Designing Steps and Simulation Results of a Pulse Classification System for the Electro Chemical Discharge Machining (ECDM) Process – An Artificial Neural Network Approach

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Abstract. This paper presents the designing steps and simulation results of a pulse classification system for the ECDM process using artificial neural networks (ANN). An Electro Discharge Machining (EDM) machine was modified by incorporating an electrolyte system and by modifying the control system. Gap voltage and working current waveforms were obtained. By observing the waveforms, pulses were classified into five groups. A feed forward neural network was trained to classify pulses. Various neural network architectures were considered by changing the number of neurons in the hidden layer. The trained neural networks were simulated. A quantitative analysis was performed to evaluate various neural network architectures.

Keywords: ECDM, Artificial Neural Networks, Pulse Classification, ECDM process Control

1 Introduction

Electro Chemical Discharge Machining (ECDM) is a hybrid non-conventional manufacturing process which combines the features of Electro Chemical Machining (ECM) and Electro Discharge Machining (EDM) (Mediliyegedara et al. 2004). The ECDM process consists of a cathodic tool and an anodic workpiece, which are separated by a gap filled with electrolyte, and pulsed DC power applied between them. This leads to electrical discharges between the electrodes, thus achieving both electrochemical dissolution and electro-discharge erosion of the workpiece (De Silva et al. 1995). One of the major advantages of ECDM, over ECM or EDM, is that the combined metal removal mechanisms in ECDM, yields a much higher machining rate (De Silva, 1988).

The performance of ECDM, in terms of surface finish and rate of machining, is affected by many factors. Relationships between these factors and machining performance are highly non linear and complex in nature. Therefore, it is very difficult to develop a relationship between those factors and the machining performance with conventional mathematical modelling. This fact makes it very hard to formulate control strategies for the process control of ECDM (Mediliyegedara et al. 2004). Pulse classification plays a vital role in the formulation of control strategies. Strategies for pulse classification in EDM have been studied in the past but there remains a need for an effective and efficient pulse classification system for ECDM.

Tasi and Wang (2001) have utilised ANNs to model the metal removal rate in electro-discharge machining. Both Liu and Tarng (1997) and Kao and Tarng (1997) employed feed-forward neural networks for the on-line recognition of pulse types in the EDM process. Based on their results, discharge pulses were identified and then employed for controlling the EDM process. Pajak and Wieczorowski (1998) have employed unidirectional multilayer neural networks for the classification of discharges in Electro Contact Discharge Machining. They classified these electrical discharges into three groups such as “simple electric discharges”, “multiple electric discharges” and “continuous electrical discharges”. Mean current intensity and value of the amplitude harmonic spectrum of the current intensity were utilised as inputs for the neural network.

Without an efficient pulse classification system, there are many drawbacks in the ECDM process. Firstly, a distortion of the workpiece surface can result due to overheating. This distortion leads to a poor surface quality. Secondly, the rate of metal removal will reduce due to the enlarging of the machining gap, because of any inefficiency in the pulse classification system, the control algorithm will make a wrong decision leading to a larger machining gap. Therefore, pulse classification plays a vital role in the formulation of control strategies. Thus, an intelligent pulse classification system for ECDM is a useful research approach to pursue.

2 Pulse Types in the ECDM Process

It is possible to identify five distinct types of pulses in the ECDM process such as Electro Chemical Pulse (ECP), Electro Chemical Discharge Pulse (ECDP), Spark

Pulse (SP), Arc Pulse (AP) and Short Circuit Pulse (SCP). SP and AP are also known as Normal Discharge Pulse and Abnormal Discharge Pulse respectively. Open Circuit Pulse (OCP) is not present in ECDM as some electrochemical current flows even with a larger gap (De Silva et al. 1995). De Silva (1988) has presented a detailed analysis of various pulses in ECDM.

3 Experimental Setup

An EDM machine was modified by incorporating an electrolyte system and changing the control system. $NaNO_3$ was used as the electrolyte (Figure 1). A mild steel work piece and copper electrode were used. The duty ratio and pulse duration were set to be 50% and 100µs respectively. The above mentioned five types of pulses were acquired using a storage oscilloscope at a sampling frequency of 1 MHz. The MATLAB 6 software package was used to model and to simulate the Pulse Classification System (PCS).

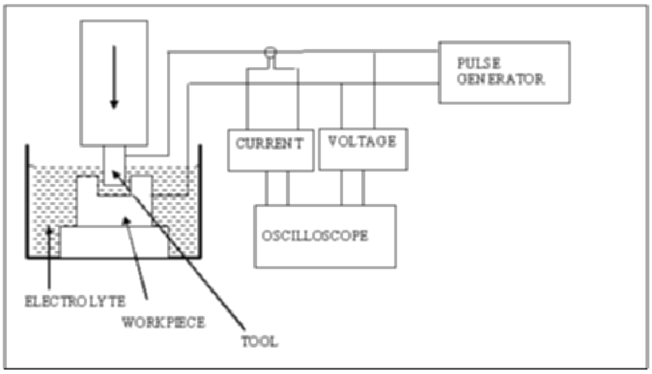

Figure 1: A schematic diagram of the experimental set-up

4 Designing of the Classification System

When an ANN is used for the pulse classification it necessary to identify the most appropriate neural network architecture. As far as real time implementation is concerned, there are many important parameters that must be investigated. Firstly, a suitable neural network architecture must be identified. Secondly, one has to identify the features that can be effectively used to classify pulses. Thirdly, it is necessary to prepare a suitable training data set and a test data set. Fourthly, the optimum number of layers and the number of neurons in the each layer has to be decided. Fifthly, it is necessary to investigate an activation function that is easy to implement, while providing acceptable classification accuracy. Finally, a training algorithm, which provides efficient training, has to be identified. In this particular application, training can be performed offline at the designing phase. Therefore this application does not demand an investigation of efficient training algorithms.

4.1 Neural Network Architecture

In the past, researches have found that the feed-forward neural network architecture will provide the better performance in the pulse classification of EDM process (Liu and Tarng, 1997 and Kao and Tarng, 1997). Therefore, It is decided to use a feed-forward ANN classify pulses in the ECDM process. One of the most widely used artificial neural networks is the feed-forward neural network architecture also known as Multi-Layered Perception (MLP) (Bermak and Bouzerdoum, 2002). The popularity of the MLP architecture stems from the existence of efficient training techniques based on the back-propagation algorithm. In a feed-forward architecture the information propagates from the input to the output in a feed-forward manner, passing through intermediate processing layers called hidden layers. A feed-forward architecture may contains one or more hidden layers. Each hidden layer comprises processing elements, or neurons that receive inputs only from the neurons in the preceding layer; there is no information flow between neurons residing in the same layer. The general architecture of the MLP neural network is shown in Figure 2.

4.2 Feature Extraction

Four different features were considered when classifying pulses such as Peak Voltage (PV), Average Voltage (AV), Peak Current (PC) and Average Current (AC). Since the four features are used as inputs, four neurons are used in the input layer such as I_1, I_2, I_3 and I_4. Similarly, since there are five distinct types of pulses, five output neurons are used in the output layer such as O_1, O_2, O_3, O_4 and O_5.

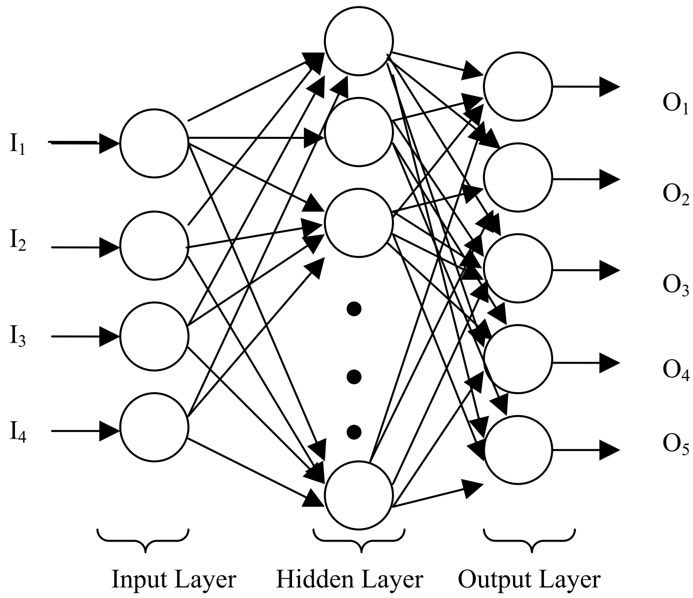

Figure 2: The general architecture of the MLP neural network

4.3 The Preparation of a Training Data Set and a Test Data Set

One hundred pulses were selected from each pulse type and the following values were calculated, Peak Voltage (PV), Average Voltage (AV), Peak Current (PC) and Average Current (AC). PV, AV, PC and AC were used as the features (inputs) in the ANN. Outputs of the ANN were prepared as follows. If a pulse belongs to ECP, '1' is assigned to the ECP and '0' is assigned to the other pulses. Similarly, 'ones' and 'zeros' are assigned to all the pulse types to prepare an output matrix. The data set was divided into two sets, the training data set and the test data set. The training data set and the test data set consist of 70 and 30 data points respectively for one type of pulses. Therefore, altogether the training data set and the test data set consist of 350 and 150 data points.

4.4 Number of Layers and Number of Neurons in Each Layer

In real time implementation point of view, the lesser the number of layers the lesser the calculation cycle time. Therefore a FFNN with a one hidden layer was considered in this study. There are four inputs in the input layer. PV, AV, PC and

AC were used as the inputs. There are five outputs such as ECP, ECDP, SP, AP and SCP. Now, one has to investigate the optimum number of neurons in the hidden layer and the best activation function having less complexity. Logistic Sigmoid Function (LOGSIG) activation function was used in each neuron.

5 Definition of Classification Accuracy

It is necessary to have a method to measure the performance of a PCS to investigate the most suitable neural network architecture. Classification Accuracy (CA) is introduced to compare the performance of the PCS One can define classification accuracy of the PCS as the average CA of each type of pulses. In general, the CA of a 'X' type pulse can be defined as follows.

$$\mathrm{CA} = \left\{ \frac{\sum_{i=1}^{n_x} x_i}{n_x} - \frac{\sum_{i=1}^{n_y} y_i}{n_y} \right\} \times 100\ \% \qquad (1)$$

Where,

x_i - Simulated output value from 'X' output for *i*th pulse when the input values correspond to 'X ' type pulses,

y_i - Simulated output value from all other outputs for the *i*th pulse when the input correspond to 'X' type pulses,

n_x - Number of 'X' type of pulses,

n_y - Number of all other type of pulses (Since there are 150 data points in test data set, $n_y = 150 - n_x$)

6 Simulated Results

The simulated results, which are shown in the following Figures, are corresponding to a trained ANN having six neurons in the hidden layer (i.e. N=6). The test data set as outlined in section 4.3, consisted of 150 data points, 30 of each of the five types of pulse. Vertical axes (Y) of the following graphs indicate the output values of the neural network. In the ideal situation, if a pulse is an ECP, then the output value from node O_1 should be equal to '1'. Other output values (O_2, O_3, O_4 and O_5) should be equal to '0'.

Figure 3 shows the output O_1 is nearly equal to '1', for the first 30 pulses. That means the first 30 pulses have been classified as ECP by the ANN. Similarly Figure 4, Figure 5, Figure 6 and Figure 7 show the output values from node O_2, O_3, O_4 and O_5.

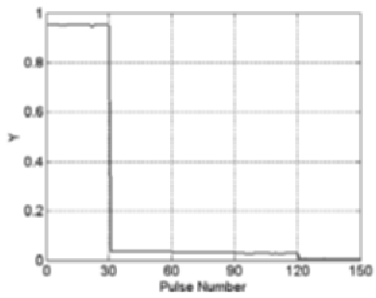

Figure 3: Simulated Output from Node O_1

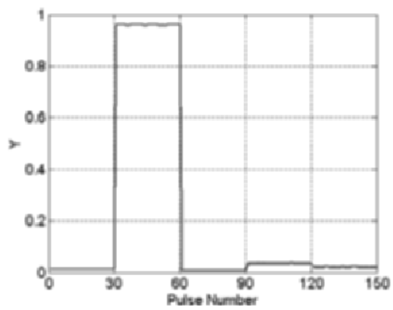

Figure 4: Simulated Output from Node O_2

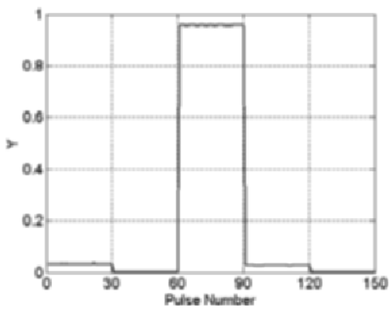

Figure 5: Simulated Output from Node O_3

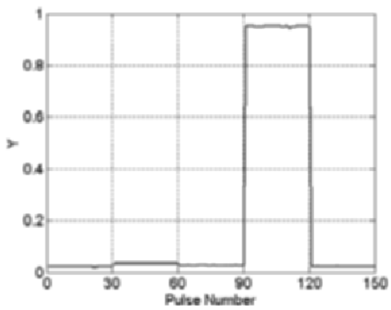

Figure 6: Simulated Output from Node O_4

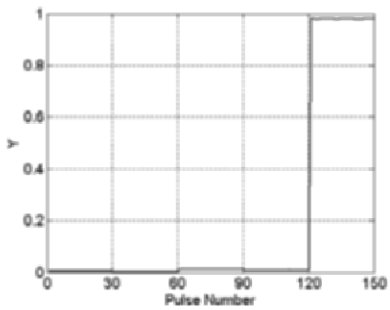

Figure 7: Simulated Output from Node O_5

7 Classification Accuracy

The CA of the each type was calculated using equation (1). Table 1 shows the classification accuracies for the five different pulse types mentioned above. The overall classification accuracy of the proposed neural network is 91%.

Table 1: Classification accuracies

Pulse Type	Classification Accuracy (%)
EC P	90.24
ECDP	88.05
SP	92.93
AP	89.31
SCP	95.43
Average	91.19

8 Process Control System

It can be observed that the various machining performances can be obtained by maintaining the proper percentages of the above mentioned pulse types. ECDPs and SPs are more favourable for fast metal removal rates whereas ECPs are more favourable for higher surface finish. However, APs and SCPs must be avoided, since they damage the work surface. Percentages of each type of pulses can be used to estimate the gap condition. The estimated gap condition can then be used as a feedback signal in the process control system. An algorithm must be developed to estimate the gap condition from the percentages of the pulse types.

9 Conclusions

In this paper, an ANN model for pulse classification in the ECDM process has been established and analysed based on the ECDM process variables. Designing stages such as feature extraction, preparation of training and test data set, selection of number of layers and number of neurons in the neural network and selection of activation function were described. Four features such as PV, AV, PC and AC were used successfully for the classification of pulses in the ECDM process. Classification accuracy has been defined to measure the accuracy of a pulse classification system. Simulation results showed that the feed forward network with six neurons in the hidden layer could be successfully used in pulse classification of the ECDM process.

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