Optimization of End Milling Parameters under Minimum Quantity Lubrication Using Principal Component Analysis and Grey Relational Analysis

K. Sundara Murthy
profksm@gmail.com
Jayam College of Engineering and Technology
Department of Mechanical Engineering
636 813 Dharmapuri, Tamil Nadu, India

Dr. I. Rajendran
irus_rajendran@yahoo.co.in
Dr. Mahalingam College of Engineering & Technology
Department of Mechanical Engineering
642 003 Pollachi, Tamil Nadu, India

Machining is the major reliable practice in accomplishment of metal cutting industries. The accelerated growing competition demands top superior and large quantity with low cost products. Metal working fluids have significant fragment of manufacturing cost and causes ecological impacts and health problems. This work attempts to advance a competent machining alignment with no ecological impacts. The prediction of quality characteristics and enhancement of machining field are consistently accepting great interest in machining sectors to compress the accomplishment costs. In this paper, GA based ANN prediction model proposes to envisage the quality characteristics of surface roughness and tool wear. The comparison of predicted and experimental values acknowledges the precision of the model. The end milling experiments are conducted beneath minimum quantity lubrication. This paper as well deals with the multiple objective optimization with principal component analysis, grey relational analysis and Taguchi method. ANOVA was carried out to determine each parameter contribution percentage on quality characteristics. The results show that cutting speed is the most influencing parameter followed by feed velocity, lubricant flow rate and depth of cut. The confirmation tests acknowledge that the proposed multiple-objective methodology is able in determining optimum machining parameters for minimum surface roughness and tool wear.

Keywords: *end milling, MQL, principal component analysis, grey relational analysis, optimization*

Introduction

The metal cutting industries are facing a lot of adverse complexities during machining in particular with attainment of higher surface quality and tool life. David et al. (2006) mentioned that in a machining system, cutting tool is the most diagnostic element. The cutting tools are subjected to acute loads due to rubbing of work and chip, high stress and temperature, and their gradients. Persistent all-encompassing analysis has been carried out to advance the adequacy of cutting tools. Jacob and Joseph (2005) pointed out that the product quality and ability of machining action depend on cutting tool condition. The tool wear is provoked by adhesion, abrasion, diffusion and/or oxidation (Lorentzon and Jarvstrat, 2009). Biswas et al. (2008) reported that the tool wear directly influences the power consumption, quality of the surface finish, tool life, productivity, etc. Hence, tool wear leads to poor surface finish, decrease in accuracy and increase in cutting forces, temperature and vibration.

Authors (Sundara Murthy and Rajendran, 2010) addressed the surface roughness prediction and analysis forth with the significance and characteristics of machined surface. Figure 1 describes the three stages of cutting tool wear, i.e. initial wear stage, progressive wear stage and a rapid wear stage. Micro-cracking is developed and propagated during the initial wear stage, then almost constant in progressive wear stage and added in accelerated amount in rapid wear stage which leads to the cutting tool failure. The crater and flank wear on the faces of the cutting tool during machining are shown in Fig. 2. Flank wear occurs on relief or flank face of the tool due to abrasion of tool with part machined surface. Generally, it is initiated at the cutting edge and propagated downwards. Crater wear is a concave scar caused by erosion due to sliding of chip on tool rake face. Notch wear is an aggregate of flank and crater which occurs abreast to the intersection of cutting tool and machined surface. Chipping is abatement of micro-particles of tool material. The absolute dismissal of cutting point is alleged as critical failure. But Yong et al. (2007) identified that the flank and crater wears are the major wear patterns.

Abrasive wear is a mechanical wear which occurs at low speeds, chiefly due to the scratching of hard impurities of work material. One of the means to abstain this wear is providing harder coating on cutting tool. Adhesive wear is due to strong sticking of work material on the cutting tool surfaces and this can occur at high temperatures and pressures caused by high cutting speeds. High hot hardness and thermal conductivity can reduce the adhesive wear. Diffusion wear is because of atomic transfer between the work and tool materials and can occur in two ways. Tool elements can diffuse into the work material or work elements can diffuse into the tool material. Rajesh (2010) revealed that metallurgical bonding attraction between tool and work material leads to diffusion and this could increase rapidly at elevated temperatures. Nouari and Molinari (2005) acknowledged that the work material flow rate nearest to rubbed area and the average contact temperature between tool-work are the major authoritative factors of diffusion wear. Oxidation can be observed on the rack and flank faces of the tool due to high temperatures, atmospheric air and coolant. The oxidation can prevent adhesion and diffusion to a certain extent. The soft oxidation layers are quickly washed out by chip and work, but continuation leads to oxidation wear. Chun (2010) presented that high cutting speed and feed rate could increase the oxidation rate due to reduction of hardness and strength of the tool. The parameters which could cause the tool wear are shown in Fig. 3. Tool wear has major impact on product quality and process cost. The tool wear also resulted in increased cutting force, cutting temperature, machine vibration and surface roughness. Because of the importance of tool wear, there have been several attempts to foretell and analyze the wear through mathematical and soft computing techniques.

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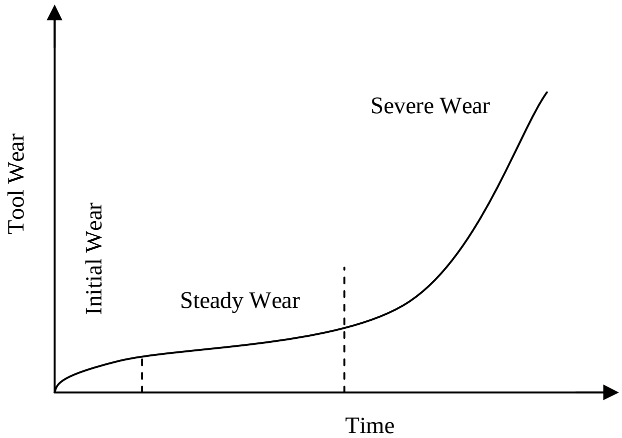

Figure 1. Various stages of cutting tool wear.

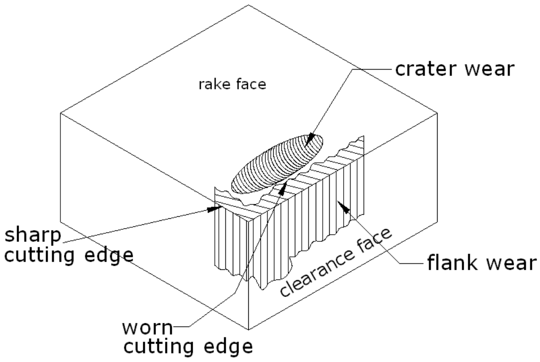

Figure 2. Flank and crater wear on the faces of cutting tool.

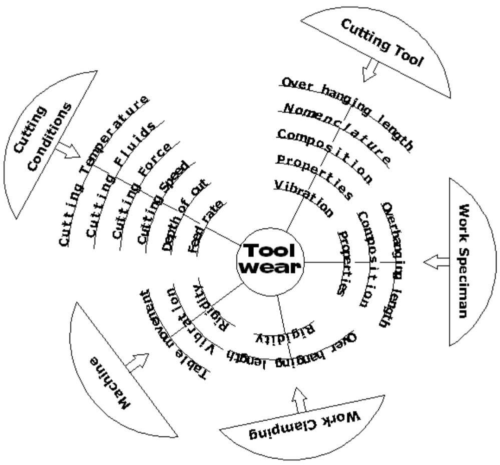

Figure 3. Factors influencing tool wear.

Milling tests on titanium alloys with uncoated and coated carbide tool were conducted and performance in terms of tool life and surface quality was evaluated and presented by Nagi et al. (2008). Dimla (2002) machined EN24 with coated inserts; observed wear through vibration signals against time and suggested that the analysis of vibration signals are very effective in tool-wear monitoring. A coherence function model was developed by Mantana and Asa (2008) to describe the relationship between tool wear and tangential and feed vibration components. A fuzzy logic on line monitoring technique was proposed by Susanto and Chen (2003) for face milling with resultant cutting force and selected machining parameters and demonstrated its adequacy. Thamizhmnaii et al. (2008) reported that higher flank wear occurred in low cutting speed with high feed rate and depth of cut in turning of SS 440 C stainless steel. A spanking new Transductive-Weighted Neuro-Fuzzy Inference Technique (TWNFIS) was proposed (Agustin et al., 2009) to model tool wear in turning and proved the accuracy by comparing with experimental values. Li et al. (2002) used vibration signals to find out drill wear and proposed a relationship between the vibration and the tool wear with fuzzy neural network model. It was also demonstrated that features of vibration signals can be used to determine the drill wear with greater accuracy. Tansel et al. (2000) proposed cutting force wear relation by Force-variation-based encoding (FVBE) and Segmental-average-based encoding (SABE) methods and proved both are excellent performance in wear estimation. Neural network was applied to predict the wear during hard turning of AISI H-13 steel and the proposed model provided better prediction capabilities (Tugrul and Yigit, 2005). An efficient and successful relationship was established by Choudhury and Bartarya (2003) between tool wear and surface roughness along with cutting temperature. An online tool wear monitoring technique was developed (Silva et al., 1998) with input signals as cutting force, spindle current, sound and vibration in turning and demonstrated efficiency of the suggested technique. Jurkovic et al. (2005) presented direct tool wear measurement methodology using machine vision with 3D picture of tool relief surface. An analytical computation of flank wear was expressed and predicted wear at various cutting speeds was compared with experimental values (Bouzid, 2005). Palanisamy et al. (2008) suggested regression analysis and artificial neural network model to forecast the flank wear which were validated through experiments.

Many researchers accept, focused on multiple objective optimization techniques, to be positive the maximum advantage from a set of optimum machining parameters. Wang et al. (2006) optimized multi-pass milling with two objectives of less machining time and cost reduction using parallel genetic simulated annealing. The optimum machining parameters during single pass turning were determined by Yang and Natarajan (2010) with objectives of minimum tool wear and maximum material removal by application multi-objective differential evolution (MODE) algorithm and non dominated sorting genetic algorithm (NSGA-II). The minimum production cost during multi-pass turning was determined with a proposed hybrid arrangement of real-parameter genetic algorithm (RGA) and sequential quadratic programming (SQP) (Abburi and Dixit, 2007). The hot turning of manganese was optimized (Tosun and Ozler, 2004) with different objectives of maximum tool life and minimum surface roughness. Ramon et al. (2006) optimized the turning parameters with multiple objectives of minimum tool wear and operation time with genetic algorithm. Tian (2009) optimized the CNC turning by applying Taguchi method and Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) and analyzed the after-effects by MINITAB with assorted objectives optimization.

The achievement of nontraditional machining was also attempted with multiple objectives by many researchers to determine the optimum parameters. Debabrata et al. (2007) applied multi-objective methodology non-dominating sorting genetic algorithm-II to optimize circuitous EDM parameters with ANN prediction model and evaluated by experimental results. Yih-fong and Fu-chen (2007) used fuzzy logic with Taguchi method in enhancement of EDM and determined pulsed duration, duty cycle, and peak current as a lot of influencing factors among the various parameters. The wire EDM parameters were optimized (Shajan and Shunmugam, 2005) to improve the performance by Non-Dominated Sorting Genetic Algorithm (NSGA).

From the literature study, it was found that there was no comprehensively application of multiple objectives optimization in Minimum Quantity Lubrication (MQL) machining technique. This proposed work attempts to optimize the machining parameters in adjustment to accord minimum surface roughness and tool wear during the end milling of aluminum 6063 beneath MQL technique.

Nomenclature

F	= *fitness function*
Xi…..Xm	= *n response variables from m experiments*
Xi(k)*	= *normalized data*
$X_{ob}(k)$	= *desired value of response variable*
Xi(j)*	= *normalized value of* j^{th} *element in* i^{th} *sequence*
Yi(k)	= *principal component*

Greek Symbols

β_{kj}	= j^{th} *element of eigen vector*
$\beta_k\sigma_{Qj}$ & σ_{Qk}	= *standard deviation of* j^{th} *and* k^{th} *response*
ξ	= *coefficient value (normally 0.5)*

Methods and Materials

End milling experiments were carried out at different combinations of cutting parameters, cutting speed, feed velocity, depth of cut and cutting liquid flow rate in a milling machine. The specifications of milling machine are given in Table 1. The workpiece material used to conduct milling experiments was aluminum 6063-T6. The chemical composition and other important properties of 6063 are given in Table 2 and Table 3, respectively. The dimensions of the workpiece were 300 × 200 × 50 mm. An end mill cutter (LT740WWL) of 20 mm diameter and unique coated inserts APGT 1003 PDER-Alu LT05, manufactured by Lamina Technologies (Swiss), were used in milling experiments. The schematic representation of experimental set up is apparent in Fig. 4. The milling experiments were done at various levels of cutting speeds, feed velocities, depths of cut and liquid flow rates. The levels and parameters used are given in Table 4. The experiments were conducted under Maximum Quantity Lubrication (MQL). The vegetable oil coolube 2210, manufactured by UNIST (USA), was employed as oil under MQL. To supply oil in MQL condition, an MQL setup was used. This setup prepares the air-lubricant mixture and supplies it at cutting point through a nozzle. This setup is also able to adjust the air and lubricant ratios and the flow rate separately. The flow rate of mixture can also be varied and the air pressure was maintained at 4 bars. In each experiment, the surface roughness and flank wear of cutting tool were measured using tool room microscope and surface roughness tester.

Table 1. Specifications of milling machine.

Type	Universal-geared
Power	3 HP
Working surface	1100 X 250 mm
Cutting speed (m/min)	15-88 m/min
Feed velocity (mm/min)	75-355 mm/min
Longitudinal travel (X)	725 mm
Cross travel (Y)	300 mm
Vertical travel (Z)	250 mm

Table 2. Chemical composition of Al 6063 in % of weight.

Mg	Si	Fe	Cu	Mn	Cr	Zn	Ti	Others		Al
								each	total	
0.45-0.9	0.2-0.6	Max 0.35	Max 0.1	Max 0.1	Max 0.1	Max 0.1	Max 0.1	0.05	0.15	Max 97.5

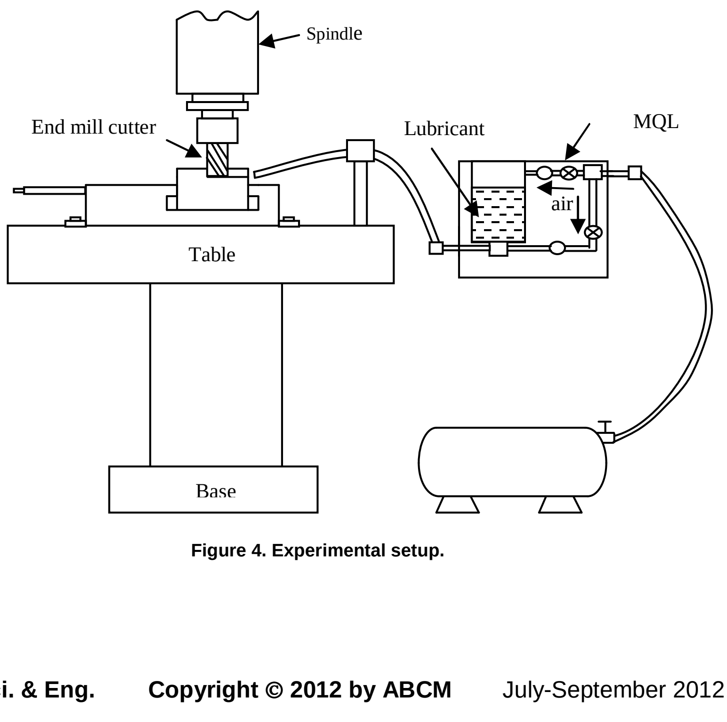

Figure 4. Experimental setup.

Table 3. Various properties of Al 6063.

Physical	
Density	2.7 g/cc
Mechanical	
Hardness (Brinell)	73
Ultimate Tensile Strength	241 Mpa
Tensile Yield Strength	214 Mpa
Elongation	12%
Modulus of Elasticity	68.9 Gpa
Machinability	50%
Fatigue Strength	68.9 Gpa
Shear Modulus	25.8 Gpa
Shear Strength	152 Mpa
Poisson's Ratio	0.33
Thermal	
Melting Point	616 - 654°C
Thermal Conductivity	200 W/m-K
Specific Heat Capacity	0.9 J/g-°C

Table 4. Machining parameters and their levels.

Designation	Parameters	Level 1	Level 2	Level 3
A	Cutting speed (m/min)	35	56	88
B	Feed velocity (mm/min)	180	250	355
C	Depth of cut (mm)	1	1.2	1.4
D	Fluid flow rate (ml/hr)	300	600	900

Genetic Algorithm Based BPN

All the engineering issues will have plenty of solutions. The greatest task is to select the best from the available solutions. Artificial Neural Network (ANN) is a model of biological neuron system. ANN can be trained by known results and the knowledge acquired from training can be used to foretell or compute the unknown output. The most popular and broadly acclimated ANN is Multi Layer Back Propagation Network (MLBPN). In BPN the weights of input-hidden layers and hidden-output layers are computed using gradient search method. This will lead the network to local optimum solutions. Moreover, the BPN is unable to work with new occurrence far from training. This research work aims to abbreviate the drawbacks of BPN by affiliation of Genetic Algorithm (GA) with a back propagation network. Although GA is not an assuring global solution it is found that GA is able of bearing adequate acceptable solutions. GA may even be accomplishing the results with less number of iterations. GA was visualized by Holland in 1975 and applied auspiciously in structural engineering. Later it was extended to all fields due to its distinctive features like random search based on natural genetics, population of points at time, etc. Anatomy of proposed hybrid genetic algorithm —neural networks system is shown in Fig. 5. The program generates preliminary population randomly. The fitness of each chromosome in population will be evaluated by weights of genes. If convergence is not reached, genetic operations reproduction, crossover and mutation will be carried out to decide the new population. Again, the fitness of new population is checked and this system will continue until the function is converged. If the convergence is attained, the program stops and gives the result. The various steps of proposed genetic algorithm based neural network system to predict the tool wear are discussed as following. In this study, an artificial neural network with input, hidden and output layers was thought about. The number of neurons and parameters used in each layer is shown in Table 5.

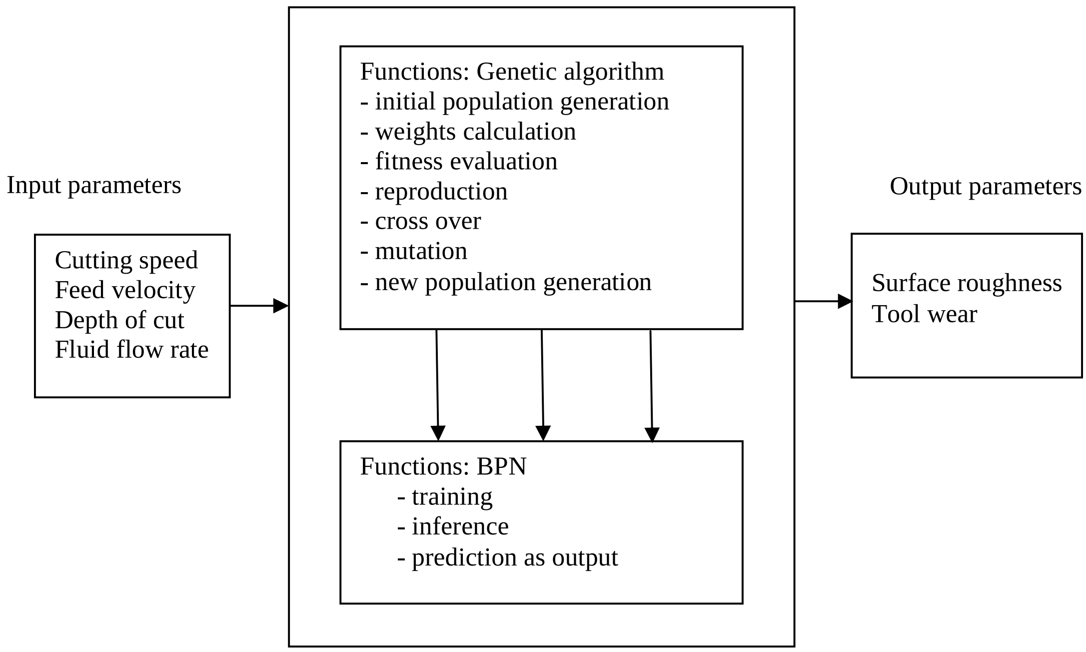

Figure 5. Hybrid GA and ANN prediction model.

Table 5. Details of ANN topology.

S. No.	Name of the layer	Number of neurons	Parameters
1	Input	4	cutting speed
			feed velocity
			depth of cut
			fluid flow rate
2	Hidden	4	-
3	Output	2	surface roughness
			tool wear

The primary step in the hybrid system is random generation of preliminary population for each input. The gene length was taken as five and string length of each chromosome was 80. The fitness function of each chromosome is given by

$$F = 1/E$$

where
$$E = \sqrt{(E_1 + E_2 + E_3 + E_4)/4}$$
$$E_1 = (O_{r1} + O_{c1})^2$$

For each chromosome in preliminary population, the fitness value was computed. The fitness function ought to be converged at least for 95% of preliminary population. In case of less, the mating pool was formed by replacing all the least fitness chromosomes with highest fitness chromosome. From this mating pool, new parent pairs were selected randomly for cross over. Offspring chromosomes were generated by a single point crossover. At randomly selected cross site the genes were swapped. Sometimes, cross over is unable to continue the regeneration. Then the bits of strings are muted independently. Mutation makes search space globally and restores the lost genetic knowledge. A low mutation rate of 0.05% was selected, because higher values could affect the fitness of the strings. After all genetic operations, a new set of population was generated to evaluate the fitness. Once fitness function was satisfied, the computed weights were accustomed to BPN model to predict the tool wear and surface roughness as outputs.

Optimization Methodology

Principal Component Analysis (PCA) and Grey Relational Analysis (GRA) are combined to optimize the cutting parameters for minimum surface roughness and tool wear. PCA is a variable reduction method which is widely applied from science to engineering issues because of its ability to receive the significant information from the more number of observed variables. The redundancy in the observed variables is determined by correlating each other. This redundancy will help reducing the number of observed variables into smaller number of principal components. The variance in the observed variables is represented by the principal components. These principal components are used to find the grey relational coefficient and corresponding S/N ratios. From the S/N ratios the optimum cutting parameters are determined. The step by step procedure followed to find the optimum cutting parameters is as follows:

Step 1. Collection of response variables

The response variables are represented as:

$$X_i = \{X_i(1), X_i(2) ....X_i(n)\}$$
.
.
$$X_m = \{X_m(1), X_m(2) ....X_m(n)\}$$

In this study, $n = 2$, surface roughness and tool wear and $m = 9$, number of experiments.

Step 2. Normalization of response variables

There are three different characteristics of normalization. They are:

(i) Higher-the-Better (HB)
$$X_i^*(k) = X_i(k)/\max X_i(k)$$

(ii) Nominal-the-Better (NB)
$$X_i^*(k) = \min\{X_i(k)\}, X_{0b}(k)\}/\max\{X_i(k)\}, X_{0b}(k)\}$$

(iii) Lower-the-Better (LB)
$$X_i^*(k) = \min X_i(k)/X_i(k)$$
$$i = 1, 2, ...m \text{ and } k = 1, 2, ...n$$

Step 3. Correlation between the responses

The correlation coefficient is given by

$$\rho_{jk} = Cov(Q_j, Q_k)/\sigma_{Q_j} \times \sigma_{Q_k}$$

where $Q_i = \{X_0^*(i), X_1^*(i), X_2^*(i) ....X_m^*(i)\}$
$i, j \,\&\, k = 1, 2, ...n$ but $j \neq k$

Hypothesis for correlation checking:

$H_0 : \rho_{jk} = 0$ no relation
$H_1 : \rho_{jk} \neq 0$ relation exist

Step 4. Principal component score calculation

The principal component $Y_i(k)$ can be determined by

$$Y_i(k) = \sum_{j=1}^{n} X_i^*(j)\beta_{kj}$$

Step 5. Individual grey relational coefficients

The grey relational coefficient is computed by

$$r_{0,j}(k) = (\Delta_{\min} + \xi\Delta_{\max})/(\Delta_{0,j}(k) + \xi\Delta_{\max})$$

where
$$\Delta_{\min} = \frac{\min\limits_i \min\limits_k \left|X_0^*(k) - X_i^*(k)\right|}{\min\limits_i \min\limits_k \left|Y_0(k) - Y_i(k)\right|}$$
$$\Delta_{\max} = \frac{\max\limits_i \max\limits_k \left|X_0^*(k) - X_i^*(k)\right|}{\max\limits_i \max\limits_k \left|Y_0(k) - Y_i(k)\right|}$$

$$\Delta_{0,j}(k) = \frac{\left|X_0^*(k) - X_i^*(k)\right|}{\left|Y_0(k) - Y_i(k)\right|} \text{ and}$$
$\xi =$ coefficient value (normally 0.5)

Step 6. Overall grey relational grade calculation

The responses of surface roughness and tool wear are combined and a single overall grey relational grade is calculated by using:

$$\Gamma_{0,j} = \sum_{k=1}^{n} w_k r_{0,j}(k)$$

Then, the Taguchi method is applied to compute the S/N ratios for overall grey relational grade. The optimum machining parameters are determined from the S/N ratios.

Results and Discussion

GA and ANN hybrid prediction model

The surface roughness and tool wear quality characteristics are predicted in this research work using genetic algorithm based artificial neural network. To foretell the surface roughness and tool wear cutting speed, feed velocity, depth of cut and cutting liquid flow rate are used as input parameters. The hybrid of GA and ANN is aided to foretell the outputs exactly. The results of the hybrid prediction method are given in Table 6. The predicted values are validated by experimental values. The positive and negative errors in prediction of surface roughness are +2.9% and –1.0%. Similarly, the errors in the prediction of tool wear are –3.3% and +1.3%. The accuracy of hybrid prediction model for surface roughness is ±2.9% and for tool wear is ±3.3%. The errors of the model are within the accustomed limit. So, it is apparent that the predicted values of hybrid prediction model have good agreement with experimental values.

Table 6. Experimental results and comparison with prediction.

Exp. No.	Surface roughness (R_a) (μm)			Flank wear (mm)		
	predicted	Exp.	prediction error (%)	predicted	Exp.	prediction error (%)
1	0.776	0.799	2.879	0.252	0.256	1.563
2	0.765	0.746	–2.547	0.237	0.24	1.25
3	0.983	0.973	–1.028	0.283	0.274	–3.285
4	0.766	0.752	1.305	0.205	0.202	–1.485
5	0.857	0.868	1.267	0.321	0.329	2.432
6	0.459	0.449	–2.227	0.359	0.37	2.973
7	0.638	0.649	1.695	0.325	0.316	–2.848
8	0.668	0.678	1.475	0.373	0.383	2.611
9	0.762	0.747	–2.008	0.388	0.395	1.772

Optimization of cutting parameters

The experimental results of surface roughness and tool wear quality characteristics in end milling of aluminum 6063-T6 under maximum quantity lubrication are shown in Table 6. Using Lower-the-Better (LB) criterion both surface roughness and tool wear experimental information have been normalized. The normalized information set is given in Table 7. Computation has been carried out subsequently, to find the correlation between the responses. Table 8 shows the Pearson's coefficient of correlation between surface roughness and tool wear. Based on this, it is obvious that both the responses are correlated. The Principal Component Analysis (PCA) has been used to eliminate the response correlation. The PCA matrix which consists of Eigen values, Eigen vectors, Accountability Proportion (AP) and Cumulative Accountability Proportion (CAP) is also given in Table 8. The independent principal component for each experiment is calculated by converting the correlated responses. Since the AP of the responses is non-zero value, the principal component scores are determined for both responses and are listed in Table 9. The quality loss estimated for each response is given in Table 10.

Table 7. Normalized data set of experimental results.

Exp. No.	Surface roughness	Flank wear
Ideal	1.000	1.000
1	0.562	0.789
2	0.602	0.842
3	0.461	0.737
4	0.597	1.000
5	0.517	0.614
6	1.000	0.546
7	0.692	0.639
8	0.662	0.527
9	0.601	0.511

Table 8. Eigen values, Eigen vectors, AP and ACP of responses.

	ψ_1	ψ_2
Eigen value	1.332	0.668
Eigen vector	$\begin{vmatrix} +0.707 \\ +0.707 \end{vmatrix}$	$\begin{vmatrix} +0.707 \\ -0.707 \end{vmatrix}$
AP	0.666	0.334
CAP	0.666	1.000

Table 9. Principal component scores.

S. No.	Principal component scores	
	ψ_1	ψ_2
Ideal	1.4140	0.0000
1	0.9488	–0.1697
2	1.0209	–0.1697
3	0.8548	–0.1888
4	1.1128	–0.3012
5	0.8003	–0.0693
6	1.0937	0.3203
7	0.9332	0.0452
8	0.8413	0.0947
9	0.7869	0.0629

Here, analyses of quality characteristics such as surface roughness and tool wear were made to optimize the cutting parameters. To optimize the multiple performance characteristics, it was converted into single aim issue by applying grey relational analysis. Table 11 shows the grey relational coefficients for the principal components. These grey relational coefficients are combined and a single grey relational grade is calculated. The grey relational grade and corresponding S/N ratios are given in Table 12.

Table 10. Quality loss for each response.

S. No.	Quality loss corresponding to individual principal components	
	ψ_1	ψ_2
Ideal	1.414	0.000
1	0.459	0.161
2	0.393	0.17
3	0.567	0.195
4	0.285	0.285
5	0.614	0.068
6	0.321	–0.321
7	0.473	–0.037
8	0.573	–0.095
9	0.627	–0.063

Table 11. Grey relational coefficients of principal components.

S. No.	Grey relational coefficients for individual principal components	
	ψ_1	ψ_2
1	0.796	0.688
2	0.869	0.668
3	0.698	0.619
4	1.027	0.491
5	0.663	0.977
6	0.969	0.454
7	0.782	1.140
8	0.693	0.870
9	0.653	1.000

Table 12. Grey relational grade and S/N ratio.

S. No	Grey relational grade	S/N ratio
1	0.742	2.595
2	0.769	2.283
3	0.659	3.625
4	0.759	2.393
5	0.82	1.724
6	0.711	2.961
7	0.961	0.349
8	0.782	2.138
9	0.827	1.654

The S/N ratios are computed by Taguchi methodology. Table 13 shows the S/N ratio response at each level and also reveals the influencing order of machining parameters. The cutting speed is a highly influencing parameter for surface roughness and tool wear. This is in acceding with beforehand studies on tool wear in turning by Joshi et al. (1999), Erol and Ali (2006) and Jenn et al. (2008) and milling by Caldeirani and Diniz (2002). Increased abrasion between the cutting tool and work material in the work of higher cutting speed causes higher tool wear and surface roughness. The cutting speed is followed by feed rate, lubricant flow rate and finally the depth of cut. From Fig. 6, the optimal levels of machining parameters are identified as A3B1C3D2.

Table 13. Response of S/N ratio.

Factors/levels	level 1	level 2	level 3	max-min	rank
Cutting speed	2.834	2.359	1.381	1.454	1
Feed velocity	1.779	2.048	2.747	0.968	2
Depth of cut	2.565	2.11	1.899	0.665	4
Fluid flow rate	1.991	1.864	2.719	0.727	3

Table 14. ANOVA result of S/N ratio.

Factors	Sum of squares	Degree of freedom	Variance	% Contribution
Cutting speed	3.297	2	1.648	48.75
Feed velocity	1.496	2	0.748	22.124
Depth of cut	0.694	2	0.347	10.262
Fluid flow rate	1.276	2	0.638	18.864
Total	6.762	8		100

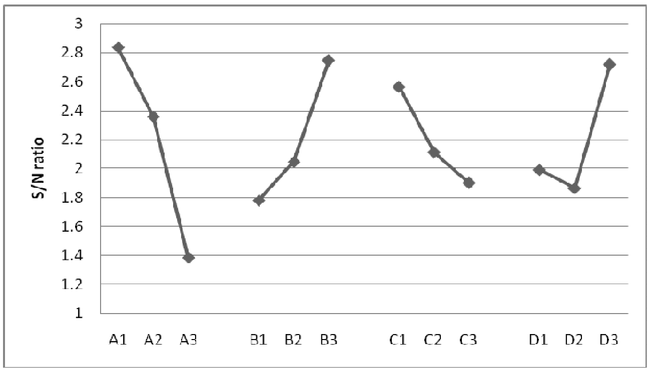

Figure 6. S/N ratio response graph.

The values of optimum parameters are cutting speed of 88 m/min, feed velocity of 180 mm/min, depth of cut of 1.4 mm and coolant flow rate of 600 ml/hr. To exactly decide the contribution of each cutting parameter, ANOVA was applied for S/N ratio of grey relational grade. The result of ANOVA is shown in Table 14. The cutting speed is the highest influencing parameter with 48.75% of contribution. The next significant parameter is feed velocity (22.12%) followed by lubricant flow rate (18.86%). The depth of cut is the least influencing factor when compare with other cutting parameters with 10.26% of contribution.

Validation tests

The optimum levels of machining parameters determined for maximum surface roughness and tool wear are A3B1C3D2. To confirm the obtained optimum set of parameters validation tests were conducted. The results of these tests show that the mean values of surface roughness and flank wear are 0.542 µm and 0.266 mm respectively. This shows that the quality characteristics thought about in the study can be optimized by adopted optimization methodology.

Conclusion

In this paper, genetic algorithm based artificial neural network hybrid prediction model is proposed to foretell surface roughness and tool wear. A multiple objective optimization methodology, by using principal component analysis, grey relational analysis and Taguchi method is also proposed to optimize the machining parameters of Al 6063 under maximum quantity lubrication. The following conclusions are made:

- The optimum machining parameters for minimum surface roughness and tool wear are cutting speed of 88 m/min, feed velocity of 180 mm/min, depth of cut of 1.4 mm and coolant flow rate of 600 ml/hr.
- Among the machining parameters: cutting speed, feed velocity, depth of cut and lubricant flow rate, the cutting speed is the most significant with percentage contribution of 48.75%, followed by feed velocity with 22.12%, liquid flow rate with 18.86% and at last depth of cut with 10.26%.
- The proposed GA based ANN hybrid prediction model has excellent agreement with experimental values, with errors of only 3.3%.
- The validity tests demonstrated that the proposed multiple objective optimization methodology is able in determining the optimum machining parameters in end milling.

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