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Towards goal programme optimisation of machining parameters during the production of TI-alloy components

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ABSTRACT

Optimisation of the manufacturing process parameters, which are often in conflicting orientations, is an important consideration for actuating efficient production processes in order to improve competitiveness. Efficient machining of the hard-to-process materials such as Titanium alloy reveals an extensive field of research and has become increasingly significant in fulfilling multiple requirements of sustainable manufacturing such as ecological, economic and legislative consideration in production activities. Throughout the past few decades, multi-objective mathematical programming had been a lively area of research in the field of the manufacturing industry, particularly for purposes of operating conditions optimisation. In this literature-based survey and experimental study, goal programming is assessed for feasibility of use for predicting and optimising the machining parameters during the turning of Ti6Al4V components. A comprehensive literature study, about the application environments of Goal Programming, had been performed. Outside turning experiments were conducted with coated carbide tools at different process parameter settings. Cutting parameters were characterised against the output parameters. Mathematical Models were developed using regression analysis, on Minitab 20 Software. The parameters characterisation results and developed mathematical models, which are all linear in nature, show applicability of goal programming once the goal targets for each machining output performance parameter are established. Survey results showed the feasibility of goal programming as a tool for predicting machining process parameters. Future research is also outlined.

Key words

Energy efficient, sustainable manufacturing, goal programming, Ti-alloys, machining parameter optimization.

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1. INTRODUCTION

Saving energy, conserving resources and increasing productivity are conflicting challenges confronting the machining manufacturing industry of Ti6Al4V (also known as Grade 5 Ti-alloy) components today (Kress, 2012). Titanium alloys are used in the aerospace, medical, defence, marine and other industries due to their excellent mechanical and chemical properties such as high strength-to-weight ratio, corrosion resistance, high temperature strength and biocompatibility properties (Budinski & Budinski, 2010). Due to these attractive properties the demand for titanium alloy parts is increasing. The high intrinsic costs of processing Ti-alloy, however, remain a setback towards the widespread use of this material which is the fourth most abundant material on earth (Ezugwu & Wang, 1997). In machining-based manufacturing the optimisation challenge is related to the desirability of achieving high material removal rate; minimising power consumption; minimising tool wear and cutting forces whilst simultaneously improving work piece surface quality. Balancing the selection of the cutting parameters such that these conflicting objectives are simultaneously addressed bodes well for the sustainability of the manufacturing process. During machining of the difficult-to-cut materials such as grade 5 titanium alloys, factors such as selection of the best combination of cutting parameters, which optimises the machining process, relay important information towards understanding the process efficiency management. Manufacturing resource use efficiency is one of the key factors of sustainability assessment in a manufacturing environment (Duflou, et al., 2011).

The real world of machining-based manufacturing is mainly faced with the challenge of balancing multiple conflicting objectives rather than singular objective, such as having to achieve minimum tool wear for example or achieving good surface finish. Inadvertently, reduced tool wear is associated with minimum material removal rate and reduced surface finish. In the production environment, these outcomes may be undesirable whilst the tool wear minimisation is realised. This may demand that tool wear minimisation be realised at the same time increasing material removal rate (productivity) and increased surface smoothness of the workpiece. These are typical conflicting objectives of a machining-based manufacturing task. This study seeks to contribute towards sustainable manufacturing of Ti6Al4V components, through developing a platform/framework for efficient machining process planning using Goal Programming (GP). Goal programme refers to a mathematical model comprising linear or non-linear functions and discrete or continuous variables, wherein all functions have been transformed into goals. The mathematical function which have to be attained or achieved at a specified level is termed the goal function, whereas, the function which serves to measure the achievement of the minimising of undesired goal deviation variables is termed as the achievement function (Aouni & Kettani , 2001). The concept of goal programming is to transform the initial multiple, and often conflicting, objectives into a single goal, of which the model solution yields a satisficing result to the conflicting objectives in the manufacturing problem, efficiently and satisfactorily. Goal normalisation is performed in order to minimise possible bias effect of the different measurement dimension units, as a way of ensuring achievement of satisfactory solution level of all the conflicting multiple objectives under consideration (Winston, 2004). Goal programming (GP), unlike linear programming which seeks to maximise or minimise (optimise) a singular objective function, minimises the sum of the deviations between the objective target values and the actual achieved results. GP and its variant models have been used to provide solutions to large-scale multi-criteria decision-making challenges (Nabendu & Manish, 2012). It affords taking into consideration simultaneously, while a decision maker seeks the most satisficing solution from amongst a set of feasible solution, several objectives. It is a special type of optimising tool which provides an analytical framework which a decision maker could employ to proffer optimal solutions to multiple conflicting objective problems. According to Sen and Nandi GP, as a modelling tool, has close correspondence with actual reality practiced in decision making (Sen & Nandi, 2012). In reality, even on the manufacturing planning floor, decision makers will be intent on achieving different goals, usually formulated as aspiration levels. In each operation, the intensity with which attempts are made at attaining the goals may differ from goal to goal. Thus, different weight assignments may be given to striving to attain different goals. Hence, the importance of each outcome at a particular instance. In machining-based production, at process level, multiple objectives arise because of different outcomes occurring on the tool/workpiece/chip interface as a result of changes made in the cutting parameter settings. Multiple objectives in machining-based production businesses, arise because of the need to fulfilling several incompatible outcomes at the cutting point. For example, conditions requiring best outcome on the work surface may be such that the tool wears out faster or conditions that minimise energy consumption are that productivity is reduced. In fact, the fundamental concept of goal programming is whether the goals are achievable or not, an objective may be outlined in which optimisation proffers a result which approaches as close as possible to the stated goals. The intention of this research is to establish if this technique can represent a viable approach to machining based manufacturing planning, noting that there is no much publications, of its use, in the machining industry, particularly those involved in the machining of Ti6Al4V.

In a number of machining production shops, decision making about the optimum setting of cutting conditions, is fundamentally, based on past experiences of the operatives. As such, judgement and intuition brings in more intricacy and difficulty. According to Misir and Misir (2007), the human intellect is not capable of perceiving, in all details more than seven parameters, on average, simultaneously. As such, manufacturing decision making in the production shops, had long ceased to be an art wherein the decision maker just apply mental models to establishing viable solutions. Rather, scientific decision making, is applied with mathematical models being applied to establish solutions to organisational problems such as determining optimum machining parameter settings decision. The main intention is to further contribute to the sustainable machining of Ti-alloy components through enhancing the machining process resource use efficiency during the planning stage.

1.1 Goal programme optimisation application in industry and business survey

Machining manufacturing companies need to incessantly improve their operations - processes and products need to be optimised on a daily basis. Thus, reliable cutting parameters selection plays a significant role in today's machining-based manufacturing business planning process. The machining optimisation problem lies in the fact that, it possesses multiple constraints which is related to more than one objective. Usually, with singular objective optimisation, the achievement of optimality in one factor lead to the aggravation of challenges in one or more other factors. Challenges related to the requirement of optimising more than one objective originate from outcomes tending to trend in different directions (Lee, 1972), and solving them had been a challenge bedeviling engineers for a long time. Typically, the use of a single optimisation technology, is not sufficiently practical in dealing with real life machining-based manufacturing problem. Consequently, manufacturing engineers frequently find themselves required to solve manufacturing planning problems with several conflicting objective functions.

Goal Programming and its variants have been utilised to solve multi-criteria decision-making problems in many fields (Sen & Nandi, 2012). The Multi-Disciplinary Optimisation Technical Committee, of the United States of American Institute of Astronautics (AIAA), explained Multi-Disciplinary Optimisation as the optimal design of complex engineering systems which require analysis that accounts for interactions amongst the disciplines, or parts of the system, and which pursues to synergistically achieve these interactions (Tamiz & Jones, 2010). Whereas the Multi-Criteria Decision Making (MCDM) relate to the solution development of problems constituted of multiple and conflicting goals and producing final solutions which represents a good compromise that is acceptable to the entire system set of objectives (Ignizio, 1978). By minimising the deviations between the target values and the actual yielded result values, goal programming is utilised to manage the optimisation problem of multiple conflicting objectives (Misir & Misir, 2007). Goal programming is a part of the multi-criteria decision analysis tools wherein it is considered as a branch of the multi-objective optimisation techniques (Orumie & Ebong, 2014,). It is utilised to manage and plan the simultaneous attainment of conflicting objectives of an operation process by minimising the variation (deviation) of the realised results from the intended or desired targeted results (Sinha & Sen, 2011). Thus, as a decision-making support technique, Goal Programming (GP) is used in the optimisation of several objective goals which in most instances will be in conflict – where in the attainment of one goal tend to aggravate the situation of the other objectives. According to Sinha and Sen, the intention of GP is to minimise the achievement of each actual goal level, such that if no-achievement is pushed to zero, then the attainment of the goal have effectively been realised (Sinha & Sen, 2011). GP is an analytical special technique framework that decision makers could use to provide optimal solutions to conflicting multiple objective production planning problems. In this manner, GP would provide solution and information for utilisation by the decision makers (Dantzig, 1948; Charnes & Cooper, 1961; Lee , 1972). A number of authors such as, Lin in concurrence with Orumie and Ebong proposed the application of Goal Programming in a number of articles to solve a myriad of problems (Orumie & Ebong, 2014,; Lin , 1980). The noted limitations of the utilisation of the Linear Goal Programming (LGP) models had been the non-availability of an algorithm capable of attaining optimality in reasonable time, however.

Generally speaking, optimisation explains the selection of the best available option from a wide range of possible options. Manufacturing business organisation objectives, in practice, may vary dependent upon the philosophy and characteristics of the business, operating environmental conditions, inter alia. Profit maximisation is regarded as the main sole objective of the business management. However, due to the pressure from society and statutory regulations, the firm will have other objectives – thus multiple objectives which may include high product quality, operations employees' safety, social contributions, good industrial and labour relations, maximising profits, among others. At machining process level, the multiple objectives may be achieving high productivity level, increasing material removal rate, minimising tool wear, achieving high surface quality, minimising energy use, maintaining good workpiece and tool bit integrity, etc. All these contrasting objectives would require the machine operating parameters to be set at different level in order to realise them. Goal programming had been used to solve multiple-and-conflicting objective optimisation problems in many fields such as Mutual Fund Portfolio selection (Sharma & Sharma, 2006), Farm cropping land determination (Jafari , et al., 2008), Plantation space occupancy planning (Nabendu & Manish, 2012) and modeling 3D trade-offs in concurrent engineering problems (Charles, et al., 2005). Fortenberry and Mitry applied GP to model and address facility location problem with multiple competing objectives, whilst Kornbluth employed GP modelling for industrial and economic planning challenge (Kornbluth, 1973), inter alia. Premchandra, (1993) modelled decision making platform for large number of interrelated activities in project planning and scheduling. In solving a multi-objective resource planning and network-based optimisation challenge, Shim and Chun (1991) utilised goal programme modelling. In soliciting optimal combinations of diverse fertilisers for the soil sustaining a rice crop, Karbasi, et al., (2012) utilised goal programme modelling to a good effect. Kornbluth (1973) presented on goal programming use for industrial and economic planning purposes. Nhantumbo and Kowero (2006) developed a multi-objective production planning model for minimising production penalties, whilst maximising profitability. Alp, et al (2011) used linear goal programme modelling in surveying engineering for vertical network adjustment. Deducing from these earlier studies, Goal Programming may be more advantageous to use as a technique in dealing with practical manufacturing problems encountered in machineshops because it tends to mirror the way humanity make decisions. It is apparent that it presents a feasible approach to production planning, however, it is not in widespread use amongst manufacturing companies particularly of discrete machined components. It affords the decision maker the scope to incorporate diverse circumstances surrounding a real life decision situation through modelling the goal levels and priorities according to what instance require to be emphasised on at that particular instance. Yet, typically, it (GP) had not been used extensively in solving cutting parameter selection decisions during the machining process planning of Ti6Al4V.

1.2 Goal programme modeling approach

Multi-objective modelling techniques - in the purview of manufacturing - were in the recent past formulated and solved, to provide information on the compromise among conflicting and competing multi-objectives. The goal programming (GP) modelling approach does not seek to directly maximise or minimise the objective function, as happen in linear programming.

Instead, GP seeks to minimise the deviations between the looked-for goals and the actual results obtained in accordance to the priorities set (Alp, et al., 2011). Thus, as a modelling technique, GP is used to manage a cluster of conflicting objectives of the modelled situation by minimising the deviations of the realised results from the target result values. The initial objectives are formulated anew as a set of constraints with target values accompanied by two auxiliary variables, being the positive deviation (d^+) and negative deviation (d^-), representing the distance from the set target values. The intention of GP is to minimise the deviations from achieving set goals, in a hierarchical order, in such a manner that goals of higher order importance receive first attention before goals of lower order priority successively. Goals of first priority are minimised in the first place, then using the attained feasible solution outcome in this stage, goals of the second priority are minimised successively and so on.

Multiple conflicting objectives, in machining-based production arise because of several opposing outcomes which result when, say the cutting parameters are adjusted on the machine in order to realise a particular outcome. Typically, for example, generally increasing the cutting conditions, say cutting speed, feed rate and depth of cut, produces high material removal rate during a cutting operation (Oosthuizen, et al., 2013). This result is a positive outcome, however, it will also be accompanied by increased tool wear and rough surface quality of the job – which are undesirable outcomes. The basic notion of goal modelling is that, whether the set goals are achievable or not, the objective may be stated in which optimisation proffers a result which comes as near as feasible to the stated goals. As a decision-making support technique, goal programming aims at optimising numerous (up to 120, software dependent) goals and simultaneously minimise the deviation of each from the intended target objective (Sen & Nandi, 2012). The intention of goal programming, is to limit the deviations in a hierarchical order system such that the goals of principal importance, for that machining operation process, receive first priority focus of attention, whilst those of second order of importance receive second priority attention, and goals of eventual orders of importance, respectively, receive eventual priority order attention as such. Successively, using the feasible solutions of the highest order priority of goals, objectives of the eventual priority order of importance are respectively focused on and minimised (Orumie & Ebong, 2014). Lower ordered goals would only be considered after the satisfaction of the higher ordered goals (Sen & Nandi, 2012).

The general steps of developing a GP is structured, thus (Rifai, 1996; Orumie & Ebong, 2014), shown in Table 1.

Table 1. Steps of developing goal programme structure

Step No	Step process
1	Discover the goals and convert them to constraints by introducing deviational variables.
2	Scrutinise the goals and establish the deviational variables exactly required for them.
3	Rank the goals in order of importance and pre-emptive priority factor assigned to each of them.
4	Where ties exist in priority ranking, assign, to each of the deviational variables in the priority, a weight to break such.

The general variants of the GP modelling are firstly the pre-emptive weighted priority goal programming, wherein both goal prioritisation and pre-emptive weights assignment are applied in the formulation of the model (Orumie & Ebong, 2011). The general expression of the model would be as presented in equation (i):

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

$$\text{st} \quad \sum_{j}^{n} a_{ij} x_{ij} + d_i^- - d_i^+ = b_i \quad (i = 1, 2, \ldots, m) \quad \text{(ii)}$$

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

$$(i = 1, 2, \ldots, m;\ j = 1, 2, 3, \ldots, n) \quad \text{(iv)}$$

Where, d_i^-, d_i^+ are the negative and positive deviation variables, b_i is the goal target, p_i is the pre-emptive priority factor, w_i is the goal priority weighting factor, z is the achievement function.

The second variant of the goal programme is called the pre-emptive or lexicographic goal programming (Orumie & Ebong, 2014,; IJiri, 1965) model. This is employed when the decision maker may not be able to determine precisely the relative importance of the goals in advance. Instead, the goals are ranked in order of importance with the most important goal being assigned first priority. The second most important goal being assigned second priority, e.tc. The solution procedure starts by concentrating on meeting the most important goal and successively in that manner until the least important goal priority is addressed. The prioritisation of the objective functions is such that the achievement of the first goal is far important than the attainment of the second goal, which itself is far important than the third goal attainment, and so on. By this arrangement lower order goals can only be attained if they do not degrade the solution achieved by higher priority goals. The pre-emptive Goal Programme model achievement is expressed thus, (Orumie & Ebong, 2011):

$$Lexi \min z = \sum_{i}^{k} p_i (d_i^- + d_i^+) \quad \text{(v)}$$

The third variant of the GP modelling is whereby weights are attached to each of the objectives in order to quantify the relative importance of the deviations from their goal targets. This is termed the Weighted Goal Programming (WGP) (Ken & Perushek, 1996)). Using WGP several objectives can be simultaneously handled with specific numeric goals established for each of the objectives and a solution which comes as close to each of the goals can be determined (Marler & Arora, 2004). The WGP model algebraic expression can be expressed as shown in equation (vi):

$$Min\ z = \sum_{i}^{m} (w_i^- d_i^- + w_i^+ d_i^+) \quad \text{(vi)}$$

Where w_i^- and w_i^+ are the numeric weights associated with the respective deviational variables (≥ 0), denoting how far the decision is from the target goal below or above the target value.

3.0 Materials and Methods

The ensuing sections present the research strategies used in the empirical study. Grade 5 Titanium alloy (Ti6Al4V) machining experiments were conducted to generate primary data which would be fed into Minitab software package for further analysis – Characterisation of the cutting parameters against the output parameters, generate mathematical models of the performance parameters as influenced by the input parameters through regression analysis. Regression equations would then be fed into the Lindo/Lingo software platform, after being converted into goal programming models, for the prediction of cutting parameters through an iterative process, once the expected performance standard for the output variable are entered.

3.1 Experimental Set-up and Design

Outside turning experiments were conducted on a precision Efamatic CNC lathe machine with the following features: Model is Efamatic RT-20 S; Slant Bed CNC lathe Machining Centre; maximum spindle speed of 4500 RPM; Main motor power, AC 11/15 kW; Machine weight, 3.8 tonnes; Maximum bar stock, 75 mm; Double axes with respective travels of 260 mm diameter on X-axis and 450 mm on the Z-axis. The workpiece material is diphase (Dabrowski, 2011) titanium alloy, Ti6Al4V (Grade 5 titanium alloy) which was supplied in annealed condition at 36 HRC as a solid round bar (Ø = 75.4 mm x 250 mm long). The work piece chemical composition and mechanical strength characteristics (as per materials certificate) are presented in Tables 2 and 3 respectively.

A 0.5 mm initial cut was conducted before the experiment iterations were started in order to remove and eliminate any prior processing induced residual stresses, uneven surface trueness and other surface defects which may adversely affect the machining results (Kalpakjian & Schmidt, 2001). The cutting tip used for the cleaning cut was not involved in the experiment iterations.

Table 2. Chemical composition of Titanium alloy (Ti6Al4V) material used

Element	Al	V	C	Fe	N	O	H	Others	Ti
% Content	6.0	4.1	0.02	0.14	0.01	0.16	0.001	0.5	89.069

Table 3. Mechanical strength properties of the Ti6Al4V alloy used

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

The research considered the simultaneous variation of cutting speed and feed rate (machining parameters) on the tool life, surface integrity, cutting forces, chip formation and energy use/consumption as responses (performance factors). Table 4 presents the turning parameters and condition levels on which the experiments were conducted. As regards the experimental design, the variable parameters in the turning experiments were: six cutting speeds (50, 70, 100, 150, 200, and 250 m/min), and three feed rates (0.1, 0.2, and 0.3 mm/revolution respectively). A set of eighteen (18) experiments were conducted using eighteen tools to cut the work specimen materials at a constant depth of 0.5 mm. Collectively a total of seventy-eight (78) machining cutting tests/runs were conducted. In each cutting test, the machining power (for machining energy), cutting and feed forces and surface roughness are measured and recorded. Tool wear was measured at the end of each machining pass of 180 mm, specimen length. The experimental set-up and the machine and data collection equipment connection, schematic arrangement, is presented in Figure 1.

Table 4. Machining parameters and conditions of the turning experiments

Parameter	Condition
Cutting Speed (V_c)	50, 70, 100, 150, 200 and 250 m/min.
Feed/rev (f_n)	0.1 – 0.3 mm/rev in 0.1mm steps.
Depth of Cut (DoC)	0.5 mm Constant.
Coolant	Flood coolant.

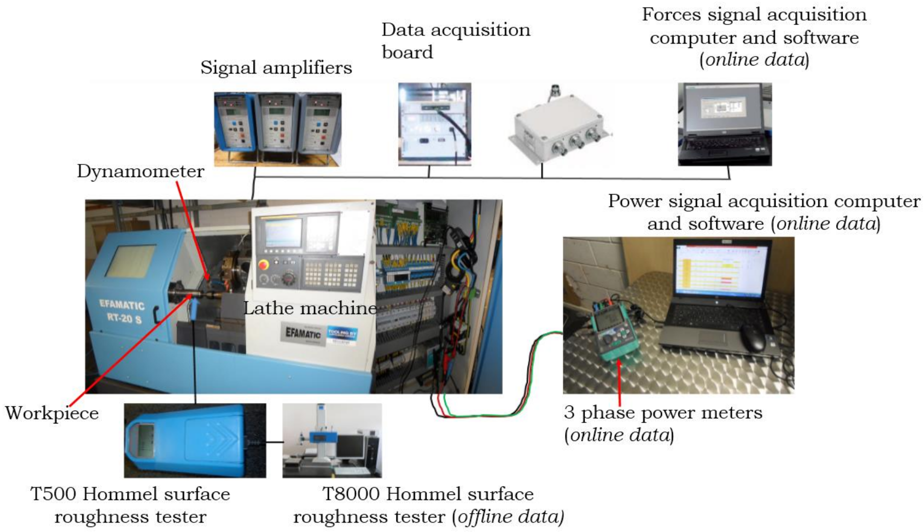

Figure 1. The experimental set-up

4.0 RESULTS:

4.1 Parameter characterisation and observation during the machining of TI 6al4v

This section present results of the characterisation, of cutting parameters on the response parameters. Regression equations models, developed, and analyses are also presented.

4.1.1 Total cutting power during machining (ToP)

Figure 2 shows the 3-dimensional plot of the feed rate f_n, cutting speed, v_c and total cutting power of the machine, ToP. It is apparent that the total machining power increases with both increasing cutting speed and feed rate. However, the increase with respect to cutting speed is steeper as compared to the increase with feed rate.

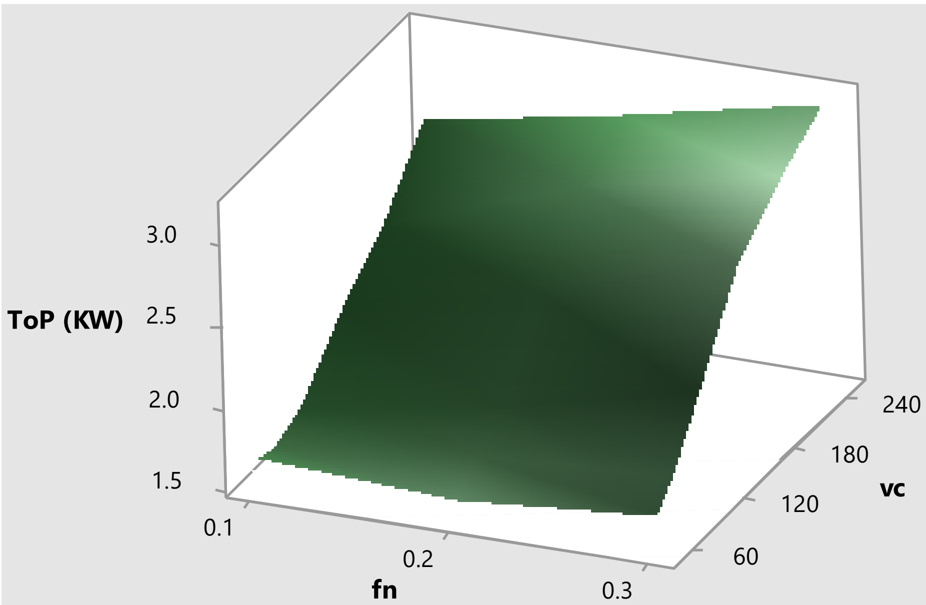

Figure 2 Surface plot of total machine power –ToP (kW) vs cutting speed - v_c (m/min) and feed rate - f_n (mm/rev)

4.1.2 Regression Analysis: Total Cutting Power During Machining (ToP)

The Regression Equation, expressing the mathematical relationship of the input factors (v_c and f_n) to the response parameter (total machining power), is shown on equation (vii). The strong representativeness, of the data by the fitted regression line, is indicated by the coefficient of determination (r^2) of 96.49% on the model summary of the total machining power (Table 5). That means the predictors explain 96.49% of the response (total machining power).

$$ToP = 0.9115 + 0.005535\ v_c + 2.268\ f_n \quad (vii)$$

Table 5. Model summary of total machining power (ToP)

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

4.2.1 Material removal rate (MRR)

The surface plot of the material removal rate versus cutting speed and the feed rate is shown in Figure 3. This summarises the joint influence of the input parameters, v_c and f_n on the response MRR. It is apparent that MRR is positively influenced by both increasing v_c and f_n. The influence of v_c tend to be more pronounced, however, when compared with the influence of f_n.

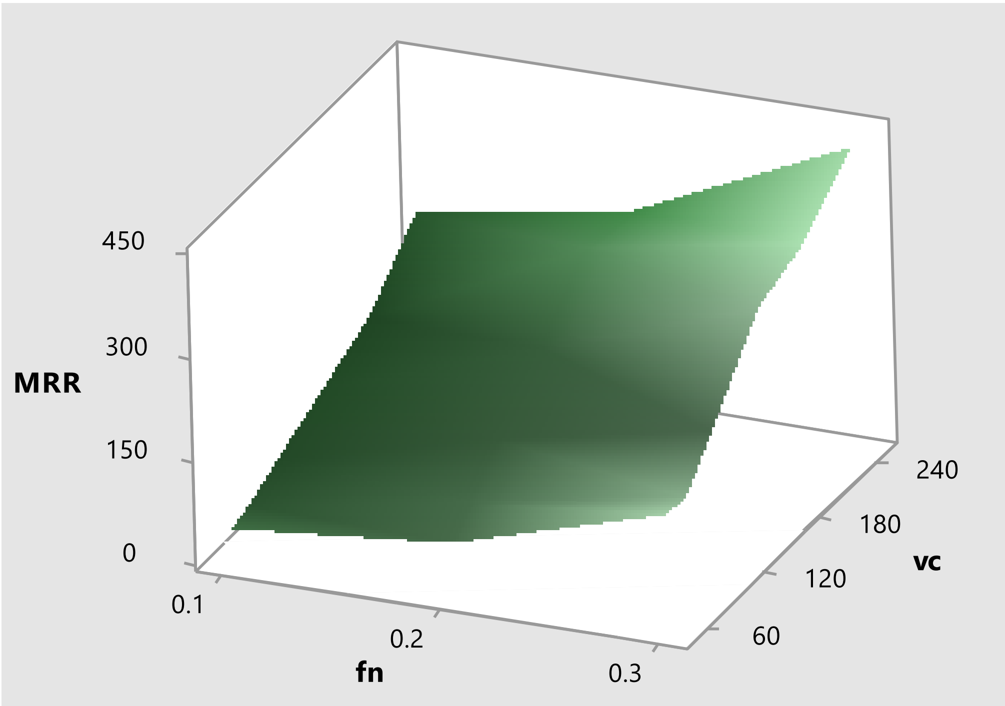

Figure 3 Surface plot of Material removal rate - MRR (mm^3/min) as a function of cutting speed - v_c (m/min) and feed rate - f_n (mm/rev)

4.2.2 Regression equation: Material removal rate (MRR)

The Regression Equation, relating the input factors to the response function (*MRR*), is given by (viii):

$$MRR = -157.1 + 1.178 v_c + 926 f_n \quad (viii)$$

The coefficient of determination of 95.93% Table 6 shows very strong representativeness of the data by the fitted regression line

Table 6. Model summary of material removal rate

S	R-sq	R-sq(adj)	R-sq(pred)
29.26	95.93%	93.09%	86.83%

4.3 Chip Morphology

The chip morphology aspects analysed are chip teeth segmentation pitch (STP), the chip segmentation shear angle (San) and chip segmentation frequency (SF).

4.3.1 Chip Segmentation pitch (STP)

Figure 4 shows the surface plot of chip segmentation pitch with respect to both cutting speed and feed rate respectively. The steepness of the STP change with the f_n is apparent whilst it is less steep with respect to v_c.

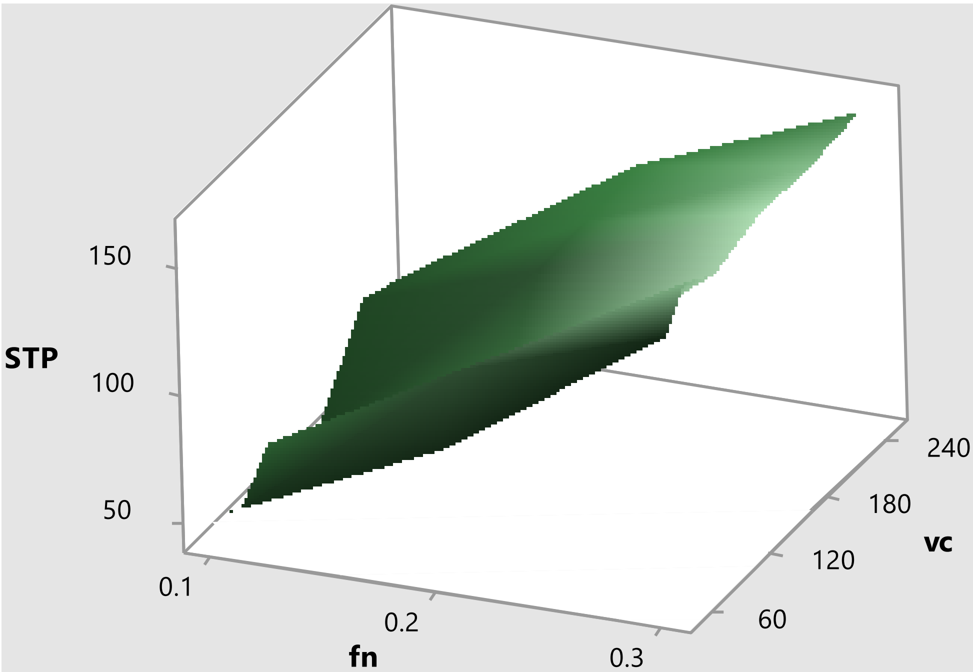

Figure 4 Segmented teeth pitch - STP (μm) vs cutting velocity - v_c (m/min) and feed rate - f_n (mm/rev)

4.3.2 Regression Equation – Chip Segmentation Pitch

The mathematical relationship between the input factors (cutting speed, v_c, and the feed rate, f_n) and the response parameter (chip segmentation pitch, *STP*) is expressed as (vix):

$STP = 4.67 + 0.1143\, v_c + 491.3\, f_n$ (vix)

The coefficient of determination, of 96.43% (Table 7), shows very strong representativeness of the data by the fitted regression line.

Table 7. Model summary of segmentation pitch

S	R-sq	R-sq (adj)	R-sq (pred)
10.62	96.43%	93.92%	88.42%

4.3.3 Tool Wear (*TW*)

Optical measurements, of the tool wear, were taken at different cutting speeds and feed rate conditions at the end of each machining pass, of 180 mm linear length of the workpiece specimen. The dominant wear mechanism observed was on the flank, followed by crater wear on the rake. Increasing cutting speed enhanced thermal and chemical activities on the tool chip interface. An increase in mechanical load (f_n) caused an increase in fracture mechanisms. Tool wear, especially flank wear, tend to affect the tool geometry resulting in significant negative influence on the energy use, cutting forces and the component surface quality during the machining process. It is reported to be the main factor which affect the metal cutting economics (Karim , et al., 2013), during machining operations. Reduced flank wear rates result in better tool life, better surface finish quality, minimised tooling costs and reduced production costs. In this section, the effect of the cutting parameters selection on tool flank wear is assessed, in order to establish which combination of v_c and f_n has more influence on the process.

The mathematical model, expressing tool flank wear as a function of the cutting conditions, was developed. Graphical presentations, characterising the various tool wear functions as they interact with energy and specific cutting energy use, are presented.

The input parameters versus tool wear relationships are plotted on the graphs in Figure 5. There is steeper variation of tool wear with increasing cutting speed than it is with increasing feed rate, as shown on the surface plot of tool wear against v_c and f_n (Figure 5). The graph, thus, show the dominance of v_c in influencing tool wear as compared to f_n.

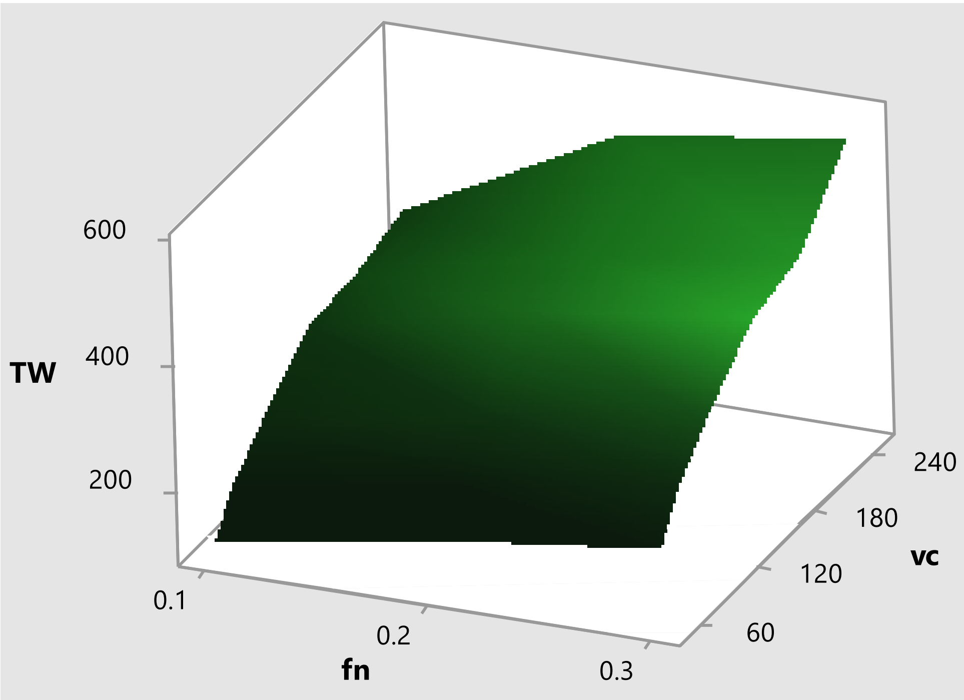

Figure 5 Surface plot of tool wear, TW (μm) as a function of cutting speed, v_c (m/min) and feed rate f_n (mm/rev)

4.3.4 Regression Analysis – Tool Wear

Linear regression analysis was used to define the model, explaining the relationship of tool wear with the two variable input parameters (v_c and f_n). The relationship between tool wear and the variable cutting parameters is approximated by (x):

$$TW = -59.0 + 1.704v_c + 632f_n \quad (x)$$

Table 8. Model Summary of tool wear

S	R-sq	R-sq (adj)	R-sq (pred)
10.46	99.58%	99.28%	98.63%

The coefficient of determination (R^2), of 99.58% (Table 8), confirms the significance of how well the regression line (equation x) approximates the real data points projecting the relationship between the predictor variables (cutting speed v_c and feed rate f_n) and the cutting tool wear. An R^2 of zero means that the dependant variable cannot be predicted from the independent variable.

4.3.5 Cutting Force ($F_{x,y,z}$)

The surface plot of the cutting force and the input parameters (v_c and f_n) is shown in Figure 6. It is apparent from the plot that as feed rate increases the cutting force increases. When the cutting speed increases the cutting force tends to decrease. Thus, in essence, cutting forces tend to generally decrease with increasing cutting speed whilst they tend to increase with increasing feed rate. Increasing the cutting speed enhances the thermo-mechanical separation process of the material, as the heat intensity increases at the cutting zone, such that demand for separating cutting forces tend to decrease as the cutting speed increases.

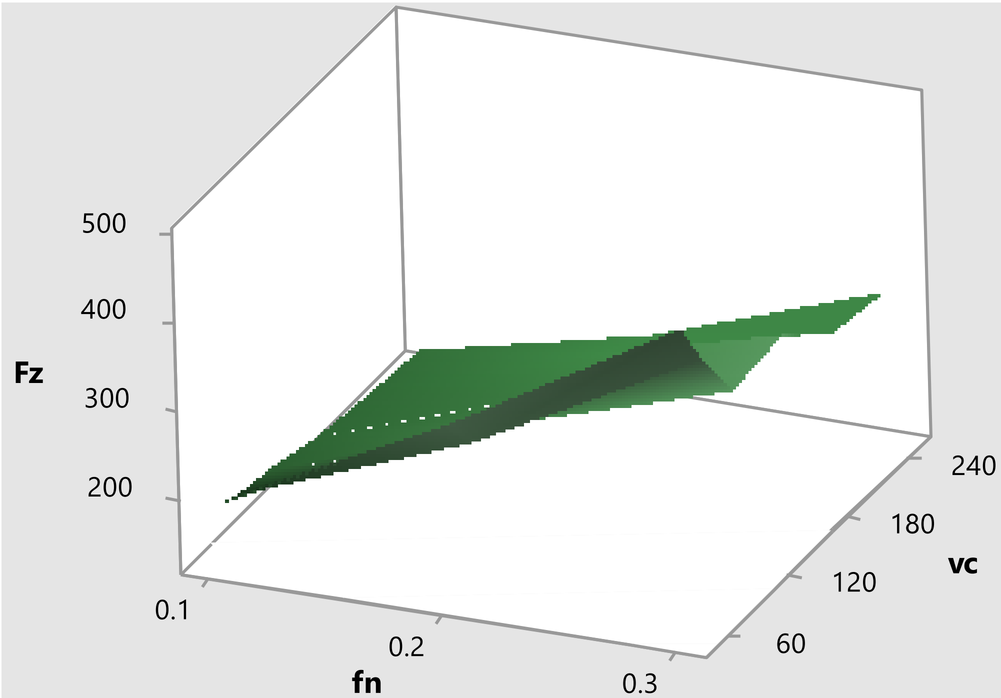

Figure 6 Surface plot of main cutting force, F_x (F_z) [N] vs feed rate, f_n [mm/rev] and cutting speed v_c [m/min]

4.3.6 Regression analysis – Cutting force (F_x)

The cutting force (F_x) regression equation is as given by equation (xi), where it is denoted as F_x

Force, $F_x = 97.7 - 0.3139v_c + 825.9f_n$ *(xi)*

Table 9. Model summary for the main cutting force (F_x)

S	R-sq	R-sq(adj)	R-sq(pred)
26.58	95.41%	92.21%	85.14%

The coefficient of determination, of 95.41%, (Table 9) shows that the model effectively represents the data of the model.

4.3.7 Surface Roughness measurement

This section present the results of surface roughness measurements (R_a, R_z and R_{max}). Figure 7 shows the variation of surface roughness with increasing cutting speed. It is apparent, from the graph that as cutting speed increases the surface roughness decreases. The plot considered surface roughness R_a, R_{max} and R_z which all tended to decrease with increasing cutting speed. The results were consistent with the findings by Mawanga (Mawanga, 2012), who investigated the surface integrity of high-speed machining of grade 4 Ti-alloys. Average surface roughness (R_a) is the most generally considered surface roughness quality standard. As such the ensuing sections considered R_a values of surface roughness.

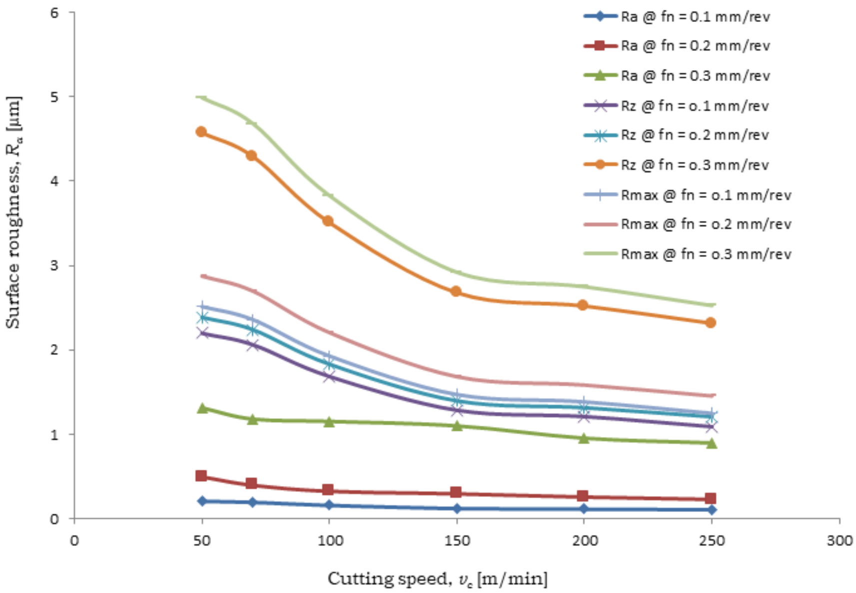

Figure 7 Surface roughness – R_a, R_z, R_{max} as a function of cutting speed (microns)

Figure 7 presents the variation of surface roughness R_a with cutting speed at the three feed rates. It is apparent that, as cutting speed increases, Ra value decreases at all 3 feed rates. Thus, higher cutting speeds produce finer surface finish. Figure 8 shows the interaction of feed rate with both the work piece surface roughness and specific cutting energy. The plot shows that increasing the feed rate produced rougher work piece surfaces, but at the same time the specific cutting energy will be reducing. This is a typical conflict in outcomes favoured by increasing the input factor, feed rate.

4.3.8 Regression Equation: Surface Roughness (R_a)

The Regression Equation explaining the mathematical relationship between cutting speed, feed rate and surface roughness is shown in equation (xii):

$$R_a = 0.1776 - 0.001308v_c + 2.607f_n \quad \text{(xii)}$$

The coefficient of determination (R^2 value in Table 10) of 98.90%, shows a very strong relationship between the surface roughness (response) and the regression model predicting it. Thus, the data is very close to the fitted regression line. The R-square of 98.90% and the adjusted R-square of 98.13% (Table 10), all, indicate a good model fit.

Table 10. Model summary of R_a

S	R-sq	R-sq(adj)	R-sq(pred)
0.0595	98.90%	98.13%	96.44%

It is apparent that equations (vii) to (xii) are all linear. This makes them candidate equations for fitting into the goal modelling constraints.

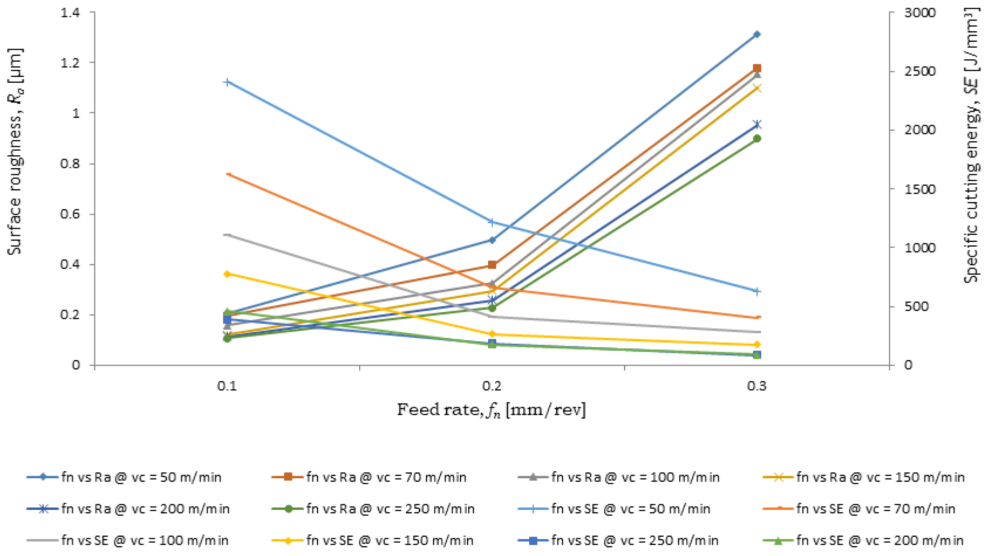

Figure 8. Surface roughness (R_a) and specific cutting energy (SE) vs feed rate (f_n)

4. CONCLUSION

In this study GP approach is discussed, for feasibility of use, as an optimisation technique and tool for the modelling of the multiple objective machining parameters predicting challenge, whilst considering the subsistence of the diverse and conflicting potential outcomes from cutting strategy environment change. It provides an analytical framework which can be used to proffer optimal solutions to multiple and conflicting objectives. A feasibility assessment on the use of goal programming application, in the optimisation challenge of machining-based manufacturing, was researched on in this write-up. A literature study in the application of GP, in diverse optimisation situations, was conducted. Titanium alloy experimental studies were carried out in, empirically, generating modelling data for the various machining performance parameters. Mathematical models were developed for the different performance outcomes and these were assessed against the background of characteristics of mathematical models which qualify for characterisation of goal programming equations. Minitab 19 software was used to aid the performance of regression analysis on the experimentally generated machining data. Each machining parameter was analysed and regression equations were, respectively, generated. The Regression Equation, expresses the mathematical relationship of the input factors (cutting speed, v_c and feed rate, f_n) to the response parameters (Rawlings, et al., 1998). In this study, the response parameters modelled were surface roughness, total cutting power, Material removal rate, chip teeth segmentation pitch, Tool wear, cutting forces and specific cutting energy. The representativeness, of the data by the fitted regression line for each respective response parameter, was analysed and indicated by the coefficient of determination (r^2) on the model summary. Pursuant to the study, conducted, the following conclusions were adduced:

Goal Programming appear to be a suitable, formidable and supple decision-making analysis support tool, for use, by the modern-day machining-based manufacturing planner, who is encumbered with multiple conflicting objectives under the complex constraining environment of opposing performance outcomes when the cutting parameters are adjusted. GP objective function intends to minimise the sum of deviations of the set targets, as much as possible as well as a technique to minimising priority deviations as much as possible. The intention is that all the set conditions be achieved as much as possible with minimum deviation from the set priority.

The discussions above, deriving from literature review, clearly project GP as a multi-criteria decision-making support tool which aims at simultaneously optimising several goals whilst also limiting the extent of deviation of each of the objectives from the desired set target. This typically maps a machining outcomes situation, during the machining of titanium alloy. Multiple goals arise, during machining production planning, due to the need to satisfying the diverse outcome scenarios of the change of cutting conditions setting.

As a multiple-objective manufacturing modelling tool, goal programming provides information on the trade-off among several objectives which need to be solved simultaneously during the manufacturing process planning.

Goal Programming, projects itself as one of the methods suitable and available for modelling machining manufacturing process due to its close proximity with decision making in practice, by machining planners. The technique corresponds significantly well to the results of behavioural theory of the industry as apparently deduced from the studied literature. The empirical findings from studies on decision-making practice, rather is convincing to demonstrate the expedient purposefulness of GP as a tool for modelling multiple-objective challenge situation such as the machining parameters selection for the manufacturing of titanium alloys. Consistent with further development from these findings, further studies would be recommended to practically test the goal programming application models in order to establish the consistency of the results deduced from practical application of the developed GP models from the experimental process.

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