Integrated Energy Use Optimisation and Cutting Parameter Prediction Model - Aiding Process Planning of Ti6Al4V Machining on the CNC Lathe

Abstract

This paper reports on the IEUOCPPTM (Integrated Energy Use Optimisation and Cutting Parameters Prediction Tool Model) designed to optimise the machining parameters planning process of titanium alloy machining on the CNC lathe. It aimed to create a novel systematic methodology for determination of optimised cutting parameters. MATLAB genetic algorithm and Visual Basic Application softwares were integrated to generate the IEUOCPPTM optimised machining process planning tool for titanium alloys. The empirical 18 full factorial experiment runs design was carried out using on Minitab. Determination of appropriate cutting parameters is vital for conserving energy and achieving sustainability for the titanium alloy machining businesses confronted with immense pressure to produce cost-effectively in record delivery times. Machining is a fundamental, and electrical energy intensive, activity in the profiling process of cylindrical T-alloy, Ti6Al4V, components used in the aerospace, Automotive and general metal working industries. Varied performance outcomes were achieved, on the machined components after predicting the input parameters using the tool as opposed to the good-guess approach currently being applied in industry. Validation experiments confirmed functionality of IEUOCPPTM in forecasting the cutting parameter settings required, to achieve desired responses during machining of Ti6Al4V within an average error range of 8%.

Keywords: *Energy use; optimisation; prediction; Surface integrity; energy efficiency; cutting parameters; Grade 5 titanium alloy; Ti6Al4V.*

1.0 INTRODUCTION

Grade 5 titanium alloy is a diphase (alpha-beta) titanium alloy grade chemically known as Ti6Al4V. It is a material used in many high value engineering applications due to its attractive properties such as high temperature strength, corrosion resistance and biocompatibility, inter alia. Ti6Al4V material is used in the aerospace industry, biomedical components manufacturing, energy and chemical industrial sectors and the offshore oil drill rig and ship building industries. All these are industries requiring highly dependable engineering materials.

Machining is one of the primary activities in the mechanical manufacturing process, (Chen, X. et al., 2021), of cylindrical Ti6Al4V component parts used in the aerospace industry. The cutting of metallic components by machine tools is considered a significant electrical energy consuming activity of the manufacturing process (abdelaoui et al., 2023). Determining the optimal machining parameter settings point which improves the energy use efficiency and escalate the process yield of grade 5 titanium alloy processing, therefore, offers significant opportunities of financial benefits for the machining industry operations. Thus, the selection of appropriate cutting parameters is vital for conserving energy and achieving energy efficiency as well as fostering manufacturing sustainability.

Furthermore, operating on optimum machining parameter settings is vital in so far as it decreases the costs of machining the product, improves machining effectiveness and enhances the predictability of the energy bill factored into the machined component. The distinctive, simultaneous, divergent and usually conflicting outcomes of response parameters deriving from the adjustment of the input machining processing parameters, during the turning of Ti6Al4V, increases the complexity of machining based manufacturing process planning with the key goal of attaining certain determinate outcomes relating to the component attributes or process quality standard. In a number of machining industry operations currently, the process parameters are determined approximately by experienced machine operators basing on trial-and-error or good-guessing approach. Thus, in this obtaining practice the methods are deficient of a systematic approach focused on promoting broad use of energy efficient methodologies in the machining industry (Feng et al., 2022). Machining operation process planning includes the determination of the most appropriate manufacturing strategy parameter settings as well as the arrangement of the sequence in which the machining process should be accomplished in the production of the given component or part in accordance with the specifications set out in the product design document (Su et al., 2015). Concurring with this assertion Chen, et al., (2019) established that appropriate selection of cutting parameters and cutting tool geometry appreciably lessen the energy use foot print and the manufacturing time through the machining process.

Machining planning is a function that is executed through systematic examination of the component design or sample in order to understand the intended requirements of the finish-machined workpiece. This process is considered in light of the information on the available machining facilities and the nature of the raw materials. Optimisation utilises mathematical programming models to take into account the various constraints and alternative conditions surrounding the machining operation (Challa & Berra, 1976). Machining process planning (MPP) is intended to transform a component design specification from the engineering drawing design model (Su et al., 2015) into a set of manufacturing instructions and specifications to actuate the design features into the physical component with the intended geometrical and topological profile as well as the desired quality features engendered into it through the machining process on the selected machine tool. Effective MPP point towards shorter and efficient manufacturing cycles characterised by improved utilization of the available facilities and resources (Challa & Berra, 1976), such as electricity energy. Emphasising the importance of good MPP, in a research focused on predicting and optimising energy consumption in high-speed milling, Duc and Trinh (2022), stressed the importance of accurately evaluating the amount of energy required to run the high speed machining process before cutting is started. Reporting in a study in the same realm, Yang et al, (2023) content that development of a manufacturing resource integrated energy use management system is advantageous in encouraging transformation of the energy utilisation system as well as facilitating the achievement of the sustainability goals of nation states. The specified features in machining include outcome aspects such as component surface quality and integrity, material removal rate, tool wear management, cutting forces minimisation as well as variable cutting parameters settings such as the cutting speed, federate and energy use management. Process optimisation include selection and setting of input parameters in order to achieve the multiple set of component quality outcomes as well as promoting efficiency in energy use of the operations. The CNC lathe machine, used in this research is capable of producing titanium alloy components with high efficiency and accuracy despite the fact that Ti6Al4V is classified as a difficult to machine material (Tayisepi, 2013), due to the mechanical and metallurgical attributes of the material.

A number of researchers have made attempts to addressing the optimisation of machining parameters as a separate problem. For example, Nayak and Sodhi (2017) used Response surface methodology in optimisation of CNC turning parameters of aluminium 6061 intending to enhance material removal rate. Yadav, Narang & Attri (2012) reported on using Taguchi methodology in an experimental study to optimise cutting parameters during turning in attempting to improve surface finish. Rao, Dave & Thakore (2017) used design of experiments to optimise milling process parameters of aluminium 6061 alloy cutting. It is apparent that all the researches employ empirical formulas to express the singular performance response parameter as a function of the considered machining parameters, in most instances by differentiating these expressions, in isolation, to obtain the optimum values of the targeted parameter. There are, however, difficulties in practically incorporating these individually determined analytical procedures into the live machining planning system. Typically, machining processes involve a number of variables which change from one job condition to another and, oftentimes, optimum output of one parameter tends to cause deterioration of the other. For example, machine settings which yield higher material removal rate could also be causing deterioration of surface quality and be associated with excessive tool wear as well as being energy consumption expensive. This complicates the practical applicability of the purely analytical methods, even in their simplest form, in complex operations that machining is (Su et al., 2015).

In the current setting of the MPP in industry, selection and determination of the machining process variable parameters is performed progressively for one particular outcome aspect after another (Su et al., 2015). This approach lead to suboptimal or trade-off outcome solutions on the component and the process and resource utilisation efficiencies, of producing it (Tayisepi et al., 2016). Determination and selection of appropriate machining parameters, during process planning, of the machining operation offer vital considerations that guarantee good machining response output such as the quality of surface finish, tool wear rate, enhanced material removal rate, energy use efficiency and, generally, ease of machinability. In this study, an Integrated Energy Use Optimisation and Cutting Parameters Prediction Tool Model (IEUOCPPTM) was designed and developed in order to optimise the machining process of grade 5 Ti-alloy components through effective integrated multi-criteria cutting parameters planning. The aim was to develop a physically implementable machining manufacturing planning system that predict the optimum cutting parameters for the integrated output responses. The intention of the tool design is to give assurance of the determinate response output of quality component parameters, generated from an efficiently planned machining process. The tool design outcome is a result of the concatenated application of experimental study and various software platforms. The tool applicability was validated with several iteration runs of experimental predictions of machining parameters and measurements of the component features outcome from the machining runs. There was good fidelity between the tool prediction and the physical machined component outcomes. Rajemi et al (Rajemi et al., 2010), content that it is vital to model machining energy use so as to project the energy use efficiency of the manufacturing process. Thus, predicting the energy use rate before machining commences meaningfully assist the machining manufacturing process planners and the operatives to keep under check the parameters which significantly influence energy use.

The limitation of the tool, however, is that although generally, its designing considered the constraints placed on the selection of machining parameters at planning stage, aspects that may be predicated on a variety of physical exigencies in the machining process are hardly addressed. The IEUOCPPTM systems focus on optimisation derive from the anticipated positive response of the physical machining process to the appropriately determined cutting parameters at the planning phase. Further assumptions, made in the study, are that the input factors predicted by the model are the only factors affecting the machining response parameters, ceteris paribus. This designed tool optimises the machining process through effectively determining the values of the machining parameters to use for each targeted outcome response. The energy efficient machining of titanium alloy (Ti6Al4V) encompasses the suitable choice of the machining strategy factors (v_c and f_n) combination intended to minimise energy use whilst maximising productivity. During machining based manufacturing, energy consumption (use) is a result of the processes meant to maximise material removal rate (*MRR*) and achieving chip teeth segmentation (*STP*) whilst simultaneously minimising surface roughness (R_a), cutting forces (F_c) and cutting tool wear (*TW*) as these provide the performance parameters which can be monitored during the machining process (Mori et al., 2011).

2.0 RESEARCH SIGNIFICANCE

The Integrated Energy Use Optimisation and Cutting Parameters Prediction Tool Model (IEUOCPPTM), is a vital tool platform intended to aid those in the business of metal machining by quickening the process of systematically determining the machining cutting parameters during process planning. The tool provides the machining operators with a reliable technological means of determining the set of required operating parameter levels as guided by the intention to realising the goal of achieving different machining outcomes energy efficiently. The IEUOCPPTM is a novel machining process planning tool particularly designed for application in the lathe machining of aircraft grade titanium alloy Ti6Al4V, with possibility of extension for application in other materials subject to model modifications from the programming code.

3.0 EXPERIMENTAL SETUP AND METHODOLOGY

The initial data set was produced from a Taguchi design of experiments full factorial design of experiments planned 18 machining experiments of Ti-alloy resultant from the input variable parameters combination generated from Table 1. The experiments were conducted on a Siemens controller run Efamatic Computer Numerically Controlled (CNC) lathe machine with a maximum spindle speed of 4500 RPM. The machine and experimental setup is shown in Figure 1.

The experimental process involved the outside turning of Ti6Al4V which was supplied in cylindrical billet form of diameter 75.4 mm. The specimens machining linear length used was 180 mm per single machining run. A cleaning cut of 0.5 mm depth was removed from the surface of each specimen, using a tool tip not involved in the experimental process, in order to avoid possibility of vibrations induced by specimen non concentricity during the experiment machining runs.

Table 1. Coding levels of the input (independent) variable test parameters.

Cutting parameter	Notation	Units	Symbol	Coding of Factor Levels					
				1	2	3	4	5	6
Cutting speed	v_c	m/min	X_1	50	70	100	150	200	250

Feed rate	f_n	mm/rev	X_2	0.1	0.2	0.3			
Depth	*DoC*	mm	X_3	0.5	0.5	0.5	0.5	0.5	0.5

Depth of cut was kept constant

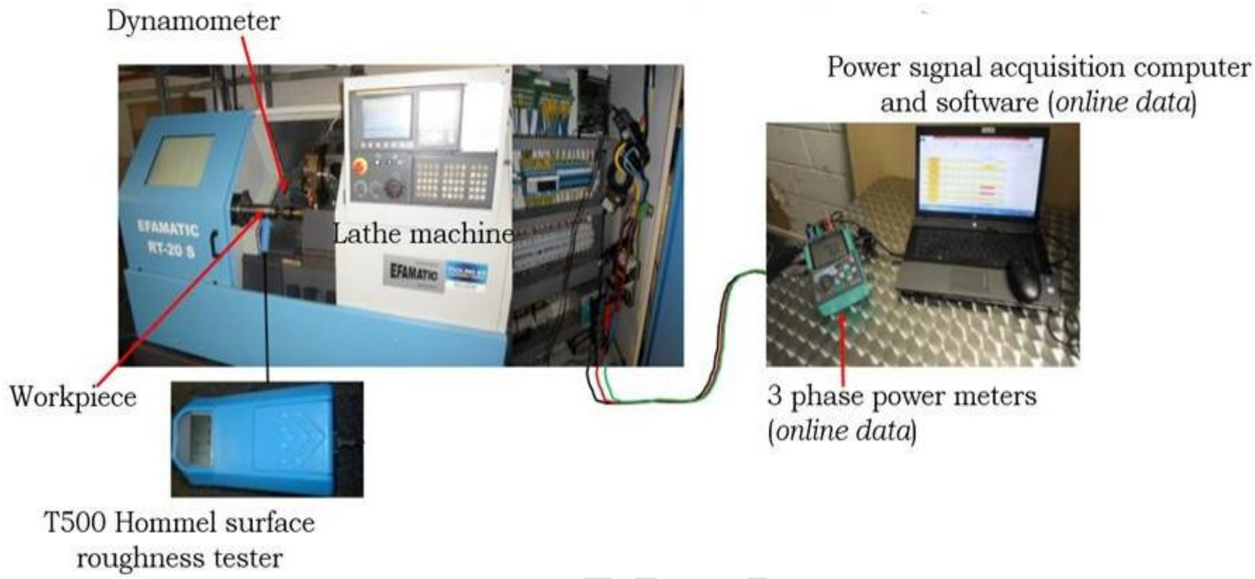

Figure. 1. Experimental machinery and equipment set-up

Data of several machining response parameters was collected online and offline, respectively, as follows, during and at the end of each experiment iteration (Che-Haron, 2001):

Online data
Energy use (power)
Cutting forces

Offline data
Surface roughness
Tool wear
Chip segmentation

Other response variables were analytically computed, such as material removal rate, spiral cutting length and specific cutting energy. The experiment iteration termination or changeover condition was tool wear of 300 micrometres (µm) (Che-Haron, 2001).

3.1 The IEUOCPPTM development

Once data was tabulated, mathematical models, expressing the response parameters as function of the input variables (cutting speed *(v_c)* and feed rate *(f_n)*), were developed using regression analysis modelling on Minitab 18 software. Further development involved expressing the performance parameters – Material Removal Rate (MRR), Segmentation Teeth Pitch (STP), Tool Wear (TW), Main cutting force (F_z) and average Surface roughness (R_a) - as functions of specific cutting energy, SE.
Equations 1 to 5 were determined as related to the individual response parameters where the variables are respectively represented thus, *y,* is the specific cutting energy J/m^3, v_c, cutting speed (m/min) and f_n, feed rate (mm/rev):

Material Removal Rate (MRR)

$$MRR = 5297.522086 - 26.82225896(v_c) + 0.0341370264(v_c)^2 + 53.6687376(v_c)(f_n) - 21084.39032(f_n) + 21093.9096(f_n)^2 \quad (1)$$

Segmentation Teeth Pitch (STP)

$$STP = 3140.64960213 - 4.4623952154(v_c) + 0.001720593333(v_c)^2 + 14.791382406(v_c)(f_n) - 19180.8816214(f_n) + 31789.178373(f_n)^2 \quad (2)$$

Tool Wear (TW)

$$TW = 514.0413 - 0.69284646(v_c) + 0.0002903616(v_c)^2 + 0.2153856(v_c)(f_n) - 256.9712(f_n) + 39.9424(f_n)^2 \quad (3)$$

Cutting Force (F_z)

$F_z = 1194.817834 + 1.814329444(v_c) + 0.001044452026(v_c)^2 - 5.490111(v_c)(f_n) - 4768.467(f_n) + 7214.625(f_n)^2$. (4)

Surface Roughness (R_a)

$R_a = 839.15086 + 1.5038845(v_c) + 0.001114765(v_c)^2 - 4.44372(v_c)(f_n) - 2997.42115(f_n) + 4428.43024(f_n)^2$ (5)

Combining these different response parameters into a singular model forms a multi-objective problem. Poles Sastry, Goldberg & Kendall (2014), posited that a multi-objective problem can be modelled as a multi-objective optimisation problem which could be solved by means of weighted functions assignment, with which the problem is transformed into a single objective problem using weights. The weights are problem dependant and must be empirically defined by the user in accordance with some established policy protocol for the entity. The decision attributes weight coefficient value, assigned, represents a measure of the decision maker's optimism or pessimism. The factor priority ranking methods available include, among others, the following; the pairwise comparison (Kumar, 2014), the law of comparative judgment (Gutowski et al., 2006) and analytic hierarchy process (Gupta, 2005).

The specific cutting energy minimisation model, developed, in this study, took the form (Wang et al., 1998):

$$\text{Min} \sqrt{\left(\sum_{i=1}^{n} c_i (f_i(x_j, x_k))^2\right)} \qquad (6)$$

Which in expanded form becomes:

$$\text{Min} \sqrt{\left[\sum \left[c_i (f_i(x_j, c_k))^2 + \ldots + c_n (f_n(x_j, x_k))^2\right]\right]^2} \qquad (7)$$

Subject to the operating constraints thus:

$$50 \le x_j \le 250$$

$$0.1 \le x_k \le 0.3$$

$$i = 1,2,3,4,5,\ldots n$$

$$j = 1$$

$$k = 2$$

Where the variable factor operating conditions provide the constraints represented. Thus, x_j is the cutting speed (v_c) in m/min, x_k is the feed rate (f_n) in mm/rev and c_i is the ranking weight factor priority coefficient associated with a performance parameter of the machining process. The pairwise comparison method was used to rank the weights of importance of the response factors in priority.

The integrated energy use optimisation and cutting parameter prediction tool model (IEUOCPPTM) was developed from equation 7 with, constituting equations 1 – 5, on the multi-criteria genetic algorithm (GA) application platform in MATLAB 13a (Sastry et al., 2014), as shown on the screen print in Figure 2.

Genetic algorithms are an evolutionary optimisation methodology which are suitable for solving intricate non-linear problem models for which the global optimum solution may be challenging to resolve (Venkatesh & Satchithanandam, 1980). GA belongs to the global search heuristics which are search techniques used in calculations to determine exact or approximate solutions to optimisation and search problems. The researcher would be reluctant to delve into extensive discussion of genetic algorithms at this stage.

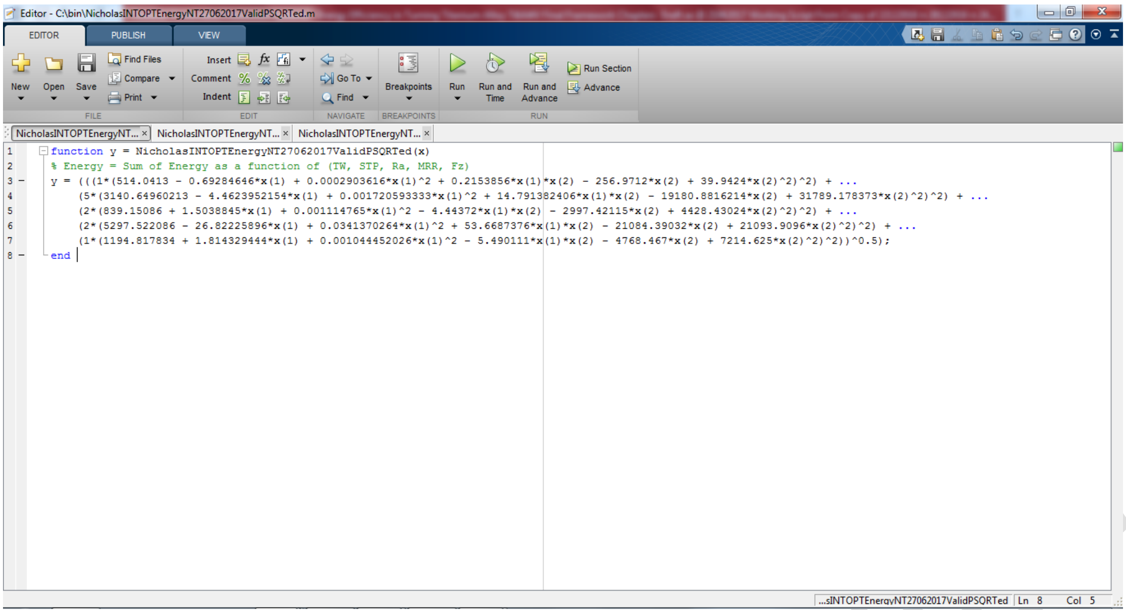

Figure. 2. Testing the IEUOCPPTM on a GA application platform

Use was made of the inbuilt GA module on MATLAB 13a (Mathworks, 2017) as a foundation platform to develop the IEUOCPPTM platform by integrating the GA M-file code instructions with Visual Basic Algorithm (VBA) to output the IEUOCPPTM tool guided user interface (GUI). Table 2 present the typical GA concept terms comparison with the machining process aspects as they were used in the tool development, and are meant to be interpreted by the tool users in application.

Table 2. The concepts comparison between GA and machining terms

Genetic Algorithm (GA)	Machining Process
Population	Feasible machining plans
Individual	A machining plan
Chromosome	Combination of parameters
Gene	parameter
Fitness	Optimum value
Selection	Record improved results
Reproduction	Change the machining parameters combination
Crossover	
Mutation	
Evolution	Generate new optimal results

(Mawanga, 2012)

Modelling machining energy utilisation is important for extrapolative energy efficient manufacturing, (Rajemi et al., 2010). Projecting the energy consumption in advance can significantly assist the machine manufacturing process planners and operatives to double-checking and maintain under control the parameters which affect energy use. This research focused on a machining manufacturing problem where the integrated energy use optimisation and cutting parameter prediction challenge required a solution to be developed basing on several conflicting objective functions. Whilst, energy consumption must, overally, be minimised, the source equations from which the mathematical models expressing the energy function with respect to the machining performance parameters, were such that some responses - such as material removal rate and teeth segmentation pitch - require to be maximised, whilst responses - such as surface roughness, tool wear and cutting forces - require to be minimised. This demands a decision making support tool with the ability to simultaneously address the requirements of these multiple conflicting goals (multi-criteria decision making). The solution generated required to be a compromise which will be acceptable in its addressing all these constituting factors.

4.0 RESULTS AND DISCUSSION

The IEUOCPPTM equation was tested for mathematical functional effectiveness, and the response output is displayed in Figure 3.

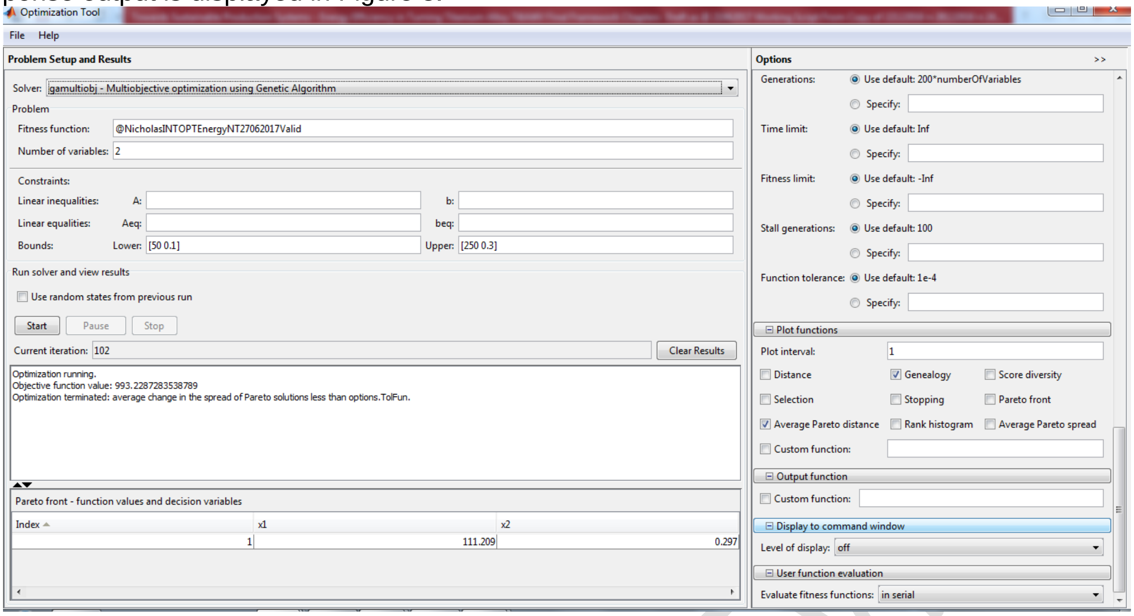

Figure. 3. IEUOCPPTM equation functionality test results on the GA application platform.

Having been satisfied with the computation response of the mathematical model uploaded on MATLAB 13a, use was then made of the Multi-Objective Genetic Algorithm Programming (MOGAP) coding to develop the Integrated Energy Use Optimisation and Cutting Parameter Prediction Tool Model (IEUOCPPTM). The IEUOCPPTM is an offline tool which can be utilised during machining process planning to establish the optimum combination of input cutting parameters to apply, during turning, on a typical machining centre - based on minimum energy use. The IEUOCPPTM establishes the cutting parameters combination based on minimum energy use of the machining process.

The concatenation of MOGAP and VBA resulted in the IEUOCPPTM tool user interface presented in Figure 4. Results of the projected machining process which can be read directly from the tool include the specific cutting energy, total energy use, actual cutting energy, the total and actual cutting power, energy efficiency, the cutting speed and feed rate which should be set on the CNC lathe machine, in order to achieve the energy outputs, are displayed.

There are five (5) main sections on the IEUOCPPM tool user interface. The functional zones are explained as follows:

Settings block: where input cutting parameters, cutting speed and federate constraining limits are set on the upper and the lower bounds. The feasible cutting parameter in each respective instance would be expected to take values between the bounds. The constraining input parameter ranges used in the experimental study were, respectively, cutting speed of 50 – 250 m/min and feed rate of 0.1 – 0.3 mm/min; **Action block:** houses Execute Analysis, Clear Results button and Clear/Reset button; ***Performance block:*** accommodate the coded programme for sub-routines and display the results on specific cutting energy as computed from the input equation and the energy efficiency of running at the displayed cutting parameters combination; ***Weights block:*** where weight assignments to each performance parameter are entered in accordance with the priority weight listing determined by the process planning requirement policy on the particular job task; ***Energy and Power Performance block:*** *accommodates* the sub-programmes and display Total Machining Energy, Actual Cutting energy, Specific Cutting Energy, the Actual Cutting Power and the Total Operating Power results.

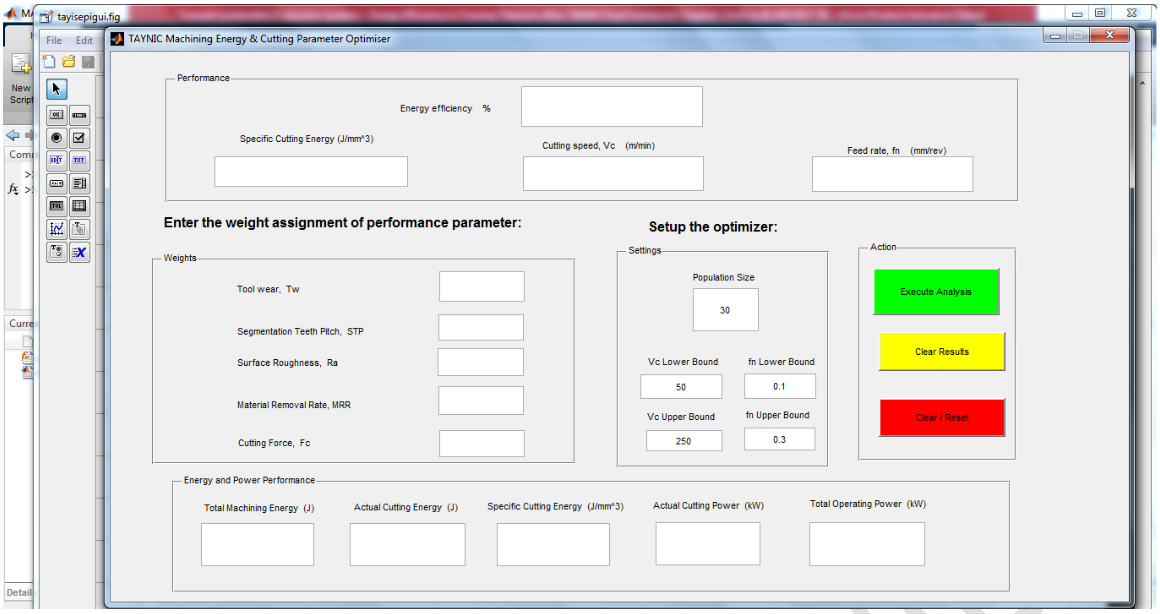

Figure. 4. The IEUOCPPTM tool user interface developed

4.1 The Basic Operation Procedure of the IEUOCPPTM

Upon successful logging in with the approved credentials onto the system, MATLAB Genetic Algorithm platform, the user is automatically presented with the user interface shown in Figure 5, which require entries to be implemented as shown in the steps indicated in Figure 6.

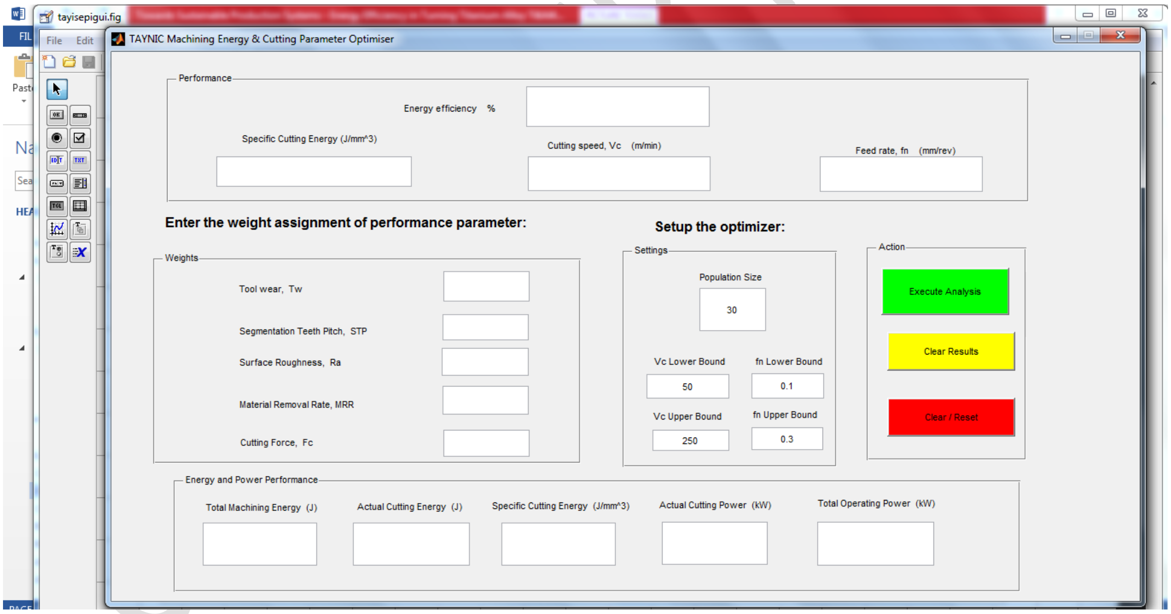

Figure. 5. The implementation level IEUOCPPTM tool user interface

The simulation iteration keeps running until, despite change in the population size, the energy use and the predicted input parameter readings do not change anymore. Otherwise keep changing the population by a factor of, say, two. For example if previous iteration was ran at a population of 30. The next iteration then must have respective successive population size of 60, 120, 240, 480 etc.

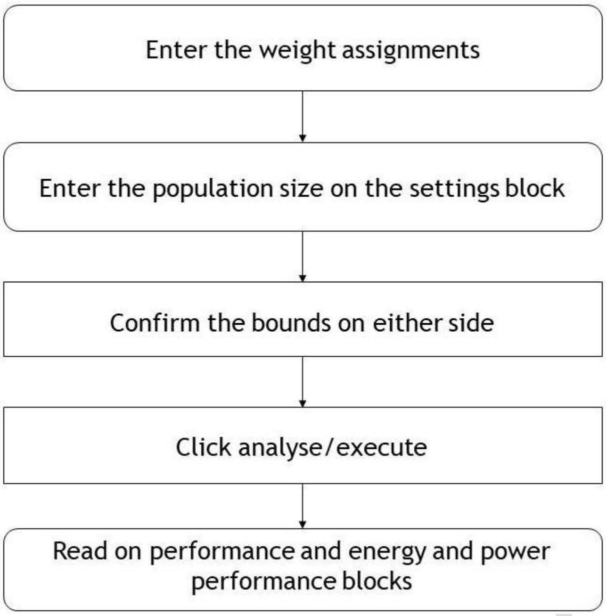

Figure. 6. Protocol procedure of entries for applying the tool.

The typical performance parameter weights entered on the IEUOCPPTM platform is presented in Figure 7. Tool wear, TW is considered the most essential parameter on the intended operation, is assigned a weight of 5, followed by the STP which is given a weight of 2. The rest of the parameters such as F_c, MRR and R_a are assigned an equal weight of 1.

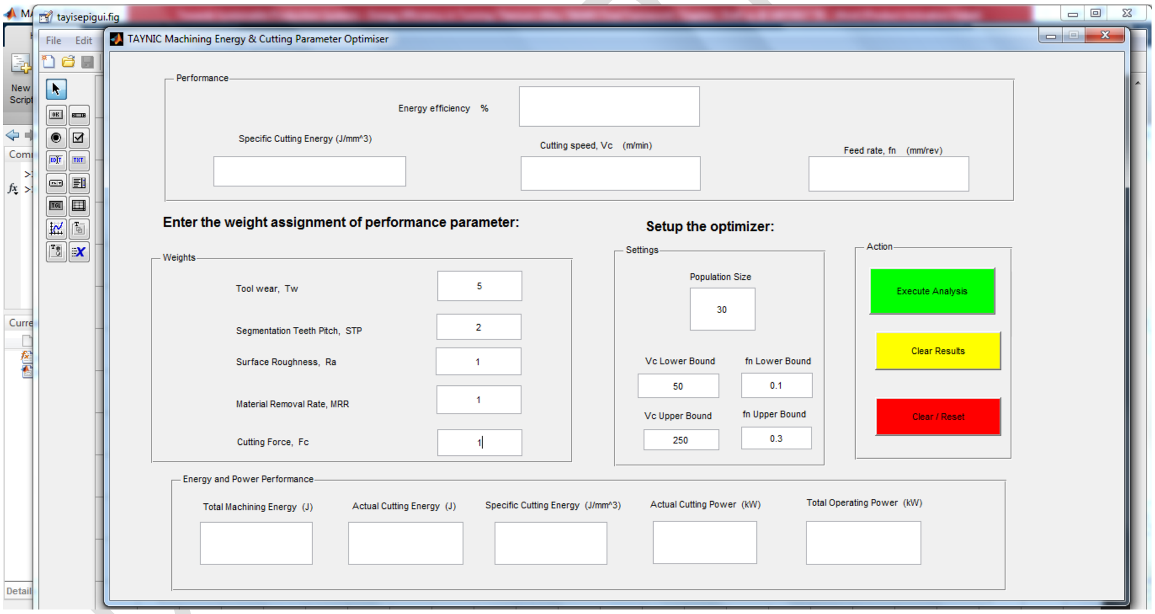

Figure. 7. Weight assignment scores entered on the IEUOCPPTM user interface.

Figure 8 displays the process running screen, before the optimum solution is attained and the performance parameter boxes are still empty.

The process simulation run complete screen is displayed in Figure 9, in which the output screen show the results of the performance parameters, indicating the projected machining energy and power process use, the energy efficiency and the cutting parameters which should be set for the cutting process recommended as v_c of 183.64 m/min and f_n of 0.298 mm/rev.

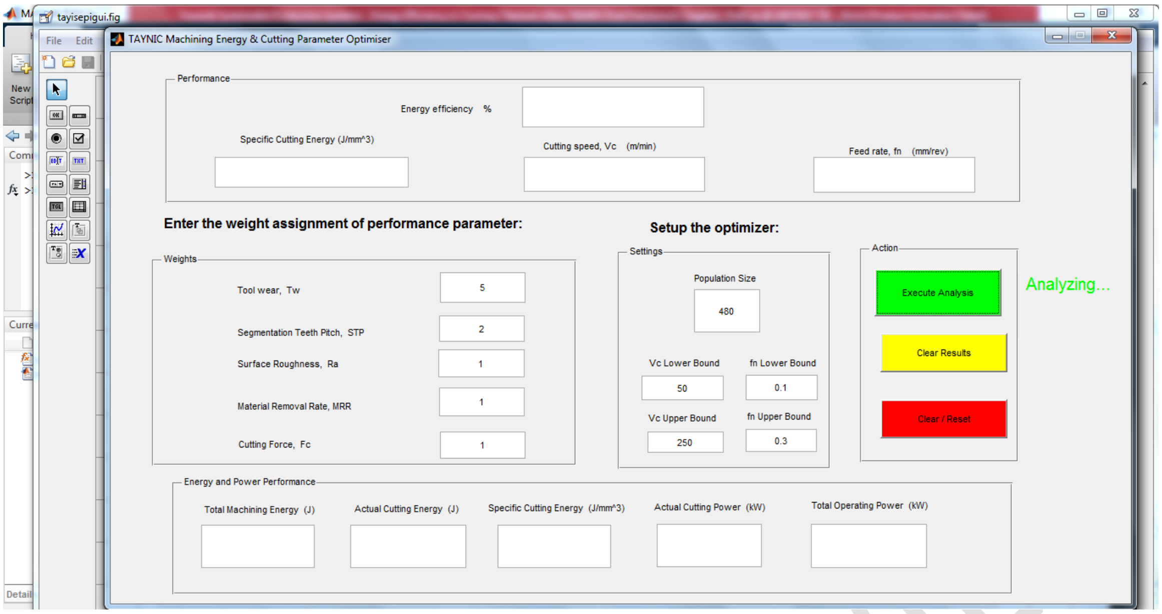

Figure. 8. Simulation run in progress screen image

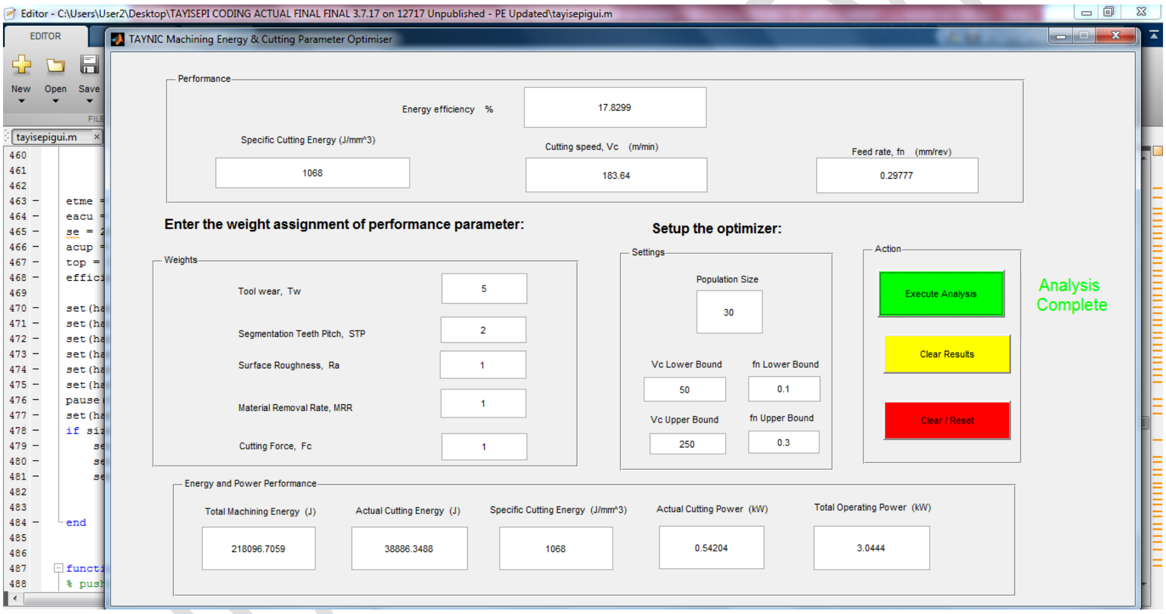

Figure. 9. Simulation run, complete, image of the IEUOCPPTM displaying results.

4.2 Case Study Example Practical Application OF THE IEUOCPPTM

Equations 1 to 5 model the performance parameter functions which impact on energy use. These model performance bounds of the physical mechanical phenomena which happen concurrently during the machining process. Establishing their combined impact on energy use as they arise is important. Practically, in real life operation there is need to weigh more on a particular performance parameter in comparison to others, dependent on the machining circumstances. For instance an urgently required order delivery may prompt that MRR be fulfilled faster. Thus making MRR a dominant factor, however whose fulfilment would be accompanied by high TW and higher cutting forces, F_c. In essence, there could be need to strike a balance between achieving these two contrasting performance objectives (high MRR and low TW) by suitably weighting these performance parameters on the integrated energy use efficiency and optimisation platform. As changes are made to the weight assignment of particular performance parameters. Subsequent to these respective weighting assignment, the total energy (y) consumed as well as the input f_n and v_c values change. The intent is to optimise energy use as the performance parameters are achieved.

Typical example case study application situations of the modelling tool, used in the machining planning of Ti6Al4V, are given in Figures 10 and 11. Examples of different process scenarios, each with an applicable weights set, are shown. Figure 10 represent the simulation results of machining operation focused on the intention to achieving optimal energy efficiency when material removal rate is considered the most weighty process parameter. This could be typical for a situation where turnaround time is of major concern for proximate product delivery or avoiding downtime due to part unavailability. Material removal rate is thus assigned a ranking weight of 6, from the weighting range of 0 to 10 based on the process of judgemental weighting. In this instance the other parameters are considered as not very significant and are assigned weights of 0. The results displayed on the model tool show that the specific cutting energy (objective function) would be 71 J/mm^3, the cutting speed to achieve that be set at 190.6 m/min and the feed rate is 0.26 mm/rev. An energy efficiency of 18.2% is also predicted.

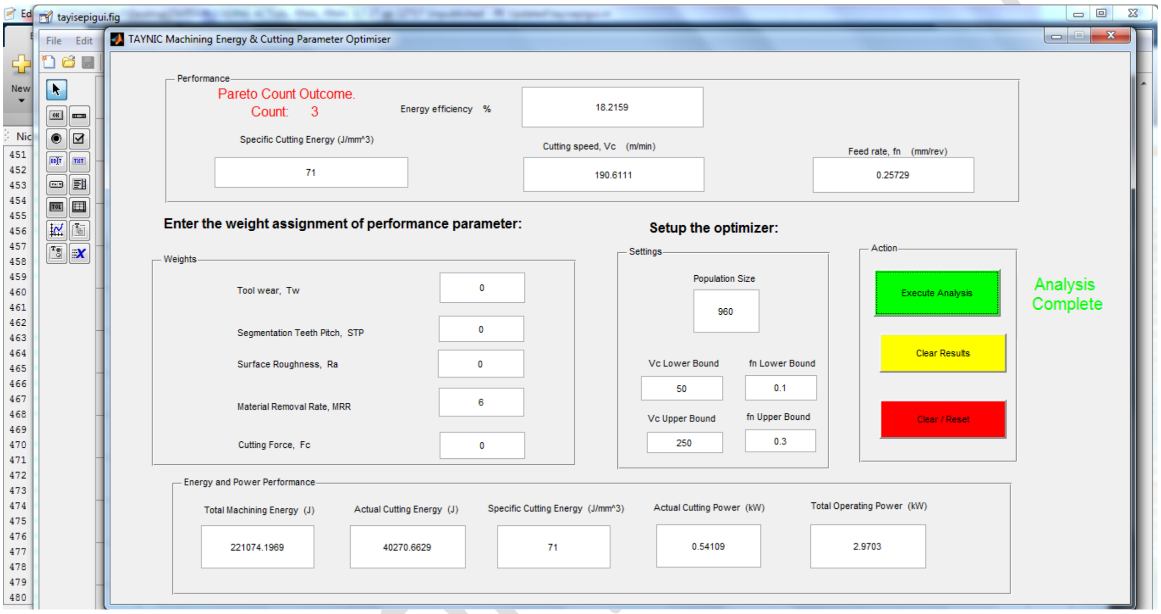

Figure. 10. IEUOCPPTM simulation run focused on MRR

The results of simulation, presented in Figure 12, represent machining scenario intended to obtain optimal energy efficiency when cutting force is contemplated as the most significant process parameter. Cutting forces could be significant for machining accuracy, tool/workpiece interface dynamic effects and machine tool rating or capacity. Cutting force is therefore assigned a weight of 6 whilst the other parameters are considered insignificant and given weights of 0. The indicated energy efficiency for the optimum cutting force is predicted at a cutting speed of 53.7 m/min and feed rate of 0.3 mm/rev. This is significantly less cutting speed than the speed predicted for optimal material removal rate above. However, a similar but slightly higher energy efficiency of 19.6% is also predicted.

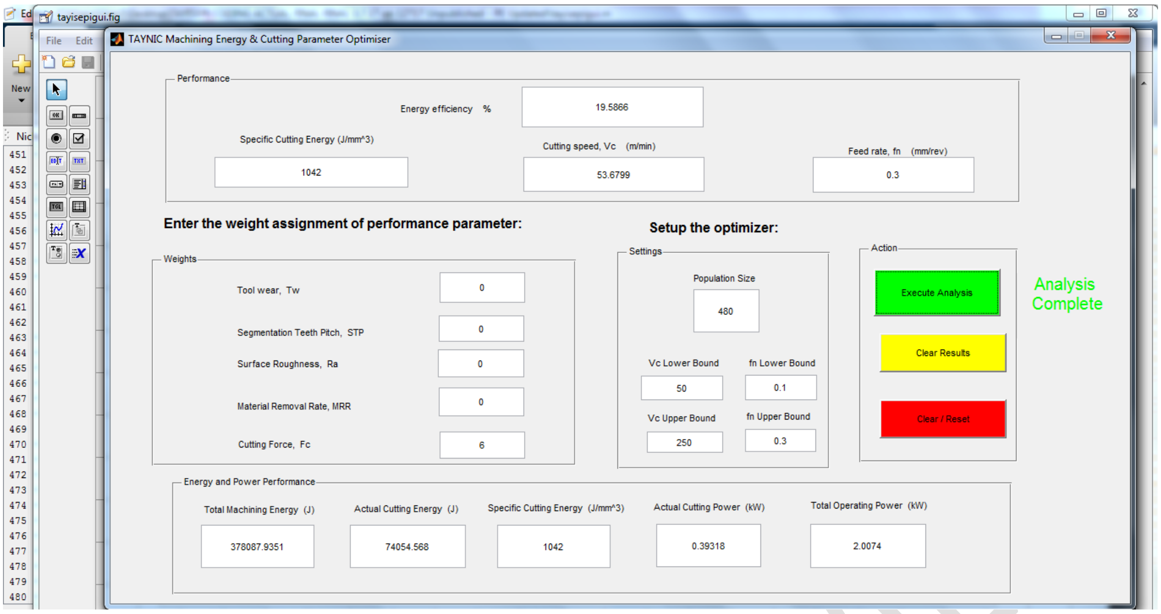

Figure. 11. IEUOCPPTM simulation run image focused on cutting forces, F_c

Simulation results of a case where tool wear - TW, followed by segmentation teeth pitch - STP are considered as the most significant process parameters are presented in Figure 12. TW is assigned a ranking weight of 5 whilst STP is assigned a weight of 2. The rest of the other response parameters were considered of equal lower level influence and were assigned a ranking weights of 1. In this instance STP is deemed more significant than material removal rate, cutting force and surface roughness because it may be effectively employed as a process evaluation parameter. Chip segmentation impact on the visual appearance of the chip which may be effectively used to evaluate the current state of the cutting process. A highly segmented chip is associated with more efficient energy use (Oosthuizen et al., 2014). The optimum feed rate and cutting speed for best efficiency (17.9%) in this machining scenario are, respectively 0.29 mm/rev and178.2 m/min. This situation could typically be required where cutting tool cost is prohibitive or their availability is not readily assured.

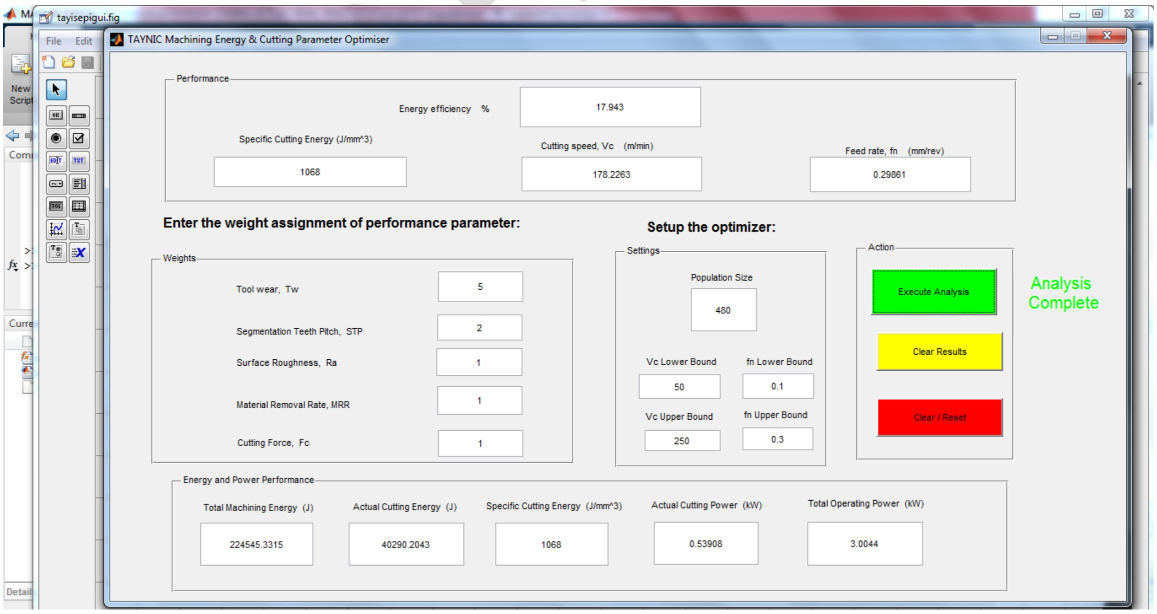

Figure. 12. Equal weight assignments for R_a, MRR and F_c and more emphasis on TW and STP

The case study results presented above show that energy efficiency of between 13 to 30 % were obtained in all the IEUOCPPTM simulation machining case applications. This level of machining energy efficiency results well agree with reported earlier findings in the literature (Rajemi et al., 2010). The optimum cutting parameters v_c and f_n, were predicted by utilising the model.

4.3 Model Validation Results

Several scenario case application simulation runs, of the energy use optimisation model were completed for different weighting combination sets. Beyond that it was considered prudent to carry out physical machining confirmation experiments (Mahendra & Neeraj, 2020; Tayisepi et al., 2016), in order to determine the validity of the IEUOCPPTM model. Several confirmation experiments were carried out to establish the real performance of the tool when compared to live practical machining, based on the model outputs. The feed rate and cutting speed results for each machining scenario, as predicted by the tool, were employed as the input parameters for conducting validation physical machining tests. The validation experiments setup was similar to the original experimental work initially conducted as explained above, save for the fact that the input parameters were now picked based directly on the model tool predicted results. In a similar type of study, focused on energy consumption prediction during stainless steel milling, Shuo, et al., (2021) utilised case study validation experiments to confirm functionality of the developed prediction models. Table 3 present results of the validation experiments conducted in this study. Energy outputs, respectively, specific cutting energy (SE) and total machining energy (ETME), as predicted by the model tool were directly compared with their equivalent values as obtained experimentally. The obtained results were consistent with the research findings by Lu, et al., (2023) who established that energy efficiency of manufacturing can significantly be improved by effective cutting parameter selection. Generally, there was good fidelity of the results of the validation experiments with the model tool predicted results. Maximum variation obtained was 8.6% for all the case scenarios simulated and confirmed experimentally.

Table 3. Validation test results of the IEUOCPPTM

Most important performance parameter	Determined input process parameter settings and response					Variability between Simulation and experiment result
	Predicted optimum input parameters		Response parameter units	Optimum value		
	v_c (m/min)	f_n (mm/rev)		Model	Case study Experiment	
Material removal rate (MRR)	190.611	0.257	SE (J/mm^3)	71	66.9	9.055%
			ETME (J)	221 074	208310	
Cutting force F_c	53.7	0.3	SE (J/mm^3)	1042	1020	2.1%
			ETME (J)	378 088	370 148	
Segmentation teeth pitch (STP)	165.43	0.2632	SE (J/mm^3)	606	658	(9%)
			ETME (J)	250 504	272 047	
Surface roughness (R_a)	186.24	0.2092	SE (J/mm^3)	163	170.498	(5%)
			ETME (J)	231 092	241 722	
Cutting force (F_c) and Tool wear (TW)	234.23	0.3	SE (J/mm^3)	999	929	7.0%
			ETME (J)	154 924	144 081	
Segmentation teeth pitch (STP) and Tool wear (TW)	178.23	0.2986	SE (J/mm^3)	1068	1066.83	18%
			ETME (J)	274 545	224 298	

4.4 The IEUOCPPTM model typical business application cases

The IEUOCPPTM could be employed in dry running typical machining production process planning. Machining business scenarios that process planners would consider to evaluate the business case for a specific cutting strategy, to optimise energy use within certain constraints, are presented in Table 4.

Table 4. IEUOCPPTM application instances in machining business

Performance parameter emphasised during machining	Explanation	Applied when dealing with:
Tool wear TW	Minimising tool wear and energy use optimisation	High tool costs or challenging availability of replacement tools reducing escalated energy costs.
Chip segmentation teeth pitch STP	Optimum energy use observed through efficient morphology of the chips removed.	Machining efficiency interpreted through chip morphology. Cyclic force frequency determination from chip morphology. Assessment of cutting progression to curtail surface microstructure alteration through excessive heating interpreted through chip colour changes. High energy costs.
Material removal rate MRR	Achieving maximum material removal rate with optimal energy use.	Desiring to supply customer order timeously through high performance machining. Dealing with high energy costs and intending to achieve tool life longevity to contain cutting tool costs.
Cutting force F_c	Optimum energy use for minimum cutting forces.	Minimise costly and excessive machine loading. Contain high energy costs and curtail chip load on the cutting tool. Processes state monitoring.
Surface roughness R_a	Optimal energy use with desirable targeted intentional average surface roughness	Handling surface roughness sensitive parts or components of high surface integrity requirements and high energy cost challenge.

5.0 CONCLUSION

Process planning stage energy use forecasting and prediction, of the optimum input cutting parameters combination to employ, in order to minimise energy consumption is vital. The design and development of the IEUOCPPTM in MATLAB 13a multi-criteria GA platform integrated with VBA was presented in this research. The tool design and development result was presented as a, VBA generated, display or dashboard (Guided user interface - GUI) on which the user enter the performance parameters, weight of the machining process performance responses. Operation of the model tool is also briefly explained. Typical results, showing the functionality of the IEUOCPPTM, are illustrated on the screen prints presented in the write-up. The tool was designed for application in the cutting parameters planning of grade 5 titanium alloy materials machined under the cutting conditions as was expounded in this experimental study. After the extensive simulation and validation tests of the model, conclusion was reached that, for the Ti6Al4V material in question, and for the range of feeds and cutting speeds evaluated the model predicted an acceptable approximation of the machining input parameters. Such that it may be confidently used as a prediction/forecasting tool to assist during process planning of machining strategies where process energy use is significant consideration. Applicability of the tool, in predicting cutting parameters, however is limited to the material and conditions validated by the experimental study. Further studies and tests may need to be conducted if there is consideration of extensional application of this novel tool in predicting the cutting conditions for different materials and on machines which are not CNC lathe.

Real world machining case studies were utilised to prove the functional validity of the designed and developed model tool and the results comparison between the simulation and experimental machining showed that infeasible machining strategies could be avoided by employing the tool. The limitation of the tool, however, is that although generally, its designing considered the constraints placed on the selection of machining parameters at planning stage, aspects that may be predicated on a variety of physical exigencies in the machining process are hardly addressed.

An effective tool for systematically and consistently predicting cutting parameters during lathe machining process planning had been developed and functionally tested, and presented in this research. Further research entail the requirement to developing a generic machining process planning tool applicable for use in determining process parameters of varied machine tools such as to include milling, grinding, shaping etc.

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