Available online at www.sciencedirect.com

ScienceDirect

Procedia CIRP 42 (2016) 34 – 39

www.elsevier.com/locate/procedia

18th CIRP Conference on Electro Physical and Chemical Machining (ISEM XVIII)

Advanced sensor signal feature extraction and pattern recognition for wire EDM process monitoring

Alessandra Caggiano[a,b,*], Roberto Perez[c], Tiziana Segreto[b,d], Roberto Teti[b,d], Paul Xirouchakis[e]

[a]Department of Industrial Engineering, University of Naples Federico II, P.le Tecchio 80, 80125 Naples, Italy
[b]Fraunhofer Joint Laboratory of Excellence on Advanced Production Technology (Fh-J_LEAPT), P.le Tecchio 80, 80125 Naples, Italy
[c]GF Machining Solutions, Rue du Pré-de-la-Fontaine 8, 1217 Meyrin 1 / Geneva, Switzerland
[d]Department of Chemical, Materials and Industrial Production Engineering, University of Naples Federico II, P.le Tecchio 80, 80125 Naples, Italy
[e]Laboratory for Computer-Aided Design and Production, Swiss Federal Institute of Technology (EPFL), Lausanne, Switzerland

* Corresponding author. Tel.: +39-081-7682371; fax: +39-081-7682362. *E-mail address:* alessandra.caggiano@unina.it

Abstract

Wire electrical discharge machining (WEDM) is investigated in the perspective of zero-defect manufacturing with the scope to detect anomalous process conditions leading to typical defects generated during WEDM, i.e. the occurrence of lines and marks on the resulting workpiece surface. A multiple sensor monitoring system is employed to acquire high sampling rate sensorial data relative to signals of voltage and current in the gap between workpiece and wire electrode. An advanced signal processing methodology is implemented to extract and select the most relevant features useful to identify the undesired process conditions through a cognitive pattern recognition paradigm.

Peer-review under responsibility of the organizing committee of 18th CIRP Conference on Electro Physical and Chemical Machining (ISEM XVIII)

Keywords: Wire EDM; Sensor monitoring; Signal processing; Sensor fusion; Pattern recognition

1. Introduction

Wire electrical discharge machining (WEDM) is today widely used in industry for the macro- and micro-machining of parts with complex and irregular shapes, requiring high profile accuracy and tight dimensional tolerances [1]. As the WEDM process is not affected by material hardness, compared to traditional machining technologies, it can be effectively used to machine a large variety of materials including cemented carbides, sintered materials as well as difficult-to-machine aerospace alloys such as nickel or titanium alloys [2, 3].

With particular reference to the fabrication of aerospace components, the aim of achieving zero-defect WEDM manufacturing processes is crucial, as excellent accuracy and surface finish without defects are required [4-6]. However, mainly due to the large number of variables and the stochastic nature of the process mechanisms involved in WEDM, this objective still represents a challenge, even with highly skilled operators and state-of-the-art CNC machines [7,8].

In the last years, research efforts have been spent to model the process through suitable mathematical techniques and different methodologies have been proposed in the literature [3-12]. However, the selection of machining parameters allowing to obtain the optimal WEDM process performance in terms of higher material removal efficiency or accuracy is still not fully solved. As a result, process monitoring and control have become a key issue and represent a major research area in the WEDM field [7,13-17].

In the perspective of WEDM zero-defect manufacturing, the most significant part quality characteristics to be addressed include recast layer thickness, surface roughness and the occurrence of lines and marks on the machined surface, in particular after the finishing pass [4-6].

In this work, WEDM process monitoring based on advanced sensor signal processing is implemented with the aim to detect the operating conditions leading in particular to the occurrence of lines and marks on the resulting surface. The study is performed through the employment of a multiple sensor monitoring system able to acquire voltage, current and

Peer-review under responsibility of the organizing committee of 18th CIRP Conference on Electro Physical and Chemical Machining (ISEM XVIII)
doi:10.1016/j.procir.2016.02.181

wire position signals in the gap between the workpiece and the wire electrode with a very high sampling rate of 50 MHz.

To examine in depth the WEDM process conditions, a detailed analysis of the voltage and current signals is carried out and an advanced sensor signal processing methodology is developed to extract the most relevant sensor signal features. The feature extraction procedure is based on a sensor fusion approach, where the features of interest are attained from the joint analysis of the current and voltage signal together.

The obtained features are employed to implement a pulse discriminating methodology and to finally construct sensor fusion pattern vectors useful to identify the critical machining conditions for WEDM process analysis and control.

In particular, the construction of sensor fusion pattern vectors which comprise features from the voltage and current signals together will be performed with the aim to correlate them to the produced quality output (the resulting surface finish) and realize a cognitive fault diagnosis system able to detect the occurrence of undesired operative conditions leading to surface defects such as lines and marks.

The correlation between the sensor fusion pattern vectors and produced surface quality will be realized through the implementation of a pattern recognition paradigm based on 3-layers feed-forward back-propagation Neural Networks (NN).

2. Sensor monitoring of Wire EDM

Sensor monitoring of WEDM processes was performed during an experimental testing campaign of WEDM surfacing processes carried out on steel plate workpieces with a height of 20 mm. The WEDM tests were performed on a GF Agie Charmilles FI 440 ccS CNC wire EDM machine. A brass wire electrode (AC Brass 900) with a diameter of 0.25 mm and a resistance of 900 N/mm2 was employed.

The sensor signal acquisition was carried out only during the surfacing phase, i.e. the last phase of the workpiece machining process which in total involves three phases: roughing, trimming and surfacing.

2.1. Experimental plan

The experimental campaign was designed according to a two-level full factorial experimental plan. Four machining parameters were selected as variables within the tests: voltage, feedrate, pulse-off time and gap (Table 1). According to the number of factors (4) and levels (2), $2^4 = 16$ experimental tests were carried out. Moreover, 2 additional tests using the reference values for voltage, feedrate and pulse-off time, but different gap values (1 μm or 9 μm) were performed.

Table 1. Levels of factors in the experimental plan.

Factor	Unit	Ref. value	High level	% modif	Low level	% modif
Voltage	V	200	200	0	180	10
Feedrate	mm/min	11.24	12.93	15	9.56	15
Pulse off time	μs	1	1.1	10	0.8	20
Gap	μm	9	9	0	1	89

Two workpieces (one for each gap value) were subdivided into 9 segments of 8 mm length and each segment was machined under different WEDM process conditions. The WEDM process time for each segment was about 37-50 s.

2.2. Sensor monitoring system

The sensor monitoring system employed for signal acquisition during WEDM surfacing comprised three sensors (Figs. 1-2): two current sensors (Pearson Current Monitor Model 6585) to acquire the upper and lower head current signals, and one voltage probe to acquire the voltage signal.

The current sensors were chosen due to their high frequency (up to 200 MHz) since the considered WEDM surfacing process is characterised by high frequency (715 kHz). In addition to the voltage and current signals, the instantaneous position of the wire during WEDM was acquired. The CNC machine control was adapted to trace the bit of the machine position and send it to a 12 bit D/A Converter (Texas Instruments TLV5638) to obtain an analog signal of the wire position. As regards the data acquisition system, a National Instruments board (NI PXIe-1082) with 4 BNC inputs was employed to acquire the data with a very high sampling rate of 50 MHz, in order to achieve a high resolution in the sparks characterisation.

The acquisition of the wire position signal together with the currents and voltage signals, using the same sampling rate, was carried out to support the search for correlations between workpiece surface defects and WEDM conditions.

Fig. 1. The sensor monitoring system mounted on the wire EDM machine

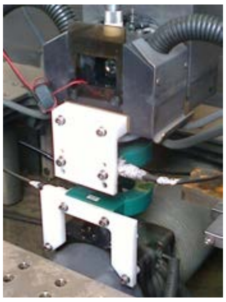

Fig. 2. Detail of the current and voltage sensors.

While defects such as lines and marks can be clearly localized on the workpiece surface, their localization within the voltage and current signals is hard to achieve, since the machining speed is not perfectly constant due to the initial acceleration. Therefore, once the position of a defect on the workpiece surface is defined, it is possible to go back to the corresponding signals of voltage and currents by using the synchronised wire position signal.

3. Surface finish investigation

The surface finish of the workpiece segments resulting from the WEDM tests was investigated with particular reference to the occurrence of lines and marks (Fig. 3). The segment surfaces presenting relevant defects such as lines or marks were examined to characterize the width and height of the defects and their position within the 8 mm length of the workpiece segment.

This analysis was performed on a 3D optical micro-coordinate system, ALICONA InfiniteFocus, with a magnification of 10x. The 3D images of the surface were post-processed so that each point of the scan was coloured according to its height with respect to a zero level, thus allowing to clearly view all the defects.

The acquired topographies represent only a band of few mm around the centre of the surface (middle height of the workpiece): since the lines generated during the WEDM process cross the entire 20 mm height of the workpiece, this allowed to notably reduce the duration of the time-consuming measures.

4. Sensor signal data processing

In order to examine the sensorial data of interest, the portions of the currents and voltage signals corresponding to a defect need to be identified and segmented. The physical position of the defect was identified with the ALICONA instrument; however, due to the combination of the ALICONA measurement errors and the wire position signal error, it was decided to further analyse a wider portion of the wire position signal to identify a signal feature well related to the presence of a defect.

By aligning the ALICONA topography of the surfaces with defects with the observation of the position signal plot, each defect corresponds to a modification of the wire position signal (Fig. 4). By analysing the voltage signal portions corresponding to modifications of the position signal, it was noted that the voltage decreased in that portion, indicating that a short circuit occurred at that machining time. Thus, it was possible to precisely identify the portions of current and voltage signals of interest for surface defects analysis.

However, the correlation between the occurrence of a short circuit and the presence of a defect on the final surface is not so straightforward: as a matter of fact, the number of short circuits in each test was higher than the number of defects measured on the final surface. This means that the sole presence of short circuit does not determine a defect on the surface.

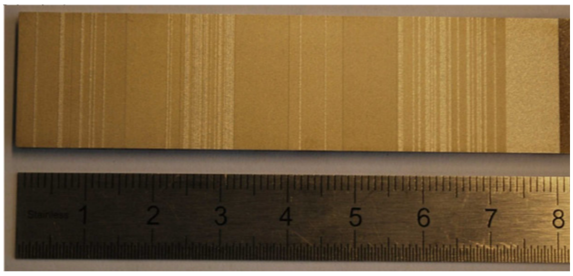

Fig. 3. The first 8 surfaces of the experimental plan.

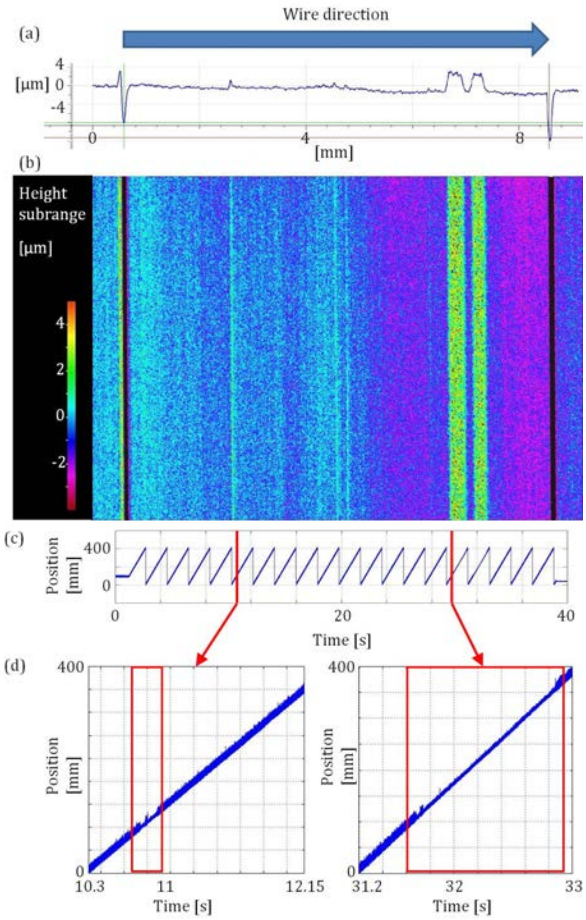

Fig. 4. (a) ALICONA surface profile and corresponding (b) coloured surface topography; (c) position signal; (d) two details of the position signal modified in coincidence with surface defects.

5. Voltage and current signal feature extraction

To observe the WEDM process conditions that could be undoubtedly related to defects such as lines and marks, a detailed analysis of the voltage and current signals corresponding to defects was carried out to extract a number of signal features for the robust identification of the critical machining conditions.

As some of the features of interest could only be extracted by taking into consideration both current and voltage data together, a sensor fusion approach was adopted. Sensor fusion combines sensory data from disparate sources so that the resulting information is more complete than would be possible when these sources are used individually [18].

Therefore, the features extracted from the sensor signals can be distinguished as follows: features extracted from current signal only; features extracted from voltage signal only; sensor fusion features extracted by combining the information provided by voltage and current signals together. All these features will be employed to construct sensor fusion feature pattern vectors to be employed for cognitive pattern recognition.

The main challenge concerning feature extraction was related to the machining parameters such as the high frequency of the sparks characterizing the considered WEDM process, resulting in voltage and current signal shapes diverging from the ideal shapes for EDM processes [14].

Among the many features that could be extracted from the signals, the following ones were selected:

- First group pulses (normal)
- Second group pulses (arc)
- Average discharge energy (only for second group)
- Average current pulse duration (only for second group)
- Third group pulses (short circuit)
- Spark frequency
- Open circuit ratio

A pulse classification procedure was developed to discriminate the different types of pulses occurring during the process. Several methods have been proposed in the literature. To estimate machining phenomena, Dauw et al. [19] classified discharge pulses into several categories based on voltage levels. However, this classification is difficult to apply to all machine models and machining conditions, in particular in case of high speed discharge current.

Therefore, another approach proposed by Watanabe et al. [20] was implemented: discharge pulses are characterized statistically by three discharge pulse profiles, called normal, arc, and short circuit pulses, respectively. These groups are classified based on the observation of the frequency distribution of spark voltage, peak current, current pulse length, pulse energy.

The first group pulses, or normal pulses, are those that generate a spark when the voltage reaches the settled voltage level (Vsp), and are considered to contribute to the metal removal process.

The second group pulses, or arc pulses, are very unstable in terms of pulse occurrence number and energy. The spark voltage is lower than for the first group as the pulse generates a spark before reaching the Vsp level.

The third group pulses, or short circuits, are those that generate a spark at lower voltage level. The occurrence of a so-called "short circuit" represents an undesired phenomenon in WEDM, since it can lead to defects on the final workpiece surface or even to the wire breakage [21,22]. The short circuit ratio, i.e. the number of short circuits over the total number of pulses, can be employed to monitor and evaluate the gap condition, and it has been successfully used as a control parameter for the adaptive control of WEDM process [23].

An important feature in WEDM is the average discharge energy, to be kept under control to maintain the stability of the process [24]. Otherwise, the deionization of the discharge zone would be affected, resulting in either low or uncontrolled material removal rate. Since the second group pulses are the more heterogeneous and unstable, it was chosen to extract the discharge energy of the second group pulses as relevant feature to discriminate the different process conditions.

For the same reason, the average discharge current pulse duration was extracted for the second pulse group.

The sparking frequency, i.e. the total number of sparks N_t divided by the machining time interval t_t, was calculated on the basis of the current signal data as the total number of sparks divided by the time interval of the signal. A variation of the sparking frequency could help identify abnormal conditions such as the occurrence of events like short circuits, and it can be employed as a control parameter for the WEDM process [15].

The open circuit ratio represents the number of open circuits over the total number of pulses of the signal. An open circuit occurs when a voltage pulse does not generate a current spark, since the dielectric is not broken, e.g. due to a large gap between the workpiece and the wire electrode. To identify the open circuits, a sensor fusion approach was used to combine information from voltage data and current data: the open circuits were identified as the voltage peaks not followed by a current peak [25].

6. Cognitive pattern recognition based on neural networks

The features extracted from the voltage and current signals were combined into sensor fusion pattern vectors (SFPV) the elements of which comprise features from both signal types and sensor fusion features. The SFPV are used as input to neural network (NN) based pattern recognition aimed at decision making on surface finish quality in terms of lines and marks defect occurrence [26].

The selected cognitive pattern recognition paradigm is based on supervised neural network data processing, which represents a valid instrument for prediction tasks through input-to-output vectors mapping.

Three different SFPV training sets (named A, B, C), each composed of 100 vectors, were constructed by extracting the selected features from three different time intervals (A = 20 ms, B = 50 ms, C = 100 ms) within the entire voltage and current signals during one WEDM test. Each set was used to train and test diverse NN architectures for cognitive pattern recognition [26].

Three-layers feed-forward back-propagation NNs were set up as follows: input layer with a number of input nodes equal to the number of features in the input SFPV; hidden layer with a number of nodes depending on the number of input nodes; output layer with one node yielding a binary code associated with line absence/line presence: 0 = absence; 1 = presence.

NN learning was carried out with each training set according to the leave-k-out method [26]: one homogeneous group of k SFPV (here, k = 1), removed from the full training set, was held back in turn for testing and the rest of the SFPV was used for training.

During testing, the NN output was considered correct if error $E = (O_a - O_d)$, where O_a = actual output and O_d = desired output, is $-0.5 \leq E \leq +0.5$; otherwise, a misclassification case occurs. The ratio of correct classifications over the total training cases yields the NN success rate (SR).

7. Results and discussion

By employing all the extracted features to construct 7-features SFPV for NN learning, three different architectures were set up by varying the number of hidden nodes: 7-7-1, 7-14-1 and 7-21-1, respectively. The NN SR values obtained by testing each NN architecture with each training set are reported in Table 2.

The table shows that the NN SR values in the identification of the line and marks surface defect occurrence are in a high range: 81% - 97%. The best results were obtained for the 50 ms and 100 ms time intervals, where the SR was always ≥ 96%. This suggests that 20 ms may not be always sufficient to determine whether the corresponding signal portion, though characterised by critical features (high number of third group pulses, low number of first group pulses, high sparking frequency, etc.) will lead to a defect or not. The recurrence of these critical features plays an important role: only when they take place for a sufficient duration, a defect is generated on the workpiece surface.

In order to verify the criticality of the diverse extracted features for NN defect identification, the 7 original features were removed one by one, in turn, from the SFPV of training sets A, B and C: 21 new training sets containing 6-features SFPV were thus set up. These new training sets were used for learning of the following NN architectures varying the number of hidden nodes: 6-6-1, 6-12-1 and 6-18-1.

The best NN performance was achieved for the 6-features SFPV training sets A’, B’ and C’, built by removing the open circuit ratio feature from the original features (Table 3). In particular, a maximum NN SR value = 100% was obtained for the 6-6-1 NN configuration, with the 6-features SFPV training set B’ built by extracting features using a 50 ms time interval.

The NN performance for training set C’ using a 100 ms time interval was also very high, whereas for training set A’ using a 20 ms time interval the NN performance was significantly lower, as already verified in the 7-features SFPV training set cases.

The above results indicate that the open circuit ratio does not positively contribute to lines and marks surface defect identification and, accordingly, could be simply neglected. Moreover, the 20 ms time interval used for feature extraction is confirmed to be the least effective for surface defect recognition. By comparing the 50 ms and 100 ms time intervals, the former is able to provide a full 100% NN performance. Thus, the 20 ms time interval seems to be too short for effective defect recognition and the 50 ms time interval performs best. This conveys the idea that the critical duration of the key features recurrence that leads to surface defects is higher than 20 ms and very near 50 ms.

Table 2. NN success rate for 7-features SFPV training sets.

	Training set A (20 ms)	Training set B (50 ms)	Training set C (100 ms)
NN architecture	NN SR	NN SR	NN SR
7-7-1	88%	97%	96%
7-14-1	81%	96%	97%
7-21-1	87%	97%	96%

Table 3. NN success rate for 6-features SFPV training sets where the open circuit ratio feature was removed.

	Training set A’ (20 ms)	Training set B’ (50 ms)	Training set C’ (100 ms)
NN architecture	NN SR	NN SR	NN SR
6-6-1	87%	100%	96%
6-12-1	87%	96%	93%
6-18-1	86%	99%	97%

Finally, the lower performance of the 100 ms time interval in comparison with the 50 ms can be attributed to the different training set composition. As a matter of fact, for the same signal portions related to surface defects, a significantly higher number of SFPV mapped to defects were obtained using the 50 ms time interval, yielding a more balanced proportion of line absence/line presence cases for training set B’ than for training set C’.

8. Conclusions

WEDM process monitoring was implemented in order to identify the operating conditions responsible for the generation of defects such as lines and marks on the final workpiece surface. An experimental campaign consisting of 18 WEDM surfacing tests on steel plates was carried out. Process monitoring was performed using voltage, current and wire position multiple sensors detecting signals from the gap between workpiece and wire electrode. The position signal was used to correlate the location of surface defects to the corresponding portion of voltage and current signals.

An advanced signal processing methodology based on sensor fusion approach was applied to the voltage and current signals to implement a pulse discriminating methodology and extract a number of sensor signal features with the aim to realize WEDM process analysis and control through the identification of the critical machining conditions responsible for surface defects.

The extracted features were used to construct sensor fusion pattern vectors to be fed in input to supervised Neural Network (NN) paradigms in order to find correlations between signal features and workpiece surface quality. The NN data processing results showed that a strong correlation exists, as the NN success rate was always ≥ 81% and reached up to a full 100% in the case where the training set was obtained by extracting the key features from 50 ms time intervals and the least effective feature (open circuit ratio) was removed from the NN training set.

Acknowledgements

This research work has been developed in collaboration between the University of Naples Federico II, GF Machining Solutions and the Swiss Federal Institute of Technology (EPFL) within the EC FP7 FoF.NMP.2011-5 large scale project on Intelligent Fault Correction and self Optimizing Manufacturing systems - IFaCOM, grant agreement n. 285489 (2011-2015).

The Fraunhofer Joint Laboratory of Excellence on Advanced Production Technology (Fh-J_LEAPT Naples) at the Department of Chemical, Materials and Industrial Production Engineering, University of Naples Federico II, is gratefully acknowledged for its contribution and support to this research activity.

References

[1] Masuzawa T, Toenshoff HK. Three-dimensional micromachining by machine tools. CIRP Annals 1997; 46/2: 621-628
[2] Ho KH, Newman ST, Rahimifard S, Allen RD. State of the art in wire electrical discharge machining (WEDM). Int. Journal of Machine Tools & Manufacture 2004; 44/12-13: 1247–1259
[3] Hewidy MS, El-Taweel TA, El-Safty MF. Modelling the machining parameters of wire electrical discharge machining of Inconel 601 using RSM. Journal of Materials Processing Technology 2005;169: 328-336
[4] Aspinwall DK, Soo SL, Berrisford AE, Walder G. Workpiece surface roughness and integrity after WEDM of Ti–6Al–4V and Inconel 718 using minimum damage generator technology. CIRP Annals 2008; 57/1: 187-190.
[5] Newton TR, Melkote SN, Watkins TR, Trejo RM, Reister L. Investigation of the effect of process parameters on the formation and characteristics of recast layer in wire-EDM of Inconel 718. Materials Science and Engineering A 2009; 513–514: 208–215.
[6] Liao YS, Huang JT, Chen YH. A study to achieve a fine surface finish in Wire-EDM. Journal of Materials Processing Technology 2004; 149: 165-171
[7] Rajurkar KP, Wang WM. Thermal modeling and on-line monitoring of wire-EDM, J. of Materials Processing Technology 1993,, 38/ 1-2: 417-430
[8] Kunieda M, Lauwers B, Rajurkar KP, Schumacher BM. Advancing EDM through Fundamental Insight into the Process. CIRP Annals 2005; 54/2: 599-622
[9] Spedding TA, Wang ZQ. Study on modeling of wire EDM process. J. of Materials Processing Technology 1997; 69: 8-28
[10] Liao YS, Woo JC. The effects of machining settings on the behavior of pulse trains in the WEDM process. Journal of Materials Processing Technology 1997; 71: 433-439.
[11] Huang Y, Ming W, Guo J, Zhang Z. Optimization of cutting conditions of YG15 on rough and finish cutting in WEDM based on statistical analyses. Int. Journal of Advanced Manufacturing Technology 2013, DOI 10.1007/s00170-013-5037-3.
[12] Hinduja S, Kunieda M. Modeling of ECM and EDM Processes. CIRP Annals 2013; 62/2: 775-797
[13] Portillo E, Marcos M, Cabanes I, Orive D. Real-time monitoring and diagnosing in wire-electro discharge machining. Int. Journal of Advanced Manufacturing Technology 2009; 44: 273–282
[14] Liao YS, Woo JC. Design of a fuzzy controller for the adaptive control of WEDM process. Int. Journal of Machine Tools & Manufacture 2000; 40: 2293-2307.
[15] Yan MT, Liao YS. Adaptive control of the WEDM process using the fuzzy control strategy. Journal of Manufacturing Systems 1998; 17: 263-274.
[16] Weck M, Dehmer JM. Analysis and Adaptive Control of EDM Sinking Process Using the Ignition Delay Time and Fall Time as Parameter. CIRP Annals 1992; 41/1: 243-246.
[17] Kunieda M, Kojima H. On-line detection of EDM spark location by multiple connection of branched electric wires. CIRP Annals 1990;39:171-174.
[18] Teti R, Jemielniak K, O'Donnell G, Dornfeld D. Advanced monitoring of machining operations. CIRP Annals 2010; 59/2: 717-739.
[19] Dauw DF, Snoeys R, Dekeyser W. Advanced Pulse Discriminating System for EDM Process Analysis and Control. CIRP Annals 1983; 32/2: 541-549.
[20] Watanabe H, Sato T, Suzuki I. WEDM monitoring with a statistical pulse-classification method, CIRP Annals 1990; 39/1: 175-178.
[21] Cabanes I, Portillo E, Marcos M, Sánchez JA. On-line prevention of wire breakage in wire electro-discharge machining. Robotics and Computer-Integrated Manufacturing 2008; 24: 287-298.
[22] Cabanes I, Portillo E, Marcos M, Sánchez JA. An industrial application for on-line detection of instability and wire breakage in wire EDM. Journal of Materials Processing Technology 2008; 195: 101-109.
[23] Yan MT. An adaptive control system with self-organizing fuzzy sliding mode control strategy for micro wire-EDM machines. Int. Journal of Advanced Manufacturing Technology 2010; 50:315-328.
[24] Gostimirovic M, Kovac P, Sekulic M, Skoric B. Influence of discharge energy on machining characteristics in EDM. Journal of Mechanical Science and Technology 2012; 26/1: 173-179.
[25] Caggiano A, Teti R, Perez R, Xirouchakis P. Wire EDM Monitoring for Zero-Defect Manufacturing based on Advanced Sensor Signal Processing. Procedia CIRP 2015;33: 315-320
[26] Hertz J, Krogh A, Palmer RG. Introduction to the theory of neural computation. New York: Addison-Wesley; 1991.