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Short communication

# Design of a fault tolerated intelligent control system for a nuclear reactor power control: Using extended Kalman filter

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ABSTRACT

In this paper an approach based on system identification is used for fault detection in a nuclear reactor. A continuous-time Extended Kalman Filter (EKF) is presented, which allows the parameters of the nonlinear system to be estimated. Also a fault tolerant control system is designed for the nuclear reactor during power changes operation. The proposed controller is an adaptive critic-based neuro-fuzzy controller. Performance of the controller in terms of transient response and robustness against failures is very good and considerable.



## 1. Introduction

Many advanced process plants and machines are extremely complex, and always depend on automatic control for satisfactory operation. In order to achieve and maintain system stability and assure satisfactory and safe operation, there is an increasing demand for dynamic systems which have the capability of continuing acceptable operation in presence of failures. Therefore failures detection has always been an important aspect of fault tolerant control system design. For example, in a nuclear power plant, tens of alarms can occur in a few second after a fault. Detecting the fault might be of utmost importance due to safety, political and other reasons. Many investigations have been performed in the field of fault detection. Frank and Keller [1] used two dedicated observers to distinguish parameter variation and instrument malfunctions. Watanabe and Himmelblau [2] applied the extended Kalman filter to identify process parameters indicative of process faults caused by the deterioration of components. 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].

In the present paper, an extended Kalman filtering algorithm is employed to identify failure on the nuclear reactor parameters, which are fuel reactivity coefficient $\alpha_f$ and coolant reactivity coefficient $\alpha_c$ The EKF is most used to estimate the variables of nonlinear models while the model parameters are kept fixed or change slightly. However, it is also possible to estimate model parameters as a part of the calculation, often referred to as 'state and parameter estimation' as distinct from just 'state estimation' [6–8].

Faulty conditions of a reactor system components lead 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. These types of control systems are known as fault- tolerant control system. A variety of control systems can be found in the literature in the field of nuclear reactor power control. Park and Cho presented a model-based feedback linearization controller with adaptive PI gains for robust control of a nuclear reactor [9]. In another attempt, Khajavi et al. introduced a robust optimal self regulator to control reactor power in a large spectrum of loads [10]. Yao and Da-fa have also designed a multistep model predictive algorithm for load following operation of nuclear reactors [11]. A robust control system using quantitative feedback theory (QFT) for controlling the power level was provided in [12].

In this paper, an adaptive critic-based neuro-fuzzy controller (ACNFC) [13] is presented. Adaptive critic design is based on reinforcement learning concept [14]. In reinforcement learning, performance of the control system is assessed by a critic agent. The controller modifies its characteristics in a way that the signal produced by the critic, namely stress is decreased. We investigate that

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**Nomenclature**

| | |
|---|---|
| $n$ | neutron density |
| $n_0$ | initial equilibrium (steady- state) neutron density (n/cm$^3$) |
| $n_r \equiv n/n_0$ | neutron density relative to initial equilibrium density |
| $c$ | core average precursor density (atom/cm$^3$) |
| $c_0$ | initial equilibrium (steady state) density of precursor |
| $c_r \equiv c/c_0$ | relative density of precursor |
| $\lambda$ | effective precursor radioactive decay constant (s$^{-1}$) |
| $\Lambda$ | effective prompt neutron life time (s) |
| $\beta$ | fraction of delayed fission neutrons |
| $k$ | effective neutron multiplication factor |
| $\rho \equiv (k-1)/k$ | core reactivity |
| $\Omega$ | 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 |
| $\mu_f$ | total heat capacity of the fuel = weight of fuel times its specific heat (MWs/°C) |
| $\mu_c$ | total heat capacity of the reactor coolant = weight of coolant times its specific heat (MWs/°C) |
| $I$ | $I'/\sum_f$ |
| $I'$ | iodine concentration (atom/cm$^3$) |
| $\sum_f$ | macroscopic fission cross-section (cm$^{-1}$) |
| $X$ | $X'/\sum_f$ |
| $X'$ | xenon concentration (atom/cm$^3$) |
| $\lambda_I$ | iodine decay constant (s$^{-1}$) |
| $\lambda_X$ | xenon decay constant (s$^{-1}$) |
| $\gamma_I$ | iodine yield |
| $\gamma_X$ | xenon yield |
| $\sigma_X$ | 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$^3$) |
| $\alpha_f(n_r)$ | fuel temperature reactivity coefficient ($\Delta k/k$ (°C)) |
| $\alpha_c(n_r)$ | coolant temperature reactivity coefficient ($\Delta k/k$ (°C)) |
| $z_r$ | control rod speed |

robustness of the proposed controller under various breakdown scenarios is considerable.

The remaining part of this paper is organized as follows. Section 2 presents mathematical model of the reactor. Section 3 describes the adaptive critic-based neuro-fuzzy controller structure and some mathematical fundamentals. Section 4 presents fault detection and parameter identification methods utilized for the reactor. In Section 5, robustness of the intelligent controller against failures is illustrated. And finally in Section 6, the conclusion remarks will be given.

## 2. 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 the point kinetics equation with one delayed neutron and the temperature feedback from the fuel and the coolant lumped temperatures. Also nonlinear feedback of xenon concentration is added to the core. Number of model parameters depends on the power level. The normalized equations with respect to an equilibrium condition are given as [15,16]:

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

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

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

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

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

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

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

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

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

$\alpha_f$, $\alpha_c$, $\mu_c$, $\Omega$ and $M$ are related to power level [17]. Eqs. (3a)–(3e) show this dependence:

$$\mu_c(n_r) = \left(\frac{160}{9}n_r + 54.022\right) \tag{3a}$$

$$\Omega(n_r) = \left(\frac{5}{3}n_r + 4.9333\right) \tag{3b}$$

$$M(n_r) = (28n_r + 74) \tag{3c}$$

$$\alpha_f(n_r) = (n_r - 4.24) \times 10^{-5} \tag{3d}$$

$$\alpha_c(n_r) = (-4n_r - 17.3) \times 10^{-5} \tag{3e}$$

Also the 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 $n_r$ describes the normalized power. The parameters used in the model are summarized in Table 1 [12,18].

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

| Parameters | Values | Parameters | Values |
|---|---|---|---|
| $T_e$ | 290 (°C) | $\beta$ | 0.006019 |
| $T_{f0}$ | 673.8 (°C) | $\Lambda$ | 0.00002 (s) |
| $T_{c0}$ | 302.2 (°C) | $\lambda$ | 0.15 (s$^{-1}$) |
| $\lambda_I$ | $2.9 \times 10^{-5}$ (s$^{-1}$) | $G_r$ | 0.0145 ($\delta K/K$) |
| $\lambda_{Xe}$ | $2.1 \times 10^{-5}$ (s$^{-1}$) | $p_0$ | 2500 (MW) |
| $\sigma_{Xe}$ | $3.5 \times 10^{-18}$ (cm$^2$) | $\mu_f$ | 26.3 (MW/°C) |
| $\gamma_I$ | 0.056 | $f_f$ | 0.98 |
| $\gamma_{Xe}$ | 0.003 | $V$ | $2.2 \times 10^5$ (cm/s) |