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Monitoring and Operational Support on Nuclear Power Plants using an Artificial Intelligence System

Paulo H. Bianchi[1] and Benedito D. Baptista F.[2]

[1] Instituto de Pesquisas Energéticas e Nucleares, IPEN - CNEN/SP
Av. Professor Lineu Prestes 2242
05508-000 São Paulo, SP
phbianchi@gmail.com

[2] Instituto de Pesquisas Energéticas e Nucleares, IPEN - CNEN/SP
Av. Professor Lineu Prestes 2242
05508-000 São Paulo, SP
bdbfilho@ipen.br

ABSTRACT

The monitoring task in Nuclear Power Plants is of crucial importance with respect to safety and efficient operation. The operators have a wide range of variables to observe and analyze; the quantity of variables and their behavior determine the time they have to take correct decisions. The complexity of such aspects in a Nuclear Power Plant influences both, the plant operational efficiency and the general safety issues. This paper describes an experimental system developed by the authors which aims to assist the operators of Nuclear Power Plants to take quick and safe decisions. The system maps the status of plant and helps the operators to make quick judgments by using Artificial Intelligence Methods. The method makes use of a small set of monitored variables and presents a map of the Plant Status in a friendly manner. This system uses an architecture that has multiple Self-Organizing Maps to perform these tasks.

1. INTRODUCTION

The concern about safety is eminent in all Nuclear Power Plants projects. The International Atomic Energy Agency – IAEA [7] provides several regulatory guides and documents about the safety of Nuclear Facilities ([8] and [9]), what reflects its concern about this subject.

The safety systems implemented could be preventive, like the radiation containment barrier, or mitigatory. The last ones could be triggered automatically, like the SCRAM (emergency shutdown), or manually by the plant operators.

The operators uses measurements from several devices installed at the plant and at the nuclear reactor. The quantity of variables generated by these measurements is too big, to a level that can harden and delay their interpretation.

The experimental system described in this paper monitors these variables in real time and interpret them, presenting the current state to the operators in a friendly and intuitive way, because it uses nomenclatures that are familiar to them, and signs easily understandable.
The variables' interpretation is done using the artificial intelligence technique known as Self-Organizing Maps (SOM) [11].

The architecture used with the SOMs is based on multiple specialists maps, each one representing a state, transient or not, of the nuclear reactor. The identification and classification of the current state is done by a competition between these maps.
Some results of the first implemented version will be presented, and can be seen in more details in [4]. These results were satisfactory, given that is the first implementation of this architecture of multiple SOMs on the monitoring of Nuclear Power Plants.

The authors also show that this architecture can be refined, to obtain more precise and detailed system responses.

2. TRANSIENT STATES OF NUCLEAR POWER REACTORS

The Nuclear Power Reactors are aimed to generate electrical energy to general consumption. There are other kinds of Nuclear Reactors, classified in relation to its ends, like Research Reactors.

The SEICT - *Sistema Experimental de Identificação e Classificação de Transitórios* (Experimental Transients Identification and Classification System), that is how we will call the system in this paper, was conceived to operate in Nuclear Power Reactors like IRIS [10].

Next, the thermo hydraulic systems that are analyzed by SEICT will be presented, and so the transient states that it recognizes.

2.1. Thermo Hydraulic Systems of the Nuclear Power Reactors

SEICT analysis the primary and the secondary systems of the Pressurized Water Reactors (PWR). In those two systems water circulates, but they have independent circulation channels, i.e., the primary system's water does not have direct contact with the secondary system's water.

The primary system executes the water heating, which transports the heat to the heat exchanger, which heats up the secondary system's water to the specific boiling point of its pressure, so that the steam can move the electricity generating turbines, as illustrated in Figure 1.

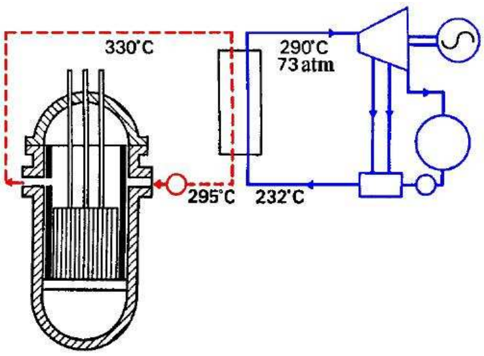

Figure 1. Primary System (Red) and Secondary System (Blue), with exemplified pressure and temperature.

The SEICT's initial project works with temperature, flow and pressure measurements only, because they are common parameters to several systems of electricity generating power plants, like gas and coal, leaving behind, for now, specific measurements of Nuclear Power Plants, like neutrons' flow in the reactor's core, for instance.

In previous works, like [1], [2], [3] and [5], theoretical models of the IRIS Reactor were used. In this paper, the data used was extracted directly from the IPEN's experimental facility called Natural Circulation Facility, or in Portuguese, *Bancada de Circulação Natural* (BCN).

The BCN, which the basic design can be seen in Figure 2, has that name because it does not uses pumps to circulate water on the primary system, but instead, the flow is generated from the pressure difference between the entrance and the exit of the heater.

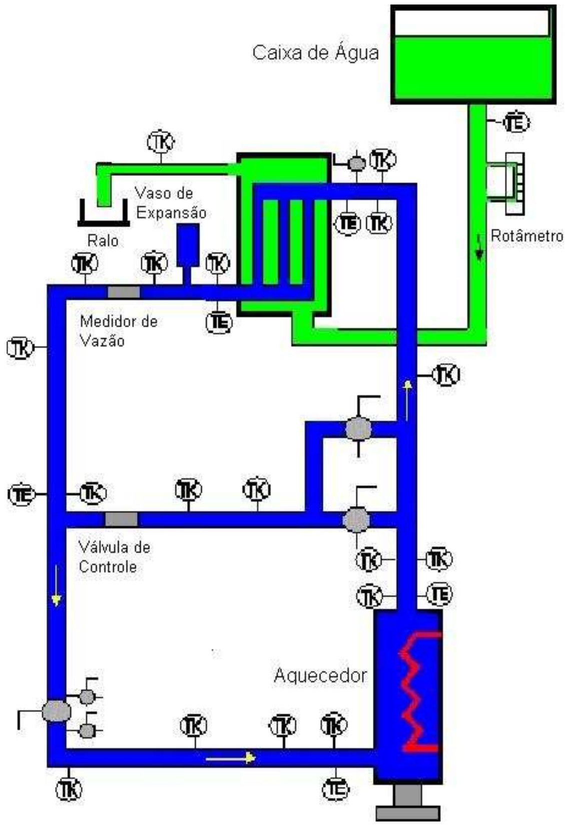

Figure 2. BCN – IPEN, Primary System in blue and the Secondary System in green.

2.2. The Transient States

Considering the BCN capabilities, the following transient states were simulated:

- Heating
- Cooling
- Steady state
- Ramps
- Steps
- Deviation channel opening on the primary system (DCO)

- Flow blocking on the primary system (PFB)
- Flow blocking on the secondary system (SFB)

The last three states are considered abnormal, i.e., accident indicators.

The parameters used in the data acquisition experiments are exposed in the Tables 1 and 2.

Table 1 – Experiments on abnormal transients

Experiment	Average heater power	Secondary system flow	Simulated transient
1	500W	60 l/h	-
2	1000W	60 l/h	PFB
3	1500W	60 l/h	-
4	2000W	60 l/h	DCO
5	2500W	60 l/h	SFB
6	500W	120 l/h	-
7	1000W	120 l/h	PFB
8	1500W	120 l/h	-
9	2000W	120 l/h	DCO
10	2500W	120 l/h	SFB

Table 2 – Experiments simulating ramps and steps

Experiment	Time frame	Simulated transient
1	10 min	Step
2	10 min	Ramp
3	20 min	Step
4	20 min	Ramp

The amount of generated data is too big to be shown here. More details can be found in [4].

The Ramp and the SFB transient states were not analyzed by SEICT because the Ramps samples could be joined with the heating and cooling data. And the SFB simulations takes too long to generate significant data, given the BCN's systems' great inertia.

3. SYSTEM IMPLEMENTATION

In this paper we highlight the features related to the SEICT's AI module's construction, which uses multiple SOMs. But first is necessary to understand the networks (SOMs) training process.

3.1 Training Process

The training process is divided into three parts:

- Subdivision to apply the Cross Validation technique;
- Vectorial normalization;
- Networks training

The SOMs training uses the Cross Validation technique [6], which in this work consists of dividing the training data in two subsets:

- Training Set
- Validation Set

The training set is used effectively on the networks training, and the validation set is put apart to be presented after the training ends. It is done to evaluate how the network behaves facing unknown data.

The use of this technique allows a better evaluation of the network's performance, and it also allows us to use a measure of the network's answer reliability, that is presented to the system operators. We call this measure "Semaphore" (Section 3.4).

3.2 SOM Training Algorithm

In the training set vectors, the data are in the buffer format, where the readings of several instruments, from a time frame, are stored, as shown in Figure 3.

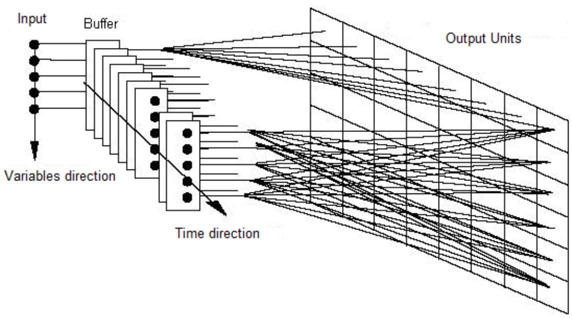

Figure 3. Data buffer of SOM's input data used on SEICT.

The SOMs have a topologic structure, called output layer, that has neurons related with another layer, called codebook, which has the network's knowledge about the universe presented to it during the training. The network organizes the data in such a way that similar information in the codebook will relate themselves with neurons close to each other in the output layer. That provides a similarity analysis based on the output's layer topology.

The algorithm used in this work is the Batch Training Algorithm [11], that has 3 steps:

1 – <u>Initialization:</u> the SOM's codebook values are filled using values from the training set.

2 – Bach Similarity Matching: all codebook codes are grouped by similarity. The grouping criterion is the Euclidean Distance, i.e., the training patterns that are more similar to the neuron will be placed on its corresponding group.
3 – Updating: Each codebook code is updated, being its new values the average of its corresponding similarity groups.
4 – Continuation: Repeat the step 2 a few times.

Its mathematical representation is:

$$w_i(n + 1) = \frac{\Sigma_j\, q_j * h_{ji}(n) * x_j}{\Sigma_j\, q_j * h_{ji}(n)} \tag{1}$$

Where $w_i(n)$ is the codebook's code with index i, in the n epoch iteration, x_j is the input training pattern with index j, h_{ji} is a function of n called "general neighborhood function", and q_j is the number of patterns belonging to the similarity group of the neuron correspondent to the code that has the index i. The general neighborhood function, when multiplied with q_j, influences the weight changing according to the distance of the neuron i to its best matching patterns.

After trained, the SOM responds indicating, in its output layer, the Best Matching Unit (BMU), i.e., the neuron that has the lowest quantization error related with the input pattern.

That quantization error is calculated by extracting the Euclidean Distance between the input pattern, and the codebook code of the neuron.

3.3 Multiple SOM Architecture

The implemented architecture on SEICT uses one SOM network to each transient state, and trains it using solely the data correspondent to its given transient, as it is shown in Figure 4.

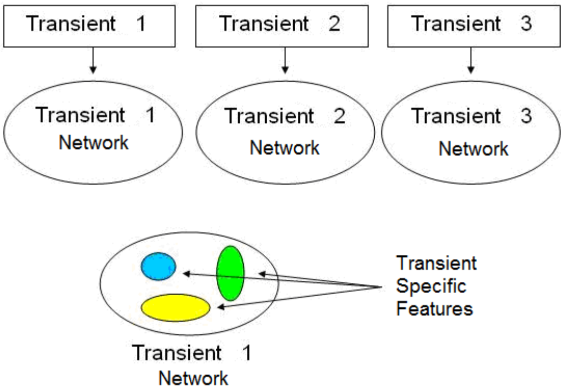

Figure 4. Diagram showing the multiple SOM architecture

The input data (plant monitoring variables) are presented to all networks. Each one of them finds its BMUs, with its correspondent quantization error. And then, these networks compete with each other, by the quantization errors' comparison of its BMUs. The network that has the lowest quantization error wins, and the system classifies the current state by verifying what transient the winner SOM network represents. The competition process is illustrated in Figure 5.

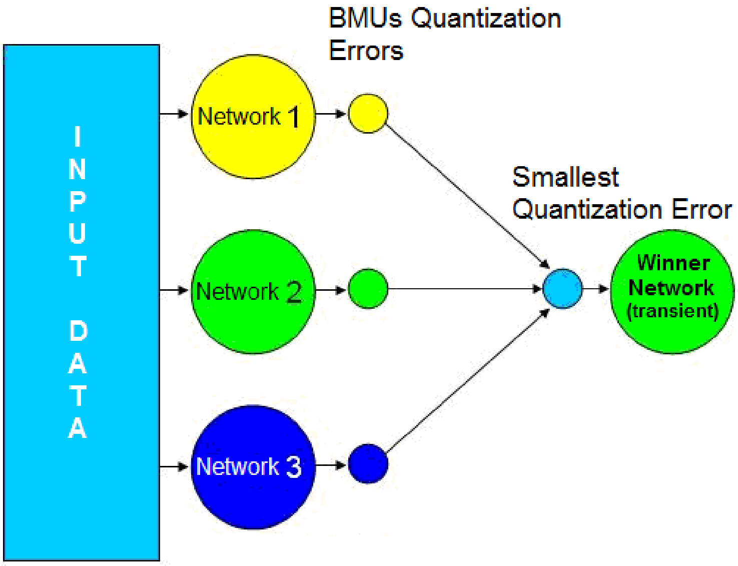

Figure 5. Networks competition

3.4 Semaphore

The semaphore is shown to the operators like traffic lights: three colors indicating reliability levels.

These reliability levels are evaluated using the quantization error of the winning network's BMU.

Its value is then compared to the quantization error averages generated when the network is presented to its training and validation set, and its standard deviations, as shown in Figure 6.

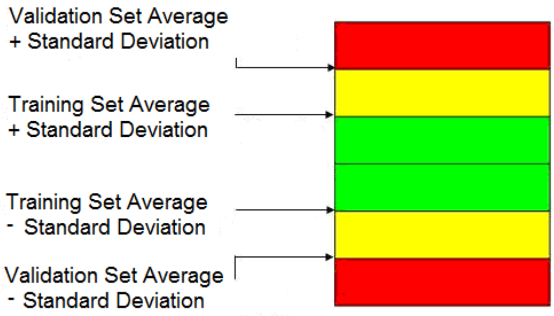

Figure 6. Intervals generated by the quantization error averages, with its standard deviations.

As the colors indicate, quantization errors that are situated in the red region are classified to the operator with a "red sign", in the yellow region with a "yellow sign", and in the green region with a "green sign".

These measures indicate the network's reliability level in its own inference, helping the operator on its interpretation of the system result.

3.5 Performance Evaluation Methodology

The primary objective of SEICT is to interpret correctly the monitoring variables as familiar terms for the operators, i.e., label them as one of the treated transients.

Given that, the system performance evaluation is made counting how many correct interpretations are made, relatively to the total amount of interpretations.

The system evaluation consists of choosing, from the several networks generated during the training (due to the training parameters variation), the best networks combination, considering that each one of them should represent a distinct transient state.

In [4] two techniques were used, but in this paper will be shown the one that had the best result, that was to cross every possible combination (Cartesian Product) of the generated networks during the training, and evaluate the percentage of correct interpretations of each combination.

Clearly, the number of possible combinations soon gets too big (for instance, 240^7 combinations in one experiment with only 7 transient states), obliging then the reduction of the used training parameter.

4. RESULTS

For using a performance evaluation that involves too many combinations, as explained in the last section, some variables where not used on the experiment shown here.

The Step transient state kind was divided into two subsets: positive and negative steps, resulting then in seven transient states, and hence, in seven specialist networks to be selected on the trainings sections.

These seven specialist networks selected by the Cartesian product evaluation used the parameters shown on Table 3 on its training sections.

Table 3 – Training parameters

	H	**C**	**SS**	**PS**	**NS**	**DCO**	**PFB**
Epochs	5	3	2	2	2	2	2
Mesh kind	HE	SQ	HE	HE	HE	HE	HE

Where:
H – Heating
C – Cooling

SS – Steady state
PS – Positive steps
NS – Negative steps
DCO - Deviation channel opening on the primary system
PFB - Flow blocking on the primary system
HE – Hexagonal mesh
SQ – Square mesh

The average performance obtained with these networks is in Table 4.

Table 4 – Performance measurements

% Correct	% Green indications	% Yellow indications	% Red indications
87,30	55,32	30,35	14,33

The amount of times that each semaphore indications happened can be better visualized in Figure 7.

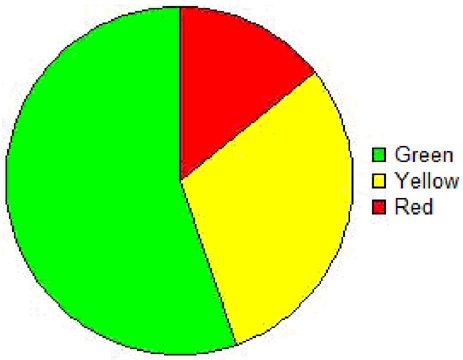

Figure 7 – Semaphore indications

Finally, the system screen shows to the operator the results, like in Figure 8.

Figure 8 – Presentation of Steady State, with green reliability (normal) to the operator

5. CONCLUSIONS

SEICT indicates that a transient classification and identification system can be implemented satisfactorily using Artificial Intelligence techniques, and can be used in Power Plants.

One advantage of using an AI based system is its performance, in terms of response quickness. SEICT still has the advantage of classifying data in a way similar to which the operators would do, but practically instantly.

This offers a bigger agility to operators' decision making, given that the system has a high level of reliability, i.e., when the system is not accurate on its classifications, it warns the operators with the semaphore.

The use of multiple SOMs allows, to future implementations, that the system provides more details about the transient states, because the SOM organizes what is presented to it during the training topologically and by similarity. By the observation of that organization is possible to give labels to the output layers' neurons, each one of them indicating an additional characteristic of the transient.

The accuracy of the system can be improved drastically, using hybrid evaluation techniques, i.e., using not only the Cartesian product technique. It is also possible to improve Evaluation by Performance Function, presented in [4].

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