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Prediction of Process Parameters of Wire EDM for AISI A2 Using ANN

KEYWORDS: Wire Electrical Discharge Machining (WEDM), Artificial Neural Network

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ABSTRACT *Wire EDM is most progressive non-conventional machining process in mechanical industries. There are many parameter affect the performance of Wire EDM. Few of them are investigated in this research paper. The effect of process parameter like Pulse ON time, Pulse OFF time, Voltage, Wire Feed and Wire Tension on MRR, SR, Kerf and Gap current is studied by conducting an experiment. Artificial Neural Network is used for Predict of output parameters of Wire EDM of AISI A2. The training, testing and validation data set are collected by conducting experiment on work piece material AISI A2.It is found that ANN is a powerful tool for data prediction and it gives agreeable result when Experimental and Predicted Data were compared.*

1. INTRODUCTION

In mechanical industry, the demands for alloy materials having high hardness, toughness and impact resistance are increasing. Nevertheless, such materials are difficult to be machined by traditional machining methods. Hence, non-traditional machining methods including electrochemical machining, ultrasonic machining, electrical discharging machine (EDM) etc. are applied to machine such difficult to machine materials. WEDM process with a thin wire as an electrode transforms electrical energy to thermal energy for cutting materials. With this process, alloy steel, conductive ceramics and aerospace materials can be machined irrespective to their hardness and toughness. Furthermore, WEDM is capable of producing a fine, precise, corrosion and wear resistant surface. A continuously travelling wire electrode made of thin copper, brass or tungsten of diameter 0.05-0.30 mm, which is capable of achieving very small corner radii. There is no direct contact between the work piece and the wire, eliminating the mechanical stresses during machining. The WEDM is a well-established machining option for manufacturing geometrically complex or hard material parts that are extremely difficult-to-machine by conventional machining processes. The non-contact machining techniques have been continuously evolving in a mere tool and die making process to a micro-scale application.

2. ARTIFICIAL NEURAL NETWORK

Artificial Neural networks (ANNs) have been used for a wide variety of applications where statistical methods are traditionally employed. ANNs can be used in the following applications; quality control, pattern recognition, resource allocation, constraints satisfaction (optimization), scheduling, maintenance and repairing, process control and planning, data base management, simulation, and robotics control. In time-series applications, NNs have been used in predicting stock market performance. As statisticians or users of statistics, these problems are normally solved through classical statistical methods, such as discriminate analysis, logistic regression, Bayes analysis, multiple regression, and ARIMA time-series models. It is, therefore, time to recognize neural networks as a powerful tool for data analysis in complex machining process like Wire EDM. Artificial Neural Networks (ANNs) are non-linear data driven self adaptive approach as opposed to the traditional model based methods. ANN is one of the branches of Artificial Intelligence (AI). ANNs are powerful tools for modelling, especially when the underlying data relationship is unknown. ANNs can identify and learn correlated patterns between input data sets and corresponding target values. After training, ANNs can be used to predict the outcome of new independent input data. ANNs imitate the learning process of the human brain and can process problems involving non-linear and complex data even if the data are imprecise and noisy. Thus they are ideally suited for the data which are known to be complex and often nonlinear. In summary, a neural network takes an input numeric pattern and produces an output numeric pattern.

3. LITERATURE REVIEW

The neural network was used to model the machinists' modifications on recommended cutting conditions suggested by the process planner. Le Tumelin et al. developed a 5 layer feed-forward network to determine sequence of operations for machining holes. The designed network receive 12 coded inputs describing the geometrical and technological features of the hole features, and generates 23 outputs, each one related to a particular machining operation. The activation of an output means that the corresponding machining operation is selected for machining the hole. Shan, et al., has proposed a system for operation sequencing in which an expert system is integrated with a neural network. G Krishna Mohana Rao et al [6] presented work that was aimed at optimizing the metal removal rate of die sinking electric discharge machining (EDM) by considering the simultaneous affect of various input parameters. The experiments are carried out on Ti6Al4V, HE15, 15CDV6 and M-250. Experiments were conducted by varying the peak current and voltage and the corresponding values of metal removal rate (MRR) were measured. Multiperceptron neural network models were developed using Neuro solutions package. M K Pradhan et al [8] in this work, two different artificial neural networks (ANNs) models: Back propagation neural network (BPN) and radial basis function neural network (RBFN) are presented for the prediction of surface roughness in die sinking Electrical Discharge Machining (EDM). The pulse current (Ip), the pulse duration (Ton) and duty cycle (t) are chosen as input variable with a constant voltage 50 volt, surface roughness is the output parameters of the model. A widespread series of EDM experiments was conducted on AISI D2 steel to acquire the data for training and testing and it was found that the neural models could predict the process performance with reasonable accuracy, under varying machining conditions. K. P. Somashekhar et al [10] reports on the development of modelling and optimization for micro-electric discharge machining (μ-EDM) process. Artificial neural network (ANN) is used for analyzing the material removal of μ-EDM to establish the parameter optimization model. A feed forward neural network with back propagation algorithm is trained to optimize the number of neurons and number of hidden layers to predict a

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better material removal rate.

4. EXPERIMENTAL WORK

Taguchi method is used for Design of Experiment. The control factors considered for the study are Pulse-on, Pulse- off, Bed speed and Current. Three levels for each control factor will be used. Based on number of control factors and their levels, L_{27} orthogonal array (OA) was selected for data collection. The constant parameters taken are Pulse Peak Current is 210 A, Pulse Peak Voltage is 2 volt, and Flushing Pressure is 12 kgf/cm^2. Table-1 represents constants and Table-2 shows experimental Levels of various control factors. Table 2 shows Experimental data for training, testing and validation.

Input Parameters	Level 1	Level 2	Level 3
Pulse ON time – (A)	115	120	125
Pulse OFF time – (B)	45	50	55
Voltage – (C)	21	23	25
Wire Feed - (D)	4	6	8
Wire Tension - (E)	2	7	10

Table-1 Levels of various control factors

Figure 3. Wire cut EDM Machine

The experiments were carried out on a wire-cut EDM machine (ELEKTRA SUPERCUT 734) of HI-TECH ENGINEERS installed at Gayatri CNC Wire cut, CTM, Ahmadabad, Gujarat, India shown in Figure-3. An AISI A2 is Air-Hardening tool steel which containing five percent chromium. They Replaces the oil hardening when safer hardening, less distortion and increased wear-resistance are required. They Provides an intermediate grade between the oil hardening and the high carbon, high chromium (D2) types. The Designations in other countries are as AFNOR Z 100 CDV 5 in France, DIN 1.2363 in Germany, JIS SKD 12 in Japan.

Sr.No	(A)	(B)	(C)	(D)	(E)	CR	SR	KERF	IG
1	115	45	21	4	2	0.92	2.21	0.30	2.3
2	115	45	21	4	7	1.02	2.42	0.29	2.7
3	115	45	21	4	10	1.10	2.50	0.31	2.8
4	115	50	23	6	2	0.83	1.71	0.32	1.9
5	115	50	23	6	7	0.86	2.00	0.33	2.1
6	115	50	23	6	10	0.86	2.11	0.36	2.0
7	115	55	25	8	2	0.83	1.83	0.35	1.9
8	115	55	25	8	7	0.84	1.89	0.37	2.0
9	115	55	25	8	10	0.85	1.94	0.38	2.0
10	120	45	23	8	2	1.39	2.76	0.30	3.7
11	120	45	23	8	7	1.45	3.11	0.35	3.8
12	120	45	23	8	10	1.53	2.88	0.33	4.2
13	120	50	25	4	2	0.99	2.33	0.36	2.5
14	120	50	25	4	7	1.12	2.30	0.39	2.9
15	120	50	25	4	10	1.12	2.51	0.38	2.9
16	120	55	21	6	2	0.82	2.07	0.31	2.2
17	120	55	21	6	7	0.88	2.08	0.32	2.1
18	120	55	21	6	10	0.91	2.17	0.34	2.2
19	125	45	25	6	2	1.70	2.79	0.33	5.0
20	125	45	25	6	7	1.62	2.96	0.34	4.6
21	125	45	25	6	10	1.62	2.97	0.35	4.6
22	125	50	21	8	2	1.51	2.58	0.30	4.0
23 to 27 are used for Validation									
23	125	50	21	8	7	1.54	2.89	0.31	4.3
24	125	50	21	8	10	1.57	2.92	0.32	4.4
25	125	55	23	4	2	1.10	2.48	0.32	2.8
26	125	55	23	4	7	1.15	2.84	0.36	3.0
27	125	55	23	4	10	1.29	2.67	0.36	3.4

Table. Experimental date

5. PREDICTION USING ARTIFICIAL NEURAL NETWORK

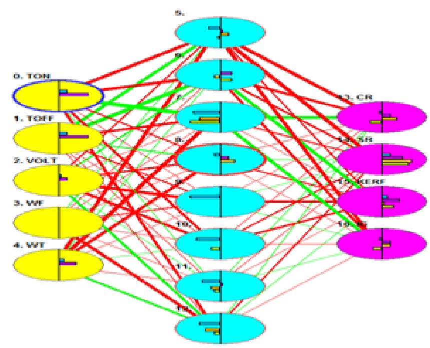
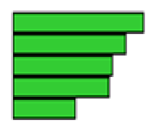


Figure 4. Developed ANN for WEDM



WEDM ANN.tvq 406 cycles. Target error 0.0100 Average training error 0.002302

The first 5 of 5 Inputs in descending order.

Column	Input Name	Importance	Relative Importance
0	TON	17.8448	
2	VOLT	15.4626	
1	TOFF	13.6753	
4	WT	13.2319	
3	WF	8.6169	

Figure 5. Importance of Input Parameters

Exp. CR	ANN CR	Error	Exp. SR	ANN SR	Error	Exp. Kerf	ANN Kerf	Error	Exp. IG	ANN IG	Error
1.54	1.49	0.05	2.89	2.96	0.07	0.31	0.32	0.01	4.3	4.0	0.3
1.57	1.50	0.07	2.92	3.00	0.08	0.32	0.34	0.02	4.4	4.0	0.4
1.10	1.08	0.02	2.48	2.34	0.14	0.32	0.32	0	2.8	2.7	0.1
1.15	1.16	0.01	2.84	2.76	0.08	0.36	0.35	0.01	3.0	3.0	0
1.29	1.21	0.08	2.67	2.81	0.14	0.36	0.36	0	3.4	3.2	0.2

Table 4.Comparison between Experimental and ANN Predicted Result

6. CONCLUSION

From Comparison of Experimental result and ANN Predicted result it is found that they are very close and error is very less. The maximum error is 0.14. ANN is powerful technique for prediction of process parameters giving very accurate result. Once we have experimental data we can predict output without conducting Experiment. Pulse on time has more importance on output parameter. Experimental results are agreeable with ANN predicted result.

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