MACHINABILITY ASSESSMENT OF SUPER ALLOY INCONEL 825 USING COATED TOOLS: AN EXPERIMENTAL INVESTIGATION

Thesis submitted by

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"Statement of Originality"

I **Rajiv Kumar Yadav** registered on 21/09/2016 do hereby declare that this thesis entitled "Machinability Assessment of Super Alloy Inconel 825 using Coated tools: An Experimental Investigation" contains literature survey and original research work done by the undersigned candidate as part of Doctoralstudies.

All information in this thesis have been obtained and presented in accordance with existing academic rules and ethical conduct. I declare that, as required by these rules and conduct, I have fully cited and referred all materials and results that are not original to this work.

I also declare that I have checked this thesis as per the "Policy on Anti Plagiarism, Jadavpur University, 2019", and the level of similarity as checked by iThenticate software is 7 %.

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Rajiv Kumar yadav 20/09/22

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Abbreviations

µm	Micro Meter
CVD	Chemical Vapour Deposition
DOE	Design of Experiment
DOC	Depth of Cut
FIS	Fuzzy Inference System
GA	Genetic Algorithm
HB	Higher-the-better
LB	Lower-the-better
mm	Millimeter
MRR	Material Removal Rate
PVD	Physical Vapour Deposition
SEC	Specific Cutting Energy
OA	Orthogonal Array
WC	Tungsten Carbide
SEM	Scanning Electron Microscopy
TEM	Transmission Electron Microscopy

Chapter 1: Background and rationale

1.1 Introduction

Aerospace parts mainly operate under an antagonistic environment that includes the strongest possible temperatures, high speeds, and pressure. Ni-Cr based super alloys are especially valuable under this type of applications because of their amazing ability to maintain high mechanical properties such as strength and prevent to fatigue even at high temperatures. On the other hand some of the properties such as the tendency to work hardening, high shear strength, poor conductor of heat, high compatible with chemicals and the presence of strong inter-metallic abrasive particles act as materials whose machinabilty is very poor. Because of its strong mechanical and chemical qualities at high temperatures, Inconel 825 is a popular choice among nickel-based super alloys in the aerospace, nuclear, and chemical industries. Due to its features such as low heat conductivity, high toughness, high hardness, and strong strain hardening behaviour, machining Inconel 825 presents challenges. Furthermore, it contains dangerous carbide particles that tend to attach to the tool's areal surface, resulting in a poor surface finish. Therefore, it is essential to examine the machinability parameters of the Inconel alloys. It has been found that enormous work has been done for Inconel alloys, particularly for Inconel 718 but less work has been focused on the machining of Inconel 825.

The present research work proposes the investigation of turning parameters viz. spindle speed (SS), feed rate (FD) and depth of cut (DOC) on different machining evaluation characteristics such as surface roughness, material removal rate (MRR), specific cutting energy (SCE), resultant machining force, chip thickness ratio and apparent coefficient of friction in machining. The work also utilizes Grey Relation

Approach, JAYA and TLBO approach in order to assess the optimized machining condition.

1.2 State of Art

1.2.1 Machining of Inconel 825

Because of its superior mechanical and chemical qualities at elevated temperatures, the nickel-based super alloy Inconel 825 is finding increased use in industries such as aerospace, nuclear, and chemical. Its poor thermal conductivity, high toughness, high hardness, and high work hardening behaviour, however, are disadvantages. Furthermore, it also contains abrasive carbide particles that stick to the tool surface, resulting in a poor surface finish. As a result, researchers focused their efforts on investigating its machinability. For the purpose of cutting Incoloy 825**, Thakur and Gangopadhyay (2016, I)** used commercially available uncoated, CVD bilayer (TiCN/Al2O3), and PVD multilayer (TiAlN/TiN) coated carbide inserts. The current investigation has consistently used dry machining to prevent the superimposing influence of cutting fluid. On an Inconel 825, a superalloy based on nickel, **Nayak et al. (2016)** concentrated on creating a complicated contour in the shape of a "I". To explore passivation, many phenomena in the IEG, including velocity distribution, pressure variation, turbulence in the flow of the electrolyte, and temperature profile, have been analytically simulated. **Thakur et al. (2014, I)** studied whether cutting settings and cutting tool types have a significant impact on the machined surface integrity of Ni-based superalloys. **Thakur et al. (2014, II)** look at how cutting speed affects tool wear and chip characteristics when dry turning Inconel 825 with uncoated and PVD multilayer coated (TiN/TiAlN) cemented carbide inserts. The surface integrity and metallurgical parameters of the machined Inconel 825 work surface were investigated by **Rahul et al. (2017)** in relation to Electrical Discharge Machining (EDM) utilising Cryogenically Treated Tool (CTT) versus Non Treated Tool (NTT) (NTT). With a focus on the assessment of sub-surface hardness and white layers, **Thakur et al. (2014, III)** examine the impact of cutting speed and CVD multilayer coating on the machined surface integrity of Inconel 825 during dry turning operation. When dry machining Inconel 825, **Thakur and Gangopadhyay (2016, II)** looked at the impact of cutting speed and tool coating on the micro-morphology of chips on the free surface and transverse plane, shear band thickness, equivalent chip thickness, and various saw-tooth distance, saw-tooth angle, chip segmentation frequency, and chip hardness characteristics. During dry machining of Inconel 825, **Thakur et al. (2014, IV)** investigate the effect of cutting speed (51, 84, and 124 m/min) and tool coating deposited using chemical vapour deposition (CVD) on machined surface roughness, tool wear characteristics, chip morphology, and chip reduction coefficient (f). Incoloy 825's machinability was assessed by **Thakur et al. (2016, III)** using an untreated tool, a CVD-grown bilayer of TiCN/Al2O3, and PVD-grown alternate layers of TiAlN/TiN-coated tools under various machining conditions. The impact of several EDM process variables, including peak current, duty factor, and pulse-on length, on various performance traits, including material removal rate, surface roughness, radial overcut, and surface crack density, was examined by **Mohanty et al. (2014)** during Inconel 825 dry turning. In their study, **Thakur et al. (2015)** investigate how different cutting speeds i.e. 51, 84, and 124 m/min affect various machining characteristics, including chip form, chip thickness ratio, tool wear, surface integrity, and sub-surface integrity. Similar research was conducted using uncoated and commercially available chemical vapour deposition multilayer coated

(TiN/TiCN/Al2O3/ZrCN) cemented carbide (ISO P30 grade) inserts. Chip morphology is a collection of chip forms that were produced using different cutting parameters. Serrated chips were found when milling Inconel 825 with both types of tools, with higher serration when using the uncoated insert**.** Investigation by **Mohanty et al. (2015)** sought to analyse and optimise the process factors (electrolytic concentration, voltage, and tool feed rate) for Inconel 825's MRR and SR during the ECM process. Fuzzy TOPSIS, a hybrid optimisation technique, has been used to determine the ideal parameter value. A thorough examination of the microstructure of machined surfaces was also provided. **Tamang and Chandrasekaran (2017)** have developed an intelligent optimization for machining Inconel 825 using the ANN-PSO technique. With the data sets acquired by conducting turning experiments, an artificial neural network is employed to construct a surface roughness prediction model. For optimising the machining process, particle swarm optimization is combined with ANN modelling. **Thakur and Gangopadhyay (2016, IV)** aims at machining of Incoloy 825 in which uncoated cemented carbide tool was used under wet and MQL environment, while TiN/TiAlN multilayer coated tool was utilised under dry environment. The study also assessed machining performance for both rough and finish modes compared in terms of cutting force (responsible for consumption of cutting power), cutting temperature, tool wear, chip characteristics and surface integrity. **(Grguras et. al. 2019)** have proposed full-body ceramic tools and performed machining on Inconel 718 utilizing them. A comparative analysis between full-body ceramic tools and carbide end tools has been studied for tool life, surface integrity, and cost analysis while machining two different materials, i.e., SS 316L and Inconel 718, under varied categories of lubrications. The study reveals that ceramic tools are better than carbide tools in terms of MRR and productivity. Yet, economically, the overall performance of ceramic tools is under the scanner. **(Venkatesan et. al. 2019)** have performed a dry turning operation on Inconel 718 using an advanced (PVD-coated (AlTiN)) carbide tool and explored several features such as surface finish, cutting forces, and tool life during the experimentation. The feed rate, cutting velocity, and cutting depth has been picked up as control factors, whereas the responses of these factors were measured in terms of CF, flank wear, and R_a by means of response surface three-dimensional plots. The study says that the minimum R_a and low CF can be obtained at low cutting depths, low feed rates, and high cutting speeds. However, to obtain minimum tool wear, the cutting speed must be low. An optimal parameter setting was also obtained utilizing a desirability function. SEM was also done to understand the wear mechanism. **(Parida, 2019)** machined Inconel 718 and examined the impact of heating temperature on the workpiece's surface. An exploration of chip geometry has been carried out for shear band configuration, chip segmentation, and equivalent chip thickness through SEM of chip roots. The results revealed that when the heating temperature increases, the values of aforesaid attributes decrease in comparison to ambient temperature machining. Further exploration in the study discovered an increment in the gap between shear bands and a decrement in the shear band thickness and shear plane length when the heating temperature upsurges. **(Parida and Maity 2018)** compared the machinability aspects of Inconel 625, Inconel 718, and Monel 400 in a hot-turning environment employing flame heating. The comparison was done regarding tool wear, surface integrity, tool life, CF, and chip morphology at temperatures of 300°C and 600°C. The results depicted that machining in a hot environment yields better outcomes for all three superalloys in comparison to machining at room temperature. **(Gandhi et. al. 2019)** have determined the influence of cutting speed by means of measuring certain machinability attributes, namely machining force, R_a, chip thickness ratio, and metal removal rate during the turning of Inconel 825. T-type and C-type inserts were employed, and the experiments were carried out on a hand-controlled lathe. The results revealed that the C-type inserts yield improved surface finish, and when the spindle speed increases, the chip thickness ratio and machining force decrease. **(Yadav et. al. 2015)** have utilized the CVD-coated tungsten carbide tool to machine Inconel 718 to know the impact of some input variables concerning tool wear and MRR. DEFORM 3D software was utilized to form a machining model. The developed model was simulated to envisage the MRR and flank wear of the tool. The simulated data were equated with the experimental data, and it was observed that both the data are identical. The use of ANOVA was also found to know about the most influential input variable for MRR and tool wear.

Superalloys can be categorized into four classes, namely Ti-based alloys, Co-based alloys, Ni-based alloys, and Fe/Ni-based alloys. As superalloys demonstrate superior mechanical characteristics especially creep resistance, corrosion resistance, and oxidation resistance at elevated temperatures, they are also called high-temperature alloys or high-resistance alloys **(Paswan et. al. 2020; Mali et. al. 2017)**. Lethal parts of gas turbines and aero-engines, which are predominantly subjected to high temperature, high pressure, and high velocity, are composed of Ni-based superalloys owing to their outstanding characteristics, namely corrosion resistance, thermal stability, and fatigue strength under extreme conditions. But the machining of Ni-based superalloys is constantly a problematic field owing to the availability of γ' and γ'' precipitates, which makes them hard-to-machine material **(Sivaiah et. al. 2020; Rahul el. al. 2017; Kumar et. al. 2018; Jafarian et. al. 2020).** Based on their chemical composition, the classification of Ni-based superalloys is done.Thakur and Gangopadhyay **(Thakur et. al. 2016 V)** classified them as Inconel 100, Inconel 718, Inconel 825, Nimonic 105, Nimonic 80 A, Nimonic 75, Hastelloy C-2000, Haynes 282, and many more. Of these superalloys, Inconel 825 is extensively utilized in aircraft, chemical, and nuclear sectors as it displays exceptional characteristics at elevated temperatures. However, its processing is problematic as it is difficult to machine due to the presence of intermetallic precipitates. Besides, the availability of carbide particles disturbs the quality of the surface finish as it sticks on the tool surface while machining **(Thakur et. al. 2016 II; Weber 2001; Yadav et. al. 2019; Kumar et. al. 2018)**.

Hence, it is essential to explore the machinability features of Inconel 825. Concerning the machinability of superalloys, scholars have explored plenty of work, but there is still scope for some alloys like Inconel 825 due to the lag of quest of their machinability aspects. The following literature reviews have spread some light over the previous attempts done by scholars. As we know the machining of Inconel 825 is more sensitive part to make a job.

It has been evident from the literatures that most of the attempt has been done to understand the machinability aspects of dry Inconel 825 in terms of surface roughness, tool wear and cutting forces, however, less work has been done to investigate the effect of nose radius on the machining responses such as, tool wear, Chip thickness ratio, surface roughness, specific cutting energy and cutting forces. Therefore, this research work highlights the affect of nose radius and feed on cutting forces, Chip thickness ratio, surface roughness, specific cutting energy and tool wear in dry turning of Inconel 825 alloy.

1.2.2 Need for optimization

Because of the widespread use of Inconel 825 in the manufacturing industry, particularly in the automotive and aerospace industries, manufacturers are paying more attention to the machinability of these alloys. As the demand for large-scale manufacturing of Inconel machined components made of Inconel 825 grows, optimising machining process factors becomes increasingly important in order to deliver high-quality products while reducing costs. Several process characteristics, such as depth of cut, feed rate, and spindle speed, all have an impact on turning operation performance. Material removal rate (MRR), surface roughness, and cutting force are all essential performance indicators when machining Inconel 825. This paper examines the machinability of the Inconel 825 alloy during turning operations. Grey relation analysis, which turns many responses into an equivalent single response known as the overall grey relation index, has been used to optimise multiple responses (OGI). A non-linear regression model was created and employed as a fitness function during the optimization process, based on OGI as a function of specified process factors. The machining process was optimised using two evolutionary methodologies known as Teaching-Learning-Based Optimization (TLBO) and JAYA algorithms.

Choudhary and Baradie (1998) have investigated the influence of cutting tools mainly coated and uncoated on the surface roughness during the machining of nickel base alloys. It has been noticed that uncoated carbide tools given the better surface face finish as compare to coated carbide tools. **Jindal et al. (1999)** looked into the effect of different types of coatings on tool life. TiAlN, TiCN, and TiN carbide tools have been adapted for cutting Inconel 718. The TiAlN coating extends the tool's life. Positive rake angle promotes greater performance when cutting high temperature metals. **Arunachalam and Mannan (2000)** have told that the machining of nickel-based high-temperature alloys, flank wear and notch wear are the most common causes of tool failure. **Arunachalam et al. (2004)** investigated the surface integrity of Inconel 718 machining with a coated carbide tool in both dry and wet environments. Negative type rake inserts are preferred for dry machining, whilst positive type rake inserts are preferable for wet machining. **Ezugwu and Bonney (2004)** studied the effect of coolant pressure during machining of Inconel 718 using coated carbide tool. Study revealed that high coolant pressure provides efficient cooling and lubrication that results into reduction in cutting force. Cutting force decreases with increase in cutting force. When machining Inconel 718, nose wear is the most common tool failure mode. Cutting forces and tool wear in dry end milling operations of Inconel 718 utilising coated carbide tools were studied by **Li et al. (2006).** Bluff cutting edges have been found to improve the cutting temperature and force. **Altinet. al. (2007)** evaluated the effect of cutting speed on tool wear and tool life in wet machining of Inconel 718. The result concluded that notch wear and flank wear are major criteria of tool failure while machining with round type insert and it has been also observed that square type insert, flank wear and crater wear are major tool failure criteria. **Devillez et al. (2007)** investigated the effects of machinability on cutting force and wear in Inconel 718 dry machining. In comparison to an untreated carbide tool, a coated carbide tool reduces cutting force. When machining Inconel 718, primary tool failure criteria include flank wear, notch wear, and cutting edge chipping. **Zhang et al. (2012)**

investigated cutting force and tool life during end milling of Inconel 718 with a coated carbide tool in dry and MCQL conditions. The rise in cutting force is due to the progression of tool wear. Furthermore, the study found that MCQL reduces cutting force by a significant amount due to reduced friction. Utilizing Taguchi-based grey relation analysis**, Maiyar et al. (2013)** optimised the machining parameters (cutting speed, feed rate, and depth of cut) for end milling Inconel 718. Machinability criteria such as surface roughness and Material Removal Rate (MRR) were studied. Cutting velocity has a considerable impact on machinability requirements. To validate the experimental results, **Ozel et al. (2013)** employed Inconel 718 dry machining results from 3-D finite element analysis. In terms of forecasting machining forces, the modified J-C model is more reliable than the original J-C model. The updated J-C model predicts a lower cutting temperature than that obtained experimentally. During dry turning, **Thakur et al. (2014 I)** studied the wear and chip characteristics of Inconel 825. In dry machining, PVD coated carbide tools outperform uncoated carbide tools.

Thakur et al. (2014 II) studied the effect of cutting speed on the machining of Incoloy 825 in dry conditions. With higher cutting velocities, tool wear and surface roughness increase. In comparison to coated carbide tools, uncoated carbide tools have a greater surface finish. Coated carbide tool inserts have a lower tool wear rate than uncoated carbide tool inserts. **Thakur et. al (2014 III)** have examined the effect of cutting velocity on various machinability criteria of machining of inconel 825 during in dry condition. According to their findings, as cutting speed increases, the chip reduction coefficient falls. The surface polish of an uncoated carbide tool is superior to that of a CVD coated carbide tool. **Vajeeha et. al. (2015)** focused on optimization of cutting parameters for end milling of Nimonic 75. Speed, Feed rate and depth of cut were taken as variable parameters. Response Surface Method (RSM) was used to analyze the data. Surface roughness and MRR were taken as decision parameters. Multi - response equation shows that at high feed rate, high depth of cut and low cutting speed provides better results. **Patil and Sadaiah (2016)** have optimized the cutting parameters (cutting velocity, feed and depth of cut) in turning of Nimonic 80A. They have focused on surface roughness and flank wear. Study revealed that feed is the most dominating factor for surface roughness whereas cutting speed is for flank wear.

Parida and Maity (2017) developed finite element model and used to investigate the effect of nose radius on cutting forces during dry machining of Inconel 718. The forces grow as the nose radius of the tool insert increases, according to the analysis. Shear plan angle reduces as nose radius increases, resulting in increased chip thickness**.** The effect of spindle speed and feed on roughness of surface and wear of tool during dry turning of Inconel 825 with an uncoated carbide tool was studied by **Munde and Pansare (2017)**. With increasing spindle speed, the surface finish degrades. Tool wear increases as feed and spindle speeds increase. **Munde and Pansare (2017)** conducted dry turning of Inconel 825 using PVD and CVD coated carbide tools. The effect of spindle speed and feed was investigated. PVD coated tool has significantly less flank wear than CVD coated tool. Flank wear increases with increase in spindle speed. **Altin (2017)** optimized the machining parameters using Taguchi L_{18} orthogonal array in dry machining of nickel based super-alloy. Feed is dominating factor during dry machining for component force. **(Mariyala et al. 2018)** developed a novel parameter-less algorithm based on ANN building. This algorithm is named as ‘TRANSFORM’ intended to optimise complicated engineering problems. Using this approach, the continuous casting process was optimised, and 13 times higher efficiency was noted leading to a saving of 92% function evaluations as compared to the traditional methods. The casting model optimisation was done using ANN aided NSGA-II method. These optimisation models were also compared with Kriging surrogates where they outshine the latter one.

(Miriyala and Mitra 2020) have formulated a non-linear twenty-two dimensional model for iron-ore in duration. A multi-objective optimisation problem was designed for this technically certified model. To simulate the iron-ore in duration, a multi-layered perception networks (MLPs) was prepared. Four different sobol sampling algorithms were utilised for finding the optimal design of MLPs using MO-INLP. The intended GA based surrogate approaches optimise the formulated model 10 times faster as compared to their contemporaries. A comparative analysis with Kriging is also done besides justification of MLPs for over fitting. **(Mariyala et al. 2016)** performed a comparative analysis of surrogate models and proposed a novel multi-objective approach for optimising computationally-hard reaction networks more quickly and effectively. Demonstration of this intended model has been done through solving a multiobjective optimisation problem on PVAc-LCB polymerization. In this work, authors have designed a competent and quick Sobol-ANN as the surrogate method and replaced the time consuming computationally difficult approach. This GA based intended approach determines the design of the neural network (NN) efficiently and eradicates heuristic-based preference for unicellular neuromorphic NN. Outcomes of this study say that the Sobol considerably decreases the computational problem and does not delete the old data irrespective of fresh point generations. The Kriging infill, which is based on the compromise between two goals, also yields the identical output as Sobol but Sobol is 1.5 times quicker than the latter.

Prior state-of-the-art depicts that a significant amount of work has been done to examine the machinability aspects of superalloys in terms of several output responses like tool wear, MRR, and R_a (average surface roughness) through developing mathematical relations between input variables. Meanwhile, the aforesaid literature also reveals that lots of attempts have been made to examine the impact of input variables on Inconel during machining, but very few efforts have been attempted in the area of process parameter optimisation. Several academicians have also attempted to optimise multiple responses using GA based novel algorithms such as NSGA-II. Different types of ANN-based sampling methods were also reported in the existed literature. The use of the Taguchi methodology has been widely observed in prior state-of-art. Since the methodology utilizes the orthogonal array (OA) concept for DOE, the number of experiments is reduced, leading to time-saving and cost-cutting. The capability of the Taguchi technique to envisage the optimum combination of machine parameters within a discrete field makes it popular amongst researchers and scientists. However, it miserably fails for multi-response optimisation problems **(Yunlu et. al. 2014; Mohan et. al. 2016; Pandey et. al. 2017; Gopal et. al. 2017; Sasikumar et. al. 2016).**

Such optimisation problems can be solved by integrating TOPSIS **(Arunramnath et. al. 2019)**, utility concept **(Kumari et. al. 2020)**, grey relation theory **(Prajapati et. al. 2020)**, MOORA **(Kalirasu et. al. 2017)**, and desirability function **(Kumar et. al. 2014)**, etc., with Taguchi methodology. These methods combine multiple performance attributes (multiple responses) and give one performance index. This unique performance index can be optimized by the Taguchi approach straightforwardly. For that reason, such optimisation approaches, namely TOPSIS-Taguchi, Utility-Taguchi, grey-Taguchi, MOORA-Taguchi, desirability-Taguchi, etc., are very famous among researchers and scientists for the real-time optimisation of multiple attributes of a process or product.

In reality, the manufacturing process has numerous conflicting outcomes. Owing to the nonlinear properties of input variables, such conflicting outcomes influence the optimum solution of the process. A process may have multiple objective functions, and at the same time, it is supposed to obtain globally optimal values in a specified search area. In such problems, conventional approaches miserably fail. Therefore, innovative optimisation algorithms are required for a feasible outcome. Such algorithms deliver the solution contiguous to the global optimum with the least arithmetic tussle and time consumption. Genetic Algorithm **(Nagaraju et. al. 2016)**, Particle Swarm Optimisation **(Dash et. al. 2020)**, Ant Colony Optimisation **(Vijaykumar et. al. 2003)**, Simulated Annealing **(Karnik et. al. 2013)** are a few names among these evolutionary approaches. They cover diverse application sectors in engineering and applied sciences.

From the prior state-of-art, it is clear that these evolutionary approaches have been severely used by scholars to determine the satisfactory machining conditions for many machining processes. But the problem associated with such strategies is that they function under the algorithm-specific set of assigned settings. Therefore, it becomes a matter of concern for a scholar to have a defined control on algorithm-specific assigned settings.

To eliminate such glitches, **(Rao et al., 2012)** have presented TLBO, a parameter-less algorithm in 2012. Due to the feature of easiness in use, it has caught the attention of several researchers across the globe. Encouraged by the accomplishment of TLBO and its implementation, **(Rao, 2016)** have suggested a second parameter-free algorithm, called JAYA. Intending to explore the JAYA algorithm, the current study makes an attempt to evaluate the optimal machine setting for Inconel 825. It also emphasizes multiple objectives, a comprehensive optimization approach instigated in Inconel 825 machining. The JAYA algorithm, presented here, absolutely differs from other innovative optimization approaches because it does not involve any algorithm-specific variables to tune, and it is accessible in understanding and implementation **(Rao et al., 2012; Rao, 2016)**.

It has been highlighted from the literature that many attempts have been made to assess the favorable machining conditions in several machining processes in order to enhance machining outcomes by the application of evolutionary algorithms. However, aforementioned evolutionary algorithms work under an outfit of assigned data of algorithm oriented parameters. Hence, it is important to have specific control over these parameters. In order to avoid this, TLBO has been proposed by (**Rao and Kalayankar, 2013; Pawar and Rao, 2013)** first parameter less algorithm which gained more attention in the field of optimization.Encouraged by the accomplishment and application capability of TLBO algorithm. **Rao (2016)** has proposed one more parameter less algorithm known as JAYA for finding the solutions of both constraint and unconstraint optimization problems. With the possibility of exploring JAYA algorithm, this study evaluates the optimal machining conditions for Inconel 825. This algorithm is different as compared to the other advanced algorithms. It is quite easy and simple in use as does not require any algorithm oriented parameters to begin **(Maiyar et al., 2013; Rao and Waghmare,**

2017; Rao and Rai, 2017; Mohanty et al., 2014)

1.3 Motivation and Objectives

In the current state of engineering, many demands are placed on parts made of Inconel 825 with advance mechanical components, machine speed and good surface roughness. The Inconel 825 is widely used due to its corrosion resistance and low thermal efficiency. (**Thakur et. al., 2014 IV**). As a result, it's critical to research Inconel 825's machining reactions and characteristics. Despite the benefits, dry machining of Inconel 825 still faces a number of significant challenges, including excessive heat generation, tool wear, and tool life shrinkage. To solve these challenges, CVD coated tool and PVD coated tool have been employed for machining, and the machining parameters have been optimised using a multi-optimization evolutionary method.

It has been found that Taguchi method has been utilized to a larger extent for parametric optimization since this method adopted Orthogonal Array (OA) design of experiment utilizing minimum number of experimental runs with less experimentation cost and time. Taguchi philosophy has the advantage of predicting the ideal combination of process parameters within a discrete area **(Yunlu et al., 2014, Pandey et al., 2017, Gopal and Prakash, 2018).** The Taguchi technique, on the other hand, has the drawback of failing to address multi-response optimization problems.

In order to overcome this, grey relation theory **(Maiyar et. al., 2013, Kant and Sangwan, 2014, Rathod et. al., 2017, Gopal and Prakash, 2018)**, desirability function **(Jeong and Kim, 2009, Singh et. al. 2013),** utility concept **(Kumar and Singh, 2014)**, TOPSIS **(Gopal and Prakash, 2018, Parthiban et. al., 2018)**, Taguchi's perspective has been incorporated into MOORA **(Manjumder and Maity, 2018)**, for example. The aforementioned methods are designed to combine (aggregate) multiple performance characteristics (multi-responses) into a single performance index that can then be easily optimized using the Taguchi method. As a result, the following optimization modules have become extremely popular in the field of manufacturing/production engineering for simultaneous optimization of multi-characteristics of product/process: grey-Taguchi, desirability-Taguchi, Utility-Taguchi, TOPSIS based Taguchi, and MOORA based Taguchi.

Because of the nonlinear features of inputs with respect to output responses, a few inconsistent reactions (i.e. output characteristics) may alter the optimal configuration in today's production process. While the main purpose is to evaluate the global optimal values inside the given search area/domain, the objective function could have multimodal (i.e. more than one local maximum or minimum). Traditional methods have been found to be ineffective in dealing with these problems; as a result, advanced development algorithms have been developed to search for possible solutions, with the goal of finding a solution that is close to the global optimum in the shortest amount of time and with the least amount of computational effort. Today, evolutionary techniques are utilised to tackle a variety of optimization issues in a variety of domains, including industrial planning, scheduling, decision making, and pattern recognition, among others. They mostly adhere to a nature-based optimization philosophy. Genetic Algorithm is the most frequent evolutionary optimization. **(Satyanarayana et al., 2017, Shunmugesh and Panneerselvam, 2016, Jiang et al., 2015)** which is based on genetics and evolution concepts and mimics biological population reproduction behaviour. Particle Swarm

Optimization **(Rao and Venikaiah, 2015)** is a heuristic technique inspired by real-life ant colonies' foraging behaviour. Simulated Annealing (SA) is a technique for reducing energy distribution by heating a substance to just above melting point and then cooling it gradually. Sustainable manufacturing is a major and tuff issue for present and future industrial applications. Inconel 825 is belonging from NI-Cr based superalloy. The industrial application of Inconel 825 is high in these days. Inconel 825 is widely used in aerospace industries for making turbine blades, rotors and boilers etc. Due to large application of Inconel 825 we have to require the study of machining parameters during machining of Inconel 825. Due to their benefits, such as being heat-resistant, maintaining their high mechanical and chemical properties at high temperatures, having high melting temperatures, high corrosion resistance, as well as resistance to thermal fatigue, thermal shock, creep, and erosion, nickel-based alloys are widely used in the aerospace industry. **(Wu, 2017; M'Saoubi et al., 2008; Guo et. al., 2009)**. Lower thermal conductivity, work hardening, chemical affinity, and the presence of abrasive particles are just a few of the features that make Ni-based superalloys difficult to machine. High cutting temperatures, rapid tool wear, and high cutting force are some of the repercussions, which lead to machined surface deterioration as well as metallurgical changes in the workpiece **(Thakur et. al., 2014 V)**. Furthermore, it contains highly abrasive carbide particles that adhere to the tool surface, resulting in a poor surface finish. During machining, a lot of heat is generated, which reduces tool life. Because typical machining procedures are ineffective for 'difficult-to-cut' materials and high-temperature alloys (Rahul et. al., 2017). Besides these techniques, response surface methodology (RSM) has been also preferred by several researchers **(Rajput et. al. 2019)**. Two most common methods in RSM are the Box-Behnken design (BBD) and the central composite design (CCD). One side, BBD has a limitation in terms of input variables, on the other side CCD, which is a two-level factorial design-based model, has the computational difficulties when the number of input variables increases. Overall, RSM cannot envisage the dynamic response correctly due to the intricacy of dynamic behaviour **(Tripathi et. al. 2020)**. Usage of Sobol, a sample size determination (SSD) method, has been also reported in a few works of literature **(Oakanmi et. al. 2016)**. This approach is easy in the calculation and saves lots of computational time by preserving the structure of the experimental design. This SSD method provides space-filling characteristic and ensures the progression of sampled points despite stimulating a fresh sample point. Other DOE methods used by the scientific community are EVOP, screening experiments, mixture experiments and reliability DOE **(Rahang et. al. 2016; Priyadarshi et. al. 2016; Wu 2013).** But most of these methods are obsolete. It has been highlighted from the literatures that most of attempts have been made to evaluate the favorable machining condition in variety of machining process in order to enhance machining yield by the application of evolutionary algorithms. However, the aforementioned evolutionary algorithms operate with a set of parameters that have been assigned to them. As a result, having exact control over these parameters is critical. To get around this, previous studies invested a lot of time and effort developing an algorithm that didn't require any algorithm-specific parameter adjustments. As a result of this, **(Rao and Kalyankar, 2013 b; Pawar and Rao, 2013)** created the TLBO (Teaching-Learning Based Optimization) method, which has gained popularity among optimization experts over time. Motivated by the TLBO algorithm's success and application potential, **(Rao, 2016)** proposed JAYA, a parameter-free algorithm for addressing constraint and unconstrained optimization issues, and demonstrated its use by tackling several benchmarking optimization problems.

The current effort is prompted by the JAYA investigation's scope and focuses on determining optimal machining conditions for Inconel 825 utilising the JAYA optimization algorithm. The suggested JAYA algorithm is easy to implement and does not require any method-specific tuning parameters, unlike earlier sophisticated optimization techniques. **(Rao, 2016; Rao and Waghmare, 2016; Zhang et al., 2016; Rao and Rai, 2017).**

The current study looked into numerous machining aspects of Inconel 825, highlighting the usage of a multi-response extended optimization methodology in Inconel 825 machining.

The objectives of this dissertation have been pointed as below:

i. To investigate the effect of feed rate and nose radius on several machining performance criteria such as surface roughness, MRR, resultant machining force, SCE, chip thickness ratio and apparent coefficient of friction in dry turning of Inconel 825.
ii. Experimental Investigation for Machining of Inconel 825 using coated tool.
iii. To identify the optimal parameter settings for Machining of Inconel 825 using different Multi-response Optimization Techniques.

1.4 Organization of the Present Thesis

Chapter 1 (Background and rationale) the first chapter gives a quick overview of the challenges of machining nickel alloys. This section included a complete literature assessment to examine the state of the art in the fields of Inconel 825 and nickel alloys. Specific research gaps have been discovered based on the literature review. The application's objectives are also indicated.

Chapter 2 (Experimental Part) deals with the detail information about work piece, cutting inserts, insert holders, machine and measuring instruments used for experimental purpose. It also includes the basic information about machining characteristics.

Chapter 3 (Result and discussion) this chapter have divided in two basic parts**:**

(1) The effect of nose radius and fee rate on various machinabilty criteria in dry machining of Inconel 825.

In dry turning of Inconel 825, the effect of machining variables such as spindle speed, feed, depth of cut, and nose radius on machining responses such as material removal rate (MRR), resultant force, and surface roughness. This chapter also discusses a multi-objective extended optimization methodology used in Inconel 825 machining. The current chapter aims to investigate the JAYA algorithm by attempting to determine the best machine setting for Inconel 825. In Inconel 825 machining, it also stresses numerous targets, a holistic optimization method. The JAYA algorithm given here is distinct from previous revolutionary optimization approaches in that it does not require tuning of algorithm-specific variables and is simple to comprehend and apply.

Chapter 4 (Executive summary and conclusions) the present work accentuated on improvement the machinability of Inconel 825.

Chapter 2: Experimentation

Turning of metal has been significantly used in manufacturing processes in order to obtain the intricate and complex geometry. The major aim while performing the turning operation is to improve the quality and productivity of the parts produced. Therefore, it is essential to understand the performance of turning operation with the variation of machining variable. This chapter discussed the detail procedure of the experimental work.

2.1 Experimental details

Experiments have been conducted in following steps.

[1] To check and prepare the centre lathe ready in order to conduct the turning operation.

[2] To calculate weight of specimen by the high precision digital balance meter before machining.

[3] To perform the straight turning operation involving various combinations of machining parameters like: spindle speed, feed and depth of cut.

[4] To calculate cutting force using dynamometer.

[5] To calculate weight of specimen after machining using digital balance meter.

[6] To measure machining time for determining MRR.

[7] To measure surface roughness with the help of a portable stylus-type 112-1502 DCN 001 (Taylor Hobson, Surtronic S128, UK).

2.2 Experimentation

Experiments have been carried on manually operated lathe Banka 40. Some technical specifications of Banka 40 lathe are Height of centres, 200 mm; Swing over bed, 400 mm; Swing over slide, 240; Width of bed, 280 mm; Spindle bore, 51 mm; Cross Slide Travel, 210; Top Slide Travel, 125; Tail Stock Sleeve, MT-3; Bed Length, 6 Feet; Tool Shank Section, 20*20 mm; Main Motor, 1.5 kW/2 HP; Weight, 900 kg. Different levels of longitudinal feed for Banka 40 are 0.667 mm, 0.750 mm etc. and spindle speed for Banka 40 are 835 RPM, 371 RPM etc.

Figure 2.1 shows the experimental set up for straight turning for Inconel 825.

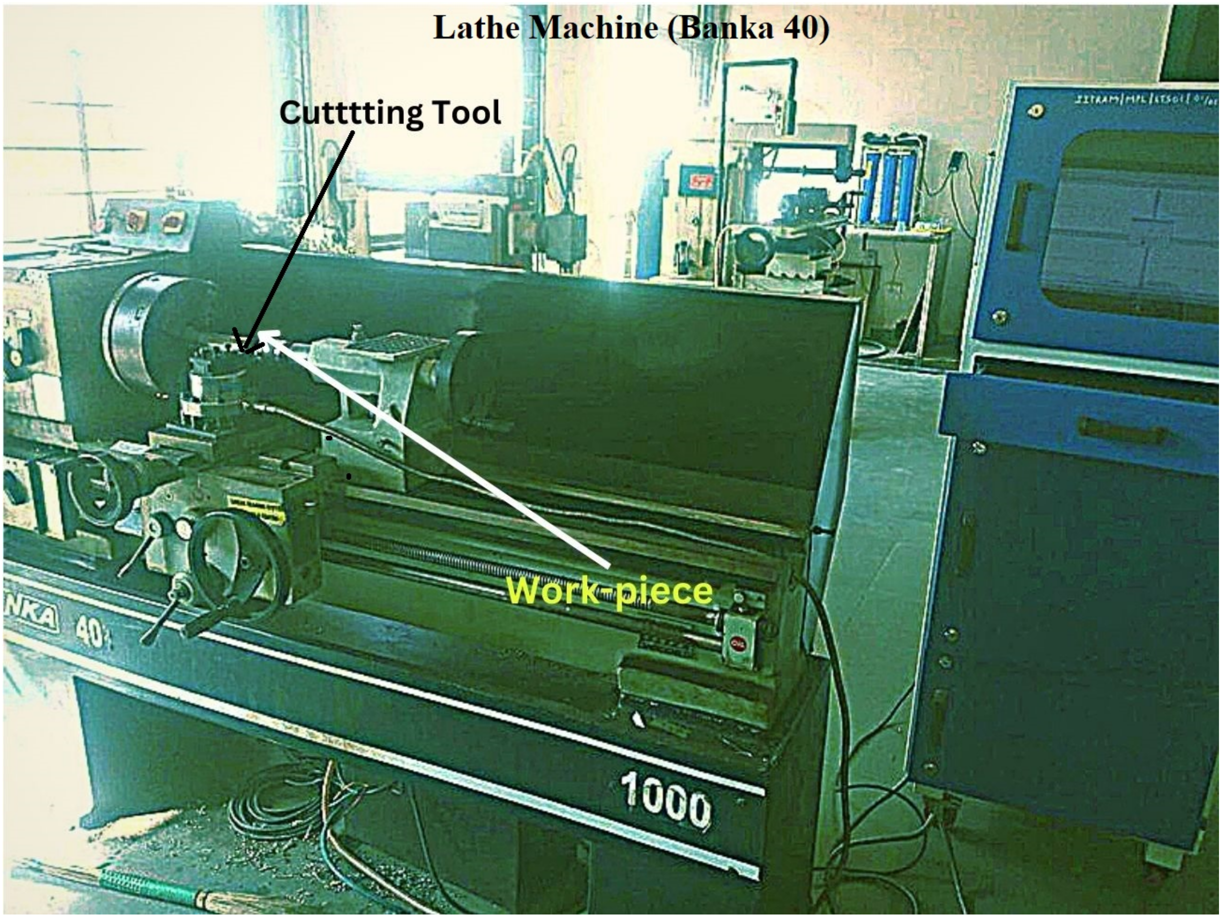

Fig. 2.1 Experimental Setup

2.2.1 Work Piece Material

The working material was Inconel 825 with dimensions of $\phi 45 \times 500$ (cutting length of 20 mm). Table 2.1 shows the chemical composition of Inconel 825.

Table 2.1 Inconel 825 Chemical Composition

Element	**Cr**	**Ni**	**Fe**	**C**	**P**	**Si**	**S**	**Mn**
Content (%)	22.695	38.246	31.083	0.036	0.012	0.362	0.017	0.118
Element	**Mo**	**Cu**	**Ti**	**Van.**	**Al**	**Co**	**W**	
Content (%)	2.77	2.77	0.65	0.055	0.045	0.036	0.355	

2.2.2 Cutting Tool

Single point turning insert TNMG160408 and CNMG120408 (KYOCERA made) have been used for the machining operation. Tool signature is 10-10-7-7-5-5- nose radius). Figure 2.2 (a), (b), (c) & (d) shows the inserts and insert holders used during machining.

Fig. 2.2 (a)

Fig. 2.2 (b)

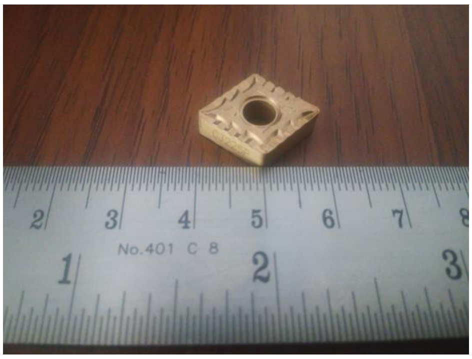

Fig. 2.2 (c)

Fig. 2.2 (d)

Fig 2.2 (a): TNMG160408 insert, (b): T - shape insert holder type: WTJNR2020K16, (c): CNMG120408 insert, (d): C- shape insert holder type: MCLNR2020K12

2.3 Experimental layout

In experimentation have done in two parts first part is for effect of nose radius and feed rate during machining of Inconel 825. Manually operated lathe (Banka 40) has been used for dry turning Inconel 825 alloy. The tool material has been used as coated carbide insert. The machining operation was carried out under variable feed rate of 0.111, 0.222 and 0.333 mm/rev for the nose radius of 0.4, 0.8 and 1.2 mm and at constant depth of cut 0.8 mm in dry environment. Table 2.2 illustrates the machining parameter which has been chosen for the experimentation.

Table 2.2 Machining Parameters with their specific range

Machining parameter	Symbol	Range
Spindle speed (RPM)	N	371
Feed rate (mm/rev)	f	0.111, 0.222, 0.333
DOC (mm)	t	0.4, 0.8, 1.2
Nose radius (mm)	r	0.4, 0.8, 1.2
Machining Environment	-	Dry

Each experimentation has been carried out for machining 20 mm in length. During the machining different forces was assessed using dynamometer. The chips formed during the machining were collected for the further analysis. The design of experiments play a crucial role in experimentation and for that three cutting parameters namely feed, depth of cut, and spindle speed has been selected as input variables at three different levels listed in Table 2.2. Table 2.3 also lists the experimental trails, prepared on the basis of Taguchi's L_9 orthogonal array.

Table 2.3 Experimental formulation using L_9 OA

Experiment No.	**N (RPM)**	**f (mm/rev)**	**t (mm)**	**r (mm)**
1	247	0.111	0.4	0.4
2	247	0.222	0.8	0.8
3	247	0.333	1.2	1.2
4	371	0.111	0.8	1.2
5	371	0.222	1.2	0.4
6	371	0.333	0.4	0.8
7	557	0.111	1.2	0.8
8	557	0.222	0.4	1.2
9	557	0.333	0.8	0.4

Design of experiments (DOE) plays a vital role in the planning and processing of the experimental works. As the experimental works consume lots of time and money, the we can't perform the experiments at each parametric setting and check them for the best possible outcomes. Therefore, the significance of DOE comes into the picture. Fig. 2.3 represents some of the DOE techniques with their importance and limitations **(Bandhu et. al., 2020).**

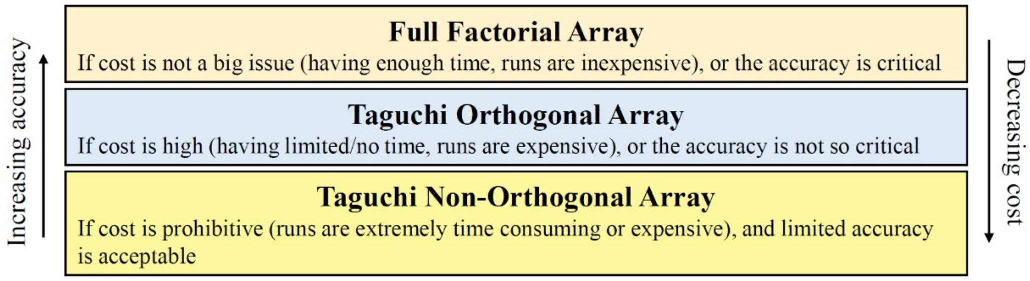

Fig. 2.3 General DOE techniques used in engineering applications **(Bandhu et. al., 2020; Rajput et. al., 2019; Tripathi el. Al., 2020; Oakanmi et. al., 2020)**

2.4 Machining evaluation characteristics

2.4.1 Resultant machining Force (R)

During machining operations, the cutting forces have been evaluated in different directions (F_x, F_y and F_z) with the help of dynamometer (Kistler made, Type 9272) as shown in Fig. 2.4. The resultant cutting force has been assessed using the following equation:

$$R = \sqrt{F_x^2 + F_y^2 + F_z^2} \tag{2.1}$$

Here, F_x is radial force (F_r), F_y is feed force (F_f), F_z is cutting force (F_c), R is resultant machining force.

Fig. 2.4 Kistler Dynamometer Type: 9272

2.4.2 Material Removal Rate (MRR)

The difference in weights of the work parts before and after the experiment was used to compute the material removal rate (MRR). SCALE-TEC high-precision digital balance metre (SAB E10) reading electrically controlled analytical balance was used to determine the weight of the work item (Fig. 2.5).

$$MRR = \frac{W_i - W_f}{\rho . t_m} \left(mm^3 / S \right) \qquad (2.2)$$

Here, W_i = weight of the work piece before turning in gm, W_f = weight of the work piece after turning in gm, ρ = work material density, t_m = time of machining in second

Corresponding MRR values have also been computed.

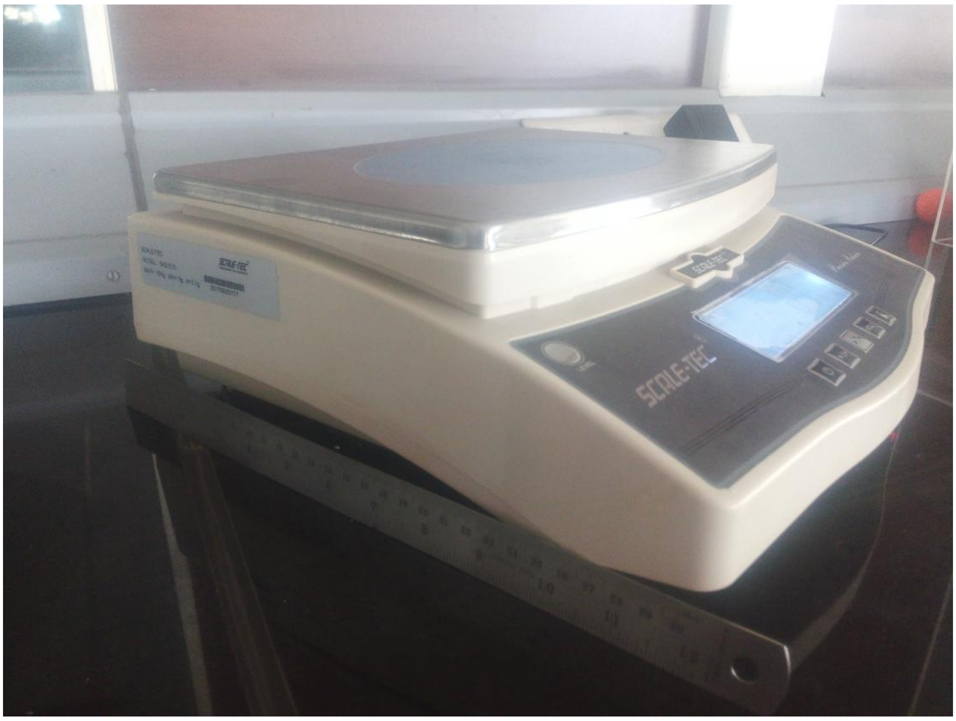

Fig. 2.5 Digital weight balance machine made by SCALE - TEC

2.4.3 Surface Roughness

The Talysurf (Taylor Hobson, Surtronic S128, UK) uses a stylus that skids over the surface in accordance with the carrier modulating principle to measure the surface roughness. The present experiment focus on the three surface roughness criteria i.e. Average surface roughness (R_a), maximum roughness profile height (R_t) and ten - point average roughness (R_z). The surface roughness was determined using (Talysurf Taylor S128, UK) having a stylus (standard stylus type 112 - 1502 DCN 001) that skids over the surface based on carrier modulating principle as shown in Fig. 2.6. The sampling length is 5 mm, and the range is up to 400 µm. Ten samples are taken for each run, and the average is used as the final output.

Fig. 2.6 Taylor - Hobson Surface Roughness Tester with Stylus

2.4.3.1 Average Surface Roughness (R_a)

Average surface roughness is defined as the average absolute deviation of the roughness irregularities from the mean line over the sampling length. It is the most universally used surface quality parameter as it gives good general description of height variation but the limitation of this parameter is, it does not give any information about wavelength and it is not sensitive to small change in profile. **[Gadelmawla et. al. 2002]**

2.4.3.2 Maximum roughness profile height (R_t)

This is very sensitive roughness parameter. It is defined as the vertical distance between the highest peak and lowest valley along the assessment length of the profile. **[Gadelmawla et. al. 2002]** .

2.4.3.3 Ten-point average roughness (R_z)

According to international ISO ten - point average roughness parameter defines as the difference in height between the average of five highest peaks and five lowest valleys along the assessment length of the profile. **[Gadelmawla et. al. 2002].**

2.4.4 Chip thickness ratio

The chip thickness ratio is the ratio of chip thickness after machining to chip thickness before machining. It is very important machinability criteria as it is directly connected with machining forces and power consumption. In oblique machining the uncut chip thickness is function of feed and approach angle.

uncut Chip thickness $T = f \cdot \sin\alpha$ (2.3)

Here, feed (f) in mm/rev, while approach angle α.

During the machining procedure, some chips are collected and their thickness is measured by using digital vernier caliper MITUTOYO ABSOLUTE DIGIMATIC Model

No: CD - 8” ASX as shown in Fig. 2.7. At every combination, fifteen readings of chip thickness are collected and their average is considered as decision output.

Fig. 2.7 Mitutoyo digital vernier meter

2.4.5 Specific Cutting Energy

SCE is defined as the effective energy required to machine unit volume of work piece. It is a good machinability index that allows to understand the whole machining process. Here, SCE is calculated based on below formula:

$$SCE = \frac{F_c.V_c}{MRR} \text{ (J/mm}^3\text{)} \tag{2.4}$$

Where, F_c is cutting force in N

V_c is cutting velocity (m/min)

MRR is material removal rate in mm^3/s. **[Rigatti et. al., 2013]**.

2.4.6 Apparent Coefficient of Friction (μ_{app})

Using Merchant's relation, here apparent coefficient of friction is calculated. According to Merchant's theory, μ_{app} is function of thrust force, cutting force and rake angle. It is calculated using equation 2.5.

$$\mu_{app} = \frac{F_c \sin\Phi + F_t \cos\Phi}{F_c \cos\Phi - F_t \cos\Phi} \tag{2.5}$$

here Φ is orthogonal rake angle in degree (°)

F_c is cutting force (N)

F_t is thrust force that is calculated from equation 2.6.

$$F_t = \sqrt{F_f^2 + F_r^2} \tag{2.6}$$

Where F_f indicates feed force (N)

F_r is radial force (N). **[Thakur and Gangopadhyay, 2016 III].**

Chapter 3: Result and Discussion

3.1 Introduction

This chapter explore the experimental investigations on the influence of process parameters i.e. spindle speed, feed rate, depth of cut and nose radius on material removal rate (MRR), surface roughness and resultant force. In first part of this chapter, comparison graph shows the significant parameter like depth of cut, feed rate and nose radius. The experimental data for Tauchi's L_9 orthogonal array is collected in the second part of this chapter. The lower the better is for surface roughness and the higher the better is for MRR and cutting force,.

This chapter classified in two basic parts: (clearly shows in flow chart also, Fig. 3.1)

1) The first is a study of the influence of nose radius and feed rate on MRR, cutting force, and surface roughness during Inconel 825 turning, as well as the effect of machining parameters (such as spindle speed, feed rate, and depth of cut) on these responses.
2) After experimental part, to determine the optimal setting with the help of various multi-objective optimization algorithms.

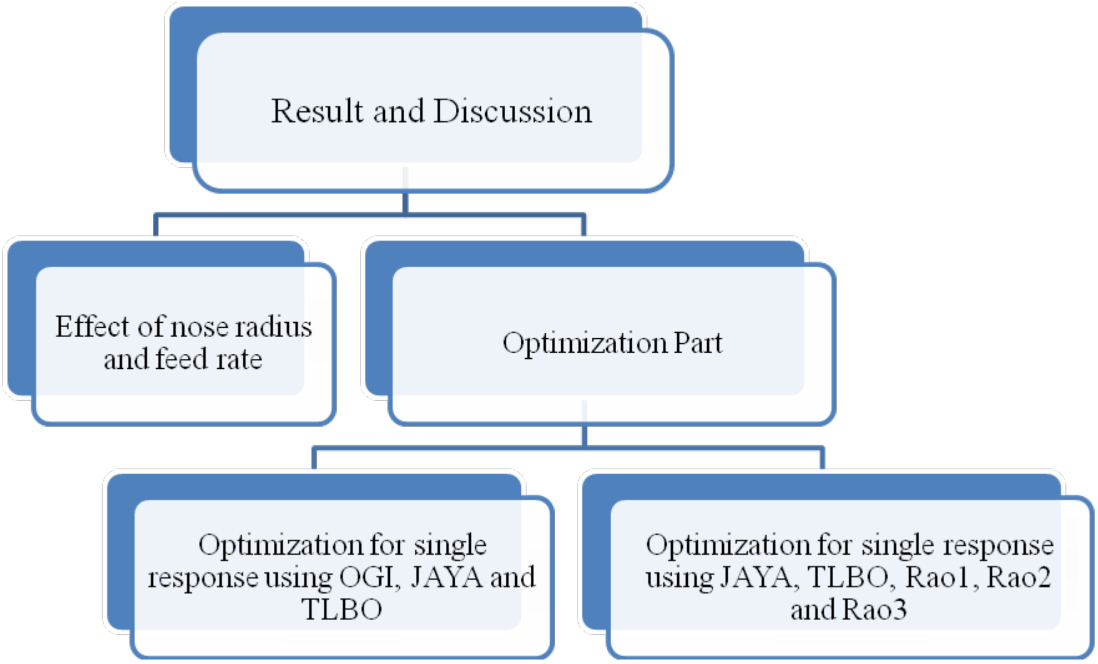

Fig. 3.1 Flow chart of plan for result and discussion

3.2 Effect of nose radius and feed rate

The present investigation dealt with the influence of feed and nose radius on various machinability aspects such as surface roughness, machining forces, chip reduction coefficient, apparent coefficient of friction and specific cutting energy during dry turning of Inconel 825 with coated carbide tools. This has been discussed as below.

3.2.1 Effect of feed and nose radius on Average surface roughness

One of the most essential machinability parameters for determining the quality of a machined surface is surface roughness. Table 3.1 shows the value of surface roughness measured by Taylor Hobson Surface roughness tester Surtronic S128. Fig. 3.2 shows the variation of surface roughness with nose radius and feed. The Fig. 3.2 clearly shows that at feed of 0.111 and 0.222 mm/rev, surface finish gradually degrades with increases the nose radius at constant speed and depth of cut of 371 RPM and 0.8 mm respectively. At feed of 0.111 and 0.222 mm/rev, nose radius of 0.4 mm provides better surface finish. The magnitude of surface roughness is much higher at 0.222 mm/rev for all values of nose radius. At higher feed of 0.333 mm/rev, nose radius of 0.4 mm provides worst result whereas nose radius of 0.8 mm and 1.2 mm provides reasonably good result.

Table 3.1 Response table for average surface roughness (R_a)

Feed (mm/rev)	**Average surface roughness (µm)**		
	CNMG120404	**CNMG120408**	**CNMG120412**
0.111	0.59	0.61	1.16
0.222	1.3	1.38	1.39
0.333	1.03	0.68	0.71

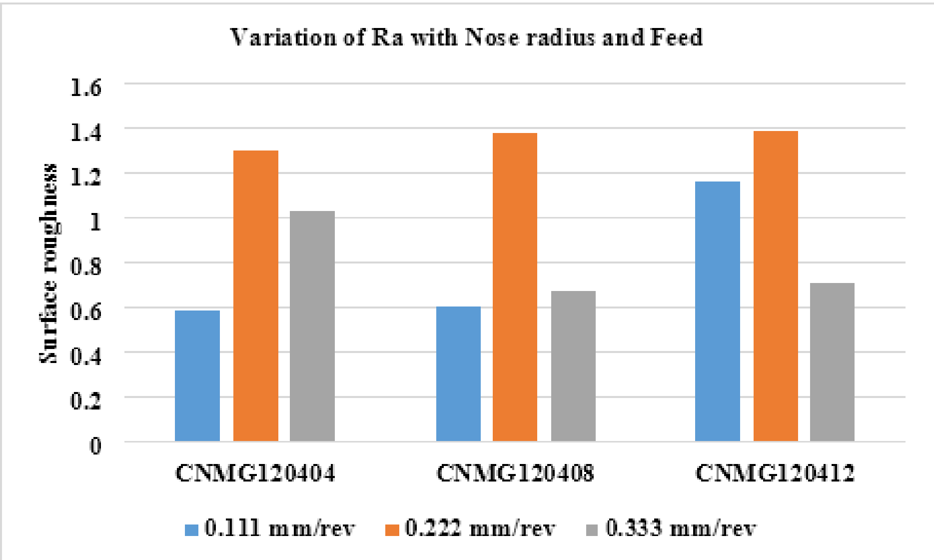

Fig. 3.2 Variation of surface roughness with nose radius and feed (it reflects feed; not nose radius)

From the experimental results, it is concluded that to achieve proper surface finish, nose radius of insert is very important criteria along with proper selection of machining parameters i.e. cutting speed, feed and depth of cut. Minimum nose radius insert with low feed provides better surface finish.

3.2.2 Effect of feed and nose radius on Maximum roughness profile height (R_t)

Table 3.2 clearly shows the feed of 0.111 and 0.222 mm/rev, R_t increases with increase in nose radius. For the nose radius of 0.4 mm, R_t increases with increase in feed but at nose radius of 1.2 mm, R_t decreases with increase in feed. In Fig. 3.3 we have seen that CNMG120408 insert provides better result at high feed of 0.333 mm/rev. Overall nose radius of 0.4 mm at low feed of 0.111 mm/rev generates low value of maximum roughness profile height i.e. 6.1 µm.

Table 3.2 Magnitude for maximum roughness profile height

Feed (mm/rev)	**Maximum roughness profile height (µm)**		
	CNMG120404	**CNMG120408**	**CNMG120412**
0.111	6.1	8	15.05
0.222	11.2	12.4	13.9
0.333	11.35	6.45	7.5

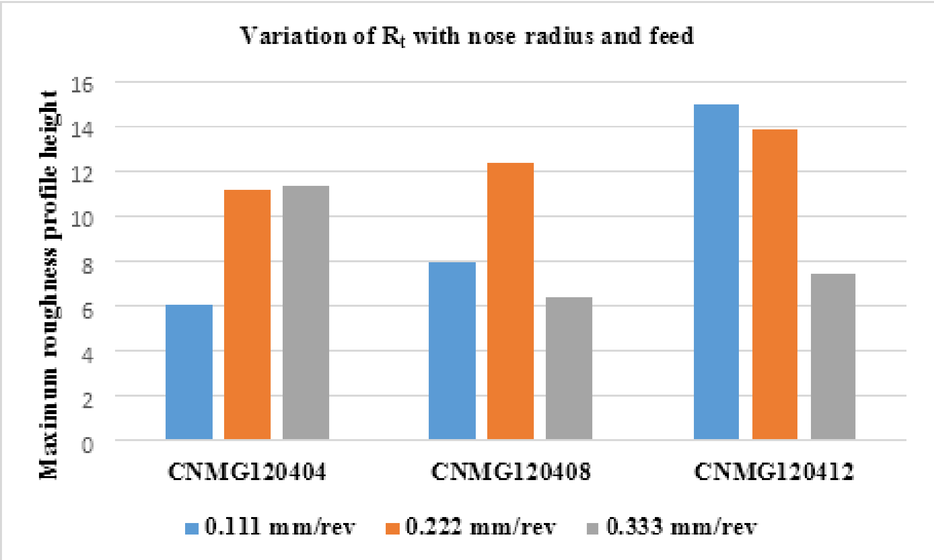

Fig. 3.3 Variation of maximum roughness profile height with nose radius and feed

3.2.3 Effect of feed and nose radius on Ten - point average roughness (R_z)

Sometimes to know the quality of machined surface ten - point average roughness plays an important role. In this the average of top five peaks and bottom five valley's average is taken into account. Here Table 3.3 shows the measured data at different combinations of feed and nose radius. Fig. 3.4 shows bar chart representation of variation of R_z with nose radius and feed.

Table 3.3 Magnitude of ten-point average roughness

Feed (mm/rev)	**Ten - point average roughness (µm)**		
	CNMG120404	**CNMG120408**	**CNMG120412**
0.111	3.5	3.65	6.35
0.222	7.2	7.15	7.15
0.333	5.65	4.15	4.5

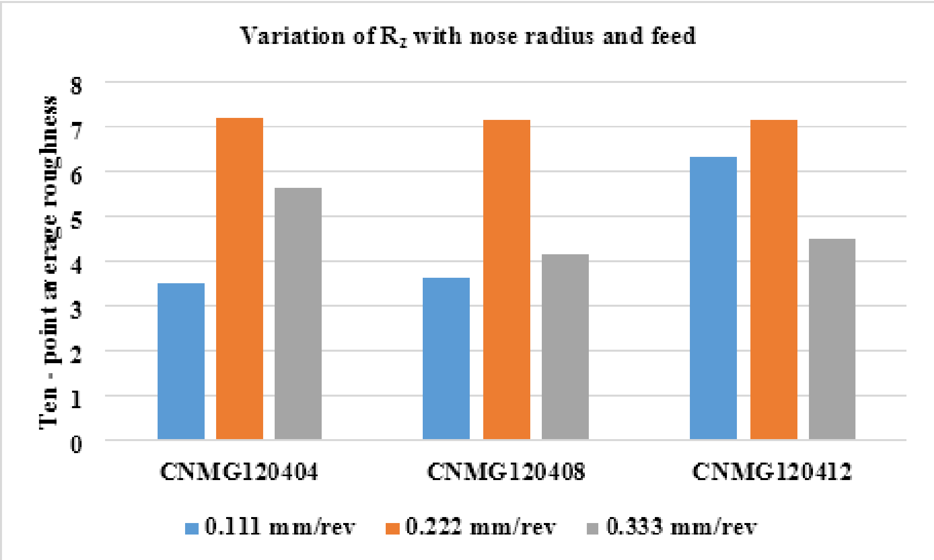

Fig. 3.4 Variation of ten - point average roughness with nose radius and feed

Fig. 3.4 clearly states that at feed of 0.222 mm/rev, R_z is maximum for each insert. For each insert almost same value of R_z is measured. At the low feed of 0.111 mm/rev, R_z increases with increase in nose radius. At high feed of 0.333 mm/rev, CNMG120408 insert provides better result. At low feed of 0.111 mm/rev with CNMG120404 optimum value of R_z is achieved.

3.2.4 Effect of feed and nose radius on machining forces

Below Table 3.4 shows the magnitude of resultant force in dry turning of Alloy 825 with coated carbide tool.

Table 3.4 Magnitude of resultant machining force

Feed (mm/rev)	Resultant force (N)		
	CNMG120404	CNMG120408	CNMG120412
0.111	259.49	298.62	410.36
0.222	382.62	503.64	523.39
0.333	573.78	657.78	558.15

The resultant force increases with increase in feed. At the feed of 0.111 and 0.222 mm/rev, the magnitude of resultant force increases with nose radius. With increase the nose radius, bluntness of tool increases that needs larger force for plastic deformation. Tool tip contact increases with increase in nose radius that increases the cutting force. Shear angle decreases with increase in nose radius that is responsible for large shear plane in primary deformation zone. We have seen that in Fig. 3.5, feed of 0.333 mm/rev, 1.2 mm nose radius insert provides better result. Cutting force contributes more compare to feed force and radial force. Sharp nose with low feed generates low resultant machining force.

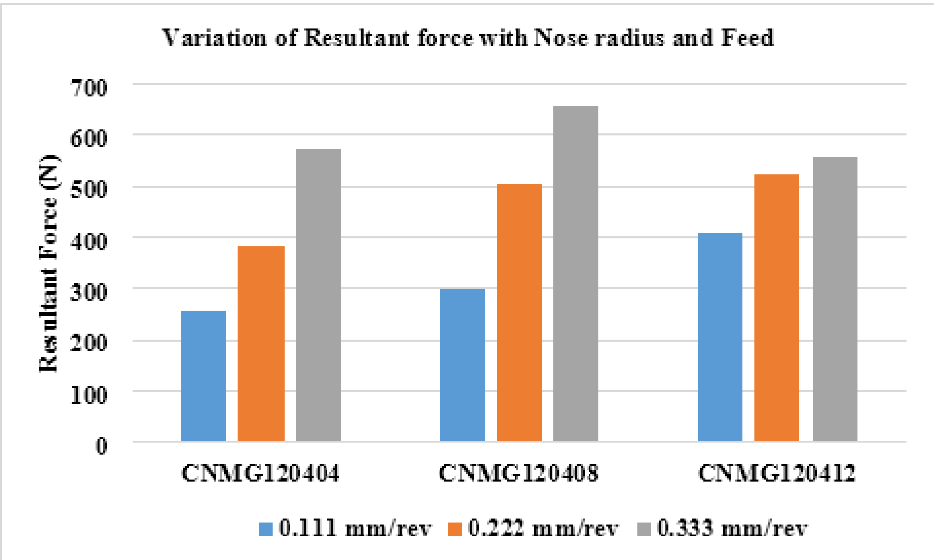

Fig. 3.5 Variation of resultant machining force with nose radius and feed

3.2.5 Effect of feed and nose radius on Specific Cutting Energy

Fig. 3.6 shows the variation of SCE with nose radius and feed in the form of bar chart. It has been observed that SCE decreases with increase in feed for all levels of nose radius. For feed of 0.111 and 0.222 mm/rev, SCE increases with nose radius. At high feed of 0.333 mm/rev, large nose radius 1.2 mm consumes less SCE compare all cases (table 3.5)

Table 3.5 Specific Cutting Energy

Feed (mm/rev)	**Specific Cutting Energy (J/mm^3)**		
	CNMG120404	**CNMG120408**	**CNMG120412**
0.111	249.59	280.80	353.42
0.222	209.19	214.23	215.36
0.333	204.78	193.89	181.32

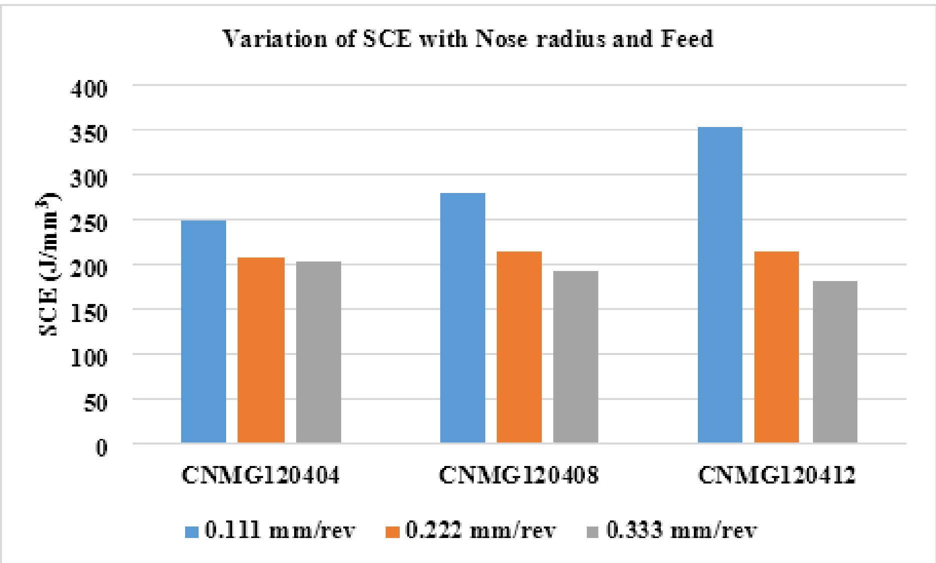

Fig. 3.6 Variation of SCE with nose radius and Feed

3.2.6 Effect of feed and nose radius on chip thickness ratio

Fig. 3.7 shows, at the feed of 0.111 and 0.222 mm/rev, Chip thickness increases with increase the nose radius. Chip thickness increases with increase in feed. For the feed of 0.111 and 0.222 mm/rev, chip thickness increases with increase in nose radius. But at high feed about 0.333 mm/rev, there is not much variation in chip thickness with variation in nose radius (Table 3.6). The chip thickness, radius of twist and the distance between two consecutive turns increase as the machining progresses. Fig. 3.8 shows the variation of chip thickness ratio with nose radius and feed. Chip thickness decreases with increase the nose radius (Table3.7).

Table 3.6 Chip thickness

Feed (mm/rev)	**Uncut chip thickness (T1)**	**Chip thickness after machining (T2)**		
		CNMG120404	**CNMG120408**	**CNMG120412**
0.111	0.11	0.14	0.16	0.21
0.222	0.22	0.25	0.26	0.27
0.333	0.33	0.33	0.34	0.31

Table 3.7 Chip thickness ratio

Feed (mm/rev)	**Chip thickness ratio**		
	CNMG120404	CNMG120408	CNMG120412
0.111	1.28	1.36	1.91
0.222	1.12	1.16	1.23
0.333	0.99	1.03	0.96

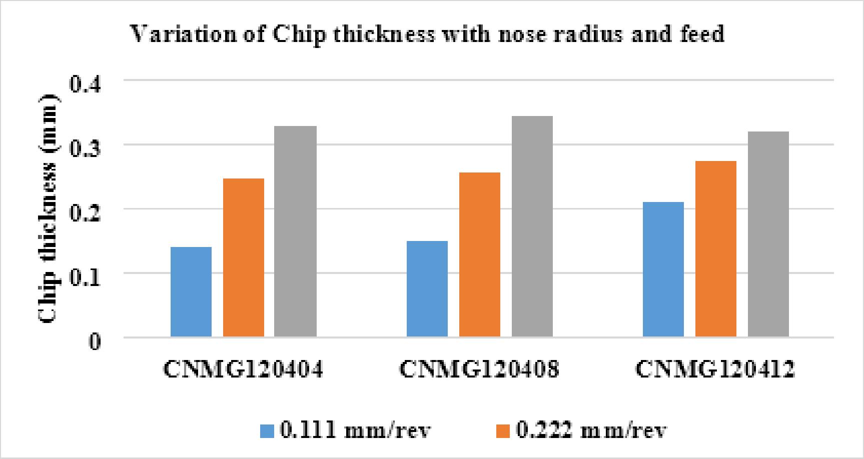

Fig. 3.7 Variation of chip thickness with nose radius and feed

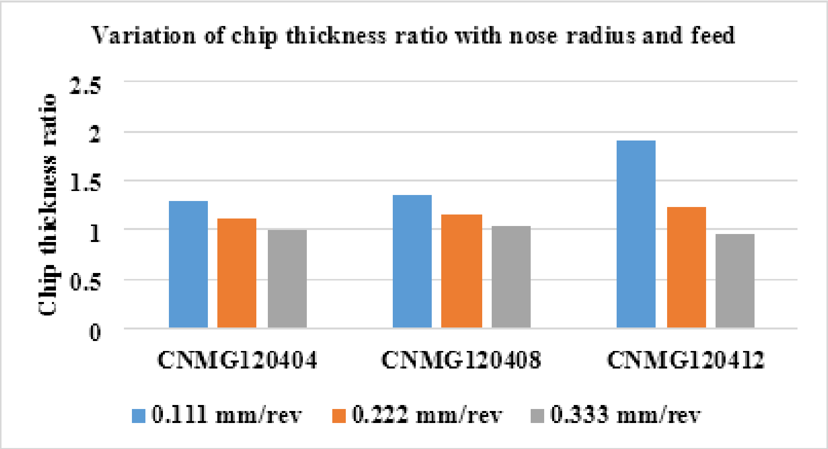

Fig. 3.8 Variation of chip thickness ratio with nose radius and feed

3.2.7 Effect of feed and nose radius on apparent coefficient of friction (μ_{app})

The apparent coefficient of friction increases with increase the nose radius (Table 3.8). Chip tool contact length increases with increase in nose radius so apparent coefficient of friction increases. With increase the feed, apparent coefficient of friction decreases. Fig. 3.9 depicts the influence of feed and nose radius on apparent coefficient of friction.

Table 3.8 Apparent coefficient of friction

Feed (mm/rev)	Apparent coefficient of friction		
	CNMG120404	CNMG120408	CNMG120412
0.111	1.06	1.20	1.51
0.222	1.01	1.10	1.12
0.333	0.97	0.99	1.01

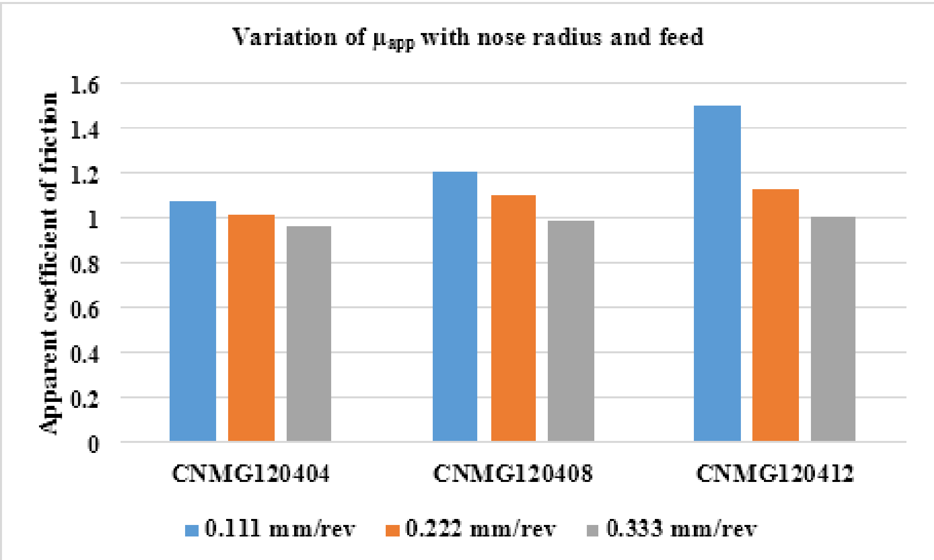

Fig. 3.9 Variation of apparent coefficient of friction with nose radius and feed

3.3 Optimization for single response using OGI, JAYA and TLBO

The Jaya algorithm is a metaheuristic method for solving optimization issues with constraints and without constraints. It is a population-based method in which the population of unique solutions is continuously altered. It is an algorithm for non-gradient optimization. There are many optimization algorithms, such as the genetic algorithm

(GA), particle swarm optimization algorithm (PSO), artificial bee colony optimization algorithm (ABC), cuckoo search algorithm, etc., but what sets Jaya apart from the others is that it lacks any extra parameters. **Pawade et. al. (2016)** have discussed the application of a novel approach called Jaya algorithm to optimize the process parameters in high speed turning of AISI S7 tool steel. Jaya is founded on the concept that a problem's solution should aim for the best answer while avoiding the worst. There are no algorithm-specific control parameters required for this algorithm. The combined effects of Teaching Learning Based Optimization (TLBO), JAYA, and Genetic Algorithm (GA) have been studied by **Sahu and Andhare (2019)** for minimising the roughness of the machined surface and forces produced during the turning of Ti-6Al-4V. **Abhishek et al. (2017)** used an advanced optimization technique called teaching learning based optimization (TLBO) to find the best machining conditions for getting good machining results. The TLBO algorithm's application potential has been compared to that of the genetic algorithm (GA). In the context of this example experimental investigation focused on CFRP composites machining, it has been observed that TLBO exploration appears to be more fruitful than GA exploration.

Table 3.9 Experimental results

S. No.	R_a (µm)	Resultant force (N)	MRR (mm^3/sec)
1	0.78	168.067	13.073
2	1.1	510.705	44.26
3	0.76	987.164	76.96
4	1.18	408.867	27.52
5	1.16	739.97	126.67

6	0.98	357.43	40.5
7	0.58	468.14	70.20
8	0.9	150.47	24.89
9	1.56	500.39	161.34

Single response optimization may not always be profitable. Its multi-performance attributes have always been used to define the performance of a product or a process, as we all know. As a result, multi-response optimization has been described in this section. Because several objective functions may have multiple optimal settings, a sui generis optimal process environment will be required to carry this out. As a result, multi-performance characteristics must be aggregated in order to produce an equal single goal function. The comparable single objective function in this situation is the overall grey relation index (OGI), and the generated OGI must be optimised to achieve the best machining environment.

Using a grey relation, which produces an analogous single performance index known as the overall grey relation index, the multi-performance output characteristics (such as cutting force, MRR, and Ra) have been combined here (OGI). In Fig. 3.10, the optimization path is shown.

To avoid conflict in criteria requirements, diverse units, and data variation range, the normalization (Table 3.10) of experimental data (Table 3.9) has been done. For MRR, higher is better criterion has been chosen, whereas for cutting force and surface roughness, lower is better criterion has been picked. The normalization has been accomplished by means of the following equations:

For the Lower- is-Better (LB) criterion:

$$Y_{ij} = \frac{\max(x_{ij}) - x_{ij}}{\max(x_{ij}) - \min(x_{ij})} \tag{3.1}$$

For the Higher- is-Better (HB) criterion:

$$\mathrm{Y}_{\mathrm{ij}} = \frac{\mathrm{x}_{\mathrm{ij}} - \min(\mathrm{x}_{\mathrm{ij}})}{\max(\mathrm{x}_{\mathrm{ij}}) - \min(\mathrm{x}_{\mathrm{ij}})} \tag{3.2}$$

Here, x_{ij} represents experimental value. The maximum and minimum observed values are denoted by $\max \mathrm{x}_{\mathrm{ij}}$ and $\min \mathrm{x}_{\mathrm{ij}}$ respectively. However, the x_{ij} value will be distinct for each experimental output responses.

Table 3.10: Normalized value and individual grey relation grade and overall grey relation grade of experimental results

Sl. No.	**N-Ra**	**N-MRR**	**N-Fr**	**Grey 1**	**Grey 2**	**Grey 3**	**OGI**
1	0.8	1.0	0.0	0.7	1.0	0.3	0.7
2	0.5	0.6	0.2	0.5	0.5	0.4	0.5
3	0.8	0.0	0.4	0.7	0.3	0.5	0.5
4	0.4	0.7	0.1	0.4	0.6	0.4	0.5
5	0.4	0.3	0.8	0.5	0.4	0.7	0.5
6	0.6	0.8	0.2	0.6	0.7	0.4	0.5
7	1.0	0.6	0.4	1.0	0.6	0.4	0.7
8	0.7	0.8	0.1	0.6	0.7	0.4	0.5
9	0.0	0.2	1.0	0.3	0.4	1.0	0.6

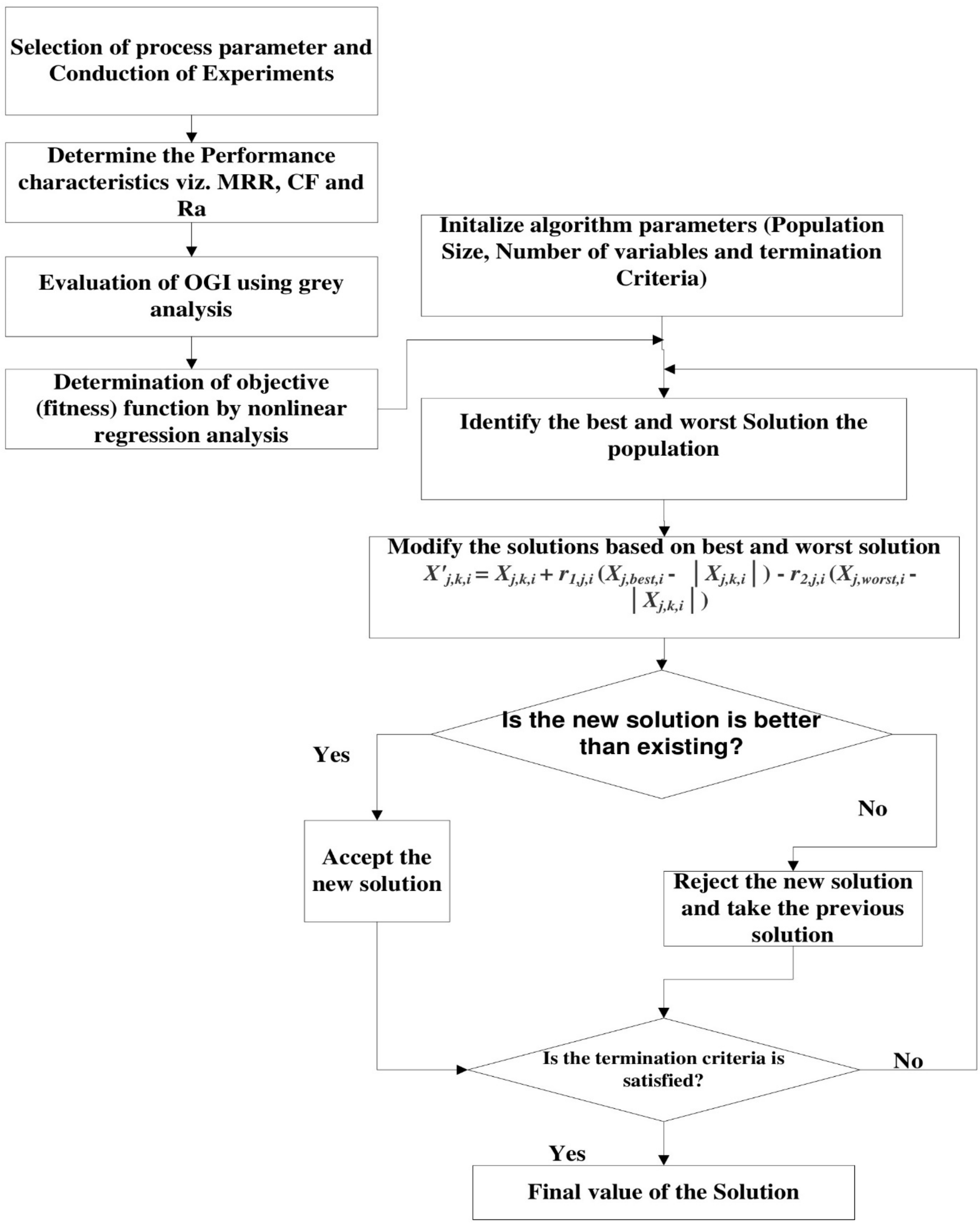

Fig. 3.10. Optimization flow chart

In order to determine the individual of the grey relational coefficient for the normalized output response (Table 3.9), the following equations have been used:

$$\gamma\left(x_0(k), x_i(k)\right) = \frac{\Delta\min + \zeta\Delta\max}{\Delta_{0j}(k) + \zeta\Delta\max} \tag{3.3}$$

$x_0(k)$ = reference sequence and $x_0(k) = 1$, $k = 1,2,3,...,m$

$$\Delta_{0j}(k) = \left\| x_0(k) - x_{ij} \right\| \tag{3.4}$$

$$\Delta\min = \min\left\| x_0(k) - x_{ij} \right\| \tag{3.5}$$

$$\Delta\max = \max\left\| x_0(k) - x_{ij} \right\| \tag{3.6}$$

ζ = distinguishing co-efficient and $0 \le \zeta \le 1$, generally $\zeta = 0.5$

Finally, It is essential to aggregate all responses into a single response i.e. overall grey relation grade. The OGI can be assessed as follows:

$$R_j = \frac{1}{k}\sum_{i=1}^{m} \gamma_{ij} \tag{3.7}$$

R_j = grey relation grade for j^{th} the experimental value

k = no. of performance characteristic

The fitness function has been implemented with JAYA. Non-regression analysis on OGI was used to generate the fitness function, often known as the goal function (where OGI has to be maximized).

$$\text{OGI} = 0.731 \times \text{V}^{(-0.011)} \times \text{f}^{(0.111)} \times \text{d}^{(-0.140)} \tag{3.8}$$

The model has been found adequate with R^2 99.4% and the actual value of the overall grey relation index has been compared with the results derived from the mathematical model. Finally, this model has been considered as a fitness function for optimization by means of JAYA algorithm. The optimal settings for maximizing MPCI has been attained as V= 247 RPM, f = 0.333 mm/rev, and d = 0.4 mm with closer to 0.7002 as a fitness function value (Table 3.11). With the same fitness function value, a similar kind of optimal settings has been achieved using TLBO algorithm (Table 3.11). The convergence plot for JAYA and TLBO algorithm has been depicted in Fig. 3.11. From Fig. 3.11, it is clear that to converge a global optimum value, the Jaya algorithm consumes lesser time as compared to the TLBO algorithm. Therefore, the JAYA algorithm is superior to the TLBO algorithm in terms of convergence timing.

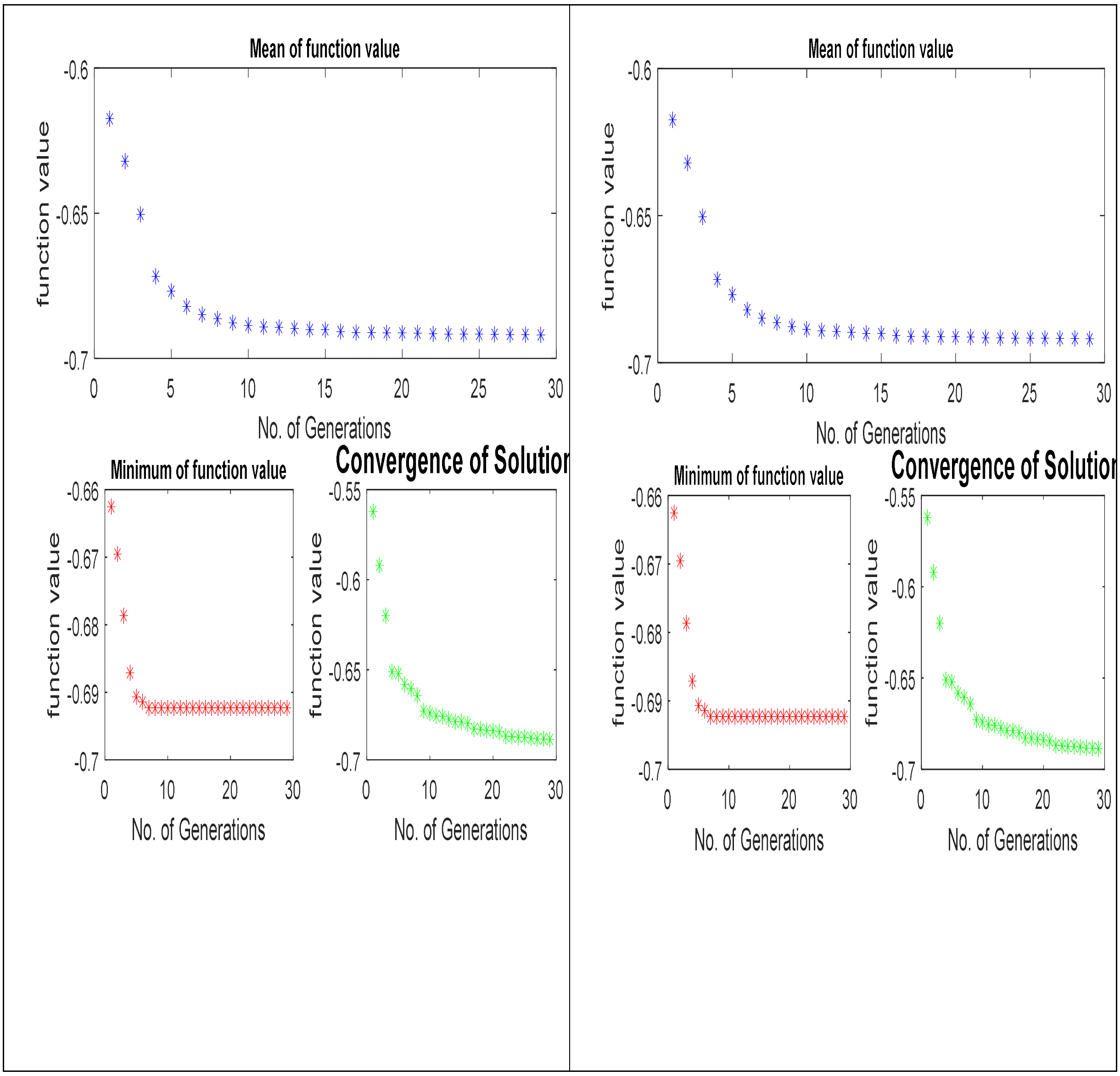

Fig. 3.11: Convergence of overall grey relation index by Jaya and TLBO algorithm

Table 3.11: Optimal parametric combination obtained by JAYA and TLBO along with fitness value

Algorithm	Responses	Optimal Parametric Combination				Fitness value
		Spindle speed	feed	Depth of cut	Nose Radius	
JAYA	OGI	247	0.333	0.4	0.4	0.70072
TLBO	OGI	247	0.333	0.4	0.4	0.70072

3.4 Optimization for multi response using TLBO, JAYA, Rao1, Rao2 and Rao3

In this work, Taguchi's OA concept is utilized due to its numerous convenient features. It is an unsophisticated model which is easily applicable in several engineering conditions, making it a robust but straight forward tool. It focuses on the mean performance characteristic value near to the target value instead of value within certain specified limits, consequently enhancing the process/product quality. It also ensures equality among all levels of all factors despite the fractionality of the design (**Pantula et. al. 2020**).

Using nonlinear regression, a relationship between the independent and dependent variables was constructed. Traditional linear regression analysis only produces linear models, but nonlinear models, which employ repeated assessment methods, produce models with a random association between dependent and independent variables.

Equation 3.9 shows a suggested numerical method for the output factor:

$$Y_u = K \times N^a \times f^b \times t^c \times r^d \tag{3.9}$$

Where, K = Constant, N = Spindle speed, f = Feed rate, t = Depth of cut, r = Nose radius a, b, c, and d = projected figures for the regression system.

The mathematical model for, MRR, Resultant Cutting Force (R_f), and Average surface roughness (R_a) have been written as follows:

$$MRR(Z_{MRR}) = -(2.184 \times N^{(0.802)} \times f^{(0.878)} \times t^{(1.125)} \times r^{(-0.484)} \tag{3.10}$$

$$R_f(Z_{RF}) = (604.877 \times N^{0.203} \times f^{0.724} \times t^{0.853} \times r^{(0.058)} \tag{3.11}$$

$$R_a(Z_{RA}) = (0.501 \times N^{0.175} \times f^{0.275} \times t^{0.015} \times r^{(0.258)} \tag{3.12}$$

The coefficient of determination (R^2) verifies that each response's suggested mathematical models are accurate. An algebraic metric known as the R^2 indicates how important the data are in relation to the established model. R^2 has a value between 0 and 100%. R^2 is frequently wanted to be greater for the model. R^2 values for MRR, R_f, and R_a are 99.3%, 99.6%, and 99.1%, respectively. The comparison shows that the developed mathematical models of MRR, R_f, and R_a are plausibly valid and used as objective functions or fitness functions in the suggested algorithm.

The objective function used in the current study for output responses like R_f and R_a has been implemented with the purpose of minimization, whereas the MRR has been used as a maximising tool. The input variables' lowest and maximum values are listed in Table 2.4 for reference. The mathematical equation is regarded as the algorithm's fitness function and must be reduced.

By giving all objectives random weights, the normalised combined objective function (Z) is expressed, as shown in equation 3.13:

$$Z = -\frac{W_1 * Z_{MRR}}{(Z_{MRR})_{\max}} + \frac{W_2 * Z_{RF}}{(Z_{RF})_{\min}} + \frac{W_3 Z_3}{(Z_{RA})_{\min}} \tag{3.13}$$

Z_{MRR} = Maximum value of MRR attained for a single objective optimisation problem in consideration of MRR as an objective function.

Z_{RF} = Minimum value of resultant force (*RF*) attained for a single objective optimisation problem in consideration of *RF* as an objective function.

Z_{RA} = Minimum value of average surface roughness (*RA*) attained for a single objective optimisation problem in consideration of *RA* as an objective function.

$W_1 W_2 W_3$= Weight attributed to the individual objective functions Z_{MRR} Z_{RF} and Z_{RA} correspondingly.

JAYA, TLBO, Rao1, Rao2, and Rao3 convergence plots for the combined objective function (Z) are provided in Fig. 3.12.

The minimum value of the normalised combined objective function is 2.03217. A comparison of the results with respect to the TLBO, JAYA, Rao1, Rao2, and Rao3 algorithms was also completed, as shown in Table 3.12.

Table 3.12. Optimal Parametric Combination

Algorithm	Optimal Parametric Combination				Fitness value
	Spindle speed (RPM)	Feed (mm/rev)	Depth of cut (mm)	Nose Radius (mm)	
TLBO	247	0.11	1.2	0.4	2.03217
JAYA	247	0.11	1.2	0.4	2.03449
Rao1	247	0.11	1.2	0.4	2.03217
Rao2	247	0.11	0.4	0.4	2.27047
Rao3	247	0.11	0.4	0.4	2.27047

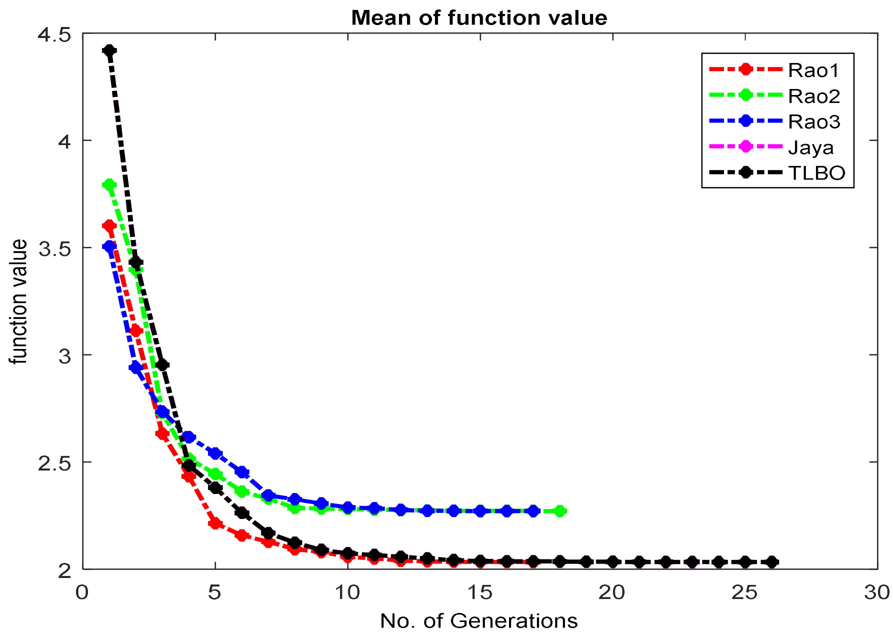

Fig. 3.12: Comparison graph between TLBO, JAYA, Rao1, Rao2, Rao3

3.5 Conclusions

During the machining of Inconel 825 alloy, the effect of feed and nose radius is highlighted in this work. Current study findings support the following conclusions:

1. A small nose radius combined with a low feed rate is recommended for an excellent surface finish.
2. Cutting force increases as feed increases. Cutting force is linearly proportional to feed for feed rates of 0.111 and 0.222 mm/rev. However, the CNMG120412 insert performs better at a high feed rate of 0.333 mm/rev.
3. Specific power consumption increases with increasing nose radius for 0.111 and 0.222 mm/rev, but decreases with increasing nose radius for 0.333 mm/rev. With increased feed, specific cutting energy falls.

4. For feed rates of 0.111 and 0.222 mm/rev, the chip thickness ratio is greater than 1. However, it is less than 1 at high feed (0.333 mm/rev). With increased feed, the chip thickness ratio drops.
5. The apparent coefficient of friction increases as the feed and nose radius increase.
6. It has also been reported that increasing the nose radius lessens the stress concentration on the nose, allowing big nose radius inserts to operate better at high feed.
7. In order to analyse the favourable machining condition during the turning of Inconel 825 alloy, the previous study offers a unified optimization route including grey relation analysis, nonlinear regression, and the JAYA optimization method. The ideal parametric combination for achieving the most favourable output responses has been established as spindle speed of 247 RPM, feed rate of 0.333 mm/rev, and depth of cut = 0.4 mm (process performance). It was also discovered that the JAYA and TLBO algorithms appear to achieve the same optimal input parametric parameters. Despite this, the JAYA algorithm has a short convergence time. As a result, its implementation is faster than the TLBO algorithm.
8. Using a comparative analysis of TLBO, JAYA, Rao1, Rao2, and Rao3, the current study intends to get optimal setup of process parameters (i.e. N, f, t, and r) during dry turning of Inconel 825. This research also emphasises the importance of optimising process parameters in order to determine the best machining (turning) conditions for Inconel 825 alloy. The ideal parametric combination for achieving the most favourable output responses has been discovered as spindle speed 247 rpm, feed rate 0.11 mm/rev, depth of cut 1.2 mm, and nose radius 0.4 mm.

Chapter 4: Exclusive summary and conclusions

4.1 Introduction

The thesis is divided into three sections: the first describes the effect of feed and nose radius on various machinability criteria during dry machining of Inconel 825, the second describes the machining performance of Inconel 825 turning, and the third section focuses on the optimal setting of machinability performance of Inconel 825 using various multi-objective optimization methods.

4.2 Summary of findings

The present work not only highlights the effect of nose radius and feed rate of turning of Inconel 825 but also examine the effect of various parameters on machinability criteria of Inconel 825. The present work also aim to study the different evolutionary algorithms, In order to get the optimal parametric combination, an integrated optimization combining grey relation analysis with JAYA, TLBO, Rao1, Rao2 and Rao3. The major findings are given below:

- To achieve good surface finish, minimum nose radius with low feed is suggested.
- Cutting force increases with increase in feed. For the feed of 0.111 and 0.222 mm/rev, cutting force is directly proportional to feed. But at high feed of 0.333 mm/rev, CNMG120412 insert perform in better manner.
- Specific power consumption increases with increase in nose radius for 0.111 and 0.222 mm/rev whereas for 0.333 mm/rev it decreases with increase in nose radius. Specific cutting energy decreases with increase in feed.

- Chip thickness ratio is greater than 1 for the feed of 0.111 and 0.222 mm/rev. But for at high feed 0.333 mm/rev it is less than 1. Chip thickness ratio decreases with increase in feed.
- Apparent coefficient of friction increases with increase in feed and nose radius.
- It has been also suggested that with increase the nose radius, stress concentration on nose is reduces so at high feed, large nose radius insert can perform in better manner.

In second part of this work, in order to determine the best machining conditions for turning Inconel 825 alloy, the thesis offers a unified optimization route including grey relation analysis, nonlinear regression, and the JAYA optimization method. The ideal parametric combination for achieving the most favourable output responses has been established as SS of 247 RPM, FR of 0.333 mm/rev, and DOC = 0.4 mm (process performance). It was also discovered that the JAYA and TLBO algorithms appear to achieve the same optimal input parametric parameters. Despite this, the JAYA algorithm has a short convergence time. As a result, its implementation is faster than the TLBO algorithm.

Using a comparative research of TLBO, JAYA, Rao1, Rao2, and Rao3, the third part of the thesis seeks to get optimal setting of process parameters (i.e. N, f, t, and r) during dry turning of Inconel 825. This research also emphasizes the importance of optimizing process parameters in order to determine the best machining conditions for Inconel 825 alloy turning. The ideal parametric combination for achieving the most favorable output responses has been discovered as spindle speed 247 rpm, feed rate 0.11 mm/rev, depth of cut 1.2 mm, and nose radius 0.4 mm.

The work highlights the important contribution of nose radius and feed rate on the output response (Cutting forces, MRR, surface roughness and Specific cutting energy). Table 4.1, 4.2 shows the optimal setting of process parameters in turning of Inconel 825.

Table 4.1 Optimal parametric combination obtained by JAYA and TLBO along with fitness value

Algorithm	**Responses**	**Optimal Parametric Combination**			**Fitness value**
		Spindle speed (RPM)	Feed rate (mm/rev)	Depth of cut (mm)	
JAYA	OGI	247	0.333	0.4	0.70072
TLBO	OGI	247	0.333	0.4	0.70072

Table 4.2 Optimal parametric combination by JAYA TLBO, Rao1, Rao2 and Rao3 along with fitness value

Algorithm	**Optimal Parametric Combination**				**Fitness value**
	Spindle speed (RPM)	**Feed (mm/rev)**	**Depth of cut (mm)**	**Nose Radius (mm)**	
TLBO	247	0.11	1.2	0.4	2.03217
JAYA	247	0.11	1.2	0.4	2.03449
Rao1	247	0.11	1.2	0.4	2.03217
Rao2	247	0.11	0.4	0.4	2.27047
Rao3	247	0.11	0.4	0.4	2.27047

4.3 Major contribution of the research work

- The proposed hybrid approach for multi-objective optimization of turning process using Grey relation analysis with JAYA and TLBO can help to obtain the optimal setting different responses.

- Because the impact of control parameters on performance characteristics in traditional turning processes has been thoroughly investigated, the suggested process parametric setting aids in turning operation planning.
- In comparison to other process factors, nose radius and feed rate were shown to be the most effective.
- In this study Rao1 and TLBO are more effective optimization method compare to JAYA Rao2 and Rao3.

4.3.1 Limitations of the study

Despite the benefits acquired through this investigation, the following may be considered limits of the study because they were not addressed in it:

- Other process parameters (such as tool angles, tool tip temperature, and tool materials, etc.) were not considered in this study. Aside from the nose radius and feed rate, the other process parameters play an important role in converting Inconel 825. The tool wear like crater wear and flank wear of tool insert is not considered in this study.

4.3.2 Scope for future work

- Other process parameters like tool tip temperature and tool geometry is also consider for the further study.
- For turning Inconel 825, a finite element analysis based on a numerical model was developed utilising simulation tools such as ANSYS, DEFORM 3D, and others.
- Tool wear have been another parameter to elaborate this research with SEM image.

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RESUME

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OBJECTIVE

To excel in the field of teaching and training with the help of providing consistently improved skills and updated knowledge and performing research activities in the field of Engineering and Technology.

EDUCATIONAL CREDENTIALS

- **Ph.D. form Jadavpur University, Kolkata (Pursuing)**
  Topic: Machinability Assessment of Super Alloy Inconel 825 Using Coated Tools: An Experimental Investigation
- **M.Tech.** in Production Engineering**, 2012-2014 (with 9.05 CGPA)**
  National Institute of Technology, Rourkela, Odisha (India)
- **B.Tech. (Mechanical)** in **2007-2011 (with 64.16%)**
  UPTU, Lucknow, U. P.

EXPERIENCE

Teaching Experience

Period : 1st July 2011 to 24th July 2012

Institute : DPG Institute of Technology and Management, Gurgaon, Haryana

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Subjects Taught : Manufacturing Technology, Industrial Engineering, Fluid Mechanics.

Period : 9th February 2015 to 23th July 2015

Institute : Poornima College of Engineering, Jaipur, Rajasthan

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PUBLICATIONS / CONFERENCE/ BOOK CHAPTER

Publications

- **Rajiv Kumar Yadav**, Anadh Gandhi, Kumar Abhishek, Siba Sankar Mahapatra, Goutam Nandi, Effect of Feed and Nose radius on various machinability criteria in dry machining of Inconel 825, *Materials Today: Proceedings,* Vol. 18 (2019), pp. 5231-5239. ***(Scopus Journal)***
- **Rajiv Kumar Yadav**, Anadh Gandhi, Kumar Abhishek, Siba Sankar Mahapatra, Goutam Nandi, Machining Performance Optimization for Turning of Inconel 825: An integrated Optimization Route Combining Grey Relation Analysis with JAYA and TLBO, *International Journal of Innovative Technology and Exploring Engineering,* Volume-8 Issue-10, August 2019, pp. 1-7. ***(Scopus Journal)***
- **Rajiv Kumar Yadav**, Kumar Abhishek, Siba Sankar Mahapatra, Goutam Nandi, A study on machinability aspects and parametric optimization of Inconel 825 using Rao1, Rao2, Rao3 approach, *Materials Today: Proceedings*, Available online 21 April 2021. ***(Scopus Journal)***

Conference

1. **Conference Name:** National Conference on "Emerging Trends in Science, Technology & Management (ETSTM-2017)

Authors: Rajiv Kumar Yadav, Kumar Abhishek , Siba Sankar Mahapatra, Goutam Nandi

Duration: Nov 11th & 12th, 2017

Paper: Numerical Simulation and Parametric Optimization in turning of Inconel 718.

Organized by: Ashoka Institute of Technology and Management, Varanasi.

2. **Conference Name:** Three Day International Conference on recent advances in mechanical Engineering, (ICRAME-2020)

Authors: Rajiv Kumar Yadav, Kumar Abhishek, Siba Sankar Mahapatra, Gautam Nandi

Duration: 26th to 28th February 2020.

Organized by: Andhra University College of Engineering, Department of Mechanical Engineering.

Paper: An Experimental investigation of dry turning of Inconel 718 using CVD coated-tool.

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20/09/22