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Prediction and Optimization of EDM Process Parameters Using Artificial Neural Network and Genetic Algorithm

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ABSTRACT
The objective of the paper is to develop empirical models and prediction of machining quality for Electrical Discharge Machining of Precipitation Hardened Stainless Steel (PH Steel) with copper tungsten electrode. The important process input parameters such as peak current, pulse on time, pulse off time and tool lift time are selected to predict the machining qualities of Material Removal Rate and Surface Roughness . Taguchi experimental design L27 orthogonal array was used to formulate the experimental design. The empirical models have been developed to predict the Material Removal Rate and Surface Roughness using Regression Analysis and Artificial Neural Network (ANN). Back propagation algorithm with experimental data used to train ANN. Prediction capability of ANN model and regression models are verified with experimental data. According to results, the ANN model is better performed as compared to the regression model to predict the MRR and SR for a given range of process parameters of EDM. Finally non-dominated sorting genetic algorithm (NSGA-II) applied to obtain non-dominated solution set to achieve the maximum material removal rate and minimum surface roughness.

Keywords - PH Steel, copper tungsten electrode, MRR, SR, ANN, NSGA-II

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I. INTRODUCTION

Electrical Discharge Machining (EDM) is one of the most extensively used nonconventional material removal processes. The EDM efficiency is measured in terms of machining characteristics viz. material removal rate, tool wear rate and surface roughness. EDM is a complex manufacturing process and improving a material removal rate and surface roughness are still challenging problems[4]. When new and advanced materials appear in the field it has not been possible to use existing models and hence experimental investigations are always required. Undertaking frequent tests is also not economically justified.Bharti et al. [1] Experiments have been carried out on die-sinking EDM by taking Inconel 718 as workpiece machined with copper. Artificial neural network with back propagation algorithm has been used to model EDM process. Controlled elitist non-dominated sorting genetic algorithm has been employed in the trained network and a set of pareto-optimal solutions is obtained. Sameh [2] developed model for EDM process. concluded that the total average prediction error of experimental results with that values predicted from the developed neural network model prediction was calculated as 4.4616 %. Well-trained neural network models provide fast, accurate and consistent results, making them superior to all other techniques. Bhavesh et al [3] for modeling Neural Network Toolbox with Mat lab 7.1 has been used. The neural network based process model has been generated to establish relationship between input process conditions and process responses. Panchal et al [4] presented a research work on Effect of process parameters has been examined for Copper electrode in Die Sinking EDM process of SS 440C using ANN. MRR decreases and Surface Quality increases and when Flushing speed increases, MRR increases. Shiba Narayan Sahu et al [5]. studied performance of EDM the machining parameters discharge current , pulse duration , duty cycle and voltage were used as model input variables during the development of the models. Krishna Mohana Rao and Hanumantha Rao [6] Work is aimed at optimizing the hardness of surface produced in die sinking electric discharge machining by considering the simultaneous affect of various input parameters. Multi perceptron neural network models were developed using Neuro solutions package. Genetic algorithm concept was used to optimize the weighting factors of the network. Das et al [7] In this research the prediction of surface roughness in Electrical Discharge Machining of SKD 11 Tool steel reported results indicate that the proposed model can satisfactorily predict the surface roughness in EDM. Ashikur Rahman Khan et al [8] proposed multi-layer perception neural architecture for the prediction of MRR on Ti-5Al-2.5Sn alloy in electrical discharge machining process. Rahman [9] presented the artificial intelligence model to predict the optimal machining parameters. Radial basis function neural network is used to develop the artificial neural network modelling. Design of experiments method used to implement the response surface method Dragan Rodic et al [10] Experiments are carried out on manganese alloyed cold-work tool steel. The results indicate that the genetic programming technique gives slightly smaller deviation of the measured values of model than fuzzy logic and neural network.

The objective of the present work is to develop empirical models of machining quality for electrical discharge machining of Precipitation Hardening Stainless steel machined with copper tungsten electrode. The empirical models have been developed for electrical discharge machining using Regression Analysis and the Artificial Neural Network to predict the Material Removal Rate and Surface Roughness. The machining parameters are optimized using NSGA-II algorithm to maximization of material removal rate and minimization of surface rough roughness. Finally a non-dominated solution set was obtained.

II. EXPERIMENTAL PROCEDURE

The Experiments were conducted using Copper Tungsten which had good electrical conductivity, high wear resistance. Due to this reason tool wear minimum while machining with Copper Tungsten. The bottom of the tool was polished using a very fine-grade emery sheet before each experiment[2]. In order to measure the MRR it is necessary to obtain the initial weights of the workpiece and tool. It has been performed using the digital electronic weighing balance AY221 1mg accuracy. At the end of each experiment, the workpiece and tool were removed, washed, dried, and weighed using digital weighing balance. The experiments are conducted for the machining time of the 10 minutes was determined using a timer. Machining was done with straight polarity and EDM oil Grade 30 used as the dielectric fluid. Gap voltage is 30 V and flushing pressure maintained constant. The input levels and number of experiments are decided based on the design of experiments. Process parameters and their levels are presented in Table. 1. In this study, an L27 orthogonal array was used for experimentation [1]. The material removed rate was calculated using equation 1.

$$MRR = 1000*(W_1 - W_2) / T \quad \text{mg/min} \qquad (1)$$

W_1: Weight of the work-piece before machining(mg)
W_2: Weight of the work-piece after machining (mg)
T : Machining time (min)

III. MATHEMATICAL MODELS FOR MRR AND SR

Regression Analysis is a statistical tool for the investigation of relationships between variables. It can be expressed as a second order model including an interaction terms written as equation [5]. Statistical software MINITAB 17 was used to develop a regression model for predicting MRR and SR. The experimental data are used to perform regression analysis and the numerical values of coefficients are determined. Developed second order regression models used for prediction of machining qualities as function of input process parameters (A, B, C and D). The Prediction models are verified against the experimental data and comparison is illustrated in Fig.1 and Fig.2. The results obtained from the model are very close to that of experiments conducted. It can be found that the predicted values and experimental values have less deviation for both MRR and SR. The average deviation estimated for MRR as 5.36% and for SR as 4.89%[6]. It is clear that the experimental data agree very well with predictions. Therefore the regression models are used to estimate the both MRR and SR for machining of Precipitation Hardening Stainless using EDM for a given range of input parameters.

Table.1 Process parameters and their levels

S.No.	Process parameters	Symbol	Level 1	Level 2	Leve 3
1	Current (A)	I	9	12	15
2	Pulse on time (µs)	Ton	50	100	200
3	Pulse off time(µs)	Toff	20	50	100
4	Lift time (µs)	Tlift	10	20	50

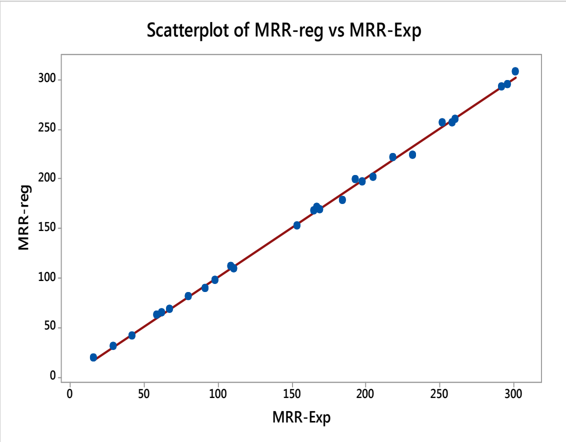

Fig.1 Comparison of predicted and experimental MRR

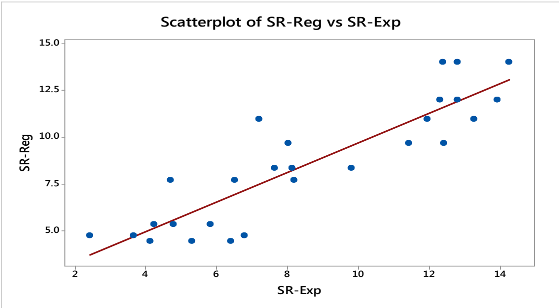

Fig.2 Comparison predicted and experimental SR

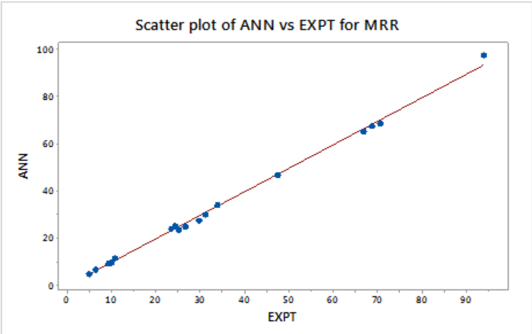

Fig.3 Comparison of ANN and Experimental MRR

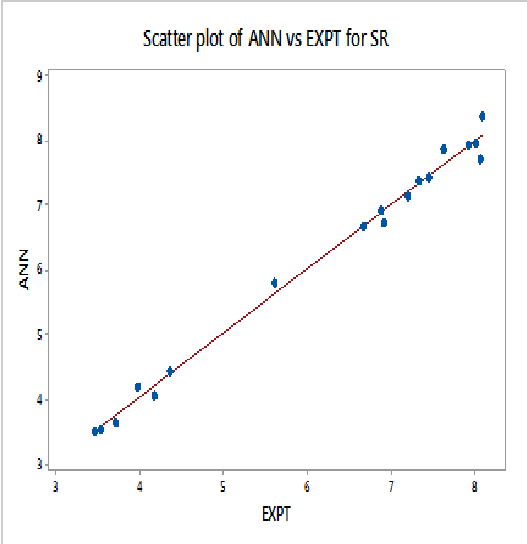

Fig.4 Comparison of ANN and Experimental SR

Table. 3 Optimal Parameters for EDM process

S.No	I (A)	Ton (μs)	Toff (μs)	Tlift (μs)	MRR (mg/min)	SR (μm)	S.No	I (A)	Ton (μs)	Toff (μs)	Tlift (μs)	MRR (mg/min)	SR (μm)
1	15	50	100	10	169.8	10.31	**10**	15	50	20	20	129.3	8.75
2	15	50	50	10	157.9	9.89	**11**	12	50	50	10	91.50	7.21
3	15	50	20	10	150.1	8.87	**12**	15	50	20	20	134.6	8.91
4	15	50	100	20	154.4	9.57	**13**	15	50	20	10	150.0	9.12
5	15	50	50	20	142.5	9.42	**14**	15	50	20	50	107.8	7.33
6	15	50	20	20	129.4	8.78	**15**	12	50	50	10	95.60	7.05
7	12	50	100	10	105.6	7.86	**16**	15	50	50	20	137.2	9.10
8	15	50	100	50	128.6	8.52	**17**	9	50	100	20	76.20	6.44
9	15	50	50	50	116.7	7.54	**18**	12	50	100	50	79.71	6.81

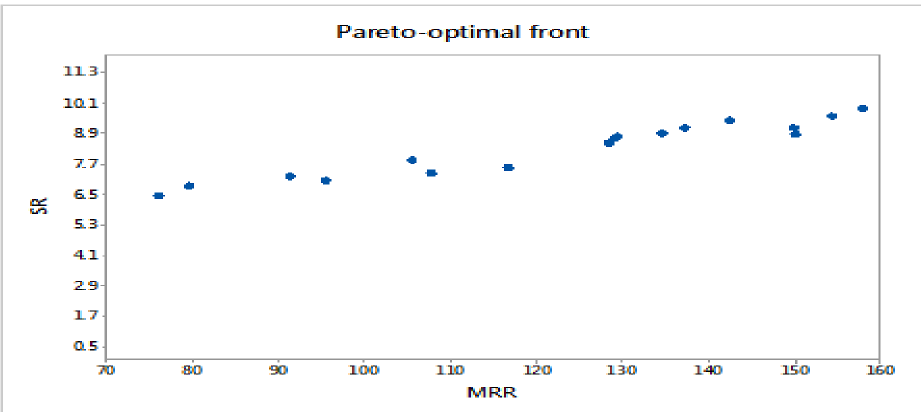

Fig.5 Pareto-optimal front

1. Development of ANN model for MRR and SR

Experimental results were used to develop an ANN model for predicting MRR and SR. In this work, four inputs and two outputs are considered as the data of ANN model. The experimental set consists of 27 data points, of which 18 data points were used for training the network and 9 data points were chosen randomly for testing the performance of the trained network [6]. After the network has successfully completed the training stage, it was tested with the experimental data that were not present in the training data set. The input and output data is scaled from 0 to 1. After several attempts of trial and error, the appropriate values of learning rate coefficient and momentum terms selected [8]. Performance of the network is determined with MSE which should be minimized. Comparison of predicted and experimental MRR and SR are shown in Fig.3 and Fig.4.

2. Multi-objective optimization

Optimization problems involving more than one objective function to be optimized simultaneously. Multi-objective optimization has been applied in many fields of science, including engineering, economics and logistics where optimal decisions need to be taken in the presence of trade-offs between two or more. Using GA random values of current, Ton, Toff, Tlift are generated and their corresponding MRR and SR values are calculated using developed equation. These values are stored in the form of string in the order of current, Ton, Toff, Tlift, MRR and SR. First a parent population of variable size is generated and strings having maximum MRR and minimum SR are stored in a file. Then crossover is performed on the strings according to the probability and similarly mutation is also performed. Then a new child is generated and NSGA-II is performed according to which each string is compared with the other strings in MRR and SR. A program was written in C language to find optimal solutions of EDM input variables. After executing the program the results obtained were shown in Table 3. Pareto-optimal front of optimum parameters are shown in Fig.5.

IV. CONCLUSIONS

In the present paper, the empirical models have been developed for EDM process for machining of Precipitation Hardening Stainless steel machined with copper tungsten electrode using Multiple Regression Analysis and ANN. The regression model developed using MINI TAB 17. The ANN model developed to predict the machining qualities using Back propagation neural network algorithm a program developed in C^{++} programming. From the experimental investigation, the following conclusions are derived

- It has been observed that, there is good agreement between the regression model and the experimental results.
- The average error observed in regression model for MRR and SR as 4.14 and 2.42.
- In ANN model the mean deviation of the predicted and experimental results of MRR and SR is very small and good agreement between both training and testing data.
- The average error observed in ANN model for MRR and SR as 3.32 and 2.25 respectively in testing stage.
- According to results the ANN model produced the better prediction for MRR and SR compared to the regression model. It is clear that, the developed ANN models can be used to estimate the results of EDM for given range of process parameters.
- The EDM process parameters were optimized using non-dominated sorting genetic algorithm and a set of non-dominated solution were obtained.
- This optimization will help to increase production rate by increasing the material removal rate and reduce the machining time.
- This optimized data base was good source of solutions for selection of optimal parameters selection for maximization of MRR and minimization of SR.

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