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Full Length Article

Optimization of WEDM process parameters using deep cryo-treated Inconel 718 as work material

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A B S T R A C T

The present work proposes an experimental investigation and optimization of various process parameters during taper cutting of deep cryo-treated Inconel 718 in wire electrical discharge machining process. Taguchi's design of experiment is used to gather information regarding the process with less number of experimental runs considering six input parameters such as part thickness, taper angle, pulse duration, discharge current, wire speed and wire tension. Since traditional Taguchi method fails to optimize multiple performance characteristics, maximum deviation theory is applied to convert multiple performance characteristics into an equivalent single performance characteristic. Due to the complexity and non-linearity involved in this process, good functional relationship with reasonable accuracy between performance characteristics and process parameters is difficult to obtain. To address this issue, the present study proposes artificial neural network (ANN) model to determine the relationship between input parameters and performance characteristics. Finally, the process model is optimized to obtain a best parametric combination by a new meta-heuristic approach known as bat algorithm. The results of the proposed algorithm show that the proposed method is an effective tool for simultaneous optimization of performance characteristics during taper cutting in WEDM process.

1. Introduction

In today's manufacturing scenario, nickel based super alloy such as Inconel 718 finds widespread application in aerospace, automobile and other major industries due to its high strength to weight ratio and wear resistance properties. However, these nickel based alloys are difficult to machine due to their superior mechanical properties in addition to the lower thermal conductivity. Cryogenic treatment brings some remarkable improvements in the thermal and mechanical properties through refining the microstructure of the materials. Deep cryogenic treatment refers to the treatment of the materials at very low temperature around −196 °C, which affects the entire cross section of the metal [1]. However, machining of such alloys is hardly carried out in conventional machining processes. Taper cutting operation using wire electrical discharge machining (WEDM) provides an effective solution for producing complicated and tapered profiles using any difficult-to-machine materials, super alloys and composites, especially in the aerospace and defense industries. It is basically an electro-thermal process in which material is eroded from the work piece by a series of discrete sparks between the work piece and the wire electrode (tool) separated by a thin film of dielectric fluid (de-ionized water) which is continuously fed to the machining zone to flush away the eroded particles [2]. During taper cutting operation in WEDM, the wire is subjected to deformation resulting deviations in the inclination angle of machined parts. As a result, the machined part loses its precision [3,4]. To achieve better output characteristics during taper cutting operation in WEDM process, simultaneous improvement on properties of wire electrodes and work piece materials seems to be vital.

To address this issue, Taguchi's design of experiment is used to study the effect of various process parameters on angular error, surface roughness and cutting speed during taper cutting of deep cryo-treated Inconel 718 with deep cryo-treated coated Bronco cut-W wire. Analysis of variance (ANOVA) is employed to find out the significance of the process parameters. However, the traditional Taguchi method cannot optimize multiple performance characteristics simultaneously. To overcome this limitation, a new approach known as maximum deviation theory is applied to convert multiple performance characteristics into an equivalent single performance characteristic. Traditional approaches hardly develop good functional relationship between process parameters and performance characteristics when the process behaves in a non-linear manner and involves large number of interacting parameters. To

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overcome this limitation, the relationship between process parameters and performance characteristics is developed through a back propagation neural network (BPNN) model. In order to achieve faster convergence, Levenberg–Marquardt algorithm (LMA) has been used. Bayesian regularization is also adopted due to is generalization capability to minimize error using minimal weights and thus avoids cross-validation. Finally, the process model is optimized by a new meta-heuristic approach known as bat algorithm.

2. Literature review

Many studies have been attempted in the past to improve the performance characteristics of wire electrical discharge machining (WEDM) process viz., surface roughness, cutting speed, dimensional accuracy and material removal rate using various traditional, multi-criteria decision making and evolutionary algorithm methods. However, the full potential of the process is not completely explored because of the complex and stochastic nature of the process and involvement of large number of variables. Tosun et al. [5] have presented an investigation on the effect of machining parameters on kerf and material removal rate in WEDM operations and multi-objective optimization of parameters using simulated annealing. Kuriakose and Shunmugam [6] have developed a multiple regression model to represent the relationship between input and output variables and multi-objective optimization method based on a Non-Dominated Sorting Genetic Algorithm (NSGA). Mahapatra and Patnaik [7] have established the relationship between control factors and responses like material removal rate (MRR), surface finish (SF) and kerf by means of non-linear regression analysis resulting in valid mathematical models. Finally, genetic algorithm is employed to optimize the WEDM process with multiple objectives. Sadeghi et al. [8] have applied Tabu search algorithm for optimization of material removal rate and surface roughness (SR) during wire electrical discharge machining process. Khan et al. [9] have used grey relational analysis for simultaneous optimization of surface roughness and micro hardness of the machined component of WEDM process. Jangra et al. [10] have also applied grey relational analysis with Taguchi method for simultaneous optimization of material removal rate and surface roughness in WEDM process for WC-Co composite. Mukherjee et al. [11] have applied six different non-traditional optimization algorithms such as genetic algorithm, particle swarm optimization, sheep flock algorithm, ant colony optimization, artificial bee colony and biogeography based optimization for single and multi-objective optimization of WEDM process.

Cryogenic processing of tool and work piece is also one of the major research issues for the significant improvement of machining performance of the electrical discharge machining (EDM) and WEDM process. In this direction, Kumar et al. [12] have investigated the machinability of Inconel 718 work material with ceramic powder mixed in dielectric fluid using cryogenically treated copper electrode in electrical discharge machining. Kapoor et al. [1] have investigated the effect of deep cryogenic treated brass wire electrode using Taguchi experimental design. From the analysis of variance, it is observed that wire type, pulse width, time between two pulses and wire tension are important parameters for improving material removal rate. Gill and Singh [13] have investigated the effect of deep cryogenic treatment of copper electrode on machinability of Ti 6246 alloy in electric discharge drilling. The study confirms that improved material removal rate, wear ratio (WR), tool wear rate (TWR) and precise drilled holes can be achieved with cryogenic treatment. However, most of the research works have focused on vertical cutting by WEDM. In today's manufacturing scenario, precision and die manufacturing not only requires productivity, tolerances and dimensional accuracy but also demands complicated profiles with inclined or curved surfaces. Hence, tapering process is one of the most important applications of WEDM process. The taper cutting using WEDM is first proposed by Kinoshita et al. in 1987 [14]. They have developed a linear model for wire deformation neglecting the forces produced during the process. Plaza et al. [3] have developed two models for the prediction of angular error in WEDM taper cutting and found that part thickness and taper angle are the most influencing variables. Sanchez et al. [4] have presented a numerical and empirical approach for the prediction of angular error in WEDM taper cutting. A simulation approach is adopted by Sanchez et al. [15] for analysis of angular error in wire-EDM taper cutting and verified by experimentation. Chiu et al. [16] have carried out an on-line adjustment of the axial force imposed by the machine on the wire in taper cutting. Huse and Su [17] have developed a theoretical model and concept of inclined discharge angle for material removal analysis of WEDM's tapering process and proposed a strategy including control of discharge power and wire tension for improving efficiency of the process. Kinoshita [18] has also proposed different methods to compensate the angular error in the taper cutting. However, limited studies deal with the taper cutting operation in WEDM, with least attention paid to optimize the process parameters of WEDM. The application of both cryogenic treated wire electrode and work piece is not adequately addressed in the literature. Therefore, the present study attempts to study the effect of input parameters on various performance measures using deep cryo-treated wire electrode and work piece Inconel 718 during taper cutting operation in WEDM process. Then, the process model is developed using artificial neural network model which is optimized by a recent meta-heuristic approach called bat algorithm.

3. Proposed methodology

The present work proposes an integrated approach for prediction and optimization of process parameters of WEDM process for cryo-treated wire electrode and work piece materials during taper cutting operation.

3.1. Maximum deviation theory

In the past, several multi-attribute decision making method approaches such as simple additive weight (SAW), weighted product method (WPM), technique for order of preference by similarity to ideal solution (TOPSIS), analytic hierarchy process (AHP), preference ranking organization method for enrichment of evaluations (PROMETHEE), desirability function have been adopted in converting multiple performance characteristics into a single equivalent characteristic [19–22]. However, weight assignment to various performance characteristics is quite subjective and arbitrary in nature. It severely affects the ranking of the alternatives. To avoid the embedded uncertainty and subjective assignment of weights by the experts, it is prudent to extract the accurate information from the available data. Maximum deviation theory, proposed by Wang [23], can address the issue quite effectively. The computational steps of maximum deviation theory are outlined below to compute the weight of each performance characteristic and finally composite score, which is maximized, is calculated for each alternative [24].

3.1.1. Step 1: Normalization of the evaluation matrix

The normalization process is needed to transform different scales and units among various attributes into common measurable units to allow the comparisons of different attributes. The decision matrix $[x_{ij}]$ is obtained from experimental data by treating the number of experiments as alternatives and performance characteristics as the attributes. Each element of the decision matrix $[x_{ij}]$ represents the value of j^{th} attribute of i^{th} alternative, where $i = 1, 2 \ldots\ldots n$ and $j = 1, 2 \ldots\ldots m$. To normalize the evaluation matrix, the following equations are used.

$$x_{ij} = \frac{\max\{x_{ij}\} - x_{ij}}{\max\{x_{ij}\} - \min\{x_{ij}\}} \quad \text{For non-beneficial attributes} \tag{1}$$

$$x_{ij} = \frac{x_{ij} - \min\{x_{ij}\}}{\max\{x_{ij}\} - \min\{x_{ij}\}} \quad \text{For beneficial attributes} \tag{2}$$

3.1.2. Step 2: Weights determination through maximum deviation method

In the present work, maximum deviation method is considered to compute the differences of performance values of each alternative. For the attribute $\{A_j | j = 1, 2, \ldots\ldots, m\}$, the deviation value of the alternative $\{S_i | i = 1, 2, \ldots\ldots n\}$ from all the other alternatives can be computed as follows

$$D_{ij}(w_j) = \sum_{l=1}^{N} d(\tilde{r}_{ij}, \tilde{r}_{lj}) w_j \tag{3}$$

Then, the total deviation values of all alternatives with respect to other alternatives for the attribute $\{A_j | j = 1, 2, \ldots\ldots, m\}$, can be defined

$$D_j(w_j) = \sum_{j=1}^{M} D_{ij}(w_j) = \sum_{i=1}^{N} \sum_{l=1}^{N} d(\tilde{r}_{ij}, \tilde{r}_{lj}) w_j \tag{4}$$

The deviation of all the attributes along all the alternatives can be represented as

$$D(w_j) = \sum_{j=1}^{M} D_j(w_j) = \sum_{j=1}^{M} \sum_{i=1}^{N} \sum_{l=1}^{N} d(\tilde{r}_{ij}, \tilde{r}_{lj}) w_j \tag{5}$$

Based on the above analysis, we have to choose the weight vector w to maximize all deviation values for all the attributes, for which we can construct a linear model as follows

$$\begin{cases} D(w_j) = \sum_{j=1}^{M} \sum_{i=1}^{N} \sum_{l=1}^{N} d(\tilde{r}_{ij}, \tilde{r}_{lj}) w_j \\ s.t \sum_{j=1}^{M} w_j^2 = 1, w_j \geq 0, j = 1, 2, \ldots\ldots, M \end{cases} \tag{6}$$

To solve the above model, we construct the Lagrange function:

$$L(w_j, \lambda) = \sum_{j=1}^{M} \sum_{i=1}^{N} \sum_{l=1}^{N} d(\tilde{r}_{ij}, \tilde{r}_{lj}) w_j + \lambda \left(\sum_{j=1}^{M} w_j^2 - 1 \right) \tag{7}$$

where λ is the Lagrange multiplier. The partial derivative of $L(w_j, \lambda)$ with respect to w_j and λ are:

$$\begin{cases} \frac{\partial L}{\partial w_j} = \sum_{i=1}^{N} \sum_{l=1}^{N} d(\tilde{r}_{ij}, \tilde{r}_{lj}) w_j + 2\lambda w_j = 0 \\ \frac{\partial L}{\partial \lambda} = \sum_{j=1}^{M} w_j^2 - 1 = 0 \end{cases} \tag{8}$$

Thus from Eq. (8) and (9) w_j and λ can be determined as

$$\begin{cases} 2\lambda = \sqrt{\sum_{j=1}^{M} \left(\sum_{i=1}^{N} \sum_{l=1}^{N} d(\tilde{r}_{ij}, \tilde{r}_{lj}) \right)^2} \\ w_j = \frac{\sum_{i=1}^{N} \sum_{l=1}^{N} d(\tilde{r}_{ij}, \tilde{r}_{lj})}{\sqrt{\sum_{j=1}^{M} \left(\sum_{i=1}^{N} \sum_{l=1}^{N} d(\tilde{r}_{ij}, \tilde{r}_{lj}) \right)^2}} \end{cases} \tag{9}$$

Further, the normalized attribute weights from the above can be determined as follows:

$$w_j = \frac{\sum_{i=1}^{N} \sum_{l=1}^{N} d(\tilde{r}_{ij}, \tilde{r}_{lj})}{\sum_{j=1}^{M} \sum_{i=1}^{N} \sum_{l=1}^{N} d(\tilde{r}_{ij}, \tilde{r}_{lj})} \tag{10}$$

3.1.3. Step-3: Calculation of composite score

The weighted normalized objective values are calculated by multiplying the normalized objective values and the objective weights. The composite score is then obtained by summing all the weighted objective function values for each alternative which is treated as the equivalent single performance characteristic for optimization.

3.2. A hybrid optimization approach using neural network and bat algorithm

In the present work, for multiple performance characteristics optimization, a hybrid approach using artificial neural network associated with bat algorithm is implemented for obtaining the optimum machining parameter setting during taper cutting in WEDM process. The methodology details are explained in the flow chart as shown in Fig. 1. An artificial neural network (ANN) is a highly flexible modeling tool with the ability to learn the mapping between inputs and outputs. Hence, in the present work the fitness function for the proposed algorithm is developed using the weights and biases obtained from the ANN model. A back propagation neural network (BPNN) architecture consisting of three layers such as input layer, hidden layer and output layer is commonly considered for developing functional relationship between input–output processes. Functioning of neural network proceeds in two stages viz., learning or training and testing or inferences. The network architecture is represented as l-m-n where l neurons are present at input layer (equal to the number of inputs in the models), m neurons at the hidden layer (optimized through experimentation) and n neurons at the output layer depending on number of outputs desired from the model. The input layer receives information from the external sources and passes this information to the network for processing. The hidden layer receives information from the input layer, does all the information processing, the output layer receives processed information from the network and sends the results out to an external receptor. In order to achieve faster convergence, Levenberg–Marquardt Algorithm (LMA) is applied in the present work. LMA is a suitable approach for non-linear optimization and significantly performs better than gradient decent, conjugate gradient methods and quasi-Newton algorithms for medium sized problems [25]. Bayesian regularization is used to provide better generalization performance and avoid over fitting.

The proposed Levenberg–Marquardt algorithm (LMA) with Bayesian regularization [26] is given as:

1. Compute the Jacobian (by finite differences or using the chain rule)
2. Compute the error gradient, $g = J^t e$
3. Approximate the Hessian using the cross product Jacobian, $H = J^t J$
   where H is the Hessian matrix, J is the Jacobian matrix that contains first derivatives of the network errors with respect to the weights and biases. e is a vector of network errors
4. Calculate the fitness function, $F = \beta^* E_d + \alpha^* E_w$, where E_d is the sum of squared errors and E_w is the sum of squared weights. α and β are the objective function parameters.
5. Solve $(H + \lambda I)\ \delta = g$ to find δ
6. Update the network weights w using δ
7. Recalculate the fitness function using the updated weights
8. If the fitness function has not decreased, discard the new weights, increase λ using v and go to step 5
9. Else decrease λ using v
10. Update the Bayesian hyper parameters using Mackay's or Poland's formulae

$$\mathrm{Y} = \mathrm{W} - (\alpha * \mathrm{tr}(\mathrm{H}^{-1}))$$

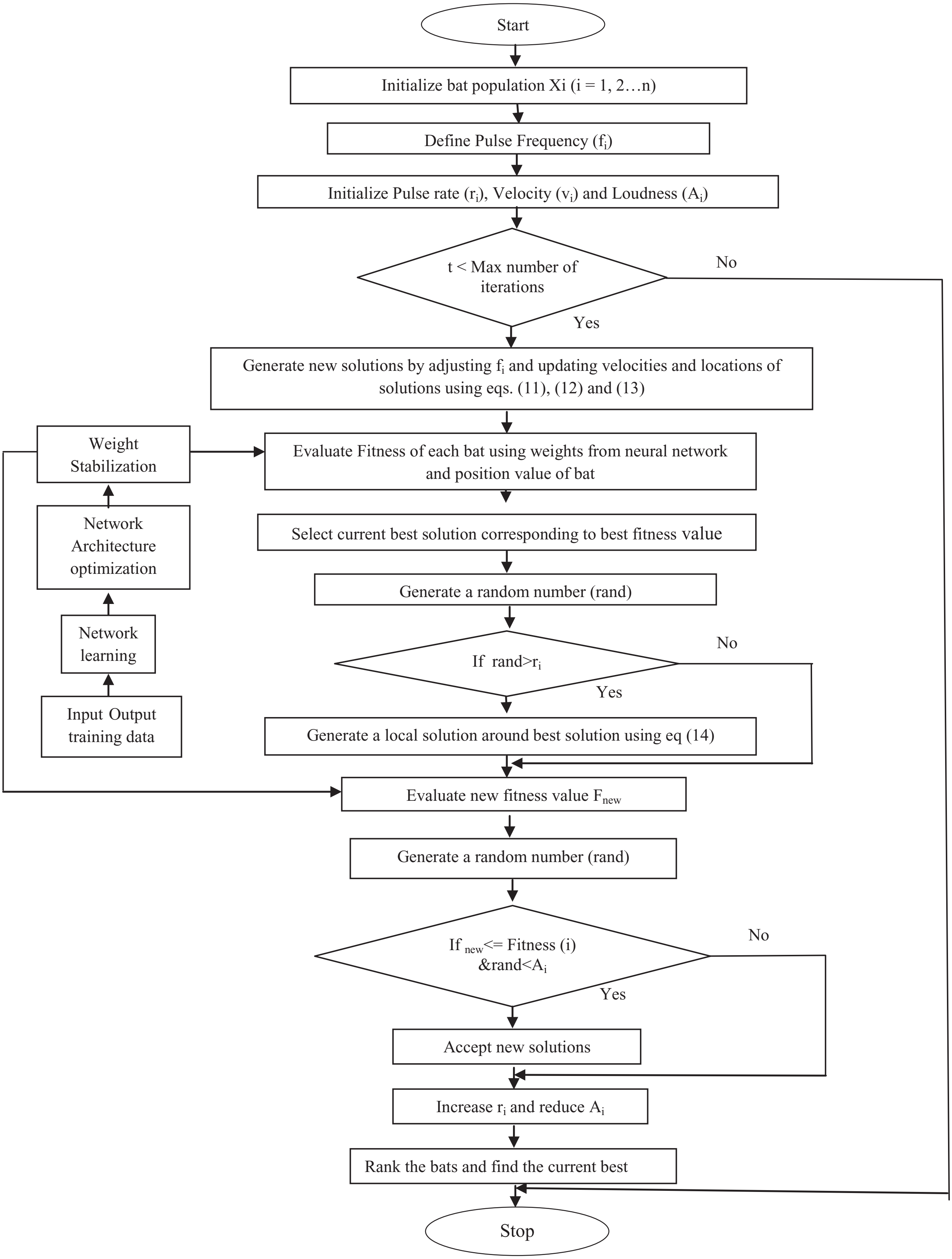

Fig. 1. Flow chart for proposed hybrid optimization bat algorithm with neural network.

$$\beta = (N - y)/2.0 * E_d$$

$$\alpha = W/(2.0 * E_W + tr(H^{-1}))$$

where W is the number of network parameters (number of weights and biases)

N is the number of entries in the training set
Y is the number of effective parameters
$tr(H^{-1})$ is the trace of the inverse Hessian matrix

Most real world design optimization problems are highly nonlinear and involve various design variables under complex constraints. Modern meta-heuristic algorithms have been developed to carry out global search with the purpose of solving large complex problems faster and obtain robust solutions. Intensification and diversification are two major characteristics of meta-heuristic algorithms. Intensification, also called exploitation, searches around the current best solutions and selects the best candidates. Diversification, also called exploration, allows the optimizer to explore the search space more efficiently, mostly by means of randomization [27]. To cope with the above issues, several meta-heuristic algorithms have been proposed by several researchers for global optimization such as genetic algorithm (GA), particle swarm optimization (PSO), simulated annealing (SA), harmony search (HS) and firefly algorithm (FA) [28–32]. In this paper, a new efficient meta-heuristic method like bat algorithm (BA) is used. BA is a bio-inspired algorithm based on the echolocation or bio-sonar characteristics of microbats, developed by X. S. Yang in 2010 [27]. Bats have a mechanism called echolocation which guides them to detect prey and avoid obstacles. In echolocation, each pulse only lasts a few thousandths of a second (up to about 8–10 ms). However, it has a constant frequency which is usually in the region of 25–150 kHz corresponding to the wavelengths of 2–14 mm. These bats emit very loud sound and listen for the echo that bounces back from the surrounding objects [33]. Thus, a bat can compute how far they are from an object and easily distinguish the difference between an obstacle and a prey even in complete darkness. Yang [27] has developed three generalized rules for bat algorithms to transform the behaviour of bats into algorithms as follows:

1) All bats use echolocation to sense distance and they also guess the difference between food/prey and background barriers in some magical way.
2) Bats fly randomly with velocity v_i at position x_i with a fixed frequency $f_{\min}$, varying wavelength λ and loudness A_0 to search for prey. They can automatically adjust the wavelength (or frequency) of their emitted pulses and adjust the rate of pulse emission $r \in [0,1]$ depending on the proximity of their target.
3) Although the loudness can vary in many ways, we assume that the loudness varies from a large (positive) A_0 to a minimum constant value $A_{\min}$.

The basic steps of BA can be explained as the algorithm shown in Fig. 1. For each bat (i), its position x_i and velocity v_i in a d-dimensional search space should be defined. x_i and v_i should be subsequently updated during the iterations. The new solutions x_i^t and velocities v_i^t at time step t can be calculated by

$$f_i = f_{\min} + (f_{\max} - f_{\min})\beta \tag{11}$$

$$v_i^t = v_i^{t-1} + (x_i^{t-1} - x^*) f_i \tag{12}$$

$$x_i^t = x_i^{t-1} + v_i^t \tag{13}$$

where β in the range of [0, 1] is a random vector drawn from a uniform distribution. Here, x^* is the current global best location (solution), which is located after comparing all the solutions among all the n bats. As the product $\lambda_i f_i$ is the velocity increment, either f_i (or λ_i) can be used to adjust the velocity change while fixing the other factor λ_i (or f_i), depends on the domain of the problem of interest. $f_{\min} = 0$ and $f_{\max} = 1$ are used in the experimentation, depending on the domain size of the problem of interest. Initially, each bat is randomly assigned a frequency, which is taken uniformly from $[f_{\min}, f_{\max}]$. In the local search, once a solution is selected among the current best solutions, a new solution for each bat is generated locally by using a local random walk which is defined as

$$x_{new} = x_{old} + \varepsilon A_t \tag{14}$$

where ε is a random number drawn between [−1, 1] and $A_t = \langle A_t \rangle$ is the average loudness of all the bats at this time step. After that the loudness A_i and the rate of pulse emission r_i is also updated accordingly as the iterations proceed. Once a bat found its prey, the loudness usually decreases, while the rate of pulse emission increases and the loudness can be chosen as any value of convenience. $A_0 = 1$ and $A_{\min} = 0$ can be used for simplicity. Assuming $A_{\min} = 0$ means that a bat has just found the prey and temporarily stops emitting any sound we have,

$$A_i^{t+1} = \alpha A_i^t,\ r_i^{t+1} = [1 - exp(-\gamma t)] \tag{15}$$

where α and γ are constants. The parameter α has a similar effect as the cooling factor in simulated annealing algorithm that controls the convergence rate of this algorithm. For any $0 < \alpha < 1$, $0 < \gamma$, we have $A_i^t \to 0$, $r_i^t \to r_i^0$ as $t \to \infty$. Hence, fine tuning of the parameters α and γ can affect the convergence rate of the bat algorithm.

4. Experimentation

The experiments were performed on AC Progress V2 high precision CNC WEDM, which is manufactured by Agie-Charmilles Technologies Corporation. The material selected for carrying out the experiments is cryo-treated Inconel 718 of diameter 25 mm and thickness of 20 mm, 30 mm and 40 mm respectively and cryo-treated coated Bronco cut-W (by Bedra), diameter 0.2 mm, has been used as the wire electrode. The cryogenic treatment was executed under dry condition where the work piece being treated was not exposed to the liquid nitrogen to eliminate the risk and damage of thermal shock. Initially the coated Bronco cut-W wire electrode of diameter 0.2 mm and Inconel 718 work piece of diameter 25 mm with three different thicknesses of 20 mm, 30 mm and 40 mm respectively was placed in the cryogenic chamber Kryo560-16. The cryogenic chamber is coupled with a liquid nitrogen tank through an insulated tubular pipe. Liquid nitrogen passes through the tubular pipe and enters into the cryogenic chamber in gaseous state. The flow of liquid nitrogen is controlled by a solenoid valve. First, both wire electrode and work piece material are placed inside the cryogenic chamber and the temperature was slowly reduced to −196 °C by computerized programmable controller at the rate of 1 °C/min. The temperature was held constant for twenty four hours at a temperature of −196 °C. Then, it was slowly brought to room temperature and then two tempering cycles were performed to both coated Bronco cut-W wire and Inconel 718 work piece to relieve the stresses induced by cryogenic treatment. The temperature was increased to +196 °C/min at the rate of 1 °C/min.

The input parameters and their levels were chosen based on the review of literature, experience, significance and their relevance as per some preliminary investigations [2,3]. Plaza et al. [3] suggested that part thickness and taper angle are the most influencing variables in WEDM taper cutting. Hence, in the present work part

Table 1
Input parameters with their levels.

Input variables	Unit	Symbol	Levels		
			Level I	Level II	Level III
Part thickness	mm	A	20	30	40
Taper angle	Degree	B	5	6	7
Pulse duration	µs	C	24	28	32
Discharge current	Amp	D	14	16	18
Wire speed	mm/s	E	90	120	150
Wire tension	N	F	12	14	16

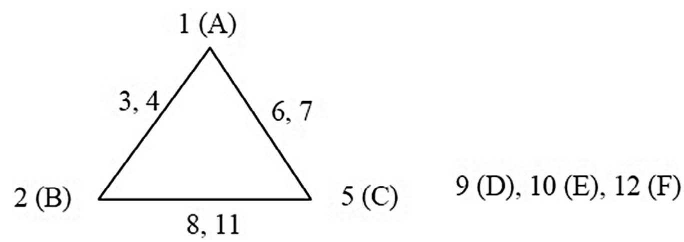

Fig. 3. Linear graph.

thickness, taper angle, pulse duration, discharge current, wire speed and wire tension are considered as the input parameters. Their limits as shown in Table 1 are set on the basis of capacity and limiting conditions of the WEDM ensuring continuous cutting by avoiding the breakage of the wire.

As discussed on the previous sections, angular error (AE), surface roughness (SR) and cutting speed (CS) are considered the three important output performance measures for optimizing machining parameters of WEDM taper cutting process. The surface roughness value (in µm) has been obtained by measuring the mean absolute deviation, Ra (surface roughness) from the average surface level using SURFCOM 130A. The angular error can be expressed in minute and calculated by the following formula:

$$\text{Angular error} = \theta - \phi$$

where θ is the programmed angle or the angle expected in the machined part.

Φ is the actual angle obtained in the machined part due to the wire deformation.

After machining, the angle of the inclined surface (ϕ) is measured with respect to the top surfaces using a Zeiss 850 CNC coordinate measuring machine. The geometry of the test part is shown in Fig. 2.

For WEDM cutting rate is also a desirable characteristic and it should be as high as possible to give least machine cycle time leading to increased productivity. In the present study, cutting rate is a measure of job cutting which is digitally displayed on the screen of the machine and is given in mm/min.

To evaluate the effects of machining parameters on performance characteristics and identify the performance characteristics under the optimal machining parameters, a special designed experimental procedure is required. In this study, the Taguchi method, a powerful tool for experimental design was used to determine optimal machining parameters during taper cutting operation in WEDM process. It is planned to study the behaviour of six control factors viz., A, B, C, D, E, and F and three interactions viz., A × B, A × C and B × C based on past experience. The standard linear graph as shown in Fig. 3 is used to assign the factors and interactions to various columns of the orthogonal array [34,35]. The experimental architecture and the values of each performance characteristics are shown in Table 2.

5. Results and discussions

The experiments are conducted as per Taguchi's L_{27} orthogonal array as described above considering cryo-treated Inconel 718 as the work piece material with cryo-treated coated Bronco cut-W wire electrode. Experimental results as shown in Table 2 are analysed to determine the influence of various process parameters on angular error, surface roughness and cutting speed by using the popular statistical software package MINITAB 16. Analysis of the results presented in Fig. 4 leads to the conclusion that the third level of part thickness (A_3), first level of taper angle (B_1), third level of pulse duration (C_3), first level of discharge current (D_1), second level of wire speed (E_2) and first level of wire tension (F_1) provide the minimum value of angular error. From Fig. 4, it is evident that increase of part thickness causes decrease in angular error because a longer length of the wire electrode in a thicker work piece provides more opportunities for the spark to occur and enough space for movement in U–V axes using upper guide and lower guide. Analysis of variance (ANOVA) is carried out to investigate the significance of each parameter and their interaction in relation to angular error. From Table 3, it is evident that part thickness, taper angle, pulse duration, discharge current and wire tension are the significant parameters for angular error during tapering process in WEDM at significance level of 0.05.

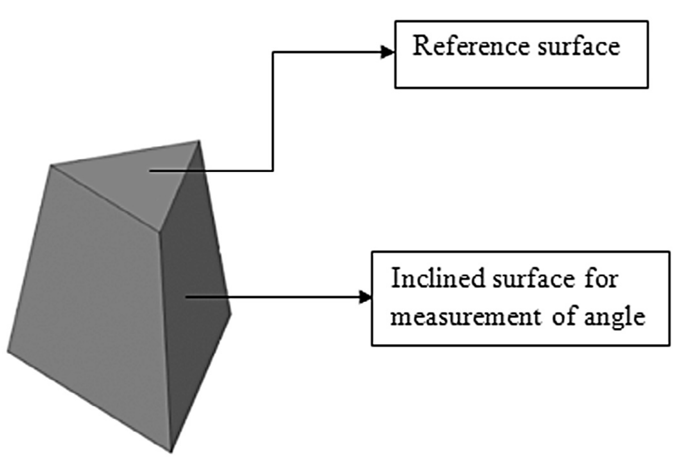

Fig. 2. Geometry of the test part for measuring angular error in WEDM experiments.

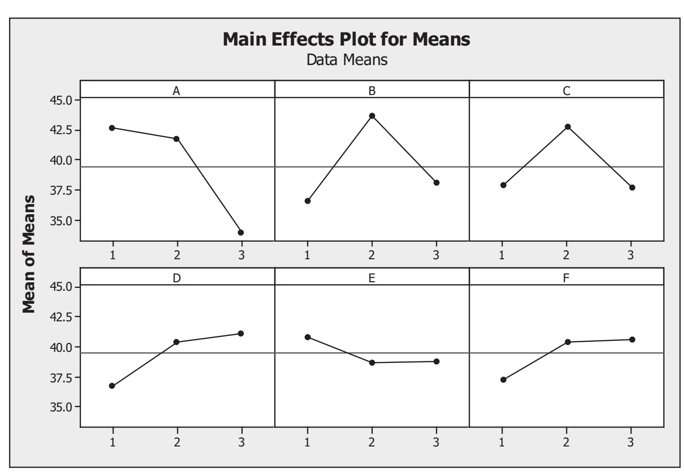

Fig. 4. Effect of control parameters on angular error.

Table 2
Experimental result of performance characteristics using L_{27} Orthogonal array.

Exp. No.	A	B	C	D	E	F	Angular error (minute)	Surface roughness (μm)	Cutting speed (mm/min)	Composite score
1	1	1	1	1	1	1	30.221	2.245	0.926	0.5963
2	1	1	2	2	2	2	37.447	2.198	1.003	0.5579
3	1	1	3	3	3	3	39.119	2.742	1.745	0.7046
4	1	2	1	2	2	3	41.546	2.884	0.928	0.3393
5	1	2	2	3	3	1	42.485	2.893	1.015	0.3602
6	1	2	3	1	1	2	45.824	2.998	1.129	0.3451
7	1	3	1	3	3	2	46.616	3.112	0.975	0.2541
8	1	3	2	1	1	3	48.847	2.661	0.996	0.3342
9	1	3	3	2	2	1	52.145	2.995	1.345	0.3596
10	2	1	1	2	3	2	50.255	2.715	0.968	0.297
11	2	1	2	3	1	3	58.654	2.871	0.971	0.1748
12	2	1	3	1	2	1	33.526	2.994	0.997	0.428
13	2	2	1	3	1	1	50.398	3.115	0.932	0.1966
14	2	2	2	1	2	2	53.254	2.996	0.981	0.2099
15	2	2	3	2	3	3	44.658	3.112	1.422	0.4441
16	2	3	1	1	2	3	25.257	2.783	0.943	0.5412
17	2	3	2	2	3	1	32.542	2.845	1.135	0.5225
18	2	3	3	3	1	2	27.568	3.556	1.129	0.4155
19	3	1	1	3	2	3	28.356	2.553	1.018	0.5854
20	3	1	2	1	3	1	24.736	2.114	1.185	0.781
21	3	1	3	2	1	2	26.845	2.221	1.213	0.7461
22	3	2	1	1	3	2	34.628	2.229	0.992	0.5774
23	3	2	2	2	1	3	45.265	2.415	1.125	0.4739
24	3	2	3	3	2	1	35.548	2.648	1.553	0.6903
25	3	3	1	2	1	1	33.667	2.754	0.895	0.439
26	3	3	2	3	2	2	41.529	2.889	1.258	0.4632
27	3	3	3	1	3	3	34.289	2.665	1.764	0.78

Similarly, the optimum parameter setting for minimum surface roughness is presented through the mean effect plot as shown in Fig. 5. It leads to the conclusion that the third level of part thickness (A_3), first level of taper angle (B_1), first level of pulse duration (C_1), first level of discharge current (D_1), first level of wire speed (E_1) and third level of wire tension (F_3) provide the minimum value of surface roughness. ANOVA as shown in Table 4 shows that part thickness, taper angle and pulse duration are the significant characteristics for surface roughness during tapering process of WEDM. Analysis of the result shown in Fig. 5 reveals that surface roughness initially increases with increase of thickness of work piece then decreases. However, increase of pulse duration and discharge current causes an increase in surface roughness because more discharge energy is inputted per pulse.

Table 3
ANOVA for angular error.

Factor	DF	Seq SS	Adj SS	Adj MS	F	P
Part thickness (A)	2	423.89	423.89	211.943	45.23	0.000
Taper angle (B)	2	257.27	257.27	128.634	27.45	0.001
Pulse duration (C)	2	146.97	146.97	73.484	15.68	0.004
Discharge current (D)	2	101.92	101.92	50.960	10.88	0.010
Wire speed (E)	2	24.89	24.89	12.446	2.66	0.149
Wire tension (F)	2	65.61	65.61	32.807	7.00	0.027
A × B	4	1068.94	1068.94	267.234	57.03	0.000
A × C	4	210.41	210.41	52.604	11.23	0.006
Error	6	28.11	28.11	4.686		
Total	26	2328.02				

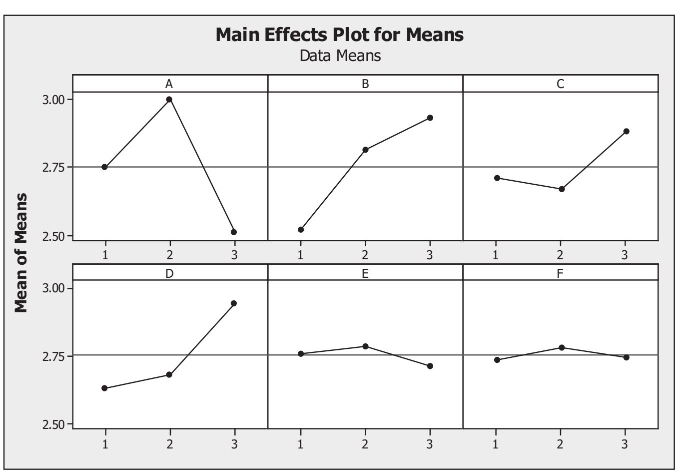

Fig. 5. Effect of control parameters on surface roughness.

Similarly, the optimum parameter setting for maximum cutting speed is presented through the mean effect plot as shown in Fig. 6. It leads to the conclusion that the third level of part thickness (A_3), first level of taper angle (B_1), third level of pulse duration (C_1), third level of discharge current (D_1), third level of wire speed (E_1) and third level of wire tension (F_3) provide the maximum value of cutting speed. ANOVA as shown in Table 5 shows that part thickness, taper angle and pulse duration are the significant characteristics for cutting speed during tapering process of WEDM.

Traditional Taguchi method can optimize a single objective function, it cannot solve multi-objective optimization problem. In the present work, all the three responses angular error (AE), surface roughness (SR) and cutting speed (CS) can be optimized individually using Taguchi technique. It may so happen that the optimal

Table 4
ANOVA for surface roughness.

Factor	DF	Seq SS	Adj SS	Adj MS	F	P
Part thickness (A)	2	1.12451	1.12451	0.56226	53.67	0.000
Taper angle (B)	2	0.77426	0.77426	0.38714	36.95	0.000
Pulse duration (C)	2	0.25301	0.25301	0.12651	12.07	0.008
Discharge current (D)	2	0.46227	0.46227	0.23117	22.06	0.002
Wire speed (E)	2	0.01634	0.01634	0.00817	0.78	0.500
Wire tension (F)	2	0.00576	0.00576	0.00288	0.28	0.769
A × B	4	0.22859	0.22859	0.05714	5.45	0.034
A × C	4	0.13472	0.13472	0.03368	3.21	0.098
Error	6	0.06286	0.06286	0.01047		
Total	26	3.06233				

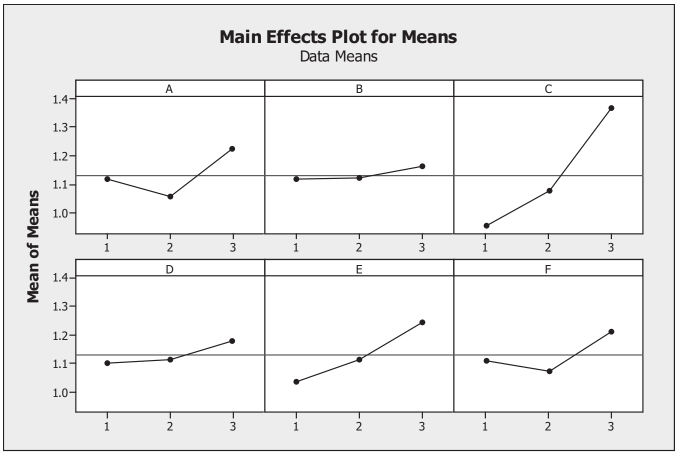

Fig. 6. Effect of control parameters on cutting speed.

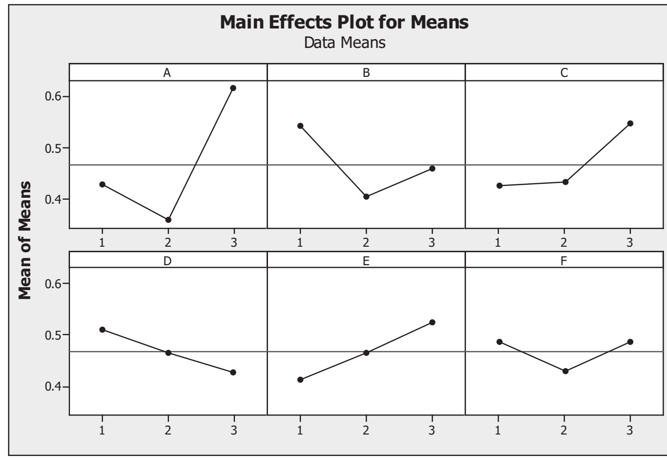

Fig. 7. Effect of control parameters on composite score.

setting for a performance characteristic cannot ensure other performance characteristics within acceptable limits. To overcome this problem in the present work, maximum deviation theory method is applied for converting multiple performance characteristics into a single equivalent performance characteristic. As discussed in section 3, the normalized objective values are calculated by using Eq. (1) for angular error and surface roughness since both the objectives are non-beneficial attributes whereas the normalized objective value for cutting speed can be calculated by using Eq. (2) since it is a beneficial attribute. The objective weights are determined for the normalized values of objectives by applying maximum deviation method using Eqs. (3–10). The weights obtained through the maximum deviation method are 0.363864, 0.307471 and 0.328664 for angular error, surface roughness and cutting speed respectively. The weighted normalized objective values are calculated by multiplying the normalized objective values and the objective weights. The composite score is obtained by summing all the weighted objective function values for each alternative which is treated as the equivalent single performance characteristic for optimization. The values of composite score are listed in Table 2. The effect of various process parameters is studied using Taguchi analysis through MINITAB 16 software package. Analysis of result as shown in Fig. 7 leads to the conclusion that the third level of part thickness (A_3), first level of taper angle (B_1), third level of pulse duration (C_3), first level of discharge current (D_1), third level of wire speed (E_3) and third level of wire tension (F_1) provide the maximum value of composite score.

Analysis of variance (ANOVA) is also carried out to investigate the significant effect of each parameter and their interaction in relation to composite score. From Table 6, it is evident that part thickness, taper angle, pulse duration, discharge current, wire speed, wire tension and the interaction of part thickness and taper angle and also interaction of part thickness and pulse duration are the significant parameters for composite score during tapering process of WEDM.

Taguchi method is quite capable of suggesting optimum parametric condition through factorial plots and developing functional relationship between the input parameters with the performance characteristics. However, the functional model in Taguchi method is mostly linear in nature. Therefore, complexity involved in the tapering operation of WEDM may not be fully captured in a linear model. Since ANN is quite capable of mapping inputs and outputs in complex situations efficiently, the optimum parametric condition defined through factorial plot is predicted through neural networks. The back propagation neural network (BPNN) has been developed using the experimental data set as shown in Table 2. Out of 27 data, 75% of data (1–20) are selected as training data and 25% of the data (21–27) have been used to test the performance of the selected neural network. To determine the number of neurons in the hidden layer, various back propagation neural network (BPNN) models have been chosen to achieve performance error equal to 0.001. Five BPNN models 6-4-1, 6-5-1, 6-6-1, 6-7-1 and 6-8-1 have been selected. Finally, BPNN architecture 6-5-1 showed minimum root mean square error (RMSE). Learning and momentum parameters are set at 0.08 and 0.50. The number of epochs run was 1000. In spite of higher number of iterations to converge at a final value, low learning rate is used to ensure the neural network to escape from local optima. Using back propagation, initially assigned weights are repeatedly adjusted to minimize the error until the error achieves the target of 0.001. It can be observed that data are well fitted because a high degree of coefficient of determination (R^2) as 0.99875 for training data as shown in Fig. 8 is obtained. Hence, using the trained neural network model the predicted value of composite score for optimum set of input parameters ($A_3B_1C_3D_1E_3F_1$) is obtained as 0.7810.

Table 5
ANOVA for cutting speed.

Factor	DF	Seq SS	Adj SS	Adj MS	F	P
Part thickness (A)	2	0.13156	0.13156	0.06578	16.23	0.004
Taper angle (B)	2	0.01132	0.01132	0.00566	1.40	0.318
Pulse duration (C)	2	0.81249	0.81249	0.40624	100.24	0.000
Discharge current (D)	2	0.02952	0.02952	0.01475	3.64	0.092
Wire speed (E)	2	0.20141	0.20141	0.10070	24.85	0.001
Wire tension (F)	2	0.09529	0.09529	0.04764	11.76	0.008
A × B	4	0.11930	0.11930	0.02982	7.36	0.017
A × C	4	0.09785	0.09785	0.02446	6.04	0.027
Error	6	0.02432	0.02432	0.00405		
Total	26	1.52306				

Table 6
ANOVA for composite score.

Factor	DF	Seq SS	Adj SS	Adj MS	F	P
Part thickness (A)	2	0.3165	0.3165	0.1582	196.62	0.000
Taper angle (B)	2	0.0861	0.0861	0.0430	53.53	0.000
Pulse duration (C)	2	0.8361	0.8361	0.0418	51.93	0.000
Discharge current (D)	2	0.0312	0.0312	0.0156	19.39	0.002
Wire speed (E)	2	0.0556	0.0556	0.0278	34.55	0.001
Wire tension (F)	2	0.0192	0.0192	0.0096	11.94	0.008
A × B	4	0.1984	0.1984	0.0496	61.62	0.000
A × C	4	0.0021	0.0210	0.0052	6.52	0.022
Error	6	0.0048	0.0048	0.0008		
Total	26	0.8166				

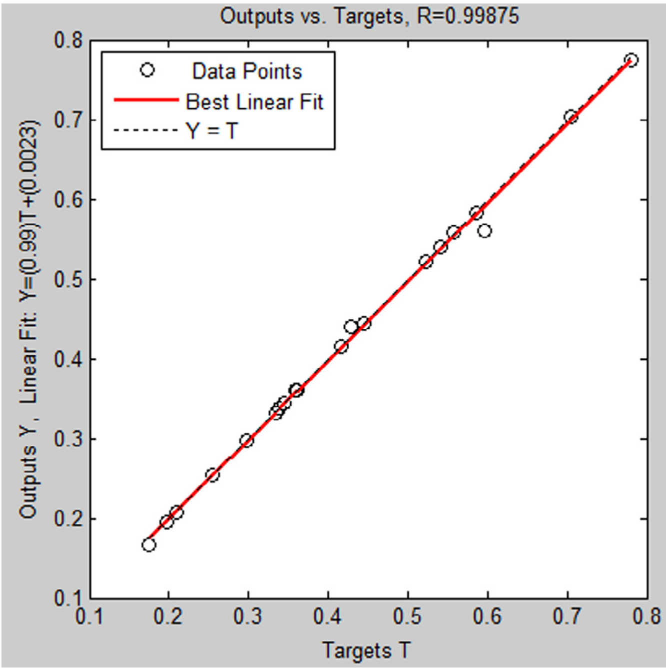

Fig. 8. Correlation plot for training data set.

Table 7
Comparison of optimum parameter setting for composite score.

Control factors and performance measures	Optimum machining condition by Taguchi method	Optimum machining condition by ANN-Bat algorithm
Part thickness (A)	40	30.3362 ≈ 30
Taper angle (B)	5	5.889 ≈ 6
Pulse duration (C)	32	30.5731 ≈ 31
Discharge current (D)	14	17.6253 ≈ 18
Wire speed(E)	120	135.571 ≈ 136
Wire tension (F)	12	12.337 ≈ 12
Composite score	0.7810	0.9857

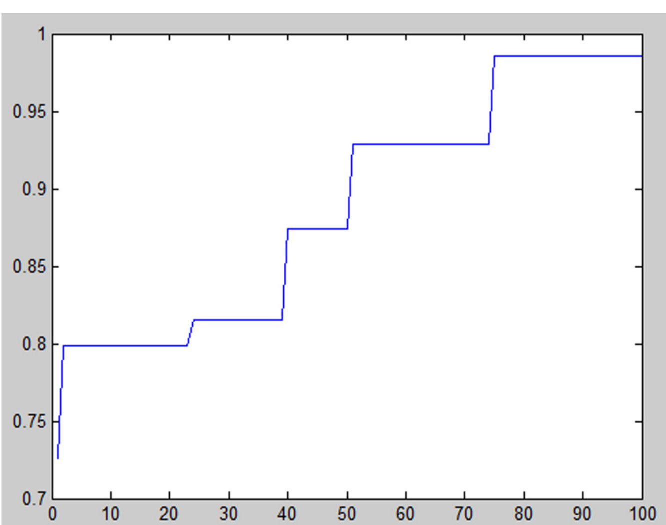

Fig. 9. Convergence plot.

In order to explore the optimization landscape to obtain best parametric setting, a new meta-heuristic approach like bat algorithm is used to obtain the best parametric combination of machining parameters. The well-trained neural network model is used as the fitness function for the process model. Finally, the developed model is optimized using bat algorithm. Bat algorithm is coded using MATLAB 13.0. The algorithm considers a bat size of 25, loudness constant 0.7, pulse rate 0.5 and maximum number of iterations 100. The other parameters are selected suitably to achieve the convergence. Finally, the maximum composite score and the statistical values of the best solution are obtained by bat algorithm as shown in Table 7. Fig. 9 illustrates that bat algorithm converges towards global optimum. Finally the result obtained from bat algorithm is compared as shown in Table 7 with the results of Taguchi's optimum setting for machining parameters to maximize composite score. Comparison of results reveals that composite score (0.9857) obtained from bat algorithm is superior than the predictive composite score value (0.7810) obtained from Taguchi analysis.

6. Conclusions

In this work, a hybrid approach is proposed for optimization of various machining parameters during taper cutting in WEDM process using deep cryo-treated coated Bronco cut-W wire electrode and Inconel 718 as the work piece material. The effect of input parameters on various performance characteristics such as angular error, surface roughness and cutting speed is also analysed individually after taper cutting operation in deep cryo-treated Inconel 718. In order to optimize, multiple performance characteristics simultaneously, maximum deviation theory is used to convert multiple performance characteristics into a single equivalent performance characteristic. As the process is a complex one, the functional relationship between the process parameters and performance characteristic during taper cutting process in WEDM process has been developed using BPNN. For faster training of ANN, Levenberg–Marquardt algorithm is used. The suggested process model can be used in any taper cutting operation for prediction of various performance characteristics before experimentation because a high degree of correlation is obtained. A latest evolutionary algorithm known as bat algorithm has been successfully used to predict the optimal parameter setting so as to produce the optimal result in the process. Although the approach is applied in taper cutting using WEDM, the approach is quite generic and can be applied in any complex machining situation for developing the process model.

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