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State-Space Model Predictive Control Method for Core Power Control in Pressurized Water Reactor Nuclear Power Stations

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ABSTRACT

A well-performed core power control to track load changes is crucial in pressurized water reactor (PWR) nuclear power stations. It is challenging to keep the core power stable at the desired value within acceptable error bands for the safety demands of the PWR due to the sensitivity of nuclear reactors. In this paper, a state-space model predictive control (MPC) method was applied to the control of the core power. The model for core power control was based on mathematical models of the reactor core, the MPC model, and quadratic programming (QP). The mathematical models of the reactor core were based on neutron dynamic models, thermal hydraulic models, and reactivity models. The MPC model was presented in state-space model form, and QP was introduced for optimization solution under system constraints. Simulations of the proposed state-space MPC control system in PWR were designed for control performance analysis, and the simulation results manifest the effectiveness and the good performance of the proposed control method for core power control.

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1. Introduction

Nuclear power has been developed promptly due to its cleanliness [1]; there are > 400 nuclear power stations built, > 60 under construction, and > 150 in preparation in the world.

Though nuclear energy is blossoming, it is accompanied by security issues that merit great attention. For pressurized water reactor (PWR) nuclear power stations, one of the most significant operations is to control the core power to follow the load changes. As nuclear reactors are time-varying and

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sensitive, designing a well-performed core power control system is a challenge. Nowadays, proportion integration differentiation (PID) control methods are still the predominant control methods used in PWR nuclear power stations for core power control. Undoubtedly, PID control methods have numerous assets. However it is becoming hard for PID control methods to meet our needs of controlling core power in a fleet and exact way [2].

A few researchers have applied various methods to control the core power in PWR power stations, such as constant axial offset strategy [3], fuzzy logic methods [4], neural network methods [5], robust optimal control systems [6], and intelligent control systems [7]. The researchers have had success but there still remain challenges, as it is difficult to control the core power well because of the sensitivity of nuclear reactors. Thus, there is still room for other control methods to be applied to control the core power in PWR accurately and swiftly.

Model predictive control (MPC), also called receding horizon control, has received much attention in control fields due to its ability to handle time-varying systems. MPC is comprised of three basic elements: prediction model, rolling optimization, and feedback compensation. MPC is a kind of closed-loop optimization control based on models and has the merits of fabulous control effects and strong robustness, on account of its characteristics of online optimization and receding horizon optimization. A considerable amount of researches [8–11] based on MPC have been centered on dealing with nonlinear systems that might be replaced by a series of piecewise linear systems [12].

In this paper, the MPC method was applied to core power control in PWRs. The MPC model was based on differential equation models including neutron dynamics models, thermal hydraulic models, and reactivity models. Compared with the PID control method, simulation results demonstrate that the stability of the core power in PWRs was improved and guaranteed by the proposed state-space MPC method.

2. Mathematical models in PWRs

The model for core power control was based on mathematical models including neutron dynamics models, thermal hydraulic models, and reactivity models [13–17] in PWRs.

2.1. Neutron dynamics models

Point-reactor kinetic equations of multigroup delayed neutrons will cause a heavy calculation workload, so these equations can be simplified by multigroup delayed neutrons being equivalent to one single group of delayed neutrons [5]. The simplified kinetic equations are as follows:

$$\frac{dn}{dt} = \frac{\rho - \beta}{\Lambda} n + \lambda c \tag{1}$$

$$\frac{dc}{dt} = \frac{\beta}{\Lambda} n - \lambda c \tag{2}$$

where n is the neutron density; t is time; ρ is total reactivity; β

is the total fraction of effective delayed neutrons; Λ is time of neutron generation; λ is the decay constant of delayed neutron precursors; and c is the concentration of delayed neutron precursors.

By the normalization method, Eqs. (1) and (2) can be represented as follows:

$$\frac{dn}{dt} = \frac{\rho - \beta}{\Lambda} n + \frac{\beta}{\Lambda} c \tag{3}$$

$$\frac{dc}{dt} = \lambda n - \lambda c \tag{4}$$

The core power is relevant to the neutron density, and the core power can be described as follows:

$$P_a(t) = n P_0 \tag{5}$$

where $Pa(t)$ is the actual core power; and P_0 is the nominal core power. P_0 is constant, so n can represent relative core power.

2.2. Thermal hydraulic models

In light of the law of conservation of energy in PWRs, the following equations were obtained:

$$\begin{cases} P_c(t) = \Omega(T_f - T_c) \\ P_e(t) = M(T_l - T_e) \end{cases} \tag{6}$$

where $P_c(t)$ is the heat quantity transferred from fuel to cooling water; $P_e(t)$ is the heat quantity transferred from cooling water to the secondary circuit; Ω is the heat transfer coefficient between fuel and cooling water; M is the heat capacity of mass flow rate of cooling water; T_f is the average temperature of fuel; T_c is the average temperature of cooling water; T_l is the outlet temperature of cooling water; and T_e is the inlet temperature of cooling water.

In PWRs, the inlet temperature of cooling water is generally constant and stable in the vicinity of 300°C; the difference between the inlet and the outlet temperature of cooling water is about 30°C. The physical parameters of cooling water were assumed to be constant during heat exchange between fuel and cooling water in this study. Therefore, we got the following equations:

$$\begin{cases} T_c = \frac{1}{2}(T_l + T_e) \\ \delta T_e = 0 \end{cases} \tag{7}$$

where δ is the deviation value relative to the balance point.

Thermal hydraulic models in PWRs are as follows:

$$f_f P_a(t) = \mu f \frac{dT_f}{dt} + P_c(t) \tag{8}$$

$$\left(1 - f_f\right) P_a(t) + P_c(t) = \mu_c \frac{dT_l}{dt} + P_e(t) \tag{9}$$

where f_f is the fraction of reactor power deposited in fuel; μ_c is the heat capacity of cooling water; and μ_f is the heat capacity of fuel.

2.3. Reactivity models

The reactivity models in PWRs are as follows [18]:

$$\delta\rho = \delta\rho_r + \alpha_f(T_f - T_{f0}) + \frac{\alpha_c(T_l - T_{l0})}{2} + \frac{\alpha_c(T_e - T_{e0})}{2} \tag{10}$$

$$\frac{d\delta\rho_r}{dt} = G_r Z_r \tag{11}$$

where G_r is the total reactivity worth of control rod; Z_r is the velocity of the control rod; T_{l0} is the initial outlet temperature of cooling water; T_{f0} is the initial steady-state fuel temperature; T_{e0} is the initial inlet temperature of cooling water; $\delta\rho_r$ is the reactivity produced by the movement of control rod; α_f is the reactivity coefficient of fuel; and α_c is the reactivity coefficient of cooling water.

According to Eq. (7) and Eq. (10), the following equation was obtained:

$$\delta\rho = \delta\rho_r + \alpha_f(T_f - T_{f0}) + \frac{\alpha_c(T_l - T_{l0})}{2} \tag{12}$$

3. Model for core power control

The proposed MPC method applied to core power control was based on MPC theory. The model for core power control was modeled based on mathematical models of the reactor core, the state-space MPC model and quadratic programming (QP).

In PWRs, a state-space model can be described as follows [19]:

$$\begin{cases} \dot{x} = A_d x + B_d u \\ y = Cx + Du \end{cases} \tag{13}$$

where matrix x is the variable of the state space; $\dot{x}$ is the derivative of x; y is the output quantity of the state space; A_d, B_d, C, and D are coefficient matrixes; and u is the controlled quantity of the state space.

3.1. Mathematical models of reactor core

In accordance with the linearized theory of slow perturbation around the balance point, the value of δn is much smaller than n_0. Thus neutron density can be described as follows:

$$n = n_0 + \delta n \tag{14}$$

where n_0 is the balance value of neutron density. δn is the deviation value of neutron density relative to the balance point. So Eq. (3) could be linearized and simplified, giving the following equation:

$$\frac{d\delta n}{dt} = \frac{-\beta}{\Lambda}\delta n + \frac{\beta}{\Lambda}\delta c + \frac{\delta\rho}{\Lambda}n_0 \tag{15}$$

In this model, the variable, the output quantity, and the controlled quantity of the state space were chosen as follows:

$$\begin{cases} x = \begin{bmatrix} \delta n & \delta c & \delta T_f & \delta T_l & \delta\rho_r \end{bmatrix}^T \\ y = [\delta n] \\ u = [z_r] \end{cases} \tag{16}$$

Based on Eqs. (4–6), Eqs. (8 and 9), Eqs. (11 and 12), and Eqs. (15 and 16), the state-space model Eq. (13) was solved by the knowledge of linear algebra and differential geometry. In this model, the values of matrix A_d, matrix B_d, matrix C, and matrix D are as follows:

$$A_d = \begin{bmatrix} -\dfrac{\beta}{\Lambda} & \dfrac{\beta}{\Lambda} & \dfrac{\alpha_f}{\Lambda}n_0 & \dfrac{\alpha_c}{2\Lambda}n_0 & \dfrac{n_0}{\Lambda} \\ \lambda & -\lambda & 0 & 0 & 0 \\ \dfrac{f_f}{\mu_f}P_0 & 0 & -\dfrac{\Omega}{\mu_f} & \dfrac{\Omega}{2\mu_f} & 0 \\ \dfrac{1-f_f}{\mu_c}P_0 & 0 & \dfrac{\Omega}{\mu_c} & -\dfrac{2M+\Omega}{2\mu_c} & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}; \quad B_d = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ G_r \end{bmatrix};$$

$$D = [0]; \quad C = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \end{bmatrix}.$$

3.2. MPC model

In line with the system theory of MPC, at current sampling instant k, the discrete form of the state-space model (13) was obtained as follows [20–25]:

$$\begin{cases} x(k+1|k) = Ax(k) + B\Delta u(k) \\ y(k+1|k) = Cx(k+1|k) + Du(k) = CAx(k) + CB\Delta u(k) \end{cases} \tag{17}$$

where matrix A and matrix B are discrete forms of matrix A_d and matrix B_d; $x(k)$ is the value of the variable of the state space at current sampling time k; $(k+1|k)$ is the predictive value of the next sampling time $k+1$, predicted at current sampling time k; and Δ is the increment.

According to MPC theory, $u(k)$ is constant, namely $\Delta u(k) = 0$, out of the control horizon. Objective function J for receding horizon strategy is described as follows:

$$J = (R_s - Y)^T(R_s - Y) + \Delta U^T R_w \Delta U \tag{18}$$

where

$Y = [y(k+1|k) \ y(k+2|k) \ \cdots \ y(k+Np|k)]^T$; $R_s = [1 \ 1 \ 1 \ \cdots \ 1]^T r(k)$, and the column vector R_s contains Np elements; $r(k)$ is the reference trajectory; Nc is the control horizon; Np is the prediction horizon; $\Delta U = [\Delta u(k) \ \Delta u(k+1) \ \cdots \ \Delta u(k+Nc-1)]^T$;

$R_w = R_1 \begin{bmatrix} 1 & & & \\ & 1 & & \\ & & \ddots & \\ & & & 1 \end{bmatrix}$, and matrix Rw is a diagonal matrix and the weight matrix with $Nc \times Nc$ dimensions.

$$\text{Let} \quad \Phi = \begin{bmatrix} CB & 0 & 0 & \cdots & 0 \\ CAB & CB & 0 & \cdots & 0 \\ CA^2B & CAB & CB & \cdots & 0 \\ \vdots & \vdots & \vdots & & \vdots \\ CA^{Np-1}B & CA^{Np-2}B & CA^{Np-3}B & \cdots & CA^{Np-Nc}B \end{bmatrix};$$

$$F = \begin{bmatrix} CA \\ CA^2 \\ \vdots \\ CA^{Np} \end{bmatrix}$$

Then we got the following equation:

$$Y = Fx(k) + \Phi\Delta U \tag{19}$$

According to MPC theory, when objective function J gets its minimum value, the optimum solution of MPC system is obtained. To get the optimum solution of the MPC system, we

had to take the derivative of J with respect to ΔU, namely $\frac{\partial J}{\partial \Delta U}$. According to the extreme value theory of functions, when $\frac{\partial J}{\partial \Delta U} = 0$, objective function J gets its extreme values. We assumed $\frac{\partial J}{\partial \Delta U} = 0$, then according to Eqs. (18) and (19), the only solution was obtained as follows:

$$\Delta U = \left(\Phi^T \Phi + R_w \right)^{-1} \Phi^T (R_s - Fx(k)) \tag{20}$$

where there is only one solution, so objective function J gets its extreme value, and the optimum solution of MPC system is obtained, when $\frac{\partial J}{\partial \Delta U} = 0$. So the optimum solution of MPC system is obtained, when $\Delta U = (\Phi^T \Phi + R_w)^{-1} \Phi^T [R_s - Fx(k)]$.

3.3.   QP for constraint optimal solution

Generally, because of mechanical constraints, the maximum speed of the control rod is 72 steps per minute; the range of the position of the control rod is from 0 to 1; and it is about 300 steps for the control rod to move from 0 to 1. So in this model, the range of $u(k)$ is described as follows:

$$-0.004 \leq u(k) \leq 0.004 \tag{21}$$

As $u(k)$ was constrained, the optimum solution problem transformed into a constrained optimum solution problem. QP is perfect to handle this kind of problem [26]. According to Eqs. (18) and (19), the objective function J can be described as follows:

$$J = (R_s - Fx(k))^T (R_s - Fx(k)) - \Delta U^T \Phi^T (R_s - Fx(k)) \\ - \left(\Delta U^T \Phi^T (R_s - Fx(k)) \right)^T + \Delta U^T \left(\Phi^T \Phi + R_w \right) \Delta U \tag{22}$$

where matrix $\Delta U^T \Phi^T (R_s - Fx(k))$ has only one element, so we got the following equation:

$$\Delta U^T \Phi^T (R_s - Fx(k)) = \left(\Delta U^T \Phi^T (R_s - Fx(k)) \right)^T \tag{23}$$

Then according to Eqs. (22) and (23), the objective function J can be described as follows:

$$J = [R_s - Fx(k)]^T [R_s - Fx(k)] - 2 \left[\Phi^T (R_s - Fx(k)) \right]^T \Delta U \\ + \Delta U^T \left(\Phi^T \Phi + R_w \right) \Delta U \tag{24}$$

To introduce QP, we defined a new objective function J_{QP} as follows:

$$J_{QP} = \frac{1}{2} \Delta U^T \left(\Phi^T \Phi + R_w \right) \Delta U + \left[\Phi^T (R_s - Fx(k)) \right]^T \Delta U \tag{25}$$

According to MPC theory and extreme value theory of functions, we got $\frac{\partial J_{QP}}{\partial \Delta U} = 0$, when $\frac{\partial J}{\partial \Delta U} = 0$. So the new objective function J_{QP} is qualitatively equivalent to the objective function J for the MPC system. In other words, the optimum solution of the MPC system is obtained, when J_{QP} gets its minimum value.

In line with MPC theory, we got the following equation:

$$-M \leq U \leq M \tag{26}$$

where $U = [u(k) \ u(k+1) \ \cdots \ u(k+Nc-1)]^T$, and the column vector U contains Nc elements; $m = 0.004$, $M = [m \ m \ \cdots \ m]^T$, and the column vector M contains Nc elements.

In line with MPC system theory, we got the following equations:

$$\begin{cases} u(k) = u(k-1) + \Delta u(k) \\ u(k+1) = u(k-1) + \Delta u(k) + \Delta u(k+1) \\ \quad \vdots \\ u(k+Nc-1) = u(k-1) + \Delta u(k) + \cdots + \Delta u(k+Nc-1) \end{cases} \tag{27}$$

According to Eq. (27), we got the following equation:

$$U = A_{QP} \Delta U + u(k-1) B_{QP} \tag{28}$$

where $A_{QP} = \begin{bmatrix} 1 & 0 & \cdots & 0 \\ 1 & 1 & & 0 \\ \vdots & & \ddots & \vdots \\ 1 & 1 & \cdots & 1 \end{bmatrix}$, and A_{QP} is a triangular matrix with $Nc \times Nc$ dimensions; $B_{QP} = [1 \ 1 \ 1 \ \cdots \ 1]^T$, and the column vector B_{QP} contains Nc elements.

According to Eqs. (26) and (28), we got the following equations:

$$\begin{cases} -A_{QP} \Delta U \leq M + u(k-1) B_{QP} \\ A_{QP} \Delta U \leq M - u(k-1) B_{QP} \end{cases} \tag{29}$$

According to Eqs. (25) and (29), we got the following equations:

$$J_{QP} = \frac{1}{2} \Delta U^T H \Delta U + W^T \Delta U \tag{30}$$

$$G_{QP} \Delta U \leq T_{QP} \tag{31}$$

where $G_{QP} = \begin{bmatrix} -A_{QP} \\ A_{QP} \end{bmatrix}$; $T_{QP} = \begin{bmatrix} M + u(k-1) B_{QP} \\ M - u(k-1) B_{QP} \end{bmatrix}$; $H = (\Phi^T \Phi + R_w)$; $W = \Phi^T (R_s - Fx(k))$.

As Eqs. (30) and (31) were obtained, we could employ QP to solve the constrained optimum solution problem to get the optimum solution of the control system. Therefore, QP was introduced to:

Maximize $J_{QP} = \frac{1}{2} \Delta U^T H \Delta U + W^T \Delta U$

Subject to $G_{QP} \Delta U \leq T_{QP}$

Using MATLAB programming, ΔU was obtained. Then based on Eq. (27), u was obtained.

4.   Simulation results

Generally, in PWR power stations, the core power has to follow the load changes, which is difficult to implement, because of the sensitivity of nuclear reactors. To assess the robustness and the performance of the proposed control method, simulations of the proposed state-space MPC method were designed to compare with the PID control strategy. Data used for simulations are shown in Table 1.

According to MPC theory, the prediction horizon is greater than the control horizon, namely $Np \geq Nc$. In this paper, R_1 was assumed as 0.1, Nc was assumed as 4, and Np was assumed as 19. To assess the robustness and the performance of the proposed state-space MPC method, the proposed control scheme was applied to the core power control to track the load changes.

Table 1 – Data used for simulation.	
Parameter	Value
Initial equilibrium relative neutron density $n_0(1)/m^{-3}$	1
Initial equilibrium relative neutron density $n_0(2)/m^{-3}$	0.5
Total reactivity worth of control rod $G_r(1)$	0.0145
Total reactivity worth of control rod $G_r(2)$	0.0145
Nominal core power P_0/MW	25,00.0
Reactivity temperature coefficient of fuel $\alpha_f/^{\circ}C^{-1}$	$(n_0 - 4.24) \times 10^{-5}$
Decay constant of delayed neutron precursors λ/s^{-1}	0.15
Heat capacity of coolant $\mu c/MW \cdot s \cdot {^{\circ}}C^{-1}$	$\left(\frac{160}{9}n_0 + 54.002\right)$
Total fraction of effective delayed neutrons β	0.006019
Heat transfer coefficient between fuel and coolant $\Omega/MW \cdot s \cdot {^{\circ}}C^{-1}$	$\left(\frac{5}{3}n0 + 4.9333\right)$
Fraction of reactor power deposited in fuel f_f	0.92
Heat capacity of mass flow rate of coolant $M/MW \cdot s \cdot {^{\circ}}C^{-1}$	$(28.0n_0 + 74.0)$
Neutron generation time Λ/s	0.00002
Reactivity temperature coefficient of coolant $\alpha c/^{\circ}C^{-1}$	$(-4n_0 - 17.3) \times 10^{-5}$
Thermal capacity of fuel $\mu f/MW \cdot s \cdot {^{\circ}}C^{-1}$	26.3

Figs. 1–4 show the load tracking performance of the proposed control system, with Figs. 1 and 2 for the desired core power level changing from 100%→60%→100% nominal core power and Figs. 3 and 4 for the desired core power level changing from 50%→60%→50% nominal core power. Figs. 1 and 3 reveal that the proposed state-space MPC system did track the load changes swiftly and stabilized at the desired value of the core power quickly and smoothly, and that the overshoots were small, after the load changed. Figs. 2 and 4 disclose that the velocity of the control rod changed
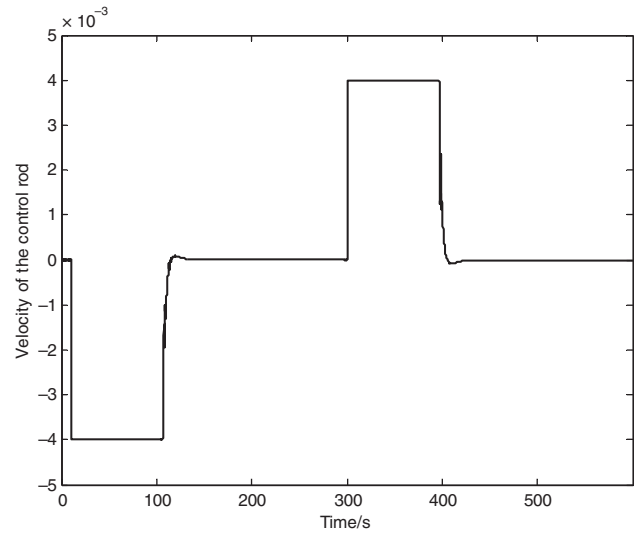

Fig. 2 – The velocity of the control rod of the proposed control system for the desired core power level changing from 100%→60%→100% nominal core power.

smoothly. To summarize, the proposed state-space MPC system can control the core power well and track the load changes swiftly and exactly.

Figs. 5 and 6 show the load tracking performance of the PID control system for the desired core power level changing from 50%→60%→50% nominal core power. Fig. 7 shows the comparison of the relative core power output between the proposed control system and the PID control system for the desired core power level changing from 50%→60%→50% nominal core power. Figs. 5–7 reveal that though the PID control system could also track the load changes, the overshoots were much bigger than those of the proposed state-space MPC system, that the velocity of the control rod of the PID control system changed acutely, and that it took much longer for the PID control system to stabilize at the desired core power after the load changed.
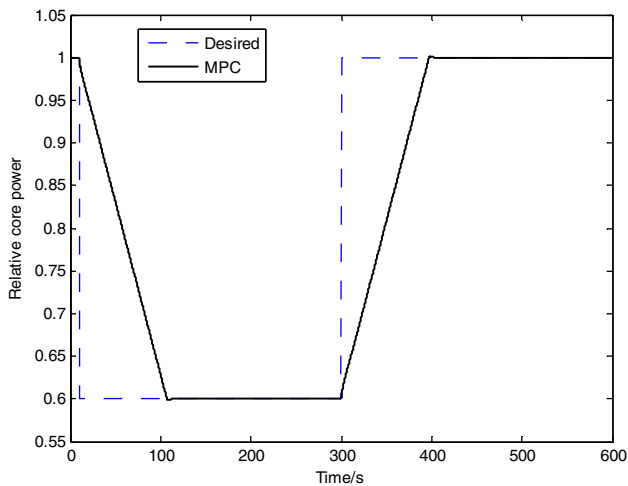

Fig. 1 – The relative core power output of the proposed control system for the desired core power level changing from 100%→60%→100% nominal core power. MPC, model predictive control.
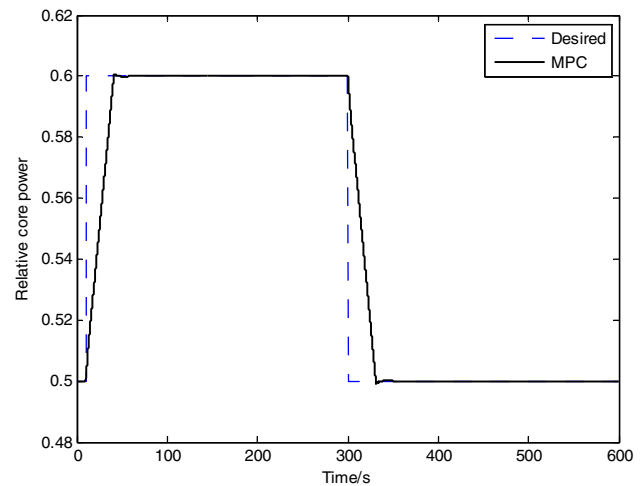

Fig. 3 – The relative core power output of the proposed control system for the desired core power level changing from 50%→60%→50% nominal core power. MPC, model predictive control.
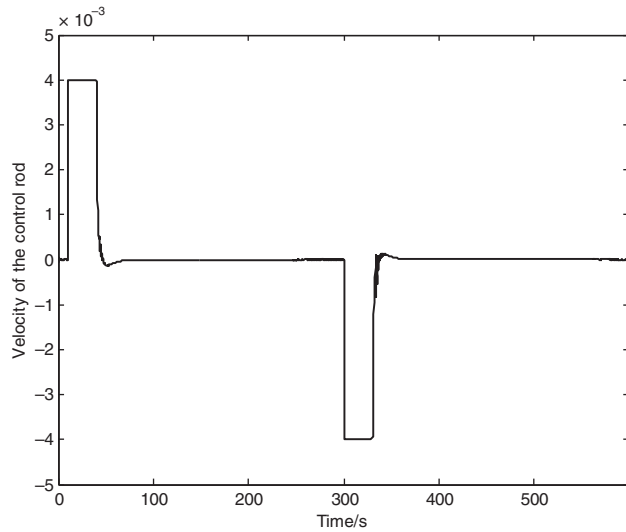
Fig. 4 − The velocity of the control rod of the proposed control system for the desired core power level changing from 50%→60%→50% nominal core power.
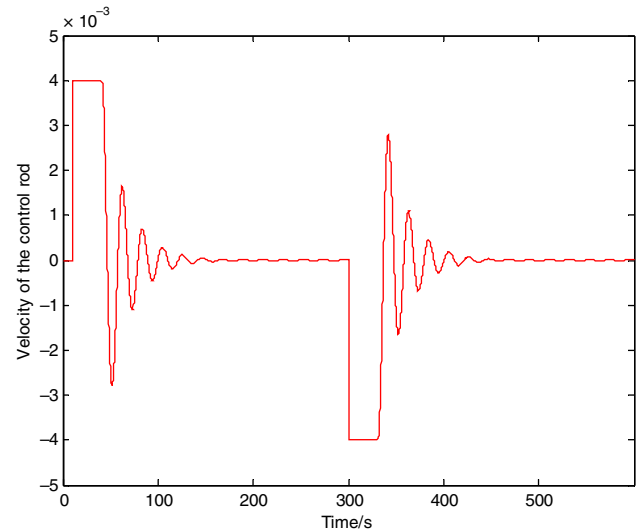

Fig. 6 − The velocity of the control rod of the PID control system for the desired core power level changing from 50%→60%→50% nominal core power. PID, proportion integration differentiation.

5.   Conclusion

In this paper, a state-space MPC method was applied to the core power control for load tracking in PWR nuclear power stations. MPC is a kind of closed-loop optimization control based on models with the merits of excellent control effects and strong robustness on account of its characteristics of online optimization and receding horizon optimization. Thus, MPC is one of the most promising methods for core power control in PWRs, as it is challenging for the current prevalent control methods (PID control methods) to control core power well. The proposed control method was based on the mathematical models of the reactor core, the state-space MPC model, and QP.

The simulation results demonstrate the effectiveness and the high performance of the proposed state-space MPC method for load tracking. After the load changed, the proposed control system reflected swiftly and stabilized at the desired core power quickly and smoothly. The advantages of the proposed state-space MPC method are verified by the comparison between the proposed state-space MPC method and the PID control method. Furthermore, the proposed control system also possesses strong robustness.
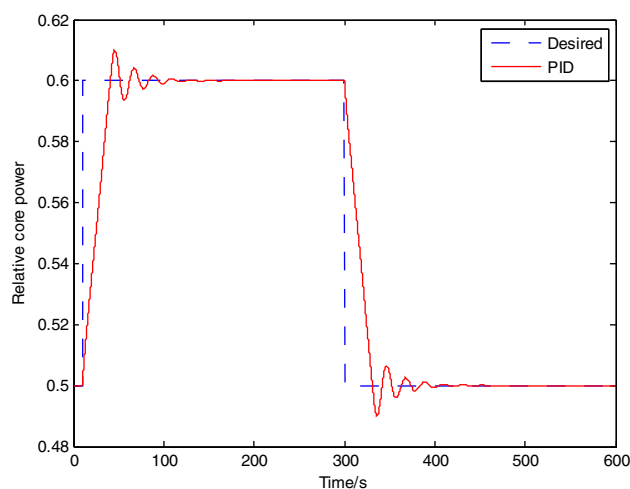

Fig. 5 − The relative core power output of the PID control system for the desired core power level changing from 50%→60%→50% nominal core power. PID, proportion integration differentiation.
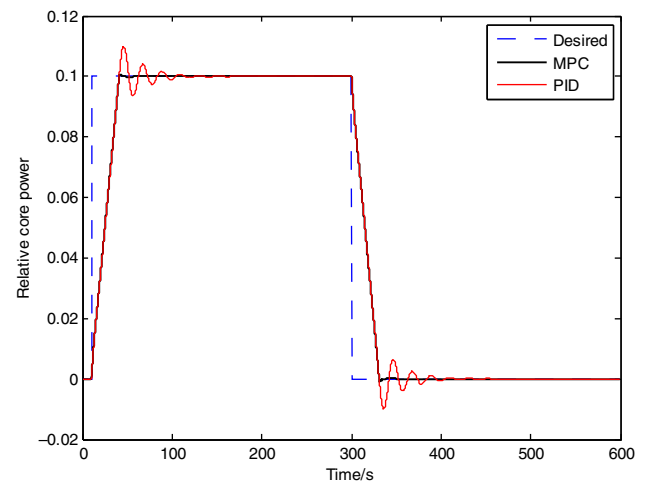

Fig. 7 − The comparison between the proposed control system and the PID control system for the desired core power level changing from 50%→60%→50% nominal core power. MPC, model predictive control; PID, proportion integration differentiation.

Conflicts of interest

Acknowledgments

R E F E R E N C E S

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