An adaptive neuro-fuzzy inference system (ANFIS) model for wire-EDM

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ABSTRACT

A wire electrical discharge machined (WEDM) surface is characterized by its roughness and metallurgical properties. Surface roughness and white layer thickness (WLT) are the main indicators of quality of a component for WEDM. In this paper an adaptive neuro-fuzzy inference system (ANFIS) model has been developed for the prediction of the white layer thickness (WLT) and the average surface roughness achieved as a function of the process parameters. Pulse duration, open circuit voltage, dielectric flushing pressure and wire feed rate were taken as model's input features. The model combined modeling function of fuzzy inference with the learning ability of artificial neural network; and a set of rules has been generated directly from the experimental data. The model's predictions were compared with experimental results for verifying the approach.

1. Introduction

Rapid progress in the manufacturing technology has stimulated the application of non-traditional machining (NTM) processes in modern machining to economically machine materials that are usually difficult to machine with the conventional tools (Chakraborty & Dey, 2007). A wire electrical discharge machining (WEDM) is one of the most widely applied NTM process for machining and shaping hard, fragile and difficult-cutting in the tool and die industry process, which with a thin wire as an electrode transforms electrical energy into thermal energy for removing materials (Hasçalı & Çaydas, 2004). In WEDM, the erosion mechanism has been described as melting and/or evaporation of the surface material by the heat generated in the plasma channel. A spark is produced between the wire electrode (usually smaller than 0.3 mm) and workpiece through deionized water, (used as dielectric medium surrounding the workpiece) and erodes the workpiece to produce complex two and three dimensional shapes (Kim & Kruth, 2001). The top surface of the workpiece resolidifies and subsequently cools extremely quickly to form a hard skin on the workpiece. This layer causes an increase in surface roughness and makes the surface hard and brittle. Thus, surface roughness and white layer thickness determine the economics of machining and rate of production. In setting the machining parameters, the main goal is the minimum surface roughness and white layer thickness. It is difficult to utilize the optimal functions of a machine owing to there being too many adjustable machining parameters.

Artificial intelligent techniques, such as artificial neural networks (ANNs) and fuzzy logic, etc., have been successfully applied to machining processes through recent years. A broad literature survey has been conducted on the application of artificial intelligence systems to EDM/WEDM. Tarng, Tseng, and Chung (1997) developed a fuzzy pulse discriminator to classify various discharge pulses in EDM. A simulated annealing algorithm was applied to construct the suitable membership function. Trapezoid-shaped membership function was found suitable for the developed fuzzy pulse discriminator which could quickly and accurately classified the discharge pulses under varying cutting conditions. Wang, Gelgele, Wang, Yuan, and Fang (2003) developed a hybrid ANN and genetic algorithm (GA) methodology to model and optimize the EDM process. Yilmaz, Eyercioglu, and Gindy (2006) introduced a user-friendly fuzzy-expert system for the selection of the EDM parameters. The fuzzy model and the system were supported by experiments. Fuzzy-expert rules (if–then rules), membership functions and defuzzification methods were all used to eliminate the complexity of the situation. As a result, a more precise selection of EDM parameters that are difficult to measure to be taken into consideration were allowed by the developed fuzzy model. Zhang et al. (2002) developed an adaptive fuzzy control system for electro discharge machining with ultrasonic vibration. The discharge pulse parameters and the gap between the tool electrode and the workpiece material were controlled by developed system in a timely manner. Yan and Fang (2007) applied a genetic algorithm based fuzzy logic control in wire transport system of wire-EDM machine. Smooth wire transportation was achieved with no wire breakage during wire feeding. The proposed genetic algorithm based fuzzy
logic controller lead to faster transient and smaller steady-state error than a PI controller. Salman and Kayacan (2008) modeled the workpiece (cold work tool steel) surface roughness after EDM by using the genetic expression programming (GEP), an artificial intelligence method, technique. Current, pulse duration, pulse interval duration and gap voltage were used as model variables. The mathematical relationship obtained with the GEP approach gave higher performance with predicting very close to the actual values. Kaneko and Onodera (2004) used a simplified fuzzy inference with only two input signals such as a frequency of short circuit and a frequency of arcing to improve the machining performance of die-sinking EDM. A remarkable improvement in machining speed and the maximum depth of cut was achieved by controlling the jump heights and approaching movement of the tool electrode. Lin, Chung, and Huang (2001) used a fuzzy logic control to improve the machining accuracy at corner parts for wire-EDM. They concluded that the machining errors of corner parts, especially in rough cutting, could be reduced to less than 50% of those in normal machining, while the machining process time increased not more than 10% of the normal value. Tzeng and Chen (2007) applied a fuzzy intelligence method, technique. Current, pulse duration, pulse interval duration and gap voltage were used as model variables. The mathematical relationship obtained with the GEP approach gave higher performance with predicting very close to the actual values. Kaneko and Onodera (2004) used a simplified fuzzy inference with only two input signals such as a frequency of short circuit and a frequency of arcing to improve the machining performance of die-sinking EDM. A remarkable improvement in machining speed and the maximum depth of cut was achieved by controlling the jump heights and approaching movement of the tool electrode. Lin, Chung, and Huang (2001) used a fuzzy logic control to improve the machining accuracy at corner parts for wire-EDM. They concluded that the machining errors of corner parts, especially in rough cutting, could be reduced to less than 50% of those in normal machining, while the machining process time increased not more than 10% of the normal value. Tzeng and Chen (2007) applied a fuzzy intelligence method, technique. Current, pulse duration, pulse interval duration and gap voltage were used as model variables. The mathematical relationship obtained with the GEP approach gave higher performance with predicting very close to the actual values. Kaneko and Onodera (2004) used a simplified fuzzy inference with only two input signals such as a frequency of short circuit and a frequency of arcing to improve the machining performance of die-sinking EDM. A remarkable improvement in machining speed and the maximum depth of cut was achieved by controlling the jump heights and approaching movement of the tool electrode. Lin, Chung, and Huang (2001) used a fuzzy logic control to improve the machining accuracy at corner parts for wire-EDM. They concluded that the machining errors of corner parts, especially in rough cutting, could be reduced to less than 50% of those in normal machining, while the machining process time increased not more than 10% of the normal value. Tzeng and Chen (2007) applied a fuzzy

2. Principal component analysis (PCA)

PCA is a mathematical transformation in which linear combinations of the input variables are created; the new variables, called principal components (PCs), explain as much of the variation as possible in the original data (Bastianoni, Pulsel, Focardi, Tiezzi, & Gramatica, 2008; Sengur, 2008b). The PCA decomposition algorithm ensures that the first PC explains the maximal amount of variance of the original data, the second PC explains the maximal remaining variance in the data subjected to being orthogonal (uncorrelated) to the first PC, and so on. PCs can be derived from either the raw data (via the covariance matrix) or from standardized data (via the correlation matrix). Standardized data treats all variables as equally important regardless of their scale of measurement. PCA provides a way of reducing the dimensionality of the data (Bastianoni et al., 2008; Dubey & Yadava, 2008). In PCA, the original dataset is converted into PC which is a linear combination of multi-responses obtained in a trial run. The procedure of PCA can be described as follows (Dubey & Yadava, 2008):

1. Firstly the data set obtained from the experiment are normalized as

   \[ x'_i(j) = \frac{x_i(j) - \min(x_i)}{\max(x_i) - \min(x_i)} \]  

   where \( x'_i(j) \) is the new value of the normalized data for jth parameter in ith experiment, \( x_i(j) \) is the value of jth parameter in ith experiment.

2. The new normalized multi-response array for m parameters and n experiment can be represented by matrix \( X' \) as

   \[
   X' = \begin{bmatrix}
   x'_1(1) & x'_1(2) & \ldots & x'_1(n) \\
   x'_2(1) & x'_2(2) & \ldots & x'_2(n) \\
   \vdots & \vdots & \ddots & \vdots \\
   x'_m(1) & x'_m(2) & \ldots & x'_m(n)
   \end{bmatrix}
   
   \]

3. The correlation coefficient array (Rjl) of matrix \( X' \) is written as follows

   \[
   R_{jl} = \frac{\text{cov}(x'_j, x'_l)}{\sigma_{x'_j} \times \sigma_{x'_l}}, \quad j, l = 1, 2, \ldots, m;
   \]

   where \( \text{cov}(x'_j, x'_l) \) is the covariance of sequences \( x'_j \) and \( x'_l \); \( \sigma_{x'_j} \) is the standard deviation of sequence \( x'_j \).

4. The eigenvalues and eigenvectors of matrix (Rjl) are calculated.

5. The PC are computed as follows

   \[
   p_i(k) = \sum_{j=1}^{m} x'_i(j) \times v_k(j)
   \]

   where \( p_i(k) \) is the kth PC corresponding to ith experiment, \( v_k(j) \) is jth element of kth eigenvector.

6. The total principal component index (TPCI) corresponding to ith experiment (Pi) is computed as follows

   \[
   P_i = \sum_{k=1}^{m} p_i(k) \times e(k)
   \]

   \[
   e(k) = \frac{\text{eig}(k)}{\sum_{k=1}^{m} \text{eig}(k)}
   \]
where $\text{eig}(k)$ is the $k$th eigenvalue.

7. The TPCI for each experimen is used to find out the average factor effect at each level. The optimum parameter level that corresponds to the maximum TPCI is also predicted.

3. Adaptive neuro-fuzzy inference system (ANFIS)

The adaptive network based fuzzy inference system (ANFIS) is a useful neural network approach for the solution of function approximation problems (Burgagohan & Mahanta, 2008). An ANFIS gives the mapping relation between the input and output data by using hybrid learning method to determine the optimal distribution of membership functions (Ying & Pan, 2008). Both artificial neural network (ANN) and fuzzy logic (FL) are used in ANFIS architecture (Avci, 2008). Such framework makes the ANFIS modeling of membership functions (Ying & Pan, 2008). Both artificial neural network and fixed in the system (Buragohain & Mahanta, 2008).

For a first order two-rule Sugeno type (Buragohain & Mahanta, 2008). Basically, five layers are used to construct this inference system. Each ANFIS layer consists of several nodes described by the node function. The inputs of present layers are obtained from the nodes in the previous layers. To illustrate the procedures of an ANFIS, for simplicity, it is assumed those two inputs $(x, y)$ and one output ($f_i$) are used in this system.

The rule base of ANFIS contains fuzzy if-then rules of Sugeno type (Buragohain & Mahanta, 2008). For a first order two-rule Sugeno fuzzy inference system, the two rules may be stated as (Ying & Pan, 2008; Sengur, 2008a; Übeyli, 2008):

**Rule 1:** If $x$ is $A_1$ and $y$ is $B_1$ then $z$ is $f_1(x, y)$

**Rule 2:** If $x$ is $A_2$ and $y$ is $B_2$ then $z$ is $f_2(x, y)$

where $x$ and $y$ are the inputs of ANFIS, $A$ and $B$ are the fuzzy sets $f_1 (x, y)$ is a first order polynomial and represents the outputs of the first order Sugeno fuzzy inference system. The architecture of ANFIS is shown in Fig. 1, and the node function in each layer is described below. Adaptive nodes, denoted by squares, represent the parameter sets that are adjustable in these nodes, whereas fixed nodes, denoted by circles, represent the parameter sets that are fixed in the system (Buragohain & Mahanta, 2008).

- **Layer 1:** This layer contains adaptive nodes with node functions described as:

\[
O_{1j} = \mu_{A_i}(x) \quad \text{for } i = 1, 2
\]

\[
O_{1j} = \mu_{B_j}(y) \quad \text{for } i = 3, 4
\]

where $x$ and $y$ are the input nodes, $A$ and $B$ are the linguistic labels, $\mu(x)$ and $\mu(y)$ are the membership functions which are usually adopted a bell shape with maximum and minimum equal to 1 and 0 respectively, as follows:

\[
\mu(x) = \frac{1}{1 + \left(\frac{x - c_1}{a_i}\right)^2}
\]

or
\[
\mu(x) = \exp \left\{-\left(\frac{x - c_1}{a_i}\right)^2\right\}
\]

where $a_i$, $b_i$, and $c_i$ are the parameter set. The bell shaped functions vary while the values of this parameter are changing. These parameters are named as premise parameters (Buragohain & Mahanta, 2008).

- **Layer 2:** Every node in this layer is a fixed node, marked by a circle and labeled II, with the node function to be multiplied by input signals to serve as output

\[
O_{2i} = \omega_i = \mu_{A_i}(x) \cdot \mu_{B_i}(y) \quad \text{for } i = 1, 2
\]

The output $\omega_i$ represents the firing strength of a rule.

- **Layer 3:** Every node in this layer is a fixed node, marked by a circle and labeled III, with the node function to normalize the firing strength by calculating the ratio of the $i$th node firing strength to the sum of all rules' firing strength.

\[
O_{3i} = \frac{\omega_i}{\sum_{i=1}^{2} \omega_i} = \frac{\omega_i}{\omega_1 + \omega_2} \quad \text{for } i = 1, 2
\]

- **Layer 4:** Every node in this layer is an adaptive node, marked by a square, with node function

\[
O_{4i} = \omega_i \cdot f_i \quad \text{for } i = 1, 2
\]

where $f_1$ and $f_2$ are the fuzzy if-then rules as follows:

- **Rule 1:** If $x$ is $A_1$ and $y$ is $B_1$ then $f_1 = p_1x + q_1y + r_1$

- **Rule 2:** If $x$ is $A_2$ and $y$ is $B_2$ then $f_2 = p_2x + q_2y + r_2$

where $p_i, q_i$ and $r_i$ are the parameters set, referred to as the consequent parameters.

- **Layer 5:** Every node in this layer is a fixed node, with node function to compute the overall output by

\[
O_{5j} = f_{out} = \sum_{i=1}^{2} \omega_i \cdot f_i = \text{overall output}
\]

![Fig. 1. ANFIS architecture.](image-url)
From the ANFIS structure mentioned above, the overall output can be expressed as linear combination of the consequent parameters (Ozturk, Arslan, & Hardalac, 2008). The final output $f_{\text{out}}$ in Fig. 1 can be written as:

$$
f_{\text{out}} = \omega_1 f_1 + \omega_2 f_2 = \frac{\omega_1}{\omega_1 + \omega_2} f_1 + \frac{\omega_2}{\omega_1 + \omega_2} f_2
$$

$$
= (\mu_1 x_1) p_1 + (\mu_1 y) q_1 + (\mu_2 x_2) p_2 + (\mu_2 y) q_2 + (\mu_2) r_2
$$

The hybrid learning algorithm of the ANFIS combines the gradient method with the least squares method to update the parameters (Ying & Pan, 2008). In the forward pass of the learning algorithm, consequent parameters are identified by the least squares estimate (Sengur, 2008a; Übeyli, 2008). In the backward pass, the error signals, which are the derivatives of the squared error with respect to each node output, propagate backward from the output layer to the input layer. In this backward pass, the premise parameters are updated by the gradient descent algorithm (Buragohain & Mahanta, 2008).

4. Materials, test conditions and measurements

The experimental studies were performed on a Sodick A 320D/EX21 WEDM machine tool. AISI D5 tool steel was used in this study and its chemical composition is given in Table 1. A CuZn37 master brass wire with 0.25 mm diameter (900 N/mm² tensile strength) was used as tool electrode. Tap water was used as dielectric medium. Different settings of pulse duration, open circuit voltage, dielectric flushing pressure and wire feed rate were used in the experiments. A full factorial experimental design with 24 runs was used to perform the experiments. The factors and level of each factor are illustrated in Table 2. For each combination, the workpiece is cut for a length of 10 mm. Surface finish measurements obtained using Mitutoyo S-211 portable device. Ra value given is an average of measurements taken at nine places. The white layer thicknesses were measured by an optical microscope.

As it will be mentioned in the following section, the number of the features that was used for estimating Ra and WLT was four. The dimension of the feature vector was reduced to two with the PCA algorithm which was described in Section 2. The hybrid learning algorithm has been used in ANFIS structure because it is highly efficient in training. Fig. 2 shows the flowchart of PCA and ANFIS used in this study. A Gauss type membership functions and three membership functions were used in the ANFIS model. The MATLAB Neural Network Toolbox functions were used in both feature reduction via PCA and parameter prediction by using ANFIS. The training of ANFIS was stopped after 500 iteration. The ANFIS architecture and training parameters were illustrated in Table 3.

5. Results and discussion

In this study, an ANFIS model based on both ANN and FL has been developed to predict surface roughness and WLT in WEDM process. Four machining parameters namely pulse duration, open circuit voltage, dielectric circulation pressure and wire feed rate were taken as input features. A full factorial experimental design was adopted to study to collect Ra and Wlt values. The measured performances were normalized as 0 and 1 interval by using standard min–max normalization procedure. To obtain distinctive features for training of ANFIS, the size of data set was reduced by...
using PCA. The usage of PCA also decrease the complexity of the ANFIS structure. The normalized and reduced data set was used as inputs of ANFIS in training and testing stage. The experiments were devied into two group for training (the first 16 experiment) and testing (remaining) of ANFIS. For this purpose, computer simulations were carried out and statistical validation indexes were used for determining the performance of the proposed methodology. According to the experimental results, the proposed method is efficient for estimating of the surface roughness and WLT in WEDM process. Figs. 3 and 4 depict the comparison of experimental and ANFIS results for the surface roughness and WLT, respectively. It proved that the method used in this paper is feasible and could be used to predict the Ra and WLT in an acceptable error rate for WEDM. The compared lines seem to be close to each other indicating with good agreement.

6. Conclusion

The paper has presented the use of the adaptive neuro-fuzzy inference system method based on the full factorial experimentation for predicting surface roughness and WLT in the WEDM process. Normalisation, feature reduction and ANFIS tests were performed to predict the desired performances. As a result, this approach can greatly improve the process responses such as surface roughness and WLT in the wire electrical discharge machining process.

References


