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ORIGINAL ARTICLE

Multi-criteria end milling parameters optimization of AISI D2 steel using genetic algorithm

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Abstract This paper focuses on using multi-criteria optimization approach in the end milling machining process of AISI D2 steel. It aims to minimize the cost caused by a poor surface roughness and the electrical energy consumption during machining. A multi-objective cost function was derived based on the energy consumption during machining, and the extra machining needed to improve the surface finish. Three machining parameters have been used to derive the cost function: feed, speed, and depth of cut. Regression analysis was used to model the surface roughness and energy consumption, and the cost function was optimized using a genetic algorithm. The optimal solutions for the feed and speed are found and presented in graphs as functions of extra machining and electrical energy cost. Machine operators can use these graphs to run the milling process under optimal conditions. It is found that the optimal values of the feed and speed decrease as the cost of extra machining increases and the optimal machining condition is achieved at a low value of depth of cut. The multi-criteria optimization approach can be applied to investigate the optimal machining parameters of conventional manufacturing processes such as turning, drilling, grinding, and advanced manufacturing processes such as electrical discharge machining.

Keywords End milling · AISI D2 steel · Surface roughness · Energy consumption · Genetic algorithm

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Nomenclature

GA	Genetic algorithm
n	Number of bits for each variable
w	Rotational speed, rpm
f	Feed rate, mm/min
d	Depth of cut mm
D	Target depth, cm
P_d	Power dissipation, Watt
E	Energy dissipation, kWh
t	Machining time, hr
T	Torque in the cutting tool, N.cm
N	Number of passes
t_p	Time per pass, hr
R_a	Average surface roughness, μm
R_{a0}	Target average surface roughness, μm
K_1	Unit cost factor of surface roughness, US$/μm.m^2
K_2	Unit cost factor of energy dissipation, US$/kWh
X_A	Actual value of decoded variable
X_L	Lower limit of variable
X_U	Upper limit of variable

1 Introduction

AISI D2 is an air-hardened steel that has many applications such as in the manufacturing of stamping or forming of dies. End milling is one of the most common machining operations used in AISI D2 steel fabrication. It is a preferred process when a high surface quality is required. The machining of steel using the end milling process has been investigated by different researchers and has been extensively reviewed by Dewes and Aspinwall [1].

Determining optimum machining parameters are very important in manufacturing where the lower cost of machining operations can lead to a competitive advantage [2]. Moreover, the selection of optimal machining parameters leads to quality improvement [3]. Machining parameters are usually selected by operators based on their experience or by referring to machining handbooks. However, the optimum values are not usually guaranteed by such selection methods [4].

Achieving optimal machining parameters in milling operations by minimizing the surface finish has also been investigated by different researchers. Vivancos et al. [5] presented a mathematical model to optimize machine parameters of a high-speed milling of hardened steels used for injection molds. A factorial design was used to model the behavior of the surface roughness as a function of speed, feed, and depth of cut. Öktem et al. [6] used a response surface methodology to determine the optimum cutting conditions for the surface roughness in milling mold surfaces. They combined the surface response methodology with the genetic algorithm. Their hybrid methodology improved the surface roughness by 10 %. Yildiz [7] used a novel approach by combining the immune and the hill climbing local search algorithms to optimize the machining parameters of milling operations. He concluded that this approach could be used as an alternative to the traditional machining handbooks. A neural network was used by Zain et al. [8] to predict the surface roughness performance in milling processes. They used different network topologies for the input, hidden, and output layer. They found that the 3-1-1 structure is the best artificial neural network structure to predict the surface roughness.

Surface finish is mainly used for predicting machining quality. Mechanical properties such as wear and corrosion are highly affected by the surface finish. Many product properties such as surface friction, heat transmission, fatigue resistance, and coating acceptance are affected by the quality of the surface finish [9]. Average surface roughness is one of the main components used to quantify surface finish.

There are many parameters that can affect the value of the surface roughness, which Benardos and Vosnaikos [10] have listed in a fishbone diagram. The most important machining parameters that affect the machining process are the spindle speed, feed rate, and depth of cut. Rashid et al. [11] used the Taguchi method to determine the optimal cutting parameters (feed, speed, depth of cut, and tool diameter) for AL 6351-T6 using a CNC vertical milling machine. Ozcelik and Bayramoglu [12] developed a statistical method for estimating the surface roughness in a high-speed flat end milling under wet cutting conditions. They ranked the spindle speed, feed rate, depth of cut, and step over machining variables according to their significance in determining the surface roughness. Ghani et al. [13] used the Taguchi method to optimize the end milling parameters. They found that the optimal solution is guaranteed by running the milling process at a high cutting speed, a low feed rate, and a low depth of cut. Vivancos et al. [14] showed that speed, feed, and depth of cut are the most influential factors affecting the surface roughness in a high-speed side milling of a hardened die steel.

Reducing the energy consumption by the manufacturing processes has been driven by the increasing awareness of environmental concerns. The electrical energy consumed by the manufacturing processes has a considerable effect on the environment [15]. Different approaches have been investigated to estimate the energy consumption in a manufacturing environment. Some approaches estimate the energy consumption during the life cycle of a product. Pineda-Henson and Culapa [16] used the analytical hierarchy technique (AHP) to estimate the energy consumption of products throughout the entire manufacturing process. Heet al. [17] proposed a modeling method to determine task-oriented energy consumption. They used an event graph approach to model the energy consumption as discrete events driven by task flow. Rahimifard et al. [18] presented an approach to energy-efficient manufacturing where they suggested a detailed breaking down of the energy usage of products throughout the entire production process. Fang et al. [19] used a mixed integer programming formulation of the job shop scheduling problem to minimize energy consumption and the associated carbon footprint.

In addition, the energy consumed due to the cutting forces required to accomplish machining processes has also been studied. Kara and Li [20] used the design of experiments to model the energy requirements for the material removal based on the process variables of speed, feed, and depth of cut under wet and dry cutting conditions. Newman et al. [21] developed a theoretical framework to include the energy consumption produced from cutting processes in a multi-criteria process planning. Bhushan [22] used the response surface methodology to optimize the cutting conditions of speed, feed, depth of cut, and nose radius in a CNC turning of 7075 Al alloy by power consumption and tool life.

Different conventional and nonconventional techniques have also been used to optimize cutting conditions in milling operations. Soft computing approaches such as genetic algorithms (GAs) are more recent trends for optimizing the machining process [23]. GA is a technique that mocks the process of natural evolution to optimize multidimensional nonlinear problems.

Optimizing machining parameters using genetic algorithms has been reported by different researchers. The technique was used for different machining processes such as end milling [24, 25], turning [26–28], drilling [29], electrochemical machining [30], grinding [31], and electrical discharge machining [32]. The researchers investigated different machining parameters to form the optimization objective functions. The feed, speed, and depth of cut are mainly the process parameters used in the end milling and turning optimization. Other parameters were used such as rake angle in end milling and coolant pressure in turning. Different objective functions were used such as machining time, surface roughness, production cost, cutting temperature, torque, and tool wear.

This work is different than previous works as it attempts to optimize two conflicting criteria in milling AISI D2 steel. It aims to maximize surface quality while minimizing electrical energy consumption. It combines two objective functions to solve for the optimal machining conditions. The objective functions are simultaneously optimized to reduce the cost associated with a poor surface finish and the energy consumption of milling AISI D2 steel. Optimization is performed using genetic algorithm. A predictive model for each of the objective functions is obtained using multiple regressions.

2 Methodology

Experimental results were used to model the average surface roughness and energy consumption. Two regression models were built based on the experimental data collected for the regressor variables feed, speed, and depth of cut and the two responses average surface roughness and energy consumption. A cost objective function combining the two regression models was also constructed and optimized using a genetic algorithm.

2.1 Case study

A CNC machine was used to perform the end milling process on AISI D2 steel. The AJAX AJ540 CNC machine was used with a maximum cutting speed of 5,000 rpm. Ceramic cutting inserts (TCMT16T308E PFZ) were used to conduct the machining operations and a double-insert tool holder with a 6-cm diameter was used.

The data were collected for four levels of the machining factors under consideration as shown in Table 1. The levels are deterministic and selected based on a common range used in a milling process. More levels of machining variables are preferred to increase the regression model accuracy. From a practical point of view, only four levels of each variable are considered to reduce the experimental runs. A 4^3 full factorial design of experiment with three replicates is prepared randomly for each run. A total of 192 observations were collected on 12×10×3 cm D2 steel samples using different cutting speeds, feed rates, and depths of cut in a dry environment. The target depth of cut (D) for each experimental run was set to 0.6 mm.

A force dynamometer was used to measure the torque on the cutting tool. The dynamometer was attached to the cutting tool and connected to a data acquisition system. The torque acquired by the data acquisition system is represented by a cloud of points as shown in Fig. 1. Each point in the cloud represents the torque recorded at a specific time based on a sampling rate set by the user. A smaller sampling rate produces denser cloud but requires more time to collect and analyze. The sampling rate was selected to acquire a reasonable amount of data without sacrificing accuracy. Variations in the torque data are caused by different factors such as material resistance to torque and the degree of insert wear. To reduce the effect of insert wear, a new insert was used every 20 runs. The average torque from the cloud was recorded as a response for each experimental run. A dynamometer calibration was performed at each run. The datum of the torque was set to 30 N cm.

The machine tool removes material of a 50×60 mm area at each pass. The schematic of the machining process is shown in Fig. 2. Machining was interrupted periodically to measure the average surface roughness using a stylus-type profilometer.

2.2 Calculations of the energy consumption

To find the relationship between the input variables (d, f, w) and the energy E consumed during the machining, the torque (T) in newton centimeter was transformed into electrical energy in kilowatt-hour using the following calculations:

$$P_d = Tw \tag{1}$$

Where P_d is the power and can be expressed in watt as:

$$P_a(\text{watt}) = \frac{T(\text{N.cm})w(\text{rpm})2\pi(\text{radiane/rev})}{60(\text{sec/min})100\text{cm/meter}} = \frac{\pi Tw}{3,000} \tag{2}$$

$$E = P_d t/1,000 \tag{3}$$

t is the machining time in hours and can be calculated as:

$$t = Nt_p \tag{4}$$

Table 1 Machining factors and their levels

Level	Depth of cut "d" (mm)	Feed rate "f" (mm/min)	Cutting speed "w" (rpm)
I	0.05	25	500
II	0.10	50	750
III	0.15	75	1,000
IV	0.20	100	1,250

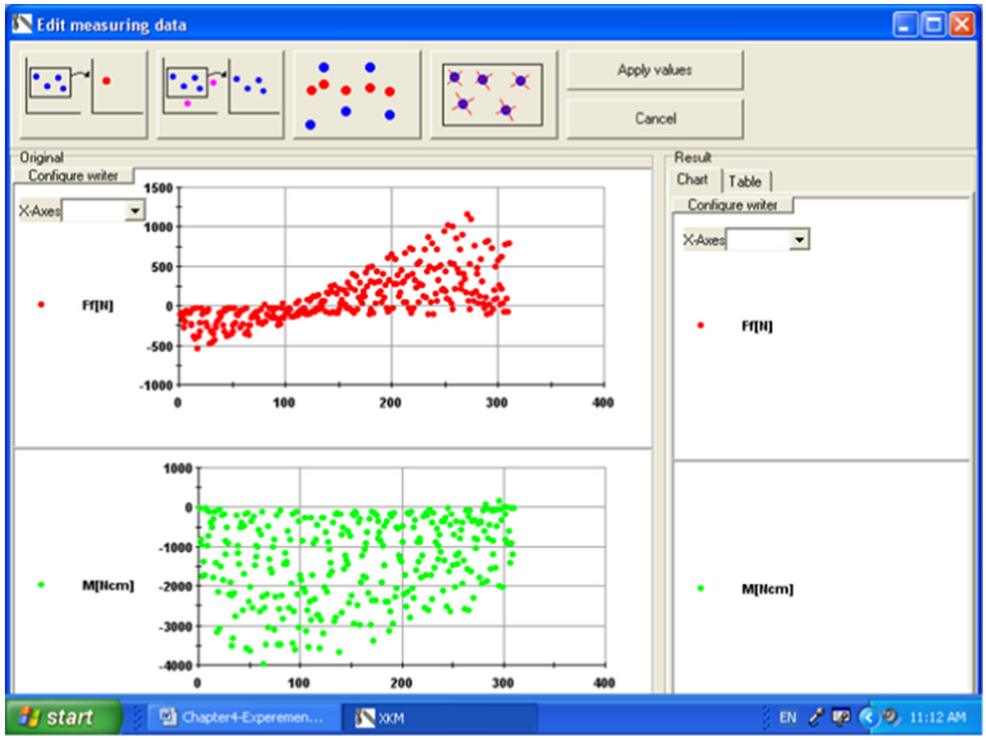

Fig. 1 Torque cloud at each run

N is number of passes and t_p is the time per pass and can be calculated as:

$$N = D/d \quad (5)$$

D is the target depth and d is the depth of cut

$$t_p = \text{travel distance}/\text{feed rate} \quad (6)$$

The travel distance for each pass is 60 mm, so t_p can be rewritten as:

$$t_p = 60/f \quad (7)$$

Since the travel distance in millimeter and the feed rate in millimeters per minute, t_p is in minutes. It can be expressed in hours as:

$$t_p = (60/f)\ (1/60) = 1/f \quad (8)$$

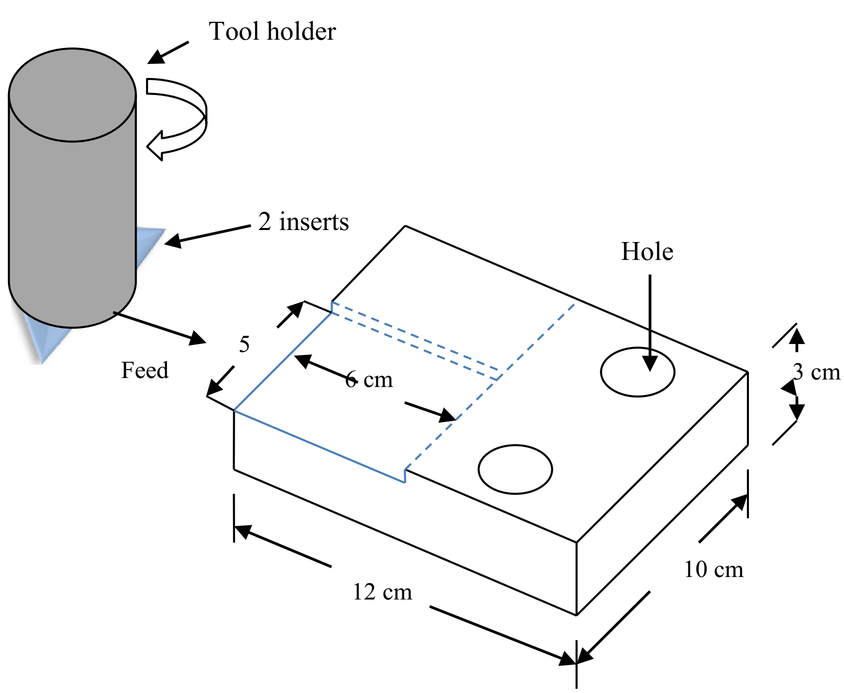

Fig. 2 Machining process schematic

The machine time t can be rewritten as:

$$t = \frac{D}{fd} = \frac{0.6}{fd} \tag{9}$$

The energy consumed in kilowatt-hour is:

$$E = \frac{\pi T w}{5,000,000 fd} \tag{10}$$

The electrical energy consumed is the pure mechanical energy due to machining without regarding the machine efficiency.

2.3 Regression model

A multiple regression analysis was carried out on both the surface roughness and energy consumption as a function of feed, speed, and depth of cut. Different models were tested to select the best predictive model. The full quadratic model was used to represent the surface roughness and energy consumption. The terms in the quadric model include linear terms (f, w, d) square terms ($f*f$, $w*w$, $d*d$) and interaction terms ($f*w$, $f*d$, $w*d$). The F test is used to determine the contribution of these terms to the model. Each term is considered insignificant if the p value of the test is greater than a significant level (α). At a significant level α of 0.1, some of the terms are found to be insignificant and dropped from the models. Table 2 Shows the Minitab regression's output for the surface roughness. As can be seen, the p values of the quadratic term ($d*d$) and the intersection ($w*f$, $w*d$) terms are greater than 0.10. All these terms were dropped from the model, and Table 3 shows the ANOVA output of the least square coefficients estimates and their corresponding confidence intervals. The final predictive model is presented in Eq. 11. Using the same procedure, the energy consumption predictive model is found with ANOVA output shown in Table 4 and the model is presented Eq. 12.

$$R_a = 6.25763 - 0.00479592w - 0.0360092f - 1.53167d + 2.175 \times 10^{-6} w^2 + 2.3548 \times 10^{-4} f^2 + 0.090827 fd \tag{11}$$

$$E = 0.076699 + 0.000293871w - 0.00412254f - 1.4275 \times 10^{-7} w^2 + 0.00002309 f^2 \tag{12}$$

The energy consumption is based on material removal of 0.003 m^2 (60×50 mm). The energy consumption for removing 1 m^2 is calculated by multiplying Eq. 12 by 1,000/3.

2.3.1 Model verification

Several assumptions of the regression model are needed to be verified before building the cost function. A residual analysis and mutli-colinearity test is used to check for model adequacy. Figure 3 shows the residual plots of the surface roughness. Residuals appear to be normally distributed as shown by the normal and histograms plots and are largely random (shown by residuals against their fitted values and in their observation order). The variance inflation factor (VIF) is used as an indicator for mutli-colinearity. Mutli-colinearity exists when VIF is greater than 4. As shown in Table 2, all VIF values are less than 4 for all significant terms. The coefficient of determination R^2 of the surface roughness model is 82.8 % indicating that the mode has a good fit. Model adequacy for the

Table 2 Regression output of the surface roughness quadratic model

Source	df	Adj SS	Adj MS	F	p	VIF
Regression	9	195.161	21.6846	95.9470	0.000	
Linear	3	125.504	41.8346	185.1044	0.000	
W	1	73.621	73.6212	325.7496	0.000	2.11
F	1	13.072	13.0723	57.8406	0.000	1.57
D	1	38.810	38.8104	171.7230	0.000	1.88
Square	3	48.392	16.1307	71.3729	0.000	
$w*w$	1	23.979	23.9790	106.0991	0.000	12.53
$f*f$	1	23.893	23.8930	105.7186	0.000	10.87
$d*d$	1	0.519	0.5190	2.2964	0.130	3.64
Interaction	3	21.265	7.0884	31.3637	0.000	
$w*f$	1	0.497	0.4970	2.1991	0.140	3.21
$w*d$	1	0.521	0.5210	2.3053	0.130	5.36
$f*d$	1	20.247	20.2471	89.5868	0.000	1.82
Residual error	179	40.455	0.2260			
Total	188	235.616				
R^2	82.8 %					

Table 3 ANOVA table for the surface roughness least square predictive model

Term	Coef	SE Coef	T	p	95 % CI	
Constant	6.25763	1.04591	5.982953	0.000	4.19405	8.32121
w	−0.0047959	0.00213	−2.2516	0.026	−0.009	−0.00059
f	−0.0360092	0.01639	−2.19702	0.029	−0.06835	−0.00367
d	−1.53167	0.753774606	−2.032	0.043	−3.01887	−0.04447
$w*w$	0.000002175	9.8312E−07	2.212345	0.028	2.35E−07	4.11E−06
$f*f$	0.00023548	0.000088	2.675909	0.008	6.19E−05	0.000409
$f*d$	0.09332	0.03801	2.455143	0.015	0.018326	0.168314

energy regression model is verified using the same procedure. The results are omitted to avoid repetition.

2.4 Objective function

The objective function is the combined cost based on the energy consumption and the extra machining required due to a poor quality of the surface roughness. Extra machining cost can be seen as the cost to reduce the surface roughness. The combined cost C_c (US\$/m^2) can be expressed as:

$$C_c = K_1(R_a - R_{a0}) + (K_2E) \tag{13}$$

where R_{a0} is the target value of surface roughness at which the product is considered with acceptable quality in terms of surface finish. The extra machining cost factor K_1 can be defined as the machining cost of reducing the surface roughness of 1 m^2 of the AISI D2 steel by 1 μm. K_2 is the cost factor associated with the energy consumption E. It is the cost in dollars of 1 kWh paid for the electric power company. While R_{a0} is specific for a job order, K_1 and K_2 are specific for a machining center.

3 Optimization by genetic algorithm

Genetic algorithms are heuristic search algorithms used for optimization by mimicking the processes of natural evolution. They perform a random search within a defined search space to solve a problem. The searching procedure starts with an initial set of random solutions represented by binary strings called chromosomes.

3.1 Parameter bounds

Genetic algorithms require boundary constraints. The lower and upper limits of the parameters were selected for the material and cutting tool to simulate the actual production. The constraints for feed, speed, and depth of cut are as follows:

$$25 \le f \le 100 \tag{14}$$

$$500 \le w \le 1250 \tag{15}$$

$$0.05 \le d \le 0.2 \tag{16}$$

One more constraint was added to avoid a negative cost is:

$$R_a - R_{a0} > 0 \tag{17}$$

3.2 Encoding

Each solution point is encoded in a string (chromosome). The chromosomes consist of bits of binary numbers. In this work, a binary chromosome of three genes is constructed with a total length of 30 bits. Each machining

Table 4 ANOVA table for the energy consumption least square predictive model

Term	Coef	SE Coef	T	p	95 % CI	
Constant	0.07769	0.0377	2.060743	0.0400	0.003277	0.152072
w	0.0002938	0.000084	3.497619	0.0006	0.000128	0.00046
f	−0.004122	0.000603	−6.83582	0.0000	−0.00531	−0.00293
$w*w$	−0.00000014	6.034E−08	−2.32	0.0201	−2.6E−07	−2.1E−08
$f*f$	0.00002309	0.0000048	4.810417	0.0000	1.36E−05	3.26E−05

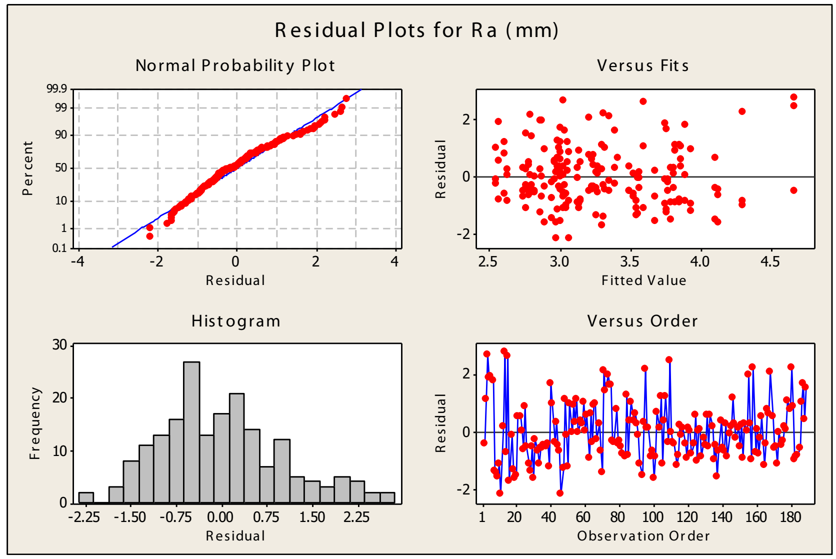

Fig. 3 Residual plot for surface roughness

variable is represented by 10 bits. Figure 4 shows an example of a chromosome.

3.3 Generations of initial population

In this step, a population of a fixed number of chromosomes is defined. Each bit in every chromosome is assigned randomly by a 0 or 1. The current chromosomes are considered the initial solutions for the objective function. In this research, the population size is limited to 20 chromosomes.

3.4 Decoding

Chromosomes in the initial population are decoded to decimal values. The decimal values are transferred to the actual values between the upper and lower values of the machining variables using the following formula [33]:

$$X_{\mathrm{act}} = X_L + \frac{(X_U - X_L)}{2^n - 1}(\text{Decoded value}) \qquad (18)$$

where:

X_{act}	The actual value of the variable
X_L	The lower limit of the variable
X_U	The upper limit of the variable
N	The substring length (=10) for each variable
Decoded value	The transformed decimal value of the binary numbers

3.5 Evaluation

Evaluation is the step to find the chromosome with the optimal fitness function $f(x)$. In maximization problems, $f(x)$ is the same as the objective function $g(x)$. For minimization problems, the fitness function is transformed to:

$$f(x) = \frac{1}{1 + g(x)} \qquad (19)$$

To minimize the combined machining cost C_c, the fitness function can be written as:

$$f(x) = \frac{1}{1 + C_c} \qquad (20)$$

The maximum value of $f(x)$ occurs when C_c is at its minimum and the minimum value occurs when C_c is at its maximum value. As C_c goes to 0, $f(x)$ goes to 1. On the other hand, as C_c goes to ∞, $f(x)$ goes to 0. The range of $f(x)$ will be between 0 and 1 with 1 being the best possible machining quality (minimum surface roughness and energy consumption).

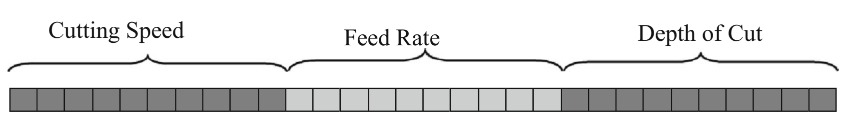

Fig. 4 An example of a chromosome

3.6 Selection method

In this step, chromosomes from the current population are selected for the reproduction of the next generation. Different selection methods are listed in the literature which includes proportional selection, tournament selection, truncation selection, roulette wheel selection, and ranking selection [33]. The ranking selection method is used in this research. Populations are ranked based on the order of its fitness. Chromosomes with higher ranks have a higher probability to be selected as parents to produce the next generation.

3.7 Reproduction (crossover and mutation)

New generations of chromosomes are reproduced from parents' chromosomes by crossover and mutation operation. Generally, crossover involves exchanging bits to selected parents at a single point randomly chosen along the bit strings. Figure 5 shows an example of a random crossover. The bits on the right side of the mating point are exchanged forming new chromosomes.

Mutation is the alteration of the value of a string position. A portion of the new individuals will have some of their bits swapped from 1 to 0 or vice versa. The mutation process is only performed randomly on the child chromosomes using a certain probability distribution. Figure 6 shows an example of a mutation operation.

The new offspring obtained from the crossovers and mutations are treated as parents for the second iteration. The objective function and the corresponding fitness value are calculated for the new generation. The procedure is repeated until the termination criteria are satisfied.

3.8 Algorithm termination

Termination is the step by which the genetic algorithm stops and returns the current chromosomes as the optimal solution. It can be performed by different methods such as number of generations limit, time limit, and fitness threshold. In this research, fitness threshold of 1×10^{-6} is used to terminate the algorithm within a maximum of 10,000 generations.

4 Results and discussion

To implement the methodology, K_1, K_2, and R_{a0} should be identified. These factors depend on the machining cost for a particular machining center and the acceptable surface finish of a particular job order. The range of optimal machining parameters was found using different values of K_1, K_2, and R_{a0}. K_1 was selected from US\$0.2 to US\$100/m^2 as the cost for reducing the surface roughness by 1 μm while K_2 was selected from US\$0.05 to US\$0.3 kWh. The range of K_2 is selected to cover the common electricity cost charged by the electric power companies worldwide. The optimal solutions for all combinations were investigated. The combined cost was optimized using a genetic algorithm simulator designed in this research. The genetic algorithm parameters such as population size, number of generations, mutation probability, and crossover were set by the user. Different parameter values were tested and reached the same optimal solutions with negligible variations. The final crossover and mutation probabilities were set to 0.6 and 0.2, respectively. A large number of optimum machining parameters were found for different combinations of K_1, K_2, and R_{a0}. Figure 7 shows an example of these combinations for the feed. Other examples for the feed and the speed produced similar results with relatively small variations. It was found that the number of optimal solutions can be limited as explained below. The results are obtained as follows:

1. Target surface roughness (R_{a0}): It was found that R_{a0} should be less than 2.4 μm to meet the positive cost constraint.
2. Depth of cut: The optimum depth of cut is 0.05 mm for all combinations regardless the value of K_1, K_2, and R_{a0}.

   The optimum value of the speed and feed varies based on the values of K_1 and K_2. However, many combinations produce similar optimum solutions within a US\$0.3/m^2 difference of the total cost.
3. Feed: In all combinations, the optimum feed ranges from 70 to 90 mm/min. Figure 8 shows the optimum solutions for the feed at different values of K_1 and K_2 within a US\$0.3/m^2 difference of the total cost. The optimum value of the feed decreases as K_1 increases and remains

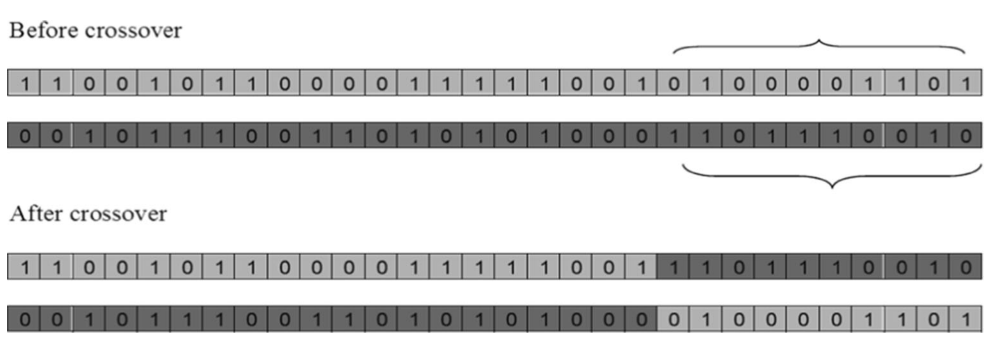

Fig. 5 An example of a random crossover

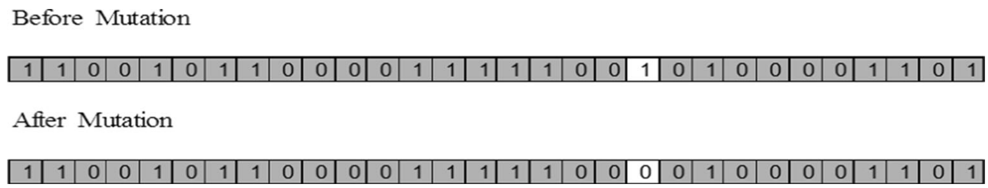

Fig. 6 An example of a mutation operation

constant at a value of 70 mm/min for K_1 greater than US$25.

4. Speed: The optimum value of the speed is defined based on two distinctive cases. For the value of K_2 [0.05 0.3]

   (a) The optimum value of the speed is 500 rpm when K_1 is less than 0.5 and 1,250 rpm when K_1 is between 0.5 and 2.

   (b) The optimum value of the speed is distributed between 1,100 to 1,250 rpm when K_1 is greater than 2. Figure 9 shows the optimum solutions for the speed at different values of K_1 and K_2 within a US$0.3/m^2 difference of the total cost. The optimum value of the speed decreases as K_1 increases and remains constant at a value of 1,100 rpm for K_1 greater than US$40.

The above results represent compromised solutions for the energy consumption and the surface quality. While a high speed and a low feed are expected to produce a high-quality surface finish, high energy consumption is required. To determine the effect of the energy consumption without the effect of the surface roughness, K_1 was set to 0 and K_2 was set to 0.3. The optimum solution of the speed was at the lowest level (500 rpm), and the optimum solution of the feed was at the highest level (100 mm/min). On the other hand, setting K_2 to 0 cancels the effect of energy consumption. A high speed and a

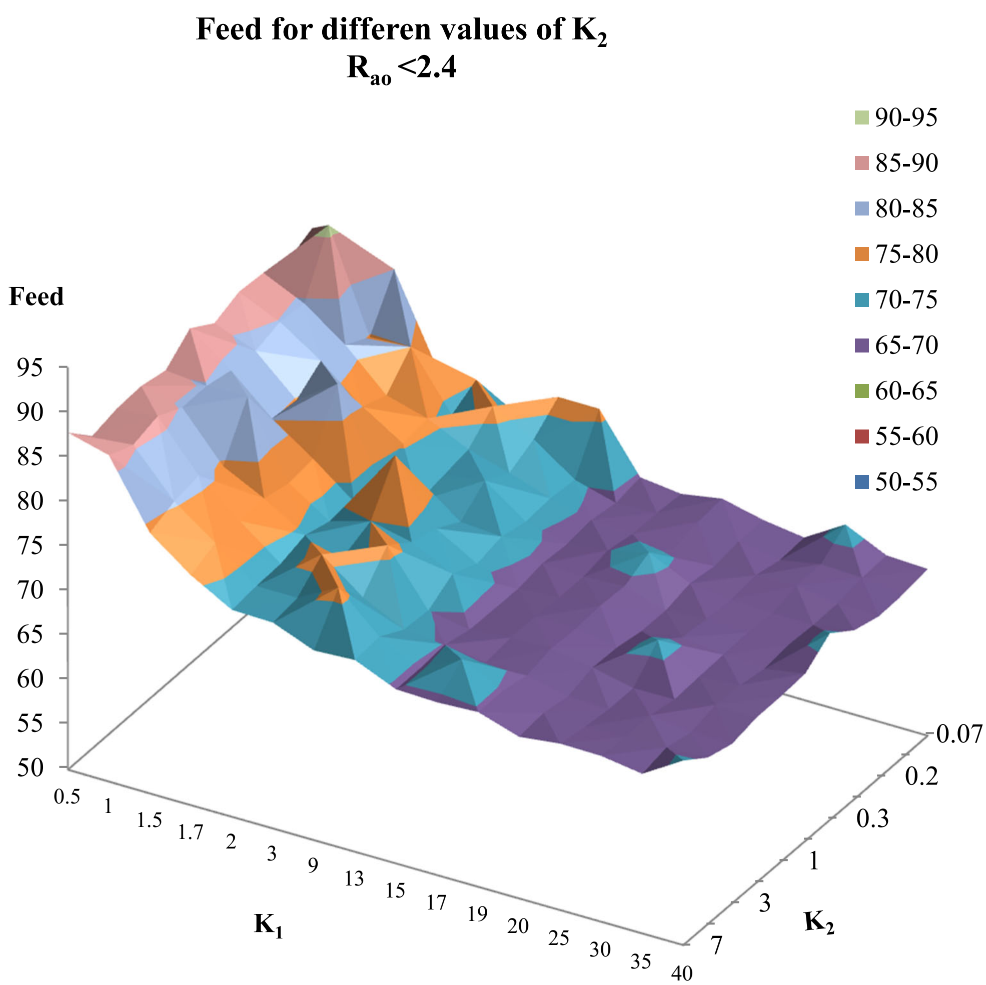

Fig. 7 An example of optimal solutions for the feed at different values of K_2

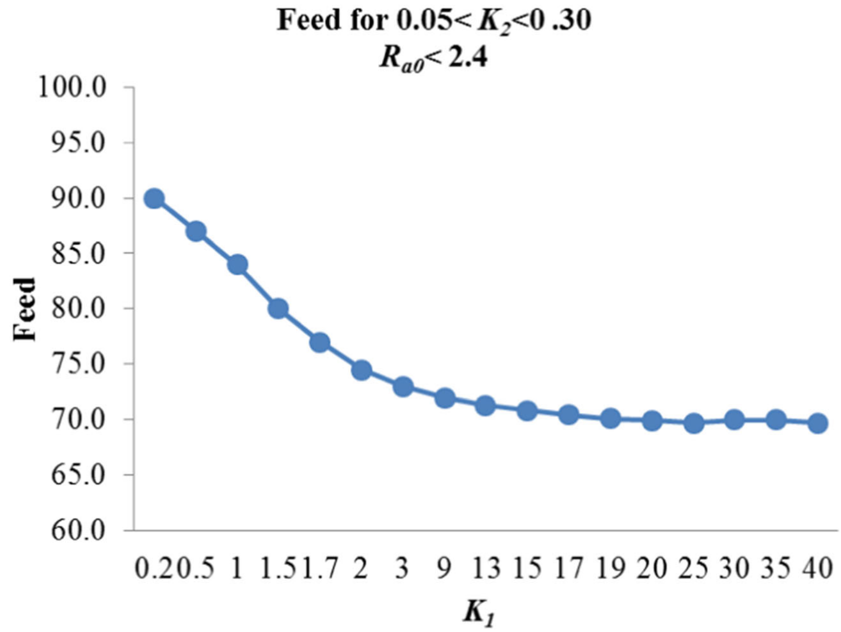

Fig. 8 Optimum solutions for the speed at different values of K_1 and K_2

relatively low feed were obtained based on the surface roughness alone. Testing other levels outside the range of the machining variables used in this research produced the same results. However, this conclusion should be interpreted with caution since the regression models were developed based on these levels.

The results can be accepted worldwide since it covers a wide range of electricity cost per kilowatt-hour. It was found that the same results are still valid up to an electricity cost of US$0.70/kWh. This figure is less than the current maximum cost of electricity for industrial applications worldwide.

The above results can be utilized by machine operators to set up machining parameters based on different surface finish requirements. For example, an operator who wants to improve the surface quality when the cost of reducing the surface roughness by 1 μm is US$3/m^2 and the cost of electricity is within US$0.3 kWh will find that the optimal feed is about 73 mm/min based on Fig. 8 and the optimal speed is about 1,150 rpm based on Fig. 9. The optimal values are valid up to 2.4 μm of surface roughness reduction. Running the machine under these conditions with a low value of depth of cut

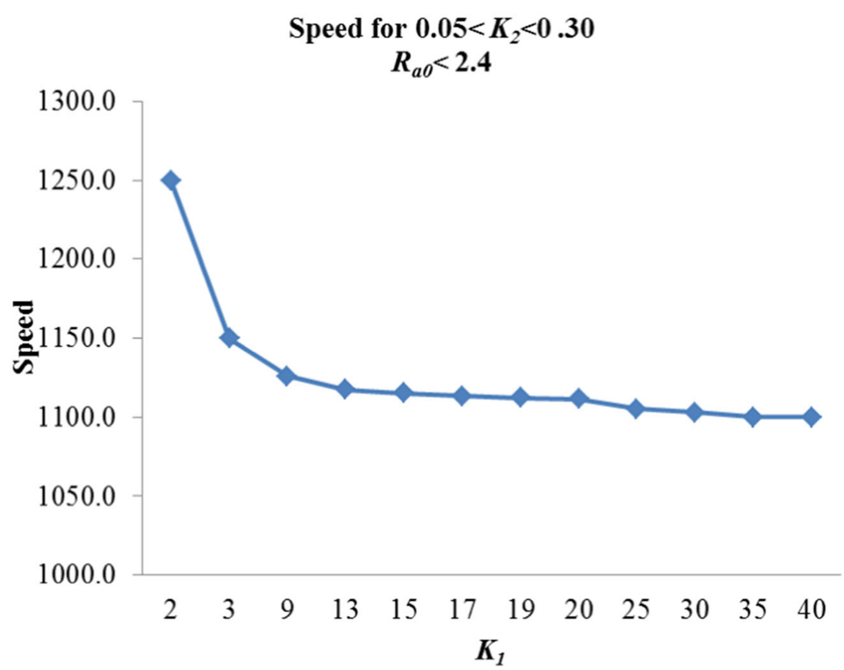

Fig. 9 Optimum solutions for the feed at different values of K_1 and K_2

insures the minimum cost associated with extra machining and electricity consumption.

The proposed methodology can be used for future work to investigate the optimal machining parameters for different materials and manufacturing processes. The generalized methodology is summarized as follows:

- Select a machining process (milling turning, drilling, etc.).
- Identify machining performance criteria to optimize (surface roughness, energy consumption, tool wear, production cost, etc.).
- Identify machining parameters that control the machining performance (feed, speed, flow rate, etc.).
- Measure and collect data under different machining parameters and machining performance criteria.
- Find predictive functions that relate machining parameters and the machining performance criteria.
- Form one objective function that includes predictive functions for (multi-criteria optimization).
- Optimize the objective function using genetic algorithm.

5 Conclusion

In this paper, a multi-criteria approach for machining parameter optimization of AISI D2 during the end milling process is introduced. A genetic algorithm approach is used to optimize two conflicted objectives. A cost function is formed based on the cost associated with extra machining required to reduce the surface roughness and the energy consumption. Feed, speed, and depth of cut are the machining parameters used for optimization. Different scenarios that simulate the actual machining costs are investigated. A range of optimum solutions for the feed and speed has been found and documented in graphs. Machine operators can use these graphs to determine the optimal machining parameters. It was found that the optimal values of the feed and speed decreases as the cost of extra machining increases. Moreover, it was found that minimizing the cost function can be achieved by running the machine with the lowest possible value of depth of cut. As an extension of this work, the same procedure can be adopted for other materials, machining processes, and machining conditions.

References

1. Dewes R, Aspinwall D (1997) A review of ultra high speed milling of hardened steels. J Mater Process Technol 69:1–17
2. Baskar N, Asokan P, Saravanan R, Prabhaharan G (2006) Selection of optimal machining parameters for multi-tool milling operations using a memetic algorithm. J Mater Process Technol 174:239–249
3. Cakir M, Ensarioglu C, Demirayak I (2009) Mathematical modeling of surface roughness for evaluating the effects of cutting parameters and coating material. J Mater Process Technol 209:102–109
4. Yusup N, Zain A, Hashim S (2012) Evolutionary techniques in optimizing machining parameters: review and recent applications. Expert Syst Appl 39:9909–9927
5. Vivancos J, Luis C, Costa L, Ortiz J (2004) Optimal machining parameters selection in high speed milling of hardened steels for injection moulds. J Mater Process Technol 155–156:1505–1512
6. ktem H, Erzurumlu T, Kurtaran H (2005) Application of response surface methodology in the optimization of cutting conditions for surface roughness. J Mater Process Technol 170:11–16
7. Yildiz A (2009) A novel hybrid immune algorithm for optimizing of machining parameters in milling operations. Robot Comput Integr Manuf 25:261–270
8. Zain A, Haron H, Sharif S (2010) Prediction of surface roughness in the end milling machine using Artificial Neural Network. Expert Syst Appl 37:1755–1768
9. Huang B, Chen J (2003) An in-process neural network-based surface roughness prediction (INN-SRP) system using a dynamometer in end milling operations. Int J Adv Manuf Technol 21:339–347
10. Benardos P, Vosnaikos G (2003) Predicting surface roughness in machining: a review. Int J Mach Tools Manuf 43:833–844
11. Rashid A, Gan S, Muhammad N (2009) Mathematical modeling to predict surface roughness in CNC milling. World Acad Sci Eng Technol 53:393–396
12. Ozcelik B, Bayramoglu M (2006) The statistical modeling of surface roughness in high-speed flat end milling. Int J Mach Tools Manuf 46: 1395–1402
13. Ghani J, Choudhury I, Hassan H (2004) Application of Taguchi method in the optimization of end milling parameters. J Mater Process Technol 145:84–92
14. Vivancos J, Luis C, Ortiz H (2005) Analysis of factors affecting the high-speed side milling of hardened die steels. J Mater Process Technol 162–163:696–701
15. Park C, Kown K, Kim W, Min B, Park S, Sung I, Yoon Y, Lee K, Lee J, Seok J (2009) Energy consumption reduction technology in manufacturing—a selective review of policies standards and research. Int J Precis Eng Manuf 10(5):151–173
16. Pineda-Henson R, Culaba A (2004) A diagnostic model for green productivity assessment of manufacturing processes. Int J LCA 9(6): 379–386
17. He LB, Zhang X, Gao H, Liu X (2012) A modeling method of task-oriented energy consumption for machining manufacturing system. J Clean Prod 23(1):167–174
18. Rahimifard S, Seow Y, Childs T (2010) Minimising embodied product energy to support energy efficient manufacturing. CIRP Ann 59(1):25–28
19. Fang K, Uhan N, Zaho F, Sutherland J (2011) A new approach to scheduling in manufacturing for power consumption and carbon footprint reduction. J Manuf Syst 30(4):234–240
20. Kara S, Li W (2011) Unit process energy consumption models for material removal processes. CIRP Annals-Manuf Technol 60:37–40
21. Newman S, Nassehi A, Imani-Asrai R, Dhokia V (2012) Energy efficient process planning for CNC machining. CIRP J Manuf Sci Technol 5:127–136
22. Bhushan R (2013) Optimization of cutting parameters for minimizing power consumption and maximizing tool life during machining of Al alloy SiC particle composites. J Clean Prod 39:242–254
23. Zain A, Haron H, Sharif S (2010) Application of GA to optimize cutting conditions for minimizing surface roughness in end milling machining process. Expert Syst Appl 37:4650–4659

24. Saffar R, Razfar R (2010) Simulation of end milling operation for predicting cutting forces to minimize tool deflection by genetic algorithm. Mach Sci Technol 14(1):81–101
25. Parent L, Songmene V, Kenné J (2007) A generalised model for optimising an end milling operation. Prod Plan Control 18(4):319–337
26. Sultana I, Dhar N (2010) GA based multi objective optimization of the predicted models of cutting temperature, chip reduction coefficient and surface roughness in turning AISI 4320 steel by uncoated carbide insert under HPC condition. Proceedings of the 2010 International Conference on Mechanical. Ind Manuf Technol MIMT 2010:161–167
27. Duran O, Barrientos R, Consalter L (2007) Multi objective optimization in machining operations. Analysis and Design of Intelligent Systems using Soft Computing Techniques 455–462
28. Xie S, Pan L (2010) Selection of machining parameters using genetic algorithms. ICCSE 2010—5th International Conference on Computer Science and Education, Final Program and Book of Abstracts 1147–1150
29. Kilickap E, Huseyinoglu M, Yardimeden A (2011) Optimization of drilling parameters on surface roughness in drilling of AISI 1045 using response surface methodology and genetic algorithm. Int J Adv Manuf Technol 52(1–4):79–88
30. Jain N, Jain V (2007) Optimization of electro-chemical machining process parameters using genetic algorithms. Mach Sci Technol 11(2):235–258
31. Mohanasundararaju N, Sivasubramanian R, Alagumurthi N (2008) Optimisation of work roll grinding using response surface methodology and evolutionary algorithm. Int J Manuf Res 3(2):236–251
32. Gao Q, Zhang Q, Su S, Zhang J (2008) Parameter optimization model in electrical discharge machining process. J Zhejiang Univ Sci A 9(1):104–108
33. Kumar A, Khan M, Thiraviam R, Sornakumar T (2006) Machining parameters optimization for Alumina based ceramic cutting tools using genetic algorithm. Mach Sci Technol 10:471–489