

This is the author-created version of the following work:

Laghari, Rashid Ali, Pourmostaghimi, Vahid, Laghari, Asif Ali, Chalak Qazani, Mohammad Reza, and Sarhan, Ahmed A.D. (2025) *Genetic modeling for enhancing machining performance of high-volume fraction 45% SiCp/Al particle reinforcement metal matrix composite*. Arabian Journal for Science and Engineering, 50 pp. 9043-9059.

Access to this file is available from:

<https://researchonline.jcu.edu.au/86691/>

© King Fahd University of Petroleum & Minerals 2024

Please refer to the original source for the final version of this work:

<https://doi.org/10.1007/s13369%2D024%2D09330%2Dw>

Genetic modelling for enhancing machining performance of high-volume fraction 45% SiCp/Al Particle reinforcement Metal Matrix Composite

Rashid Ali Laghari¹, Vahid Pourmostaghimi², Asif Ali Laghari³, and Mohammad Reza Chalak Qazani⁴, and Ahmed A.D. Sarhan^{5,6}

¹ *Department of mechanical engineering technology, Sindh Institute of Management and Technology, Karachi, Sindh, Pakistan Email: rashidalilaghari@gmail.com*

² *Department of Manufacturing and Production Engineering, Faculty of Mechanical Engineering, University of Tabriz, Tabriz, Iran. Email: vahidvpm@tabrizu.ac.ir*

³ *Department of Computer Science, Sindh Madressatul Islam University, Karachi, Pakistan Email: asifalilaghari@gmail.com.*

⁴ *Faculty of Computing and Information Technology, Sohar University, sohar, 311, Oman. Email: mqazani@su.edu.om*

⁵ *Department of Mechanical Engineering, King Fahd University of Petroleum and Minerals, Dhahran, 31261, Saudi Arabia ahsarhan@kfupm.edu.sa*

⁶ *Interdisciplinary Research Center of Intelligent Manufacturing and Robotics, King Fahd University of Petroleum and Minerals, Dhahran, 31261, Saudi Arabia*

Correspondence: Ahmed A.D. Sarhan and Vahid Pourmostaghimi

Abstract

Metal matrix composites (MMCs) have gained great recognition in recent decades in a wide range of applications, including aerospace, automobiles, engine cylinders, and other sectors. MMCs possess excellent properties including light in weight, high corrosion resistance, stiffness, and strength. However, they are categorized as difficult-to-cut materials where machining of these materials remains a challenging task. To improve the machining process quality and to avoid unnecessary experiments in a cost-effective manner, this article aims to develop an

artificial intelligence model, using the genetic programming (GP) method to predict the cutting force, surface roughness, and tool life during the machining process of SiCp/Al at different cutting parameters including cutting speed, feed rate, and depth of cut. The developed genetic programming-based prediction model is designed and developed using MATLAB software. Meanwhile, the GP parameters including mean square error, root means square error, normalized mean square error, mean error, variation of error, correlation coefficient, and R-square are used for the validating of the proposed model. The GP model results are compared with our previous response surface methodology (RSM) model results that were employed to estimate the machining characteristics of the SiC particle-reinforced metal matrix composites (45% SiCp) with different cutting parameters. The GP results prove the higher efficiency with the prediction of the cutting force, surface roughness, and tool life, 43.07%, 37.82%, and 115.64%, respectively, compared with the previous RSM method.

Keywords: SiCp/Al metal matrix composite; machining characteristics; tool wear, cutting force, surface roughness; genetic programming; response surface methodology.

1. Introduction

In recent years, SiCp/Al composites have rapidly replaced traditional materials due to their excellent properties such as high strength, high hardness, high specific strength, good heat resistance, and special commercial and technical values. The application of SiCp/Al in the industry is becoming more extensive [1-3]. However, with the addition of SiC particles as reinforced and the addition of aluminium as a matrix during fabrication to form SiCp/Al composite, it became a hard-to-machine material. The machining of SiCp/Al composite causes rapid tool wear during processing leading to high processing costs, low processing efficiency, and poor surface quality, which has become a major problem that hinders wide applications in numerous fields [3,4]. At present, scholars have carried out a series of research on the machinability process of SiCp/Al composites [6-8]. In terms of tool wear, surface roughness, and cutting forces, extensive work has been done by several researchers and developed various predictive, simulation, intelligence, and analytical models [9-11]. The study was performed on the tool wear mechanism by Hung et al. [12] with verified experiments. Authors recommended

the polycrystalline diamond (PCD) tool, on the experimental basis, for machining operation of SiCp/Al. furthermore; the author develops the tool wear models for machining SiC particle-reinforced metal matrix composites. The model results show that it is more productive and economical to employ the uncoated WC inserts for rough cutting and PCD tools for finishing operation. El-Gallab et al. [13-15], conducted high-speed dry milling experiments under different parameters when studying the cutting performance of Al/SiC/20p composites, emphasizing the surface quality and the degree of damage under the surface. Authors believed that the performance of PCD tool was consistent for machining SiCp/Al, however, it reveals that in high-speed milling surface quality of part will be reduced. Li et al. [16] Conducted milling experiments to investigate the tool wear on machining 5% SiCp/Al composites using coated carbide cutters at milling speed (up to 88 m/min). The tool wear is increased at higher milling speed. As the speed increases, the abrasive wear on the flank is the main form causing wear. Sahin et al. [17] studied the effect of reinforcement on the machinability of SiCp/Al composites. They found that the tool wears increased with the increase of the average particle size and volume fraction of the reinforcement phase. In other research work such as [18], it is observed that chipping often occurs in addition to the typical flank wear of CBN tools in cutting SiCp/Al composites. As the size of the reinforcing particles increases, the chipping became more serious [18-19]. In addition, it is observed that the machinability of SiCp/Al faces lots of challenges such as sudden breakage of the tool, degraded surface quality generation at higher amounts of vibration, temperature, and cutting forces [2, 20-22]. In turning of SiCp/Al MMCs [22], apart from the cutting parameters, the machining performance and part quality typically depend on SiC particle size, volume percentages, reinforcing techniques, fabrication methods, and interface bonding strength of a particular matrix. With this regard, a machinability study at a 15% volume fraction of SiC-A356 Al at various ranges of depth of cut was conducted by Chambers et al. [23]. It is clearly seen that tool life shows a declining trend as the depth of cut values increases at much extent during machining.

A similar study [24], declared that with the increasing of feed rate, tool wear is highly increased. In addition, reducing the feed rates increasing the tool life due to the decrease of the physical contact between the tool-part and work part surface as well as the less contact along with abrasive Silicon particles [13]. Zhou and Liu [25] studied the cutting performance of the CVD diamond coated cemented carbide cutting tools during machining MMCs at a feed rate of 0.05-

0.3 (mm/rev) and cutting speed of 1-6 (m/s), cutting depth of 1-2 (mm) with the inclusion of coolants. It is depicted in the results that a higher amount of feed rate and cutting speed is increasing the tool wear, and hence the coating fails as stresses increase in the machining process. Furthermore, it is depicted that the major factors affects the tool life are the depth of cut, cutting speed and material characteristics (SiC particles size, volume percentages, reinforcing techniques, fabrication methods) of SiCp/Al composite. The quality of the machined surface is also affected by the tool materials (grain size and chemical composition, and edge hardness) used for machining the SiCp/Al composite [26-28].

One of the recently developed powerful machine learning tools which has been widely utilized in the modeling of manufacturing processes is Genetic Programming (GP). Having been inspired by the biological model of evolution and natural selection, GP has been applied to solve many real-world problems. The main goal of GP is to extract a genetic equation for a given set of values and variables. Numerous applications of GP have been reported in machining processes.

Kovacic et al. [29] proposed the modeling of cutting force in milling of aluminum and steel. On the basis of the experimental data, different models for cutting forces prediction were obtained by genetic programming. Research shows that genetically developed models fit the experimental data. Milfelner et al. [30] studied the development of the genetic equation for the cutting force for ball-end milling process. The obtained results show that the developed genetic equation fits very well with the experimental data. Garg and Tai et al. [37] proposed a modified GP method using a stepwise regression approach such that the genes of lower performance are eliminated and only the high performing genes are combined. In their work, the proposed method was applied in modelling the surface roughness in the turning of hardened AISI H11 steel. The results showed that the model produces better performance than those of support vector machine and artificial neural networks. Kumar Abhishek et al. [31] illustrates the applicability of genetic programming with the help of Adaptive Neuro Fuzzy Inference System (ANFIS) towards generating prediction models for cutting force in the drilling operation of GFRP composites. F. Čuš and Uros Zuperl [32] investigated the applications of GP in steelmaking process and evaluated the ability of GP in modeling various machining characteristics such as surface roughness, tool wear and cutting force.

Due to the lack of research on the machinability of high-volume fraction (over 30%) metal matrix composites, this paper aimed to investigate the machinability of 45% SiCp/Al composites using carbide cutting tools. This work is performed to investigate the effects of the machining parameters on cutting forces, surface roughness, and tool life in machining SiCp/Al composite materials. The RSM and GP prediction models are developed to explore the impact of machining parameters in turning SiCp/Al composite.

2. Materials and Methods

2.1. Experimental Work

Figure.1 shows the experimental setup. In this experimental work, the cutting forces, tool life, and surface roughness, were measured. The workpiece material used is SiCp aluminium metal matrix composite with a volume fraction of 45%, which is commonly used as a structural material in aerospace and automobile industries. The workpiece material is prepared in the advance materials lab, Harbin Institute of Technology, Harbin, China. The SiCp/Al sample workpiece for turning process is carefully chosen with the shape of a cylindrical bar having a diameter of 48.2 (mm) and a length of 98.9 (mm). Table 1 shows the chemical composition of SiCp/Al 45%. While Table 2 shows the material properties of the specimens (SiCp/Al 45%). For the machining experiments, the carbide cutting tool (CNMG120408-PM) is used in this research work, which has a nose radius of 0.8 (mm) and possesses a relief angle of 7°. The CNC lathe machine “Shenyang lathe CAK50135di” is employed for the cutting operation. The experiment is design based on 3 factors and 4 levels with total number of combinations of 16 experiments. The Cutting Parameters levels and the experimental matrix used are shown in Table 3 and 4. The working range of these cutting parameters v , f , d , shown in Table 3, are selected based on the tool maker recommendation for the best achievement in turning of SiCp/Al using the carbide cutting tool (CNMG120408-PM).

New carbide cutting tool is used for each experiment. The surface roughness and cutting forces were measured after each cutting operation. The experiments were performed continuously without removing the test equipment devices except for changing the worn cutting tool at 0.3 mm flank wear according to the ISO 3685 (ISO, 1993) standards [1]. The “TR200V1.5-meter Anyty” and the “3R-WM401-WIFI” devices were used to measure the tool's surface roughness

and wear, respectively. The detailed devices and equipment used in the experimental setup are shown in Figure. 1 which consist of turning machine with SiCp/Al specimen, carbide cutting tool, the sample of tool wear, surface roughness, cutting force. The cutting forces measured using Kistler three-way dynamometer, a charge amplifier, a data acquisition card, and a computer equipped with data analysis software DynoWare software.

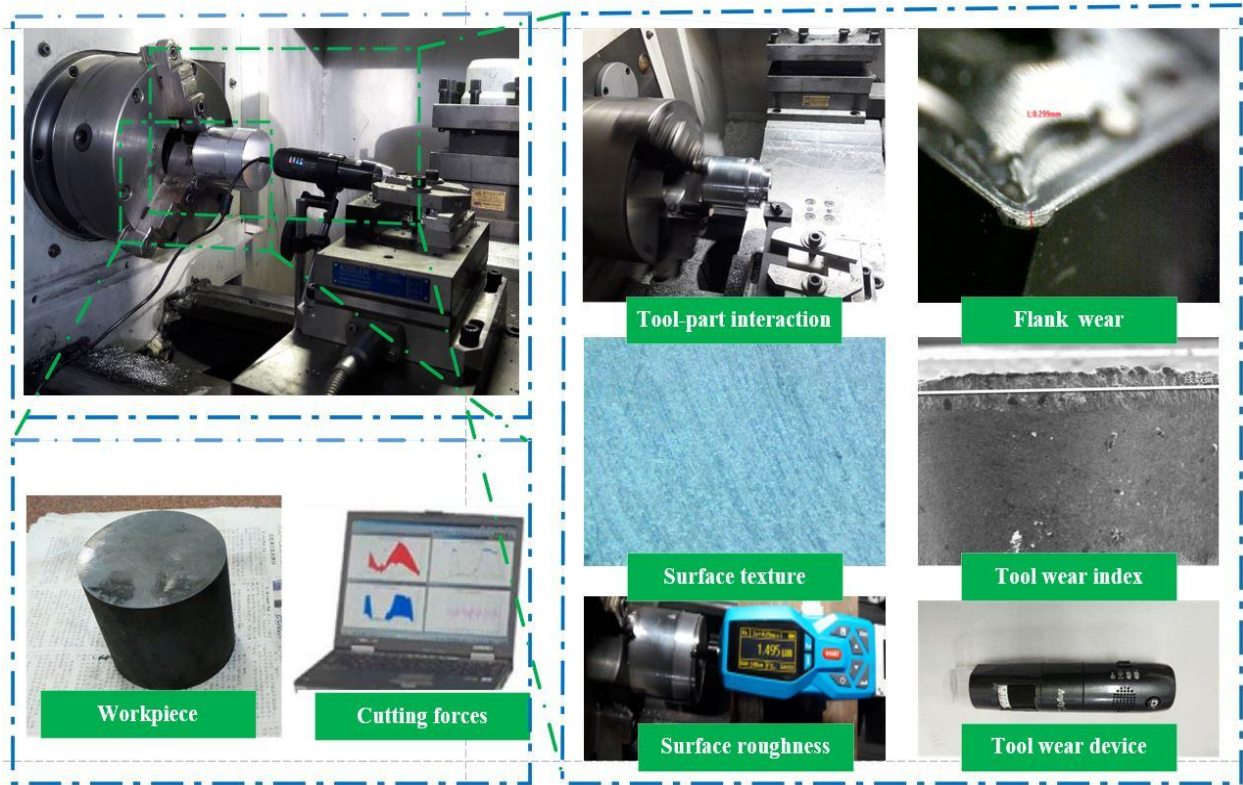


Figure.1 Experimental setup

Table 1. Chemical composition of SiCp/Al 45%

Element	Si	C	O	Fe	Mn	Cu	Mg	K	S	Al
Percentage	39.8	22.7	7.9	8.9	0.5	1.1	0.3	1.2	0.3	balance

Table 2. Material properties of SiCp/Al 45%

Yield Strength MPa	Young's modulus GPa	Thermal conductivity ($\text{W}\cdot\text{m}^{-1}\cdot\text{K}^{-1}$)	Coefficient of thermal expansion ($10^{-6}/^{\circ}\text{C}$)	Mass density (g/cm^3)
200-500	161	185-200	11.2	2.88–2.92

Table 3. Cutting Parameters levels [1,2]

Cutting parameters	Levels			
	First Level	Second Level	Third Level	Fourth Level
Cutting Speed (m/min)	6.283	12.566	18.85	25.133
Feed rate (mm/r)	0.01	0.015	0.02	0.025
Depth of cut (mm)	0.2	0.5	1	1.5

Table 4. Experimental matrix [1,2]

No.	Cutting Speed (m/min)	Feed Speed (mm/r)	Depth of Cut (mm)
1	6.283	0.01	0.2
2	6.283	0.015	0.5
3	6.283	0.02	1
4	6.283	0.025	1.5
5	12.566	0.01	0.5
6	12.566	0.015	0.2
7	12.566	0.02	1.5
8	12.566	0.025	1
9	18.85	0.01	1
10	18.85	0.015	1.5
11	18.85	0.02	0.2
12	18.85	0.025	0.5
13	25.133	0.01	1.5
14	25.133	0.015	1
15	25.133	0.02	0.5
16	25.133	0.025	0.2

2.2. Response Surface Methodology

Response surface methodology (RSM) is frequently used in various fields for predicting and developing mathematical models based on statistics to measure the relationship between the response and independent variables. It is a kind of approach that incorporates the results from the experimental data followed by statistical methodologies to break down the complex problems into possible solutions and eliminate the insignificant factor. The RSM technique is used in this study to optimize the influence of the machining parameters, including cutting speed, feed rate, and depth of cut on the responses considering tool wear, surface roughness, and cutting forces. The quadratic equation for various responses and variables is shown in Eq. (1).

$$Y = F[v, f, d] \quad (1)$$

Where, Y represents the desired function, F in the equation represents the response, and the rest of the parameters are v , f , d are cutting speed, feed rate, and depth of cut, respectively. The quadratic model for Y is given in Eq. (2).

$$Y = a_0 + \sum a_i X_i + \sum a_{ii} X_i^2 + \sum a_{ij} X_j \quad (2)$$

Parameters of Eq. (2) are well-defined as, a_0 constant, a_i , a_{ii} , and a_{ij} represent the coefficient of linear, quadratic, and cross-product terms, respectively. X_i shows the variables which correspond to the studied machining parameters.

2.3. Genetic Programming

Recently, nature-inspired algorithms have found special popularity in solving optimization problems, especially bio-inspired ones. Classified in the bio-inspired category of algorithms, the GA is an evolutionary optimization method that imitates chromosome behavior to reach the optimum answer. One of the frequently applicable alternative domains applying GA is GP which operates on a string of codes and functions in addition to numbers. Koza and Poli have introduced this automatic programming method in 1992. He combined evolutionary techniques and automatic programming principles to achieve a modeling-based optimization methodology [33]. Like GA, the crossover and mutation operations are applied to chromosomes to produce the next generations in GP. Therefore, this method can optimize more complicated structures than GA [34, 35]. Moreover, GP can connect the independent input cutting parameters and output measured characteristics precisely with a mathematical equation. Figure 2 illustrates a sample of chromosomes in GP, the crossover operation of two parents' chromosomes, and mutation operation along with produced offspring.

The major drawback of all the data driven modelling approaches is the black box nature of these models, i.e., the user cannot easily identify what is happening in model which computes the outputs corresponding to the inputs supplied to the model. One of the key advantages of genetic programming as a modelling tool is its ability to develop simple mathematical models. However, the uniqueness of genetic programming is that it performs various

mathematical operators over symbolic expression or formulae or programs rather than over numbers which represent the candidate solutions. Thus, in genetic programming the candidate solutions are symbolic expressions or formulae. In a modelling framework these symbolic expressions or formulae or programs are candidate models to simulate a physical phenomenon. Thus, the optimal formula that is evolved by genetic programming can be used as a best fit model for predicting the physical phenomenon under consideration.

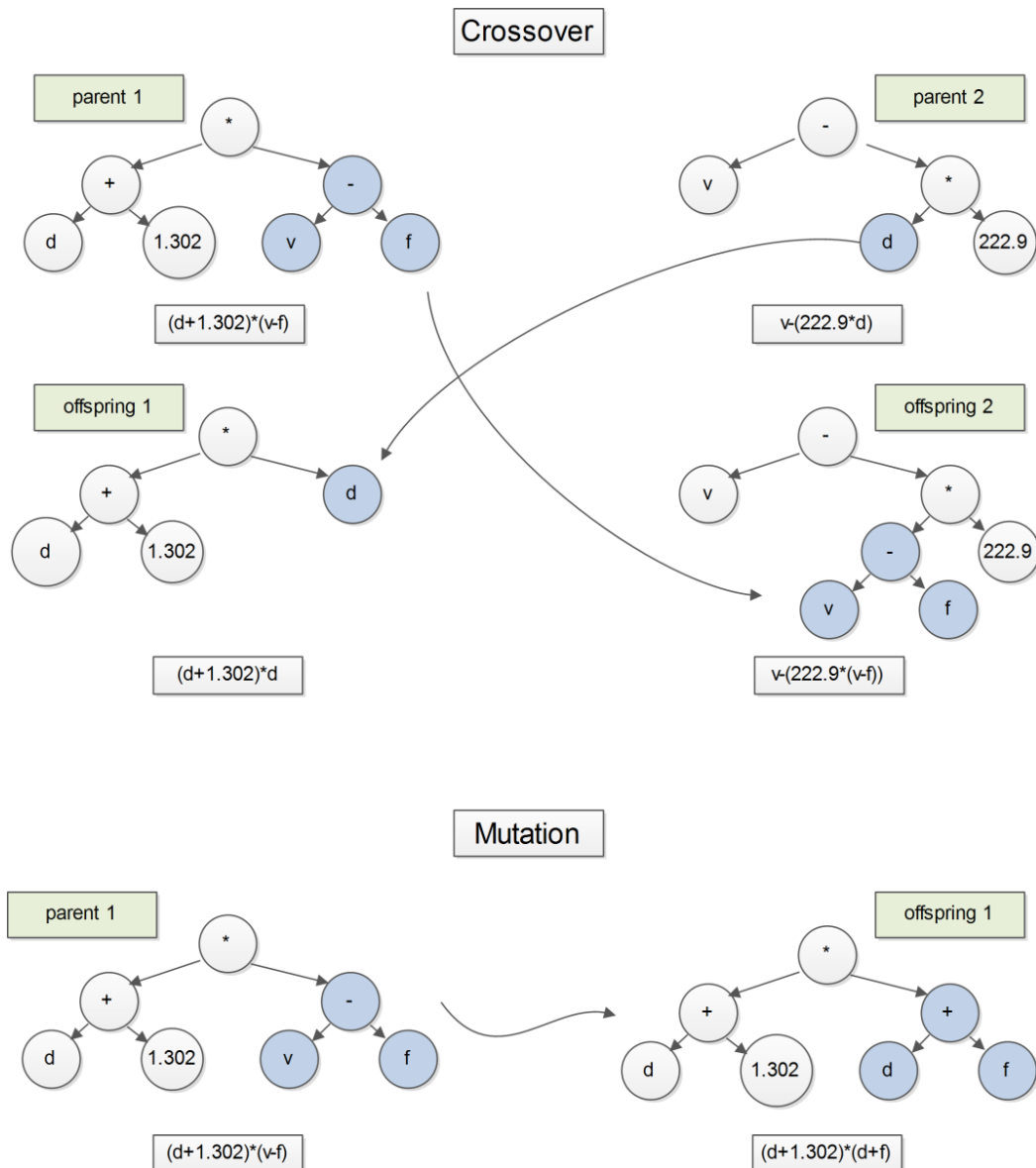


Figure 2. GP method mathematical operations [35].

GP is frequently applied in modeling various phenomena in manufacturing processes, especially machining operations. Some successful applications of this relatively modern computing technique have been reported in milling tool path determination, tool wear prediction in hard turning [36, 37]. Formulation of generalized power consumption of machining [38], grinding complex geometrical features [39], modeling of burr height of the drilling process [40], tool-chip contact length prediction [35] and prediction of energy consumption of machine tools [41].

The modeling process by the GP method starts with the generation of a random initial population composed of functions, operations, and numbers. Then, the fitness value based on the defined optimization problem is calculated for each member of the population. Once the certain fitness threshold is fulfilled, the GP algorithm is terminated, and the member with the best fitness value is introduced as the answer to the defined optimization problem. In the next step, a new population, generated by applying genetic operators to the previous generation, replaces the previous generation. The fitness values according to defined functions are calculated to determine if the best answer is reached [42]. A schematic flowchart of the GP modeling process is shown in Figure 3.

In this research, a set of genetic equations were developed to extract the relation between input independent cutting parameters (v_c , f , and a_p) and output parameters consisting of cutting forces, surface roughness, and tool life in the machining process of SiCp/Al using carbide cutting tools. Arithmetic functions were set as $T = [+,-,\times,\div,1/x,x^2,x^3,\sqrt{x}]$. In the present study, the number of chromosomes was selected $M_s = 30$. The number of generations to terminate the algorithm was selected $G = 200000$. The evolutionary operation rates were selected based on trial and error: 0.1 for mutation and 0.044 for crossover.

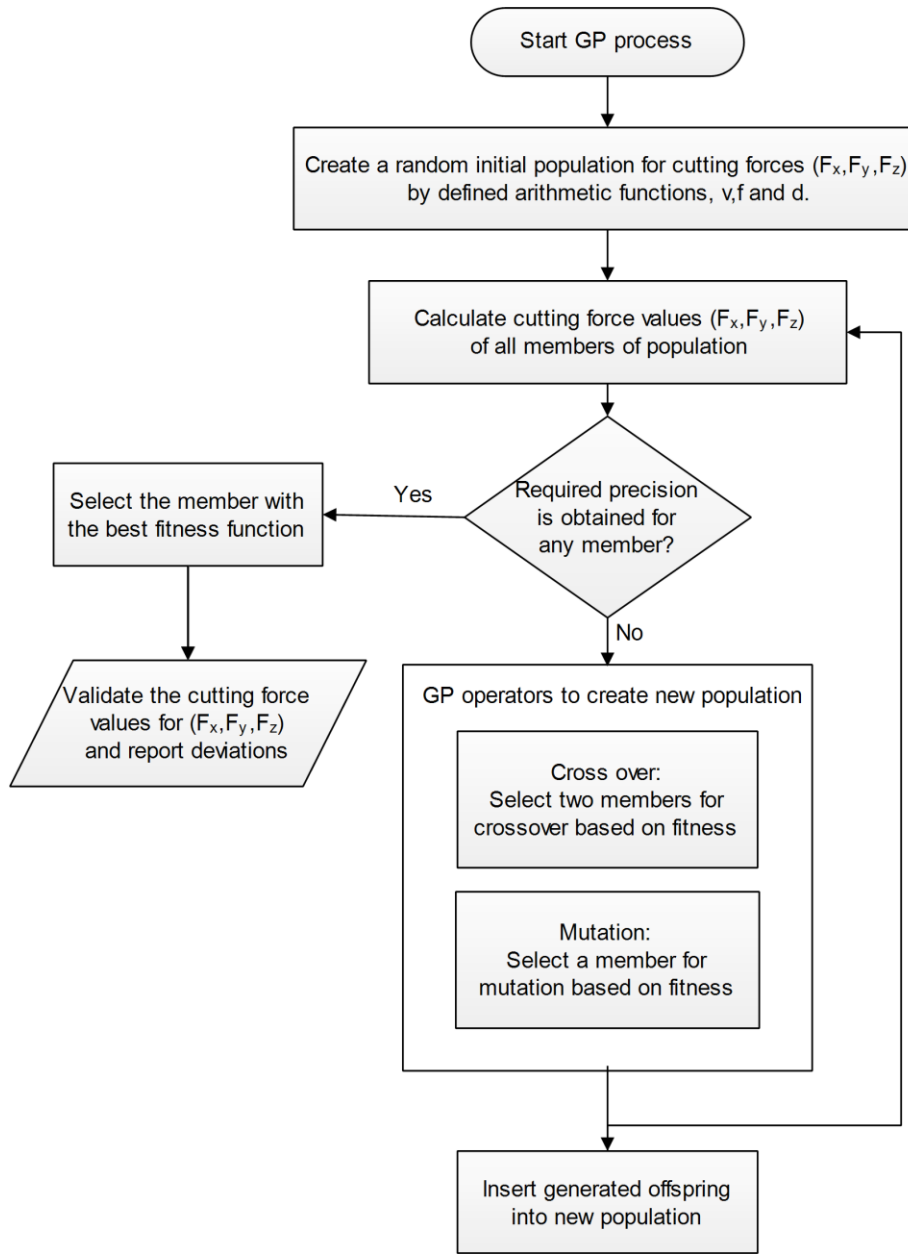


Figure 3. A schematic flowchart of the GP modelling process

3. Result, Analysis and Discussion

3.1 The experimental results

The experimental results on tool life, surface roughness, and cutting forces are shown Table 5. The cutting forces values listed in Table 5 are the average cutting forces at every cutting condition. In addition, as can be seen in Table 5, all three processing parameters of cutting speed, feed speed, and cutting depth influence the processing response. The results obtained from the

machining process reveal that the influence of each parameter is equal on the workpiece surface roughness. In contrast, in the case of tool wear, it is observed that the cutting speed is more significant followed by the feed rate and depth of cut. In case of the cutting forces, F_x and F_z are affected by the depth of cut followed by the cutting speed and feed rate. While, for F_y the depth of cut is still showing the most significant effecting, however, the cutting speed and feed rate are also significantly affecting F_y compared to the case of F_x and F_z in machining of SiCp/Al composite materials [43,44] .

Table 5. Experimental results on tool life, surface roughness, and cutting forces[1,2].

No.	Tool Life (min)	Surface Roughness Ra (μm)	F_x Force (N)	F_y Force (N)	F_z Force (N)
1	10.511	1.13	74.13	170.01	79.98
2	5.407	1.11	134.01	249.9	138.23
3	5.322	0.616	261.09	295.03	199.81
4	6.365	0.629	375.29	385.11	275.12
5	6.359	0.265	143.11	250.07	126.06
6	4.03	0.849	84.33	231.96	96.11
7	3.411	0.230	409.98	319.99	289.88
8	3.271	0.378	290.11	315.06	221.02
9	3.017	0.056	274.42	317.1	171.3
10	2.567	0.044	519.8	364.89	311.05
11	2.198	0.241	69.01	214.87	86.42
12	1.714	0.221	169.04	293.15	149.79
13	2.237	0.110	529.98	355.23	278.31
14	1.878	0.190	327.16	361.01	207.04
15	1.465	0.049	149.97	269.96	135.61
16	1.594	0.151	89.96	256.14	104.97

3.2 GP and RSM based prediction models analysis.

3.2.1 Cutting force analysis.

For determining the relationship between cutting parameters (v , f , and d) and response parameters (cutting forces, surface roughness, and tool life) in the machining of SiCp/Al, the GP and RSM based prediction models were developed in Minitab-17 and MATLAB software. The measured response parameters (cutting force, surface roughness, and tool life) at different cutting parameters (cutting speed, feed rate, and depth of cut), shown in Table 5, are used as train and verification data for the proposed GP and RSM models.

The best-extracted models using RSM considering mentioned arithmetic functions for cutting forces (F_x , F_y and F_z) are shown in Eqs. (3a to 3c). In addition, the best genetically extracted models using GP considering mentioned arithmetic functions for cutting forces (F_x , F_y and F_z) are shown in Eqs. (4a to 4c). The RSM model summary for the cutting forces are given in the value of R^2 , R^2 -adjusted and R^2 -adjusted. The values for F_x are obtained as $R^2=99.3\%$ and R^2 (adj)= 98.26% ; and R^2 (pred)= 95.11% for F_y they are obtained as $R^2=92.56\%$, R^2 (adj)= 81.39% ; and R^2 (pred)= 0.00% and for F_z they are obtained such as $R^2=99.20\%$ and R^2 (adj)= 97.99% . and R^2 (pred)= 92.67% .

$$F_x = 50.8 - 6.30v + 3317f + 110.7d - 0.029v \times v - 23,275f \times f + 57.8d \times d + 136v \times f + 9.13v \times d - 2977f \times d \quad (3.a)$$

$$F_y = 104 + 6.19v + 1845f + 146d + 0.056v \times v + 85650f \times f - 41.9d \times d - 284v \times f - 0.71v \times d + 1342f \times d \quad (3.b)$$

$$F_z = 56.1 - 4.58v + 4334f + 79.0d - 0.0515v \times v - 144000f \times f + 18.0d \times d + 224v \times f + 3.30v \times d + 81f \times d \quad (3.c)$$

$$F_x = (d + 1.302) \times v \times f \times 38.7328 + [v^2 \times f \times d \times (0.123 - d)]^2 + 222.96 \times d - v + 32.002 \quad (4.a)$$

$$F_y = (3.21 \times d + f - 5.679)^3 + [((48.896 - v) \times f \times d)^3]^3 + \frac{4.95}{d} + 2.801 + 2.801 \times v - \frac{1}{2.265 \times f} + 13.021 \times d - 956.378 \times f + 315.443 \quad (4.b)$$

$$F_z = (d + 5.36248)^3 + 9.0478 \times (d - 10.0574) + [(f + 8.207) \times d \times f \times (v \times f + v)]^3 + (d - 12.8468)^2 \times f^2 \times 204.1869 \quad (4.c)$$

The experimentally measured values for cutting forces F_x , F_y and F_z along with values obtained from RSM- and GP-based prediction models are given in Table 6 in and plotted in Figure. 4 (a-c). While the errors between the experimentally measured and predicted cutting forces using RSM- and GP-based prediction models are shown in Table 7 and plotted in Figure. 5.

Considering the genetically obtained equations for cutting forces in three directions as Eqs. (4a to 4c) reveal that any increase in cutting speed corresponds with a little decrease in F_x and drastic

increase in F_y , while the resultant change in F_z is negligible. Also enhanced values of feed rate results sharp increase in F_x, F_z and partial decrease in the amount of F_y . In the case of the effect of depth of cut it can be realized that the values of F_x, F_z show severe increase by increasing the depth of cut, but F_y has a slight change.

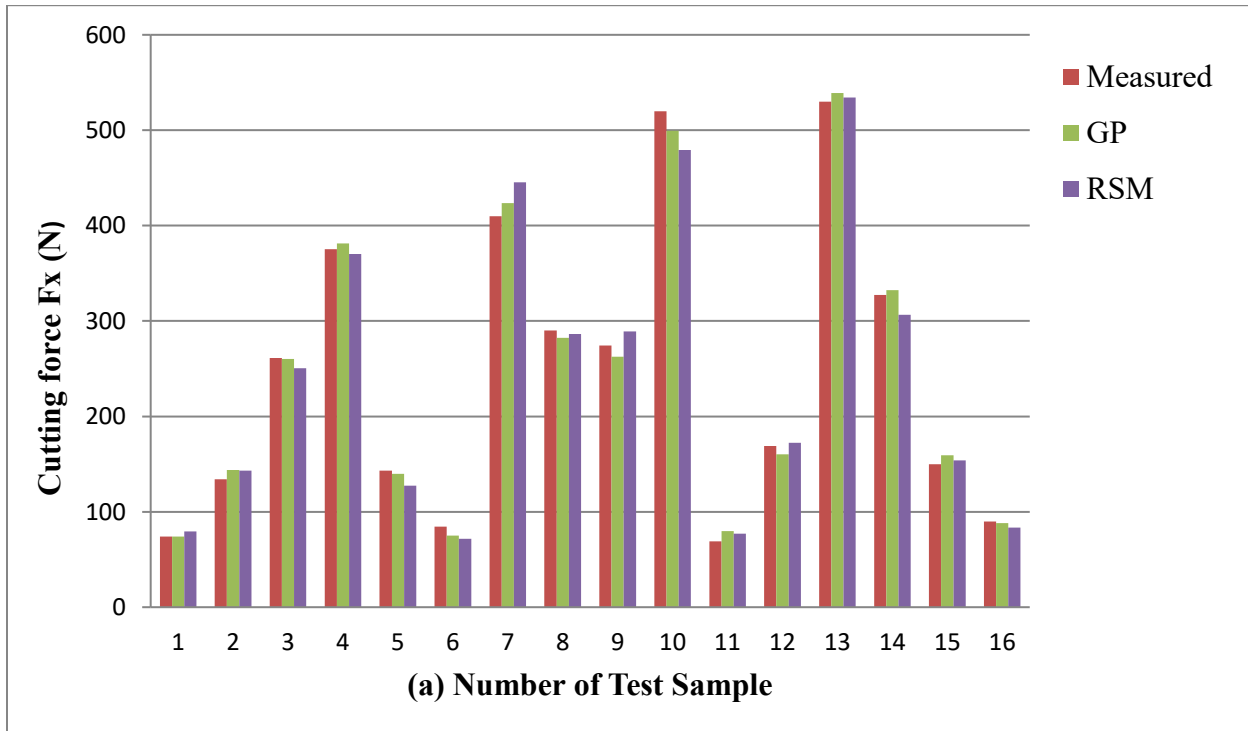
In addition, the accuracy of obtained genetic equations was evaluated for both training and validation data, using the coefficient of determination, R^2 , MSE , $RMSE$, and CC . The values of mentioned fitness functions for obtained genetic equations are given in Table 8. Meanwhile, the error histogram between the measured and predicted cutting force along the x, y and z-axis for RSM and GP-based prediction model is plotted in Figures. 6, 7 and 8 respectively.

Table 6. The experimentally measured and predicted cutting forces F_x, F_y and F_z using RSM- and GP-based prediction models.

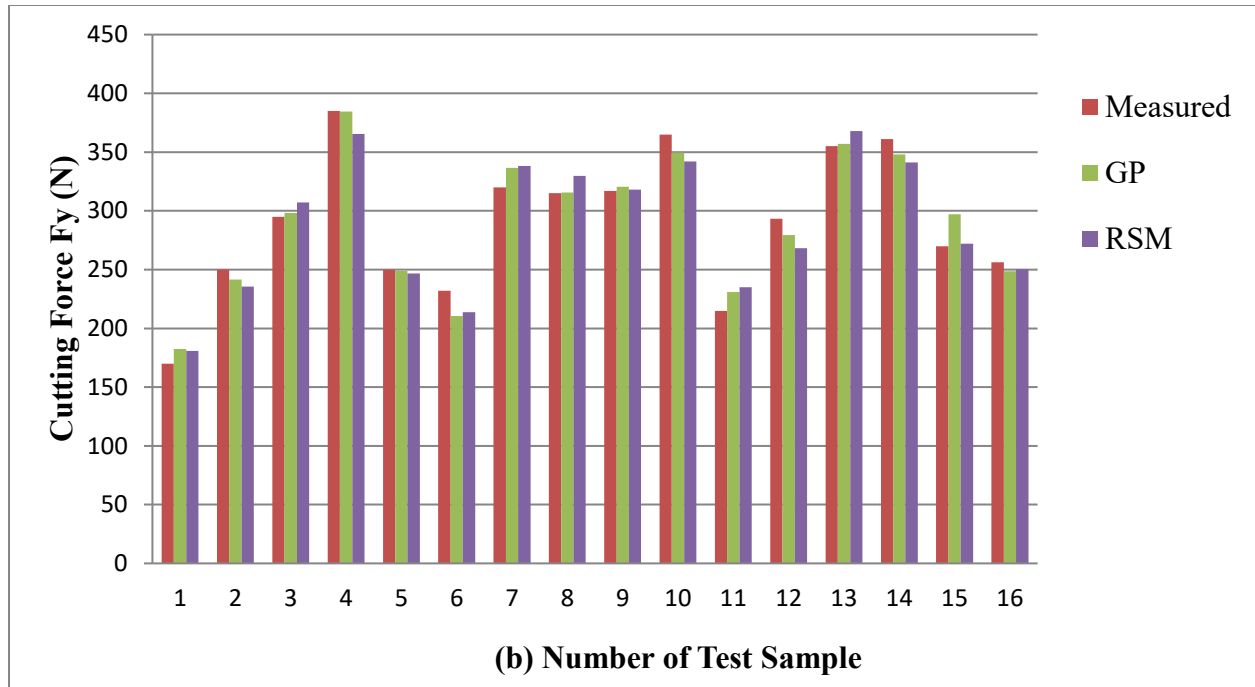
No	F_x			F_y			F_z		
	Exp	GP	RSM	Exp	GP	RSM	Exp	GP	RSM
1	74.13	73.97	79.39	170.0	182.47	180.91	79.98	86.40	88.41
2	134.0	143.79	143.19	249.9	241.61	235.64	138.2	123.26	132.12
3	261.0	260.36	250.51	295.0	298.16	307.05	199.8	192.45	183.87
4	375.2	381.36	370.3	385.1	384.46	365.5	275.1	279.88	231.42
5	143.1	139.78	127.26	250.0	249.02	246.72	126.0	118.79	108.14
6	84.33	75.00	71.6	231.9	210.38	213.8	96.11	90.78	89.58
7	409.9	423.70	445.4	319.9	336.64	338.24	289.8	294.23	258.92
8	290.1	282.39	286.26	315.0	315.67	329.83	221.0	218.71	201.62
9	274.4	262.63	289	317.1	320.44	318.19	171.3	183.36	182.64
10	519.8	499.47	479.16	364.8	349.52	342.06	311.0	299.55	307.19
11	69.01	79.69	77	214.8	230.94	234.88	86.42	97.08	100.82
12	169.0	160.33	172.49	293.1	279.51	268.2	149.7	145.61	160.91
13	529.9	538.81	534.27	355.2	357.14	368	278.3	280.59	277.87
14	327.1	332.49	306.6	361.0	348.06	341.21	207.0	215.56	206.67
15	149.9	159.10	153.94	269.9	297.23	271.92	135.6	138.94	136.41
16	89.96	88.07	83.43	256.1	248.54	250.17	104.9	105.84	101.06

Table 7. The error between the experimentally measured predicted cutting forces using RSM- and GP-based prediction models.

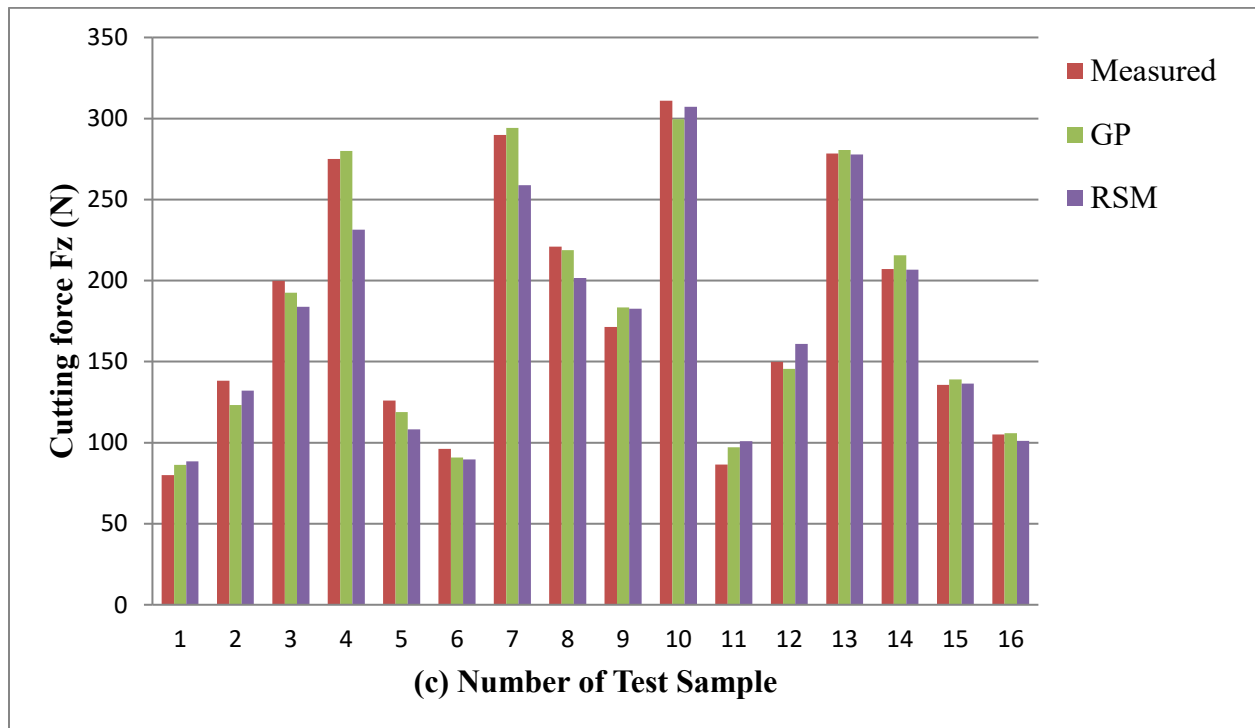
No	F_x		F_y		F_z	
	GP Error%	RSM Error%	GP Error%	RSM Error%	GP Error%	RSM Error%
1	0.220859	7.09	7.327238	6.41	8.027721	10.5
2	7.297538	6.85	3.318062	5.7	10.83045	4.42
3	0.278585	4.05	1.06232	4.07	3.685636	7.97
4	1.617817	1.32	0.168207	4.31	1.730594	16
5	2.330219	11.06	0.418058	1.32	5.76442	14.2
6	11.06955	15.09	9.303665	7.82	5.55079	6.79
7	3.346869	8.53	5.203852	5.7	1.498965	10.6
8	2.660254	1.32	0.193331	4.68	1.046521	8.77
9	4.296416	5.31	1.051779	0.34	7.038494	6.62
10	3.910757	7.81	4.213469	6.25	3.695787	1.24
11	15.47396	11.57	7.476658	9.3	12.33474	15.7
12	5.154159	2.04	4.652541	8.51	2.793061	7.4
13	1.666551	0.8	0.537417	3.59	0.817982	0.15
14	1.629854	6.28	3.587359	5.48	4.116785	0.17
15	6.090496	2.64	10.1016	0.72	2.459083	0.58
16	2.096492	7.25	2.965536	2.33	0.827611	3.7



(a): F_x



(b): F_y



(c): F_z

Figure 4. (a, b, c) Experimental and predicted cutting forces using RSM and GP-based prediction models.

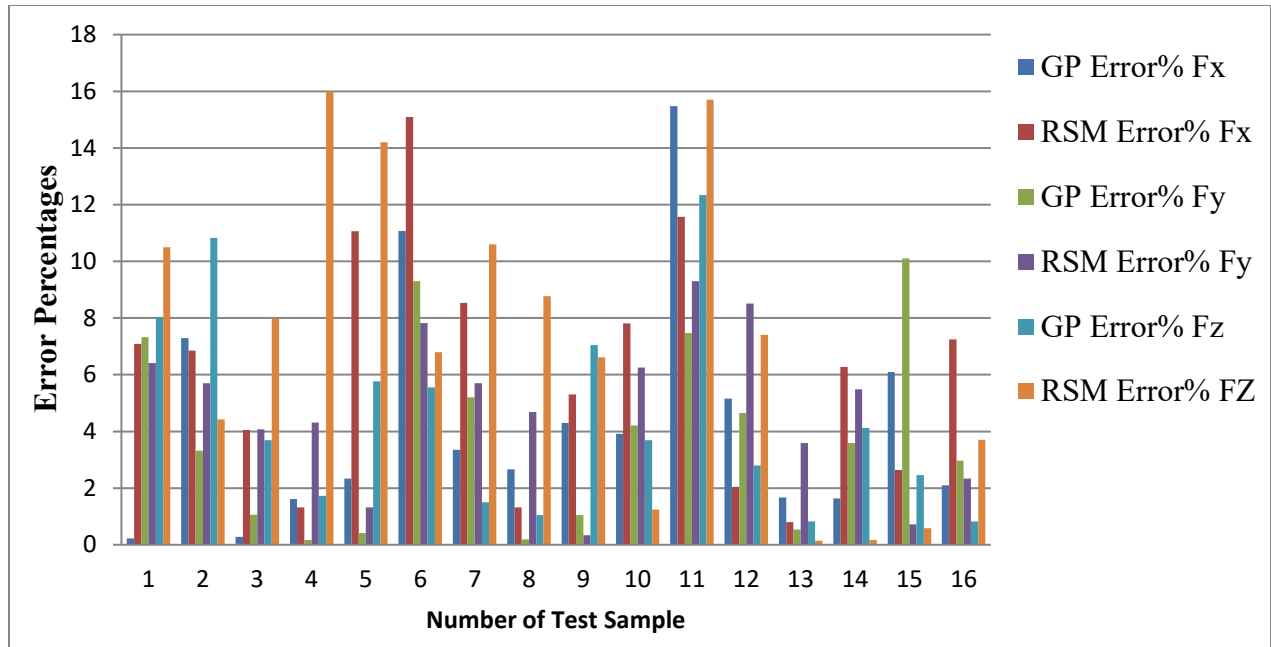


Figure 5. The error between the experimentally measured predicted cutting forces using RSM- and GP-based prediction models.

Table 8. Fitness values of the training and validation data for obtained genetic equations.

	F_x		F_y		F_z	
	Training	Validation	Training	Validation	Training	Validation
R ₂	0.99693347	0.99117733	0.95406034	0.91934722	0.98963881	0.98852505
MSE	55.2017866	232.382963	133.309334	303.322987	59.7935854	56.2645546
RMS	7.42979048	15.2441124	11.5459661	17.4161702	7.73263121	7.50097024
CC	0.999027	0.99913	0.996848	0.999022	0.997528	0.999683

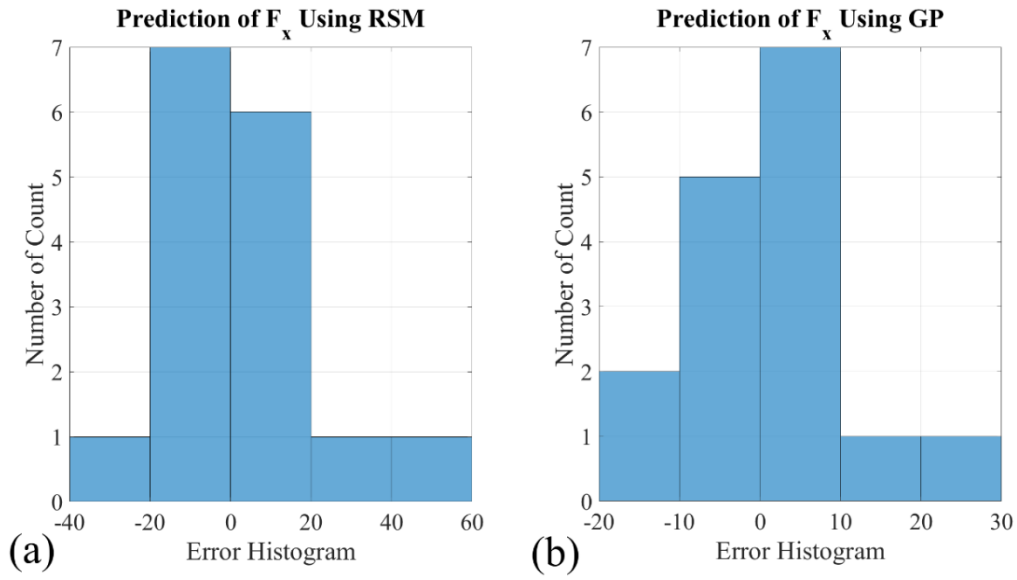


Figure. 6: The error histogram between the measured and predicted cutting force along the x-axis for (a): RSM-based prediction model; (b): GP-based prediction model

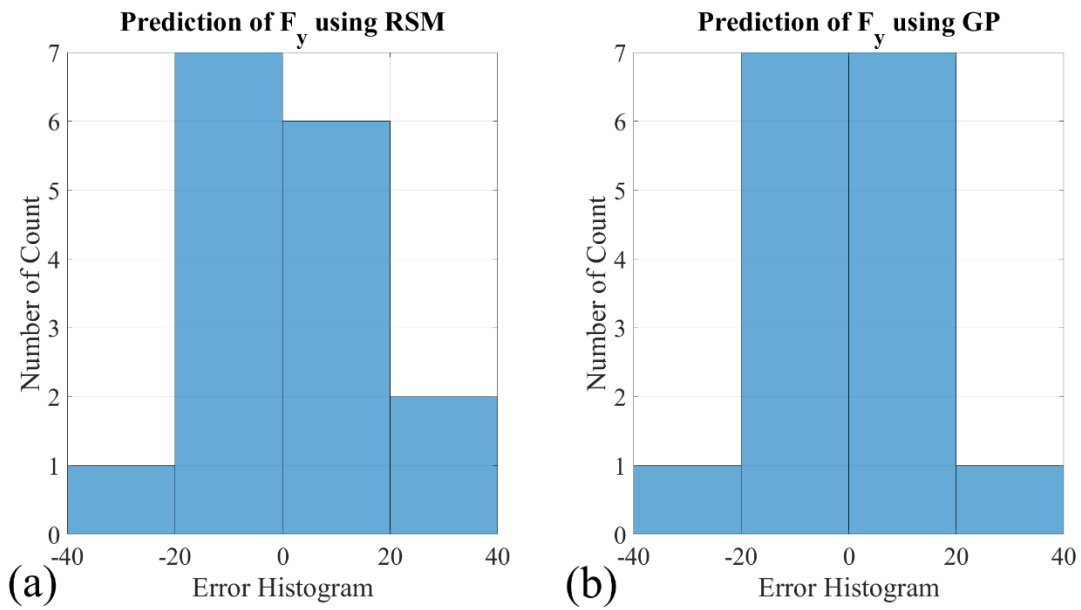


Figure. 7: The error histogram between the Measured and predicted cutting force along the y-axis for (a): RSM-based prediction model; (b): GP-based prediction model

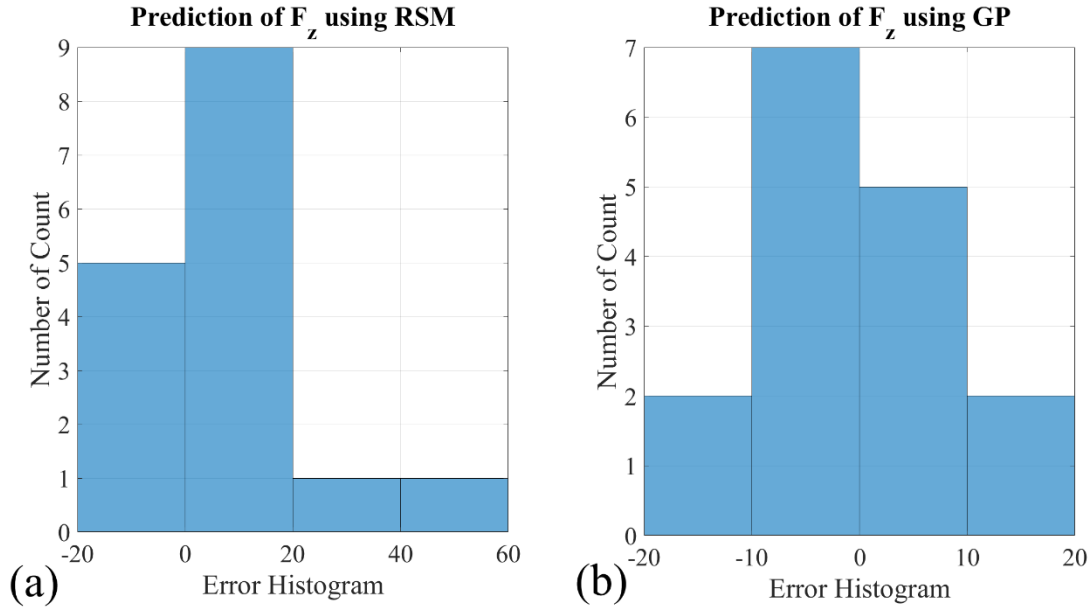


Figure. 8: The error histogram between the measured and predicted cutting force along the z-axis for (a): RSM-based prediction model; (b): GP-based prediction model

As can be seen in Figure 4 (a, b, c) and Figure 5, the measured and predicted cutting force using RSM and GP-based prediction models, the correlation coefficient between the measured and predicted F_x using are 0.994 and 0.998, respectively. The highest correlation coefficient for the most accurate prediction would be 1 with 100% accuracy. Also, the correlation coefficient between the actual and predicted F_y using RSM- and GP-based prediction model are 0.9645 and 0.9754 based on the represented results in Figure 4 (c) F_z Figure 4 (b) Lastly, the correlation coefficient between the actual and predicted F_z using RSM- and GP-based prediction model are 0.9815 and 0.9947 based on the represented results in Figure 4 (c) F_z Then, it can be concluded that the usage of the GP-based prediction model over the previous RSM-based prediction model can increase the correlation coefficient between the actual and predicted F_x , F_y and F_z with 0.4%, 1.13% and 1.34%, respectively. Also, using the root means square error (RMSE) to evaluate the accuracy of the proposed model, the RMSE between the actual and predicted F_x using RSM and GP are 16.5282 and 9.4027 (N), respectively. It proves that GP-based prediction model can decrease the RMSE between the actual and predicted F_x with 43.11% in comparison with previous RSM-based prediction model. Based on Figure 4 (c) F_z Figure 4 (b) the RMSE between the actual and predicted F_y using RSM and GP are 15.579 and 12.8526 (N), respectively. It

shows 17.50% more accuracy in point of RMSE between actual and predicted F_y using GP model in comparison with RSM model. Also, based on the represented results in Figure 4 (c) F_z the RMSE between the actual and predicted F_z using RMS and GP models are 16.6988 and 7.6897 (N), respectively. The higher accuracy of the GP-based model in comparison with the RSM-based model is obvious based on the represented results.

These results are also supported by the results of Figures 6, 7, and 8. As can be seen in Figure. 6.a, the average and variation of the error between the measured and predicted F_x cutting force using RSM-based prediction model are 1.9744 and 16.9480 (N), respectively. While the average and variation of the error between the measured and predicted F_x cutting force using GP-based prediction model are 0.0281 and 9.7110 (N), shown in 6.b.

In addition, Figure 6(a and b) and Figure 7 and Figure 8 (a and b) show the error histogram between the Measured and predicted F_y and F_z using RSM and GP models, respectively. Based on the represented results, The mean error of the F_y and F_z using RSM-based model are 2.3225 and 6.4406 (N), respectively. While the mean error of the F_y and F_z using GP-based model are -0.0194 and -0.0206 (N), respectively.

3.2.2 Surface Roughness and Tool Life analysis

The best models using RSM for the prediction of surface roughness and tool life were obtained as SR and T, shown in Eqs. 5 (a and b). While the best models using genetic programming (GP) for surface roughness and tool life were obtained as SR and T , shown in Eqs. 6 (a and b). The RSM model summary for the tool life and surface roughness are given in the value of R^2 , R^2 -adjusted and R^2 -adjusted. The values for For the tool life (T) value for the $R^2 = 97.80\%$ R^2 (adj) = 94.49% and R^2 (pred) = 83.31%. For the surface roughness (SR) $R^2 = 95.23\%$, R^2 (adj) = 88.08% and R^2 (pred) = 56.57%.

$$SR = 4.44 - 0.1959v + 40.2f - 2.390d + 0.002693v \times v - 972f \times f + 0.259d \times d - 1.21v \times f + 0.0459v \times d + 13.3f \times d \quad (5.a)$$

$$T = 6.28 - 0.0833v - 252.1f - 1.566d + 0.001294v \times v + 3575f \times f + 0.246d \times d + 0.33v \times f - 0.0109v \times d + 39.2f \times d \quad (5.b)$$

$$SR = \frac{1}{v - (2.4307 - d) \times 1/d} + [(\sqrt{(3.9875 + d) \times (f + 5.1494)})^3]^3 \quad (6.a)$$

$$+ \frac{1}{v + d + \frac{v \times d}{4.3652} - 6.0227}$$

$$T = \frac{(3.2891 \times d + 29.634 \times f)^2}{v} \quad (6.b)$$

$$+ \frac{1}{(d - 0.4517) \times (10.1322 - v) \times (3.7943 \times d - v)}$$

$$+ \frac{1}{v \times f \times d^2 + (3.31181 + v) \times f}$$

Considering the genetically obtained equations for SR as Eq. 6a reveals that depth of cut has a minor effect on the output value. While increasing the feed rate will worsen the surface roughness, increasing the cutting speed will decrease the obtained surface roughness.

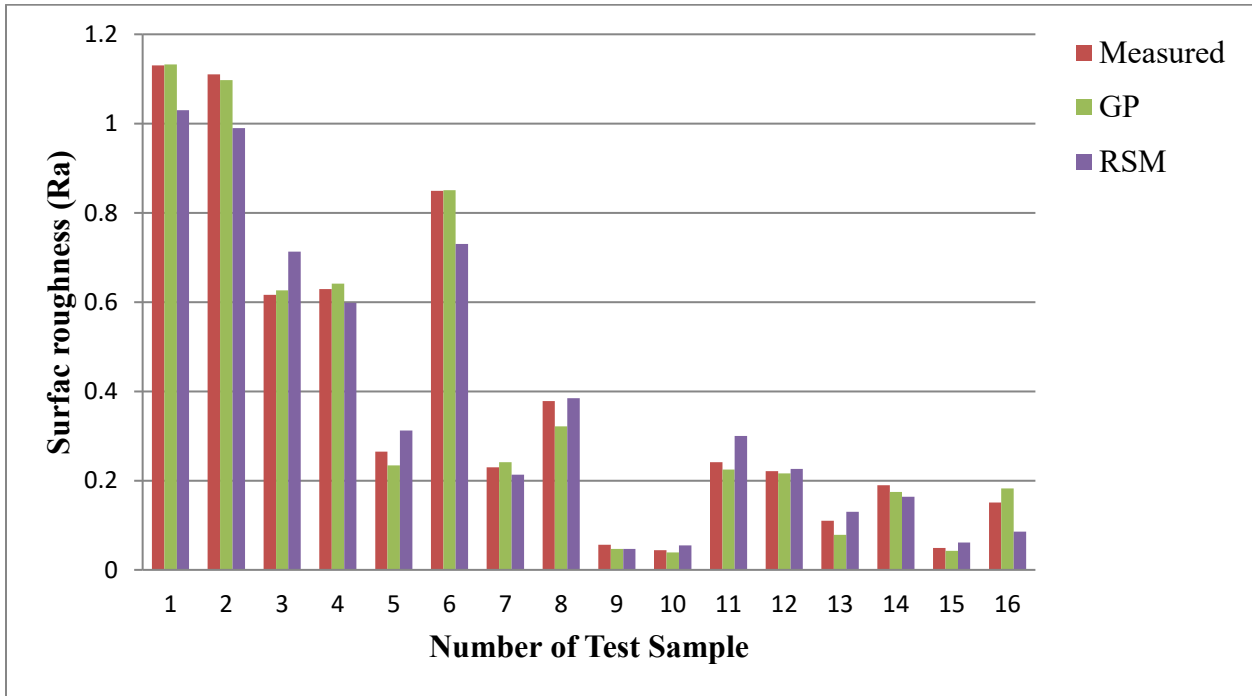
Meanwhile, as can be seen from Eq. 6b, all the cutting parameters have negative effects on tool life. However, the effect of cutting speed is much more than other parameters on tool effective life.

The experimentally measured and predicted values of surface roughness and tool life using RSM- and GP-based predictive models are given in Table 9 and plotted in Figure. 9 (a and b). However, the error between the experimentally measured and predicted values of surface roughness and tool life using RSM- and GP-based predictive models are shown in Table 10 and plotted in Figure. 10. The values of fitness functions for obtained genetic equations for surface roughness and tool life are given in Figure. 10. The error between the experimentally measured and predicted values of surface roughness and tool life using RSM- and GP-based predictive models. In addition, the accuracy of obtained genetic equations was evaluated for both training and validation data, using the coefficient of determination, R², MSE, RMSE, and CC. The values of mentioned fitness functions for obtained genetic equations are given in Table 11.

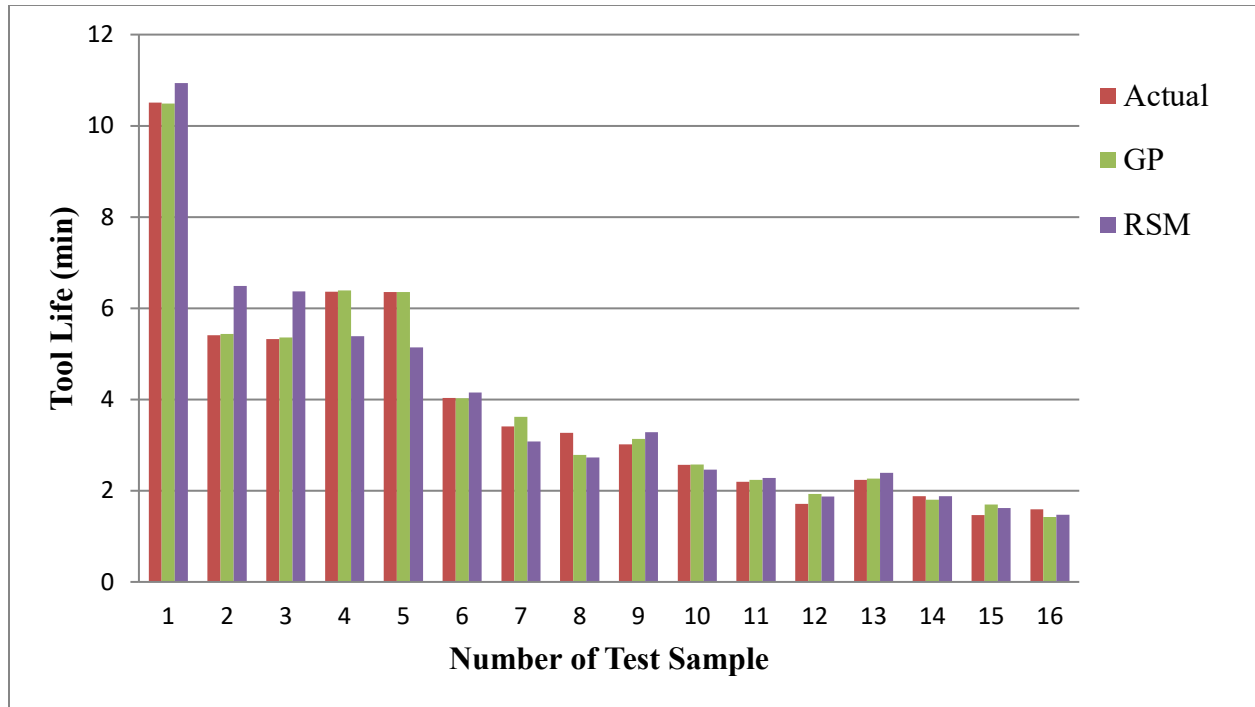
Table 9. The experimentally measured and predicted values of surface roughness and tool life using RSM and GP-based predictive models.

No	Surface Roughness, <i>SR</i>			Tool Life, <i>Tl</i>		
	Exp	GP	RSM	Exp	GP	RSM
1	1.13	1.132284964	1.03	10.511	10.48802199	10.94
2	1.11	1.097138221	0.99	5.407	5.438950914	6.49
3	0.616	0.626397744	0.713	5.322	5.356913048	6.37
4	0.629	0.641071109	0.598	6.365	6.391510969	5.39
5	0.265	0.234140281	0.312	6.359	6.354948292	5.14

6	0.849	0.850819239	0.73	4.03	4.028335181	4.15
7	0.23	0.24129845	0.213	3.411	3.619877105	3.08
8	0.378	0.321933898	0.385	3.271	2.784127701	2.72
9	0.056	0.0472238	0.047	3.017	3.134200549	3.28
10	0.044	0.039358	0.055	2.567	2.575179823	2.46
11	0.241	0.224634754	0.3	2.198	2.239666403	2.28
12	0.221	0.21594552	0.226	1.714	1.930362881	1.87
13	0.11	0.078376525	0.13	2.237	2.268145666	2.39
14	0.19	0.174518607	0.164	1.878	1.804636966	1.88
15	0.049	0.042491191	0.061	1.465	1.698305492	1.62
16	0.151	0.182410525	0.086	1.594	1.425199234	1.47



(a) Surface roughness



(b) Tool life

Figure. 9. The experimentally measured and predicted values of surface roughness and tool life using RSM- and GP-based predictive models

Table 10. The error between the experimentally measured and predicted values of surface roughness and tool life using RSM- and GP-based predictive models

No	Surface Roughness, <i>SR</i>		Tool Life, <i>TL</i>	
	GP Error%	RSM Error%	GP Error%	RSM Error%
1	0.202209	9.7	0.218609	4.08
2	1.158719	12.2	0.590918	19.90
3	1.687945	13.6	0.656014	19.80
4	1.919095	5.18	0.416512	15.28
5	11.64518	15.1	0.063716	18.90
6	0.21428	15	0.041311	3.10
7	4.91237	7.98	6.123633	9.50
8	14.8323	1.81	14.88451	16.60
9	15.6717857	19.1	3.884672	8.80
10	10.55	19.9	0.318653	3.90
11	6.790559	17.6	1.895651	3.80
12	2.287095	2.21	12.62327	9.50

13	28.74861	15.3	1.392296	7.10
14	8.148	15.1	3.906445	0.21
15	13.283	19.6	15.92529	10.60
16	20.80167	7.5	10.58976	7.50

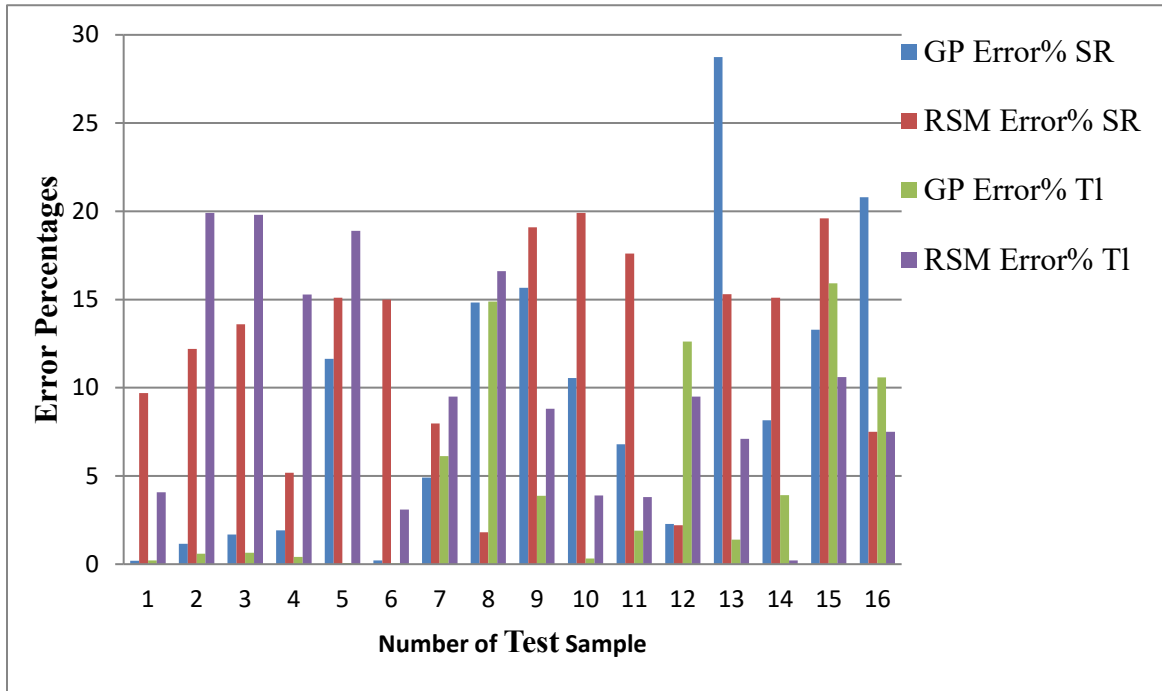


Figure. 10. The error between the experimentally measured and predicted values of surface roughness and tool life using RSM- and GP-based predictive models

In addition, the accuracy of obtained genetic equations was evaluated for both training and validation data, using the coefficient of determination, R^2 , MSE , $RMSE$, and CC . The values of mentioned fitness functions for obtained genetic equations are given in Table 11.

Table 11 Fitness values of Training data and validation data for obtained GP

Index	Surface Roughness, SR		Tool Life, T	
	Training	Validation	Training	Validation
R2	0.987317356	0.965081369	0.997806292	0.977275166
MSE	0.001684544	0.003129276	0.01304247	0.088747055
RMSE	0.041043199	0.05593993	0.114203633	0.29790444
CC	0.995219	0.993935	0.99945	0.99762

As can be seen Figure 9 (a) the correlation coefficient between the measured and predicted surface roughness using RMS- and GP-based models are 0.9888 and 0.9922, respectively. Also, the RMSE between the measured and predicted surface roughness using RSM- and GP-based prediction models are 0.0616 and 0.0442 (μm). As can be seen Figure 9 (b), the correlation coefficient between the measured and predicted tool life using RMS- and GP-based models are 0.9707 and 0.9976, respectively. Also, the RMSE between the measured and predicted tool life using RSM- and GP-based prediction models are 0.5848 and 0.1650 (min). Figure. 10. Representing the error percentages between the experimentally measured and predicted values of surface roughness and tool life using RSM- and GP-based predictive models. The majority of the experimental data points of the developed RSM and GP models are in good agreement with the experimental data few data points such as experiment number 6 and 11 for cutting force and experiment number 5, 8, 9, 13, and 16 for surface roughness and for tool life experiment number 8, 12, 15 and 16 has higher error percentage than 10%, however 13 number data point has higher error percentage which is due to equipment's measurement error. The higher error percentages in few data point are experienced due to the availability of lower amount of experimental data points for training of the model. Usually the training of the models with lower data points gives higher error percentages, however the RSM model prediction value for the machining process with few error percentages lower than 20% considered in majority of cases.

Conclusion

The orthogonal machining experiment was performed on SiCp/Al metal matrix composite materials with percentages of SiC particles of 45% to find out the effect of three different factors of cutting parameters such as cutting speed, feed rate, and depth cut and effect of SiC particles on machining performances.

- While reviewing the machining process of different volume of SiCp/Al, from literature it is found that the turning experiment of difficult to cut materials depicts that the higher the SiC content and the course the particle size, the greater the cutting force due to tool wear morphology and sudden wear of the flank at higher cutting parameters.
- When machining the SiCp/Al composites with the different cutting parameters, the increasing cutting speed and lower depth of cut reduces the cutting forces and increases the tool life and improves the surface integrity. It is also found that the wear tool has a

severe influence on the cutting force fluctuation curve; as tool wear increases, it also became the cause of increments in the cutting forces.

- RSM and GP mathematical models were developed and predicted the experimentally obtained data. The majority of the experimental data point result shows good agreement with the data. GP model was found to be more accurate than the RSM model. The error percentages several experimental data point for both models are in the acceptable range, except the few data points such as cutting force F_x experiment number 6 and experiment number 11 has error percentage higher than 10% for GP and RSM. For the tool life the experiment number 8, 12, 15 and 16 has more than 10% of error for GP model and for the surface roughness experiment number 5, 8, 9, 13, and 16 has more than 10% error percentage for GP model. While the RSM model has more error percentage compare to the GP model. Some experimental data points have higher error percentages; it is also due to lower data sets during training of the models.
- The composite desirability for optimization i.e. minimization of cutting forces, which suggest that the optimum cutting parameters for tool life are 10.511(min) cutting speed $v_c=6.283$ m/min, feedrate ($f=0.01$ mm/rev), and depth of cut ($a_p=0.2$ mm) and for surface roughness Ra is (0.044 μ m) cutting speed ($v_c=18.85$ m/min), feed rate ($f=0.015$ mm/rev) and depth of cut ($a_p=1.5$ mm) for the cutting forces the cutting parameters are included such as cutting speed (v_c 6.283m/min), feed rate ($f=0.01$ mm/rev) and depth of cut ($a_p=0.2$ mm) and as (d) desirability of optimization noted at 0.9576, cutting force F_x , F_y , and F_z SiCp/Al45% are 79.5160(N), 183.3829(N) and 89.1095 (N) respectively. Table 11 shows the Fitness values of Training data and validation data for obtained GP model.
- The measured parameters for the genetic algorithm are taken as mean square error, root means square error, normalized mean square error, mean error, variation of error, correlation coefficient, and R-square, are proposed for model validation. The developed genetic algorithm model results prove the higher efficiency with the prediction of the cutting force, surface roughness, and tool life, 43.07%, 37.82%, and 115.64%, respectively, compared with the previous RSM method.

Conflict of interest: Authors declare there in no conflict of interest.

Acknowledgements

The authors would like to acknowledge King Fahd University of Petroleum & Minerals. This research work is funded by the KFUPM Internal Funded Grant (DSR) Project Code: DF191046.

References

- [1] R. A. Laghari, J. Li, Z. Xie, and S. Wang, "Modeling and Optimization of Tool Wear and Surface Roughness in Turning of Al/SiCp Using Response Surface Methodology," *3D Res.*, vol. 9, no. 4, p. 46, Dec. 2018, doi: 10.1007/s13319-018-0199-2.
- [2] R. A. Laghari and J. Li, "Modeling and optimization of cutting forces and effect of turning parameters on SiCp/Al 45% vs SiCp/Al 50% metal matrix composites: a comparative study," *SN Appl. Sci.*, vol. 3, no. 7, p. 706, Jul. 2021, doi: 10.1007/s42452-021-04689-z.
- [3] Ü. A. Usca et al., "Estimation, optimization and analysis based investigation of the energy consumption in machinability of ceramic-based metal matrix composite materials," *J. Mater. Res. Technol.*, vol. 17, pp. 2987–2998, Mar. 2022, doi: 10.1016/j.jmrt.2022.02.055.
- [4] J.-P. Chen, L. Gu, and G.-J. He, "A review on conventional and nonconventional machining of SiC particle-reinforced aluminium matrix composites," *Adv. Manuf.*, vol. 8, no. 3, pp. 279–315, Sep. 2020, doi: 10.1007/s40436-020-00313-2.
- [5] F. Hakami, A. Pramanik, and A. K. Basak, "Tool wear and surface quality of metal matrix composites due to machining: A review," *Proc. Inst. Mech. Eng. Part B J. Eng. Manuf.*, vol. 231, no. 5, pp. 739–752, 2017, doi: 10.1177/0954405416667402.
- [6] R. A. Laghari, J. Li, A. A. Laghari, and S. Wang, "A Review on Application of Soft Computing Techniques in Machining of Particle Reinforcement Metal Matrix Composites," *Arch. Comput. Methods Eng.*, vol. 27, no. 5, pp. 1363–1377, Nov. 2020, doi: 10.1007/s11831-019-09340-0.
- [7] M. Wan, S. E. Li, H. Yuan, and W. H. Zhang, "Cutting force modelling in machining of fiber-reinforced polymer matrix composites (PMCs): A review," *Composites Part A: Applied Science and Manufacturing*, pp. 34–55, 2019, doi: 10.1016/j.compositesa.2018.11.003.
- [8] K. K. Alaneme, E. A. Okotete, A. V. Fajemisin, and M. O. Bodunrin, "Applicability of metallic reinforcements for mechanical performance enhancement in metal matrix composites: a review," *Arab Journal of Basic and Applied Sciences*, vol. 26, no. 1, pp. 311–330, 2019, doi: 10.1080/25765299.2019.1628689.
- [9] J. Li and R. A. Laghari, "A review on machining and optimization of particle-reinforced metal matrix composites," *Int. J. Adv. Manuf. Technol.*, vol. 100, no. 9–12, pp. 2929–2943, 2019, doi: 10.1007/s00170-018-2837-5.

- [10] S. A. Niknam, S. Kamalizadeh, A. Asgari, and M. Balazinski, "Turning titanium metal matrix composites (Ti-MMCs) with carbide and CBN inserts," *Int. J. Adv. Manuf. Technol.*, vol. 97, no. 1–4, pp. 253–265, 2018, doi: 10.1007/s00170-018-1926-9.
- [11] K. T. Thilagham et al., "Optimization of Machining AA4015/B 4 C Metal Matrix Composites by Taguchi Method," *Surf. Rev. Lett.*, Mar. 2024, doi: 10.1142/S0218625X24501087.
- [12] K. K. A. HUNG N P, BOEY F Y C, "Machinability of Cast and Powder-Formed Aluminum Alloys Reinforced With SiC Particles," *J. Mater. Process. Technol.*, vol. 48, pp. 291–297, 1995.
- [13] M. El-Gallab and M. Sklad, "Machining of Al/SiC particulate metal-matrix composites Part I: Tool performance," *J. Mater. Process. Technol.*, vol. 83, no. 1–3, pp. 151–158, 1998, doi: 10.1016/S0924-0136(98)00054-5.
- [14] M. El-Gallab and M. Sklad, "Machining of Al/SiC particulate metal matrix composites Part II: Workpiece surface integrity," *J. Mater. Process. Technol.*, vol. 83, no. 1–3, pp. 277–285, 1998, doi: 10.1016/S0924-0136(98)00072-7.
- [15] M. El-Gallab and M. Sklad, "Machining of Al/SiC particulate metal matrix composites part III: comprehensive tool wear models," *J. Mater. Process. Technol.*, vol. 101, no. 1–3, pp. 10–20, Apr. 2000, doi: 10.1016/S0924-0136(99)00351-9.
- [16] X. Li and W. K. H. Seah, "Tool wear acceleration in relation to workpiece reinforcement percentage in cutting of metal matrix composites," *Wear*, vol. 247, no. 2, pp. 161–171, 2001, doi: 10.1016/S0043-1648(00)00524-X.
- [17] Y. Sahin and G. Sur, "The effect of Al₂O₃, TiN and Ti (C,N) based CVD coatings on tool wear in machining metal matrix composites," *Surf. Coatings Technol.*, vol. 179, no. 2–3, 2004, doi: 10.1016/S0257-8972(03)00802-8.
- [18] C. F. Cheung, K. C. Chan, S. To, and W. B. Lee, "Effect of reinforcement in ultra-precision machining of Al6061/SiC metal matrix composites," *Scr. Mater.*, vol. 47, no. 2, 2002, doi: 10.1016/S1359-6462(02)00097-0.
- [19] I. Ciftci, M. Turker, and U. Seker, "CBN cutting tool wear during machining of particulate reinforced MMCs," *Wear*, vol. 257, no. 9–10, pp. 1041–1046, Nov. 2004, doi: 10.1016/j.wear.2004.07.005.
- [20] R. A. Laghari, J. Li, and M. Mia, "Effects of Turning Parameters and Parametric Optimization of the Cutting Forces in Machining SiCp/Al 45 wt% Composite," *Metals (Basel)*, vol. 10, no. 6, p. 840, Jun. 2020, doi: 10.3390/met10060840.
- [21] R. A. Laghari, J. Li, and Y. Wu, "Study of Machining Process of SiCp/Al Particle Reinforced Metal Matrix Composite Using Finite Element Analysis and Experimental Verification," *Materials (Basel)*, vol. 13, no. 23, p. 5524, Dec. 2020, doi: 10.3390/ma13235524.
- [22] R. Yousefi, M. A. Kouchakzadeh, J. Rahiminasab, and M. A. Kadivar, "The Influence of

SiC Particles on Tool Wear in Machining of Al/SiC Metal Matrix Composites Produced by Powder Extrusion,” *Adv. Mater. Res.*, vol. 325, pp. 393–399, Aug. 2011, doi: 10.4028/www.scientific.net/AMR.325.393.

- [23] A. R. Chambers, “The machinability of light alloy MMCs,” *Compos. Part A Appl. Sci. Manuf.*, vol. 27, no. 2, pp. 143–147, 1996, doi: 10.1016/1359-835X(95)00001-I.
- [24] A. Manna and B. Bhattacharayya, “A study on machinability of Al/SiC-MMC,” *J. Mater. Process. Technol.*, vol. 140, no. 1-3 SPEC., pp. 711–716, 2003, doi: 10.1016/S0924-0136(03)00905-1.
- [25] Y. K. Chou and J. Liu, “CVD diamond tool performance in metal matrix composite machining,” *Surf. Coatings Technol.*, vol. 200, no. 5–6, pp. 1872–1878, 2005, doi: 10.1016/j.surfcoat.2005.08.094.
- [26] R. Ali Laghari et al., “Carbide tool life prediction and modeling in SiCp/Al turning process via artificial neural network approach,” in *IOP Conference Series: Materials Science and Engineering*, Aug. 2019, vol. 600, no. 1, p. 012022, doi: 10.1088/1757-899X/600/1/012022.
- [27] X. Ding, W. Y. H. Liew, and X. D. Liu, “Evaluation of machining performance of MMC with PCBN and PCD tools,” *Wear*, vol. 259, no. 7–12, pp. 1225–1234, 2005, doi: 10.1016/j.wear.2005.02.094.
- [28] M. Jamil, N. He, W. Zhao, A. M. Khan, and R. A. Laghari, “Tribology and machinability performance of hybrid Al₂O₃ -MWCNTs nanofluids-assisted MQL for milling Ti-6Al-4V,” *Int. J. Adv. Manuf. Technol.*, vol. 119, no. 3–4, pp. 2127–2144, Mar. 2022, doi: 10.1007/s00170-021-08279-6.
- [29] M. Kovacic, J. Balic, and M. Brezocnik, “Evolutionary approach for cutting forces prediction in milling,” *J. Mater. Process. Technol.*, vol. 155–156, no. 1–3, 2004, doi: 10.1016/j.jmatprotec.2004.04.318.
- [30] M. Milfelner, J. Kopac, F. Cus, and U. Zuperl, “Genetic equation for the cutting force in ball-end milling,” *J. Mater. Process. Technol.*, vol. 164–165, pp. 1554–1560, May 2005, doi: 10.1016/j.jmatprotec.2005.02.147.
- [31] K. Abhishek, B. N. Panda, S. Datta, and S. S. Mahapatra, “Comparing Predictability of Genetic Programming and ANFIS on Drilling Performance Modeling for GFRP Composites,” *Procedia Mater. Sci.*, vol. 6, pp. 544–550, 2014, doi: 10.1016/j.mspro.2014.07.069.
- [32] F. Čuš and U. Župerl, “Real-Time Cutting Tool Condition Monitoring in Milling,” *Strojniški Vestn. – J. Mech. Eng.*, vol. 57, no. 2, pp. 142–150, Feb. 2011, doi: 10.5545/sv-jme.2010.079.
- [33] J. R. Koza and R. Poli, “Genetic Programming,” in *Search Methodologies*, Boston, MA: Springer US, 2005, pp. 127–164.
- [34] M. Zadshakoyan and V. Pourmostaghimi, “Cutting Tool Crater Wear Measurement in

- Turning Using Chip Geometry and Genetic Programming,” *Int. J. Appl. Metaheuristic Comput.*, vol. 6, no. 1, pp. 47–60, Jan. 2015, doi: 10.4018/ijamc.2015010104.
- [35] M. Zadshakoyan and V. Pourmostaghimi, “Genetic equation for the prediction of tool–chip contact length in orthogonal cutting,” *Eng. Appl. Artif. Intell.*, vol. 26, no. 7, pp. 1725–1730, Aug. 2013, doi: 10.1016/j.engappai.2012.10.016.
- [36] J. Barclay, V. Dhokia, and A. Nassehi, “Generating Milling Tool Paths for Prismatic Parts Using Genetic Programming,” *Procedia CIRP*, vol. 33, pp. 490–495, 2015, doi: 10.1016/j.procir.2015.06.060.
- [37] V. Pourmostaghimi and M. Zadshakoyan, “Designing and implementation of a novel online adaptive control with optimization technique in hard turning,” *Proc. Inst. Mech. Eng. Part I J. Syst. Control Eng.*, vol. 235, no. 5, pp. 652–663, May 2021, doi: 10.1177/0959651820952197.
- [38] A. Garg and J. S. L. Lam, “Improving environmental sustainability by formulation of generalized power consumption models using an ensemble based multi-gene genetic programming approach,” *J. Clean. Prod.*, vol. 102, pp. 246–263, Sep. 2015, doi: 10.1016/j.jclepro.2015.04.068.
- [39] J. Griffin, “The prediction of profile deviations when Creep Feed grinding complex geometrical features by use of neural networks and genetic programming with real-time simulation,” *Int. J. Adv. Manuf. Technol.*, vol. 74, no. 1–4, pp. 1–16, Sep. 2014, doi: 10.1007/s00170-014-5829-0.
- [40] A. Garg, K. Tai, V. Vijayaraghavan, and P. M. Singru, “Mathematical modelling of burr height of the drilling process using a statistical-based multi-gene genetic programming approach,” *Int. J. Adv. Manuf. Technol.*, vol. 73, no. 1–4, pp. 113–126, Jul. 2014, doi: 10.1007/s00170-014-5817-4.
- [41] S. Pawanr, G. K. Garg, and S. Routroy, “Prediction of energy consumption of machine tools using multi-gene genetic programming,” *Mater. Today Proc.*, no. xxxx, pp. 1–5, Jan. 2022, doi: 10.1016/j.matpr.2022.01.156.
- [42] M. Zadshakoyan and V. Pourmostaghimi, “Metaheuristics in Manufacturing,” 2018, pp. 118–142.
- [43] M. Seeman, G. Ganesan, R. Karthikeyan, and A. Velayudham, “Study on tool wear and surface roughness in machining of particulate aluminum metal matrix composite-response surface methodology approach,” *Int. J. Adv. Manuf. Technol.*, vol. 48, no. 5–8, pp. 613–624, 2010, doi: 10.1007/s00170-009-2297-z.
- [44] M. Mia, M. A. Khan, and N. R. Dhar, “Study of surface roughness and cutting forces using ANN, RSM, and ANOVA in turning of Ti-6Al-4V under cryogenic jets applied at flank and rake faces of coated WC tool,” *Int. J. Adv. Manuf. Technol.*, vol. 93, no. 1–4, pp. 975–991, Oct. 2017, doi: 10.1007/s00170-017-0566-9.