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Prediction and analysis of radial overcut in holes drilled by electrochemical machining process

Research Article

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Abstract: Radial overcut predictive models using multiple regression analysis, artificial neural network and co-active neuro-fuzzy inference system are developed to predict the radial overcut during electrochemical drilling with vacuum extraction of electrolyte. Four process parameters, electrolyte concentration, voltage, initial machining gap and tool feed rate, are selected to develop the models. The comparison between the results of the presented models shows that the artificial neural network and co-active neuro-fuzzy inference system models can predict the radial overcut with an average relative error of nearly 5%. Main effect and interaction plots are generated to study the effects of process parameters on the radial overcut. The analysis shows that the voltage, electrolyte concentration and tool feed rate have significant effect on radial overcut, respectively, while initial machining gap has a little effect. It is also found that the increase of the voltage and electrolyte concentration increases the radial overcut and the increase of the tool feed rate decreases the radial overcut.

Keywords: Electrochemical drilling • Radial overcut • Regression • Artificial neural network • Co-active neuro-fuzzy inference system

1. Introduction

In electrochemical drilling (ECD), a tubular electrode is used as the cathodic tool. The electrolyte is pumped from the centre of the tool and exits through the side machining gap, formed between the walls of the tool and the drilled hole. Machining occurs at high current densities in the frontal interelectrode gap between the tool face and the work-piece. Side electrochemical dissolution acts laterally between the sidewalls of the tool and the workpiece. The produced hole diameter is therefore greater than the tool diameter by an overcut [1].

A theoretical analysis of electrochemical machining (ECM) of curvilinear surfaces in order to predict the work-piece shape evolution on the example of shaping surface of negligibly small size in the direction of the axis (flat issue) and a hydrodynamic machine blade was done by Paczkowski and Sawicki [2]. An experimental apparatus was designed and built by Tang [3] for the hybrid process of laser enhanced electrochemical machining. The results showed that the hybrid process has advantages in machining accuracy, surface quality, and machining efficiency.

The effects of applied voltage, current, pulse duration, and the concentration of the electrolyte on the behaviour of wire electrochemical discharge machining of Al_2O_3 particle reinforced aluminium alloy 6061 materials have studied by Liu *et al.* [4]. Thanigaivelan and

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Arunachalam [5] investigated the effect of tool electrode tip shape on electrochemical micromachining (EMM) for 304 stainless steel sheets. The objective of taking up their study was to identify simple and economical ways of improving the circulation of the electrolyte in the inter electrode gap (IEG), so that the accuracy as well as the machining rate can be improved. The integration of vacuum extraction of electrolyte with ECD to enhance the stability of the machining process was demonstrated and verified by Wang *et al.* [6]. Their work showed that it is feasible to machine small holes using ECD by vacuum extraction of electrolyte. The improvement of machining accuracy and stability in inclined ECD by modifying the electrolyte flow distribution with a wedged electrode to enhance the uniformity of electrolyte flow and reduce the flow field disrupting processes was performed by Wang *et al.* [7]. An investigation was done by Sharma *et al.* [8] to optimise the operating parameters of shaped tube electrolytic machining (STEM) such as voltage and tool feed rate using high-speed steel (HSS). They found that much accurate holes can be obtained by a combination of low voltage and comparatively high feed rate which results in low values of equilibrium inter-electrode gap. Bilgi *et al.* [9] investigated the process capabilities of pulse-current shaped-tube electrochemical drilling (PC-STED) of nickel-based superalloy and illustrated the effects of operating parameters (voltage, tool feed rate, pulse on-time, duty cycle, and bare tip length of tool) on the responses, namely, depth-averaged radial overcut (DAROC), mass metal removal rate (MRRg) and linear metal removal rate (MRRl). Electrochemical micro-drilling was performed by Fan and Hourng [10] to investigate the influence of various parameters such as pulsed on-times, applied voltages, electrolyte concentrations, pulsed frequencies, tool feeding rates, tool diameters, tool rotational rates, and hole depth, on the overcut and conicity of the hole. Mithu *et al.* [11] investigated the effects of applied frequency and duty cycle on the shape and size of the fabricated micro holes, machining time, and actual material removal rate in electrochemical micro drilling of nickel plates. Tsui *et al.* [12] used a micro helical tool as a novel solution to the problem of using a micro cylindrical tool in an electrochemical micro drilling (ECMD) process.

Regression and intelligent techniques, including neural network, fuzzy logic, neuro-fuzzy, etc. have been used widely in different machining operation. For example, Zare Chavoshi and Tajdari [13] modelled the surface roughness in hard turning operation of AISI 4140 using regression analysis and artificial neural network. Analysis and estimation of state variables in computer numerical control (CNC) face milling operation of AL6061 was performed by Soleymani Yazdi and Zare Chavoshi [14]. Several adaptive neuro-fuzzy inference systems (ANFIS) models for predicting in machining operations have been developed. Co-active neuro-fuzzy inference system (CANFIS) is a dynamic-statistical model that incorporates classification and regression trees with a neuro-fuzzy inference system. The CANFIS has been mostly used in areas like earth and weather sciences. Zare Chavoshi used CANFIS models for predicting performance parameters in electrochemical drilling and tool flank wear in CNC turning [15, 16].

In the present work, the effect of process parameters like electrolyte concentration, voltage, initial machining gap and tool feed rate on the radial overcut during electrochemical drilling with vacuum extraction of electrolyte has been studied using main effect and interaction plots. Vacuum extraction of electrolyte greatly facilitates the application of reverse flow in electrochemical drilling. Reverse flow using vacuum extraction enhances the process stability while diminishing sparking and formation of striations. In continuation, the regression, artificial neural network and co-active neuro-fuzzy inference system models were used to assess the radial overcut in the electrochemical drilling operation with vacuum extraction of electrolyte. The results of regression, artificial neural network (ANN) and neuro-fuzzy models are compared in order to specify which model is more accurate.

2. Experimental procedure

ASTM 304 stainless steel was used as the anode material. $NaNO_3$ electrolytic solution at 25°C was used. Electrolyte feed hole diameter, electrode diameter and machining depth were 400 μm, 800 μm and 2 mm, respectively. Figure 1 shows a schematic diagram of the electrochemical drilling with vacuum extraction of electrolyte.

For conducting the experiments, the orthogonal array was selected for four design variables namely electrolyte concentration, voltage, initial machining gap and tool feed rate. The orthogonal array is selected based on the degrees of freedom (DOF). In this work, there are four parameters at four levels. The DOF of a four level parameter is three; hence total DOF for the experiment is twelve. In this study, an L_{16} (4^5) mixed orthogonal array is used. This array has 5 columns and 16 rows. In the present study only four ECD parameters were involved, therefore the remaining one column in the L_{16} orthogonal array was kept unused.

Previous experiments showed that machining was not

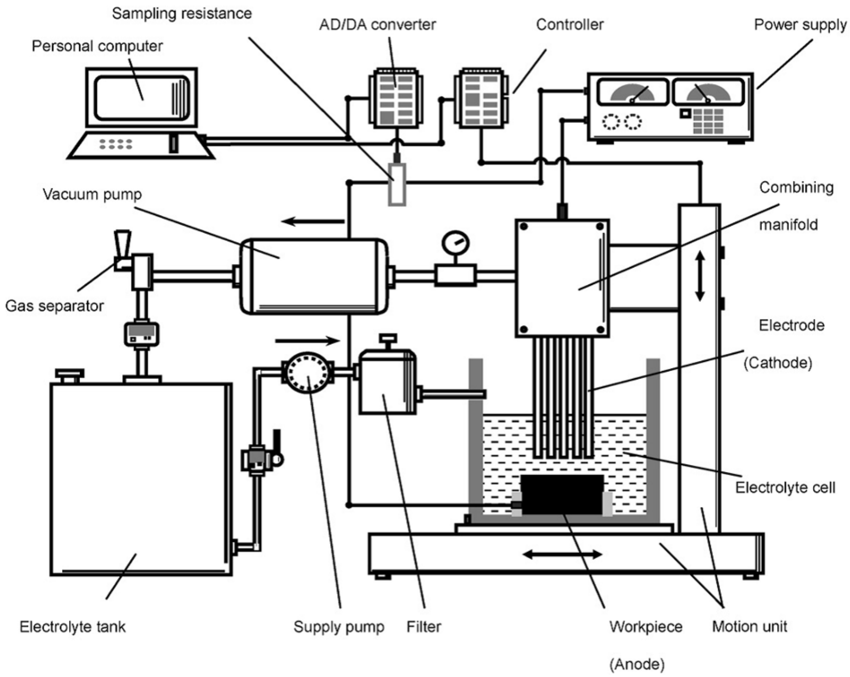

Figure 1. Schematic diagram of the experimental set-up [6].

possible when the tool feed rate is over 15 μm/s at the applied voltage 15 V. Spark and short circuit occurred frequently when initial machining gap was below 50 μm. Thus, experiments were performed at different electrolyte concentrations (14, 16, 18, and 20 wt.%), voltages (9, 11, 13, and 15 V), initial machining gaps (50, 60, 70, and 80 μm), and tool feed rates (6, 9, 12, and 15 μm/s). Each of the experiments was conducted 4 times. The section of the machined surface was measured by measuring microscope series with an accuracy of 0.1 μm [6].

3. Results

A main effect plot is a plot of the mean response values at each level of a design parameter or process variable [17]. From Figure 2, it can be observed that:

- The increase of the voltage and electrolyte concentration increases the radial overcut.
- The increase of the tool feed rate decreases the radial overcut.
- The voltage, electrolyte concentration and tool feed rate are the most effective parameters on the radial overcut, respectively; the initial machining gap has a little effect.

As the machining voltage increase, the stray current flow increases in the machining zone, in turn influencing more material removal from the larger area of work-piece which causes an increase in overcut. A higher concentration of ions would also reduce the localization effect of electrochemical material removal reactions. As such, material removal rate by the stray current would increase with increasing electrolyte concentration, and would in turn enlarge the radial overcut. The stray current attack range would be greatly reduced when the electrode advances into the work-piece, owing to the restricting control of the electric current lines by the anode material. Thus an bell-mouth shape is formed in the hole entrance. The bell-mouthed opening could be reduced by increasing tool feed rate and decreasing initial machining gap. In the machining process of ECD with vacuum extraction, the anode material should be immersed into the electrolyte. This facilitates the stray current machining before the operative end of the electrode advances into the anode surface. Thus lower initial machining gap and higher tool feed rate would decrease the stray current machining time, resulting in a better entrance shape [6].

For more comprehensive investigating of process parameters and responses, interaction graph was created. This interaction plot is used in order to determine the interaction effects of ECD process parameters on radial overcut. Also, if two process parameters have

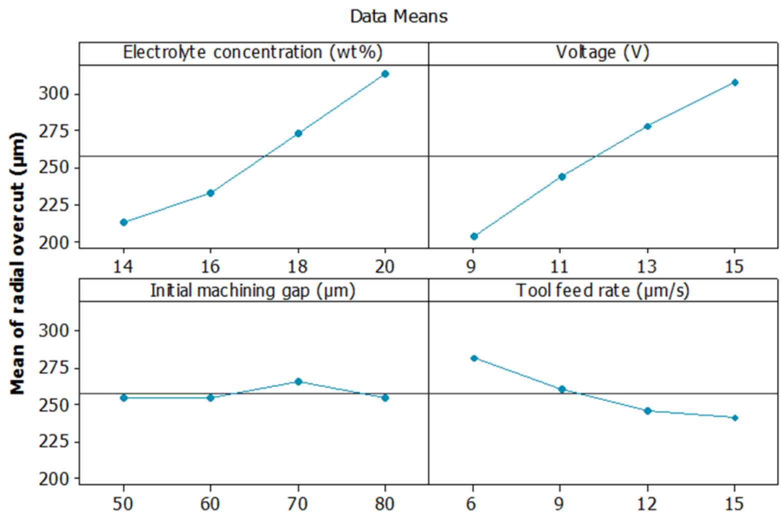

Figure 2. Main effect plot of the process parameters on radial overcut.

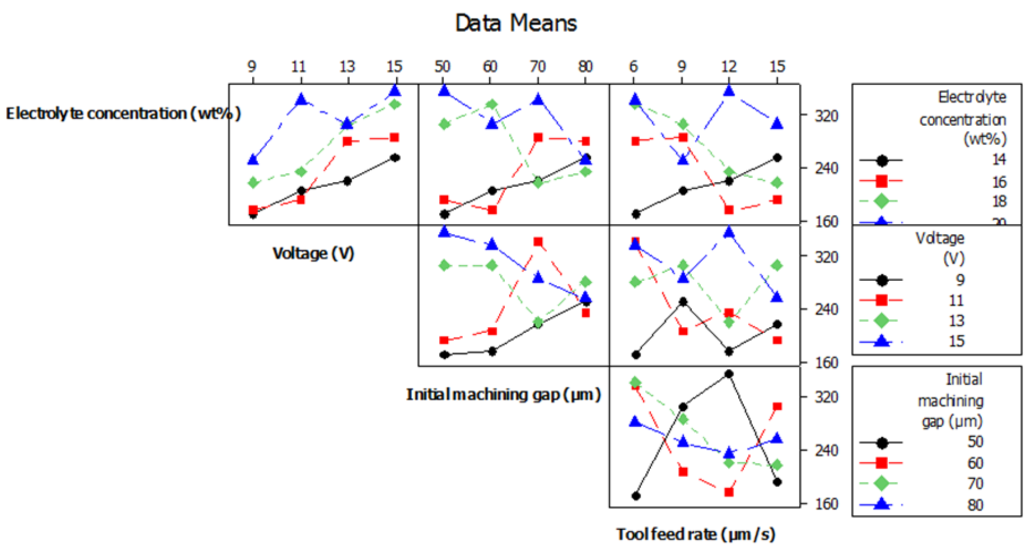

Figure 3. Interaction plot of factors for radial overcut.

interaction effect on each other, it must be considered in process modelling and if not, it must be removed in process modelling.

Interaction effects are illustrated in Figure 3. An interactions plot is a powerful graphical tool which plots the mean response of two factors at all possible combinations of their settings. Non-parallel lines is an indication of the presence of interaction between the factors [17]. From the Figure 3, it is clearly found that in electrochemical drilling with vacuum extraction of electrolyte, the electrolyte concentration, voltage, initial machining gap and tool feed rate have an interactive effect on each other with regard to the radial overcut.

4. Regression model

The multiple regression analysis was performed to demonstrate the fitness of experimental values. Applying regression analysis on the experimentally determined

Table 1. Test for regression model for radial overcut analysis.

Degree	R-Sq (%)	R-Sq (adj) (%)
Linear	96.6	94.7
Linear + Interaction	100	99.8
Linear + Squares	97.3	90
Interaction + Squares	99.6	95.3
Full Quadratic	94.7	91.6
Linear + Quadratic	97.2	89.8
Quadratic + Interaction	99.1	90.1
Quadratic + Squares	97.3	90.1

data, the regression coefficients were obtained and thereby the regression equation for the radial overcut as well. Regression model was developed using the MINITAB 16 software.

Equation (1) presents the linear plus interaction relationship between factors, factors effects and radial overcut (response) which is the result of response surface regression analysis.

$$\begin{aligned} \mathrm{RadialOvercut}(\mu m) = & -1140 + 83.6 \cdot C + 38.4 \cdot E \\ & + 12.8 \cdot G - 21.6 \cdot V \\ & - 1.85 \cdot C \cdot E - 0.810 \cdot C \cdot G \\ & + 0.685 \cdot C \cdot V + 0.0151 \cdot E \cdot G \\ & + 0.201 \cdot E \cdot V + 0.0312 \cdot G \cdot V \end{aligned} \tag{1}$$

where C is electrolyte concentration (wt.%), E voltage (V), G initial machining gap (μm) and V tool feed rate (μm/s). Table 1 indicates that regression model is the best one in comparison with the others that can be used with these factors and factor levels by R^2_{adj} test (The R-Sq (R^2) value indicates that the predictors explain 100% of the variance in radial overcut). R-Sq (adj) (R^2_{adj}) is 99.8% which accounts for the number of predictors in the model. Both values indicate that the model fits the data well. In Table 1, it is observed models that have been developed by interactions are more accurate than the others.

5. Co-active neuro-fuzzy inference system (CANFIS)

The architecture of ANFIS is a one-output fuzzy inference system based on an adaptive network. CANFIS is a generalized form of ANFIS. CANFIS enables to obtain more than one output and has the advantage of non-linear rule formations. The CANFIS model integrates fuzzy inputs with a modular neural network to quickly solve poorly defined problems. The fundamental component of CANFIS is a fuzzy axon, which applies membership functions to the inputs. This system can be viewed as a special three-layer feed forward neural network. The first layer represents input variables, the middle (hidden) layer represents fuzzy rules and the third layer represents output variables [18].

Table 2. MSE values of CANFIS model for training and testing data.

Data	MSE
Train	0.004798319812
Test	0.051888528424

For this system the electrolyte concentration, voltage, initial machining gap and tool feed rate are the input variations. The model has one output variable respected to the predicted value of radial overcut. Four data sets were selected randomly as the testing data and the remaining twelve data sets were used for training. A developed CANFIS model used the gaussian membership function (MF) with two MFs per input, momentum (MOM) learning rule during training process and TSK fuzzy model proposed by Takagi, Sugeno and Kang [19] for fuzzy part in these hybrid systems. TSK fuzzy model has been selected instead of the Mamdani model [20] for its simplicity and its compactness. The TSK model was developed to reduce the total number of rules required by the Mamdani model. Consequently, the number of rules in a TSK model is typically less than that in a Mamdani model, assuming that they approximate the same function to about the same accuracy. The simplicity and the compactness of the TSK model further simplify the optimization problem that estimates the model parameters. Mean squared error (MSE) values of CANFIS model are summarized in Table 2. Figure 4 shows the changing of active cost (MSE value) during 200 epochs training process. Network architecture for co-active neuro-fuzzy model is as follows:

1. No. of input Processing Elements = 4
2. No. of Membership functions for each input = 2
3. Type of membership functions = Gaussian
4. No. of output processing elements = 1
5. No. of output membership functions = 2
6. No. of hidden layers for output layer = 0
7. Transfer function of output layer = Axon
8. Learning rule = Momentum (MOM)
9. Learning rate Step size = 1
10. Target error = 0.01

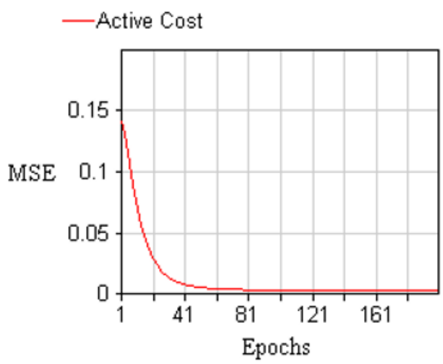

Figure 4. Active cost graph.

11. Termination criteria = MSE
12. Maximum epochs for each run = 200
13. Type of Fuzzy model = TSK
14. No. of weights and biases = 1893
15. No. of training datasets = 12
16. No. of testing datasets = 4

6. Artificial neural network model

ANN based methods are data analysis methods and algorithms based on nervous systems of humans and animals. Artificial neural network consists of a large number of simple processing units linked by weighted connections. The feed-forward neural network was used in this work as one kind of ANN. It has been applied successfully in many different problems since the advent of error back-propagation learning algorithm. A feed-forward network consists of an input layer, one or more hidden layers of computation nodes and an output layer. Electrolyte concentration, voltage, initial machining gap and tool feed rate are considered as the input variables and radial overcut is the output. Four data sets were selected randomly as the testing data and the remaining twelve data sets were used for specifying the neural networks. In order to have accurate models, several back propagation Multilayer Perceptron (MLP) neural networks, which are not shown in this section, have been used to obtain the best neural network architecture and learning coefficients.

For constructing the model, the tahnaxon transfer function and the momentum (MOM) learning rule were used for training this model. Network with four inputs, nine neurons in first hidden layer, two neurons in second hidden layer and one neuron in output layer, 4:9:2:1, has been considered. The proposed neural network model is shown in Fig 5. The final MSE values for training and testing data are shown in Table 3. Figure 6 shows the MSE value during 200 epochs training process. The related training parameters for the network were optimised as the learning rate = 0.7, maximum number of iteration/epochs = 200 for target error of 0.01.

Table 3. MSE values of CANFIS model for training and testing data.

Data	MSE
Train	0.010450492074
Test	0.017646909150

7. Discussion

The predicted radial overcut using the training dataset is shown in Table 4. Average relative errors for the training data obtained using the regression, CANFIS and ANN methodologies are 0.422242%, 2.42877% and 2.93053%, respectively. This indicates that the regression model offer the best predictions for the training data.

For each designed network, apart from training error, testing error was also found. Testing error is the error in the prediction for testing data. Many researchers use the term 'cross-validation' for 'testing'. Design of the network is finalized based on the training as well as the testing error. Once the design has been finalized, the performance of the network can be studied by supplying some validation data to it. Researchers using the term 'cross-validation' for 'testing' use the term 'testing' for 'validation'.

The validation of regression, CANFIS and ANN models was performed with the testing dataset. Testing dataset is shown in Table 5. Relative errors obtained using regression, CANFIS and MLP neural network methodologies have been compared, and the results of testing are shown in Table 6. The average relative errors of regression, ANN and CANFIS models are 7.90396%, 5.01829% and 5.08647%, respectively. The results illustrate that the ANN and CANFIS models have much better predicting capability than the regression model. It means that both the artificial neural network and co-active neuro fuzzy inference system models are more applicable than the regression model for the prediction of radial overcut in electrochemical drilling with vacuum extraction of electrolyte.

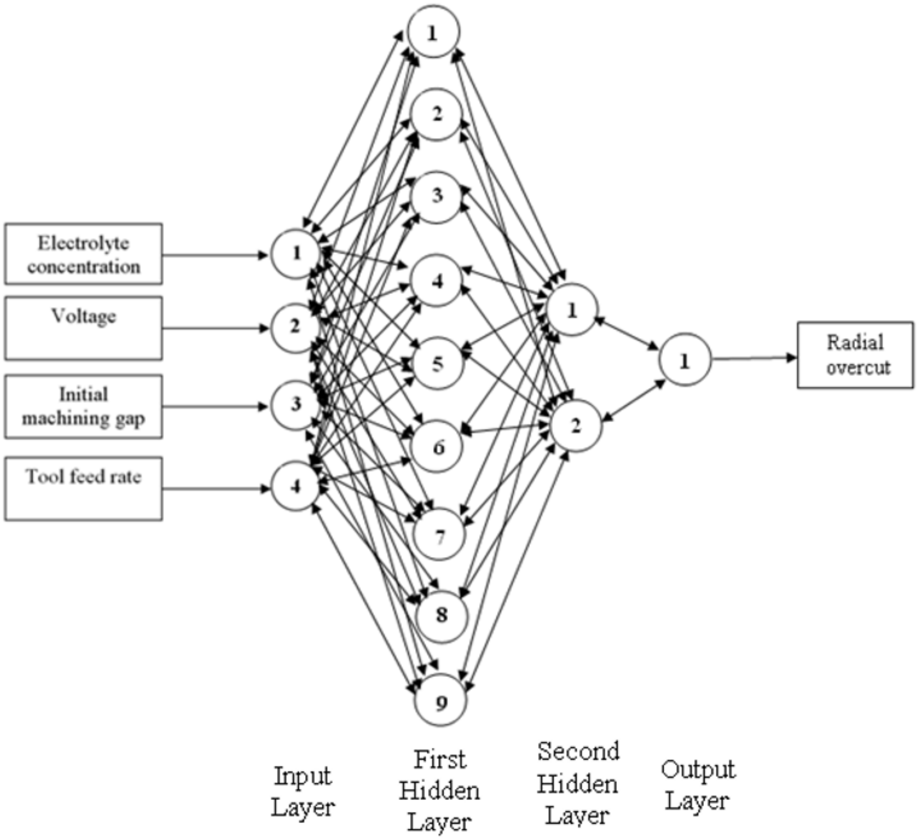

Figure 5. Proposed neural network model.

Table 4. Predicted radial overcut and average relative errors for the training data.

Experiment	Regression	CANFIS	ANN
170.4	170.849	167.8298	195.1941
220.5	222.285	222.0482	219.9345
254.5	255.335	245.3993	255.9048
191.2	191.67	203.3762	196.5356
280.1	281.718	277.3393	277.4819
285	285.286	295.2428	288.0272
216.2	216.458	206.4531	198.3821
234.7	237.032	244.1028	233.6134
304.3	306.042	296.7516	304.1505
250	251.117	250.8612	251.0896
305.3	306.753	305.9222	307.5138
354.9	354.425	351.8213	336.7806
Average relative errors (%)	0.422242	2.42877	2.93053

Table 5. Testing dataset.

Electrolyte concentration (wt.%)	Voltage (V)	Initial machining gap (μm)	Tool feed rate (μm /s)	Radial overcut (μm)
14	11	60	9	204.9
16	9	60	12	174.6
18	15	60	6	335.8
20	11	70	6	342.1

Table 6. Testing dataset.

Regression	CANFIS	ANN	Relative error obtained by Regression (%)	Relative error obtained by CANFIS (%)	Relative error obtained by ANN (%)
194.123	198.012	198.721	5.2596	3.3617	3.0154
191.846	180.352	195.869	9.8774	3.2945	12.1815
321.792	334.802	334.957	4.1715	0.2971	0.2511
299.997	296.284	326.277	12.3072	13.3925	4.6252
Average relative errors (%)			7.90396	5.08647	5.01829

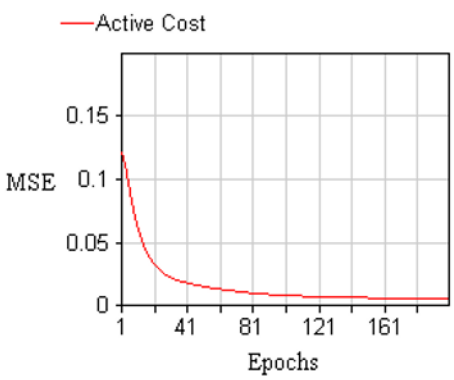

Figure 6. Progression of training (Active cost graph).

8. Conclusions

In this work, the effect of the process parameters on the radial overcut in electrochemical drilling with vacuum extraction of electrolyte was studied. The following remarks can be pointed out:

- The increase of the voltage and electrolyte concentration increases the radial overcut.
- The increase of the tool feed rate decreases the radial overcut.
- The voltage, electrolyte concentration and tool feed rate are the most effective parameters on the radial overcut, respectively; the initial machining gap has a slight effect.
- The electrolyte concentration, voltage, initial machining gap and tool feed rate have an interactive effect on each other with regard to the radial overcut.

This research proposed three different techniques, regression analysis, artificial neural network (ANN) and co-active neuro fuzzy inference system (CANFIS), for the prediction of radial overcut in electrochemical drilling with vacuum extraction of electrolyte. The radial overcut values predicted by regression, CANFIS and ANN were compared with the experimental results in order to determine the error of the models. The predictive ANN and CANFIS models were found to be much more accurate in predicting of radial overcut when compared with the regression model. The ANN and CANFIS models could predict the radial overcut for different process conditions with an average relative error of 5.01829% and 5.08647%, respectively.

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