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Integration of Parameter Approximation and Real-Time Optimization for Load Change of HTR-PM

Cheng Yang, Kexin Wang, Zhijiang Shao

College of Control Science and Engineering, Zhejiang University, Hangzhou 310027, China (e-mail: szj@zju.edu.cn).

Abstract: Obtaining desirable process model and determining its applicable range play an important role in realizing the significant load change for HTR-PM. Based on the observation that several parameters in HTR-PM model change with conditions and sufficient sampling is impractical, a trust-region based load change strategy is developed in an iterative framework that integrates parameter approximation and real-time optimization. According to this method, the basic model is determined through a systematic approach for parameter estimation that is designed to get rid of unreliable estimation. Plant derivatives are exploited to extend applicability of the local basic model. When applying the extended model to operation of load change in the trust-region framework, model evaluation is implemented in each iteration so that the applicable range of the approximate model is appropriately determined. Consequently, both model accuracy and applicable range of the local model are considered in this iterative framework. Case study of load change from 100% to 50% reactor full power demonstrates effectiveness of the proposed method.

Keywords: parameter approximation, real-time optimization, trust-region method, HTR-PM.

1. INTRODUCTION

High temperature gas-cooled reactor (HTR) is one of the promising technologies in building the Generation IV nuclear energy systems (Demick L. et al. 2010). The first in the world multimodular HTR demonstration plant, HTR pebble bed module (HTR-PM), has been under construction since 2012 at Shidaowan, China (Zhang Z. et al., 2016) and is expected to start commercial operation in 2018.

The multi-modular structure of HTR-PM is illustrated in Fig. 1. Each nuclear steam supply system (NSSS) mainly includes one reactor, one steam generator and one helium blower. Steam from the two NSSS modules shares a common steam header and promotes the turbine jointly to generate electricity (Dong Z. and Huang X., 2013).

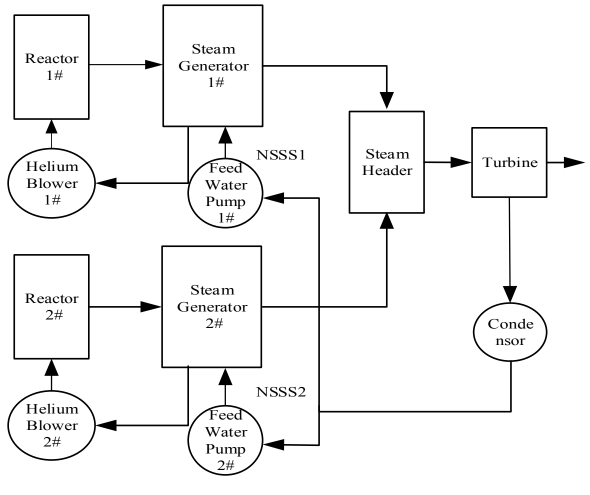


Fig. 1. Schematic of HTR-PM.

Thermal-hydraulic process is essential to HTR-PM. The cold helium (about 523.15K) is pressurized by the blower and then goes into the cold gas duct. It cools the side reflector when flowing through its channels from the bottom to top. Then the helium reaches the reactor core and passes through the pebble bed from the top to bottom, during which it absorbs a large amount of heat and is heated to about 1023.15K. The hot helium flows through the hot gas duct into the primary side of the steam generator, transferring heat through the metal tube wall to the water flowing in the secondary side. After this heat exchange, the water turns into superheated steam and the helium is cooled back to 523.15K.

Mechanism of HTR-PM is complex (Li H. et al., 2008) and little experience can be borrowed from operation of its single reactor counterpart. Moreover, the reactor of each NSSS is designed to have a wide operating range, from 30% to 100% reactor full power (RFP). The accurate mechanism model that is applicable to the full operating range is usually not available. In addition, some key outputs of HTR-PM have design values. Deviating far from these values would jeopardize safe, reliable and economical operation of the plant and thus is forbidden. These factors present challenges to operation and control. Strategies are therefore desirable to address significant load change of HTR-PM, which is typical in coping with the ever-changing power demand.

A trust-region based load change strategy is proposed in this paper, which integrates parameter approximation and real-time optimization. The systematic approach for parameter estimation provides locally accurate model with limited measurements. In order to extend the applicable range of the local model, parameters varying with conditions are approximated using plant derivatives. So far, an appropriately determined applicable range of the approximated model is needed to confine the optimization problem to a valid model. Consequently, the framework of trust-region method is adopted, which applies a sequence of local models in sought of the optimal operations for the significant load change of HTR-PM.

2. ITERATIVE FRAMEWORK FOR HTR-PM OPERATION

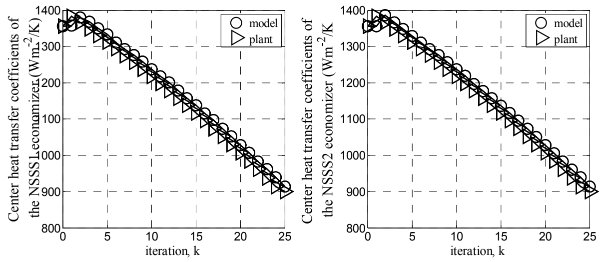
Significant load change of HTR-PM usually cannot be completed once at all for safety and operation limitations. A direct method is to implement the task by taking a sequence of relatively small load change steps. This can be addressed by implementing parameter estimation (PE) and real-time optimization (RTO) in an iterative manner. At each step, (i) apply the current inputs to the plant and solve a PE problem with the corresponding measurement to determine the model parameters; (ii) use the model with the estimated parameters to determine the inputs that minimize some performance index.

Referring to framework of classical iterative two-step (ITS) method, the stepsize of maximal load change in each RTO step is given by 2%RFP (conservative) and 8%RFP (aggressive), respectively. The freedom for operation leaves to 7 inputs, including external reactivity, helium inlet flow rate, and feedwater flow rate of both NSSS modules, and opening of the valve prior to the turbine. The RTO objective is chosen for the load change task to be the differences between the model predicted and design values of the key outputs at the target load level. The RTO problem is formulated as

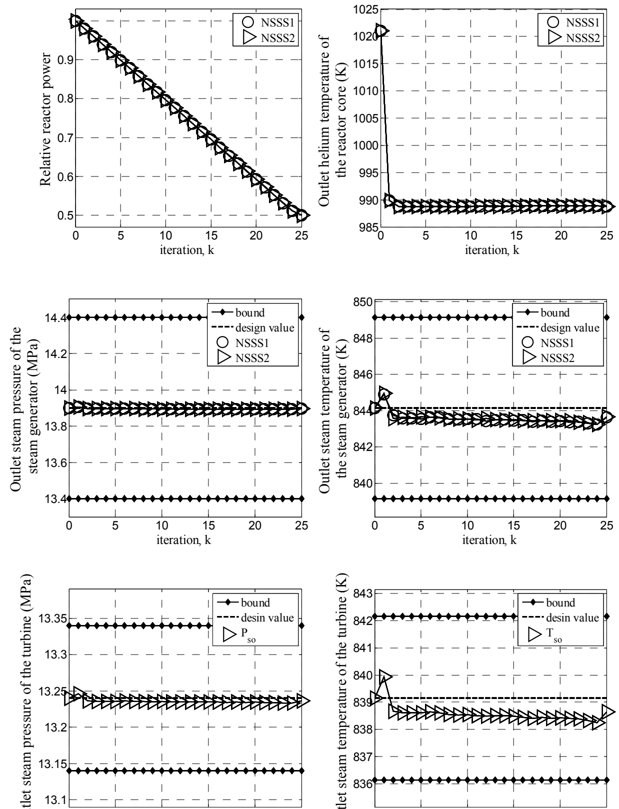
$$
\begin{aligned}
&\min_{u} \varphi(u) = \sum_{j=1}^{n_e} q_j (y_j^e - y_j^{e^*})^2 \\
&s.t \quad f_m(x, y, u, p) = 0 \\
&\qquad c(u) \le 0 \\
&\qquad |\Delta n_r| \le \text{constant}
\end{aligned}
\tag{1}
$$

where objective function $\varphi(u)$ measures the differences between vectors of key outputs $y^e \in R^{n_e}$ and their design values $y^{e^*} \in R^{n_e}$ at the target load level, and q represents the weighting factor. $y \in R^{n_y}$, $u \in R^{n_u}$ and $x \in R^{n_x}$ are the process outputs, inputs and states, respectively. $p \in R^{n_p}$ are parameters. f_m denotes the plant model which has 996 variables and c are constraints on the inputs. The last constraint confines the level of load change in each RTO step to a given constant, which can be reflected by the change of relative reactor power n_r .

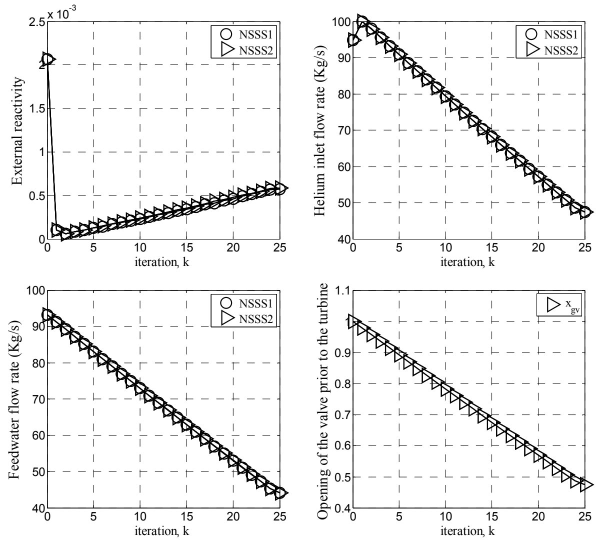
Figs. 2 and 3 illustrate the performance of the ITS method in the case where both reactors change from 100%RFP to 50%RFP synchronously. Results of the estimated heat transfer coefficients, the optimal operations based on the estimated model and the resulting key plant outputs are analyzed here. Clearly, aggressive strategy suffers larger model mismatch as shown in Figs. 2a and 3a about the heat transfer coefficients by the model and the plant, because of larger steps. The resulting outputs and corresponding inputs by these two strategies are presented in Figs. 2b-2c and Figs. 3b-3c, respectively. Being less efficient than aggressive strategy (25 steps VS 7 steps), the conservative one leads to safe operation while the aggressive one gives rise to safety violation from outlet steam temperature of the turbine. Moreover, aggressive strategy has all the key outputs deviated more from design values than those of the conservative one, which can be reflected from plant performance at the target load (77.98 VS 67.24), i.e. the objective function in problem (1) evaluated with the real plant outputs at the end of load change. This can be attributed to more obvious mismatch of aggressive strategy than that of the conservative one, which indicates the stepsize, confining the magnitude of input correction, has important influence on the performance of the ITS method.



(2a) Heat transfer coefficients

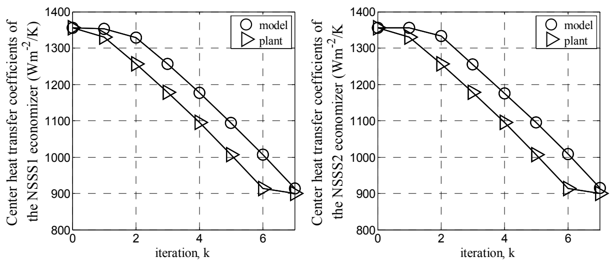


(2b) Key outputs of HTR plant

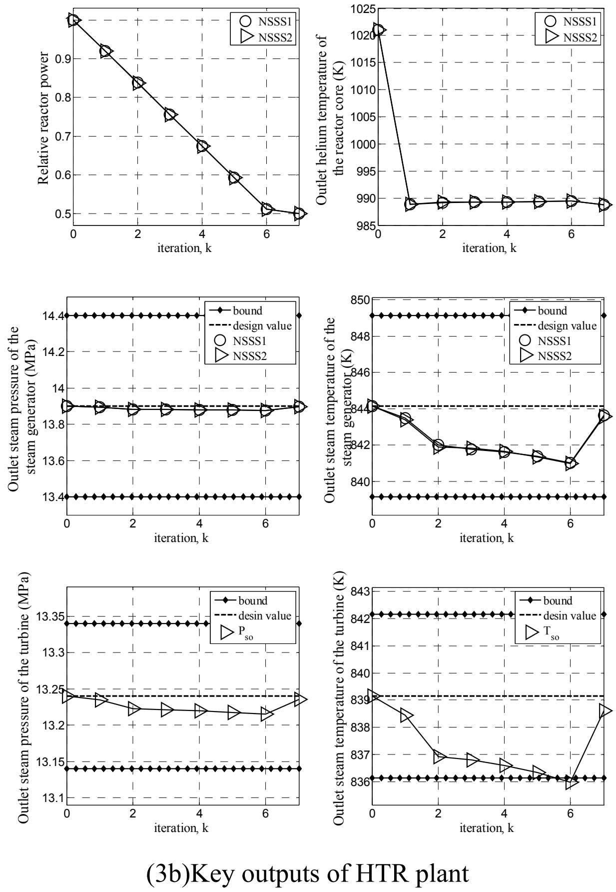


(2c) Input sequence

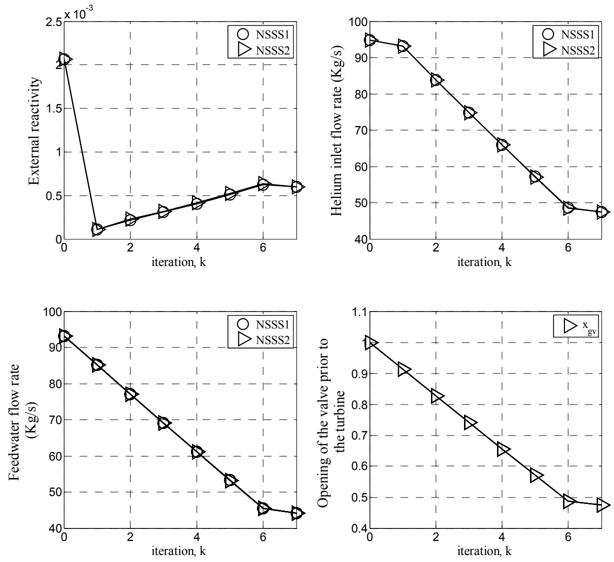
Fig. 2. Load change by ITS method with conservative steps.



(3a) Heat transfer coefficients



(3b)Key outputs of HTR plant



(3c) Input sequence

Fig. 3. Load change by ITS method with aggressive steps.

Another implementation of the iterative framework is the integrated system optimization and parameter estimation (ISOPE) method, which improves convergence performance of the ITS method with RTO problem reformulation (Chen C. and Joseph B., 1987; Yip W.S. and Marlin T.E., 2004). Methods of this class were developed later to remove the PE stage to be more efficient, at the cost of losing the knowledge of parameters with physical meaning (Marchetti A. et al., 2009; Tatjewski P. et al., 2001). In addition, the issue remains unsolved that how much input correction should be implemented from one iteration to the next.

3. INTEGRATION OF LOCAL MODEL WITH REAL-TIME OPTIMIZATION

As can be seen in Section 2, the locally accurate model around the current conditions may be unable to handle the relatively small load change steps without proper application range. This is because the new arriving status of the plant after the load change step is different from the one where the model was estimated before. The mismatch between the plant and model may lead to invalid operations and safety requirements posed on key outputs may be violated. Hence, a predictive model with extended applicability is desirable. Moreover, correction of inputs should be confined to a valid model. These two aspects contribute to motivation for the proposed strategy in this paper.

3.1 Parameter Selection and Local Model Extension

The parameter estimation problem can be formulated in the standard weighted least-squares form

$$\begin{aligned} &\min_p E(p) = \sum_{i=1}^{n_y} w_i \left(y_i - \tilde{y}_i \right)^2 \\ &s.t. \quad f_m(x, y, u, p) = 0 \\ &\qquad c_p(p) \le 0 \end{aligned} \tag{2}$$

where $E(p)$ measures the goodness of fit between the model prediction $y \in R^{n_y}$ and the measured outputs $\tilde{y} \in R^{n_y}$. c_p are constraints on the parameters and w represents the weighting factor.

Determining the estimable parameter set is an important step for avoiding the ill-conditioning caused by over-parameterization, data insufficiency and noise. Reliability evaluation of the estimation should be focused on as well, which in turn refines the parameter subset. Accordingly, parameter set selection characterized by subset selection, reliability evaluation and subset refinement runs through the procedure of parameter estimation. The overall steps for parameter estimation are illustrated as follows:

(i) To select the estimable parameter set, numerically linear dependent parameters are clustered into the same group (Chu Y. and Hahn J., 2008). In each group, the parameter with the largest effect on outputs is selected to make up the initial subset for estimation.

(ii) Problem (2) is solved. As the resulting parameter subset from (i) may be refined after reliability analysis of the estimates, problem (2) will be re-solved until all the estimates meet the reliability requirements.

(iii) Confidence intervals are computed to access validity of the obtained estimates (Marsili-Libelli S. et al., 2003). If not all the estimates are desirable, the parameter with the most serious violation of the requirements is fixed at the nominal value, and the others in the reduced subset are re-estimated by solving problem (2). Otherwise, the optimal subset and corresponding estimates are obtained.

However, the model derived from single data set can be only appropriate for operations around this point. And extension of the applicability is necessary to acquire a predictive model. Parameters $p \in R^{n_p}$ in HTR-PM model can be divided into two categories. $\overline{p} \in R^{n_c}$ is the vector of parameters that vary slowly with respect to load change, and thus can be treated as constants. An example of such parameters is helium leakage ratio. $p^t \in R^{n_t}$ is the vector of are parameters that are also estimable under the current conditions whereas change significantly with load, and thus have varying values. The example is heat transfer coefficients as shown in Figs 2a and 3a. To extend applicability of the model determined by u_k, plant derivatives are exploited to approximate the load-related parameters p^t by

$$m_k^{p^t}(u) = \hat{p}_k^t + (\partial p^t / \partial u_k)^T \cdot (u - u_k) \tag{3}$$

This is nothing but a linear approximation of p^t around condition u_k where the estimates $\hat{p}_k^t$ are obtained. The linearization term $\partial p^t / \partial u_k$ represent the sensitivities of parameters p^t with respect to the inputs. Finite difference is applied to calculate $\partial p^t / \partial u_k$ in this paper, which requires consecutive perturbations to the process inputs and the corresponding estimation of p^t.

3.2 Trust-Region Based Load Change Strategy

Taking advantage of the extended local model, the overall RTO problem for load change is formulated as

$$\begin{aligned} &\min_u \varphi(u) = \sum_{j=1}^{n_e} q_j \left(y_j^e - y_j^{e^*} \right)^2 \\ &s.t \quad f_m\left(u, \overline{p}, m_k^{p^t}(u)\right) = 0 \\ &\qquad c(u) \le 0 \\ &\qquad \left\| u - u_k \right\|_\infty \le \Delta_k \end{aligned} \tag{4}$$

where $c(u)$ are constraints on the inputs, Δ_k is iteration related and constrains operation u to a limited region around the current conditions u_k. The last constraint is imposed to confine the optimization to a valid model. x and y are omitted in f_m as they are determined by u.

The algorithm is stated below, where the merit function ϕ is exploited to balance between reducing the objective function and satisfying the constraints, and the input irrelevant part $\overline{p}$ is omitted for simplicity of description.

Algorithm: Trust-region based iterative model approximation and RTO

Step 0 (Initialization): Give the current operation conditions u_0 which correspond to the initial level of load and the initial trust-region radius Δ_0. Choose constants $0 \le \eta_0 \le \eta_1 < 1$ (with $\eta_1 \ne 0$), $0 < \gamma < 1 < \gamma_{inc}$, $\Delta_{\max} > \Delta_0 \ge \Delta_{\min}$, and termination tolerance ε_t. Set $k \leftarrow 0$.

Step 1 (Parameter estimation): If merit function of plant $\left\| \phi(u_k, p^t(u_k)) \right\| \le \varepsilon_t$, stop. Otherwise, estimate the heat transfer coefficients to obtain $\hat{p}_k^t$.

Step 2 (Model approximation): Calculate sensitivities $\partial p^t / \partial u_k$ and approximate the parameters with (3).

Step 3 (Step calculation): Solve problem (4) with solution u_{k+1}.

Step 4 (Model evaluation): Apply u_{k+1} to the plant and compute

$$\rho_k = \frac{\phi(u_k, p^t(u_k)) - \phi(u_{k+1}, p^t(u_{k+1}))}{\phi(u_k, \hat{p}_k^t) - \phi(u_{k+1}, m_k^{p^t}(u_{k+1}))}$$

If $\rho_k < 0$, restore $u_{k+1} \leftarrow u_k$.

Step 5 (Trust-region radius adaptation): Set

$$\Delta_{k+1} = \begin{cases} \min\{\gamma_{inc}\Delta_k, \Delta_{\max}\} & \text{if } \rho_k \ge \eta_1, \\ \max\{\gamma\Delta_k, \Delta_{\min}\} & \text{if } \eta_0 \le \rho_k < \eta_1, \\ \Delta_{\min} & \textit{otherwize.} \end{cases}$$

Let $k = k + 1$, go to Step 1.

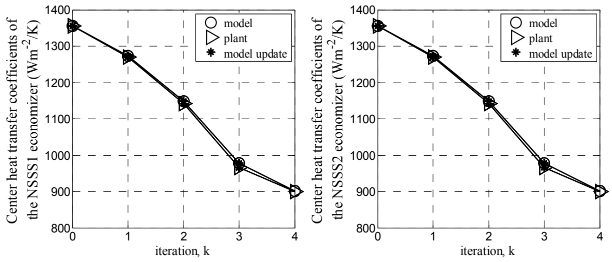
According to this method, the local model is obtained by parameter approximation which extends applicability of the basic estimated model through plant derivatives. When realizing load change in the trust-region framework, the resulting approximate model is evaluated in each iteration, based on which its applicable range is appropriately determined. Therefore, parameter approximation and real-time optimization is implemented iteratively, and accordingly, the load change progress is promoted through the more predictive model with proper application range.

4. NUMERICAL RESULTS

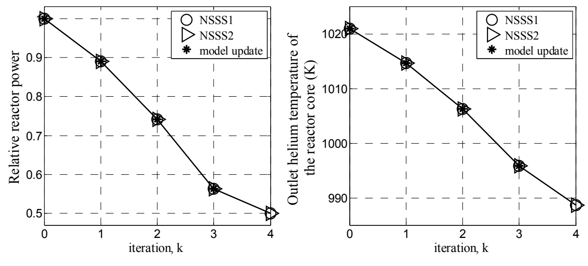
Result of parameter selection is first given. For HTR-PM, there are 33 measured outputs. After procedures of parameter selection and estimation, only the estimation of helium leakage ratio and load related centre heat transfer coefficient of the economizer in both NSSS modules meet the reliability requirement. We conclude in this case that based on the available single data set, at most four of the parameters can be estimated with desired level of reliability.

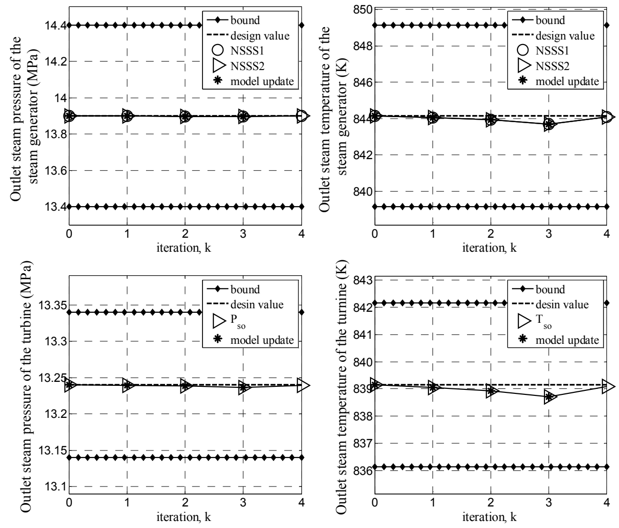
Based on the estimated model, the same load change of HTR-PM as in Section 2 is realized here by the trust-region based strategy. Fig. 4 displays the resulting heat transfer coefficients, key outputs and process inputs, with the performed model updates at iterations marked by '*'.

In this case, $\rho_k > 0$ indicates all the iterations are successful. And a sequence of operations are generated, which lead key outputs to meet the safety requirements during the load change process. Moreover, much fewer steps (4 steps) are implemented to achieve the target load and plant performance at the end of iterations significantly reduces to 1.18 compared with strategies in Section 2. In particular, at the end point, key outputs as shown by Fig. 4b stay apparently closer to their design values than the outputs in Figs. 2b and 3b. This suggests advantages of the predictive and appropriately used model, due to the step-wise update of model and trust-region radius.

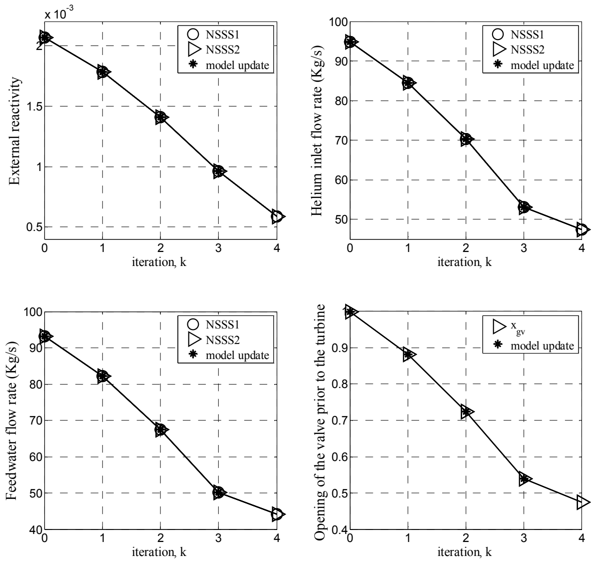


(4a) Heat transfer coefficients





(4b) Key outputs of HTR plant



(4c) Input sequence

Fig. 4. Load change by trust-region based strategy.

5. CONCLUSIONS

A trust-region based strategy for significant load change of HTR-PM is developed in this paper, which aims at constructing a desirable model and properly determining its applicable range. Applicability of the basic model, which can be estimated well via single data set, is extended through exploiting plant derivatives so that a local model is acquired. Here, parameter selection and estimation contribute to the reliable basic model. When applied to the load change task in trust-region framework, the extended model is confined to an appropriate operating range which is determined by model evaluation. At the same time, model update is performed at each iteration to maintain a valid approximation to the plant. The case study of load change from 100%RFP to 50%RFP demonstrates effectiveness of the proposed strategy.

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