Journal of Scientific & Industrial Research
Vol. 81, September 2022, pp. 911-921
DOI: 10.56042/jsir.v81i09.55874

Application of Artificial Neural Networks and Genetic Algorithm for Optimizing Process Parameters in Pocket Milling of AA7075

M. Rajyalakshmi[1,2]* & M Venkateswara Rao[3]

[1]Acharya Nagarjuna University, Guntur 522 510, Andhra Pradesh, India

[2]PVP Siddhartha Institute of Technology, Vijayawada 520 007, Andhra Pradesh, India

[3]Department of Mechanical Engineering, Bapatla Engineering College, Bapatla 522 102, Andhra Pradesh, India

Received 06 October 2021; revised 23 August 2022; accepted 24 August 2022

Mould preparation is an important phase in the injection moulding process. The surface roughness of the mould affects the surface finish of the final plastic product. Quality product with a better production rate is required to meet the competition in the present market. To achieve this objective, manufacturers try to select the best combination of parameters. Multi-objective optimization is one such technique to obtain the optimal process parameters that give better quality with a good production rate. The current paper describes the application of Multi-Objective Genetic Algorithms (MOGA) on the Artificial Neural Network (ANN) model for pocket milling on AA7075. Through the application of ANN with MOGA minimum Surface Roughness (SR) is achieved with a better Material Removal Rate (MRR). From the confirmation experiments, it is evident that follow-periphery tool path gives a better surface finish with higher MRR and the percentage error observed is 1.9553 and 1.8282 respectively.

Keywords: Aluminium, ANN, Multi objective genetic algorithms, RSM, Tool trajectory

Introduction

Pocket milling is the process used in mould preparation in the plastic industry. Plastic product is accepted when the surface quality of the product is fine. Surface quality is dependent on the surface roughness of the mould used for injection moulding. To generate the mould pockets different tool trajectories are used, which are broadly classified as linear and non-linear tool paths.[1] Selection of tool path along with optimal process parameters leads to efficient performance in mould preparation with minimum surface roughness.[2] Though several machining parameters influence the machining conditions, Spindle speed, table feed, and depth of cut influence the surface integrity of the workpiece.[3] Path followed by the tool while generating the pocket profiles affect the surface roughness.[4] In addition to these parameters, proper selection of stepover and tool path strategy selected to generate pockets also influences the surface roughness.[5] Many researchers tried to optimize the process parameters for better surface quality and MRR. With the application of Response surface methodology (RSM) Alauddin *et al.* developed a model to predict surface roughness. From the study, they have identified Feed is the dominating factor for surface roughness.[6]

Routara *et al*. studied the influence of tool trajectories on surface roughness by modeling with RSM. They have identified that selection of proper tool path affects the surface roughness.[7] Bouard *et al.* developed a toolpath computation method with a Uniform Cubic B-spline curve.[8] A Constraint-based optimization algorithm is applied to the model to produce the pocket with less energy. Rajyalakshmi and babu studied the influence of process parameters to minimize surface roughness in Al7075 alloy using response surface methodology.[9] Several researchers applied modern and Evolutionary algorithms to optimize machining parameters to get minimum surface roughness.[10–17]

Multiple Response Optimization (MRO) is a new technology in manufacturing that selects optimal settings to save machining cost and time. Gök *et al.* discovered that the tool's trajectory, in addition to the cutting parameters, influences tool acceleration.[18] They investigated the effect of cutting settings and tool routes on tool acceleration, which directly

*Author for Correspondence
E-mail: j.rajyalakshmi@gmail.com

influences surface roughness, through testing. Gjelaj *et al*. used multi objective GA (MOGA) to improve milling settings.[19] According to the experimental data, it provides Pareto output that optimise the machining settings and have accurateness in the trail values. Zubaidi *et al*. investigated the use of ANN in milling parameter analysis and optimization.[20] They discovered that when compared to standard methods, ANN predicts superior values. Zain *et al*. used three types of tools to estimate surface roughness using a neural network model (ANN) feed-forward model.[21] In the network, they employed various configurations of hidden layers. They concluded from their experimental results that increasing the number of hidden neurons can enhance surface roughness. Ghosh *et al*. used ANN and RSM to improve machining settings by modelling surface roughness.[22] They also used particle swarm optimization (PSO) method to solve regression equations generated by RSM. Through confirmation experiments, they discovered a high degree of agreement between the trail and anticipated values of SR. Venkatesh and Suresh Kumar used ANN and simulated Annealing to predict and optimise the cutting conditions for the lowest surface roughness (SA).[23] comparing the projected values of RSM to that of experimental values, they discovered that ANN can be well adapted for parameter modeling and optimization. Yanis *et al*. used RSM and ANN to improve process parameter in side milling with an environmental friendly coolant.[24] They found from the experimental data that the ANN simulation is in excellent accordance with the verification test results.

The majority of the studies on single response optimization were found in the aforementioned papers. Pocket milling has received very little attention, with step over being one of the driving elements. The study can also take into account the impact of tool trajectories on responses. One of the best methods for enhancing process parameters has been proven to be ANN. Artificial neural networks can be effectively used for multi-response optimization when paired with GA. As a result, the goal of the current study is to optimise the process parameters by applying ANN and MOGA to the experimental data obtained from the two tool movements- Follow Periphery (FP) and ZigZag (ZZ).

Materials and Methods

Materials

Aluminium and its alloys are the commonly used materials in many fields of engineering. Their properties such as lightweight, ease of machinability, corrosion resistance etc., make them qualify for diversified applications.[25]

AA7075 with a specimen size of 80 × 70 mm with a depth of 10mm is used in the present study. AA7075 is an aluminium alloy with Zinc as the primary constituent. It has good fatigue strength, when un-heat-treated, it has high tensile and yield strengths. But it has low weld ability and average machinability. Because of its high strength, thermal properties, low density, and specific strength, AA7075 finds applications in marine, aircraft building, automotive and moulding industries. The composition of the selected material is given in Table 1.

Experimental Procedure

Design of Experiments (DOE) is a statistical approach for deciding experiments required for high and more complex engineering issues economically. One such approach is Response Surface Methodology (RSM), which reduces the experimental runs required to obtain maximum data from the components and levels of selected parameters. For determining the number of experimental runs in RSM, two models are available: Central Composite Design (CCD) and Box-Behnken Design (BBD). When compared to CCD, the BBD is more cost effective when the experiment contains three components and three levels.[26]

The Box-Behnken model produces consistent findings and uses separate quadratic equations to determine coefficients.[27] They do not, however, show the results of a factorial experiment. The BB model has factors at three levels. The parameter configurations are located in the process space's midpoints and in the centre. To produce design combinations, each element must have three levels.

Table 1 — Chemical composition of AA7075

Element	Aluminium (Al)	Zinc (Zn)	Magnesium (Mg)	Copper (Cu)	Others
% Comp. by wt.	90–92%	5.6–6.1%	2.1–2.5%	1.2–1.6%	Less than 0.5%

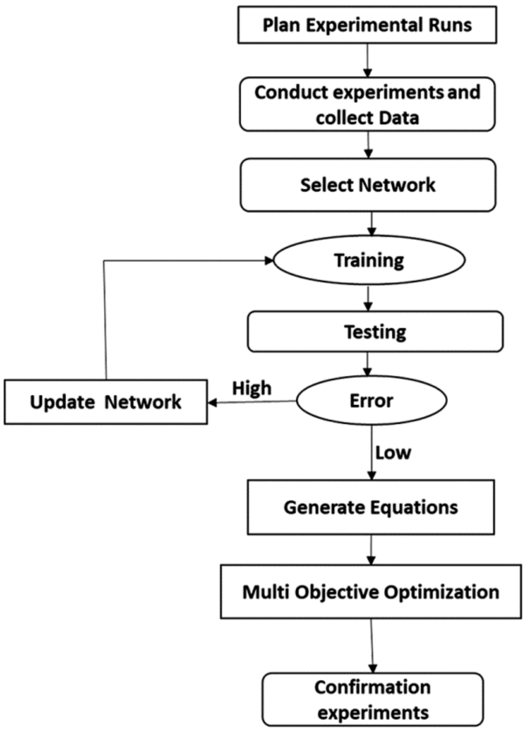

Fig. 1 — Procedural map

When compared to central composite designs, the designs have limited orthogonal blocking potential.

ANN modelling is used to the experimental data. The modelled data is used to generate second-order regression equations. The MATLAB optimization toolkit is used to apply multi-objective genetic algorithms to these regression equations. The process for multi-objective optimization is depicted in Fig. 1 by a flow chart. Data predicted from ANN is also presented to ANOVA to identify the most influential parameter for the outputs in two tool trajectories.

Modeling and Simulation

Siemens Nx.11 software is used to model and simulate the specified pocket milling profile. To test the tool progressing directions, two tool path techniques viz., zigzag and follow periphery, are mimicked in this model. Simulation of the tool paths id depicted in Fig. 2. Following simulation, NC code for each approach is created independently.

Experimental Factors

Despite the fact that there are various modifiable factors, the current study uses speed (RPM), feed (mm/min), and step-over (percent). From literature search, production hand book, and trial experiments, three levels for each variable are identified.

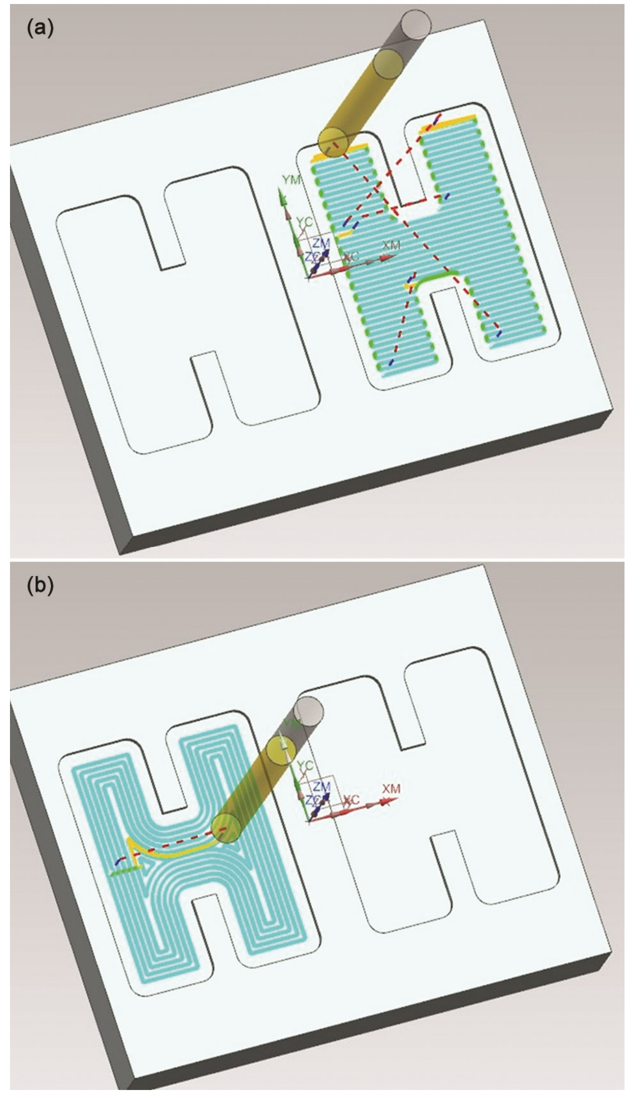

Fig. 2 — Tool path simulation in a) Zigzag and b) Follow periphery tool paths

Responses include surface roughness and Material Removal Rate (MRR). The levels and codes of controllable factors are depicted in Table 2.

Experimental procedure

Because there are three parameters, each with three levels, the series of experimental trials was determined via Box-Behnken design in RSM. Design Expert is used to construct experimental runs using programmed run orders, as shown in Table 3.

Experimental Setup

Pocket machining operations were performed using an AMC MCV-350 Vertical Machining Center with a Fanuc controller. Pockets are produced on the selected specimen with a 6 mm diameter four-flute

Table 2 — Range of process parameters with codes

Symbol	Machining characteristics selected for study	Units	Levels of selected parameters			Responses of interest
			1	2	3	
S	Speed	RPM	3000	4000	5000	Surface roughness (microns)
F	Feed	mm/min	500	1000	1500	Material removal rate (g/s)
SO	Step over	%	20	40	60	
	Level codes		−1	0	1	

tool having tungsten carbide coating. Experiments were performed as per the run order shown in Table 3. Surface roughness is measured with the Mitutoyo Surf test SJ-210. The sample length is set at 2.5 mm. Surface roughness is defined as the average of five sample lengths (Ra). With a precision balance having a least count of 0.01 gm, the work piece's weights prior to and after machining were measured. Equation 1 is used to compute the Material Removal Rate (MRR):

$$MRR = \frac{w_2 - w_1}{n} \quad \ldots (1)$$

where, w_1,w_2 indicate weights of the specimen before and after machining respectively. 'n' indicates the processing time in seconds to generate the profile.

Table 3 — Order of experimental run

Std. order	Experimental order	S (RPM)	F (mm/min)	SO (%)
1	7	−1	−1	0
2	4	−1	−1	0
3	6	−1	1	0
4	14	1	1	0
5	3	−1	0	−1
6	9	1	0	−1
7	2	−1	0	1
8	1	1	0	1
9	5	0	−1	−1
10	11	0	1	−1
11	10	0	−1	1
12	12	0	1	1
13	8	0	0	0
14	15	0	0	0
15	13	0	0	0

Results and Discussion

Experimentation was carried out in accordance with the previous discussion. At the end of each experiment, the surface roughness measured is entered in the respective table. Before and after machining, the work piece is weighed. To determine MRR, the division of absolute variation of weights with machining time of the respective experiment is calculated. Similar procedure is followed for the two tool configurations. The values obtained for both outcomes for the two specified tool trajectories are presented in Table 4.

Analysis of Experimental Data

The experimental results are analyzed using design expert software to identify the relation between input variables and the selected responses. Regression equations are generated and theoretical response values are calculated. The error observed is less than five percent between the predicted and experimental values. ANOVA is applied to the experimental data to identify the most influencing factor for SR and MRR in both tool trajectories. The F-value in the ANOVA results indicate the influence of the parameters on the response. It is observed that for surface roughness in FP tool path the F- value for speed (103.44) is the highest compared to other parameters. Similarly, for MRR, the F-value against step over is 1151.33 which is the highest value than that of speed and feed. For zigzag tool path, F-value for step over in the SR analysis is observed as 79.16 and in MRR analysis F-value for feed is 86.51 which are the highest values compared to other parameter f- values. The mean effect plots shown in Fig. 3 also indicate that speed is the most influencing factor for surface roughness in follow periphery tool path, whereas step over is influencing MRR. For the ZZ tool path Surface roughness is affected by step over and MRR is influenced by Feed.

Modelling with ANN

In the present scenario, ANN is gaining more attention in the field of modelling and optimization due to its efficiency in improving the results. The ANN model consists of artificial neurons connected by hidden layers from the input to the output nodes. The response is obtained as a non-linear function generated with assignment of weights to each node in the inputs. With reference to training data sets, the weights linked with neurons may be adjusted. ANN

Table 4 — Experimental results for the two tool paths

Experiment. no	FP		ZZ	
	Surface roughness (microns)	Material removal rate (g/s)	Surface roughness (microns)	Material removal rate (g/s)
1	1.266	0.04175	1.251	0.05221
2	1.088	0.07615	1.032	0.08279
3	1.528	0.0998	0.9383	0.09843
4	1.155	0.05566	0.95	0.06327
5	1.112	0.23524	1.137	0.1354
6	1.425	0.10667	1.522	0.11467
7	0.934	0.06238	1.229	0.06936
8	0.792	0.15563	1.361	0.08651
9	1.421	0.10688	1.506	0.11467
10	0.79	0.03984	0.834	0.05039
11	1.384	0.10936	1.5	0.11881
12	1.322	0.22818	0.98	0.09635
13	1.276	0.02434	0.91	0.04435
14	0.938	0.0998	1.033	0.044225
15	1.103	0.0835	0.767	0.05584

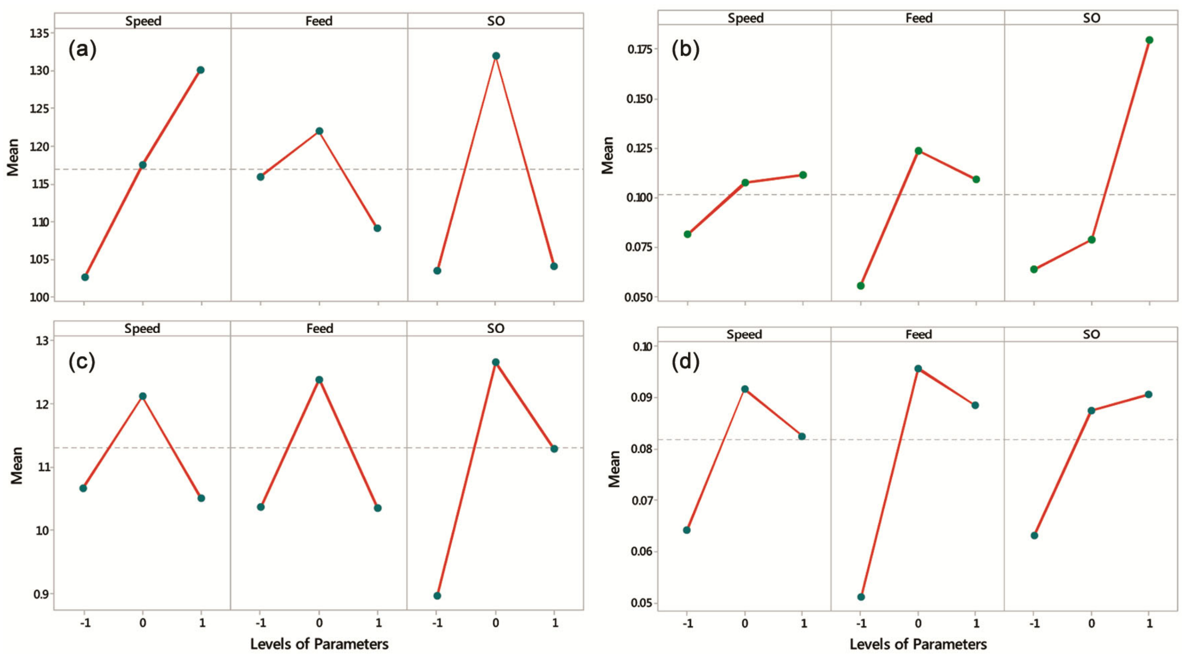

Fig. 3 — ANOVA plots for the responses (a) Follow periphery surface roughness (FP) (b) FP material removal rate (c) Zigzag (ZZ) Surface roughness (d) ZZ Material removal rate tool paths

modelling also be employed in situations with many variables. In ANN architecture, feed forward and feedback networks are often applied.[28] Feed forward neural networks are those in which the signal flows from input to output direction. The signal in the feedback network moves in both directions to generate loop in cyclic networks.

Because the replies have competing aims, the experimental data collected from the FP tool trajectory is normalised to generate an efficient network model. The trial-and-error approach is used in ANN to select the suitable model useful for optimisation. Minimum MSE (Mean Square Error) is a key markers of a robust ANN model. By employing the Levenberg-Marquardt approach to train the data, a superior ANN model is created with the given data set. After training, the network receives three inputs and produces two outputs. An network model with six neurons in the hidden layer is depicted in Fig. 4.

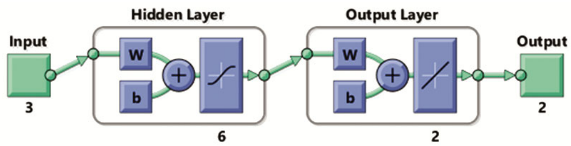

Fig. 4 — ANN model with 6 neurons

The MSE determines the number of neurons necessary in the hidden layer for optimal network training. By varying the number of neurons in the hidden layer as 5, 6, and 7 the model is trained to identify the network with minimum MSE value.[29,30] According to the performance graphs in Fig. 5, network with six neurons in the hidden layer is showing least mean square error. The MSE values for neurons 5, 6, and 7 are also provided as 0.050997, 00027661, and 0.0073642, respectively. As a result, to train the data set, the neural network with 6 neurons in the hidden layer is used.

The experimental data used as input to the model may be divided into three categories: training, validating, and testing data. To train the model, create a training set. Validation is configured to halt training when there is no progress of network output and testing is set to verify anticipated values and assess error in comparison to actual values.[30] Training, Validation and Testing data sharing is done based on the trails by changing the training data percentage in MATLAB Neural Network.[31] Three kinds of training, verification, and assessment data sets are used to assess the network's capabilities. The R-value that shows the performance of the network for the selected three choices for six neurons is displayed in Fig. 6.

Compared to testing and validation of 15% and 20%, the R-value for 10% testing and validation data is much higher (0.98451) as shown in Fig. 6. This might be due to the dataset provision of intensive training samples (80%) for adequate model training. As a result, the Neural Network having six hidden layer neurons with 80% training, 10% validation, and 10% testing data set is deemed best.

The experimental data collected from the zigzag tool trajectory is also subjected to ANN modelling, and the ANN findings produced for the two factors in both tool paths are displayed in Table 5.

For both the outcomes an analytical relationship is established with design expert software, using the collected results. According to the ANOVA findings of ANN models, speed for SR and step over for MRR in FP tool path, stepover for SR and feed for MRR in

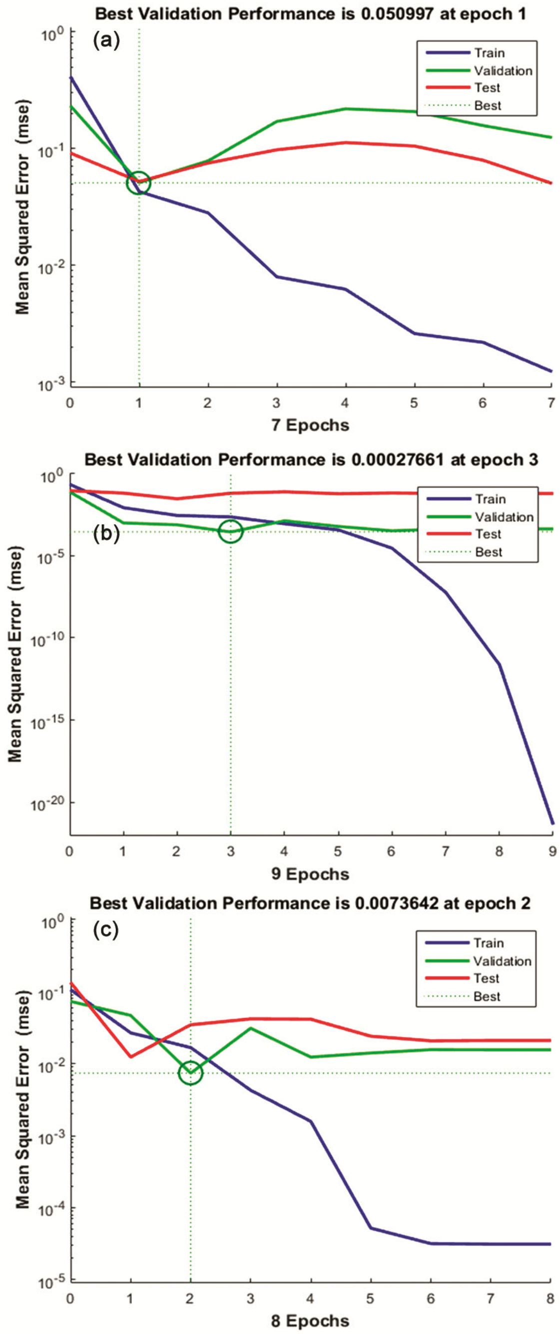

Fig. 5 — Performance plots for with (a) 5 Neurons, (b) 6 Neurons and (c) 7 Neurons in the hidden layer of ANN modeled data

ZZ tool trajectory are identified as impacting factors. The ANOVA plots are depicted in Fig. 7.

Multi Objective Optimization

According to prior research, Genetic Algorithms (GA) are one of the best optimization strategies for multi-objective optimization.[29] The concept of GA is derived from natural selection and survival of the

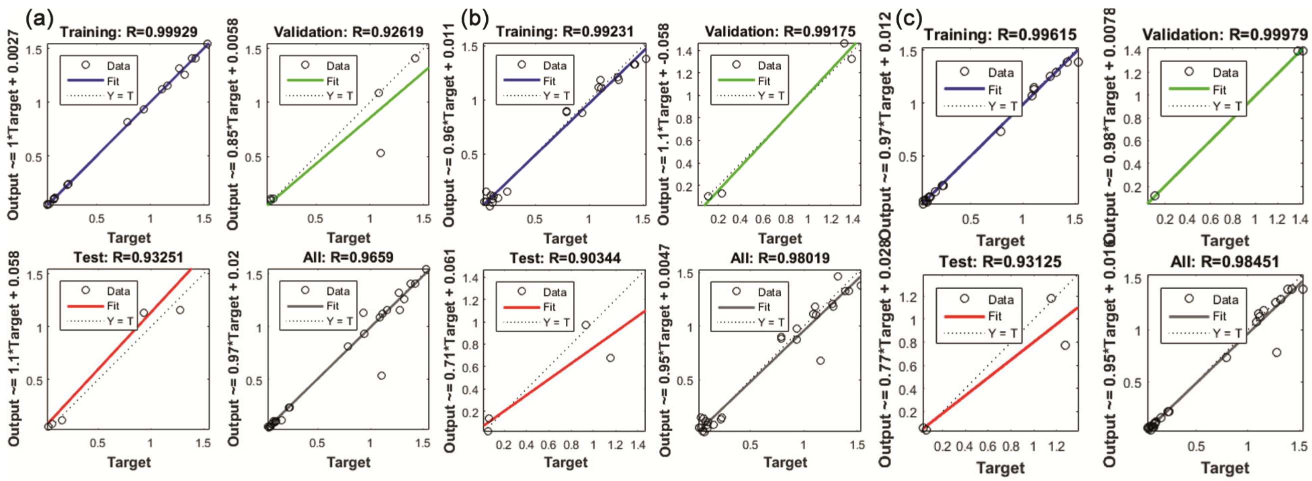

Fig. 6 — Overall R values for (a) 20% Validation (b) 15% validation (c) 10% validation

Table 5 — Error calculation of the responses for ANN and experimental values inboth the tool paths

Run	ANN Model				Error Percentage			
	FP		ZZ		FP		ZZ	
	SR (microns)	MRR (g/s)	SR (microns)	MRR (g/s)	SR (microns)	MRR (g/s)	SR (microns)	MRR (g/s)
1	1.28371	0.04216	1.24919	0.05281	1.3991	0.9820	0.1447	1.1492
2	1.06005	0.07438	1.03166	0.07931	2.5689	2.3244	0.0329	4.2034
3	1.53173	0.10414	0.95837	0.09352	0.2441	4.3487	2.139	4.9883
4	1.19945	0.05703	0.94802	0.06186	3.8485	2.4614	0.2084	2.2285
5	1.13173	0.22674	1.12221	0.13020	1.7743	3.6133	1.3008	3.8405
6	1.41734	0.10757	1.49343	0.11324	0.5375	0.8437	1.8771	1.2471
7	0.93474	0.06469	1.16857	0.06943	0.0792	3.7031	4.9170	0.1009
8	0.81537	0.16156	1.30419	0.08487	2.9508	3.8103	4.1741	1.8957
9	1.41734	0.10757	1.49343	0.11324	0.2576	0.6456	0.8347	1.2471
10	0.81566	0.03945	0.83280	0.05151	3.2481	0.9789	0.1439	2.2227
11	1.41734	0.10757	1.49343	0.11324	2.4090	1.6368	0.4380	4.6882
12	1.36166	0.22053	1.00621	0.10108	3.0000	3.3526	2.6745	4.9092
13	1.21328	0.02461	0.94558	0.04626	4.9154	1.1093	3.9099	4.3067
14	0.97652	0.09976	1.00299	0.04519	4.1066	0.0401	2.9051	2.1820
15	1.10604	0.08397	0.75546	0.05338	0.2756	0.5629	1.5046	4.4054
	Average Percentage Error				2.10763	2.0275	1.81365	2.9077

fittest. Solutions that meet a specified for the object function requirement are passed on to the successor stage. Otherwise, the solution is rejected through the genetic operators "Reproduction, Cross over, and Mutation". After determining the fitness function, the starting population is chosen from the population and exposed to the genetic operators. Many generations are examined using genetic operators and fitness functions to find the best solution. When the solution set's value does not improve, the solution search is discontinued. The MAT LAB toolkit is used to do multi-objective optimization using GA. The genetic operators chosen for multi-objective optimization for both tool routes are shown in Table 6, where, P_{cp} is the crossover probability and P_M is the mutation probability.

Table 6 — Genetic operators values selected

Genetic operational parameters	Value selected
Population	100
P_{cp}	80%
P_M	10%
Generations	200

Optimization with ANN Model using Multi-Objective Genetic Algorithms

Second-order response equations formulated with the theoretical values of the Neural Network model are subjected to multi-response optimization using the MATLAB optimization toolbox. From the toolbox, the Multi-Objective Genetic Algorithm (MOGA) is selected and the objective function is defined as follows.

For follow periphery trajectory

Minimize $f_1 = 1.42 + 0.146S - 0.0324F - 0.013SO - 0.1316SF + 0.1481SSO + 0.1348FSO - 0.0608S^2 - 0.1157F^2 - 0.2708SO^2$

Minimize $f_2 = -(0.1076 + 0.0133S + 0.02643F + 0.0567SO + 0.00547SF + 0.01714SSO + 0.03613FSO - 0.00965S^2 - 0.03902F^2 - 0.03719SO^2)$

For zigzag trajectory

Minimize $f_1 = 1.493 + 0.00896S - 0.00798F + 0.1085SO - 0.1285SF - 0.1436SSO + 0.0586FSO - 0.18256S^2 - 0.2304F^2 - 0.2865SO^2$

Minimize $f_2 = -(0.11324 + 0.0091S + 0.0173F + 0.0144SO + 0.00438SF - 0.00243SSO + 0.023841FSO - 0.02013S^2 - 0.0276F^2 - 0.01344SO^2)$

where, f_1 and f_2 are the surface irregularity and MRR. For the control factors speed, feed, and stepover, the bounds of the parameters are [−1, 1]. The parameter set is comparable to that of the regression model. The Pareto output values achieved are displayed in Table 7 for the Neural Network model. The Pareto results obtained from MOGA are shown in Fig. 8 for both the tool paths.

The coded parameter values are decrypted, and verification experiments for randomly picked Pareto outcomes are conducted. Four validation experiments

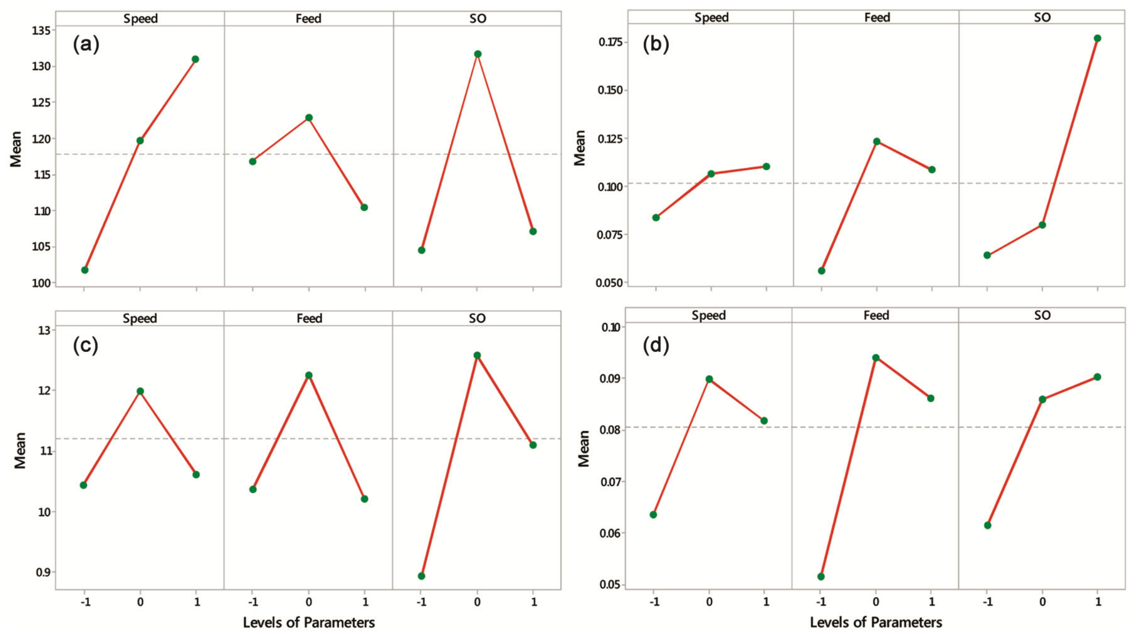

Fig. 7 — ANOVA plots for the responses in ANN for the two tool paths (a) FP surface roughness; (b) FP material removal rate (c) ZZ surface roughness (d) ZZ material removal rate

Table 7 — Pareto Results of responses for both the tool paths

Run	FP		ZZ	
	SR (microns)	MRR (g/s)	SR (microns)	MRR (g/s)
1	0.74861	0.22375	0.69055	0.11868
2	0.94562	0.28338	1.14975	0.13079
3	0.94036	0.27816	1.14975	0.13079
4	0.71194	0.21843	1.13357	0.13068
5	0.84839	0.25134	0.76982	0.12185
6	0.86182	0.25353	0.94968	0.12793
7	0.90198	0.26505	0.69055	0.11868
8	0.82603	0.24579	0.99353	0.12886
9	0.69057	0.21457	0.79946	0.12281
10	0.72181	0.22039	1.08767	0.13042
11	0.84135	0.24901	1.05747	0.12999
12	0.88175	0.26011	0.84012	0.12466
13	0.70058	0.21666	0.92068	0.12629
14	0.73159	0.22357	0.92446	0.12733
15	0.89296	0.26214	0.86460	0.12528

are conducted for both the tool trajectories. For FP tool path the validation experiments are conducted by selecting minimum surface roughness values and for zigzag tool path, medium value surface roughness is taken as reference. The confirmation test results are shown in Table 8.

From the Pareto results, it is observed that surface roughness and material removal rate in follow periphery tool path is better than that of the zigzag tool path. From the Pareto graph also, it is evident that the FP tool trajectory can be selected for better surface finish and material removal rate. The percentage error observed is shown in Fig. 9.

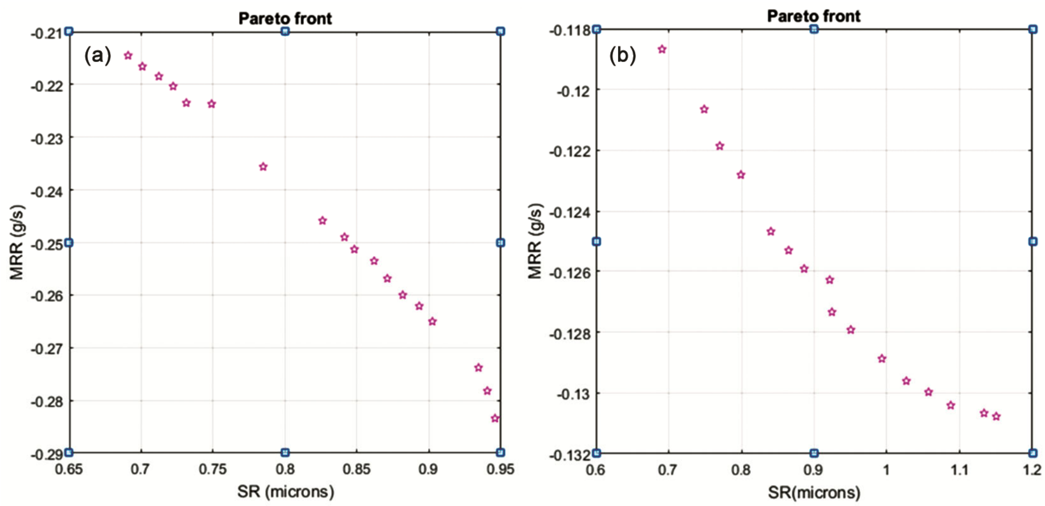

Fig. 8 — Pareto values of neural network models for tool paths (a) Follow periphery (b) Zigzag

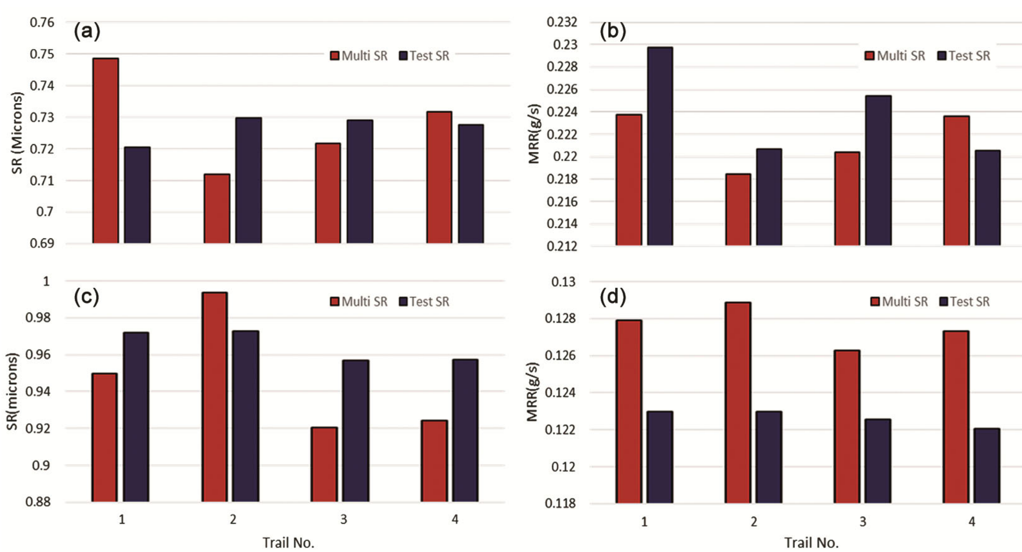

Fig. 9 — Comparison of validation test and predicted values for ANN model with multi-objective GA (a) FP surface roughness, (b) FP material removal rate, (c) ZZ surface roughness, (d) ZZ material removal rate

Table 8 — Error calculations of with pareto and verification experimental results

Run	Pareto results				Confirmation Expt. results				Percentage error			
	FP		ZZ		FP		ZZ		FP		ZZ	
	SR (microns)	MRR (g/s)	SR (microns)	MRR (g/s)	SR (microns)	MRR (g/s)	SR (microns)	MRR (g/s)	SR (microns)	MRR (g/s)	SR (microns)	MRR (g/s)
1	0.7486	0.2238	0.9497	0.1279	0.7204	0.2297	0.9720	0.1230	3.7723	2.6797	2.3537	3.8687
2	0.7119	0.2184	0.9935	0.1289	0.7297	0.2206	0.9730	0.1230	2.4974	1.0129	2.0694	4.5731
3	0.7218	0.2204	0.9207	0.1263	0.7291	0.2254	0.9571	0.1225	1.0101	2.2723	3.9543	2.9688
4	0.7316	0.2236	0.9245	0.1273	0.7276	0.2206	0.9573	0.1221	0.5413	1.3478	3.5496	4.1452
	Average error								1.9553	1.8282	2.9817	3.8889

According to the confirmation test findings, the mean error percentage for surface roughness and material removal rate is 1.9553 and 1.8282 for the FP tool path and 2.9817 and 3.8889 for the Zigzag tool trajectory.

Conclusions

The current work used the Response Surface Method in conjunction with ANN and multi-objective optimisation, to discover the best combination of parameters in pocket machining of AA7075 using two tool path approaches. The following conclusions may be drawn from the studies:

1. While speed for surface roughness and step over for material removal rate are seen as influencing variables from ANOVA for individual responses in the FP tool route, stepo ver for surface roughness and feed for material removal rate are identified as the main influencing factor in both tool paths.
2. The R^2 values of the network models are 0.9597, 0.9641, 0.874, and 0.9437, illustrating the effective association between the ANN model's input and output parameters.
3. Multi-response optimization values for surface roughness and material removal rate produced using Genetic Algorithms for both tool path techniques are confirmed using confirmation experiments done at randomly selected parameter values of the Pareto findings.
4. When compared to ZZ values, the mean error observed for follow periphery surface roughness is 1.9553 percent and MRR is 1.8282 percent for the ANN model, and confirmation experiments show that the anticipated values accord well with the experimental results.
5. The study shows that, while the zigzag tool route approach produces superior surface roughness, the variance in the surface integrity value of the Pareto outcomes is higher than that of the followperiphery tool path, but the MRR is greater in the followperiphery tool movement. As a result, the follow periphery trajectory of the tool is recommended for AA7075 to save manufacturing costs.

The combination of multi-objective GA with artificial neural network model yields a global outcome to the given objective function. Optimisation of process variables yields better results combined with production quality to minimize machining time and hence production cost.

References

1 Kramer T R, Pocket milling with tool engagement detection, *J Manuf Syst*, **11(2)** (1992) 112–123, doi:10.1016/ 0278-6125(92)90042-E

2 Benardos P G & Vosniakos G C, Predicting surface roughness in machining: A review, *Int J Mach Tools Manuf*, **43(8)** (2003) 833–844, doi:10.1016/S0890-6955(03)00059-2

3 Agarwal N, Surface roughness modeling with machining parameters (Speed, Feed & Depth of cut) in CNC milling, *Mech Eng*, **2(1)** (2012) 55–61.

4 Toh C K, A study of the effects of cutter path strategies and orientations in milling, *J Mater Process Technol*, **152(3)** (2004) 346–356, doi:10.1016/j.jmatprotec.2004.04.382

5 Gologlu C & Sakarya N, The effects of cutter path strategies on surface roughness of pocket milling of 1.2738 steel based on taguchi method, *J Mater Process Technol*, **206(1–3)** (2008) 7–15, doi:10.1016/j.jmatprotec.2007.11.300

6 Alauddin M, El Baradie M A & Hashmi M S J, Computer-aided analysis of a surface-roughness model for end milling, *J Mater Process Technol*, **55(2)** (1995) 123–127, doi:10.1016/0924-0136(95)01795-X

7 Routara B C, Bandyopadhyay A & Sahoo P, Roughness modeling and optimization in CNC end milling using response surface method: Effect of workpiece material variation, *Int J Adv Manuf Technol*, 40(11–12) (2009) 1166–1180. doi:10.1007/s00170-008-1440-6

8 Bouard M, Pateloup V & Armand P, Pocketing toolpath computation using an optimization method, *CAD Comput Aided Des*, **43(9)** (2011) 1099–1109, doi:10.1016/j.cad. 2011.05.008

9 Rajyalakshmi M P S B, optimization of process parameters for pocket milling of AL7075 using response surface methodology, *Int J Mech Prod Eng Res Dev*, **9(4)** (2019) 649–658.

10 Mahesh T P & Rajesh R, Optimal selection of process parameters in CNC end milling of Al 7075-T6 aluminium alloy using a taguchi-fuzzy approach, *Procedia Mater Sci*, **5** (2014) 2493–2502, doi:10.1016/j.mspro.2014.07.501

11 Rawangwong S, Chatthong J, Boonchouytan W & Burapa R, An investigation of optimum cutting conditions in face milling aluminum semi solid 2024 using carbide tool, *Energy Procedia*, 34 (2013) 854–862. doi:10.1016/j. egypro. 2013.06.822

12 Mohammed Iqbal U, Senthil Kumar V S & Gopalakannan S, Application of Response Surface Methodology in optimizing the process parameters of Twist Extrusion process for AA6061-T6 aluminum alloy, *Meas J Int Meas Confed*, 94 (2016) 126–138, doi:10.1016/j.measurement.2016.07.085

13 Dweiri F, Al-Jarrah M & Al-Wedyan H, Fuzzy surface roughness modeling of CNC down milling of Alumic-79, *J Mater Process Technol*, **133(3)** (2003) 266–275, doi:10.1016/S0924-0136(02)00847-6

14 Perez H, Diez E, Perez J & Vizan A, Analysis of machining strategies for peripheral milling, *Procedia Eng*, **63** (2013) 573–581, doi:10.1016/j.proeng.2013.08.193

15 Sukumar M S, Venkata Ramaiah P & Nagarjuna A, Optimization and prediction of parameters in face milling of

Al-6061 using taguchi and ANN approach, *Procedia Eng*, **97** (2014) 365–371, doi:10.1016/j.proeng.2014.12.260

16 Selvam M D, Karuppusami G & Dawood A K S, Optimization of machining parameters for face milling operation in a vertical CNC milling machine using genetic algorithm, *Eng Sci Technol Int J (ESTIJ)* **2(4)** (2012) 2250–3498.

17 Çolak O, Kurbanoğlu C & Kayacan M C, Milling surface roughness prediction using evolutionary programming methods, *Mater Des*, **28(2)** (2007) 657–666, doi:10.1016/j.matdes.2005.07.004

18 Gök A, Gök K, Bilgin M B & Alkan M A, Effects of cutting parameters and tool-path strategies on tool acceleration in ball-end milling, *Mater Tehnol*, **51(6)** (2017) 957–965, doi:10.17222/mit.2017.039

19 Gjelaj A, Berisha B & Smaili F, Optimization of turning process and cutting force using multiobjective genetic algorithm, *Univers J Mech Eng*, **7(2)** (2019) 64–70, doi:10.13189/ujme.2019.070204

20 Al-zubaidi S, Ghani J A, Hassan C & Haron C, Application of ANN in milling process : A review, *Model Simul Eng*, (2011) doi:10.1155/2011/696275

21 Mohd A, Haron H & Sharif S, Expert systems with applications prediction of surface roughness in the end milling machining using artificial neural network, *Expert Syst Appl*, **37(2)** (2010) 1755–1768, doi:10.1016/j.eswa.2009.07.033

22 Ghosh G, Mandal P & Mondal S C, Modeling and optimization of surface roughness in keyway milling using ANN, genetic algorithm, and particle swarm optimization, *Int J Adv Manuf Technol*, 2017.

23 Mundada V & Kumar Reddy Narala S, Optimization of milling operations using artificial neural networks (ANN) and simulated annealing algorithm (SAA), *Mater Today Proc*, **5(2)** (2018) 4971–4985, doi:10.1016/j.matpr.2017.12.075.

24 M Yanis, Mohruni A S, Sharif S, Yani I, Arifin A & Khona'ah B, Application of RSM and ANN in predicting surface roughness for side milling process under environmentally friendly cutting fluid, *J Phys Conf Ser*, **1198(4)** (2019) 042016, doi:10.1088/1742–6596/1198/4/042016

25 AZOM, Aluminium - Specifications , Properties , Classifications and Classes, *Azom Mater*, (2005) 1–13. https://www.azom.com/article.aspx?ArticleID=2863. Accessed July 23, 2021.

26 11.2.2 - Box-Behnken Designs | STAT 503. https://online.stat.psu.edu/stat503/lesson/11/11.2/11.2.2, Accessed April 11, 2022.

27 Ferreira S L C, Bruns R E, Ferreira H S, et al. Box-Behnken design: An alternative for the optimization of analytical methods, *Anal Chim Acta*, **597(2)** (2007) 179–186, doi:10.1016/j.aca.2007.07.011

28 Karkalos N E, Galanis N I & Markopoulos A P, Surface roughness prediction for the milling of Ti-6Al-4V ELI alloy with the use of statistical and soft computing techniques, *Meas J Int Meas Confed*, **90** (2016) 25–35. doi:10.1016/j.measurement.2016.04.039

29 Hatem N, Yusof Y, Kadir A, Mohammed M A, A review of tool path optimization in cnc machines : Methods and its applications based on artificial intelligence, **29(4)** (2020) 3368–3380.

30 Mukkamala U & Gunji S R, Comparison of regression model with multi-layer perceptron model while optimising cutting force using genetic algorithm, **7(2)** (2020) 265–272.

31 Rajyalakshmi M & Venkateswara Rao M, Multi-response optimisation of process parameters in pocket milling using artificial neural networks and genetic algorithms, *J Inf Knowl Manag*, **21(02)** (2022) 2250026, doi:10.1142/S0219649222500265