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4.6 Energy consideration in machining operations - towards explanatory models for optimisation results

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Abstract

This paper reports the application of a systematic research methodology for uncovering the reasons behind results obtained when energy is considered in machining optimisation. A direct search optimisation method was used as a numerical experimentation rig to investigate the reasoning behind the results obtained in applying Taguchi methods and Genetic algorithm (GA). Representative data was extracted from validated machining science equations and studied using graphical multivariate data analysis. The results showed that over 80% of reduction in energy consumption could be achieved over the recommendations from machining handbooks. It was shown that energy was non-conflicting with the cost and time, but conflicting with quality factors such as surface roughness and technical factors such as power requirement and cutting force. These characteristics of the solutions can provide an explanative motif required for practitioners to trust and use the optimisation results.

Keywords:

Direct search method, energy minimisation, machining optimisation, sustainable machining operation

1 INTRODUCTION

Minimising the energy consumption for the machining process can lead to benefits for the environment as well as contribute to economic and social well being of the society. Duflou et al. [1] concluded that optimising manufacturing process is one of the strategies to reduce energy demand and resource consumption. The specific methods for optimising manufacturing process include reducing auxiliary energy consumption, reducing idle production time, optimising process parameters and energy-efficient process planning. Previous research [2] of the authors looked at the improvement of energy efficiency for end milling operation. An energy prediction model and energy-efficient profiling toolpath strategy have been proposed. The aim of this paper is to continue investigating energy minimisation methods by considering optimisation of process parameters to further improve the energy usage for machining operation. The characteristics of machining operation when energy is considered as a significant factor will be investigated. A direct search optimisation method will be used to uncover the reasoning of the optimal results which are obtained when using Taguchi method and genetic algorithm.

1.1 Problems for Machining Optimisation

The observation from literatures and practice is that currently, too many optimisation methods (such as Genetic Algorithm (GA), Simulate Annealing (SA), Particle Swam Optimisation (PSO) and tribe/ant-colony) have been proposed. The optimisation methods are more like "black box" tools. The consequence of this problem is that in practice, the practitioners do not trust the optimal results because they cannot understand how the results are obtained from the optimisation methods.

1.2 Research Question and Research Design

The following research questions are going to be answered in this paper:

How the nature of the energy-minimising machining optimisation problem be explained?

How the reasoning process of the algorithms for solving the energy-minimising machining problem be explained?

To address the challenge posed by these research questions, this paper presents in section 3 an exploration of techniques for explaining the characteristics of the optimisation problem and in section 4 the reasoning behind the algorithms for solving the optimisation problem. A review of related research is presented in section 1.3 to introduce the development of machining optimisation and identify the gaps of knowledge.

1.3 Related Research in Machining Optimisation

The research of improving machining performance by selecting optimal process parameters have been conducted for over 100 years since Taylor published his tool life equations in the early 1900s [3]. Early researchers (1950s to 1970s) proposed optimal suggestion based on analysis of machining variables. The optimisation process usually followed procedures of (1) data collection through conducting physical experiments, (2) mathematically modelling (3) analysing the mathematical equation, and (4) proposing optimal solutions. Following this type of approach, Brewer and Rueda applied a monograph technique to optimise tool life with the consideration of a group of independent variables for turning variety of materials. The results showed that for non-ferrous materials, the best cutting conditions are regarded as the high material removal rate which the machine will permit. For difficult-to-machine material the range of feasible parameters is much narrower than non-ferrous material [4]. Crookall proposed a concept of performance-envelope to represent the permissible and desirable operation regions of machining based on the characteristics of machining cost and time with the constraints of machining tool capability (power), cutting tool failure, and surface roughness [5].

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On the basis of early research, conventional optimisation methods started to be applied in machining optimisation during 1980s to 1990s. Researchers from University of Manchester used a grid search method to solve machining optimisation [6]. Enparatza [7] developed a tool selection module for end milling operation and conducted an optimisation procedure of cutting conditions by considering economic criteria. The result reported that the machining cost can be minimised by selecting optimal cutting speed. The optimisation procedure also showed how constraints (tool life, cutting force, machining power and tool deflection) affect the search space. By comparing different algorithms, Tolouei-Rad and Bidhend selected feasible direction method to optimise general milling operation based on economic criteria. They reported that the optimisation of end milling is a non-convex, non-linear, multi-variable and multi-constrained problem. A case study of machining a multiple-feature component showed that up to 350% improvement in profit rate can be achieved over the recommendation from machining handbook [8].

Taguchi method was introduced to improve product and process design as a fractional factor design method which can significantly reduce time and resource needed compared to conventional Design of Experiment (DOE) methods. In addition, because it can be easily implemented and has a good applicability, the Taguchi method has been widely used in many machining optimisation research to determine important process parameters based on economic criteria (e.g. cost, productivity) and surface roughness [9].

With the rapid development of computer technology in early 21st century, new optimisation methods which are generally known as Evolution Computing or Meta-Heuristic search algorithms have become popular in machining optimisation. Heuristic algorithms are widely used to solve parameter optimisation problems, especially when the search space is very large and complex. Khan et al. [10] claimed non-conventional algorithms such as Genetic Algorithm (GA) and Simulated Annealing (SA) are more suitable than traditional methods for machining optimisation due to its non-linear and non-convex solution space. Baskar et al. [11] compared the performance of four non-conventional methods: Ant Colony Algorithm, GA, PSO and Tabu Search. They applied theses methods to determine the optimal process parameters when time, cost and profit rate are the objective functions. The results showed that PSO has better performance than the other algorithms. It was reported that 440% and 54% of improvement in profit rate was achieved compared to handbook recommendation and optimal result by using feasible direction method. However, comparison of the results obtained from GA and PSO showed that the optimal results for these algorithms do not differ by more than 4%.

Until recently, energy was indirectly considered in machining optimisation through including power as a constraint in the optimisation problem. Energy was first considered as a primary objective by Fillippi and Ippolito in 1980 [12], but it was not until the mid of the 1990s that Sheng et al. [13] formulated an environmentally-conscious multi-objective model which considered energy consumption as an important component. It also provided a possible way to carry out an optimisation procedure from environmental perspective. Based on consideration of energy minimisation, Rajemi and Mativenga [14] conducted research on optimising cutting parameters for dry turning operations. A prediction model was developed in terms of feed rate, cutting velocity and tool life to calculate energy consumed. Further research by Mativenga and Rajemi [15] showed that by optimising tool life through direct search method, up to 64% energy can be reduced compared to that obtainable by using cutting parameters recommended by tool suppliers. In addition, the optimal value of cost can be achieved at the same time with optimal energy consumption. Mori et al [16] conducted a series of experiments based on Taguchi method. The results showed that cutting performance can be improved by adjusting cutting speed, feed rate, depth and width of cut. Up to 66% power consumption for milling operation can be reduced by selecting high level of cutting conditions within a value range which does not compromise tool life and surface finish. The machining time can also be shortened with significant increase in material removal rate.

1.4 Summary of Gaps from Literature

The environmental challenge provides a new opportunity to apply the results of decades of optimisation and process planning research. However, as identified by Roy et al [18], most of academic optimisation results have not been used by industry because practitioners mostly prefer to select optimal parameters based on expert experience. The reasoning behind practices on optimisation [11-16] is not clear and needs to be transparent by addressing the following requirements:

- The optimisation procedure must be based on comprehensive understanding of the problem.
- The primary objective (energy) must be related to the conventional objectives such as cost, time and quality which the practitioners are familiar with and interested in.
- The optimisation method adopted must be concise and explicit which is relevant to practitioners' knowledge or obvious general principle.
- The optimisation results must be easily visualised.

2 NATURE OF MACHINING OPTIMISATION

2.1 Nature of Search Space

Search space can be explained as a set of all the possible solutions. Each point in the search space represents a combination of process parameters. The size of the search space increases exponentially with the increase of number and levels of variables. Thus, for 3 levels of 4 variables the total number of size of the search space is 3^4. The increasing the number of levels by 1 will expand the size to 4^4 which increases search space by over 300%.The unconstrained search space of machining optimisation is a multi-dimensional space located in the positive interval of the coordinate space.

2.2 Nature of Variables

The variables involved in end milling operation have already been identified and classified into independent and dependent variables by several researchers [2, 4, 7, 8, 11, 16]. These variables are listed below.

Independent variables: Depth of cut ap (mm), Width of cut ae (mm), Feed rate fz (mm/tooth), Spindle speed n (rev/min), Diameter of tool d (mm), Number of flutes z.

Dependent variables: Energy E (kJ), Cost C, Time T (min), Material Removal Rate MRR, Tool Life TL (min), Cutting Force F (N), Power P (W), Surface Finishing Ra, Cutting Speed Vc, Feed Rate f (mm/min)

2.3 Nature of Objectives and Constraints

Previous machining research contributions [4, 7, 8, 10, 11] have used as objectives cost, time, surface roughness and tool life, and as constraints the following variables:

- The surface roughness should be satisfied with the quality requirement (rough machining or finishing)
- The cutting force should at least make sure the machining operation can take place but not break the cutting tool.
- The power required for machining should not be over the limitation of the machine tool
- Physical constraints of independent variables determined by the capability of machine tools (design power) and cutting tools geometries (diameter of the tool).

In this paper, energy is added to these dependent variables and can be considered either as the objective function or constraint. For the purpose of investigating the problem any of the other factors can also be either an objective or constraint or both.

3 CHARATERISATION OF ENERGY CONSUMPTION

3.1 Design of Numerical Experiment

Numerical experiments carried out in this paper are mainly based on predictive models obtained from previous experiments conducted by the authors [2] when milling Aluminium 7050 on a HAAS TM-1CE 3-axis vertical milling machine. Equations for variables such as tool life and surface roughness are obtained from the contributions of other researchers [2, 8, 11]. The design of numerical experiment is shown in Table 1. Table 2 lists the mathematical expressions of the dependent variables for the numerical experiments. Four process parameters are considered as independent variables which are: depth of cut, width of cut, spindle speed and feed rate per tooth.

Table 1: DOE for numerical experiment

Process Parameter	Value Range
Depth of cut ap (mm)	1-5 mm
Width of cut ae (mm)	1-10 mm
Spindle Speed n (rpm)	500-4000 rpm
Feed rate fz (mm/z)	0.01-0.1 mm/tooth
Diameter of tool (mm)	10 mm
Number of flutes	3
Cutting Tool: carbide flat end mill	
Workpiece material: Aluminium 7050	

3.2 Characteristics of Machining Operation with Energy Consideration

Since the studies of other factors have been considered by other researchers [4-7], this paper will only focus on the factors in relation to energy consumption. Numerical experiments were carried out based on the prediction models in Table 2 in the range of process parameters in Table 1. The effects of four independent variables on energy consumption are shown as in Figure 1. The results show that the energy consumption for machining specific volume material monotonously decreases with the increase in depth of cut, width of cut, feed rate and spindle speed. It means choosing higher machining parameters is more energy efficient than using lower parameters.

Table 2: Mathematical expressions of dependent variables

Feed Rate: $f = n \cdot z \cdot f_z$
Mater Removal Rate: $MRR = a_p \cdot a_e \cdot f$
Cutting Speed: $v_c = n \cdot \pi \cdot d$
Cutting Force: $F_t = 2K_t \cdot MRR / (n \cdot z \cdot d)$
Force Coefficient: $K_t = c_{k0} \cdot a_p^{c_{k1}} \cdot a_e^{c_{k2}} \cdot d^{c_{k3}} \cdot z^{c_{k4}} \cdot f_z^{c_{k5}} \cdot n^{c_{k6}}$ Where c_{k0} to c_{k1} are coefficients for Kt
Total Power: $P_{total} = P_{machining} + P_{auxiliary} = \frac{F_t \cdot v_c}{60} + P_{constant} + P_{variable}$ Where the other components are power consumptions for machining, auxiliary functions (constant and variable)
Tool Life: $TL = \frac{c_{tl}}{v_c^{\,m} \cdot f^{\,p} \cdot a_p^{\,q}}$ Where m, p, q are tool life coefficients
Total Time: $t_{total} = t_{machining} + t_{setup} + t_{tc} = \frac{V_m}{MRR} \cdot \left(1 + \frac{t_{change}}{TL}\right) + t_{setup}$ Where the other components are time consumptions for machining, setup, tool change(tool change/time)
Total Energy: $E_{total} = E_{machining} + E_{auxiliary} + E_{setup} + E_{tc} = t_{total} \cdot P_{total} + (t_{setup} + t_{tc}) P_{constant}$ Where the other components are energy consumptions for machining, auxiliary function, setup, tool change
Total Cost: $C_{total} = C_{Labour} + C_{Energy} + C_{tool}$
Ra: $R_a = c_{r0} \cdot a_p^{c_{r1}} \cdot a_e^{c_{r2}} \cdot d^{c_{r3}} \cdot z^{c_{r4}} \cdot f_z^{c_{r5}} \cdot n^{c_{r6}}$ Where c_{r0} to c_{r1} are surface roughness coefficients

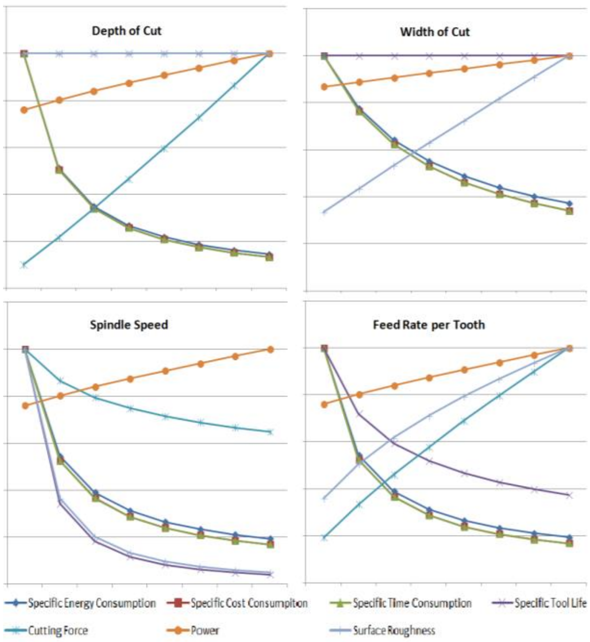

Figure 1: Characteristics of Machining Operation

Another observation from the energy plots of figure 1 is that the improvement trend of energy is less pronounced with the increase of process parameters. One reason is that the increase of process parameters can only reduce the energy consumed by machining operation, but cannot reduce the constant energy consumption such as the energy consumed for setting up the machine tool. The comparison between energy consumption and other criteria shows that energy is non-conflicting with the cost and time for all four independent variables. However, energy consumption is conflicting with cutting force in depth of cut and width of cut, surface roughness in width of cut and feed rate per tooth, tool life in spindle speed and feed rate per tooth, and power in all four independent variables.

4 INVESTIGATION OF OPTIMISATION METHODS

4.1 Development of Experimentation Rig based on Direct Search Method

The principle of direct search method is similar to full factorial DOE. Grids will be created based on numbers and levels of independent variables which represent all the possible solutions which will be used to create the experimentation rig. Table 3 shows a 3 levels DOE plan. 81 grids points will be created.

Table 3: 3 Levels Design of Experiment

Process Parameter	Level 1	Level 2	Level 3
Depth of cut a_p (mm)	1	3	5
Width of cut a_e (mm)	5	7.5	10
Spindle Speed n (rpm)	500	2250	4000
Feed rate f_z (mm/z)	0.01	0.055	0.1

The experimentation rig can be graphically displayed in Figure 2. The label of horizontal axis was removed since it only represents the numerical order of samples (1 to 81) which does not have any physical meaning. The original data after initial multivariate data analysis shows the energy consumption is changing with some pattern which can be displayed as dash squared areas to represent the original searching space of 3 level 4 variables full factor design. Each small dash square area contains 9 grid points which correspond to every 9 points on the original energy plot. The blue arrows shows the increasing direction of the 4 process parameters (e.g. No. 5 block contains the data when ap=3, n=2250, ae=5-10 and fz=0.01-0.1). The highlighted green area shows the data after being sorted with the increase of material removal rate per tooth (MRRz). The red curve shows the samples after being organised with continuing decrease of specific energy consumption.

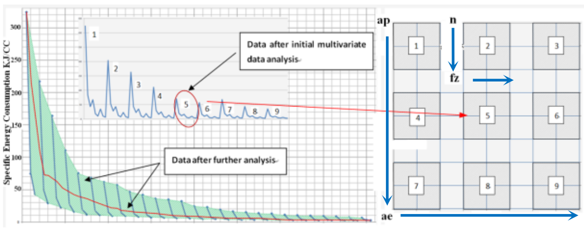

Figure 2: Experimentation rig of specific energy consumption.

4.2 Explanation of Taguchi Method

Taguchi method is an experiment-based optimisation method which uses a concept of “signal and noise (S/N)” ratio to evaluate the impact of the variables by considering the average value and standard deviation. For the objective of minimising energy consumption, the smaller the better equation will be chosen to calculate S/N ratio:

$$S/N_s = -10\log\left(\frac{1}{n}\sum_{i=1}^{n}Y^2\right) \quad (1)$$

Table 4 shows an L9 DOE plan according to Taguchi orthogonal experimental design. 9 out of 81 samples were selected to carry out the analysis.

Table 4: Experimental results of Taguchi method

Number	ap	ae	n	fz	SEC
1	1	5	500	0.01	323.945
2	1	7.5	2250	0.055	11.207
3	1	10	4000	0.1	4.274
4	3	5	2250	0.1	4.856
5	3	7.5	4000	0.01	11.855
6	3	10	500	0.055	12.761
7	5	5	4000	0.055	3.954
8	5	7.5	500	0.1	7.165
9	5	10	2250	0.01	10.265

The graphical explanation is shown in Figure 3. The black dots on the grids represent the selected samples in Table 5. From the observation of these dots, it can be found that each dot is located on a unique position of each dash area (e.g. upper left, middle, lower right). It means each level of parameters only interacts once, hence avoids overlapping consideration. The basic principle of Taguchi method is to use S/N ratio to analyse the fractional effect of the variables to identify which level of which parameter has greater influence on the machining performance. The optimal results then will be determined by adjusting cutting conditions based on the fractional effects. Figure 3 shows the analysing process of depth and width of cut. It can be found that the analysis follows the increase of the variables. It shows that the nature of the Taguchi method is actually the same as gradient search or feasible direction method.

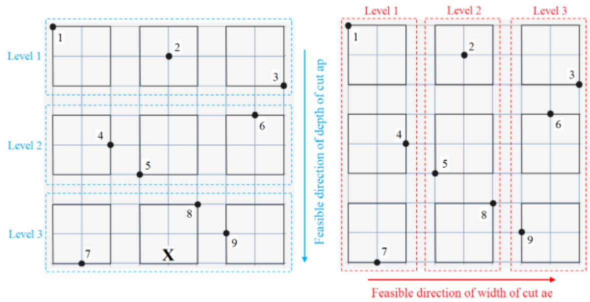

Figure 3: Display of Taguchi samples

In using the Taguchi method for optimisation of process parameters, the first observation obtained from the S/N plot of figure 4 is that optimal values of energy is obtained at the highest levels for all the 4 parameters. The second observation is that for improving the energy consumption it is more efficient to increase the process parameters in the order feed rate, depth of cut, spindle speed and lastly width of cut. While these observations can be obtained by other conventional data analysis methods as the characterisation of figure 1, the Taguchi method makes this information much clearer. However as pointed out in the literature, this usage of the Taguchi method for optimisation is only a first level approximation as it could miss the real optimal value. For example in figure 3, if the optimum is at point X, the optimum indicated by applying the Taguchi method as describe above will not be the real optimum. For cases like this the use of Taguchi method will require an iterative approach, in which the experiment is repeated in the vicinity of optimum obtained in a previous step. When the results obtained in this iterative application the Taguchi method are considered, the method will be it appears similar to the feasible direction or steepest ascent/decent optimisation methods.

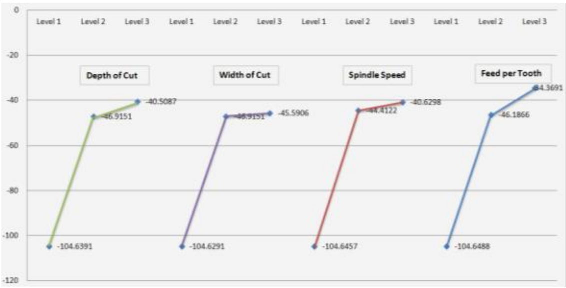

Figure 4: S/N ratios for process parameters.

4.3 Explanation of Genetic Algorithm (GA)

Table 5: Concept comparison between GA and machining

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

Table 5 shows the explanation of GA in machining terms. Typical GA-based optimisation steps and the explanation in machining optimisation terms are presented below.

1. Random selection of starting points (process parameters). It is difficult to find a completely random selection of starting process parameters in practical machining operation. Even for a novice practitioner who is working on new machining operations (e.g. new material, tool and machine tool) where the best process parameters are not known yet, the selection of the process parameters would be guided by suggestions from machining handbook, tool catalogue or the experience of senior practitioners. A possible explanation of this random selection cannot also be justified by a case of an intelligent machine tool designed to adaptively determine the cutting parameters since database values would usually provide initial values.

2. Generate new individuals by conducting crossover and mutation. The function of crossover is to rapidly explore a search space within the initial data range which is the same as changing the combination of process parameters to achieve the new machining plans. The function of mutation is to provide a small amount of random search which can expand the search space by extending data range. It is the same as replacing a process parameter with a new value (e.g. increase the depth of cut from 1mm to 3mm or vice versa) which leads to a new set. The randomisation explanation of step 1 applies here too.

3. Select and keep the best individual. The function of selection is to compare the machining plans and keep record of the optimal plans for further operation. The best machining plan can be determined by repeating above operations. Figure 5 graphically shows how the optimal result is obtained by using GA for an example. The optimal result can be determined after repeating the algorithm 4 times. The green dash arrow shows the overall search path of implementing GA which is similar to feasible direction optimisation method. However, the results obtained from crossover and mutation operations are not always positive. In this case, the actual optimisation path (grey arrow) is similar to hill climbing method which can determine the local optimal value within the data range. However, the repeated mutation operation can help jump out of previous local search space and eventually find the real optimal specific energy consumption.

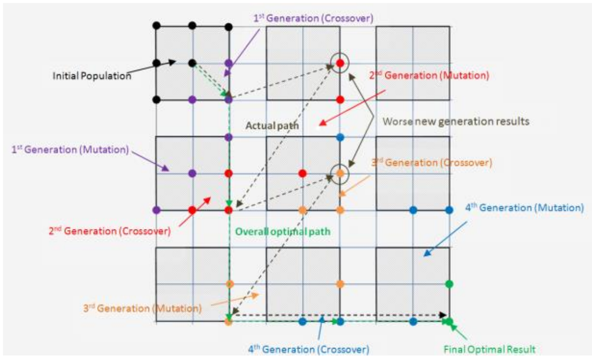

Figure 5: Determination of optimal results by using GA.

In addition, the sample size and location of the initial population also affect the performance especially the speed of optimisation process in terms of interaction numbers, number of generations and computing time. However, they will not affect the value of optimal results.

5 OPTIMISATION PROCEDURE

According to characteristics of machining operation, the optimisation procedure was conducted by using direct search algorithm. The optimal result is located on the boundary of the search space. Figure 6 shows 1 of the 9 solution landscapes for the 3 level, 4 variable energy-minimisation machining problem. In the figure, Specific Energy Consumption, SEC reduces with the increase in feed rate and spindle speed.

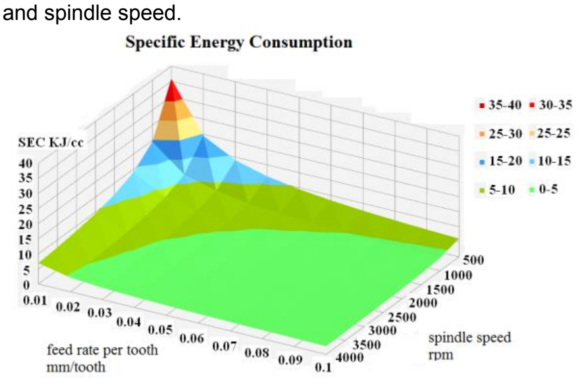

Figure 6: 3D Contour plot of SEC

Figure 7 shows search space with the constraints by the cutting force and surface roughness factor displayed. The green area represents the feasible region of search space when cutting force is no more than 400N and surface roughness is smaller than 0.05mm. So the optimal cutting condition based on energy consideration is the optimal points highlighted in the figure. The optimal result in Table 6 shows that over 80% of improvements in energy, cost and time can be achieved compared to machining handbook recommendation [18].

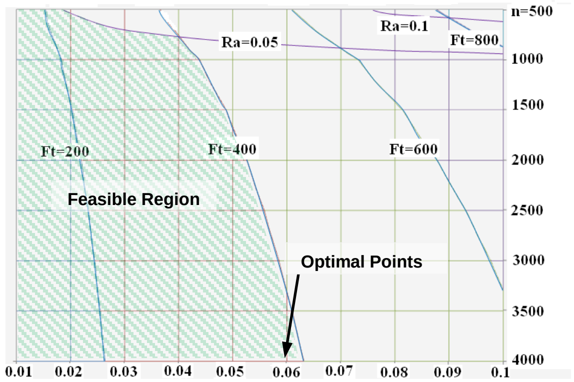

Figure 7: Constrained Optimal Results.

Table 6: Optimal Results Comparison

Variables	Handbook	Optimal	Improvement
ap (mm)	1	5	
ae (mm)	5	10	
n (rpm)	1500	4000	
fz (mm/tooth)	0.067	0.06	
Energy (KJ/cc)	18.612	3.079	83.46%
Cost (£/cc)	0.123	0.016	86.99%
Time(sec/cc)	43.968	5.833	86.73%

6 CONCLUSION

This paper presented a systematic research methodology for uncovering the reasons behind results obtained when energy is considered in machining optimisation. It provided the answers to the research questions in the following aspects:

- Energy consumption monotonously decreases with the increase of process parameters. It is non-conflicting with the cost and time, but conflicting with surface roughness, power requirement, tool life and cutting force.
- Explanation models developed show that Taguchi and GA are similar to feasible direction methods. The transparency from the explanations can help practitioners to trust and implement optimisation results.
- The constrained optimisation result shows that over 80% of improvement of energy, cost and time can be achieved by using optimal process parameters compared to machining handbook recommendation.

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