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USE OF EXPERIMENTAL DATA FOR THE DEVELOPMENT OF THE SOFTWARE FOR IDENTIFICATION AND CLASSIFICATION OF TRANSIENTS (SICT)

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ABSTRACT

The safety of nuclear power plants is always a concern when this technology is considered as an option for power generation. The Software for Identification and Classification of Transients (SICT) was developed as a contribution for improving safety and performance of nuclear plants. It is based in neural networks using Self-Organizing Maps and its main purpose is to monitor reactor operation identifying and signalizing transients and accidents in real time. The development of this software had several phases and one of them was the demonstration of the capability of SICT to identify and classify transients in an experimental facility online. This demonstration was achieved using experiments in a thermal hydraulic facility, the Circuito Térmico #1 (CT1) in CDTN. SICT was trained to recognize different operational states possible in the installation before using experimental data acquired from CT1 instrumentation. SICT training was performed using results from simulations of steady states, normal and abnormal transients and accidents calculated using the RELAP5 code. Therefore another important point in the development process was to check how this particular artificial neural network, which was trained with simulation data, would perform when monitoring real experimental data obtained from the installation. This is an important issue since most accidental conditions in a nuclear reactor will never have experimental data available to train the network, which will have then to be trained with data provided by simulations. This paper presents the current status of SICT development and results achieved when experiments carried out in CT1 were monitored by SICT, which had been previously trained using simulation data.

1. INTRODUCTION

The safety of nuclear power plants and their operational availability are among the factors that must be improved in order to allow new projects to be accepted by the public and attractive to power utilities. SICT - Software for Identification and Classification of Transients - was developed as a tool that can contribute to improve the safety and reliability of Nuclear Power Plants (NPP) [1] through the identification and classification of its operational status, i.e., if it is in a steady state, transient or accident condition.

Baptista and Barroso [2] presented in 2003 a first viability study of a program to identify the operational status of a NPP using an Artificial Neural Network fed with around ten thermal hydraulic parameters obtained from the reactor. SICT is an evolution of this exploratory work and of that presented in 2007 [3]. It was based on a particular type of Artificial Neural Network (ANN) created by Kohonen, the Self-Organizing Maps (SOM) [4], whose main characteristic is the production of a low dimensional representation from the high dimensional input space after an unsupervised training. SICT was developed using an object oriented programming language, C++.

An experimental program was planned and carried out in Circuito Térmico #1 (CT1) [5], which covers several different conditions of operation such as steady states, power changes, loss of cooling, pressurization and depressurization. The main goals of this experimental program were to demonstrate the capability of SICT to respond quickly enough to changes in operational conditions and most importantly to evaluate how this ANN performs using experimental data, which is usually associated with noise, considering that it was trained with data obtained from simulations with RELAP5, which is usually smooth without noise.

SICT was developed to monitor the installation operation through a small number of thermal hydraulic parameters, such as temperature, pressure, flow and power. During its development better results have been obtained in identifying the installation operational status if some parameters derivative were also used jointly with the parameter set. Some results of applying SICT to experimental data are discussed and compared with its use with simulation data showing its adequacy to its proposed goals.

2. THE EXPERIMENTAL DATA

The experiments were carried out in Circuito Térmico #1 – CT1 in Centro de Desenvolvimento da Tecnologia Nuclear – CDTN. A schematic drawing of CT1 with the physical quantities measuring points is shown in Fig. 1. The measured physical quantities are: 10 temperatures along the primary and secondary loops, 2 pressures in primary, 2 mass flow rates in primary and in secondary and the power delivered to the test section. The recording of these parameters during the experiments form a data base that is available to use in SICT training and testing, although not all of them have been used in the versions developed so far.

2.1. The Used Installation and the Experiments

Table 1 shows a list of the twenty seven experiments comprising different operational conditions of CT1 that were carried out in order to provide a data base to check SICT performance after its training with simulation data. While some experiments, 1 to 5, 8 and 9, were carried out for validation and calibration of the circuit and of the data acquisition system, experiments 11 to 14 and 18 to 21 covered power changes of 10% in steps and in ramps of 30 s, 120 s and 240 s duration at atmospheric pressure. Experiments 17 and 22 to 27 addressed pressure changes and loss of heat removal due to heat exchanger isolation or due to loss of secondary flow. Experiments 6, 7, 10, 15 and 16 dealt with abnormal power changes, larger than 20%, and accidental conditions.

Experiment 3 allowed establishing the scheme used for data acquisition, i.e., each physical quantity measurement signal was acquired only once after a proper time to capture and convert it in the data acquisition card, in opposition to the technique of reading several times a channel as fast as possible during a defined period and then making an average of the acquired data. Using this scheme it was possible to read and store a complete set of data measurements in less than 0.5 seconds corresponding to a frequency of 2 Hz.

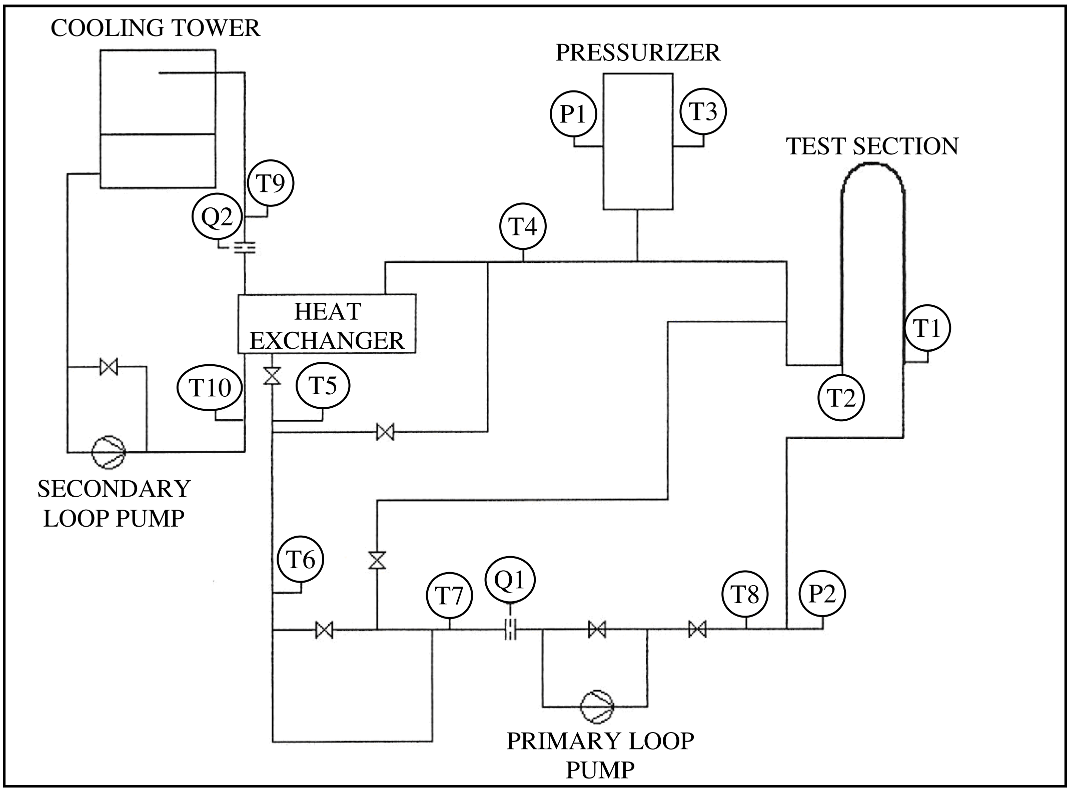

Figure 1. Schematic of CT1 with the measurement points.

Table 1. Executed test matrix

Identification	Description
Exp01_22Jun	First experiment for CT1 commissioning.
Exp02_09Jul	Operational Accident: step of 15 instead of 1.5.
Exp03_16Ago	Definition of data acquisition scheme (loops, delays and grounding).
Exp04_17Ago	Temperature measurement calibration.
Exp05_22Ago	Temperature measurement calibration using grounding in order to check cross channel influence due to pump and power changes.
Exp06_03Set	Power change in steps and ramps and heat exchanger isolation.
Exp07_05Set	Power changes of 50% and 100%. Accident due to closed valve.
Exp08_10 set	T10 Temperature measurement calibration
Exp09_11Set	T10 Temperature measurement calibration. Safety measures implemented in data acquisition program.
Exp10_14Set	Power changes 0-5, 5-4, 4-1.5, 1.5-0.
Exp11_01Out	Power change in increasing steps of 10%.

Table 1 – continuation

Identification	Description
Exp12_02Out	Power change in decreasing steps of 10%.
Exp13_03Out	Power change in increasing ramp of 10% in 30 s.
Exp14_04Out	Power change in decreasing ramp of 10% in 30 s
Exp15_05Out	Steady state at 90% and 50% to check bubbles observed at temperatures bellow saturation.
Exp16_09Out	Ramps of different powers and time gradients
Exp17_10Out	Depressurization
Exp18_23Out	Power change in increasing ramp of 10% in 240 s.
Exp19_25Out	Power change in increasing ramp of 10% in 120 s.
Exp20_26Out	Power change in decreasing ramp of 10% in 120 s.
Exp21_03Nov	Power change in decreasing ramp of 10% in 240 s.
Exp22_15Dez	Steady state, pressurization, depressurization and secondary pump off
Exp23_22Dez	Secondary pump off with pressure; Depressurization; Power changes in steps and ramps at different pressures.
Exp24_24Dez	Power change in increasing steps at increasing pressure
Exp25_26Dez	Opening and closing of pressurizer valve.
Exp26_28Dez	Turning off primary and secondary pumps with different pressures.
Exp27_29Dez	Opening and closing of pressurizer valve with heat exchanger bypass opened

2.2. The Measured Signal and its Derivatives

The measured values of these physical quantities show different characteristics for each group of them. The measurement of constant temperatures showed a variation of 4 values, as can be observed in Fig. 2, where the four acquired temperature values are 24.81 ^{o}C, 25.09 ^{o}C, 25.38 ^{o}C and 25.66 ^{o}C. Considering that the time interval between two adjacent points is around 0.5 s, the measurements of a constant temperature during the experiments show a derivative in the range ±1.5 ^{o}C/s.

Pressure measurements showed a dispersion similar to that of the temperatures, as can be observed in Fig. 3, where the values for a steady pressure varied between 0.4255 MPa and 0.4269 MPa leading to derivatives in the range ±0.025 MPa/s.

Fig. 4 shows a sample of mass flow rate measurement of a steady flow varying from 0.5875 kg/s to 0.6411 kg/s leading to derivatives in the range ±0.07 kg/s. Mass flow rate is the physical quantity, which measurement shows the largest dispersion, however since the mass flow rate usually does not change significantly during operation, neither in the NPPs, its derivative has not been used in SICT.

Measurements of a constant power perform like the sample shown in Fig. 5, where the acquired values varies between 51.915 kW and 53.944 kW leading to derivatives in the range ±3.4 kW/s.

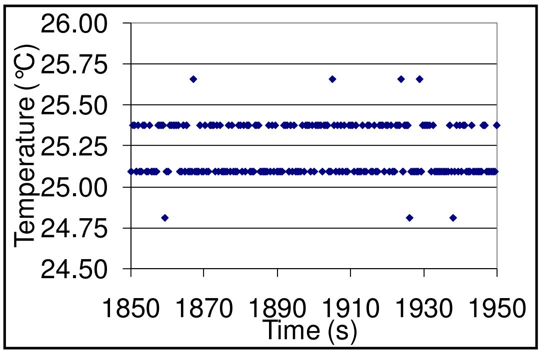

Figure 2. Sample of temperature measurement.

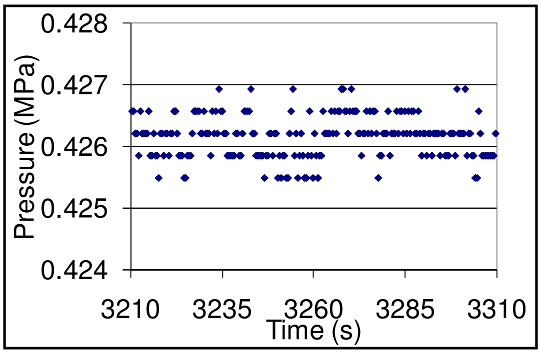

Figure 3. Sample of pressure measurement.

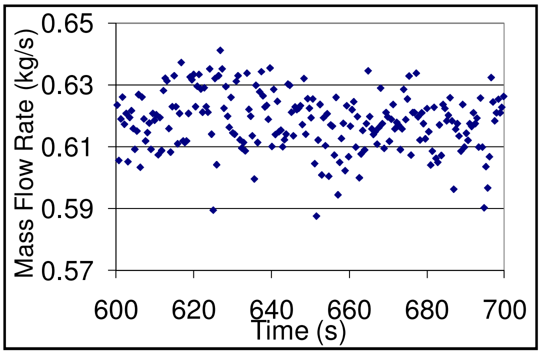

Figure 4. Sample of mass flow rate measurement.

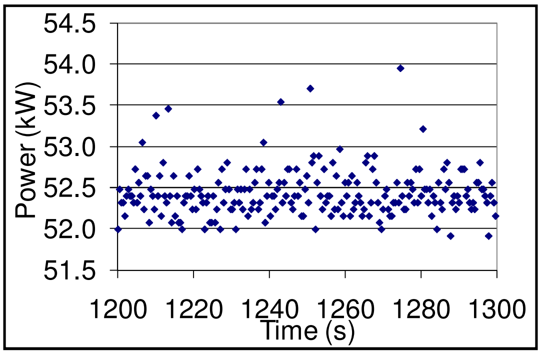

Figure 5. Sample of power measurement.

An evaluation of temperature evolution at test section outlet during a step power change of 10% in experiment 11 of Table 1 shows that the temperature variation is around 6 ^{o}C in 35 s leading to a derivative of approximately 0.18 ^{o}C/s, as can be seen in Fig. 6 and Fig. 7 respectively. Fig. 7 shows the difference between the derivative of experimental and RELAP5 simulation data, making clear that it is meaningless to use the derivative of the experimental data to identify a given condition in SICT since the associated noise is larger than the value itself. The value of the derivative of the temperature in this step power change is around 0.18 ^{o}C/s, as shown by the solid black curve from simulation (RLP), and this value is approximately the value of variation of a measurement of a steady temperature discussed previously.

The derivatives of pressure and power show a similar behaviour making them unusable for identifying transients in SICT. Therefore in SICT the derivatives were calculated using a time interval of 20 s as described by eq. 1. Using the lagged derivatives calculated in this way, the values shown in Fig. 7 are transformed in those shown in Fig. 8, where can be observed a good agreement between the derivative of the temperatures from the experiment with that from the simulation.

$$\frac{dy(t)}{dt} = \frac{y_t - y_{t-20s}}{t_t - t_{t-20s}} = \frac{y_t - y_{t-20s}}{20} \qquad (1)$$

Fig. 9 shows the lagged derivative of the temperature at test section outlet during a power change of 10% in a ramp of 240 s and again there is a good agreement between the derivatives from simulation and experimental data. Similar behaviour is observed for the lagged derivatives of pressure and power making viable the use of lagged derivatives of temperatures, pressures and power in SICT for training and monitoring.

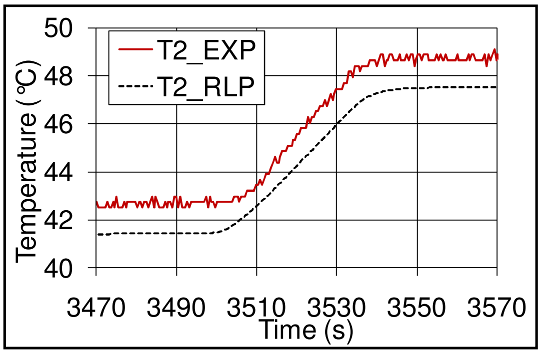

Figure 6. Experimental and calculated temperature at test section outlet.

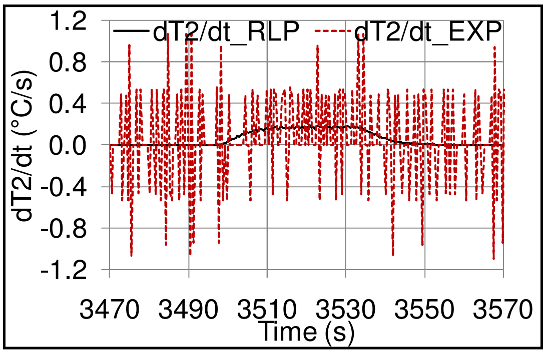

Figure 7. Derivative of experimental and calculated temperature at test section outlet.

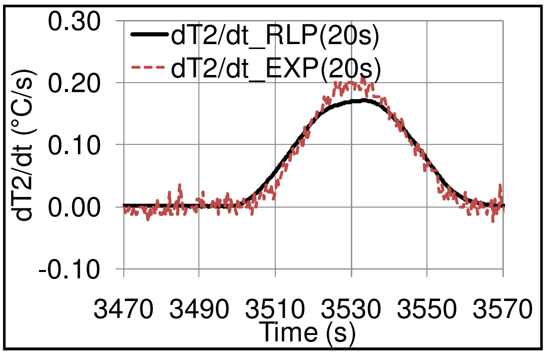

Figure 8. 20 s Lagged derivative of experimental and calculated temperature at test section outlet (step).

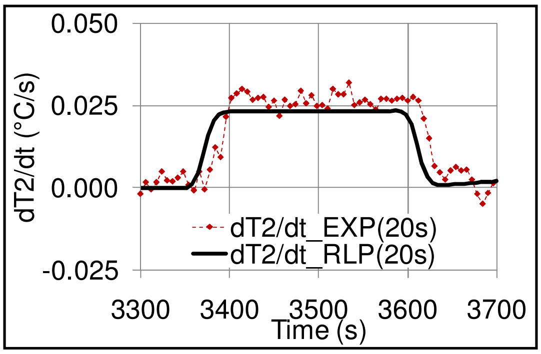

Figure 9. 20 s Lagged derivative of experimental and calculated temperature at test section outlet (ramp 240).

3. SICT TRAINING

The data base of RELAP5 simulations of CT1 to train SICT did not contain any real experiment simulation but a matrix of simulations that included all the power changes, i.e., in steps and ramps of 30 s, 120 s and 240 s. It included also several transients as turning off and on the secondary pump, isolation of the heat exchanger, pressurization and depressurization. This data base comprehended all experiments phenomena without reproducing any particular experimental conditions and evolution. In total 58 simulations were available and used for training of SICT. From this data base it was build one set of buffers to train SICT that addressed the steady states, power changes in steps and ramps and most of the transients that were simulated, but it did not contain the most abrupt changes. To address all this condition this set contained 6498 buffers and the training with 8500 (2500 +6000) epochs took around 10 hours.

Ten physical quantities were selected to be part of the training input space of SICT for CT1:

- six parameters were temperatures in fixed positions shown in Fig. 1:
  - inlet of test section (T1)
  - inlet of primary side of heat exchanger (T4),
  - outlet of primary side of heat exchanger (T5),
  - middle path between heat exchanger and main pump (T6),
  - main pump outlet (T8) and
  - outlet of secondary of heat exchanger(T9),
- two mass flow rates
  - in the primary loop (Q1)and
  - in the secondary loop (Q2),
- power in test section and the
- pressure in pressurizer (P1).

These parameters form the input vectors or buffers, which were organized in buffers containing ten instances of each parameter sampled at intervals of six seconds. In this way one buffer had the history of the parameters evolution for 60 seconds.

A scheme that enhanced the performance of SICT in identifying the transients was the addition of the derivatives of some parameters in the buffer. The use of the derivatives posed no problem in the beginning when just simulation data were used for testing the monitoring process, however using derivatives based on experimental measured data proved to be unfeasible, since they changed erratically due to noise in the signals. Therefore it was introduced in the training and in monitoring an approximated derivative calculated using the data from a given instant in relation to the data from 20 seconds earlier.

Training buffers were then formed of 10 instances of the ten parameters jointly with the lagged derivatives of the power, pressure and of all temperatures. The input space for training the ANN was then represented by one buffer with 10 instances of 18 parameters composing one input vector with 180 dimensions.

The input buffers were then used in the training process of SICT that updated the neuron weights according to the usual rule presented by Kohonen [4] that can stated by equation 2:

$$w_n^{i+1} = w_n^i + \eta(i,p) * (e^i - w_n^i) \tag{2}$$

In this equation $\eta(i, p)$ represents a neighbourhood factor that decreases with the iteration number, i, and with geometric distance, p, between the input buffer, e^i , and the neuron being updated, w_n^i.

Kohonen recognizes two phases in the training process: an ordering phase, where the buffers change the weights of many neurons even far from the winning neuron, and a convergence phase, where the buffers are associated with a neuron in the immediate neighbourhood of the winning neuron in previous iterations. Equation 2 is used along both phases.

At the end of the convergence phase of training process each cell in the output space will be associated with a certain number of buffers. At this point it was introduced a neuron weight optimization in the training, where the weights of each neuron were changed to an average of the buffers associated with it, i.e., the neuron weights were updated following equation 3:

$$w_i = (\sum_{j=1}^{m} e_{i,j})/m \tag{3}$$

In equation 3, i is the index of the dimension of the input vector, e, and of the winning neuron weight vector, w, and m is the maximum dimension of the vector that in this case is 180.

4. RESULTS

Current version of SICT can work with different bi-dimensional geometric representations of the output space such as:

- triangular network with triangular cells,
- squared network with triangular cells,
- squared network with squared cells,
- hexagonal network with hexagonal cells and
- hexagonal network with triangular cells.

SICT can also produce a three-dimensional output in the form of a cube with squared cells in the faces. These three-dimensional networks have a particular characteristic: the fact that every cell has neighbours in each of it sides, while in the bi-dimensional networks the cells on their borders do not have neighbours in all of their sides; this means that the cells in the three-dimensional network are more homogeneous than in the bi-dimensional ones.

A set of criteria was established in order to check if a SICT configuration obtained from a given training was able to perform its envisaged goal, i.e., identify and classify correctly in real time the operational state of a thermal hydraulic installation it is monitoring. These criteria were checked to analyse the results of monitoring of all simulations with RELAP5 and of most relevant experiments. The defined criteria included:

- inspection of the maximum distance evolution during training;
- visual inspection of the clustering at the end of training
- visual inspection of the activated neurons during monitoring;
- visual inspection of activated neurons during similar transients;
- (*buffer*) input vector – winning neuron weights distance during monitoring;
- neurons activated by transients must be different from those activated by steady states;
- neurons activated by increasing power changes must be different from those activated by decreasing ones;
- identify correctly all inspected transients and steady states and
- neurons activated by steady state must be the same for similar conditions independent of the path used to get to this condition.

The training of SICT for CT1 was carried out using 2500 epochs for the ordering phase and 6000 for the convergence phase followed by the averaging processes just described. The evolution of the maximum distance of a winning neuron weights to the associated input buffer in a given epoch is one measure of the efficiency of the training process. Fig. 10 and Fig. 11 provide the information to evaluate one of the listed criteria. Fig. 10 shows a typical evolution of maximum distance during the ordering phase and Fig. 11 the evolution during the convergence phase. These figures show that both phases of the ordering implemented in SICT as well as their selected parameters are performing correctly.

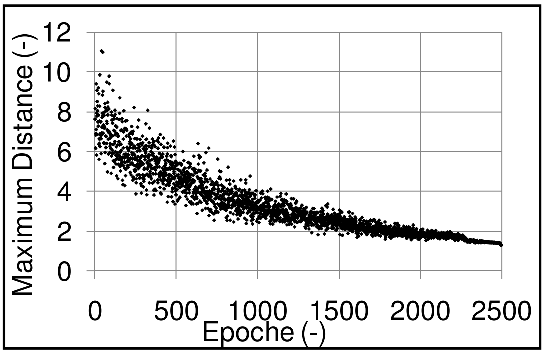

Figure 10. Evolution of maximum distance during the ordering phase.

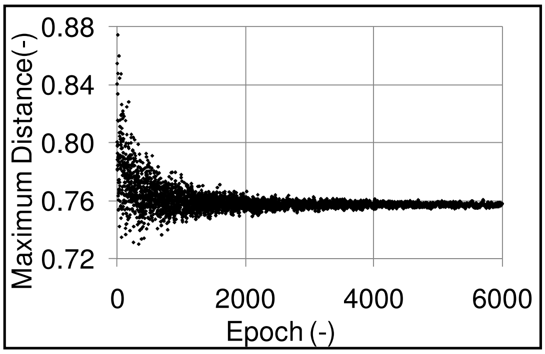

Figure 11. Evolution of maximum distance during the convergence phase.

Fig. 12 shows the code to understand the clustering obtained at the end of training process that is shown in Fig. 13 for a hexagonal output map and in Fig 14 for a three-dimensional cubic output. Fig. 13 and Fig. 14 allow confirming that the training process satisfied the clustering criteria of similar operational states in the output space of SICT specified previously.

One of the most important results that SICT provides during the monitoring is the (buffer) input vector to winning neuron weight distance, which indicates how good is the identification done by SICT of the installation. Fig. 15 shows the evolution of this distance for a simulation that started with a jump from zero power to 100% in 0 s, changed the power at 3000 s from 100% to 90% in a step and changed again from 90% to 80% at 6000 s. SICT had not been trained for power changes higher than 20% and the comparison of the high value of the distance in the first 1000 s in Fig. 15, which corresponds to the 0-100% power change, compared to the lower values after 3000 s clearly indicates that SICT does not know these initial conditions. This mechanism can be used to avoid accepting false identification done by SICT when it does not really recognize a certain condition.

Fig. 16 shows that the distances during a step power change from 40 kW to 50 kW for both experimental data and simulation data are very similar. Due to this result that was also observed in many other cases it could be concluded that SICT is capable of identifying the conditions occurring in CT1 through monitoring of real data even having been trained with noiseless simulation data. The curves show also that for slow conditions, as those of the steady state before 0 s in Fig. 16, the distance is lower than for transients and accidents.

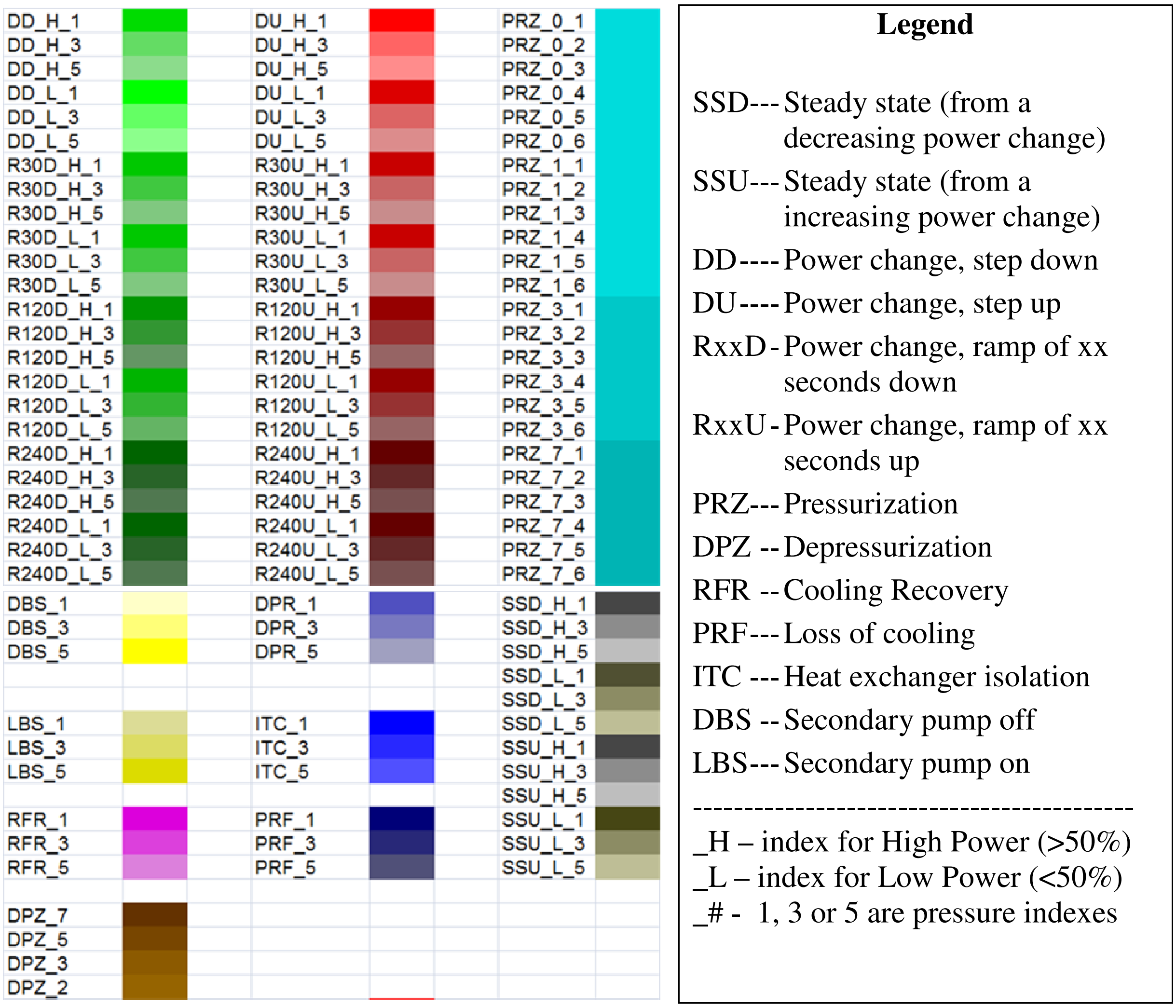

Figure 12. Colors used to identify cells associated characteristics and their clustering

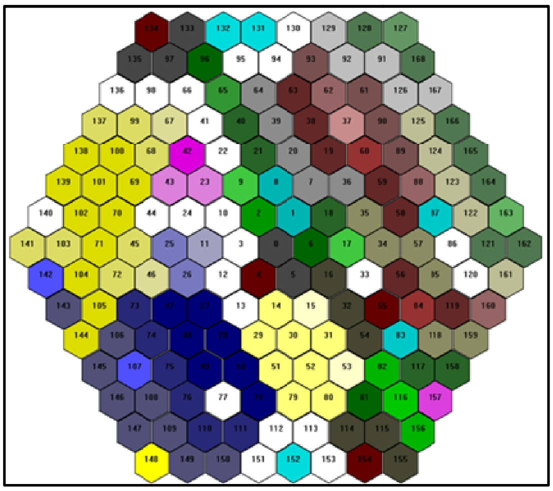

Figure 13. Clustering view of a hexagonal network at the end of training

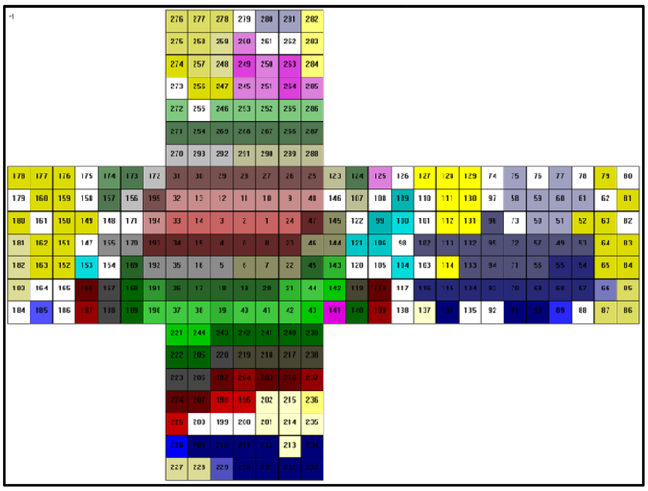

Figure 14. Clustering view of a cubic network at the end of training

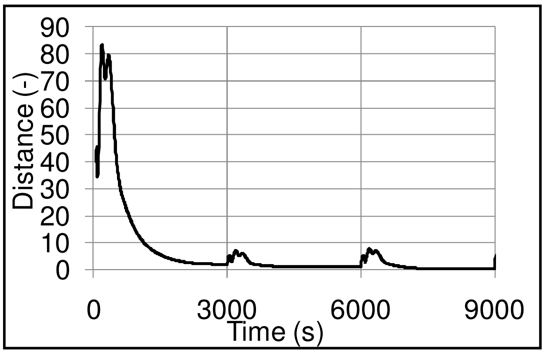

Figure 15. Buffer – winning neuron distance for decreasing power change in step.

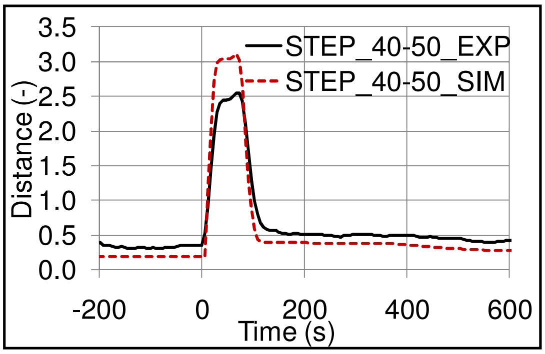

Figure 16. Buffer – winning neuron distance for power change in step

5. CONCLUSIONS

The Software for Identification and Classification of Transients (SICT) was developed using C++ with the goal of identifying the operational conditions of a nuclear power plant, i.e., identify if condition of operation are those of a steady state, a transient or an accident.

The training process of SICT was carried out using data from CT1 simulations with RELAP5. These simulations comprehended some experiments and 58 simulations of series of transients that form a simulation data base. For the evaluation of SICT performance in an actual installation experiments were conducted and recorded in CT1 comprising steady states, transients and even accidents. The experimental and the simulation data bases are available for future investigation in this field.

In order to evaluate SICT performance there were defined a set of criteria that was used in the results from training and from monitoring results from experiments and from simulations. The evaluation of several configurations of training parameter and of geometric output maps showed that was possible to obtain SICT versions that satisfied the established criteria.

The results showed that although SICT is trained with noiseless data from simulation it can perform well with typical measured data like those from CT1.

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