RAPID RECONSTRUCTION OF TEMPERATURE FIELD OF COKE CHAMBER BASED ON POD-BP AND TIKHONOV METHOD

by

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As the key equipment of delayed coking unit, the coking chamber generally uses the cycle heating and cooling process to produce products. Due to the large temperature rise and fall process of the cycle, the coke chamber runs under harsh thermal conditions for a long time, and the thermal stress generated by temperature fluctuation is one of the main reasons for the failure of the coke chamber structure. However, the working state of coking chamber is complex, and the traditional numerical method cannot realize timely monitoring, so it is of great practical significance to study the new method to realize timely monitoring. In this paper, POD-BP reduced order models under the second and third thermal boundary conditions are established by studying the coke chamber in the production process. The models are applied to the inversion of the spatial heat flux distribution and the calculation of the temperature field of the coke chamber, which greatly improves the calculation speed of the inversion. It has been proved that the proposed method has the advantages of good real-time performance, high precision, strong anti-interference ability and strong operability, which provides a detection method for the real-time reconstruction of temperature field and production state of coke chamber.

Key words: *heat, POD-BP, Tikhonov, inverse, reconstruction*

Introduction

As the key equipment in the delayed coking device, coke chamber is widely used in various petrochemical enterprises [1]. The main purpose of the equipment is to convert low value materials such as high sulfur and high asphaltene residue into high value light component oil, and it can also provide coke generation function. In the process of coke chamber production, cyclic heating and cooling process are generally included in product production. Drastic temperature changes will make coke chamber by greater thermal stress, in extreme cases may cause coke chamber deformation, induced damage, or even explosion and other accidents [2].

Therefore, it is necessary to study the temperature field of the coke chamber. Generally speaking, the temperature field of an object is affected by the external environment and the physical properties of the medium [3, 4]. Due to the existence of vapor, liquid and solid media in the coke chamber, the working conditions are complex and harsh, and it is difficult to reconstruct the temperature field of the equipment by pyrometer, thermocouple, and optical methods in the traditional temperature measurement methods [5]. Through data collection and analysis,

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it is found that the inverse heat transfer problem is one of the powerful tools to reconstruct the temperature field of coke chamber.

The inverse derivation of the input conditions from the output results is the solution idea of the inverse problem, which is mainly applied to obtain some parameters and conditions that are not easy to measure directly. The inverse problem of heat transfer is one direction in which the inverse problem can be applied. The inverse heat transfer problem is mainly used in the actual production obtain some physical parameters in the heat transfer model which are not easy to measure directly, or the boundary conditions which can't be directly given by the model [6]. Beck *et al.* [7] studied the following five methods for solving the inverse thermal conductivity problem: analysis method, de Sollza method, Weber method, *Rb* method, and Hill-Hensel method. Since Beck *et al.* [7] proposed the concept of sensitivity coefficient and applied it to inverse problems, methods derived from the concept (such as direct sensitivity coefficient) have been successfully applied to steady-state and unsteady inverse heat conduction problems. Huang *et al.* [8] studied the inverse problem of multidimensional thermal conductivity by using the method of space propulsion and used the control volume method to solve the temperature field of complex shaped containers. Sladewski *et al.* [9] achieved temperature measurement in a furnace through an acoustic temperature measurement system.

Due to the ill-posed nature of the heat transfer inverse problem: the error of the temperature measurement information of the external has a great influence on the inversion result of the temperature field. It is necessary to study the anti-ill posed method of inverse problem. Jaremkiewicz *et al.* [10] carried out temporal and spatial smoothing processing for the measured exterior wall temperature information, which greatly improved the calculation accuracy. Most numerical methods are applied to well posed problems and are difficult to apply to ill posed problems. Because the ill-posed problem is involved in this paper, a regularization method is proposed to deal with it. Regularization is one of the earlier methods used to solve ill-posed problems. It uses prior knowledge to replace the original ill-posed problem with a similar well-posed problem, to restore the stability of the solution of the ill-posed problem [11]. The Tikhonov method was proposed by mathematician Tikhonov [12] in 1963 by establishing and solving the ill-conditioned inverse problem of Tikhonov functional minimum inversion, which is one of the most used regularization methods for solving inverse problems. Cheng *et al.* [13] adopted regularization method to solve the inverse thermal conductivity problem of relative scale. Yang *et al.* [14] simplified Tikhonov regularization method based on Holder shape stable solution, and numerical test results showed that the method was effective and stable. Xiong *et al.* [15, 16] proposed a generalized Tikhonov regularization method, which extended the application scope of Tikhonov method. Cheng *et al.* [17] improved a Tikhonov regularization method based on the order optimal solution solve the inverse thermal conductivity problem of the 3-D co-ordinate system.

The inverse problem has some computational drawbacks, such as there are repeated forward calculation [18], and each time the traditional gradient method is used to solve the sensitivity calculation in real-time measurement is essential in the matrix, and to establish a kind of approximate model or proxy model instead of the numerical simulation process, to improve the efficiency of forward calculation. Proper orthogonal decomposition (POD) reduces the DoF of the computational process by projecting high-dimensional space from lower order sub-spaces. Compared to traditional numerical calculation methods, it has the advantage of fast computational speed.

Aling *et al.* [19] first attempted to develop a POD-Galerkin rapid heat treatment temperature field modelling order reduction model based on POD and approximate inertial manifold, aiming to retain a physical understanding of the relationship between the system and some core parameters. Alonso *et al.* [20] combined POD and genetic algorithm to minimize the residuals of the momentum and boundary conditions, and proposed a reduced-order model for studying back stepping heat transfer. Raghupathy *et al.* [21] proposed the POD-Galerkin reduced order model of heat transfer, and combined POD-Galerkin and finite volume methods to develop a reduced-order model with independent boundary conditions, and successfully implemented the theory in one and two dimensions.

Through the current research on reduced order models, scholars have focused too much on the construction of physical field models and not enough on the approximate relationship between the input parameters and the target, resulting in an overall lack of research [22]. The ANN method proposed by American scientists Pitts and Meculloch in 1943 [23] is widely used in fault diagnosis, digital simulation and other fields. This paper intends to study a numerical model which has a mapping relationship between heat flux (unknown parameter) and space temperature or POD coefficient. This model can be used to numerically simulate the temperature at all grid nodes and to obtain the corresponding computational results. This approach enables the measurement of data and temperature variations across the temperature domain of the device, which has great engineering applications. In order to address the problems that exist in the practice of coke oven production, an idea of combining POD and back propagation (BP) in the second and third thermal boundary conditions is developed, which is combined with Tikhonov regularization build a reduced-order model. By applying the POD-BP model to the Tikhonov inversion system, the speed of the inversion calculation is greatly improved at the cost of a small amount of accuracy, and the temperature field of the coke chamber can be reconstructed rapidly.

Heat transfer model of coke chamber

This chapter describes the principle of the FEM, establishes the physical model and mathematical model of the coke chamber, based on the FEM, sets the material and thermal boundary conditions of the coke chamber, and verifies the correctness of the finite element heat transfer model of the coke chamber through numerical simulation:

- *Coke chamber geometry*: The research object of this paper is a typical coke chamber. The simplified coke chamber provided by a petrochemical enterprise under the thermal insulation layer is shown in fig. 1. Upper cylinder wall thickness δ = 28 mm, lower cylinder wall thickness δ = 32 mm. A simplified model of the coking chamber is established in space.
- *Coke chamber materials*: This paper assumes that the physical parameters of the material are uniform, taking into account all the materials of the chamber body and skirt, and welding materials as metal Q245R. The physical parameters are shown in tab. 1.

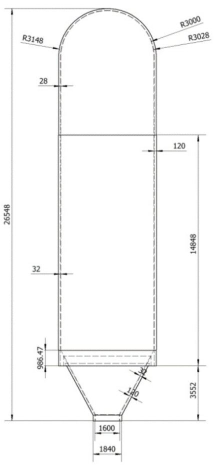

Figure 1. Coke chamber model geometry size

Table 1. The physical parameters of material Q245R

	Thermal conductivity	Density	Specific heat capacity
Value of correlation	30.96 [Wm^{-1}K^{-1}]	7870 [kgm^{-3}]	465 [Jkg^{-1}K^{-1}]

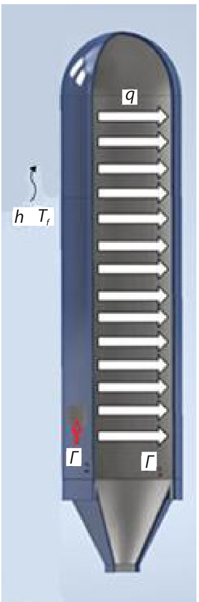

Figure 2. Schematic diagram of coke chamber

Due to the complex process of coke chamber, the medium inside the chamber is unstable during the working process, and all working conditions of coke chamber are expressed in the form of heat flux. The heat flux is distributed on the inner wall of the coke chamber by interpolation along the height direction. The external medium of coke chamber is air, the convective heat transfer coefficient is 10 W/m^{2}K, and the ambient temperature is 293.15 K.

– *Mathematical and physical models*: The constructed model of coke chamber is shown in fig. 2, and the heat flux is evenly distributed along the circumferential direction. The inner wall of the coke chamber Γ_1 is subjected to the effect of distributed heat flux, and the outer wall of the coke chamber Γ_2 is applied with a thermal insulation layer. The outer wall of the thermal insulation layer conducts convection heat transfer with the environment. The other surfaces Γ_3 is adiabatic, and the specimen Γ_2 surface is arranged with a thermocouple, and the temperature can be directly measured. To facilitate POD downscaling, the thermal conduction resistance of the insulation layer is considered as the convection heat transfer resistance, that is, without the insulation layer, the reduced convection heat transfer coefficient between the outer wall of coke chamber and the environment is used for heat dissipation.

The $x = (\phi, \theta, y)$ is denoted as the spatial co-ordinate vector, and the governing equation of the temperature field in the spatial region V is:

$$\frac{1}{r}\frac{\partial}{\partial r}\left(\lambda(\boldsymbol{x})r\frac{\partial T(\boldsymbol{x})}{\partial r}\right)+\frac{1}{r^2}\frac{\partial}{\partial \varphi}\left(\lambda(\boldsymbol{x})\frac{\partial T(\boldsymbol{x})}{\partial \varphi}\right)+\frac{\partial}{\partial y}\left(\lambda(\boldsymbol{x})\frac{\partial T(\boldsymbol{x})}{\partial y}\right)=0 \tag{1}$$

Boundary conditions:

$$-\lambda(\boldsymbol{x})\frac{\partial T(\boldsymbol{x})}{\partial n}=q(\boldsymbol{y}),\ \boldsymbol{x}\in\Gamma_1 \tag{2}$$

$$-\lambda(\boldsymbol{x})\frac{\partial T(\boldsymbol{x})}{\partial n}=h_2\left(T(\boldsymbol{x})-T_{\text{amb}}\right),\ x\in\Gamma_2 \tag{3}$$

$$-\lambda(\boldsymbol{x})\frac{\partial T(\boldsymbol{x})}{\partial n}=0,\ x\in\Gamma_3 \tag{4}$$

where $q(y)$ is the axial y heat flux distribution of coke chamber wall, h_2 – the heat transfer coefficient of surface Γ_2 part, T_{amb} – the ambient temperature of the coke chamber, n – the outer normal direction of coke chamber surface, and λ_n – the thermal conductivity of coke chamber body material. If the heat flux distribution $q(y)$, thermal physical property parameters and other thermal boundary conditions are known, the temperature field $T(\boldsymbol{x})$ of coke chamber can be determined by the heat transfer model.

– *Heat transfer simulation*: Finite element method has the characteristics of clear physical concept and wide application range. This topic uses its mature theory in the field of heat transfer to lay a foundation for subsequent research. The mesh physical field model adopts finite element software to control the mesh sequentially, and adaptively refined to generate a free quadrilateral mesh. To verify the accuracy of finite element, we consider a typical inverse problem case. The heat transfer model, thermophysical parameter settings and boundary conditions are the same as those in [24]. As shown in fig. 3, it can be seen clearly that the results predicted by the FEM are in good agreement with the exact solution of [24], which indicates the present FEM model could accurately predict the radial heat transfer problem.

In general, the influence of mesh on the results should be considered in simulation, and the accuracy of the results is related to the quality of mesh division. Verifying the irrelevance of the grid is an indispensable part.

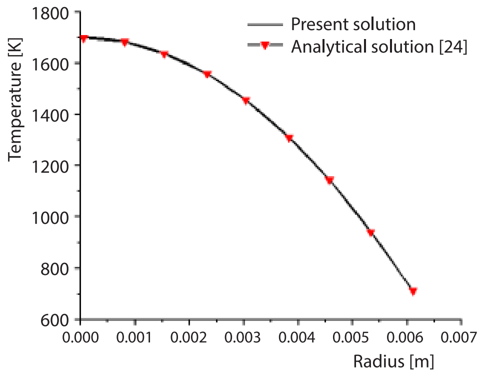

Figure 3. Comparison between present computational solution and exact solution [24]

Table 2. Kinds of grid division observation point temperature calculation data T_{FEM}

T_{FEM}/K	1	2	3	4	5
Coarsening	501.91	502.37	495.46	484.17	487.38
Normalization	489.69	489.71	490.82	481.24	481.34
Refine	487.19	487.05	487.28	478.18	477.33
More detailed	487.19	487.05	487.29	478.18	477.33

Compared with the data in tab. 2, the grid division of the model is changed from coarser to more refined. With the gradual refinement of the grid division, the output temperature data changes less and less, and the temperature data basically do not change until the refinement reaches more refined. The calculation time gradually increases from 5-54 seconds, especially in the process of grid refinement to finer, the calculation time increases from 19-54 seconds. It can be concluded that during the gradual refinement of grid division, there is a certain deviation between the temperature obtained by coarser grid division and that by finer grid division. However, after the grid division reaches the refinement level, the temperature obtained by simulation calculation basically does not change. In this paper, the focal chamber model is selected for refinement and meshing based on the principle of optimizing calculation accuracy and calculation time. In this case, the coke chamber contains 50104 domain elements, 33280 boundary elements and 1214 boundary elements after refinement and dispersion.

The POD-BP reduced order model

The POD method takes experimental data or numerical results as samples and expresses the general physics problem as a set of POD base functions and corresponding coefficients in a low-order form of linear superposition. The provided basis functions satisfy the energy optimal condition in the sense of least squares. The linear combination of the basic functions and corresponding coefficients can realize the low dimensional description of the high dimensional data.

Most POD dimensionality reduction algorithms combine Galerkin projection method to establish order reduction model. The purpose of POD decomposition or SVD decomposition for the constructed sample set is to obtain M POD bases with the highest information content, and then project the information on POD bases to other high dimensional spaces of the whole model through Galerkin projection method, to achieve low dimensional expression of the physical field of the whole model.

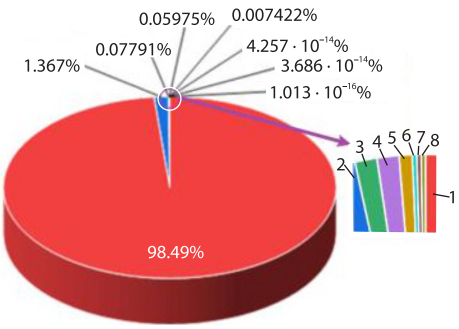

Figure 4. Diagram of information proportion of eigenvalue of basis function from No. 1 to No. 8

The POD basis selection

For the selection of POD basis functions, in principle, the more basis functions, the more information obtained, and the more accurate the solution. However, in practice, algebraic equations may be ill-posed due to excessive POD basis information. Experiments show that after the POD basis functions are arranged by size, the first six basis functions can reflect more than 99.99% of the information, accurately describe the overall distribution and details of the temperature field, and the smaller basis functions will be omitted. The details of the first eight basis functions are shown in fig. 4.

The POD base coefficient calculation and analysis based on POD-BPNN

Due to the inconvenient use of the Galerkin method for dealing with complex physical models of coke chamber, it includes the treatment of boundary conditions, heat transfer coefficient and temperature field dimension reduction*, etc.* The ANN can achieve function approximation, prediction, classification and other functions. We use neural network to solve the coefficient of POD basis function.

By comparing BP network and other neural networks, BP network has simple structure and fast operation speed. The BP network is introduced to optimize POD method. The main research object is POD basis coefficient. Through BP network, the complex adaptive non-linear relationship between input and output is established according to the transfer function of neuron. In this chapter, using the advantage of BP neural network interpolation, the implicit basis coefficient of POD method is accurately calculated, which makes the temperature field calculation of coke chamber have a relatively ideal temperature field in the complex region, and improves the ability of fast reconstruction a certain extent. The specific details are detailed in [25, 26].

In order to extract information that can ensure sufficient accuracy, we choose to extract a set of data within 1 minute at the observation point of the coke chamber. Through inversion and finite element analysis, 4000 sets of finite element data of two cycles are taken as the sample set. Through the known temperature of the measurement point and the temperature field obtained by the FEM, the BP network is trained on the basis function coefficient of POD. The calculated results were compared with those of the FEM, tab. 3:

Table 3. Finite element results and calculation results and errors of POD-BP

	POD base coefficient and its error					
Coefficient	1	2	3	4	5	6
ξ_{FEM}	$1.3437 \cdot 10^{07}$	$2.7905 \cdot 10^{06}$	$7.5802 \cdot 10^{05}$	$-3.6600 \cdot 10^{05}$	$-1.4805\ 10^{04}$	1.2781
$\xi_{\text{POD-BP}}$	$1.3436 \cdot 10^{07}$	$2.7903 \cdot 10^{06}$	$7.5786 \cdot 10^{05}$	$-3.6588 \cdot 10^{05}$	$-1.4818\ 10^{04}$	1.2836
Error	$3.6204 \cdot 10^{-05}$	$6.7150 \cdot 10^{-05}$	$2.1175 \cdot 10^{-04}$	$-3.3305 \cdot 10^{-04}$	$-9.0180 \cdot 10^{-04}$	$0.43 \cdot 10^{-02}$

Through the relative error formula:

$$\text{error} = \frac{\xi_{\text{POD-BP}} - \xi_{\text{FEM}}}{\xi_{\text{FEM}}} \tag{5}$$

where $\xi_{\text{POD-BP}}$ is the POD-BP coefficient of temperature field of coke chamber, and ξ_{FEM} – the coefficient of temperature field of coke chamber obtained by traditional finite element simulation method. The errors of POD basis coefficients of temperature field after POD-BP dimension reduction calculation are all below 0.5%. Selecting six POD basis functions can ensure the accuracy of POD solution under the condition of minimal computational load.

Temperature field reconstruction system of coke chamber

The operating process of the temperature field reconstruction system of coke chamber designed in this paper is shown in fig. 5:

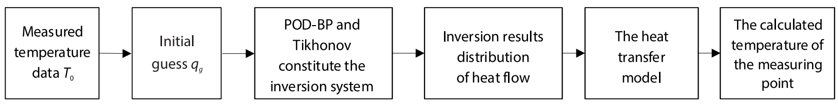

Figure 5. Operation flow chart

– *Tikhonov regularization principle*: Consider the discomfort operator equation:

$$\boldsymbol{Ax} = \boldsymbol{b} \tag{6}$$

where $\boldsymbol{A}$ is the mx order matrix ($m \geq n$), $\boldsymbol{b}$ – the right end of the m-dimensional equation, and $\boldsymbol{x}$ – the n-dimensional unknown vector. The actual situation is that the right end item $\boldsymbol{b}$ of eq. (6) has a certain error δ more or less, that is, the error limit between the right end item $\boldsymbol{b}$ and its true value $\boldsymbol{b}_{\text{ture}}$ is $||\boldsymbol{b}_{\text{ture}} - \boldsymbol{b}\,|| < \delta$, where $\delta > 0$.

Tikhonov regularization method provides an effective way to solve ill-conditioned problems. Its core idea is to impose a weak smoothness constraint on a set of acceptable solutions. Tikhonov regularization of eq. (6) is transformed into solving the minimum value problem:

$$\min = \left\|\boldsymbol{Ax} - \boldsymbol{b}\right\|^2 + \lambda\left\|\boldsymbol{x}\right\|^2 \tag{7}$$

where $||\cdot||$ is the norm of the vector and $\lambda > 0$ is the regular parameter. The solution x of the previous formula satisfies the normal equation:

$$\left(\boldsymbol{A}^T\boldsymbol{A} + \lambda\boldsymbol{I}\right)\boldsymbol{x} = \boldsymbol{A}^T\boldsymbol{b} \tag{8}$$

The matrix $\boldsymbol{A}$ used in this paper refers to the temperature field basis function, which is obtained by numerical experiment and POD method.

– *Selection criterion of Tikhonov regularization parameters*: The Tikhonov regularization method is adopted to solve the ill-posed problem, and the selection of appropriate regularization parameters is the key link, which determines the degree of approximation between the solution of the regularization constructed approximation problem and the real result, as well as the ability to extract the real solution by resisting the influence of measurement error and rounding error. Tikhonov regularization parameter selection is too small, the ability to reduce the discomfort problem is reduced, the selection is too large, the numerical solution and the actual solution is too big difference. The selection of regularization parameters directly affects the solution of the equation. After applicability analysis, L-curve criterion [27] is used for selection in this project.

Results and discussion

Accuracy analysis of calculation results

The forward problem in the Tikhonov inverse system of coke chamber, namely the finite element model, was replaced with the established POD-BP model, and the result deviation of the inversion system was adjusted by positive feedback through the POD-BP model. According to the actual measuring points provided by the enterprise, ten heat flux values distributed along the height Y-direction are applied to the inner wall of the coke chamber by interpolation method, corresponding to the ten temperature measuring points set on the outer wall of the coke chamber.

The measured temperature is stored in POD-BP-Tikhonov inversion system and FEM-Tikhonov inversion system, respectively. The initial guess value $\boldsymbol{q}_g = \beta[1000, 1000,\ldots, 1000, 1000]$ W/m^2, $\beta = 1$. Five verification points were selected to compare the calculation results of POD-BP-Tikhonov inversion system and FEM-Tikhonov inversion system, RMSE and relative average error η of POD-BP and FEM, and the results were shown in tab. 4.

Table 4. Calculation results and errors of temperature verification points

	Calculated value of temperature verification point [K]					error	
Point of observation	M1	M2	M3	M4	M5	RMSE [K]	η [%]
T_{FEM}	530.09	536.53	524.94	522.91	519.47	–	
$T_{POD\text{-}BP}$	530.85	537.26	525.99	524.43	521.72	1.38	0.26

As can be seen from the calculation results, there is little difference between the FEM-Tikhonov inversion system and POD-BP-Tikhonov inversion system, with an error difference of 0.26%. As the FEM model is closer to the real heat transfer situation, there is a certain error between the POD-BP reduced order model and the FEM model in calculation, but the whole calculation process takes 34.83 seconds for the FEM-Tikhonov inversion system, while the POD-BP-Tikhonov inversion system only takes 0.64 seconds. This is because each iteration calculation needs to call forward problem and calculate across software, while POD-BP step-down model with faster calculation speed saves the transmission time between software by using forward problem calculation constructed by software, which greatly reduces the calculation time and cost of Tikhonov system.

Numerical experiments on factors influencing the calculation results

When POD-BP reduced order model is used as the forward problem of Tikhonov inversion system, the calculation results and calculation speed are ideal. In this section, numerical experiments are conducted to analyze the influence of initial guess value, measurement error and number of temperature measurement points on inversion results of Tikhonov inversion system based on POD-BP reduced order model. It is assumed that the distribution of heat flux in the inner wall of coke chamber is actually:

$$q(y) = \begin{cases} 10000 & y < 5000 \\ \left(\dfrac{y-5000}{2614} + 11\right) \times 1000 & 5000 \le y \le 28520 \\ 21000 & y > 28520 \end{cases} \tag{9}$$

where y [mm] is the axial co-ordinate of the coke chamber and $q(y)$ [Wm^{-2}] – the relative position heat flux.

In fact, due to the inevitable measurement error, the calculation result of measured temperature T_k^{mea} can be obtained through eq. (10) in the numerical experiment:

$$T_k^{\text{mea}} = T_k^{\text{exa}} + \omega\sigma \quad (k = 1, 2, \ldots, K) \tag{10}$$

where T_k^{exa} is the heat flux in the inner wall of a given coke chamber, the *exact value* of the temperature at the measured point is obtained by solving the forward problem, ω – the random number within [–2.576, 2.576] that follows the standard normal distribution, and σ – the standard deviation of measurement error.

When the temperature measurement error (σ = 0 K) is not considered, the target parameter ε = 0.01 is taken. When $\sigma \neq 0$ K, set according to deviation principle $\omega = K\sigma^2$.

– *The effect of the initial guess value*: The temperature measurement error σ = 0.01 K, the number of temperature measurement points K = 12. During the inversion, the initial guess value. Then $\boldsymbol{q}_\text{g} = \beta$[1000,1 000,…,1000, 1000] W/m^2. When β values are different, the results of heat flux inversion are shown in tab. 5.

Table 5. Error of inversion results with different initial guesses

β	Root mean square error [K]	Relative mean error, η [%]
0.1	5.69	0.22
0.5	5.56	0.19
1.0	5.59	0.19
2.0	5.47	0.20

As can be seen from tab. 6, the inversion results of heat flux distribution obtained by Tikhonov method are in good agreement with the real value in numerical experiments, and there is little difference between the inversion results of different initial guesses, which proves that the initial guesses have little influence on the calculation results of Tikhonov inversion system constructed in this paper.

– *The impact of measurement error*: Take the initial guess value $\boldsymbol{q}_\text{g}$= [1000, 1000,…,1000, 1000] Wm^2, and the number of temperatures measuring points K = 12. The influence of measurement error on inversion results is studied by changing the standard deviation σ of temperature measurement error during inversion. The inversion results are shown in tab. 6.

Table 6. Inversion errors of different temperature measurement errors

σ	Root mean square error [K]	Relative mean error, η [%]
0.01	5.29	0.19
0.5	6.19	0.26
1.0	7.49	0.38
1.5	8.67	0.51

It can be seen from tab. 6 that when the standard deviation σ of the measurement error gradually increases from 0.01-1.5, the relative mean error of the inversion results gradually increases from 0.19-0.51%, and the RMSE increases from 5.29-8.67 K, indicating that the measurement error has a certain influence on the inversion results of the Tikhonov inversion system. But the effect was not significant. The inversion system can still effectively calculate the heat flux distribution of the coke chamber wall, which indicates that the Tikhonov inversion system constructed in this paper has a good anti-interference ability to the measurement error.

– *The influence of the number of measuring points*: The measured heat flux qexa, the initial guess value $\boldsymbol{q}_g$ = [1000, 1000,…,1 000, 1000] W/m^2, and the standard deviation of measurement error σ = 0.01 K are taken to discuss the influence of temperature measurement points K = 10, K = 20, and K = 30 on the inversion results. The inversion results are shown in tab. 7.

Table 7. Inversion errors of different temperature measurement points

K	Root mean square error [K]	Relative mean error, η [%]
10	5.50	0.23
20	4.38	0.18
30	3.46	0.16

It can be seen from tab. 7 that with the increase of the number of temperature measurement points, the mean relative error and RMSE of the inversion result and the real value decrease, indicating that the input information is complete, and the accuracy of the constructed Tikhonov inversion system is higher. However, overall, the wall heat fluidity of the coke chamber whose inversion result is consistent with the real heat flux value is at a higher level. The results show that the inversion results of the Tikhonov system constructed in this paper are less affected by the number of temperatures measuring points, which proves that the system has good anti-discomfort.

Conclusions

In this paper, Tikhonov inversion system is faced with huge computational cost and cannot be applied in engineering practice due to the high mathematical expression freedom of the traditional FEM in the heat transfer model of coke chamber and the huge number of solving variables (the order of magnitude is usually 10^7 to 10^8). In view of the aforementioned problems, this paper mainly does the following work: the Tikhonov system for the spatial distribution of heat flux in coke chamber was constructed to realize effective inversion of the spatial distribution of heat flux in the inner wall of coke chamber. Aiming at the complex physical model of coke chamber, the POD-BP reduced order model was constructed, which greatly reduced the calculation number of positive problems in Tikhonov system. Numerical experiments verify the accuracy of the POD reduced order model, the calculation error is less than 0.41%, but the calculation time is reduced from 2.17 minutes to 2.4 seconds, which is about 1.84% of the finite element model. The calculation time has been drastically reduced. Prospects:

- The follow-up study, the influence of the deformation of the coke chamber itself on the temperature field should be considered and the heat transfer model of the coke chamber should be highly simulated to achieve the accurate expression of the temperature field of the coke chamber.
- During the calculation time of Tikhonov inversion system, the temperature field in the coke chamber does not change much. In the same process, the temperature field in the calculation time is approximately analyzed to achieve the purpose of real-time reconstruction of the coke chamber temperature field. But this will inevitably make the result of temperature field reconstruction rougher. If the computer performance is good enough, the calculation time can be shortened again, and the real-time reconstruction result of temperature field can be more realistic.

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