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Load following control and global stability analysis for PWR core based on multi-model, LQG, IAGA and flexibility idea

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ABSTRACT

The work is to design a nonlinear Pressurized Water Reactor (PWR) core load following control system and analyze the global stability of this system. On the basis of modeling a nonlinear PWR core, linearized models of the core at five power levels are chosen as local models of the core to substitute the nonlinear core model in the global range of power level. The combination control strategy of the Linear Quadratic Gaussian (LQG) control and the Proportional Integral Derivative (PID) control with an optimization process of Improved Adaptive Genetic Algorithm (IAGA) proposed is used to contrive a combined controller with the robustness of a core local model as a local controller of the nonlinear core. Based on the local models and local controllers, the flexibility idea of modeling and control is presented to design a decent controller of the nonlinear core at a random power level. A nonlinear core model and a flexibility controller at a random power level compose a core load following control subsystem. The combination of core load following control subsystems at all power levels is the core load following control system. The global stability theorem is deduced to define that the core load following control system is globally asymptotically stable within the whole range of power level. Finally, the core load following control system is simulated and the simulation results show that the control system is effective.

1. Introduction

Nowadays, much energy provided by nuclear reactors in the world is used to produce electrical power in response to electricity loads. With more and more load requirements on electric grids, the load following operation of nuclear power plants (NPPs) is a developing trend. This operation mode of NPPs has been researched (Meyer et al., 1978; Chari and Rohr, 1997). The load-follow capability is to control and regulate the reactor power according to practical or predictable load demands on an electric network. Hence, developing high-performance control techniques of reactor power in the load tracking mode is necessary for the improvement of safety and availability of NPPs.

The control principle of reactor power is to generate the insertion or extraction speed of control rods such that the reactor power output can be regulated at a demand value. Though a conventional reactor power control has been used in the base load mode, the performance and stability of the conventional control system cannot be guaranteed in the load following mode. However, continuous efforts have been made to establish advanced control methodologies for nuclear reactors in the past decades, which can contribute to implement the reactor load following operation. Edwards et al. (1990) and Edwards (1991) presented the state feedback assisted classical control (SFAC) which incorporates the merits of the output and state feedback control methods, and designed SFAC based controllers for nuclear reactors; Eliasi et al. (2012) proposed the robust nonlinear model predictive control (NMPC) with robust constraints on both input and output variables for the load following operation of a PWR core; Chao-Chee Ku et al. (1992) contrived the diagonal recurrent neural network controller (DRNNC) including a neurocontroller and a neuroidentifier to control a PWR core power and the core coolant exit temperature; Khajavi et al. (2002) devised a neural network controller (NNC) for the power regulation of a nuclear reactor. However, the controllers in references (Edwards et al., 1990, 1991; Eliasi et al., 2012) are all designed based on a linearized or nonlinear core model at a power level, and not always optimal or even ineffective for large or drastic load maneuvers; the controllers in literature (Chao-Chee Ku et al., 1992; Khajavi et al., 2002) are designed based on the neural network intelligent approach. The approach needs to obtain training samples which are usually given by either a linearized model or actual data of reactor cores, the sample based on a

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linearized model limits the working range of intelligent controllers and extracting or training actual data is inconvenient, time-consuming and expensive. Based on the considerations in the paper, new strategies including the linear multi-model modeling, the combined control of LQG and PID with IAGA, the flexibility idea and the global stability theorem are utilized to devise a PWR core load following control system.

PWRs are complex time-varying nonlinear systems and their parameters vary with time and the power level. The linear multi-model method is an effective modeling way of a nonlinear system (Johansen and Foss, 1999) and used to model the nonlinear PWR core in the paper. Linearized models of the core at five power levels are respectively selected as local models of the core and the set of local models is used to substitute the nonlinear core model.

The combination control strategy of the LQG optimal control and the PID control based on IAGA is utilized to design a controller with robustness of a core local model as a local controller of the nonlinear core. The LQG optimal control is essentially the state feedback control which is based on the optimal control theories and the optimal estimation theories (Athans, 1971; Balakrishnan, 1984). Major advantages of LQG controller are that it possesses the robustness and can be designed for single-variable or multi-variable plants including open loop unstable ones. The application of LQG control to the nuclear science field has appeared. Berkan and Upadhyaya (1989) used the LQG control to accomplish a reactor power regulation and the drum level control; Belyakov et al. (1999) utilized the LQG methodology for the ITER plasma current, position and shape control system as well as power derivative management system; Parikh et al. (2011) designed the LQG controller to control a nuclear steam generator. However, a LQG controller is calculated and obtained after subjectively choosing decent weighting matrixes in the LQG optimal control. And it cannot be guaranteed that control performances based on a LQG controller are always satisfactory. In order to attaining desirable control performances such as a small overshoot, a short adjustment time and a small static error, the PID control follows the LQG control and is utilized to further improve the dynamic performances. The effect of the PID control depends on parameters setting of PID. Setting PID parameters via Genetic Algorithm (GA) is an intelligent way to search the best combination of PID parameters in the stable region of a system. But it has three defects such as the premature convergence; the slow convergence caused by the weak ability of searching locally in the later period of evolving; the nondirectional operators of crossover and mutation. In the paper, on the basis of Adaptive Genetic Algorithm (AGA) proposed by Srinivas and Patnaik (1994), IAGA is proposed to make up the defects.

In terms of the local models and local controllers, the flexibility idea of modeling and control is proposed to design a flexibility controller of the nonlinear core at a random power level. A nonlinear core model and a flexibility controller at a random power level compose a core load following control subsystem. The combination of core load following control subsystems at all power levels is the core load following control system.

The design and simulation work of the core multi-model control strategy is more than that of SFAC, NMPC, DRNNC and NNC in the aforementioned references, but, of the strategy, the combination control of LQG and PID with the optimization of IAGA absorbs the characteristic of the state feedback like SFAC and the optimization idea of intelligent approaches like the neural network to generate good control laws instead of training samples as designing DRNNC and NNC, using the multi-model and flexibility idea ensures a stronger robustness than one of SFAC and NMPC.

Based on one criterion (Dorf and Bishop, 2009) and three theorems (Isidori, 1995; Liu and Tang, 2007), the global stability theorem is deduced and adopted to define that the core load following control system is globally asymptotically stable within the whole range of power level.

Simulation results illustrate that the nonlinear core load following control system can be used to satisfactorily carry out the core load following operation. Finally, conclusions are drawn.

2. Model PWR core

2.1. Nonlinear model

According to the lumped parameter method, the nonlinear core model is established via using the point kinetics equations with six groups of delayed neutrons and reactivity feedbacks due to changes in fuel temperature and coolant temperature. The expressions of the nonlinear model are as follows

$$\frac{\mathrm{d}n_r}{\mathrm{d}t} = \frac{\rho-\beta}{\Lambda}n_r + \sum_{i=1}^{g}\frac{\beta_i c_{ri}}{\Lambda} \tag{1}$$

$$\frac{\mathrm{d}c_{ri}}{\mathrm{d}t} = \lambda_i n_r - \lambda_i c_{ri}, i = 1,2,\ldots,g \tag{2}$$

$$\frac{\mathrm{d}T_f}{\mathrm{d}t} = \frac{f_f P}{\mu_f}n_r - \frac{\Omega}{\mu_f}T_f + \frac{\Omega}{2\mu_f}T_i + \frac{\Omega}{2\mu_f}T_e \tag{3}$$

$$\frac{\mathrm{d}T_e}{\mathrm{d}t} = \frac{\left(1-f_f\right)P}{\mu_c}n_r + \frac{\Omega}{\mu_c}T_f + \frac{2M-\Omega}{2\mu_c}T_i - \frac{2M+\Omega}{2\mu_c}T_e \tag{4}$$

$$\rho = \rho_{\text{rod}} + \alpha_f\left(T_f - T_{f0}\right) + \frac{\alpha_c}{2}(T_i - T_{i0}) + \frac{\alpha_c}{2}(T_e - T_{e0}) \tag{5}$$

where n_r-normalized relative neutron density; Λ-neutron generation time, s; ρ-total reactivity; β-effective delayed neutron fraction; c_{ri}-ith group normalized precursor concentration; g-delayed neutron group number, $g = 6$; λ_i-ith delayed neutron group decay constant, s^{-1}; T_f -fuel average temperature, °C; T_{f0} -fuel average temperature at the initial point, °C; f_f-fuel power coefficient; P-reactor power, W; μ_f -fuel total heat capacity, J/°C; Ω-coefficient of heat transfer between fuel and coolant, W/°C; T_i-coolant inlet temperature, °C; T_{i0}-coolant inlet temperature at the initial point, °C; T_e-coolant outlet temperature, °C; T_{e0}-coolant outlet temperature at the initial point, °C; μ_c-total heat capacity of coolant, J/°C; M-mass flow heat capacity, W/°C; ρ_{rod}-reactivity due to control rod movement; α_f-fuel temperature coefficient of reactivity, °C^{-1}; α_c-coolant temperature coefficient of reactivity, °C^{-1}.

2.2. Linearized model

The small perturbation linearization methodology is utilized to linearize the nonlinear core model and then the linearized core model is calculated.

Eqs. (1)–(5) are linearized and the linearized equations are the followings

$$\frac{\mathrm{d}\delta n_r}{\mathrm{d}t} = -\frac{\beta}{\Lambda}\delta n_r + \sum_{i=1}^{g}\frac{\beta_i}{\Lambda}\delta c_{r_i} + \frac{n_{r0}}{\Lambda}\delta\rho \tag{6}$$

$$\frac{\mathrm{d}\delta c_{ri}}{\mathrm{d}t} = \lambda_i\delta n_r - \lambda_i\delta c_{ri}, i = 1,\ldots,g \tag{7}$$

$$\frac{\mathrm{d}\delta T_f}{\mathrm{d}t} = \frac{f_f P}{\mu_f}\delta n_r - \frac{\Omega}{\mu_f}\delta T_f + \frac{\Omega}{2\mu_f}\delta T_i + \frac{\Omega}{2\mu_f}\delta T_e \tag{8}$$