

Goal Programming Optimisation of Machining Parameters during the Production of Ti-Alloy Components on the CNC Lathe

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Abstract— This experimental study, presents results of goal programming forecasting and optimising Ti6Al4V alloy components cutting conditions. During machining the optimising challenge concerns desirability of minimising power consumption; cutting tool wear and cutting forces whilst simultaneously realising elevated material removal rate and advancing workpiece surface quality. Cutting process parameters optimisation is essential consideration triggering proficient manufacturing activities thereby enhancing competitiveness. Harmonising the miscellany machining conditions such that these contradictory intentions are, simultaneously, tackled portends well for sustainability of the machining activity. In this research, outside cutting tests were carried out, on the lathe machine, with coated carbide tipped tools at various parameter setting levels. Cutting speed and feed rate were characterised against dependent factors. Mathematical Modeling, was carried out in Minitab 22.1 Software. The models were uploaded on goal programme optimiser, LINDO/LINGO software, to predict the appropriate cutting parameters for a determinate machining situation. Goal Programme simulation results, with the performance factors equally weighted, produced optimum cutting parameters, $v_c = 227 \text{ mmmin}^{-1}$ and $f_n = 0.2416 \text{ mmrev}^{-1}$. Validation experiments confirmed applicability of goal modeling in machining planning parameter prediction. Results showed fidelity of goal programming consistency as forecasting tool for titanium cutting parameters on the CNC lathe. Future research is delineated.

Keywords: Efficient, optimisation, sustainable manufacturing, goal programming, Ti-alloys.

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1. Introduction

Manufacturing procedures and machined artefacts require to be optimised incrementally, in order to lower production costs. Thus, consistent cutting strategy choice plays a substantial function in today's machine tool-centered manufacturing practice. Effectual engineering of the hard-to-process materials that grade 5 T-alloy (Ti6Al4V) is, disclose a broad domain of investigation and has become progressively substantial in satisfying manifold prerequisites of sustainable engineering such as environmental, cost-effective and statutory consideration in manufacturing operations. Mechanical cutting resource utilisation efficiency is one of the crucial considerations of sustainability evaluation tools in a production ecosystem [1],[2].

Reducing energy consumption, economising resources utilisation and escalating throughput are contradictory contests challenging the metal mechanical cutting industry of Ti6Al4V componentry today, [3],[4]. Ti6Al4V is utilised in the medical, aerospace, marine, defence and more industries owing to their exceptional chemical and mechanical attributes such as excellent corrosion resistance, elevated strength-to-weight relationship, astronomical temperature potency in addition to biocompatibility acreages [5]. Owing to these desirable properties, the demand for Ti6Al4V components is rising. The high-pitched inherent expenses of machining-manufacturing titanium alloy components, nevertheless, linger as an impediment with regard to the extensive application of this alloy which is the number four most abundant mineral on earth [6]. During machining-based cutting the optimisation test is concerned with appropriateness of attaining prominent material removal rate; decreasing power consumption; diminishing cutting tool wear and cutting forces while, at the same time, enhancing the quality of the workpiece surface. Harmonising the assortment of the machining parameters such that the divergent goals are realised concurrently, augurs satisfactorily for the prolonged subsistence of the cutting process. In manufacturing of the hard-to-process materials - such as titanium alloy, Ti6Al4V - by mechanical cutting, factors such as the choice of cutting strategy parameters for optimisation of the machining process, transmit significant information regarding comprehension of the process efficiency management.

The practical world of mechanical cutting founded manufacturing is largely confronted with the challenge of harmonising several contradictory intents as distinct from focusing on a singular objective, such as achievement of modicum tool wear, as an example, or attaining good quality surface texture. Purposely, minimum tool wear is associated with reduced material removal rate as well as diminished component surface quality [7]. Yet, in a typical manufacturing setting, these outcomes may be unfavourable while tool wear minimisation is achieved. This may necessitate that cutter erosion containment be achieved while simultaneously increasing MRR (production rate) and improved workpiece component surface texture quality. Such are emblematic contradictory intentions of a mechanical cutting based engineering task. The current study strives for contributing towards sustainable manufacturing of grade 5 titanium alloy components, in developing a cutting parameter optimisation framework for proficient cutting activity preparation employing Goal Programming (GP). Goal programming describes mathematical modelling constituted of linear or non-linear expressions as well as continuous otherwise discrete variables, where all constraint expressions have been converted to goals. The mathematical expression which should be realised, at a stipulated achievement level is designated the goal expression, while, the equation serving to evaluate the realisation of the diminishing of unintended goal deviation functions is known as the goal accomplishment function [8]. The notion of GP is to transmute the original manifold, and every so often contradictory, intentions into a singular objective function (OF) goal, from which is yielded a satisficing result, to the model representation of the multiple conflicting objective manufacturing challenge setting, effectively.

Goal standardisation is implemented in an effort to mitigate possibilities of biasing consequence of the distinctive measurement component entities, in order to ensure the attainment of reasonably satisfying levels of solution for all the several inconsistent goals in consideration [9]. GP, disparate to linear programme modelling, which pursues the intention to optimise (minimise or maximise) one particular objective function, addresses the multi-objective challenge by minimising the sum of deviations of the target objective values from the realised actual results achieved. Goal programming as well as its variation representations have been exploited to providing resolutions to large-scale multiple-criteria decision making encounters [10]. It allows the decision maker to, simultaneously consider various objectives, as they seek the most satisficing resolution from among the several practicable solution options. It is a specialised brand tool for optimisation which offers a framework for analytical investigation, which could be employed by decision makers to determine optimum results to compound contradictory objective problems situation. Goal programme modelling tools have proximate resemblance with physical reality exercised in making decisions [11]. In practice, on the mechanical cutting planning floor, decision makers would be intending to achieve divergent goals, which are typically expressed as aspiration levels. In every undertaking, the strength with which efforts are exerted towards reaching the aspirations might fluctuate from goal to goal. In consequence,

diverse weight ratings may be allotted in endeavouring to accomplish diverse goals. Henceforth, the prominence of every result at certain instances. During mechanical cutting based manufacturing, at process level, manifold objectives occur due to differences in effects happening in the tool/chip/workpiece interaction zone consequentially to the adjustments effected in the cutting strategy back drop.

Multiple goals in mechanical cutting based manufacturing enterprises surface due to the requirement to simultaneously accomplishing many incompatible outcomes from the same machining process contact point. Typically, as an illustration, conditions conducive for the production of the best result in the workpiece surface quality could result in excessive and expensive tool wear or cutting strategy that minimises energy expenditure could be such that productivity rate is significantly is reduced, which aspect would be undesirable. In essence, the structural precept of goal programming is founded on whether the set targets are realisable or not. An intent could be delineated from which optimisation offers an outcome which approximates as near as conceivable towards the expressed intended goals. As a manifold-objective mechanical machining simulation instrument, GP offer evidence on the compromise amongst several goals which require to be resolved simultaneously, a function popular in the cutting process planning. The intent of the current study is to determine if GP modelling can epitomise a feasible methodology for mechanical cutting-based manufacturing planning, observing the fact that there is limited academic journal record of its utilisation in the mechanical machining industry, especially those concerned with the mechanical cutting of Ti6Al4V. This research's key purpose, also, is to broaden contribution towards the sustainable cutting of Ti-alloy material via augmenting the machining activity resources utilisation effectiveness during the planning phase.

1.1 Goal Programming Optimisation Application in Industry and Business

Mechanical cutting-based manufacturing enterprises require, as a matter of imperative, to continuously enhance their operations - activities and workpieces need to be optimised incrementally. Thus, dependable machining strategy choice plays a substantial function in the machining planning phase. The cutting process optimisation challenge lies in the detail that it has numerous constraints that are ascribed to multiple purposes. Ordinarily, in single parameter optimisation objective, the optimality attainment of one aspect point towards the aggravating challenge of one or more other input parameters. Challenges associated with the necessity to optimising multiple objectives emanate from consequences inclining towards dissimilar directions [12], and resolving such had been a problem confronting manufacturing engineers for an extended duration. Characteristically, the application of a singular parameter optimisation technique is, practically, not sufficient in handling real live mechanical cutting-based manufacturing challenges. Accordingly, manufacturing engineers often encounter situations where they are expected to resolve production preparation challenges boasting of numerous contradictory objectives.

Goal Programming (GP), as well as its variations, had been employed to resolve multi-criteria determination of decisions for challenges in a number of application fields [11]. By diminishing the variation concerning the targeted quantities and the actual value results yielded, goal programme modelling is employed in managing the optimisation challenge of multiple inconsistent objectives [13]. GP have its place in the family of the multi-objective decision making tools which is considered an arm of the multi-criteria optimisation algorithms [14]. It is employed to administer and strategise the concurrent realisation of incompatible goals in a mechanical cutting process parameters optimisation, by diminishing the variation of the achieved results from the forecasted or expected target outcomes [15]. Accordingly, as a decision science support tool, goal programme modelling (GPM) is exploited in the simultaneous optimisation of a number of contradictory goal objectives—wherein the accomplishment of a singular objective tend to exacerbate the achievement state of the other competing goals. Alam [15], explains the intent of goal programming, being in the direction of minimising the achievement deviation of every realistic objective level, so that when non-attainment is thrust to nil, at that juncture the achievement of the goal target had essentially been realised. GPM is a

special investigative methodology structure which decision makers may well use the services of to search for optimum solutions of multiple discordant goal manufacturing planning challenges. Several researchers, for instance, Kaur et al. [14] in consensus with Khezri and Mahmoudi [16], propositioned the relevance of goal programme modelling, in a few publications, to resolve a variety of challenges. The notable shortcomings in the utility of Linear Goal Programme modelling (LGPM) relate to the unavailability of procedures proficient in achieving optimality in judicious period [16].

Machining establishments' organisation goals, in practical operation, could differ contingent upon the attitude and characteristics of the enterprise, environmentally friendliness condition of the operation, inter alia. At the mechanical cutting activity level the manifold intentions could include, attaining elevated level of productivity, increasing material removal rate, minimising of tool wear, attaining eminent surface texture quality, reducing energy consumption rate, sustaining satisfactory component piece as well as cutting tool integrity, etc. These dissimilar and antagonistic intentions would demand the machinery operational conditions to be established at distinctive levels in order to, respectively, achieve the desired performance. Goal programme modelling had been employed to resolve manifold contradictory objectives optimisation problems in several disciplines. It had been applied in diverse fields, such as Mutual Fund Portfolio selection [17], Farm cropping land determination [18], besides fashioning 3D trade-offs in contemporary engineering challenges [19]. Dave [20] applied GPM to simulate and deal with facility siting difficulty with multifarious contending objectives, whilst Kornbluth [21] utilised it in modelling challenges in industrial and economic planning and Hayes, et al. [22] used this multi-objective tool in reinforcement learning and planning autonomous age modelling. Typically, GPM had not been exploited considerably in resolving cutting strategy choice decisions in the mechanical cutting planning process of Ti6Al4V.

Typically, in a machining based manufacturing production operation, according to earlier research findings, increasing the machining parameters condition, say, feed rate, cutting speed and depth of cut, generates higher material removal rate of during a cutting process [23]. This outcome is a positive result, nevertheless, it will also go together with aggravated cutter erosion and rougher surface texture quality of the workpiece – which apparently, are unfavourable responses. The essential concept of goal programme modelling is that, even if the established goals are achievable or not, the purpose may well be averred wherein optimisation tenders an outcome that comes as proximate as practically possible to the specified goals. As a decision crafting aiding tool, goal programme modelling aspires to simultaneously optimise several (up to 120, software dependent) objectives and concurrently minimise the variation of each from the envisioned goal of intent [11]. The emphasis of goal programme modelling is to diminish the deviations in a ranked arrangement scheme such that the objectives of highest order significance, for the mechanical cutting activity, are given first priority concentration of consideration, whereas those of lower orders of significance, respectively, receive secondary focal point priority attention, and goals of subsequent ranking eminence, respectively, get succeeding priority order focus as such. Consecutively, utilising the practical resolutions of the higher ranking precedence order of goals, aspirations of the subsequent primacy ranking prominence of goal substance are in turn attended and minimised [14]. Inferior ordered prominent objectives would simply be considered subsequently following the fulfilment of the superior ordered priority goals [11].

According to Rifai [24], the conventional stages for the development of a GMP structure goes along the steps indicated in Table 1,

Table 1. Development Steps of goal programme modelling

Stage No	Process step
1	Determine the objectives and translate them into goal constraints through establishing deviational variables.

2	Assess the goals and instate the required deviational variables, exactly.
3	Ranking the objective targets in order of significance and proactive precedence priority allotted to every one of them.
4	In the event of existence of ties in significance ranking, allocate a weight, to each one, of the prioritised deviational variables in order to break then ties.

The conventional mathematical representation model of GPM could be structured as constituted in equations (i -iv) expression [25]:

$$\text{Min } z = \sum_i^m w_i p_i (d_i^- + d_i^+) \quad (1)$$

st

$$\sum_j^n a_{ij} x_{ij} + d_i^- - d_i^+ = b_i \quad (2)$$

$$x_{ij}, d_i^-, d_i^+ \geq 0, w_i > 0 \quad (3)$$

$$(i = 1, 2, \dots, m; j = 1, 2, 3, \dots, n) \quad (4)$$

In which, d_i^+, d_i^- stand for, respectively, the positive and negative aberration variables, b_i is the targeted goal, p_i is the proactive precedence consideration, w_i is the goal primacy weighting component, z is the attainment determination.

2. Materials and Methodology

Lathe machine external cutting tests were performed on the precise Efamatic Computer Numerical Control (CNC) machinery which boasts of the ensuing characteristics: Slant Bed CNC lathe Machining Centre; Model is Efamatic RT-20 S; Major motor power, AC 11/15 kW; Machine weight, 3.8 tonnes; maximum spindle speed of 4500 RPM; Maximum bar stock, diameter 75 mm; Dual axes, respectively, with travel of 260 mm diametric span on X-axis and 450 mm linear travel on the Z-axis. The component specimens material was diphase [26] titanium compound, Ti6Al4V (Grade 5 titanium alloy) which existed delivered in annealed state at, 36 on the Rockwell Hardness scale, as a sturdy cylindrical billet (250 mm length by 75.4 mm diameter). The mechanical strength and chemical composition of the specimens material, characteristics are, respectively, detailed in Tables 2 and 3 (deriving from the certificate of the material).

Table 2. Ti6Al4V alloy mechanical strength properties

Mechanical Characteristic	State/Value
Treatment Condition	Annealed
Tensile Strength (MPa)	969
Yield Strength (MPa)	847
Elongation (%)	13
Reduction of Area (%)	28

Table 3. Chemical composition of Titanium alloy (Ti6Al4V) material used

Element	% Content
Titanium	89.069
Aluminium	6.0
Vanadium	4.1
Others	0.5
Oxygen	0.16
Ferrite	0.14
Carbon	0.02
Nitrogen	0.01
Hydrogen	0.001

An initial clearing cut of 0.5 mm was performed, on each of the specimens billet, before the commencement of experiment iterations in earnest. This cut was carried out in order to eradicate, on the experiments material, any preceding processing caused lingering stresses, unequal surface cylindricity as well as erstwhile surface imperfections which could adversely militate the cutting results [27]. The machining tip utilised for the initial cleaning run would not be employed in the cutting experiment iterations.

Taguchi full factorial design of experiments technique was utilised in planning the external turning experiments on the computer numerical control (CNC) lathe machine tool. The investigation contemplated the concurrent varying of f_n and v_c (machining strategy factors) on longevity of the tool lifespan, surface texture integrity, formation system of chips, cutting force as well as the expenditure rate of energy utilisation, as the performance response factors. The machining experiments cutting factor planning combination arrangement levels were detailed as presented Table 4. As regards the experimental scheme, the adjustable input factors in the exterior turning investigations were: six cutting speeds, v_c (50, 70, 100, 150, 200, and 250 m/min), and three feed rates, f_n (0.1, 0.2, and 0.3 mm/revolution in that order). Overallly, 18 external cutting tests were carried out, utilising 18 turning tool tips to machine the component specimens at varied v_c and f_n combinations at unchanged depth of cut of 0.5 mm. Cumulatively, a full series of seventy-eight (78) external cutting experiment runs were carried out, on the slant bed CNC lathe machine. The design of experiments approach was utilised in planning the cutting tests. In all the cutting experiments, respectively, cutting power (for cutting energy), cutting and feed force as well as surface roughness were considered and logged. Tool wear measurements were taken at the termination of each cutting run pass of 180 mm linear length.

Table 4. Machining process factor levels and settings of the external cutting tests

Parameter	Condition						
Cutting Speed (v_c)	50	70	100	150	200	250	m/min
Feed/rev (f_n)	0.1	0.2	0.3	-	-	-	mm
Depth of Cut (DoC)	0.5	0.5	0.5	0.5	0.5	0.5	mm
Coolant	Flood cooling						

The experiment setting as well as the machinery and statistics recording apparatus connectivity layout is shown in Figure 1.

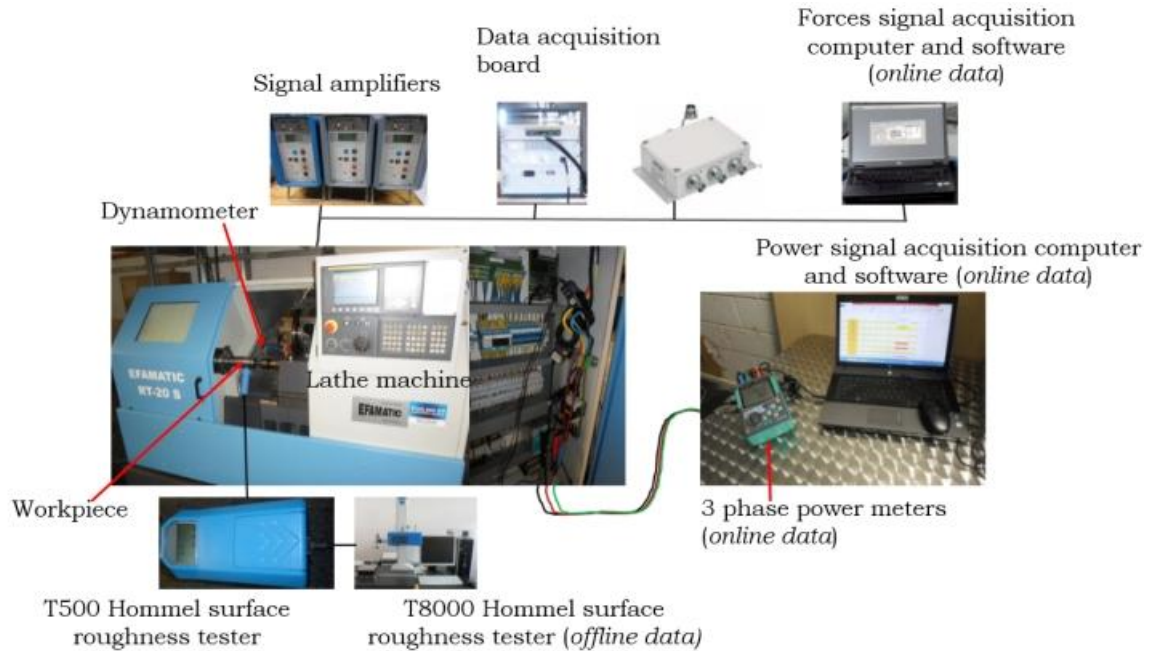


Figure 1. Power System Components

2.1 Goal Programming Prediction and Optimisation Model

GP optimisation model was implemented using LINDO software version 20.0.1 running on a laptop running on Windows 11 Pro. The mathematical models of the problem were generated through regression analysis.

3. Result and Discussion

Results were produced and are presented under the sections as detailed:

3.1 Characterisation of cutting parameters with output responses

Figure 2 shows the changing of surface texture coarseness along by means of increasing v_c , at the three f_n which were used. The surface roughness measurement results presented, in this instance, are the R_a , R_z and R_{max} . It subsists evident, as of the graphical results that as cutting swiftness gets elevated the texture quality of the surface, generally reduces. The results analysis pondered on surface texture coarseness R_a , R_{max} and R_z which all leaned towards decline alongside rising cutting speed. These findings subsisted coherent alongside the results presented by Mawanga [28], who examined the surface veracity of lofty speed cutting of grade 4 titanium alloy. The average surface roughness (R_a) is the mainly by and large contemplated surface roughness characteristic standard, however [29]. As such the following presentation segments cogitated R_a assessments of surface jaggedness. It is perceptible that, as cutting speed escalates, R_a value declines on all 3 feed rates. Accordingly, elevated cutting speed tended to generate better-quality surface texture.

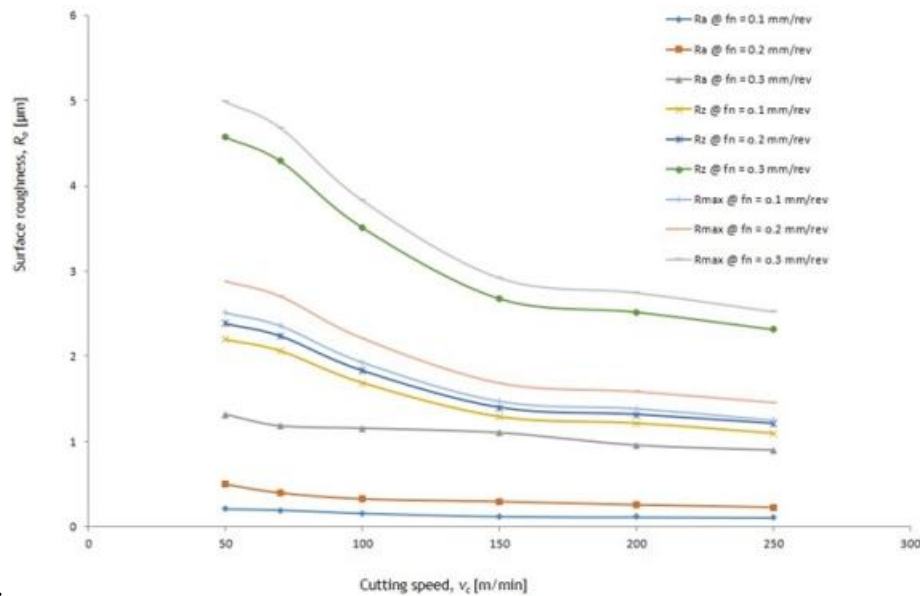


Figure 2. Surface roughness – R_a , R_z , R_{max} under the influence of cutting speed (microns)

Figure 3 shows the relationships of feed rate with both the specimens component surface texture quality (roughness) and specific cutting energy. The graphical results clearly illustrate that increment in feed rate leads to coarsened component surface texture quality, but simultaneously, there is associated decrease in specific cutting energy also. This subsists as an emblematic contradiction in consequences prompted by increasing the feed rate, input factor.

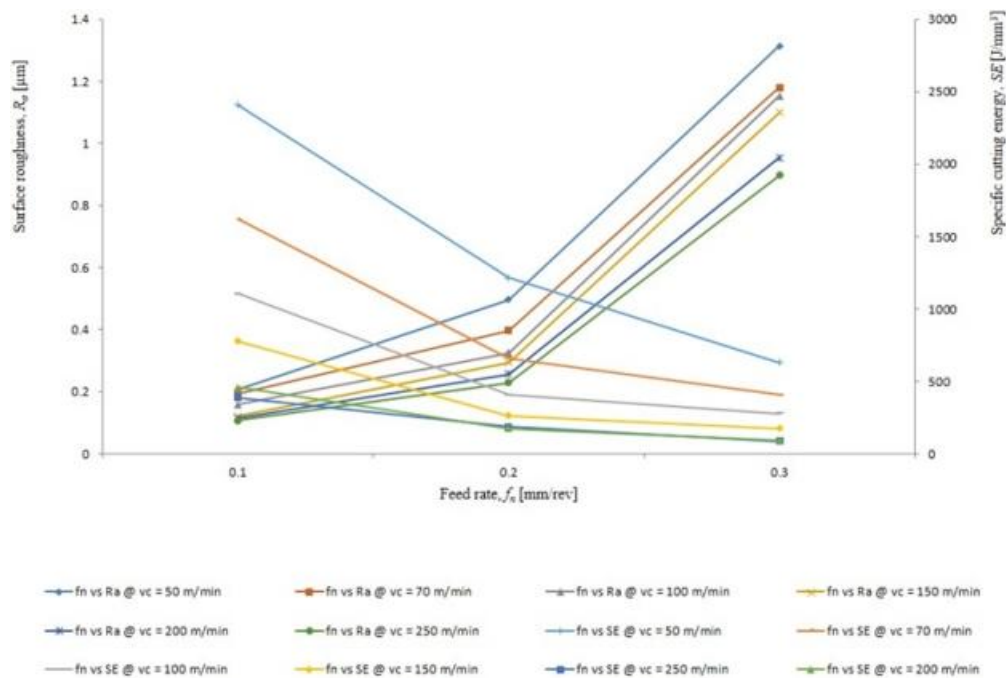


Figure 3. Surface coarseness (r_a) and explicit cutting energy (SE) versus feed rate (f_n)

Minitab 22 statistical package was utilised to assist in performing the regression analysis of the empirically produced cutting data. All the cutting factor results were examined and the respective regression models were developed. The regression model, articulates the numerical relational connectivity of the independent parameters (feed rate, f_n and cutting speed, v_c) with the dependent factors [30]. In this investigation, the modelled dependent factors, were total cutting power, surface

roughness, chip teeth segmentation pitch, Tool wear, explicit (specific) cutting energy, Material removal rate and cutting forces. The firm representativeness, of the regression model to the fitted data, is indicated in the high model coefficient of determination (r^2) shown in Table 5. This connote the fact that predictors elucidate 96.49% of the dependent factor, total machining power (ToP).

Table 5. Total Machining power (ToP) model summary

S	R-sq	R-sq (adj)	R-sq(pred)
96.49%	96.49%	94.04%	88.64%

The Regression model revealing the scientific connection of surface coarseness, response, as a function of the independent factors, feed rate and cutting speed is represented by equation (5):

$$Ra = 0.1776 - 0.001308v_c + 2.607f_n \quad (5)$$

The coefficient of determination (r^2) factor, 98.90%, presented in Table 6, exhibits an exceptionally robust association of the response factor, surface roughness with the regression model representing it. In this manner, the statistical data is vastly reflected in the installed regression contour profile. The 98.90%, r^2 intensity as well as the adjusted 98.13% value R-square, both signify sound model fit.

Table 6. Model summary of Ra

S	R-sq	R-sq (adj)	R-sq(pred)
0.0595429	98.90%	98.13%	96.44%

The results summary of characterisation of machining input parameters with output responses, as well as the regression models of the response parameters (Appendix 1, Table 7) was arrived at through a two-step analysis process of the machining experiments data. Graphical presentations were produced for each and regression models were respectively produced for each of the response parameters - total machining power, cutting force, Material removal rate, specific cutting energy, chip teeth segmentation pitch and Tool wear.

The Figure in Appendix 1, Table 7 on (a) presents the 3 sided element representation scheme of total machining power (ToP), respectively, as a dependent response of f_n and v_c . The increment of ToP with the escalation of the two input factors, rate of feed and cutting speed, is evident from the graphical plot. Observably, the effect of cutting speed increase is more pronounced on the ToP escalation than as prompted by the effect of feed rate incremental change. The regression equation of the ToP is presented in equation (6) in Table 7. The R-square of 96.49% indicate a good model fit. On the other hand, the surface plot of MRR as a function of, respectively, both rate of feed and cutting speed is exhibited in Figure Table 7 on (b). This encapsulates the multiparty effect of the independent factors, f_n and v_c on the dependent material removal rate factor. From this result display, it is plain, as the nose on the human face, that material removal rate is optimistically impacted on by jointly escalating v_c and f_n . The impact of cutting speed seem to be prominently well-defined, nevertheless, when contrasted with the effect of feed rate. The Regression model, expressing the connection of the contributing parameters to the dependent factor, (MRR), is presented in equation (7) on Table 7. The determination constant factor, 95.93%, presented in Table 7 exhibits enormously sturdy representativeness of the installed regression profile by the data.

Chip Morphology was analysed for its perceived indication of the machining process characteristics. The fragment morphology features examined were pitch of the segmented teeth (STP), shear segmentation angle of the chip (San) and frequency of segmentation (SF). However the aspect reported in this paper is the chip segmentation pitch. The Figure in Table 7 on (c) cabarets the surface map of flake partition timbre as a function of the variable input parameters, respectively, feed rate as well as cutting speed. The gradient of the STP variation as a dependent response of feed rate is evident although it is not as much precipitous as a result of the influence of the cutting speed input factor. The

computational affiliation of variable input parameters, v_c , and f_n with the dependent factor, STP is conveyed by equation (8) in Table 7. The 96.43% r^2 factor demonstrates appreciably robust representativeness of the installed regression trail to the data.

Tool erosion, particularly flank abrasion, incline towards affecting the cutter conformation occasioning substantial adverse effect on the machining energy expenditure, material separating force and the work piece surface texture attribute, in the course of the cutting activity. It is described as a key element which influence the material machining economics during the cutting process [30]. Abridged flank attrition levels answer to enhanced tool life, superior surface texture condition, reduced costs of tooling and minimised costs of production. In this research, the impression of the independent machining factors choice upon the cutter flank wear is evaluated, in order to determine the machining strategy combination, of v_c and f_n , with dominant effect on the process. Optical dimensions, of the cutter crater erosion progression, stood recorded, at distinctive cutting strategy situation, at the completion of every cutting pass, of 180 mm straight distance on the workpiece component. The domineering scuffing system, reflected, existed on the flank, stalked before crater erosion atop the rake face. Intensifying cutting speed led to amplified heat energy and chemical reaction behaviour in the workpiece-chip-tool boundary zones. Escalation in the mechanical burden from escalated feed rate instigated intensification of fracture mechanisms in the chip shearing region. The joint variable independent factors against tool wear associations are mapped in the graphical illustration presented in Table 7 on (d). There is sharper change in tool wear alongside escalated cutting speed compared to the change which arise when feed rate is increased. The graphical plot, thus, display the supremacy of cutting speed in prompting tool wear as contrasted with feed rate. The numerical archetypal, articulating tool flank deterioration as occasioned by the machining conditions is shown in equation (9). This is the linear regression model used to approximate and explain the affiliation of cutter scuffing as a function of the independent factors, feed rate and cutting speed. The r^2 , value of 99.58% (presented in Table 7), substantiates the substance of how sound the regression track guesstimates the actual data elements forecasting the association of the independent factors (v_c and f_n) with the cutter erosion, response factor.

The surface plot of the material separating forces and the independent factors (feed rate and cutting speed) is represented by Figure (e) in Table 7. Ostensibly it is evident, according to the plot, that increasing f_n also causes the escalation of the cutting forces. Whereas, v_c elevation is associated with tending decrease in the cutting force. Thus, in quintessence, cutting force, generally incline towards reduction with rising cutting speed whereas, it tended to escalate in response to increased rate of tool feed. Increased v_c heightens the thermo-mechanical estrangement activity of the workpiece material, aided by the heat intensification within the cutting zone, leading to the trend of cutting force, demanded to push the material separation process, to decrease. The regression model, of the cutting force (F_z), presented in equation (10), has a determination factor, r^2 of 95.41%, which confirms the model's effective representativeness of the data.

The results presented in the surface plot in Figure (f) on Table 7 show that specific cutting energy decreases as both v_c and f_n are increasing. This speaks to the dimension of increased material removal rate, an aspect which also subsist when the cutting parameters are increased.

3.2 Goal Programming Optimisation

Equations (12) to (23), presents, a summarised cluster of equations representing goal programme objective function and the seven constraints derived from the possible machining response outcomes by which the process characteristics can be assessed as well as the subordinate and superior confines of the cutting strategy. The deviation variables, (d_i^+ and d_i^-), of each machinability outcome with respect to the parameters were, respectively, added in each equation (equations 13 – 19). Thus, converting the machinability assessment outcome equations into the objective function achievement functions for the goal programme model. These outcomes result, inadvertently, as the cutting parameters are adjusted. As explained, in the parameters characterisation and graphical presentation

above, some outcomes are such that desirability for good performance is that the cutting parameters be increased whilst others, such as tool wear and power, are such that cutting parameter settings need to be low. This conflicting type of outcome situations is typical of the struggle machining engineers are faced with regarding the decision on the best cutting parameters combination which will realise efficient machining process with minimum to none negative machining consequences, on the tooling or workpiece or the machine system as a whole, during the process. The generally published literature currently approach the machining parameter optimisation challenge by optimising one or two parameters at a time [31]. In practical reality, during material profiling by machining a number of factors are at play simultaneously. Thus, generating varied and contradictory consequences on the component. The optimisation model and set of constraint equations for the cutting operation in this study is presented in (12 - 23). All goal objectives were deemed to be equally important for this component machining:

$$\text{Min } d_{1+} + d_{2+} + d_{3-} + d_{4+} + d_{5+} + d_{6+} + d_{7+} \quad (12)$$

S.t

$$R_a = 0.1776 - 0.001308v_c + 2.607f_n - (d_{1+} - d_{1-}) \quad (13)$$

$$\text{ToP} = 0.9115 + 0.005535 v_c + 2.268 f_n - (d_{2+} - d_{2-}) \quad (14)$$

$$\text{MRR} = -157.1 + 1.178v_c + 926f_n - (d_{3+} - d_{3-}) \quad (15)$$

$$\text{STP} = -4.67 + 0.1143 v_c + 491.3f_n - (d_{4+} - d_{4-}) \quad (16)$$

$$\text{TW} = -59.0 + 1.704v_c + 632f_n - (d_{5+} - d_{5-}) \quad (17)$$

$$\text{Fz} = 97.7 - 0.3139v_c + 825.9f_n - (d_{6+} - d_{6-}) \quad (18)$$

$$\text{SE} = 2693.0 - 7.737v_c - 2233f_n - (d_{7+} - d_{7-}) \quad (19)$$

$$v_c \geq 50 \quad (20)$$

$$v_c \leq 250 \quad (21)$$

$$F_n \geq 0.1 \quad (22)$$

$$F_n \leq 0.4 \quad (23)$$

$d_{1+}, d_{1-}, d_{2+}, d_{2-}, d_{3+}, d_{3-}, d_{4+}, d_{4-}, d_{5+}, d_{5-}, d_{6+}, d_{6-}, d_{7+}, d_{7-} \geq 0$, where,

v_c is the cutting speed in m/minute

F_n is the feed rate in mm/revolution

d_{1+} is the deviation variable for over achieving the desired target surface quality

d_{1-} is the deviation variable for under achieving the desired target surface quality

d_{2+} is the deviation variable for over achieving the desired target total operating power

d_{2-} is the deviation variable for under achieving the desired target total operating power

d_{3+} is the deviation variable for over achieving the desired target material removal rate

d_{3-} is the deviation variable for under achieving the desired target material removal rate

d_{4+} is the deviation variable for over achieving the desired target segmentation teeth pitch

d_{4-} is the deviation variable for under achieving the desired target segmentation teeth pitch

d_{5+} is the deviation variable for over achieving the desired target tool wear

d_{5-} is the deviation variable for under achieving the desired target tool wear

d_{6+} is the deviation variable for over achieving the desired target cutting force

d_{6-} is the deviation variable for under achieving the desired target cutting force

d_{7+} is the deviation variable for over achieving the desired target specific cutting energy

d_{7-} is the deviation variable for under achieving the desired target specific cutting energy

This goal programme optimisation model, of the machining planning process, was uploaded onto the Lindo platform environment as shown in the screen print shown in Figure 4.

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Min    d1P + d2P + d3M + d4M + d5P + d6P + d7P
s. t.
Ra)      - 0.001308Vc + 2.607Fn + d1M - d1P = 149.8224
Top)      0.005535Vc + 2.268Fn + d2M - d2P = 0.4885
MRR)      1.178Vc + 926Fn + d3M - d3P      = 457.1
STP)      0.1143Vc + 491.3Fn + d4M - d4P      = 144.67
TW)       1.704Vc + 632Fn + d5M - d5P      = 259
Fz)       - 0.3139Vc + 825.9Fn + d6M - d6P      = 202.3
SEC)      -7.737Vc -2233Fn + d7M - d7P      = - 2297
Fn_LB)    Fn >= 0.1
Fn_UB)    Fn <= 0.4
Vc_LB)    Vc >= 50
Vc_UB)    Vc <= 250

```

Figure 4. Goal programming model in the LINDO platform environment

3.2.1 LINDO Goal Programme results and interpretation

The optimisation model results, display in the LINDO environment, is displayed on the screen print shown in Figure 5.

OBJECTIVE FUNCTION VALUE		
1)	282.0845	
VARIABLE	VALUE	REDUCED COST
D1P	0.000000	1.000000
D2P	1.316770	0.000000
D3M	0.000000	1.000000
D4M	0.000000	0.692625
D5P	280.767731	0.000000
D6P	0.000000	1.000000
D7P	0.000000	0.783585
VC	227.151138	0.000000
FN	0.241617	0.000000
D1M	149.489624	0.000000
D2M	0.000000	1.000000
D3P	34.221741	0.000000
D4P	0.000000	0.307375
D5M	0.000000	1.000000
D6M	74.050934	0.000000
D7M	0.000000	0.216415
ROW	SLACK OR SURPLUS	DUAL PRICES
RA)	0.000000	0.000000
TOP)	0.000000	1.000000
MRR)	0.000000	0.000000
STP)	0.000000	-0.307375
TW)	0.000000	1.000000
FZ)	0.000000	0.000000
SEC)	0.000000	0.216415
FN_LB)	0.141617	0.000000
FN_UB)	0.158383	0.000000
VC_LB)	177.151138	0.000000
VC_UB)	22.848862	0.000000

Figure 5. GP Model solution display in LINDO platform

The objective function value of 282.0845 indicates the total deviation from the summed set of desired goals deviation. The optimum variables parameters setting on the machine, therefore are respectively, cutting speed (v_c) equal 227.151138 mmin-1 and rate of feed (f_n) equal 0.241617 mmrev⁻¹. This parameter setting state represent the achieved levels of optimality which realises the least computed deviation of 282.0845, from the overall target goal.

Further reading from the model results, tabulated in presentation in Figure 5, show that goals number four (segmentation teeth pitch) and goal number seven (on specific cutting energy) were fully satisfied as they have zero deviation on either side of the goal targets. The model's deviations, D2P and D5P, show that the total operating power (ToP) goal is 1.316770 units below target, and the tool wear goal is 280.767731 units short of its desired level. The zero deviations for D1P, D3M, D4M, D6P, and D7P indicate that the goals have been achieved fully with zero deviation. The reduced costs indicate the change in the objective value for a one-unit change in each variable. For example, increasing v_c by a single element would increment the objective function value by 0.000000 units.

A positive dual price (0.216415) for Specific cutting energy (SEC) means that increasing the SEC goal by a singular element would escalate the objective function value by 0.216414 units, indicating that increasing SEC worsens the solution. A negative dual price (-0.307375) for Segmented teeth pitch (STP) means increasing the STP goal by one unit would decrease the objective function value by 0.307375 units, indicating that decreasing STP is beneficial. A zero dual price (0.000000) for

Surface roughness (R_a) means that changing the R_a goal by one unit would not affect the objective function value, indicating that capacity is not a limiting factor.

The objective coefficient ranges, presented in the tabulation in Figure 6, indicate the allowed variation in the objective coefficients without changing the optimal solution. For example, the coefficient for D5P can be decreased and increased by 1.000000 and 2.264127, respectively, without affecting the optimum solution. The right-hand side ranges indicate the allowed variation in the right-hand values of the constraints without changing the optimal solution. For example, Specific cutting energy can be decreased and increased by 164.911591 and 256.600403 respectively without affecting the solution.

RANGES IN WHICH THE BASIS IS UNCHANGED:			
VARIABLE	CURRENT COEF	OBJ COEFFICIENT RANGES	
		ALLOWABLE INCREASE	ALLOWABLE DECREASE
D1P	1.000000	INFINITY	1.000000
D2P	1.000000	473.416077	1.000000
D3M	1.000000	INFINITY	1.000000
D4M	1.000000	INFINITY	0.692625
D5P	1.000000	2.264127	1.000000
D6P	1.000000	INFINITY	1.000000
D7P	1.000000	INFINITY	0.783585
VC	0.000000	0.488106	1.099873
FN	0.000000	317.437805	140.873703
D1M	0.000000	47.201679	1.000000
D2M	0.000000	INFINITY	1.000000
D3P	0.000000	0.541690	0.240393
D4P	0.000000	INFINITY	0.307375
D5M	0.000000	INFINITY	1.000000
D6M	0.000000	0.153709	0.346360
D7M	0.000000	INFINITY	0.216415
ROW	CURRENT RHS	RIGHTHAND SIDE RANGES	
		ALLOWABLE INCREASE	ALLOWABLE DECREASE
RA	149.822403	INFINITY	149.489624
TOP	0.488500	1.316770	INFINITY
MRR	457.100006	34.221741	INFINITY
STP	144.669998	37.030613	26.764252
TW	259.000000	280.767731	INFINITY
FZ	202.300003	INFINITY	74.050934
SEC	-2297.000000	256.600403	164.911591
FN_LB	0.100000	0.141617	INFINITY
FN_UB	0.400000	INFINITY	0.158383
VC_LB	50.000000	177.151138	INFINITY
VC_UB	250.000000	INFINITY	22.848862

Figure 6. Coefficient and right-hand side ranges

3.3. Validation test

After establishing the optimum operating parameters, from the GP computational model, the resolved machining variable input conditions were congealed on the CNC machine tool and confirmation experiment tests were performed. The results of the validation tests are presented in Table 8 in Appendix 2. A string of validation tests were carried out to determine the real functioning of the GP analytic model as competed with the real physical machining, founded on the simulation outputs. The validation results tabulation format mirrors the form of results presentation employed in Tayisepi [32] in a genetic algorithm based multi-criteria multi-objective optimisation research during the high speed machining of Ti6Al4V focusing on energy use minimisation. Diverse performance focus was emphasized on in different instances, as indicated in the first column of the validation results Table. The input factors v_c and f_n results for each parameter prediction scenario, from the model, were as such entered as input settings on the lathe machine in executing the validation

experiments. Three response factors, specific cutting energy (SE), total machining energy (ETME) and total machine operating power (ToP) were recorded and reported under each emphasised machining response scenario. The variability level of less than 10%, for all the measured response parameters, confirm functionality of the model in predicting, effectively, the cutting factor levels to set on the CNC lathe machine.

4. Conclusion

Machining engineering business ought to continuously advance their processes. The study set out to investigate the feasibility of applying goal programming optimisation technique in solving the multiple constraint challenge of determining machining parameters setting levels during the operation planning of Ti6Al4V. Taguchi design of experiments L18 orthogonal array was used in planning the experimental cutting process. Regression modeling was employed in profiling the response parameters as function of the independent parameters. Factors characterisation was also carried out. Subsequently the multiple response mathematical models were uploaded into the Lingo goal modelling platform for optimum parameters determination. GPM simulation results, with all the performance factors equally weighted, produced the optimum cutting parameters being, $v_c = 227 \text{ mmmin}^{-1}$ and $f_n = 0.2416 \text{ mmrev}^{-1}$. Deducing from the research results, Goal Programming emerges as an appropriate, flexible and powerful process planning technique and decision analysis support tool to aid the troubled modern decision making machining scientist, who is encumbered with achieving multiple conflicting objectives, on grade 5 titanium alloy components cutting, under complex environmental constraints. The modelling approach does not attempt to maximize or minimize the objective function directly as in the case of conventional Linear Programming. GP modelling pursues the objective to reduce the variations between the sought after target aspirations and the actual results to be obtained according to the assigned priorities. In conclusion the research had established that goal programming is a viable tool to apply in predicting the parameter settings in a multiple constraint machining process planning of aircraft grade 5 titanium alloy components.

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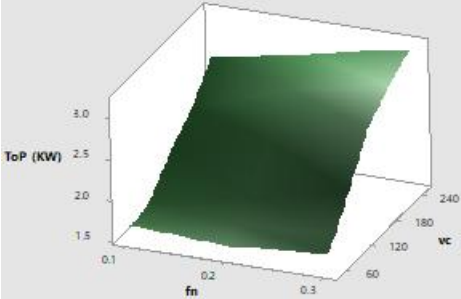
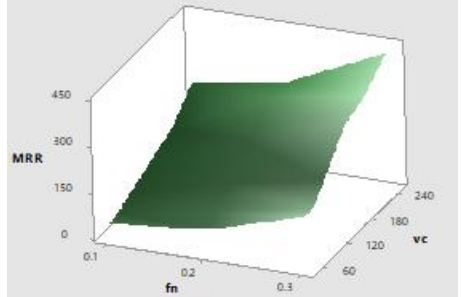
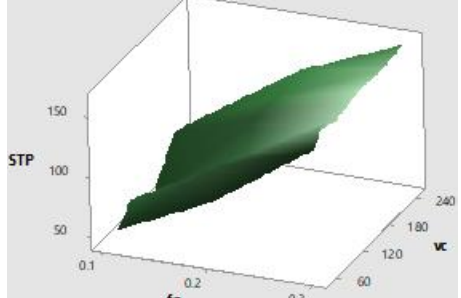
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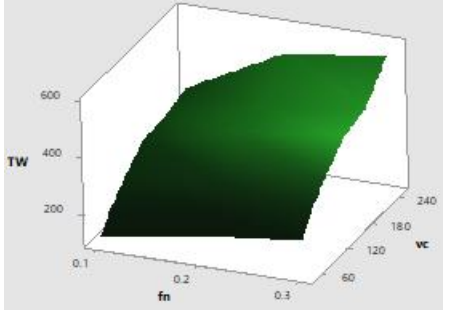
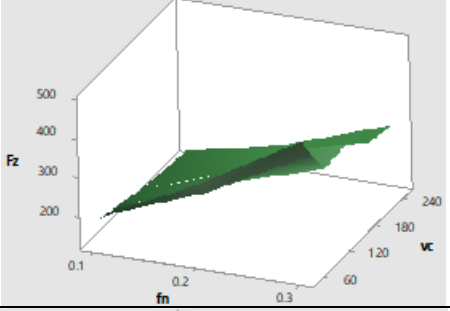
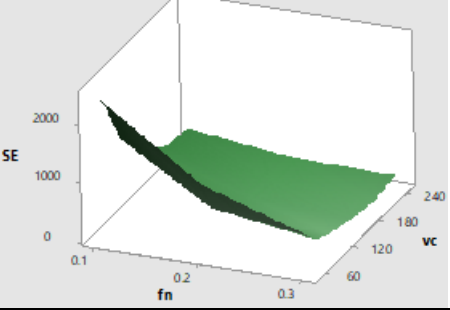
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Appendices

Appendix 1 Table 7. Parameters summary characterisation and regression models summary

Output response factor	Graphical Plot of results	Regression Model	Coefficient of determination	Equation number
(a) Total machining power - ToP		$ToP = 0.9115 + 0.005535 v_c + 2.268 f_n$	96.49%	(6)
(b) Material removal rate - MRR		$MRR = -157.1 + 1.178 v_c + 926 f_n$	95.93%	(7)
(c) Chip segmentation pitch -STP		$STP = -4.67 + 0.1143 v_c + 491.3 f_n$	96.43%	(8)

Output response factor	Graphical Plot of results	Regression Model	Coefficient of determination	Equation number
(d) Tool wear - TW		$TW = -59.0 + 1.704v_c + 632f_n$	99.58%	(9)
(e) Cutting forces - Fz		$F_z = 97.7 - 0.3139v_c + 825.9f_n$	95.41%	(10)
(f) Specific cutting energy - SE		$SE = 2693.0 - 7.737v_c - 2233f_n$	83.83%	(11)

Appendix 2. Table 8 Validation experiment runs results

Driving performance parameter	Optimal process parameter settings and responses					Simulation Model and Validation experiment result variability
	Optimum input parameters		Response	Optimal value		
All factors are rated at same level of weight	v_c (m/min)	f_n (mm/rev)		SE (J/mm ³) ETME (J) ToP (kW)	Model	Confirmation Experiment
	227.151	0.24162	102		99.2	
			228 057		237 821	
			2.9908		3.073	
Material removal rate (MRR)	193.701	0.269	SE (J/mm ³)	76.2	68.9	(9.58%)
			ETME (J)	233 065	255 392.627	
			ToP (kW)	2.9975	2.6899	
Cutting force F _c	85.6	0.298	SE (J/mm ³)	1072	1041	2.89%
			ETME (J)	391 086	370 359	
			ToP (kW)	2.0768	2.1891	
Segmentation teeth pitch (STP)	189.76	0.274	SE (J/mm ³)	898	859.56	7.73%)
			ETME (J)	228 693	246.37	
			ToP (kW)	2.978	3.0488	
Surface roughness (R _a)	187.19	0.2167	SE (J/mm ³)	905	863.37	(4.6%)
			ETME (J)	238 087	227 134	
			ToP (kW)	2.9826	3.1254	

Tool wear (TW) and Cutting force (F _c)	235.32	0.3	SE (J/mm ³)	96	102.72	(7%)
			ETME (J)	165 812	177 418.84	
			ToP (kW)	3.5268	3.9036	
Tool wear (TW) and Segmentation teeth pitch (STP)	179.42	0.2887	SE (J/mm ³)	1076	1 119.04	4%
			ETME (J)	234 212	243 594	
			ToP (kW)	3.205	3.318	

Key: (x%) - means negative deviation. Otherwise positive