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Process Sensors Characterization Based on Noise Analysis Technique and Artificial Intelligence

Roberto N. de Mesquita[1], Sergio R. P. Perillo[1] and Roberto C. dos Santos[1]

[1] Instituto de Pesquisas Energéticas e Nucleares (IPEN / CNEN - SP)
Av. Professor Lineu Prestes 2242
05508-000 São Paulo, SP
rnavarro@ipen.br, sperillo@ipen.br, rcsantos@ipen.br

ABSTRACT

The time response of pressure and temperature sensors from the Reactor Protection System (RPS) is a requirement that must be satisfied in nuclear power plants, furthermore is an indicative of its degradation and its remaining life. The nuclear power industry and others have been eager to implement smart sensor technologies and digital instrumentation concepts to reduce manpower and effort currently spent on testing and calibration. Process parameters fluctuations during normal operation of a reactor are caused by random variations in neutron flux, heat transfer and other sources. The output sensor noise can be considered as the response of the system to an input representing the statistical nature of the underlying process which can be modeled using a time series model. Since the noise signal measurements are influenced by many factors, such as location of sensors, extraneous noise interference, and randomness in temperature and pressure fluctuation – the quantitative estimate of the time response using autoregressive noise modeling is subject to error. This technique has been used as means of sensor monitoring. In this work a set of pressure sensors installed in one experimental loop adapted from a flow calibration setup is used to test and analyze signals in a new approach using artificial intelligence techniques. A set of measurements of dynamic signals in different experimental conditions is used to distinguish and identify underlying process sources. A methodology that uses Blind Separation of Sources with a neural networks scheme is being developed to improve time response estimate reliability in noise analysis.

1. INTRODUCTION

The need for the development of smart sensor technology has increased together with nuclear power industry need to fulfill norm based procedures for protection system that includes periodic tests for process sensors monitoring. This technology development includes new digital instrumentation and sensor monitoring concepts in order to establish optimized inspection procedures reducing manpower and costs [1]. One of the main parameters used to indicate sensors degradation and remaining life is time response of pressure and temperature sensors.

Noise analysis techniques have been extensively used to process sensors monitoring [2]. This technique has presented restriction in time response quantitative estimate due to impossibility to determine which factors (or sources) have influenced both noise signal itself and noise signal measurements. The output sensor noise has been considered as the system response to an input which represents the statistical nature of underlying processes. These underlying procedures include fluctuations caused by random variations in neutron flux, heat transfer, pump vibrations and others. These random variations should be (summed up) and used as stochastic time signal input to a model system that could estimate sensor parameters as result.

This work tries to develop techniques that could contribute with new information about noise signal sources. For this purpose, Blind Separation of Sources (BSS) technique is applied to pressure sensor noise signals acquired in an experimental loop. The BSS technique is intended to separate linear mixed signals by usually applying Independent Component Analysis (ICA) to the mixed signal. A neural network scheme is proposed to provide supervised training over the system in order to obtain more reliable quantitative process sensor parameters estimate.

A set of pressure sensors installed in one experimental loop adapted from a flow calibration setup (Figure 1) is used to test and analyze signals in a new approach using artificial intelligence techniques. A set of measurements of dynamic signals in different experimental conditions is used to distinguish and identify underlying process sources. The results are compared to time response results obtained in laboratory measurements using a Dynamic Pressure Test Unit (DPTU) specially developed for this purpose, where a step and ramp response are used as input directly obtaining these parameters.

1.1. Noise Analysis

The impulse and step responses of the dynamic system are modeled by the fitted autoregressive model, where, for a given noise measurement:

$$y_k = \sum_{i=1}^{n} a_i y_{k-i} + v_k, \cdots\cdots k = 1,2,... \tag{1}$$

The dynamics of the process is represented by the autoregressive parameters a_i and the dynamic information is given by the poles of the equivalent z-transform [2]. The impulse response can be evaluated by recursively computing y_k as a function of previous y when $v_k = 0$, $k \geq 1$ and $v_0 = cte$ [2],

$$y_k^I = \sum_{i=1}^{n} a_i y_{k-i}^I, \cdots\cdots y_0^I = cte, y_{-l}^I = 0, l > 0 \tag{2}$$

2. METHODOLOGY

Some main objectives were established for the method development. They are described as follows.

2.1. Experimental loop

A modified flow calibration setup was used to initial experiments in order to obtain pressure sensor noise signals.

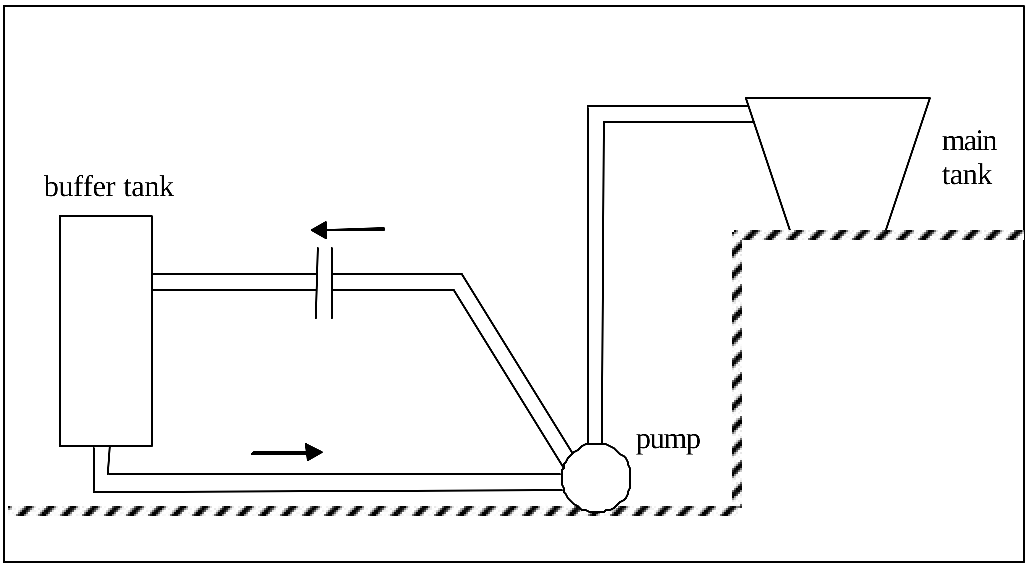

Figure 1. Experimental loop adapted from a flow calibration setup.

Three different pressure sensors/transmitters were calibrated for the experiment:

1. Fisher (0 – 800mmHg);
2. Fisher (0 – 1600mmHg);
3. Smar LD200 (0 – 1470 mmHg).

The circuit is being tested with different configurations in order to establish controlled conditions to noise signal sources. The experiments use the use of different amplifiers to acquire noise signals, all set to a cut frequency of 50Hz.

2.2. Noise Sources Analysis

The methodology proposes for basic steps in noise source analysis. At first, the sensors are characterized using conventional direct measurements with DPTU developed for this purpose. Some conventional Time-Series Noise Analysis [2] is applied to acquired noise signals to obtain time-constants values depending on autoregressive model order (Equation 2).

The third step a modified ICA algorithm [5] is applied to noise signals trying to identify different source components. This step also uses simulated noise signals to test ICA algorithm efficiency in identification of different noise sources. At fourth stage, a supervised neural network train is done in order to estimate sensor parameters. Finally the estimated values are compared with the direct measurements obtained at first stage.

3. PRELIMINARY RESULTS

The first stage was done using the pressure sensors previously described and the obtained values are summarized in table 1.

Table 1. Time-Constant with direct measurement

Sensor	Time-constant
Fisher 1	2.2s
Fisher 2	100ms
SMAR LD200 1	1s
SMAR LD200 2	90ms

During second phase, traditional time-series noise analysis was done. The obtained time-constant obtained are plotted with the corresponding auto-regression model order in figures 2, 3 and 4.

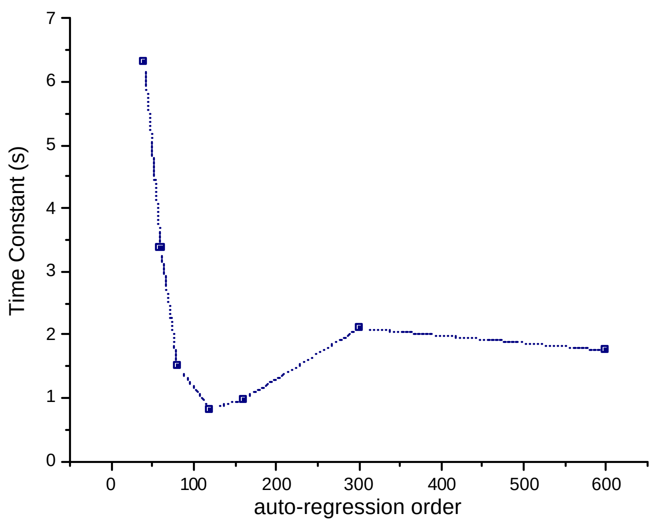

Figure 2. Time constant estimates for different auto-regression model order base on noise analysis (smar01).

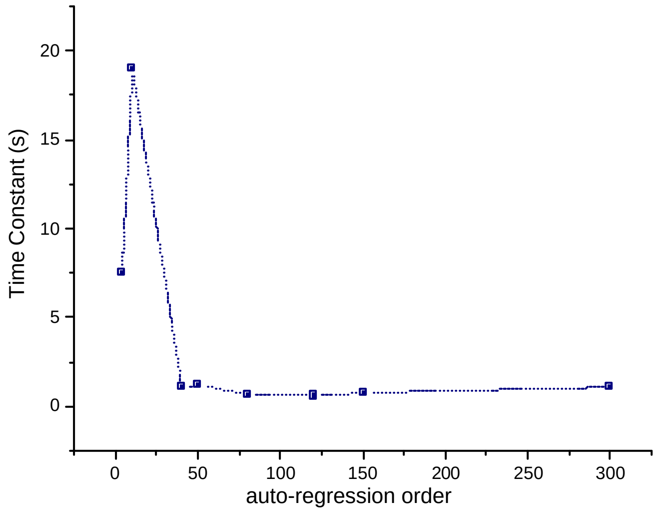

Figure 3. Time constant estimates for different auto-regression model order base on noise analysis (smar02).

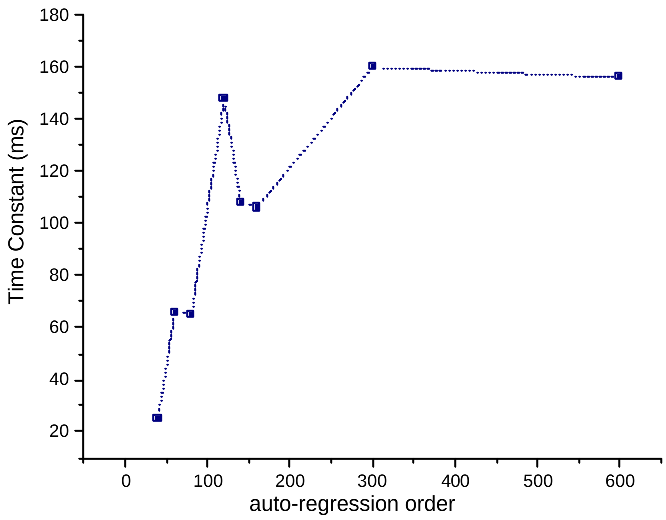

Figure 4. Time constant estimates for different auto-regression model order base on noise analysis (fischer02).

The third stage, using modified fastICA algorithm has shown some promising results. A set of different acquisition setups are being added to improve confidence in the obtained results.

4. CONCLUSIONS

The results obtained until now show a promising methodology to improve knowledge about noise signal analysis, enabling promising control over spurious influences on noise signal measurements, and better time-constants estimate.

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