Early fault detection with SOM based methods and visualizations – new contents for wide monitoring screens

Miki Sirola, Jukka Parviainen, Jaakko Talonen, Golan Lampi, Tuomas Alhonnoro, Risto Hakala
Helsinki University of Technology
Department of Information and computer science
P.O. Box 5400, FIN-02015 TKK, Finland
Miki.Sirola@tkk.fi, Jukka.K.Parviainen@tkk.fi, Jaakko.Talonen@tkk.fi, Golan.Lampi@tkk.fi, Tuomas.Alhonnoro@tkk.fi, Risto.M.Hakala@tkk.fi

Abstract

The modernization process in control rooms of nuclear power plants has risen up new needs. For instance, wide monitoring screens set up many new requirements for presentation techniques. New contents are called for. In this paper we present various visualizations developed in an industrial project during several years period. Many of them are based on Self-Organizing Map (SOM) neural method. The industrial partner in the project is Teollisuuden Voima Oy (TVO), Olkiluoto nuclear power plant. The main goal in this project is early detection of faults including identification and separation of various failure types. Related work about process presentation is also shortly discussed.

1. INTRODUCTION

Many control rooms of nuclear power plants are going through modernization projects right now. The possibilities in process presentation are changing. For instance, wide monitoring screens set up many new requirements for presentation techniques. New contents for these wide screens are needed. Just displaying the same figures in bigger scale is not a big improvement.

In this paper we present visualizations developed in an industrial project during several years period. Many of them are based on a neural method Self-Organizing Map (SOM) [1]. The work is done in NoTeS project (Nonlinear Temporal and Spatial forecasting: modelling and uncertainty analysis) [2], which is a large research project including 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. This work is done in a subproject concentrating to support operational decisions at nuclear power plants. The industrial partner in this test case is Teollisuuden Voima Oy (TVO), Olkiluoto nuclear power plant. The main goal in this project is early detection of faults. This includes both identification and separation of various failure types.

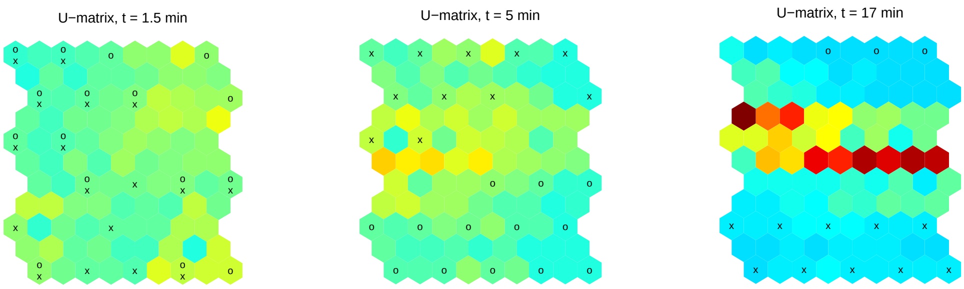
About process presentation and visualization also other studies are made. For example, in nuclear field [3] and other industrial branches [4][5] various techniques have been developed. Also decision support visualizations [6][7] can be found from the literature. A modern training simulator construction and assessment including the user interface in the Finnish Loviisa plant is described in [8].

2. PROCESS VISUALIZATION

In this section process visualization techniques and visualizations are presented. Several separate studies will be shortly introduced concentrating on the visualization issues. All studies have various other goals in operator support in addition.

2.1 Feature selection on process fault detection

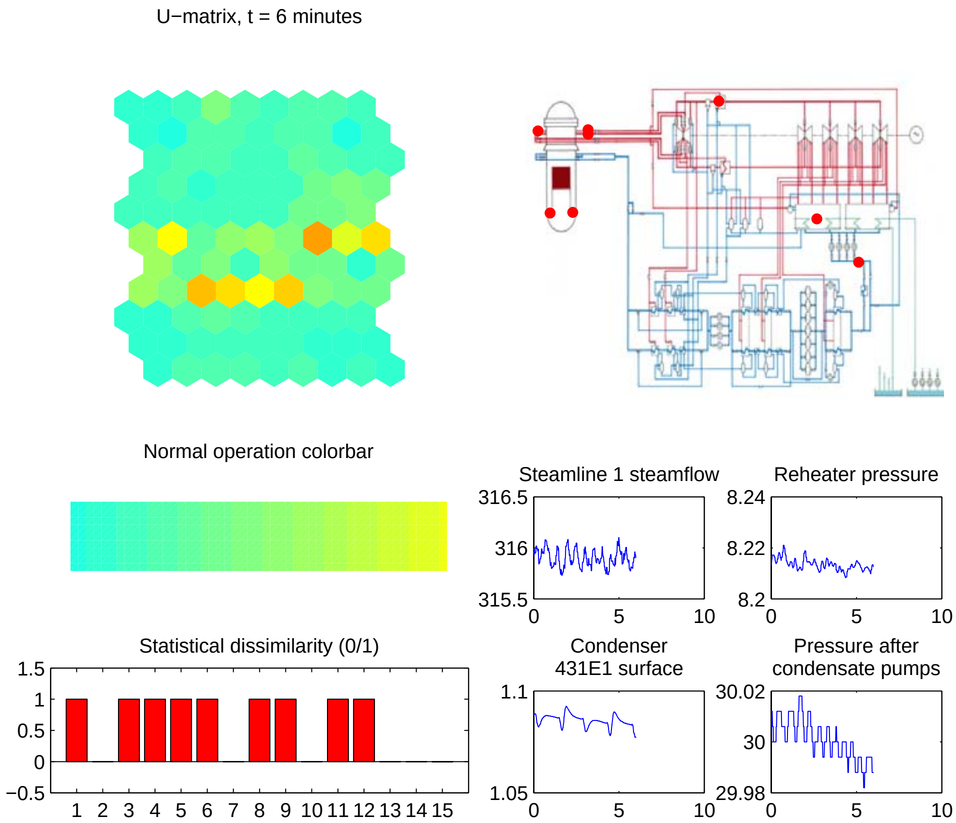
Feature subset selection is an essential part in data mining applications. Here, feature subset selection is integrated into real time process fault detection [9]. Various methods based both on dependency measures and cluster separability measures are used. A tool for process visualization is developed. Experiments on nuclear power plant data are carried out to assess the effectiveness and performance of the methods. The visualizations of this work help in early detection of failures. In a leak scenario an illustrative example is seen. The data used in this study is from the Olkiluoto nuclear power plant training simulator.



"Figure 1. Scenario: 0–10% leakage in the main circulation pump. SOM visualization of three different moments. Normal reference state and current state are marked with "o" and "x" respectively".

In Figure 1 SOM mappings are seen from three different moments. In the first one the leak scenario is just about to begin, and all colours are in the normal colour range. In the third one the plant is already shutdown, and the failure is obvious, as also the SOM mapping shows it with the many colours that are out of the normal colour bar (see also Figure 2). The interesting part is the second one in the middle in Figure 1, where only minor changes have happened in the process in the beginning of the scenario, but already some colour changes can be noted in the SOM map. This is a good example of the possibility for an early detection of faults with this tool.

In Figure 2 various visualization of the X-detector tool are seen. It presents the same scenario as Figure 1. The shot is from quite beginning of the scenario. In addition to the SOM map colouring changes also the KS-test can detect anomalities already in an early phase, when e.g. the changes in the time curves are still very small. Note also that the locations of the interesting variables selected at each moment are marked in the PI diagram. The most important events of the leak scenario are listed in Table 1.



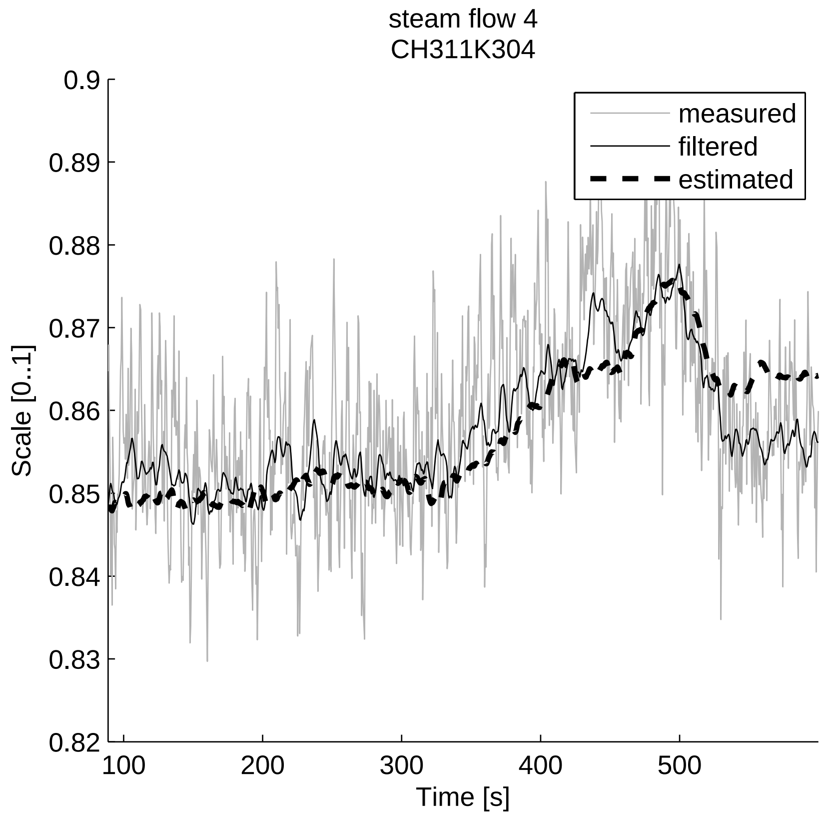
"Figure 2. Control room visualization, Man-Machine Interface (MMI): FISS (Fault Indication SubSystem) combined with statistical Kolomgorov-Smirnov test (KS-test), process flow diagram and selected process variable graphs. A red bar on a given variable indicates negative KS-test i.e. dissimilarity between two probablility distributions".

"Table 1. The most important events in the leak scenario. P1 is the main circulation pump".

Time (min)	Event
1:00	The fault starts evolving
5:48	Controlled are floor drain sensor triggered
9:34	Rotation difference in P1 detected
13:49	Reactor scram triggered by leakage control

2.2 Leakage detection by adaptive process modelling

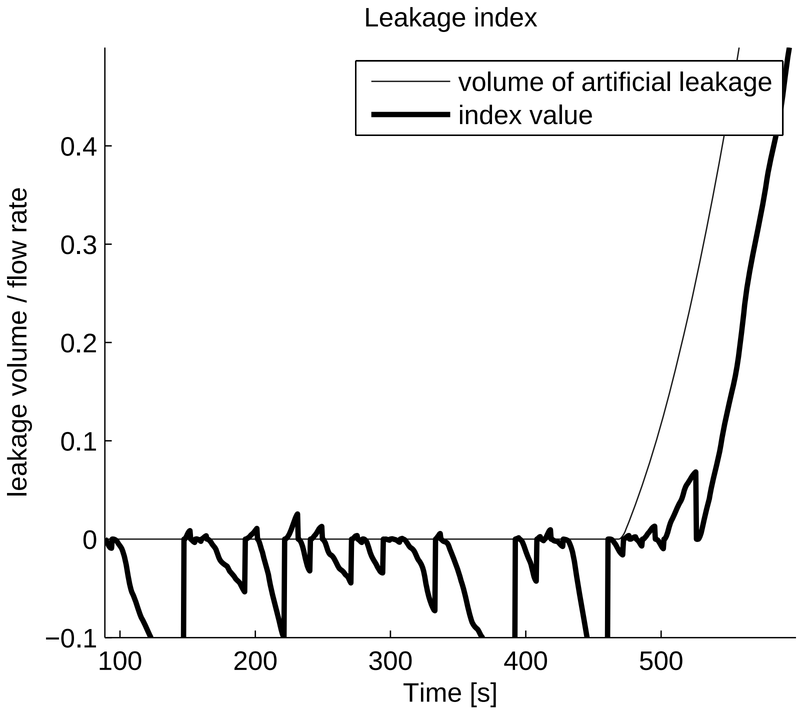
An adaptive approach for time series modelling and steam line leakage detection is used in another our study [10]. Here, weighted recursive least squares (WRLS) method is used in modelling. Interpretive variables of an adaptive model should be linearly correlated to ensure a robust model. In this study it is ensured by examing eigenvalues and eigenvectors of the principal component analysis (PCA).



"Figure 3. Model with artificial leakage. Leakage starts at t = 470 s. Steam flow 4 is estimated using three interpretative features: sum of steam flows, high-pressure turbine-inlet pressure and high-pressure turbine feed water (HPFW) piston position. All data vectors were scaled from zero to one, minimum to maximum value of each variable".

The method is applied to a time series from boiling water reactor (BWR) type nuclear power plant. The method is updated and used each time step to detect leakages in steam lines. Developed leakage detection index is based on the model estimation error. The method is more convincing in small pipe flows, because there are other ways to detect bigger volume leakages, such as moisture meters and flow or level meters in floor drains. Data from design based events from Olkiluoto plant was analyzed. Because no real leak scenario was found from these data sets, the data was manipulated to be able to test and demonstrate the leakage detection method.

The visualizations of leakage detection method are seen in Figure 3 and Figure 4. In Figure 3 in the end of the scenario the clear difference between filtered and estimated values reveals the leak. A visual expression for the leakage index itself is seen in Figure 4. In this scenario expressed in both figures the leak appears to one of the main steam lines.

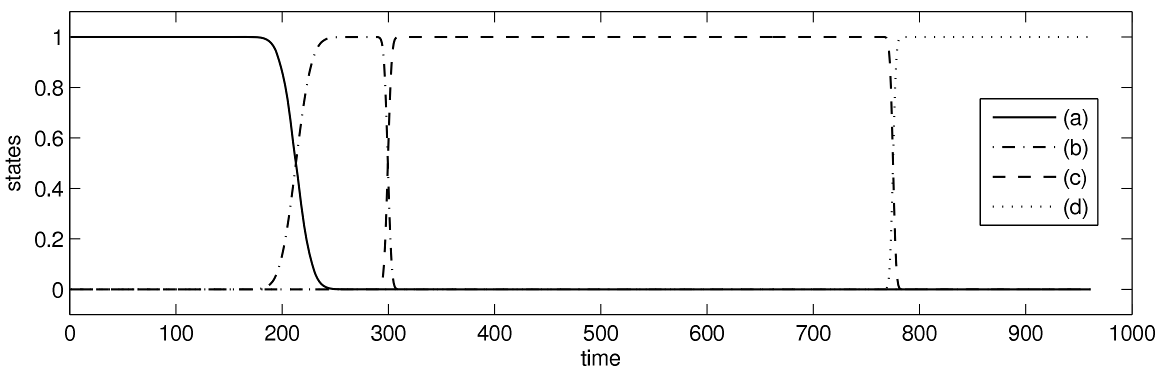


"Figure 4. The leakage index. Thin line is propotional to steam flow 4. Wide line is estimated leakage index value".

2.3 Process state and progress visualization

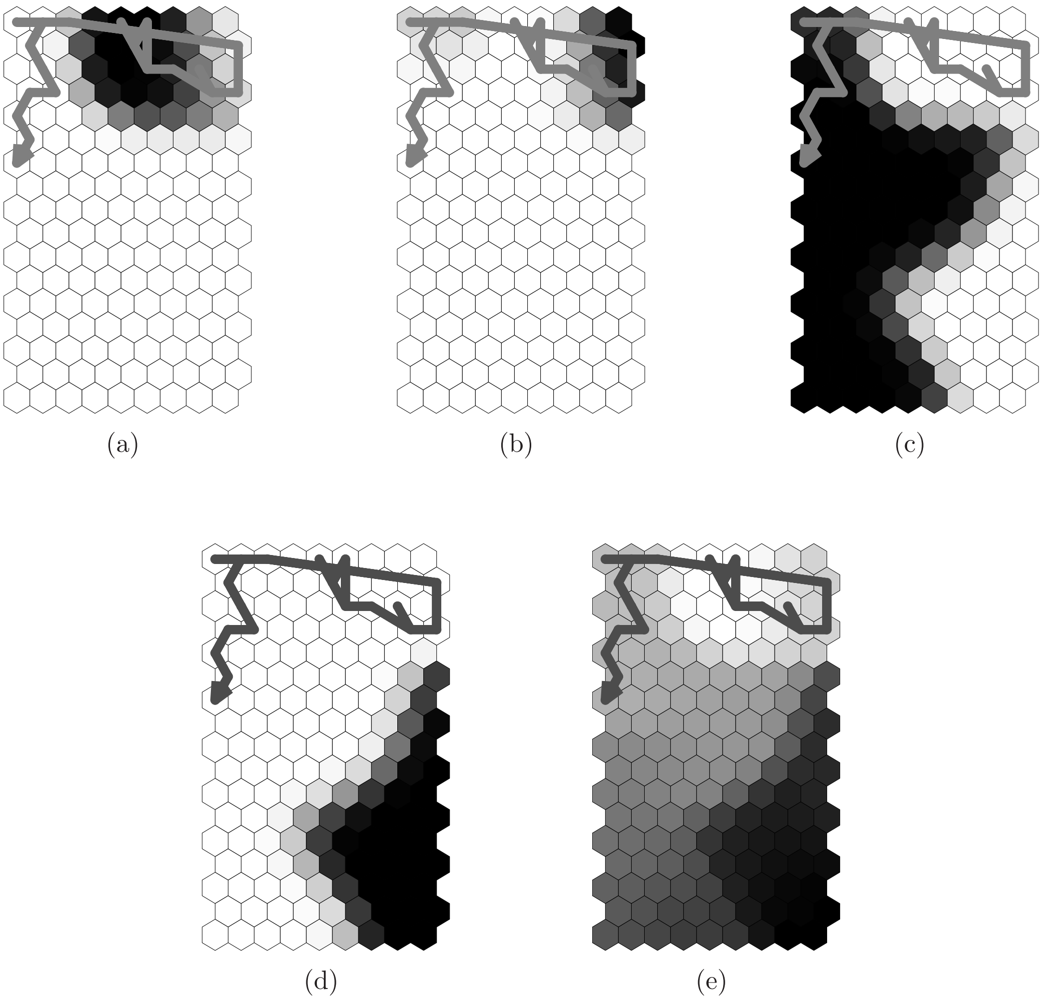
In a little earlier study the self-organizing map (SOM) is used in data analysis for resolving and visualizing nonlinear relationships in complex data [11]. An application of the SOM for depicting state and progress of a real time process is presented. The self-organizing map is used as a visual regression model for estimating the state configuration and progress of an observation in process data.

The technique is used for examining full-scope nuclear power plant simulator data from Olkiluoto power plant training simulator. One aim is to depict only the most relevant information of the process so that interpreting process behaviour would become easier for plant operators. In our experiments, the method was able to detect a leakage situation in an early stage and it was possible to observe how the system changed its state as time went on.



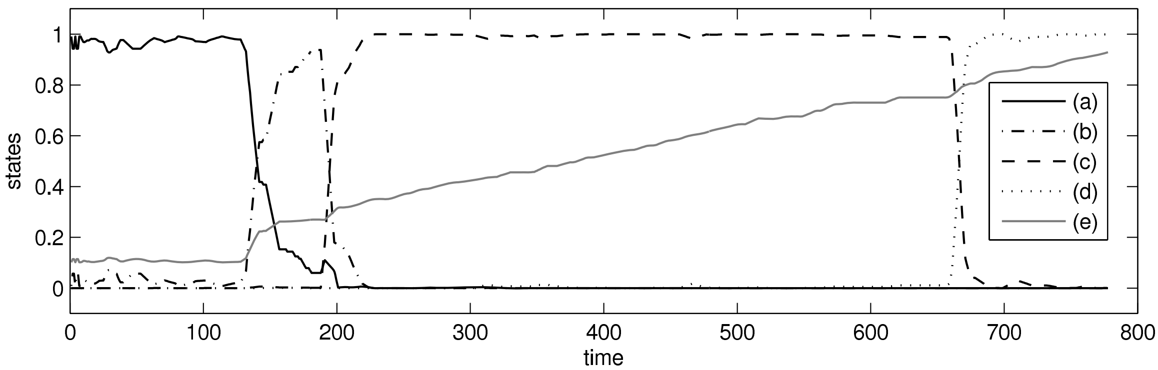
"Figure 5. The states in one data set (I) as a function of time. (a) corresponds normal state, (b) leakage state, (c) partial reactor shutdown state, and (d) reactor shutdown state".

The scenario analyzed in this study has many similarities to the scenario in section 2.1. In the beginning the process is in normal operation state. The leakage appears to high-pressure preheater and the process drifts into an abnormal state. The leakage leads to a bypass of the preheater, which is followed by a partial reactor shutdown and the reactor pressure drops dramatically. As a result of the bypass, feed water temperature starts to decrease. Finally, after a few minutes, the turbine and reactor are shutdown. Four different states in this scenario are presented in Figure 5.



"Figure 6. A component plane representation of the trained SOM. Only component planes corresponding (a) normal state, (b) leakage state, (c) partial reactor shutdown state, (d) reactor shutdown state, and (e) progress are displayed. Dark colour on a cell indicates high component value. The trajectory depicts a sequence of observations x(100)-x(250) from data set (II) mapped on the SOM. The process starts in normal state and progress to the partial reactor shutdown state".

Two different data sets are used in this study. They represent approximately the same leak scenario with somewhat deviating ramps. The first data set (I) is used in teaching the SOM, and the other (II) in the analysis. In Figure 6 a component plane representation of trained SOM is seen including the progress variable. The predictions for state and progress are seen in Figure 7. The progress valiable in this study is a unique concept, which can also be argued.



"Figure 7. A 10-second running average of the predictions of state and progress for data set (II). (a) corresponds normal state, (b) leakage state, (c) partial reactor shutdown state, (d) reactor shutdown state, and (e) progress. The progress values have been scaled so that they are plotted relatively on the same scale as time values in the training data but between [0,1]. Also the sum of state values for each time value equals one as in the training data".

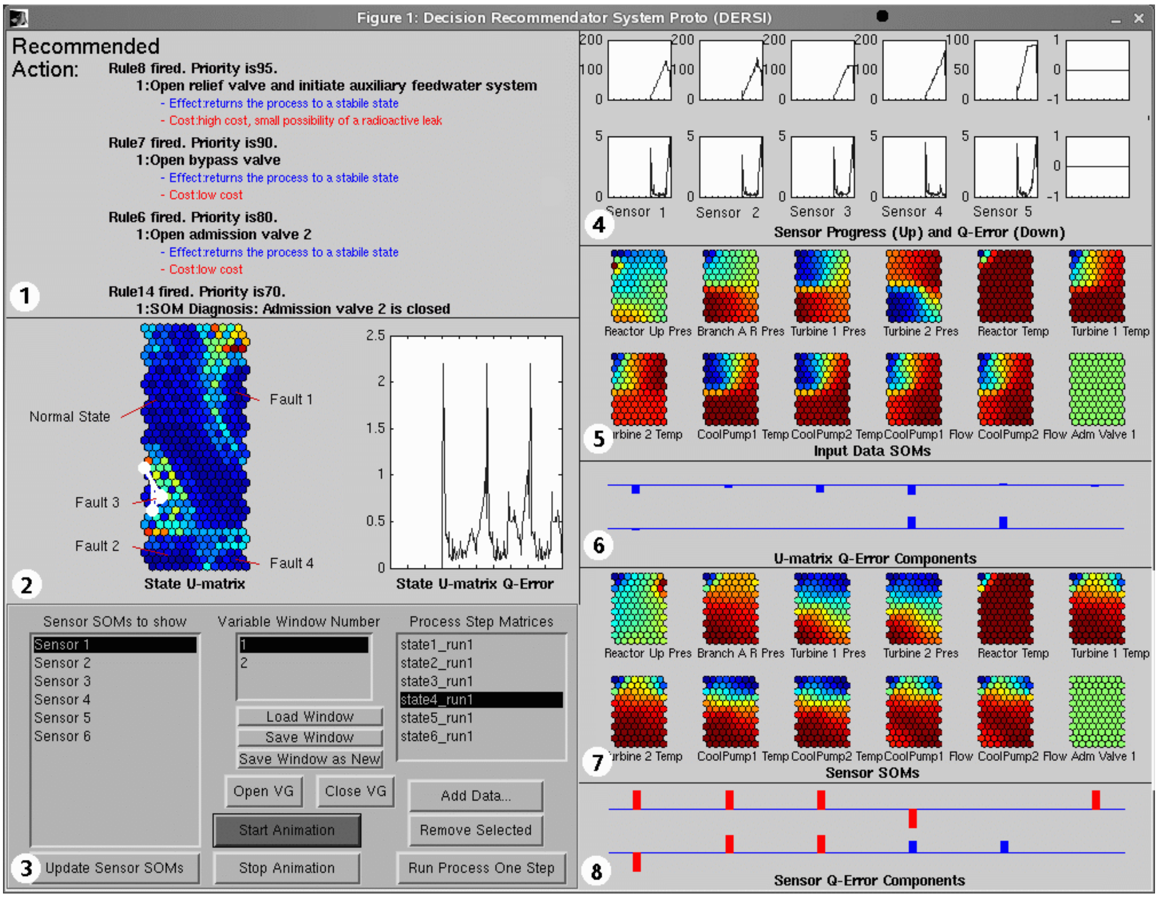
The study examines an application of the SOM to process state monitoring. The purpose is to depict a complex process so that it would be easily observable for plant operator. Instead of visualizing a set of process variables, the prediction of state and progress are visualized. The operator can observe the state and progress in real time. The strength of this method is in hiding unnecessary information from the operator. With this method it is possible to in addition to determining the state to see how the process has reached the state.

2.4 Failure detection and separation

A SOM-based decision support system is under development [12]. It is a prototype of a control room tool for opearator or analysis tool for expert user. It is supposed to be applied in failure management of nuclear power plants. The tool combines neural methods and knowledge-based methods. It gives informative decision support visualizations based mainly on Self-Organizing Map (SOM) methods, and gives advice produced by rule-based reasoning. The plan is to install the new version of the tool for test use in Olkiluoto plant.

The prototype is named DERSI. It is a Matlab software program built on top of Matlab extension SOMToolbox [13]. 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 (compare section 2.3) and normal time curves. The DERSI Man-Machine Interface (MMI) is seen in Figure 8.

The failure management scenario analyzed in Figure 8 is shortly presented in the following. The scenario is simulated with a Simulink process model. The problem is an admission valve that is stuck in closed position. The rule base is reasoning several proposals with varying priorities to help the operator, see Frame 1 in Figure 8. The scenario is analyzed in detail in [12].

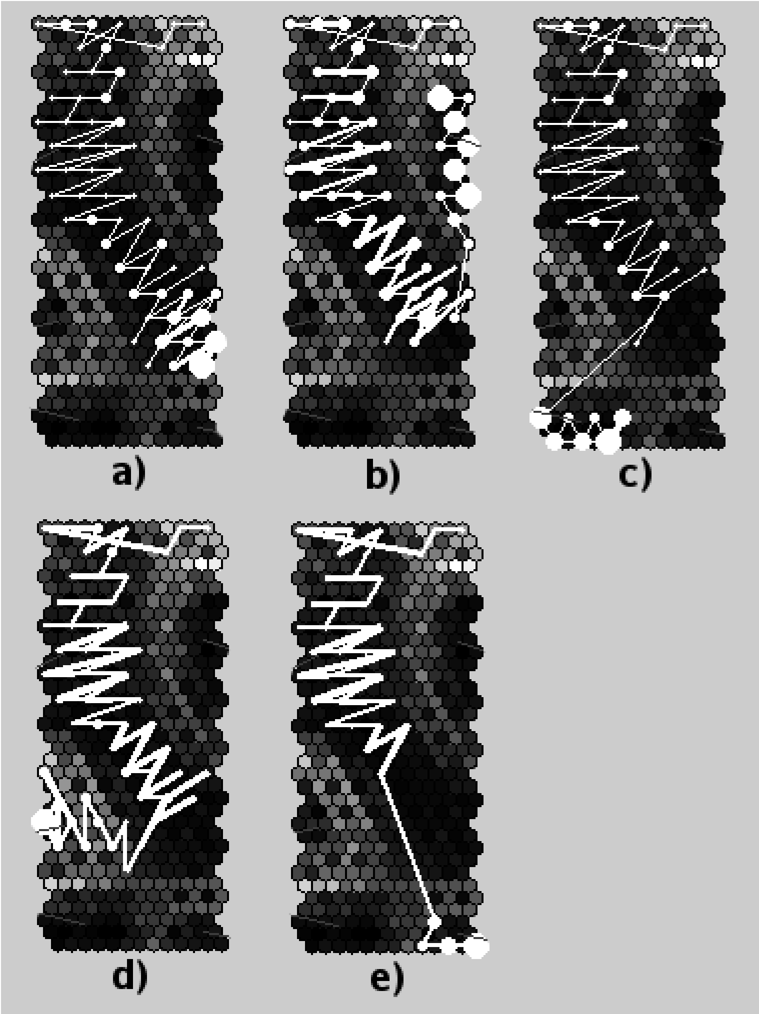


"Figure 8. DERSI Man-Machine Interface (MMI)".

In Frame 2 of Figure 8 the trajectory in the state U-matrix places oneself on specific fault area. The U-matrix quantisation error is seen in the same frame. Frame 3 inludes menus and buttons to operate the tool. In Frame 4 are seen the state and progress visualizations, and quantisation errors of sensors. The Frames 5 and 7 gives SOM mappings for selected variables for failure data and normal data. In comparing these mappings for instance lost correlation in turbine pressures (see Frame 5) can be noticed. Frames 6 and 8 show the component plane quantisation errors as bars of varying height and colour.

Quantisation error is a clear indicator of a failure in many cases in fault detection. U-matrix trajectory crossing cluster borders in another indicator of failure. Failure separation with these techniques is studied more in [14]. In Figure 9 five different failure management scenarios are separated from each other with U-matrix trajectory visualizations.

The five scenarios in Figure 9 are a) normal process state, b) leakage between reactor and preheater, c) leakage between turbine and condenser, d) admission valve accidentally closes (same as in Figure 8), and e) leakage in the cooling system. The scenarios are discussed in detail in [14]. In each scenario the temperatures and pressures in the corresponding area react abnormally.



"Figure 9. U-matrix with trajectories for different failure scenarios".

3. CONCLUSIONS

Results from an industial project concentrating on visualization issues have been presented. These visualizations are all potential contents for wide monitoring screens for new modernisized control rooms among many other alternatives. The use of these visualiztions is possible of cource also in normal size displays. Most of these visualizations have connections to data analysis techniques.

From the industrial point of view it is useful for the experts to understand various phenomena in the process. For instance, regular isolation valve experiments carried out in nuclear power plants seem to have unknown factors. Also instrument calibration problems in nuclear power plants could be revealed by data analysis methodologies. The design basis events are one interesting area. The basic construction of a nuclear power plant [15] has to be taken into account in the analysis.

Some promising results in the early fault detection have been achieved in the project. This has been named as one of the very key issues in this test case. Many visualizations developed in the project presented here help in this important task. Note that in real colours some of the visualizations are even more informative. In printed proceedings these figures have to be conformed into grey scale colouring. Depending on the visualization and the case for some part the grey scale visualization does a little better. For just separating the important factors the grey scale is good enough.

Part of the data-analysis techniques and concepts may seem difficult for the control room operators. Some tools are possibly more suitable for plant experts to help them in the process analysis. They may suit better to help them to understand better various phenomena in the process. By training and education also operators could widen their conceptualization, which would make it possible to introduce also new kind of tools in the control room use.

In future more feedback from the industrial partners will be taken into the design loop of these tools. Also practical point-of-views are needed. Developing and applying more specific data analysis techniques will go on, as well as the basic data analysis of new data sets.

4. REFERENCES

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

[2] 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 Technology Programme 2005 – 2009 Yearbook 2007, pp. 179-188, Tekes, 2007.

[3] J. Paulsen, “Design of process displays based on risk analysis techniques”, PhD thesis, Technical University of Denmark and Risø National Laboratory, Roskilde, Denmark, 2004.

[4] J. Vesanto, “Data exploration process based on the self-organizing map”, PhD thesis, Helsinki University of Technology, 2002.

[5] S. Laine, “Using visualization, variable selection and feature extraction to learn from industrial data”, PhD thesis, Helsinki University of Technology, 2003.

[6] E. Kazancioglu, K. Platts, and P. Caldwell, “Visualization and visual modeling for strategic analysis and problem solving”, Proceedings of International Conference on Information Visualization (IV’05), IEEE, 2005.

[7] O. Kwon, K. - Y. Kim, and K. C. Lee, ”MM-DSS: integrating multimedia and decision-making knowledge in decision support systems”, Expert Systems with Applications, Elsevier, 2006.

[8] J. Näveri, “Instructor station development in Loviisa power plant training simulator renewal”, Mater’s thesis (in Finnish), Helsinki University of Technology, 2007.

[9] T. Alhonnoro, and M. Sirola, “Feature selection on process fault detection and visualization”, Proceedings of European Symposius of Artificial Neural Networks (ESANN’08), 2008.

[10] J. Talonen, “Fault detection by adaptive process modeling for nuclear power plant”, Master’s thesis, Helsinki University of Technology, 2007.

[11] R. Hakala, T. Similä, M. Sirola, and J. Parviainen, ”Process state and progress visualization using self-organizing map”, Proceedings of International Conference on Intelligent Data Engineering and Automated Learning (IDEAL’2006), Springer-Verlag, 2006.

[12] M. Sirola, G. Lampi, and J. Parviainen, ”SOM based decision support in failure management”, International Scientific Journal of Computing, Vol. 4, Issue 3, pp. 124-130, 2005.

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

[14] 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.

[15] B. Pershagen, *Light water reactor safety*, Pergamon press, 1989.