Modelling and optimization of process parameters of wire electrical discharge machining

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Abstract: The optimum selection of process parameters is essential for advanced machining processes as these processes incur high initial investment, tooling cost, operating cost, and maintenance cost. Wire electrical discharge machining (WEDM) is a widely accepted advanced material removal process used to manufacture components with intricate shapes and profiles. The present work highlights the development of mathematical models using response surface modelling (RSM) for correlating the inter-relationships of various WEDM parameters such as pulse-on time, pulse-off time, peak current, and servo feed setting on the machining speed and surface roughness. A recently developed advanced optimization technique, known as artificial bee colony (ABC), is then applied to find the optimal combination of process parameters with an objective of achieving maximum machining speed for a desired value of surface finish.

Keywords: wire electrical discharge machining, response surface modelling, process parameter optimization, artificial bee colony algorithm

1 INTRODUCTION

In recent years an increasing demand for machining of complex shapes made of hard and difficult-to-machine materials with exact tolerances and surface finish requirements has resulted in the development of many advanced machining processes based on chemical, electro-chemical, thermal, electro-thermal, mechanical, and other means of material removal. Wire electrical discharge machining (WEDM) is one of the widely accepted advanced machining processes used to machine components with intricate shapes and profiles. It is considered as a unique adaptation of the conventional EDM process which uses an electrode to initialize the sparking process. As shown in Fig. 1, WEDM utilizes a continuously travelling wire electrode made of thin copper, brass, or tungsten. On application of a proper voltage, discharge occurs between the wire electrode and the workpiece in the presence of a flood of deionized water of high insulation resistance. The material is eroded ahead of the wire through a series of repetitive sparks between electrodes, i.e. workpiece and the wire.

WEDM has been gaining wide acceptance in modern tooling applications, in the machining of advanced ceramic materials and modern composite materials owing to the following reasons [**1**].

1. As the wire diameter is small (0.05–0.3 mm), the process is capable of achieving very small corner radii.
2. The wire is kept in tension using a mechanical tensioning device, reducing the tendency to produce inaccurate parts.
3. During the WEDM process there is no direct contact between the workpiece and the wire, eliminating the mechanical stresses during machining.
4. The WEDM process is able to machine exotic, high-strength, and temperature-resistive (HSTR) materials and eliminate the geometrical changes occurring in the machining of heat-treated steels.

WEDM manufacturers and users always want to achieve higher machining productivity with a desired accuracy and surface finish. Performance of the WEDM process, however, is affected by many factors such as servo feed setting, peak current, pulse-on time, pulse-off time, wire tension, etc. and a single

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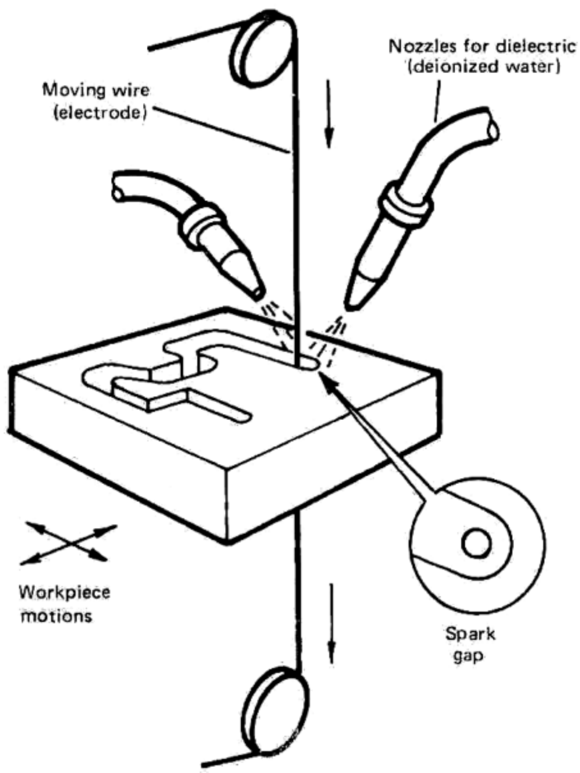

Fig. 1 Basic scheme of WEDM process

parameter change will influence the process in a complex way. The many variables and the complex and stochastic nature of the process mean that achieving the optimal performance, even for a highly skilled operator with a state-of-the-art WEDM machine, is rarely possible. An effective way to solve this problem is to discover the relationship between the performance of the process and its controllable input parameters by modelling the process through suitable mathematical techniques and optimization using a suitable optimization algorithm. In the present work, response surface methodology (RSM) is used to model the process whereas the optimum parameter setting is achieved through a recently developed evolutionary optimization algorithm known as the artificial bee colony (ABC) algorithm.

The next section presents a brief review of the past research work done on the modelling and optimization of WEDM process parameters.

2 REVIEW OF PAST RESEARCH WORK

Several attempts have been made in the past to study the influence of different process parameters on the important performance measures of the WEDM process by using various problem-solving tools. Huang and Liao [**2**] used grey relational and signal-to-noise (S/N) ratio analysis to demonstrate the influence of table feed and pulse-on time on the material removal rate (MRR). It was found that the table feed rate had a significant influence on the metal removal rate, while the gap width and surface roughness were mainly influenced by pulse-on time. Tosun *et al.* [**3**] investigated the effect of the pulse duration, open circuit voltage, wire speed, and dielectric flushing pressure on workpiece surface roughness. It was found that the increasing pulse duration, open circuit voltage, and wire speed increases the surface roughness whereas the increasing dielectric fluid pressure decreases the surface roughness. The variation of surface roughness with machining parameters was modelled by using a power function.

Hewidy *et al.* [**4**] developed a mathematical model based on response surface methodology or modelling (RSM) for correlating the inter-relationships of various WEDM parameters of Inconel 601 material – such as peak current, duty factor, wire tension and water pressure – on the metal removal rate, wear ratio, and surface roughness. Kanlayasiri and Boonmung [**5**] presented an investigation of the effects of machining variables on the surface roughness of wire electrical discharge machined DC53 die steel. The machining variables investigated were pulse-peak current, pulse-on time, pulse-off time, and wire tension. The authors had developed a mathematical model using the multiple regression method to formulate the pulse-on time and pulse-peak current to the surface roughness. The developed model was validated with experimental data. Hascalyk and Caydas [**6**] showed through experimental investigations that intensity of the process energy affects significantly the amount of recast, surface roughness, and microcracking but the wire speed and dielectric fluid pressure do not have significant influence.

Quite a few researchers have tried to optimize the cutting performance by adopting various traditional and non-traditional optimization techniques. Metal removal rate and surface finish were optimized by Scott *et al.* [**7**] by explicit enumeration based on S/N ratio. Further, they split the problem into optimization of MRR with surface finish constraint and optimization of surface finish with MRR as constraint and applied a dynamic programming method. Tarng *et al.* [**8**] used a simple weighting method to transform the cutting velocity and surface roughness into a single objective and arrived at the optimal parameters by employing a simulated annealing technique. They considered pulse-on/off duration, peak current, open circuit voltage, and servo reference voltage; electrical capacitance and table speed are the critical parameters for the estimation of the cutting rate and surface finish. Liao *et al.* [**9**] applied a method of feasible direction for optimization of the process parameters such as table feed rate and pulse-on time with an objective to maximize the MRR with surface roughness and spark gap as constraints.

Spedding and Wang [10] optimized the process parameter settings by using artificial neural network modelling to characterize the WEDM workpiece surfaces. They obtained the optimum combination of the parameters, namely pulse width, time between two pulses, wire mechanical tension, and wire feed space for maximum cutting speed, keeping the surface roughness and waviness within the required limits. Kuriakose and Shunmugam [11] presented a multiple regression model to represent relationship between input variables and two conflicting objectives, i.e. cutting velocity and surface finish. A multi-objective optimization method based on a non-dominated sorting genetic algorithm (NSGA) was then used to optimize the WEDM process. Tosun *et al.* [12] presented an investigation on the optimization and the effect of machining parameters on kerf and the MRR in WEDM operations. The simulated annealing algorithm was then applied to select optimal values of machining parameters for a multi-objective problem considering minimization of kerf and maximization of MRR.

Sarkar *et al.* [13] obtained pareto optimal combinations of process variables – namely pulse-on time, pulse-off time, peak current, servo reference voltage, wire tension, and dielectric flowrate – for maximization of cutting speed with constraint on surface roughness and dimensional deviation; however, the method of optimization is not specified. Konda *et al.* [14] applied the design of experiments (DOE) technique to optimize the possible effects of process variables during process design and development and validated the experimental results using S/N ratio analysis. Gokler and Ozanozgu [15] provided the selection of the most suitable cutting and offset parameter combination to obtain the desired surface roughness for a constant wire speed and dielectric flushing pressure.

Although various researchers have considered the effect of different process variables on various performance measures, these efforts need to be further extended by considering more performance measures and more input variables. Machining speed and surface finish are considered to be crucial performance measures for WEDM, hence they are considered in the present work. A mathematical model is developed relating these performance measures to four important process parameters, namely pulse-on time (T_{on}), pulse-off time (T_{off}), peak current (I_{p}), and servo feed setting (F), and using a second-order RSM technique, as first-order models often give lack of fit [16].

Furthermore, it is observed from the literature that mathematical programming techniques such as the method of feasible direction, Taguchi methods, etc. have been used in the past to solve optimization problems in the WEDM process. These traditional methods of optimization do not fare well, however, over a broad spectrum of problem domains. Moreover, traditional techniques may not be robust and they tend to obtain a local optimal solution. Considering the drawbacks of traditional optimization techniques, attempts are being made to optimize the machining problem using evolutionary optimization techniques. These methods use the fitness information instead of the functional derivatives, making them more robust and effective. These methods thus avoid the problem of becoming trapped in local optima and enable a global (or nearly global) optimum solution to be obtained. Efforts are continuing to use more recent optimization algorithms, which are more powerful, robust, and able to provide an accurate solution. The ABC algorithm developed by Karaboga [17] and Karaboga and Basturk [18, 19] is one of the recent algorithms; no effort has yet been made to optimize the process parameters of any machining processes by using this algorithm. Hence, in the current paper, an attempt is made to apply the ABC algorithm for optimization of the process parameters of the WEDM process.

The next section describes the development of a mathematical model for a WEDM process.

3 RESPONSE SURFACE MODELLING

Response surface modelling is a collection of statistical and mathematical methods that are useful for modelling and optimization of engineering science problems. RSM quantifies the relationship between the controllable input parameters and the obtained responses. In modelling of manufacturing processes using RSM, sufficient data are collected through designed experimentation. An experiment is designed with 2^k (where $k =$ number of variables; in this study $k = 4$) factorial with central composite–second-order ratable design. This consists of the number of corner points $= 16$, number of axial points $= 8$, and a centre point at zero level $= 4$. The axial points are located in a coded test condition space through parameter 'α'. For the design to remain rotatable, 'α' is determined as $(2^k)^{1/4} = 2$. Thus the coded level for the axial points is at 2. The centre point is repeated four times to estimate the pure error. The coded value corresponding to the actual value for each process variable is derived using the following formula

$$\text{Coded test condition} = \frac{\begin{matrix}\text{actual test} \\ \text{condition}\end{matrix} - \begin{matrix}\text{mean test} \\ \text{condition}\end{matrix}}{\text{range of test conditions}/2} \tag{1}$$

As an illustration, if the actual test condition of 'pulse-on time (T_{on})' is 5, then the corresponding coded value is $5-[(4+8)/2]/[(8-4)/2]=-0.5$. The coded numbers are thus obtained from the following transformation equations

$$x_1 = \frac{T_{on} - T_{on_0}}{\Delta T_{on}} \tag{2}$$

$$x_2 = \frac{T_{off} - T_{off_0}}{\Delta T_{off}} \tag{3}$$

$$x_3 = \frac{I_p - I_{p_0}}{\Delta I_p} \tag{4}$$

$$x_4 = \frac{F - F_0}{\Delta F} \tag{5}$$

where x_1, x_2, x_3, and x_4 are the coded values of the variables T_{on}, T_{off}, I_p, and F respectively. T_{on_0}, T_{off_0}, I_{p_0}, and F_0 are the values of pulse-on time, pulse-off time, peak current, and servo feed setting at zero level. ΔT_{on}, ΔT_{off}, ΔI_p, and ΔF are the intervals of variation in T_{on}, T_{off}, I_p, and F respectively. Table 1 shows coded values of the process variables. The details of the experimental set-up used for data collection are given below

Machine type/make: CNC-WEDM, Elektra ELPULSE-30
Wire material: brass
Wire diameter: 0.25 mm
Wire tension: 8 N
Dielectric fluid: deionized water
Workpiece specification: rectangular, cavity of size: 60 mm × 110 mm × 12 mm, oil hardened and nitrided steel (OHNS)
Surface roughness measuring device: Hommel tester T-500

The experimental matrix that was adopted in the present study in the coded form is shown in Table 2. To study the effect of process parameters, i.e. T_{on}, T_{off}, I_p, and F, on performance measures, i.e. machining speed (V_m) and surface roughness (R_a), a second-order polynomial response is fitted into the following equation

Table 1 Coded values of process variables

Factors	Coded levels −2	−1	0	+1	+2
Pulse-on time	2	4	6	8	10
Pulse-off time	6*	10	20	30	40
Peak current	65	90	115	140	165
Servo feed setting	20	30	40	50	60

*Although by using equation (1) the coded value is '0', the minimum possible value of '6' is considered.

$$y = b_0 + \sum_{i=1}^{k} b_i x_i + \sum_{i=1}^{k} b_{ii} x_i^2 + \sum_{j>1}^{k} b_{ij} x_i x_j \tag{6}$$

Where y is the response and x_i (1, 2, ..., k) are coded levels of k quantitative variables. The coefficient b_0 is the free term, the coefficients b_i are the linear terms, the coefficients b_{ii} are the quadratic terms, and the coefficients b_{ij} are the interaction terms. Equations (7) and (8) are then derived by determining the values of the coefficients using the least-squares technique for the observations collected as shown in Table 2, for machining speed (V_m) and surface roughness (R_a) respectively.

$$\begin{aligned} V_m = {} & 1.555 + 0.1095x_1 - 0.187x_2 + 0.0929x_3 \\ & + 0.1279x_4 + 0.0393x_1x_2 - 0.0793x_1x_3 \\ & - 0.01188x_1x_4 - 0.01688x_2x_3 - 0.0493x_2x_4 \\ & - 0.0606x_3x_4 - 0.03219x_1^2 + 0.02031x_2^2 \\ & - 0.0909x_3^2 - 0.06094x_4^2 \end{aligned} \tag{7}$$

$$\begin{aligned} R_a = {} & 3.6 + 0.2979x_1 - 0.2979x_2 - 0.1479x_3 \\ & - 0.03542x_4 + 0.021875x_1x_2 - 0.2031x_1x_3 \\ & + 0.04062x_1x_4 + 0.01562x_2x_3 - 0.1531x_2x_4 \\ & - 0.1031x_3x_4 - 0.3182x_1^2 - 0.3807x_2^2 \\ & - 0.4057x_3^2 - 0.2682x_4^2 \end{aligned} \tag{8}$$

Table 2 Design of experiments and the results

Serial number	T_{on} (μs)	T_{off} (μs)	I_p (A)	F	V_m (mm/min)	R_a (μm)
1	−1	−1	−1	−1	1.15	1.6
2	1	−1	−1	−1	1.50	2.5
3	−1	1	−1	−1	0.93	1.5
4	1	1	−1	−1	1.16	1.8
5	−1	−1	1	−1	1.54	2.2
6	1	−1	1	−1	1.58	2.3
7	−1	1	1	−1	1.13	1.7
8	1	1	1	−1	1.30	2.0
9	−1	−1	−1	1	1.58	2.3
10	1	−1	−1	1	1.90	3.7
11	−1	1	−1	1	1.05	1.5
12	1	1	−1	1	1.48	2.4
13	−1	−1	1	1	1.90	3.1
14	1	−1	1	1	1.57	2.4
15	−1	1	1	1	1.10	1.5
16	1	1	1	1	1.28	2.1
17	0	0	0	0	1.55	3.4
18	0	0	0	0	1.55	4.0
19	0	0	0	0	1.56	3.5
20	0	0	0	0	1.56	3.5
21	2	0	0	0	1.75	3.3
22	−2	0	0	0	1.13	1.6
23	0	2	0	0	1.35	1.8
24	0	−2	0	0	1.95	2.6
25	0	0	2	0	1.60	1.2
26	0	0	−2	0	0.81	3.0
27	0	0	0	2	1.70	1.6
28	0	0	0	−2	0.95	3.7

To test whether the data are well fitted in the model or not, the values of standard error of estimate (S) of the regression analysis for machining speed and surface roughness are obtained as 0.148 and 0.644 respectively. The values of standard deviation (S_y) for machining speed and surface roughness are obtained as 0.443 and 1.186 respectively. $S < S_y$ indicates that both regression models have merit. The actual extent of improvement by using regression analysis is quantified by coefficient of determination R^2. R^2 varies from 0 to 1 and a value of $R^2 = 1$ indicates a perfect fit and $R^2 = 0$ indicates no improvement. The calculated values of R^2 for machining speed and surface roughness models are 0.89 and 0.71 respectively. The R^2 value is moderately high for the machining speed model and is moderate for the surface roughness model. Hence, the models developed for machining speed and surface roughness fit the data well. Furthermore, F-statistics are used in the present work to check whether these results with such high values of R^2 have occurred by chance. Probabilities that these high values of R^2 have occurred by chance are calculated as 0.000 459 and 0.008 05 for machining speed and surface roughness models respectively. As these probability values are very small, it can be concluded that the regression analysis presented in this work is useful in predicting the responses.

Now an advanced optimization method based on the ABC algorithm is used to optimize the WEDM process parameters. The next section briefly describes the algorithm.

4 ARTIFICIAL BEE COLONY ALGORITHM

A branch of nature-inspired algorithms, called swarm intelligence, is focused on insect behaviour in order to develop some meta-heuristics which can mimic insects' problem-solving abilities. Interaction between insects contributes to the collective intelligence of the social insect colonies. These communication systems between insects have been adapted to scientific problems for optimization. The foraging behaviour, learning, memorizing, and information sharing characteristics of honey bees have recently been one of the most interesting research areas in swarm intelligence. The ABC algorithm is developed to model the intelligent behaviours of honey bee swarms [**17–19**]. The honey bee swarms consist of two essential components (i.e. food sources and foragers) and define two leading modes of behaviour (i.e. recruitment to a nectar source and abandonment of a source).

4.1 Food sources

The value of a food source depends on different parameters such as its proximity to the nest, richness of energy, and ease of extracting this energy. For simplicity, the 'profitability' of a food source can be represented with a single quantity.

4.2 Foragers

Foragers can be unemployed, employed, or experienced.

4.2.1 Unemployed foragers

If it is assumed that a bee has no knowledge about the food sources in the search field, the bee initializes its search as an unemployed forager. There are two possibilities for an unemployed forager.

1. Scout bee: if the bee starts searching spontaneously without any knowledge, it will be a scout bee. The percentage of scout bees varies from 5 per cent to 30 per cent according to the information into the nest. The mean number of scouts averaged over conditions is about 10 per cent.
2. Recruit: if the unemployed forager attends to a waggle dance done by some other bee, the bee will start searching by using the knowledge from the waggle dance.

4.2.2 Employed foragers

When the recruit bee finds and exploits the food source, it becomes an employed forager and memorizes the location of the food source. After the employed foraging bee loads a portion of nectar from the food source, it returns to the hive and unloads the nectar to the food area in the hive. There are three possible options related to the residual amount of nectar for the foraging bee. If the nectar amount has decreased to a low level or become exhausted, the foraging bee abandons the food source and becomes an unemployed bee. If there is still a sufficient amount of nectar in the food source, the bee can continue to forage without sharing the food source information with the nest mates, or it can go to the dance area to perform a waggle dance to inform the nest mates about the same food source. The probability values for these options are highly related to the quality of the food source.

4.2.3 Experienced foragers

These types of foragers use their historical memories for the location and quality of food sources. This type of forage can be an inspector, controlling the recent status of a food source already discovered. It can also be a reactivated forager by using the information from the waggle dance. It tries to explore the same food source discovered by itself if there are some other bees to confirm the quality of the same food source. It can become scout bee to search out new patches if the whole food source is exhausted. It can also become a recruit bee, searching out a new food source declared in the dancing area by another employed bee.

Communication among bees related to the quality of food sources occurs in the dancing area. The related dance is called the waggle dance. As information about all the current rich sources is available to an onlooker on the dance floor, she probably could watch numerous dances and choose to employ herself at the most profitable source. There is a greater probability of onlookers choosing more profitable sources because more information is circulating about the more profitable sources. Employed foragers share their information with a probability, which is proportional to the profitability of the food source, and the sharing of this information through waggle dancing is longer in duration. Hence, the recruitment is proportional to profitability of a food source. An illustrative example is discussed in the next section to demonstrate and validate the ABC algorithm for determining the optimum WEDM parameters.

5 EXAMPLE

Now to demonstrate and validate the ABC algorithm, an example is considered for the optimization of WEDM process parameters, based on the model developed in section 3.

Objective function: maximize V_m (specified by equation (7))

Constraint: Constraint is to ensure that the surface roughness value R_a should not exceed permissible surface roughness R_{per} as specified by

$$R_{per} - R_a \geqslant 0 \tag{9}$$

where R_a is the surface roughness value as specified by equation (8).

Parameters and parameter bounds: The four process parameters considered in the present work are pulse-on time (T_{on}), pulse-off time (T_{off}), peak current (I_p), and servo feed setting (F). The upper and lower bound values for these parameters are as given below

$$4 \leqslant T_{on} \leqslant 8\,\mu s \tag{10}$$

$$10 \leqslant T_{off} \leqslant 30\,\mu s \tag{11}$$

$$90 \leqslant I_p \leqslant 140\,A \tag{12}$$

$$30 \leqslant F \leqslant 50 \tag{13}$$

Now various steps of ABC algorithms are applied as described below.

Step 1: Parameter selection. As discussed in section 4, food source represents a possible solution to the problem of minimization of production time in the present work. The number of initial solutions (i.e. the number of food sources) considered in this work is five. The value of each food source depends on the fitness value of the objective function given by equation (7).

For every food source there is only one employed bee (employed forager). In other words, the number of employed bees is equal to the number of food sources. Hence, in the present work, the number of employed bees is considered to be *five*. The unemployed forager can be a scout or an onlooker bee. The number of onlooker bees must be greater than the number of employed bees. As the number of onlooker bees and hence the population size increases, the algorithm performs better in terms of convergence rate. However, after a sufficient value of the number of onlooker bees, any increment in the value does not improve the performance of the algorithm. For the problem considered in this work, the number of onlooker bees is considered to be 11, which can provide an acceptable convergence speed for search. The colony size is the sum of the number of employed bees and the number of onlooker bees. Hence the colony size is 16. The number of scout bees is usually 5–30 per cent of the colony size. In the present work, the number of scout bees is taken as 5 per cent of the colony size, i.e. *one*. The parameters of optimization thus selected in this work are summarized below:

(a) number of employed bees = 5;
(b) number of onlooker bees = 11;
(c) number of scout bees = 1;
(d) maximum number of iterations = 50.

Step 2: Calculate the nectar amount of each food source. The employed bees are moved to the food sources and the nectar amount of these food sources is evaluated based on their fitness value as defined by the objective function given by equation (7), subject to the constraints given by equation (9).

Step 3: Determine the probabilities by using the nectar amount. If the nectar amount of a food source θ_i is F_i, then the probability P_i of an onlooker bee is choosing this food source expressed as

$$P_i = \frac{\sum_{k=1}^{S} (1/f_k)^{-1}}{f_i} \tag{14}$$

where S is the number of food sources.

Step 4: Calculate the number of onlooker bees, which will be sent to food sources. Based on the probabilities calculated in step 3, the number N of onlooker bees sent to the food source θ_i is calculated as

$$N = P_i \times m \tag{15}$$

where m is the total number of onlooker bees.

Step 5: Calculate the fitness value of each onlooker bee. After watching the dances of employed bees, an onlooker bee goes to the region of the food source θ_i by the probability given by equation (14). The position of the selected neighbour food source is calculated as

$$\theta_i(c+1) = \theta_i(c) \pm \phi_i(c) \tag{16}$$

where c is the number of generations, $\phi_i(c)$ is a randomly produced step to find a food source with more nectar around θ_i, $\phi_i(c)$ is calculated by taking the difference of the same parts of $\theta_i(c)$ and $\theta_k(c)$ (k is a randomly produced index) food positions. If the nectar amount $F_i(c+1)$ at $\theta_i(c+1)$ is higher than at $\theta_i(c)$, then the bees go to the hive and share information with others and the position $\theta_i(c)$ of the food source is changed to $\theta_i(c+1)$, otherwise $\theta_i(c)$ is kept as it is. If the position θ_i of the food source i cannot be improved through the predetermined number of trials, then that food source θ_i is abandoned by its employed bee and then the bee becomes a scout. The scout starts searching for a new food source and, after finding the new source, the new position is accepted as θ_i.

Step 6: Evaluate the best solution. The position of the best onlooker bee is identified for each food source. The global best of the honey bee swarm in each generation is obtained and it may replace the global best at a previous generation if it has a better fitness value.

Step 7: Update the scout bee. The worst employed bees, as many as the number of scout bees in the population, are respectively compared with the scout solutions. If the scout solution is better than the employed solution, then the employed solution is replaced with the scout solution. Else the employed solution is transferred to the next generation without any change.

Table 3 shows the optimum values of process variables for various values of surface roughness as per the customer requirement. For $R_{per} = 2.0\,\mu s$, optimality of the above-mentioned solution could be confirmed from Figs 2 to 5. Figure 2 shows the variation of machining speed and constraint value with pulse-on time. As shown in Fig. 2, the machining speed increases with increase in pulse-on time; hence a higher value of pulse-on time is desired. Thus the selection of the upper bound value of pulse-on time $T_{on} = 8\,\mu s$ is appropriate. It is also observed that the surface roughness initially increases and then decreases with pulse-on time. Hence, the constraint is initially violated beyond the value of $T_{on} \cong 5.3\,\mu s$, however, it is satisfied again at $T_{on} = 8\,\mu s$. Variation of machining speed and constraint with pulse-off time is shown in

Table 3 Results of optimization using ABC algorithm for various permissible values of R_a

Permissible R_a value	T_{on} (μs)	T_{off} (μs)	I_p (A)	F	V_m (mm/min)
2.0	8	30	132.57	50	1.422
2.1	4	21.65	140	50	1.465
2.2	4	19.68	140	50	1.522
2.3	4.05	10	139.50	50	1.827
2.4	4.14	10	138.25	50	1.835

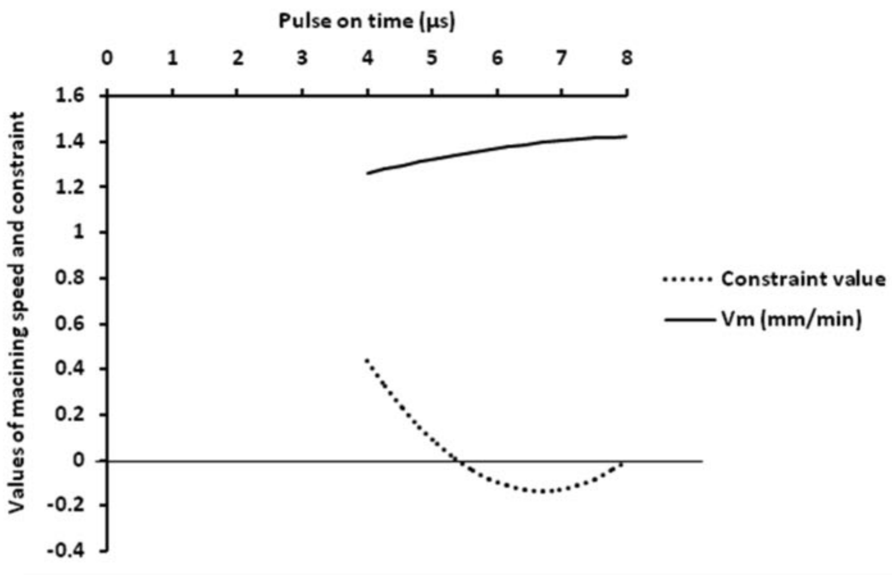

Fig. 2 Variation of machining speed and constraint value with pulse-on time

Fig. 3. As shown in Fig. 3, machining speed decreases but surface finish increases with the increase in pulse-off time. Thus, from the machining speed point of view, a lower value of pulse-off time is desired. However, the upper bound value (30 μs) of pulse-off time is selected as for any value below 30 μs, the surface roughness constraint is violated.

Figure 4 shows variation of machining speed and constraint value with peak current. As shown in Fig. 4, the machining speed initially increases slightly with peak current up to a certain value (≅107 A) and then decreases with increases in peak current. Values of peak current up to 107 A cannot be selected, as for these values the constraint is violated. From this point of view, a lower value of peak current should be selected. As the value selected for peak current of 132.52 A is the lowest value at which the constraint is satisfied, it is appropriate. Figure 5 shows variation of machining speed and constraint value with servo feed setting. It is observed from Fig. 5, that servo feed setting has less effect on machining speed but affects the surface roughness significantly. Better surface

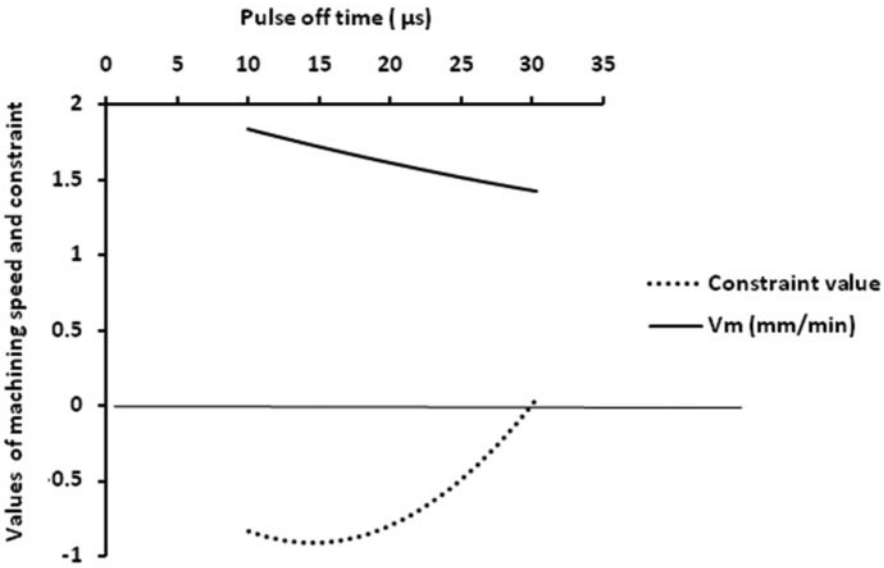

Fig. 3 Variation of machining speed and constraint value with pulse-off time

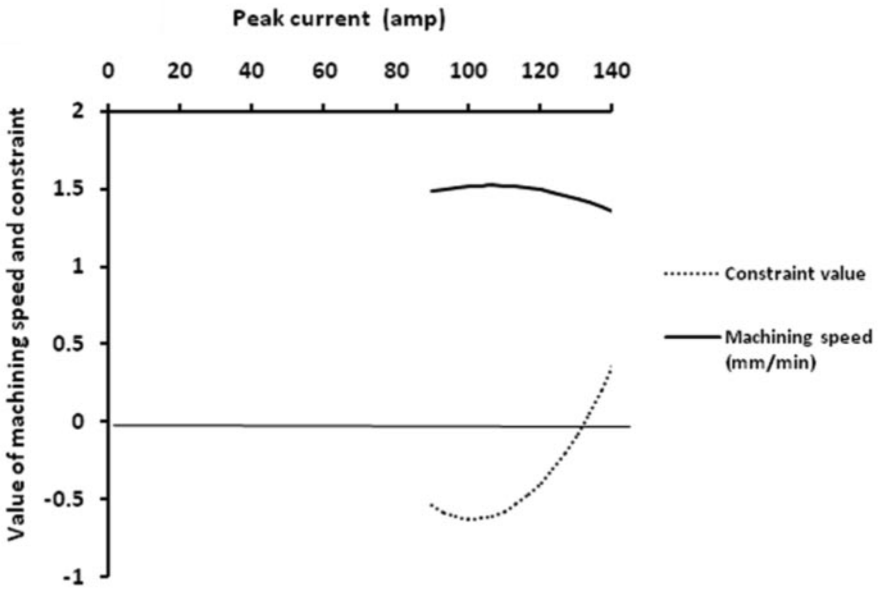

Fig. 4 Variation of machining speed and constraint value with peak current

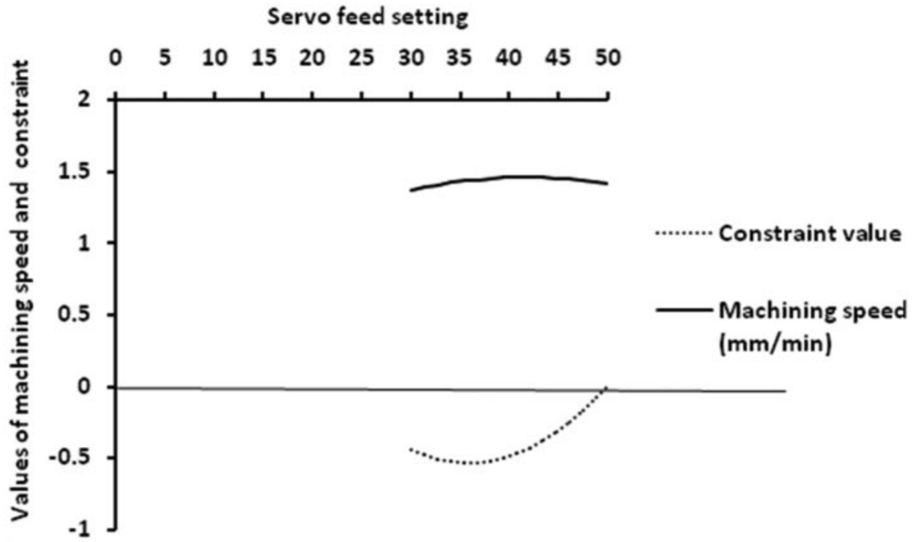

Fig. 5 Variation of machining speed and constraint value with servo feed setting

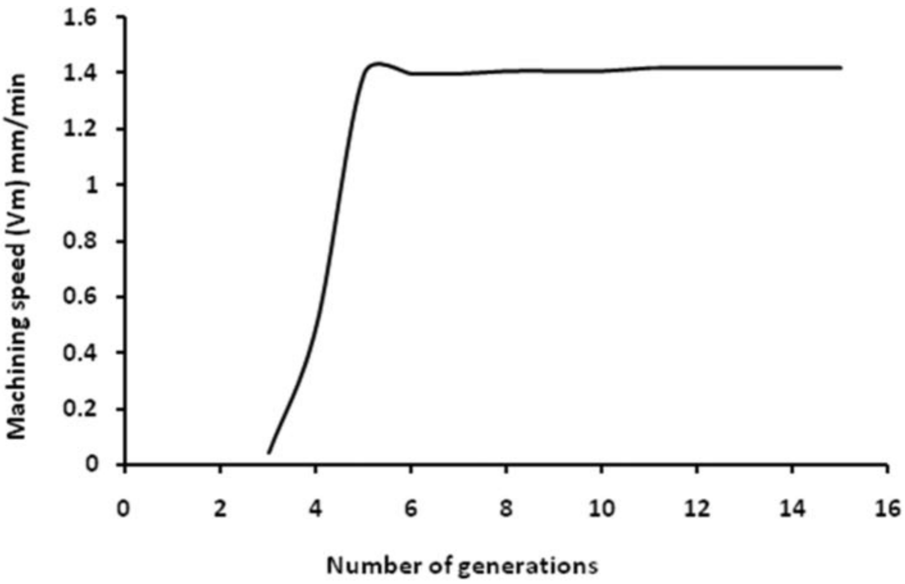

Fig. 6 Convergence of ABC algortihm

finish can be achieved for a higher value of servo feed setting. From this point of view, selection of the upper bound value of servo feed setting (=50) is appropriate.

The model formulated in this work is highly multimodal as it has a number of local optima. As an illustration, for the desired value of $R_a = 2.1\,\mu$m, one of the local optimum solutions is $T_{on} = 4$, $T_{off} = 10$, $I_p = 90$, and $F = 31$, with corresponding value of $V_m = 1.106$ mm/min and constraint value zero, thus showing no scope for further improvement. The global optimum solution obtained using ABC, however, provides $V_m = 1.465$ mm/min, showing about 32 per cent improvement over the local optimum solution that is generally obtained by using traditional methods of optimization. This clearly justifies the use of an advanced optimization algorithm such as ABC, as in the present study, to solve such multimodal problems.

6 CONCLUSIONS

In the present work modelling and optimization aspects of WEDM process parameters are considered. The objective considered is maximization of machining speed subject to the surface roughness constraint. A mathematical model is developed based on the RSM approach for correlating the combined effects of pulse-on time, pulse-off time, peak current, and servo feed setting on machining speed and surface roughness. The optimum setting of the process parameters is then obtained using a recently developed ABC optimization algorithm.

The performance of the ABC algorithm is studied in terms of convergence rate and accuracy of the solution. The ABC algorithm combines both the stochastic selection scheme carried out by onlooker bees and the greedy selection scheme used by onlookers and employed bees to update the source position. Also, the neighbour source production mechanism in ABC is similar to the mutation process, which is self-adapting. The random selection process carried out by the scout bees maintains diversity in the solution. The convergence rate of the ABC algorithm is also very high and the algorithm requires only 20–30 iterations for convergence to the optimal solution, as shown in Fig. 6. The ABC algorithm is thus flexible, simple to use, and a robust optimization algorithm, which can be used effectively in the optimization of multi-modal and multi-variable problems. The algorithm can also be easily modified to suit optimization of process parameters of other advanced machining processes such as electrochemical machining, laser beam machining, plasma arc machining, and so on.

REFERENCES

1 **Ho, K. H., Newman, S. T., Rahimifard, S.,** and **Allen, R. D.** State of the art in wire electrical discharge machining (WEDM). *Int. J. Mach. Tools Mf.*, 2004, **44**, 1247–1259.

2 **Huang, J. T.** and **Liao, Y. S.** Optimization of machining parameters of wire-EDM based on grey relational and statistical analyses. *Int. J. Prod. Res.*, 2003, **41**(8), 1707–1720.

3 **Tosun, N., Cogun, C.,** and **Inan, A.** The effect of cutting parameters on workpiece surface roughness in wire EDM. *Mach. Sci. Technol.*, 2003, **7**(2), 209–219.

4 **Hewidy, M. S., El-Taweel, T. A.,** and **El-Safty, M. F.** Modelling the machining parameters of wire electrical discharge machining of Inconel 601 using RSM. *J. Mater. Processing Technol.*, 2005, **169**, 328–336.

5 **Kanlayasiri, K.** and **Boonmung, S.** Effects of wire-EDM machining variables on surface roughness of newly developed DC 53 die steel: Design of experiments and regression model. *J. Mater. Processing Technol.*, 2007, **192–193**, 459–464.

6 **Hascalyk, A.** and **Caydas, U.** Experimental study of wire electrical discharge machining of AISI D5 tool steel. *J. Mater. Processing Technol.*, 2004, **148**, 362–367.

7 **Scott, D., Boyina, S.,** and **Rajurkar, K. P.** Analysis and optimization of parameter combination in wire electrical discharge machining. *Int. J. Prod. Res.*, 1991, **29**(11), 2189–2207.

8 **Tarng, Y. S., Ma, S. C.,** and **Chung, L. K.** Determination of optimal cutting parameters in wire electrical discharge machining. *Int. J. Mach. Tools Mf.*, 1995, **35**(12), 1693–1701.

9 **Liao, Y. S., Huang, J. T.,** and **Su, H. C.** A study on the machining parameters optimization of wire electrical discharge machining. *J. Mater. Processing Technol.*, 1997, **71**(3), 487–493.

10 **Spedding, T. A.** and **Wang, Z. Q.** Parametric optimization and surface characterization of wire electrical discharge machining process. *Precision Engng*, 1997, **20**(1), 5–15.

11 **Kuriakose, S.** and **Shunmugam, M. S.** Multi-objective optimization of wire-electro discharge machining process by non-dominated sorting genetic algorithm. *J. Mater. Processing Technol.*, 2005, **170**, 133–141.

12 **Tosun, N., Cogun, C.,** and **Tosun, G.** A study on kerf and material removal rate in wire electrical discharge machining based on Taguchi method. *J. Mater. Processing Technol.*, 2004, **152**, 316–322.

13 **Sarkar, S., Mitra, S.,** and **Bhattacharyya, B.** Parametric analysis and optimization of wire electrical discharge machining of γ-titanium aluminide alloy. *J. Mater. Processing Technol.*, 2005, **159**, 286–294.

14 **Konda, R., Rajurkar, K. P., Bishu, R. R., Guha, A.,** and **Parson, M.** Design of experiments to study and optimize process performance. *Int. J. Qual. Reliability Manag.*, 1999, **16**(1), 56–71.

15 **Gokler, M. I.** and **Ozanozgu, A. M.** Experimental investigation of effects of cutting parameters on surface roughness in the WEDM process. *Int. J. Mach. Tools Mf.*, 2000, **40**(13), 1831–1848.

16 **Montgomery, D. C.** *Design and analysis of experiments*, 1997 (Wiley, New York).

17 **Karaboga, D.** An idea based on honey bee swarm for numerical optimization, technical report-TR06, Computer Engineering Department, Erciyes University, Turkey, 2005.

18 **Karaboga, D.** and **Basturk, B.** A powerful and efficient algorithm for numerical function optimization: artificial bee colony (ABC) algorithm. *J. Global Optimization*, 2007, **39**(3), 459–471.

19 **Karaboga, D.** and **Basturk, B.** On the performance of artificial bee colony (ABC) algorithm. *Appl. Soft Comput.*, 2008, **8**, 687–697.