

NEURO-FUZZY PROCESS CONTROL SYSTEM FOR SINKING EDM

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ABSTRACT

Electrical-Discharge machining (EDM) stands for highly accurate and very sophisticated metal shaping. The physical process takes advantage of electric field effects between two electrodes, a tool and a workpiece. Material is removed by sequences of electrical discharges. The electrically efficient gap width, which is determined among other parameters by the electric conductivity of the gap and the geometrical distance of the electrodes varies from spark to spark. This leads to a highly non-linear control problem. Various optimization control algorithms have been developed to improve the performance of EDM sinking machines.

Soft computing technologies like Fuzzy logic and Neural Networks gained much popularity in this field. The following article introduces a process control system consisting of a Fuzzy gap-width controller adapted by a Neural Network. By combining a Neural Network with a Fuzzy controller in this way a learning process control system is achieved. Experimental results show the working efficiency of this Neuro-Fuzzy system.

INTRODUCTION

The operating efficiency of an ED-machine strongly depends on the gap-width controller. This controller has to adjust the size of the inter-electrode gap in order to achieve a high workpiece removal rate and a low tool-electrode wear. A model based controller synthesis cannot completely be applied in EDM, because of the insufficient model of the removal system and the chaotic fluctuations of the gap state.

To cope with these problems optimization systems have been developed to adapt the gap-width controller to the continuously changing working conditions and process situations. Most of these systems operate by systematic controller parameter variation using heuristic methods [4], [5], and [12]. Fuzzy technologies follow a different approach. Fuzzy-controllers are designed by integrating the experience of human users in so-called membership functions and rulebases. In EDM Fuzzy-technologies gained much popularity. In numerous research projects it has been shown, that efficiency of ED-machines can be improved by using Fuzzy gap-width controllers [13], [16], [17]. Commercial EDM sinkers with Fuzzy technologies are already available at the market today [11].

For the construction of these Fuzzy controllers optimization algorithms [17] or Neural Networks [13] are often used. In the second case a Neural Network creates automatically on the basis of the desired controller output the membership functions and rulebases of a Fuzzy-Controller. In this context the term "Neuro-Fuzzy" is often used [9]. In fact the role of the Neural Network is limited to the controller development phase only. The Fuzzy gap-width controller carries out all control actions.

In another approach the Neural Network is used for the online adaptation of the running Fuzzy-gap-width controller. In this case the Neural Network becomes a vital part of the process control system itself. In comparison to the above-mentioned "Neuro-Fuzzy" approach the actions of the Neural Network are not limited to the controller development phase any more. By including the Neural Network into the EDM gap-width control system, the ability of learning is available and working efficiency can be improved.

The work presented in this paper follows this approach. A Neural Network adapts the output of a fuzzy-gap-width controller based on the actual process situation measured and computed online.

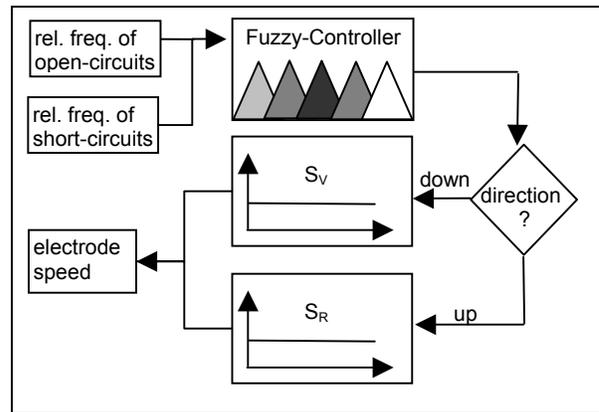
FUZZY GAP-WIDTH CONTROLLER

For the multiple cases in which ED-machining is used in practice the gap width controller has to provide a stable and efficient removal process. The electrical efficient gap width is difficult to measure, because of surface roughness and the distribution of the dielectric properties in the gap. Therefore the electrical efficient gap width itself can not be used for controller feedback.

Most of modern ED-machines make use of the ignition delay time (t_d) as input value for the gap width controller [12]. It is easy to measure and t_d can characterize the most important kinds of ignitions. The disadvantage of t_d for control operations is its considerable variance. As consequence of this fact a flutter movement of the electrode often may be observed. Because of the very small geometrical gap width this flutter movement can lead to instable process conditions [10]. For this reason the implemented gap-width-controller uses alternative input values. The relative frequency of short circuits

and open circuits during an inspected period were used as input parameters. A highly efficient removal process shows a very low number of these pulses [1].

This gap-width-controller is implemented using Fuzzy-technologies. The output of this controller is multiplied by scaling factors to compute the target-speed of the tool-electrode. Different scaling factors can be defined for forward and backward movement. Figure 1 shows the Fuzzy-gap-width controller.



1. FUZZY-GAP-WIDTH CONTROLLER

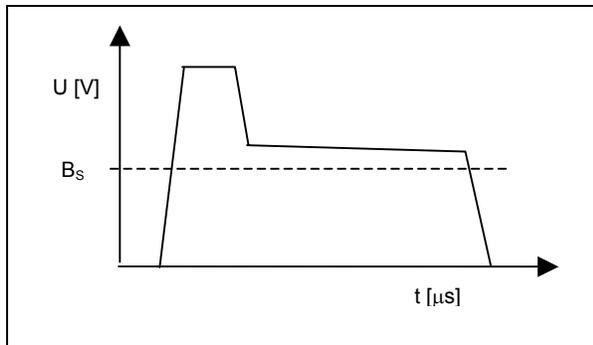
The gap width controller offers two parameters:

- S_V : Proportional gain for forward movement of the tool electrode (gap reduction).
- S_R : Proportional gain for backward movement of the tool electrode (gap enlargement).

ARC DETECTION

To avoid surface damage due to overheating, highly efficient arc detection is needed. There are several concepts to decide, if an ignition raises the danger of arcing or not. Very often the ignition-delay time (t_d) or the level of the ignition voltage is used as an arcing criterion [5], [12], [13].

Different examinations of the arcing phenomenon show, that these arc detection strategies give only an insufficient indication [2], [3], [6]. The introduced process control system uses a threshold level BS as an indication for arcing. This threshold is active during the burning phase.



2. ARC DETECTION BY THRESHOLD LEVEL ON BURNING VOLTAGE

In case of arcing the current is switched off. If arcing is again detected when restarting, a flushing movement of the electrode is released. The arc detection and flushing mechanism works independent from the gap-width-control.

OPTIMIZATION OF THE GAP-CONTROLLER

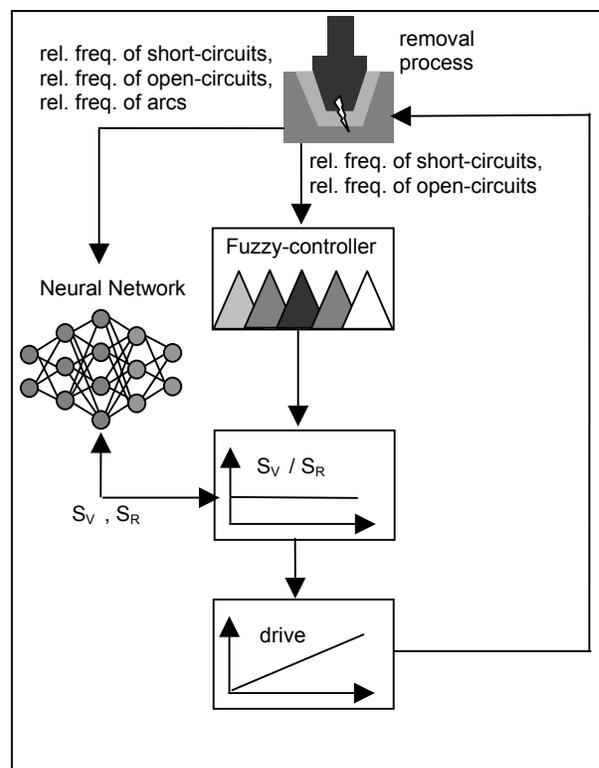
In order to guarantee a secure erosion process and to avoid destructions on the electrode surfaces, the gap-width controller and the arc detection module are the most important components within the introduced process control system. In addition to the aspect of safety the process control system should strive for a highly efficient removal process. This demand can only be filled if:

- Arcs are avoided as much as possible, because the frequent occurrence of arcs will cause a flushing movement and the process is disturbed for seconds.
- The number of open circuits must be limited, because each open circuit means a loss of time.

The two above requirements are conflictive, because with increasing the number of open-circuits the tendency towards arcing can be reduced. Neither the gap-width controller nor the arc detection module can follow these requirements on its own, because both work autonomously from each other.

For example the gap-width controller can strive for a process showing a reduced portion of open-circuits, but the numbers of arcs are not included in his control strategy since this value is not a controller input.

In order to achieve a highly efficient removal process a superior authority is needed that adapts the gap-width controller permanent to the actual process situation. In case of increased arcing more open-circuits might be tolerated to stabilize the process. In stable process situations the number of open circuits should be reduced, to increase material removal. This task is fulfilled by a Neural Network which works as a process optimization.

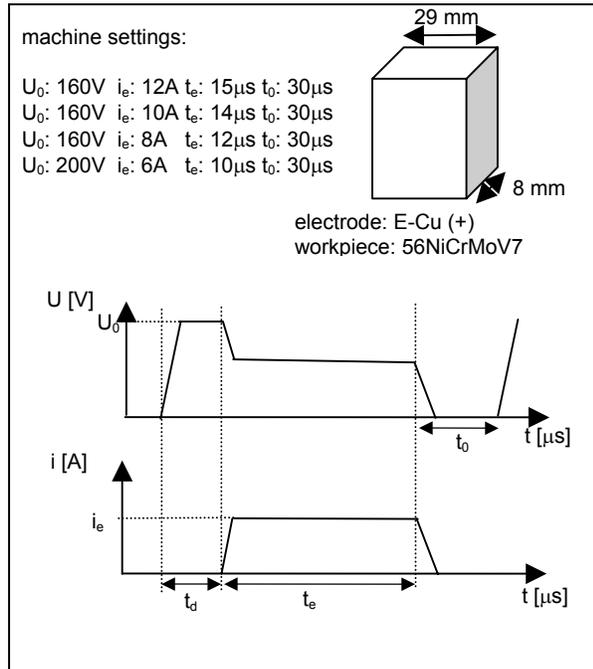


3. OPTIMIZATION OF THE CONTROLLER BY NEURAL NETWORK

The Neural Network adapts the gap-width controller by changing the scaling factors (S_V , S_R) at the controller output. This Neural Network receives as input data the relative frequencies of arcs, open circuits and short circuits measured during a longer period of time. Also the actual settings of S_V and S_R are given as input data (see figure 3).

COLLECTING THE TRAINING DATA

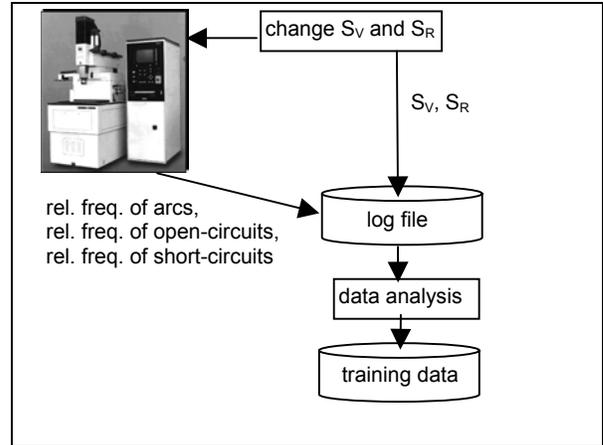
The accuracy with which the Neural Network calculates its outputs strongly depends on the quality of information that is used for training [6]. To obtain this training data many experiments were carried out. Figure 4 shows the test conditions.



4. TEST CONDITIONS FOR EXPERIMENTS

During these experiments an experienced user adapted the gap-width controller manually by changing S_V and S_R . The continuous logging of the relative frequencies of short-circuits, open-circuits and arcs allowed the later evaluation of these adaptations.

With the aid of a subsequent analysis of the logged data those adaptations could be identified that influenced the process behavior positively (reduced number of arcs, short-circuits, open-circuits). They were used as training data for the Neural Network. Figure 5 shows the process of obtaining the training data. Altogether 94 adaptations that improved the process behavior could be extracted. These data sets were grouped in two sets: One set of 73 data-samples for training the Neural Network (training data). Another set of 21 data-samples for testing if the output of the trained Neural Network is correct (test data).



5. PROCESS OF OBTAINING THE TRAINING DATA

When looking at the training data it is possible, to identify some rough rules for the adaptation of the gap-width controller:

- In case of many short-circuits S_R is increased.
- In case of many open-circuits S_R is reduced and S_V is increased.
- In case of many arcs S_V is reduced.

DESIGN AND TRAINING OF THE NETWORK

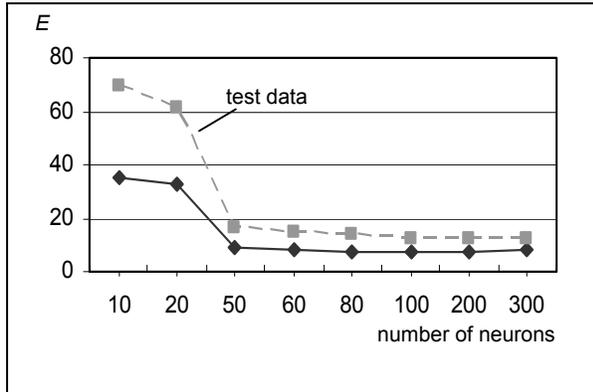
A multiplayer-perceptron was chosen as the Network architecture [15]. This network was trained using a back-propagation algorithm [14]. Due to the used software tool (Matlab Neural Network Toolbox, Version 6, Release 12) only two layered Networks could be implemented. In order to optimize the number of neurons in the hidden layer the training progress using different networks (with a different number of neurons in the hidden layer) had to be studied.

The error E indicates the difference between the actual and the desired output of the Neural Network:

$$E = \sum_{j=1}^{az} (y_j - a_j)^2 \rightarrow Min$$

- y_j : desired output
- a_j : calculated output
- az : number of training examples

Figure 6 shows the remaining error after training different Neural Networks. The grey line represents the error that can be observed when the test-data set (21 data samples) is presented to the trained Neural Network. This error indicates the ability of generalization of the Neural Network and is of major interest for the further use of this Neural Network.



6. ERROR WITH DIFFERENT NEURAL NETWORKS

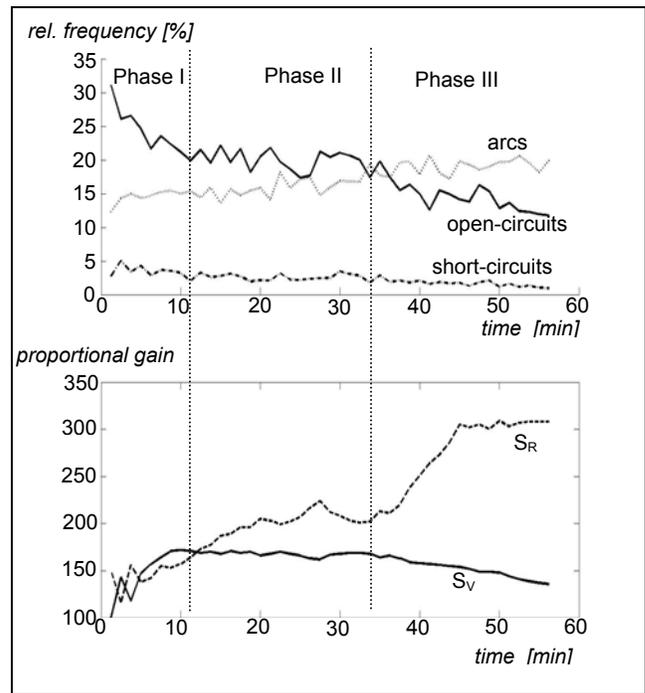
From Figure 6 it can be seen, that at least 50 neurons in the hidden layer are needed for a successful training. If more than 200 neurons are used, the ability of generalization is reduced. It might be possible to reduce the number of neurons even more by adding more layers, but this was not supported by the employed software tool.

APPLICATION OF THE NEURAL NETWORK

The adaptation of the gap-width controller by a Neural Network works in the sense of pattern recognition. The Neural Network is trained with adaptations that improve the process behavior in specific process situations.

Through the ability of generalization the trained Neural Network recognizes similarities between the learned process situations and the actual process situation. As a result an adaptation is carried out, that is related to the adaptation learned for a similar situation [5]. Figure 7 demonstrates the practical operation of the Neural Network. To visualize the process behavior, the progression of the relative frequencies of open-circuits, short-circuits and arcs are visualized in the upper part of figure 7.

The lower part of this figure shows the values of S_V and S_R which were calculated by the Neural Network.



7. PRACTICAL OPERATION OF THE NEURAL NETWORK

For a better explanation of figure 7 the process behavior is portioned into three phases:

Phase I

Many open-circuits and short-circuits are visible. This is typical for a beginning erosion-process, because both electrode surfaces are not exactly in parallel to each other. Therefore short-circuits can easily happen and the reaction of the gap-width controller causes the high amount of open-circuits. The Neural Network increases S_V in order to reduce the open-circuit portion.

Phase II

There is still an increased portion of short-circuits (between 2% and 3% in comparison to 0.5% and 1%, which is finally reached in phase III). The open-circuits are reduced successfully by the former activities of the Neural Network. In this Phase the Neural Network increases S_R in order to speed up backward movement in case of short circuits.

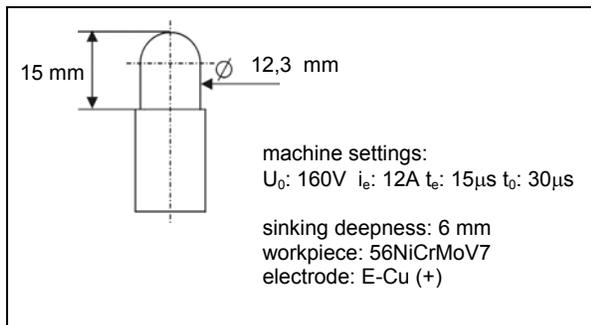
Phase III

While the portion of open-circuits is reduced, the number of arcs is raised. This results from the flushing conditions, which are deteriorating the deeper the sinking process is going on (all experiments in this paper were carried out without external flushing). To cope with this problem, the Neural Network reduces S_V . The portion of short-circuits is kept low by increasing S_R .

EXPERIMENTAL RESULTS

To prove the capabilities of the developed Neuro-Fuzzy process control system, two typical applications were selected and performed with and without the Neural-Network adaptation.

In the first application a spherical electrode had to be reproduced (figure 8). Because of the very small electrode surfaces at the beginning of operation this application has a high risk of arcing and the gap-width controller has to work very sensible.



8. EXPERIMENT WITH SPHERICAL ELECTRODE

With Neural Network:
Processing time 82.3 minutes
Relative electrode wear \cup 8.48 %

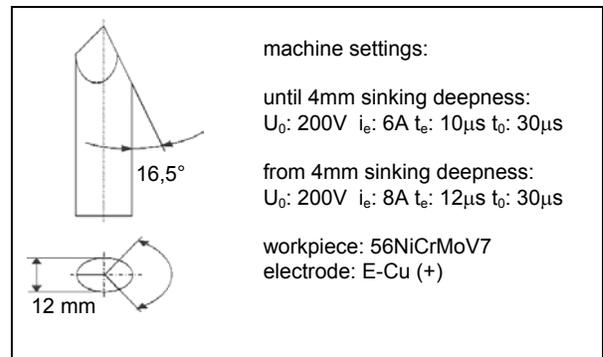
Without Neural Network:
Processing time 101.6 minutes
Relative electrode wear \cup 8.13 %

These Results show a gain of time of 19% when using the Neural Network. The relative electrode wear remains nearly the same.

In the second application a wedge-shaped electrode had to be reproduced (figure 9). The sinking process is started with a small current in order to reduce electrode wear. Current is increased later on. So the Neural Network had to adapt the gap-width controller to this changing circumstance.

With Neural Network:
Processing time 106.6 minutes
Relative electrode wear \cup 7.75 %

Without Neural Network:
Processing time 126.7 minutes
Relative electrode wear \cup 7.68 %



9. EXPERIMENT WITH WEDGE-SHAPED ELECTRODE

Using the wedge-shaped electrode, the wear at the top of the electrode is critical. If the wear at the electrode top is increased, accuracy is reduced. Using the Neural Network no increased wear at the electrode top could be observed.

In both experiments (with and without Neural Network optimization) a final surface roughness of $R_a = 1.6 \mu m$ was achieved.

CONCLUSION

For a highly efficient removal process a permanent adaptation of the gap-width controller to the changing process conditions is necessary. The presented process control system uses a Neural Network for this purpose.

The benefit of this implementation compared to a pure Fuzzy system is the ability of learning that comes with the Neural Network. In comparison to other process control systems using the term "Neuro-Fuzzy", the introduced system uses the Neural Network as a vital part of the control system itself.

The aspects of Neural Network architecture and training were explained in detail. The efficiency of this system was proven by practical examples.

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