PROCEEDINGS OF SCIENCE

NARX neural prediction of oscillational instability at the IBR-2M reactor

Mihai-Tiberiu Dima[a]*, **Maria Dima**[a], **Madalina Mihailescu**[b]

a *Joint Institute for Nuclear Research,*
Joliot Curie 6, Dubna, Moscow region, Russia-141980

b *Hyperion University,*
Calea Calarasi 169, Bucharest, Romania-030615

E-mail: mtdima@jinr.ru

During the start-up regime of the IBR-2M power fluctuations appear, which the Automatic Regulator system dampens. Their origin is not completely clear, however it is known that the major reactivity sources are from design – respectively the OPO and DPO reflectors: their axial fluctuations towards the active zone and their relative phase of intersecting each other facing the center of the active zone. A neuromorphic solution is sought to anticipate (5-10 s) such fluctuations. We present encouraging preliminary results obtained with a Non-linear Autoregressive Exogenous (NARX) neural network, the main features of the fluctuations being anticipatable.

The 6th International Workshop on Deep Learning in Computational Physics (DLCP2022)
6-8 July 2022
JINR, Dubna, Russia

*Speaker

PoS(DLCP2022)031

Introduction

The safety operating regime of nuclear reactors displays both active and passive measures. Among the passive measures are negative reactivities with temperature induced by neutron absorbers such as *Gd* and *Er* mixed into the fuel; the convection circulation of the cooling agent. In case of malfunction - at CANDU-reactors for instance the moderator can sink the "*zero*" remanent power - rather very small, considering the only 0.7% fissile ratio. Other measures include: the steel mantle of the reactor, automated depressurisation valves, etc. The active ones are automatic control rods, pressurised *Gd* liquid injection (CANDU), etc. Protection systems generally come in triplet form and are redundant.

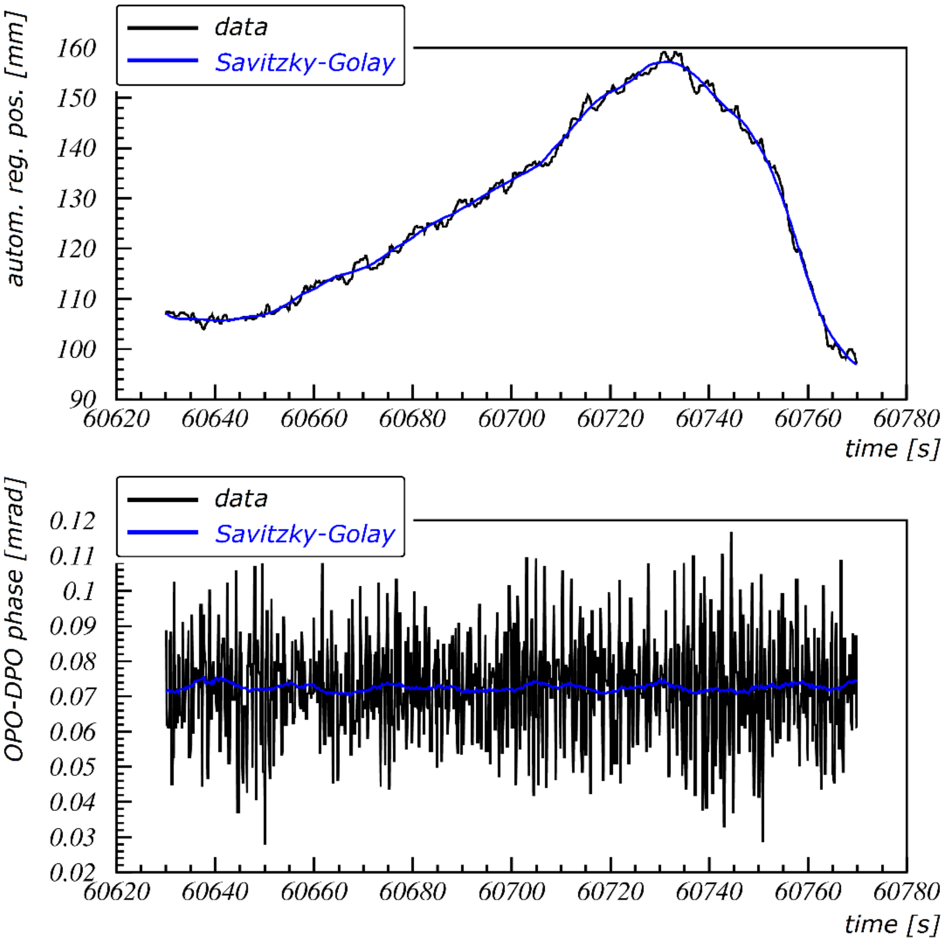

Figure 1: Savitzky-Golay filter usage examples: top, automatic regulator evolution, bottom OPO-DPO phase noise.

For IBR-2M the main security element is its design, the reactor being profoundly sub-critical. Criticality is attained with two rotative reflectors which only by simultaneous crossing in front of the active zone lead to super-criticality, namely pulses of 200 μs (of 1830 MW) at 0.2 s intervals. IBR-2M has an EPS shutdown system, however due to its high sensitivity to reactivity fluctuations – by design, in order to produce very short pulses of 10^{17}n/cm^{2}s, the tuning margin up to the EPS threshold is very small. For example the fluctuations in a power production reactor are ca. ×15 times smaller.

IBR-2M has a negative feedback to over-heating and an automatic power regulator (AR) using a control rod.

The protection and control system of the IBR-2M [1] comprises of mobile tungsten blocks in the inox matrix of the static reflectors: two compensating blocks, two emergency rods, a system of manual regulation and a system of automatic power regulation. The emergency system immerses 2 rods with over 80 mm in 100 ms, respectively 210 mm in 200 ms, taking out 0.24% of reactivity in 100 ms.

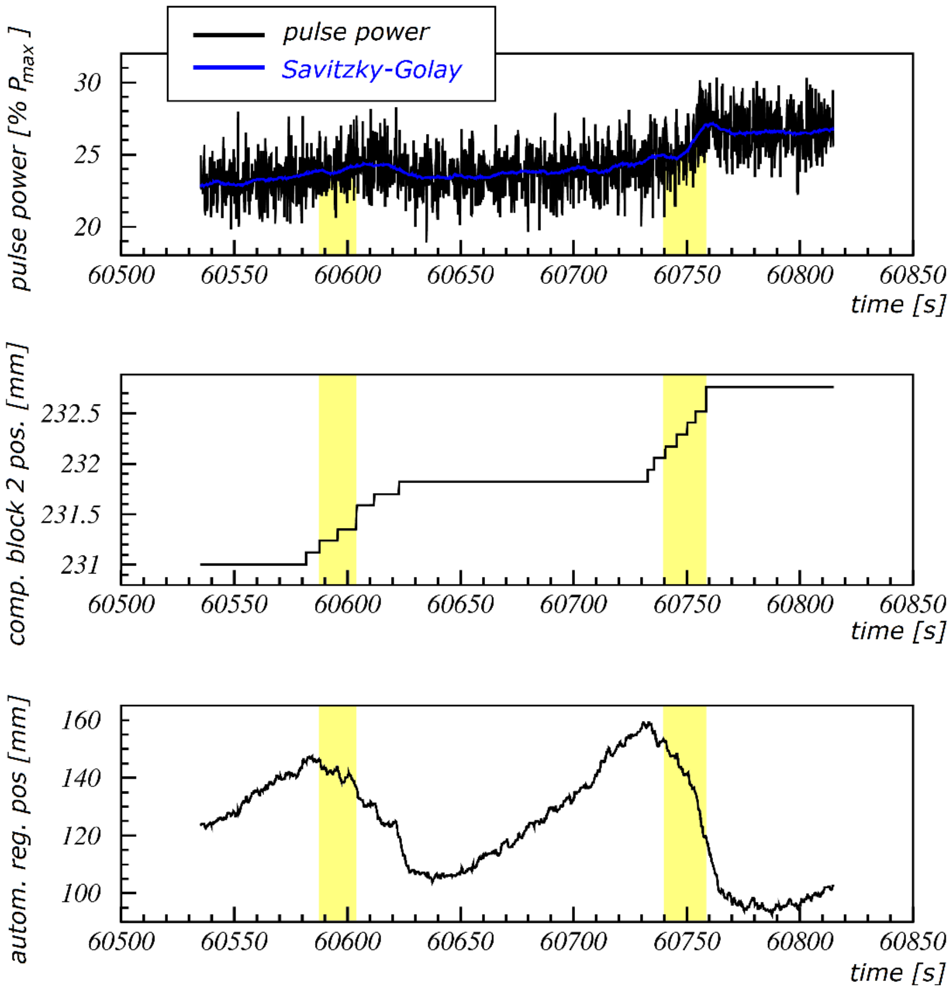

Figure 2: Neutron noise during reactor ramp-up (top - in black) together with the pedestal (in blue); middle - compensator block 2; bottom the automatic regulator. The pale yellow bands represent regions of instability onset.

The compensation blocks can move both with low and high speed, in steps no longer than 4s - the emergency speed being 41 mm/s. In case of emergency the automatic power regulator acts with a maximum speed of 16.7 mm/s. The manual system of power regulation acts with 0.79 mm/s in steps no longer than 7 s.

At start-up an external ^{252}Cf source is introduced in a channel in the central part of the active zone, and the automated regulator (AR) gradually allows the rise in power. When the AR reaches its max range, compensator block 2 is pulled back 1 unit (in steps) and the AR moves back to mid-range. The process is repeated in steps for ca. 1 h up to nominal power.

During this process power fluctuations appear, which the AR system dampens. Their origin is not completely clear, however it is known that the major reactivity sources are from design – respectively the OPO (main) and DPO (auxiliary)-reflectors – axial fluctuations towards the active zone and their relative phase of intersecting each other facing the center of the active zone.

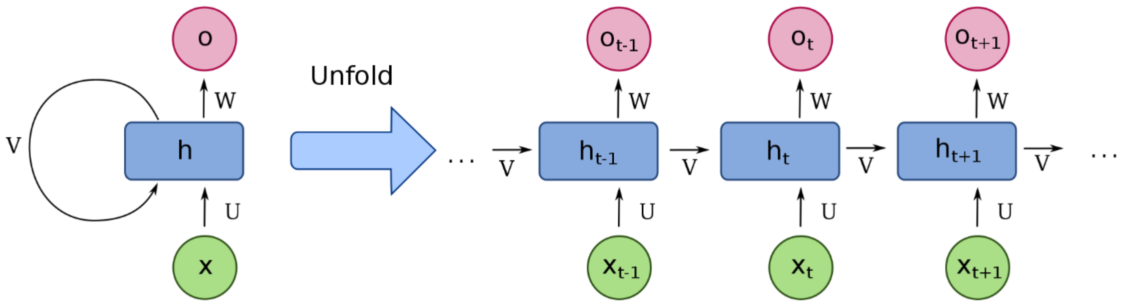

Figure 3: The equivalent of a NARX neuromorphic cell. The classifier's output is re-applied successively as one of the inputs.

To be able to follow the parameters of reactor power in time we need to deconvolute the neutron noise from the power average (pedestal, see figure 1, in blue).

A very robust method is a Savitzky-Golay [3] filter. In this method the current point is given by the free term of a fit on 2K+1 bins, to the left and right of the current bin:

$$\sum_{i=-K}^{+K}(Cx_i^3 + Ax_i^2 + Dx_i + Y - y_i)^2 = min \tag{1}$$

We obtain the coefficients by taking the derivatives with respect to them, respectively:

$$\sum_{i=-K}^{+K}(Cx_i^3 + Ax_i^2 + Dx_i + Y - y_i)x_i^q = 0 \tag{2}$$

where $q = \overline{0,3}$.

Notice that due to the symmetric summation to the left and right of the current bin, the sums of odd powers are null, hence:

$$\begin{aligned} CS_6 + DS_4 &= Y_3 \\ AS_4 + YS_2 &= Y_2 \\ CS_2 + DS_2 &= Y_1 \\ AS_2 + Y &= Y_2 \end{aligned} \tag{3}$$

where $S_q = \sum_{i=-K}^{+K} x_i^q$ si $Y_q = \sum_{i=-K}^{+K} y_i x_i^q$.

The solution of the system is thus (with $\lambda_4 = S_4/S_2$):

$$C = \frac{Y_3/\lambda_4 - Y_1}{S_6/\lambda_4 - S_4}$$
$$A = \frac{Y_2/S_2 - Y_0}{\lambda_4 - S_2}$$
$$D = \frac{Y_1 S_6/\lambda_4 S_2 - Y_3}{S_6/\lambda_4 - S_4} \tag{4}$$
$$Y = Y_0 - AS_2$$

This solution is very much CPU intensive, therefore for real-time monitoring we need a procedure that re-uses the previous bin calculations. In this respect, we implemented in C++ the following procedure:

$$\begin{aligned} Y_0' &= Y_0 + (y_{next} - y_{last}) \\ Y_1' &= Y_1 - Y_0 + (2K+1)(y_{next} - y_{last}) \\ Y_2' &= Y_2 - 2Y_1 + Y_0 + (2K+1)^2(y_{next} - y_{last}) \\ Y_3' &= Y_3 - 3Y_2 + 3Y_1 - Y_0 + (2K+1)^3(y_{next} - y_{last}) \end{aligned} \tag{5}$$

where Y_k' are the sums for the current bin - expressed function of those for the previous bin. This is possible because, for a given $y_i i^q$, the translation means going to $y_i(i-1)^q$, respectively addition of an update equal to $y_i[(i-1)^q - i^q]$ - which is expressed function of all other power sums already known for the previous bin.

In this way, for Savitzky-Golay polynomials of higher orders and extensive 2K+1 ranges, it is possible to update fast, real-time pedestal monitoring becoming possible for a number of simultaneously monitored quantities.

2. Autoregressive neuromorphic software

Neuromorphic software is heuristically a learning model based on biological neurons, used to estimate a function that depends on a large number of entries, usually without a known behavior.

The program emulates a set of interconnected neurons. Each neuron receives at input the signal generated by the other neurons, or directly from the network's entries, and generates a transformed signal to the hierarchically superior neurons. These characteristics of neuromorphic software allow it to ``learn" from a set of training data. Neuromorphic software can identify easily data patterns presented to it during training, which it can signal out.

From a practical point of view the training stage is an optimisation of the inter-neuron link weights until the training data set is classified with minimal error. A robust engine for this procedure is the Nelder-Mead [4] algorithm.

Recurrent neural software sports additionally one or more connections between outputs and inputs - such that the predicted quantities become themselves part of the input data. The output data fed back in are delayed one or more iterations and are kept in a buffer of modest dimension. In this context a class of marked interest is that of auto-regressive exogenous software (NARX) [5; 6].

This software, aside recurrent data, takes as inputs also quantities that bring new impact (non-anticipatable in an auto-regressive model).

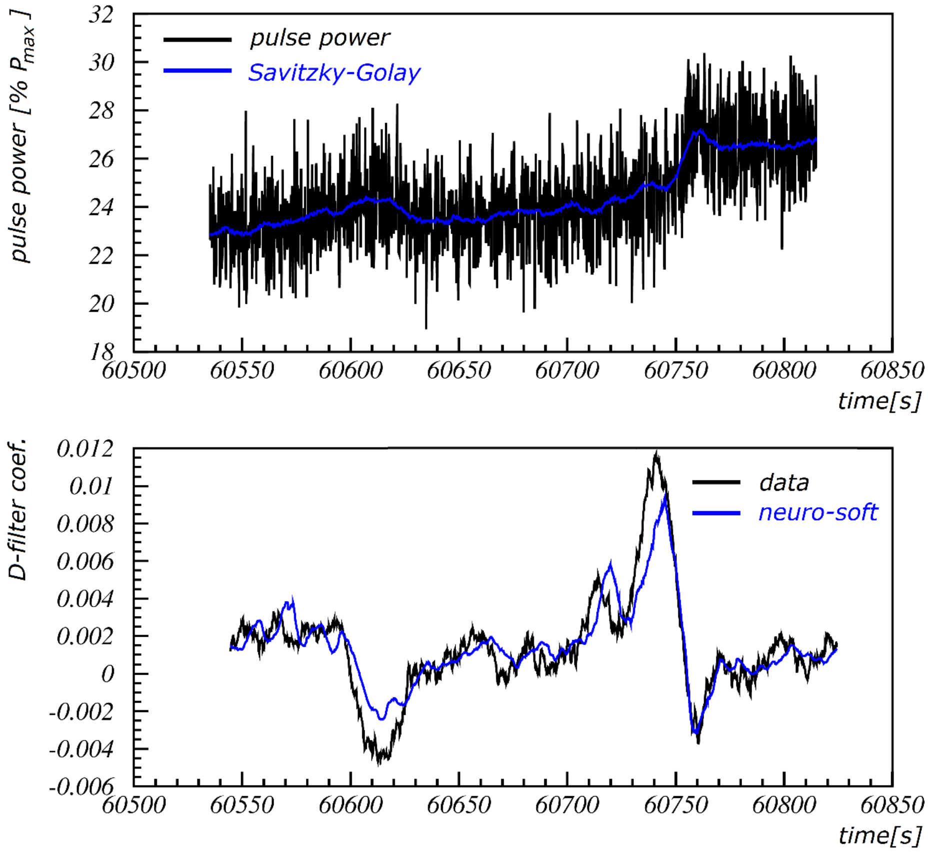

Figure 4: Prediction of the NARX neuro-software for the evolution of coefficient *D* of the Savitzky-Golay filter (down - in blue) and the data (in black). Top - for correlation, the pulse power (black) and its pedestal (in blue).

The applications of NARX software vary from that of software predictor (in a measurement chain), to classifier, signal recognition, controller intelligent design, non-linear filters, etc.

The software package that we used was the freeware NARXSim [7], from the Facultat d'Informatica de Barcelona (Universitat Polytecnica de Catalunya).

3. Ramp-up instability prediction

It is of interest to predict the ramp-up instabilities [2] sufficiently in advance for them to be monitored, or fed back into the control system of the reactor. Figure 2 (top) displays the neutron noise (in black) together with the Savitzky-Golay obtained pedestal (in blue). Two instabilities can be observed, at t = 60600 s and at t = 60750 s. These we marked with pale yellow bands and then correlated with the evolution of compensator block 2 (middle plot) and of the automatic regulator (bottom plot). It can be noticed that the instabilities appear when compensator block 2 allows raising the power and when the automatic regulator compensates these instabilities. For the time that compensator block 2 is stationary the power is driven by actuating the automatic regulator.

For the prediction of instabilities we chose as representative quantity the D coefficient of the Savitzky-Golay filter, which represents *d(pedestal)/dt*. We chose a NARX neuromorphic software for modelling, because most of the influences on the filter's D coefficient are exogenous (compensator block 2, the automatic regulator, the phase between OPO and DPO, cooling agent flow (Na), temperature of the cooling agent).

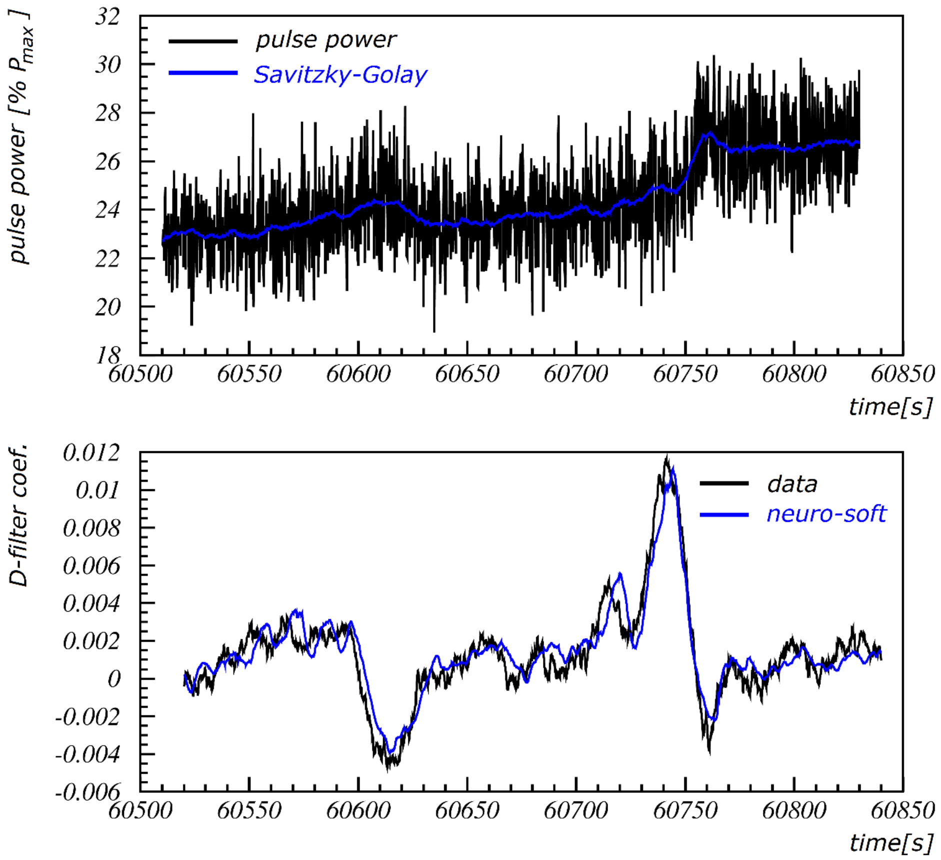

Figure 5: Prediction of the NARX neuro-software for the evolution of coefficient *D* of the Savitzky-Golay filter (down - in blue) and the data (in black). Top - for correlation, the pulse power (black) and its pedestal (in blue). It is an improvement to figure 4 by including also the Savitzky-Golay parameter C of the phase between the OPO and DPO reflectors.

The parameter to be anticipated is the average slope of pedestal variation in the interval [-2K, 0] around the current bin (for K = 100 bins, i.e. 10 s). The exogenous parameters that we used were:

- parameters D, A, C of the Savitzky-Golay filter for the power pulses, as well as the quadratic mean noise of this filter averaged in the interval [-2K, 0] around the current bin
- parameters Y, D, A of the Savitzky-Golay filter for compensator block 2, as well as the quadratic mean noise of this filter averaged in the interval [-2K, 0] around the current bin
- the real time value of the automatic regulator, as well as parameter D of the Savitzky-Golay filter for this quantity
- parameter D of the Savitzky-Golay filter for the phase between OPO and DPO, as well as the quadratic mean noise of this filter averaged in the interval [-2K, 0] around the current bin.

We trained the NARX neural network on 5 ramp-up sets from 2014, 2016 and 2019, keeping the ratio of 40% instabilities and 60% normal ramp-up in my training data. We then ran the software on a 2019 ramp-up set (different from those used in the training). The result we show in figure 4.

4. Conclusion

The prediction of the NARX neuro-software for the evolution of the Savitzky-Golay filter D parameter is shown in blue, vs the data (in black) - bottom part. In the top part is the pulse power (black) and its pedestal (blue) for correlation. Notice that the NARX software can predict partially the pedestal evolution in the instability zone – with some latency. To see which parameters have more impact, we kept separate the Savitzky-Golay parameter C of OPO-DPO phase. Re-training the network with this parameter also, we obtained a much better result, figure 5.

This indicates the significant impact that the OPO-DPO phase has among other parameters as source of instability. The rest of regions are more chaotical and there are no evident correlations that can give any significant prediction power. It is an important result that the NARX neuro-software has the ability to predict instabilities. Further improvement at this point would be to re-train the software with a larger data set.

References

[1] Yu.G. Dragunov et al. *Modernization of the IBR-2 pulsed research reactor*, Atomic Energy **113**, p. 29-34 (2012).

[2] Yu.N. Pepyolyshev, A.K. Popov, D. Sumkhuu. *Model of the IBR-2M pulsed reactor dynamics for investigating transition processes in a wide range of power variation*, Annals of Nuclear Energy **85**, p. 488-493 (2015).

[3] A. Savitzky, MJE. Golay. *Smoothing and Differentiation of Data by Simplified Least Squares Procedures*, Analyt. Chem. **36**, 1627-1639 (1964).

[4] JA. Nelder, R. Mead. *A simplex method for function minimization*, Computer Journal **7**, 308-313 (1965).

[5] MF. Thielbar, DA. Dickey. *Neural Networks for Time Series Forecasting: Practical Implications of Theoretical Results (2011)*, North Carolina State University.

[6] M. Binkowski, G. Marti, Ph. Donnat. *Autoregressive Convolutional Neural Networks for Asynchronous Time Series, Proceedings 35th International Conference on Machine Learning*, Vol. **80**, p. 580-589 (2018), Ed's J. Dy, A. Krause, PMLR, Stockholmsmassan, Stockholm, Sweden.

[7] *Pachet software neuromorfic*. NARXSim de la Facultat d'Informatica de Barcelona (Universitat Polytecnica de Catalunya), 2019.

PoS(DLCP2022)031