Adaptive predictive control of average coolant temperature based on chaotic particle swarm optimization

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Abstract. Aiming at the problem that the average temperature control system of nuclear reactor coolant under variable conditions is nonlinear and time-varying, and the traditional fixed model cannot meet the control requirements, an improved generalized predictive control method with adaptive identification of model parameters is proposed. First, the structure of the coolant average temperature model is determined through mechanism derivation, and the forgetting factor recursive least square algorithm is used to identify the model parameters online and in real time. Secondly, the chaotic particle swarm algorithm is used to optimize the control increment during rolling optimization. The simulation is carried out on the MATLAB platform, and the results show that the tracking ability of the average coolant temperature is significantly better than the traditional PI control under variable conditions.

1. Introduction

As the proportion of nuclear power in power production increases, in order to enable units to meet the requirements of grid load tracking, the research on the performance of the average coolant temperature control system is crucial. Under variable load, the reactor core system is inherently non-linear, and due to fuel burnup, internal reactivity feedback and other reasons, its dynamic characteristics are time-varying and non-linear, causing model parameters to vary with power. These factors all increase the difficulty of controlling the average temperature of the core coolant.

Experts and scholars have continuously explored and studied the average temperature control of the core coolant.

Scholars such as Liu C[1] proposed a fuzzy PID control strategy based on fuzzy control theory, using genetic algorithm (GA) to select the shape and type of the membership function, but the fuzzy rules that play a key role need to be summarized based on the rich experience of the operator. Otherwise, it is difficult to achieve precise control effect. Ben-Abdennour A [2] et al. designed a robust state feedback controller (SFAC) based on the optimal control theory, and Arab-Alibeik H [3] et al. designed a linear Gaussian quadratic programming (LQG/LTR) controller, Wang GX [4] and other scholars designed model predictive control controller (MPC) based on quadratic programming (QP). The control strategies proposed by these scholars are designed near a specific operating point. It is a local approximate linearization process based on a fixed model, and the control effect is better in a limited range, but if it exceeds the range, the controller needs to be redesigned. In the case of variable load, the parameters of the model change with the power. If it is only based on a fixed model, designing a control scheme near a specific operating point obviously cannot achieve the expected control effect.

Based on the Chaos Particle Swarm Optimization (CPSO), this paper proposes an improved generalized predictive control (JGPC) method with adaptive identification of model parameters. Firstly,
through mechanism derivation, the average coolant temperature model structure is obtained, which provides the basis for online identification of model structure and model parameters for the design of generalized predictive control [5], and adopts the forgetting factor recursive least squares algorithm (FFRLS), online Real-time identification of model parameters is a good solution to the problem of time-varying model parameters under variable working conditions and the inapplicability of fixed models. Secondly, the optimization scheme based on CPSO algorithm is proposed. Compared with PSO algorithm, it obviously reduces the number of iterations and is not easy to fall into the local optimal solution. Finally, Matlab is used to simulate the advantages of the CPSO algorithm compared to the PSO algorithm. The tracking ability of the average coolant temperature under the CPSO-JGPC control scheme is compared with the traditional PI control effect, and the control scheme has a certain degree of anti-interference ability.

2. Prediction model of average core coolant temperature

The internal change mechanism of the reactor core is complicated. The reactivity indirectly changes the average temperature of the coolant by changing the core power. When the reactor is operating in the high-power section, the temperature feedback effect has a greater impact on the operating characteristics. The average temperature system of the core coolant of the reactor is shown in Figure 1.

![Figure 1. System structure of average coolant temperature.](image)

Where $\Delta \rho_r$ is the reactivity change introduced by the rod, $\Delta \rho_T$ is the reactivity change caused by the total temperature change; $K_i G_r (s)$ is the core transfer function, $\Delta P$ is the core power change; $G_2 (s)$ is the coolant average temperature transfer function; $F_1 (s)$ and $F_2 (s)$ are the fuel average temperature transfer function and The average temperature transfer function of the moderator, $\Delta T_m$ is the average temperature change of the coolant.

2.1 Model research based on reactor dynamics

Due to the complex and nonlinear internal mechanism of the system under variable load, the traditional fixed model can no longer be applied well. Therefore, this paper divides the high-power section into four working conditions, and determines the model structure through mechanism derivation, which provides the basis for the model structure and online identification of model parameters for the design of the JGPC below. Secondly, according to the data collected on the laboratory simulator, the model parameters under the four working conditions are identified and used as the actual controlled object. The core transfer function of the reactor with temperature feedback can be expressed as follows:

$$G_i (s) = \frac{\Delta P(s)}{\Delta \rho_r (s)} = \frac{n_0}{\Lambda} \left( s^4 + A s^3 + B s^2 + C \right)$$

(1)

where $A, B, C, D, E, F$ and $G$ can be expressed as follows:

$$A = \omega_f + \omega_m + \lambda, \quad B = \omega_f \omega_m + \lambda \omega_f + \lambda \omega_m, \quad C = \lambda \omega_f \omega_m, \quad D = \omega_f + \omega_m + \beta / \Lambda$$

$$E = a \alpha \omega_f + \omega_f \omega_m + (\omega_v + \omega_n) \beta / \Lambda, \quad F = \left[ \omega_f \omega_m \beta + a n (\alpha_r \omega_m + b \alpha_m + \lambda \alpha_f) \right] / \Lambda$$

(2)

$$G = \alpha_0 (\alpha_f \omega_m + b \alpha_m) / \Lambda$$

where $a$ and $b$ are the constant coefficient, $\omega_f$ and $\omega_m$ are the decay constant of fuel temperature and moderator temperature, $\lambda$ is the decay constant of delayed neutrons, $\beta$ is the total delayed neutron fraction, $\alpha_f$ is the temperature coefficient of reactive moderator, $\alpha_f$ is the temperature coefficient of reactive fuel, $\Omega$ is the steady-state value of the neutron density, $\Lambda$ is the neutron generation time.
There is a heat exchange between the core and coolant of a nuclear reactor. According to the principle of thermal hydraulics, the transfer function between the average coolant temperature and the core output power is expressed as follows:

$$G_c(s) = \frac{\Delta T_c(s)}{\Delta P(s)} = \frac{H - s}{I \cdot s + J}$$  \hspace{1cm} (3)$$

Considering Eq. (1) and (3), the coolant average temperature system model can be expressed as follows:

$$G(z) = \frac{\Delta T_c}{\Delta P} = \frac{b_0 + b_1 \cdot z^{-1} + b_2 \cdot z^{-2} + b_3 \cdot z^{-3} + b_4 \cdot z^{-4} + b_5 \cdot z^{-5}}{1 + a_1 \cdot z^{-1} + a_2 \cdot z^{-2} + a_3 \cdot z^{-3} + a_4 \cdot z^{-4} + a_5 \cdot z^{-5}} = \frac{B(z^{-1})}{A(z^{-1})}$$  \hspace{1cm} (5)$$

where $a_i$ and $b_i$ are expressed as follows:

$$a_1 = [-5 - 4(I + J) - 3(E + JD) - 2(F + EJ) - (IG + FJ)], \hspace{0.5cm} a_2 = [10I + 6(ID + J) + 3(IE + JD) + (FI + EJ)]$$

$$a_3 = [1 + D + E + F + G], \hspace{0.5cm} a_4 = (5I + ID + J), \hspace{0.5cm} a_5 = -I$$

$$b_0 = \frac{n(1 + A + B + C)(1 - H)}{m(1 + A + B + C)(1 - H)}, \hspace{0.5cm} b_2 = \frac{n(4 - 3A - 2B - C + 3 + 2A + B)H}{m(4 - 3A - 2B - C + 3 + 2A + B)H}, \hspace{0.5cm} b_3 = \frac{n(6 + 3A - B - (3 + A)H)}{m(6 + 3A - B - (3 + A)H)}$$

where $A$--$J$ are all irrelevant constants.

The JGPC adopts the CARIMA model as the predictive model, and according to the model order determined by Eq. (5), the predictive model of the average temperature of the core coolant can be expressed as follows:

$$A(z^{-1})T_c(k) = z^{-d}B(z^{-1})\rho(k) + \xi(k) / \Delta$$  \hspace{1cm} (7)$$

where $z$ is the difference operator, $T_c$ is the average temperature output of the core coolant, $\rho$ is the reactive input introduced by the control rod of the reactor, $d$ is the pure delay, $\xi(k)$ is the white noise.

2.2 Online identification of predictive model parameters

The FFRLS algorithm is used for online identification and correction of the prediction model parameters. Considering Eq. (7), it can be transformed into the identification structure of the least squares method as follows:

$$\Delta T_c(k) = [1 - A(z^{-1})][\Delta T_c(k)] + B(z^{-1})\rho(k - d) + \xi(k) = \varphi'(k)\hat{\theta} + \xi(k)$$  \hspace{1cm} (8)$$

where $\varphi(k)$ is vector for input and output, $\hat{\theta}$ is the predictive model parameter, they are expressed as follows:

$$\varphi'(k) = [-\Delta(k - 1), -\Delta(k - 2), \ldots, -\Delta(k - 5), \Delta(k - 1), \Delta(k - 2), \ldots, \Delta(k - 5)]$$

$$\hat{\theta} = [a_1, a_2, b_0, b_2, b_3]$$

The whole process updates online by Eq. (10).

$$\hat{\theta}(k) = \hat{\theta}(k - 1) + K(k)[\Delta T_c(k) - \varphi'(k)\hat{\theta}(k - 1)]$$

$$K(k) = \frac{P(k - 1)\varphi(k)}{\lambda + \varphi'(k)P(k - 1)\varphi(k)}$$

$$P(k) = [I - K(k)\varphi'(k)]P(k - 1) / \lambda$$

where $\lambda$ is forgetting factor, $\lambda = 0.95$. 

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3. Rolling optimization based on CPSO algorithm

CPSO-JGPC obtains the system's future output predicted value according to the output prediction model, combined with the obtained reactive increment constraint conditions, performs rolling optimization based on CPSO, and finds the optimal solution of the input control increment when the objective function is minimized.

3.1 Output prediction of average coolant temperature based on CARIMA model

Considering Eq. (7), the minimum variance of the system of future moment output prediction model can be expressed as follows:

\[ T_{av}^* = T_n + G \Delta r. \]  

where \( T_{av}^* \) is the predicted value of the system's future output, \( T_n \) is the known output value of the system, \( \Delta r \) is the input control increment. They are expressed as follows:

\[
T_n = \begin{bmatrix}
T_n(k), T_n(k+1), \ldots, T_n(k+N)
\end{bmatrix}^T
\]

\[ \Delta r = [\Delta r_1, \Delta r_2, \ldots, \Delta r_{N-d}]^T \]

\[ \Delta r(k+i) = \rho(k+i) - \rho(k+i-1), i = 0, 1, \ldots, N-d \]

\[ T_n(k+j) = -a_{k-1} \cdot t_n(k+j-i) + \sum_{i=1}^{j} b_{k-1} \cdot \Delta r(k+j-d-i) + \xi(k+j-i), j = 1, 2, \ldots, N \]

Considering Eq. (11) and Eq. (13), we can infer a result as follows:

\[ b_j = b_{j-1} - \sum_{i=1}^{j} a_{j-i} \cdot b_{j-1} = 0, j = 2, \ldots, N-d+1 \]

where \( j_i = \min\{j-1, 5\} \), if \( j > 4 \), \( b_{j-1} = 0 \).

Therefore, the output prediction of future moment can be inferred as follows:

\[
T_n^*(k+j) = \begin{bmatrix}
\alpha_{k-1} \cdot T_n(k+j-1) + \alpha_{k-2} \cdot (T_n(k+j-2) - T_n(k+1)) + \sum_{i=1}^{j} b_i \cdot \Delta r(k+j-d-i) \\
T_n(k+j)
\end{bmatrix}^T
\]

\[ \alpha \in [0,1] \] is for the output softening coefficient, \( \omega(k) \) is the set value, the selected prediction time domain \( N = 6 \) and control time domain \( M = 3 \).

3.2 The objective function of JGPC rolling optimization

In order to make the future output predicted value as close as possible to the set value, the performance index function of JGPC can be described as follows:

\[
J = E\left[ (T_{av}^* - T_{ref}) \cdot Q (T_{av}^* - T_{ref}) + \Delta r \cdot R \Delta r \right] = E\left[ \sum_{j=1}^{N} q_j [T_n^*(k+j) - T_{ref}(k+j)]^2 + \sum_{j=1}^{M} \omega_k \cdot \Delta r(k+j-1)^2 \right]
\]

where \( Q \) and \( R \) is the output error weighting matrix and the control weighting matrix, \( T_{ref} \) is the reference trajectory, \( \alpha \in [0,1] \) is for the output softening coefficient, \( \omega(k) \) is the set value, the selected prediction time domain \( N = 6 \) and control time domain \( M = 3 \).

3.3 Solving the optimal control increment

In the standard particle swarm algorithm, particles update their own speed and position according to individual extreme values and global extreme values. The traditional PSO algorithm requires multiple iterations to obtain the optimal solution and there is a local optimal solution, which is prone to premature
convergence. While CPSO algorithm can avoid these problems well.

At the same time, the position and velocity of the population particles are initialized according to the chaotic sequence shown in Eq. (17) to increase the ergodicity of the initialized particles in the feasible solution domain and improve the convergence speed of the particles.

\[
\begin{align*}
    x_{n+1} &= \frac{x_n}{0.4}, \quad 0 < x_n \leq 0.4 \\
    (1-x_n)/(1-0.4), &\quad 0.4 < x_n \leq 1
\end{align*}
\]  

(17)

In the optimization process, the particles that exceed the optimization boundary are mapped to the feasible solution space through Eq. (18).

\[ x_i = x_{min} + (x_{max} - x_{min}) \cdot x_i^* \]  

(18)

Where \( x_{min} \) and \( x_{max} \) are the lower and upper boundaries of the optimized space respectively, \( x_i^* \) are the chaotic individuals randomly generated by Eq. (17).

4. Simulation analysis of coolant average temperature control system

Experiments are carried out according to the nuclear power simulator in the laboratory, and the data is filtered and smoothed. The determined model structure is derived according to Eq. (8). The model parameters under four working conditions are obtained through system identification, and this model is taken as the actual controlled object.

The ratio of the actual load value of the unit to the full power \( I/1089 \) is used as the model switching condition, and the switching range is \([0.8,1]\). Corresponding to different models under different working conditions the load value drops from 100%FP at a rate of 5%FP/min to 80%FP, and then rises to 100%FP at a rate of 5%FP/min.

4.1 CPSO and PSO optimization performance analysis

In the simulation process of load reduction, select the optimization curve of CPSO and PSO at the time of 300s, as shown in Figure 2, CPSO completes the iteration at 53 times, the minimum value of the objective function is 0.00542, and PSO needs to iterate 101 times. The minimum value of the objective function is 0.191, which indicates that the convergence speed of CPSO is significantly faster than that of PSO. According to the fitness value information, the PSO optimization result 0.191 is the local optimal solution, and the CPSO optimization result 0.00542 is the global optimal solution. It can be inferred that PSO has fallen into the local optimal solution due to premature convergence, and CPSO can avoid this problem.
4.2 Analysis of tracking effect of coolant average temperature under variable working conditions

The calculation formula for the evaluation index of the tracking effect of the average coolant temperature is:

\[ e = \sqrt{\frac{\sum(T_m - T_{ref})^2}{n}} \]  

(19)

Calculated from equation (19), the average coolant temperature tracking effect evaluation index in 2000s under ACPSO-JGPC control is \( e_{\text{JGPC}} = 0.023863 \), and the average coolant temperature tracking effect evaluation index under PI control is \( e_{\text{PI}} = 0.701380 \), which shows that in CPSO-JGPC, the tracking ability of the average coolant temperature under the control of CPSO is significantly better than that of the traditional controller, and it can be seen from Figure 3 that the traditional PI control can not deal with the control of the average coolant temperature under variable working conditions. JGPC control can quickly and stably follow the change of the set value.

5. Conclusion

This paper solves the problem of the inapplicability of invariant models under variable conditions. The proposed forgetting factor recursive least squares method can quickly and accurately track the changes of predictive model parameters, and overcome the effects of model nonlinearity and parameter time-varying. In the rolling optimization, the CPSO algorithm is used to solve the optimal control increment, which also better compensates for the shortcomings of the PSO algorithm. Through MATLAB simulation analysis, it shows that CPSO-JGPC control can make the average coolant temperature quickly and accurately track the change of the set value during the load rise and fall, which has certain reference value for the average coolant temperature control.

Acknowledgements

1. Shanghai Key Laboratory of Power Station Automation Technology, Project Number 13DZ2273800.
2. This work is sponsored by Shanghai Science and Technology Committee, Project Number 18020500900.
3. This work is supported by National Natural Science Foundation of Shanghai, (Research on Uncertainty Reasoning and Correlation Mechanism in Nuclear Power Risk Assessment, Project Number 19ZR1420700.)

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