Machining Performance Optimization of FSW Using ANN-based PCA - A Hybrid approach for AA6061

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Abstract. In this study, Friction stir welding (FSW) of AA6061 shows the importance of machining parameters such as tool rotational speed (TRS), feed rate (FR) and Tool Pressure angle (TPA). The machining performance has been measured through the ultimate tensile strength (UTS) and Vickers hardness (VH). The Taguchi's philosophy has been considered in designing the experiment. The machining characteristics were analyzed using the main effect plot and analysis of variance (ANOVA). A principal component analysis (PCA) based composite principal component (CPC) has been used to optimise multi-response. The TRS has been found to be the most significant parameter for obtaining the optimum parameter setting. The performance has been enhanced using ANN technique of the process.

Keywords: FSW, AA6061, UTS, PCA, ANN.

1 Introduction

Aluminum and its alloys have become one of the most mandated metals in determining the capabilities of the present scenario. It is most extensively material in the research community as well as vast application in the aerospace and automobile industries due to its beneficial properties. In the automobile industry, aluminium alloy is used to reduce the total load without decreasing the safety factors. The lightweight vehicle may consume less fuel, up to 20% and reduce CO_2 emissionsby up to 10%. Aluminum Alloys have distinctive properties like high strength-to-weight ratio, corrosion etc. Among the aluminium alloy, AA6061 have vast application in the field of automotive components and is well suited to manufacturing yachts, bicycle frame, scuba tanks etc. this material is coming under strong material and light material vast application due to its properties like superior ductility, outstanding weldability, and machinability. Using the conventional methods (fusion welding) to weld two similar materials may deteriorate the quality of the surface because of its hot VH properties by the welding electrode. This method has a propensity after the solidification and cracks appear on the surface, porosity, and the vaporization of alloying elements because of the presence of hydrogen. This welding technique requires high energy and highly skilled

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labour to perform a quality joint. So, this may increase the production cost of the product. Friction stir welding (FSW) has fewer defects than fusion welding, including massive deformations, solidification cracking, macro and microsegregation, shrinkage porosities and excess energy consumption.

The principle behind this type of welding is to rotate the tool into the workpiece, causing heat to be generated by friction between the tool and the workpiece or metal to be connected, therefore softening the metal on the side being joined. Mechanical characteristics and corrosion rate are both modified by the presence of high heat due to friction and non-uniform cooling rate, and this heat also induces metallurgical transformation over the whole Heat Affected Zone (HAZ) and weld metal (WM). Obtaining a high-quality weld requires careful attention to the Friction Stir Welding (FSW) parameters set for the joining materials. A number of factors, including TRS, welding speed, pin shape, and (TPA), must be considered during this particular welding procedure. When it comes to the quality of the weld, this aspect is crucial.

Many prominent researchers have thoroughly studied the different issues of FSW. Kumbhar et al., [1]studied the joining of two dissimilar aluminium alloy materials using FSW. The authors found that there is good mechanical behavior at the welding joint with low normal load and spindle torque with high rotation speeds. Kimapong et al., [2] employed friction stir welding (FSW) to combine the aluminium alloys, and after analysing the impacts of pin rotation speed, pin axis location, and pin diameter on tensile strength, we found that the pin could only revolve at a particular speed to form a suitable junction. As the pin's rotation speed was too low, the weld didn't become hot enough to prevent fatigue, and the pin wore out rapidly. Chiumenti et al., [3]investigate four-pin tools with circular, triflate, trivex, and triangular profiles using a validated FSW process model, and the output is examined using a piecewise linearized Norton-Hoff constitutive model and a two-stage plan depending on the tool geometry. Rajakumar et al., [4]examined the results of an FSW study into the influence of process and tool factors on the tensile strength properties of welded joints made from aluminium alloy. Eventually, the author concludes that welding does not include melting and that the metals are bonded in a solid state owing to the heat created by friction and the rotating speed of the tool at 1400 rpm, which resulted in a faultless immaculate union. A welding speed of 60 mm/min contains no defect. Zettler et al., [5]performed tensile tests on the friction stir welded aluminium alloy material using Schenk-Trebel Testing Machine powered by a Zwick controller with a 100kN load-capable actuator. Finally, the author concluded that tensile tests could not be performed on the small quantity of the workpieces. Ghangas et al., [6]investigated the effect of tool profile and machine parameters on mechanical and microstructural qualities using FSW on AA7039 T6.Later using optimized technique GRA using PCA is executed to get better results in optimum process parameters Vishnu et al., [7]examined welding parameters rotating speed, welding speed, and pin profiles are adjusted with many responses such as UTS (UTS) and VH on aluminium welded alloys. The PCA method has been adopted for optimizing the process parameter combinations to get the maximum UTS and VH. Banik et al.,[8]FSW on aluminium alloy was investigated with the three distinct tool geometries to determine the best tool geometry in terms of good quality characteristics (UTS, VH and Elongation). For best solution hybrid approach combining TOPSIS with PCA method is proposed. Bobbili et al.,[9]have evaluated the impact of MRR-based machining settings using DA and ANN techniques. Senapati et al.,[10]have investigated the effect of process parameters of FSW (on AA 1100 al alloy) TRS, depth resulting on the microstructural and mechanical characteristics. The optimization has been carried out by using an ANN-based Levenberg-Marquardt algorithm.

The literature review reveals that very few works (as per the authors' best knowledge) are attempted to explore the machining behaviour of AA6061 using FSW context. Moreover, identifying the optimum parameter setting for anticipated performance using a hybrid ANN-based PCA optimization technique is still unrecognized in FSW method. So, the present study is based on identifying the optimum parameter setting using an artificial intelligence technique combination of the PCA concept of AA6061 using FSW.

2 Experimental Procedures

The experiments are carried out on the machine FSW15 300NC in the fixed Z-axis position. The setup is shown in Fig. 1, and a schematic diagram of the setup is shown in Fig 2. The largest machine capability is 5KN of axial force. The range of TRS is 1800rpm. After the completion of the welding process, the specimens were prepared as per ASTM E8 for the tensile test and welding hardness test. During the welding hardness test, the load was used as 0.2 kg with a dwell time of 10 seconds at the welding zone. The machine parameters are shown in below Table 1. AA 6061 Al alloy material is used as the workpiece, and its dimensions are (1000×600×3) mm.

2.1 Material selection

AA6061 alloy has been used for this study due to its most desirable properties. Due to its high VH and wear resistance, AISI H13 steel is used in this welding process. The composition of the tool has shown in Table 2, and the tool geometry has shown in Table 3. The tool used during the experiment has shown in Fig 3.

Table 1: Machine parameters

Parameter	Units	Symbol	Level I	Level II	Level III
TRS	rpm	A	900	1100	1400
FR	mm/min	B	20	30	40
TPA	Degree	C	0	1	2
Fixed parameter					
Axial Force	kN	5			
Welding speed	mm/min	15			

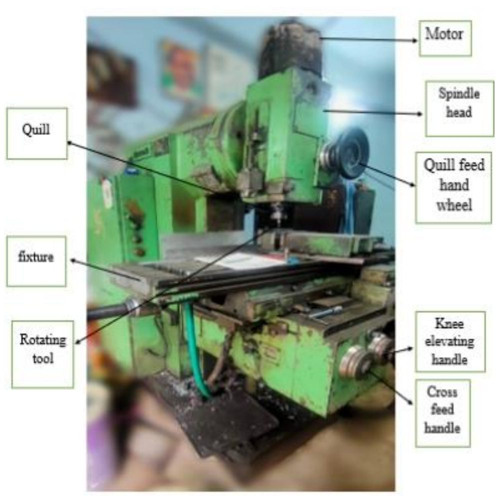

Fig. 1. Setup of FSW Machine

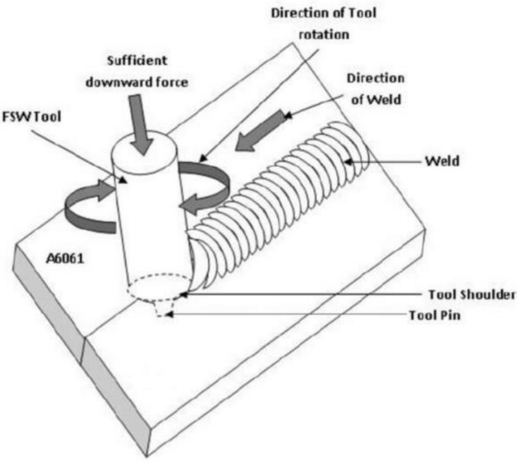

Fig. 2. Schematic diagram of FSW

Table 2. Compositions of work piece and tool material

AA 6061 Grade									
Element	Al	Cr	Mn	Cu		Si		Total	
Weight%	97.90	0.22	1	0.28		0.6		100	
H13 Steel									
Element	C	Cr	Mo	V	Mn	Si	Cu	Fe	Total
Weight%	0.42	5.04	1.33	1.06	0.35	0.88	0.02	Balance	100

Table 3. Tool Geometry

Pin Length, L (mm)	3
Tool shoulder diameter, D (mm)	16.2
Pin diameter, d (mm)	5.4
Taper angle (degrees)	11.23
Tool Shape	Taper
Shoulder length(mm)	35

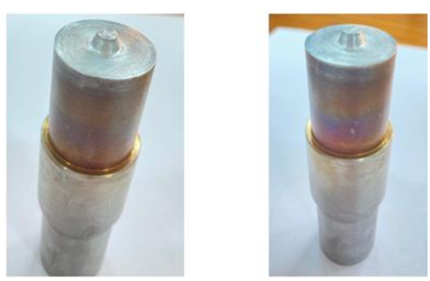

Fig. 3. FSW tool

4 Methodology

The selection of the best solution in the commodities of welded material is the most challenging task due to the vast number of input parameters. The data handling book influences the best solutions in industrial applications. This book will not give the best solutions, it affects the production cost. Principal Component Analysis (PCA) has been introduced as one of the optimization techniques. The PCA-like composite primary component (CPC) has been subjected to analysis of variance (ANOVA). In this article, we introduce Artificial Neural Networks (ANNs). To determine the optimal value of CPC based on ANN, which reveals the machining parameter's overall performance, FF BPNN is executed. Comparisons of means between many groups can be examined using Analysis of Variance (ANOVA), a statistical method. It is used to test the hypothesis that the means of different groups are equal or not. ANOVA is a powerful tool for comparing group means and determining whether the differences between them are significant. The significant applications of ANOVA are in the field of manufacturing industries, especially in quality control, to compare the different means of production processes or products and market research for comparing the means of different goods of consumers.

4.1 Principal Component Analysis (PCA)

The principal component analysis is used in multivariate statistics. By reducing a large number of interrelated variables to a smaller number of random variables and independent principle components, principal components analysis (PCA) may significantly reduce the data loading and complexity of a dataset. By employing linear permutation, it can preserve as much distinct data as is practically possible. The use of principal components analysis (PCA), For such reason, it simplifies a multi-objective optimization problem into a single-objective problem. The results in the PCA technique will be used by the method of variance-covariance with the help of linear combinations.

The following are the PCA methods:

Step I: Attributes of measured performance are expressed as

$$S = \begin{pmatrix} X_{11} & X_{12} & \ldots & X_{1l} \\ X_{21} & X_{22} & \ldots & X_{2l} \\ \ldots & \ldots & . & .. \\ X_{j1} & X_{j2} & \ldots & X_{jl} \end{pmatrix}$$

Where, j represents the number of test trials, l shows the responses.

Step II: Optimize multiple quality characteristics..

The greater the UTS and VH, the better the performance, and the observed may be normalized as per Eq. $Y_j(l) = \dfrac{X_j(l) - \min X_j(l)}{\max X_j(l) - \min X_j(l)}$

Where, Yj(l) shows normalized number of the lth response, min $X_j(l)$ shows the minimum of $X_j(l)$ for l^{th} response, and max $X_j(l)$ is greater value of $X_j(l)$ for l^{th} lth response.

Y is normalized array

$$Y = \begin{pmatrix} Y_{11} & Y_{12} & \dots & Y_{1l} \\ Y_{21} & Y_{22} & \dots & Y_{2l} \\ \dots & \dots & \dots & \dots \\ Y_{j1} & Y_{j2} & \dots & Y_{jl} \end{pmatrix}$$

Step III: Calculate the variance-covariance matrix using the normalized data..

$$P = \begin{pmatrix} N_{11} & N_{12} & \dots & N_{1l} \\ N_{21} & N_{22} & \dots & N_{2l} \\ \dots & \dots & \dots & \dots \\ N_{j1} & N_{j2} & \dots & N_{jl} \end{pmatrix}$$

$$N_{lm} = \frac{Cov(Y_j(l), Y_j(m))}{\sqrt{\mathrm{var}(Y_j(l) \times Y_j(m)}}$$

where, m = 1,2,3, . . ., l and $Cov(Y_j(l), Y_j(m))$ is the covariance of sequences $Y_j(l), Y_j(m)$

Step IV: Evaluate the correlation coefficient matrix's eigenvalues and eigenvectors, denoted by λ_i and Vi, respectively.

Step V: Analyze the principal components γ_i

The eigenvector Vi shows the parameter of i number of performance characteristics of the i^{th} principal component. Qi stands for the i^{th} performance characteristic.

$$\gamma_i = V_{1i}Q_1 + V_{2i}Q_2 + \dots V_{ii}Q$$

where, γ_1 shows first primary component, γ_2 represents as second component ….

Step VI Find the CPC from the test

The composite primary component t (CPC) is a multi-composite quality indicator for multi-performance qualities. It is the mixture of the primary components.

Individual eigenvalues

$$CPC = \sum_{i=1}^{l} \left(\sqrt{\gamma_i^{\,2}} \right)$$

Since all the major components are independent of one another, the overlapping model is suitable here. A higher CPC number indicates higher quality and greater process performance.

Step VII: Find the optimum settings and execute.

5 Results and discussion

5.1 The impact of machining on UTS and VH quality characteristics

The main characteristic concerns are UTS and VH to assess the quality of FSW joints. The responses of the UTS and VH are shown in Table 4. The main effect (means) was calculated at each process variable to evaluate these quality characteristics. Fig 4-5 shows that increasing the FR enhances the values of the UTS and VH. Increasing the TRS, the values of VH increase to a certain extent and then go constant; in the case of UTS, it diminishes. It is observed that the quality characteristics mainly depend on the FR which is given to the specimen during the process. This rate will impact the workpiecemore for the distortion and porosity. In the case of VH, by improving the TPA, it is increasing, but in UTS, the values are decreasing.

5.2 Taguchi approach optimization based on PCA

The higher-the-better category has been used to identify the S/N ratio for UTS and VH. These values have been used to identify CPC by using PCA methodology shown in Table 5.

Table 4. Experimental responses

Run no	A(rpm)	B(mm/min)	C(◦)	UTS (kPa)	VH (HR)
1	900	20	0	190.24	201
2	900	30	1	143.57	222
3	900	40	2	176.48	241
4	1100	20	0	90.44	227
5	1100	30	1	80.44	245
6	1100	40	2	161.76	222
7	1400	20	0	155.3	235
8	1400	30	1	178.52	218
9	1400	40	2	164.32	247

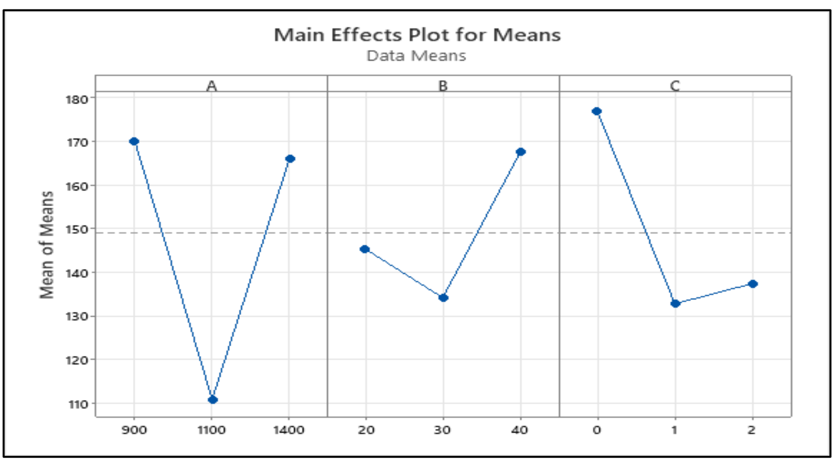

Fig. 4. Effect of machining parameters on UTS

5.3 Authorization Using a Soft Computing Method (ANN)

ANN is a soft computing method that improves performance by replicating the human nervous system. It consists of various layers (hidden and output), as shown in Fig. 6. The training function Levenberg Marquardt (LM) and the learning function LEARNGDM are used to train the FF-BPNN. The regression plot of the data network is shown in Fig. 7. The performance curves of the encrypted data are shown in Fig. 8. ANN is used in this case to determine the best performance, compute the best CPC, and get the optimum ranking. Fig. 9 shows the CPC versus rank. The percentage contribution is shown in Fig. 10. The CPC values are interpreted as rank, and the best is considered the optimal solution. From the CPC values best process parameter is Run no 9, which is a tool speed of 1400 rpm, FR 40 mm/min, TPA is 1°. The residual error is 0.0102. The last column of Table 6 shows the % PCR of the given parameters. The ANN's maximum value determined on CPC is 1.29, ranked 1, the experiment number nine.

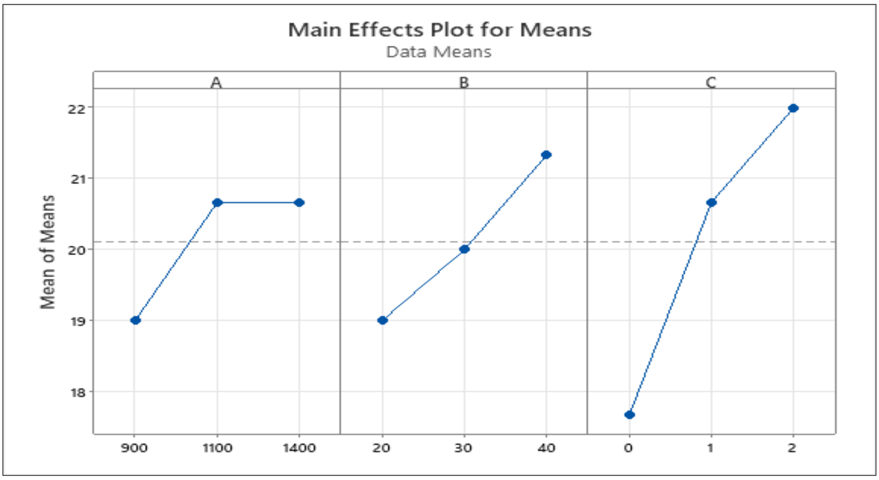

Fig. 5. Effect of machining parameters on VH

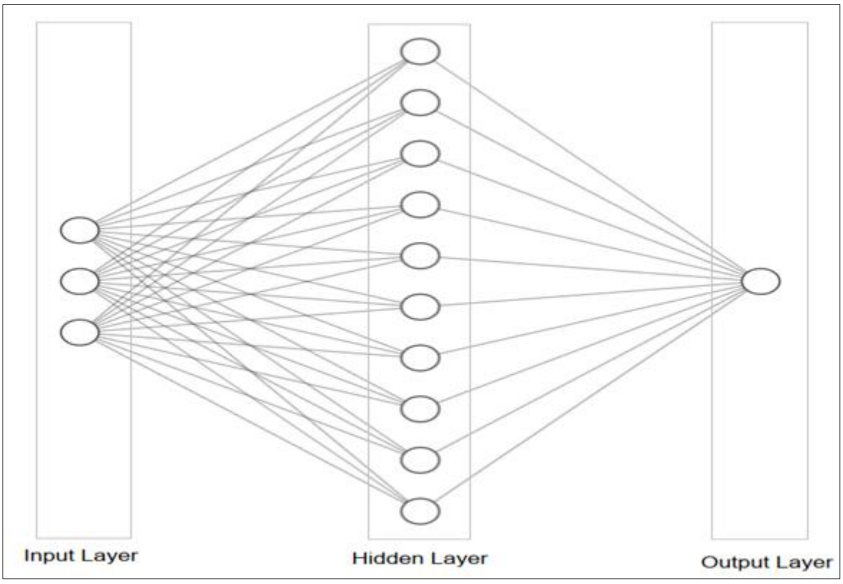

Fig. 6. ANN 3-10-1 Architecture

Table 5. Analysis of PCA using CPC(ANN)

Run no	SNRA1	SNRA2	N-UTS	N-UTS	VPC1	VPC2	CPC	CPC(ANN)	RANK
1	45.58	46.06	1	0	0.7	-0.7	0.99	0.95	6
2	43.14	46.92	0.67	0.48	0.13	-0.81	0.82	0.85	8
3	44.93	47.64	0.91	0.88	0.02	-1.26	1.26	1.22	2
4	39.12	47.12	0.13	0.59	-0.32	-0.67	0.6	0.6	9
5	38.1	47.78	0	0.96	-0.67	-0.67	0.96	0.97	5
6	44.17	46.92	0.81	0.48	0.23	-0.91	0.96	0.94	7
7	43.82	47.13	0.76	0.75	0.04	-1.07	1.07	1.07	3
8	45.03	46.76	0.92	0.39	0.37	-0.93	1	1	4
9	44.31	47.85	0.82	1	-0.12	-1.29	2.0	1.29	1

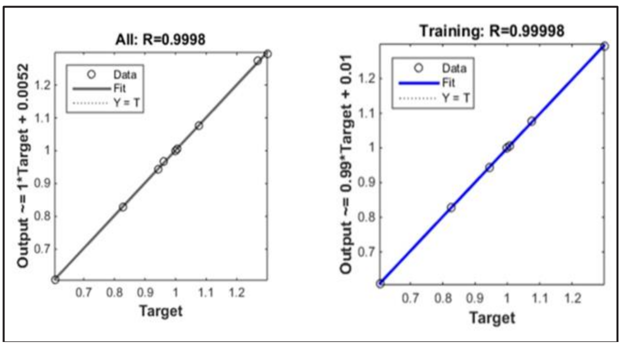

Fig. 7. ANN regression curve

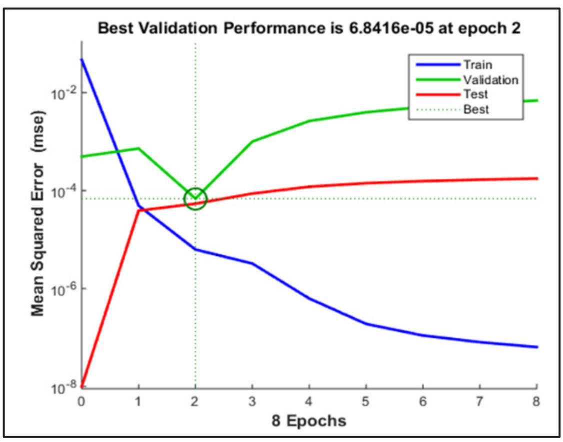

Fig 8. ANN Best Validation performance curve

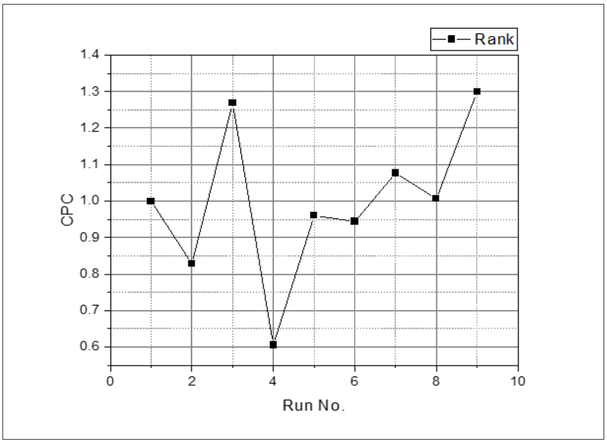

Fig. 9. Graph showing CPC values corresponding to the Run numbers

Table 6. ANOVA for Composite Principal Component (ANN)

Source	Degrees of freedom (DF)	Sum of Squares (SS)	Mean Square (MS)	F-Ratio	PCR (%)
A	2	11.114	5.557	3.66	41.63
B	2	10.124	5.062	3.34	37.28
C	2	5.265	2.633	1.74	19.83
Residual Error	2	3.034	1.517		2.27
Total	8	29.537			100

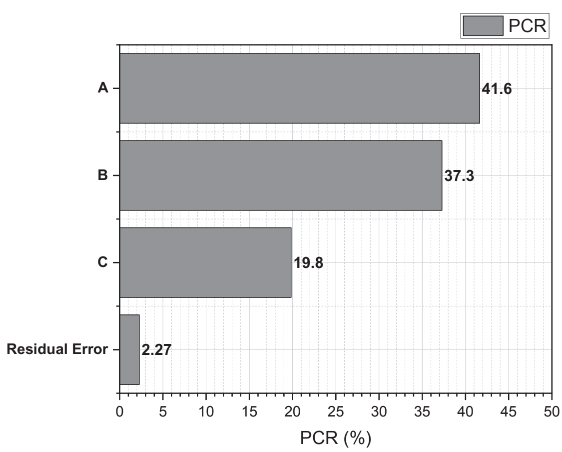

Fig. 10. Percentage contribution ratio of PCA-ANN

6 Conclusions

This paper shows FSW on AA 6061 grade aluminium alloy under distinct levels of machining parameters. The procedures were carried out according to the Taguchi's L_9 array.

In order to enhance the effectiveness of the optimization process, a soft computing technique is used for optimization called PCA-based ANN. The conclusions of this present study are as follows:

- The percentage contribution of TRS (PCR 37.63%) has been identified as the most effective and influencing parameter on the performance outputs obtained from ANOVA for a multi-optimization strategy.
- The hybrid technique of PCA-based ANN approach has been effectively used to generate the multi-objective parameter settings, i.e., TRS = 1400 rpm, FR= 40 mm/min, TPA= 1°.

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