Failure detection and separation in SOM based decision support

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***Abstract*—** Failure management in process industry has difficult tasks. Decision support in control rooms of nuclear power plants is needed. A prototype that uses Self-Organizing Map (SOM) method is under development in an industrial project. This paper has focus on failure detection and separation. A literature survey outlines the state-of-the-art and reflects our study to related works. Different SOM visualizations are used. Failure management scenarios are carried out to experiment the methodology and the Man-Machine Interface (MMI). U-matrix trajectory analysis and quantization error are discussed more in detail. The experiments show the usefulness of the chosen approach. Next step will be to add more practical views by analyzing real and simulated industrial data with the control room tool and by feedback from the end users.

1 Introduction

Failure management in process industry is a difficult task. Especially in certain safety critical applications the responsibilities and requirements for the best possible planning are extremely high. Our industrial application example is a Boiling Water Reactor (BWR) type nuclear power plant. The operator in the control room should be provided with appropriate decision support [1].

A prototype of a decision support tool combining neural methodologies and knowledge-based methodologies has been under development for several years [2]. This tool utilizing Self-Organizing Map (SOM) [3] in data analysis has been built and is first applied in an industrial project in co-operation with Teollisuuden Voima Oy Olkiluoto nuclear power plant. The tool will be evaluated by the control room operators controlling the plant or experts and analysts trying to understand and explain different phenomena in the process.

The basic problems discussed in this paper are failure detection and separation. Early detection of faults is one specific goal in this project, and our initial studies show that for example water or steam leaks in the primary circuit are potential scenarios to handle with this approach, because they often progress slowly and therefore give more time to react.

In addition it is useful for the experts to understand various phenomena in the process. Regular isolation valve experiments carried out in the nuclear power plants are one example where there seems to exist unknown factors. Also instrument calibration problems in nuclear plants can be revealed by data analysis methodologies.

To display and ennoble information for the operator or expert user with visualizations and possible operational guidance is another problem area that we are looking for possible solutions. The control rooms of nuclear power plants are just going through modernization phase, which gives us also a lot of challenges and new possibilities. For instance, we are looking for new contents for the new big monitoring screens that will appear into the modern control rooms.

One research method used in the project is prototyping and using the prototype tool as a kind of test bench for different methodologies and combinations of them. The methodologies are such as data preprocessing, data mining and analysis. We also develop new visualization tools. In this paper we have focus on literature survey and failure separation with SOM methods, such as U-matrix trajectory analysis and quantization error. The literature survey includes also a little wider perspective in decision support than what is written in the title of this article.

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2 Literature survey

There has been a lot of effort to do failure detection with complex data analysis methods. Process fault detection is a widely studied area. In most cases traditional control processes and event based control has been used instead of decision support systems.

Decision support systems have enormous amount of applications. Everything from agriculture fertilization, customer segmentation, investing and marketing campaigns, traffic organization, etc. need decision support [4,5,6,7,8]. A lot of failure-detection research has been done in the context of medical diagnostic decision support systems [9,10].

Three classes of articles were found in the literature survey. They are referred as type I, type II and type III. Type I are articles that describe how a new method or model can be utilized for decision support. A lot of methods or models are used in failure detection. One of the most used ones is multilayer perception (MLP) [9,10]. In addition fuzzy-rule inference and decision trees are used [11,12,13]. But the scale is wide and everything from derivations of PCA to traditional rule based inference was found [14,15,16].

From previous works about using U-matrix for decision support [17] should be mentioned. In referred work bigger map size and smaller data node relation is used. Cluster borders are easy to notify in this method.

Type II are articles that describe a constrained decision support system prototype or tool for a specific application. Different frameworks are presented. Implementations of utility theory are common. One example is Web-HIPRE, a Web based decision analysis tool [18]. Reviewed Decision Support System (DSS) frameworks that are based on utility theory did not specify how features used as utility attributes are calculated [19].

A lot of articles describe DSS prototypes for process optimization rather than for failure detection [20,21]. A few exceptions are RODOS and ComPASS. RODOS (Real-time On-line DecisiOn Support system) is a decision support system for nuclear emergency management. It is a large scale DSS for providing support before, during and after an accident. RODOS is a distributed project and includes up to 40 institutes from 20 countries [22]. ComPASS is a DSS for manufacturing machine tool fault diagnosis. It is based on multi-agent architecture [23].

Many operator support system prototypes for nuclear power plants have been developed by OECD Halden Reactor Project together with its co-operation institutes all over the world. One example of those is CAMS [24], which consists of many integrated parts responsible for different tasks, such as signal validation, tracking simulator, predictive simulator, strategy generator, critical function monitoring and Man-Machine Interface (MMI). The CAMS is also a decision support system prototype for severe nuclear accidents.

Critical part of a DSS is MMI and associated visualizations. Most of reviewed articles did not describe or evaluate DSS visualizations in detail. It is another research problem more associated with psychology what is the best way to visualize process information to minimize human error [25].

Type III articles describe a process how DSS is constructed, models selected or DSS validated. A process for DSS construction is at least as complex as construction of any information system. Information system building starts with specification of requirements [26]. In DSS construction this is the most demanding phase. High-level requirements can be used to choose the most suitable model, method, user interface and visualizations.

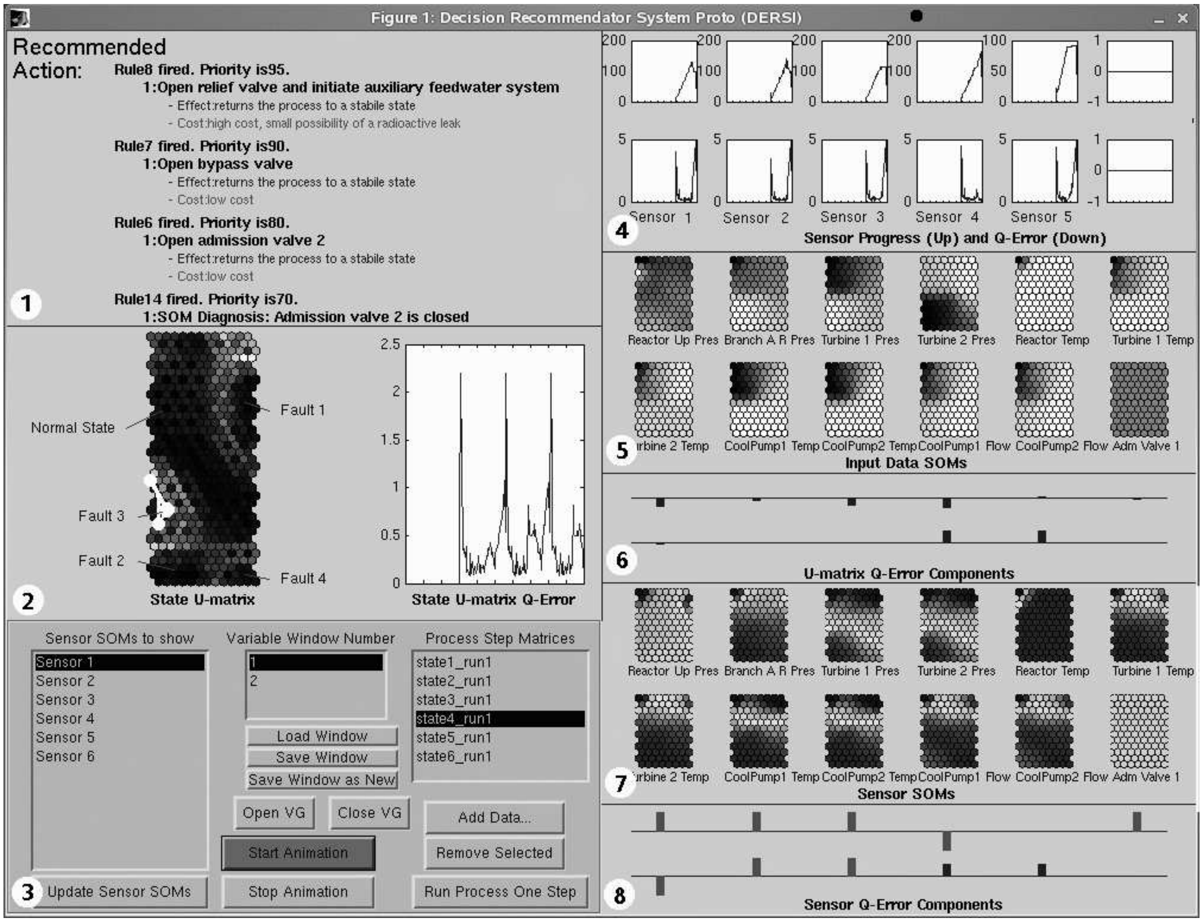
An interesting research question is how to choose a model for a decision support application. In a study [9] there was a comparison of different models and the simplest model with sufficient high classification accuracy was preferred and chosen. When the cost of one type of classification error is much higher than another, better quality decision support can be achieved by choosing training sets that minimize only the high cost classification error. This situation occurs in medical diagnostics. The modified training sets were chosen by utilizing topological ordering property of SOM.

Validation and evaluation of DSS is important because failure in decision support can be very expensive [16]. A DSS evaluation scheme for RODOS is described in [27]. In [28] there is a comparison of different DSS software suites and process for choosing the right one. In rule-based system the completeness and consistency of rule base should be verified [29].

3 Prototype visualizations

DERSI prototype [2] is a Matlab software program built on top of Matlab extension SOMToolbox [30]. It is a decision support framework, where application specific knowledge can be fed in by an expert user interface. DERSI includes a simple rule base for example scenarios. A process model of a simplified boiling water nuclear power plant built in Matlab Simulink environment also exists. DERSI Man-Machine Interface (MMI) including different decision support visualizations is seen in Figure 1. The window is divided into eight frames.

The scenarios presented in this paper are simulated with the Simulink process model. Data from the simulation is used both as training data and test data. Scenario test data can be chosen from “Process Step Matrices” list in Frame 3 of Figure 1. In all SOM maps in this paper 11 process variables are used.



Recommended Action:

Rule8 fired. Priority is95.
1:Open relief valve and initiate auxiliary feedwater system
- Effect:returns the process to a stabile state
- Cost:high cost, small possibility of a radioactive leak

Rule7 fired. Priority is90.
1:Open bypass valve
- Effect:returns the process to a stabile state
- Cost:low cost

Rule6 fired. Priority is80.
1:Open admission valve 2
- Effect:returns the process to a stabile state
- Cost:low cost

Rule14 fired. Priority is70.
1:SOM Diagnosis: Admission valve 2 is closed

Figure 1: DERSI Man-Machine Interface (MMI). The MMI has eight different frames that are numbered in the figure.

The failure management scenario in Figure 1 is analyzed in detail in [2]. 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 1. Important aid is got also from the graphical visualizations of the control room tool.

In addition to normal time series curves several SOM based visualizations are realized in DERSI. The time series curves are normally seen in Frame 4, but in Figure 1 other visualization has replaced them. These changes are operated from Frame 3 which consists of Graphical User Interface (GUI) control components.

Variable correlations can be clearly seen from component plane SOM maps. By comparing failure SOM maps to normal data SOM maps changes in variable correlations may reveal the problem in the process. In this scenario in Figure 1 correlation of turbine pressures (Frame 7) turn into reverse correlation in the failure (Frame 5).

The behavior of the trajectory in the U-matrix is clear visual indication of a failure, see Figure 1 Frame 2. The trajectory moves to the failure area when the scenario progresses.

Quantization error both in component levels (Frames 6 and 8) and especially in U-matrix (Frame 2) is another very clear visual indication of a failure, see Figure 1. Here the quantization error is increasing in the failure scenario, but the peaks caused by the model initial transient makes the picture somewhat difficult to read and interpret. Because the U-matrix SOM has been taught with both normal state data and fault state data, the quantization error actually first increases and then decreases.

The U-matrix is built from SOM, which is taught by data from all process states. Data matrices from separate process states are combined to one big data matrix that is taught to this SOM. The U-matrix trajectory is drawn to this SOM from the test data.

Three or four different kind of units are in use in this application: U-matrix SOM unit, unit with SOMs for automatic state identification, unit with component plane SOMs from teaching data, and unit with component plane SOM maps from input test data. The component plane SOM maps from teaching data and test data are used in variable correlation visualization.

In this scenario fault states are shown as clear clusters in the U-matrix, but in another scenario it is possible that fault state variable values grow without bound and a distinct cluster is not formed in the U-matrix. Quantization error and U-matrix trajectory analysis are analyzed more in detail and discussed more in the next section.

Process state and progress visualization [31] is also implemented in DERSI MMI, see Frame 4 in Figure 1. This visualization reveals the progress of this scenario by an increasing ramp. A leak scenario in Olkiluoto training simulator in analyzed with this method in [31].

In Frame 4 there are also quantization errors from separate SOM state classifier sensors. Every sensor is taught with different process state data. Quantization error of sensor 4 is low compared to quantization errors of other sensors, although all the sensor time series have high peaks on the left side because of the model initial transient.

The frames 6 and 8 show components of distance vector from the current process variable vector to corresponding BMUs in the process state SOM (Frame 6) and chosen sensor SOM (Frame 8). They are visualized as bar charts. Bar charts show which variables deviate from corresponding BMU values.

All SOMs used in the prototype are constructed using SOMToolbox with default settings. They use hexagon grid and map unit amount is defined automatically (approximately 10% of teaching samples). Map shapes are defined by data distribution shape in 2D PCA projection of the teaching data. Only exceptions are component plane SOM maps that use predefined topology and map size. The reason for this is to keep the outlook of GUI as static as possible.

4 Failure separation

Quantization error is a clear indicator of a failure in many cases in fault detection. For instance in leak scenarios the quantization error increases rather fast when the leak begins to cause remarkable changes in the process dynamics. In some cases the quantization error can be used even for failure separation, but usually other methods are required for support. In this chapter we concentrate in failure separation with U-matrix trajectories.

In failure detection with U-matrix the trajectory crossing cluster borders is one indication of failure. Different SOM's taught with different process state data sets are used for classifying fault states. The process state is determined to correspond to the SOM with smallest quantization error.

Five different failure scenarios are experimented with the Simulink process model. U-matrix with trajectories for normal data and each failure scenario are seen in Figure 2. In these scenarios the trajectories move into separate areas in each scenario, and therefore the separation of these cases is rather clear. This is no proof that it would be always the case. When separation comes more difficult, also other methodologies and combinations of various methodologies need to be taken in use. Appropriate feature selection and preprocessing is necessary for successful failure separation.

In the first U-matrix the data is from the normal process state, see Figure 2a. In the second U-matrix there is a data of a leakage between reactor and preheater. The water level of the reactor core begins to decrease and the reactor temperature begins to increase. The U-matrix trajectory in Figure 2b moves into the *Fault 1* area. (The fault areas are labeled in the Figure 1 in the previous section).

In the third U-matrix the data is from a leakage that appears between one turbine and condenser. Pressure drops in the corresponding section and the temperature increases. The trajectory moves into the *Fault 2* area in this scenario, see Figure 2c.

In the fourth U-matrix the admission valve accidentally closes. The pressure in that turbine branch increases. The trajectory moves into the

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Fault 3 area in Figure 2d. This is the same scenario that is seen in Figure 1 in the previous section.

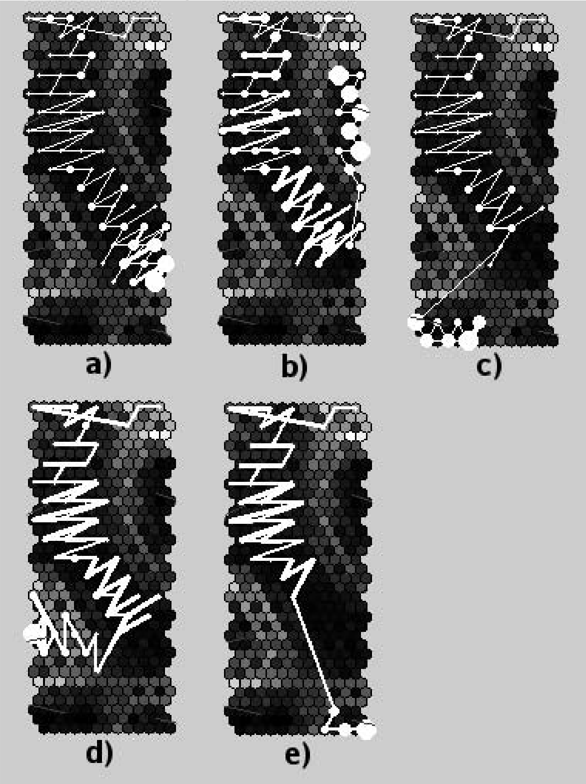

Figure 2: U-matrix with trajectories for different failure scenarios.

In the fifth U-matrix there is a leakage in the cooling system. This causes increasing temperatures near by in the process. The trajectory in Figure 2e moves into the *Fault 4* area. The data of the fifth failure scenario, which is a disturbance in the reactor power, is not visualized in this paper.

This example shows that with U-matrix trajectories it is possible to separate various failures in simple cases with a limited number of states. The cases with the real industrial data are more complicated and more difficult to handle.

5 Prototype Analysis

DERSI has three essential parts, simple rule-based inference engine, SOM of all states and set of classification SOMs for every state.

Rule-based inference has been common in DSS [1] but no other system was found that uses SOM as a classifier and SOM quantization error as a feature for rule-based inference. Although some studies were found that integrate other neural networks with a rule base [32]. Most of decision support with SOM U-matrix were for marketing or investment decisions [5,6].

DERSI does not use utility theory for decision support. It seems that utility theory is more suitable for isolated decision situation with limited amount of alternatives rather than real-time decision support with possibly unclear connection between recommendations and process goals.

In further development of the prototype feedback from an industrial partner will be utilized. The feedback will be provided by a potential end user. Real process data from the Olkiluoto nuclear power plant and training simulator is also available. It is currently under study whether this data can be used for building a DERSI demo scenarios or decision support models.

6 Discussion

The strength of SOM is topological ordering of multidimensional space and projection to lower amount of dimensions. Visual inspection of the neighborhood of state U-matrix trajectory head reveals process states that are more likely in the near future than states far from the trajectory head. Other classifier than SOM could have been used in the sensors, but SOM was used for its ability to do visual correlation hunting. Visual correlation hunting is slow and in future it could be better to do automatic correlation handling by interpreting SOM component planes as vectors and calculating distances between these vectors. Correlations can also be detected with some other methods than SOM.

An interesting question is if SOM based fault separation gives additional value in safety-critical Decision Support Systems (DSS). A DSS can also fail and a safety-critical process operator has to evaluate if he (or she) believes to the recommendations of a DSS or not. The operator needs to understand why a DSS worked like it did. Simple rules are easy but a neural network like SOM is essentially a black box and it is difficult for the operator to understand why the network gave a specific result.

Actually many of these SOM based representations are difficult for the operators. The operators will need special training to be able to adopt the ennobled information in this form. We need to be critical in what representations are possible to use in various contexts. A special challenge is to define the contents in the big screens of forthcoming modern control rooms in nuclear power plants.

We have also made some tests with the BWR training simulator data. Unfortunately we met with some obstacles that made it impossible to report those tests in this paper. The state identification seems to work also with that data, but DERSI prototype needs some further development to be capable for analyzing thoroughly real industrial data. We try to make the framework as flexible as possible to be able to handle all kind of data in the future.

DERSI prototype development is now in a phase where feedback from the industrial users will give the next guidelines. Various visualizations have been examined more in somewhat academic basis, and the next step is to enlighten more practical views by the end users. Failure management with quantization error and U-matrix trajectory analysis have already given hints how to proceed into that direction. Variable correlations and changes in them read from the component plane SOM maps is another similar example.

In the literature survey it was easy to find information about different methods but difficult to find information about implementations of ready DSSs. One reason is that many of them are commercial products and the manufacturers do not want to reveal details to possible competitors.

7 Summary

A SOM based decision support approach applied in nuclear power plant control room environment has been presented. Literature has been surveyed to summarize the state-of-the-art, and to reflect our approach to related studies. A prototype has been developed to test the ideas in practice. The power of the prototype visualizations, and failure detection and separation has been shown with example scenarios. The methods are shown to be useful by practical examples. Our next step is to analyze the industrial data more in detail. As conclusion the failure separation with SOM works with tested data sets.

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