J Intell Manuf (2014) 25:1463–1472
DOI 10.1007/s10845-013-0753-y

Estimation of optimal machining control parameters using artificial bee colony

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Received: 24 November 2012 / Accepted: 23 February 2013 / Published online: 14 March 2013

Abstract Modern machining processes such as abrasive waterjet (AWJ) are widely used in manufacturing industries nowadays. Optimizing the machining control parameters are essential in order to provide a better quality and economics machining. It was reported by previous researches that artificial bee colony (ABC) algorithm has less computation time requirement and offered optimal solution due to its excellent global and local search capability compared to the other optimization soft computing techniques. This research employed ABC algorithm to optimize the machining control parameters that lead to a minimum surface roughness (R_a) value for AWJ machining. Five machining control parameters that are optimized using ABC algorithm include traverse speed (V), waterjet pressure (P), standoff distance (h), abrasive grit size (d) and abrasive flow rate (m). From the experimental results, the performance of ABC was much superior where the estimated minimum R_a value was 28, 42, 45, 2 and 0.9 % lower compared to actual machining, regression, artificial neural network (ANN), genetic algorithm (GA) and simulated annealing (SA) respectively.

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Keywords Machining · Abrasive waterjet · Optimization

Introduction

The manufacturing industries nowadays face many challenges such as market competition, expensive machining cost, customer high request and complexity of the product. For manufacturers, the main objective is to produce high quality of product with less cost and time constraints. Today, modern machining processes are widely used in manufacturing industries because it has some advantages (for example in terms of cost) compared to traditional machining processes (Ridwan et al. 2012; Mokhtar and Xu 2011; Zain et al. 2012a). According to Nagendra Parashar and Mittal 2007, traditional machining processes are costly and inefficient because it is incapable to machine the materials cost-effectively because of the tools is harder than the workpiece. The alteration or new traditional machining methods are also needed because in several cases, the methods might not be operated. Roy and Mehnen (2008) suggest that new method need to be developed in order to guarantee fast, safe and cost efficient production. The modern machining process can be categorized into four types which are (i) mechanical (e.g. abrasive waterjet (AWJ), ultrasonic machining (USM)), (ii) chemical (e.g. chemical machining (CHM)), (iii) electrochemical (e.g. electrochemical machining (ECM), electrochemical grinding (ECG)) and (iv) thermoelectric (e.g. electrobeam machining (EBM), laserbeam machining (LBM)).

AWJ machining was considered in this research to compute a minimum R_a value. (Zain et al. 2012b) AWJ used a high powerful flow of water in order to cut the workpiece. The high pressure of water (usually more than 900 mph) enables it to cut metal, non-metal, composite and heat sensitive workpiece. The advantage of AWJ is that it never gets dry

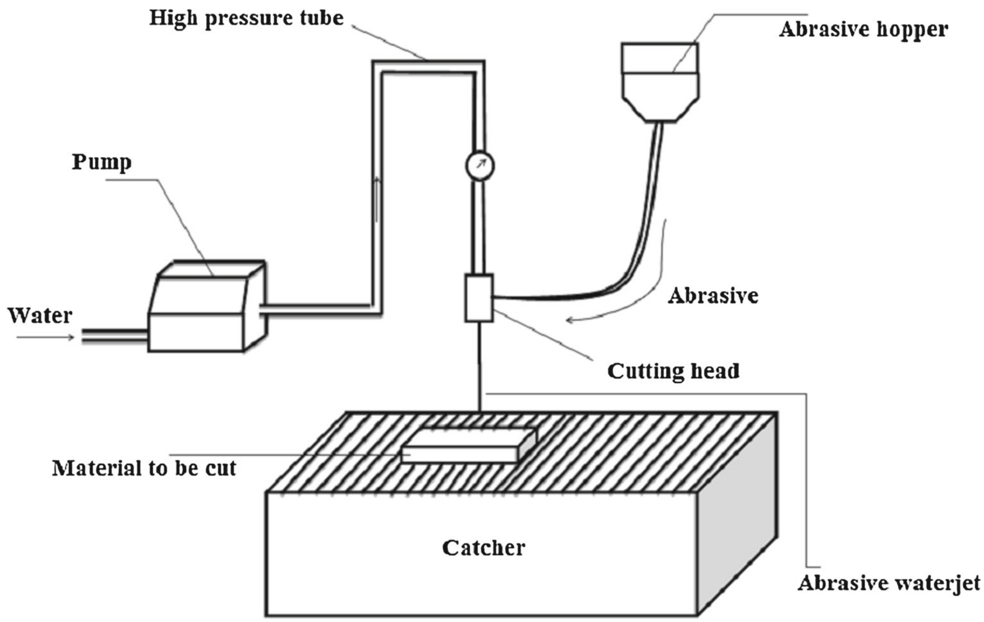

Fig. 1 Abrasive waterjet cutting process (Selvan and Raju 2011)

and overheat compared to other cutting machining. Today, the CNC AWJ is usually used to cut softer materials while the recent developed AWJ machining technology is used for cutting harder materials. In AWJ, abrasive particles such as silicon carbide and aluminium oxide were used to enhance the metal removal rate. The abrasive thoroughly mixed with water to increase the penetration power (Singh 2008). The diagram of abrasive waterjet cutting process is illustrated in Fig. 1. According to Caydas and Hascalik (2008), the various advantages of AWJ are including no thermal distortion, high machining versatility and flexibility, also small cutting forces which means the machining has less pressured on the workpiece. AWJ downsides and restrictions include producing deafening sound and untidy operational setting. At a high traverse rates, the cutting of the material may build narrowed edges on the kerf (Azmir and Ahsan 2008).

The current trends of research show soft computing techniques have been used by many researchers to optimize the machining control parameters of traditional and modern machining (Pal et al. 2011; Topal and Çoğun 2011). Evolutionary optimization technique that was inspired by nature or animal behaviour such as genetic algorithm (GA), simulated annealing (SA), ant colony optimization (ACO), particle swarm optimization (PSO) and artificial bee colony (ABC) have been employed in place of conventional techniques such as sequential unconstrained minimization technique, non-linear programming and goal programming (Salehi and Bahreininejad 2011; Li et al. 2012; Zain et al. 2010a, b, c). From our literature review, there is a deficiency of research in optimizing machining control parameters of surface roughness (R_a) in modern machining areas particularly using ABC optimization technique. Yusup et al. (2012) have summarized and compared the latest 5 year researches from 2007 to 2011 that used evolutionary optimization techniques such as GA, SA, PSO, ABC and ACO to optimize machining control parameter of both traditional and modern machining. In paper overview by Oduguwa et al. (2005), the authors stated that successful applications of evolutionary computing (EC) suggest that EC will have a good prospective in the future particularly in machining industry

In the research of Samanta and Chakraborty (2011), three modern machining was considered which are ECM, electrochemical discharge machining (ECDM) and electrochemical micromachining (ECMM). ABC was employed to find optimal control parameters by combination of the three machining operations. The results from single and multi objective optimization show better performance compared to the past researches. In Zain et al. (2011), GA and SA have been used to optimize the machining control parameters of AWJ. There are five machining control parameters considered in the research which are traverse speed, waterjet pressure, standoff distance, abrasive grit size and abrasive flow rate. The minimum R_a achieved using GA was 1.5549 μm. The R_a achieved was 27 and 41 % lower compared to experimental data and regression model respectively. For SA technique, the R_a achieved was 1.5355 μm. The outcomes of SA show a modest increments where it minimize the R_a by 28 and 42 % compared to data and regression model respectively. Three optimization techniques namely ABC, harmony search (HS) and PSO were considered by Rao et al. (2010) to optimize the machining control parameters of USM. The five machining control parameters considered in this study are amplitude of ultrasonic vibration, frequency of ultrasonic vibration, mean diameter of abrasive particles, volumetric concentration of abrasive particles, and static feed force. The objective considered is maximization of MRR subjected to the constraint of R_a. The results show that ABC, HS and PSO outperformed the GA result. GA was considered by Maji and Pratihar (2010) to optimize the machining control parameters of EDM. In the study, three machining control parameters of EDM such as peak current, pulse-on-time and pulse-duty-factor were employed. Regression analysis was developed and GA was used to determine optimal machining control parameters of EDM for ensuring the maximum MRR and minimum R_a. The results conclude that the regression models had performed well in predicting the results of some test cases. In Pasam et al. (2010), optimizing machining control parameters of WEDM titanium alloy (Ti6Al4V) was studied. The performance of eight machining control parameters such as ignition pulse current, short pulse duration, time between two pulses, servo speed, servo reference voltage, injection pressure, wire speed and wire tension on surface finish was studied using Taguchi parameter design. A mathematical regression model was developed and the optimization of R_a was using GA. The minimum R_a obtained was 1.85 μm with selected optimum machining control parameters of WEDM. The study of Chen et al. (2010) analyzed WEDM control parameters during manufacture of pure tungsten profiles. The pulse on time, the pulse off time, arc off time, the servo voltage, the wire feed rate, the wire tension and the water pressure were selected as the WEDM control parameters. Three considered machining performances are the cutting velocity, surface roughness and roughness maximum. Integrate back-propagation neural network (BPNN/SA) approach was proposed and SA technique was used to find the most optimal machining control parameters. The estimated optimal machining control parameters are: pulse on time of = 0.42 (μs), pulse off time of = 12.15 (μs), arc off time = 13.73 (μs), servo voltage = 45.17 (V), wire feed rate = 10.32 (m/mm), wire tension = 1751.07(gf), and water pressure = 15.21 (kgf/cm$^{2)}$. The predicted machining performance cutting velocity = 7.8558 (m/min), surface roughness = 1.1786 (μm) and roughness maximum = 10.7873 (μm).

The non-dominated sorting GA (NSGA-II) was employed by Senthilkumar et al. (2010) to optimize machining control parameters of ECM. The optimization of four machining control parameters which are electrolyte concentration, electrolyte flowrate, applied voltage and tool feed rate was considered to maximize MRR and minimize R_a. The optimized value of R_a obtained through NSGA-II was 2.172 μm and the corresponding MRR was 0.413 g/min. The optimal combination of machining control parameters achieved was electrolyte concentration = 17 g/L, electrolyte flow rate = 8 L/min, applied voltage = 16 V and tool feed rate = 0.9 mm/min. ABC was considered by Rao and Pawar (2009) to find optimal combination machining control parameters of WEDM such as pulse-on time, pulse-off time, peak current, and servo feed setting with an objective of achieving maximum machining speed for a desired value of surface finish. The optimal machining control parameters of AWJ machining of 6063-T6 aluminum alloy have been investigated by Kolahan and Hamid (2009) using SA. Four machining control parameters considered in this work are water pressure, abrasive flow rate, jet traverse rate and diameter of focusing nozzle. It was found that SA was effective to estimate particular optimal machining control parameters. In Somashekhar et al. (2009), the optimization machining control parameters of micro-WEDM (μ-WEDM) such as gap voltage, capacitance and feed rate were studied. A regression model was developed for the experimental results of R_a and overcut of the micro slots produced on the aluminium. GA was employed to determine the desired output value of μ-WEDM. The minimum R_a achieved was 4.557 μm and the overcut value was 33.2 μm. In the research of Saha et al. (2008), BPNN technique was considered to optimize four machining control parameters of WEDM such as pulse-on-time, pulse off-time, peak current and capacitance, and the 4-11-2 network architecture has been found to be the optimal one for overall R_a mean prediction error.

Methodology

The summary of four phases that was implemented in this research is given as follows:

i. The first phase was the assessment of the experimental data by (Caydas and Hascalik 2008). In this phase, a set data of machining control parameters and machining performance were referred.
ii. In the second phase, a regression model was developed by Zain et al. (2011) using the machining control parameters from the case study in the experimental phase. A multilinear stepwise regression analysis was performed to predict the R_a value. The predicted equation for R_a was based on the second-order polynomial regression developed by (Caydas and Hascalik 2008).
iii. In the third phase, ABC was employed to optimize machining control parameters of AWJ that will lead to a minimum R_a value. The objective function selected was based on the predicted equation of the regression model.
iv. In the last phase, the minimum R_a value achieved was compared to the experimental, regression, ANN, GA and SA and the performance of ABC was evaluated.

The flow of research work is depicted in Fig. 2.

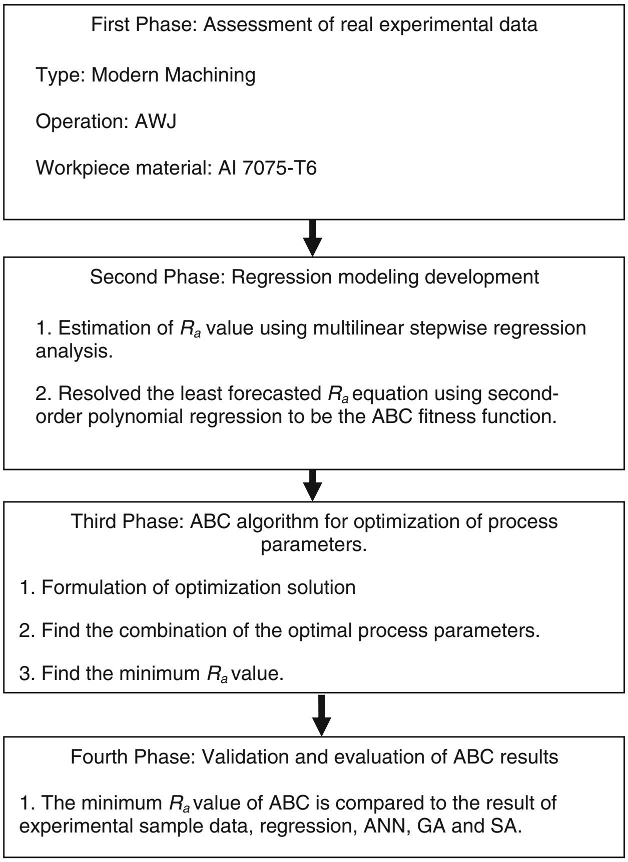

Fig. 2 The flows of research work

Table 1 Levels of process parameters and coding identification

Level in coded form				
Independent variables	Units	1	2	3
Traverse speed, V	mm/min	50	100	150
Waterjet pressure, P	MPa	125	175	250
Standoff distance, h	Mm	1	2.5	4
Abrasive grit size, d	lm	60	90	120
Abrasive flow rate, m	g/s	0.5	2	3.5

Assessment of real experimental data

The experimental assessment is based on the work of Caydas and Hascalik (2008). The material of machined workpiece was Al 7075-T6 wrought alloy (AlZnMgCu1.5). The chemical composition of Al 7075-T6 wrought alloy includes A1 91.02%, Cu 1.65%, Mg 2.0%, Cr 0.23%, Zn 5% and Mn 0.1%. The coded level form for the machining is based on DOE for the five control parameters as defined in Table 1. During the experiments, a distance of 5mm from the top of the cutting surface was taken for the measurements. A handy device named SJ-201 was used to measure the average R_a. In order to examine the machined surface, another device named LEO 32 scanning electron microscope (SEM) was used.

Table 2 R_a values for real machining (Caydas and Hascalik 2008)

No	Setting values of experimental process parameters					$R_a (\mu$m)
	V (m/min)	P (MPa)	h (mm)	d (μm)	m (g/s)	
1	50	125	1	60	0.5	2.124
2	50	125	1	60	2	2.753
3	50	125	1	60	3.5	3.352
4	50	175	2.5	90	0.5	4.311
5	50	175	2.5	90	2	4.541
6	50	175	2.5	90	3.5	5.123
7	50	250	4	120	0.5	6.789
8	50	250	4	120	2	7.524
9	50	250	4	120	3.5	9.123
10	100	125	2.5	120	0.5	3.575
11	100	125	2.5	120	2	4.457
12	100	125	2.5	120	3.5	5.628
13	100	175	4	60	0.5	7.010
14	100	175	4	60	2	7.535
15	100	175	4	60	3.5	7.893
16	100	250	1	90	0.5	8.121
17	100	250	1	90	2	8.312
18	100	250	1	90	3.5	9.163
19	150	125	4	90	0.5	4.328
20	150	125	4	90	2	5.120
21	150	125	4	90	3.5	5.852
22	150	175	1	120	0.5	6.143
23	150	175	1	120	2	6.721
24	150	175	1	120	3.5	7.780
25	150	250	2.5	60	0.5	8.890
26	150	250	2.5	60	2	9.120
27	150	250	2.5	60	3.5	10.035
R_a(minimum)						2.124

A total of 27 experimental trials have been performed based on L27 Taguchi's orthogonal array to find the minimum and average value of R_a in AWJ machining. The lowest R_a values is 2.124 μm which was obtained by the following control parameters $V = 50$, $P = 125$, $h = 1$, $d = 60$, $m = 0.5$. The values for each experimental AWJ control parameters and optimal R_a are shown in Table 2.

Regression modeling development

To predict the minimum R_a, a regression model was developed by (Zain et al. 2011). The calculation of the R_a value in abrasive waterjet machining is defined mathematically in Eq. (1):

$$R_a = cV^{\mathrm{q}} P^{\mathrm{r}} h^{\mathrm{s}} d^{\mathrm{t}} m^{\mathrm{u}} \varepsilon \quad (1)$$

where R_a is the experimental (measured) in μm, V is the traverse cutting speed in mm/min, P is the waterjet pressure in MPa, h is the standoff distance in mm, d is abrasive grit size in μm, m is the abrasive flow rate in g/s, $\varepsilon\prime$ is experimental error, and c, q, r, s, t, and u are the model parameters to be estimated using the experimental data.

To develop the Regression model for estimating the R_a value, the mathematical model given in (1) is linearized by performing a logarithmic transformation as follows:

$$\ln R_a = \ln c + q\ln V + r\ln P + s\ln h + t\ln d + u\ln m + \ln \varepsilon\prime \quad (2)$$

Subsequently, (2) can be written as:

$$y = b_0x_0 + b_1x_1 + b_2x_2 + b_3x_3 + b_4x_4 + b_5x_5 + \varepsilon \quad (3)$$

where y is the logarithmic value of the experimental R_a, $x_0 = 1$ is a dummy variable, x_1, x_2, x_3, x_4 and x_5 are the control parameter values (logarithmic transformations) of V, P, h, d and m, respectively, ε' is the logarithmic transformation of experimental error ε and b_0, b_1, b_3, b_4 and b_5 are the model parameters to be estimated using the experimental data. Next, (3) can also be written as follows:

$$\hat{y} = y - \varepsilon = b_0x_0 + b_1x_1 + b_2x_2 + b_3x_3 + b_4x_4 + b_5x_5 \quad (4)$$

where $\hat{y}$ is the logarithmic value of the predictive (estimated) R_a. Equation (4) can be extended to form a second-order polynomial regression for surface roughness predicted equation and given as follows:

$$\begin{aligned}\hat{y} = R_a &= \mathrm{b}_0 + \mathrm{b}_1V + \mathrm{b}_2P + \mathrm{b}_3h + \mathrm{b}_4d + \mathrm{b}_5m \\ &+\mathrm{b}_{11}V^2 + \mathrm{b}_{22}P^2 + \mathrm{b}_{33}h^2 + \mathrm{b}_{44}d^2 + \mathrm{b}_{55}m^2 \\ &+\mathrm{b}_{12}V^{\mathrm{P}} + \mathrm{b}_{13}V^{\mathrm{h}} + \mathrm{b}_{14}Vd + \mathrm{b}_{15}Vm + \mathrm{b}_{23}Ph \\ &+\mathrm{b}_{24}Pd + \mathrm{b}_{25}Pm + \mathrm{b}_{34}hd + \mathrm{b}_{35}hm + \mathrm{b}_{45}dm \end{aligned} \quad (5)$$

As of the results of Caydas and Hascalik (2008), the final regression model for surface roughness obtained is written as follows:

$$\begin{aligned}R_a = &-5.07976 + 0.08169V + 0.07912P - 0.34221h \\ &-0.08661d - 0.34866m - 0.00031V^2 \\ &-0.00012P^2 + 0.10575h^2 + 0.00041d^2 \\ &+0.07590m^2 - 0.00008Vm - 0.00009Pm \\ &+0.03089hm + 0.00513dm \end{aligned} \quad (6)$$

ABC optimization

ABC is a swarm-based algorithm that mimics the foraging behaviour of swarm honey bee. Similar to the concept of ACO and PSO, this exploration algorithm is capable of tracing good quality of solutions. There are three types of bees in the colony which are employed, onlookers and scouts bees. Each type of bee bears a different task. Employed bees that are currently exploiting and searching are linked with the food sources. The unemployed bees or scouts bees are associated with establishing new food sources either by searching the environment surrounding the hives or waiting for the employed bees to share the best food source location in the hives. The onlookers bees that watched the waggle dance are positioned on the food sources by using a probability based selection process. The probability value which the food source is favoured by onlookers increases while the quantity of the nectar amount increases which is calculated in Eq. (7). There are three important control parameters in ABC which are colony size, limit and maximum cycle.

The detailed ABC pseudocode to solve the optimization is as follows, (Karaboga and Akay 2009):

1. Initialize the population of solutions xi,j
2. Evaluate the population
3. Cycle=1
4. Repeat
5. Produce new solutions (food source positions) υi,j in the neighbourhood of xi,j for the employed bees using the formula υi,j = xi,j + Φij(xi,j − xk,j) (k is a solution in the neighbourhood of i, Φ is a random number in the range [−1,1]) and evaluate them
6. Apply the greedy selection process between xi and υi
7. Calculate the probability values P_i for the solutions xi by means of their fitness values using the Eq. (7):

$$P_i = \frac{fit_i}{\sum_{i=1}^{SN} fit_i} \quad (7)$$

In order to calculate the fitness values of solutions we employed the following Eq. (8).

$$fit_i = \begin{cases} \frac{1}{1+f_i}, & if\ f_i \geq 0 \\ 1 + absf\,(i)\,, & if\ f_i < 0 \end{cases} \quad (8)$$

8. Normalize P_i values into [0,1].
9. Produce the new solutions (new positions) υi for the onlookers from the solutions xi, selected depending on Pi, and evaluate them.
10. Apply the greedy selection process for the onlookers between xi and υi.
11. Determine the abandoned solution (source), if exists, and replace it with a new randomly produced solution xi for the scout using the Eq. (9).

$$x_{ij} = \min_j + \mathrm{rand}\,(0, 1)^* (\max_j - \min_j) \quad (9)$$

12. Memorize the best food source position (solution) achieved so far
13. Cycle=cycle+1
14. Until cycle= Maximum Cycle Number (MCN)

The program to optimize machining control parameters of AWJ that will lead to a minimum Ra value was developed and run using MATLAB (R2010a) software. In the experiment, three control parameters of ABC have been employed which are colony size where it refers to the number of bees in the colony, limit where it controls the number of trials to improve certain food source. The colony size was set to 10; limit and maximum cycle was set to 50. The range of AWJ machining control parameters are given in the Eq. (10a–10e).

$$50\text{mm/min} \ < x_1 < 150 \text{ mm/min} \quad (10a)$$

$$125\text{Mpa} \ < x_2 < 250\text{Mpa} \quad (10b)$$

$$1\text{mm} \ < x_3 < 4\text{mm} \quad (10c)$$

$$60\mu\text{m} < x_4 < 120\mu\text{m} \quad (10d)$$

$$0.5\text{g/s} < x_5 < 3.5\text{g/s} \quad (10e)$$

where x_1 is the traverse cutting speed (V) in mm/min, x_2 is the waterjet pressure (P) in MPa, x_3 is the standoff distance (h) in mm, x_4 is the abrasive grit size (d) in μm and lastly, x_5 the abrasive flow rate (m) in g/s. The objective function is defined in Eq. (11):

$$\begin{aligned} R_a = \ & -5.07976 + 0.08169x_1 + 0.07912x_2 - 0.34221x_3 \\ & -0.08661x_4 - 0.34866x_5 - 0.00031x_1^2 \\ & -0.00012x_2^2 + 0.10575x_3^2 + 0.00041x_4^2 \\ & +0.07590x_5^2 - 0.00008x_1x_5 - 0.00009x_2x_5 \\ & +0.03089x_3x_5 + 0.00513x_4x_5 \end{aligned} \quad (11)$$

In optimizing control parameters of AWJ machining, the minimum R_a value found was 1.5223μm. The optimal solution of the ABC are 50 mm/min for cutting speed, 125 Mpa for waterjet pressure, 1.5504 mm for standoff distance, 102.5213μm for abrasive grit size and 0.5 g/s for abrasive flow rate. It was found out that a minimum R_a value is obtained with a smallest value of 10 colony size, 50 maximum cycle and 10 runs are adequate. A maximum cycle value of 10 and 20 did not give a good result in all bee colony sizes. The average minimum R_a value of 1.5223μm is achieved on the sixth runs. Figure 3 shows the experimental results of using 50 maximum cycles. Figure 4 shows the comparison of the effect of colony size in AWJ.

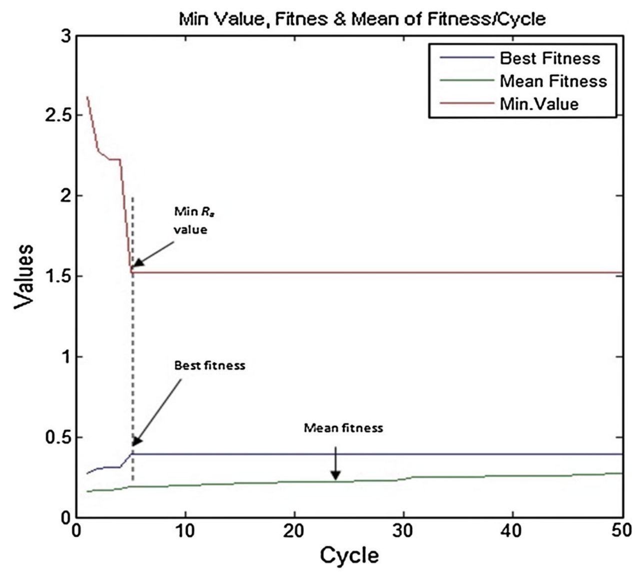

Fig. 3 Experimental results using 50 max cycles

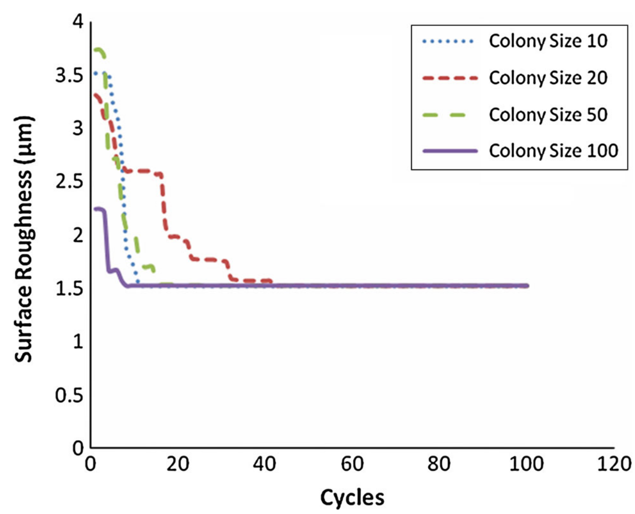

Fig. 4 Effect of colony sizes in optimizing R_a value of AWJ

Validation and evaluation of ABC results

To validate the results of ABC, a t-test two sample assuming equal variances was used and the results are shown in Table 3. There was a statistically significant decrease from experimental (Mean = 6.3452, and variance = 4.7955) to ABC (Mean = 1.6220, variance = 0.0164, t(52) = 11.1882). The α value is 0.05 and the one-tailed p value is less than 0.0001. If $p < 0.05$, it shows that the observed different within two methods are significant. Then, eta squared statistic was calculated to show the magnitude of the intervention's effect using Eq. (12). The results of eta squared statistic was (.71) indicated a large effect size.

$$\text{Eta squared} \ = \text{t}^2/\text{t}^2 + \text{N} - 1 \quad (12)$$

Considering the combination of optimal control parameter values estimated by ABC, validation of the results using Eq. (11) is given as follows.

Table 3 Results of t-test

Variable	Mean	Variance	N	Correlation	Pooled variances	df	t Stat	$P(T \leq t)$ one-tail	t Critical one-tail
Exp	6.3452	4.7955	27	0.0260	2.4059	52	11.1882	9.42126E-12	1.67469
ABC	1.6220	0.0164	27						

Table 4 Conditions to define the scale for optimal process parameters of AWJ

Decision	Independent variables				
	V (mm/min)	P (MPa)	h (mm)	d (μm)	m (g/s)
Lowest	$50 \leq xi < 70$	$125 \leq xi < 150$	$1.0 \leq xi < 1.6$	$60 \leq xi < 72$	$0.5 \leq xi < 1.1$
Low	$70 \leq xi < 90$	$150 \leq xi < 175$	$1.6 \leq xi < 2.2$	$72 \leq xi < 84$	$1.1 \leq xi < 1.7$
Medium	$90 \leq xi \leq 110$	$175 \leq xi \leq 200$	$2.2 \leq xi \leq 2.8$	$84 \leq xi \leq 96$	$1.7 \leq xi \leq 2.3$
High	$110 < xi \leq 130$	$200 < xi \leq 225$	$2.8 < xi \leq 3.4$	$96 < xi \leq 108$	$2.3 < xi \leq 2.9$
Highest	$130 < xi \setminus \leq 150$	$225 < xi \leq 250$	$3.4 < xi \leq 4.0$	$108 < xi \leq 120$	$2.9 < xi \leq 3.5$

$$
\begin{aligned}
R_a = & -5.07976 + 0.08169\,(50) + 0.07912\,(125) \\
& -0.34221\,(1.5504) - 0.08661\,(102.5213) \\
& -0.34866\,(0.5) - 0.00031\,(50)^2 - 0.00012\,(125)^2 \\
& +0.10575\,(1.5504)^2 \\
& +0.00041\,(102.5213)^2 + 0.07590\,(0.5)^2 \\
& -0.00008\,(50)\,(0.5) \\
& -0.00009\,(125)\,(0.5) + 0.03089\,(1.5504)\,(0.5) \\
& +0.00513\,(102.5213)\,(0.5) \\
& = 1.52228 \approx 1.5223\mu\text{m}
\end{aligned}
$$

In order to evaluate the optimal control parameters of ABC for AWJ, the values of the cutting condition level noted as 1, 2 and 3 as given in Table 1, are classified as the lowest, lower, medium, high, highest scales. With xi = optimal cutting conditions of AWJ, Table 4 shows the conditions used to define the scale of the levels for the five optimal control parameters.

The set values of optimal control parameters of ABC optimization that lead to the minimum R_a value are 50 mm/min for traverse speed, 125 MPa for waterjet pressure, 1.5504 mm for standoff distance, 102.5213 μm for abrasive grit size and 0.500 g/s for abrasive flow rate. This confirmed that the optimal control parameters are within the range of minimum and maximum value of experimental design as shown in Table 1.

Effectiveness of ABC algorithm for improving machining process

In this paper, ABC algorithm was proposed for optimization of machining control parameters. By perusing the structure of ABC algorithm, it is clarified that ABC is a meta-heuristic optimization approach with different local and general search strategies compared to other evolutionary approaches. As well, its exploration and evaluation results reported by researchers have verified that the popular effectiveness of ABC is related to flexibility, simplicity, convergence rate, diversity, and accuracy of the solutions. Although effectiveness of ABC algorithm has been reported by previous researchers, but it has not been previously considered for some problems such as optimization of modern machining process. Consequently, in this research a machining case study on the AWJ, classified as one of modern machining processes, was considered to illustrate the robustness of ABC algorithm in optimization of machining control parameters. ABC algorithm was employed to optimize five machining parameters of AWJ which are cutting speed, waterjet pressure, standoff distance, abrasive grit size, and abrasive flow rate to estimate a minimum surface roughness value. In addition, a dataset of 27 experimental machining data on AWJ is considered in this study. Then effectiveness of the proposed ABC on AWJ process is summarized.

Improvement in the quality of machining could be indicated by referring to a machining performance known as surface roughness. Optimization, which is defined as the process of approximation of the optimal solutions of machining cutting conditions, could become the choice to the experimentation process in order to improve surface roughness. In difference way, based on the advanced system, ABC algorithm is considered as an intelligent approach in this study to help machinist selecting an optimal solutions for estimating a desired minimum surface roughness value. Basically, the intention of machining process is to obtain a minimum value of machining performance such as surface roughness as low as possible and it is given by the optimal solution of control parameters. The optimal solution is the optimal points of combination of machining control parameters that affect machining performance at the possible minimum value.

Table 5 Comparison of the optimal process parameters for minimum R_a

Technique	Process parameters					Minimum R_a
	(V)	(P)	(h)	(d)	(m)	
Experimental (Caydas and Hascalik 2008)	50	125	1	60	0.5	2.124
Regression (Caydas and Hascalik 2008)	50	125	1	60	2	2.629
ANN (Caydas and Hascalik 2008)	50	125	1	60	2	2.744
GA (Zain et al. 2011)	50.024	125.018	1.636	94.73	0.525	1.554
SA (Zain et al. 2011)	50.003	125.029	1.486	107.737	0.500	1.533
ABC	50	125	1.550	102.521	0.500	1.522

A question related to this issue is how to know specifically the potential values of the machining control parameters for giving a possible minimum value of machining performance when practiced through experimental trial? Conventionally, to estimate the possible minimum value of machining performance, the experimental trial process has been done many times at different combination of control parameter values. It is fully depend to mechanist experience who conducts the experiment. Therefore the optimization process based on computational approach is a way to guide the non-experience machinist to study the potential value of machining cutting conditions to gain the minimum value of machining performance. ABC is seen as a good strategy to estimate a combination of optimal control parameter values to gain the minimum value of machining performance. The main factor to avoid of using experimental trial in finding the optimal solution of machining control parameters is the cost. Meanwhile, the mechanists have to use a large number of machining workpieces. Meanwhile, the cost for providing a large number of workpieces is also increased. Based on the intelligent scheme throughout this study, it was confirmed that ABC has effectively assisted the machinist to identify the possible optimal machining control parameters through computational estimation strategy. Trial and error process is done by an informal process by altering the ABC's parameters such as bee colony size and number of cycles. This study proposed several combinations of ABC's parameters such as 10-10-50 represents the ABC's parameters combination of colony size-max cycles-limit that leads to a minimum surface roughness value of 2.7090 μm. The value of surface roughness is improved by 40 % when the max cycles per run value increased to 20. Next, when the max cycles per run are increased to 50 and 100, the minimum surface roughness value found is 1.5223 μm. This minimum surface roughness value is enhanced by 44 % compared to the first control variables combinations. It was also confirmed that ABC has estimated the accurate predicted surface roughness value for AWJ machining process by using a smaller number of bee colony size of 10, limit and maximum number of cycles of 50 gave the best result.

It was proved that ABC is an effective optimization algorithm applied for probabilistic exploration includes local and global searches. This effectiveness was obviously clear by comparing the mean and variance values of machining experimental and ABC optimization results by using a t-test two sample. The reason for this result can be demonstrated from the theory of ABC algorithm enables to employ three exploration strategies simultaneously; they are probabilistic, greedy and stochastic. Probabilistic exploration includes local and global searches. A local search is performed by employed and onlooker bees to find food sources. Global search is carried out by onlooker bees to find the most profitable sources. Greedy exploration which is a local search is performed by onlooker and employed bees to replace a good next candidate solution instead of current one. Also, stochastic exploration which is a global search carried out by scout bees to find an abandoned solution and replaced it with a new random solution. Therefore, exploration ability of ABC algorithm is enhanced by considering these three strategies. Also, stochastic exploration is effective to control exploration process of the algorithm to avoid being trapped into local optimal for optimization of experimental machining process parameters.

Results of evaluation indicated that the recommended ABC setting parameters have given a much minimum surface roughness value compared to the predicted surface roughness values of experimental, standard ABC and several established computational approaches. Table 5 presents the predicted surface roughness value of ABC in comparison to experimental and others computational approaches. As it is clear from the Table 5, the minimum surface roughness value estimated by ABC was the lowest compared to experimental and other computational approaches. ABC optimization technique noticeably minimized the surface roughness value of machining experimental. Results of the evaluation test also confirmed the optimal machining control parameters estimated by ABC algorithm are within the predefined range of values of machining experimental. The relationship between input machining parameters and minimum surface roughness of ABC algorithm is also comprehensible. As indicated in Table 5, it was found that traverse speed and waterjet pressure are the dominant factors and the most influence process parameters in giving a minimum surface roughness value. The level of the optimal machining control parameters that leads to a minimum predicted surface roughness value are lowest for traverse speed, waterjet pressure, standoff distance, abrasive flow rate, and high for abrasive grit size. This result indicated the capability of ABC algorithm has reduced the machining experimental performance value effectively. It is based the theories that ABC algorithm could balance the local and global searches, enhance diversity of the solutions and avoid from premature convergence, and the most significant incident in the ABC algorithm is a dancing area between bees. This unique area could improve probability of finding the most global profitable sources by onlooker for improving the performances of machining experimental process.

Conclusion

The role of machining control parameters in AWJ is significant in order to produce a minimum value of surface roughness. The minimum surface roughness influences the quality of the product end results characteristic such as the appearance, functionality and dependability. It was demonstrated that the ABC technique is capable in estimating the lowest value of surface roughness compared to machining experimental.Therefore ABC could be labelled as a useful computational technique to build process model on the basis of the expertise of human operators for producing desired product in shorter time and reduce operational cost. All in all, ABC algorithm which inspires from honeybee swarms behaviours is an effective algorithm in optimization of different complex problems as well as optimization of AWJ machining control parameters. Furthermore, the robustness of basic ABC algorithm compared to other evolutionary algorithms is considerable to be enhanced in the feature works.

Acknowledgments Special appreciative to reviewers for useful advices and comments. The authors greatly acknowledge the Research Management Centre, UTM and Ministry of Higher Education Malaysia (MOHE) for financial support through the Exploratory Research Grant Scheme (ERGS) No.Q.J13000078284L003.

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