Algorithm for Modeling Wire Cut Electrical Discharge Machine Parameters using Artificial Neural Network

G.Sankara Narayanan[#1], D.Vasudevan[#2]

[#]Department of Mechanical Engineering,
[#1]SBM College of Engineering and Technology, Dindigul-624 005, Tamilnadu, India.
[#2] PSNA College of Engineering and Technology Dindigul-624 622, Tamilnadu, India.
[#1]sankaranarayanandgl@gmail.com
[#2]drdvasudevan@gmail.com

Abstract- Unconventional machining process finds lot of application in aerospace and precision industries. It is preferred over other conventional methods because of the advent of composite and high strength to weight ratio materials, complex parts and also because of its high accuracy and precision. Usually in unconventional machine tools, trial and error method is used to fix the values of process parameters which increase the production time and material wastage. A mathematical model functionally relating process parameters and operating parameters of a wire cut electric discharge machine (WEDM) is developed incorporating Artificial neural network (ANN) and the work piece material is SKD11 tool steel. This is accomplished by training a feed forward neural network with back propagation learning Levenberg-Marquardt algorithm. The required data used for training and testing the ANN are obtained by conducting trial runs in wire cut electric discharge machine in a small scale industry from South India. The programs for training and testing the neural network are developed, using matlab 7.0.1 package. In this work, we have considered the parameters such as thickness, time and wear as the input values and from that the values of the process parameters are related and a algorithm is arrived. Hence, the proposed algorithm reduces the time taken by trial runs to set the input process parameters of WEDM and thus reduces the production time along with reduction in material wastage. Thus the cost of machining processes is reduced and thereby increases the overall productivity.

Keyword- WEDM, Artificial Neural Network, SKD11, Levenberg-Marquardt algorithm

I. INTRODUCTION

Wire cut Electrical Discharge Machine (WEDM) is an unconventional machining process which is widely used to produce a precise, complex intrinsic – extrinsic irregular shaped job and difficult to machine electrically conductive materials due to its high strength, high bending stiffness, better fatigue characteristics, good damping capacity and low thermal expansion which make them potential material for modern day industrial applications like super alloys, ceramics and composites. It is also used in manufacturing of moulds for plastics, dies for forgings and castings of press tools, automotive, aerospace and surgical components [1].

Basically, WEDM is a thermo electric process and there is no contact between the tool electrode and the work piece. The material removal take place by the ignition of swift and recurring spark discharges between the gap of work piece and tool coupled in an electric circuit [1].

The wire electrode of various diameters like 0.05 to 0.3 mm is incessantly supplied from coil to work piece with a maintained gap of 0.025 to 0.05 mm between wire electrode and work piece. The selection of process parameters for obtaining higher cutting efficiency and accuracy is still not fully solved; even with the most updated CNC WEDM [2].

The WEDM process is governed by the various process parameters such as Pulse ON Time, Pulse OFF Time, Power Energy Selection, Working Current Range, Working Gap Range, Feed Rate, Rapid Capacitor, Spindle Feed and Electrode Tube Diameter, Flushing Pressure [3].

There were lots of research works regarding the optimization and modeling of input machining parameters [4] but research and literature lacks much to say about the setting of input parameters without trial and error for machining tool steel materials by using WEDM. So the need has been felt towards the highlighting the process with the goal of achieving mathematical models to select the process parameters for maximum utilization of WEDM with improved process machining performance.

Here we have considered the tool steel SKD11 material as work piece, since it is one of the mostly machined on WEDM process than any other material comparatively [5]. This work incorporates Artificial Neural Network (ANN) and Mat lab (7.0.1; R14) package. ANN is used widely for modeling and optimizing the experimental data [5],[6] because ANN model is found to be capable of better calculations and predictions within the range that they have trained [7]. An ANN model is developed which adapts Levenberg-Marquardt algorithm which is one of the better algorithm for instructing reasonable- sized feed forward neural networks [8]. Moreover, minimizing the MSE is the best known advantage of Levenberg-Marquardt algorithm and these advantages make this algorithm the much favorite one in this work and has been set up to calculate the process parameters based on the operating parameters without conducting trials.

II. NOMENCLATURE

WEDM	- Wire Electrical Discharge Machine
ANN	- Artificial Neural Network
LM	- Levenberg-Marquardt
ONT	- Pulse on Time
OFT	- Pulse off Time
VS	- Power Energy Selection
IP	- Working Current Range
VG	- Working Voltage Gap Range
F	- Feed Rate
C	- Rapid Capacitor
S	- Spindle Feed
ED	- Electrode Tube Diameter
P	- Flushing Pressure
SB	- Stable
TI	- Time
T	- Thickness
W	- Wear
Mse	- Mean square error
rse	- root square error

III. METHODOLOGY

The different sets of machining experiments were performed on Ocean technologies wire EDM in a small scale industry from South India. SKD11 tool steel with various thicknesses ranging from 3 to 50 mm was used for experimentation. WEDM electrode materials need to have properties that easily allow charge and yet resist the erosion that the WEDM process encourages and stimulates in the metals it machines. When selecting WEDM electrodes, the most important considerations are its form and function such as material's conductivity or resistivity and its erosion resistance. Conductivity promotes cutting efficiency, since electric current is the "cutting tool". Erosion resistance, which is a factor of melting point, hardness, and structural integrity gives the electrode a longer service life and lowers the frequency of replacement [9]. These properties, which vary almost exclusively by the type of alloy or material used, must be the deciding factors when selecting an electrode.

Here, we have considered brass electrode as tool. Brass materials are used to form WEDM wire and small tubular electrodes. Brass alloy wire consists of Cu 63% and Zn 37%, which improves the cutting speed. It is relatively a good conductor and by its ample mechanical properties and tension capability, it yields about three time's surface finish than that of copper electrode [9]. WEDM wire does not need to provide wear or arc erosion resistance since new wire is fed continuously during the WEDM wiring cutting process.

The electrode and other machining conditions are brass electrode and its diameter with 0.3mm. Specific resistance of die electric fluid was $5 \times 10^4\ \Omega$cm and dielectric temperature was taken as 25 to 35 ^{o}C.

The machining was performed and the experimental values were noted for various process parameters such as pulse on time, pulse off time, power energy selection, working current range, working gap range, reed rate, rapid capacitor, spindle feed and electrode tube diameter, flushing pressure and stable as listed in the Table I. During machining, operating parameters such as thickness, wear and time was measured and as listed in the Table II. A Levenberg – Marquardt algorithm had been written for ANN by using MATLAB package and it was used to train the normalized parameters. In our model development, ANN was trained by considering the values of the operating parameters as input values and values of the process parameters as the output values.

The material properties and the mechanical properties of the work piece SKD11 is as listed in the Tables III and IV respectively. The process parameters and operating parameters were normalized to take values between 0 and 1. The effect Training a feed forward network back propagation learning technique was used. As a result of training, operating parameters are obtained and the result is validated by comparing this data with the actual data obtained from trial runs. Finally, the relation between the process parameters and operating parameters are formulated. Using this proposed formulae process parameters can be calculated.

TABLE I
Process Parameters

S.No	Process Parameters	Symbol	Steps
1	Pulse ON Time	ONT	5 ~ 99: 95 steps
2	Pulse OFF Time	OFT	5 ~ 99: 95 steps
3	Power Energy Selection	VS	1 ~ 3: 3 steps
4	Working Current Range	IP	0 ~ 31
5	Working Gap Range	VG	0 ~ 99
6	Feed Rate	F	0 ~ 99: 100 steps
7	Rapid Capacitor	C	0 ~ 6: 16 steps
8	Spindle Feed	S	0 ~ 6: 16 steps
9	Electrode Tube Diameter	ED	0 ~ 3.0
10.	Flushing Pressure	P	1 ~ 3: 3 steps
10.	Stable	SB	0 ~ 6: 16 steps

TABLE II
Operating Parameters

S.No	Operating Parameters	Symbol
1	Wear	W
2	Time	Ti
3	Thickness	T

TABLE III
Material properties of work piece

Mo: 0.40 ~ 0.60; V: 0.15 ~ 0.30
Cr: 11.00 ~ 12.50; C: 1.45 ~ 1.70;
Si: ≤ 0.4; Mn: ≤ 0.40
S: ≤ 0.030; P: ≤ 0.030;
Ni: To allow the residual content of ≤ 0.25
Cu: To allow the residual content of ≤ 0.30

TABLE IV
Mechanical properties of work piece

Hardness :235 HSB (annealing)
Pre heating Temperature: 788^{o}C
Tempering Temperature: 522 ^{o}C
Hardening Medium : Air Cooling
Working Condition: Cold working

IV. ANN MODEL DEVELOPMENT AND TRAINING

Function estimation is the task of learning and constructing a function that produces the same outputs from input vectors based on available training data [10]. An ANN is tagged directed graph arrangement where nodes perform some simple calculation and each connection arranges a signal from one node to another tagged by a number called the weight representing the degree to which a signal is augmented or lessened by a connection. All such graph cannot be called as a neural network. Only such graphs whose weights are primarily random, and if a learning algorithm conclude the values of weights that will accomplish the preferred task, are called a neural network [11]. The ways nodes are linked comprise different neural network architecture. Again there are quite a few node functions such as sigmoid, ramp, step, Piecewise linear function, etc and learning algorithms such as back propagation learning, competitive learning, hebbian learning, etc., and architecture such as fully connected network, acrylic networks, feed-forward network, modular neural networks, etc., are available [10],[11].

Cybenko et al. and Barron have revealed that a feed forward neural network with one hidden layer and sigmoid node function can estimate a continuous function with random accuracy [12]. Hal, 1996 has exposed that an ANN, if trained on large data sets and properly tested, can be pretty flourishing on purely predictive problem [13]. Depending upon these results, feed forward, single hidden layer ANNs with sigmoid neural function are used because they provide improved estimations than other systems.

In this, input layer nodes simply transmit input values to the hidden layer nodes and do not perform any calculation and other layers possess sigmoid nodes [10]. Back propagation learning was used for training because it was most appropriate for training a feed forward neural network and it rapidly confines plotting implicit with a given set of input-output pattern pairs. The values of primary weights and bias of ANN were arbitrarily assigned. The bias is a neuron parameter, which is summed with the neuron's weighted inputs and conceded through the neuron's transfer function to engender the output. Any learning rate between 0.1 and 0.001 is allocated by trial and error. The learning rate denotes the magnitude change of weights during back propagation training. A low learning rate entails slow learning and a large learning rate entails quick learning but creates other problems.

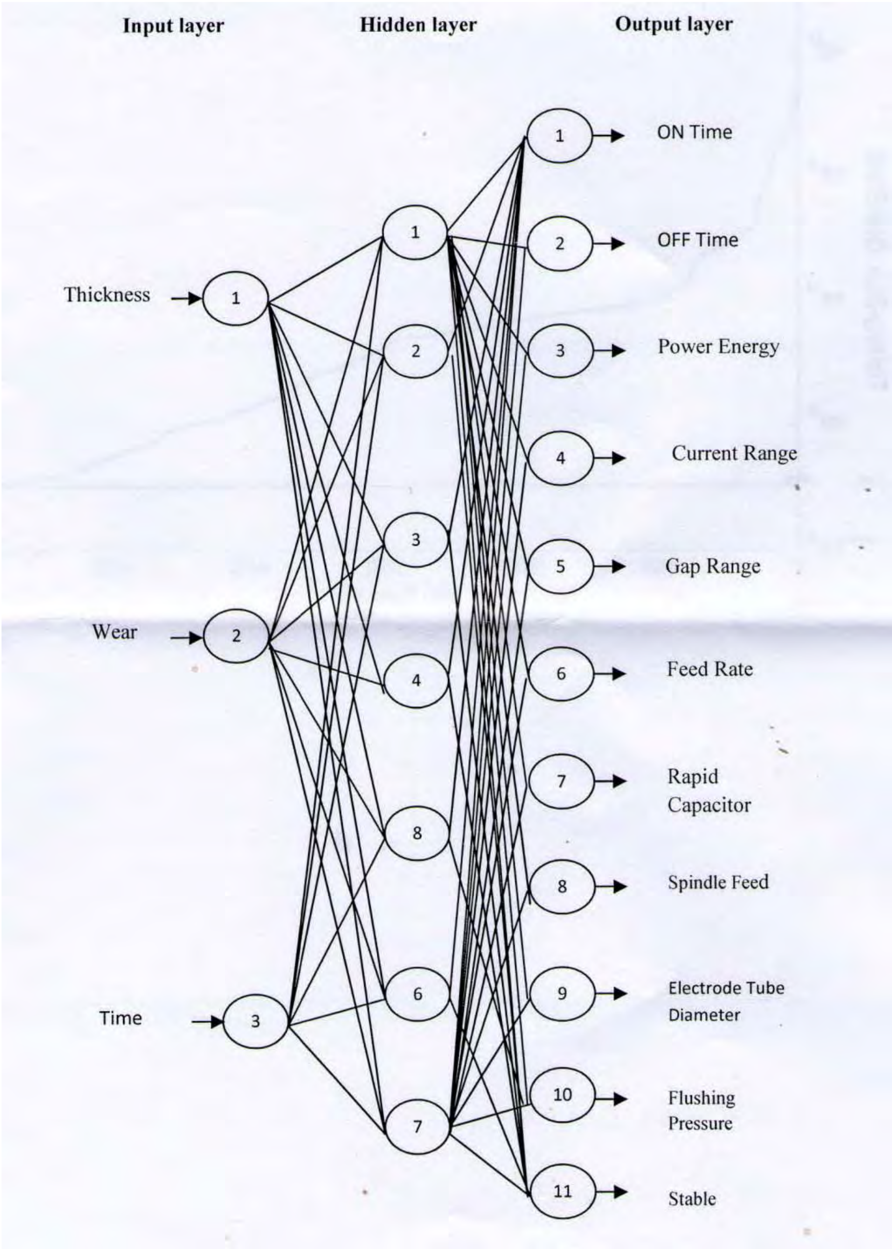

Fig. 1 ANN topology

The number of nodes in the input layer of ANN is made equal to number of input vectors and number of nodes in the output layer is made equal to number of the output vectors as found in the training set for which the ANN is to be trained. The number of nodes in the hidden layer is finalized by using adaptive algorithms. Kwot et al. suggests a method that the network is to be started with large number of nodes and sequentially some nodes are to be detached until network performance is within satisfactory level [14].

Training was done after specifying the number of cycles of learning (epochs) or target MSE. After the training, the ANN was tested by giving unfamiliar inputs, which was not used in training to train the ANN. The attained outputs were then compared with real values to validate whether the trained ANN was working acceptably or not. After training and testing, the ANN with definite values of weights and bias are acquired. When this ANN is compacted, a closed structure solution to establish sample size or acceptance number was obtained depending upon the training sets [10]. Training and testing were done using Matlab package of version 7.0, release 14 with

ANN toolbox and in this way once, the network went through the learning process it is capable of predicting output parameters. After training to the ANN model an equation was developed for each process parameter and presented in equations (1-11).

$$\mathrm{ONT} = \mathrm{F21 \; x \; 0.1694} - \mathrm{F22 \; x \; 0.3964} + \mathrm{F23 \; x \; 14.1444} + \mathrm{F24 \; x \; 0.0537} + \mathrm{F25 \; x \; 0.2920} + \mathrm{F26 \; x \; 0.5223} + \mathrm{F27 \; x \; 0.0194} - 0.8905 \quad (1)$$

$$\mathrm{OFT} = -\mathrm{F21 \; x \; 0.5082} + \mathrm{F22 \; x \; 0.0121} + \mathrm{F23 \; x \; 19.3888} + \mathrm{F24 \; x \; 6.7291} - \mathrm{F25 \; x \; 6.4343} - \mathrm{F26 \; x \; 0.0266} - \mathrm{F27 \; x \; 0.6024} + 0.5444 \quad (2)$$

$$\mathrm{VS} = -\mathrm{F21 \; x \; 0.6006} - \mathrm{F22 \; x \; 0.1735} + \mathrm{F23 \; x \; 2.4286} - \mathrm{F24 \; x \; 2.7105} + \mathrm{F25 \; x \; 2.6075} + \mathrm{F26 \; x \; 1.7665} + \mathrm{F27 \; x \; 0.0047} + 0.0110 \quad (3)$$

$$\mathrm{IP} = -\mathrm{F21 \; x \; 1.2480} - \mathrm{F22 \; x \; 0.8128} + \mathrm{F23 \; x \; 20.5130} + \mathrm{F24 \; x \; 2.0864} - \mathrm{F25 \; x \; 1.6229} + \mathrm{F26 \; x \; 1.0243} - \mathrm{F27 \; x \; 0.2388} + 0.4147 \quad (4)$$

$$\mathrm{VG} = -\mathrm{F21 \; x \; 5.6104} + \mathrm{F22 \; x \; 0.9835} - \mathrm{F23 \; x \; 6.0878} - \mathrm{F24 \; x \; 0.3690} - \mathrm{F25 \; x \; 1.5229} + \mathrm{F26 \; x \; 1.0682} - \mathrm{F27 \; x \; 0.3531} + 6.6108 \quad (5)$$

$$\mathrm{F} = \mathrm{F21 \; x \; 2.1339} + \mathrm{F22 \; x \; 0.1130} + \mathrm{F23 \; x \; 1.5830} + \mathrm{F24 \; x \; 7.6473} - \mathrm{F25 \; x \; 7.1887} - \mathrm{F26 \; x \; 1.0626} - \mathrm{F27 \; x \; 0.1935} - 1.9929 \quad (6)$$

$$\mathrm{C} = \mathrm{F21 \; x \; 0.0678} - \mathrm{F22 \; x \; 0.1339} - \mathrm{F23 \; x \; 1.8151} - \mathrm{F24 \; x \; 12.4775} + \mathrm{F25 \; x \; 12.4511} + \mathrm{F26 \; x \; 0.0406} + \mathrm{F27 \; x \; 0.1502} - 1.0360 \quad (7)$$

$$\mathrm{S} = -\mathrm{F21 \; x \; 9.5039} + \mathrm{F22 \; x \; 0.1083} + \mathrm{F23 \; x \; 0.3493} + \mathrm{F24 \; x \; 0.0370} - \mathrm{F25 \; x \; 0.0454} - \mathrm{F26 \; x \; 0.1025} - \mathrm{F27 \; x \; 0.0061} + 8.5005 \quad (8)$$

$$\mathrm{ED} = \mathrm{F21 \; x \; 0.5612} - \mathrm{F22 \; x \; 1.0389} + \mathrm{F23 \; x \; 14.0487} - \mathrm{F24 \; x \; 0.8245} + \mathrm{F25 \; x \; 1.0134} + \mathrm{F26 \; x \; 1.3232} - \mathrm{F27 \; x \; 0.0973} - 1.4810 \quad (9)$$

$$\mathrm{P} = -\mathrm{F21 \; x \; 2.4987} + \mathrm{F22 \; x \; 0.5253} - \mathrm{F23 \; x \; 13.6653} - \mathrm{F24 \; x \; 5.6277} + \mathrm{F25 \; x4.8367} - \mathrm{F26 \; x \; 0.2297} + \mathrm{F27 \; x \; 0.2164} + 2.5795 \quad (10)$$

$$\mathrm{SB} = \mathrm{F21 \; x \; 3.7325} + \mathrm{F22 \; x \; 0.2068} + \mathrm{F23 \; x \; 3.6830} + \mathrm{F24 \; x \; 3.4577} - \mathrm{F25 \; x \; 3.8111} + \mathrm{F26 \; x \; 0.4713} - \mathrm{F27 \; x \; 0.4462} - 3.4974 \quad (11)$$

V. RESULTS AND DISCUSSIONS

Mathematical model was developed by training and testing 3-7-11 feed forward ANN with sigmoidal neural function. With the help of the weights and bias values of each node the prevailing values were calculated easily. The prediction tool was greatly used for predicting any values of the experiments and also provided the error within the experimental and predicted values of the ANN model. The training was performed in batch mode with the following learning factors: Learning rate = 0.1; Momentum constant= 0.65; Target for MSE=0.00000001; Maximum number of epochs = 2400. During training, the network compares its predicted value to the actual output and adjusts all the weights to improve the model. Once the MSE of the training data reached the target value, the training is terminated and the weights and biases are automatically saved by the program. The MSE target is achieved in 589 epochs and the variation of MSE during the training is shown in Figure 2. The result for the Mean square error of the process i.e. Mse of performance was obtained as 0.0000009973 while the goal was 0.0000001 MSE of test was obtained as 0.00008655. The r^2 values are calculated and the r^2 value of testing data set for all process parameters was as shown in Table V. The values are closer to unity, showing that the ANN model is able to capture and learn the behavior of the trained data set.

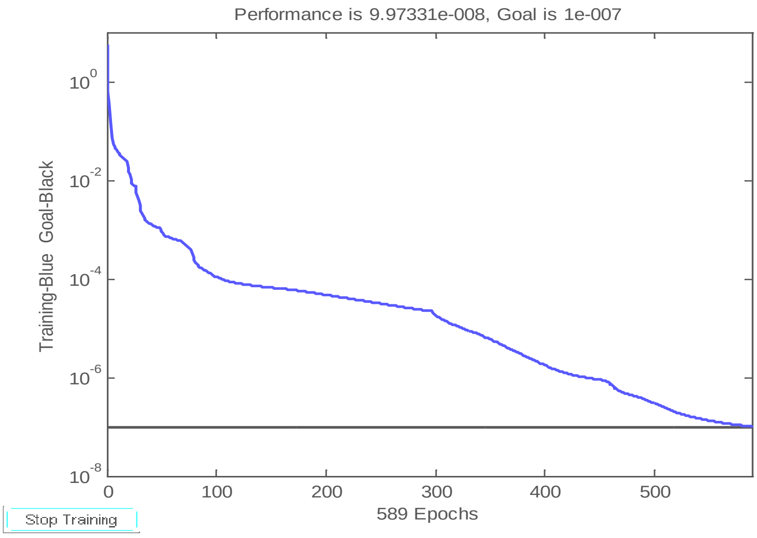

Fig. 2 Variation of mse during training the network

TABLE V
Values of r^2

r2 = Columns 1 through 11										
0.9993	1.0000	1.0000	0.9998	1.0000	1.0000	1.0000	0.9997	0.9999	0.9258	0.9946

6.0. CONCLUSION

From the experiments that were carried out on SKD11 material in WEDM and the ANN models developed, the following conclusions were drawn.

The mathematical models developed after training 3-7-11 ANN with one hidden layer were useful for calculating and fixing the process parameters of WEDM and effectively utilized for prediction of process parameters of SKD11 in wide spread engineering applications.

The proposed ANN algorithm paves way for reduction in production time and set-up time, along with the reduction in cost in WEDM processes with increase in productivity and also it gives way for automation.

The ANN has proved its flexibleness and effectiveness for calculating the process parameters from the operating parameters.

This technique can be focused to calculate process parameters of other unconventional machining process also and this leads to the focus of our further research work.

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