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# A Neuro-Fuzzy Controller for Xenon Spatial Oscillations in Load-Following Operation

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## Abstract

A neuro-fuzzy control algorithm is applied for xenon spatial oscillations in a pressurized water reactor. The consequent and antecedent parameters of the fuzzy rules are tuned by the gradient descent method. The reactor model used for computer simulations is a two-point xenon oscillation model. The reactor core is axially divided into two regions and each region has one input and one output and is coupled with the other region. The interaction between the regions of the reactor core is treated by a decoupling scheme. This proposed control method exhibits very fast responses to a step or a ramp change of target axial offset without any residual flux oscillations.

## 1. Introduction

The axial xenon oscillation in nuclear reactors is a highly nonlinear phenomenon that is a function of several time-variant parameters such as boron level, rod position and power level. Axially nonuniform buildup and removal of xenon cause the core power distribution to oscillate between the core top and its bottom with a period of 20 to 30 hours.

Maintaining the local core power within acceptable limits is a common objective for control problems. The core power distribution is usually manually regulated by the control rods and the control rods are inserted in radially symmetric groups. The radial power shape can be changed by moving independent rod groups. Control of the xenon oscillations is mostly concentrated in the axial dimension. Axial power shaping in PWRs is achieved by insertion or withdrawal of groups of full-length and part-length control rods and changes in boron concentration in the coolant [1].

Since the xenon oscillation control has been one of the most challenging control problems in the nuclear field, there has been extensive research in this area, especially using optimal control methods. The design of an optimal controller is in general based on an assumed linear model that is an approximate representation of a nonlinear plant. Moreover, the controller needs precise measurements or estimations of plant variables. On the contrary to this model-based controller, the neuro-fuzzy controllers do not rely on an accurate description of the plant but are generally based on an expert's knowledge of the underlying process. Also, the controller can be designed to be automatically fine-tuned or calibrated using the process data to obtain the desired performance.

Fuzzy logic and neural network methods were applied by Akin and Altin [2], Ramaswamy, Edwards and Lee [3], and Heger, Alang-Rashid and Jamshidi [4] for the power control of a nuclear reactor. However, fuzzy logic and neural network methods have not been applied for xenon spatial oscillations.

The reactor core is axially divided into several regions and each region has one input and one output. Therefore, we can apply a conventional neuro-fuzzy controller for each region. However, since each region is coupled with other regions, we should take into account the interaction among these regions to obtain good performance. It is accomplished through an approximate decoupling scheme.

A two-point (bottom and top) xenon oscillation model [5] is used in computer simulations for the demonstration of the proposed controller.

## 2. Design of a Neuro-Fuzzy Control System

While the conventional neuro-fuzzy control schemes may be capable of dealing with single-variable linear or nonlinear systems, considerable difficulty is encountered when applied to multivariable nonlinear systems like the xenon oscillation control. The difficulty stems not from the development of control algorithm but from the construction of the rule base which is important to implement the neuro-fuzzy controller. It is difficult to construct a rule-base due to the presence of interactions between control channels. From now on, a neuro-fuzzy controller will be described for a SISO process and then a decoupling scheme will be referred.

In a fuzzy control system of a channel, the $i$-th rule can be described using the first-order Sugeno-Takagi type [6] as follows:

$$R_i: \text{ if } x_1 \text{ is } A_{i1} \textit{ AND } \cdots \textit{ AND } x_m \text{ is } A_{im}, \text{ then } u \text{ is } f_i, \tag{1}$$

where $f_i = \sum_{j=1}^{m} q_{ij}x_j + r_i$: the output value of the $i$-th rule. (2)

Generally, there is no restriction on the shape of a membership function. In this paper, the following symmetric Gaussian membership function is used:

$$w_{ij}(x_j) = e^{-\frac{(x_j - c_{ij})^2}{2\sigma_{ij}^2}}, \tag{3}$$

where $c_{ij}$ is the center position of a peak of a membership function for the $i$-th rule and the $j$-th input and $\sigma_{ij}$ is the sharpness for the $i$-th rule and the $j$-th input.

The output of the fuzzy inference with $n$ rules is given as follows:

$$u = \sum_{i=1}^{n} \overline{w_i} \cdot f_i, \tag{4}$$

where $\overline{w_i} = w_i / \sum_{i=1}^{n} w_i, \quad w_i = \prod_{j=1}^{m} A_{ij}(x_j).$

Fuzzy system parameters such as membership functions and the connectives between layers in a fuzzy neural network must be optimized for the good performances of the controller. The gradient descent method is used to tune the parameters of the membership functions by minimizing the objective function defined as follows:

$$E = \frac{1}{2}\left\{ \sum_{p=1}^{t} \lambda^{t-p}\left(\alpha u_p^2 + [u_p - u_p^r]^2\right)\right\}, \tag{5}$$

where $\lambda$ is a forgetting factor. A forgetting factor is introduced to take into account for an exponential decay of the past data so that the control rules are modified fast according to the change of process dynamics. And also, the membership function parameters are tuned so that excessive control effort is not called for by containing an input-squared term in the objective error function [7].

The membership function parameters $c_{ij}$ and $\sigma_{ij}$ or consequent parameters $q_{ij}$ and $r_i$ which minimize the above objective functionare can be updated as follows:

$$c_{ij}(t+1) = c_{ij}(t) - \eta_a \sum_{p=1}^{t} \lambda^{t-p}[(\alpha + 1)u_p - u_p^r](f_i - u_p)\overline{w_i}\frac{(x_j - c_{ij})}{\sigma_{ij}^2}, \tag{6}$$

$$\sigma_{ij}(t+1) = \sigma_{ij}(t) - \eta_\sigma \sum_{p=1}^{t} \lambda^{t-p}[(\alpha + 1)u_p - u_p^r](f_i - u_p)\overline{w_i}\frac{(x_j - c_{ij})^2}{\sigma_{ij}^3}, \tag{7}$$

$$q_{ij}(t+1) = q_{ij}(t) - \eta_q \sum_{p=1}^{t} \lambda^{t-p}[(\alpha + 1)u_p - u_p^r]\overline{w_i}x_j, \tag{8}$$

$$r_i(t+1) = r_i(t) - \eta_r \sum_{p=1}^{t} \lambda^{t-p}[(\alpha + 1)u_p - u_p^r]\overline{w_i}. \tag{9}$$

The procedure of designing a SISO neuro-fuzzy controller described above indicates that only little qualitative knowledge about the process being controlled is required for deriving the rule-base. Such a controller will not function well when applied to multivariable systems in the presence of interactions among channels. To achieve better performance, it is necessary to take coupling effects into account.

It is assumed that dominant interactive sources are suitably identified. Then, we try to use an approximate adaptive technique [8] to counter interactive effects. The proposed neuro-fuzzy controller is given in Fig. 1.

## 3. Application of the Proposed Controller to the Axial Xenon Oscillation Model

The axial xenon oscillation model, developed previously, was modified and then used to demonstrate the proposed control algorithm[6][9]. The model employs the nonlinear xenon and iodine balance equations and a one-group, one-dimensional, neutron diffusion equation having nonlinear power reactivity feedback. The total power of the reactor core is held constant even though the power density varies as a function of both time and position.

The sampling period is assumed to be 5 min. The axial xenon oscillation model was divided into a lower and an upper region what is called as a two point model. Therefore, the proposed control system consists of two channels. The first and second channel inputs to the neuro-fuzzy controller are chosen as follows:

$x_1^1(t) = w_1(t) - y_1(t)$: the difference between the normalized target flux and the normalized neutron flux in the lower half of the reactor,

$x_2^1(t) = \Sigma_{a1}(t) - \Sigma_{a1}(t-1)$: the difference in absorber cross section $\Sigma_{a1}$ between two neighboring time steps in the lower half of the reactor.

$x_1^2(t) = w_2(t) - y_2(t)$, $x_2^2(t) = \Sigma_{a2}(t) - \Sigma_{a2}(t-1)$.

The dominant interaction inputs for the first and second channels are chosen as $x_1^2$ $(= w_2(t) - y_2(t))$ and $x_1^1$ $(= w_1(t) - y_1(t))$, respectively. The additional inputs for decoupling of the first and second channels consist of one term only as follows:

$$\hat{u}_d^{\,1} = \hat{l}_a^{\,1}(w_2 - y_2), \tag{10}$$

$$\hat{u}_d^{\,2} = \hat{l}_a^{\,2}(w_1 - y_1). \tag{11}$$

The adaptive laws for $\hat{l}_a^{\,1}$ and $\hat{l}_a^{\,2}$ are as follows:

$$\hat{l}_a^{\,1}(t+1) = \hat{l}_a^{\,1}(t) + \eta_l^1 u_f^1 (w_2 - y_2), \tag{12}$$

$$\hat{l}_a^{\,2}(t+1) = \hat{l}_a^{\,2}(t) + \eta_l^2 u_f^2 (w_1 - y_1), \tag{13}$$

where $u_f^1$ is the first channel output of the controller in case that the decoupling is not taken into account. Figure 2 shows the control architecture for the axial power distribution.

The input from the adaptive controller [9] developed previously is used as the desired output of the proposed controller for learning the fuzzy neural network, since the adaptive controller gives good performance. The variation between two neighboring time steps is used for control input. A measurement noise signal that has a Gaussian distribution with mean 0 and variance 0.0001, is added to the normalized flux to simulate more realistic plant environment. The proposed controller has 9 rules and two inputs for each channel and the number of the channels is two.

Three different simulations were performed in order to demonstrate the proposed controller for three cases; 1) tracking of the target axial shape which changes by step or ramp [refer to Fig. 3], 2) simulation without the decoupling unit to investigate the decoupling effect [refer to Fig. 4], and 3) dampening of the oscillations induced by a perturbation [refer to Fig. 5]. In all simulations, it is assumed that the reactor has been in steady state at 100 percent power level with steady-state xenon concentration before this controller is applied.

## 4. Conclusions

A neuro-fuzzy control algorithm with a learning function was investigated which can automatically construct and tune the rule base and membership functions. A forgetting factor was introduced to account for an exponential decay of the past data so that the control rules should be modified fast according to the change of process dynamics. The proposed controller has on-line or off-line learning function based on the gradient descent method.

When there exist interactions among channels, it is necessary to take coupling effects into account to achieve better performance. An approximate adaptive decoupling technique was applied to counter interactive effects.

The proposed algorithm is demonstrated by using the two-point xenon oscillation model. This controller traces the desired axial shape without delay although system parameters changes by step and ramp and damps without delay some oscillations induced by external means. Also, this algorithm uses two kinds of measurements signals only: the neutron flux measurements and the macroscopic cross sections of absorbers (control rod position and boron concentration) at each location without estimating the xenon and iodine concentrations. However, Although its parameters are tuned automatically, it is known that its performance is affected a little by the assumed initial values of the parameters.

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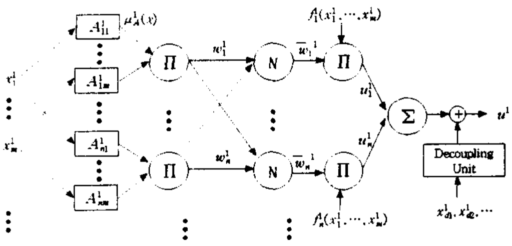



Fig. 1. A fuzzy neural network.

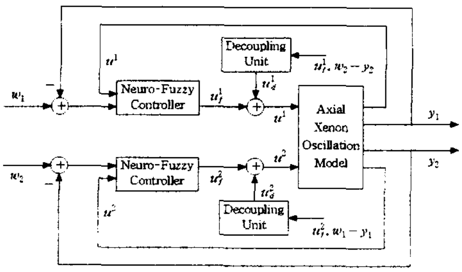
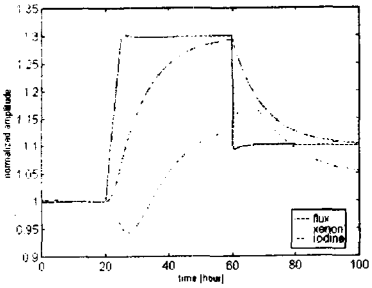
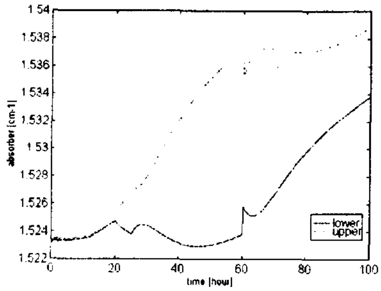


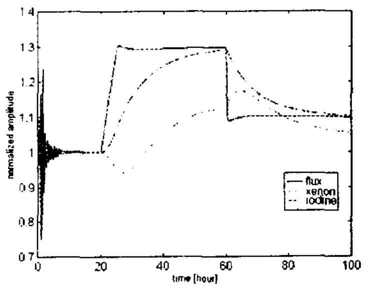

Fig. 2. A simplified block diagram of the proposed neuro-fuzzy control system.



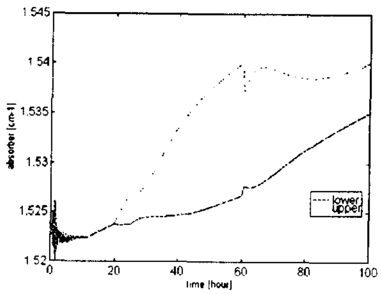

(a) Normalized flux, xenon, and iodine responses at the lower half of the reactor core.
Fig. 3. Performance of the proposed controller due to ramp and step changes of target axial shape (with the decoupling unit).



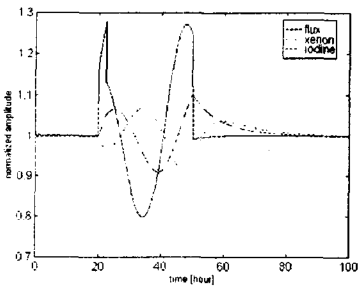

(b) Macroscopic cross sections of the absorber in the lower and upper halves of the reactor core.
Fig. 3. Continued.



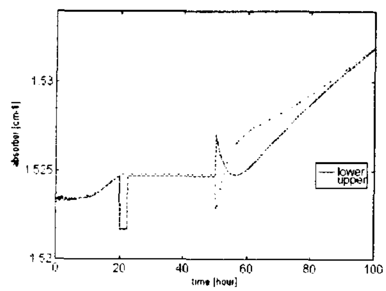

(a) Normalized flux, xenon, and iodine responses in the lower half of the reactor.
Fig. 4. Performance of the proposed controller due to ramp and step changes of target axial shape (without the decoupling unit).




(b) Macroscopic cross sections of the absorber in the lower and upper halves of the reactor core.
Fig. 4. Continued.




(a) Normalized flux, xenon, and iodine responses in the lower half of the reactor core.
Fig. 5. Performance of the proposed controller for the removal of free oscillations.




(b) Macroscopic cross sections of the absorber in the lower and upper halves of the reactor core.
Fig. 5. Continued.