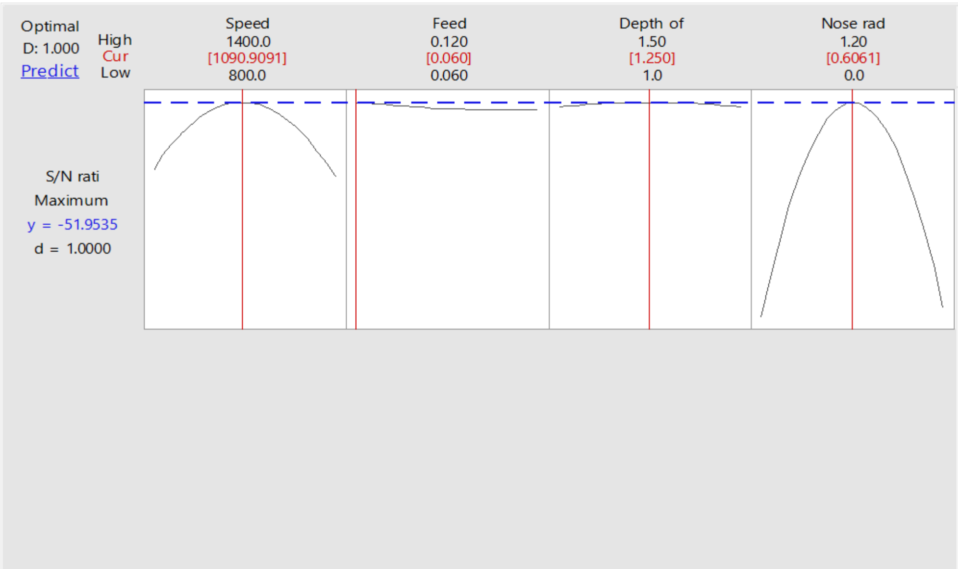
Table 6 Multiple response prediction

Interestingly, the analysis of variance shows that when the model is linear all the factors in the boring operation were insignificant to the model due to their high *p*-values. Besides, when the model is squared, only the nose radius was significant to the model with a *p*-value of 0.000. But when the model is a 2-way interaction, all the factors were also not significant to the model due to their high *p*-values, Table 5. Besides, the model summary shows R-square and adjusted R-square values of 78.55% and 63.53%, respectively, S is 1.0736 while the predicted R squared is 0.00%. Notwithstanding, the adjusted R-square value, signifies that the model is not significant to our aim, Table 5. Now, the response optimisation of the signal-noise ratio shows that the optimum setting for the speed, feed, depth of cut and nose radius are 1090.91, 0.06, 1.2 and 0.606061. But the regression equation in uncoded units reveals that

S/N ratio = -70.00 + 0.0233 speed -3 feed +3.8 depth of cut +10.92 nose radius -0.000010 speed × speed + 35 feed × feed -1.6 depth of cut × depth of cut -7.72 nose radius × nose radius 0.0000 speed × feed -0.00092 speed × nose radius -9.2 feed × nose radius (1)

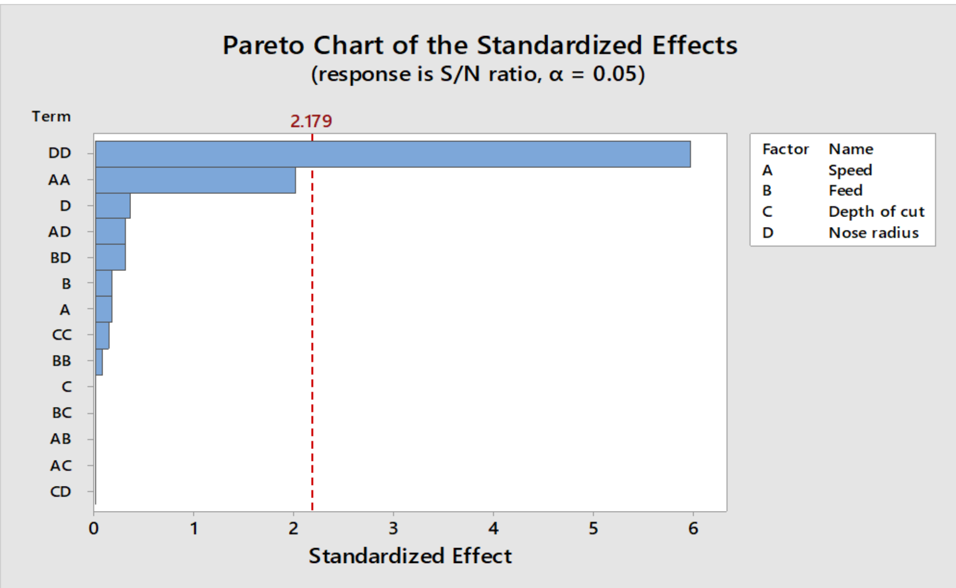
Furthermore, the contour plot of the signal-noise ratio from the analysis shows the range at which various factors in the boring operation would be okay. For instance, from the nose radius versus speed, contour plots, the nose radius would be okay in the boring operation within the range 0.50-0.72. Finally, the surface plots of the S/N ratios also show areas at which the variance parameter would be significant to the model.

The optimization plot (Fig. 2) shows that the optimal parameters to achieve the best signal to noise ratio of (-51.9535) dB are 1090.9091 rpm for speed, 0.06 mm/rev for feed, 1.250 mm for depth of cut, and 0.6061 mm for nose radius.



Note: the units of the cutting parameters: Speed, metres per second; feed, mm per revolution; depth of cut, mm; nose radius, mm.

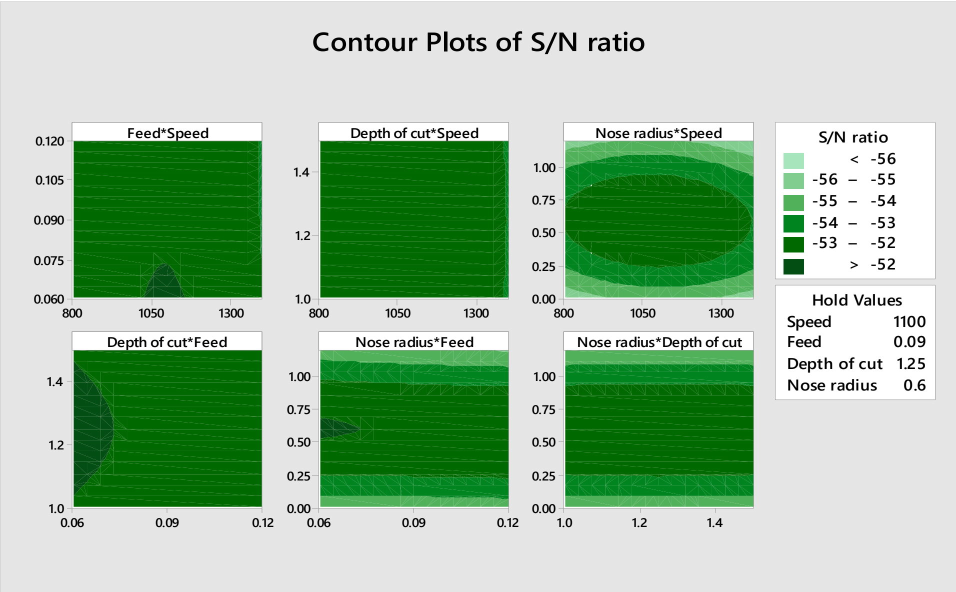
Fig. 2 Optimization plot of Box Behnken approach



Note: the units of the cutting parameters: Speed, metres per second; feed, mm per revolution; depth of cut, mm; nose radius, mm.

Fig. 3 Pareto chart for standard effect

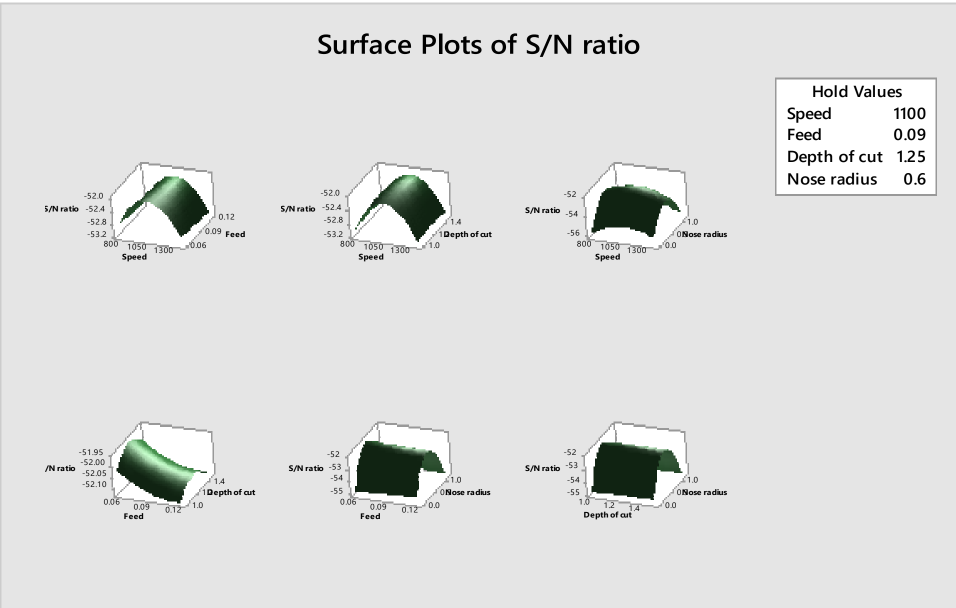
The Pareto chart (Fig. 3) shows that all factors under consideration falls under 20% vital few of the Pareto principles, that is to say that all factors are important in achieving optimal signal to noise ratio. And that they are equally significant in achieving optimal surface roughness according to the Pareto chart.



Note: the units of the cutting parameters: Speed, metres per second; feed, mm per revolution; depth of cut, mm; nose radius, mm.

Fig. 4 Surface Plots of Signal to noise ratio

The contour plots (Fig. 4) show that to achieve the optimal signal to noise ratio greater than -52 dB the combinations of depth of cut and speed, nose radius and speed, nose radius and depth of cut are not feasible or significant in that regards. But a combination of feed and speed in the range of 0.06 to 0.075 mm/rpm for feed and 950 to 1150 rpm for speed are feasible to achieve the optimal signal to noise ratio value greater than -52 dB. Also, a combination of depth of cut and feed, and that of nose radius and feed are also feasible to achieve signal to noise ratio value greater than -52 dB.



Note: the units of the cutting parameters: Speed, metres per second; feed, mm per revolution; depth of cut, mm; nose radius, mm.

Fig. 5 Surface plots of signal to noise ratio ("A" region of Taguchi–ABC–Box Behnken approach)

The surface plots (Fig. 5) of various combination pair of parameters with the signal to noise ratio shows that when the speed parameter is increased there is a corresponding increase in signal to noise ratio to an optimal point. With further increase in the speed at this optimal point, the signal to noise ratio begins to decrease to a minimum value. The feed parameter is behaves such that with constant increase in the feed parameter. The signal to noise ratio tends be in constant decline, the depth of cut parameter increases the signal to noise ratio to its optimal value. But with further increment in depth of cut parameter, the signal to noise ratio decreases steadily. Lastly, the nose radius parameter behaves in similar manner with the depth of cut parameter with reference to the signal to noise ratio. Thus, an average speed, depth of cut, and nose radius promotes high signal to noise ratio while a low feed promotes high signal to noise ratio.

4.2 Taguchi-ABC-Box Behnken Design

To implement the Taguchi-ABC-Box Behnken design (TABC-BBD) method, the Taguchi method was analyzed using the ABC classification approach adopted from inventory analysis. Compared to the Pareto principle, which was used to analyse the Taguchi method based on the 80-20 rule where the 80% of the experimental trials by the cumulative values of the signal-noise ratio, the ABC analysis cuts off the signal-noise ratios at 0-6%, 70-80% and 81-100% for the A, B and C elements of the ABC classification schemes imposed on the Taguchi scheme. Thus, the ABC principle in the responses for the Taguchi approach was analyzed using the ABC principle and the resulting segmentation of the responses of segments A, B and C of the ABC scheme were individually introduced into the Box-Behnken design response surface.

However, in applying the ABC principle, the signal-noise ratios of the sixteen experimental trials were rearranged from the highest signal-noise ratio to the lowest signal-noise ratio. Notwithstanding, the re-arrangement also applies to the orthogonal arrays simultaneously of each experimental trial. Upon re-arrangement, the cumulative of the signal-noise ratios were computed. However, an instance of experimental trial 1 is given here. For this trial, the signal-noise ratio is -52.04121098 is regarded as the first cumulative signal-noise ratio while the second cumulative signal-noise ratio while the second cumulative signal-noise ratio is computed by adding the first cumulative signal-noise ratio to the second re-arranged experimental trial signal-noise ratio. For instance, -52.04121098 is the first cumulative signal-noise ratio is -52.04121319 which is obtained by adding -52.04121098 and -52.04121319 to give -104.0824242 to be known as the second re-arranged experimental trial signal-noise ratio.

Furthermore, the third cumulative signal-noise ratio is also computed by adding the second cumulative signal-noise ratio to the third re-arranged signal-noise ratio it gives -156.1236394. Besides, this same procedure is then applied to the 4th to the 16th experimental trials signal-noise ratio to compute their cumulative values, respectively (Table 7).

Experimental Trial	Speed	Feed	Depth of Cut	Nose radius	Speed	Feed	Depth of Cut	Nose Radius	Re-arranged S/N ratio	% Cumulative SN ratios
1	1	1	1	1	800	0.06	1.00	0.80	-52.04121098	6%
3	1	3	3	3	800	0.10	1.40	0	-52.04121319	12%
4	1	4	4	4	800	0.12	1.50	0	-52.04121319	18%
2	1	2	2	2	800	0.08	1.25	1.20	-52.04122024	24%
6	2	2	1	4	1000	0.08	1.00	0	-53.97940446	30%
5	2	1	2	3	1000	0.06	1.25	0	-53.97940689	36%
7	2	3	4	1	1000	0.10	1.50	0.80	-53.97941268	42%
8	2	4	3	2	1000	0.12	1.40	1.20	-53.97941492	49%
9	3	1	3	4	1200	0.06	1.40	0	-55.56303093	55%
12	3	4	2	1	1200	0.12	1.25	0.80	-55.56303169	61%
10	3	2	4	3	1200	0.08	1.50	0	-55.56303181	68%
11	3	3	1	2	1200	0.10	1.50	1.20	-55.5630324	74%
16	4	4	1	3	1400	0.12	1.00	0	-56.90196305	80%
15	4	3	2	4	1400	0.10	1.25	0	-56.90196428	87%
14	4	2	3	1	1400	0.08	1.40	0.80	-56.90916658	93%
13	4	1	4	2	1400	0.06	1.50	1.20	-56.90196898	100%

Table 7 Optimum settings

Next is the computation of the percentage cumulative signal-noise ratio, which is computed by dividing all the cumulative signal-noise ratios by the total of the re-arranged signal-noise ratio, which was computed as -873.9424883 and multiplying them by 100. For instance, for the first experimental trial, the value of 6% is obtained as -52.04121098 is divided by -873.9424883 and multiplied by 100. This gives the first percentage cumulative signal-noise ratio. The computation of the percentage cumulative signal-noise ratio is followed by applying the ABC principle. In doing this, the percentage cumulative signal-noise ratio of 0-67% is labelled as region C, 68-79% is labelled as region B while 80–100% is labelled as region A. With this, the re-arranged signal-noise ratio has been successfully segmented into three categories A, B and C (Table 7). These now lead to the introduction of the Box-Behnken design approach where the parametric selection and optimisation for the boring of IS 2062 E250 plates using the Taguchi method are achieved. Here, each of the regions segmented S/N ratio is then introduced into the Box Behnken design i.e. regions A, B and C's S/N ratios are individually introduced into the Box Behnken design approach. The Minitab 18 (2020) is used to generate response surface, Box Behnken design using four factors and default of three-level design.

				Region A				
SO	**RO**	**PT**	**B**	**S**	**F**	**DoC**	**NR**	**SNR**
1	1	2	1	800	0.06	1.25	0.6	-56.9020
2	2	2	1	1400	0.06	1.25	0.6	-56.9020
3	3	2	1	800	0.12	1.25	0.6	-56.9020
4	4	2	1	1400	0.12	1.25	0.6	-56.9020
5	5	2	1	1100	0.09	1.00	0.0	-56.9020
6	6	2	1	1100	0.09	1.50	0.0	-56.9020
7	7	2	1	1100	0.09	1.00	1.2	-56.9020
8	8	2	1	1100	0.09	1.50	1.2	-56.9020
9	9	2	1	800	0.09	1.25	0.0	-56.9020
10	10	2	1	1400	0.09	1.25	0.0	-56.9020
11	11	2	1	800	0.09	1.25	1.2	-56.9020
12	12	2	1	1400	0.09	1.25	1.2	-56.9020
13	13	2	1	1100	0.09	1.00	0.6	-56.9020
14	14	2	1	1100	0.06	1.00	0.6	-56.9020
15	15	2	1	1100	0.12	1.50	0.6	-56.9020
16	16	2	1	1100	0.06	1.50	0.6	-56.9020
17	17	2	1	800	0.12	1.00	0.6	-56.9020
18	18	2	1	1400	0.09	1.00	0.6	-56.9020
19	19	2	1	800	0.09	1.50	0.6	-56.9020
20	20	2	1	1400	0.09	1.50	0.6	-56.9020
21	21	2	1	1100	0.06	1.25	0.0	-56.9020
22	22	2	1	1100	0.12	1.25	0.0	-56.9020
23	23	2	1	1100	0.06	1.25	1.2	-56.9020
24	24	2	1	1100	0.12	1.25	1.2	-56.9020
25	25	0	1	1100	0.09	1.25	0.6	-56.9020
26	26	0	1	1100	0.09	1.25	0.6	-56.9020
27	27	0	1	1100	0.09	1.25	0.6	-56.9020

Note: Key: SO - Std Order, RO - Run Order, PT - Pt Type, B – Blocks, S – Speed, F – Feed, DoC - Depth of Cut, NR – Nose Radius, SNR - S/N ratios

Table 8 Re-arranged S/N ratio & computation of % cumulative

Considering the Design summary for Region A, 1 is assigned to the Factors 4 Replicates, 27 is attached to the Base runs 27 Total runs, 1 to the Base blocks 1 Total blocks and there are three centre points. Again, from the design, it was observed that the total number of the run is 27, introducing the A region signal-noise ratio which was of four experimental trials, giving four signal-noise ratios of the ABC principle into the Box Behnken design in the Minitab 18 software. Analyzing the response surface design was not possible as the number of runs has to equal to the number of responses. In this work, to make the numbers or runs equal to the numbers of responses, the responses of the experimental trials 16, 15, 14, 13 were repeated for all other experimental trials as the experimental trial responses for 16, 15, 14 and 13 are all rounded up to be the same as a correctional strategy in the computations. In the Minitab 18 software, see Table 10 for regions A, B and C, respectively.

Upon completion of the responses, the analysis is carried out and the outputs of the analysis are given in Tables 9 to 12.

		Region A			
Source	**DF**	**Adj SS**	**Adj MS**	**F-value**	***p*-value**
Modal	14	0.000000	0.000000	7.60	0.01
Linear	4	0.000000	0.000000	25.45	0.000
Speed	1	0.000000	0.000000	8.80	0.012
Feed	1	0.000000	0.000000	17.81	0.001
Depth of Cut	1	0.000000	0.000000	29.95	0.000
Nose Radius	1	0.000000	0.000000	45.24	0.000
Square	4	0.000000	0.000000	0.70	0.607
Speed x Speed	1	0.000000	0.000000	1.40	0.260
Feed x Feed	1	0.000000	0.000000	1.40	0.260
Depth of cut x Depth of cut	1	0.000000	0.000000	1.0	0.260
Nose radius x Nose radius	1	0.000000	0.000000	1.40	0.260

Table 9 Analysis of Variance for the boring process parameters for Regions A, B and C

		Region A			
Source	DF	Adj SS	Adj MS	F-value	*p*-value
2-way Interaction	6	0.000000	0.000000	0.30	0.923
Speed x Feed	1	0.000000	0.000000	0.30	0.591
Speed x Depth of Cut	1	0.000000	0.000000	0.30	0.591
Speed x Nose radius	1	0.000000	0.000000	0.30	0.591
Feed x Nose Radius	1	0.000000	0.000000	0.30	0.591
Depth of cut x nose radius	1	0.000000	0.000000	0.30	0.591
Error	12	0.000000	0.000000	0.30	0.591
Lack of fit	10	0.000000	0.000000	0.30	0.591
Pure Error	2	0.000000	0.000000	0.30	0.591
Total	26	0.000000	0.000000	0.22	0.591

Table 9 Analysis of Variance for the boring process parameters for Regions A, B and C (Cont'd)

In the response surface regression for signal-noise ratio, versus, speed, feed, depth of cut and nose radius, the analysis of variance shows that when the modal is linear, all the factors in the boring operation is significant, with *a p*-value of 0.012, 0.01, 0.000 and 0.000, for speed, feed, depth of cut, and nose radius respectively, but when the modal is square all the factors in the boring operation are not significant to the modal, and when the modal is a 2-way interaction all the factors in the boring operation are still not significant to the modal, due to their high p-value which happens to be greater than 0.05, making the factors insignificant. The modal summary shows an R-square and adjusted R-square value greater than 65%, which make it important to the boring operation.

The response optimisation of the signal-noise ratio shows that the optimum setting for the speed feed, depth of cut and nose radius are 1050.61, 0.0715152, 1 and 0 respectively. The contour plot of the signal-noise ratio from the analysis also shows the range at which variance parameter would be ok in the boring operation. Similarly, the surface plots of the S/N ratio also show areas at which the various parameters would be significant to the modal (see contour plot and surface plot). Finally, from the Box-Behnken design, analysis of the optimum setting of the parameters in the boring operation is 1060.61 for speed, 0.0715152 for feed, 1 for depth of cut and 0 for nose radius.

The modal summary for the Analysis of variance (Region A) reveals an S of 0.0000011, R-Sq of 89.87%, R-Sq (adj) of 78.05% and R-sq (pred) of 58.59%. However, the Regression Equation in uncoded Units is given as

$$\begin{aligned} \text{S/N radius} = {} & -56.9020 + 0.000160\ \text{Feed} \\ & + 0.000024\text{Depth of cut} \\ & + 0.000004\ \text{Nose radius} - 0.000603\ \text{feed} \\ & \times \text{feed}\ 0.000009\ \text{Depth of cut} \\ & \times \text{Depth of Cut} - 0.000002\ \text{Nose radius} \\ & \times \text{Nose Radius} - 0.00039\ \text{feed} \\ & \times \text{Depth of cut} - 0.000016\ \text{Feed} \\ & \times \text{Nose radius} - 0.000002\ \text{Depth of cut} \\ & \times \text{Nose radius} \end{aligned} \tag{2}$$

Besides, Fig. 7-11 show the plots for region A of the ABC classification scheme.

Region	Response	Goal	Lower	Target	Upper	Weight	Importance
A	S/N ratio	Maximum	-56.9020	-56.9020		1	1
B	S/N Ratio	Maximum	-56.2231	-55.5630		1	1
C	S/N Ratio	Maximum	-55.5630	-52.0412		1	1

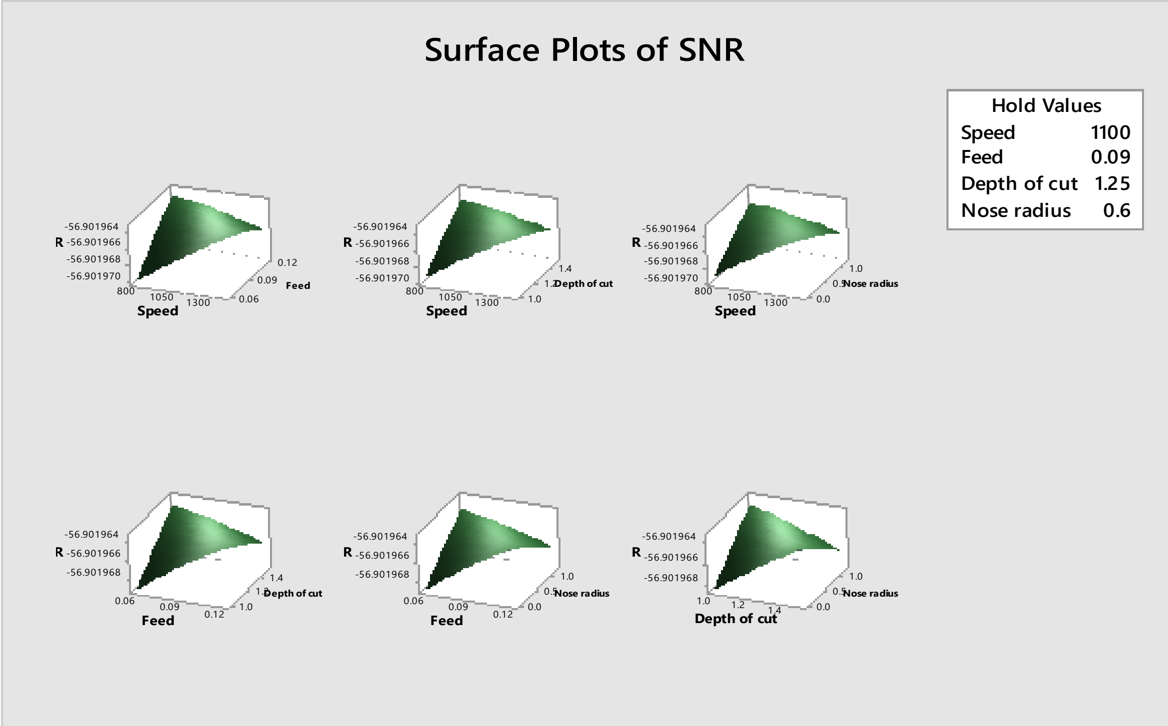
Table 10 Parameter solution

Region	Solution	Speed	Feed	Depth of cut	Nose radius	S/N ratio Fit	Composite desirability
A	1	1060.61	0.0715152	1	0	-56.9020	1
B	1	800	0.06	1	0.606061	-55.2880	1
C	1	1096.97	0.06	1.13131	1.2	-51.1826	1

Table 11 Solution to optimization

	Region A	Region B	Region C
Variable	Setting	Setting	Setting
Speed	1060.61	800	1096.97
Feed	0.0715152	0.06	0.06
Depth of Cut	1	1	1.13131
Nose radius	0	0.606061	1.2

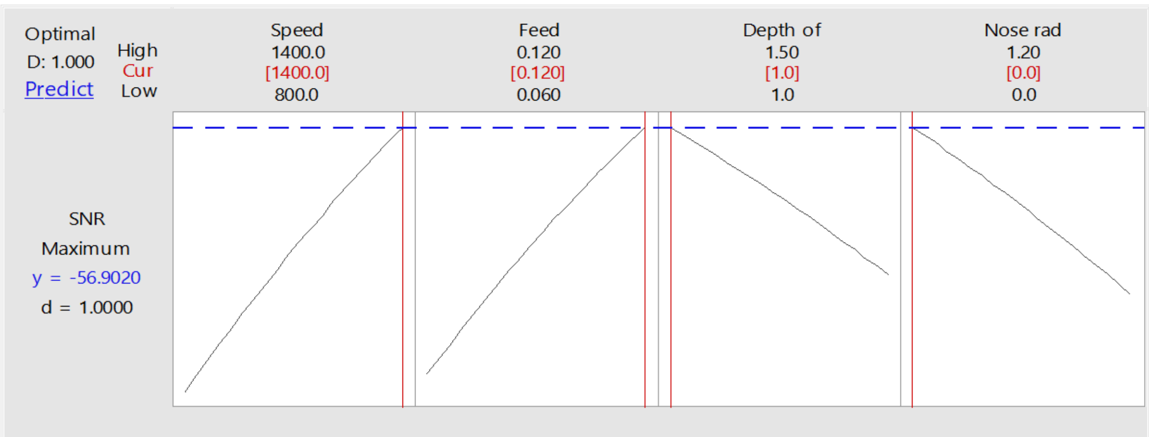
Table 12 The optimum setting for regions A, B and C



Note: the units of the cutting parameters: Speed, metres per second; feed, mm per revolution; depth of cut, mm; nose radius, mm.

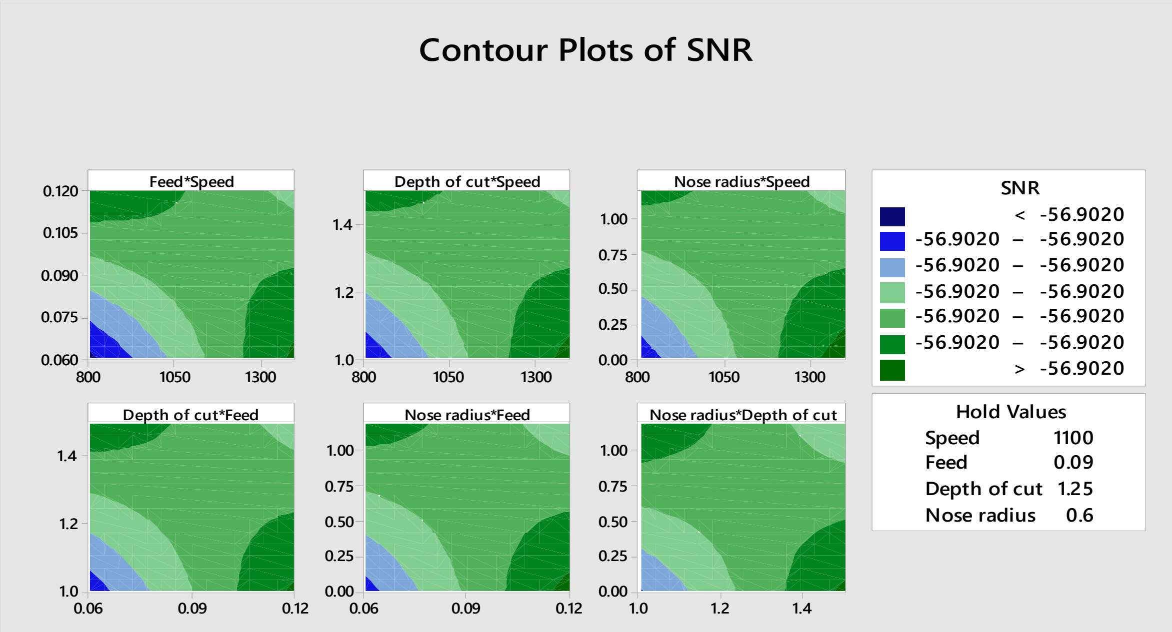
Fig. 6 Optimization Plot for Box Behnken Approach ("A" region of Taguchi – ABC – Box Behnken Approach)

The surface plots (Fig. 6) of various combination pair of parameters with the signal to noise ratio shows that when the speed parameter is increased there is a corresponding steady(constant) signal to noise ratio, The feed parameter behaves such that with constant increase in the feed parameter, the signal to noise ratio tends decline to a minimum value such with further increase in the feed rate the signal to noise ratio begins to increase to the maximum signal to noise ratio, the depth of cut parameter increment increases the signal to noise ratio to it optimal value but with further increment in depth of cut parameter the signal to noise ratio decreases steadily, and lastly with increase in nose radius parameter, the signal to noise ratio increases steadily. Thus, if the speed parameter is maintained within it bounds of 800 to 1400 rpm, then this would promote an optimal signal to noise ratio, and that an average feed does not promote an optimal signal to noise ratio. Furthermore, an average depth of cut value promotes optimal signal to noise ratio, and lastly, the high nose radius promotes optimal signal to noise ratio. The optimization plot (Fig. 7) shows that optimal parameters to achieve optimal signal to noise ratio of -56.9020 are 1096.9697 rpm for speed, 0.06 for feed rate, 1.1313 for depth of cut and 1.2 for nose radius.



Note: the units of the cutting parameters: Speed, metres per second; feed, mm per revolution; depth of cut, mm; nose radius, mm.

Fig. 7 Contour Plots of Signal to Noise Ratio ("A" region of Taguchi – ABC – Box Behnken Approach)



Note: the units of the cutting parameters: Speed, metres per second; feed, mm per revolution; depth of cut, mm; nose radius, mm.

Fig. 8 Residual Plots for Signal to Noise Ratio ("A" region of Taguchi – ABC – Box Behnken Approach)

The contour plots (Fig. 8) show that to achieve the optimal signal to noise ratio greater than -52, the combinations of depth of cut and speed, nose radius and speed, depth of cut and feed are not feasible or significant in that regards, but a combination of feed and speed, nose radius and feed, and nose radius and depth of cut are feasible to achieve the optimal signal to noise ratio value greater than -52.

From the Design Summary for Region B, the factors considered are 4 Replicates, 1 while the base runs are twenty-seven total runs and the base block is 1. By introducing the B region signal-noise ratio, which was of only 2 experimental trials, giving 2 signal-noise ratios of the ABC principle into the Box Behnken design in the Minitab 18 software was obvious. Analyzing the response surface design was not possible, as the number of the run has to equal the number of responses. To make the numbers of runs equal to the numbers of responses, the responses of the experimental trial 10 and 11 were repeated in an orderly for all experimental trials to complete the 27 runs, Table 12.

Upon completion of the responses, the analysis is carried out and the output of the analysis is given in Table 18, 19, 20 and 21. The modal summary is S as 0.269488, R-Sq as 70.33%, R-Sq (adj) as 35.71% and R-Sq (pred) as 35.71%. The Regression equation in uncoded units is given as

S/N ratio = -56.03 + 0.0024 speed + 3.7 feed + 1.76 Depth of cut + 0.18 Nose radius -0.000001 speed x speed -61 feed × feed -0.88 depth of cut × depth of cut -0.153 Nose radius × Nose radius (3)

In the response surface regression for signal-nose ratio, versus speed, feed, depth of cut, and nose radius, the analysis of variance shows that the speed and the feed are the only two factors significant to the modal when the modal is linear. When the modal is square all the parameters in the boring operation are not significant to the modal, and when the modal is a 2-way interaction all factors are also not significant to the modal due to their high *p*-value, Table 18. The modal summary shows an R-sq and adjusted R-square value of 70.33% and 35.71%, respectively. The adjusted R-sq falls below the accepted value of 65%, making it becomes insignificant. The response optimisation of the signal-noise ratio shows that the optimum setting for the speed feed, depth of cut, and nose radius are 800,0.06 1 and 0.606061 respectively. Finally, the contour plot of the signal-noise ratio from the analysis also shows the range at which various parameters would be ok in the boring operation see contour plot for the B region, similarly, the surface plot of the S/N ratio also shows areas at which the various parameter would be significant to the modal. In the following paragraphs, plots, pareto charts and residual plots were made but not reported in this work for conciseness. Thus, regions B and C have not been explain in fiures as they follow the same pattern as for region A of the ABC analysis. However, quantitative descriptions are given. The optimization plot (not reported) shows that optimal parameters to achieve optimal signal to noise ratio of -55.2880 are 800 rpm for speed, 0.06 for feed rate, 1.0 for depth of cut and 0.6061 for nose radius. The surface plots (not reported) of various combination pair of parameters with the signal to noise ratio shows that the feed, depth of cut and the nose radius all results to an optimal signal to noise ratio value at their average values. While the speed parameter increment results to a decrease in the signal to noise ratio value, this is to say that an average feed, depth of cut and nose radius promotes optimal signal to noise ratio and a high speed decreases the signal to noise ratio value. The contour plots (not reported) show that to achieve the optimal signal to noise ratio greater than -55.4, almost all the combination of parameter will not lead to the optimal signal to noise ratio of -55.4 in this regards, the only combination that leads to the optimal signal to noise ratio is the feed and speed combination with a range of 0.06 to 0.07 for feed and 800 to 850 for speed. The Pareto chart (not reported) shows that all factors under consideration falls under 20% vital few of the Pareto principles, that is to say that all factors are important in achieving optimal signal to noise ratio. They are equally significant in achieving optimal surface roughness according to the Pareto chart. Furthermore, it is observed that not all part of the speed parameter and the feed is within the 20% vital few. Furthermore, the Design Summary for Region C reveals factors of 4 Replicates, 1, base runs of 27, base blocks of 1 total block. Introducing the C region signal-noise ratio, which was of 10 experimental trials, giving 10 signal-noise ratios of the ABC Principle, into the Box Behnken design in the Minitab 18 software analyzing the response surface design was not possible, as the numbers of the run have to equal the numbers of responses. To make the numbers of runs equal to the numbers of responses, the response of the experimental trial 1-4 is repeated for the experimental trial 11-14, the responses for the experimental trial 5-8 is repeated for the experimental trial 15-18, and the experimental trials 9-10 is repeated for the experimental trial 19-20, again experimental trial 1-4 is again repeated for 21-24, and finally, experimental trials 5-7 are repeated for 25-27 experimental trials. The analysis is carried out and the output of the analysis is given as Tables 22, 23, 24 and 25. The modal summary reveals S as 0.967593, R-sq as 74.75%, R-Sq (adj) as 45.30% and R-sq (pred) as 0.00%. The Regression Equation in Uncoded Units is given as

$$\text{S/N ratio} = -518 + 0.0011\ \text{speed} - 344\ \text{feed} + 22.3\ \text{depth of cut} - 0.20\ \text{Nose radius} + 1908\ \text{feed} \times \text{feed} - 9.86\ \text{Depth of Cut} \times \text{depth of cut} + 0.98\ \text{Nose radius} \times \text{Nose radius} \tag{4}$$

The response surface regression for signal-noise ratio, versus speed, feed, depth of cut and nose radius, the analysis of variance show that the speed, feed, depth of cut and the nose radius are all not significant to the modal when the modal is linear. When the modal is square, the feed parameter is the only significant factor with a P-value of 0.001 and when the modal is a 2-way interaction, all parameters in the being operation are not significant to the modal.

The modal summary shows an R-sq and adj R-sq of 74.75% and 45.30% respectively. The adjusted R-sq falls below the acceptable value of 65% making it insignificant. The response optimisation of the signal-noise ratio of the region shows that the optimum setting for the speed, feed, depth of cut and nose radius are 1096.97, 0.06, 1.13131 and 1.2 respectively. Finally, the contour plots of signal-noise ratio for the C region from the analysis also show the range at which various parameters would be ok in the boring operation, see contour plots for Region C. Similarly, the surface plots of the S/N ratio of the C region also show areas at which the various parameters would be significant to the modal, plots. The surface plots (not reported) show that with all parameters at their various average values, the optimal signal to noise ratio is obtainable.

The Pareto chart (not reported) shows that all factors under consideration falls under 20% vital few of the Pareto principles, that is to say that all factors are important in achieving optimal signal to noise ratio. And that they are equally significant in achieving optimal surface roughness according to the Pareto chart, it is observed that not all part of all the factors are is within the 20% vital few. The contour plots (not reported) show that to achieve the optimal signal to noise ratio greater than -56.9020, only two combinations would achieve the aim of a maximum signal to noise ratio greater than -56.9020, they are the nose radius and feed, and the nose radius and depth of cut, all other combination would not achieve this aim. The optimization plot (not reported) shows that optimal parameters to achieve optimal signal to noise ratio of -56.9020 are 1060.6061 rpm for speed, 0.0715 for feed rate, 1.0 for depth of cut and 0.0 for nose radius.

4.3 Comparison of Results of TP-BBD and TABC–BBD Methods

The TP-BBD and TABC-BBD methods were instituted using the Box Behnken design method to unite each of them. From the results, it was noted that the TP-BBD method captures higher values of experimental trials (i.e. 69%). The number of experimental trials is also higher in the TP-BBD method than in the TABC-BBD method. From the results, it may be observed that the optimum parametric values in the context of prioritization depend on the values of the captured signal-to-noise ratios corresponding to the experimental trials. The optimum parametric values cum prioritized states for the TP-BBD method was at roughly 80% cut off while for the TABC-BBD method, it was roughly at 69% cut off point.

4.4 Advantages of the Proposed Methods

The proposed TP-BBD and TABC-BBD methods exhibit multiple benefits, including:

(1) The two methods require a fewer number of runs in tackling the concern of where experimental boundaries ought to be and specifically to evade extreme treatment combinations.

(2) It considers analysis in a Pareto or an ABC scale thereby establishing priorities for the parameters where the most important parameters are separated from the less important.

(3) It provides both quantitative and qualitative data from limited information.

(4) By extracting information from the statistically significant data, the two methods could explore the benefits of the Taguchi method by evading the offspring population and subsequently avoiding the substantial computational cost.

5. Conclusions

This study optimized the boring process parameters of IS 2062 E250 plate on the computerized numeric controlled (CNC) machine through two methods, namely the Taguchi-Pareto-Box Behnken Design (TP-BBD) and Taguchi-ABC-Box Behnken design (TABC-BBD) methods. For the TP-BBD method and using the analysis of variance (ANOVA), only the nose radius among other parameters of speed, feed and depth of cut was significant to the model when the model is squared. However, the insignificance of all the parameters was observed for the linear and 2-way interactions. But for the TABC-BBD method, the ANOVA showed that when the model is linear, all the factors in the boring operation are significant with *p*-values ranging from 0 to 0.012. Furthermore, when the model is squared and also considered along with a 2-way interaction, all the factors are insignificant. The results of the TP-BBD method reveal that only the nose radius is the most important factor whereas, for the TABC-BBD method, all the parameters, namely speed, feed, depth of cut and nose radius are important in the optimisation of the surface roughness response for the boring operation of IS 2062 E250 plate.

For the TP-BBD method, the results showed a good agreement between the experimental and predicted values for R^2 (0.7855), and adjusted R^2(0.5353). For the TABC-BBD method, the results also revealed a good agreement between the experimental and predicted values for R^2 (0.7475) and adjusted R^2 (0.4530). Besides, the response optimisation of the signal-to-noise ratios for the TP-BBD method shows that the optimal parametric setting for enhanced surface roughness of the IS 2062 E250 plate was identified as 1090.91 rpm, 0.06mm/rev, 1.2 mm and 0.61mm for speed, feed, depth of cut and nose radius, respectively. However, for the TABC-BBD method, three different results for the percentage cumulative of C (6-61%), B (68-74%) and A (80-100%) were obtained and reported in the results and discussion part of this work. But group A (80-100%) is reported here as the most important result. For group A (80-100%) the TABC-BBD method reveals the response optimisation of the signal-to-noise ratios with the optimal parametric setting for enhanced surface roughness of the IS2062 E250 plate given as 1060.61rpm, 0.07mm/rev, 1mm and nil for speed feed, depth of cut, and nose radius, respectively. From the predictions, it can be concluded that the most important parameter in the boring operation of IS 2062 E250 plate on CNC machine is speed while the least important parameter is feed as indicated by the predicted signal-to-noise response. Besides, in this article, the optimised parameters for the TP-BBD and TABC-BBD were not the same; TP-BBD tends to exhibit higher parametric values than the TABC-BBD generally. But optimised parameters are tools employed by process engineers to set standards of performance for the boring process to be used by operators during the boring operation. The idea is that it is better to choose the method that yields higher parametric values than those of the lower category. This drives the operator towards more productivity and performance. On comparing the experimental delta values and the ranking with that of the predicted signal-noise responses, the delta values were different but in similar proportions, as the ranking are in complete agreement and are the same in both scenarios.

Also, in this article, the R-square value is very low in some instances possibly due to the omission of some important predictors in the work. However, this issue is beyond what the present authors could tackle in this work since experimental data already collected by Patel and Deshpande [14] was used. What this information suggests is that future studies must be extended beyond the scope of three predictors (speed, feed and depth of cut) for the outcome of the study so that a robust R-square value may be obtained.

Additionally, the present paper has revealed that the two methods of Taguchi-Pareto-Box Behnken design and Taguchi-ABC-Box Behnken design are economic approaches to determining the optimal parametric settings of the IS 2062 E250 plate in the boring process under the CNC machines. In the future, it may be beneficial to study the influence of more advanced methods on the optimal parametric settings by introducing the particle swarm optimisation (PSO) and the genetic algorithm (GA) differently and jointly into the two methods form advanced methods containing the Taguchi-Pareto, Taguchi ABC, Box Behnken design [36], PSO and GA. Furthermore, the introduction of a quality control tool that will indicate when the parameters are within and outside control bounds with and without the introduction of the PSO and GA into the Taguchi-Pareto-Box Behnken design and Taguchi-ABC-Box Behnken design frameworks may be beneficial to the boring operations literature.

References

[1] G. Vohra, H.S. Sodhi & S.A. Bansal. "Prediction of optimised parameters for CNC boring process using taguchi method for steel", *International Journal of Mechanical Science and Civil Engineering*, pp. 30-36, 2013.

[2] M.P. Groover. *Fundamentals of Modern Manufacturing: Materials, Processes, and Systems* (4th edition ed., pp. 519-520). John Wiley & Sons, Inc., 2020.

[3] T.T. Kumar, M. Peeraiah, S.M. Sudhan, C. Reddy. "Optimization of machining parameters of stainless steel 410 for boring operation in a lathe based on GRA", *Journal of Emerging Technologies and Innovative Research*, vol. 6, no. 5, pp. 231-240, 2019b. http://dx.doi.org/10.13140/RG.2.2.19949.84967

[4] D.P. Singh & S. Prakash. "Experimental study of taguchi vs

GRA parameters during CNC boring in steel plate (SS-304)", *International Research Journal of Engineering and Technology*, vol. 6, no. 8, pp. 1310-1315, 2019.

[5] K.A. Kumar, C. Ratnam, K.V. Rao & B.S.N. Murthy. "Experimental studies of machining parameters on surface roughness, flank wear, cutting forces and work piece vibration in boring of AISI 4340 steels: Modelling and optimization approach", *SN Applied Sciences*, vol. 1, no. 1, Article 26, 2019.

[6] D. Panchal. "Optimization of surface roughness of EN-36 alloy steel on CNC turning machine using Box Behnken method under RSM", *International Journal for Research in Applied Science and Engineering Technology,* vol. 8, pp. 608-625, 2020.

[7] I.T. Abiola, S.A. Oke. "Performance evaluation of surface roughness in the boring operation of IS 2062 E250 plate on CNC machine using combined entropy-decision tree-VIKOR approach", *Indonesian Journal of Industrial Engineering & Management*, vol. 2, No. 1, pp. 1-15, 2021. http://dx.doi.org/10.22441/ijiem.v2i1.10190

[8] I.T. Abiola, S.A. Oke. "Fuzzy analytic hierarchy process and Markov-chain-WSM/WPM/WASPAS approach to solving the surface roughness problem in the boring of IS 2062 E250 steel plates on CNC machines", *Indonesian Journal of Industrial Engineering & Management*, vol. 3, no. 1, pp. 47-71, 2022. http://dx.doi.org/10.22441/ijiem.v3i1.13242

[9] P. Kumar, J.S. Oberoi, C. Singh & H. Dhiman. "Analysis and optimization of parameters affecting surface roughness in boring process", *International Journal of Advanced Mechanical Engineering* , vol. 4, pp. 647–655, 2014b.

[10] B.A. Yuvaraju & B.K. Nanda. "Prediction of vibration amplitude and surface roughness in boring operation by response surface methodology", *Materials Today: Proceedings,* vol. 5, pp. 6906–6915, 2018.

[11] K.V. Rao, B.S. Murthy & N.M. Rao. "Cutting tool condition monitoring by analyzing surface roughness, workpiece vibration and volume of metal removed for AISI 1040 steel in boring", *Measurement* , vol. 46, pp. 4075–4084, 2013.

[12] G. Schneider. "Cutting tool applications, Chapter 10: boring operations and machines-American Machinist", *Modern Machine Shop, http://www. americanmachinist. com,* 2010.

[13] K. Krishnaiah & P. Shahabudeen. *Applied Design of Experiments and Taguchi Methods.* PHI Learning Pvt. Ltd., New Delhi, India, 2012.

[14] M. Patel & V. Deshpande. "Application of taguchi approach for optimization roughness for boring operation of E 250 B0 for standard IS: 2062 on CNC TC", *International Journal of Engineering Development and Research*, vol. 2, no. 2, pp. 2528-2537, 2014.

[15] W. Nugroho, N.B. Baba & A. Saptari. "Optimization on surface roughness of boring process by varying damper position", *ARPN Journal of Engineering and Applied Sciences*, vol. 11, no. 20, pp. 11911-11918, 2006.

[16] N.K. Nayak & H.S. Sodhi. "Optimization of CNC turning parameters for Al-6061 using response surface methodology", *International Journal of Mechanical and Production Engineering Research and Development* , vol. 7, pp. 127–138, 2017.

[17] V.K. Sukhdeve & S.K. Ganguly "Comparison of process parameter optimization of a jig boring process using taguchi based grey analysis and genetic algorithm", *i-Manager's Journal on Future Engineering and Technology,* vol. 14, Article 58, 2019.

[18] M. M. Abdulrazaq, A.S. Jaber, A.S. Hammood & A.G. Abdulameer. "Optimization of machining parameters for MRR and surface roughness for 7024 Al-alloy in pocket milling process", *Association of Arab Universities Journal of Engineering Sciences,* vol. 26, pp. 10–16, 2019.

[19] P.A. Kumar, C.H. Singh & H.I. Dhiman. "Analysis and optimization of parameters affecting bore deviation in boring process", *International Journal of Innovative Technology and Research,* vol. 2, pp. 967–972, 2014a.

[20] A. Abdullah, B.M. Khirulrizwan & A. Azman. "Cylindrical concentricity and coaxiality optimization for boring process by using taguchi method," *Journal of Computational and Theoretical Nanoscience,* vol. 17, pp. 707–714, 2000.

[21] D. Vivek & K. Ramesh. "Optimization of the cutting responses in boring operation using response surface methodology", *International Journal of Engineering Research,* vol. 3, no. 5, pp. 1739-1744, 2014.

[22] A. Suresh & G. Diwakar. "Investigation of effects of working parameters in turning of twip steel rods with eco-friendly cutting fluids using response surface methodology on CNC machines", *Gazi University Journal of Science*, vol. 34, no. 3, pp. 68-78, 2021.

[23] G. Balamurugamohanraj, K. Vijaiyendiran, P. Mohanaraman & V. Sugumaran. "Prediction of surface roughness based on machining condition and tool condition in boring stainless steel-304", *Indian Journal of Science and Technology,* vol. 9, pp. 1–6, 2016.

[24] M. Munawar, J.C.-S. Chen, N.A. Mufti. "Investigation of cutting parameters effect for minimization of sur face roughness in internal turning", International Journal of Precision Engineering and Manufacturing, vol. 12, no. 1, pp. 121-127, 2011. http://dx.doi.org/10.1007/s12541-011-0015-x

[25] G.J. Satish, H.K. Madhusudhana, B.H. Nishant & B.B. Kotturshettar. "Optimising cutting parameters in boring operation for C45 steel", *IOP Conference Series: Materials Science and Engineering*, vol. 872, p. 012080, 2020.

[26] K.V. Rao & P.B. Murthy. "Modeling and optimization of tool vibration and surface roughness in boring of steel using RSM, ANN and SVM", *Journal of Intelligent Manufacturing,* vol. 29, pp. 1533–1543, 2018.

[27] R.S. Patil & S.M. Jadhav, "Boring parameters optimization for minimum surface roughness using CNC boring machine with passive damping material", *2017 2nd International Conference for Convergence in Technology (I2CT)*, pp. 300–303, 2017.

[28] I. Ramu, P. Srinivas & K. Vekatesh. "Taguchi based grey relational analysis for optimization of machining parameters of CNC turning steel 316", *IOP Conference Series: Materials Science and Engineering*, vol. 377, p. 012078, 2018.

[29] H. Sonar, V. Saxena, V. Kshirsagar & S.P. Deshpande. "Process parameters optimization of CNC turning machine for aluminium alloy using taguchi method", *International Journal of Research in Engineering and Technology,* vol. 5, pp. 36–39, 2016.

[30] M. Thomas, Y. Beauchamp, A.Y. Youssef & J. Masounave. "Effect of tool vibrations on surface roughness during lathe dry turning process", *Computers & Industrial Engineering,* vol. 31, pp. 637-644, 1996.

[31] A. Batwara & P. Verma. "Influence of process parameters on surface roughness and material removal rate during turning in CNC lathe–an artificial neural network and surface response methodology", *International Journal of Recent Advances in Mechanical Engineering,* vol. 5, no. 1, pp. 47-59, 2016.

[32] H. Dave, L. Patel, , & H. Raval. "Effect of machining conditions on MRR and surface roughness during CNC turning of different materials using TiN coated cutting tools–A taguchi approach", *International Journal of Industrial Engineering Computations,* vol. 3, pp. 925–930, 2012.

[33] S.K. Saini & S.K. Pradhan. "Optimization of multi-objective response during CNC turning using Taguchi-fuzzy application", *Procedia Engineering* , vol. 97, pp. 141–149, 2014.

[34] Y.-K. Yang, S.-S. Lin & J.-L. Wen. "Optimization of 6061T6 CNC boring process using the taguchi method and grey relational analysis", *The Open Industrial & Manufacturing Engineering Journal*, vol. 2, no. 1, pp. 14-20, 2009. http://dx.doi.org/10.2174/1874152500902010014

[35] M. Muhammad, J.C. Chen & N.A. Mufti. "Investigation of rake angle effect for minimization of surface roughness in internal turning", *International Journal of Precision Engineering and Manufacturing*, vol. 12, no. 1, pp. 121-127, 2011.

[36] S.L.C. Ferreira, R.E. Bruns, H.S. Ferreira, G.D. Matos, J.M. David, G.E. Brandao, E.G.P. da Silva, L.A. Portugal, P.S. dos Reis, A.S. Souza, L.A. Portugal, P.S. dos Reis, A.S. Souza, W.N.L. dos Santos, "Box Behnken design: An alternative for the optimisation of analytical methods", *Analytica Chimica Acta*, vol. 597, no. 2, pp. 179-186, 2007. https://doi.org/10.1016/j.aca.2007.07.011.

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Abbreviations

Adj MS: Adjusted Mean Square
Adj SS: Adjusted Sum of Squares
ANOVA: Analysis of variance
B: Blocks
CNC: Computer Numerical Control
dB: Decibel
DC: Depth of Cut
DF: Degree of Freedom
DoC: Depth of Cut
DOE:Design of Experiment
F: Feed
GA: Genetic Algorithm
NR: Nose Radius
pred: Predicted
PSO: Particle Swarm Optimization
PT:Pt Type
RO: Run Order
S: Speed
SN: Signal to Noise
SNR: Signal to Noise Ratio
SO: Standard Order
Sq: Square
TABC-BBD:Taguchi-ABC-Box Behnken design
WSM:Weighted Sum Method
TP-BBD:Taguchi-ABC-Box Behnken design
WPM:Weighted Product Method
VIKOR: VlseKriterijuska Optimizacija Komoromisno Resenje
WASPAS: Weighted Aggregated Sum Product Assessment