Controller Design for Electrical Discharge Machining

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Abstract

EDM process is unstable especially in the case of fine regimes of machining. To avoid unstable processing a number of different adaptive process control can be applied. In the present research we are proposing an adaptive controller which should replace the operator's manual functions when guiding the process in the region of stable conditions. The main part of such a controller is the knowledge and the strategy of the adaptive control. Since a large amount of knowledge about the process control exists in the form of operator's skill and engineering knowledge about the principles of material removal in EDM, we explored the possibilities of using the existing knowledge in building EDM control. We tried out three different approaches of process control, differing in the controller design.

The three strategies were tested in the case of process control in critical and unstable region of machining. A comparison of the three approaches is presented by qualitative estimation of the effectiveness of the process control and by quantitative measurements of process performance. Further research directions are proposed in order to develop and upgrade the methods of knowledge acquisition for process control in EDM.

Key words: adaptive control, process strategy, machine learning, cloning approach

1 Introduction

In electrical discharge machining (EDM), one usually expects high precision of machined parts, especially by fine regimes, attained at as short time as possible. Both the process stability and process effectiveness can not be permanently sustained since they are mutually exclusive. The trade-off between these two factors is usually attained by means of adaptive control of the process according to the preset optimisation strategy. The optimisation strategy of most EDM process partly remains in the hands of the operator. Since the process itself is very complex, effective strategy of adaptive control can be acquired by the operator only after a long period of practice. Apart from operator's skill, the knowledge of fundamental principles of machining by EDM is crucial. In our research we focused on acquisition of the EDM knowledge represented in descriptive, non-numerical and non-symbolic form. The controller must be designed as a an open system, which should be flexible enough to adapt to the process, as well as to the human being and his way of thinking and decision making. Therefore all the basic functions in the controller design including identification, decision making and control are performed by the computer. This involves the numerical aspekts of process identification as well as characteristic human decision making based on qualitative and probabilistic estimations.

2 System for adaptive control of EDM

The parameters which are constant between the process are set before the operation starts thus characterising the type of the regime. They are called *the setting parameters* and are as follows: pulse time ($t_i = t_i + t_o$), pulse current (I_o), open voltage (U_i), polarity and the type of the dielectricum. The parameters which can be adjusted during the process are used for optimisation purposes and the stabilisation of the process. They are called *the controlling parameters*. The most important controlling parameters are the gap between the tool and the workpiece, and the dielectricum flow. There are four distinct control actions: gap increase & decrease, flow increase & decrease.

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, the spark pulses C and short circuit pulses D are harmful causing burns and cracks of the material. The sum of all pulses is normalised to 1, for this reason the short circuit pulses are not measured. Along with pulse detection the average effective current I is measured on line.

So the measured process variables are: A, B, C (portions of the three types of pulses) and I (the effective current).

The measured data are fed into the computer where the average values and corresponding standard deviation of the afore mentioned process measures are computed on the time intervals of 3 and 20 seconds. The choice of time interval lengths is made according to the human reaction time and to the specific way of process observation. The state of the system at a particular time t_n is described by 16 attributes, each attribute representing the statistic values of the four process measures:

$$
\mathrm{State}(t_n) = \begin{bmatrix}
\mathrm{avg}(A(t_n),20s) & \mathrm{avg}(A(t_n),3s) & \mathrm{std}(A(t_n),20s) & \mathrm{std}(A(t_n),3s) \\
\mathrm{avg}(B(t_n),20s) & \mathrm{avg}(B(t_n),3s) & \mathrm{std}(B(t_n),20s) & \mathrm{std}(B(t_n),3s) \\
\mathrm{avg}(C(t_n),20s) & \mathrm{avg}(C(t_n),3s) & \mathrm{std}(C(t_n),20s) & \mathrm{std}(C(t_n),3s) \\
\mathrm{avg}(I(t_n),20s) & \mathrm{avg}(I(t_n),3s) & \mathrm{std}(I(t_n),20s) & \mathrm{std}(I(t_n),3s)
\end{bmatrix}
$$

$$
\mathrm{avg}(X(t_n),\Delta t) = \frac{1}{\Delta t \cdot f} \cdot \sum_{i=n-(\Delta t \cdot f)}^{n} X_{(i)}
$$

$$
\mathrm{std}(X(t_n),\Delta t) = \sqrt{\frac{1}{\Delta t \cdot f} \cdot \sum_{i=n-(\Delta t \cdot f)}^{n} \left[X_{(i)} - \mathrm{avg}(X_{(i)})^{2}\right]}
$$

f ... sampling frequency$[1/s]$

X ... identification number

Detailed information about the system and the experiments are given in [1] and [2].

3 Three approaches to controller design

Three different approaches to knowledge acquisition have been tried (***Figure 1***). It is important to take advantage of the operator's knowledge and control skill regarding the process [2]. Two design strategies take this into account: the first from the operator's verbal interpretation of the control strategy, and the second by means of inductive learning from examples [3]. The third approach is to derive a controller from engineer's knowledge regarding EDM sinking process.

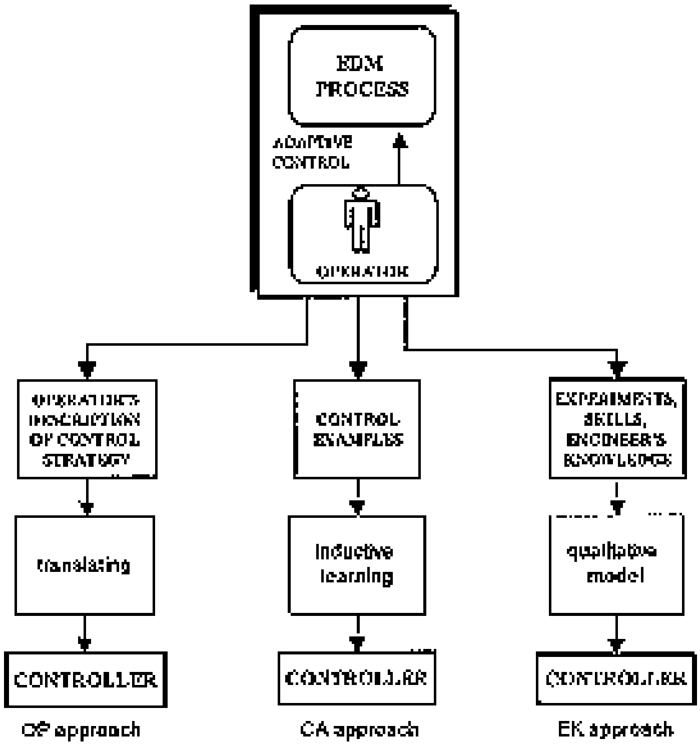


Figure 1: Different approaches for control acquisition:
OP — Controller design based on translation of operator's description of his skill
CA — Controller design based on cloning approach
EK — Controller design based on engineer's knowledge of the EDM process

3.1 Operator's interpretation of the control strategy

The most direct approach to the design of a controller is to translate the operator's verbal description of his own skills into IF-THEN control rules. However such an approach has two main difficulties [4]: (1) The difference between the form of verbal description and the resulting set of IF-THEN rules is remarkable. Namely, the operator does not make use of statistics for process evaluation; therefore, we use them in order to define better the attributes that are actually used by the operator. The original operator's attributes are essentially qualitative in nature and are quite difficult to be reproduced numerically. (2) In addition, there is also a difference between what operator says he do and what he actually does [2]. Manual control is relatively intuitive and mechanical, and is, therefore, difficult to interpret verbally.

Figure 2 shows a controllers derived from the operator's verbal description. Figure 2 can be read as:

If the average value of the effective current in last three seconds is less than 'factor of hazard' times 1.5 ampere and the average of C pulses in last twenty seconds more then 'factor of hazard' times 10 percent then increase the gap and flushing counters by 1.

If the gap counter is more than 1 then increase gap, if the gap counter is less than -1 than decrease the gap.

If the flushing counter is more than 1 then increase flushing, if the flushing counter is less than -1 than decrease flushing.

By changing 'factor of hazard' we can move the state of the process more to the region 5 (factor less than *1*) or more to the region 2 (factor more than *1*) (**Figure 4**) as explained later.

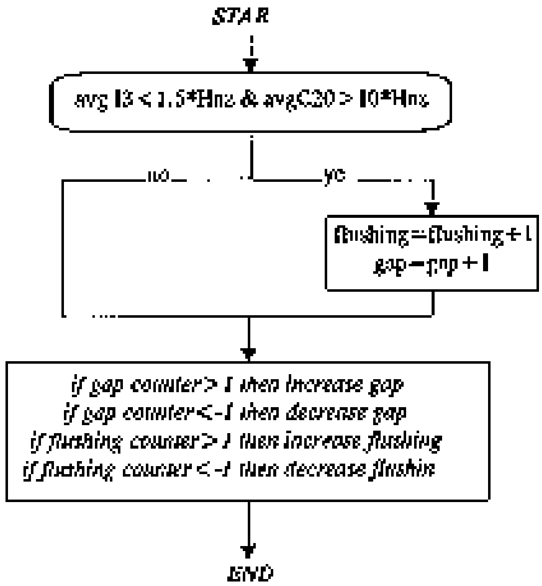


Figure 2: One control cycle derived from the operator's verbal description

3.2 Cloning approach

This approach partly bridges the problem of interpretation of the operators control actions as well as translation of the operator's knowledge into symbolic form. By inductive learning it is possible to derive the controller strategy from the records of operator's control decisions [5]. We used the learning system FORS [3], which finds the relationship between the process state and the control action using records of operator's control demonstration (records of process state and operator's control actions represented numerically). Detailed information on this subject is given in [6].

This approach produces separate control rules for gap and flushing. They were integrated into one controller which is shown on ***Figure 3***. In general a desirable properties of a controller is it's comprehensibility. Such a controller is easy to understand and extend with new rules. The strategy resulting from inductive learning method we used is not as comprehensible as the strategy derived from engineer's knowledge and the strategy derived from operator's interpretation. The obtained rules were interpreted by the expert and the process states deriving from the rules are divided into 6 regions representing respective process performance in the two dimensional diagram (***Figure 4***).

The individual process state interpretations are as follows:

In the region "0" the metal removal intensity is the highest and the machined surface integrity is acceptable.

Region "1" depicts the unstable process behaviour. It is manifested by unstable feed movements of the electrode. A large portion of arc pulses occurs, the material removal and the machined surface quality is low while the heat affected zone is growing. The process remains in this region and does not break down.

Region "2" covers extremely unstable process behaviour. It is characterised by a large portion of arc pulses which cause quick degradation of the process culminating in evolution of the constant arc. The damage of the surface is more then *1* mm deep and can not be eliminated.

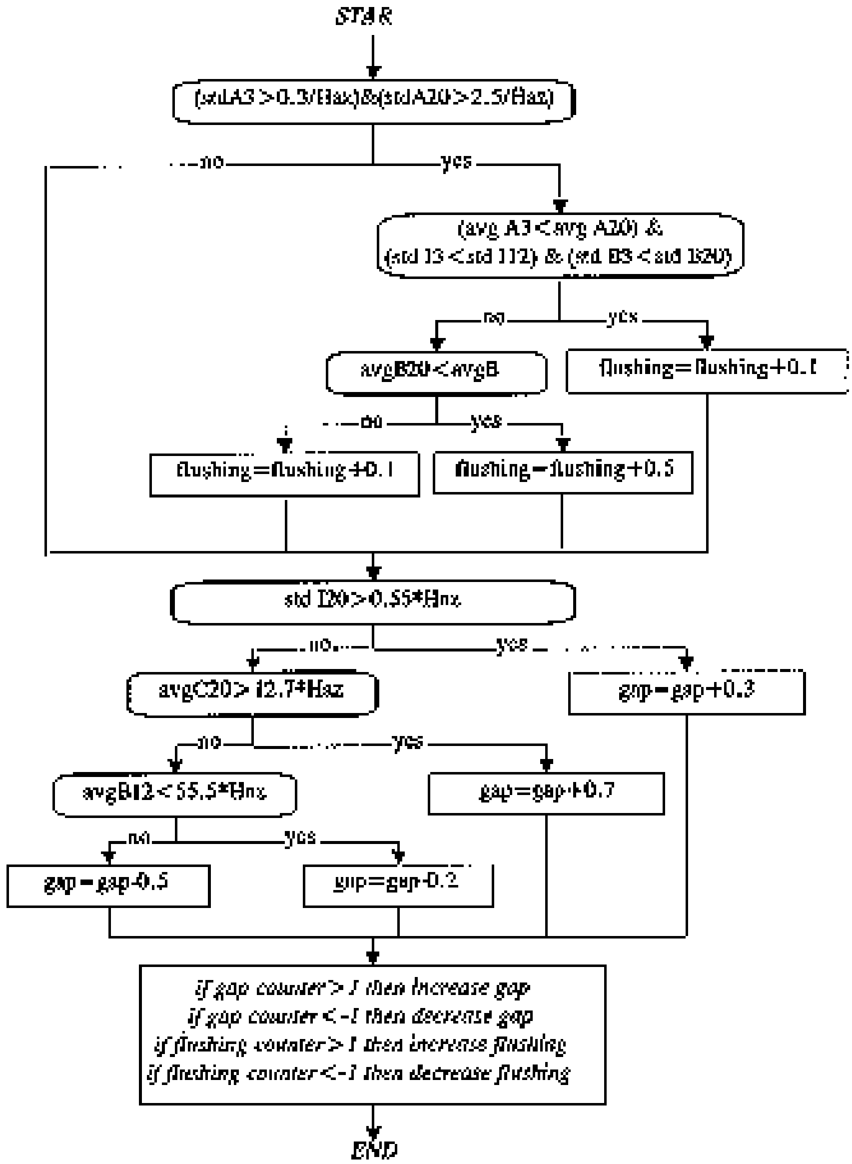


Figure 3: One control cycle resulting from cloning. This strategy increases and decreases gap but only increases flushing.

The region "3" represents the process with weak flushing and thus the dielectricum in the gap is filled with metal particles causing the increase of arc pulses. This process state usually develops gradually from the process state in the region "0" and after quite a period of time (several minutes) culminates in the process break down. The operator usually prevents the transformation from process state "0" to process state "3".

The region "4" is characteristic for the process state with low portion of arc pulses. Because of law metal removal rate obtained in this process state, it should be avoided, though now harm is done to the surface.

In the region "5" the machining does not occur, because the gap is too wide and only free pulses are taking place.

According to the above described interpretation, the induced rules were evaluated by the expert. The suggested actions were plotted into the process performance diagram (*Figure 4*). For each rule of the control strategy the vector defining the action of setting the gap and the flow magnitude and direction was depicted in the diagram. One can easily see from the diagram that the vectors representing control actions point towards the boundary dividing the stable and unstable process states

For example the arcing process behaviour states in the region "3" tend towards the region of higher stability while the ineffective process states in the region "4" tend towards the region of more intensive machining. Along with that we can observe that many vectors point towards the optimal process state region "0". These actions correspond to the primarily goal of the control.

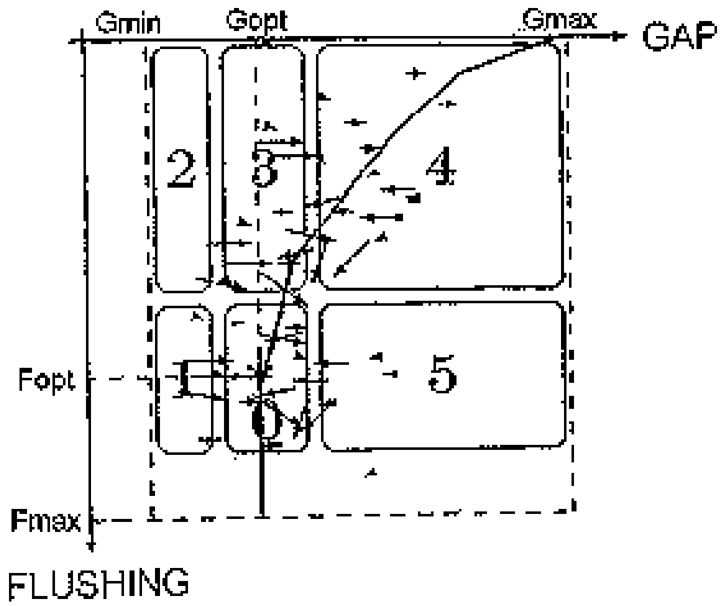


Figure 4: Diagram of characteristic performance regions and control actions of learned rules [6].

3.3 Control strategy derived from engineer's knowledge regarding the EDM-sinking process

Appropriate actions of the controller can be derived from deep knowledge of the EDM process, such as process engineer's knowledge. The simplicity and clarity of the resulting controller (*Figure 5*) are remarkable advantages of such an approach. Furthermore the resulting controller's performance is very good in the speed of response to changes in the process as well as in achieving process intensity.

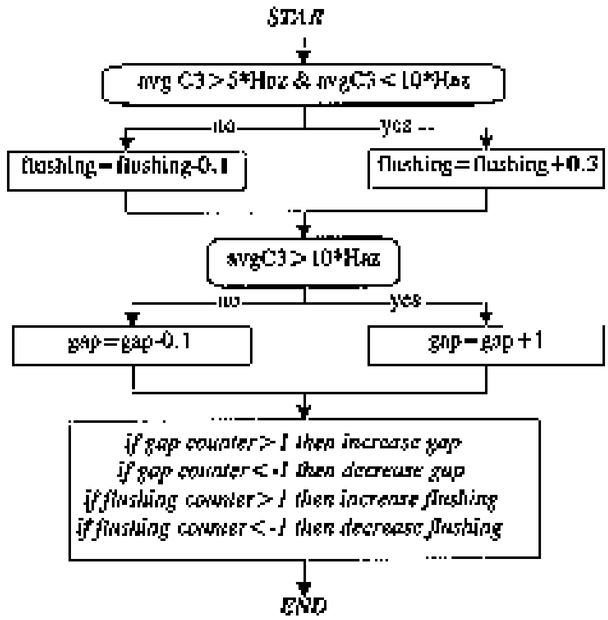


Figure 5: Control cycle derived from engineer's knowledge

4 Expert evaluation of the results

The three approaches to the controller design were tested under real working conditions. The control strategies were applied to the process regime for which they were not specialised. This was set deliberately in order to test and compare the robustness of the respective control algorithms. The real circumstances in which the control should be executed are even more demanding from the point of view of the robustness of the control algorithms. The electrode probe was of cylindrical shape with the diameter of 20 mm. The flushing was performed from the outside of the electrode, which has made the working conditions even harder. Results of strategies /EK1, OP1, OP2, EK2, OI, CA/ are represented on ***Figure 6*** and on ***Figure 7***.

The first test was controlled by the algorithm *"Control strategy derived from engineers' knowledge regarding the EDM-sinking process"*. After ten minutes of operation the process broke down /EK1/. In order to prevent the break down we introduced the strategy offering the possibility of defining the *factor of hazard (Haz)*. If the factor of hazard is less then *1* we move the process towards the process performance region 5 (***Figure 4***).

To explore the reasons of the process break down an experienced operator manually controlled the process under the same starting parameter's setting /OP1/. The process evolution remained the same which led the operator to change the starting position of flushing valve from 0,8 l/min to 2,8 l/min /OP2/. This time the process remained stable. From that we drew the conclusion that under unknown process conditions the expert intuition showed to be indispensable to locate the proper process setting.

Under this newly defined setting the three strategies were tested and evaluated. Because the duration of the process was relatively short, removal rate is not so informative. The most significant attribute is the damage of the surface. Surface roughness is also important, but we should be aware that the process setting parameters (voltage, pulse time etc.) are more influencing the surface roughness than the controlling parameters (gap, flow).

/EK1/ /OP1/

/OP2/ /EK2/

/OI/ /CA/

Figure 6: Results of the experiments: surfaces photographs

The best result was obtained by manually controlling the process /OP2/ and by strategy derived from engineer's knowledge /EK2/ (*Figure 6*). Other two strategies /OI, CA/ had produced surface with some damage but it can be removed later on by grinding.

When comparing the removal rate and the surface roughness of different strategies, the strategy derived from operator's interpretation /OI/ showed to be the best. This is a surprising result especially if we consider that this strategy does not enable the intensification of the process. This is due to the short time of duration of the process and very difficult operating conditions.

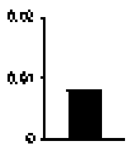
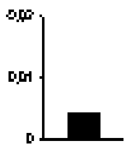
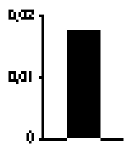
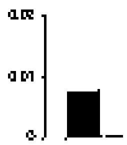
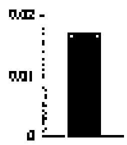
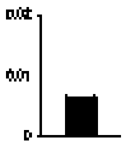
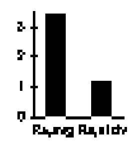
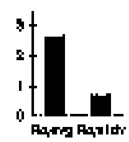
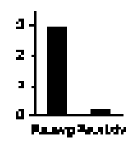
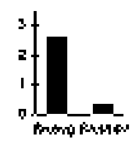
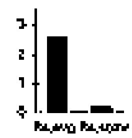
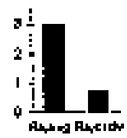
Algorithm						
Strategy	EK1	OP1	OP2	EK2	OI	CA
Hazard	0,3	-	-	0,3	0,5	0,5
Starting position of flushing valve [l/min]	0,8	0,8	2,8	2,8	2,8	2,8
Experiment						
Duration of the process [min]	15	3	15	32	10	30
Removal rate W_w [g/min]						
Roughness R_a [μm]						

Figure 7: Results of the experiments: removal rate and roughness R_a.

5 Conclusions

Operator's interpretation of the control strategy offers effective stabilisation measures but lacks process intensification measures which have not been taken into account by the operator when making the strategy. The process moves from the region of effective machining after the first occurrence of instability and performs on in the region of ineffective machining.

The strategy obtained by operator's *cloning approach*, controls the process well, but lacks quick and drastic measures in the critical states of the process (region "3" in *Figure 4*). The strategy should be upgraded by other sources of knowledge, such as the operator's and the technologist's knowledge.

The *strategy derived from engineer's knowledge of EDM-sinking process* showed weaknesses exhibited in continuos oscillation of the process stabilisation and process intensification measures.

The equilibrium of the process is reached by switching between the two opposite measures. Because of the delay of the control actions which is due to the calculation of the process parameters statistic values, the constant switching causes unnecessary development of short circuit pulses in spite of the fact that the process performs in the optimal region "0" (*Figure 4*). The strategy should be upgraded by the measures which would stop the control actions in the optimal region of process performance.

Because of the complexity of the majority of machining processes their models are hard to build. It is very important that as much of the existing knowledge about the process as possible is taken into account. In our research the three proposed strategies showed to be more or less successful in controlling the EDM process. In order to use these strategies efficiently on the shop floor in real industrial environment the identified shortcomings should be avoided. This can only be done by taking into account the existing knowledge from different sources. Our further research work will therefore focus on the development of the adaptive controller integrating the strategies obtained from different sources of knowledge.

6 References

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