Self-Organized Maps in the Identification of IRIS Reactor Transients

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Abstract - IRIS, the International Reactor Innovative and Secure, is an international program that aims to develop an integrated primary system reactor with innovative features that can meet most of the requirements considered in the Generation IV Roadmap Study as a Near-Term Deployment System. IRIS philosophy is the *Safety by Design Approach*. The IRIS concept raises many challenges that only can be addressed by an international cooperative effort. This paper analyzes and presents many results of a possible solution for one of these challenges, *the transients' classification and identification* that may be used to help the safe operation of IRIS. The approach studied in this paper is based on self-organized maps (SOM), a specialized class of artificial neural networks (ANN). The results presented complement previous reports and show that SOM is a quite promising tool in the identification of initiating transients of the IRIS reactor. The ability of this kind of ANN in promptly identify the deviation from normal operation, with the aid of only few process sensors signals, may be used to develop the IRIS Transient Identification System (TIS).

I. Introduction

IRIS is an international cooperation effort to design a nuclear energy system capable of meeting many of the requirements for the new generation of nuclear power plants. IRIS takes advantage of its integral configuration to implement a safety by design approach to meet challenging safety goals [Carelli et al., 2001]. In this philosophy, every possible source of "safety vulnerability" has to be addressed and adequately coped with [Packer, 2002]. Safety by design and the safety barriers recommended by the principle of defense in depth can eliminate some and attenuate many of the consequences of mechanical, electrical and human fails, but to provide a really confident plant, modern tools to provide "good information" for the operation team are required.

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This paper describes a promising tool able to identify transient events, classifying them into normal or abnormal transients. The system under study can provide operator support, helping the safe operation of IRIS. The approach is based on self-organized maps (SOM), a special class of artificial neural networks (ANN), operating on-line with the reactor instrumentation. This kind of representation can allow to the operator to watch how a given transient is evolving with respect to its severity, as the time path of the activated units is migrating towards the border of a new class of transients.

The central idea is to develop a system capable of identify and classify a transient type in its early stage. This system was first described in 2003 [Baptista and Barroso, 2003], and after this time it was improved and tested with more data considering a greater set of transient simulations. The data consist of sets of eight key process variables recorded in the first 30 seconds of several types of transients, normal and abnormal and also in steady state conditions.

II. IRIS Brief Description

IRIS is a modular, integral, light water cooled reactor, designed for a power of 335 MW(e)/module. The most relevant technical characteristics of IRIS are discussed in detail in references {[Carelli et al., 2000], [Carelli et al., 2001a], [Carelli et al., 2001b], [Petrovic et al., 2000], [Oriani et al., 2001], [Conway et al., 2001]}. Its "safety by design" approach, where accidents are "designed out" to the maximum extent possible, instead of engineering how to cope with their consequences is presented in [Carelli et al., 2001].

The IRIS integral vessel houses the reactor core, its support structures, upper internals, control rod drives, eight steam generators, internal shields, pressurizer and heaters, and eight reactor coolant pumps (Fig.1). Hot coolant rising from the reactor core to the top of the vessel is pumped into the steam generators annulus. The integral vessel configuration is essential to the safety by design approach as shown in [Conway et al., 2001] and thus it is key to satisfy the enhanced safety requirement.

III. Self-Organized Maps

Self-organized maps are artificial neural networks with a single layer where the units are placed in a 1-D or 2-D grid. In the 2-D SOM, the units are placed in a square or hexagonal lattice (Fig.2). The training of the SOM is based on the competitive learning concept: units compete with each other to be activated when a specific pattern is presented and the result is that just a single unit is really active at a given moment. The original idea of the competitive learning –winner takes all– was proposed in 1958

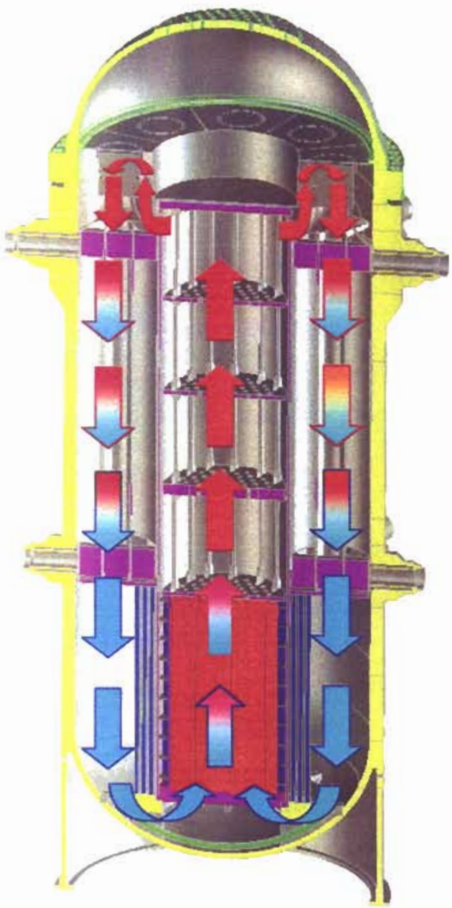


Fig. 1. IRIS Integrated Primary System.

[Rosenblatt, 1958] but the most general model was developed in the 80's [Kohonen, 1982].

The principle of the topographical maps formation, as formulated by Kohonen is: the spatial location of an output unit in a topographical map corresponds to a domain or peculiar feature extracted from the input space. This concept reproduces one of the features of the brain: the organization of the sensorial inputs in the higher planes, represented by topographical maps. The units in this grid are assigned to specific features of the input, producing topographical maps related to specific classes of patterns, i.e., the spatial locations of the units are indicative of the statistical features of the input patterns. These indications can be seen as a non-linear generalization of the Principal Component Analysis (PCA).

In the SOM there are not any known or desired output. The objective of the network is to search similarities among patterns and to promote the classification of the input data into groups, in a non-supervised learning method. An incoming pattern triggers a competition among the units and the winner weights are updated to become more close to the input pattern. These maps are such that, patterns close to that which have previously activated one unit, will either activate the same unit or one of its

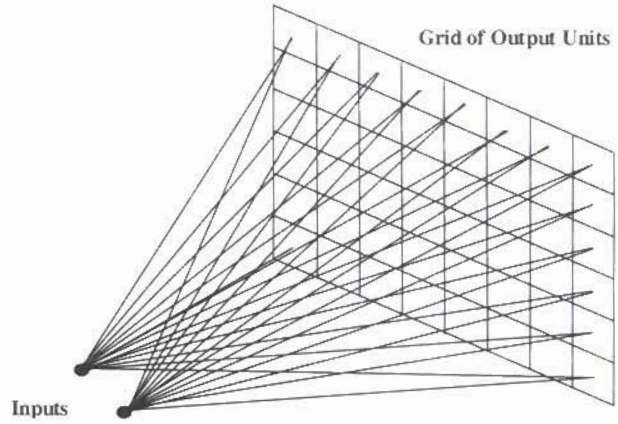


Fig. 2. 2-D SOM.

neighbors. The winner unit is the one whose weights vector is the closest to the input pattern, based on a Euclidean distance. There are lateral communications between the units in the grid, which obey a neighborhood function, usually represented by a gaussean like function:

$$V_{j,j^0}(n) = \exp\left(-\frac{\left\| r_j - r_j^0 \right\|^2}{2\sigma^2(n)}\right) \tag{1}$$

where j0 indicates the winner unit; ||rj – rj0|| is the Euclidean distance between the unit j and the winner unit. s(n) defines the width of the neighborhood, which starts as wide as possible and decreases with increasing n, i.e., with training:

$$\sigma(n) = \sigma_0 \exp\left(-\frac{n}{\tau_\sigma}\right) \tag{2}$$

The weights are updated according with:

$$w_j(n+1) = w_j(n) + \eta(n)\,[x(n) - w_j(n)] \tag{3}$$

where x(n) is the input vector. The learning rate, h, varies as a function of the distance between the unit j and the winner unit (by the V function) and as function of the time (n):

$$\eta(n) = \eta_0 \exp\left(-\frac{n}{\tau_\eta}\right) V_{i,j^0}(n) \tag{4}$$

SOM is an excellent tool for the exploratory phase of data analysis. It projects the input space into prototypes of lower dimensionality, i.e., into 1-D or 2-D regular-in-shape grids that can be used to explore the data features. "Visualization" is the first step in the pattern classific ation, and it is completely done by SOM in an unsupervised mode.

In this step only qualitative features of the input data can be obtained. "Selection" is the "extraction" of the chara c-teristics. The next step is "classification," when the s e-lected characteristics of the input data are assigned to individual classes. It is know that, in the pattern classification phase, the performance is improved if the "sele ction" is followed by a supervised classification, i.e., it is convenient the use of an "adaptive pattern classifier." In the previous work we have used the learning vector quantization (LVQ) scheme proposed by Gersho [Gersho and Gray, 1992], now we present results without quantization.

IV. The TIS Conception and Testing

A. The Transient Identification System

A nuclear reactor can be subjected to different kinds of transients. In this paper only few of them are considered: positive and negative step load changes of 10% of full power; positive and negative ramp load transients at a rate of 5%/min.; a turbine trip; SCRAM; the inadvertent relief valve opening; a large power excursion simulated by a step of 50% of full power; a negative power step of 70% of full power; and, a small loss of coolant accident. Together with these transients, the training data set contains several steady state conditions patterns from 20% to 110% of full power.

It is important to observe that the response of the reactor systems to each one of these transients depends on the control system, which is being developed. At this early stage of development, when the control architecture and parameters are not optimized, simplified models are good enough to provide basic data to characterize IRIS behavior. Barroso [Barroso et al., 2003] describes the simplified tools that produced the data used in this paper and also presents results for many transients. Fig.3 illustrates the temperature response during a SCRAM from full power.

The Transient Identification System (TIS) was conceived with the idea that the behavior of few variables, like the reactor and the steam generators power; the temperature at different points; and the pressurizer pressure and water level, can characterize a single transient, as the transient identity. The system has a buffer to collect data for few seconds of the main variables, which will form a spectrum, being the input for the SOM. Fig 4 illustrates how the pressure variation during a small loss of coolant accident (left side) is translated into 16 seconds packages (each package contains information of 16 seconds of transient time and the time difference between packages is 1 second).

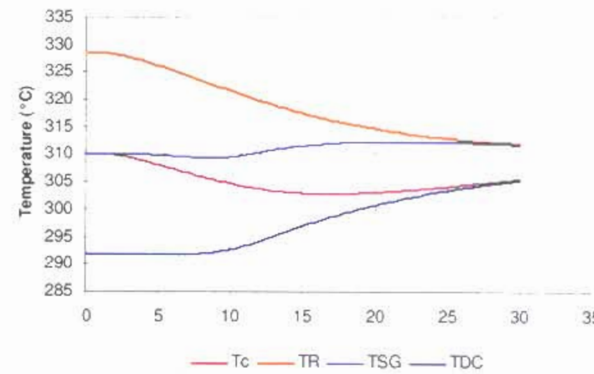
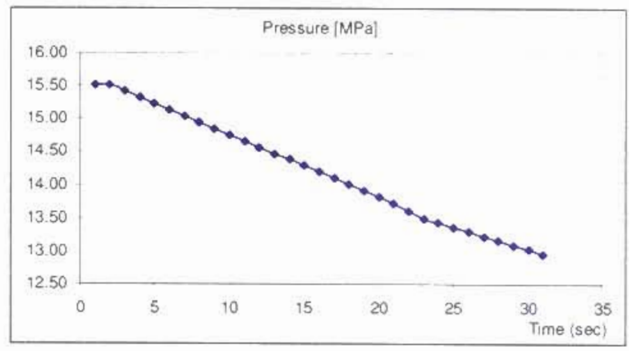
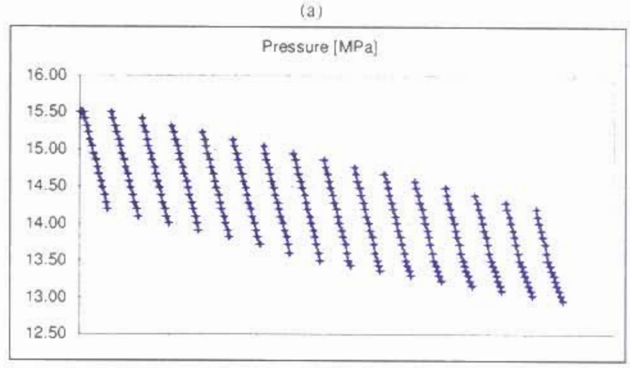


Fig.3. SCRAM: Temperature Response.



(a)



(b)

Fig.4. LOCA: Pressure variation (a) and Contents (b) for a 16 sec. buffer.

Fig.5 shows a diagram that represents the basic idea of TIS; where the input is a 2-D matrix with the vertical direction representing the variables and the horizontal direction the time. At each moment the buffer contains a package of few seconds of the acquired variables values and its contents is changed at each second.

Considering that each cell is previously assigned to a kind of transient, its lightening will revel the kind of transient in course. The TIS' screen will light a single cell each second. Although we have tested two different-size buffers (from 6 to 16 seconds) with different acquisition times, the data presented in this paper was limited only to the results for a 16-seconds buffer, containing data of the first 30 seconds of each transient beginning (previous

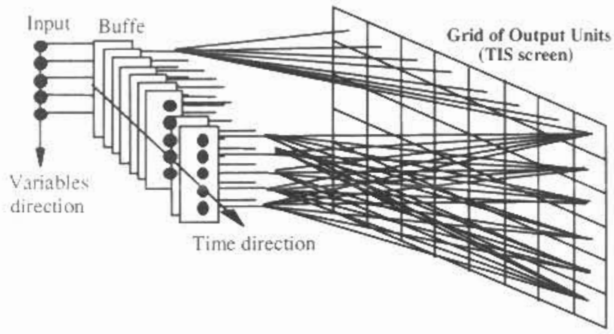


Fig. 5. Schematics of the Transient Identification System.

works present data from 20-seconds buffer-size with 2 minutes of acquisition time).

B. Transient data and training results

Eight variables were selected to be the input for TIS [in previous works this number was 9]: reactor power, SG's power, core outlet temperature, riser mean temperature, SG mean temperature, downcomer temperature, primary system pressure, and pressurizer water level. It was used a sampling interval of 1 seconds during 30 seconds for each transient. Fourth five different transients/conditions were used in the system training; more twelve conditions in its testing. The overall transients list is presented in Table 1: the transients not presented in the training phase are in bold text.

In the previous work, the data was normalized only with respect to each variable value; the new system has an option for the buffer contents normalization. The paper presents results for a network with a 10x10 square array, trained in the unsupervised mode for 2000 époques[1]. The objective was to verify TIS ability to make clear distinction between four kinds of operating conditions: steady state, ramp transients, step transients, and abnormal and accidental events.

After the training the sensibility of each cell of the SOM was tested and assigned to the "most closest transient class." This "most closest class" refers to the shortest Euclidean distance of the cell to the input: the shortest distance to a specific class assigns the class number of the input to the cell class (1 for steady-state, 2 for ramps, 3 for steps and 4 for not normal events).

After training, TIS was tested in the monitoring mode showing which cell lights, at each second, when a specific transient is presented. Each transient presented is a set of 16x8x16 data (16 buffer contents of 8 variables by 16 acquisition periods).

TABLE I
TRANSIENT LIST

Normal Transients			
1	20% Steady state	28	100% Ramp –5%/min
2	**25% Steady state**	29	90% Ramp –5%/min
3	30% Steady state	**30**	**80% Ramp –5%/min**
4	35% Steady state	31	70% Ramp –5%/min
5	40% Steady state	32	60% Ramp –5%/min
6	45% Steady state	**33**	**50% Ramp –5%/min**
7	50% Steady state	34	40% Ramp –5%/min
8	55% Steady state	35	30% Ramp –5%/min
9	60% Steady state	36	100%→ Step –10%
10	**65% Steady state**	37	90% → Step –10%
11	70% Steady state	**38**	**80% → Step 10%**
12	75% Steady state	39	70% → Step –10%
13	80% Steady state	40	60% → Step –10%
14	85% Steady state	**41**	**50% → Step 10%**
15	90% Steady state	42	40% → Step –10%
16	95% Steady state	43	30% → Step –10%
17	100% Steady state	44	20% → Step +10%
18	**105% Steady state**	45	30% → Step +10%
19	110% Steady state	**46**	**40% → Step +10%**
20	25% Ramp +5%/min	47	50% → Step +10%
21	30% Ramp +5%/min	48	60% → Step +10%
22	**40% Ramp +5%/min**	**49**	**70% → Step +10%**
23	50% Ramp +5%/min	50	80% → Step +10%
24	60% Ramp +5%/min	51	90% → Step +10%
25	**70% Ramp +5%/min**		
26	80% Ramp +5%/min		
27	90% Ramp +5%/min		
Abnormal transients			
52	100%→ Step –70%		
53	Safety Valve Opening		
54	100% Small LOCA		
55	100% SCRAM		
56	60%→ Step +50%		
57	**100% Turbine trip**		

Fig.7 shows the classes assignment for each cell for one training performed with pattern normalization in the buffer, and the sequence of cells lighted for few samples. The cells with the number "1" are assigned to steady -state conditions. The cells with number "2" are assoc iated to the ramp transients, the cells with number "3" to the step transients and the cells with number "4" to the not normal transients. The wide red line traces the sinuous path of steady-state conditions from 20% to 110% of full power. The thin blue lines represent the sequence of cells lighted during the presentation of positive steps of 10% of power and the thin green lines the negative steps. The brown lines represent the beginning of ramp transients from the power fractions of 30%, 40%, 50%, 60%, 70%, 80% and 90%. Three abnormal and accidental events were represented in Fig. 7 by the thick dotted lines, the turbine trip, SCRAM and a Small LOCA. The separation between normal and abnormal events is evident. It was observed also, that the most abrupt events provoke the lightening of cells farther from the steady-state line.

[1] *Époque* means "a single presentation of the complete training set.

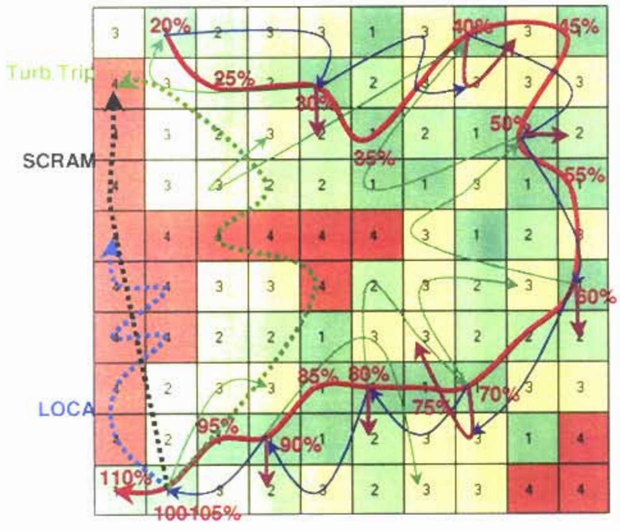


Fig. 7. TIS screen: results obtained in the monitoring mode.

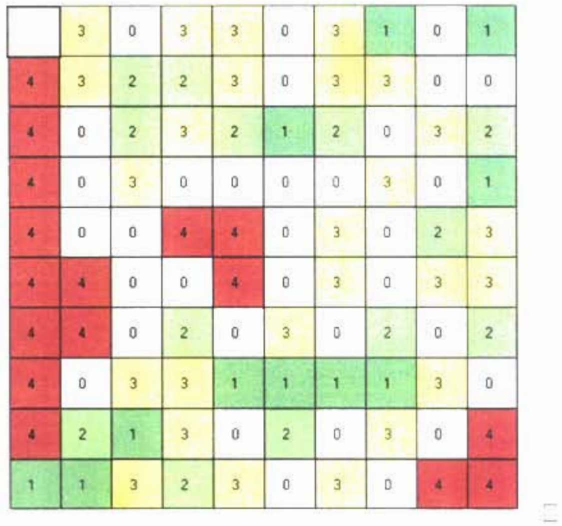


Fig. 8. TIS screen: Sensitivity by frequency.

In Fig. 7, the cells classification was based on the minimum Euclidean distance, i.e., the Euclidean distance between the input vector and the weight vector of each cell is checked and the cell class is set as the class of the corresponding data class. This method of sensitivity measurement may cause the imperfect response to patterns not present in the training set. The inadequate transient classification may also be responsible for imperfect responses; further refinement with vector quantization may improve the system accuracy but will not be discussed in this paper.

Fig. 8 shows the results after a identical training but with the classification performed in accordance with the frequency of activation, i.e., each cell class is set by the most frequent activating transient class: if the cell activation is more frequent for abnormal events, it class is set to "4". The result showed a perfect agreement with the previous classification method.

Fig.8 shows that many cells are not associated with any one of the transient classes (the 'white-cells" with a '0" class association); these are the 'never lighted cells." These cells did not 'win" for any input pattern of the training set. Although these cells can respond to new patterns, they were not associated with any one of the first three classes. The main conclusion of this analysis is that, up to this moment, the classification on the basis of the

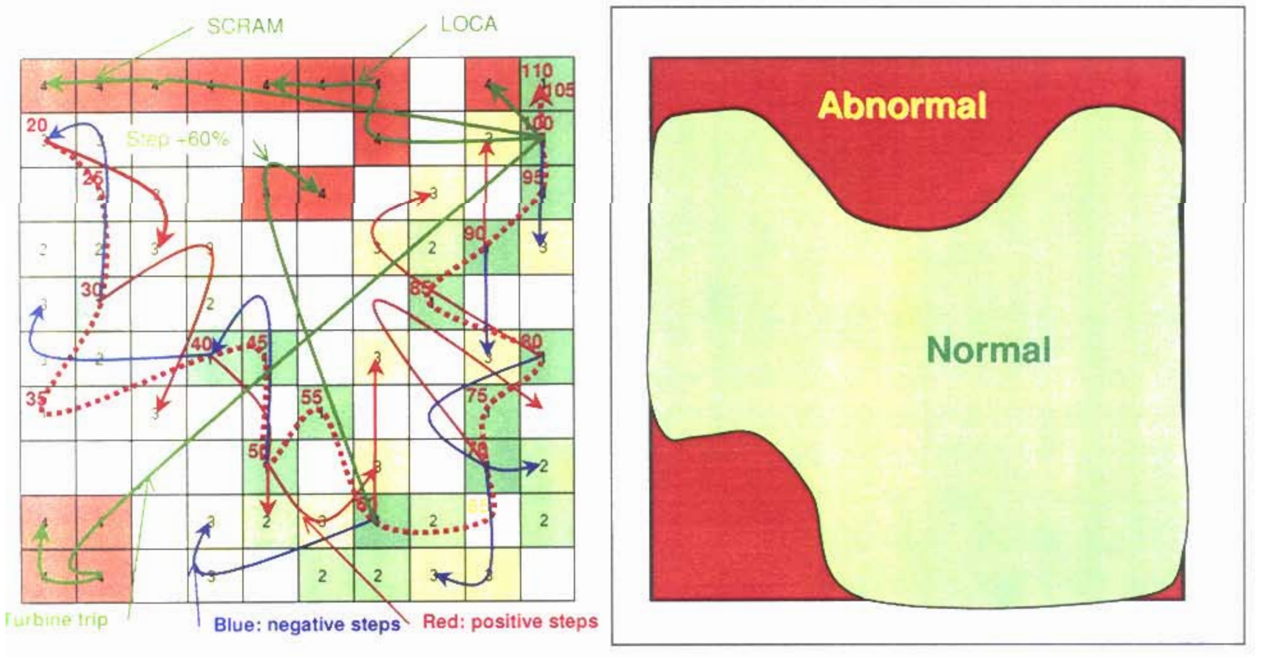


Fig. 9. TIS screen: Training with a reduction on the power influence.

minimum Euclidean distance seems to be a good choice.

The strong association observed between transient type and power was analyzed to verify if its cause was the use of two variables associated with the thermal power, i.e., the reactor and steam generators power. To do this analysis, the normalized power values were divided by two, reducing their influence on the input pattern. At the same time the temperature-normalizing factor was reduced to increase their relative importance. The sensitivity by frequency method was applied and few tests were performed. The results are plotted in Fig. 9, which shows that, besides the different topological arrangement that was constructed due the different initial weights, the general arrangement of cells classes around the sinuous power line follows similar pattern. Fig. 9 right shows the contour that separates the normal from abnormal transients.

Similar results were obtained for different buffers size. Results for systems with bigger grids size will be presented in future.

C. Tests of the system performance

Grids with 5x5 to 25x25 cells were tested in a 2.2MHz clock Intel Pentium 4 PC. The CPU time spent in the training task. Fig.10, showed a squared relation with N, the number of lines and/or columns of the grid.

Tests with different buffers size were performed to measure the relation between buffer size and the relative importance of each type of transient attributed during the classification process and also the effect of data normalization. The analysis consists of counting the number of units associated with each class, in proportion with the quantity of correspondent data used in the training. Fig.11 shows the results for the training with and without normalization in the buffer data.

The classes defined in Fig.11 correspond to the transient classes: C-1 to steady-state conditions, C-2 to ramp transients, C-3 to steps and C-4 to abnormal and accidental events. Two main effects observed due normalization were: the sensitivity with buffer size has greater mean deviation; but the differentiation of classes by grid area assignment is greater. To better analyze this aspect, the results were averaged with respect to the buffer size and after this, corrected proportionally to the number of transients per class. The results showed that the SOM had associated much more importance to the abnormal events, followed by step, then ramps and finally the steady-state conditions: the corrected values, in this order, is in Table 2.

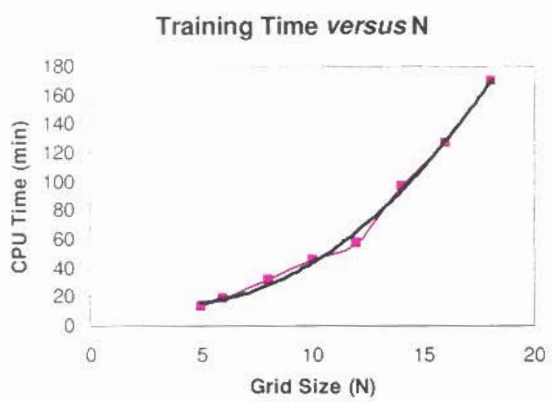


Fig. 10. CPU-time versus grid size.

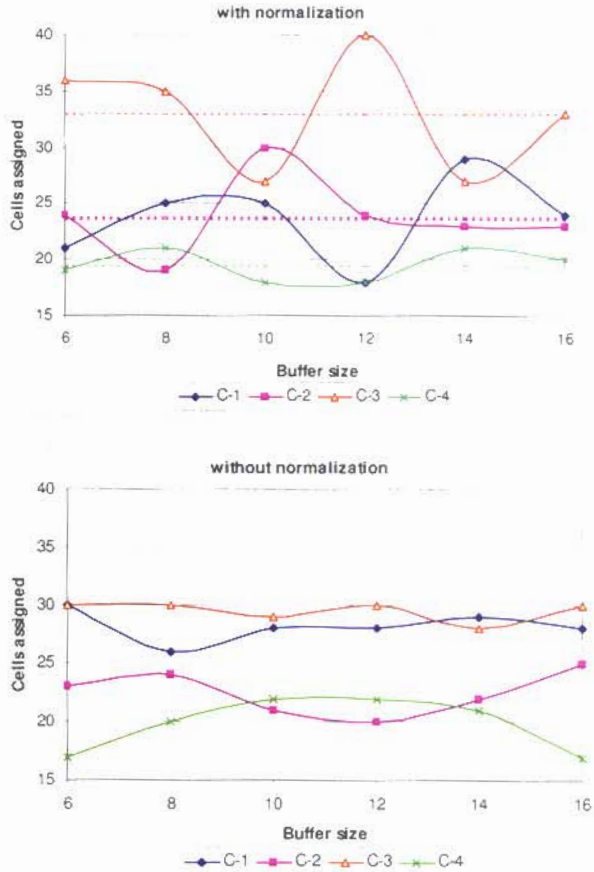


Fig. 11. Assignment of cells to the classes of transients.

TABLE 2
TRANSIENT ASSOCIATION LIST

SS	Ramp	Step	Abnormal
15	20	27	39

D. Future work

Next steps will consider the following tasks: a) New analyses with grid sizes up to 25 x 25 cells, or more; b) Detailed studies on the number and type of input variables; c) Testing of different schemes of vector quantization; d) Implementation and testing of a triangular pitch grid; e) Studying the use of the 'Mexican hat"-type neighborhood function; and, f) Development of an algorithm to convert the irregular topological map into a regular display screen.

V. CONCLUSIONS

The results presented in this paper, together with previous published results, confirm that the TIS concept based on SOM looks very promising. Its capability in identifying transient and operating conditions, in special normal from abnormal transients, was demonstrated.

It was possible to observe that relatively slow processes near the sinuous line that represents the steady-state conditions characterize the behavior of a reactor under operational transients. Abnormal and accidental events provoke the prompt detachment from the neighborhood of this line.

The present work reports results of TIS being trained with very short portions of transients, i.e., 30 seconds, following a recommendation cited in [3].

The recommendation to analyze the effect of 'buffer content normalization," a task considered important to improve SOM performance, also was performed, although not yet ended.

VI. NOMENCLATURE

ANN – Artificial Neural Network

DOE – US Department of Energy

GIF – Generation IV International Forum

I-NE+RI – International Nuclear Energy Research Initiative

IPSR – Integrated Primary System Reactor

IRIS – International Reactor Innovative and Secure

LVQ – Learning vector quantization

NE – Nuclear Engineering

PCA – Principal Component Analysis

SCRAM – 'Safety Control Rod Axe Man": the sudden shutting down of a nuclear reactor

SG – Steam Generator

SOM – Self-Organized-Map

TIS – Transient Identification System.

VI. ACKNOWLEDGMENTS

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