Int J Adv Manuf Technol (2013) 67:2021–2032
DOI 10.1007/s00170-012-4628-8

ORIGINAL ARTICLE

Multi-objective optimization of material removal rate and surface roughness in wire electrical discharge turning

S. Aravind Krishnan · G. L. Samuel

Received: 5 August 2011 / Accepted: 5 November 2012 / Published online: 25 November 2012

Abstract Wire electrical discharge turning (WEDT) is an emerging area, and it can be used to generate cylindrical forms on difficult to machine materials by adding a rotary axes to WEDM. The selection of optimum cutting parameters in WEDT is an important step to achieve high productivity while making sure that there is no wire breakage. In the present work, the WEDT process is modelled using an artificial neural network with feed-forward back-propagation algorithm and using adaptive neuro-fuzzy inference system. The experiments were designed based on Taguchi design of experiments to train the neural network and to test its performance. The process is optimized considering the two output process parameters, material removal rate, and surface roughness, which are important for increasing the productivity and quality of the products. Since the output parameters are conflicting in nature, a multi-objective optimization method based on non-dominated sorting genetic algorithm-II is used to optimize the process. A pareto-optimal front leading to the set of optimal solutions for material removal rate and surface roughness is obtained using the proposed algorithms. The results are verified with experiments, and it is found to improve the performance of WEDT process. Using this set of solutions, required input parameters can be selected to achieve higher material removal rate and good surface finish.

Keywords Wire electro-discharge turning (WEDT) · Artificial neural network (ANN) · ANFIS · Multi-objective optimization · Genetic algorithm (GA) · Material removal rate (MRR) · Surface roughness

S. A. Krishnan · G. L. Samuel (✉)
Manufacturing Engineering Section, Department of Mechanical Engineering, Indian Institute of Technology Madras, Chennai 600 036, India
e-mail: samuelgl@iitm.ac.in

1 Introduction

Wire electrical discharge machining (WEDM) has become one of the most extensively used non-conventional material removal process. Its unique feature of using thermal energy to machine electrically conductive parts regardless of hardness has been its distinctive advantage. It is being extensively used in the aerospace, nuclear, and automotive industries to machine difficult-to-machine materials with intricate shapes. Material is removed using a numerically controlled travelling wire electrode by a series of discrete sparks between the work-piece and the wire electrode (tool) separated by a thin film of dielectric fluid. Wire electrical discharge turning (WEDT) is an emerging area, and it can be used for generating cylindrical forms on difficult-to-machine materials by adding a rotary axes to WEDM. The selection of optimum cutting parameters in WEDT is an important step for achieving required production rate and quality of the machined components.

Several researchers have studied the characteristics of the WEDT process considering various input and output parameters. Qu et al. [20, 21] mathematically modelled the material removal rate (MRR), and compared MRR for WEDM and WEDT. Mohammadi et al. [18, 19] developed a mathematical relation between machining parameters on MRR using regression analysis. Haddad and Tehrani [5, 6] and Matoorian et al. [17] developed a mathematical relation between the machining parameters and MRR using response surface methodology and observed that power, voltage, pulse off time, and rotational speed have much effect on MRR. Qu et al. [20, 21] developed a mathematical model for arithmetic average surface roughness in WEDT. Haddad and Tehrani [5, 6] modelled the surface roughness and roundness using response surface methodology for AISI D3 steel. Mohammadi et al. [18, 19] studied the variation in surface finish and roundness of the parts with machining parameters by developing a mathematical model using regression analysis. Janardhan and Samuel [9] used pulse train data analysis to study the effect of machining parameters on MRR, surface roughness, and roundness error.

The optimization and the selection of optimal machining parameters of the EDM and wire EDM processes have been carried out by various researchers. Tarng et al. [26] used a simple weighting method to transform the cutting velocity and surface roughness into a single objective and arrived at the optimal parameters for WEDM by simulated annealing. In another attempt, optimizing the process parameters for maximizing MRR taking surface roughness and spark gap as constraints was carried out by the feasible-direction non-linear programming method by Liao et al. [13]. Optimization of the EDM parameters, from the rough cutting to the finish cutting stage, has been done by Su et al. [25]. Spedding and Wang [24] arrived at the optimal combination of parameters for maximum cutting speed, keeping the surface roughness and waviness within the required limits, using the combination of artificial neural network (ANN) and time series techniques. Gao et al. [4] used ANN and GA together to establish the parameter optimization model for EDM. An ANN model which adapts Levenberg–Marquardt algorithm was set up to represent the relationship between MRR and input parameters, and GA was used to optimize the parameters.

Multi-objective optimization has been done extensively to optimize the WEDM and EDM process. Lin et al. [14] reported the use of the grey relational analysis based on an orthogonal array and fuzzy-based Taguchi method for optimizing the multi-response EDM process. Both the grey relational analysis method without using the signal-to-noise (S/N) ratio and fuzzy logic analysis are used in an orthogonal array table in carrying out experiments for solving the multiple responses in the EDM process. Experimental results showed that both approaches can optimize the machining parameters with considerations of the multiple responses effectively. Huang and Liao [7] applied grey relational analyses to determine the optimal selection of machining parameters for the WEDM process. Based on Taguchi quality design concept, an L-18 mixed-orthogonal array table was chosen for the experiments. Ramakrishnan and Karunamoorthy [22] studied a multi-response optimization method using Taguchi's robust design approach for WEDM operations. Experiments were planned as per Taguchi's L16 orthogonal array. Each experiment was performed under different cutting conditions of pulse on time, wire tension, delay time, wire feed speed, and ignition current intensity. The machining parameters were optimized with multi-response characteristics of the MRR, surface roughness, and wire wear ratio. Tzeng and Chen [27] applied fuzzy logic analysis coupled with Taguchi methods to optimize the precision and accuracy of the high-speed EDM process.

Wang et al. [28] used genetic algorithm (GA) with ANN to find out optimal process parameters for optimal performances. Two output parameters, MRR and surface roughness, were considered here to be optimized as a process performance. Mahapatra and Patnaik [15] employed a combination of the Taguchi method and GA to optimize MRR, surface finish, and kerf in WEDM. Using Taguchi's parameter design, significant machining parameters affecting the performance measures were identified. The relationship between control factors and responses like MRR, surface finish, and kerf were established

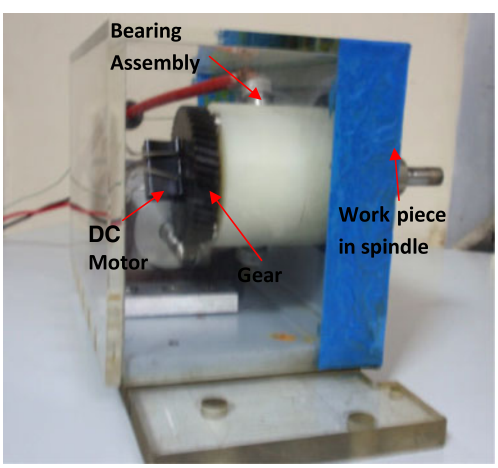


Fig. 1 Detailed view of rotary spindle

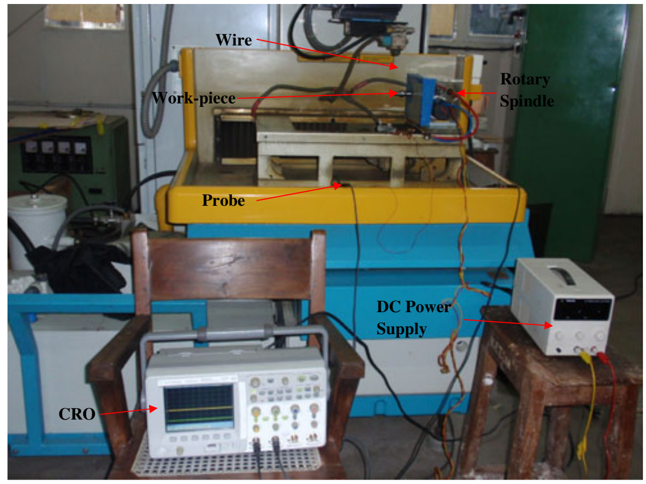


Fig. 2 Detailed view of experimental setup

Table 1 Machining parameter settings

Machining parameter	Parameter levels		
	Level 1	Level 2	Level 3
Pulse off time (μs)	30	35	42
Spark gap (μm)	30	50	80
Servo feed (level)	3	5	8
Flushing pressure (bar)	1.263	1.893	3.267
Rotational speed (rpm)	30	70	100

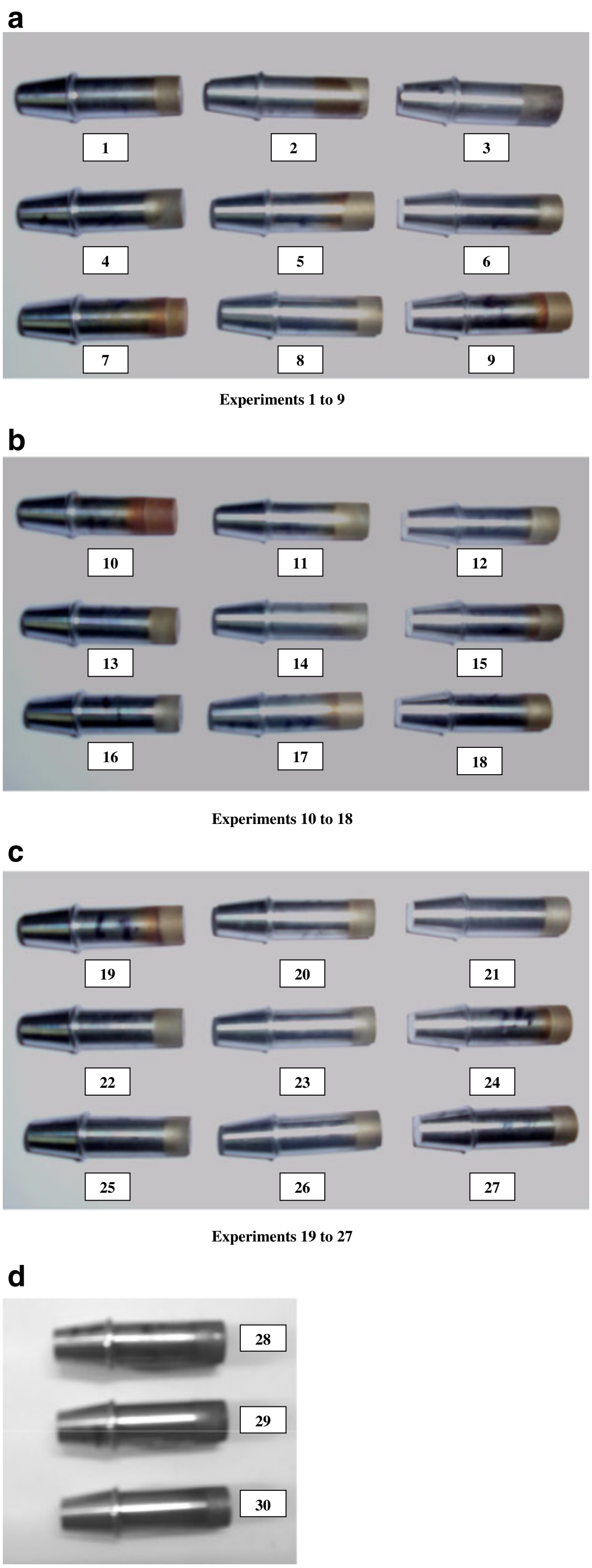
Table 2 Experimental results with various input parameters

Exp no	Pulse off-time (µs)	Spark gap (µm)	Servo feed	Rotational speed (rpm)	Flushing pressure (bar)	MRR (mm^3/min)	R_a (µm)
Training set							
1	30	30	3	30	3.267	1.24	2.396
2	30	50	5	70	3.267	2.21	3.756
3	30	80	8	100	3.267	2.60	4.134
4	34	30	5	100	3.267	1.73	3.172
5	34	50	8	30	3.267	3.78	5.009
6	34	80	3	70	3.267	1.45	2.827
7	42	30	8	70	3.267	1.50	2.899
8	42	50	3	100	3.267	0.95	2.116
9	42	80	5	30	3.267	1.68	3.133
10	30	30	3	30	1.893	1.16	2.311
11	30	50	5	70	1.893	2.20	3.539
12	30	80	8	100	1.893	2.47	4.003
13	34	30	5	100	1.893	1.40	2.694
14	34	50	8	30	1.893	3.72	4.897
15	34	80	3	70	1.893	1.37	2.502
16	42	30	8	70	1.893	1.46	2.895
17	42	50	3	100	1.893	0.82	2.069
18	42	80	5	30	1.893	1.65	3.124
19	30	30	3	30	1.263	1.10	2.264
20	30	50	5	70	1.263	1.48	2.860
21	30	80	8	100	1.263	2.22	3.794
22	34	30	5	100	1.263	1.34	2.506
23	34	50	8	30	1.263	3.20	4.576
24	34	80	3	70	1.263	1.35	2.520
25	42	30	8	70	1.263	1.37	2.588
26	42	50	3	100	1.263	0.78	2.048
27	42	80	5	30	1.263	1.54	2.987
Testing set							
28	30	50	8	70	3.267	2.80	4.281
29	34	80	5	50	1.893	1.44	2.744
30	42	50	3	50	1.263	0.98	2.149

by means of nonlinear regression analysis. Finally, GA was employed to optimize the WEDM process with multiple objectives.

Kuriakose and Shunmugam [12] adopted non-dominated sorting genetic algorithm (NSGA-II) to optimize machining parameters in WEDM considering surface roughness and cutting speed as the output parameters. Mandal et al. [16] used ANN to model the WEDM process and adopted NSGA-II to optimize the machining parameters considering the MRR and the tool wear rate as the output parameters. A pareto-optimal front of 100 optimized parametric sets was generated and reported. Yuan et al. [29] developed reliable multi-objective optimization based on Gaussian process regression to optimize the high-speed wire cut EDM process, considering mean current, on-time, and off-time as input features and MRR and surface roughness as output responses. NSGA-II was used to generate cluster class centres of Pareto front as the optimal solutions. Joshi and Pande [10] developed an intelligent approach for process modelling and optimization of EDM integrating finite element method, ANN, and NSGA-II for both roughing and finishing operations.

WEDT is a complex and stochastic process; it is very difficult to determine optimal parameters for best machining performance with high MRR and good surface finish. On the other hand, these performance parameters are conflicting in nature. Higher MRR is required to achieve high productivity, and lower surface roughness is required to achieve better surface quality. In WEDT process, it is difficult to find a single optimal combination of process parameters for the performance parameters, as the process parameters influence them differently. Hence, there is a need for a multi-objective optimization method to arrive at the solutions to



Experiments 1 to 9

Experiments 10 to 18

Experiments 19 to 27

Experiments 28 to 30

Fig. 3 Photograph of specimen machined using WEDT

this problem. Classical methods for solving multi-objective problem suffer from several drawbacks. These methods transform the multi-objective problem into single objective by assigning some weights based on their relative importance. GA is observed to be a good tool for solving multi-objective optimization in EDM process to determine the optimal solutions and to capture a number of solutions simultaneously. In the present work, a back-propagation feed-forward artificial neural network is used to model the WEDT process, and NSGA-II has been used to obtain the optimal combination of process parameters. MRR and surface roughness have been considered as output parameters for optimization.

2 Experimental details

The material selected for carrying out the experiments is AISI D3 (DIN X210Cr12) tool steel. The typical chemical composition of AISI D3 tool steel is 12 % chromium, 2.2 % carbon, 1 % vanadium, 0.25 % silicon, and 0.3 % manganese. The Brinell hardness of AISI D3 tool steel is about 212 to 248 HB. This material is a difficult to machine material and is finding increasing application for the manufacture of dies and moulds. The experiments were conducted on the ELECTRONICA ECOCUT CNC WIRE EDM. The diameter of the work-piece is 10 mm, and the depth of cut selected is 0.1 mm. Generally, the wire EDM is designed to cut various profiles in 2-D and 3-D components. However, by adding a precise rotary spindle, cylindrical work pieces can be turned using the wire EDM. Also, in wire EDM, the linear cutting speed of the machine is controlled by the servo mechanism. In order to maintain the constant spark gap between the wire and the workpiece, as soon as the material is removed by the spark, the work piece or the wire will be moved closer. In wire EDM, the wire will be continuously replenished so that the fresh electrode wire surface will be available for sparking. If the linear feed increases, and if sparks occur before the fresh wire is fed, the wire will break.

In the present work, a precise rotary spindle set-up developed by Janardhan and Samuel [8] is used to provide rotary motion to the workpiece. A straight shank ER11 collet adaptor was modified and used as the spindle shaft. The collet is locked with a nut. Electrical insulation to the bearings is achieved by press fitting two sleeves made of nylon into the spindle shaft, and stainless steel deep groove ball bearings are inserted over them. The housing is also made of nylon to provide electrical insulation to the bearings. Brass cylinder is inserted into the housing, to avoid damage of housing bore during the installation of bearings and to improve rotational accuracy. Housing is provided with threaded holes along its circumference for inserting carbon brush holder and brush contact with the spindle shaft is adjusted with a screw. The real model of the spindle after assembling all the individual components is shown in Fig. 1.

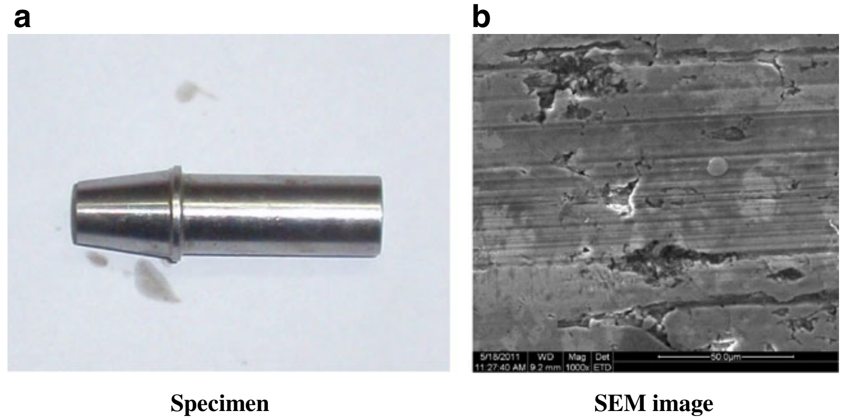


Fig. 4 Typical surface characteristics of specimen before machining

Both the spindle shaft and the motor shaft are connected by a worm gear made of plastic for insulation. The bearing assembly is fixed to the vertical face of the L-section. The motor is fixed to the base of the L-section. The total spindle is covered with a casing made of acrylic plates to protect from flushing.

Figure 2 shows the detailed picture of the setup used for conducting the experiments. The rotary spindle is mounted on the work table, and the wire moves longitudinally to the rotating work piece. The DC power supply powers the rotary spindle, and the rotational speed can be varied by varying the voltage input from the DC power supply.

WEDT involves higher operating and maintenance cost, hence the minimum number of experiments was planned according to Taguchi fractional factorial design. The process parameters which can be varied are pulse off-time (microseconds), spark gap (micrometers), servo feed, rotational speed (rotations per minute), and flushing pressure (bar). In the present work, these parameters were varied over three levels. These parameter levels have been detailed out in Table 1. Thirty experiments were conducted by varying various input parameters, and the results for output parameters, i.e., MRR and surface roughness obtained are given in Table 2. The data of first 27 experiments are used for training the neural network, and the remaining data are used for testing performance of the neural network. The photographs of the specimen machined using WEDT process are given in Fig. 3.

3 Machining performance evaluation

3.1 Material removal rate

In the present work, MRR and surface roughness are considered for evaluation of machining performance. The MRR is calculated as the volumetric MRR using the Eq. 1.

$$\text{MRR for WEDT} = \pi \times \left(\mathrm{D}_f^2 - \mathrm{D}_i^2\right) \times \mathrm{V}_f \qquad (1)$$

Where D_f and D_i are the diameters of the work piece in millimeters after and before machining and V_f is the feed velocity in millimeters per minute. The MRR calculated for various experiments is given in Table 2.

3.2 Surface characteristics

In order to have an insight into the surface characteristics before and after machining by WEDT, the scanning electron

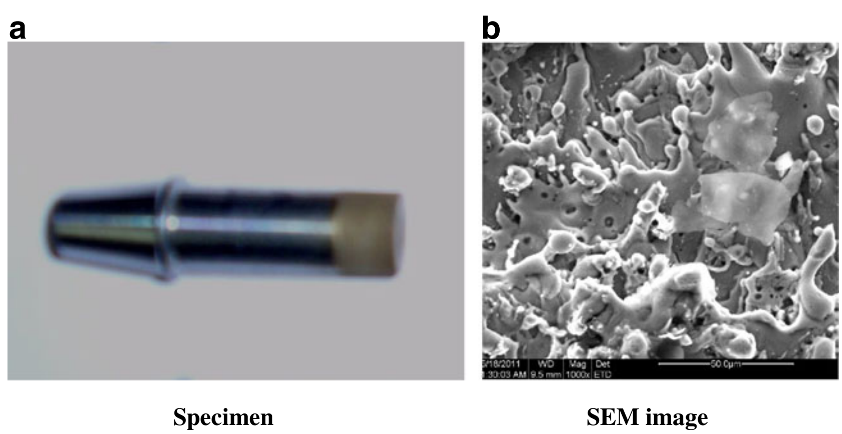


Fig. 5 Typical surface characteristics of specimen after WEDT machining

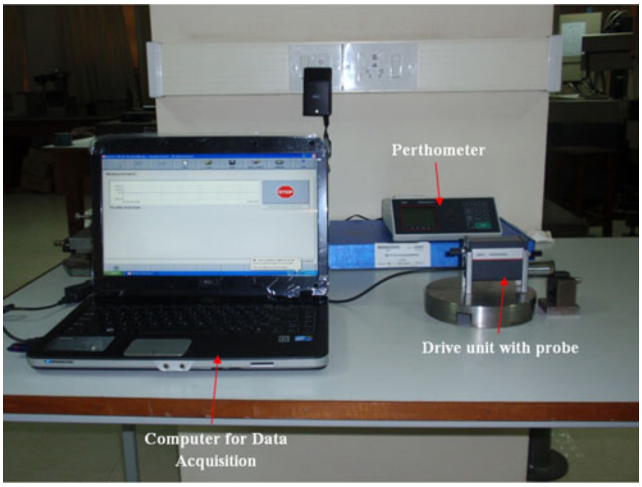


Fig. 6 Setup for measuring surface roughness of specimen

microscope images of the specimens were obtained at ×1,000. Figure 4 shows the specimen and nature of the surface before machining. The surface appears to be smoother with tool marks. Figure 5 shows the specimen and SEM image of the machined surface after WEDT. This surface shows the pits formed due to the sparks and the re-solidified molten metal particles sticking onto the surface.

3.3 Surface roughness

The surface roughness of the machined components is measured using a MAHR Perthometer using MarSurf XR 20 software, with a cut-off length of 0.25 mm. Figure 6 shows the setup used for measuring the surface roughness of the specimen. The surface roughness value is quantified in terms of the R_a value. Roughness profiles are taken along three different sections on the work piece, and the average of the three values is considered.

Figures 7, 8, and 9 show the typical roughness profiles and SEM image of the machined area of specimen machined with different input parameters. It is observed that the surface characteristics vary significantly when the input parameters are varied during machining.

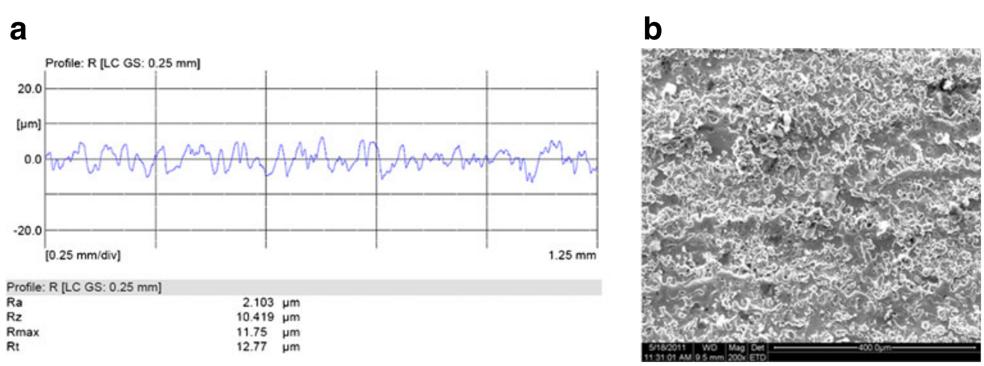
4 Process modelling using back-propagation neural network

As WEDT process is stochastic and random in nature, it is very difficult to predict the output characteristics accurately by mathematical equation. In the present work, an ANN with feed-forward back-propagation algorithm has been adopted to model the WEDT process since the process can be effectively represented by ANN model. This technique is especially valuable in processes where a complete understanding of the physical mechanisms is very difficult, or even impossible to acquire, as in the case of WEDT process. It can also be trained to accurately predict process dynamics.

Neural network is a logical structure with multi-processing elements, which are connected through interconnection weights. The knowledge is presented by the interconnection weights, which are adjusted during the learning phase. Back-propagation learning algorithm uses a gradient search technique to minimize the mean square error of the output of the network. In this work, neural network architecture with five inputs and two outputs, and two hidden layers have been used to model the process, as shown in Fig. 10. The five input parameters are pulse off-time, spark gap, servo feed, rotational speed, and flushing pressure. The output parameters are material removal rate and surface roughness. Experimental data obtained from experiments 1 to 27 (refer Table 2) is used for training the network. The parameters have been normalized between 0 and 1. Sequential mode of training has been used for the training of the network. For testing the prediction ability of the model, prediction error in each output node has been calculated as follows.

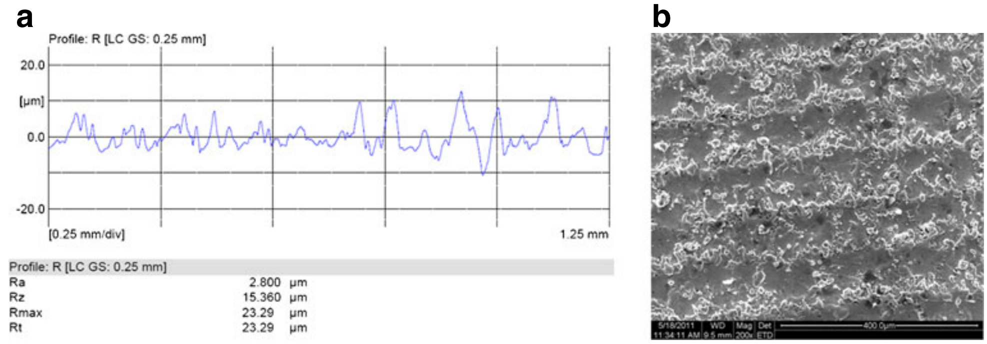
4.1 Selection of network architecture

Network architecture and number of hidden neurons of feed-forward neural networks are important factors for the training, in order to avoid over-fitting in the function approximation, generally decided on the basis of experience [3]. On one side, the number of hidden units could be stated a priori



The surface roughness profile (R_a = 2.103 µm) **SEM image of machined area**

Fig. 7 Surface profiles of specimen machined with pulse off-time of 42 µs, spark gap 50 µm, servo feed 3, rotational speed 100 rpm, and dielectric pressure of 3.267 bar



The surface roughness profile (R_a = 2.800 μm) **SEM image of machined area**

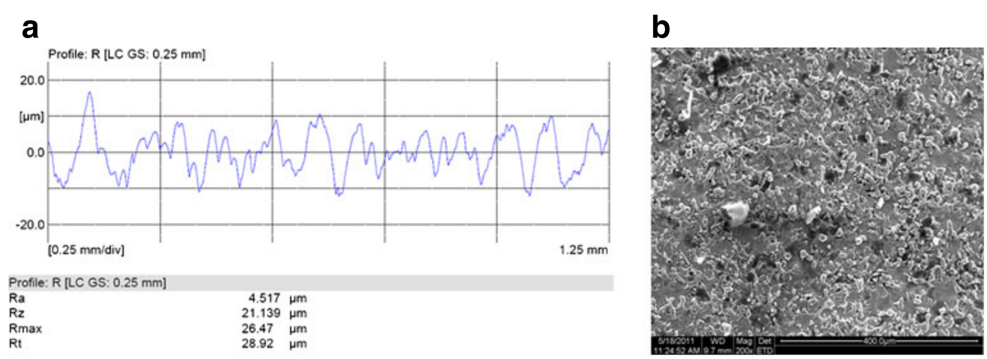
Fig. 8 Surface profiles of specimen machined with pulse off-time of 42 μs, spark gap 30 μm, servo feed 8, rotational speed 70 rpm, and dielectric pressure of 3.267 bar

by means of empirical equations provided [11, 23]. On the other hand, it is possible to select the best network by estimation, for a given problem, of the network architecture and parameters within a set of aspirant configurations. In the present work, ANN model with 5-17-11-2 architecture is found to be the most suitable for the current model, and it gives the lowest RMS error. The best method to find out the most suitable ANN network for modeling of manufacturing process is trial and error method. Hence, initially 60 networks were formed with single hidden layer, five input neurons, and two output neurons starting with 5-1-2, 5-2-2, 5-3-2 … till 5-60-2 configurations. Furthermore, another 60 networks were formed with the same network architecture as above but with two hidden layers with configurations 5-1-1-2, 5-2-2-2 … 5-60-60-2. Out of the 120 networks formed, the best network for prediction 5-14-14-2 was selected based on the one that has the least mean square error of 0.00048 while training and testing. The regression ratio while training, validation, testing, and overall were 1, 0.89, 0.99, and 0.98 respectively. The simulated multi-layer feed-forward ANN architecture consists of five neurons in the input layer (corresponding to five process inputs) and two neurons in the output layer (corresponding to two outputs, Ra and MRR). Two hidden layers with 14 neurons each was employed in the present study.

4.2 Training the network and prediction performance

In order to ensure the optimal performance of the neural network, the samples of the validation set is selected approximately 10 % from the entire number of samples [1]. Hence, out of the 30 experimental data sets, the first 27 have been used for training the network and the last three have been used for testing the network. The ANN took 2 s for training. (The code was written in MATLAB 7.10.0 to train and implement the neural network.) The ANN training simulation was carried out using the variable learning rate training procedure “traingdx” of the ‘MATLAB’ NN toolbox. The maximum, minimum, and mean prediction errors for this network are 18.77 %, 5.28 %, and 10.56 %. Mean prediction error has been calculated by taking the average of all the individual errors, for all the testing patterns. Actual and predicted values from the network for MRR and surface roughness have been shown in Figs. 11 and 12.

Table 3 gives a snapshot of the ANN performance for both the output parameters across the testing patterns. It is seen that the highest percentage error in prediction performance is 18.77 % for the third testing set for R_a. The lowest percentage error of 5.28 % is for the second testing set for R_a.



The surface roughness profile (R_a = 4.517 μm) **SEM image of machined area**

Fig. 9 Surface profiles of specimen machined with pulse off time of 34 μs, spark gap 50 μm, servo feed 8, rotational speed 30 rpm, and dielectric pressure of 1.263 bar

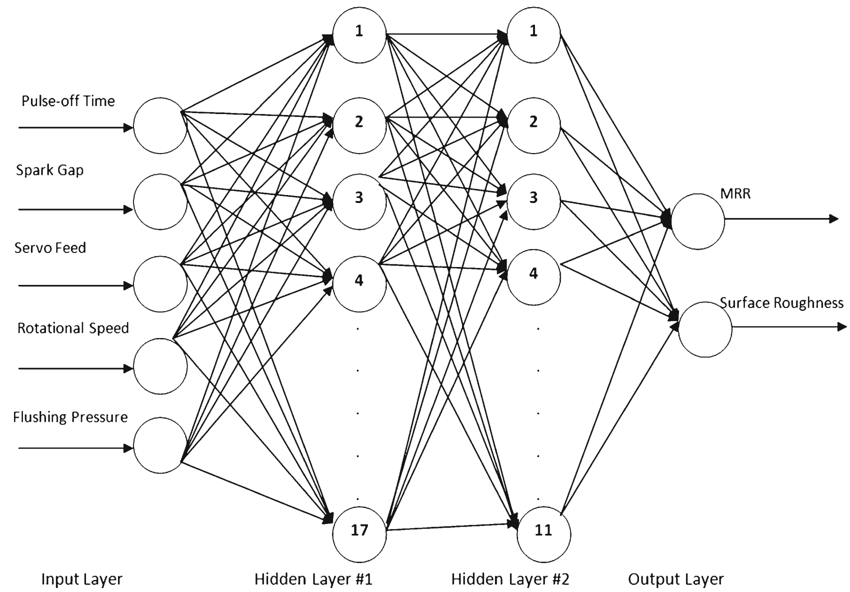


Fig. 10 Architecture of the neural network model

5 Process modelling using ANFIS

The adaptive neuro-fuzzy model has been developed for the prediction of surface roughness and material removal rate separately. There are two methods that adaptive neuro-fuzzy inference system (ANFIS) learning employs for updating membership function parameters: (1) back-propagation for all parameters (a steepest descent method) and (2) a hybrid method consisting of back-propagation for the parameters associated with the input membership and least-squares estimation for the parameters associated with the output membership functions.

5.1 ANFIS network architecture

Separate ANFIS networks were formed for modelling surface roughness and material removal rate. The combination of various input and output membership function types available in MATLAB 7.10.0 fuzzy logic tool box was used. A total of 96 networks were formed for Ra and MRR (48 each). From this, the one with least error in training and testing was selected for modeling.

The best network was found to be the one with following architecture

1.	No. of membership function at each input level	2 2 2 2 2
2.	Input membership function type	gauss2mf
3.	Output membership function type	Constant
4.	Optimization method	Hybrid
5.	Error tolerance	0
6.	No. of epochs	500

The ANFIS model could predict the Ra and MRR for training data with an average percentage deviation of 3.86 % and 2.01 % respectively. The ANFIS model could predict the surface roughness and material removal rate for testing

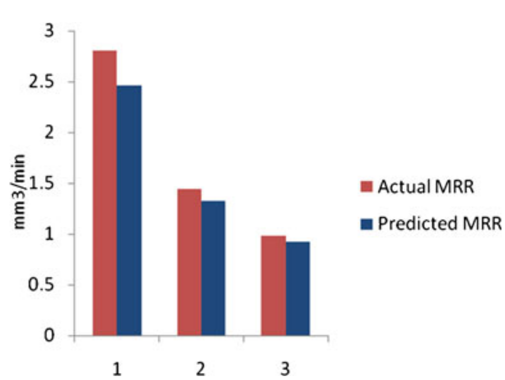


Fig. 11 Comparison of performance of ANN model for MRR

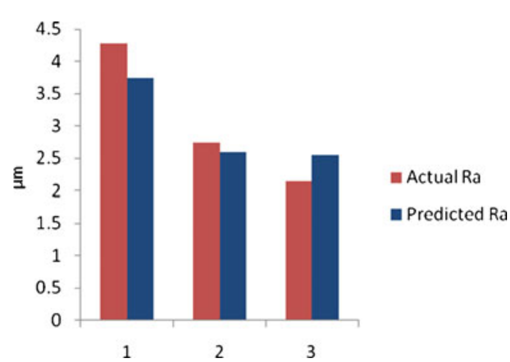


Fig. 12 Comparison of performance of ANN model for surface roughness (R_a)

Table 3 Performance of ANN model

Test MRR (mm^3/min)	Test R_a (μm)	Simulated MRR (mm^3/min)	Simulated R_a (μm)	Percentage error in MRR (%)	Percentage error in R_a (%)
2.80	4.280	2.46	3.734	12.09	12.78
1.44	2.743	1.32	2.599	8.24	5.28
0.98	2.148	0.92	2.552	6.26	18.77

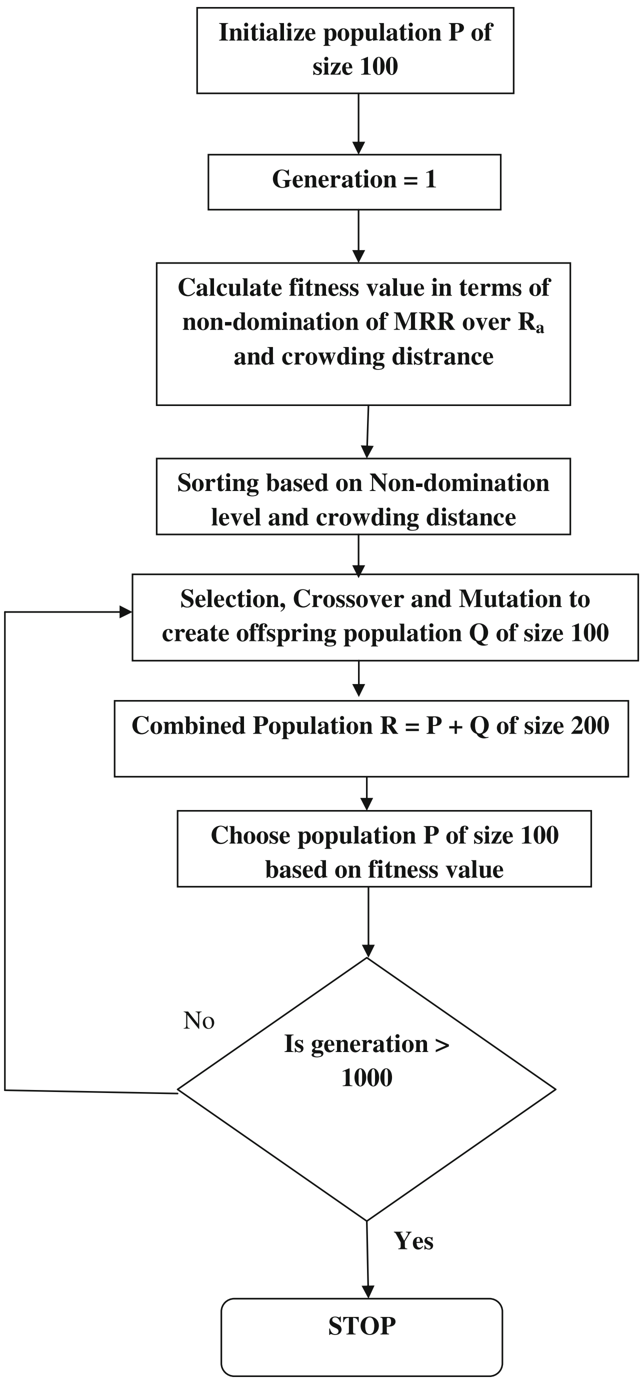


Fig. 13 Flowchart for implementation of NSGA-II

or validation data set with an average percentage deviation of 38 % and 18.72 %, respectively.

6 Multi-objective optimization using NSGA-II

In this paper, objectives are maximization of MRR and minimization of surface roughness, which are functions of decision variables namely, current, pulse on-time, and pulse off-time. The NSGA-II algorithm is applied for minimizing both the objectives. In order to convert the first objective (MRR) for minimization, it is suitably modified.

The objective functions are;

Objective 1 Maximize MRR=−MRR
Objective 2 R_a (surface roughness)

Figure 14 shows the integrated approach being used for the optimization of the WEDT process. In this study, ANN model has been developed to establish the relation between input (decision variable) and output (objectives). This trained ANN model has been used to determine the objective function values. It combines the approximation or pattern recognition abilities of the ANN to model the process and the NSGA-II's robustness to optimize the process.

NSGA-II is fast and elitist multi-objective GA, proposed by Dev et al. [2]. In this method, a non-dominating sorting approach is used for each individual to create a Pareto rank, and a crowding distance assignment method is applied to implement density estimation. The crossover and mutation operators remain as usual, but selection operator works differently from simple GA. Selection is done with the help of crowded-comparison operator, based on ranking (according to non-domination level) and crowding distance that is briefly explained below. Randomly, an initially parent population (solution) P of size N is generated. In order to identify the non-domination level, each solution is compared with every other solution and checked whether the solution under consideration satisfies the rules as given below:

$$\mathrm{Obj.1[i]} > \mathrm{Obj.1[j]} \text{ and } \mathrm{Obj.2[i]} \geq \mathrm{Obj.2[j]}, \tag{2}$$

$$\text{or } \mathrm{Obj.1[i]} \geq \mathrm{Obj.1[j]} \text{ and } \mathrm{Obj.2[i]} > \mathrm{Obj.2[j]},\ \mathrm{i} \neq \mathrm{j} \tag{3}$$

where, i and j are chromosome numbers.

Now if the rules are satisfied, then the selected solution is marked as dominated. Otherwise, the selected solution is marked as non-dominated. This process continues until all the solutions are ranked. Solutions belong to a particular rank or non-domination level; none of the solutions is better with respect to other solutions present in that non-domination level. After identifying the rank of each solution, crowding distance of each solution belongs to a particular non-nomination set or level is calculated. The crowding distance is the average distance of two points on either side of this selected solution point along each of the

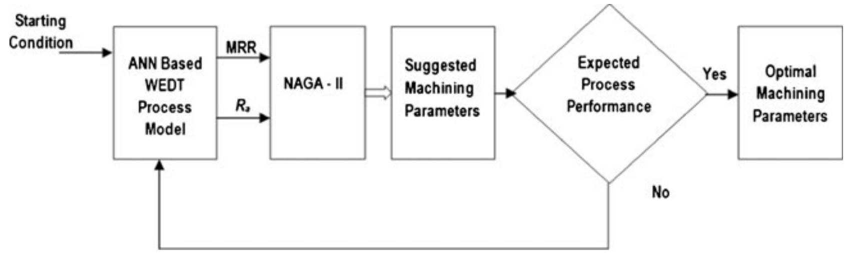


Fig. 14 Integrated ANN–NSGA-II approaches for WEDT optimization

objectives function. Figure 13 lays out the algorithm for the NSGA-II multi-objective optimization approach. The flowchart details the working of the NSGA-II algorithm for every generation until it terminates once the required number of generations has been reached (Fig. 14).

An initial population of 100 is used, and 1,000 generations are used for better convergence. A hundred non-dominated solutions are obtained at the end of 1,000 generations.

NSGA-II has been implemented using a code written in MATLAB 7.10.0. The code has been implemented using eight different functions which execute the different steps in the NSGA-II algorithm. Initially, the population size and the stopping criteria or the total number of generations, after which the algorithm will automatically be stopped, are entered as input arguments to the function. A set of 100 non-dominated solutions are obtained at the end of 1,000 generations. The MRR and the corresponding Surface roughness (Ra) values are shown in Fig. 15.

7 Comparison of ANN, ANFIS, and NSGA-II prediction models

The comparison of the all the three methods used for the prediction of surface roughness and material removal rate are shown in the following Fig. 15. It can be observed from the above figure that all the three prediction models give results fairly close to each other. GA II method shows a linear increase in the R_a value with increase in MRR throughout the range which is the characteristic feature of any machining process. The ANN model was also able to predict Ra and MRR very close to GA II. In the ANFIS model, there were points with lower R_a and MRR away from the trend line; however, the band of deviation was not more than 0.6 μm (R_a) (the average deviation of ANFIS model). The ANFIS model had an average error in testing of about 27 %.

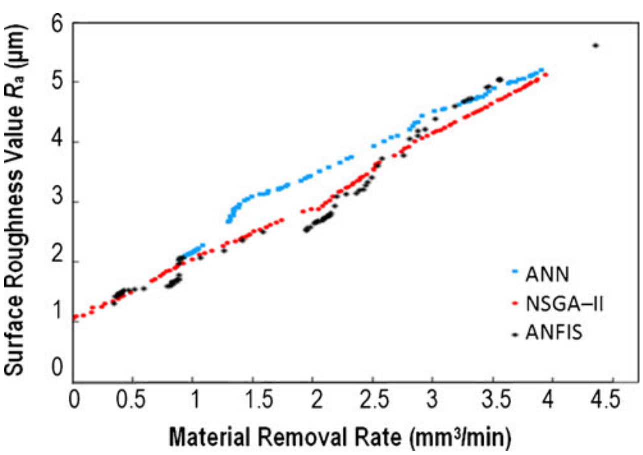


Fig. 15 Comparision of ANN, NSGA-II, and ANFIS models

8 Results and discussions

The non-dominated solution set obtained using the proposed algorithms is plotted in Fig. 15. This shows the formation of the pareto-optimal front leading to the final set of solutions. Since none of the solutions in the pareto-optimal front is absolutely better than any other, any one of them is an acceptable solution. The choice of one solution over the other depends on the process and product requirements. It is observed from the pareto-optimal set that the WEDT process can be used for both finishing and rough cutting operations. For MRR value of 0.03 mm^3/min, an R_a value of

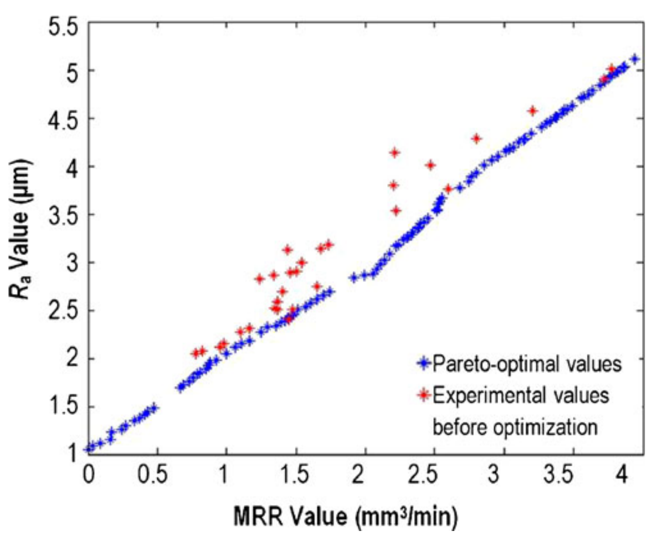


Fig. 16 Optimized values of MRR and R_a at the pareto-optimal front

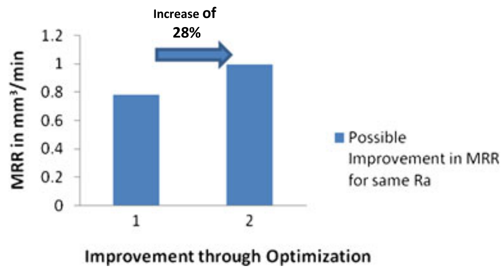


Fig. 17 Improvement in MRR for R_a=2.05 μm

1.086 μm is obtained which increases to 1.235 μm for an MRR of 0.17 mm^3/min. The highest MRR and R_a combination is 3.94 mm^3/min and 5.115 μm. This also shows that the pareto-optimal front obtained is fairly diverse and spread out across the full range of MRR and surface roughness.

In case an R_a value of 2.5 μm is required, suitable parameter settings can be selected to obtain maximum MRR using the present pareto-optimal front. From Fig. 16, it is also observed that the pareto-optimal set is clearly better than the experimental readings of MRR and surface roughness. For any given value of surface roughness, the pareto-optimal front gives the highest MRR possible. For every value of R_a, the pareto-optimal front gives a better value of MRR as compared with the experimental readings. The impact of the optimization strategy is further verified by conducting experiments with input parameters suggested by the pareto-optimal front.

Figure 17 demonstrates how an improvement in MRR for the same R_a value is obtained after optimization. From the experimental results, a particular set of parameters yields an MRR value of 0.78 mm^3/min (experiment 26) and a R_a value of 2.048 μm. By setting the parameters suggested by NSGA-II algorithm, it is seen that the MRR is increased to 0.99 mm^3/min for the same surface finish, with an increase of 28 % in MRR.

9 Conclusions

Optimization of WEDT process parameters is very much essential since this is an extensively used and costly process. Optimization will help to increase production rate considerably by improving the MRR and reducing the machining time. In this project, the WEDT process parameters have been optimized by non-dominated sorting genetic algorithm-II. A set of 30 experiments were conducted by varying input parameters such as pulse off-time, spark gap, servo feed, rotational speed, and flushing pressure while machining AISI D3 die steel. The MRR and surface roughness have been evaluated for each experiment. An ANN model has been trained within the experimental data. The [5-17-11-2] 5-14-14-2 architecture is found to be the best architecture (with a mean prediction error of 10.56 %). ANN model could predict R_a and MRR for training data with an average percentage deviation 5.53 % and 3.28 %, respectively. ANN model could predict the surface roughness and material removal rate for testing data with an average percentage deviation of 27.16 % and 20.38 %, respectively. The objectives such as MRR and surface roughness have been optimized using a multi-objective optimization method based on non-dominated sorting genetic algorithm-II. A pareto-optimal set of 100 solutions is obtained on which any value of surface roughness yields the highest MRR possible.

The obtained optimal set of parameters is further validated with experiments, and it is found that there is an improvement of 28 % on MRR for required surface roughness. Furthermore, the performance of the ANN model can be improved by training it with a larger experimental set of data. This approach can be extended to optimize MRR while the roundness error is reduced with minimum power consumption. At present, MRR and roughness are considered for optimization; similarly, experiments will be conducted for conflicting parameters like power consumption and roughness, power consumption and form error, etc., with added computational work.

Acknowledgments The authors would like to thank Mr. A. Arun, PSG Institute of Technology, Coimbatore, India for his contribution as part of his Summer Fellowship Programme at Indian Institute of Technology Madras, Chennai, India.

References

1. Balabin RM, Safieva RZ, Lomakina EI (2009) Universal technique for optimization of neural network training parameters: gasoline near infrared data example. Neural Comput Appl 18:557–565
2. Dev K, Pratap A, Agarwal S, Meyarivan T (2002) A fast and elitist multiobjective genetic algorithm: NSGA-II. IEEE Trans Evol Comput 6(2):182–197
3. Furferi R, Governi L (2008) The recycling of wool clothes: an artificial neural network colour classification tool. Int J Adv Manuf Technol 37(7–8):722–731
4. Gao Q, Zhang Q, Su S, Zhang J (2008) Parameter optimization model in electrical discharge machining process. J Zheijang Univ 9 (1):104–108
5. Haddad MJ, Tehrani AF (2008) Material removal rate (MRR) study in the cylindrical wire electrical discharge turning (CWEDT) process. J Mater Process Technol 199:369–378
6. Haddad MJ, Tehrani AF (2008) Investigation of cylindrical wire electrical discharge turning (CWEDT) of AISI D3 tool steel based statistical analysis. J Mater Process Tech 198:77–85
7. Huang JT, Liao YS (2003) Optimization of machining parameters of wire-EDM based on grey relational and statistical analyses. Int J Prod Res 41(8):1707–1720
8. Janardhan V, Samuel GL (2009) Investigations into turning of cylindrical components using wire electrical discharge machine. Proceedings of the International Conference on Advances in Mechanical Engineering, S.V. National Institute of Technology, Surat, India, 835–839
9. Janardhan V, Samuel GL (2010) Pulse train data analysis to investigate the effect of machining parameters on the performance of

wire electro discharge turning (WEDT) process. Int J Mach Tool Manuf 50:775–788
10. Joshi SN, Pande SS (2011) Intelligent process modelling and optimization of die-sinking electric discharge machining. Appl Soft Comput 11:2743–2755
11. Kinser JM (1996) The determination of hidden neurons. Opt Mem Neural Network 5(4):245–262
12. Kuriakose S, Shunmugam MS (2005) Multi-objective optimization of wire electro discharge machining process by non-dominated sorting genetic algorithm. J Mater Process Technol 170:133–141
13. Liao YS, Huang JT, Su HC (1997) A study on the machining-parameters optimization of wire electrical discharge machining. J Mater Process Technol 71:487–493
14. Lin CL, Lin JL, Ko TC (2002) Optimization of the EDM process based on the orthogonal array with fuzzy logic and grey relational analysis method. Int J Adv Manuf Technol 19:271–277
15. Mahapatra SS, Patnaik A (2006) Optimization of wire electrical discharge machining (WEDM) process parameters using Taguchi method. Int J Adv Manuf Technol 34:911–925
16. Mandal D, Pal SK, Saha P (2007) Modeling of electrical discharge machining process using back propagation neural network and multi-objective optimization using non-dominating sorting genetic algorithm-II. J Mater Process Technol 186:154–162
17. Matoorian P, Sulaiman S, Ahmad MMHM (2008) An experimental study for optimization of electrical discharge turning (EDT) process. J Mater Process Technol 204:350–356
18. Mohammadi A, Alireza FT, Ehsan E, Davoud K (2008) Statistical analysis of wire electrical discharge turning on material removal rate. J Mater Process Tech 205:283–289
19. Mohammadi A, Alireza FT, Ehsan E, Davoud K (2008) A new approach to surface roughness and roundness improvement in wire electrical discharge turning based on statistical analysis. Int J Adv Manuf Technol 39:64–73
20. Qu J, Shih AJ, Scattergood RO (2002) Development of the cylindrical wire electrical discharge machining process: part1: concept, design, and material removal rate. J Manuf Sci Eng 124(3):702–707
21. Qu J, Shih AJ, Scattergood RO (2002) Development of the cylindrical wire electrical discharge machining process: part2: surface integrity and roundness. J Manuf Sci Eng 124(3):708–714
22. Ramakrishnan R, Karunamoorthy L (2006) Multi response optimization of wire EDM operations using robust design of experiments. Int J Adv Manuf Technol 29:105–112
23. Rocco F, Maurizio G (2010) Yarn strength prediction: a practical model based on artificial neural networks. Adv Mech Eng Appl 2010:1–11
24. Spedding TA, Wang ZO (1997) Parametric optimization and surface characterization of wire electrical discharge machining process. Precis Eng 20(1):5–15
25. Su JC, Kao JY, Tarng YS (2004) Optimisation of the electrical discharge machining process using a GA-based neural network. Int J Adv Manuf Technol 24:81–90
26. Tarng YS, Ma SC, Chung LK (1995) Determination of optimal cutting parameters in wire electrical discharge machining. Int J Mach Tool Manuf 35:1693–1701
27. Tzeng Y, Chen F (2007) Multi-objective optimization of high-speed electrical discharge machining process using a Taguchi fuzzy-based approach. Mater Des 28:1159–1168
28. Wang K, Gelgele HL, Wang Y, Yuan Q, Fang M (2003) A hybrid intelligent method for modelling the EDM process. Int J Mach Tool Manuf 43:995–999
29. Yuan J, Wang K, Tao Y, Fang M (2008) Reliable multi-objective optimization of high speed WEDM process based on Gaussian process regression. Int J Mach Tool Manuf 48:47–60