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Design of a fault tolerated intelligent control system for load following operation in a nuclear power plant

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A B S T R A C T

Fault detection has always an important role in maintaining the system stability and assuring satisfactory and safe operation. In this paper a method based on system identification is used for fault detection on a nuclear reactor. The combination of Extended Kalman Filter and recursive Least Square are used to identify the system parameters. Another goal of this paper is design of a fault tolerant control system for a nuclear reactor during power change operation. The proposed controller is an adaptive neuro-fuzzy controller based on emotional learning. Performance of the controller in term of transient response and robustness against failure is very good and outstanding.

Introduction

A nuclear reactor is a nonlinear and complicated plant whose parameters vary with power level, fuel burn up, etc. Despite all efforts to prevent of failure, the possibility of failure is inevitable. Any failure in nuclear reactor if not detected early may result in catastrophic and irreversible damages. When systems are complex, they need to work with minimal downtime or poor performance. Therefore, the needs for automated detection of failure in modern facilities are increasing rapidly. Frank and Keller [1] used two dedicated observers to distinguish parameter variation and instrument malfunctions. Hwang used an artificial neural network to estimate the degree of failures in a nuclear reactor [2]. The developments in fault detection methods up to the respective times are also summarized in the books by Mangoubi [3], Chen and Patton [4], and Patton et al. [5]. Recently Hatami and Salarieh applied the extended Kalman filter to identify process parameters indicative of process faults in nuclear reactors [6].

One of the most popular methods for fault detection is the method based on system identification. This method is based on principle that occurrence of any fault in the system shows itself in changing the system parameters. In this study the recursive least squares method is used to identify the parameters in fault detection. In most design methods it is assumed that all state variables are available, whereas in practice it is necessary that for measurement each of state variables one sensor and measurement system is placed which involves high cost. Reasonable solution to resolve this problem is to estimate the state variables using the measured output. This operation is done by a dynamic system called state observer. Thus at first, we use the Extended Kalman Filter to estimate state variables of system and then proceed to identify the parameters. Faulty condition of the reactor system components leads to drastic reduction or loss of stability and performance properties. Therefore, it is necessary to design control systems which are capable of tolerating potential faults in order to improve the reliability, while providing desirable performance. This type of control systems are known as fault- tolerant control system. In this paper, a neuro-fuzzy controller based on emotional learning is used. The structure of neuro-fuzzy controller with emotional learning is very simple compared to other similar techniques and has a high strength in solving the control problems. At the end, the robustness of the emotional controller under various scenarios breakdown will be investigated.

The remaining part of this paper is organized as follows. Section 'Reactor model' presents mathematical model of the reactor. Section 'Emotional learning based intelligent controller' describes the emotional learning based intelligent controller structure and some mathematical fundamentals. Section 'Fault detection' presents Fault detection method and parameter identification of the reactor. In Section 'Simulation', robustness of the intelligent

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Nomenclature

n	neutron density
n_0	initial equilibrium (steady- state) neutron density (n/cm^3)
$n_r \equiv \frac{n}{n_0}$	neutron density relative to initial equilibrium density
c	core average precursor density (atom/cm^3)
c_0	initial equilibrium (steady state) density of precursor
$c_r \equiv \frac{c}{c_0}$	relative density of precursor
λ	effective precursor radioactive decay constant (s^{-1})
Λ	effective prompt neutron life time (s)
β	fraction of delayed fission neutrons
k	effective neutron multiplication factor
$\rho \equiv \frac{k-1}{k}$	core reactivity
Ω	heat transfer coefficient between fuel and coolant (MW/°C)
M	mass flow rate times heat capacity of the water (MW/°C)
T_f	average reactor fuel temperature (°C)
T_{f0}	initial equilibrium (steady state) fuel temperature (°C)
T_l	temperature of the water leaving the reactor (°C)
T_c	average reactor coolant temperature (°C)
T_{c0}	initial equilibrium (steady state) coolant temperature (°C)
f_f	fraction of reactor power deposited in the fuel
μ_f	total heat capacity of the fuel = weight of fuel times its specific heat (MWs/°C)
μ_c	total heat capacity of the reactor coolant = weight of coolant times its specific heat (MWs/°C)
I	$\frac{I'}{\sum_f}$
I'	iodine concentration (atom/cm^3)
$\sum_f$	macroscopic fission cross-section (cm^{-1})
X	$\frac{X'}{\sum_f}$
X'	xenon concentration (atom/cm^3)
λ_I	iodine decay constant (s^{-1})
λ_X	xenon decay constant (s^{-1})
γ_I	iodine yield
γ_X	xenon yield
σ_X	microscopic absorption cross-section (cm^2)
$\Phi \equiv nV$	neutron flux (n/cm^2 s)
V	thermal neutron speed (cm/s)
X_0	initial equilibrium (steady state) Xenon concentration (atom/cm^3)

controller against failures is illustrated. And finally in Section 'Conclusion', the conclusion remarks will be given.

Reactor model

In this work, a 7th order model is used for nonlinear simulation of a PWR nuclear reactor. The reactor core is modeled by considering point kinetics equation with one delay neutron and temperature feedback from lumped fuel and coolant temperatures. Also nonlinear feedback of Xenon concentration is added to core. The number of model parameters depends on the power level. The normalized equations with respect to an equilibrium condition are as follow [7,8]:

$$\frac{dn_r}{dt} = \frac{\rho - \beta}{\Lambda} n_r + \frac{1}{\Lambda}\beta c_r \tag{1a}$$

$$\frac{dc_r}{dt} = \lambda n_r - \lambda c_r \tag{1b}$$

$$\frac{dT_f}{dt} = \frac{f_f p_0}{\mu_f} n_r - \frac{\Omega}{\mu_f} T_f + \frac{\Omega}{2\mu_f} T_l + \frac{\Omega}{2\mu_f} T_e \tag{1c}$$

$$\frac{dT_l}{dt} = \frac{(1 - f_f)p_0}{\mu_c} n_r + \frac{\Omega}{\mu_c} T_f - \frac{(2M + \Omega)}{2\mu_c} T_l + \frac{(2M - \Omega)}{2\mu_c} T_e \tag{1d}$$

$$\frac{dI}{dt} = -\lambda_I I + \gamma_I \Phi \tag{1e}$$

$$\frac{dXe}{dt} = \lambda_I I + (\gamma_{Xe} - \sigma_{Xe} Xe)\Phi - \lambda_{Xe} Xe \tag{1f}$$

$$\frac{d\rho_r}{dt} = G_r z_r \tag{1g}$$

where (1a) and (1b) are point kinetics equation with one delay neutron, Eqs. (1c) and (1d) are thermal hydraulics model of the reactor, Eqs. (1e) and (1f) represent Xenon concentration and Eq. (1g) shows the changes of reactivity due to changes in control rod speed. Finally the reactivity input is represented as follow:

$$\rho = \rho_r + \alpha_f(T_f - T_{f0}) + \alpha_c(T_c - T_{c0}) - \sigma_{Xe}(Xe - Xe_0) \tag{2}$$

$\alpha_f, \alpha_c, \mu_c, \Omega$ and M are related to power level [9]. Eqs. (3a)–(3e), show this dependence:

$$\mu_c(n_r) = \left(\frac{160}{9} n_r + 54.022\right) \quad (\text{MWs}/^\circ\text{C}) \tag{3a}$$

$$\Omega(n_r) = \left(\frac{5}{3} n_r + 4.9333\right) \quad (\text{MWs}/^\circ\text{C}) \tag{3b}$$

$$M(n_r) = (28 n_r + 74) \quad (\text{MW}/^\circ\text{C}) \tag{3c}$$

$$\alpha_f(n_r) = (n_r - 4.24) \times 10^{-5} \frac{\delta k}{k} \Big/ {}^\circ\text{C} \tag{3d}$$

$$\alpha_c(n_r) = (-4 n_r - 17.3) \times 10^{-5} \frac{\delta k}{k} \Big/ {}^\circ\text{C} \tag{3e}$$

Also Reactor power is expressed as follows:

$$p(t) = p_0 n_r(t) \tag{4}$$

where $p(t)$ is the reactor power (MW), p_0 is the nominal power (MW) and n_r is normalized power. The parameters used in the model are summarized in Table 1 [10,11].

Table 1
The parameters used in the modeling of the Reactor with one delayed neutron.

Parameters	Values	Parameters	Values
β	0.006019	T_e	290 (°C)
Λ	0.00002 (s)	T_{f0}	673.8 (°C)
λ	0.15 (s^{-1})	T_{c0}	302.2 (°C)
G_r	0.0145 (δ K/K)	λ_I	2.9×10^{-5} (s^{-1})
p_0	2500 (MW)	λ_{Xe}	2.1×10^{-5} (s^{-1})
μ_f	26.3 (MW/°C)	σ_{Xe}	3.5×10^{-18} (cm^2)
f_f	0.98	γ_I	0.056
V	2.2×10^5 (cm/s)	γ_{Xe}	0.003