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Sustainable Optimization of Dry Turning of Stainless Steel based on Energy Consumption and Machining Cost

Salem Abdullah Bagaber[a,b] and Ahmad Razlan Yusoff[a]*

[a]*Faculty of Manufacturing Engineering, Universiti Malaysia Pahang, 26600 Pekan, Pahang, Malaysia*
[b] *Seiyun Community College, Seiyun, Hadhramout, Yemen*

* Corresponding author. Tel.: +609-424-5873; fax: +609-424-5888. E-mail address: razlan@ump.edu.my

Abstract

Reducing energy consumption and machining cost under dry conditions should be considered for sustainable machining. The selection of cutting parameters is an important task for dry turning steel and has a significant influence on energy consumption and operation cost. In this work, the influence of cutting parameters, namely, cutting speed, feed rate, and depth of cut, on energy, cost, and tool wear are first analyzed. A multi-response parameter is then optimized to minimize energy and machining cost, and this parameter is solved using the NSGA II algorithm. Finally, a confirmation validation test is conducted to validate the proposed model. This method also effectively reduces environmental effects by using noncutting fluid and requiring less energy than other methods, and this reduction results in sustainable machining.

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Keywords: cutting speed; feed rate; depth of cut; energy consumption; operation cost.

1. Introduction

Operation cost is an important factor that is used as an optimization response. The basic concept in any production process is to produce an acceptable component with the minimum possible cost [1]. Several measures, such as optimizing the cutting parameters, cooling system, energy consumption and tool life to minimize the production cost and maximize the production rate, are undertaken to achieve this objective. Several works regarding machining have been performed to reduce cost. More et al. [2] used Gilbert's approach to analyze the cost on the basis of the total machining cost between the cBN coated with PCBN in turning a AISI 4340 steel, similar to Sahoo [3]. Other research [4] used a polynomial network and multi-cutting production cost problems [5], developed cutting time and production cost models [6], and applied the simulated annealing approach to solve the optimization cost problem [7]. Various equations, namely, [2]–[4], [8] can express the machining cost of the manufacturing operation. Nonetheless, other machining elements, such as energy and cutting fluid costs, are not considered in these equations. The cutting tool factor is effective in cutting performance in terms of production rate, cost, and surface quality. This factor comprises 2%–4% of the total machining cost [9]. Results in [2] showed that the total machining cost per part using CBN–TiN-coated inserts is 12%–30% lower than that of PCBN-tipped tools. Lubrication fluids are also considered an additional product cost and negatively affect the environment [10], human health [11], and energy consumption [12]; the additional cutting cost is 7%–17% of the total cost. Environment cutting should be practiced whenever possible by performing dry cutting strategies, which are advantageous in terms of environmental impact and economic studies. Most previous cost models use Gilbert's approach. Hence, the completed cost objective for the turning process presented in this work considers the cost of energy consumption, edge cutting tool, and overall cost.

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Saving energy and reducing CO_2 emissions are currently the most important issues for manufacturers. Energy conservation machining systems can be divided into those that relate to new cutting technologies and those that consider the relationship between input cutting process parameters. Machining parameter condition and optimum value selection play important roles in decreasing energy consumption [13]. Hence, the second type of energy-saving improvement is the preferred choice for existing machines. However, only a few studies have considered energy saving in process optimization [14]. Rajemi et al. [15] developed an energy model by obtaining optimum machining conditions. A summary of these efforts for energy saving revealed that studies commonly applied experimental optimization methods to select the optimum cutting condition.

Analysis of the effect and appropriate selection of process parameters helps decrease power consumption [16], increase production rate [4], reduce cost and tool wear, and ensure quality. Multi-objective optimization simultaneously optimizes a collection of objective functions (i.e., surface roughness, energy, tool wear, and machining cost). Various multi-optimization techniques, such as response surface methodology, Taguchi method, and other statistical methods, have been studied [17], [18]. With the increasing use of evolutionary methods, new techniques for multi-response optimization are advanced to improve the single-optimization genetic algorithm to multi-objective genetic algorithm. NSGA II is one of the most remarkable evolutionary algorithms that is widely applied for multi-objective optimization.

Nevertheless, the proposed method is limited to a particular response. The multi-objective method and the mathematical optimum model of the machining process about cutting parameters are rarely studied. The energy of some elements is not considered. Consequently, a mathematical model for energy objective, including all machining tools and their functions correlated with the variable optimisation method, must be developed. Many studies have reported the performance of cutting processes on the basis of traditional objective optimization, and a few studies have investigated energy saving [14] and machining cost. Considering all machining tools and using different cutting tools under dry condition, no combined model of energy and cost objectives for the turning process has been presented yet. Therefore, the multi-optimization proposed in this research is necessary to consider the trade-off for a balance between process efficiency and environmental issues. In the present study, the NSGA II is used to determine the Pareto solutions of the optimum parameters of multi-optimization models.

2. Experimental details

2.1. Experimental setup

Turning operations are considered to study the effect of cutting parameters on tool wear, energy consumption, and cost. A stainless steel cylindrical workpiece with 20 mm cutting length is turned. The workpiece is machined on a turning CNC 420 with a rotating speed range of 100–4,000 r/min. The CBN cutting tool used for this study is designated as ISO CNMG 120408, with a sharp 80° diamond tip and 0° relief angle. Figure 1 presents the experimental setup, equipment, workplace, and data flow.

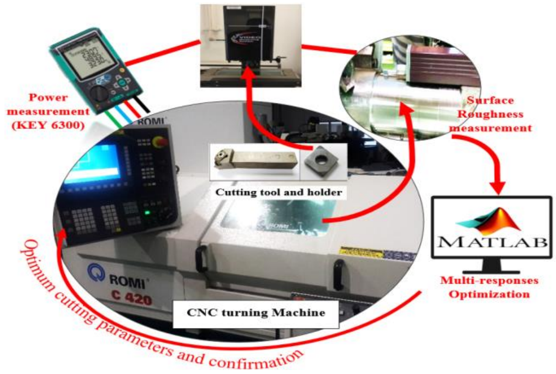

Figure 1. Experimental setup

2.2. Methodology

The experimental details of using the design expert to determine and analyze the cutting parameter range are presented. The multi-optimization proposed in this present study is based on a mathematical model for energy and cost objectives and correlated with the variables cutting speed, depth of cut, and feed rate during the turning of AISI 316 under dry conditions. Afterward, the optimum range results obtained by NSGA II and results are experimentally evaluated and verified.

The machining parameters and the corresponding tool wear, cost, and energy values obtained in this study are shown in Table 1.

Table 1. Machining parameters and obtained responses

Run	v	fr	a_p	Tool wear (mm)	Energy consumption (kWh)	Machining cost (RM)
1	140	0.15	1.1	0.115	0.771	18.30
2	140	0.06	1.1	0.0959	1.631	35.14
3	90	0.15	1.1	0.0952	1.089	22.27
4	110	0.2	1.4	0.0926	0.813	16.95
5	170	0.1	0.8	0.1148	0.838	21.26
6	110	0.1	1.4	0.105	1.360	27.61
7	190	0.15	1.1	0.1437	0.621	17.86
8	140	0.15	1.6	0.131	0.884	19.24
9	170	0.2	0.8	0.0996	0.485	14.96
10	170	0.2	1.4	0.157	0.620	16.63
11	140	0.23	1.1	0.0926	0.572	14.78
12	140	0.15	1.1	0.1096	0.771	18.30
13	140	0.15	1.1	0.1296	0.771	18.30
14	140	0.15	1.1	0.103	0.771	18.30
15	110	0.1	0.8	0.1074	1.224	26.64
16	140	0.15	1.1	0.116	0.771	18.30
17	140	0.15	0.6	0.106	0.658	16.99
18	110	0.2	0.8	0.0833	0.677	15.86
19	170	0.1	1.4	0.123	0.974	22.73
20	140	0.15	1.1	0.1296	0.771	18.30

2.3. Energy and cost models

The total energy consumed during dry turning machining can be calculated on the basis of Equation 1.

$$E_{dry}\, P_0 t_0 + P_{st} t_{st} + P_{air} t_{air} + P_{air} \frac{\pi.D.l}{v.f} + k\, \frac{\pi.D.l.a_p}{60}\, P_{st} t_t \left(\pi.D.l.v^{(\alpha-1)}.f^{(\beta-1)} a_p{}^{\gamma}.c^{-\alpha}\right) \quad (1)$$

where E_{dry} is the direct total energy requirement for dry cutting; P_0, P_{st}, and P_{air} (watts) are the power requirements of the machine during start-up, setup state, and rotating spindle without cut state, respectively; D is the average diameter of the workpiece (mm); l is the length of cut (mm); t_0, t_{st}, t_{air}, t_t, and t_c (s) are the start-up, setup, rotating spindles without cut state, tool change time, and cutting time, respectively; and k is the specific energy requirement in cutting operations (kJ/cm^3).

Equation 2 presents the machining cost of the dry turning process.

$$C_{total/dry} = x_eP_0t_0 + x_eP_{st}t_{st} + x_eP_{air}t_{air} + x_eP_{air}\frac{\pi.D.l}{v.f} + x_ek\left(\frac{\pi.D.a_p.l}{60}\right) + x_eP_{st}.t_t\ \left(\pi Dlv^{(\alpha-1)}f^{(\beta-1)}a_p{}^{(\gamma)}.c^{-\alpha}\right) + x\left(t_0 + t_{st} + t_{air} + t_t + \frac{\pi.D.l}{v.f}\right) + (x\,t_t + y)\left(\pi Dlv^{(\alpha-1)}f^{(\beta-1)}a_p{}^{(\gamma)}c^{-\alpha}\right) \quad (2)$$

where x, denotes the estimated total cost of labor charge, machine charge, and overhead; x_e is the energy cost rate; c is the coefficient related to the cutting conditions; α, β, and γ are positive constant parameters depending on tool material and workpieces.

Certain data, parameters, and coefficients must be determined in advance to implement the multi-optimization of energy and cost model. Start-up energy, start-up, setup state, and rotating spindle without cut state should be obtained as energy data. The cost of cutting tool, machining cost, and energy consumed cost should also be determined. According to a mechanical engineering manual and Kalpakjian and Schmid[9], the coefficients in the optimization model, including α, β, γ, c, n, x, y, and k, are determined, and on the basis of the current machining practice, the total charge (x) of the labor charge, machine charge, and overhead is estimated as RM 25 per hour. The cost of power *(x_e)* is 6.91 cent/kWh, and the single-tip uncoated carbide tool (CNMG 120408) costs RM 28.5 per piece. Therefore, the mean value of a single uncoated cutting edge (y) is RM 14.25. According to these data, the optimization model for the multi-objective problem for dry condition can be established as follows*:*

$$C_{total/dry} = 23.2 * 10^{-4} + 15.25 * 10^{-3}a_p + 253v^{-1}f^{-1} + 800 * 10^{-3}a_pv^{-1}f^{-1} + 12 * 10^{-3}a_p^{0.3}vf^{0.2} \quad (3)$$

$$E_{total/dry} = 0.03364\ +\ 12.036 \times \left(\frac{1}{v.f}\right) +\ 0.226 *\ a_p +\ 9.49 * 10^{-6}a_p^{0.3}vf^{0.2} \quad (4)$$

which is subject to the following:

$0.6 \leq a \leq 1.6$;
$90 \leq v \leq 190$;
$0.06 \leq f \leq 0.23$.

3. Results and discussion

3.1. Evaluation of tool wear

The flank wear results are provided in Figure 2. A maximum flank wear of 0.3 mm is used as the tool life [17]. The main effects are presented by a continuous line, whereas the parallel line presents the prediction results. The results show that the speed and depth of cut are the most significant parameters, whereas feed has no influence. The cutting conditions are cutting speed of 110 m/min, feed rate of 0.2 mm/rev, and depth of 0.6 mm.

3.2. *Evaluation of energy and cost*

Figure 3 shows the plot for energy consumption. The feed rate and cutting speed show a negatively significant effect, whereas the depth shows a positively significant effect. This plot indicates that the feed rate factor is more significant than the other parameters. This result shows that the energy value significantly decreases from 1.18 kWh to 0.7 kWh when the feed changes from low to high level. Similar results were reported in [14,15].

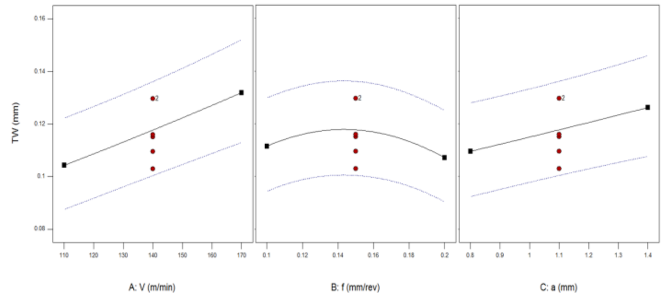

Figure 2. Effect on tool wear against parameters

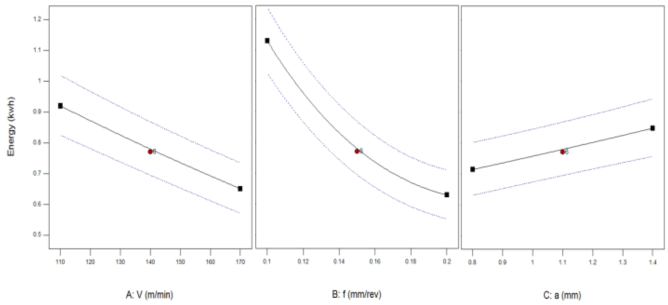

Figure 3. Effect on energy consumption against parameters

Figure 4 presents the influence of cutting parameters on machining cost. Among the input parameters, feed rate and cutting speed exhibit the most significant factor relationships sequentially. Moreover, the depth of cut exerts no influence on machining cost.

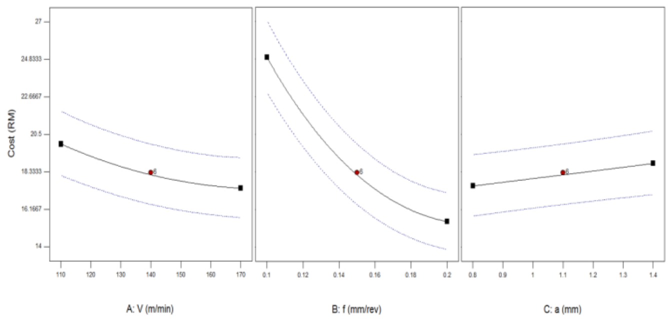

Figure 4. Effect on cost against parameters

3.3. Multi-objective optimization-based NSGA II algorithm

The Pareto optimal front is obtained by the multi-objective optimization-based NSGA II algorithm (MO-NSGA II). MATLAB R2013 is used to plot the Pareto optimal front and simulate the multi-optimization model. Notably, this front lies in the middle of the curve for problems where all two objectives are to be minimized. The proposed model minimizes the value of machining cost (i.e., Objective 1) and energy consumption (i.e., Objective 2). In this multi-optimization, two models are applied under the same machining process and conditions using NSGA II, where the optimization options are set as follows: 1,000 population size; 0.9 crossover probability; 0.1 mutation probability; and 200 iterations. Figures 5 shows that the Pareto optimal front resembles a slight curve, which indicates the reduction at the peak of the Pareto bend between Objectives 1 and 2. Table 2 provides the function and variable values, including the five most remarkable optimal points, and the optimum machining parameters obtained are as follows: v=116 m/min, f=0.195

mm/rev, and a_p = 0.818 mm, whereas the optimal objective values are 0.513 kWh and RM 14.951.

3.4. Verification result

The present results obtained are verified using two approaches. The first approach is standard error calculated on the basis of predicted test. Equation 5 is used to estimate the optimum predicted response values to verify the model developed by multi-objective NSGA II as follows:

Table 2. Response values and decision variables by NSGA II

Energy(kWh)	*Cost(RM)*	*V(m/min)*	*F(mm/rev)*	*a_p(mm)*
0.513	14.951	116.00	0.195	0.818
0.516	14.914	116.20	0.191	0.816
0.521	14.954	116.45	0.192	0.812
0.529	15.013	116.20	0.191	0.816
0.527	15.021	115.45	0.192	0.812

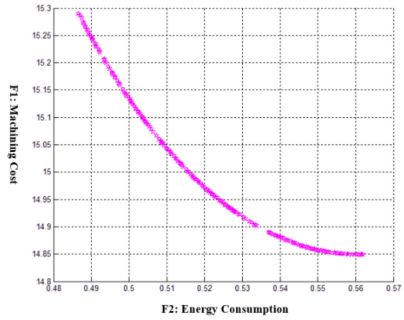

Figure 5. Pareto chart of multi-responses for models (F1 unit: RM and F2 unit: kWh)

$$Y_{predicted} = Y_{mean} + \sum_{i=1}^{n}(Y_i - Y_{mean}) \quad (5)$$

where Y_{mean} is the overall mean value and Y_i is the average response at the optimum design variable level. The obtained results are 0.0425 (95.75%) and 0.0733 (92.66%) for energy and cost, respectively. From the accuracy percentage, good agreement is noted between the predicted and experimental optimum results.

In the second approach, the average value of the center point is selected for the initial setting and compared with the optimal point obtained. The results of the confirmation test show an improvement in energy saving of 33.46%, and the machining cost is reduced by 17.81%. The results obtained with the multi-optimization parameter setting by using NSGA II methods for energy consumption and machining cost are better than those from the initial setting.

4. Conclusions

This study provides a new model that is based on a multi-response optimization method of machining parameters. The optimization problem includes minimum energy consumption, machining cost, and tool wear, which are influenced by cutting speed, feed rate, and depth of cut. The main effect plot presents the response mean for each factor level. The minimum value of power consumption is obtained at high cutting speed and feed rate and low depth of cut. This significant energy result is the same as that of machining cost. Tool wear is minimized when the cutting speed and depth of cut are at their lowest levels. The NSGA II results indicate that cutting parameter optimization is beneficial for cost and energy saving during turning machining. The energy saving is 33.46%, and the machining cost is reduced by 17.81%. The proposed model effectively minimizes machining cost and energy, thereby resulting in the overall enhancement of sustainable machining.

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