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Abstract

Early fault detection is an important issue in nuclear industry. Methods based on self-organizing map (SOM) in dynamic systems are discussed and developed to help operators and plant experts in their decision making and used together with other methods. Visualization issues are in an important role in this research. Prototype systems are built to be able to test the basic principles. Five different studies are presented in detail. This report summarizes the test case 4 (TC4) "Decision support at a nuclear power plant" in NoTeS and NoTeS2 projects in TEKES MASI research program.

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Introduction

This report is a summary of the test case 4 (TC4) “Decision support at a nuclear power plant” in NoTeS (Nonlinear temporal and spatial forecasting: modelling and uncertainty analysis) and NoTeS2 projects carried out in the years 2006 – 2008 in TEKES MASI research program. The industrial partner in this subproject (TC4) was Teollisuuden Voima Oy (TVO Olkiluoto). TVO Olkiluoto provided us in TKK with plant data from design based events and with training simulator data. With the training simulator we executed together with TVO simulator experts data from various scenarios during two separate simulator sessions. The leak scenarios turned out to be the most fruitful in studying early detection of faults.

In NoTeS projects [1] a generic toolset for spatio-temporal forecasting and forecast uncertainty analysis was developed. Five different test cases were analyzed in different subprojects: time series estimation of electricity grid loading, analysis of large industrial data set (a pulp mill case), estimation and prediction for control in web production, decision support at a nuclear power station, and a robust segmentation method for premature infant brain MRI. The projects were done in co-operation with technical universities from Helsinki, Lappeenranta, Turku and Tampere. Several Finnish companies (Metso Automation, Nordkalk, Process Vision and Teollisuuden Voima) and research institutes (KCL: Oy Keskuslaboratorio and VSSHP: Varsinais-Suomen sairaanhoitopiiri) were also involved in the projects.

In “test case 4” (TC4) early detection of faults was studied including both identification and separation of failures. The following tasks were studied more in detail: process and progress visualization, failure detection and separation, leakage detection with adaptive modelling, feature selection and process fault detection, and detecting pre-stage of process fault. The self-organizing map (SOM) [2] was used in data analysis for resolving and visualizing nonlinear relationships in a complex process. An application of the SOM describing state and progress of a real time process was studied. The self-organizing map is used as a visual regression model for estimating the state configuration and progress of and observation in process data. One main tool was the process state trajectory in the process component plane. The failure detection is done with prototype systems.

In this report first the topic of SOM in dynamic systems is discussed, and then five different concrete studies in NoTeS projects TC4 are presented. Most of the studies use self-organizing map (SOM) method, but also many other methods are used and also combined with SOM. Visualization issues are paid special attention to. Two Master’s theses and many scientific papers were written about these studies in TC4, see e.g. References of this report.

SOM in dynamic systems

Self-organizing map (SOM) is an effective method in neural computing for analysis and visualization of multidimensional data. The SOM algorithm [2] resembles vector quantization (VQ) algorithms. The difference to VQ techniques is that the neurons are organized on a regular grid and along with the selected neurons also its neighbours are updated. The SOM performs an ordering of the neurons. The SOM is a multidimensional scaling method projecting data from input space to a lower, typically 2-dimensional output space.

A SOM consists of neurons organized in an array. The number of neurons may vary. 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 vector. The neurons are connected to adjacent neurons by a neighbourhood relation, which defines the structure of the map. Rectangular and hexagonal neighbourhoods are the most used topologies.

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 are calculated using some distance measure. The neuron c whose weight vector is closest to the input vector x is called the Best-Matching Unit (BMU):

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

where || . || is the distance measure.

Since BMU is found, the weigh vectors of 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 treated in similar way. The adaptation procedure stretches the BMU and its topological neighbours toward the sample vector. The SOM update rule for the weight vector of the unit i is:

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

where t is time. The x(t) is the input vector randomly drawn from the input data set 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 the distance of unit i from the winner unit c. It defines the region influence that the input sample has on the SOM.

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 [3].

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. 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 [4].

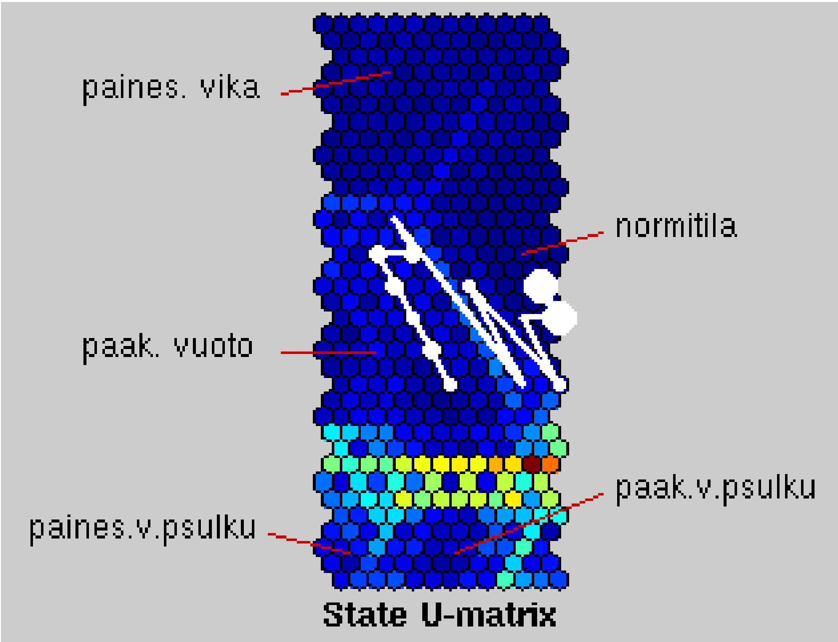

Figure 1. U-matrix trajectory shows dynamical behaviour in the process.

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].

The self-organizing map has been used in industry analysis [14]. The SOM method has been utilized in various applications, such as preprocessing of optic patterns, acoustic preprocessing process and machine monitoring, diagnosis of speech voicing, transcription of continuous speech, texture analysis, contextual maps, organization of large document files robot-arm control, telecommunications and SOM as an estimator [2].

Major application areas of image processing in practice are industrial machine vision – especially robot vision, printing, image transmission, medical imaging and remote sensing [2]. Especially for pattern recognition purposes uniform areas in pictures must be segmented and labelled for their identification. Medical image processing constitutes a major problem area of its own.

System theoretic aspects of industrial processes constitute their own problematic area. Such tasks as identification of the process state, error detection, fault diagnosis, diagnosis of machine vibrations, and plant diagnostic symptoms should be mentioned. One promising application area for the SOM is the visualization of system and engine conditions and large scale diagnostic problems [15].

Other industrial applications can be mentioned such as [2] monitoring paper machine quality, analysis of particle jets, flow regime identification and flow rate measurement, grading of beer quality, velotopic maps for well-long inversion, shear velocity estimation, intrusion detection, estimation of torque in switched reluctance motor, composite damage assessment, heating and cooling load prediction, identification of car body steel, operation guidance in blast furnace, controlling of 1000 amps, calculation of energy losses in distributed systems, evaluation of solid print quality, location of buried objects, analysis of brakes in a paper machine, classification of wooden boards, and timbre classification.

In this section we have introduced the Self-Organizing Map (SOM) algorithm, discussed about the use of SOM method in dynamic systems, and we went through some examples about the attempts to use SOM in time dependent applications. Finally we made a brief look into the industrial applications of SOM. The SOM method was not originally planned to handle dynamic behaviour, but many attempts to this direction e.g. in process modelling and monitoring have been made. Trajectory expression is one concrete way to show dynamical behaviour with SOM concepts.

Decision support at a nuclear power plant

Early detection of faults has been named as one key issue in NoTeS/NoTes2 project test case four (TC4). Tools have been developed to help the control room 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 methodologies. The design basis events are one important area.

Older nuclear power plants are going through modernization projects. This development 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 project with our industrial partner Teollisuuden Voima Oy (TVO) we have developed new visualizations and visualization techniques, which can be utilized either in new control rooms of new nuclear power plants or in modernized old control rooms of old nuclear power plants.

We have developed a prototype of a control room tool to test various combinations of methodologies. Neural method Self-Organizing Map (SOM) has been one central method in this research. Also various visualization methods have been tested with this tool. We have also done traditional data analysis with nuclear power plant data, and training simulator data, and developed tools and methods to help this process in the nuclear field. Also here the visualization issues are an important part of this work.

Early fault detection includes both identification and separation of failures. In the following we will go through five different studies, where also process visualizations have been developed in an industrial project. Various datasets have been in use, including real design basis failures from the Finnish Olkiluoto plant as well as all possible scenarios with the Olkiluoto training simulator such as water or steam leaks in the primary circuit.

Part of the data-analysis techniques and concepts are difficult for the current control room operators. More education and training are needed before this kind of concepts can be introduced in a real control room. Some tools and methods suit better for the plant experts to help them in their process analysis: to aid them to understand better what is going on in the process.

Process and progress visualization

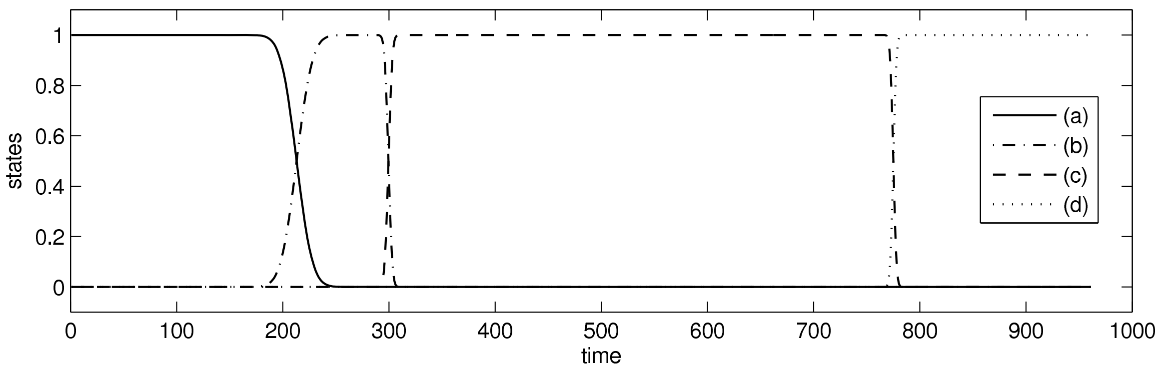

Figure 2. The states in one data set (I) as a function of time. (a) corresponds normal state, (b) leakage state, (c) partial reactor shutdown state, and (d) reactor shutdown state.

The self-organizing map (SOM) is used in data analysis for resolving and visualizing nonlinear relationships in complex data [16]. An application of the SOM for depicting state and progress of a real time process is studied. 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.

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 2.

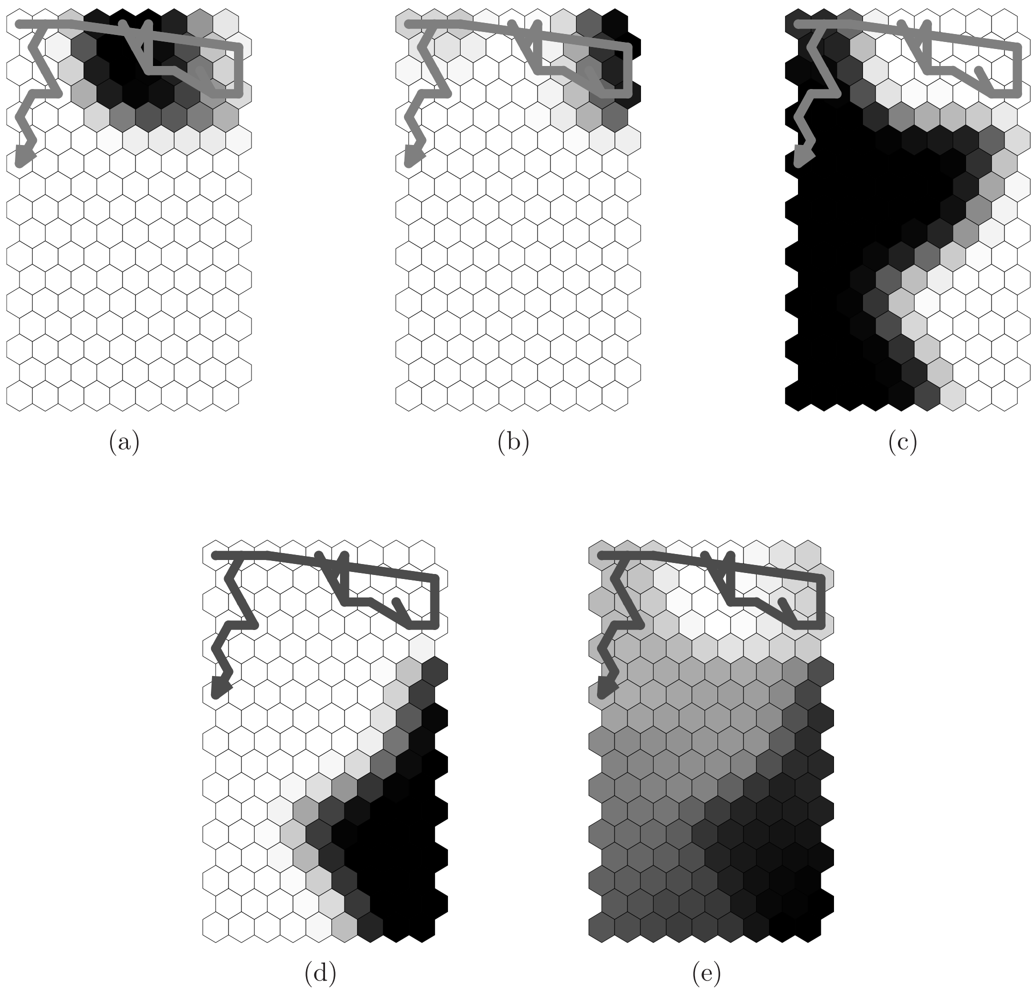

Figure 3. A component plane representation of the trained SOM. Only component planes corresponding (a) normal state, (b) leakage state, (c) partial reactor shutdown state, (d) reactor shutdown state, and (e) progress are displayed. Dark colour on a cell indicates high component value. The trajectory 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 3 a component plane representation of trained SOM is seen including the progress variable. The predictions for state and progress are seen in Figure 4. The progress variable in this study is a unique concept, which can also be argued.

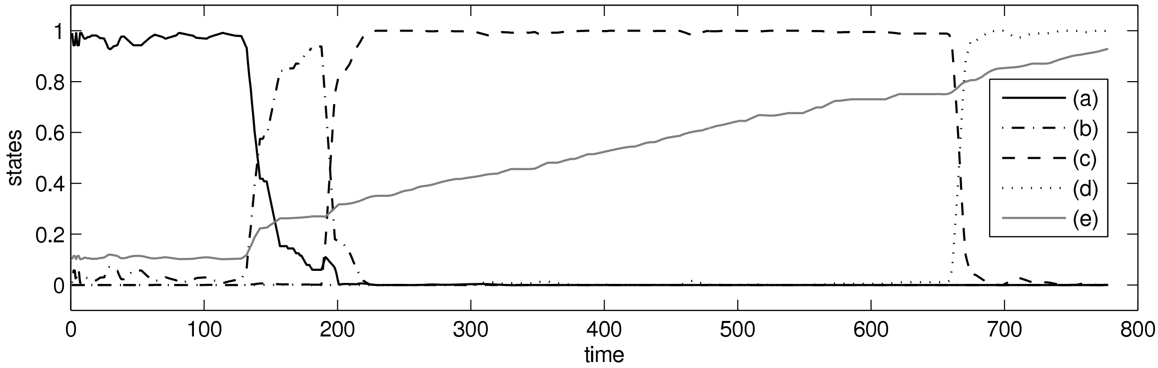

Figure 4. A 10-second running average of the predictions of state and progress for data set (II). (a) corresponds normal state, (b) leakage state, (c) partial reactor shutdown state, (d) reactor shutdown state, and (e) progress. The progress values have been scaled so that they are plotted relatively 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.

Failure detection and separation

A SOM-based decision support system was developed [17] [18]. It is a prototype of a control room tool for operator or analysis tool for expert user. It is intended 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 tool will be installed for test use in Olkiluoto plant.

The prototype is named DERSI. It is a Matlab software program built on top of Matlab extension SOMToolbox [19]. 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 previous section) and time curves. The DERSI Man-Machine Interface (MMI) is seen in Figure 5.

The failure management scenario analyzed in Figure 5 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 base is reasoning the first diagnosis of the event, see Frame 1 in Figure 5.

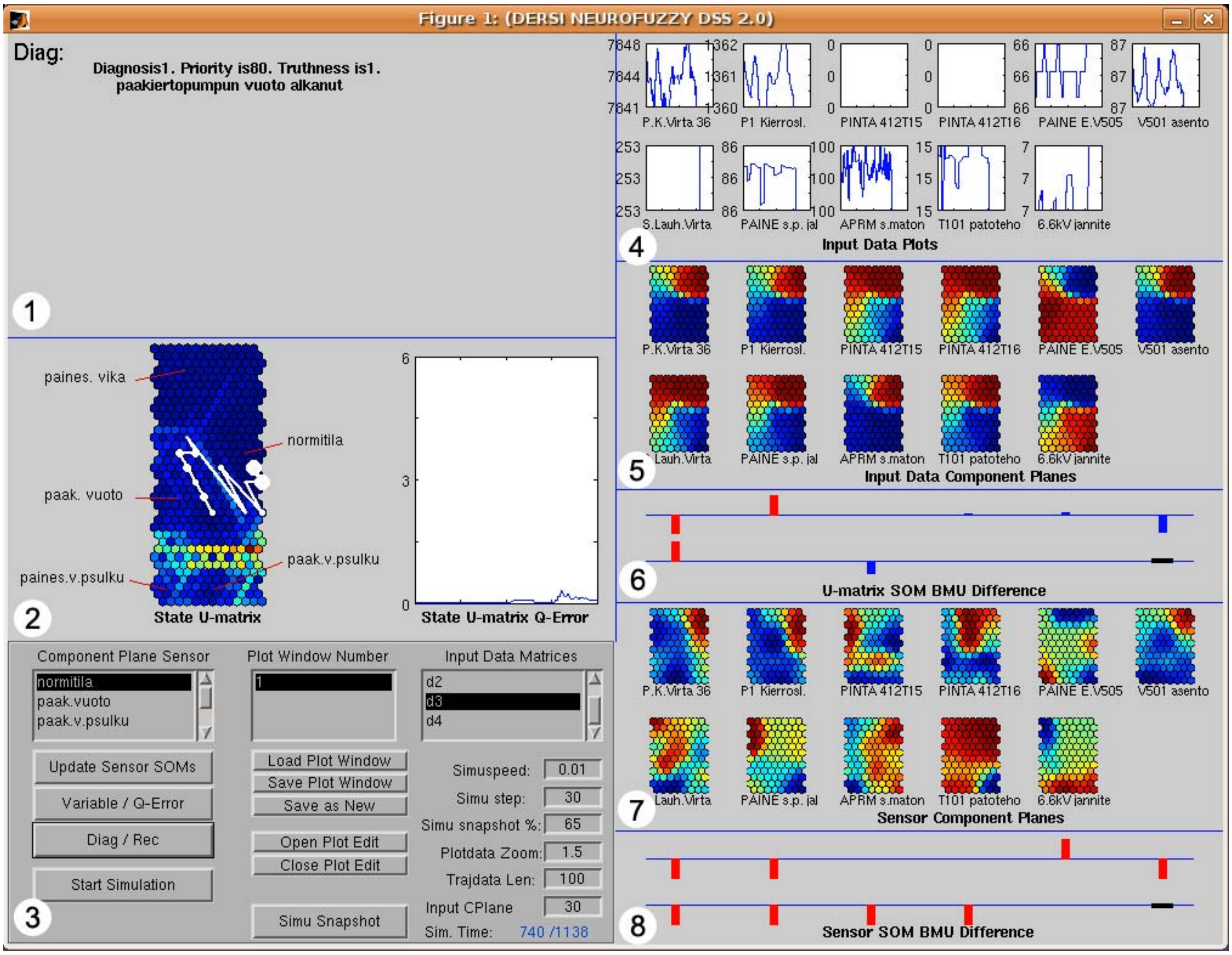

Figure 5. DERSI Man-Machine Interface (MMI).

In Frame 2 of Figure 5 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 includes menus and buttons to operate the tool. In Frame 4 are either the state and progress visualizations and quantisation errors of sensors, or the time series plots for currently selected variables as seen now. The Frames 5 and 7 gives SOM mappings for selected variables for failure data and normal data. Clear differences can be noted in the normal operation SOM maps (Frame 7) and failure SOM maps (Frame 5). In the Frames 6 and 8 the component plane quantisation errors as bars of varying height and colour are seen.

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 [4]. In Figure 6 five different failure management scenarios are separated from each other with U-matrix trajectory visualizations. These scenarios were executed with a separate Simulink model [17].

The five scenarios in Figure 6 are a) normal process state, b) leakage between reactor and preheater, c) leakage between turbine and condenser, d) admission valve accidentally closes, and e) leakage in the cooling system. The scenarios are discussed in detail in [4]. In each scenario the temperatures and pressures in the corresponding area react abnormally.

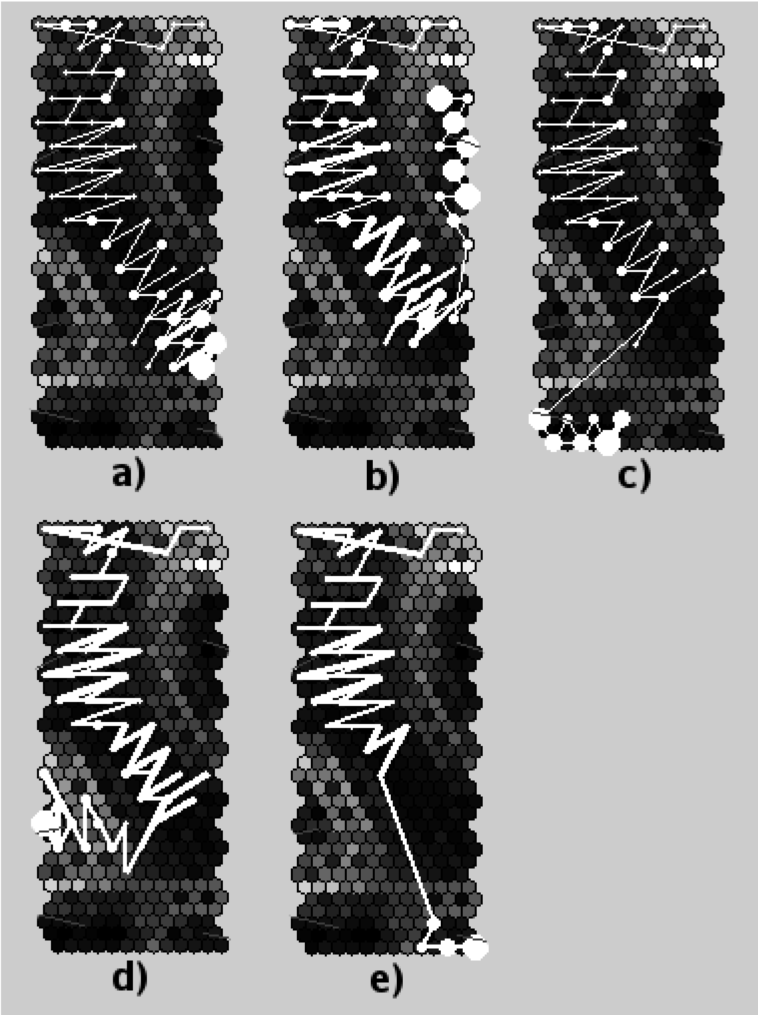

Figure 6. U-matrix with trajectories for different failure scenarios.

Leakage detection by adaptive process modeling

An adaptive approach for time series modelling and steam line leakage detection is used [20] [21]. 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 examining eigenvalues and eigenvectors of the principal component analysis (PCA).

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 7 and Figure 8. In Figure 7 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 8. In this scenario expressed in both figures the leak appears to one of the main steam lines.

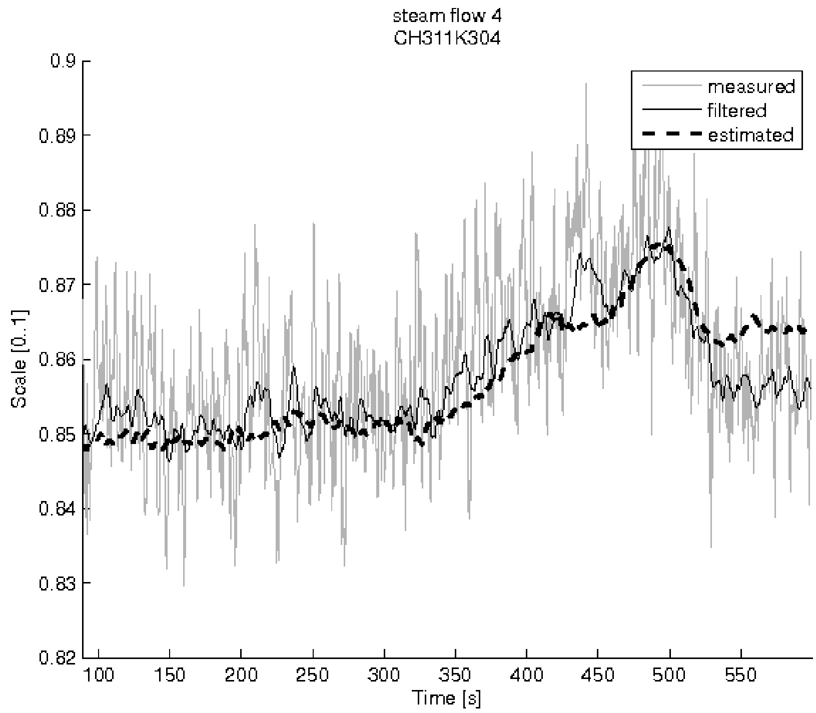

Figure 7. Model with artificial leakage. Leakage starts at t = 470 s. Steam flow 4 is estimated using three interpretative features: sum of steam flows, high-pressure turbine-inlet pressure and high-pressure turbine feed water (HPFW) piston position. All data vectors were scaled by using minimum and maximum values of each variable in the database.

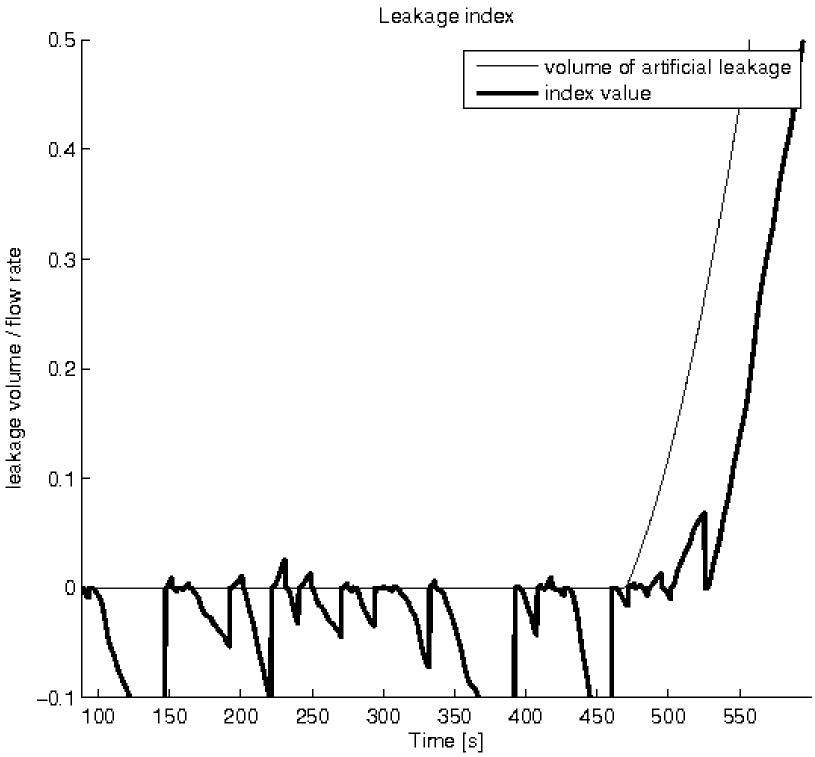

Figure 8. The leakage index. Thin line is propotional to steam flow 4. Wide line is estimated leakage index value.

Feature selection on process fault detection

Feature subset selection is an essential part in data mining applications. In this study the feature subset selection is integrated into real time process fault detection [22]. 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.

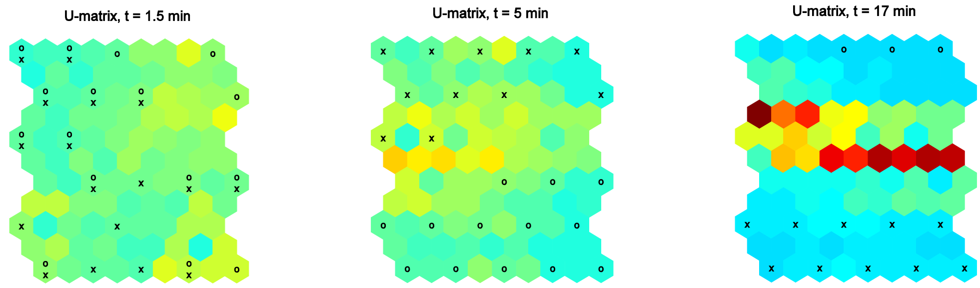

Figure 9. Scenario: 0–10% leakage in the main circulation pump. SOM visualization of three different moments. Normal reference state and current state are marked with "o" and "x" respectively.

In Figure 9 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 10). The interesting part is the second one in the middle in Figure 9, 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 10 various visualization of the X-detector tool are seen. It presents the same scenario as Figure 9. 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.

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

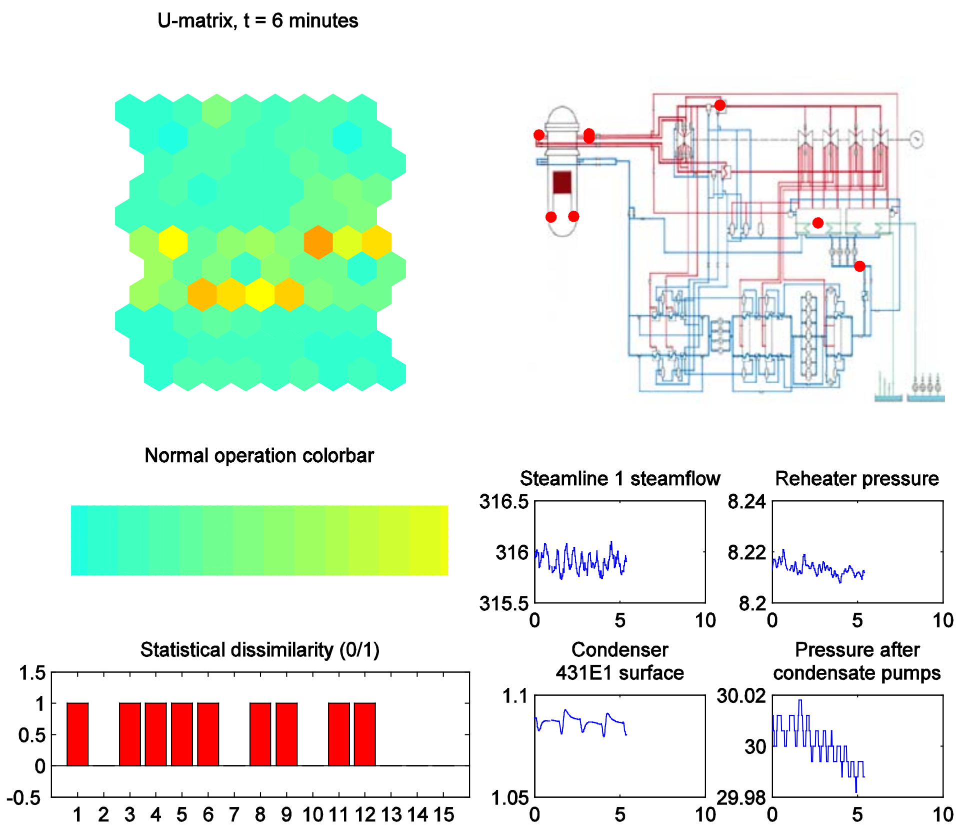

Figure 10. Control room visualization, Man-Machine Interface (MMI): FISS (Fault Indication SubSystem) combined with statistical Kolomgorov-Smirnov test (KS-test), process flow diagram and selected process variable graphs. A red bar on a given variable indicates negative KS-test i.e. dissimilarity between two probablility distributions.

Detecting pre-stage of process fault

Detecting pre-stage of process fault from an Olkiluoto dataset is one of our latest studies in this project [23]. Process data was stored in two months period in 2007. This 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 [24]. Minimum and maximum values of each process variable have been collected from dozens of datasets of OL1 and OL2 reactor units and stored in the database.

The aim was to create simple enough process visualization for operators. SOM's of certain signals were visualized in time steps and four time step visualizations are shown in Figures 11 and 12.

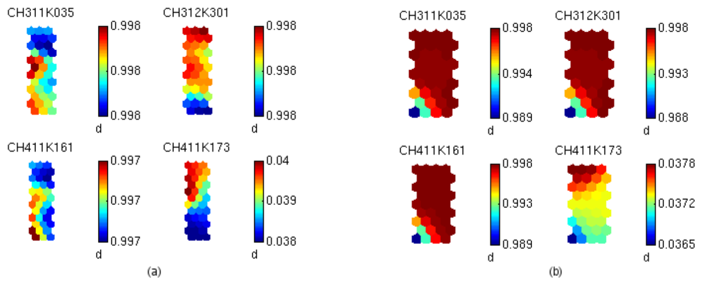

Figure 11. SOM's before fault in turbine section, (a) normal operation condition, one day before process fault, (b) process one hour before fault.

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-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 dependences 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 11 (a).

Pre-stage of the process fault is detected by change of scale of the map and correlation between three variables in Figure 11 (b). In this situation operators are expected to use their knowledge of the process or decision support to make right corrections to the process.

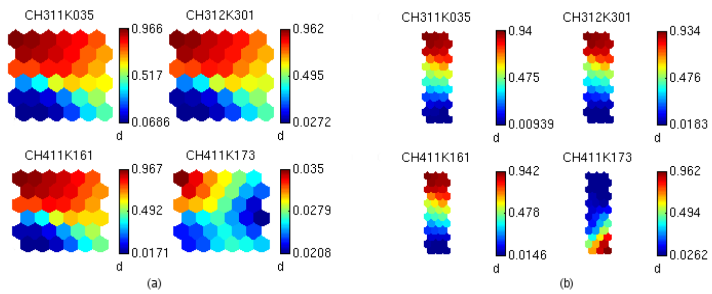

Figure 12. SOM's after fault in turbine section. (a) Fault situation. (b) Process one day after process fault including recovery to normal process.

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 12 (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 12 (b). Normal condition is reached when maps are similar to those in Figure 11 (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 very early. This is a promising result in the early detection of faults with the developed visualizations.

Summary

This report summarizes the test case 4 (TC4) “Decision support at a nuclear power plant” in NoTeS (Nonlinear temporal and spatial forecasting: modelling and uncertainty analysis) and NoTeS2 projects in TEKES MASI research program (2005-2009). Early fault detection and various abnormality visualizations were special focus areas in this subproject. The industrial partner was Teollisuuden Voima Oy, Olkiluoto nuclear power plant. Both design based events data from the plant and simulator data from the training simulator were analyzed.

Five different studies in the TC4 subproject were described more in detail: process and progress visualization, failure detection and separation, leakage detection with adaptive modeling, feature selection and process fault detection, and detecting pre-stage of process fault. Self-organizing map (SOM) method was used in most of these studies and combined with other methods. The SOM method in dynamic systems is discussed in a separate chapter.

Promising results in early detection of faults have been achieved in this subproject. Many of the developed visualizations can reveal to the operator or plant expert in an early phase that something exceptional is going on in the process. The used methodologies have some advantages in this kind of information process compared to many traditional methods used in the control rooms.

The next step could be to add practical co-operation with the plants using these developed concepts. Getting feedback from operators about visualized information would be essential. Using data analysis methods in training simulator assessment is also in our future plans.

Acknowledgement

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References

[1] Ritala R., Alhoniemi E., Kauranne T., Konkarikoski K., Lendasse A., and Sirola M. Nonlinear temporal and spatial forecasting: modeling and uncertainty analysis (NoTeS) - MASIT20. MASI Programme 2005 - 2009 Yearbook 2008. Tekes Review 228/2008.

[2] Kohonen T. The self-organizing map. Springer, Berlin, Heidelberg, 1995.

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

[4] Sirola M., Lampi G., and Parviainen, J. Failure detection and separation in SOM based decision support. Workshop on Self-Organizing Maps (WSOM 2007). Bielefeld, Germany, 2007.

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

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

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

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

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

[10] Dobrzewski B., Ruwisch D., and Bode M. 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] Fancourt C., and Principe J. 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] Euliano N. R., and Principe J. C. Spatio- temporal self-organizing feature maps. International Joint Conference on Neural Networks (IJCNN 96). Washington, USA, 1996.

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

[14] Simula O. et al. The self organizing map in industry analysis. Industrial applications of neural networks. CRC press, 1999.

[15] Monostori L., and Bothe A. Industrial and engineering applications of artificial intelligence and expert systems. International Conference IEA/AIE-92. Springer, Berlin, Heidelberg, 1992.

[16] Hakala R., Similä T., Sirola M., and Parviainen J. 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.

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

[18] Lampi G. Self-organizing map in decision support: a decision support prototype. Master's thesis, Helsinki University of Technology, 2009.

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

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

[21] Talonen J., Sirola M., and Parviainen J. Leakage detection by adaptive process modeling. Proceedings of International Conference on Data Mining (DMIN 08), 2008.

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

[23] Sirola M., Talonen J., and Lampi G.. SOM based methods in early fault detection of nuclear industry. Proceedings of European Symposium on Artificial Neural Networks (ESANN 2009). Bruges, Belgium, 2009.

[24] Pyle D. Data preparation for data mining. Morgann Kauffman, 1999.

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