International Journal of Advanced Mechanical Engineering.
ISSN 2250-3234 Volume 4, Number 6 (2014), pp. 667-674

http://www.ripublication.com

Prediction of Surface Roughness in WEDM Process Using Feed Forward Back Propagation Neural Network

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ABSTRACT

The surface roughness quality significantly influences the machined parts during their useful life. It is very hard to develop a comprehensive model involving all the input parameters because of the complexity of the machining process. In the present study, surface roughness is measured during wire cut electrical discharge machining (WEDM) process for different values of pulse-on time, gap voltage and wire feed rate using L27 OA. Artificial neural network is used to model the surface roughness which is trained and validated using feed forward back propagation method, Levenberg-Marquardt (LM) training algorithm, tansig transfer function using one hidden layer, four neurons and 1000 epochs were carried out. The LM model has produced absolute fraction of variance (R^2) values of 0.98069 for the training data, 0.99906 for validation and overall to be 0.96721. The mean square error decreased from 0.005 to 0.000005 during ANN training. The predicted ANN data was well within the limits and the simulation also showed good accuracy. The results indicated that well trained neural network model is quite effective for prediction of surface roughness within and beyond the experimental domain.

Keywords: Surface roughness, Wire electrical discharge machining, Artificial neural network.

INTRODUCTION

WEDM is a non-conventional precision machining process that is widely used in tool and dies making industry. The machining principle is based on erosion of the work-piece material using a successive discrete discharges occurring between the wire electrode and workpiece. Die-making industry is very important to down-stream industries and any technological changes in the die-making industry surely affect those down-stream manufacturing. New materials with high hardness and toughness, such as die and tool steels, are being developed which are difficult to be machined by conventional manufacturing techniques. Hence, non-traditional machining processes are employed. WEDM is widely used to machine these. Surface roughness describes the geometry and surface textures of the machined parts. Artificial neural network is composed of many artificial neurons that are linked together according to a specific network architecture. The objective of the neural network is to transform the inputs into meaningful outputs.

LITERATURE SURVEY

Yiming and Panagiotis constructed a roughness estimator. Wong and Hamouda investigated the feasibility of using a neural network to represent machinability data. Rodolfo and Alique presented an intelligent supervisory system from a model-based approach. Grzesik and Brol made an assessment of surface quality in turned ground and honed specimens by means of computer-based processing of digitized surface profiles. Pendse and Joshi postulated earlier that the size of reinforcement particulate in the composite material would significantly affect the surface roughness when its magnitude is comparable to the feed-rate and tool-nose radius employed in machining. Myers and Montgomery developed a response surface-based D-optimal design consisting 29 experimental runs that considers five factors. Motorcu and Sahin have machined the hardened AISI 1040 steel with triangular and square tools in different machining conditions and modeled the surface roughness. Lin has formulized experimental results of surface roughness and cutting forces by regression analysis, and modeled the effects of them in his study using S55C steel. Davim et al. extended the classical Merchants theory of metal cutting to machining of MMCs. Arno et al. investigated the performance of coated diamond tools on machining fibre-reinforced polymers. Kanlayasiri et. al. investigated the influence of WEDM machining variables on surface roughness of newly developed DC 53 die steel. Panda et. al. has developed an ANN model (using feed forward neural architecture) using Levenberg-Marquardt learning algorithm and logistic sigmoid transfer function to predict the material removal rate. Pradhan et. al. compared the performance and efficiency of backprop neural network (BPN) and radial basis function neural network (RBFN) for the prediction of SR in EDM.

EXPERIMENTAL DETAILS

WORK PIECE MATERIAL, PARAMETERS, SURFACE ROUGHNESS RESULTS

The workpiece material is AISI D3 die steel. The process parameters, levels and surface roughness results are shown in Table 1.

Table 1 : Parameter levels and Surface Roughness obtained

Expt No.	Ton	Vg	F	Mean Ra
1	30	10	15	4.8625
2	30	10	20	4.7525
3	30	10	25	4.67
4	30	20	15	4.8425
5	30	20	20	4.7675
6	30	20	25	4.61
7	30	30	15	4.85
8	30	30	20	4.67
9	30	30	25	4.57
10	40	10	15	4.995
11	40	10	20	5.395
12	40	10	25	4.9425
13	40	20	15	5.345
14	40	20	20	5.0825
15	40	20	25	5.215
16	40	30	15	5.1425
17	40	30	20	5.345
18	40	30	25	5.1675
19	50	10	15	6.225
20	50	10	20	5.755
21	50	10	25	5.9075
22	50	20	15	5.7825
23	50	20	20	6.12
24	50	20	25	5.9425
25	50	30	15	6.35
26	50	30	20	6.0975
27	50	30	25	6.2925

ARTIFICIAL NEURAL NETWORKS

BACK-PROPAGATION NETWORK ALGORITHM

The general architecture of a 3-layered multilayer perceptron (MLP) consists of input layer, hidden layer, output layer. MLP uses back propagation algorithm (BPA) for training the network in a supervised manner and forms the basis for majority of practical applications.

GENERATING THE ANN MODEL, PRE-TRAINING, TESTING DATA

The ANN model was selected by sequentially varying the number of neurons and selecting those which gave the best performance and thus was generated for 1 hidden layer, 4 neurons, tansig transfer function, LM training algorithm using feed forward backpropagation method. To produce similar output for similar input and thus to avoid overfitting, pre-training (normalization) is carried out (Table 2) using the equation suggested by Sanjay and Jyothi :

$$x_i = \frac{x_i - \min_i}{\max_i - \min_i} * 0.8 + (0.1) \quad (1)$$

for each value x_i of i^{th} attribute, min_i and max_i are the minimum and maximum value of that attribute over the training set in Table 1.

Using Table 2, 23 readings were randomly selected for training data (Table 3).

Table 2: Normalised Data

Exp	Ton	V	F	R
1	0.1	0.1	0.1	0.231333
2	0.1	0.1	0.5	0.181943
3	0.1	0.1	0.9	0.1449
4	0.1	0.5	0.1	0.222353
5	0.1	0.5	0.5	0.188678
6	0.1	0.5	0.9	0.11796
7	0.1	0.9	0.1	0.22572
8	0.1	0.9	0.5	0.1449
9	0.1	0.9	0.9	0.1
10	0.5	0.1	0.1	0.290825
11	0.5	0.1	0.5	0.470425
12	0.5	0.1	0.9	0.267253
13	0.5	0.5	0.1	0.447975
14	0.5	0.5	0.5	0.330113
15	0.5	0.5	0.9	0.389605
16	0.5	0.9	0.1	0.357053
17	0.5	0.9	0.5	0.447975
18	0.5	0.9	0.9	0.368278
19	0.9	0.1	0.1	0.843095
20	0.9	0.1	0.5	0.632065
21	0.9	0.1	0.9	0.700538
22	0.9	0.5	0.1	0.644413
23	0.9	0.5	0.5	0.79595
24	0.9	0.5	0.9	0.716253
25	0.9	0.9	0.1	0.89922
26	0.9	0.9	0.5	0.785848
27	0.9	0.9	0.9	0.873403

Table 3: Training Data

Ton	V	F	R
0.1	0.1	0.1	0.231333
0.1	0.1	0.5	0.181943
0.1	0.1	0.9	0.1449
0.1	0.5	0.1	0.222353
0.1	0.5	0.5	0.188678
0.1	0.9	0.1	0.22572
0.1	0.9	0.5	0.1449
0.1	0.9	0.9	0.1
0.5	0.1	0.1	0.290825
0.5	0.1	0.5	0.470425
0.5	0.5	0.1	0.447975
0.5	0.5	0.5	0.330113
0.5	0.5	0.9	0.389605
0.5	0.9	0.1	0.357053
0.5	0.9	0.5	0.447975
0.5	0.9	0.9	0.368278
0.9	0.1	0.5	0.632065
0.9	0.1	0.9	0.700538
0.9	0.5	0.1	0.644413
0.9	0.5	0.5	0.79595
0.9	0.5	0.9	0.716253
0.9	0.9	0.1	0.89922
0.9	0.9	0.9	0.873403

TRAINING THE ANN AND POST TRAINING

The ANN model generated (Fig) was trained for the training data (Table 6) using LM training algorithm for 1000 epochs (cycles of learning). The training results are shown in Fig 4. Post training of the ANN was performed using the command ‘postreg’ (Fig 5).

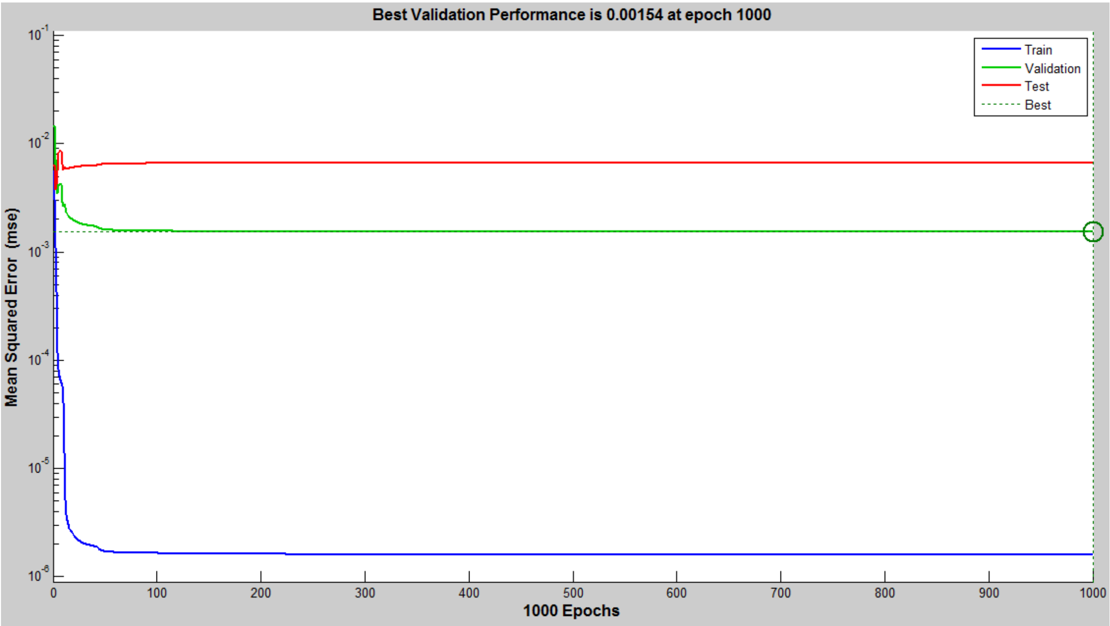

Fig 1: Training the ANN

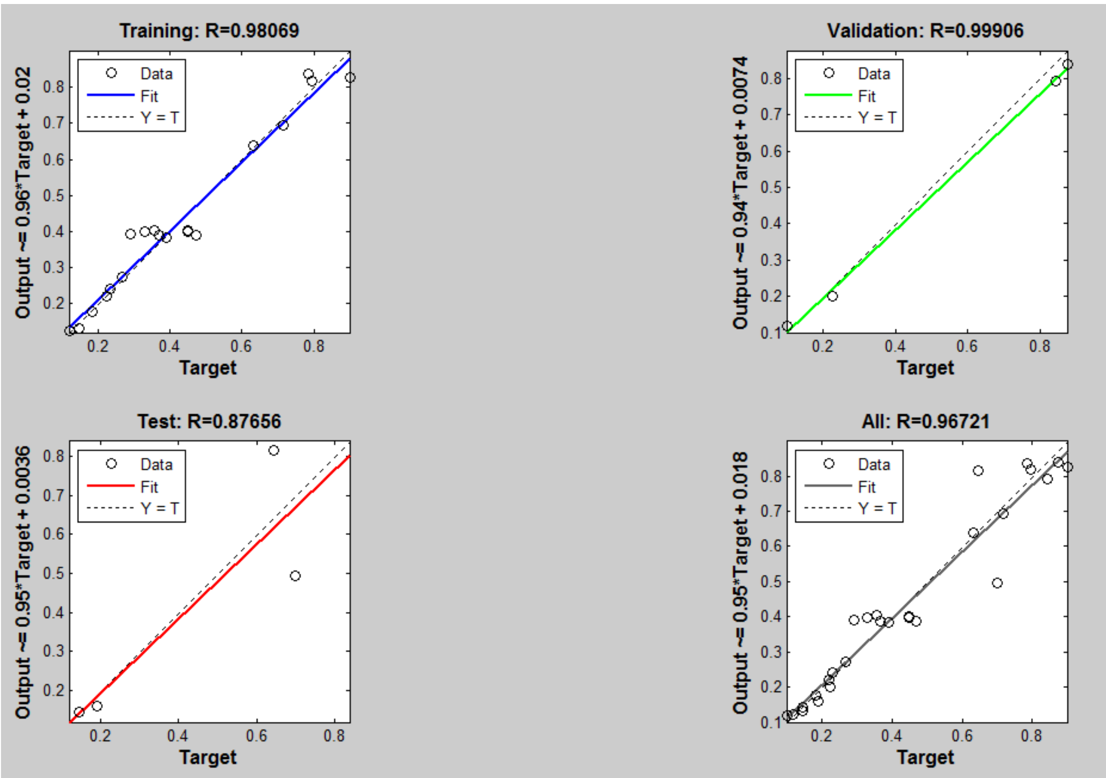

Fig 2: Post training the ANN

4.4 ANN PREDICTED OUTPUT

The generated ANN model which was trained was now used for the prediction of the surface roughness. In this, the data not used for ANN training, i.e. experiment no. 6, 12, 19, 26 were given as input to the ANN model and the output for these was now predicted and then compared with the experimental output (Table 1) to find out the deviation (Table 4).

Table 4: Testing the ANN accuracy

Ton	V	F	Experimental Ra	ANN predicted R_a	% Error
0.1	0.5	0.9	0.11796	0.12344	4.645643
0.5	0.1	0.9	0.2672525	0.27237	1.914856
0.9	0.1	0.1	0.843095	0.79287	-5.95722
0.9	0.9	0.5	0.785848	0.83623	6.411163

DISCUSSION OF RESULTS

During the ANN training using LM training algorithm the mean square error decreased from 0.005 to 0.000005 as seen from Figure 1. The LM model has produced absolute fraction of variance (R^2) values about 0.98069 for the training data, 0.99906 for validation and overall to be 0.96721 as seen from Figure 2.

The ANN predicted output is within the acceptable range as seen from Table 4.

The well trained ANN model is quite effective for prediction of surface roughness without actually going for experimentation and thus can save time and money.

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