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SELF-ORGANIZING MAP BASED VISUALIZATION TECHNIQUES AND THEIR ASSESSMENT

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Abstract: *Our research group has been studying data-analysis based techniques in decision support and visualization. We had a long industrial research project in co-operation with a Finnish nuclear power plant Olkiluoto. We developed many decision support schemes based on Self-Organizing Map (SOM) method combined with other methodologies. Also several visualizations based on various data-analysis methods were developed. Data from the Olkiluoto plant and training simulator was used in the analysis. In this paper some of these visualizations are presented, analyzed, and assessed with a psychological framework. Measuring the information value of the visualizations is a real challenge. The developed visualizations and visualization techniques are also compared with some existing visualizations and techniques in current plants and research laboratories. The visualizations and the visualization techniques are developed further, and completely new visualizations and techniques are developed. We point out what additional value the new visualization techniques can produce. A detailed test case of using Self-Organizing Map (SOM) method with Olkiluoto plant data is presented. With this practical example the information value of this method is shown, and it is also pointed out how it can be assessed, and what are the most reliable criteria in this assessment.*

Keywords: *self-organizing map; data analysis; neural methods; visualization.*

1. INTRODUCTION

The visualization in process industry is a tricky issue. The need for presenting the information content in the control rooms has changed along the developing technology and with time. In nuclear industry, many modernization projects have been carried out. For instance, wide monitoring screens set up many new requirements for the presentation techniques, and open new possibilities as well.

Early fault detection is an important research issue in the nuclear industry. The earlier the abnormal behaviour in the process is detected, the better possibilities there are to identify the problem in time and handle the recovery procedure properly. We have developed tools for helping operators in their work, and to help experts to understand better different phenomena in the process [1].

Prototyping has been one important research methodology used in our research group. In many prototypes a neural method self-organizing map is used and combined with other more or less traditional methods [1]. We have also done traditional data analysis with nuclear power plant data and training simulator data, and developed methods and tools for helping decision support in the nuclear field. Visualization is an important part of this research. Many tools and methods could be easily generalized or modified to other application areas as well.

Process failure detection with complex data analysis methods is a widely studied research area. Also about process presentation and visualization other studies are made. For instance, in the nuclear field [2] and other industrial branches [3], [4] many techniques have been developed. Decision support visualizations [5], [6] are also presented in the literature.

In this paper, we study the use of the self-organizing map [7] in visualization of process data in dynamic systems. Also user interface and visualization assessment are discussed. Assessment criteria are presented and compared. In a case example with the Olkiluoto nuclear power plant data, we show the information value of the method also in more practical sense. Two data sets from the same transient event are studied: one from the turbine section and one from the reheater section of the plant.

2. SELF-ORGANIZING MAP IN DYNAMIC SYSTEMS

Self-organizing map (SOM) is an effective method in neural computing for the analysis and visualization of multidimensional data. The SOM algorithm [7] resembles vector quantization (VQ) algorithms. The difference with regard 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 = [m1, … , mn], 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):

$$\|x - m_c\| = \min_i \{\|x - m_i\|\} \qquad (1)$$

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 a 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:

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

where t is time. The x(t) is the input vector randomly drawn from the input data set t and hci(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 data sets. Many attempts to use the SOM method in the analysis of dynamic data have been done. It has been used in many time-related problems especially in process modelling and monitoring. These issues are discussed for instance in [8].

One possibility to describe dynamical behaviour is the 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 the desired regions of the map.

An example of using trajectory expression in a 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 come from the 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. In the example of Figure 1 there is a leak in the main circulation. Different scenarios are somewhat separable in the U-matrix [9].

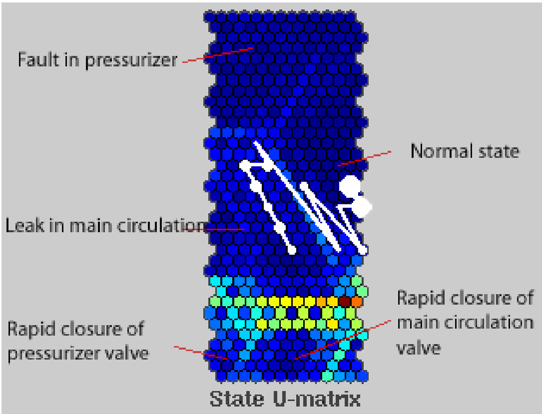

Fig. 1 – Dynamical behavior in the process is show by U-matrix trajectory

More examples about handling spatio-temporal problems with the SOM method are written in [1]. In section V we go through an industrial case example where the SOM method is used with data from a Finnish nuclear power plant.

3. USER INTERFACE AND VISUALIZATION ASSESSSMENT

In control room various things need to be shown to the operator. Typical displays in the control rooms of process industry are such as process chart, task display, trend chart, alarm list, event display, report chart, sequence display, maintenance display and diagnostic display [10].

In many psychological studies operators decision making is looked from several points of view. In cognitive ergonomics, the model of operator decision making is defined by the following steps: activation, detection, recognition, interpretation, task definition, selection of performance rule and task realization [10].

The situation awareness of an operator may be restricted by attention reduction, limitations of short memory, work load, threat, fatigue, stress, information overload, complexity, flaw mental model, out of the loop, etc. The requirements for process control are based on dynamical issues, complexity issues and uncertainty issues. The state properties are physical, social and virtual. [10]

Assessment is a part of the design process. To ensure that the ergonomic requirements are taken into account, following things are concerned: systematic approach, ergonomics part of the interdisciplinary design process, operation concept as design core, assessment enabling iterative operations, and user organization participation.

There are certain principles to the coherence and recognition in the displays. Functionality is one property in visual expression. The functionalities between human and computer can be divided according to security criteria, competence, cognitive and affective criteria, tasks, etc. The displays should be clear and readable, and adequate.

Assessment is done in many phases in the design process. Important assessment criteria are compatibility, information clarity, situation awareness, controllability, mental load, support group work, understandability, error density, limit marginal, and the structure of control room [10].

Commonly used assessment methods are “walk through” and “talk through” observation. Other methods are such as expert opinion, experimental methods, physical measurements, assessment of alteration, and paper and pen techniques: ergonomic check lists, use of history data, task analysis and qualitative reliability analysis.

Commonly accepted principles in the assessment are: verification and validation should be part of the design process, importance of preplanning, realistic, coverage, availability of assessment material, expertise; practical, systematic, and well documented methods, quantitative methods when possible, and documentation. [10]

Detailed requirements of displays are defined in standards. Alarm handling is one special case. Risk analysis is one method used. Safety in abnormal situations is very important.

Basic criteria for usability are productivity, efficiency and pleasure [11]. Five quality components are defined as learning, efficiency, memory, error rate, pleasure and profit. Availability, attractiveness, ease of use, accessibility, user experience and use experience are also important.

Ten usability heuristics are defined as [11]: Visibility of system status, match between system and the real world, user control freedom, consistency and standards, error prevention, recognition rather than recall, flexibility and efficiency of use, aesthetic and minimalistic design, user help in recognition, diagnose and recover from errors, help and documentation. These heuristics are not used in our examples, unless they overlap with the other criteria mentioned in this paper.

The measurement of usability is based on satisfaction, learning, remembering, errors and efficiency. In addition conservation, flexibility, tiredness, concentration and various positions can be measured.

A user interface can be consistent or innovative. The assessment can be done by cognitive methods, scenario based or by empirical testing.

In assessment the following things are checked: observable options, understandability, data ordering, data consistency, control equipment, interaction, performance and load, acceptability, assembly and connectivity, other information and guidance. Assessment tools are tools for testing, checking, requesting, modeling and simulation. Automation of assessment is difficult.

4. ASSESSMENT CRITERIA AND THEIR COMPARISON

Some assessment criteria have been listed already in the previous section. In [12] is defined a comprehensive “placeness profile”, which includes a large amount of user interface properties. Part of them can be considered as criteria for user interface and visualization assessment as well. Three types of control room concepts (or metaphors) are used: illustrative control room, interactive control room and boundless control room.

In [12] there are defined more than fifty properties, but here we concentrate on only the most interesting ones. We have picked up real-time information, trend information, illustration of parameter relations, some criteria about transients, predictive information, history of events, monitoring and set point criteria, accuracy and feedback of operation, spatial relations, multi-unit connections, remote operations, allocation of tasks and operational experience for our analysis. Some of these properties and criteria are paid more attention than the others. These properties and criteria partly overlap with the criteria mentioned already in the previous section.

In Figure 2 is seen a component plain representation of a trained SOM in a leak scenario, where the process starts in normal state and progress to partial reactor shutdown state. The component planes are corresponding (a) normal state, (b) leakage state, (c) partial reactor shut down state, (d) reactor shutdown state, and (e) progress. Dark colour on a shell indicates high component value. The trajectory depicts a sequence of observations from a data set from Finnish nuclear power plant Olkiluoto training simulator mapped on the SOM. This example is presented more in detail in [1].

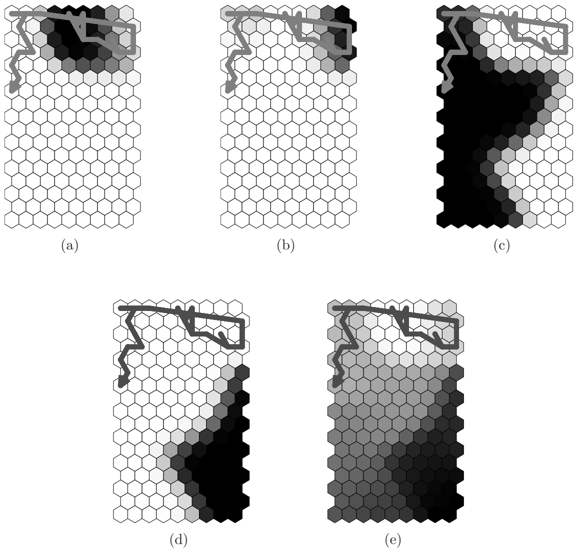

Fig. 2. – Our visualization where a trajectory shows the dynamical behavoiur in a SOM map

Reflecting our visualization example against the defined assessment criteria, it can be noticed that certainly general criteria information clarity and understandability are very important. Also compatibility, error density and limit marginal make sense. If the operator is familiar with this concept, this visualization also increases the situation awareness. On the other hand it is very difficult to estimate the mental load or the structure of the control room, which need completely different methods and tools to be measured.

From the placeness profile properties the most interesting ones for the example are real-time information, transients, predictive information, history of events and monitoring. The rest of the criteria are here for less interest. The placeness profile as a whole could be considered as one potential psychological method to be used in the assessment of SOM visualizations in general, and in production of some kind of measurement framework for this purpose as well.

5. USING INDUSTRIAL DATA IN A CASE EXAMPLE

In our newest research, real data from the reactor unit 1 of Olkiluoto nuclear power plant (NPP) have been used. In April 2009, more than 700 signals were stored, every tenth second. In a six-hour period, a change in a valve position was performed. Changes of the process signals in the reheater section and other parts of the NPP were captured in the recorded data. In this example, signal measurements at the main pipelines of turbine section (413x) are analyzed. These signals are located after the reheater. The position of the control valve at the reheater was changed. At 8 – 10 p.m. process was controlled manually, at 10 – 12 p.m. after the first part of the measurements the process was stabilized. Then the control valve was opened for two hours.

In this example it is shown how to use the SOM method to observe changes between the process signals. Which are the signal values in each state? Which signals depend on the others? In the variable selection phase, all signals from the turbine section were selected, totally 42 signals. In our visualization 10 signals were selected from the turbine, see Table 1 and Figure 3.

Table 1. Explanation for the Signal Measurements and Their Units in the Turbine Section

Signal name	Explanation	Unit
413K567	steam temperature before reheater 1	C
413K568	steam temperature before reheater 2	C
413K576	water pipes	C
413V501	valve position	%
413V505OM	control piston position	%
413V513	control piston position	%
413K573	water pipes	C
413K574	water pipes	C
413V501OM	control piston position	%
413V503	valve position	%

The effect of the control valve test in the reheater part is visualized by SOM component planes. Signal dependencies can be examined. Roughly, it seems that the steam temperatures before the reheater are negatively correlated with the control piston and the valve positions. However, the control piston position 413V513 correlates positively with temperatures. The component planes show the limits for current process signal values.

The visual inspection of the U-matrix and labeling is shown in Figure 4. From the U-matrix visualization, it can be seen that there are essentially three clusters: manual control, the first hour of stabilization period and in the same cluster the second hour of stabilization, and when the control valve is open.

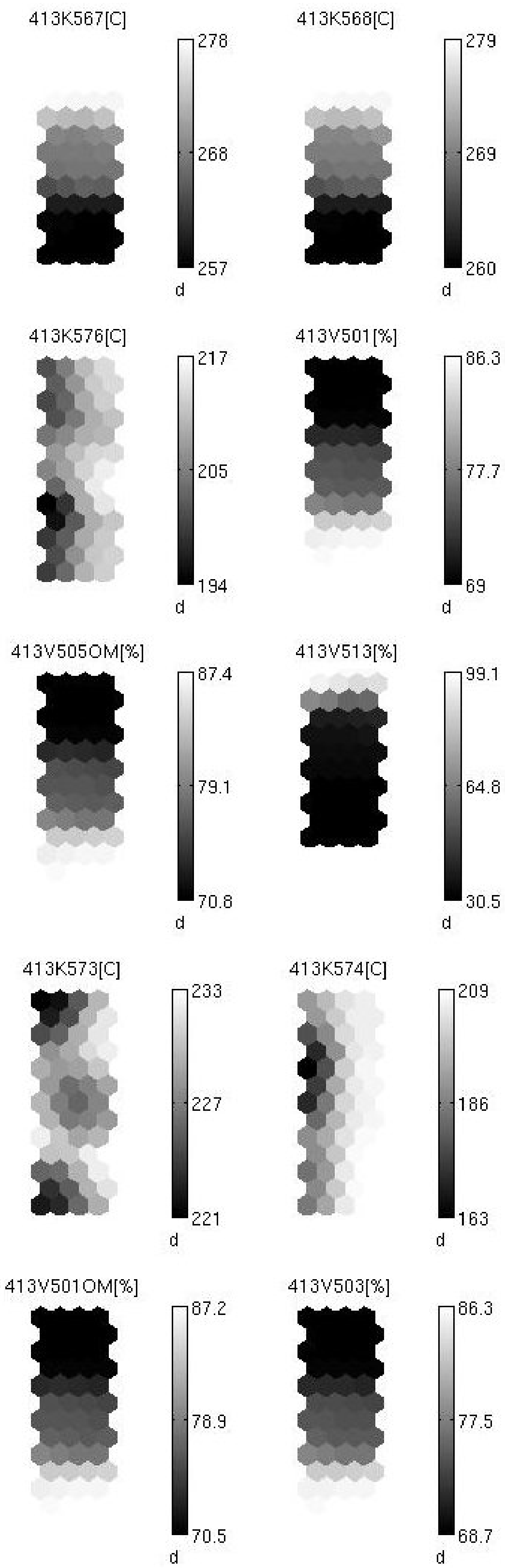

Fig. 3 – In the turbine section 10 process signals were monitored. Denormalized scales are shown on the right side of the component planes

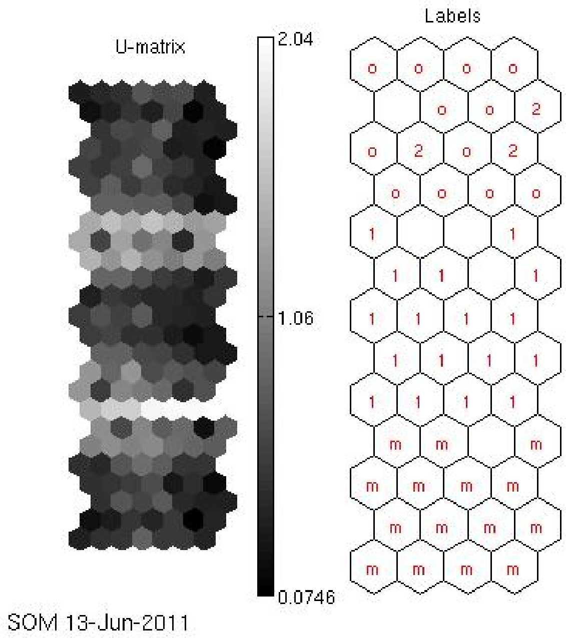

Fig. 4 – In the labels, m: the process was controlled manually, o: the control valve is open, 1: the first hour of the stabilization period, and 2: the second hour of the stabilization period. The U-matrix reveals that the process states 'm', '1' and '2 & o' are clustered very clearly

Interesting remarks are that variable 413K573 has the lowest values when the control valve is open or controlled manually. Signal 413V513, control piston, and temperatures before the reheater get the highest values when the control valve is open.

A similar study has been carried out for the reheater section. In the variable selection phase all signals from the reheater section were selected, totally 125 signals. In our visualization eleven signals were selected from the reheater area and three were selected elsewhere for the analysis, see Table 2.

Table 2. Explanations for the signal measurements and their units in the Reheater Section

'412K571'	'temperature after 412T23'	'C'
'412K584'	'steam temperature before V5'	'C'
'412K576'	'412T22 emergency dump V22'	'C'
'412K466'	'level 412T15'	'%'
'412K720'	'V312 position'	'%'
'412K301'	'412T9 and 445T302 flow'	'kg/s'
'412K490'	'level 412T15'	'%'
'412K188'	'412T11 pressure'	'BAR G'
'412K705'	'V41 position'	'%'
'412K517D'	'rate of change 412E1 phase 2'	'C/MIN'
'412K513D'	'rate of change 412E2 phase 1'	'C/MIN'
'431K457'	'condenser 431E1 level'	'm'
'431K551'	'condenser 431E1 temperature'	'C'
'413V501xM'	'average of piston positions'	'%'

The control valve test in the reheater part did not affect to the reactor pressure and steam flows. They are situated before the reheater and many other process parts. The condenser is located after the reheater and before the reactor. Three signals shown in the last rows of Table II were selected, because signal measurements are after the reheater. Last signal is derived from the redundant measurement. Four measurements are averaged. Next step in the analysis is the visual inspection of the U-matrix, component planes and labeling, see Figure 5.

From the U-matrix visualization, it can be seen that there are essentially three clusters (process was controlled manually, the stabilization period and the control valve is open). The component planes show the limits for current process signal values. Also '412K571', '412K584' and '412K576' in the reheater part have high linear correlation with the condenser and the vacuum system part signal '431K551'. Other interesting remark is that another variable '431K457' from this area has the highest values in the end of the stabilization period. In other words, the level of the condenser is the highest after four hours the experiments were started, although the highest temperature was detected at the end of the experiments.

More exact analysis can be done by the principal component projection, see Figure 6. For example, '412K466' and '412K490' get higher values when the control valve is open than when it is controlled manually.

Both data sets in this case example are from the same event. Logical behaviour in both components in this respect can be identified. The similarities noticed have a clear basis.

6. DISCUSSION

With the SOM method the dynamical development of the process can be seen by using the U-matrix trajectories, and the clustering structure of the data with the U-matrix itself [1]. The correlations of certain variables are seen with the component plane SOM maps. The faulty development in the data can be detected for instance with the quantization error.

The shape of the SOM map also reveals important things about the distribution of the data, if the shape of the map is not restricted or prohibited. Detecting the pre-stage of the fault is possible with various ways [1]. The visualization of the process and its progression with SOM maps, and leak detection with an adaptive process model are also discussed in [1].

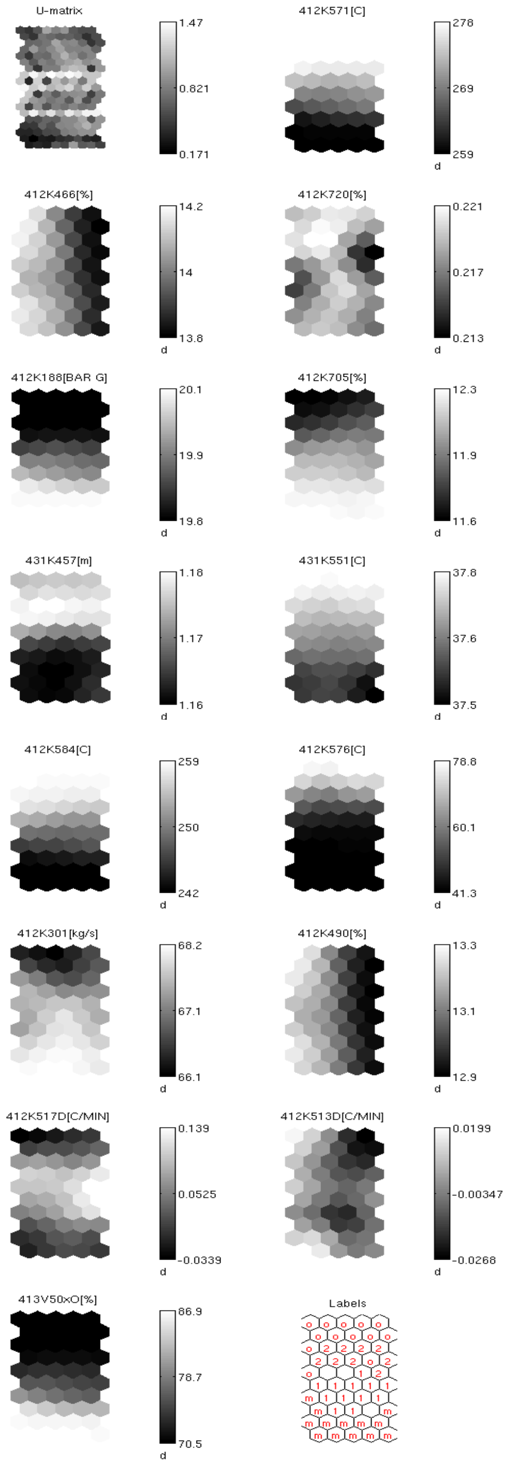

Fig. 5 – In the reheater section 14 process signals were monitored. In the labels, m: the process was controlled manually, o: the control valve is open. 1: the first hour of stabilization period and 2: the second hour of the stabilization period. The U-matrix reveals that the process states 'm' and 'o' are clustered very clearly. The SOM component planes show the values for each process state

Comparing the SOM method with the PCA (Principal Component Analysis) method [13] we noticed that with the SOM method the non-linear behavior is seen better than with the PCA method, which is able to show only the linear dependence.

To assess the information value of SOM maps and other visualizations that we have used is very difficult. To find out concrete measurable criteria here is almost impossible. Qualitative assessment with qualified criteria is more tempting option than trying to develop systematic quantitative measuring methods. This kind of analysis we have done with some example visualizations.

The assessment criteria we have used in Section III and Section IV can be applied also with the SOM concept used in the industrial case example in Section V. As we did not discover very many new observations compared with the already earlier analyzed example, we did not complete that analysis here any further. Interesting viewpoints were detected though to be realized in becoming further studies.

Some further co-operation is planned with a psychology group in the Finnish Technical Research Centre, and research groups in the Norwegian OECD Halden Reactor Project (Institutt for Energiteknikk) within this topic.

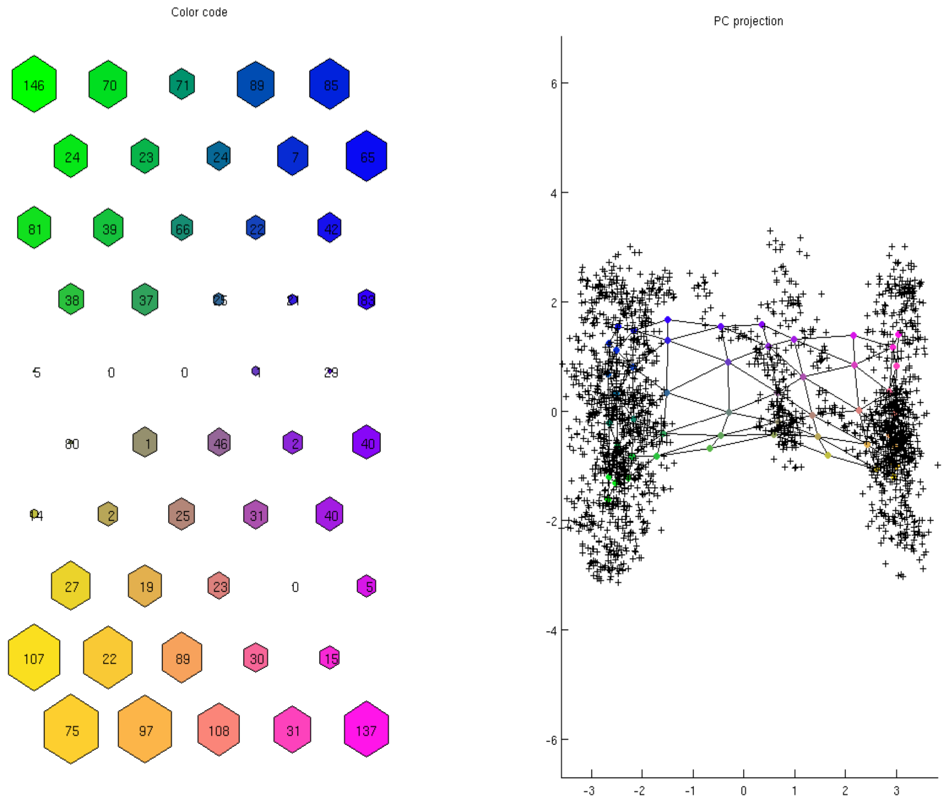

Fig. 6 – A principal component projection (PCP). The color map is another type of visualization for U-matrix. Distance matrix information is shown as zero hits for each part of the map (number inside the object). The longer distances are visualized by smaller objects. From the PCP three different clusters can be detected. The first and the last points of the stabilization cluster are situated near to the other two clusters

7. CONCLUSION

We have shown with a case example by using industrial data the information value of the self-organizing map in the process visualization. With some verbal comparisons, we have tried to differentiate this method from some other commonly used methods. The information value can be clearly seen although the use of this method in a real control room would need special attention and capabilities from the operators. The operator training would therefore meet new challenges.

The measurement of the information value with any concrete way is a very difficult task. Some useful criteria can be found to estimate these values. We have made some reflections to psychological studies in this respect.

There are a lot of open questions and demanding challenges studying this issue further in the future. The SOM method alone is not enough to find out all necessary information out of the process, but it can add additional information value compared with many more traditional methods. The best results can be achieved by using many different methodologies in a well-selected combination.

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