Neural Network-Based Predictive Control for the Thermal Power of a MHTGR-Based NSSS

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INTRODUCTION

Modular high temperature gas-cooled reactor, which uses helium as coolant and graphite as both moderator and structural materials, is a typical small modular reactor (SMR) with strong inherent safety feature. An MHTGR-based nuclear steam supplying system (NSSS) composed of a one-zone pebble-bed MHTGR, a helical-coil once-through steam generator (OTSG) arranged side-by-side with the MHTGR and some connecting pipes is shown in Fig. 1(a), which is a module of the under-constructed two-modular plant HTR-PM designed by the Institute of Nuclear and New Energy Technology (INET) of Tsinghua University [1]. Power-level control of NSSS is crucial in strengthening safety as well as providing operational stability and efficiency for NPPs, which realizes maintaining, maneuvering or even load-following of the power-level through properly adjusting the speed of control rods, the rotational velocity of pumps or blowers and the opening of valves. Model predictive control (MPC) method, which generates current control input by solving an optimization problem for a finite future, was introduced to the field of nuclear reactor control by Na et al. [2] for optimizing the dynamic responses of NPPs. In this paper, by regarding the error of the NSSS thermal power relative to its setpoint as well as the revision to the setpoint of normalized nuclear power as the output and input respectively, a multi-layer perception (MLP) is applied to approximate the input-output (IO) behavior of the system constituted by the MHTGR-based NSSS and its existing power-level controller. An online training algorithm of the MLP weighting matrices is proposed, which guarantees a globally bounded approximation error. A MLP-based MPC for NSSS thermal power is developed based on this MLP model. This MPC is applied to optimize the response of the NSSS of HTR-PM plant, numerical simulation results show that both the overshoot and transition period of thermal power and live steam temperature given by this MPC are smaller than those given by the nonlinear controller (NC) in [3].

MAIN RESULTS

List the research results, and discuss the significance. This idea leads to a NSSS control system with hierarchy structure shown in Fig. 1(b), where the current existing power-level control law is in the inner loop, and the MPC-based optimizer is located in the outer loop. Suppose the existing controller can provide globally asymptotic stability, the response of the NSSS thermal power induced by adjusting the setpoint of nuclear power must be bounded. Thus, to develop the NSSS thermal power controller, it is reasonable to consider the regulation problem of system

$$\dot{\boldsymbol{y}} = -\boldsymbol{y} + \boldsymbol{G}(\boldsymbol{y}, \boldsymbol{u}, t) \tag{1}$$

where $\boldsymbol{y} \in \mathrm{R}^p$ is the system output, $\boldsymbol{u} \in \mathrm{R}^q$ is the system input, vector function $\boldsymbol{G}$ is norm-bounded and continuous differentiable. In the following parts of this section, a multi-layer perception (MLP) based estimator for system (1) is firstly given, an optimal predictive control is then proposed, and finally the closed-loop stability is analyzed.

Due to the universal approximation ability of the MNN, $\boldsymbol{G}$ can be given by

$$\boldsymbol{G}(\boldsymbol{y}, \boldsymbol{u}, t) = \boldsymbol{W}^{\mathrm{T}} \boldsymbol{S}\left(\boldsymbol{V}^{\mathrm{T}} \boldsymbol{Z}\right) + \boldsymbol{d} \,, \tag{2}$$

where approximation error $\boldsymbol{d}$ is bounded, vector $\mathbf{Z} \in \mathrm{R}^m$ is the input of MNN, $\boldsymbol{V} \in \mathrm{R}^{m\times h}$ and $\boldsymbol{W} \in \mathrm{R}^{h\times p}$ is respectively the first-to-second and second-to-third layer interconnection weight matrix,

$$\boldsymbol{S}\left(\boldsymbol{V}^{\mathrm{T}}\boldsymbol{Z}\right) = \left[s\left(\boldsymbol{v}_1^{\mathrm{T}}\boldsymbol{Z}\right) \quad s\left(\boldsymbol{v}_2^{\mathrm{T}}\boldsymbol{Z}\right) \quad \cdots \quad s\left(\boldsymbol{v}_h^{\mathrm{T}}\boldsymbol{Z}\right) \quad 1 \right]^{\mathrm{T}}, \tag{3}$$

$\boldsymbol{v}_k$ (k=1, …, h) is the kth column of matrix $\boldsymbol{V}$, s is the sigmoid function given by

$$s(x) = \frac{1}{1+e^{-x}}, x \in \mathrm{R} \,. \tag{4}$$

The following Proposition 1 gives the estimator and the learning laws for its weighting matrices, and Proposition 2 gives the MPC design and stability analysis, which are the main result of this paper.

Proposition 1. Consider the following MNN-based estimator of system (1)

$$\dot{\hat{\boldsymbol{y}}} = -\hat{\boldsymbol{y}} + \hat{\boldsymbol{W}}^{\mathrm{T}} \hat{\boldsymbol{S}}\left(\hat{\boldsymbol{V}}^{\mathrm{T}} \boldsymbol{Z}\right), \tag{5}$$

where $\hat{\boldsymbol{y}} \in \mathrm{R}^p$ is the estimation of output $\boldsymbol{y}$, matrices $\hat{\boldsymbol{V}} \in \mathrm{R}^{m\times h}$ and $\hat{\boldsymbol{W}} \in \mathrm{R}^{h\times p}$ are respectively the estimations of interconnection weight matrices $\boldsymbol{V}$ and $\boldsymbol{W}$, vector $\hat{\boldsymbol{S}}$ is defined by

$$\hat{\boldsymbol{S}}\left(\hat{\boldsymbol{V}}^{\mathrm{T}}\boldsymbol{Z}\right) = \left[s\left(\hat{\boldsymbol{v}}_1^{\mathrm{T}}\boldsymbol{Z}\right) \quad s\left(\hat{\boldsymbol{v}}_2^{\mathrm{T}}\boldsymbol{Z}\right) \quad \cdots \quad s\left(\hat{\boldsymbol{v}}_h^{\mathrm{T}}\boldsymbol{Z}\right) \quad 1 \right]^{\mathrm{T}}, \tag{6}$$

$\hat{\boldsymbol{v}}_k\ (k = 1, \cdots, l)$ is the k^{th} column of $\hat{\boldsymbol{V}}$, s is the sigmoid function (4). The learning laws of $\hat{\boldsymbol{V}}$ and $\hat{\boldsymbol{W}}$ given by

$$\dot{\hat{\boldsymbol{W}}} = -\boldsymbol{\Gamma}_{\mathrm{W}} \left(\hat{\boldsymbol{S}} - \hat{\boldsymbol{S}}' \hat{\boldsymbol{V}}^{\mathrm{T}} \boldsymbol{Z} \right) \boldsymbol{e}^{\mathrm{T}} \tag{7}$$

$$\dot{\hat{\boldsymbol{V}}} = -\boldsymbol{\Gamma}_{\mathrm{V}} \boldsymbol{Z} \boldsymbol{e}^{\mathrm{T}} \hat{\boldsymbol{W}} \hat{\boldsymbol{S}}' \tag{8}$$

provides globally bounded estimation, where

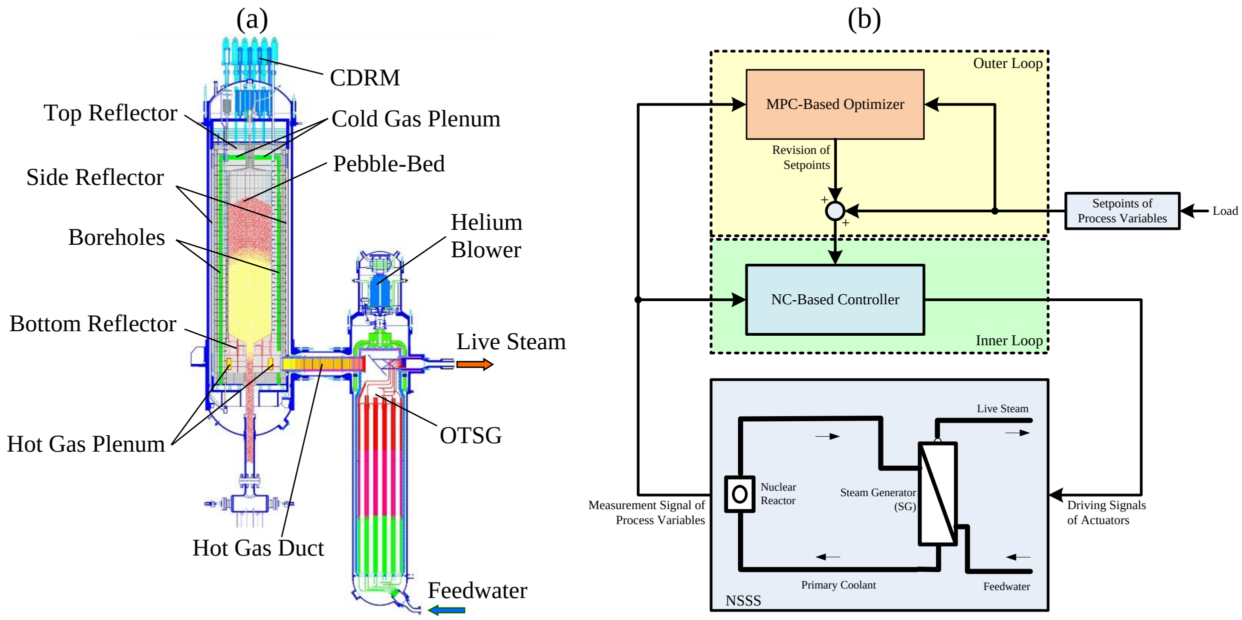

Fig. 1. Schematic diagram of the (a) MHTGR-based NSSS and (b) its MPC strategy.

$$\hat{\boldsymbol{S}}'\left(\hat{\boldsymbol{V}}^{\mathrm{T}}\boldsymbol{Z}\right)=\mathrm{diag}\left(\left[s'\left(\hat{\boldsymbol{v}}_1^{\mathrm{T}}\boldsymbol{Z}\right) \quad s'\left(\hat{\boldsymbol{v}}_2^{\mathrm{T}}\boldsymbol{Z}\right) \quad \mathrm{L} \quad s'\left(\hat{\boldsymbol{v}}_h^{\mathrm{T}}\boldsymbol{Z}\right) \quad 0\right]^{\mathrm{T}}\right), \quad (9)$$

$$s'(x)=\frac{\mathrm{d}s(x)}{\mathrm{d}x}=\frac{e^{-x}}{\left(1+e^{-x}\right)^2}, \quad (10)$$

$\boldsymbol{\Gamma}_{\mathrm{W}}$ and $\boldsymbol{\Gamma}_{\mathrm{V}}$ are diagonal positive-definite matrices, $\boldsymbol{e}$ is the estimation error defined by $\boldsymbol{e}=\hat{\boldsymbol{y}}-\boldsymbol{y}$. □

Proposition 2. Consider system (1) with function $\boldsymbol{G}$ being norm-bounded and continuous differentiable, and the performance index to be minimized is given by

$$J=\frac{1}{2}\left\|\tilde{\boldsymbol{y}}\left(t+T_{\mathrm{p}}\right)\right\|_2^2, \quad (11)$$

where

$$\tilde{\boldsymbol{y}}\left(t+T_{\mathrm{p}}\right)=\hat{\boldsymbol{y}}\left(t+T_{\mathrm{p}}\right)-\boldsymbol{y}_{\mathrm{r}}\left(t+T_{\mathrm{p}}\right) \quad (12)$$

is the tracking error, positive constant T_{p} denotes the predictive period, $\hat{\boldsymbol{y}}$ is the prediction given by MNN estimator (5), and $\boldsymbol{y}_{\mathrm{r}}$ is the referenced system output. Then, model predictive control law

$$\boldsymbol{u}=\mathrm{proj}\left\{-\lambda_{\mathrm{u}}\left(\frac{\partial\boldsymbol{Z}}{\partial\boldsymbol{u}}\right)^{\mathrm{T}}\hat{\boldsymbol{V}}\hat{\boldsymbol{S}}'\hat{\boldsymbol{W}}\left[\hat{\boldsymbol{y}}(t+T)-\boldsymbol{y}_{\mathrm{r}}(t+T)\right], \quad u_{\mathrm{m}}\right\}, \quad (13)$$

where λ_{u} is a positive scalar, $u_{\max}$ is the maximal norm of $\boldsymbol{u}$, function $\mathrm{proj}\{\cdot,\cdot\}$ is defined as

$$\mathrm{proj}\{\boldsymbol{x},x_{\max}\}=\begin{cases}\dfrac{x_{\max}}{\|\boldsymbol{x}\|_2}\boldsymbol{x}, & \|\boldsymbol{x}\|_2>x_{\max}, \\ \boldsymbol{x}, & \|\boldsymbol{x}\|_2\le x_{\max},\end{cases} \quad \begin{matrix}\boldsymbol{x}\in\mathrm{R}^n \\ n\in\mathrm{N} \\ x_{\max}>0\end{matrix} \quad (14)$$

can provide globally bounded closed-loop stability. □

SIMULATION VERIFICATION

MLP-based predictive control (13) is applied to for regulate the thermal power of the NSSS module of HTR-PM plant shown in Fig. 1(a). The control system has a typical cascaded structure, where the MLP-based thermal power predictive controller is in the outer loop for optimization, and the model-free adaptive controller in [3] is in the inner-loop for stabilization. The input and output of the thermal power controller are respectively the current thermal power error tracking error and the revision to the setpoint of normalized nuclear power. This simulation is performed on the Matlab/Simulink environment, and the program includes the dynamic models of the MHTGR, OTSG and secondary loop system. The simulation results in the case of 1# NSSS module power ramping between 100% and 50% RFP are given here. Initially, the HTR-PM plant operates at full power. The power setpoint of 1# NSSS module starts to decrease from 100% to 50% RFP with the constant speed of 5%RFP/min at 5000s, and then starts to maneuver back to 100%RFP also with the same speed at 10000s. The dynamic responses of the normalized nuclear power, reactor outlet helium temperature, OTSG live steam temperature and NSSS module thermal power with and without the optimization of MLP-based predictive controller are given in Fig. 2. The responses of control rod speed signal, helium flowrate and feedwater flowrate with and without the MLP-based predictive controller as well as revision of nuclear power setpoint that generated by the newly-built controller are shown in Fig. 3. From Figs. 2 and 3, the MNN-based MPC for thermal power can provide an optimized responses.

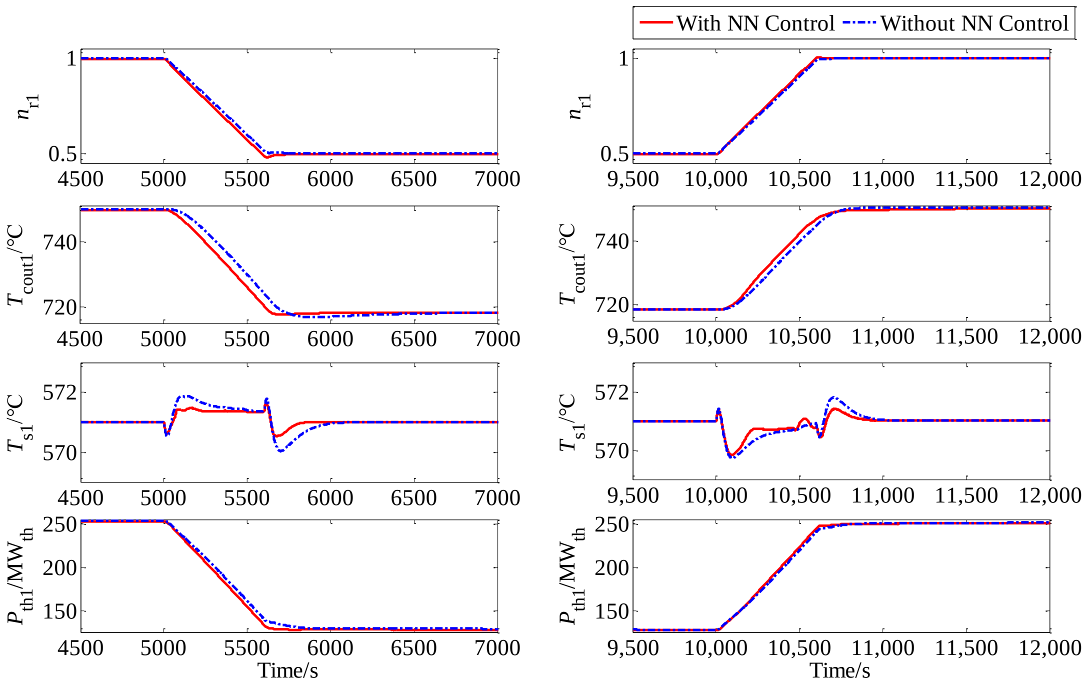

Fig. 2. Responses of key process variables of 1# NSSS module, n_{r1}: normalized nuclear power, T_{cout1}: reactor outlet helium temperature, T_{s1}: live steam temperature, P_{th1}: NSSS thermal power.

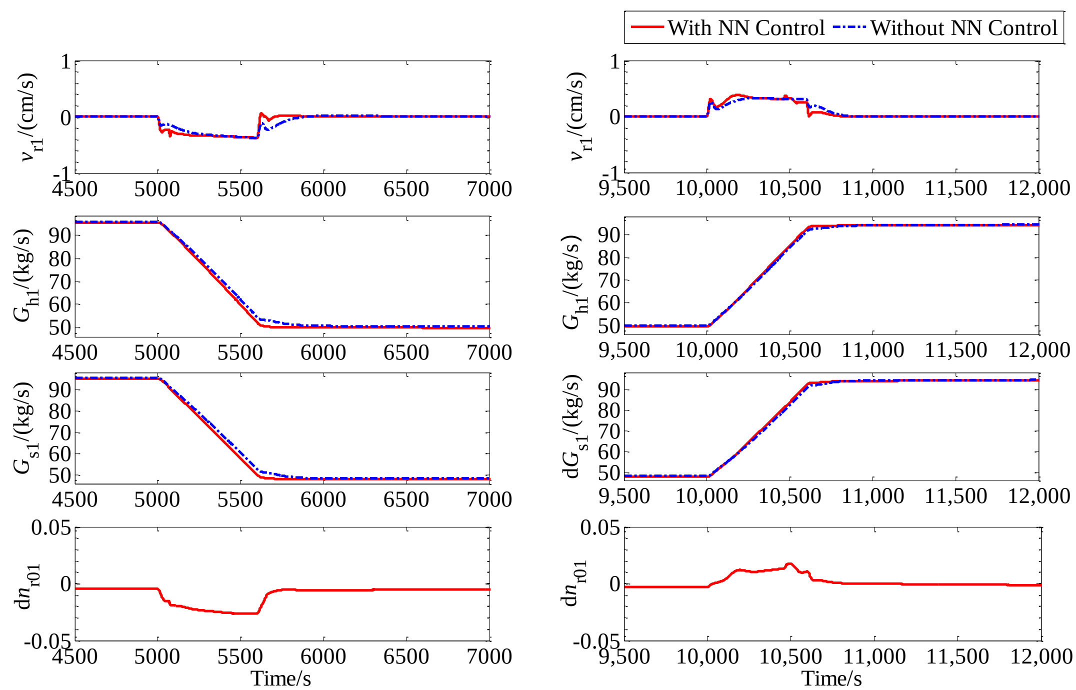

Fig. 3. Responses of control inputs of 1# NSSS, v_{r1}: control rod speed, G_{h1}: primary helium flowrate, G_{s1}: OTSG feedwater flowrate, dn_{r01}: revision to the setpoint of normalized nuclear power.

CONCLUSION

Motivated by the necessity of optimizing the thermal power response, a novel MNN-based predictive controller is proposed in this paper. The thermal power is predicted by an MLP, and the control input is designed to be in the direction opposite to the gradient of performance index, which guarantees the globally-bounded closed-loop stability. This newly-built MLP-based MPC can be implemented by retaining the current NSSS controller in the inner loop for stabilization. Numerical simulation results the satisfactory improvement in optimizing the thermal power and live steam temperature responses.

ENDNOTES

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REFERENCES

1. Z. Zhang, Y. Dong, F. Li, Z. Zhang, H. Wang, X. Huang, H. Li, B. Liu, X. Wu, H. Wang, X. Diao, H. Zhang, J. Wang, "The Shandong Shidao bay 200MWe high-temperature gas-cooled reactor pebble-bed module (HTR-PM) demonstration power plant: An engineering and technological innovation," *Engineering*, **2**, 112-118 (2016).
2. M. G. Na, S. H. Shin, W. C. Kim WC. "A model predictive controller for nuclear reactor power," J*ournal of the Korean Nuclear Society*, **35**, 399-411 (2013)
3. Z. Dong, Y. Pan, Z. Zhang, Y. Dong, X. Huang. "Model-free adaptive control for nuclear superheated-steam supply systems," *Energy*, **135**, 53-67 (2017).