ARCHIVES of
Computational Materials Science and Surface Engineering

International Scientific Journal published quarterly by the Association of Computational Materials Science and Surface Engineering

2009 • Volume 1 • Issue 3 • 161-167

EDM process optimisation via predicting a controller model

R.A. Mahdavinejad*
School of Mechanical Engineering, Faculty of Engineering, University of Tehran, Tehran, Iran
* Corresponding author: E-mail address: mahdavin@ut.ac.ir

Received in a revised form 06.05.2008

ABSTRACT

Purpose: Electro-discharge machining is an important manufacture technology in machining difficult-to-cut materials and to shape complicated contours and profiles with high material removal rate, low tool wear and good tolerances.

Design/methodology/approach: In machining of carbon-based materials such as WC-Co and non-oxide ceramics which are growingly used, the complexity and non-linear nature of EDM is a serious problem. EDM is the best and nearly the only non-conventional method for machining of these kind of materials, but it shows high instability and tendency to arcing, compared with machining of steel. Occurrence of instability phenomenon due to the different input setting up parameters make the modeling of EDM process impossible with conventional methods. To achieve instantaneous data from machining condition, the new method of fuzzy analysis of single machining pulses and computing the magnitude of system condition in the form of a real number between 0 and 1, has been used.

Findings: Some tests with WC-Co material are carried out and finally, the results of implementation of control system on a sinking ED machine and an EDM system that has been set with an expert user, has been compared.

Practical implications: The optimization and control of EDM process using the neural model predictive control method. A genetic algorithm has also been employed to optimize the input parameters and to create the optimized setting collection of process.

Originality/value: The testing results from ED machining of WC-Co confirms the capability of the system of predictive controller model based on neural network with 32.8% efficiency increasing in stock removal rate.

Keywords: EDM; Optimisation; Fuzzy logic; Model predictive control

Reference to this paper should be given in the following way:

R.A. Mahdavinejad, EDM process optimisation via predicting a controller model, Archives of Computational Materials Science and Surface Engineering 1/3 (2009) 161-167.

MANUFACTURING AND PROCESSING OF ENGINEERING MATERIALS

1. Introduction

The object of special interest of researchers is increasing the machine's efficiency and reliability, during the process of designing the machines [1]. The necessity for frequent product line changes causes the development in flexible production systems [9]. Some specifics of modern machine tool are included over modules, as rotation table, precise high RPM spindle, bar magazine, tools magazine, workpiece magazine, laser zero point measurement system, cutting forces dynamometers for process diagnostics, frequencies sensor, acoustic sensors [8]. The instability phenomenon in electro discharge machining (EDM) is the most important factor in rapid tool wear and great decrement in stock removal rate. Occurrence of this phenomenon especially in machining of carbon-based materials such as carbides and non-oxide ceramics due to carbon immanency of workpiece and convenient dielectric is inescapable. The researches show that the arcing phenomenon as the symbol of instability in EDM, has unknown stochastic distributions caused by different input parameters. According to instantaneous changes in discharge conditions such as dielectric pollution, the physical model for the process is valid only for small time durations which cause the instantaneously changes in arc distribution function factors. Input setting parameters to obtain the desired outputs such as high stock removal rate and low tool wear ratio has been accomplished manually based on user's experience and without any optimization. Generally, methods used to model the processes in form of "black box" has been suggested for modeling of such processes. Therefore, a method for physically modeling will be effective and reliable that updates its knowledge about the process regularly. One of the most fundamental criteria in the design of modern mechanical structures are their dynamical propreties, as they have a direct impact on the vibrations of the system, noise emission, fatigue resistance, controllability and stability [6]. Challenging problems for scientific research are the requirements concerning mechatronic system, for example their exact positioning working velocity, control and dimensions [2]. Optimization of non-linear models with unknown transfer functions usually is possible using methods based on artificial intelligence. The first research to distinguish the pulse type with artificial intelligence is carried out in 1997 by Kao and Tarng [7]. They tried to make distinctions among pulse types instantaneously via artificial neural networks. Also, Liu and Tarng in the same time modeled the EDM using neural networks. In 1997 Spedding and Wang tried to optimize the surface characterization and input parameters via modeling of wire-EDM process [10]. According to the determination of transformation function via the mathematical relations between input and output vectors, the capability computation of the fitness function value in optimization process will be determined [11]. On the other hand, in the process not being mathematically formulated, the relationship between input and output vectors must be presented, so that the output vectors with any input and desired accuracy respect to the physical process, should be available [4]. The artificial neural networks are the best choice to model the physical processes in the black box format [7,12]. Although parameters such as stock removal rate, tool wear ratio and surface roughness are the main output parameters of EDM process; it is possible to achieve high stock removal rate and low tool wear ratio with good surface finishing if the stability of machining process as an effective mode in output parameters is guaranteed [12]. There are four completely distinct pulses in EDM and this system is unstable when the number of non-successive pulses such as; arcing, short circuit and open circuit are increasing against normal discharges during machining process. Although the voltage frequency characteristics of normal discharge is completely different from non-successive pulses, the system's output covers wholly a continuous space, so that, the stability and non-stability of the system is not quite clear.

In this paper, the method of model predictive control based on artificial neural networks with output parameters of the system to minimize the number of non-successive pulses is used. To determine the value of stability process parameter, a fuzzy analysis method is developed to distinguish the single pulse discharge type. As the optimizing algorithm of model predictive controller, a genetic algorithm on parameters of pulse on and off time, discharge current, gap size and its variations rate, are used. Finally, the method of execution of changes on a convenient ED machine is explained.

2. EDM instability process

In electro discharge machining process, to create plasma channel and efficient discharges, a high potential difference is used between tool and workpiece. The electrical field between two electrodes emerged in dielectric tank causes ionization, ion stimulation and creation of vapor and plasma channel. The plasma channel will be out of concentration and an approximately constant current with low oscillation will pass through the gap whenever the necessary condition of discharge is provided. In most EDM applications, especially in die sinking EDM, the hydrocarbon liquid with linear structure, is used as dielectric. In machining of carbide materials, the existence of free carbon created from dielectric decomposition with the high chemical activity from one hand, and the immanency between this free carbon and that one in the structure of carbide workpiece on the other hand, causes the carbon deposition on the workpiece and afterwards, tendency to arcing. So that, the continuance of the process leads to form a carbon bridge between electrodes and makes the machining impossible. Some other factors such as; gap size not exactly set up and tool's head reaction speed, due to the abnormal pulses, also have affection in creation of non-successive pulses as open circuits and short circuits. Generally inexact setting of each input parameter makes the machining process unstable. Anyway, the pulse shape recorded from machining zone can be used as an indicator to determine the pulse types. Variations of gap voltage, discharge current, discharge delay time and high frequency elements on voltage-time recorded diagrams can be used to distinct normal from other pulse types. Up to now, the distinction of pulse type has been done based on average gap voltage, due to its easy accessibility and controllability. According to the time constant measuring device, the low level of gap voltage represents the large number of arc and short circuit and its high level represents the large number of open circuit pulses. The middle bound of gap voltage approximately means that the system is working normally. However, due to possibility of arcing at any setting of system, even a suitable level of gap average voltage, means that there are probably all kinds of discharge pulse types in pulses train. Significant changes in average gap voltage from normal to higher or lower levels, indicates the system instability. Control of average gap voltage to maintain the effective gap size is the simplest method to control the EDM process, but, it is not necessity the best way. The best method for this subject is indeed the method based on multi-factor indecisive decision.

3. Pulse distinction using fuzzy logic

Up to now, the distinction of pulse type based on detection of normal discharge from arc and other abnormal pulses has been accomplished with different methods. Determination of a threshold on discharge voltage so that its lowest level is higher than arcing voltage level, measuring the discharge delay time which is zero or very small in quasi arcing and arcing discharge and analysis of high frequency elements on gap voltage-time diagram pulse by pulse, are the fundamentals of classical pulse distinction methods in EDM. Although the pulse type distinction with artificial intelligence-based methods are usually successful, but, the stability analysis of the system via studying of single pulse and assigning a relative instability factor is possible only by using fuzzy logic. The fuzzy approach to microscopic pulse distinction obtained from pulse train in gap, is based on two main reasons:

- The stable and unstable machining boundary zone especially in carbide materials is quite ambiguous.
- Too many linguistic rules are used by EDM specialists in pulse interpretation. The second expression not only shows the fuzzy analytical ability of pulse train, but, the decision based on fuzzy interpretation in EDM process [10]. An example of such linguistic rules about single-pulse interpretation is; if<discharge delay time is small> and <average gap voltage is low> then <the discharge is arc>.
- The factors used in fuzzy analysis are as follows:
- Average discharge voltage from breakdown to the end of pulse on-time.
- Discharge delay time.
- High-frequency elements on pulse voltage-time diagram.

The third factor is neglected due to the unnecessary of process analysis in frequency field and avoiding of massive calculations. The first two mentioned factors determine the pulse type by using linguistic rules bellow:

- If <the delay time is too short> and <the average discharge voltage is low> then <the pulse is arc>.
- If <the delay time is medium> and <average discharge voltage is medium> then <the pulse is normal>.
- If <the discharge average voltage is too low> then <the pulse is short circuit>.
- If <the delay time is long> and <average discharge voltage is high> then<the pulse is open circuit>.

The above linguistic rules with fuzzy of two parameters (discharge delay time and average discharge voltage) and suitable fuzzy operators' creation and also using appropriate fuzzy related to the input parameters will be able to allocate a number between 0 and 1 to the discharge condition of any pulses. Therefore, after nom-fuzzy operations, this fuzzy analysis is able to determine numerically the condition of any machining pulses. For n pulses recorded, the condition factor of system is as follows:

$$\lambda_k = \frac{1}{n}\sum_{i=1}^{n}\gamma_i \ , k = 1,2,\cdots,n \qquad (1)$$

where γ_k is numerical average condition factor of each pulse. It is obvious that, the more number of pulses recorded, the higher accuracy in condition factor of system results, indeed. This subject refers to the situation of dielectric in machining zone, so that, any debris in this position may cause abnormal discharges. Therefore, increasing in number of pulses recorded decreases the total errors. In this manner, condition factor of the system especially after any set up variation in current domain, pulse on and off time, gap size and the speed of head displacement due to voltage variation, will be determined via the fuzzy system created. Therefore, this system acts as a fuzzy sensor for machining process. This subject is very important in closed loop control systems. Figure1 shows the number of pulses recorded from machining zone with open-circuit voltages equal to 250V. The condition factor of the system is calculated from 15 sample of the pulse train.

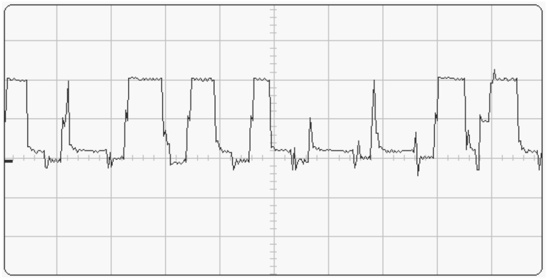

Fig. 1. Typical pulse train sampled by an oscilloscope

4. Modeling of EDM Process

A neural network is a bulky system of interconnected calculator elements which are connected parallelism to each of these elements named node does not have capability of data acquisition separately, but, the necessary data to interpolate are stored along several connected nodes.

In recent years, the artificial neural network is transformed to a very useful tool for modeling complex systems. This capability is mainly because of the high power of neural network in learning and education. Besides, the behaviour of artificial neural networks is similar with predicting systems. Neural networks are able to model non-linear processes via catching the desired input and output vectors and the training of homologous algorithm. In the other word, the training capability of neural networks eliminates the needs of explicit equation for process modeling.

In this research the three layered perceptions neural network and sigmoid transfer function at the first and second layer and linear function at external layer, is used to model EDM sinking process. In 1987 Cybenco and Nielsen proved that this network is able to estimate any non-linear function with desired accuracy [5]. The neuron numbers of external layer is determined with the number of output parameters. The error back propagation is used as a training algorithm. This kind of neural network is very usual and skilled in simultaneously monitoring and at the same rank, very simple in communications and network structure.

4.1. Multi-layer perceptions neural network

The multi-layer perceptions neural network is formed from numerous neurons with parallel connection, which are jointed in several layers [3]. The structure of this network contains of network's input data, numbers of hidden middle layers with numerous neurons in each layer and an external layer with neurons connected to output. A perception neural network with three layers as matrix form is shown in Figure 2.

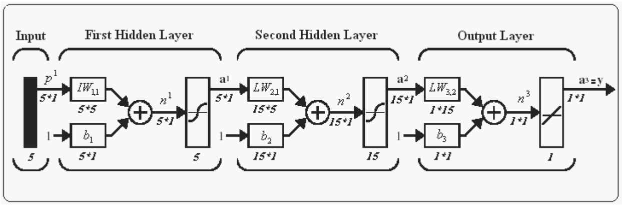

Fig. 2. Matrix demonstration of supposed neural network

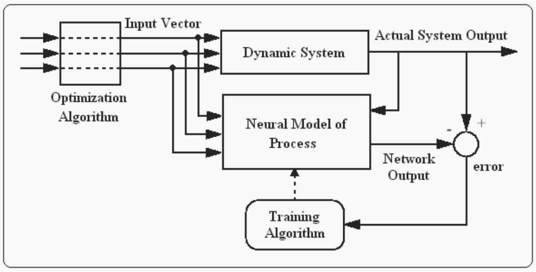

Fig. 3. Diagram of Nero-model predictive control method

This kind of network due to its sigmoid transferred function in the middle layers and linear transferred function at the external layer has universal approximation capability. According to the complexity and reciprocal affections of various machining parameters, the nature of EDM process is not completely cleared to the user; therefore, the kind of the selected network should have universal approximation capability. Generally, the application of linear function in the last layer, guarantees the adhesion of output parameters. Input and output parameters classification defines the cell's kind of network somehow. In particular, the single output parameter of the desired network is considered as EDM condition system. This parameter is the output of fuzzy sensor and a real number between zero and one. This output parameter is a direct function of the input of the network, gravimetric values and connected bias terms. Therefore, naturally to create a meaningful similarity between input and output vectors terms in data training network, the components value of gravimetric matrix and bias vector in each neuron connection, is varied. The network training with real data means the creation of optimized values of components in gravimetric matrixes and biases with the aim of one by one similarity creation between input and output parameters terms. The error back propagation and Levenbergg-Marquardt algorithms are used for training of multi-layered perception neural networks. On and off pulse times, discharge current, gap size and its variation rate are the input parameters of network. Most of these parameters are varied steeply and non-continually in their domain and indeed the machines structure does not let them to vary continually. But, usually, the setup steeply gap, does not make so much error to cause serious variation in the stage of operational sets. It is possible even to set up the step duration and afterwards error minimization via small software and hardware variations.

5. Control predicting model

The control predicting model is not usually an exact method of process control, but, it is directly related to process optimization and absolute optimum point determination of output function with respect to various input vectors. Although this approach limits the application of this control method in physical processes, but, due to the definition of optimum point as the best operational point of system in most processes, this method is widely used in control applications. When the artificial neural networks are used as model process in control, it is not needed a mathematical model replacement. Figure 3 shows the block diagram of this control method via neural networks.

This model makes available the mathematical model for non-linear and complexity systems with low information and different behaviours. When the input and output parameters are also numerous, neural network is considered as first solution. Feed forward Perceptron network as multi-layered neural network which has universal approximation conditions is used. Constrained optimization can also be carried out via an arithmetic explicit method or with a method based on artificial intelligence as genetic algorithm. In optimization operation, it should be under consideration that the total converging time of optimization algorithm and training of neural network, determines the factor of total starting time of the controller. But, during the control process, the length of control cycle is usually low. Therefore, the starting of controller can be divided into three times phases as follows:

- Neural network training phase with real data.
- Data phase optimization according to neural model.
- Up to dating phase of the model via data observed during control operation if it is needed.

The third phase in process in which the physical conditions and the model between input and output are variable during various process operations is very important. In this model, generally, the primary model which is trained with numerous input and output couples and out of training data during processing, are used to up to date neural model. This continuous training process causes to remain the network knowledge with good accuracy in desirable level.

The control of predicting EDM model via neural network to optimize WC-Co machining process on a die sinking machine with gap control system is carried out. The capability of the system with and without gap control system is compared. Table 1 shows the testing conditions.

According to the criteria system condition the train of pulses recorded, the system stability factor is defined as follows:

$$s.s.f = \frac{1}{T}(\lambda_{k+1} - \lambda_k) \qquad (2)$$

where T, λ_k and λ_{k+1} are the time between two samples recorded, condition factors in recorded pulses k and $k+1$ respectively. Sampling is done via a digital oscilloscope with sampling capability to 20 MHz as voltage respect to time diagram and the results are analyzed as a matrix form in phase systems, box tool of MATLAB software. The reason of such high frequency-time selection respect to long pulse times is to increase machining data and guarantee the recording pulse capability as much as possible.

Table 1.
ED Machining parameters of sampled pulse train

Tool	Copper with 10 mm dia.
Workpiece	WC-Co
Machine	CHARMILLES-20 ZNC
Dielectric	Kerosene
Open Circuit Voltage(V)	225
Max. Allowed Current (A)	1.5,3.5,7.5,11
Pulse On - Time (μS)	35~1000
Pulse Off - Time (μS)	35~1000
Gain of Gap Magnitude(KΩ)	120~980
Gain of Head Reaction Speed(KΩ)	1.32~91.2
Oscilloscope Setting	100 V/div & 100 μS/div
Oscilloscope Sampling Rate	312 Samples/sec
Pulse Train Condition Factor	0.6247

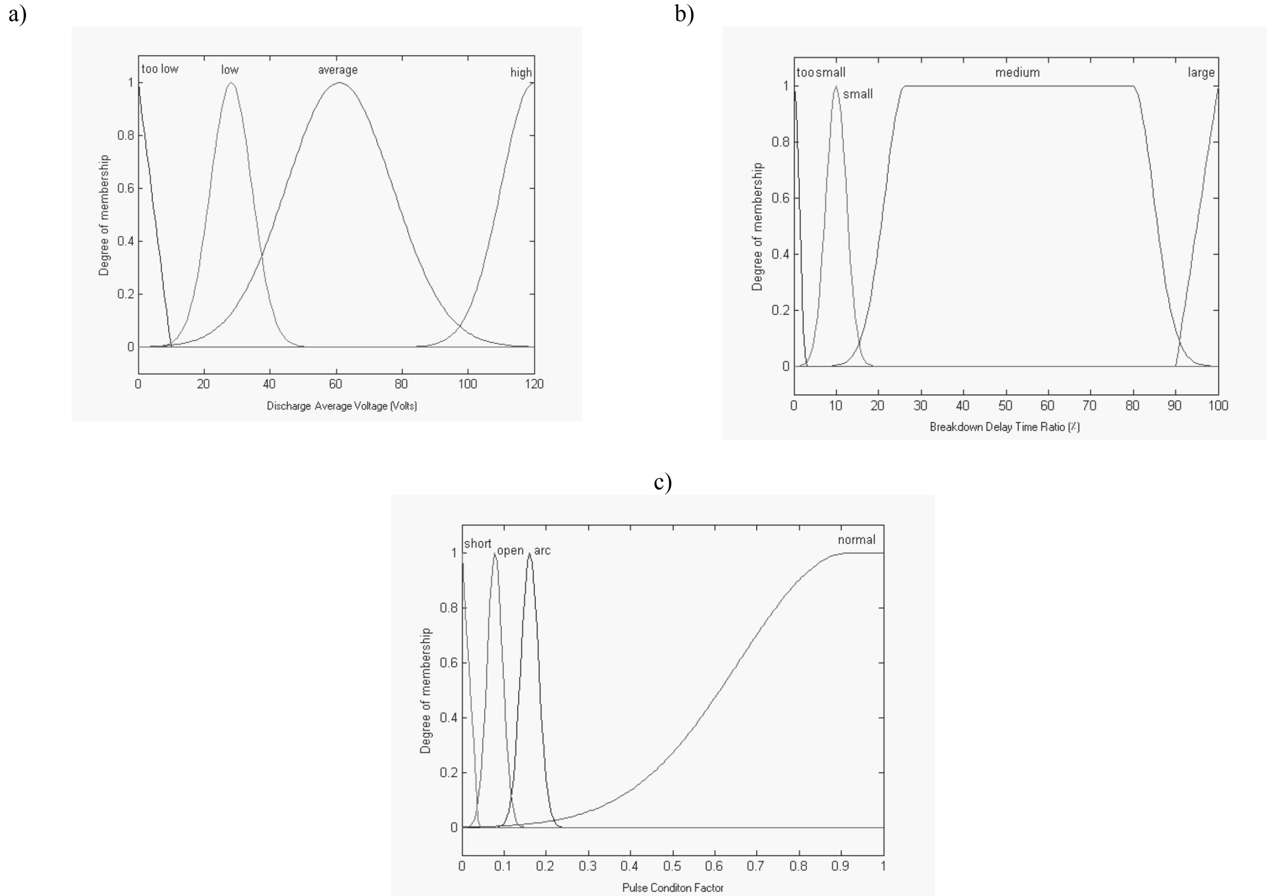

Fig. 4. Membership function of: (a) discharge average voltage, (b) breakdown delay time ratio and (c) pulse condition factor as an input of fuzzy system

The system stability factor is defined as the instantaneous derivative of EDM condition-time diagram if the shortest time needed to return the system to machining starting condition with new set up when the discharge affections with various primary conditions, is obliterated to the extent possibility. The results of machining phase analysis contains instantaneous system condition which is a real number between zero and one, is used to create couple training data of neural network. Input data are: discharge voltage, discharge current (numbers of activated transistors), gap size, head reaction speed and pulse on-off times. The neural network training is based on error back propagation and via Levenberg-Marquardt. Stopping condition is defined when the error is equal to 1×10^{-5} in training cycles. The phase sensor elements such as preliminaries and their membership functions are shown in Figure 4. Figure 5 shows the converging method of neural network training process.

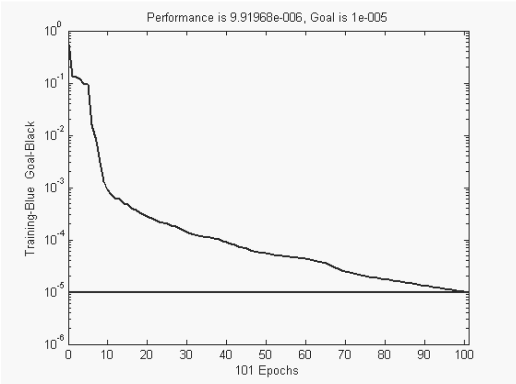

Fig. 5. Convergence diagram of supposed neural network

These factors are used to determine the system condition via time-related functions mentioned in section 3 with the same effecting gravity. The surface transmitted from two inputs and single output parameters is shown in Figure 6.

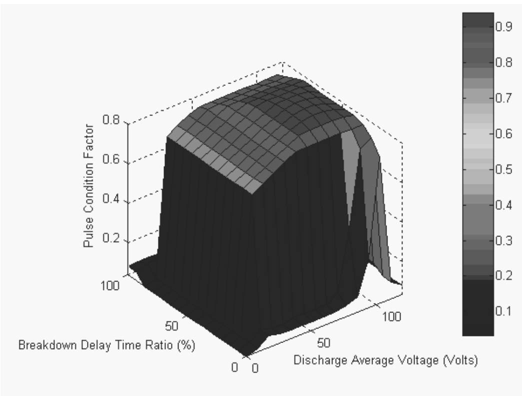

Fig. 6. Fuzzy assigning surface of two input and one output parameter

6. Optimization

After neural network training with primary input data which is storaged in computer's lateral memory and its corresponding output data which is output data is done via optimization algorithm. In complex and non-linear physical processes optimization, since the trapping of optimization algorithm in relativistic extremums is sometimes possible, necessity preparations to increase the mutation and instantaneous variation of generation conditions via generic algorithm should be under consideration. Primary data test which are later training data of neural network, also should cover space of the input variations condition. The last obtained data as input data which leads the system to the maximum number of condition and real condition number after system parameters variation are used for training of neural network and increase its knowledge. The continuous training process of network can be stopped after certainty of any following conditions has been established:

- The number that indicates the final condition of system is reached to the necessity state and approved distance of desired number.
- The network's training number and its re-optimization does not exceed to the operator's desired number.
- For several serial optimizations, system parameters should cause a decrease in condition number. This subject can be as a warning for over-training of network.

Figure 7 shows the flow chart of optimization process via predicting control based on neural network model of EDM process.

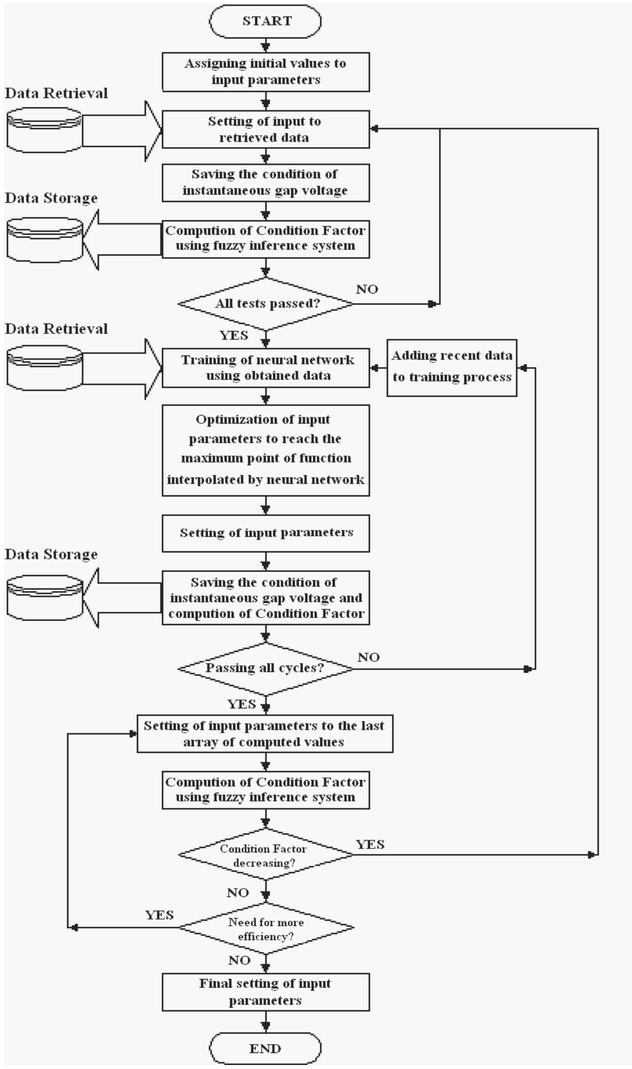

Fig. 7. Execution Flowchart of Neuro-Model Predictive Control

7. Discussion and results

Two grades of WC-Co are tested in this research. Testing conditions are shown in Table 1. The results obtained from predictive controller model based on neural network and also by expert user are shown in Figure 8.

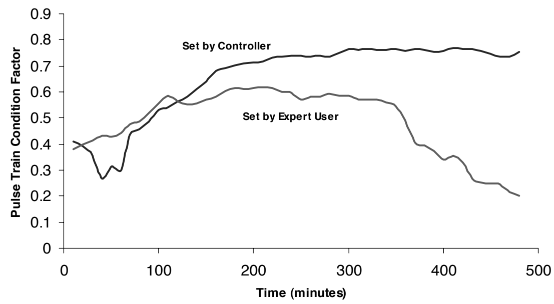

Fig. 8. Condition - Time diagram of ED machining of WC-Co

This Figure shows that how the carbon bridge between two electrodes is distinguishable via the extremely dropped of instantaneous condition/time curve. The stock removal rate for both samples is shown in Figure 9.

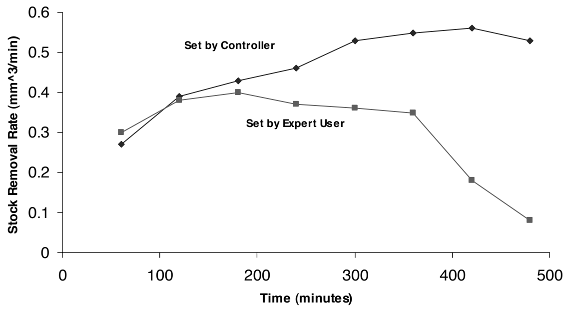

Fig. 9. Stock Removal Rate - Time diagram of ED machining of WC-Co

The structure of predictive controller model is done via PC in MATLAB software area with hard wary parallel contour and the desired sets up are carried out by suitable connector circuits on EDM system.

The testing results from ED machining of WC-Co confirms the capability of the system of predictive controller model based on neural network with 32.8% efficiency increasing in stock removal rate. The comparison between the set up obtained via machine and expert user on EDM is done with 8 hours machining that has proved the capability of the system. To improve ED machining parameters on carbon-based materials the predictive controller system based on neural network is designed and dismantled and the results from testing carried out on WC-Co via electro discharge sinking machine is analyzed. The following results from comparison between experimental data analysis and machining data with EDM sets up via expert user are obtained:

- ED sinking machine equipped with predictive controller model of neural process is caused 32.8% improvement in stock removal rate in comparison with EDM system which is set up by expert user.
- A fuzzy system is used to distinguish the condition factor of single pulse. In the correct parameters set up of membership functions, the input parameters have the main role in the correctness of the value obtained as the single pulse condition parameter.
- The input parameters such as pulse and pause times, discharge current, gap size and reaction speed of head are analyzed and varied dynamically during the control of system via optimizer program based on genetic algorithm. In controlling structure of the system the escape from instability condition is under consideration.
- By hardware dismantling of controller it is possible to decrease the cost of PC usage in control of the system in addition to increase of the operation speed of the system. This subject causes necessity of the decreasing in the flexibility of the system.

References

[1] A. Buchacz, Investigation of piezoelectric in influence on characteristics of mechatronic system, Journal of Achievements in Materials and Manufacturing Engineering 26/1 (2008) 41-48.

[2] A. Buchacz, Dynamical flexibility of torsionally vibrating mechatronic system, Journal of Achievements in Materials and Manufacturing Engineering 26/1 (2008) 33-40.

[3] N. Constantin, Adaptive Neural Predictive Techniques for Nonlinear Control, Studies in Informatics and Control 12 (2003) 285-291.

[4] N. Constantin, I. Dumitrache, Advanced Adaptive Techniques for Multivariable Nonlinear Processes, Proceedings of the 14th IFAC World Congress, 1 (1999) 174-180.

[5] J.S. Donat, N. Bhat, T.J. McAvoy, Neural Net Based Model Predictive Control, International Journal of Control 54 (1991) 1453-1468.

[6] T. Dzitkowski, A. Dymarek, Design and examining sensitivity of machine driving systems with required frequency spectrum, Journal of Achievements in Materials and Manufacturing Engineering 26/1 (2008) 49-56.

[7] J.Y. Kao, Y.S. Tarng, A Neural Network Approach for the On-Line Monitoring of the Electrical Discharge Machining Processes, Journal of Material Processing Technology 69 (1997) 112-119.

[8] J. Kopac, High precision machining on high speed machines, Journal of Achievements in Materials and Manufacturing Engineering 24/1 (2007) 405-412.

[9] D. Reclik, G. Kost, J. Świder, The signal connections in robot integrated manufacturing systems, Journal of Achievements in Materials and Manufacturing Engineering 26/1 (2008) 89-96.

[10] T.A. Spedding, Z.Q. Wang, Study on Modeling of Wire-EDM Process, Journal of Material Processing Technology 69 (1997) 18-28.

[11] Y.S. Tarng, S.C. Ma, L.K. Chung, Determination of Optimal Cutting Parameters in Wire- Eletrical Discharge Machining, International Journal of Machine Tools and Manufacture 35 (1995) 1435-1443.

[12] Y.S. Tarng, S.C. Ma, P.J. Wang, K.M. Tsai, Semi-Empirical model of Work Removal and Tool Wear in Electrical Discharge machining, Journal of Material Processing Technology 114 (2001) 89-96.