TOWARDS INTELLIGENT CONTROL OF ELECTRICAL DISCHARGE MACHINING

Miha Junkar
Joško Valentinčič
Laboratory of Alternative Technologies
University of Ljubljana
Ljubljana
Slovenia

KEYWORDS
Machine Learning, EDM, knowledge acquisition, controller design

ABSTRACT
One of the basic problems in Electrical Discharge Machining (EDM) is to achieve stable process conditions. To avoid unstable processing and arcing, different control strategies can be applied. We have explored the possibilities of using the existing operators’ and engineers’ knowledge to build the EDM controller.

In our paper we present the application of Machine Learning (ML) for the design of the EDM controller. The most successful form of ML has been learning from examples, also called inductive learning or “empirical learning”. In learning from examples, the learning program generalizes the examples into general rules. In our case learning examples were taken from actions of the operator guiding the EDM system, and the obtained rules were used for building the EDM controller. Through examination of the EDM process, one notes that the time between the successive pulses has predominant effect on the conductivity of the dielectric in the gap, which consequently affects process stability. For this reason our EDM device was adapted so that the interval time, in addition to the gap and the flushing, became one of the control parameter and was included in the control algorithm as such. Experiments carried out by the upgraded controller demonstrated both process stability, detected by observing the in-process measured parameters (frequency of characteristic pulses), as well as good process performance, obtained by the evaluation of the off-line measured parameters (electrode wear, metal removal rate and surface roughness). Thus the integration of different sources of knowledge improved the EDM process control decisively. Additional advantage of the designed controller is its open architecture, allowing further upgrading by integration of new knowledge.

INTRODUCTION
Since information is to a great extent interpreted qualitatively by the domain experts, the trend of introducing Intelligent Machining systems using techniques like Artificial Intelligence (AI) and Neural Networks to acquire knowledge for EDM and other machining, such as grinding, cutting and laser machining, is increasing considerably /Aberkane, Dornfeld, Monostori, Row/.
The EDM process is widely used for production of forming tools and injection molds. Material removal is caused by electrical discharges between the workpiece and the electrode, which are sunk into the dielectricum. Material of the workpiece melts and partly evaporates. On the surface of the workpiece a crater and a heat affected zone is produced.

We distinguish between two kinds of input parameters in the process: regime and control parameters. Process mode (size of craters) is determined by regime parameters. By control parameters the process is driven in such a manner that the highest material removal ($V_w$) and the lowest tool wear ($V_e$) are achieved and at the same time no surface damage is caused. Regime parameters are voltage level, pulse current, pulse duration and polarity, while control parameters are the gap between the workpiece and the electrode (gap), the flow of dielectricum through the gap (flushing) and the time interval between two electrical impulses (pulse interval). The gap is controlled by the feedback system. The process voltage value is measured on-line and compared with reference voltage value. A servo system compares both voltage values and controls the gap according to them. The gap control is adjusting by reference voltage.

Optimal control parameters (optimal point) depend on the gap conditions, which are changing by the depth of machining. The optimal point must be searched throughout the machining.

In our work the operator made the search and his knowledge was translated into the form understandable to the computer by Machine Learning (ML). A First Order Regression System (FORS) as the ML method was used to translate operator’s knowledge into if-then-else rules. These rules (strategy) were implemented into the process controller as a reference model. The system FORS was developed in Laboratory of Artificial Intelligence, Faculty of Computer Science and Information, University of Ljubljana /Karališ/.

**EDM CONTROL SYSTEM**

The controller is designed as a feedback system. It monitors the quality of discharges at the process output, and consequently, changes the process parameters at the process input (Figure 1). The feedback transfer function is defined by the strategy expressed in terms of if-then-else rules. Such a software control strategy is very flexible and its advantages have already been confirmed in the case of fuzzy controllers of AGIE EDM sinking machines /Boccadoro/.

**Process Identification**

The process is identified through different types of pulses, which are of random shape. Four distinct types of pulses are defined according to their contribution to the process performance. The so-called free pulses where no material removal is taking place are denoted by letter A. The effective pulses B characterise the stable region of the process where the major quantity of material is removed. The remaining two types, arc pulses C and short circuit pulses D are harmful causing burns and cracks of the material. The sum of all the pulses is normalised to 1 and for this reason short circuit pulses are not registered. The matrix in Eq. 1 defines the state of the process, which encompasses calculated statistic parameters of each of the process parameters.

Different types of discharges are identified by the analyser (Figure 1). Electric voltage in the gap is the input value to the analyser. Outputs of the analyser are portions of pulses A, B and C on a sample of 100 discharges in the form of voltage values which are fed into the process computer calculating the state of the process (Figure 1). Time interval (1 second and 10 seconds) is adopted since it reflects the operator’s behaviour when observing the process.

**EQ. 1:**

\[
\text{State}(t) = \begin{bmatrix}
\text{avg}(A(t_n),1s) & \text{avg}(A(t_n),10s) & \text{std}(A(t_n),1s) & \text{std}(A(t_n),10s) \\
\text{avg}(B(t_n),1s) & \text{avg}(B(t_n),10s) & \text{std}(B(t_n),1s) & \text{std}(B(t_n),10s) \\
\text{avg}(C(t_n),1s) & \text{avg}(C(t_n),10s) & \text{std}(C(t_n),1s) & \text{std}(C(t_n),10s)
\end{bmatrix}
\]

\[
\text{avg}(X(t),\Delta t) = \frac{1}{\Delta t \cdot f} \sum_{i=n-(t_f)}^{n} X(t_i), \quad \text{... average of pulses X in time interval } \Delta t
\]

\[
\text{std}(X(t),\Delta t) = \frac{1}{\Delta t \cdot f} \sum_{i=n-(t_f)}^{n} [X(t_i) - \text{avg}(X(t),\Delta t)]^2, \quad \text{... first central moment of pulses X in time}
\]

\[
f \quad \text{... sampling frequency [s}^{-1}] \\
X \quad \text{... percentage of X pulses on a sample of one hundred discharges, where X means A, B or C pulses}
\]
Typical for EDM are both, fast events on the level of discharges and low material removal (causing long machining time). These facts have been taken into account when building process identification strategy.

Control of the Process Parameters
The control action, an increase or a decrease of the gap has the strongest influence on the process. It effects directly the transformation regime and provokes a drastic response in the process performance. Wider gap causes lower conductivity, higher rate of free pulses and lower material removal rate. The length of the pulse interval has strong impact on the process since it facilitates the complete deionization of the dielectricum. If the pulse interval is not long enough the process tends towards the region of arc pulses. A considerable response is also achieved by changing the dielectric flow, which enables the removal of the melted material from the gap, because these particles are causing arc discharges. On the other hand higher flow rate implies higher tool wear.

Synthesis of the control algorithm
A large database (several controlling examples) of control demonstration records was built by recording operator’s actions and process states (Eq. 1) by the system shown on Figure 1. The operator controlled the process only by changing the gap and the flushing. We developed a new generator, which enables independent changes of pulse interval on wide interval as well, but the operator was not skilled enough to use the new generator control option.

Control demonstration records were used as an input to the system FORS, which induced the control strategy in the form of if-then-else rules (Figure 2).

The rules were upgraded with engineer’s knowledge for controlling pulse interval and built into the process control algorithm (Figure 3). By this approach we have taken into account the results of our previous research /Junkar/, in which we claimed that it is necessary for qualitative controller to combine the knowledge of both, the shop floor and the technological level.

EXPERIMENTS
The knowledge acquisition and tests of the developed controller were made under the same sets of the regime parameters. We have chosen fine regime of machining because it is more unpredictable then rough machining. Regime parameters are as follows: voltage $u_i=80\,V$, current $i_e=3\,A$, pulse time $t_i=45\,\mu s$, electrode polarity $=+$. By these parameters we can achieve surface roughness ($R_a$) approximately down to $4\,\mu m$. Of course this is not the finest possible regime. If the finest regime is adopted then jumping electrode function (lifting electrode periodically off of the workpiece for a few millimetres) has to be used to avoid workpiece surface damage. Since we did not want to use this function we have chosen such regime parameters that still enable testing of the controller.

The results of the process controlled by the operator were used as our reference results. Four other experiments have been carried out in which the derived controller was controlling the process. Each test of the controller started from different control parameters
point as shown in Table 1 and lasted for 10 minutes.

As we can see on the surface of a workpiece made by the operator (Table 1), the surface was slightly damaged although the operator controlled the process at a very stable regime with a very low percentage of arc pulses (Figure 4.A). Comparing the process controlled by the operator and the process controlled by the controller one can notice quite a difference in the obtained content of each pulse type. Operator achieved very low percentage of arc pulses and very high percentage of effective pulses by controlling the process. On the other hand the controller achieved higher percentage of arc pulses (Figure 4.A, 4.B). This is due to the fact that the controller is not an exact model of the operator's strategy. By comparing the results in Table 1 there is practically no difference in the material removal and the surface quality between the workpiece achieved by the operator (test_1) and the controller (test_2 through test_5).

In all tests made by the controller the diagrams of process parameters look the same as the one on Figure 4.B. The difference is evident only in the first minute of machining because the controller requires a period of time to establish stable process conditions. For this reason only comparison between the process controlled by the operator (test_1) and by the controller (test_2) is made since the starting process parameters are the same in both cases.

<table>
<thead>
<tr>
<th>Experiment</th>
<th>Operator</th>
<th>Controller</th>
</tr>
</thead>
<tbody>
<tr>
<td>STARTING values of the control parameters</td>
<td>test_1</td>
<td>test_2</td>
</tr>
<tr>
<td>gap</td>
<td>7</td>
<td>7</td>
</tr>
<tr>
<td>flushing</td>
<td>1.24</td>
<td>1.24</td>
</tr>
<tr>
<td>pulse interval</td>
<td>40</td>
<td>40</td>
</tr>
</tbody>
</table>

Electrode: electrolytic copper, diameter Ø 20 mm

Workpiece surface (hardness 60 HRc)

Material removal ($V_w$) g/min: 0.13, 0.14, 0.26, 0.14, 0.12

Electrode wear ($V_e$) g/min: 0, 0, 0, 0, 0

Surf. rough. $\mu$m: $R_a$ 4.1, 4.5, 4.1, 4.0, 3.7; $R_z$ 24.0, 25.5, 24.5, 24.1, 23.8

| Figure 4: Pulse A, B, C percentage A) Process driven by the operator (test_1) and B) Process driven by the controller (test_2) |
CONTROLLER BEHAVIOUR
The derived controller turned out to be robust enough in spite of the different starting values of the control parameters. On Figure 5 we show how process parameters have been changed both by the controller and by the operator. The controller has always found the same optimal values of control parameters defining the optimal area which is slightly different compared to the optimal area set by the operator. Significant difference has been detected between the two corresponding optimal flushing values (Figure 5).

![Figure 5: Controller Trajectories in the Space of Control Parameters](image)

The control strategy of the controller consists of three stages: controlling of the gap, controlling of the flushing and controlling of the pulse interval.

Controlling of the flushing has some drawbacks. By running the process, the flushing is increased to the maximum value and then remains constant. In the database of the control demonstration records there are no examples of decreasing the flushing. This is due to the influence of the flushing on the process. By machining deeper into the workpiece, higher flushing values are required. A skilled operator can control the flushing only by increasing it. Since the database does not contain examples of decreasing flushing actions, the system FORS could not induce the appropriate if-then-else rules. From the derived rules it follows that the operator controls the flushing on behalf of the stability of A pulses:

\[ IF \ std \ A_1 > 0.003 \ & \ std \ A_{10} > 0.025 \ THEN \ ... \]

If the gap and the pulse interval had been controlled well the corresponding process states indicate strong contamination of the gap with removed workpiece particles. In such case, it is possible to stabilise the process only by increasing the flushing. The developed controller is obviously not able to control the flushing only by increasing actions.

The main information that the operator is using for the flushing control is the stability of free (A) pulses. The operator was able to explain his control strategy for controlling the gap before the control demonstration records were acquired, while he could not say anything in particular about controlling of the flushing. The thesis that it is possible to induce knowledge, which is beyond human consciousness by Machine Learning /Urbančič/, has been confirmed again.

![Figure 6: Diagram of Process States](image)

A slight diversity between the gap control performed by the operator and by the controller has been noticed. The operator uses higher values of the gap and the difference in process parameters (pulses A, B and C) are seen on Figure 4, while there is practically no difference noticed on tested workpieces (Table 1).

On Figure 6 we can observe the gap and the pulse interval values and the corresponding process parameters (which type of pulses are dominant). One can notice that it is possible to obtain different process parameters for the same gap and the pulse interval values at different process periods. The optimal process parameters are in the area where efficient pulses “+” are predominant. The controller in all the test cases tends towards the optimal region of process parameters.

CONCLUSIONS
EDM control strategy, which was beyond human consciousness, had been induced by Machine Learning /Urbančič/.
Learning method. The thesis that it is possible to induce such knowledge has been confirmed again. The controller is robust enough to achieve optimal process parameters regardless to their starting values. The optimal parameters differ slightly from those used by the operator, which have no effect on machining results.

Controlling of the flushing is the controller’s drawback. In the control demonstration records the control actions for decreasing the flushing are missing and the system FORS could not induce if-then-else rules for decreasing the flushing. The developed controller is obviously not able to control the flushing only by increasing actions.

In comparing the process performance measures i.e. the material removal and the surface quality achieved by both, the operator and the controller, no significant difference has been noticed between the two.

Some drawbacks of the controller performance are due to the specific character of the if-then-else rules. By these rules, the values at which some actions have to be done are strictly defined. Such boundaries in reality do not exist. Better results are expected by using fuzzy logic.

REFERENCES