STATISTICAL EVALUATION OF THE WEDM PROCESS DEGRADATION

Andrzej Nowakowski, Piotr Majerski

S u m m a r y

The paper presents two statistical models for prediction of wire breaking in WEDM process. First model used moving average MA(x) of the delay time of discharges as a too and the process state evaluation depended on minimal and maximal value of MA(x). The second one took advantage of time series analysis of values 0/1 derived from discrimination of gap voltage pulses and process state evaluation results from estimation of transition probabilities. Models were pre-verified with off-line method using data logged during stable process and before wire breaking. Robust versions of the worked out methods are also proposed and discussed.

Keywords: moving average, random process, WEDM, wire electrode rupture

Statystyczna ocena degradacji procesu WEDM

S t r e s z c z e n i e

Opracowano dwa modele statystyczne, które umożliwiają wyróżnienie procesu stabilnego obróbki WEDM i stanu poprzedzającego zerwanie elektrody drutowej. W pierwszym – wykorzystano proces średniej ruchomej MA(x) do analizy wartości czasu opóźnienia kolejnych wyładowań. Podstawą oceny stanu procesu były zmiany minimalnych i maksymalnych wartości MA(x). W drugim – rozważano szeregi czasowe o wartości 0/1, uzyskane w klasyfikacji kolejnych impulsów napięcia między-elektrodowego. Obszar bezpiecznej obróbki ustalono przez określenie prawdopodobieństwa przejścia pomiędzy stanami zmiennej losowej. Modele zweryfikowano obliczeniowo w trybie off-line. Stosowano dane rejestrowane podczas wycinania stabilnego i przed zerwanie drutu oraz dokonano ich weryfikacji.

Słowa kluczowe: WEDM, średnia ruchoma, proces losowy, zerwanie elektrody ruchowej

1. Introduction

The main problem of the WEDM process i.e. the breaking of the wire electrode has been investigated by many researchers. Since direct measurements of the wire electrode state are impossible, a number of methods and models based on the gap electrical measurements were developed. Jennes et al. [1] showed that the breakage is a result of the heating of the wire due to time

Address: Andrzej NOWAKOWSKI, Ph.D. Eng., The Institute of Advanced Manufacturing Technology, Wrocławska 37a , 30-619 Kraków, e-mail anowak@ios.Krakow.pl, Piotr MAJERSKI, M.Sc., AGH University of Science and Technology, Faculty of Applied Mathematics, al. Mickiewicza 30, 30-059 Kraków

and spatial concentration of the discharges. Obara [2, 3], Shoda et al. [4] Kunieda et al. [5] developed methods and models to detect the position of the discharges along the wire electrode and confirmed the appearance of the concentrations of the discharges before the wire breakage. Lauwers et al. [6] worked out a thermal model considering the heat input from the discharges and the heat evacuation by conduction through the wire and convection to the dielectric. The thermal model of the distribution of the temperature along the wire used a finite element method. Cabanes et a. [7] proposed a methodology of an early detection of the unstable machining and the wire breakage. Using three input values: peak current, ignition delay time and energy of discharges the authors defined indicators for the wire breakage monitoring, observed in a sliding time window. Based on the analysis of the indicators, two sets of heuristic rules have been deduced, consisting of 3 levels of wire breakage risk. Rajurkar and Wang [8] proposed a stochastic model with the low pass filter to estimate the frequency of the discharges to predict the wire breakage. The monitoring system detected the gap voltage, current, and the high frequency signal generated by the sparking frequency to identify time ratios of five EDM gap states. The real time stochastic model calculated on-line servo speed feed, related to current gap conditions. A stochastic model proposed by Liao et al. [9] compared delay time of discharges with a defined threshold and the calculated percentage of normal (shorter) and abnormal (longer) discharges to build a model aimed to control current pulse intervals. A system discriminating the voltage pulses into three classes according to their amplitude was proposed by Watanabe et al. [10]. A method of discrimination of the stable process from the process before the wire breaking with the trains of pulses modelled and analyzed as two-state random sequences was presented by Nowakowski and Szkutnik [11]. Two kinds of pulses were found by the discrete wavelet transform (DWT): the normal and the short-circuit ones. Three different approaches to the analysis of pulse sequences produced similar results. The best separation of the stable and disturbed processes was achieved at the 60 mm thickness of the workpiece. For 20 mm, the separation was somewhat worse. No separation could be achieved for 100 mm. Another approach – a fuzzy logic controller with adaptive capability was proposed Liao at el. [12]. Worked out algorithms allowed to keep the sparking frequency below a critical level, safe for wire rupture, and to control the servo feed rate [13]. Tarng et al. [14] also reported a design of the fuzzy logic pulse discriminator to monitor and classify gap voltage and current pulses. Portillo at el. [15, 16] evaluated the WEDM process degradation using neural network models. Analyzer could detect different types of degraded behaviors, that have been previously identified during the analysis phase. Authors carried out processing of the measured data with software platform of the LabView™ Real-Timemodule. The current paper presents some algorithms for the WEDM process degradation assessment, aimed to an easy incorporation into the existing the WEDM generator controller. Proposed methods ensure

a short data processing time during on-time process control. Algorithms take advantage of statistical formulas for time series processing.

2. Data acquisition and processing

Measuring stand consist of WEDM MEWIOS-30 machine type, dedicated pulse analyzer with data logger and the PC computer with the software for downloading registered data. The working gap voltage was tested with fast comparators. The two parameters were registered as an output value of the analysis: time of the delay of discharges as an integer number and the type of discharges as digital value 0 or 1. The delay of discharges was measured with the resolution of 1/16 μs. The type of the discharge was classified by the hardware comparator according to the gap voltage just before breakdown, and stored as number 0 (low voltage discharge) or number 1 (high voltage discharges) as illustrated by Fig. 1.

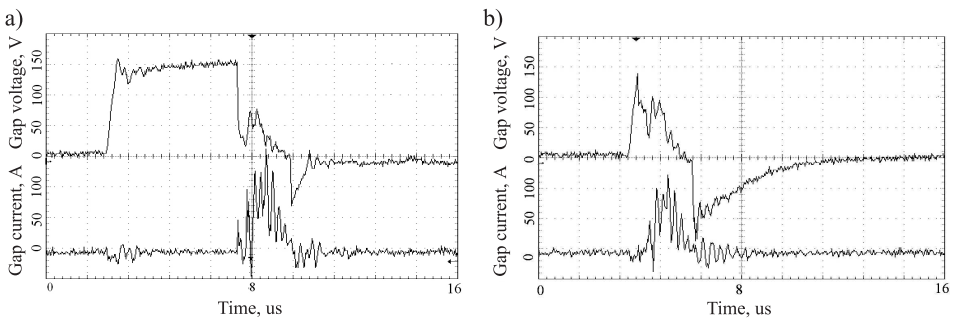

Fig. 1. High voltage (a) and; ow voltage (b) discharges. Gap voltage and working current

To avoid the the impact of an extremely high electrical noise during discharges, comparators and the data logger were synchronized with the pulse control circuit of the generator. Since the intention of the presented research was to include later the discrimination and processing units into existing generator controller, it was given that discharges analysis and the data processing, should be simple and convenient for fast calculations. As it was proved by a number of researchers, due to the high frequency and high energy of discharges during the WEDM process, the data processing should last no longer than several milliseconds, so with the high frequency of the data acquisition, it is a challenge even for the ARM microprocessors type. The data logger build with 128 kB static RAM memory allowed data registering during 1.3-7 s process time. The time of acquisition depended on programmed parameters of the generator and the process dependent average delay of discharges. Two sets of data were

registered with similar parameter settings: degraded before wire rupture and stable process. Data logging were stopped automatically after wire rupture or manually during stable process measurements. Measurements were carried out within the often found workpiece thickness range of 20 mm up to 100 mm, with two sets of parameters corresponding to low and high energy of working current pulses.

3. Analysis of time series

3.1. Data input and the moving average process

Two random process were considered. Using a DWT based device developed in Nowakowski and Szkutnik [11] we deal with a sequence of gap voltage pulses classified as normal (encoded as 1) or short circuit ones (encoded as 0). Thus, we observe the random proces:

$$X_1,...,X_t,...,X_T \tag{1}$$

where for any $t = 1,...,T$, $X_t \in \{0,1\}$ and T is either a number of observed gap voltage pulses before the wire break for a degenerated process, or their number before the process is stopped in the case of a stable process. The second sequence under study was the process of delay time of discharges:

$$Y_1,...,Y_t,...,Y_T \tag{2}$$

where for any $t = 1,...,T$, $Y_t \in \{0,1,...\}$ and with T defined as in (1).

The main tool used in the analysis of a state of the process is the so called moving average (MA) (see, e.g. Brockwell and Davis [17]). Given a sequence of real numbers $X_1, X_2,...$ and a nonnegative integer *q*, the moving average process of the process X is defined by:

$$MA_t(X) := \frac{1}{2q+1}\sum_{j=-q}^{q} X_{t+j} \tag{3}$$

with $t = q+1, q+2,...$. The parameter q plays a role of a smoothing parameter as well as a ‘memory’ window.

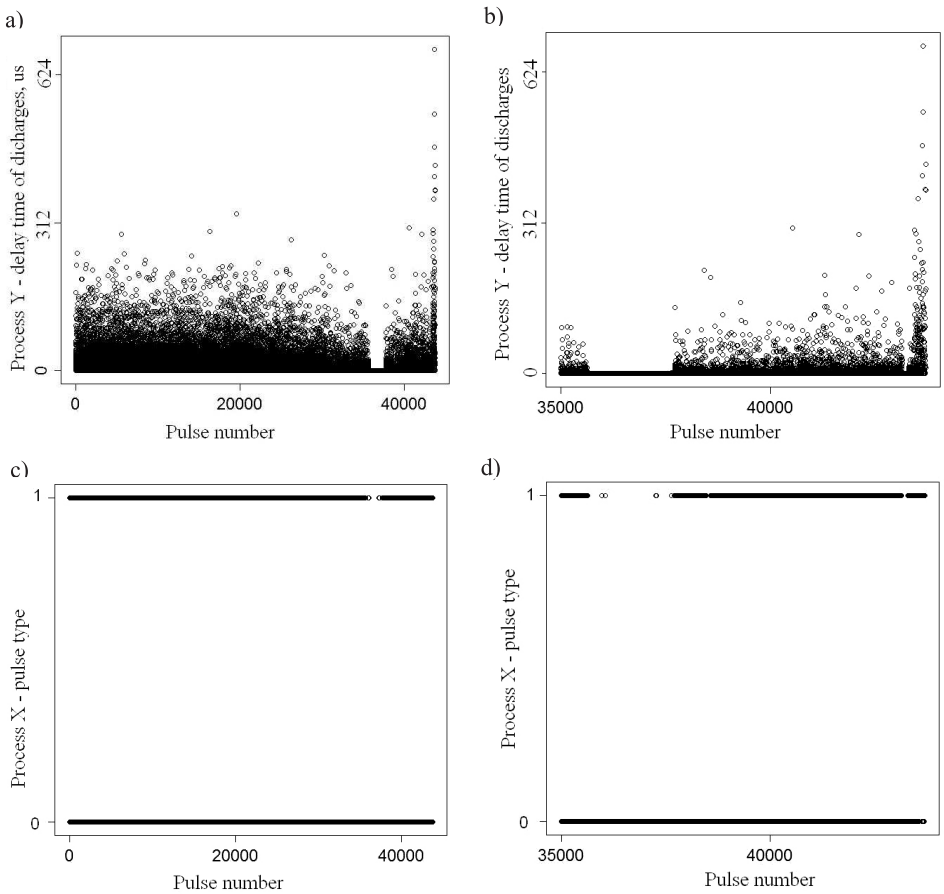

Fig. 2. Both processes for the degenerated machining. Workpiece thickness 100 mm: a) process *Y*, c) process *X*, b), d) their remainders from the 35000th pulse

The MA was performed for each set of data and for both processes X and Y with many different values of q. To avoid both the undersmothing and the oversmothing, q has been experimentally chosen as 300. So all calculated moving averages were considered with q = 300. The examination of graphs showed that $MA(X)$ and $MA(Y)$ are correlated (see Fig. 2) and that usually $MA(Y)$ provides a better information of the process stability. Therefore, the research has been narrowed to the MA process for Y only. Fig. 3 illustrates a behavior of both processes and their correlation function. The lines are scaled by different factors and shifted for an easier presentation in one graph.

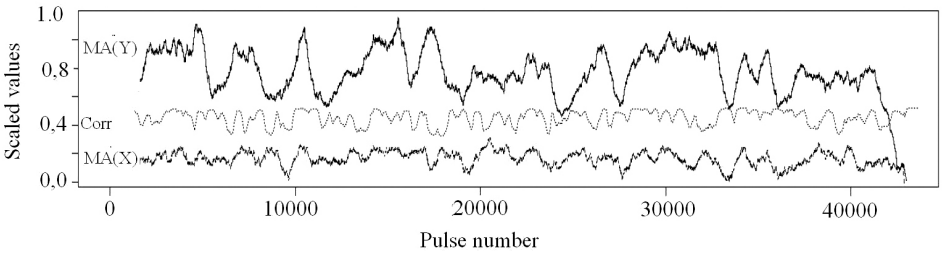

Fig. 3. Scaled and shifted graphs of the MA for *X* (lower line), for *Y* (upper line) and their correlation function (middle line). Degenerated process, workpiece thickness: 20 mm

3.2. The moving average of the delay time of discharges process

It has been observed that the minimum value of the $MA(Y)$ depends on its maximum value (see Fig. 4). The dependence seems to be linear, except for several data sets, which stand out of the main trend. All the outlying points in Fig. 4 correspond to the degenerated process. After elimination of the outliers the line estimated via the method of least squares (Rao [18]) takes the form:

$$MA(x)_{\max} = 1.66 \cdot MA(x)_{\min} + 155 \tag{4}$$

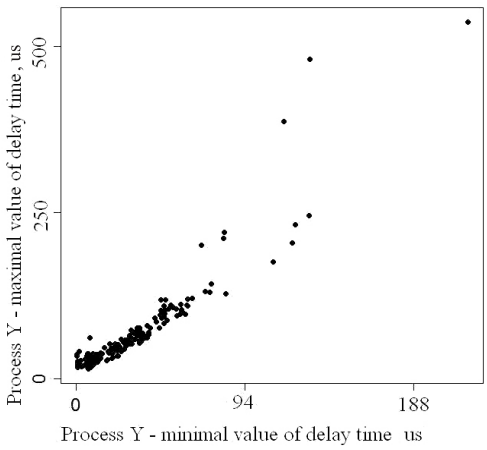

Fig. 4. The dependence of the minimum on the maximum value for the *MA(Y)*. All data sets

There is no significant separation between the stable and degenerated processes (Fig. 5a). Instead, the level of the energy of working current pulses has

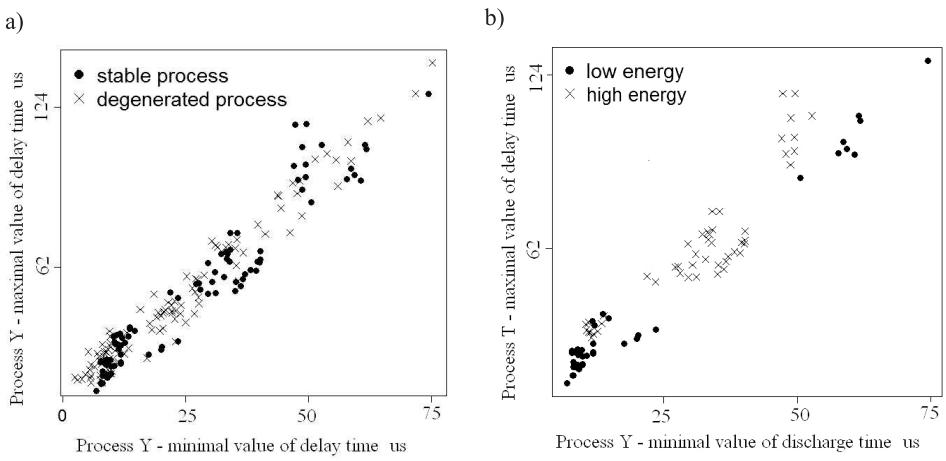

Fig. 5. The dependence of the minimum on the maximum value for the *MA(Y)*. The outlying data sets eliminated: a) points classified into stable and degenerated process, b) the classification into the level of energy of working current pulses for the stable process data sets

an influence on the location of the corresponding points (Fig. 5b). Hence, to avoid an ambiguity, apart from the thickness of the workpiece one has to involve the energy of working current pulses into the considerations. This new classification proved to be correct. For each workpiece thickness and for both levels of working current pulses the points corresponding to the stable processes are grouped in some regions on the plane, while points corresponding to degenerated processes usually do not fall within that area. This yields to a concept of the minimum enclosing rectangle (MER) estimated from the data sets for stable processes. The results of the estimation is presented in Tab. 1 and Fig. 6.

Table 1. Parameters of the minimum enclosing rectangles estimated from the all stable processes

Parameters		**20 mm**		**40 mm**		**60 mm**		**80 mm**		**100 mm**	
		low energy	**high energy**	**low energy**	**high energy**	**low energy**	**high energy**	**low energy**	**high energy**	**low energy**	**high energy**
Minimum	**L**	809	753	192	473	125	561	124	167	110	349
	U	1190	843	289	643	190	643	188	220	361	498
Maximum	**L**	1406	1482	510	1025	379	882	308	488	224	808
	U	2082	1892	621	1214	427	1046	401	611	533	967

Looking into the graphs in Fig. 6 one sees that the region which covers the points corresponding to the degenerated process data sets is usually larger than

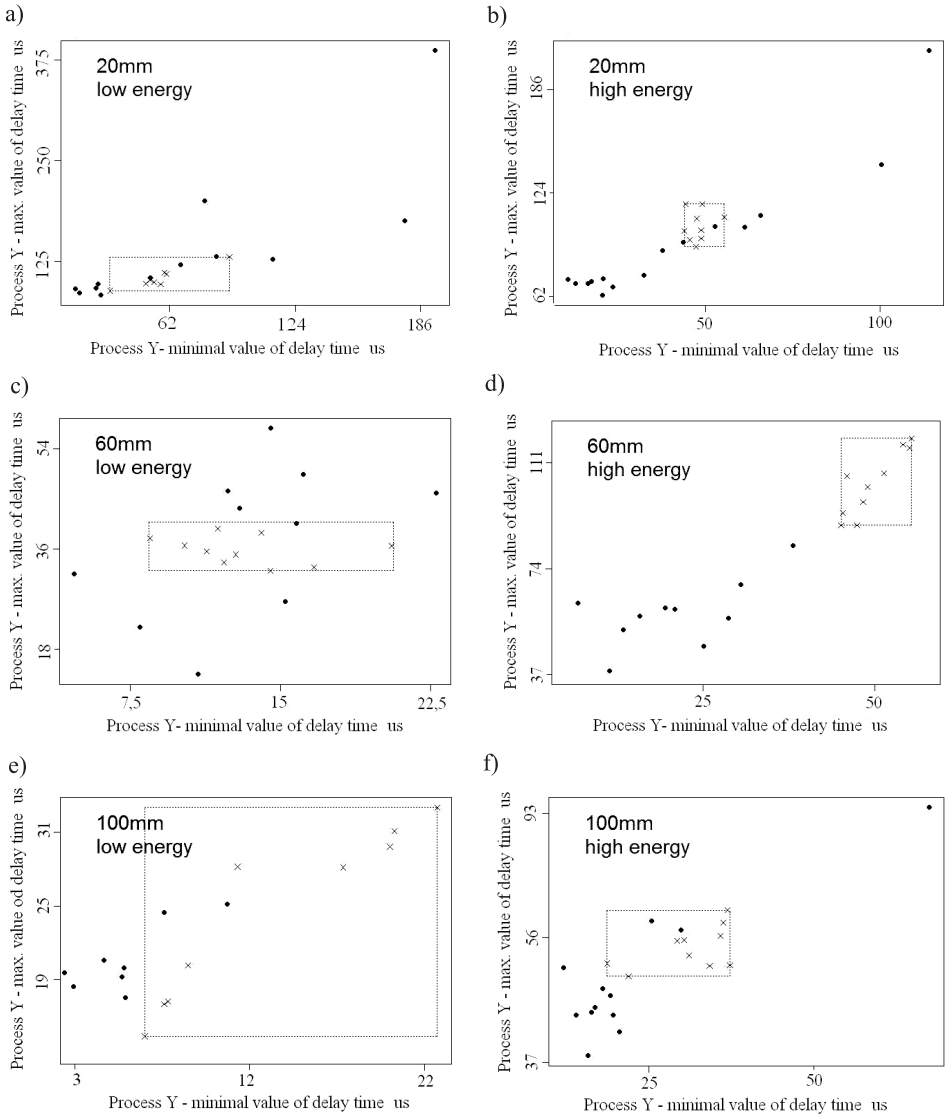

Fig. 6. The dependence of the minimum on the maximum value for the *MA(Y)*. Workpieces thickness 20, 60, and 100 mm. Low (a, c, e) and high (b, d, f) energy of working current pulses. Stable process (cross) and degenerated process data sets (dot)

that MER. In 87% cases the point for a degenerated process does not fall into the MER. Note also, that the best separation is achieved for 60 mm thickness, what somewhat squares with the results reported in Nowakowski and Szkutnik [11]. Here, however, the separation works quite well also for the other workpiece thickness. It is also easy to see, that the assumed classification plays an

important role in distinguishing the significantly different cases. For a given MER with sides (L_1, U_1, L_2, U_2) and a given point with coordinates (x_1, x_2) let's define a distance:

$$d(x_1, x_2) = d_1(x_1, x_2) + d_2(x_1, x_2) \tag{5}$$

where:

$$d_i(x, y) = \begin{cases} L_i - x, & \text{for} \quad x < L_i \\ 0, \quad \text{for} \quad L_i \le x \le U_i \\ y - U_i, & \text{for} \quad x > U_i \end{cases}, \quad \text{for} \quad i = 1, 2.$$

Now, one can construct the process degradation measure as a consecutive percentile of nonzero values of the distance d for the points corresponding to the degenerated process. Using this methodology, the threshold values of d and the corresponding levels of degradation have been calculated.

3.3 The gap voltage pulses process

The analysis of the $MA(Y)$ process gives rice to consider the long-range behavior of the gap voltage pulses process. Following Nowakowski and Szkutnik [11] let p_{ij} denote the transition probability of the state j, given that the previous state of the process X was i, with $i, j = 0.1$. Two transition probabilities were estimated from the collected data:

- p_{00} – conditional probability of the abnormal pulse, given the previous pulse was the abnormal pulse,
- p_{01} – conditional probability of the normal pulse, given the previous pulse was abnormal.

The probabilities p_{00} and p_{01} were estimated via the maximum likelihood estimators (see Nowakowski and Szkutnik [11]) for the all data sets. Fig. 7a) shows the points with the coordinates (p_{00}, p_{01}) classified according to the normal and the degenerated process, while the graph 7b) presents this classification for the normal process only. Three grouping lines for the normal process have been found and estimated with the least squares method (Fig. 7c). The low energy of the working current pulses forms a one group of points, while the high energy forms two groups of points according to the workpiece thickness. The first one corresponds to the 20 and 40 mm, and the second one to 60-100 mm. The three fitted regression lines, as listed above, are:

$$p_{01} = 0.4525 \cdot p_{00} + 0.0147 \tag{6}$$

$$p_{01} = 0.4815 \cdot p_{00} + 0.0879 \tag{7}$$

$$p_{01} = 0.7053 \cdot p_{00} - 0.0199 \tag{8}$$

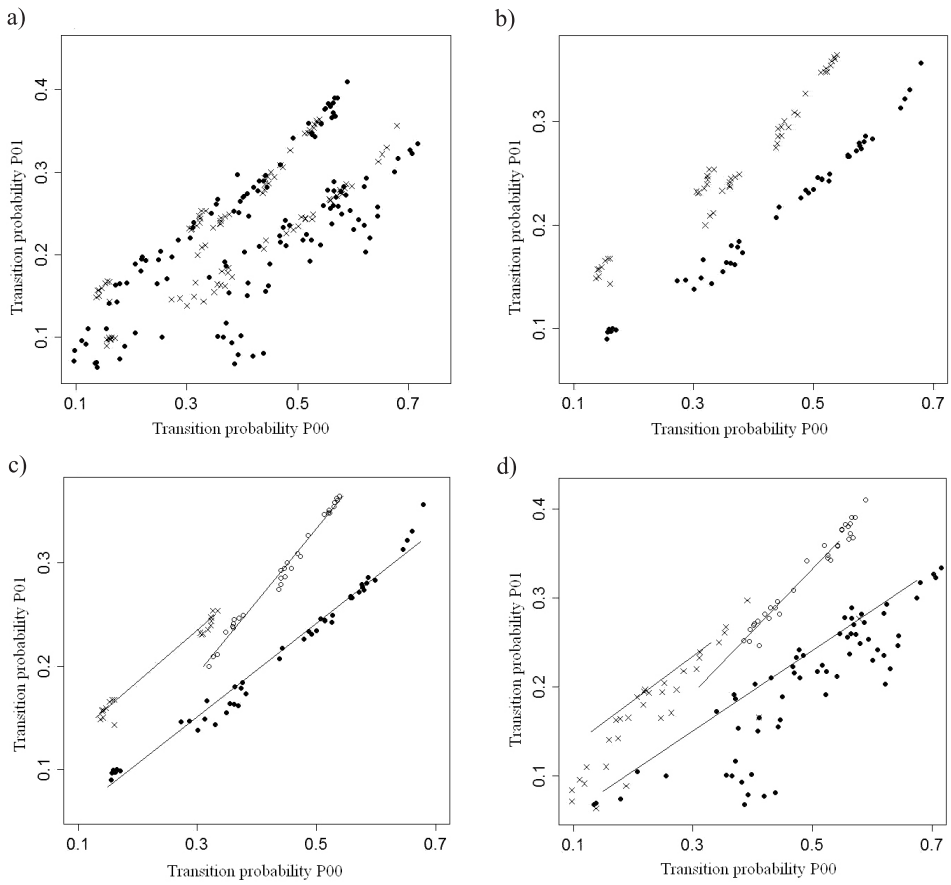

Fig. 7. Transition probability pairs (p_{00}, p_{01}) for: a) all data sets: degenerated process (black dot), stable process (cross), b) stable process: low energy (black dot), high energy (cross), c) linear regression lines fitted to the three groups of points found in b): low energy (black dot), high energy 20, 40 mm (cross) and high energy 60, 80, 100 mm (white dot), d) the location of points for the degenerated process around the stable process lines

The underlying assumption of the regression model is the normality of the distribution of the error. The Shapiro-Wilk test made for the three groups does not rejects the hypothesis of normality of the errors. One can therefore use Chauvenet's outliers identification criterion (see Taylor [19]) and consequently construct a measure of degradation of the process. To this end we chose the

threshold probabilities as the following powers of the value 0.5: 1,2,3,4,5, 8,10,20,30,40 and use them in the Chauvenet's criterion obtaining Table 2.

Table 2. Threshold values and corresponding level of process degradation within the selected groups of data

Degradation level	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Low energy, 20-100 mm	0.0259	0.0283	0.0305	0.0327	0.0346	0.0401	0.0433	0.0571	0.0683	0.0778
High energy, 20-40 mm	0.189	0.214	0.233	0.251	0.269	0.317	0.346	0.466	0.561	0.645
High energy, 60-100 mm	0.0456	0.0503	0.0547	0.0587	0.0625	0.0730	0.0791	0.1054	0.1266	0.1449

3.4. The minimum of the *MA(Y)* process

The measures of degradation worked out in the previous sections base on the long distance information about the process. During the analysis it has been observed, that very often the $MA(Y)$ for the degenerate process decreases or increases just before the wire brake (Fig. 3c, f). It has been also verified that the minimum of the $MA(Y)$ process is normally distributed. Indeed, the performed Shapiro-Wilk tests for all the data sets are consonant in this respect. We can therefore evaluate the final degradation in terms of minimum value of the $MA(Y)$ process by checking if it falls into the 95% confidence interval. The endpoints of the intervals constructed upon the registered data are given in Table 3.

Table 3. The endpoints of the 95% intervals covering the mean value of the minimum of the $MA(Y)$ process

Pulse energy	**Low**	**High**	**Low**	**High**	**Low**	**High**	**Low**	**High**	**Low**	**High**
Material thickness, mm	**20**	**20**	**40**	**40**	**60**	**60**	**80**	**80**	**100**	**100**
Average	969	783	246	543	221	450	150	598	146	186
Std. dev.	99	25	35	41	94	49	18	31	18	17
Left endpoint	897	765	222	515	154	415	137	576	133	174
Right endpoint	1041	802	271	572	288	484	162	619	158	199

3.5. The adaptive estimation

All the proposed methods depend on the registered data sets. However, aside from the parameters, that were considered during the analysis, there could

be some uncontrolled parameters, which make it not feasible to reconstruct the original conditions of the experiment. One way to protect ourselves against this disadvantage is to make the estimators dependent on the currently observed data. Consider for instance the estimators of the MER sides of section 3.3. The sides may be estimated from the part of the $MA(Y)$ process observed so far, and (5) is then computed with this MER instead of the one from the Table 1. Note that this approach does neither depend on the workpiece thickness nor on the energy of the working current pulses. In the practical implementation it is convenient to hold the information about the minima and maxima of the $MA(Y)$ in blocks of 300 registers. Another approach to make the MER dependent on the observed data is its manual choice during the stable machining, e.g. with the push-button.

The adaptive estimation is easily extended to the $MA(Y)$ minimum analysis of section 3.3, but, clearly, can be not used to that of section 3.2 regarding the gap voltage pulses process.

4. Final remarks

Off-line verification of presented models with registered data showed their good reliability. Afterwards algorithms derived from models will be applied in microprocessor controller and verified on-line during machining. The proposed methods of the WEDM process monitoring are insufficient for general process control. Worked out values of the process degradation level could be the input for the higher level CNC process controller with ability to modify the generator settings and servo drives velocity to keep stable machining. Proposed wire rupture risk coefficient based on threshold values is influenced by multiple process parameters as working current settings, workpiece thickness and material, dielectric fluid pressure and conductivity, wire rewinding velocity, tension and material. Basing on known process parameters the machine CNC controller should evaluate current model settings. Another approach could be the adaptive evaluation of threshold values.

Acknowledgments

This work was supported by the Ministry of Science and Higher Education under grant no. N N503 360135.

References

[1] M. JENNES, R. SNOYES, W. DEKEYSER: Comparison of various approaches to model of the thermal load on the EDM wire electrode. *Annals of the CIRP*, **33**(1984), 93-98.

[2] H. OBARA, M. ABE, T. OHSUMI: Control of wire breakage during EDM. *Int. Journal of Electrical Machning*, **4**(1999)1, 53-58.

[3] H. OBARA: Detection of discharges position on the wire EDM. Proc. Int. Symp. for Electr. Mach. ISEM X, Magdeburg, 1992, 404-409.

[4] K. SHODA, Y. KANEKO, H. NISHIMURA, M.X. FAN: Adaptive control of WEDM with on-line detection of sparc location. Proc. Int. Symp. for Electr. Mach. ISEM X, Magdeburg 1992, 410-416.
[5] M. KUNIEDA, S. TAKESHITA, K. OKUMIYA: Study on wire electrode temperature in WEDM. Proc. Int. Symp. for Electr. Mach. ISEM XII, Aachen 1998, 119-128.
[6] B. LAUWERS, J.P. KRUTH, P. BLEYS, B. VAN COPENOLLE, L. STEVENS, R. DERIGHETTI: Wire rupture prevention using on-line pulse localisation in WEDM. Proc. Int. Symp. for Electr. Mach. ISEM XII, Aachen 1998, 203-213.
[7] I. CABANES, E. PORTILLO, M. MARCOS, J.A. SANCHES: An industrial application for on-line detection of instability and wire breakage in wire EDM. *Journal of Materials Processing Technology*, **195**(2008), 101-109.
[8] K.P. RAJURKAR, W.M. WANG: On-line monitor and control system for wire breakage in WEDM. *Annals of the CIRP*, **40**(1991)1, 219-222.
[9] Y.S. LIAO, Y.S. CHU, M.T YAN: Study of wire breaking process and monitoring of EDM. *Int. Journal of Machining Tools and Manufacturing*, **37**(1997)4, 555-567.
[10] H. WATANABE, T. SATO, I. SUZUKI: WEDM Monitoring with a statistical pulse classification method. *Annals of the CIRP*, **39**(1990)1, 175-178.
[11] A. NOWAKOWSKI, Z. SZKUTNIK: Using random sequences for WEDM process states discrimination. Proc. VIIth International Conference on Monitoring and Automatic Supervision in Manufacturing, Zakopane 2004.
[12] Y.S. LIAO, M.T. YAN: A self-learning fuzzy controller for wire rupture prevention in wire EDM. *Int. J. of Adv. Manuf. Technol.*, **114**(1996)4, 267-275.
[13] H.P. LI, J.F. LIANG, M.T. YAN: The application of fuzzy control strategy in servo feed Control of wire electrical discharge machining. *Int. J. of Adv. Manuf. Technol.*, **15**(1999), 780-784.
[14] Y.S. TARNG, C.M. TSENG, L.K. CHUNG: A fuzzy pulse discriminating system for electrical discharge machining. *Int. Journal of Machining Tools and Manufacturing*, **37**(1997)4, 511-522.
[15] E. PORTILLO, M. MARCOS, I. CABANES, D. ORIVE: Real-time monitoring and diagnosing in wire-electro discharge machining. *Int. J. Adv. Manuf. Technol.*, (2009)44, 273–282.
[16] E. PORTILLO, I. CABANES, M. MARCOS, J.A. SANCHES: Anticipation of wire breakage in WEDM based on neural networks. Proc. 15th Inter. Symposium on Electromachining. Pittsburgh 2007, 133-138.
[17] P.J. BROCKWELL, R.A. DAVIS: Time seried: theory and methods (2nd ed.). Springer-Verlag, New York 1991.
[18] C.R. RAO: Linear statistical inference and its applications (2nd ed.). John Wiley & Sons, New York 1973.
[19] J.R. TAYLOR: An introduction to error analysis (2nd ed.). University Science Books, Sausalito – California 1997.

Received in October 2010