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Full Paper

Optimisation of high-speed milling process parameters using statistical and soft computing methods

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Abstract: This paper describes the application of statistical and soft computing methods for optimisation of cutting process parameters in high-speed milling by minimising the surface roughness. An analysis of variance is employed to generate empirical functions to demonstrate the effect of the cutting parameters on the cutting force, surface roughness and tool wear. Computational intelligence, viz. a soft computing method, was utilised in the manufacturing process to improve productivity and product quality. In this study experiments on and milling of AISI 1043 steel were performed using an HS Super MC500 machine based on a high-speed milling model. The experimental data were then used to generate empirical functions. A particle swarm optimisation algorithm is proposed to obtain the optimal cutting conditions by considering the boundary conditions that are determined from the empirical relationships of the factors that affect the machining process. The integration of statistical and soft computing methods facilitates the accurate and efficient generation of optimal cutting parameters for high-speed milling process.

Keywords: high-speed milling, optimal cutting conditions, particle swarm optimisation, ANOVA

INTRODUCTION

High-speed machining (HSM) has emerged as a key technology in manufacturing applications due to its advanced characteristics such as high material removal rates and improved productivity [1, 2]. In comparison with traditional machining, HSM is a more complex process. The

HSM cutting mechanism differs from that of traditional machining and the process is associated with high cutting speeds and feed rates [1]. In the literature numerous studies have been conducted on statistical methods and soft computing techniques for the HSM process to improve the quality of machined parts [3].

Statistical approaches such as the factorial design, Taguchi method, response surface methodology (RSM), analysis of variance (ANOVA), grey relational analysis, and statistical regression have been used for the design of experiments and the generation of regression models. The signal-to-noise response analysis and Pareto ANOVA have been used to analyse the data from experimental runs. The Taguchi optimisation method was proposed to optimise the machining parameters to minimise the cutting force and to improve surface roughness in HSM cutting of stainless steel using a coated carbide tool [1]. This method was also used for modelling and optimising surface roughness in the end milling of aluminum silicon carbide composite plates (Al2024-SiCp) using carbide end mills [4]. Hashmi et al. [2] used the RSM to establish a relationship between the surface roughness as the output and the machining parameters for high-speed milling of titanium alloy (Ti-6Al-4V) using carbide inserts tooling. A mathematical model for surface roughness was developed using the RSM with the cutting speed, feed and axial depth of cut as input parameters. The experimental data facilitated the development of a regression model for optimisation of the surface finish in end milling of titanium alloy under dry conditions [5]. The rotatable central composite design was used to analyse the experimental data to develop an empirical model that demonstrated the relationship between the surface roughness (outcome) and the spindle speed, feed rate, depth of cut and step over as machining variables [6].

In machining processes, it is not possible to theoretically derive equations that accurately describe the effects of machining factors on the machining responses such as surface roughness, cutting force and tool wear. In this regard the aforementioned studies have demonstrated the effectiveness of using statistical methods to develop empirically derived equations. However, the study of the simultaneous effects of machining parameters (cutting speed, feed rate and depth of cut) on the surface roughness and cutting force is limited, and so is that of machining parameters and machining time on tool wear, as well as the application of empirically derived equations as an objective function (minimisation of surface roughness) or constraint function (cutting force and tool wear). Therefore, in our study experiments were conducted to acquire and analyse data to determine the relationships between cutting parameters (cutting speed, feed rate and radial depth of cut) and machining responses in the form of empirical functions. Once the mathematical relationships between the cutting parameters and machining responses are established, the underlying processes associated with HSM will be better understood. In addition, the optimisation process will be easier.

Soft computing techniques such as artificial neural networks, fuzzy logic, particle swarm optimisation (PSO) and genetic algorithms are used to generate the optimal solutions for special applications such as the acquisition of optimal machining parameters [7, 8]. Artificial-intelligence-based modelling techniques have been used for high-speed milling processes [3]. These techniques can be grouped into several categories, e.g. Bayesian networks; fuzzy logic, neural and fuzzy-neural networks-based methods; evolutionary algorithms, genetic algorithms, genetic programming and particle swarm optimisation; hidden Markov models; clustering and classification methods. The artificial neural network (ANN) technique using MATLAB ANN Toolbox was utilised in the developing of a model to predict the surface roughness in milling operations [9]. The ANN technique was also used to predict the cutting forces during machining processes. PSO was then employed to generate the optimal cutting speed and feed rate [10, 11]. Regarding the technological and economic aspects, the optimisation of parameters results in the best machining quality at the lowest manufacturing cost. Therefore, the optimisation of the process parameters of emerging HSM technologies is of significant interest. Robust optimisation algorithms with low computational cost, fast convergence and easy implementation can facilitate self-optimisation control of cutting parameters, a new trend in the development of intelligent and autonomous machine tools.

There is a new trend of research in the integration of statistical methods and soft computing techniques to generate optimal machining processes. The quality of machined products is evaluated using several criteria and the surface roughness associated with the machining process is one of the most important requirements. During the machining process, numerous factors such as workpiece properties, cutting tools, machine tools and cutting parameters affect the surface roughness. Among these factors, the cutting parameters or process parameters are the ones that can be effectively controlled to achieve optimum machining outcome. Tseng et al. [12] used Minitab™ to perform ANOVA and regression analysis using the experimental data acquired during traditional milling of Aluminum 6061 T6. Fuzzy logic was then used to predict the surface roughness. Taguchi optimisation method and PSO have been used to predict surface roughness in face milling of AISI1045 steel parts [13]. In this case the Taguchi optimisation method was used to generate the regression model with a surface roughness response. Subsequent optimisation was based on PSO to generate the optimal machining parameters using MATLAB™ software.

Unlike these previous studies, we apply ANOVA to the development of mathematical models to demonstrate the following relationships during high-speed milling: surface roughness and cutting force with cutting parameters, and tool wear with cutting parameters and machining time. PSO is then used to generate the optimal cutting condition required to minimise the surface roughness (objective function), whereas the tool wear and cutting force are used as constraint functions. Therefore, two primary issues are addressed in this study:

- Establishing empirical formulas that describe the relationship between cutting process parameters and surface roughness, cutting force and tool wear, using experimental data and ANOVA.
- Determining optimal cutting parameters for minimising surface roughness by applying PSO.

MATERIALS AND METHODS

Figure 1 shows an engineering model developed for the optimisation of machining process parameters. Firstly, the experimental data such as cutting force, surface roughness, vibration and tool wear are measured for different cutting parameters, viz. cutting speed, feed rate and radial depth of cut. Secondly, according to the ANOVA of factorial experiments, the cutting parameters that significantly affect machining responses, viz. surface roughness, cutting force and tool wear, are identified. Thirdly, the mathematical models for machining responses based on the cutting parameters are established. The optimisation of the machining parameters is then performed to minimise the surface roughness using a PSO algorithm. Finally, the optimal cutting parameters are sent to the machine to control the operations such that the surface quality of the machined part is within the defined specifications

To connect devices in a machining system to the application software, protocols such as MTConnect and OPC (process control protocol for linking and embedding objects) are used [14, 15]. In this study the OPC protocol is used to connect the computer numerical control machine tools and other equipment in the machining system, such as robots, workpiece and transporter.

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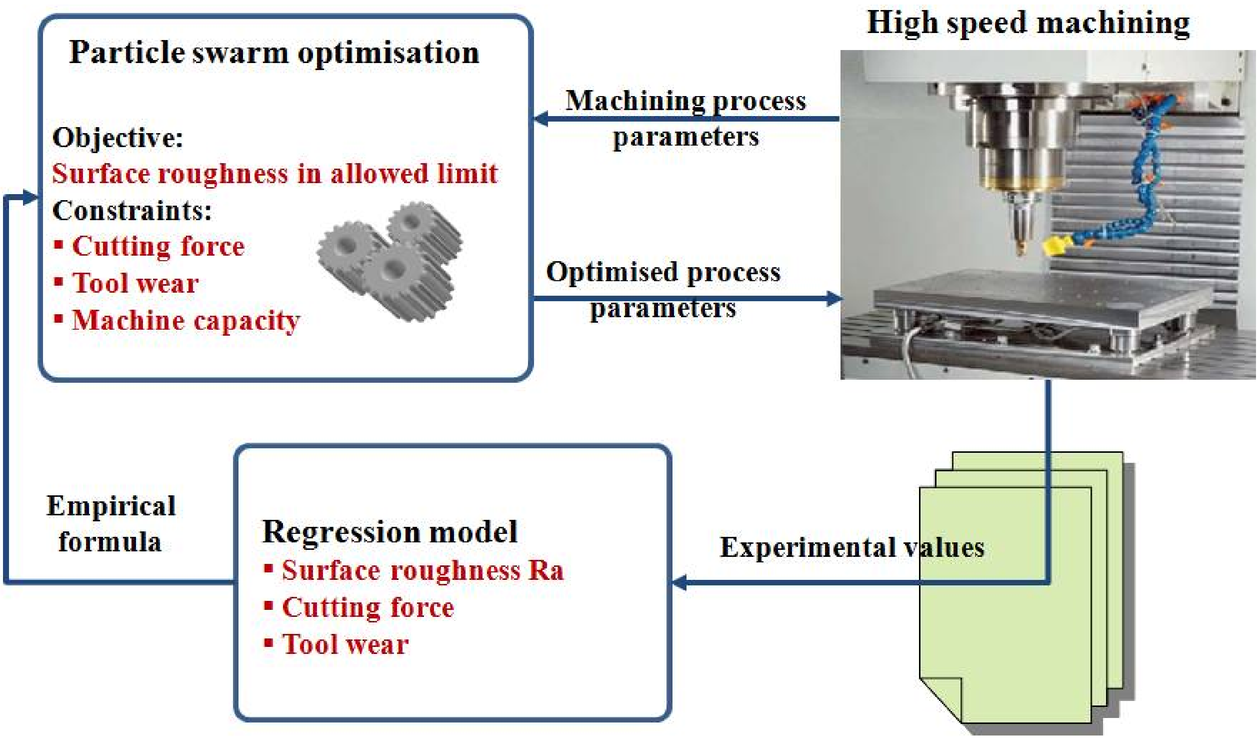

Figure 1. Engineering model for optimisation of cutting parameters

Contour profile milling using a flat end mill tool without coolant was performed using a high-speed vertical machining centre (HS Super MC500, Fuhong Machinery Co., Taiwan), as shown in Figure 2. The workpiece was AISI 1043 carbon steel, which is a commonly used material in mechanical engineering. The cutting tool selected was a titanium aluminum nitride (TiAlN) Sandvik flat end mill (Ø20 mm, 4 teeth).

Based on the theoretical study of high-speed cutting processes and the factors that affect the machining response, the experiments were performed using the following input cutting parameters:

- Cutting speed on the high-speed milling machine, v (m/min.)
- Radial depth of cut, a_r (mm)
- Axial depth of cut, (a_p): 10 mm
- Feed rate, f (mm/min.)

Based on the experimental planning, we chose the range of input cutting parameters as follows:

v_{min} = 370m/min., v_{max} = 595 m/min.
f_{min} = 2357mm/min., f_{max} = 3790 mm/min.
$a_{r\,min}$ = 0.1mm, $a_{r\,max}$ = 0.95 mm

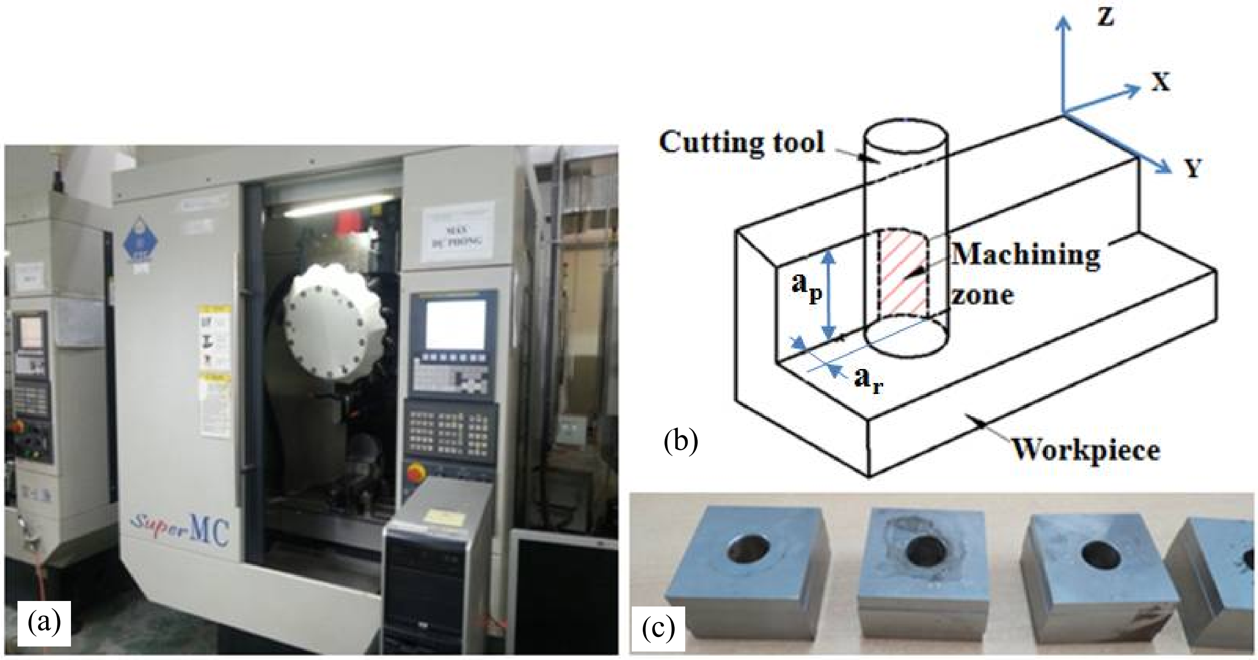

Figure 2. Model used to perform the experiments: (a) high-speed vertical machining centre, (b) milling diagram, (c) experimental workpieces

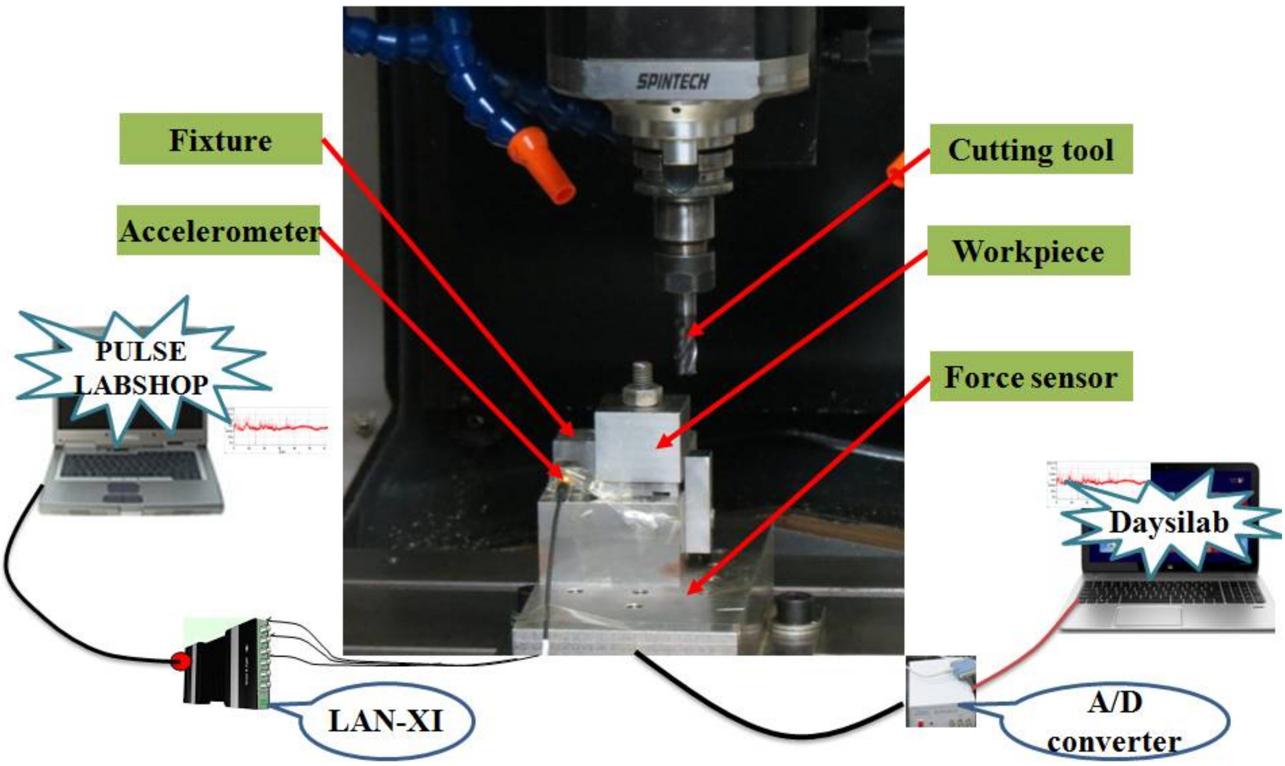

Figure 3. Experimental set-up

The aim of the experiment is to assess the effect of cutting parameters on the cutting force, surface roughness and tool wear during high-speed milling. These acquired results will serve as the basis for developing the mathematical models that describe the relationships between the cutting parameters and the cutting forces (F_x, F_y, and F_z), surface roughness (*Ra*) and tool wear (*VB*).

The experimental set-up, as shown in Figure 3, was used to obtain the experimental data. A surface roughness tester (Mitutoyo Surftest SV-2100, Mitutoyo Corporation, Japan) was used to measure the surface roughness and a Kistler 9257B force sensor (Kistler Instrument AG, Switzerland) was used to measure the cutting force. The signals from the sensor to the computer were converted using an A/D converter and the data were processed using DASY Lab 10.0 software.

The acceleration amplitude of vibration of the workpiece was measured using a Triaxial DeltaTron Accelerometer with TEDS-Type 4525-B-001, LAN-XI (Brüel & Kjær, Denmark) for data acquisition and a PULSE FFT 7770 (Brüel & Kjær, Denmark) to analyse the data. The tool wear was measured using a profile projector (V12B-Nikon digital protractor, Nikon, Japan).

Regression Model

This study used ANOVA to generate the empirical functions to show the effects of the cutting parameters on the cutting force, surface roughness and tool wear. To minimise the number of experiments, an optimal design is required. In this study eight experiments are required with three variables (or factors): cutting speed, feed rate and radial depth of cut for full factorial design. The allowable deviation of variables that does not affect the response is less than 10%. The centre point (coded 0) is quite often the centre of the domain of factors [16]. The design is improved by adding three centre points (or null point) [17]. The centre points appear in rows 9, 10 and 11 in Table 1. With a linear response or a linear relationship, the centre point value is the mid value between the low and high settings for each factor [18]. In the case of a nonlinear relationship or the response surface, the centre point value is above or below the plane, which is indicative of curvature of the response surface [19]. In this investigation the value of the centre point is rounded and not in the middle of the factors, as shown in Table 1, to make it easier to set the parameters as well as for nonlinear relationships. Results were obtained for 11 experiments and the values and codes are as shown in Table 1. The axial depth of cut, a_p, was kept constant (10 mm) during the experiment.

Several factors affect the surface quality of the workpiece, including tool life and machining performance. In this study we focused on the controlled factors and their effects on the machining process while other parameters are considered as boundary conditions or disturbance signals. When milling a profile using a flat end mill, the machining responses during and after cutting, such as cutting force, surface roughness and tool wear, are measured and evaluated. These outputs depend primarily on the cutting parameters, i.e. cutting speed, feed rate and radial depth of cut.

The mathematical functions of the machining output responses in relation to the cutting parameters are as follows:

- Cutting force: $F = f(v, f, a_r)$
- Surface roughness: $Ra = f(v, f, a_r)$
- Tool wear: $VB = f(v, f, a_r, t)$, where t is machining time

Table 1. Experimental values of input parameters

Experi-ment no.	Coding			Cutting speed v (m/min.)	Feed rate f (mm/min.)	Radial depth of cut a_r (mm)
	x_1 (Cutting speed)	x_2 (Feed rate)	x_3 (Radial depth of cut)			
1	-1	-1	-1	370	2357	0.1
2	+1	-1	-1	595	2357	0.1
3	-1	+1	-1	370	3790	0.1
4	+1	+1	-1	595	3790	0.1
5	-1	-1	+1	370	2357	0.95
6	+1	-1	+1	595	2357	0.95
7	-1	+1	+1	370	3790	0.95
8	+1	+1	+1	595	3790	0.95
9	0	0	0	495	3153	0.6
10	0	0	0	495	3153	0.6
11	0	0	0	495	3153	0.6

The study of the simultaneous effects of cutting speed, feed rate and radial depth of cut on the output parameters indicates that the relationship is nonlinear [5]. The mathematical models of surface roughness, cutting force and tool wear during high-speed milling in terms of the cutting parameters, can be expressed as follows:

$$Ra = C_1 v^{k1} f^{l1} a_r^{m1} \tag{1}$$

$$F = C_2 v^{k2} f^{l2} a_r^{m2} \tag{2}$$

$$VB = C_3 v^{k3} f^{l3} a_r^{m3} t^{h3} \tag{3}$$

where v is cutting speed (m/min.); f is feed rate (mm/min.); a_r is radial depth of cut (mm); t is machining time (min.), and C_i, k_i, l_i, m_i (i=1÷3) and h_3 are estimated experimental coefficients.

PSO Algorithm for Optimising Cutting Parameters

Soft computing techniques such as artificial neural networks, PSO, fuzzy logic, genetic algorithms, simulated annealing, ant colony optimisation and artificial bee colony algorithms have been applied to the study of artificial intelligence in manufacturing fields [7, 8, 10].

Many tools have been developed for visualisation and monitoring of the progress of these algorithms. These tools run on different platforms using both commercial and non-commercial software. To generate solutions based on the PSO algorithm, SwarmViz, VISPLORE and PSOLeT software have been developed and applied as reported in the literature. SwarmViz is a visualisation tool for PSO and is used for teaching and research in swarm intelligence techniques. This tool is an open-source software written in C++ with the goal of simulating robotic learning and benchmark functions [20]. VISPLORE, which runs on Mathematica, is a toolkit that is used to run and analyse

PSO experiments. This toolkit facilitates visualising solutions from particle swarm optimisation for different levels including individual, population, experimental and collection of experiments [21]. PSOLeT, running on MATLAB™, is a tool for learning and evaluating basic optimisation designs. This tool facilitates the changing of the PSO parameters, such as the number of existing particles in the population and the maximum velocity allowed for each particle, to generate an optimisation design [22].

In this study the PSO algorithm is used to optimise the cutting parameters (v, f and a_r) in high-speed milling such that the objective function is minimised. We developed an application to predict surface roughness and generate the optimal cutting parameters using MATLAB™. The objective function is the surface roughness:

$$Y = Ra = C_1 v^{k1} f^{l1} a_r^{m1}$$

The boundary conditions as well as the limitations of the machining system are also considered in the determination of the cutting parameter values. The boundary conditions are as follows:

- Cutting power:

  $$v F_y \leq P\eta 6000,$$

  where P is cutting power (kW), η is coefficient of efficiency, F_y is cutting force in Y-direction (N), and v is cutting speed (m/min.). The cutting force component in the Y-direction has the largest effect on the cutting process.
- Cutting speed:

  $$v_{min} \leq v \leq v_{max}$$
- Feed rate:

  $$f_{min} \leq f \leq f_{max}$$
- Radial depth of cut:

  $$a_{rmin} \leq a_r \leq a_{rmax}$$

In order to implement the application using the PSO algorithm, the MATLAB™ software was used for programming. An outline of the proposed algorithm is shown in Figure 4 and the following parameters are used:

+ w: inertia constant;
+ $rand_1$ and $rand_2$: random vectors that assume values in the range [0÷1], which are generated at each iteration step;
+ p_{besti}: best position up to the present time of the i^{th} individual in the population;
+ g_{best}: best location for the entire population at the present moment.

The steps of the algorithm as shown in Figure 4 are explained as follows:

- Step 1: Initialise the population with position vector x_i and velocity vector v_i for i^{th} individual, where i = 1÷n (for each P_i in the population P(n)); calculate the position vector x_i (v_i, f_i, a_{ri}) for each value of v_i, f_i, and a_{ri} in population P; and define the boundary conditions.
- Step 2: Initialise the information for the best location of individuals and the entire population:

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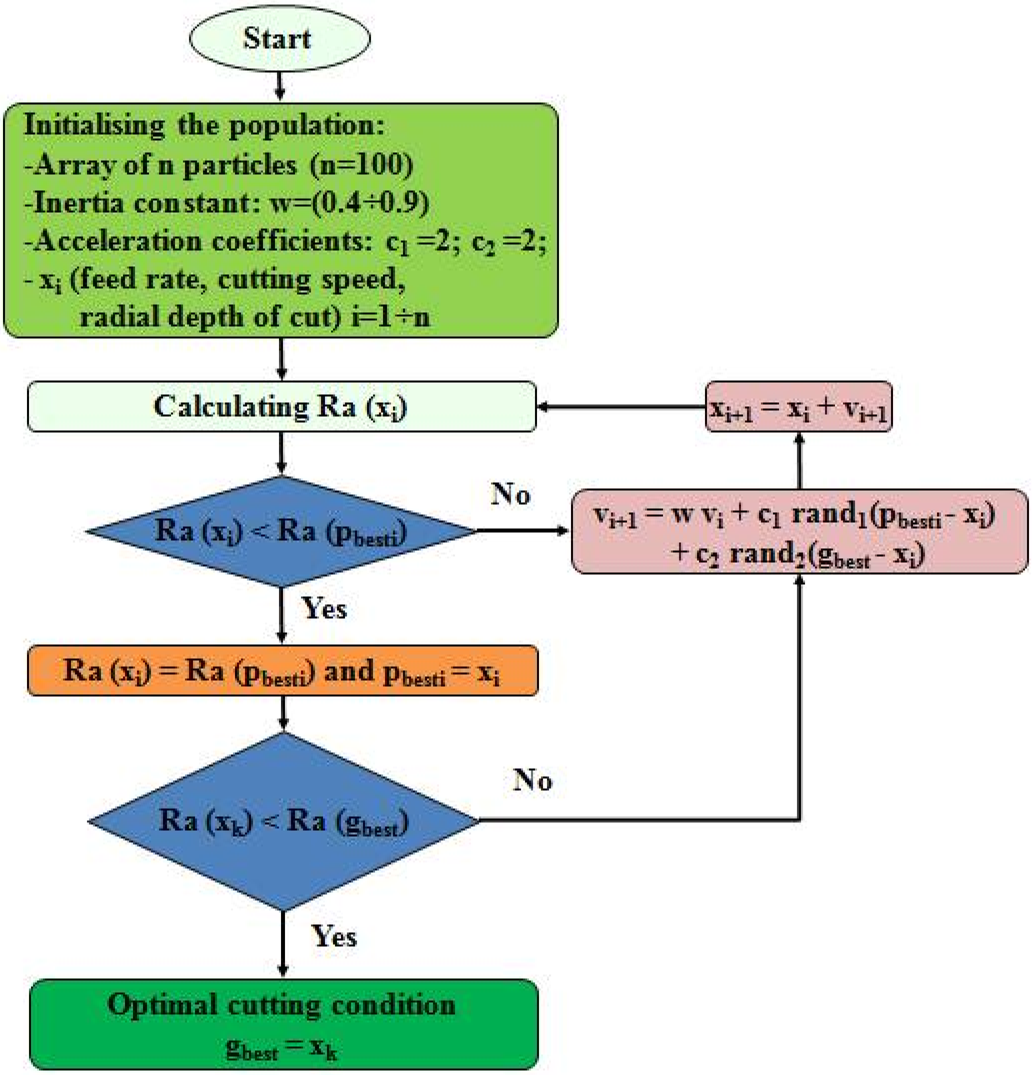

Figure 4. PSO algorithm for the optimisation of cutting parameters

+ $p_{besti} = x_i$; initialisation of the best position of ith instance (current initial position);
+ $g_{best} = \min(Ra(x_i))$, i = 1÷n; initialisation of the best position of entire population for the smallest position in all positions for all initial instances.

- Step 3: Find the best position in the population.

  For i = 1÷n; for each instance:

  $v_{i+1} = w\ v_i + c_1 rand_1(p_{besti} - x_i) + c_2 rand_2(g_{best} - x_i)$; update of the motion of the next generation according to the best current motion of the individual and the motion of the best individual in the population;

  $x_{i+1} = x_i + v_{i+1}$; update the location based on the current location and the latest movement direction;

  if $Ra(x_i) < Ra(p_{besti})$, then $p_{besti} = x_i$; update the best position of each individual by comparison with the current position.

  For i = 1÷n; for the population:

if $Ra(x_k) < Ra(g_{best})$, then $g_{best} = x_k$; update the best location of the population by comparison with the best present individual;

For each x_i value, the boundary conditions are compared. If satisfied, go to step 4; do not continue to step 3.

- Step 4: Finish, return the best g_{best} value.

RESULTS AND DISCUSSION

Table 2 presents the results for the measured cutting force and surface roughness. The experimental measurements show that the force in the Y-direction is greater than that in the X- and Z-directions. Therefore, in this study the force component in the Y-direction is used to analyse the effects on the surface roughness and tool wear. Table 3 presents the results obtained for tool wear. Given that four factors (or variables), namely cutting speed, feed rate, radial depth of cut and machining time, are considered in tool wear, the required number of experiments for full factorial design is 16. The centre point that appears in row 17 in Table 3 was added to improve the experimental design.

Table 2. Experimental values of the cutting force (F_y) and surface roughness (Ra)

Experi-ment no.	Cutting speed *v* (m/min.)	Feed rate *f* (mm/min.)	Radial depth of cut a_r (mm)	F_y (N)	Ra (μm)
1	370	2357	0.1	128.91	0.389
2	595	2357	0.1	97.57	0.325
3	370	3790	0.1	148.44	0.537
4	595	3790	0.1	104.57	0.494
5	370	2357	0.95	397.34	0.518
6	595	2357	0.95	347.99	0.488
7	370	3790	0.95	485.50	0.566
8	595	3790	0.95	367.64	0.471
9	495	3153	0.6	296.10	0.421
10	495	3153	0.6	296.90	0.422
11	495	3153	0.6	296.72	0.425

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Table 3. Experimental values for the extent of tool wear (VB)

Experi-ment no.	Cutting speed v (m/min.)	Feed rate f (mm/min.)	Radial depth of cut a_r (mm)	Machining time t (min.)	VB (µm)
1	370	2357	0.1	3.5	17
2	595	2357	0.1	3.5	39
3	370	3790	0.1	5.4	51
4	595	3790	0.1	5.4	70
5	370	2357	0.95	8.7	90
6	595	2357	0.95	8.7	102
7	370	3790	0.95	13	161
8	595	3790	0.95	13	267
9	370	2357	0.1	19.2	153
10	595	2357	0.1	19.2	285
11	370	3790	0.1	25	368
12	595	3790	0.1	25	456
13	370	2357	0.95	19.2	294
14	595	2357	0.95	19.2	366
15	370	3790	0.95	17.4	288
16	595	3790	0.95	18.4	468
17	495	3153	0.6	20.9	489

In Table 4 with n observations and k variables the regression degrees of freedom (DFR), the error degrees of freedom (DFE) and the total degrees of freedom (DFT) are calculated. For calculating total sum of squares (SST), regression sum of squares (SSR) and error sum of squares (SSE), the mean of the n observations ($\bar{y}$) and the estimated values obtained using the regression model ($\hat{y}$) must be determined. From the sum of squares (SS) and degree of freedom (DF) values, the mean square (MS) is calculated. F-statistic (F) is equal to the ratio of the regression mean square (MSR) to the error mean square (MSE).

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Table 4. Corresponding factors in ANOVA table

	Degree of freedom (DF)	Sum of squares (SS)	Mean square (MS)	F-statistic (F)
Regression	DFR = k	$\mathrm{SSR} = \sum_{i=1}^{n}(\hat{y}_i - \bar{y})^2$	MSR= SSR/DFR	MSR/MSE
Residual error	DFE= n-k-1	$\mathrm{SSE} = \sum_{i=1}^{n}(y_i - \hat{y}_i)^2$	MSE= SSE/DFE	
Total	DFT = n-1	$\mathrm{SST} = \sum_{i=1}^{n}(y_i - \bar{y})^2$		

To determine the constants and exponents of equations 1, 2 and 3, the mathematical models are linearised using a logarithmic function, and rewritten as follows:

$$\ln Ra = \ln C_1 + k_1 \ln v + l_1 \ln f + m_1 \ln a_r; \quad (4)$$
$$\ln F_y = \ln C_2 + k_2 \ln v + l_2 \ln f + m_2 \ln a_r; \quad (5)$$
$$\ln VB = \ln C_3 + k_3 \ln v + l_3 \ln f + m_3 \ln a_r + h_3 \ln t. \quad (6)$$

The linear models of the above equations are as follows:

$$y_1 = b_{01} + b_{11} x_1 + b_{21} x_2 + b_{31} x_3; \quad (7)$$
$$y_2 = b_{02} + b_{12} x_1 + b_{22} x_2 + b_{32} x_3; \quad (8)$$
$$y_3 = b_{03} + b_{13} x_1 + b_{23} x_2 + b_{33} x_3 + b_{43} x_4, \quad (9)$$

where y_1, y_2, and y_3 are the true responses of the surface roughness, cutting force and tool wear respectively; b_{ij} (i = 0÷4, j = 1÷3) are the parameters to be estimated; and x_1, x_2, and x_3 are the logarithmic transformations of the cutting speed, feed rate and radial depth of cut respectively. The problem becomes an empirical regression when the experiments are performed. Tables 5, 7 and 9 present the results of the regression statistics, and Tables 6, 8 and 10 summarises the effects of the cutting parameters on the cutting force, surface roughness and tool wear respectively.

Table 5. Results of regression statistics on F_y

Regression statistics	
Multiple R	0.987860295
R square	0.985725168
Standard error	0.045020821
Observations	11

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Table 6. Effects of cutting parameters on F_y

	DF	SS	MS	F	Significance F
Regression	3	3.3048	1.1016	543.497109	1.18718E-08
Residual error	7	0.01419	0.002027		
Total	10	3.31899			
	Coefficients	Standard error		P-value	
Intercept	7.490523586	0.67048		1.026E-05	
x_1	-0.55326353	0.0666		7.1581E-05	
x_2	0.238912613	0.06661		0.00889547	
x_3	0.533985076	0.01353		1.7426E-09	

Table 7. Results of regression statistics on Ra

Regression statistics	
Multiple R	0.956340479
R square	0.937205092
Standard error	0.125808478
Observations	11

Table 8. Effects of cutting parameters on Ra

	DF	SS	MS	F	Significance F
Regression	3	0.148101838	0.049367279	3.119028745	0.007349575
Residual error	7	0.110794412	0.015827773		
Total	10	0.258896250			
	Coefficients	Standard error		P-value	
Intercept	-1.937080761	1.872516072		0.335321521	
x_1	-0.302270348	0.186072584		0.148302540	
x_2	0.382423871	0.186106481		0.078961233	
x_3	0.057248255	0.035951295		0.155326056	

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Table 9. Results of regression statistics on VB

Regression statistics	
Multiple R	0.9850
R square	0.9702
Standard error	0.2197
Observations	17

Table 10. Effects of cutting parameters on VB

	DF	SS	MS	F	Significance F
Regression	4	18.83143752	4.70785938	97.53452945	4.81594E-09
Residual error	12	0.579223716	0.048268643		
Total	16	19.41066123			
	Coefficients	Standard error		P-value	
Intercept	-4.053885999	2.330512121		0.10751012	
x_1	0.620523746	0.230995237		0.019804696	
x_2	0.240912233	0.232434691		0.320417164	
x_3	0.082289036	0.049579456		0.12285262	
x_4	1.387586098	0.075312788		3.62771E-10	

From the values of DF, SS, MS and R square, the P-values from Tables 5-10 indicate that at least one of the regression coefficients is nonzero and represents a high level of statistical significance. The expressions for y_i (i = 1-3) are as follows:

$$y_1 = 7.4905 - 0.5533\, x_1 + 0.2389\, x_2 + 0.5340\, x_3 \quad (10)$$
$$y_2 = -1.9371 - 0.3023\, x_1 + 0.3824\, x_2 + 0.0572\, x_3 \quad (11)$$
$$y_3 = -4.0539 + 0.6205\, x_1 + 0.2409\, x_2 + 0.0823\, x_3 + 1.3876\, x_4 \quad (12)$$

From equations 1-3, and 10-12, the cutting force component in the Y-direction, surface roughness and tool wear as a function of v, f and a_r are respectively expressed as follows:

$$F_y = 1791\, v^{-0.5533} f^{0.2389} a_r^{0.5340} \quad (13)$$
$$Ra = 0.1441\, v^{-0.3023} f^{0.3824} a_r^{0.0572} \quad (14)$$
$$VB = 0.0174\, v^{0.6205} f^{0.2409} a_r^{0.0823} t^{1.3876} \quad (15)$$

According to the established formulas (13)-(15), if the cutting speed increases during the high-speed milling process, the magnitude of the surface roughness and cutting force is reduced; however, the tool wear increases. Therefore, the selection of the most appropriate cutting parameters to meet the machining requirements is a difficult process. This study uses the PSO algorithm to determine the optimal cutting parameters to minimise surface roughness and tool wear by considering the cutting force required to achieve allowable limits. The module for optimising the cutting parameters was programmed using MATLAB^{TM}. A screenshot of the developed module is shown in Figure 5. This figure also shows an example that demonstrates the functionality of the developed system, in which the population size is 200 individuals, the iteration number is 500, and the acceleration coefficient is 1.49445 (denoted by 1 in Figure 5). The boundary conditions (denoted by 2) are as follows:

- Minimum cutting speed (G2): 370 m/min.
- Maximum cutting speed (G3): 595 m/min.
- Minimum feed rate (G4): 2357 mm/min.
- Maximum feed rate (G5): 3790 mm/min.
- Minimum radial depth of cut (G6): 0.1 mm
- Maximum radial depth of cut (G7): 0.95 mm
- Maximum acceleration amplitude of vibration (G8): 2 (10^{-3} m/s^2)
- Maximum tool deformation (G9): 0.02 mm
- Maximum tool wear (VB): 300 µm
- Maximum surface roughness: 0.38 µm

The maximum tool wear, surface roughness and inertia constant are inputted from the interface of the developed system (denoted by 3 in Figure 5).The initial cutting parameters are feed rate (2357.0004 mm/min.), cutting speed (595 m/min.) and radial depth of cut (0.1 mm). After 4 min. of machining, the system predicts that the amount of tool wear is 43.779 µm and the surface roughness is 0.368 µm (denoted by 4). Based on the information of tool wear and surface roughness, the optimal cutting parameters are updated as 2398.43 mm/min. for the feed rate and 549.962 m/min. for the cutting speed (denoted by 4).

The initial cutting parameters were calculated for the fresh cutting tool (extent of tool wear = zero). Considering the finished machining that requires minimum surface roughness, tool wear was used as the constraint function, as shown in empirical equation (15), to generate new optimal cutting parameters.

To verify the correct output of the developed system, the PSO algorithm was also compared with the experimental results, as shown in Table 11. Using the same boundary conditions and only varying in the cutting speed or feed rate, the experimental results and predictions are within the allowed limits.

Table 11. Surface roughness from PSO algorithm predictions and experimental results

Experiment	v (m/min.)	f (mm/min.)	a_r (mm)	Experimental measurement Ra (µm)	PSO prediction Ra (µm)	Error (%)
Test 1	594.999	2357.0004	0.1	0.353	0.35687	1.1
Test 2	595.001	2357	0.1	0.341	0.35595	4.4
Test 3	595	2357	0.1	0.332	0.35675	7.5
Average	595	2357.0001	0.1	0.342	0.35652	4.2

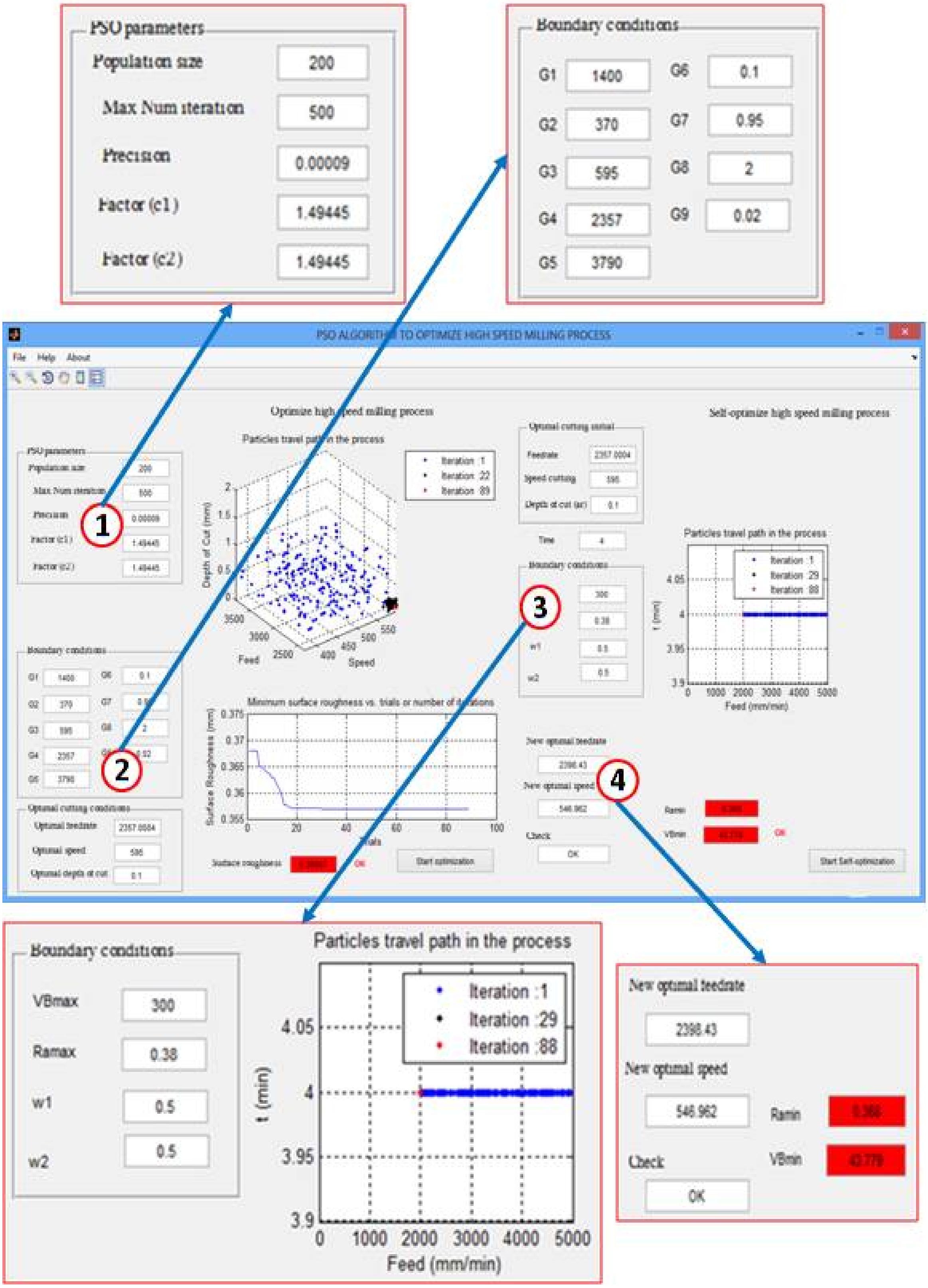

Figure 5. Screenshot of the module used to optimise cutting parameters

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CONCLUSIONS

In this study the mathematical relationships between cutting parameters in the high-speed milling process and surface roughness, cutting force and tool wear have been established using ANOVA. The engineering model and experiment have been systematically designed. The empirically-derived formulas were used as the objective function (surface roughness) or constraint functions (tool wear, cutting force) for determining the optimal cutting parameters to minimise surface roughness. The optimum cutting parameters were obtained by using the PSO algorithm. The module for predicting surface roughness and generating the optimal cutting parameters was developed using MATLAB^{TM}.

The accuracy of the developed module was validated by comparing the experimental values of surface roughness with the predicted ones obtained by PSO algorithm. The integration of the statistical and soft computing methods enabled the generation of the optimal cutting parameters for accurate and efficient high-speed milling. The application of these results to the development of a system for online monitoring and adjustment of the cutting conditions to achieve the desired machined part quality during the HSM process will be pursued in future studies. This study has contributed to the development of intelligent control techniques for machining processes.

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