ESANN'2009 proceedings, European Symposium on Artificial Neural Networks - Advances in Computational Intelligence and Learning. Bruges (Belgium), 22-24 April 2009, d-side publi., ISBN 2-930307-09-9.

SOM based methods in early fault detection of nuclear industry

Miki Sirola, Jaakko Talonen and Golan Lampi

Helsinki University of Technology - Department of Information and Computer Science
P.O.Box 5400, FI-02015 TKK - Finland

Abstract. Early fault detection in nuclear industry is studied. Tools have been developed for control room operators and experts in an industrial project. Self-Organizing Map (SOM) method has been used in combination with other methods. Decision support visualizations are introduced. The usability of methods have been tested and verified by constructing prototype systems. The use of SOM method in dynamic systems is discussed. Applications for industrial domain are presented. Data sets from a Finnish nuclear power plant have been analyzed. Promising results in failure management are achieved.

1 Introduction

Early fault detection is an important research issue in nuclear industry. The earlier the abnormal behavior in the process can be detected, the better possibilities there are to identify the problem in time and handle the recovery procedure as well as possible. We have developed tools to help operators in their daily work, and to help experts to understand better various phenomena in the process. For instance, regular isolation valve experiments carried out in nuclear power plants have unknown factors. Also instrument calibration problems can be revealed by using data analysis methods. The design basis events are also one important area.

Older nuclear power plants are going through modernization projects. This development has brought out new needs. For instance wide monitoring screens set up new requirements for presentation techniques. New contents are needed. In our industrial project we have developed new visualizations and visualization techniques for either new control rooms of new nuclear power plants or modernized old control rooms of old nuclear power plants.

This work is done in NoTeS project (Nonlinear Temporal and Spatial forecasting: modeling and uncertainty analysis) [1], which is a large three year research project participated by many Finnish universities and industrial partners. In NoTeS project a generic toolset for spatio-temporal forecasting and forecast uncertainty analysis is developed. Five different test cases are analyzed in different subprojects. In our subproject the industrial partner is Teollisuuden Voima Oy (TVO), Olkiluoto nuclear power plant.

As one research method prototypes of control room tools are develop to test different combinations of methodologies in practice. Somewhat similar verification procedures are used for instance in robotics, where intelligent movements are tested by building prototype robots. These sort of experimental results are very concrete, but not easily quantitatively measurable.

In many of our prototypes neural method Self-Organizing Map (SOM) [2] is in a central role and combined with other more or less traditional methodologies. We have also done traditional data analysis with nuclear power data, and training simulator data, and developed tools and methods to help this process in the nuclear field. Visualization issues are important part of both these research directions. Many methods and tools could be rather easily generalized or modified to cover other application areas too.

Process failure detection with complex data analysis methods is a widely studied research area. Many applications of decision support also exist. The literature can be divided into three categories. In the first category is described how a new method or model is utilized in decision support. The second category articles describe a constrained decision support system prototype or tool for a specific application. The third category describes how a decision support system is constructed, validated, or models selected. A more detailed literature survey and analysis is in [3].

2 SOM method in dynamic systems

Originally the SOM algorithm was not designed for changing time. The SOM is able to analyze ideally only static sets of data. Still many attempts to use SOM method in the analysis of dynamic data have been made. It has been used in many time-related problems especially in process modelling and monitoring. These problems have been discussed for instance in [4].

One possibility to describe dynamical behaviour is visualization of trajectories, which link together the adjacent winner neurons (BMU) in the SOM grid. The SOM trajectories have such features as linked BMUs, where each BMU represents a certain instant of time. The operator can learn to adjust the control variables according to the visual impression so that the process stays in desired regions of the map.

An example of using trajectory expression in dynamic system is in Figure 1. Here the trajectory of the U-matrix shows visually how an imaginary accident scenario proceeds in a nuclear power plant. U-matrix is a visualization method that reveals the cluster structure of the data. The data is from Finnish Olkiluoto nuclear power plant training simulator. In normal operation the trajectory stays in a certain region in the U-matrix, but when the transient becomes big enough the trajectory moves out to another region. Different scenarios are somewhat separable in the U-matrix [3].

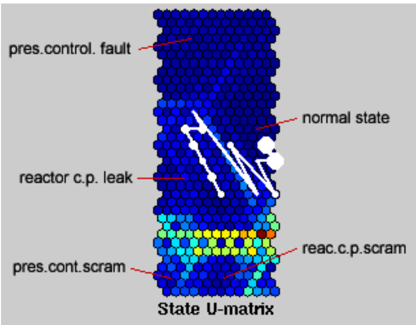

Fig. 1: U-matrix trajectory shows dynamical behaviour in the process.

ESANN'2009 proceedings, European Symposium on Artificial Neural Networks - Advances in Computational Intelligence and Learning. Bruges (Belgium), 22-24 April 2009, d-side publi., ISBN 2-930307-09-9.

In the following we go through some examples of the attempts to handle spatio-temporal problems with SOM method. In operator maps the dynamical behaviour is described with linear or nonlinear estimators. Also probabilistic models can be used. The operator maps with linear estimators have been applied in various problems. One example of this is image segmentation with textures [5].

Often the time dependency is described by a vector built from sequences [6] [7]. Data coding or time warping can be used as well [8]. Known SOM models for temporal sequence processing are Temporal Kohonen Map (TKM) and Recurrent Self-Organizing Map (RSOM) [9]. In these models the details of learning algorithms and models are different, but in both models each neuron of an ordinary SOM is supplied with a leaky integrator that gives a kind of memory to the system.

Wave propagation in self-organizing maps can be used in the representation of temporal sequences [10]. A neighbourhood map is an example of building a predictor for piecewise segmentation and identification of time series [11]. A model called SOFTPAR is based on a travelling wave through the nodes of a Self-Organizing Feature Map (SOFM) [12]. This kind of model has been used for instance in a robot application for landmark recognition. Also some biologically inspired versions of self-organizing maps have been developed, such as Dynamic SOM (DSOM) [13].

3 Applications for industrial domain

Applications for industrial domain concentrating on visualization issues developed in our project are reported in [14]. Several smaller studies are carried out in this project named as process and progress visualization, failure detection and separation, leakage detection by adaptive process modelling, and feature selection on process fault detection.

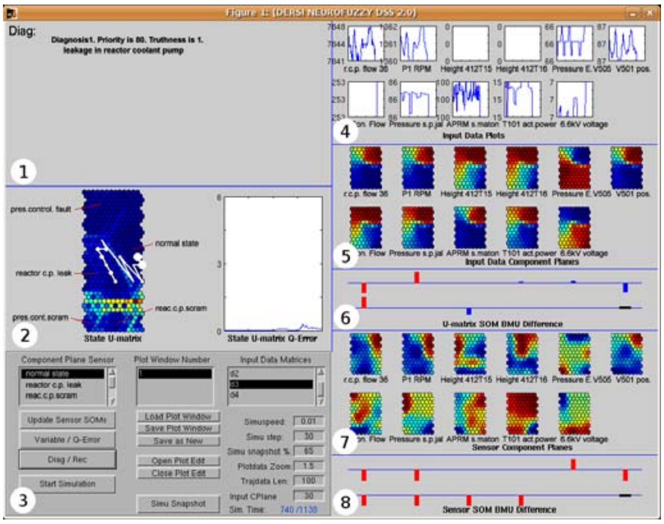

Fig. 2: DERSI Man-Machine Interface (MMI).

A SOM based decision support system for industry is under development [3]. It is a prototype of a control room tool for operator or analysis tool for expert user. It will be used in failure management of nuclear power plants. The tool combines neural methods and knowledge-based methods. Informative decision support visualizations based mainly on Self-Organized Map (SOM) methods and advice by rule-based reasoning are given. The tool will be installed for test use in Olkiluoto plant.

The prototype named DERSI is a Matlab software program built on top of Matlab extension SOMToolbox [15]. DERSI includes such visualizations as SOM maps for normal data and failure data, state U-matrix, quantisation error for both state U-matrix and component plane, progress visualizations and time curves, see DERSI Man-Machine Interface (MMI) in Figure 2.

The failure management scenario analyzed in Figure 2 is simulated with the Olkiluoto training simulator. A leakage has appeared in the main circulation pump. The control room tool has just identified the leak, and the rule-based is reasoning the first diagnosis of the event. The trajectory in the state U-matrix places oneself on specific fault area. Clear differences can be noted in the normal operation SOM maps and failure SOM maps.

Detecting pre-stage of process fault from an Olkiluoto dataset is one of our current studies. Process data was stored in two months period in 2007. Set has more than 300 variables. Most of the variables are from turbine section of the plant, where exists an event in this period. Relevant signals were selected by using a priori information of the process. These signals were monitored by SOM.

Signals are pre-processed during the analysis. Signals are filtered by moving average (MA) and range scaled in every time step [16]. Minimum and maximum values of each process variable have been collected from dozens of datasets of OL1 and OL2 reactor units and stored to database.

Aim was to create simple enough process visualization for operators. SOMs of certain signals were visualized in time steps and four time step visualizations are shown in Figures 3 and 4. The variation in the shape of the SOM maps is a feature of SOMToolbox [15], not a feature of SOM method itself. It is also possible to standardize the size of the map to observe more carefully only the variations in the variable correlations. Although the sizes of maps change here, the number of neurons does not change.

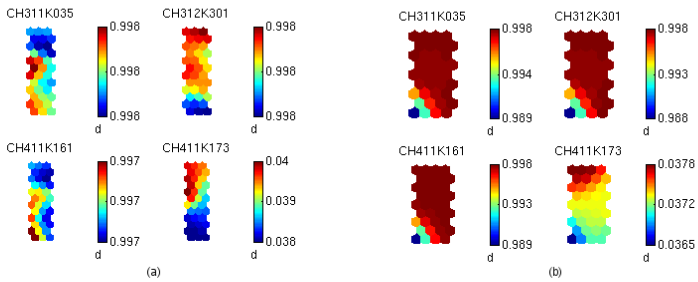

Fig. 3: SOMs before fault in turbine section, (a) normal operation condition, one day before process fault, (b) process one hour before fault.

There is an advantage in range scaling compared to zero mean unit variance-normalization, when SOM cell visualization is used. When range scaling is used, pre-

ESANN'2009 proceedings, European Symposium on Artificial Neural Networks - Advances in Computational Intelligence and Learning. Bruges (Belgium), 22-24 April 2009, d-side publi., ISBN 2-930307-09-9.

processing can be performed every time step and SOM have meaningful values. Scales in maps are comparable to the maximum values of the signals. Operators see directly, if process signal values are in right operational area. Process changes and correlations to other signals from visual representation can be detected.

In the normal condition the nuclear power plant energy production is maximized. Variables CH311K035 – sum of steam flows, CH312K301 – feed water flow and CH411K161 – pressure before high-pressure turbine are near maximum values (0.997 – 0.998). CH411K173 – pressure after low-pressure turbine 2 is near minimum value (maximum and minimum values are stored values in database). There is no clear dependences between these variables and the shape of maps are high and narrow, see Figure 3 (a).

Pre-stage of the process fault is detected by change of scale of the map and correlation between three variables in Figure 3 (b). In this situation operators are expected to use their knowledge of the process or decision support to make right corrections to the process.

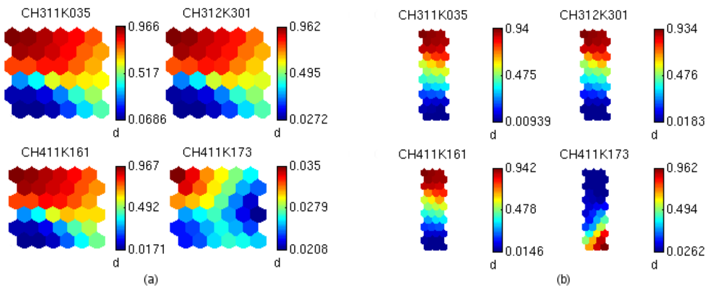

Fig. 4: SOMs after fault in turbine section. (a) Fault situation. (b) Process one day after process fault including recovery to normal process.

When fault has occurred, maps are wide and all signals are correlated. Also scales of three variables are almost from zero to one, see Figure 4 (a). This fault state can also be detected by other indicators at the power plant. State of the process begins to recover after corrections by operators. Pressure after low-pressure turbine is clearly negative correlated to other signals and maps are again narrow, see Figure 4 (b). Normal condition is reached when maps are similar to those in Figure 3 (a).

With the SOM maps the process transition can be noticed hours before the fault. It is possible to begin the planning and the realization of the corrective actions already then. One difficulty is to find the boundary surface from the dynamical changes in the SOM maps. In this kind of study it is also difficult to define repetitive measurable criteria, which are commonly used in studies concentrating on methodology development.

4 Discussion

SOM based methods in combination with some more or less traditional methods have been used in early detection of faults in nuclear industry. The methods and various combinations of them have been tested. The usability is shown e.g. by prototyping tools taking also into account practical views for instance in visualization.

Promising results in early fault detection have been achieved with the developed visualizations. For real operators part of the data-analysis techniques and concepts seem difficult. These tools are more suitable for plant experts to help them in process analysis by increasing understanding of various phenomena. With efficient training it is possible to introduce new tools for control room operators as well.

References

[1] R. Ritala, E. Alhoniemi, T. Kauranne, K. Konkarikoski, A. Lendasse, and M. Sirola, Nonlinear temporal and spatial forecasting: modeling and uncertainty analysis (NoTeS) – MASIT20. MASI Programme 2005 – 2009 Yearbook 2008, Tekes, 2008.

[2] T. Kohonen, *The self-organizing map*. Springler, 1995.

[3] M. Sirola, G. Lampi, and J. Parviainen, Failure detection and separation in SOM based decision support. Proceedings of Workshop on Self-Organizing Maps (WSOM'07), 2007.

[4] G. Barreto, A. Araujo, H. Ritter. Time in self-organizing maps: an overview of models. International Journal of Computer Research, 2001.

[5] J. Lampinen, E. Oja. Self-organizing maps for spatial and temporal models. Scandinavian Conference on Image Analysis (SCIA). Helsinki, Finland, 1989.

[6] J. Kangas. On the analysis of pattern sequences by self-organizing maps. Ph.D. Thesis, Helsinki University of Technology, 1994

[7] D. L. James, R. Miikkulainen. SARDNET: A self-organizing feature map for sequences. Advances in Neural Processing Systems. MIT Press, Cambridge, 1995.

[8] K. Torkkola. Warpnet: self-organizing time warping. Workshop on Self-Organizing Maps (WSOM 1997).

[9] M. Varsta, J. Millan, J. Heikkonen, J. Lampinen. On the convergence properties of the temporal Kohonen map and the recurrent self-organizing map.

[10] B. Dobrzewski, D. Ruwisch, M. Bode. Wave propagation in self-organizing feature maps as means for the representation of temporal sequences. International Conference on Artificial Neural Networks (ICANN 1997). Lausanne , Switzerland, 1997.

[11] C. Fancourt, J. Principe. A neighborhood map of competing one step predictors for piecewise segmentation and identification of time series. International Conference of Neural Networks (ICNN 96). Washington, USA, 1996.

[12] N. R. Euliano, J. C. Principe. Spatio- temporal self-organizing feature maps. International Joint Conference on Neural Networks (IJCNN 96). Washington, USA, 1996.

[13] C. M. Privitera , L. Shastri. Temporal compositional processing by DSOM hierarchical model.

[14] M. Sirola, J. Parviainen, J. Talonen. G. Lampi, T. Alhonnoro, R. Hakala. Early fault detection with SOM based methods and visualizations - new contents for wide monitoring screens. EHPG-Meeting of OECD Halden Reactor Project. Loen, Norway, 2008.

[15] J. Vesanto, J. Himberg, E. Alhoniemi, and J. Parhankangas. Self-Organizing Map in Matlab: the SOM Toolbox. Proceedings of Matlab-DSP conference, 1999.

[16] D. Pyle. Data preparation for data mining. Morgan Kauffman, 1999.