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Review Article

Combining Neural Methods and Knowledge-Based Methods in Accident Management

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Accident management became a popular research issue in the early 1990s. Computerized decision support was studied from many points of view. Early fault detection and information visualization are important key issues in accident management also today. In this paper we make a brief review on this research history mostly from the last two decades including the severe accident management. The author's studies are reflected to the state of the art. The self-organizing map method is combined with other more or less traditional methods. Neural methods used together with knowledge-based methods constitute a methodological base for the presented decision support prototypes. Two application examples with modern decision support visualizations are introduced more in detail. A case example of detecting a pressure drift on the boiling water reactor by multivariate methods including innovative visualizations is studied in detail. Promising results in early fault detection are achieved. The operators are provided by added information value to be able to detect anomalies in an early stage already. We provide the plant staff with a methodological tool set, which can be combined in various ways depending on the special needs in each case.

1. Introduction

Accident management grew into an own and popular research branch in the early 1990s. This trend was a kind of delayed reflection of the two serious industrial accidents in the 1980s in Bhopal (1984) and in Chernobyl (1986). It was noticed that most of the earlier studies about abnormal events did not cover very well the severe accident cases. Already the Three Mile Island accident (1979) made the nuclear power plant control room a major focus for the studies of human factors, human reliability, and man-machine interface technology [1]. The Fukushima accident in 2011 has risen the accident management issue up again, although the nature and origin of this accident were completely different.

The problem area in the 1990s was identified to begin with information needs and reliability, to be completed with accident mitigation. The presentation methods and information structuring were located to central issues, as the human being was considered often to be the weakest link in the safety systems. The fault diagnosis of abnormal events and the support of operator decision making were naturally completing this entity [2].

Computerized accident management was studied in the 1990s, for instance, in OECD Halden Project, and prototyping systems including also strategic planning features in operator support or technical support centre were carried out in several projects the author is participating in [3]. Methodology was developed and decision models were built for selected application areas.

Early fault detection and information visualization are important key issues in accident management also today that we have been concentrating on in our recent studies [4]. We have combined different methods, including knowledge-based techniques and neural methods, to help the decision making of operators and experts in the control room of nuclear power plants. Self-organizing map (SOM) method [5] has been one of the important methods used.

2. Background

Research in computerized decision support systems has been carried out for the last fifty years. The field of computerized support systems (CSSs) can be divided into two main branches: decision support systems (DSSs) and expert systems (ESs). The introduction of knowledge-based systems (KBSs) in the 1980s led to the development of intelligent decision support systems (IDSSs). A large variety of different types of computerized support systems with a large variety of properties and characteristics can be recognized in later studies of this field [6].

The CAMS project [7] was an attempt to build a large-scale computerized support system for nuclear industry that would cover also severe accident management [8]. The CAMS (computerized accident management support) system was planned to provide support to various user groups in all states of the nuclear power plant, including accident states. The CAMS was composed from the following components: signal validation, tracking simulator, predictive simulator, strategy generator, critical function monitoring, and an MMI (man-machine interface) system.

As a part of CAMS project and a followup, a knowledge-based decision support system was developed [9]. The concept was based partly on decision theory including value theory, utility theory, and decision analysis [10, 11]. In addition to the control room tool prototype, a decision tool including a case-based criteria database in maintenance was developed [12]. In maintenance the problem area is somewhat different. Two important areas can be recognized: event-driven decisions and plant life management.

During the last decade we have added the neural methods to the decision support concept. We participated a few years ago in a large industrial research program studying nonlinear temporal and spatial forecasting: modeling and uncertainty analysis, called NoTeS project. In cooperation with a Finnish nuclear power plant, we studied early fault detection with various methods and developed many decision support visualizations mostly based on neural methods [4]. The self-organizing map method was combined with knowledge-based methods in a decision support system prototype. The following tasks were studied more in detail: process and progress visualization, failure detection and separations, leakage detection with adaptive modeling, feature selection and process fault detection, and detecting the prestage of a process fault.

The fault dynamics and dependencies of power plant elements and variables were inspected in our recent studies to open the way for modeling and creating useful statistics to detect process faults. We succeeded in using data mining to learn from industrial processes and finding out dependencies between variables by principal component analysis (PCA) [13] and self-organizing map (SOM). Also a segmentation method was developed to detect automatically different process states of stored datasets.

3. Self-Organizing Map Method in Decision Support

Self-organizing map (SOM) [5] is an effective method in neural computing for analysis and visualization of multidimensional data. An SOM consists of neurons organized in an array. The SOM is trained iteratively. The best-matching unit (BMU) is calculated with a selected distance measure. The SOM map is updated with the SOM update rule at each time step.

Originally the SOM algorithm was not designed for temporal data mining. The SOM is able to analyze ideally only static sets of data. Many attempts to use SOM method in the analysis of dynamic data have been made. The problems of using it in time-related problems in process modeling and monitoring are discussed in [14]. One possibility to describe dynamical behaviour is the visualization of trajectories, which link together the adjacent winner neurons (BMU) in the SOM grid.

The self-organizing map (SOM) is used here in data analysis for resolving and visualizing nonlinear relationships in a complex process. An application of the SOM describing the state and progress of the real-time process is 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 important tool is the process state trajectory in the process component plane. The failure detection is done with prototype systems.

Early detection of faults is a key issue in nuclear industry. Tools have been developed to help the operators in their daily work and to help experts to understand better various phenomena in the process. Older nuclear power plants are going through modernization projects. This development has initialized new needs. Wide monitoring screens set up new requirements for presentation techniques, for instance. New contents are needed.

We have developed new visualizations and visualization techniques and developed prototypes of control room tools for testing various combinations of methodologies [4]. Two examples are presented in this paper more in detail. Information visualization concentrates on the use of computer-supported tools to explore large amount of process data. Visualization technique is the technical realization of information visualization. The new aspects in these visualizations and visualization techniques are the versatile use of self-organizing map (SOM) method and also combining it with various other methods as well in the field of data analysis and other fields such as knowledge-based methods.

A decision support system that combines knowledge-based methods and neural methods is seen in Figure 1. It is a prototype of a control room tool for operators or an analysis tool for experts [4]. It is developed for failure management in nuclear power plants. It gives informative decision support visualizations based mostly on self-organizing map (SOM) method and gives advice produced by rule-based reasoning. A Finnish nuclear power plant in Olkiluoto has tested the control room tool.

The prototype is a Matlab software program built on the top of Matlab extension SOM Toolbox [15]. It includes visualizations of SOM maps of normal data and failure data, state U-matrix, quantisation error for both state U-matrix and component planes, progress visualization, and time curves. Note the U-matrix trajectory showing the dynamical behavior in the process in Figure 1. U-matrix is visualization technique that reveals the clustering structure of the data.

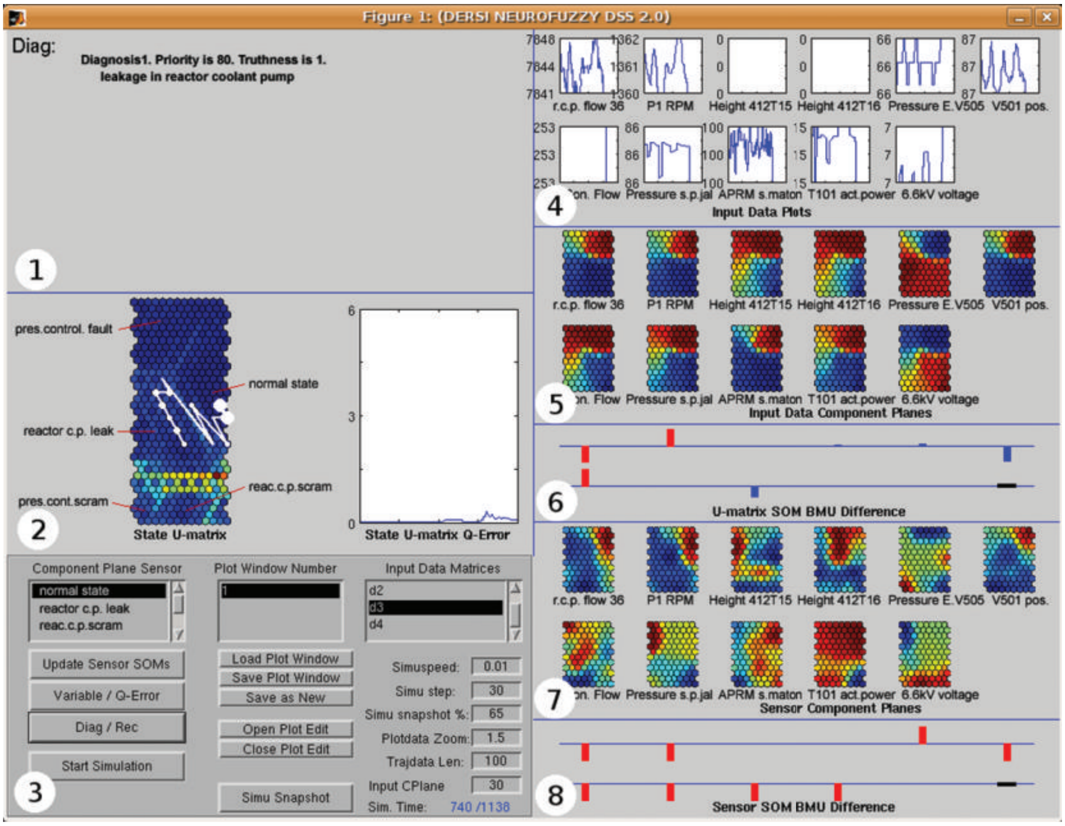

Figure 1: A SOM-based decision support system.

Quantisation includes the numerical evaluating. Quantisation error is a cumulative measure notifying differences in the data.

The failure management scenario analyzed in Figure 1 is simulated with the Olkiluoto training simulator. A leakage has appeared at the primary circuit near 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 Field 1 in Figure 1. The U-matrix trajectory is revealing the problem as well as the U-matrix quantisation error; see Field 2 in Figure 1. The trajectory (white line) is moving from the normal operation area into the specific leak problem area in the U-matrix, and the quantisation error is increasing. Clear differences can be seen in the normal operation SOM maps and the failure SOM maps; see Fields 5 and 7 in Figure 1. Variable correlations should be observed. If, for example, two variables have similar colouring shape, then they strongly correlate. Many strong variable correlations in normal operation get weaker in the failure, for instance, the reverse correlation of flow and pressure. Also time curves (see Field 4 in Figure 1) and the quantisation errors of component planes (see Fields 6 and 8 in Figure 1) point out abnormal behaviour. In this particular case, these differences are not as clear as those in the SOM maps and U-matrix. Field 3 in Figure 1 is for the user to control this decision tool.

Feature subset selection is essential in data mining applications. Here the feature subset selection is integrated into real-time process fault detection [4]. Methods based both on dependency measures and cluster separability measures are used. A tool for process visualization is developed; see Figure 2. Experiments on nuclear power plant data are carried out to assess the effectiveness and performance of the methods. We show with a leak scenario produced by the Olkiluoto Nuclear Power Plant training simulator that the visualizations help in the early detection of failures.

Already in an early phase of the scenario, the colouring of the SOM mapping begins to change, see upper left part of Figure 2. Some colours in the SOM map are already out of the normal operation colourbar. In addition the statistical Kolmogorov-Smirnov test (KS-test) detect anomalies in an early phase (lower left part of Figure 2), when changes, for instance, in the time curves are still very small (lower right part of Figure 2). In KS test the most varying variables are marked with red coloured bars. Also the locations of the interesting variables selected at each moment are marked in the PI diagram; see the upper right part of Figure 2.

These two examples show the value and effectiveness of the SOM method together with some other methods in visualization and early fault detection. These visualizations make the operators or analysts aware of the problems already when the changes in the process variables are still rather small and difficult to notice. Suitable visual changes figure the mental model of the operator more effectively than small changes in numbers or curves and give remarkable aid in the difficult decision-making process.

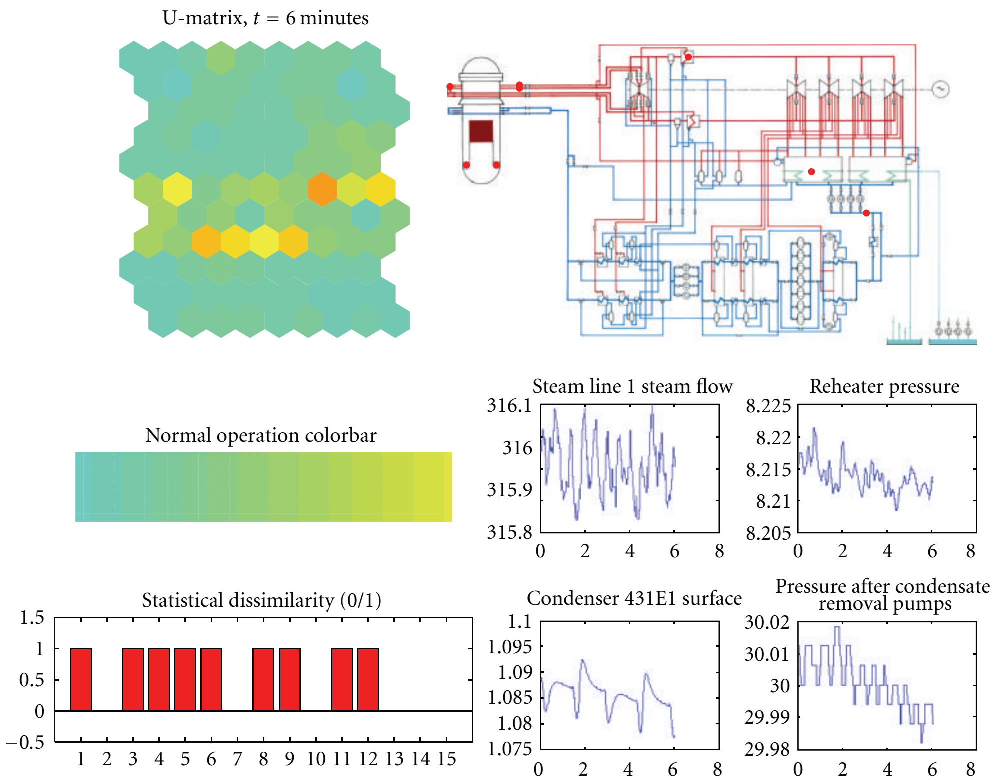

FIGURE 2: Control room visualization detecting abnormalities in an early phase of a leak scenario.

4. Detecting Pressure Drift on the Boiling Water Reactor by Multivariate Methods

Multivariate methods make it possible to model process offline, and research results can be used to understand the process dynamics. The transmitters that have drifted out of tolerance have to be identified. It provides cost savings for utilities, including direct reductions in working hours and indirect savings, caused by improved instrument reliability and plant safety.

A large amount of high-dimensional data is monitored by the univariate control charts. Redundant or in some cases high correlating signal measurements are compared with each other to detect deviation and a need for calibration. This makes it possible to know when instrument adjustment is necessary. In practice a sensor drift is detected when the sensor readings deviate from the calibrated value.

Continuous online validation will provide the most expedient status identification. The principal component regression (PCR) and the partial least square (PLS) are introduced as techniques to indicate calibration status. PCR is a regression analysis that uses principal component analysis (PCA) when estimating regression coefficients. It is a procedure to overcome problems which arise when the explanatory variables are close to being collinear. PLS is a statistical method that bears some relation to PCR. PLS family of methods is known as bilinear factor models.

In this paper the calibration status is measured as index value, which is a correlation between predicted and measurement values. When the difference of index and calibration value is considered significant by a certain criterion (e.g., D(index) $>$ 5%), the channel is suspected to be out of calibration. After each transmitter calibration, the model is updated.

The nuclear industry currently practices a conservative approach by testing the process, such as temperature sensors and pressure transmitters. These components are fully calibrated on the refueling outages.

The dataset was captured in May 2009 from the Finnish Olkiluoto Nuclear Power Plant. More than 700 signals were recorded: 10 hours, every 10 seconds. About 100 signals have quality problems, and missing values. These variables were not used in the analysis. Because we did not have separate training data, the data was divided into training and testing parts. In our experiments it is assumed that the training part is recorded after the calibration. It was used for the input signal selection to find redundant or high correlating signals; see Figure 3. Techniques for removing noise were not used.

In Figure 3 on the y-axis are the variable names, and on the x-axis the corresponding Matlab variable indexes (variable codes). As the variable has always strongest correlation with itself, the corresponding variable name of these variable indexes can be found by following the diagonal, which have the largest values. The colourings of the variable values are in the right side of the Figure 3.

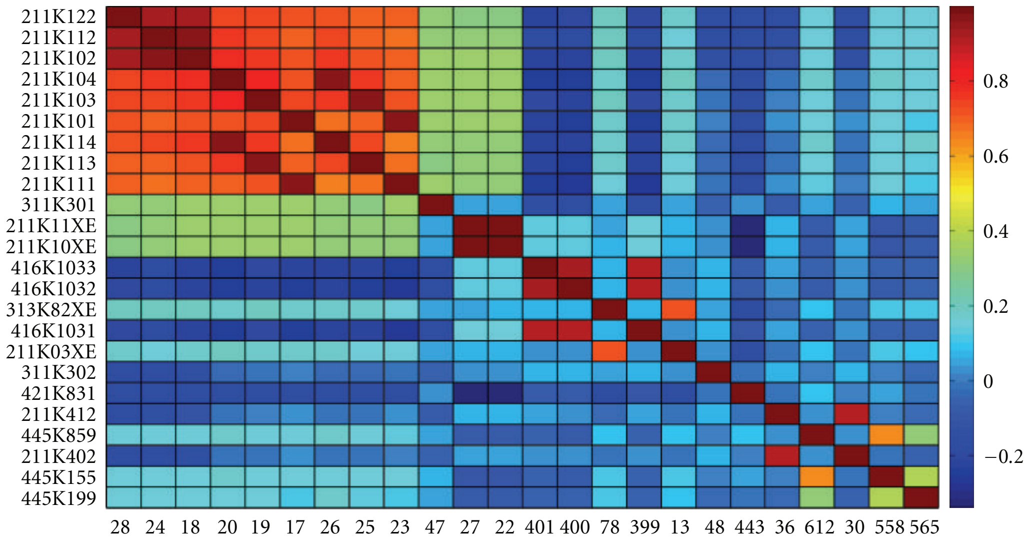

Figure 3: The target variable 211K122 (reactor pressure) is modelled by correlating variables. Variable code names are shown on y-axis and variable codes on x-axis. z-axis is correlation (colour coding in the figure), for example, the reactor pressure has the largest negative correlation with the variable 421K831 (Matlab variable index 443) and the largest positive correlation with the variable 211K112.

Normalized data was divided into separate sets for estimation and validation. Simple validation was performed, and 2/3 of the data in the learning set and 1/3 in the validation set were selected.

First 2400 samples were selected for the learning set. Two sampling types of were tested: (a) first 2400 points are in the learning set and the rest are for validation; (b) points were selected randomly. Methods like multilinear regression (MLR), principal component regression (PCR), and partial least squares (PLSs) do not take into account the time dimension; see Figure 4. Random sampling is used to get more reliable results.

In Figure 4 the parameters are the explanation stage of the teaching set (R2) and the explanation stage of the test set (R2v). Explanation stage is a related concept to correlation (in both, 1 is the highest possible value). The blue curve presents the teaching set and the green curve the test set.

Mostly, the problem with the MLR is multicollinearity when there is a lot of data available. The collinearity problem is essentially caused by redundancy in the data. However, none of the measurements is completely useless, because each of them delivers some information. The solution is dimension reduction. Feature extraction transforms the data on the high-dimensional space to a space of fewer dimensions. The data transformation may be linear, as in the principal component analysis (PCA), but also many nonlinear dimensionality reduction techniques exist.

The principal component analysis (PCA) is a useful tool for finding relevant variables for the system and the model. It is a linear transformation to a new lower-dimensional coordinate system while retaining as much as possible of the variation. In the PCR the components are used as dependent model variables. In the PLS again a small number of latent variables are used between the input and output. Now the goal is to maximize covariance between dependability and interpretability.

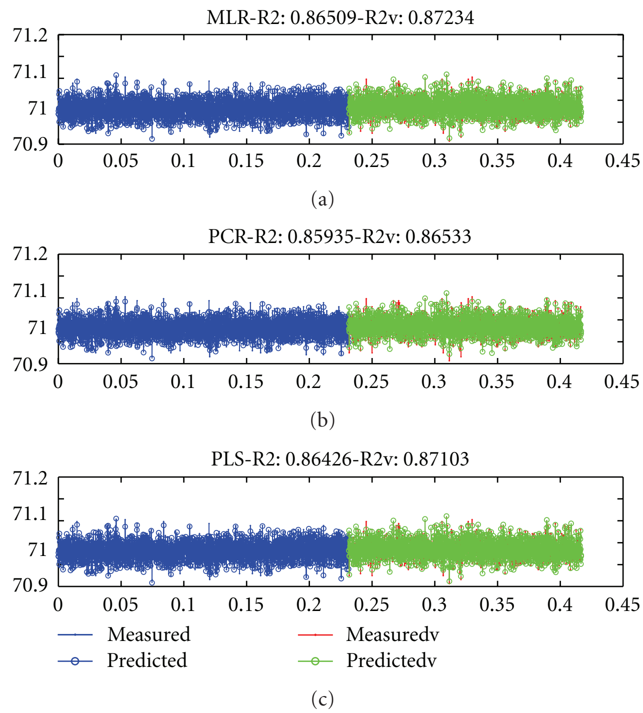

Figure 4: Modelling example: in this case all these multivariate methods indicate that process variable is in a good calibration. Correlation between model and measured values is even better before than after the calibration. x-axis: time in days. y-axis: interpretative variable 211K122 (reactor pressure). Calibration limits (5%) in this case are MLR: 0.8218, PCR: 0.8164, PLS: 0.821.

5. Discussion

With the self-organizing map, promising results in early fault detection have been achieved. 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 advantages in given information value compared to the traditional methods used in the control rooms. The combination of many rather different methods together gives the best results in this respect. The difficulty of new concepts may require extra training for the operators to be properly understood. The severe accident management has special needs that need to be taken into account.

The SOM method shows the dynamical development of the process with the U-matrix trajectories. U-matrix also reveals the cluster structure of the data. The component plane SOM maps show clearly, for example, the variable correlations. Quantisation error is one good indicator in detecting failures. The SOM method has strength also in analyzing nonlinear behaviour, compared to, for instance, the PCA method.

The case example shows in a concrete way how these methods work in practice. The variable selection, multilinear regression, and principal component regression including their visualization structures in each phase show in an offline process model how to increase instrument reliability and plant safety in some limits of measurement accuracy.

The prototyping is used as a research methodology, because it is not possible to produce such solid experimental setups and proofs that are common in pure methodological studies. Using prototyping as an analysis tool is used also, for example, in robotics, where exist similar difficulties in the experimental setup.

The suitability of these methods in accident management needs still careful assessment, as the licensing path in nuclear industry is rather long and tricky. It is not easy to convince that more traditional methods are not enough in all circumstances. In the research laboratories always new concepts have been tried out, but only very few of them end up to the control rooms of the real nuclear power plants. Still the modernization of control rooms brings many changes anyway, and also the used methodology behind all displays should be rethought.

Our methodology has been developed during a rather long period and has perspective from many generations. The knowledge-based methods used together with neural methods are introduced based on long experience in this field. The most suitable combination of methods varies case by case. The methodology can therefore be seen as a kind of tool set available for various needs.

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