Neural Network Models on Surface Finish in Wire Electrical Discharge Machining Process

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Abstract

This study presents an investigation on applicability neural network-based models for the prediction of surface finish, obtaining the desired surface roughness on AISI 4340 hardened steel in Wire Electrical Discharge Machining (WEDM) process. The Radial Based Neural Network (RBNN) and Multilayer Perceptron (MLP) Neural Network are developed to establish the process model. The experiments are conducted according to the Central Composite Design (CCD) to construct the Artificial Neural Network (ANN) modeling. The predictive models are compared for goodness of fit. The performance of each ANN model used in this research is evaluated with Mean Squared Error (MSE) and Correlation Coefficient (r). Also, different network structures are experimented to obtain the best performance. Optimum architecture network structure is achieved to obtain the minimum MSE. Finally, it is found that the feasibility and effectiveness of the developed models are acceptable.

Key words: Wire Electrical Discharge Machining, Surface Finish, Artificial Neural Network

1. Introduction

In the recent years, Wire Electrical Discharge Machining (WEDM) has become an important non-traditional machining process, and it has been used in the aerospace and automotive industry. WEDM is extensively performed to manufacture two-or three-dimensional components with complex shapes and profiles. The WEDM process is more economical, if it is used to cut difficult to machine materials with complex, precise and accurate contours in low volume and greater variety [1, 2]. This is because the WEDM process provides an effective solution for machining hard materials with intricate shapes, which are difficulty machined by conventional machining methods.

Investigations into the influences of the machining input parameters on the performance of WEDM process have been widely reported. Many attempts have been made to model performance parameters of WEDM process using Artificial Neural Network (ANN) [3, 4]. But the full potential utilization of this process is not completely solved because of its complex and stochastic nature and more number of variables are involved in this operation. Surface quality is an important requirement for many machine parts produced in WEDM process. The calculation of the surface roughness (R_a) through analytical formula is very difficult. In the past, empirical models and the relationship between surface roughness and cutting parameters for WEDM

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process were developed. Today, the use of new methods has begun to solve this problem. Some researchers [5-7] have investigated the suitability of different empirical models to predict surface roughness in WEDM process. They have attempted to improve the performance characteristics namely surface roughness, cutting speed, dimensional accuracy and material removal rate. Pradhan et al. [8] compared the performance and efficiency of Back Propagation Neural Network (BPNN) and Radial Based Neural Network (RBNN) for the prediction of surface roughness in WEDM. Bharti et al. [9] made an attempt to select the best back propagation algorithm from the list of training algorithms that are present in the MATLAB Neural Network Toolbox, for the training of ANN model of WEDM process. Khan et al. [10] proposed an ANN model with Multilayer Perception (MLP) neural architecture for the prediction of surface roughness on first commenced Ti-15-3 alloy in WEDM process.

In this work, RBNN and MLP networks, which are available in NeuroSolutions 6 [11], are performed to model in WEDM process. In the proposed models process parameters such as pulse duration, open circuit voltage, wire speed and dielectric flushing pressure to develop a mapping with the target surface roughness are used. The experiments are conducted and implemented using Central Composites Design (CCD) of Response Surface Methodology (RSM) with four input factors at four levels for prediction of surface roughness in the WEDM process of AISI 4340 hardened steel. The performance of the ANN models is evaluated on the basis of Mean Squared Error (MSE) and Correlation Coefficient (r).

2. Experimental Details

In this experimental study, all the experiments are conducted on an Acutex WEDM machine. WEDM machining set up is shown in Figure 1.

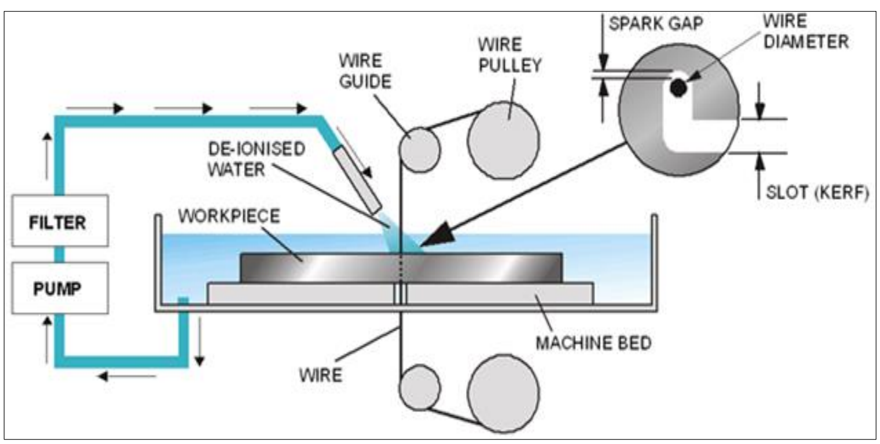

Figure 1. WEDM machining set up

Pulse duration (ns), open circuit voltage (v), wire speed (m/s) and dielectric flushing pressure (MPa) are selected as input parameters and surface roughness is selected as output parameter. Surface roughness measurements are made by using Phynix TR–100 portable surface roughness tester. To obtain a reliable database, each experiment is repeated two times and their average is taken as surface roughness value mean values. The work material, electrode and other machining conditions are given in Table 1.

Table 1. Machining conditions in WEDM process

Machining Conditions	
Work piece	AISI 4340
Electrode	CuZn37
Work piece dimensions (mm)	150x150x10
Table feed rate (mm/min)	8,2
Pulse interval time (s)	18
Wire diameter (mm)	0,25
Wire tensile strength (N/mm2)	900
Cut-off length (mm)	0,8

3. Artificial Neural Network Modeling

Artifical Neural Network (ANN) are analytical systems that address problems whose solutions have not been explicitly formulated. They have been applied to many manufacturing processes for pattern identification, parameter selection, process modeling, monitoring, and controlling. These techniques are especially valuable in processes where a complete understanding of the physical mechanisms is very difficult, or even impossible to acquire. Generally, neural networks are characterized by their architecture, activation functions, and learning algorithms or rules. In these networks, connections among neurons are based on signal links with associate weightings [12, 13].

Figure 2 gives the flow chart studied in this research for prediction values of surface roughness.

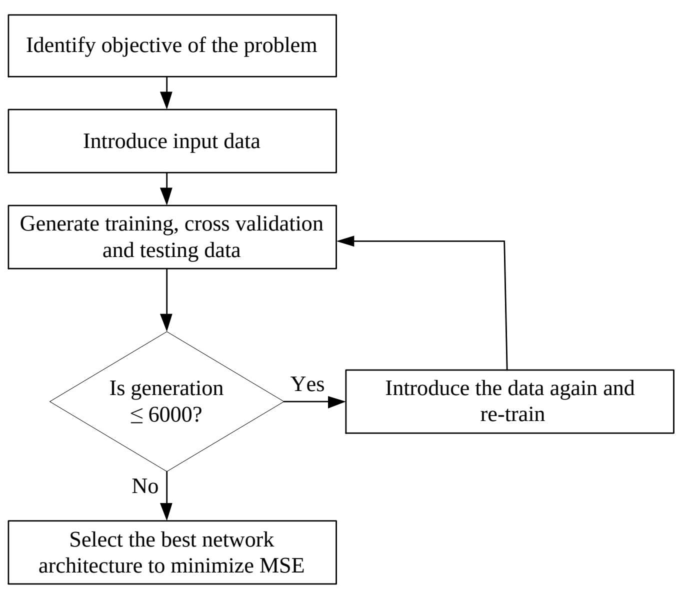

Figure 2. Flow chart for the predicted values of surface roughness

RBNN are feed-forward networks trained using a supervised training algorithm. They are typically configured with a single hidden layer of units whose activation function is selected from a class of functions called basis functions. In RBNN, the weights into the hidden layer basis units are usually set before the second layer of weights is adjusted. The other common neural network model is also MLP. This type of neural network is known as a supervised network because it requires a desired output in order to learn. The goal of this type of network is to create a model that correctly maps the input to the output using historical data so that the model can then be used to produce the output when the desired output is unknown [13, 14]. The MLP and many other neural networks learn using an algorithm called back propagation. With back propagation, the input data is repeatedly presented to the neural network. With each presentation the output of the neural network is compared to the desired output and an error is computed. This error is then fed back to the neural network and used to adjust the weights such that the error decreases with each iteration and the neural model gets closer and closer to producing the desired output [15, 16].

In the present study, MLP and RBNN models are used to model the WEDM process that has an inherent random and complex nature. In the proposed models, process parameters such as pulse duration, open circuit voltage, wire speed, and dielectric flushing pressure to develop a mapping with the target surface roughness are used. The design of experimental data is performed to train and test for the various process models. The experiments are planned and implemented using CCD with four input factors at four levels. The process parameters for ANN architecture at four levels have been selected according to the design matrix as shown in Table 2.

Table 2. The process parameters for ANN architecture

Level	Pulse Duration (ns)	Open Circuit Voltage (V)	Wire Speed (m/min)	Dielectric Flushing Pressure (kg/cm^2)
(-2)	200	60	4	6
(-1)	375	120	6	9
0	550	180	8	11
(+1)	725	240	10	14
(+2)	900	300	12	16

For the prediction of surface roughness in WEDM process, the nonlinear activation function is typically chosen to be the sigmoid function. Training of the ANN models is performed with Lavenberg-Marquardt algorithm. The system functions obtained by ANN models are simulated using the input, weights and output responses. The error at each neuron is calculated and the weight for each neuron is modified until the desired error between the actual and the required output is achieved. The performance parameters for evaluating the ANN models for testing and training procedures are taken as MSE (%) and r, which are the default performances evaluating parameters assumed by NeuroSolutions 6.

4. Experimental Results and Data Analysis

In WEDM process, it is difficult to predict its output characteristics accurately by mathematical models. Therefore, in the present study, ANN models are applied as an effective tool for modelling and predicting surface roughness.

A total number of 30 experimental data are divided to a training sample (60%), a cross validation sample (15%) and a testing sample (25%). The iteration is completed when the error is reduced to an acceptable value. The training of the algorithm is stopped at 6000 iterations. To obtain an improved ANN model, generally ANN architectures, learning/training algorithms and number of hidden neurons are varied, but the variation so far has been made in a random manner. Different network structures are experimented to obtain the best performance. As can be seen in Figure 3 and Figure 4, the RBNN architecture that achieved the minimum MSE for both trained and predicted surface roughness value is 4-6-5-1 and MLP architecture that achieved the minimum MSE for both trained and predicted surface roughness value is 4-7-1.

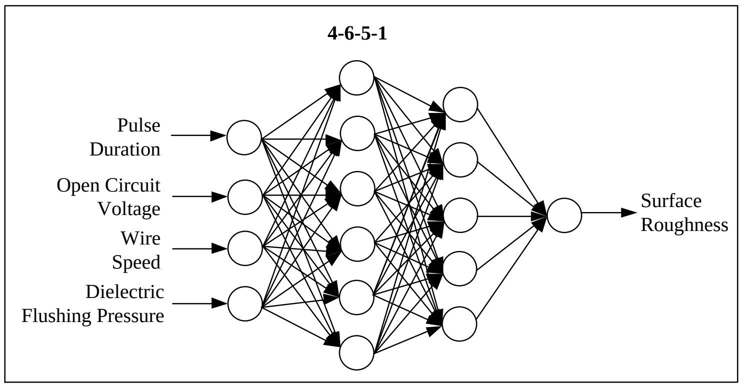

Figure 3. Optimal RBNN (4-6-5-1) architecture that achieved minimum MSE

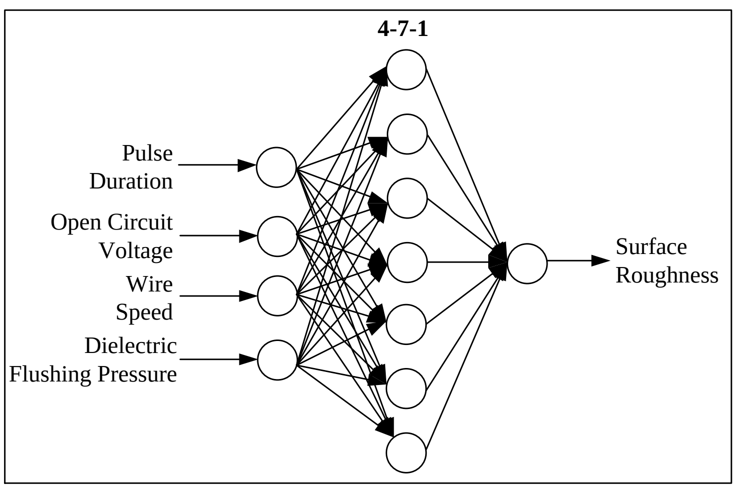

Figure 4. Optimal MLP (4-7-1) architecture that achieved minimum MSE

The surface roughness for various machining conditions can be predicted in a quick and accurate manner. The predicted values of the surface roughness obtained from each developed ANN models called RBNN and MLP network are compared with the experimental values as shown in Figure 5 and 6, respectively.

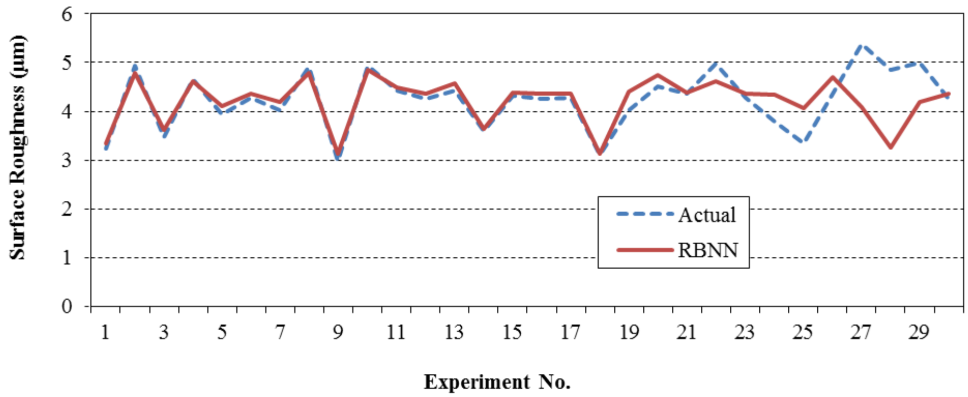

Figure 5. Comparison of experimental and predicted values for developed RBNN model (4-6-5-1)

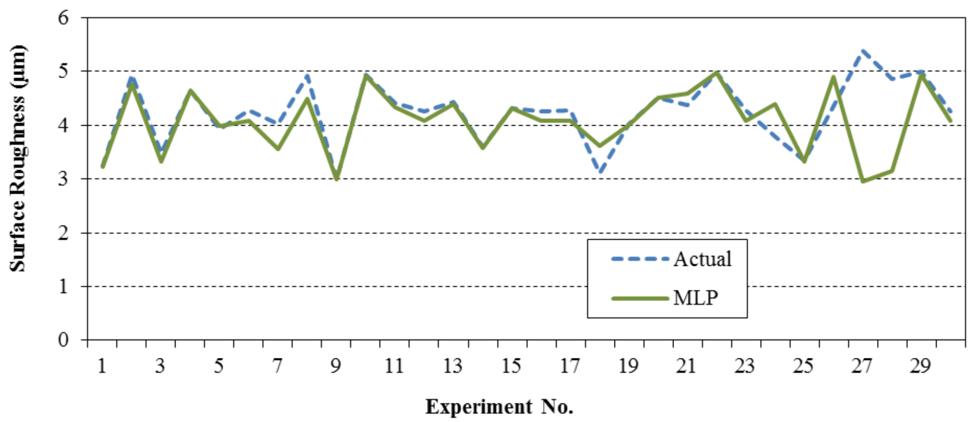

Figure 6. Comparison of experimental and predicted values for developed MLP model (4-7-1)

As can be seen in Figure 5 and 6, the predicted values are very close to the experimental values for RBNN and MLP models. So the desired surface roughness is obtained between acceptable limits. From Figure 5 and 6, it is evident that for our data the RBNN result predicts surface roughness nearer to the experimental values than the MLP results. To measure the effectiveness of the developed ANN models, two performance measures, MSE and r, have implemented. The performance of the neural networks is estimated using the training samples. In the prediction of surface roughness values, it is observed that MSE for RBNN and MLP using the training samples is calculated 1,2% and 4,8%, respectively. Figure 7 and 8 shows changing in training and cross validation MSE for RBNN and MLP with regard to epoch, respectively.

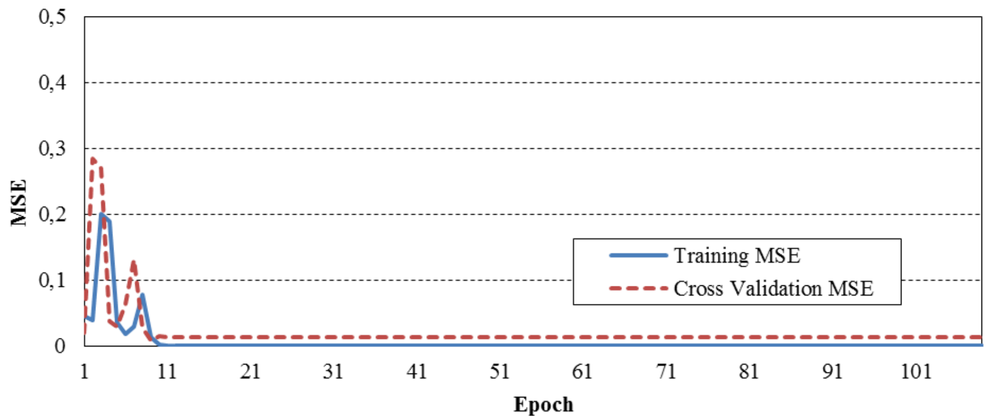

Figure 7. Change in training and cross validation MSE for RBNN model (4-6-5-1)

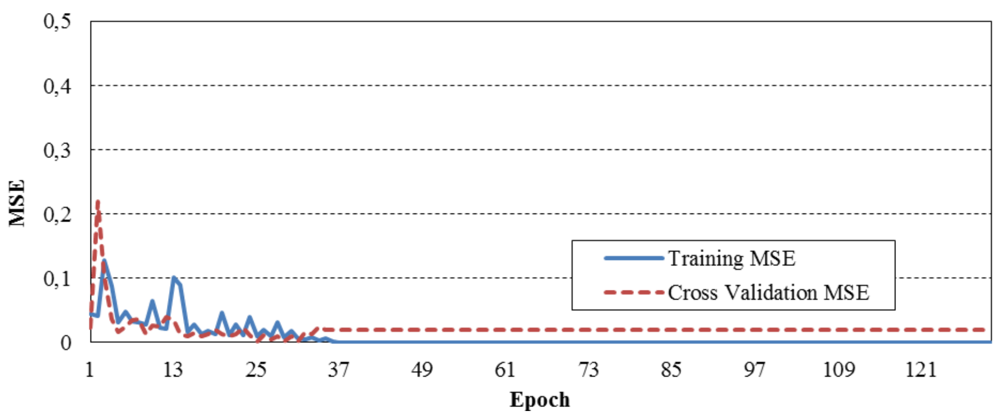

Figure 8. Change in training and cross validation MSE for MLP model (4-7-1)

On the other hand, another performance measure that represented Correlation Coefficient, r, is obtained as 0,99 for RBNN and 0,94 for MLP which means that the predicted values are very close to the experimental results. In other words, RBNN results showed that the predicted values have been found very close to experimental values. Hence, the experimental results confirm that the RBNN predicts effectively and the optimal process parameter significantly improves the WEDM process.

5. Conclusions

In this study, two neural networks named RBNN and MLP networks are employed and compared for modelling the surface roughness in the WEDM process. The performance of each ANN model used in this research is evaluated with MSE and r. An optimum architecture network structure is achieved at 6000 iterations. The minimum MSE is obtained using optimal RBNN (4-6-5-1) and MLP (4-7-1) architecture. The average MSE for RBNN and MLP using the training samples is calculated as 1,2% and 4,8%, respectively. Besides, Correlation Coefficient (r) is obtained as 0,99 for RBNN and 0,94 for MLP.

As a result, both the RBNN and MLP neural network are used to construct the complicated relationships between the process parameters and the surface roughness. The experimental results have showed that the RBNN network has better learning ability for WEDM process than the MLP network. It is evident that even with the complexity of developing a model and predicting the results in WEDM process, the neural network technique is found to be adequate in predicting the surface roughness.

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