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Application of Self Organizing Map (SOM) to model a machining process

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Abstract

Purpose – This paper aims to present a practical application of Self Organizing Map (SOM) and decision tree algorithms to model a multi-response machining process and to provide a set of control rules for this process.

Design/methodology/approach – SOM is a powerful artificial neural network approach used for analyzing and visualizing high-dimensional data. Wire electrical discharge machining (WEDM) process is a complex and expensive machining process, in which there are a lot of factors having effects on the outputs of the process. In this work, after collecting a dataset based on a series of designed experiments, the paper applied SOM to this dataset in order to analyse the underlying relations between input and output variables as well as interactions between input variables. The results are compared with the results obtained from decision tree algorithm.

Findings – Based on the analysis of the results obtained, the paper extracted interrelationships between variables as well as a set of control rules for prediction of the process outputs. The results of the new experiments based on these rules, clearly demonstrate that the paper's predictions are valid, interesting and useful.

Originality/value – To the best of the authors' knowledge, this is the first time SOM and decision tree has been applied to the WEDM process successfully.

Keywords Self Organizing Map, Decision trees, Artificial neural nets

Paper type Research paper

1. Introduction

The Self Organizing Map (SOM) is a prominent unsupervised neural network model providing a topology preserving mapping from a high-dimensional input space onto a 2D map space. This capability allows an intuitive analysis and exploration of interesting and previously unknown knowledge (Tomsich *et al.*, 2000).

The SOM is useful in many applications where the dimensionalities of the feature spaces to be analyzed and the amount of data encountered are too large to allow a fast, interactive training of the neural network. The SOM provides a form of cluster analysis by producing a mapping of high-dimensional input data onto a usually 2D output space while preserving the topological relationships between the input data items

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as faithfully as possible. It consists of a set of units, which are arranged in some topology where the most common choice is a 2D grid (Kohonen, 1995). The SOM has the ability to map a high-dimensional signal manifold on a low-dimensional topographic feature map, with most of the topological relationships of the signal domain preserved (Kohonen *et al.*, 1996).

The SOM algorithm has attracted a great deal of interest among researchers and practitioners in a wide variety of application fields (Oja *et al.*, 2001). In the literature, multivariate techniques have been successfully applied in different complex processes for different purposes such as data mining, image analysis, process monitoring and fault detection diagnosis. Successful applications have been reported in different industrial processes such as:

- start-up operation in a steel casting process in Zhang and Dudzic (2006);
- operation of a copper smelter in Ross (1988);
- monitoring product quality in the food processing industry both in Sheridan *et al.* (2006) and Yu *et al.* (2003);
- monitoring of combustion processes in Yu and MacGregor (2004);
- remote sensing image analysis in Villmann *et al.* (2003);
- discovering operational strategies in the refinery fluid catalytic cracking process in Sebzalli and Wang (2001);
- medical image analysis in Li *et al.* (2006);
- genomics data modelling in Eriksson *et al.* (2004);
- increase pharmaceutical data process understanding in Jorgensen *et al.* (2004);
- adaptive modelling of an offset lithographic printing process in Englund and Verikas (2007); and
- dynamic modelling of the maize drying process in Liu *et al.* (2006).

These wide varieties of examples demonstrate that considerable effort has been placed on applying these multivariate tools. Optimizations to $_{par}$SOM, a software-based parallel implementation of the SOM was first introduced by Tomsich *et al.* (2000) which provides a better performance compared to other implementation attempts such as the one reported in Boniface *et al.* (1999).

The SOM algorithm is employed by Koua (2003) to explore a geospatial dataset. The dataset consists of a collection of socio-economic indicators related to municipalities in a region of The Netherlands. The use of the SOM intended to uncover the structure and patterns from this dataset, and to provide graphical representations that can support understanding and knowledge construction. Spatial analysis, data mining and knowledge discovery methods were combined in this framework, with the goal of portraying the data in a visual form in order to stimulate pattern recognition and hypothesis generation. Some examples of visual representations based on the SOM include the visualization of clusters and shape of the data using unified distance matrix visualization, projections (mesh visualization), visualization of component planes (multiple linked views of component planes) and 2D/3D surface plots of the distance matrices. These techniques used spatial metaphors such as distances, regions and scale, to facilitate the representation of information.

In this work, SOM is used to model and predict the output parts' characteristics of a new material turning process which is a new type of wire electrical discharge machining (WEDM). This machining process is almost an expensive process and in addition there are a lot of variables and factors that have different effects on the quality of the final product of this process. Therefore, it is very interesting to investigate the interrelationships and interactions of the machining factors and the quality factors of the final product. Further, since, this process can be considered as a complex function between controllable factors and the output factors, it is very useful for the process operators and engineers to have a process management guideline based on the relations of different controllable factors and the required output quality. In this work, SOM provides a quick and visual method for understanding the relationships between the input and output variables of the process under study. Laine (2003) discusses the advantages of SOM algorithms over existing statistical methods, regarding characteristics of real world engineering environments because the technique is very simple and practical for process engineers to understand the underlying complex behaviour of the processes without the need for previous knowledge in statistics or artificial intelligence algorithms.

In this paper, training and visualizing SOM carried out followed by construction of a classification model which is employed for prediction. After this visually variable selection step, the decision tree algorithm is applied to extract a set of process control rules for optimizing the cost and quality of the final product.

In the applications of SOM to process modelling and monitoring, almost all existing works have applied SOM for continuous processes, such as chemical processes and steel industry processes with a huge set of process data (Simula and Kangas, 1995; Laine, 2003). In these processes, data collection is not a difficult or costly task while for the WEDM, which is discrete process; data collection is not straightforward and rather costly. We use designed experiments by means of Taguchi method (Ross, 1988) to collect data needed for network training.

The rest of this paper is organized as follows. Section 2 introduces the SOM network and Section 3 presents a brief overview of the WEDM process. The SOM results for our WEDM process are presented in Section 4 followed by the conclusions and future work in Section 5.

2. SOM network

The result of the SOM process is a topographic map of the input patterns in which the spatial locations (i.e. coordinates) of the neurons in the lattice are indicative of intrinsic statistical features contained in the input patterns (Haykin and Simon, 1999). The SOM consists of neurons organized in an array. Each neuron is represented by a n-dimensional weight vector, where n is the dimension of the space.

The neurons of SOM are connected to their adjacent neurons by a neighbourhood relation, which dictates the SOM topology or structure. Typically, the topology shape is either hexagonal lattice shape as shown in Figure 1 or a rectangular lattice as shown in Figure 2.

2.1 SOM algorithm

The goal of SOM algorithm is to tune map units' weights so these units finally are able to describe the state space. The main tasks of this algorithm are: initializing

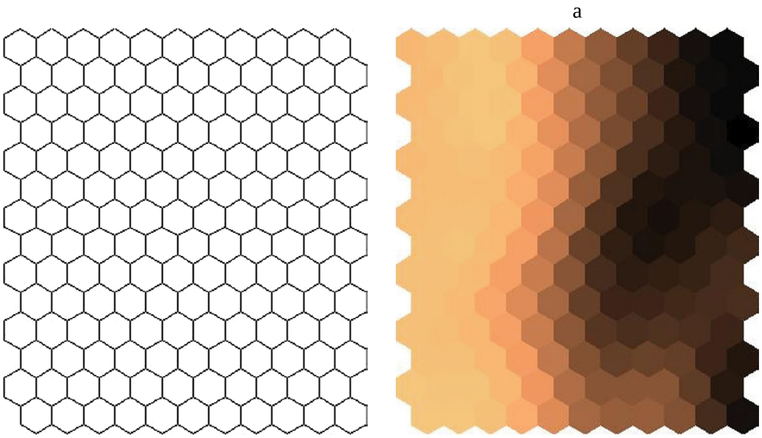


Figure 1.
Hexagonal lattice

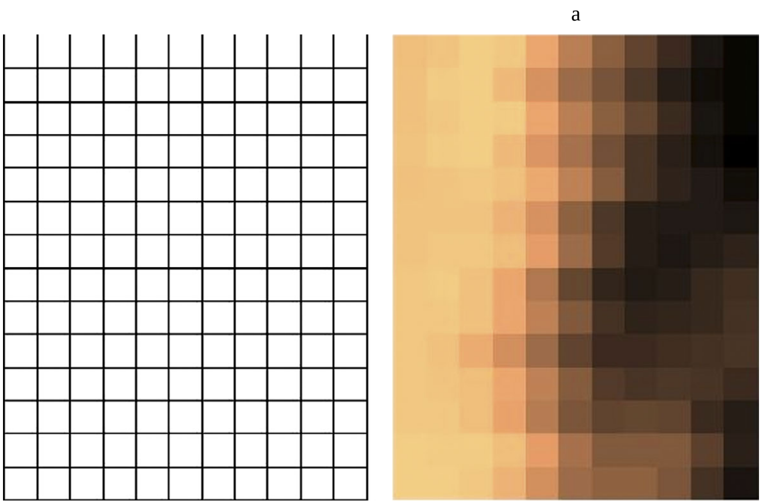


Figure 2.
Rectangular lattice

weight vectors, training them and adapting them with sample dataset. The neurons weight vectors initially take random or linearly values.

An SOM array is defined in the final output dimension, often 2D or 3D. The number of nodes in SOM array depends on the requirement to be able to best represent the input data vector set. The SOM algorithm allows the high-dimensional input data be represented by a set $\{X_j\}$ of real vectors $\mathbf{x} = [x_{i1}, x_{i2}, x_{i3}, \ldots, x_{in}]^T$. A parametric real vector $\mathbf{m}_i = [\mu_{i1}, \mu_{i2}, \ldots, \mu_{in}]^T$ is associated with each element of SOM array. A decoder function is defined based on distance $d(\mathbf{x}, \mathbf{m}_i)$ between the input vector and the nodes of SOM, to define the image of the input vector on the map.

Definition of $d()$ can be chosen based on the application, however the Euclidean distance measure is most widely used. The image is defined as the index of the node with minimum distance from the input vector:

$$c = \arg\min_i \{d(x, m_i)\} \tag{1}$$

The task is to define $\mathbf{m}_i$ in the way the mapping is ordered and descriptive of the order of $\mathbf{x}$ using vector quantization, optimized $\mathbf{m}_i$, can be obtained. As a result, a set of values $\{\mathbf{m}_i\}$ is obtained as the limit of convergence of the following sequence (Kohonen *et al.*, 1996):

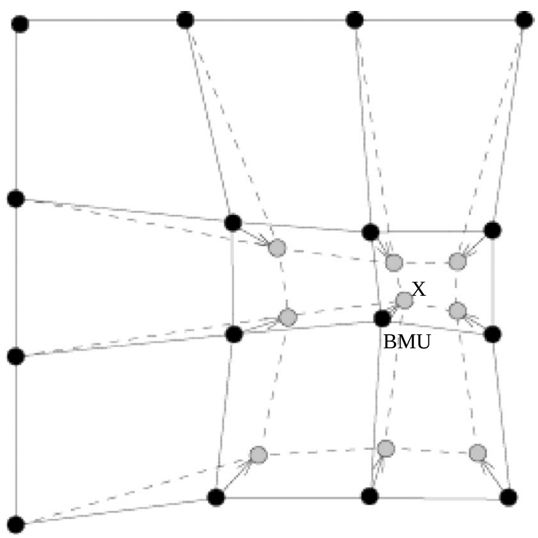
$$m_i(t+1) = m_i(t) + \alpha(t) \cdot d_{ic}[x(t) - m_i(t)] \tag{2}$$

Where $\alpha(t)$ is the monotonically decreasing learning rate and d_{ic} is the neighbourhood function, which models elastic interconnections between the adjacent nodes. The learning in such elastic environment is shown schematically in Figure 3. This elastic nature of the map helps to organize it into a shape that best represents the data.

After training the map, we must visualize the results. Common ways for visualizing the results are component planes and U-matrix[1] (Ultsch, 1993) which has been used in this work to illustrate the results.

3. WEDM process

Electrical discharge machining (EDM) is a thermoelectric process that erodes workpiece materials by a series of discrete electrical sparks between the workpiece and an electrode flushed by or immersed in a dielectric fluid. The hardness and strength of the difficult-to-machine work materials are no longer the dominating factors that affect the tool wear and hinder the machining process. This makes the EDM process particularly suitable for difficult-to-machine materials. The EDM process has the ability to machine precise, complex and irregular shapes with a CNC control system. In addition, the cutting force in EDM process is small which makes it ideal for fabricating miniature parts.



Source: Alhoniemi *et al.* (1997)

Figure 3. Updating the best matching unit and its neighbourhood towards the input x

The concept of cylindrical WEDM is shown in Figure 4. A rotary axis is added to a conventional five-axis wire EDM machine in order to produce cylindrical forms. The initial shape of the part does not need to be in cylindrical form. The *X* and *Y* slides control the electrically charged wire to remove the work material and the generation of the desired cylindrical form.

Examples of the machined parts using the cylindrical wire EDM method are shown in Plate 1.

The aim of these experiments is to discover the effects of different controllable factors of machining process on the material removal rate (MRR) and roughness (Ra) index of the output parts. The MRR is an important indicator in the efficiency and cost effectiveness of the process. The Ra index is related to the surface quality of the processed parts.

Power, time off, voltage, servo, wire tension, wire feed rate (speed) and rotational speed are the candidate variables which have effect on the quality of output parts in this process. In this work in order to collect data, we used the dataset which is collected based on two L18 ($2^1 \times 3^7$) Taguchi standard orthogonal arrays. In these experiments, all of controllable factors are sampled in three levels as their minimum, middle and maximum values. Table I shows the selected factors and their values in different levels (for more information on orthogonal arrays, the procedure of selecting an orthogonal array and assigning factors to columns, refer to Phadke (1989).

Note that this process is a complex process and someone can consider more variables for this analysis. However, in this work, based on the result of our previous experiments and in order to reduce the complexity of our analysis, we decided to fix some variables during the experiments as the process parameters. The selection of the fixed parameters and variable controllable factors has been done based on domain experts' opinions and their previous experiences with this process. The fixed parameters of our experiments are shown in Table II.

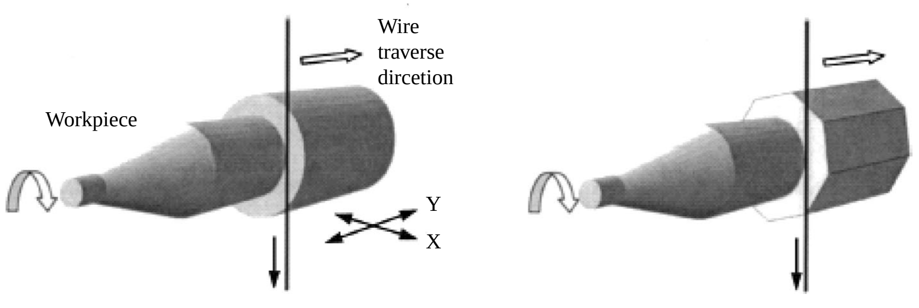


Figure 4.
The concept of turning with wire EDM

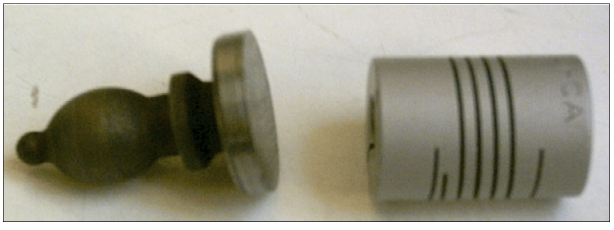


Plate 1.
A cylindrical wire EDM part

Table I.
Related factors and their levels

Factors	Factor levels 1	2	3
Power (current and ampere proportion)	10	11	12
Time off (microsecond); time interval between one discharge and the next	7	8	10
Voltage (volt); indicates potential difference during ionization of the gap	100	110	120
Servo (volt); indicates the theoretical voltage difference between wire and work piece during erosion	30	50	55
Wire tension (kilogram proportion); level of mechanical stress	14	16	18
Wire feed rate (speed) (mm/s); level of feed rate	7	8	9
Rotational speed (RPM)	16	30	45

Table II.
Parameters in these experiments

Parameter	Value
Maximum feed rate (mm/min)	1
Depth of cut (mm)	2
Diameter of specimens (mm)	10
Work piece hardness (HRC)	60-62
Material	1.7131 cemented steel
Depth of uniform hardness (mm)	2
Machining length (mm)	10

4. SOM results for WEDM process

In this work, SOM has been applied to model the WEDM process in order to discover the relations between machining controllable factors and the quality specifications of output products. Ra and MRR are process output factors; MRR is an important indicator of the efficiency and cost effectiveness of the process and Ra indicates the surface quality of the final product. These two factors indicate the machining quality. As discussed before, variables that can be controlled are power, time off, voltage, servo, wire tension, wire speed and rotational speed.

Our goal is to find a set of guiding rules to adjust the amount of controllable variables in order to maximize MRR and minimize Ra. Therefore, in the first step to reduce the complexity, it is necessary to select important variables in a simple and efficient method. Thus, we trained a SOM network with the originally collected data.

Map training and visualizing were performed in Matlab version 7, using its SOM toolbox (Alhoniemi *et al.*, 1997). The visualized results are shown in Figure 5.

As it can be seen in the Figure 5, there are ten coloured maps. The first one on the left top hand side is the U-matrix, which is a mean for finding possible clusters in the dataset. The other coloured maps are representations of seven controllable variables and two out put variables, respectively. Each cell in every matrix indicates a unique point in the state space of this process. Then, we can use these maps from two directions. First, by analyzing the values point to point and second by comparing the

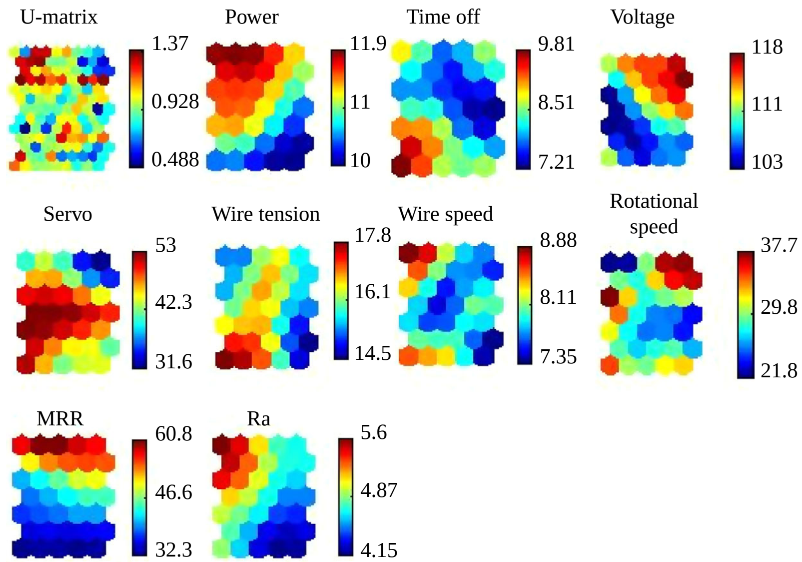


Figure 5.
U-matrix and component planes for WEDM process data

visual patterns and colour distributions in the matrices we can predict the outputs of the process for different values of input factors and we can find the most relevant variables to the output variables.

With a simple visual analysis of the coloured maps, comparing the distribution and pattern of coloured maps (each map represents one variable) the following could be concluded:

- Based on total pattern of colours, it can be seen that "power" is the most relevant attribute to "Ra" and has direct correlation with it. As the value of "power" is decreasing (from top left side of its matrix), the value of Ra is decreasing in the same direction and almost with same pattern.
- Again it is clear that "voltage" and "MRR" same as "power" and "Ra" have direct correlation with each other.
- "servo" has inverse correlation with "Ra" in some way. When the "Servo" is increasing.
- Wire tension, wire speed and rotational speed have no significant relation with outputs.

However, it is logically true, as maps show, MRR as the rate of removing material from the processed part and surface quality (inverse of Ra) are in conflict with each other. In other words, when MRR is increasing, consequently the quality of product surface is decreasing (Ra indicator is going up). Note that for the best processing condition, the MRR indicator should be high and the Ra indicator should be low.

Also, note that normally, in those cases with a lot of data, U-matrix visually illustrates the possible clusters within the processed data. Since, in our experiment, we collected data by a designed experiment, as U-matrix shows all the data are distributed uniformly and therefore, there is no peak or collection of data (cluster) in the U-matrix.

As mentioned before, our goal is to find a set of guiding rules for the WEDM process prediction, which can be helpful for controlling the output quality of products. For example, suppose that a customer order forces that the Ra should be less than five; in this case the process engineer can adjust the controllable factors regarding this quality condition and also maximizes MRR in order to minimize the processing time and consequently to minimize the production cost.

Note that although, in practice it is possible to extract the control guidelines visually from SOM maps, in this work for further analysis, we classify process outputs regarding the controllable variables.

This task is accomplished through decision tree algorithm, which is a powerful data classification algorithm using "ENVISIONER" a data mining tool developed by Neurosoft.

The final structure of the resulted decision tree is shown in Figure 6.

To test the efficiency of our results, we carried out some experiments. In these experiments, in order to produce parts with predetermined output specifications, we adjust controllable variables by the predictions of the classification tree and the results by SOM. We suggested the following experiments, including suggested values for input variables as well as their predicted output values. After execution of these experiments by the process operator and process expert, the results as shown in Table III were satisfying based on the expert opinions.

The experiments discussed here have been performed in the Machining Workshop Center of Isfahan University of Technology, Isfahan, Iran and the extracted control rules are now being applied in a look-up table which is used as guidelines for the operators.

5. Conclusions and future work

In this paper, SOM has been applied to the WEDM process as a simple and practical technique for process engineers to understand the complex relations among process variables without any mathematical or statistical computing. In order to analyze our results, we used another approach, decision trees. Both results were the same, while the SOM gave us more information about the importance of controllable variables regarding to their relations with output variables. This technique can be used as a multi-variable quality control tool in all kinds of machining processes. Although, there are a lot of different approaches for this classic process modelling problem, our claim is that since the main result of SOM is visual maps with a lot of easily extractable information for engineers, it can be very interesting tool for practitioners. Applying our suggested recommendations by the operators of this process and finding satisfying results comparing to our predictions, made both of research team and process experts happy.

The result of this work can be used as a main part of an automated process advisor and a commercial software solution.

The results of this work further can be used as an input for more advanced decision support systems, such as rule-based fuzzy expert systems, which provide smooth control rules and also are very useful in automatic prediction and control of complex processes.

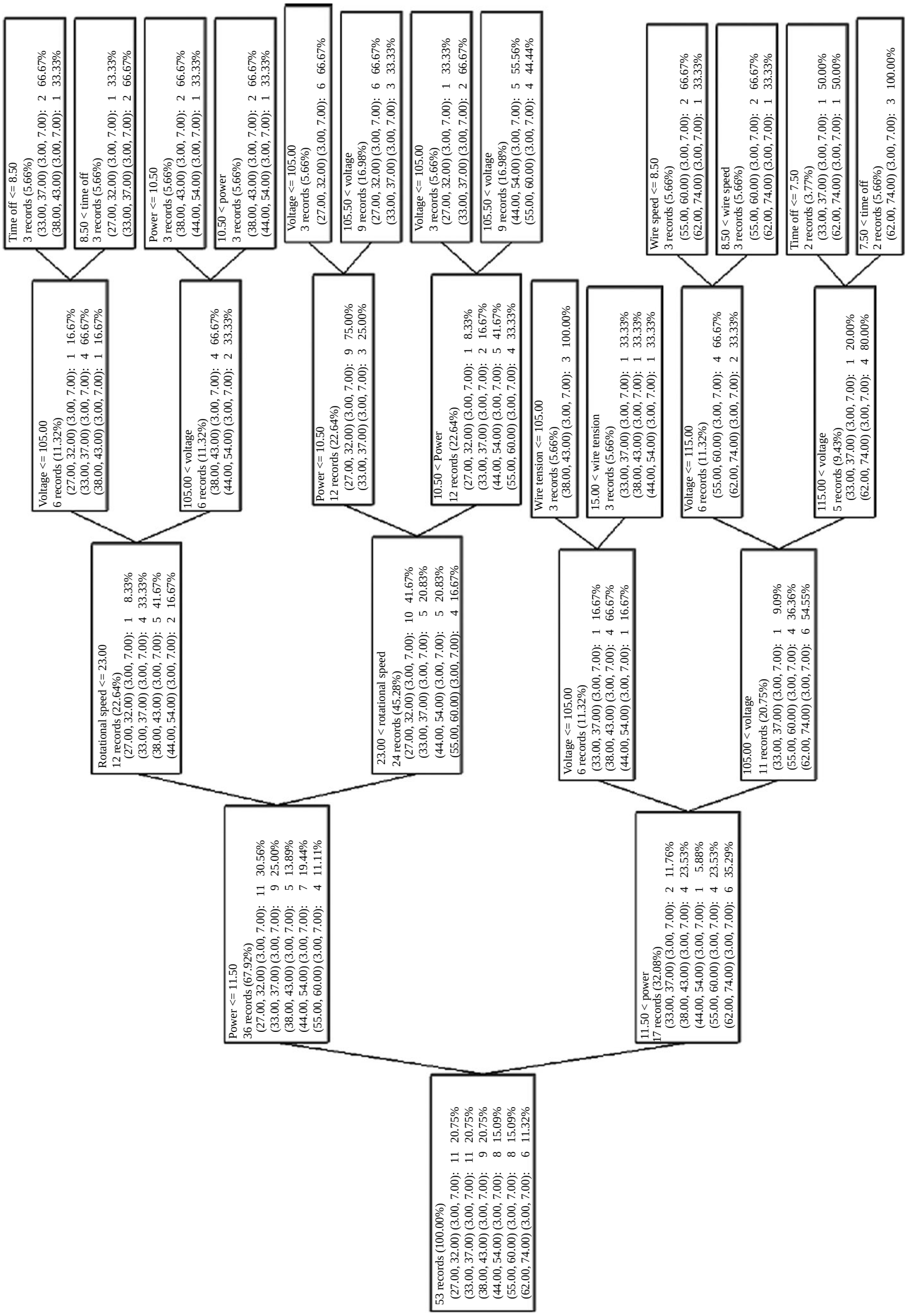


Figure 6.
Classifier decision tree

Table III.
Predicted and real outputs

Variable	Experiment 1	Experiment 2	Experiment 3
Power	$11 < p < 11.5$	Minimum = 10	12
Time off	$8.5 < t < 8.6$	8.5	8.6
Voltage	$116 < v < 118$	107	111
Servo	Minimum	42 < Servo < 45	41
Wire tension	15 < WT < 16	14.5	15.5
Wire speed	7.5 < WS < 7.8	< 7.3	9
Rotational speed	Maximum	30 < Rotational speed < 32	20
MRR	Predicted: 57 < MRR < 60 Real: 58.804	Predicted: < 32.5 Real: = 29.317	Predicted: 59 Real: 63.799
Ra	Predicted: < 4.6 Real: 4.515	Predicted: minimum value Real: 3.865 (very low for Ra)	Predicted: 6 Real: 5.758

Note

1. Unified distance matrix.

References

Alhoniemi, E., Himberg, J., Kiviluoto, K., Parviainen, J. and Vesanto, J. (1997), "SOM toolbox for Matlab", available at: www.cis.hut.fi/somtoolbox/documentation/somalg.shtml

Boniface, Y., Alexandre, F. and Vialle, S. (1999), "A bridge between two paradigms for parallelism: neural networks and general purpose MIMD computers", paper presented at International Joint Conference on Neural Networks, Washington, DC.

Englund, C. and Verikas, A. (2007), "A SOM-based data mining strategy for adaptive modelling of an offset lithographic printing process", *Engineering Applications of Artificial Intelligence*, Vol. 20 No. 3, pp. 391-400.

Eriksson, L., Antti, H., Gottfries, J., Holmes, E., Johansson, E., Lindgren, F., Long, I., Lundstedt, T., Trygg, J. and Wold, S. (2004), "Using chemo metrics for navigating in the large data sets of genomics, proteomics, and metabonomics", *Analytical and Bioanalytical Chemistry*, Vol. 380 No. 3, pp. 419-29.

Haykin, S. (1999), *Neural Networks a Comprehensive Foundation*, Prentice-Hall, Upper Saddle River, NJ.

Jorgensen, A.C., Rantanen, J., Luukkonen, P., Laine, S. and Yliruusi, J. (2004), "Visualization of pharmaceutical unit operation: wet granulation", *Analytical Chemistry*, Vol. 76 No. 18, pp. 5331-8.

Kohonen, T. (1995), *Self-organizing Maps*, Springer, Berlin.

Kohonen, T., Oja, E., Simula, O., Visa, A. and Kangas, J. (1996), "Engineering applications of the self-organizing map", *Proceeding of the IEEE*, Vol. 84 No. 10, pp. 1358-84.

Koua, E.L. (2003), "Using self-organizing maps for information visualization and knowledge discovery in complex geospatial datasets", *Proceedings of the 21st International Cartographic Conference (ICC), Durban, South Africa*.

Laine, S. (2003), "Using visualization, variable selection and feature extraction to learn from industrial data", PhD thesis, Helsinki University of Technology, Helsinki.

Li, S., Fevens, T., Kryzak, A. and Li, S. (2006), "Automatic clinical image segmentation using pathological modeling PCA and SVM", *Engineering Applications of Artificial Intelligence*, Vol. 19 No. 4, pp. 403-10.

Liu, X., Chen, X., Wu, W. and Zhang, Y. (2006), "Process control based on principal component analysis for maize drying", *Food Control*, Vol. 17, pp. 894-9.

Oja, M., Kaski, S. and Kohonen, T. (2001), "Bibliography of self-organizing map (SOM) papers", *Neural Computing Surveys*, Vol. 3, pp. 1-156.

Phadke, M.S. (1989), *Quality Engineering Using Robust Design*, Prentice-Hall, Upper Saddle River, NJ.

Ross, P.J. (1988), "Taguchi techniques for quality engineering", McGraw-Hill, New York, NY.

Sebzalli, Y.M. and Wang, X.Z. (2001), "Knowledge discovery from process operational data using PCA and fuzzy clustering", *Engineering Applications of Artificial Intelligence*, Vol. 14 No. 5, pp. 607-16.

Sheridan, C., O'Farrell, M., Lewis, E., Lyons, W.B., Flanagan, C. and Jackman, N. (2006), "Monitoring food quality using an optical fibre based sensor system – a comparison of Kohonen and back-propagation neural network classification techniques", *Measurement Science and Technology*, Vol. 17, pp. 229-34.

Simula, O. and Kangas, J. (1995), "Process monitoring and visualization using self-organizing maps", *Neural Networks for Chemical Engineers*, Elsevier, Amsterdam, pp. 371-84 (Volume 6 of *Computer-aided Chemical Engineering*, Chapter 14).

Tomsich, P., Rauber, A. and Merkl, D. (2000), "Optimizing the parSOM neural network implementation for data mining with distributed memory systems and cluster computing", paper presented at 11th International Workshop on Database and Expert Systems Applications (DEXA'00), Greenwich, London, September 6-8.

Ultsch, A. (1993), "Self organized feature maps for monitoring and knowledge acquisition of a chemical process", in Gielen, S. and Kappen, B. (Eds), *Proceedings of the International Conference on Artificial Neural Networks*, Springer, Berlin, pp. 864-7.

Villmann, T., Merenyi, E. and Hammer, B. (2003), "Neural maps in remote sensing image analysis", *Neural Networks*, Vol. 16 Nos 3/4, pp. 389-403.

Yu, H.L. and MacGregor, J.F. (2004), "Monitoring flames in an industrial boiler using multivariate image analysis", *AIChE Journal*, Vol. 50 No. 7, pp. 1474-83.

Yu, H.L., MacGregor, J.F., Haarsma, G. and Bourg, W. (2003), "Digital imaging for online monitoring and control of industrial snack food processes", *Industrial and Engineering Chemistry Research*, Vol. 42 No. 13, pp. 3036-44.

Zhang, Y. and Dudzic, M.S. (2006), "Industrial application of multivariate SPC to continuous caster start-up operations for breakout prevention", *Control Engineering Practice*, Vol. 14, pp. 1357-75.

Further reading

Guo, D., Gahegan, M. and MacEachren, A.M. (2004), "An integrated environment for high-dimensional geographic data mining", paper presented at the Third International Conference on Geographic Information Science, Adelphi, MD.

Jamsa-Jounela, S.L., Vermasvuori, M., Enden, P. and Haavisto, S. (2003), "A process monitoring system based on the Kohonen self-organizing maps", *Control Engineering Practice*, Vol. 11, pp. 83-92.

Wang, D., Ressom, H., Musavi, M. and Domnisoru, C. (2002), "Double self-organizing maps to cluster gene expression data", *Proceedings of 10th European Symposium on Artificial Neural Networks* (*ESANN 2002*)*, Bruges, Belgium*.

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