Eng. & Tech. Journal, Vol.30, No.1, 2012

Predictions on Surface Finish in EDM Based Upon Genetic Network Model

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Received on: 4/4/2011 & Accepted on: 3/11/2011

ABSTRACT

In this study, the comparisons on predictions of surface finish for borosilicate glass work material based upon genetic network model by used Simulnet program. Genetic network (GN) has been used to investigate the process control for EDM that could the Ra experimental and prediction with accuracy of 94.236%. The differences on the Ra at genetic network model for (80×60×3mm) of BSG never exceed (8%) from testing data sets.

Keywords: borosilicate glass**,** genetic network model**.**

التنبؤات للإنهاء السطحي في التشغيل بالشرارة الكهربائية على أساس موديلات شبكة جينية

الخلاصة

في هذه الدراسة، المقارنات للتنبؤات للإنهاء السطحي لمادة زجاج البوروسيليكات استندت على موديل شبكة genetic باستخدام برنامج Simulnet. استخدمت شبكة genetic لبحث السيطرة على عملية التشغيل بالشرارة الكهربائية والتي تجعل الإنهاء السطحي العملي (Ra) والمتنبأ بدقة 94. 236%. الفرق لمعدل الخشونة السطحية عند نموذج لشبكة جينية (80×60×3mm) لزجاج البوروسيليكات لايتجاوز عن (8%) من مجموعة بيانات الاختبار.

INTRODUCTION

Electrical discharge machining (EDM) is a thermal erosion process in which an electrically generated spark vaporizes electrically conductive material [1].

Electrical discharge machining is a non-traditional machining process for metals removing based upon the fundamental fact that negligible tool force is generated during the machining process. The removal of metals in the process is characterized by the erosive effects from a series of electrical sparks generated between tool and work materials with constant electric field emerged in dielectric environment. Predictions on the surface finish of work-pieces in electrical discharge machining (EDM) based upon physical or empirical models have been reported in the past years [2]. Each electrical discharge causes a focused stream of electrons to move with a very high velocity and acceleration from the cathode (or tool) towards the work piece and ultimately creates compressive shock waves on the work piece surfaces. The phenomenon is accomplished within a few microseconds and the temperature of the spot hit by electrons may rise to a very high value. Gas bubble formation and sparking phenomena as in the electrochemical discharge machining process are exhibited in Fig. (1) [3].

https://doi.org/10.30684/etj.30.1.7
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The EDM process is typically used for manufacturing cutting tools, punch dies, and other difficult-to-cut parts. Although the process has been accepted as the standard machining process in the tools, dies, and molds industry. That means, the tuning of EDM process variables for obtaining process efficiency and part accuracy has been empirical. Even though the up-to-date computer technology has been applied on the machine controller, the EDM process is still one of the expertise-demanding processes in the industry. From the literatures, the comprehensive mechanism of metal erosion during sparking is still debatable although the basic physical laws have been laid for many years. On the other hand, complex thermal conduction behaviors have been widely accepted as the principal mechanism of metal erosion based upon engineering approach. This explains why the models for correlating the process variables and surface finish are hard to be established accurately [2].

De Silva and Mc Geough (2000) [4], present the progress of EDM through the application of neural networks. They conclude that the artificial neural networks are another tool in EDM control, especially when combined with fuzzy logic.

Kuo and Pei (2001) [5], made comparisons between predictions of surface finish for various work materials with the change of electrode polarity based upon six different neural-networks models (LOGMLP, TANMLP , RBFN , Error TANMLP, Adaptive TANMLP, Adaptive TANMLP and Adaptive RBFN) and a neuro-fuzzy network model.

Kuo and Pei (2001) [6], made comparisons of modeling the MRR of the work materials considering the change of polarity based upon six different neural-networks models (LOGMLP, TANMLP, RBFN, Error TANMLP, Adaptive TANMLP, Adaptive TANMLP and Adaptive RBFN) and a neuro-fuzzy network model.

Kesheng et al. (2003) [7], developed and applied a hybrid artificial neural network and genetic algorithm methodology to modeling and optimization of EDM. They conclude that the comparison of the trained model was then tested using randomly generated test data within the range of the training data set and two peak currents (10A and 21A).

Tsutomu and Tomomasa (2004) [8], have proved the machining performance of die-sinking EDM by using self- adjusting fuzzy control. Although the maximum depth of cut is about 2.5mm without any fuzzy control, other results show the depth of cut for more than 7 mm.

The aim of this research to cut non-conducting of glass (BSG) materials and use the software Simulnet program (genetic network).

GENETIC NETWORKS

In the past decades, numerous studies have been reported on the development of neural networks based on different architectures. In general, neural networks are characterized by their architecture, activation functions, and learning algorithms or rules. Each type of the neural networks would have its own input–output characteristics, and therefore it can only be applied for modeling some specific processes [6]. The Genetic Network is a technique that is intended to deal with a potential limitation of the neural network approach to data analysis and prediction: the neural network can become trapped by a solution which may be better than a sample of alternative solutions but which at the same time is not the best possible solution. Prototypically, a neural network is asked to find a pattern within a complex data set. As an example, this data set might contain economic indicators along with the value of a currency. The sought-for pattern in this example could be the relationship between the economic indicators and the currency's value. A neural network can be expected to find such a pattern, if one exists. The network may however converge upon a pattern which might not represent the strongest, most significant, relationship between the indicators and the currency value. In addition, in the case of large and complex files, the network may fail to converge, or converge only very slowly.

One means of circumventing this potential limitation, while retaining the benefits of a neural network, is to couple the network with a genetic algorithm approach. Essentially, the genetic algorithm allows a neural network to keep exploring all possible solutions until the best possible solution, given the data set, has been found. Applying the genetic algorithm approach to a neural network involves creating a population of neural networks, each of which is allowed to independently train on the same data set.

Training of each network proceeds by presenting a network with all the training examples, and updating the network weights after each example presentation. In order to allow the network to demonstrate the level of training that it can achieve this process is repeated several times. That is, the entire set of training examples is presented to the network several times over. The actual number of sets of presentations is determined by randomly choosing a number between 1 and the value of the No. trials parameter. A new value for the number of sets of presentations is chosen in this way for each network in the population. Following the training phase, each network is tested, and on the basis of the test results the network is assigned a fitness score. Next, a new population of networks is created, with each member of the old population contributing a number of copies of itself to the new population proportional to its fitness score. Thus, highly-fit networks, those found to have achieved high test scores; contribute proportionally more copies of themselves to the new population than do less-fit networks.

An important feature of the genetic algorithm approach is that once the new population has been created, several operations are carried out on these networks. These operations are designed to re-distribute information present in the newly-created networks, and to provide a means for introducing a controlled degree of randomness or noise. The first of these operations is termed crossover, in analogy to the gene crossover phenomenon in cell reproduction. The crossover operation allows pairs of networks in the new population to exchange portions of their respective structures. Such re-distribution of information among the new population members has been shown to result in an ever-increasing proportion of highly-fit members in successive generations. A second operator is termed mutation. The mutation operator alters by a random amount, a randomly-selected portion of the structure of some of the new population members. The intent of this operator is to encourage the population of networks to keep exploring all regions of the problem search-space, while accumulating population members in the currently most rewarding regions of the space. Fig. (2) illustrates schematically the genetic algorithm approach [9,10]. These features together combine to alleviate the tendency encountered with the pure neural-network approach, of settling into local rather than global minima of the search space. In fact, however, it has also been suggested that such local minima are not prevalent in the search spaces of most problems: In a multi-dimensional hyperspace, a search procedure such as a neural network would have the opportunity to escape the local minimum by traveling along any of the multiple dimensions of the space. The higher the dimensionality of the search space, the more opportunities for escaping the local minimum. A true local minimum in a highly-dimensioned search space would be one which was a minimum in terms of all the dimensions of the space. Again, as dimensionality increases, such local minima should be encountered less frequently.

The choice of which network to use on a particular problem is probably best found by trial. A single back propagation network is generally faster to converge, while the genetic network is less prone to entrapment by local minima. Without prior knowledge about the topography of the search space, it is probably best to try both networks, at least on a subset of the available data, and compare results [9,10].

EXPERIMENTAL VERIFICATIONS

EDM system was build for machining of non-conducting cutting materials. A schematic drawing of the experimental apparatus of the EDM machine is shown in Fig. 3. All the experiments have been conducted on a milling machine model (Bridgeport 3D Vertical), located at the Machine Tool Laboratory. The EDM machine was attached with a power supply current pulses during discharging. Throughout the experiments, the dielectric fluid has been the tap water. In particular, for better control of the environment, the dielectric fluid was kept in a Pyrex (glass) container during each run of the experiments. The surface finish data were later measured by a Talysurf-4, it is produced by Rank Tayllor Hobson Company, the specifications of the apparatus is shown in Table 1.

In this study, three different virgin materials were employed for the experimentation. While steel was used as the tool (upper electrode), glass and graphite were used as the work (lower electrode). In all experiments, the pertinent process parameters and their levels for each set of the experiments are listed in Table 2. Also, the physical characteristics together with the dimensions of the tool and the works are tabulated in Table 3. In order to produce adequate data for model training, eighty sets of experimental conditions were arranged on the EDM machine.

RESULTS AND DISCUSSION

Before applying the neural networks for modeling the EDM process, the networks first need to decide the architecture and the topology; e.g. the number of hidden layers and the number of neurons in each layer in the networks. Based on the previous experiences from the work on semi-empirical model, five inputs and one output in the networks would be sufficient for this study. Therefore, the number of neurons in the input and output layer should be set to six and one, respectively. Also, the back-propagation architecture with one hidden layer is enough for the majority of applications, because it can form arbitrary mapping between a set of given inputs and outputs [2]. Therefore, the number of network sizes in the input and output nodes should be set to six (Voltage, Current, Diameter of cut, Depth of cut, Machining time and Power) and one (Ra), the hidden layer consists of the number of nodes three and the number of layers one, as shown in Fig. (4).

Fig. (5) shows the variation of Ra on the current at 3mm borosilicate glass thickness. An increase in current causes a proportionate increase in the Ra, showing that the discharge currents have a large influence on the Ra. Therefore, in order to achieve better surface finish, low current is suggested, although the machining efficiency is relatively low. At thickness 3mm the Ra is low (0.003µm) and increases with increase current density by ratio 20, 25, 28.6, 41.7 and 75% at currents 200, 250, 300, 350 and 400A respectively this may be due to the increase in gas bubble produced and temperature. In the same currents the machining time are 78, 71, 66, 62 and 57min respectively.

PREDICTION OF SURFACE ROUGHNESS (RA) AT GENETIC NETWORK (GN)

The results of training and testing data set by use of the genetic algorithm network model could predict the Ra with about 94.236% accuracy.

Fig. (6) shows the scatterplot of the measured and predicted values of the Ra of 5 data sets for 3mm thickness of BSG by using GN. This indicates that the relationship between the actual and the predicted Ra is linear. In all these data the fit between experimental and model Ra values are satisfactory.

Fig. (7) Comparison of Ra among the predicted and measured values on various test number. The two curves represent the surface finish in both measured and predicted cases. The error between measured values and predicted values is small (under 8%). Figure (8) Effect of test number on the error for genetic network the training and the check errors, are defined as follows the equation:

$$\text{Error}(\%) = \frac{(\text{Measured Ra} - \text{predictions Ra})}{(\text{Measured Ra})} \times 100\%$$

CONCLUSIONS

The main conclusions which can be deduced from this research can be summarized as follows:

1- The experimental tests show that non-conducting materials can be machined successfully.

2- 3mm thickness of glass (BSG) can be machined with surface roughness (Ra) in this method are about (0.003-0.012µm).

3- The software Simulnet program is well used in analyzing the experimental results and shows satisfactory analytical results for assisting the work.

4- The predict on the surface finish was 94.236% from genetic network program.

5- The difference on the Ra at genetic network models for 3mm thickness of BSG doesn't exceed (8%) respectively.

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Table (1) Specification of the roughness apparatus measurement.

Specification	Value
Magnification range	500-100,000 times
Switch position	1-8
Full scale represents	0.5-100µm
Small division represents	0.02-4µm
Pick-up traverse speeds	50Hz supply: 3,0-15,2-76,2mm/min 60Hz supply:3,6-18,3-91,4mm/min
Max. traversing length	11mm
Probe material	Diamond (tip width 0,0025mm)
Voltage range	From 95V to 130V and from 190V to 260V a.c.
Accuracy	Better than 3% of full scale for any magnification

Table (2) pertinent process parameters and values for the experiments.

Symbol	Factor	Level 1	2	3	4	5
PL	Polarity of upper electrode and workpiece	-	+			
ON	Discharge time (min)	78	71	66	62	57
Ip	Main power peak current (A)	200	250	300	350	400
An	Tool material (upper electrode)	St.1045				
Ca	Work material (lower electrode)	Glass	Graphite			
V	Main power voltage (V)	70				

Table (3) Physical characteristics and mechanical dimensions of the tool and the work.

Material	Composition	Density (kg/m^3)	Dimensions
Tool			
Steel	St.1045	7870	6×90mm
Work			
Glass	>99.95%	2230	Thickness 3mm
Graphite	>99.9%	1800	100×70 ×15mm

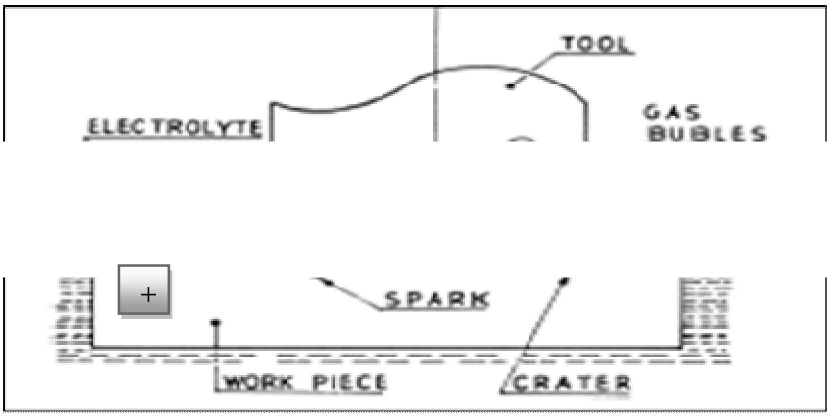

Figure (1) Material removal mechanism of EDM operation [3].

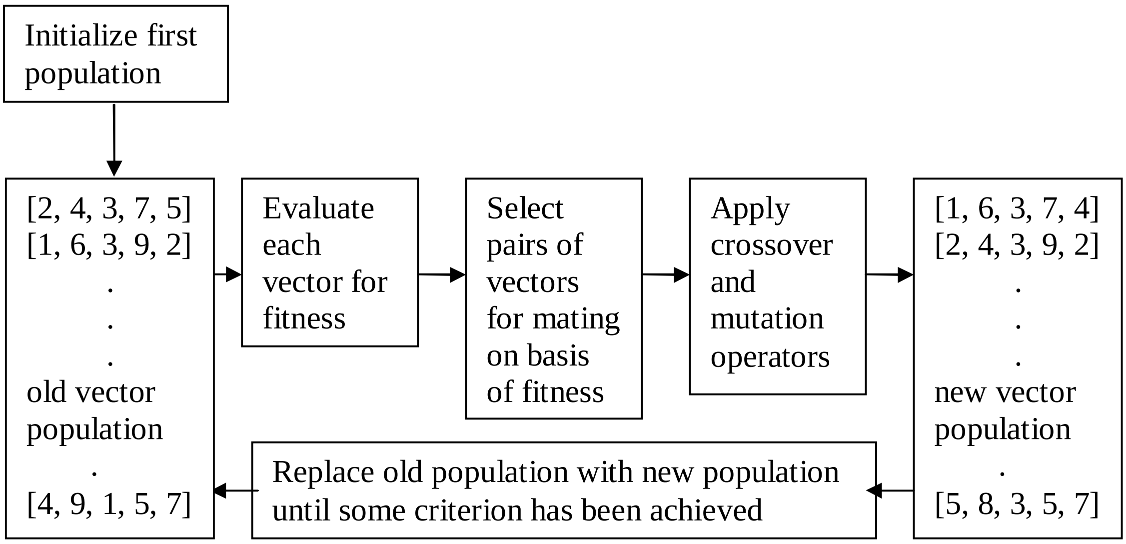

Figure (2) Schematic diagram of a genetic algorithm [10].

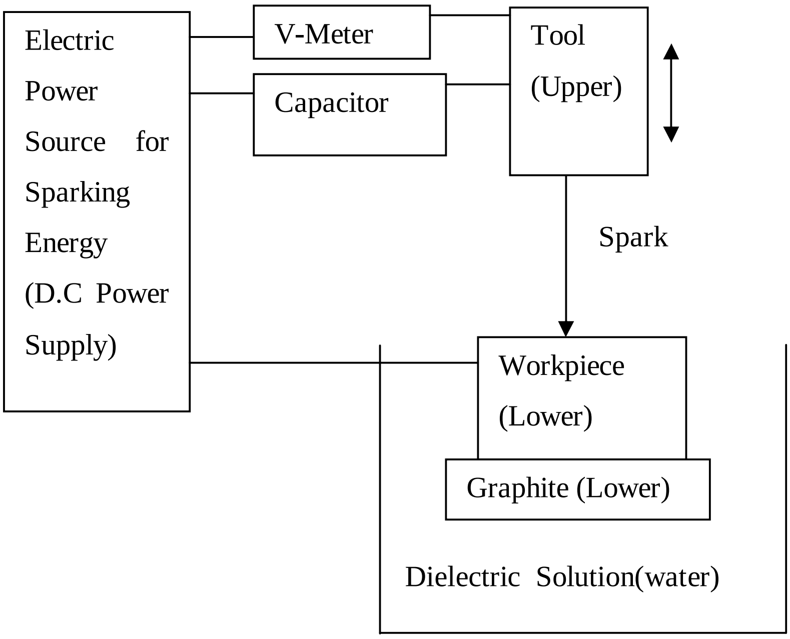

Figure (3) Schematic diagram of the experimental EDM machine

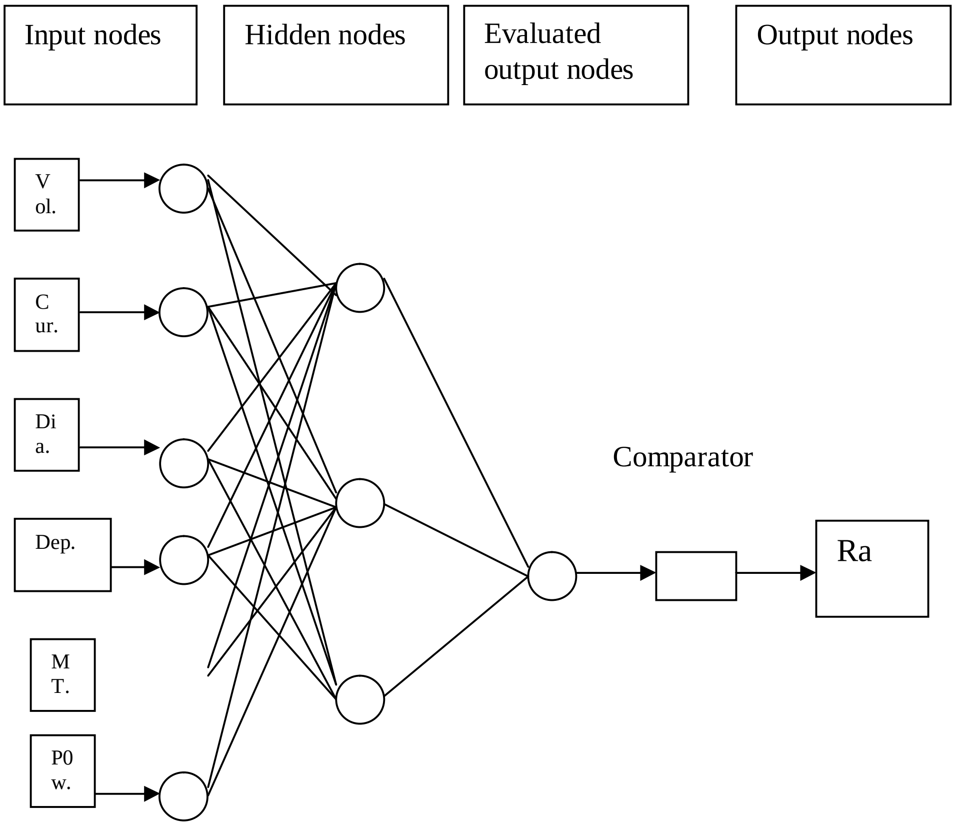

Figure (4) the structure of a genetic neural network.

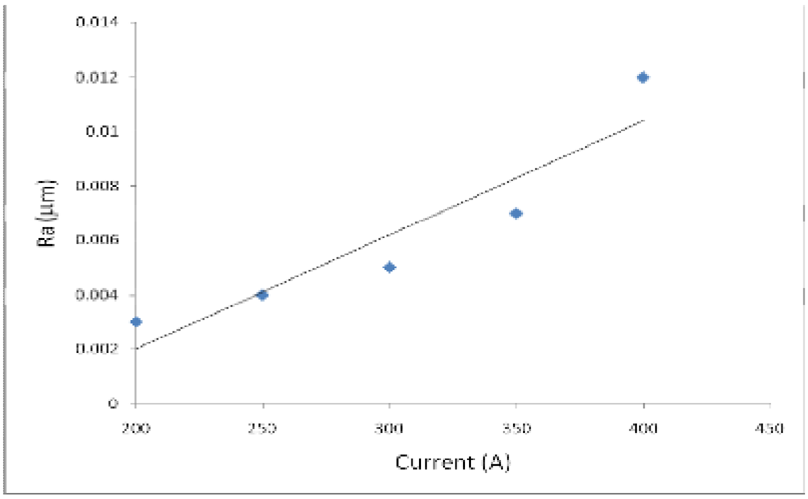

Figure (5) Effect of Ra on the current at 3mm thickness.

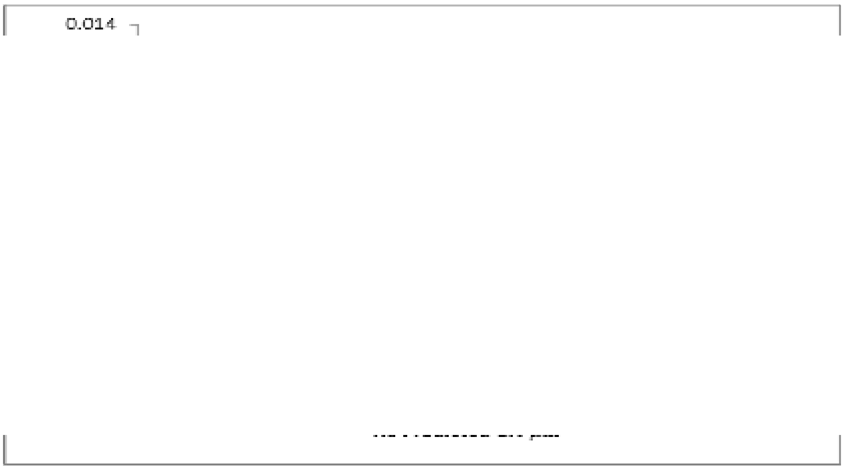

Figure (6) Scatter plot of the measured Ra and the predicted Ra by use GN.

Figure (7) Comparison of Ra among the predicted and measured values on various test number

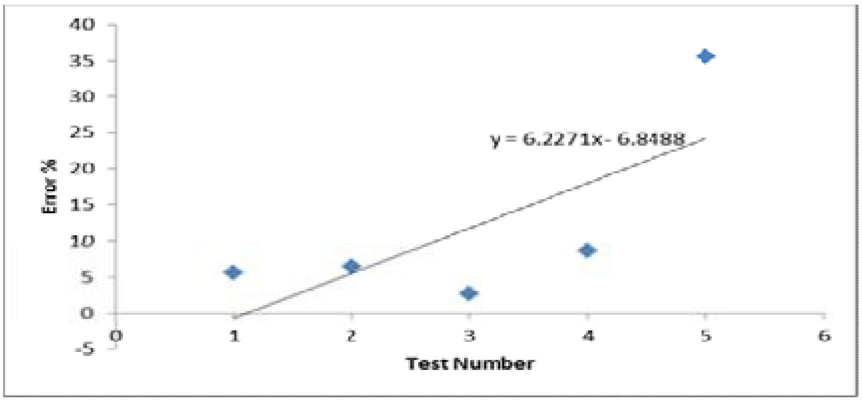

Figure (8) Effect of test number on the error for GN.