On–line data interpretation and analysis for the EDM process using self-organising maps (SOM)

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(First received April 2000; Final version October 2001)

The complexity of the EDM process, expressed by the multitude of interrelated parameters, presents a serious practical problem in the on-line analysis of the process performance. Such analysis is required for settings, optimisation and data interpretation for prompt diagnosis and control. This work attempts to improve the monitoring, diagnosis and control capability of the EDM through a graphical presentation of the on-line process tendencies. Moreover, an extended system of remote monitoring, data collection and performance through the Internet is proposed. It is expected that the implementation of the described method will facilitate and improve the performance of the EDM process.

Introduction

This work suggests that the coding of electrode features can be coupled with the specific performance of the EDM process, together with its parameters, and graphically present the results by way of an SOM (Self-Organising Map). This idea is extended to the development of a system that would present the parameters of the process on-line on component planes of an SOM. An expert system is also included for interpretation of the maps.

The electro-discharge machining (EDM) process is rather complex in its nature and requires extensive empirical results to formulate its actual performance analytically. The result will most probably be less accurate and surely not the best possible. Investigations into the electrode wear configuration under a range of EDM parameters[1] resulted in parameter correlation. The dependence of feature accuracy on the tool shape[2] and the effect of dielectric flushing on the machining results[3] have been thoroughly researched. Experimental data processed correctly could predict some of the process outputs.[4] The use of a neural network system to facilitate the tool electrode design process, has been developed.[5,6] An appropriate expert system could eliminate the need for a rather complex mathematical analysis of the correlation of process parameters. The suggested system captures data from the tool-electrode behaviour, uses a code developed to serve as an input to a back-propagation network and output values relevant to the tool design process.

The above indicates that correlation between EDM parameters, performance and electrode features does exist and can be captured by artificial intelligent programs. The SOM have been used successfully for process analysis, fault detection and process modelling tools.[7,8] The application of self-organising maps as an on-line graphical monitoring tool, with an accompanying expert system to interpret graphical results, is described in this paper.

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EDM process, theory and practice

The electro-discharge machining process is the most widely used of the non-traditional processes. EDM is based on the electrical discharge principle. When a pulsating DC source is connected to two conductors (electrode and workpiece) and a potential difference (voltage) is applied for a sufficient period (on-time) across a certain gap formed between the electrode and the workpiece, an avalanche of electrons in the form of a spark crosses the gap, vaporising or melting a small amount of metal on both the electrode (tool) and workpiece. The avalanche occurs when a dielectric breakdown of the dielectric medium, between the electrode and workpiece occurs at a certain voltage. If this electrical action is controlled in a dielectric fluid, the pulse energy can be concentrated on a small area and will effectively remove metal by creating a crater in the workpiece. Thus EDM is a complex thermo-electric process in which the metal removal rate (MRR) depends on the characteristics of the pulse energy, the gap, the characteristics of the electrode/workpiece combination, and the characteristics of the dielectric fluid. EDM can mainly be used on conducting materials.[9,10] The dielectric fluid is an important variable of the process. The main function of the dielectric is to concentrate the pulse energy of each spark on the closest points between the electrode and the workpiece. It has four other functions:

It flushes or removes the chips, cools the electrode and workpiece, insulates the electrode and workpiece and maintains a uniform resistance to the flow of current.[11] Thus, the dielectric effects the electrode wear, metal removal rate and the heat affected zone. A variety of methods for pressurised flushing are used in EDM practice. High pressure flushing also improves metal removal rates because it prevents particles from floating in the gap. Changing from very poor to very good, flushing conditions can improve efficiency and thus reduce machine time by a factor of six.[11]

Direct current power is supplied to the circuit in pulses that can be approximated by a square wave. Ideally, each pulse creates a spark where the resistance is the smallest between the electrode and the workpiece. Fig. 1 represents a typical graph plotting current and voltage against time, captured by way of a digitising oscilloscope from an actual EDM process. Electrode costs are often the most expensive part of an EDM operation. Electrode wear, material, fabri-

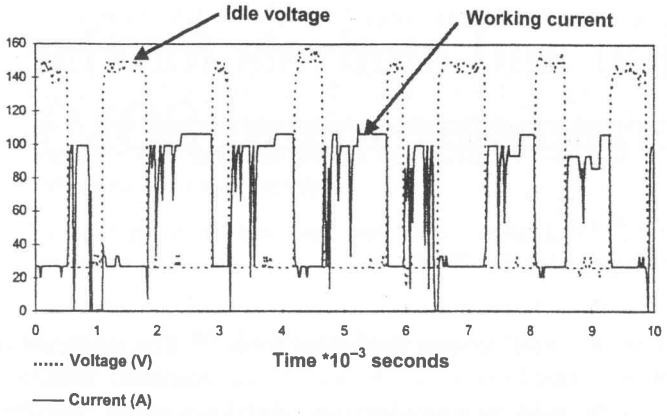


Fig. 1. Current and voltage *vs* time of an EDM process

cation and redressing costs must be carefully considered to determine the best electrode material and EDM machine settings.

The self-organising map (SOM)

Neural networks store empirical knowledge by learning from examples. They are classified in terms of the amount of guidance that the learning process receives from an outside agent. An unsupervised learning network learns to classify the input into sets without external guidance. A supervised learning network adjusts numerical weights on the basis of the difference between the values of output units and the desired values given by a "teacher", for a given input pattern.

The self-organising map (SOM) is a unsupervised neural-network model and algorithm that implements a characteristic non-linear projection, from the high-dimensional space of sensory or other input signals, onto a low-dimensional space, of sensory or other input signals, onto a low-dimensional array of neurons.[7] The SOM is able to map a structured, high-dimensional signal manifold into a much lower-dimensional network in an orderly fashion. The mapping tends to preserve the topological relationships of the signal domains. Due to this order, the image of the signal space tends to manifest clusters of input information and their relationships on the map.

Accordingly the most important applications of the SOM are in the visualisation of high-dimensional systems and processes and discovery of categories and abstractions from raw data. The latter operation is called the exploratory data analysis or 'data mining'. In engineering, the most straightforward applications of the SOM are in the identification and monitoring of complex machine and process states, otherwise very difficult to perceive and interpret. The SOM can also be utilised for the development of new pattern classification and target recognition systems, whereby categorisation of the input signal states is performed by it. In combination with reinforcement learning, the SOM can be effectively used to implement various control functions.[7]

The SOM algorithm

The SOM algorithm resembles vector quantitization (VQ) algorithms, such as k-means,[12] and is closely related to principle curves.[13] The important distinction from VQ is that the neurons are organised on a regular grid and, along with the selected neuron, its neighbours are also updated, so that the SOM performs an ordering of the neurons. In this respect, the SOM is a multidimensional scaling method projecting data from input space to a lower, typically two-dimensional, output space.[14]

An SOM consists of neurons organised in an array. The number of neurons may vary from a few dozen up to several thousand. Each neuron is represented by an n-dimensional weight vector, $m = [m_1, ..., m_n]$, where n is equal to the dimension of the input vectors. The neurons are connected to adjacent neurons by a neighbourhood relation, which dictates the topology, or structure, of the map. Typically, a rectangular (as in Fig. 2) or hexagonal neighbourhood is used.

The SOM is trained iteratively. In each training step, one sample vector x from the input data set is chosen randomly and the distance between it and all the weight vectors of the SOM is calculated, using, for example, an Euclidean distance. The neuron c, whose weight vector is the closest to the input vector x, is called the best-matching unit (BMC):

$$\| x - m_c \| = \min_i \{ \| x - m_i \| \} \tag{1}$$

where $\| \cdot \|$ denotes the distance measure.

After finding the BMU, the weight vectors of the SOM are updated so that the BMU is moved closer to the input vector in the input space. The topological neighbours of the BMU are also treated in the same way. This adaptation procedure stretches the BMU and its topological neighbours toward the sample vector as shown in Fig. 2. The

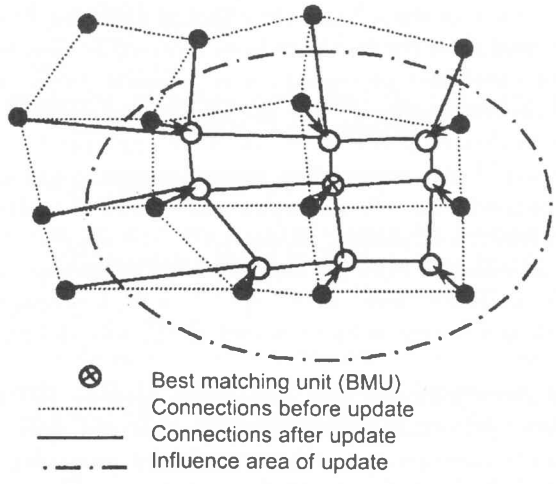


Fig. 2. Updating the BMU and its influence area towards the input sample

SOM update rule for the weight vector of unit i is:[14]

$$m_i(t+1) = m_i(t) + h_{ci}(t)[x(t) - m_i(t)] \qquad (2)$$

where t denotes time. The $x(t)$ is the input vector randomly drawn from the input data set at time t and $h_{ci}(t)$ the neighbourhood kernel around the winner unit c at time t. The neighbourhood kernel is a non-increasing function of time and of the distance of unit i from the winner unit c. It defines the region of influence that the input sample has on the SOM.

The iterative solution is expressed by Kohonen,[7] in the following steps. This algorithm, dubbed the Batch Map, resembles the familiar Linde-Buzo-Gray (LBG) algorithm for VQ,[15] where all the training samples are assumed to be available when learning begins:

1. For the initial codebook vectors m_i, take, for instance, copies of the first training samples x:
2. For each map unit i, collect a list of copies of all those training samples x, whose nearest codebook vector belongs to the neighbourhood set N_i of cell i.
3. Take for the new value of each new codebook vector the mean over the respective list
4. Repeat from step 2 a few times.

SOM interpretation

Once the SOM is trained, the results are presented in component planes or maps, one for each parameter in the data set. An additional map is presented called the unified distance matrix (u-matrix). This method[16] is used to visualise the cluster structure of the SOM (Figs. 7 to 9). Since the u-matrix represents the distance of the weight vectors of adjacent units in the two-dimensional map, the distances correspond to the colour-scaled values. Large values correspond to more definite boundaries between different clusters.

The component planes, one for each parameter in the data set, present a two-dimensional visualisation of the distribution of the weight vector component of the corresponding parameter. By comparing the corresponding positions on the component planes, dependencies among parameters can be studied. To ensure that the data used to train the SOM are evenly distributed, a hit counter can be used. With this method the number of data sets corresponding to each unit is presented. In many cases when proper clustering is achieved, small values for the hit counter correspond with large values in the u-matrix, thus indicating a transition area or boundary.

Sammon's projection is an iterative algorithm to project high-dimensional vectors in two dimensions.[17] This projection of the SOM data set can be used as a rough approximation of the form of the data since this projection tries to preserve the relative distances between input vectors. Thus, if the colours within the Sammon's projection are grouped together, it gives an indication of proper possible clustering by the SOM (Fig. 3).

The quality of an SOM analysis is measured in two ways. The first refers to the quantitization error. This error

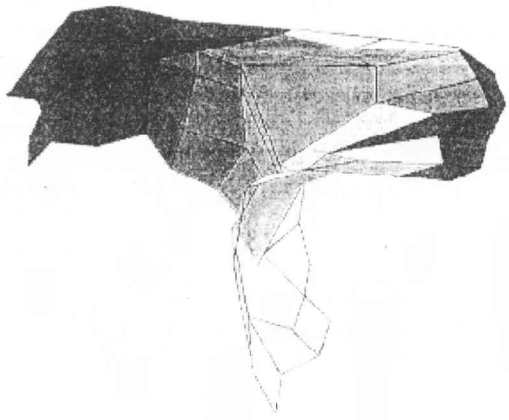


Fig. 3. Sammon's projection viewed at azimuth –38° elevation 30°

presents the average "difference" between the actual data in the high-dimensional space and the transformed lower-space data. The quantitization error would give an indication of the level at which the data were being grouped into clusters. A high quantitization error indicates that the data could not be clustered properly and thus could not properly "capture" a model of the process.

The second measure is the topological error. This error refers to a percentage of data vectors for which the first and second BMUs (best matching units) are not adjacent units. If this percentage is high, it indicates that tendencies within the data are highly unlikely. Software packages that contain all the central procedures, a number of monitoring and diagnostic programs, and exemplary data are freely available on the Internet.[18,19]

Data acquisition

The data were obtained by machining with all the electrodes in Fig. 4 to a depth of 11 mm. All the electrodes were used with the following machine settings: On-time = 0.75 ms, Off-time = 0.56 ms, Current = 15 A, Idle voltage = 100 V, and Polarity = Electrode positive. The flushing is through the centre of the electrode through a 1.5 mm diameter hole delivering 0.5 l/min dielectric fluid. During machining, the following parameters are recorded: Machining depth (mm), Efficiency (%), Power dissipated in gap (W), MRR (mm^3/min) and Energy (J/mm^3).

After machining the following wear parameters are measured: End wear, Outside corner wear, and Internal wear. Fig. 5 presents a graph of spark current versus time where Tl to T8 presents the portion of the actual on-time that did cause a spark. This graph is generated from the output of a digital oscilloscope, connected to a PC, reading the gap voltage and current during the machining process. The current threshold is set at 50% of the working current for all the experimental results.

For this specific case the efficiency is calculated as:

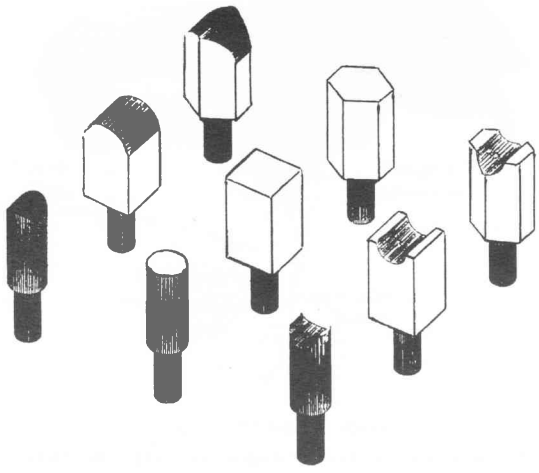


Fig. 4. Electrodes used in experiments.

$$\text{Efficiency} = \left(\frac{\sum_{i=1}^{n} T_i}{\text{on-time} \cdot n} \right) \cdot 100\% \qquad (3)$$

where n is the number of pulses which in the case of Fig. 5 is equal to 8 and T_i is the period of time for which pulse i had a current value larger than the threshold.

The power is calculated as follows:

$$\text{Power} = \frac{\left(\sum_{i=1}^{n} c_i v_i \right) \cdot t_s}{T_{\text{Total}}} \qquad (4)$$

where n = all sampled current and voltage data sets above the current threshold; c_i = sampled current; v_i = sampled gap voltage; t_s = sample time of digitising oscilloscope; and T_{Total} = total time of all samples taken.

The energy or specific energy, is defined as a parameter indicating the amount of energy needed to remove one mm^3 of the workpiece, thus with unit J/mm^3. This value is

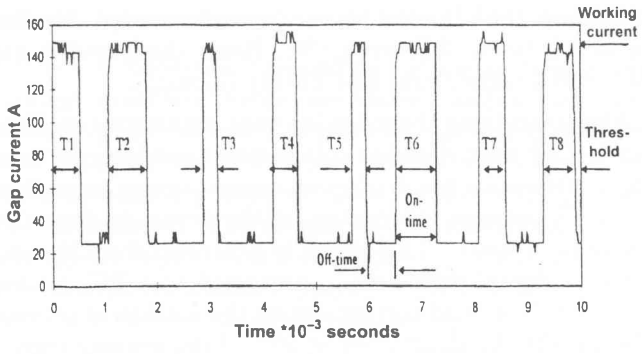


Fig. 5. Discharge current

TABLE I
SECTION OF SOM DATA MATRIX

	Machining depth (mm)				
	4.57	6.93	8.85	11.00	4.64
Power *10 (W)	211.33	211.33	215.39	217.42	172.36
MRR (mm^3/ min)	195.07	207.26	182.88	199.14	177.23
Energy (*10 J/mm^3)	65.02	60.96	71.12	65.02	56.91
Efficiency (%)	91.44	89.41	91.44	91.44	91.06
Flushing	1.00	1.00	1.00	1.00	0.00
Surface (mm^2)	256.00	256.00	256.00	256.00	256.00
Edges	8.00	8.00	8.00	8.00	8.00
Feature	0.00	0.00	0.00	0.00	0.00
Outside corner	1.98	1.98	1.98	1.98	1.08
End wear	1.62	1.62	1.62	1.62	0.82
Internal wear	0.88	0.88	0.88	0.88	0.05

calculated using a 3D-model of the electrode, the measured machining depth, and MRR values thus.

$$\text{Energy} = \text{Power/MRR} \qquad (5)$$

In order to include some of the geometrical features into the analysis, the following parameters are included: Surface area: the projected surface at the bottom of the electrode; Edges: the number of continuous edges at the bottom of the electrode; and Shape: three major groups are identified, representing the overall feature at the bottom of the electrode (concave, flat and convex). Table I presents a sample of the data used.

SOM ANALYSIS

Several separate SOM analyses are performed. One includes all the parameters, referred to as Complete. The second and third analyse the split data according to flushing, referred to as No-flushing and Flushing, respectively. The third analysis, Flushing, contains all the data sets with a flushing value of 1.

SOM quality has a complex structure. Two criteria are used: resolution or quantitization and topology preservation. If the dimension of the data set is higher than the dimension of the map grid, these usually will become contradictory goals. In this case, however, the grid map dimensions is 6 × 12, while the data set has a dimension of 12. From Table II it is evident that the SOM analysis presents the topology of the data sets very well. The quantitization errors are large but still within a very representative mapping. Another criterion involves the Sammon's projection. (Fig. 3) It is viewed at an azimuth of –38° and elevation of 30°. The projection indicates a clear distinction between certain data groupings within the complete data set. This can be seen in the separation of the light and dark colours in Fig.3.

The final criterion, a data histogram, involving the viewing of the data distribution over the BMUs (an indication of how many data sets belong to each BMU). Fig. 6 presents

TABLE II
QUANTITIZATION AND TOPOLOGICAL ERRORS

Analysis	Quantitization error	Topological error
Complete	0.9953	0.044
No-flushing	0.8937	0
Flushing	1.0566	0

such a "hit counter" of the complete data set. The data are evenly distributed throughout the map, indicating a good representative data set. The clustering of the data confirms the Sammon's projection results. The positions in Fig.6, to which zero data sets belong, can be compared to the high value locations on the u-matrix. These regions indicate transition areas or boundaries between clusters.

Observations

Analysis: Complete (Fig. 7)

1. The flushing separates the maps in two parts. The wear is directly related to flushing, indicating a very high wear with flushing and very little wear with no-flushing. This relation seems to contradict EDM in practice where the opposite is true. However, if the EDM settings (see Data acquisition) are taken into account it is observed that a very high current setting of 15A was used on electrodes, all with a machining frontal surface area of less than 256 mm^2. This setting was chosen to obtain measurable wear on the electrodes within a reasonable time-frame while machining to a depth of 11 mm.
2. The power, MRR and efficiency are directly related and inversely related to energy. Since energy is defined as J/mm^3 the above indicates that a minimum energy exists as which point the process is at optimum performance regarding MRR and efficiency.
3. As the MRR, depth and flushing maps are compared, it indicates a high MRR is reached at a very shallow depth with no-flushing and a large surface area present.

Analysis: No-flushing (Fig. 8)

1. This analysis confirms the relation in point 2. above. It is further noted that a high surface area and small depth is needed for high MRR, power, efficiency and low energy. This should also be interpreted with the high current value as explained in Complete analysis under point 1.
2. The edges and features are inversely related.

Analysis: Flushing (Fig. 9)

1. The very favourable conditions of high MRR, power, low energy correspond to low outside corner and end wear in all the areas and corresponds to certain areas of internal wear.
2. The conditions in 1. can be found throughout the complete machining depth range.
3. High end wear is connected to a low feature and surface area values while high outside corner and internal wear correspond to low edge and surface area values.
4. Internal wear is proportional to the feature value and inversely proportional to the edges values, without influence from the surface area.

The above analysis serves as an example of EDM parameters being analysed by SOM. The data used had the same machine setting and therefore the effect of different machine settings could not be analysed. Fig. 10 presents the flowchart of an expert system that optimises wear and MRR by flushing and re-design considerations. For each conclusion reached by the expert system, suggestions are implemented and altered parameters are replotted on the SOM component planes. The new position on the maps is then compared to previous ones. After a number of changes have been made, the trajectory of changes is also viewed on the component planes. Should more data be available, especially with different machine setting, an extensive rule base can be developed for optimising efficiency, wear, and MRR by altering machine settings, feature design, and flushing. The rule base is designed to allow the

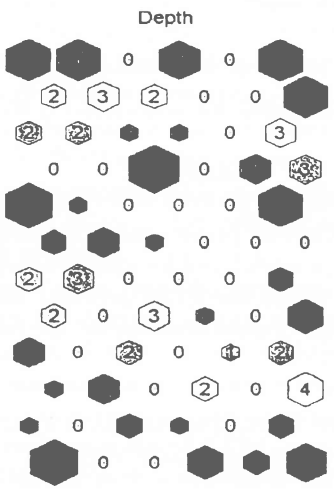


Fig. 6. Hit counter for Depth component plane

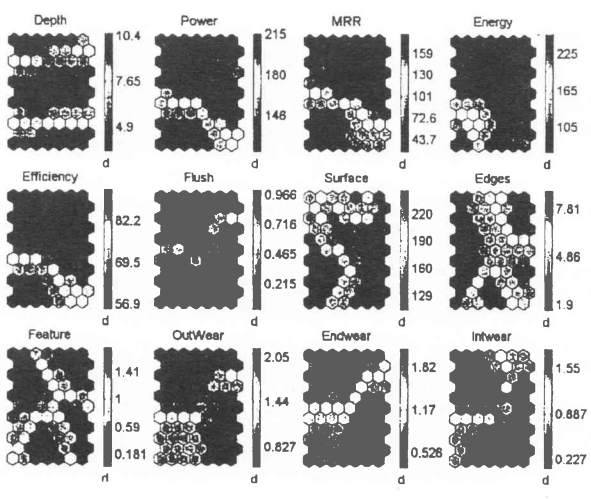


Fig. 7. Complete analysis

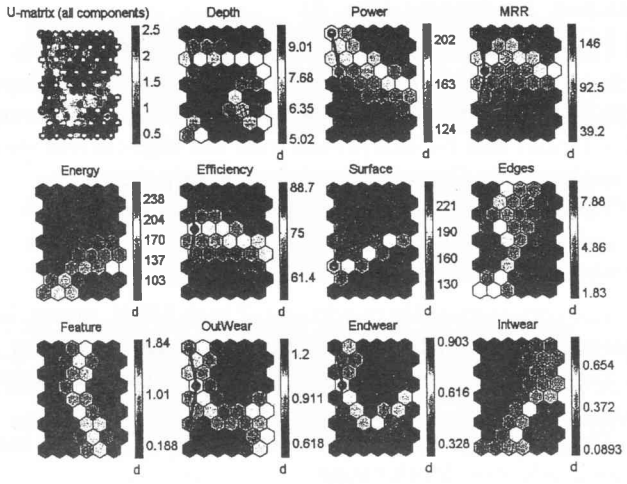


Fig. 8. No-flushing analysis

user to select the criteria for alteration such as machine settings, flushing, or electrode re-design.

After each alteration the new position on the SOM maps is plotted, while successive alterations form a trajectory on the maps.

As an example. Fig. 8 presents such a trajectory for the square concave electrode, machined without flushing. The trajectory is plotted for depths of 4.16, 9.42 and 11.14 mm. In the absence of certain information such as wear and MRR, SOM maps are trained without them or the wear can be estimated by back-propagation networks.[5,6] In order to improve the map interpretation together with expert system advice, each BMU can be labelled as a "bad" or "good" machining situation. This additional information is accumulated during the collection of the training data while observing the general behaviour of the process. This enables the user to plot his current process as well as

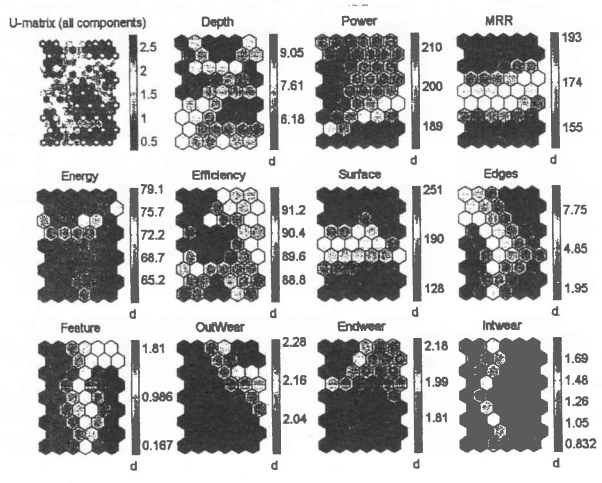


Fig. 9. Flushing analysis

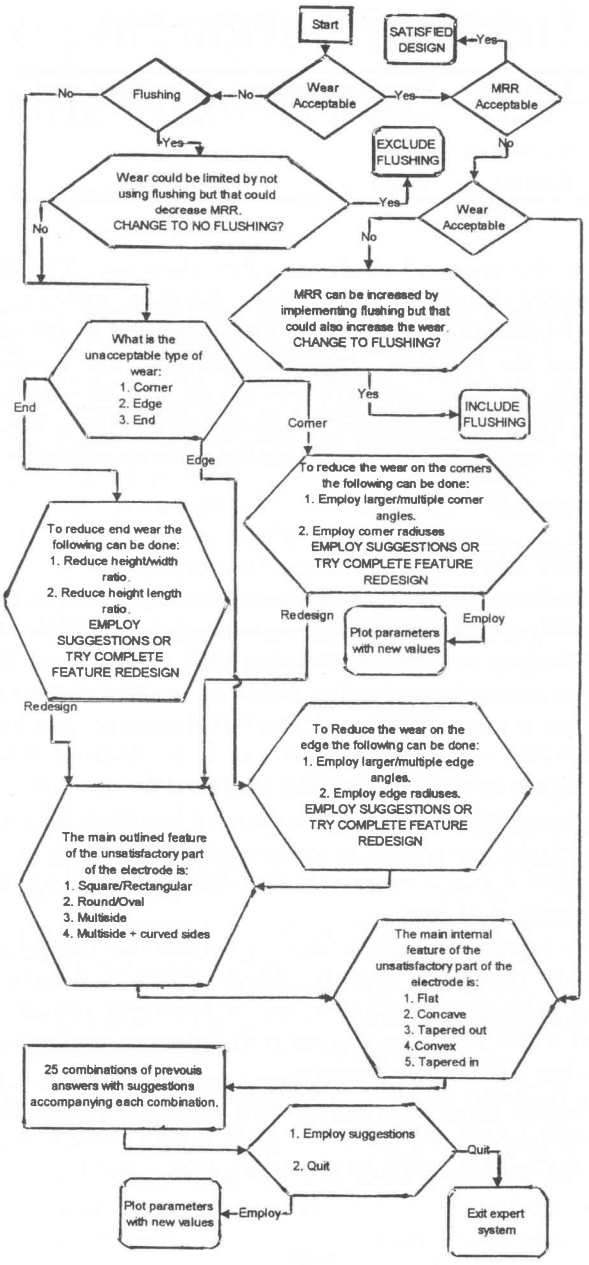


Fig. 10. Expert system for improvement of Wear and MRR

knowing how well the process is performing.

Such SOM analyses prove that SOM could be used for EDM as a very powerful tool for graphical representation of the tendencies within the EDM process. Assuming that a much wider range of data is available, the following system is proposed.

EDM Remote Monitoring, Data collection and Performance viewing

This system, presented in Fig. 11, functions as follows:

The Manufacturing Research Group EDM/SOM (MRGES) server contains the trained SOM maps, trained from ex-

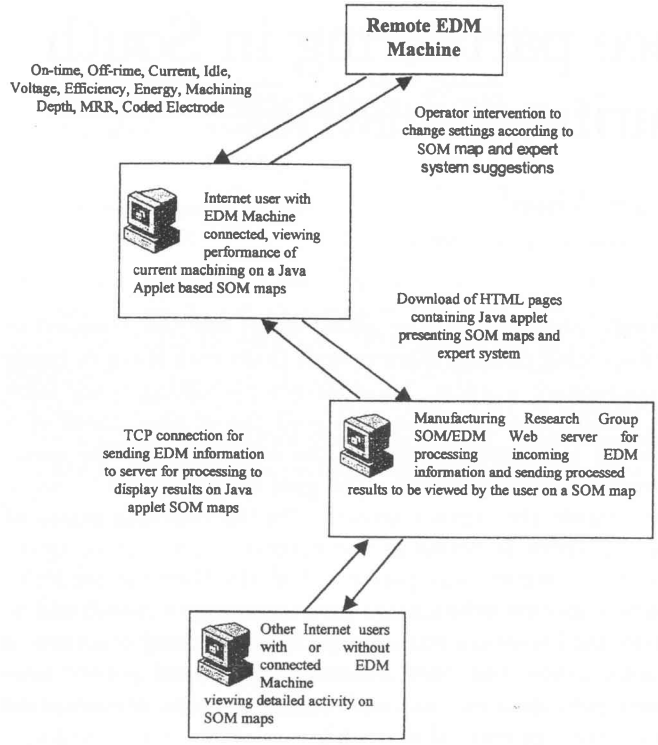


Fig. 11. Proposed EDM/SOM on-line monitoring and diagnosis . system

perimental electrodes. As an Internet user visits the Web address, an SOM map is presented. The user is presented with a choice. He can either manually enter one set of EDM information or if an EDM machine is connected to his system, this continuous stream of information can be sent to the MRGES server. The server processes the information and the results are sent back to the Java applet, presenting the user with the current position of his process on the SOM maps. In the case of a user supplying a continuous stream of data, the viewing of the process is on-line in real time and the movement of the process (trajectory) on the maps is watched and interpreted. The user can interact with the expert system, included in the applet, to obtain some advice on process improvement.

The system is also used to gather information from remote machines for SOM training purposes of new settings and electrode configurations. The electrodes are classified into certain groups (Group Technology) and an SOM is trained for each group.

The system is of great value for any person/company in possession of an EDM machine and an Internet connection. Manual input of the current conditions of the machine allows immediate view of the present status on an SOM map. This system is a very valuable source of information and evaluation for all EDM users. The Internet bandwidth needed for such a system is very low since no pictures of the SOM maps are sent over the Internet. Only the information to create them by way of the Java applet is made available.

Summary and Conclusions

This paper described the analysis of experimental results using one set of machining parameters for a variety of electrodes. The analysis was done by way of an SOM, producing tendencies within the maps, which were converted to an expert system rule base. Although a too high current setting was used in the experimentation, to obtain proper measurable wear, the above procedure proved to be viable. Extensive experimentation with a range of different machine settings and different electrodes could also be analysed in the same way.

References

[1] Berkan J. *Shape wear of tool electrodes and its influences on technology in electrical discharge machining.* Technical University of Warsaw, Poland, 1983.

[2] Sen AK, Crookall JR. *Detail transfer in EDM finishing.* Cranfield Institute of Technology, Cranfield, Bedford, 1990.

[3] Erden A. *Role of dielectric flushing on electrical discharge machining performance.* Middle East Technical University, Mechanical Engineering Department, Ankara, Turkey, 1992.

[4] Kaldos D. Erosicap, an Expert System for the computer aided planning of EDM sinking technology. *EDM Technology*, **1**, 1993.

[5] Naude JJ. A neural network/expert system based approach for design improvements of products manufactured by the EDM process. Masters dissertation, Rand Afrikaans University, Johannesburg, 1995.

[6] Katz Z, Naude JJ. A neural network/expert system approach for design improvement of products manufactured by EDM. *JMSE*, **121**, 1999.

[7] Kohonen T, Qja E, Simula 0, Visa A & Kangas J. Engineering applications of the Self-Organising Map. *Proceedings of the IEEE*, **84**, 1996.

[8] Alhoniemi E, Hollmen J, Simula 0 & Vesanto J. Process monitoring and Modelling Using the Self- Organising Map. *Integrated Computer-Aided Engineering.* IOS Press, Ohio,USA, 1998.

[9] Amstead BH & Ostwald PF. *Manufacturing Processes.* 8th edn. John Wiley & Sons, Inc, USA, 1987.

[10] Davis RJ. *Metals Handbook, Vol. 16 Machining.* ASM International, USA, 1989.

[11] Koelsch JR. EDM hits the floor running. *Manufacturing Engineer,***110**, 1993, pp.41–43.

[12] Bishop CM. *Neural Networks for Pattern Recognition.* Oxford University press, 1995.

[13] Hastie T & Stuetzie W. Principle Curves. *Journal of the American Statistical Association*, **84**, 1989, pp.502–516.

[14] Simula 0, Vesanto J, Vasara P & Helminen R. *Industrial Applications of Neural Networks*, Chapter 4. CRC Press LLC, Finland, 1999.

[15] Makhoul J, Roucos S & Gish H. Vector quantitization in speech coding. *Proceedings of the IEEE*, **PROC-73**, pp.1551–1588, 1985.

[16] Ultch A & Siemon HP. Kohonen's self organizing feature maps for exploratory data analysis. *Proc. INNC'90, Int. Neural Network Conf.*, pp.305–308, Dordrecht, Netherlands, 1990.

[17] Sammon JW Jr. A non-linear mapping for data structure analysis. *IEEE Transactions, Computers*, **C-18**, 1969, pp.401–409.

[18] Kohonen T, Kangas J & Laaksonen J. *SOM_PAK, The Self-Organising Map Program Package.* Helsinki Univ. Technol. Lab.,. Computer and Information Sci., Espoo, Finland, 1995, http://www.cis.hut.fi/research/som Ivq pak.shtml.

[19] Vesanto J, Himberg J, Alhoniemi E & Parhakangas J. SOM Toolbox for Matlab 5. Helsinki University of Technology. *Publications in Computer and Information Science*, Report **A57**, Espoo, Finland, 2000, http://www.cis.hut.fi/projects/somtoolbox/.