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Optimization of Arc Machining of Metal Matrix Composite Using ANN-Jaya Algorithm

Subhash Gautam[1], Pankaj Kumar Shrivastava[1*], Pushpendra Singh[2] and Satya Prakash Makhija[3]

[1]*Mechanical Engineering Department, AKS University, Satna, Madhya Pradesh, India*

[2]*Department of Electrical Engineering, Rajkiya Engineering College, Banda, Uttar Pradesh, India*

[3]*Department of Electrical Engineering, ITM University, Raipur, Chhattisgarh, India*

[*]Correspondence to:

Pankaj Kumar Shrivastava

Mechanical Engineering Department,

AKS University, Satna, Madhya Pradesh, India.

E-mail: psiitd@yahoo.com

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Abstract

Arc machining (AM) is one of the unconventional machining processes which is under exploration stage. In the present research AM process efficiency has been tried to improve by giving longitudinal vibration to the tool electrode. Process has been performed in metal matrix composite by using appropriate design of experiments. Artificial intelligence tools have been applied for the modelling and optimization of the process.

Keywords

Arc machining, Artificial neural network, Jaya algorithm, Modelling, Optimization

Introduction

Mostly all the newer machining processes have gained little resentment from the industrial fraternity due to poor performances in terms of various machining parameters such as removal efficiency, etc. [1]. One of the recently developing newer machining processes termed as arc machining (AM) has shown rays of hope to research fraternity [2]. Few researchers have worked on AM by changing/modifying various input control factors.

Gu et al. [3] did experiential investigations by applying blasting erosion arc machining (BEAM) process on Al/SiC metal matrix composite (MMC) and evaluated material removal rate (MRR) and surface integrity aspects. They developed regression models for various performances measures. In another research, Gu et al. [4] machined Al/SiC MMC by using BEAM and concluded that BEAM results in much more removal efficiency as compared to conventional EDM [4]. Chen et al. [5] applied BEAM on Titanium alloy and evaluated the machining responses such as MRR and relative electrode wear rate. A few other researchers [6-8] also used different variants of arc machining to evaluate MRR, tool wear rate (TWR) and various surface integrity aspects. Limited research available demonstrates that process still needs a lot of innovation to make it commercially viable. So, in the present research new combined approach of artificial neural network (ANN) and four different evolutionary optimization techniques have been carried out and best has been suggested for various process output parameters of present manufacturing requirements.

Methodology

In present research firstly ANN model was employed for both the above-mentioned response parameters i.e., for MRR and TWR. The theory of ANN was discussed in detail [9]. The developed ANN model has been optimized using four different evolutionary optimization techniques such as Jaya algorithm;

virtual frogs based Shuffled Frog Leaping Algorithm (SFLA), bio-motivated Particle Swarm Optimization (PSO) and GS (Gradient Search) [10-12]. The steps to apply Jaya Algorithm to solve the present problem have been discudiscussed below:

Step 1: At the beginning, a population of appropriate size is produced as depicted in the section below:

$$\left[U_{ij}^{min} \le U_{ij} \le U_{ij}^{max}\right], j = 1,2,3,....,D$$

$$U_i^0 = \left[u_{i1}^0, u_{i2}^0, u_{i3}^0, ..., u_{iD}^0\right]^T \quad (1)$$

i = 1, 2, 3, ……, M

Step 2: Calculation of fitness function (FF) and ranking of the initially developed population based upon its particular least value of FF.

Step 3: Depending upon the value of FF, identification of the excellent value (U_{best}) and poorest candidate (U_{worst}).

Step 4: Setting of iteration count k = 1.

Step 5: Updating of the population based on excellent value (U_{best}) and poorest candidate (U_{worst}).

$$U_i^{(k+1)} = U_i^k + rand_1\left(U_{i,best}^k - \left|U_i^k\right|\right) - rand_2\left(U_{i,worst}^k - \left|U_i^k\right|\right) \quad (2)$$

$U_{i,best}^k$ and $U_{i,worst}^k$ - is he excellent and worst obtained value, respectively of the kth variables.

$rand_1$ and $rand_2$ - is the two random numbers [0, 1].

$rand_1\left(U_{i,best}^k - \left|U_i^k\right|\right)$ - depicts the obtained result to get closer to the best solution.

$rand_2\left(U_{i,worst}^k - \left|U_i^k\right|\right)$ - depicts the obtained result to get rid of the worst solution.

Step 6: Selection of new population; $U_{i,new}^{(k+1)}$ or rejection and holding of $U_i^{(k)}$ in new population.

$$U_{i,new}^{(k+1)} = \begin{cases} U_{i,}^{(k+1)}, if[f(U_i^{(k+1)} \le f(U_i^{(k)})] \\ U_{i.}^{(k)}, Otherwise \end{cases} \quad (3)$$

Step 7: Run program which incorporates improved $U_{new,i}$. If improved, $U_{new,i}$ minimize FF go to next step. Else go to step 3.

Step 8: Enhance iteration counting k = k + 1. If $k \le k_{max}$ repetition of it from step 3. else terminate.

Experimentation

The machine tool for AM was designed and developed [9]. The three control factors such as current, velocity of flushing of dielectric and longitudinal vibration frequency of tool electrode were selected as input parameters to evaluate the responses. The normalized values of responses i.e., the MRR and TWR have been shown in figure 1.

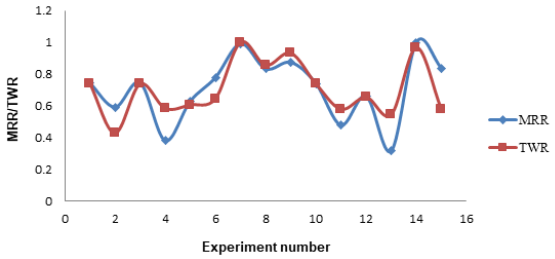

Figure 1: Experimental results.

Modeling and optimization

The ANN model developed for both the output responses by using appropriate activation functions are mentioned below:

ANN model for MRR is as follows:

$$MRR = -0.4744 * y_1 + 0.9804 * y_2 - 2.3132 * y_3 + 0.1875 \quad (4)$$

Where,

$$y_1 = \frac{1}{\left[1 + e^{-(0.10233*x_1 + -0.5966*x_2 + 3.91*x_3 + 3.9935)}\right]}$$

$$y_2 = \frac{1}{\left[1 + e^{-(3.1298*x_1 + 0.3193*x_2 + 2.0062*x_3 - 0.1356)}\right]}$$

$$y_3 = \frac{1}{\left[1 + e^{-(-2.992*x_1 + 1.437*x_2 - 2.5297*x_3 - 5.1253)}\right]}$$

Similarly, the ANN model for TWR is as follows:

$$TWR = 3.0121 * y_1 - 0.40026 * y_2 + 0.9943 * y_3 - 1.1742 \quad (5)$$

Where,

$$y_1 = \frac{1}{\left[1 + e^{-(4.01*x_1 - 2.3125*x_2 - 0.0994*x_3 - 6.5486)}\right]}$$

$$y_2 = \frac{1}{\left[1 + e^{-2.7877*x_1 - 4.5667*x_2 - 2.9991*x_3 + 4.1342)}\right]}$$

$$y_3 = \frac{1}{\left[1 + e^{-(6.002*x_1 + 4.2442*x_2 - 0.9983*x_3 + 0.2115)}\right]}$$

The mean square error for MRR and TWR ANN model was found to be 4.12×10^{-5} and 2.7×10^{-4}, respectively.

All the four optimization algorithms have been applied on obtained ANN models. The present problem contains three variables (X_1, X_2, and X_3). The limits of these variables were between $60 \le X_1 \le 120$, $X \le 6$, and $2.6 \le X_3 \le 3$.

Table 1: Comparison of different optimization algorithms for MRR.

Methodology	x_1	x_2	x_3	MRR
Jaya	**119.8041**	**5.9999**	**2.9999**	**5.2438**
SFLA	119.5946	5.9203	2.9652	5.1908
PSO	118.1445	5.9289	2.9886	5.1504
GS	118.7714	5.8272	2.9705	5.1268

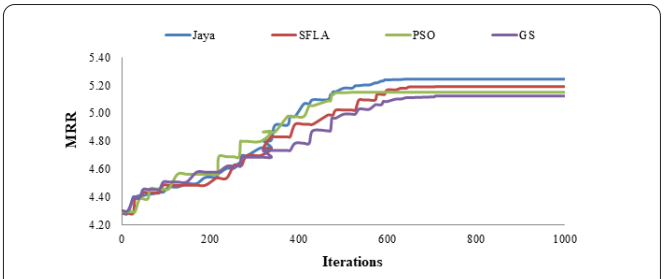

Figure 2: MRR versus number of iterations plot for all the optimization algorithms.

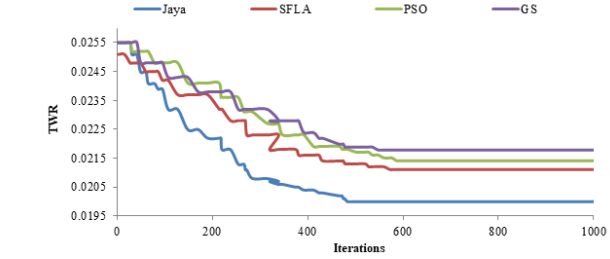

Figure 3: TWR versus number of iterations plot for all the optimization algorithms.

Table 2: Comparison of different optimization algorithms for MRR (as per statistical inference).

Optimization techniques	Arithmetic mean value of the fitness function	Median value of the fitness function	Mean deviation of fitness function	Variance of fitness function	Standard deviation of fitness function	Best value of fitness function	Worst value of fitness function	Frequency of convergence	Confidence level	Determined value for the Engg. Application	Standard error of the mean fitness function	Confidence interval of the fitness function	Length of confidence interval of the fitness function
	$(\overline{Y1})$	(m)	(d)	(s)	(σ)	$(Y1_{best})$	$(Y1_{worst})$	(f)	(γ)	(c)	(ε)	(μ)	(L)
Jaya	**5.2306**	**5.2326**	**1.00E-05**	**0.17E-03**	**0.0129**	**5.2438**	**5.1978**	**11**	**0.95**	**2.0452**	**0.0059**	**$5.2247 \leq \mu \leq 5.2365$**	**0.0243**
SFLA	5.1711	5.1753	0.50E-05	0.36E-03	0.0190	5.1908	5.1228	**12**	0.95	2.0452	0.0087	$5.1624 \leq \mu \leq 5.1798$	0.0355
PSO	5.1157	5.1226	4.00E-05	0.86E-03	0.0294	5.1504	5.0524	**10**	0.95	2.0452	0.0134	$5.1023 \leq \mu \leq 5.1291$	0.0549
GS	5.0681	5.0727	2.50E-05	1.87E-03	0.0432	5.1268	4.9828	**09**	0.95	2.0452	0.0197	$5.0484 \leq \mu \leq 5.0878$	0.0808

Optimization of MRR

Initially, 100 populations of each variable (U_1, U_2, and U_3) have been created randomly with the help of excel software depending upon the distribution characteristic of input parameters. Maximum numbers of iteration considered was 1000 and it was concluded after 643 iterations after FF becomes constant. Table 1 depicts the values of best solutions obtained by applying Jaya algorithm, SFLA, PSO, and GS techniques. Table 2 depicts the performances of all the four optimization algorithms based on the various important statistical parameters for MRR [11]. Figure 2 demonstrates the curve of MRR versus number of iterations depending upon the optimal values of all the above-mentioned techniques. It is evident that Jaya algorithm provides best results with respect to all other optimization techniques.

Optimization of TWR

The procedure, as discussed in section 4.1, has been adopted for optimization of TWR. Table 3 demonstrates the relative merits for TWR using all the four optimization algorithms. Table 4 demonstrates the relative merits of Jaya algorithm as per the statistical inference as discussed in section 4.1. Figure 3 demonstrates the curve of TWR versus number of iterations depending upon the optimal values of all the above-mentioned techniques. It is evident that Jaya algorithm provides best results with respect to all other optimization techniques for TWR.

Conclusion

Findings of the present research has been summarized by three vital points, as mentioned below:

1. With negligible mean square error, the developed ANN model for MRR and TWR are highly reliable and accurate.
2. Amongst all the evolutionary algorithms, Jaya Algorithms demonstrates the best process behavior.
3. Combined ANN-Jaya algorithm optimization method enhances both the output parameters in excellent way as it was evident from the findings that there was an enhancement of 25.21% in material removal rate and 47.19% in tool wear rate.

Table 3: Comparison of different optimization algorithms for TWR.

Methodology	x_1	x_2	x_3	TWR
Jaya	**60.6197**	**4.0031**	**2.9997**	**0.0200**
SFLA	65.3737	4.0072	2.988	0.0211
PSO	61.2655	4.0901	2.9882	0.0214
GS	62.9494	4.0947	2.986	0.0218

Table 4: Comparison of different optimization algorithms for TWR (as per statistical inference).

Optimization techniques	Arithmetic mean value of the fitness function	Median value of the fitness function	Mean deviation of fitness function	Variance of fitness function	Standard deviation of fitness function	Best value of fitness function	Worst value of fitness function	Frequency of convergence	Confidence level	Determined value for the Engg. Application	Standard error of the mean fitness function	Confidence interval of the fitness function	Length of confidence interval of the fitness function
	$(\overline{Y2})$	(m)	(d)	(s)	(σ)	$(Y2_{best})$	$(Y2_{worst})$	(f)	(γ)	(c)	(ε)	(μ)	(L)
Jaya	**0.02034**	**0.02032**	**3.00E-06**	**0.114E-06**	**0.34E-03**	**0.0200**	**0.0212**	**11**	**0.95**	**2.0452**	**0.15E-03**	**0.02018 ≤ μ ≤ 0.02049**	**0.63E-03**
SFLA	0.02170	0.02152	1.00E-06	0.301E-06	0.55E-03	0.0211	0.0229	**12**	0.95	2.0452	0.25E-03	0.02145 ≤ μ ≤ 0.02195	1.03E-03
PSO	0.02255	0.02240	1.00E-06	0.863E-06	0.93E-03	0.0214	0.0244	**11**	0.95	2.0452	0.43E-03	0.02213 ≤ μ ≤ 0.02297	1.74E-03
GS	0.02379	0.02376	4.50E-06	2.000E-06	1.42E-03	0.0218	0.0260	**10**	0.95	2.0452	0.65E-03	0.02314 ≤ μ ≤ 0.02444	2.65E-03

Conflict of Interest

The authors declare that there is no conflict of interest.

Credit Author Statement

Subhash Gautam: Conceptualization; Pankaj Kumar Shrivastava: Design and developed experimental setup; Pushpendra Singh: Experimentation; Satya Prakash Makhija: Data analysis, Modeling and optimization. All the authors read and approved the manuscript.

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