SIMULATION OF ELECTRIC HEATING PREDICTION MODEL BY INTERNET OF THINGS TECHNOLOGY AND ROOM THERMAL PERFORMANCE ANALYSIS

by

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The fault diagnosis and fault-tolerant control of electric heating distributed control system are improved by the thermal performance analysis of rooms. The given values are tracked to meet the heating requirements, and the reliability of heating is increased without increasing hardware resources, which improves the reliability and economy of electric heating. From the perspective of energy conservation of electric heating for buildings and rooms, a predictive control model based on load-side three-phase power self-balance is proposed. A fault tolerance method for the electric heating distributed control system control system heating is designed. The load-side three-phase power self-balancing method of the electric heating control system is implemented by using the advantages of the Internet of Things and the heat storage performance of a room, which is its characteristics. Simulation results show that the performance of predictive control for non-minimum phase process is significantly better than that of conventional proportion integral differential control. For complex control problems, predictive control technology can provide better control performance than proportion integral differential control technology. Without increasing any hardware resources, reliable and economical heating is achieved through software.

Key words*: predictive control algorithm, electric heating, fault tolerance rate, distributed control system, control system, fault diagnosis efficiency*

Introduction

The heat forms in the buildings mainly include the heat load of the envelope structure, the penetration of cold air and the heat load, the heat storage inside the rooms, the free heat of the building, and the heat dissipation of the radiator. The free heat and radiators of the buildings transfer heat into the room through convection and radiation heat transfer, forming thermal energy inside the rooms. The heat obtained through radiation heat transfer will be stored in the interior surface of the building in the manner of heat accumulation [1]. Experts and scholars have proposed the metered heating method for energy conservation of building heating, that is, charging heating fees based on the amount of heat used, and users can control the indoor temperature according to their needs. While applying metered heating, preliminary planning for the demand of thermal energy through electric heating pre-heating is required. The predictive

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control model is based on an advanced control algorithm, which can reflect the input-output relationship of the system and perform rolling optimization in a limited time domain [2]. Because of its excellent comprehensive quality of model control, it is suitable for the control of complex industrial processes with high real-time calculation requirements and large changes in environmental parameters. For complex control problems, predictive control technology can provide better control performance than proportional integral differential (PID) control technology, which has been applied in large-scale process control systems [3].

The technology of embedding the predictive control algorithm in the distributed control system (DCS) layer configuration control software not only comprehensively simulates the control system but also realizes the predictive control of complex industrial process objects at the DCS layer. This has important practical significance for the application of predictive control technology [4-6]. Since the field controller in the current electric heating control system usually adopts temperature-based PID closed-loop feedback control, once the temperature sensor or its detection channel fails, the control output may be saturated or vacant [7]. This will cause the electric heater to only be in the on or off state, making the room temperature in two extreme states. Therefore, the heating requirements cannot be effectively guaranteed since the system is unable to track the given values [8]. Also, when the electric heater or the execution channel fails, the temperature control requirements of the room cannot be completed. If the communication channel between the management layer, control layer, and field control layer fails, the entire DCS control system will also be paralyzed [9].

This study is based on the thermal performance analysis of the rooms; from the perspective of building heating energy conservation, an electric heating DCS control system is provided.

Method

Load-side three-phase power self-balancing method for electric heating control system

Due to the severe imbalance of the three-phase power of the current electric heating and heating system, the expansion of power transformers increases not only the initial investment but also the operating costs due to increased losses. The load-side three-phase power self-balancing method for the electric heating control system is implemented by utilizing the advantages of the Internet of Things (IoT) and the heat storage performance of the room. The heat load is divided into 1-3 levels according to the set temperature of the heat load level. In addition, the total power of loads of different levels distributed on each phase is the same, *i. e.*, the three-phase load itself is statically balanced. To simplify the analysis, it is assumed that the load of each level is the same, and the factory power of each load is the same. The temperature range of each level is set, and the temperature range is gradually reduced. Figure 1 shows the multi-agent topology of the load-side three-phase power self-balancing method of the electric heating control system.

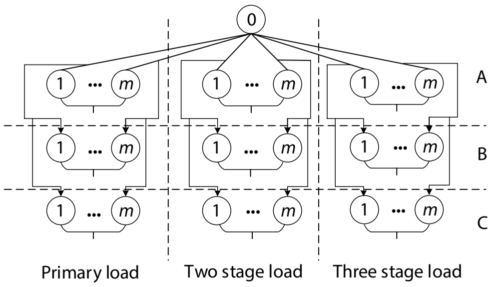

Figure 1. Topology of the load-side three-phase power self-balancing method with multi-agent

This method is different from the traditional compensation method and commutation balance method. It is based on the advantages of the IoT and the heat storage performance of the room. Since the electric heating control system is a feature of the IoT system, by collecting the working state of the electric heater, after calculation and analysis, the three-phase imbalance can be determined without the need for additional detection devices. Since it is self-balancing on the load side, it does not need to add additional balancing devices to the power supply measurement, which reduces losses and costs and improves the power supply quality.

Mechanism and model of predictive control

To ensure the safety of the production process and the reliability of the control system, it is very common in the industry to use DCS control systems based on distributed computers, especially for large-scale and complex industrial process operation control [10-12]. Predictive control uses a discrete convolution model, a rolling optimization index, and the implicit system design parameters. This study discusses the mechanism of predictive control based on the internal model control structure method. The most common feedback control system in internal model control is shown in fig. 2, where $G(z)$ and $G_c(z)$ are the pulse transfer functions of the object and the regulator, $Y(z)$, $Y_{sp}(z)$, and $D(z)$, respectively, represent the output, set value, and unmeasured interference.

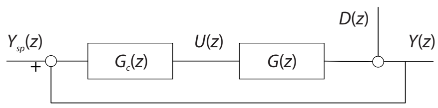

Figure 2. Feedback control system in the internal model control

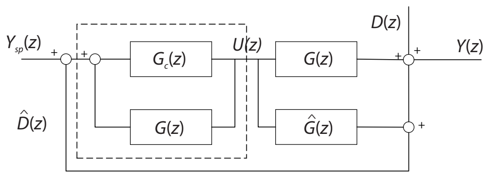

Figure 3. Structure of the internal control system

The feedback system uses the output of the process as feedback, which makes the influence of unmeasurable interference on the output mixed with other factors in the feedback amount. Sometimes, it is submerged without timely compensation. Figure 1 can be transformed into the form of an internal model control system, as shown in fig. 3, where: $G(z)$ is the mathematical model of the object $G(z)$, also known as the internal model. Due to the introduction of the internal model, the feedback has changed from the original full output feedback to the feedback of the disturbance estimator, and the design of the controller has become very easy.

Construction of prediction model: A prediction model that is convenient for describing the dynamic behavior of a process can be obtained through simple experiments, without the systematic identification for the complex operations of such modelling processes. The prediction model is a pre-description of the dynamic characteristics of the system. It predicts the future output value for a limited period based on the historical information and future inputs of the system. Since the predictive control algorithm uses online rolling optimization, during the optimization process, feedback correction is continuously performed through the difference between the actual output of the system and the predicted output of the model. Therefore, model predictive control can somehow overcome the effects of prediction model errors and certain uncertainties, thereby enhancing the robustness of the system. Furthermore, considering the large lag characteristics of the temperature control system, this study uses the single-step prediction and single-step model algorithm control to make the closed-loop prediction output equal to the expected trajectory, thereby obtaining the closed-loop prediction model of the field control layer when the communication channel fails:

$$u(k)=\frac{1}{\hat{h}_1}\left\{y_r(k+1)-\left[y(k)-y_m(k)\right]-\sum_{j=2}^{N}\hat{h}_1 u(k+1-j)\right\} \tag{1}$$

Once the channel failure is detected, the closed-loop prediction model cannot be used. At this time, the open-loop prediction model should be selected. The open-loop prediction model of the management layer can be determined:

$$u(k)=\frac{1}{\hat{h}_j}\left\{y_r(k+1)-\sum_{j=2}^{N}\hat{h}_j u(k+1-j)\right\} \tag{2}$$

where $u(k)$ is the control increment at time k, $y_r(k+1)$ – the reference trajectory at time $k+1$, $y(k)$ – the actual temperature variations measured at time k, $y_m(k)$ – the output value of the fault prediction model at time k, $\hat{h}_j$ – the temperature value collected at the j^{th} time point in the internal model, and $u(k+i-j)$ is the control sequence applied before time k.

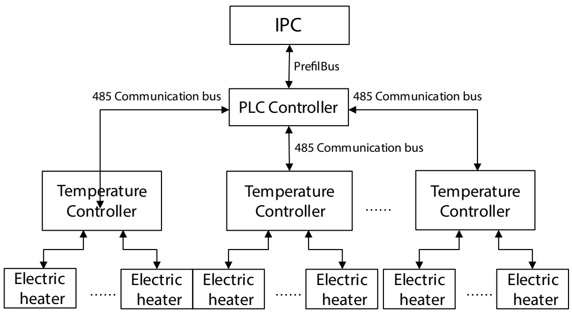

Figure 4. Schematic diagram of the DCS control system for electric heating

Construction of DCS control system for electric heating

The DCS is a microcomputer control system based on centralized control. It has better inclusiveness, effectiveness, and convenience, which is critical for the co-ordinated control of industrial production processes. The core structure of DCS is generally the same. The operator station, engineer station, and on-site I/O control station transmit information through the network, which is the indispensable and important components of the DCS system. Computer networks are equally applicable in the field of electric heating, in which their modular and standardized features can be utilized. The structure of the DCS control system for electric heating is shown in fig. 4.

The electric heating DCS control system includes the industrial control machine and PLC controller located in the control room, and the temperature controller, electric heater, and temperature controller located in each temperature-controlled room. The communication between the industrial control machine and PLC uses the PrefilBus communication bus. The communication between the PLC and the temperature controller uses the 485-communication bus. Each temperature controller is connected to at least one heater.

Fault tolerance rate and fault diagnosis method of DCS control system for electric heating

To achieve a comprehensive evaluation of the DCS control system for electric heating, this study provides a fault diagnosis method for the electric heating DCS control system. The methods are described:
– Whether the detection channel, sensor, communication channel, execution channel, and heater are faulty is detected.
– Whether the detection channel and sensor are faulty is determined based on the temperature value output by the temperature controller.
– Whether the communication channel is faulty is determined based on the delayed query method.

– The unit step disturbance is performed on the fault prediction model, and whether the execution channel and the electric heater are faulty is determined based on the difference between the output variations of the fault prediction model and the actual output variations.

The method of constructing a fault prediction model in this study is divided into two steps:

– Establishing an internal model of a temperature controller to control different numbers of electric heaters.
– Selecting an adapted internal model based on the number of electric heaters controlled by a temperature controller, and building a fault prediction model based on the selected internal model.

The fault detection of the execution channel is divided into the following steps.

– The temperature value of the environment where the temperature control is located is read, which is denoted as the initial temperature value. Then, a given step disturbance signal is sent to the temperature controller.
– The actual temperature variations in certain periods are calculated.
– Given the same initial temperature, the same step disturbance signal is applied to the fault prediction model, and the temperature variations in the same sampling period are output.
– Based on the difference between the predicted output variations and the actual output variations, whether there is a fault in the execution channel is determined, *i. e.*, the difference between the output variations of the fault prediction model and the actual output variations is greater than a threshold. Then, the detection channel is determined to be faulty.

If the temperature controller in the temperature-controlled room controls three electric heaters, the internal model of the three electric heaters controlled by the temperature controller is input into the fault prediction model, and the fault prediction model can be expressed:

$$y_m\left(k+i\right)=\sum_{j=1}^{N}\hat{h}_j u\left(k+i-j\right) \tag{3}$$

where $i = 1, 2, 3, ... P$, N – the truncation step, P – the prediction step, $y_m(k + i)$ – the output value of the prediction model at time $(k + i)$, $\hat{h}_j$ – the temperature value collected at the j^{th} time point in the internal model, and $u(k + 1 - j)$ – the control sequence, including the control amount applied before time k and the control amount to be requested at time k and thereafter. The sum of terms at $i < j$ indicates the prediction of the effect of the input variation sequence before time k on the output. When $i > j$, the sum of terms indicates the prediction of the effect of the future input sequence on the output. For easy application, the fault prediction model can also be re-written as the following incremental form:

$$y_m\left(k+i\right)=y_m\left(k+i-1\right)+\sum_{j=1}^{N}\hat{h}_j\Delta u\left(k+i-j\right) \tag{4}$$

$$\Delta u\left(k+i-j\right)=u\left(k+i-j-\quad\right) \tag{5}$$

For the case where one temperature controller controls multiple heaters, the output variations of the fault prediction model are calculated based on the internal model of the temperature controller controlling all heaters. Since the prediction model is built under the most unfavorable ambient temperature (the location farthest from the heat source), the actual output should generally be higher than the predicted output of the model. The negative difference indicates that the execution channel is faulty; otherwise, the execution channel is normal [13]. However, since the grid voltage may fluctuate downwards and the heater is aging, it is necessary to use thresholds to offset these effects during actual determination. The threshold can be selected as 10% of the temperature variation of the single heater internal model at the same initial temperature and the same sampling period. It can also be set based on field experience, *i. e.*, the difference between the output variations of the fault prediction model and the actual output variations is greater than the threshold, the detection channel is determined to be faulty, otherwise, the detection channel is normal.

Based on the difference between the output variations of the fault prediction model and the actual variations, the number of faults in the execution channel is estimated. If the temperature variation amount output by the fault prediction model is between the temperature variation amount of the internal model corresponding to (N – 1) heaters and the temperature variation amount of the internal model corresponding to N heaters, the number of fault execution channels is M – (N – 1), where M is the number of electric heaters controlled by the temperature controller.

To achieve the aforementioned objectives, this study provides a fault tolerant method for the electric heating DCS control system. The fault tolerant method are:

– Fault tolerant control method when communication channel failure occurs: Based on the closed-loop prediction model of the field control layer, the field temperature is controlled to a given temperature.
– Fault tolerant control method when the detection channel and sensor failures occur: Temperature is controlled based on the open-loop prediction model of the management.
– Fault tolerant control method when the execution channel and electric heater failures occur: The temperature set-point of the normal execution channel is increased. If all execution channels are faulty, the temperature set-point in the adjacent temperature control room is increased.

In this study, the expected trajectory chosen can be expressed:

$$y_r(k+i) = \alpha^i y(k) + (1-\alpha^i) y_{sp}, \quad i = 1, 2, \cdots, p \tag{6}$$

where $y_r(k)$ is the reference trajectory at time k. The objective of predictive control is to make the output variable of the system gradually reach the set value y_{sp} along a predetermined curve. This specified curve is called the reference trajectory $\alpha = \exp(-T/\tau)$, T – the sampling period, τ – the time constant of the reference trajectory, and $y(k)$ – the actual temperature variations measured at k. To offset the model error and other disturbance effects, the closed-loop prediction model can be expressed:

$$y_p(k+1) = y_m(k+1) + h_0\left[y(k) - y_m(k)\right] \tag{7}$$

where h_0 is the weighting coefficient vector, $y(k)$ – the output measurement value of the actual process at time k, $y_m(k)$ – the output value of the prediction model at time k, $y_m(k+1)$ – the output value of the prediction model at time (k + 1), and $y_p(k+1)$ – the output value of the closed-loop prediction model at time (k + 1).

Experimental data collection

In the electric heating DCS control system, it is assumed that a temperature controller controls a maximum of 4 electric heaters. Thus, an internal model of the temperature controller controlling the operation of 4 electric heaters, an internal model of the temperature controller controlling the operation of 3 electric heaters, an internal model of the temperature controller controlling the operation of 2 electric heaters, and an internal model of the temperature controller controlling the operation of 1 electric heater are constructed, respectively. The temperature controller controlling the operation of 4 electric heaters is taken as an example for detailed description, and AC voltage is applied to 4 electric heaters in the offline state. According to the set sampling period, the temperature values of the points are sequentially collected. The collection point refers to the position farthest from the heater to be measured in the room where the heater to be measured is located until the temperature at the collection point reaches a steady-state position.

Results and discussion

Simulation verification results of the DCS algorithm

To show that the effectiveness of the control algorithm can be predicted by using the DCS algorithm module for more complex objects, simulation verification is performed in this study. The non-minimum phase process is also often referred to as a process with inverse response characteristics in process control. This process is characterized by a zero point in the right half-s plane of its transfer function model. To ensure the stability of the closed-loop system while applying the PID controller, it is usually necessary to undertune the controller parameters. While applying the predictive control algorithm, for excellent control performance, the output prediction time-domain must be sufficiently large to include the dynamics after the initial inverse response of the process.

Figure 5 shows the simulation results of the closed-loop control of the predictive control system by using the DCS control algorithm and the conventional PID control algorithm. The setting parameters of the conventional PID controller are $K_P = 0.07$, $T_i = 1$, and $T_d = 0$. Since the two predictive control systems are completely the same, the selection of the system tuning parameters is also completely suppressed, and both are $N_1 = 1$, $N_2 = 20$, and $N_u = 2$. Simulation results show that the performance of predictive control for non-minimum phase process is significantly better than that of conventional PID control.

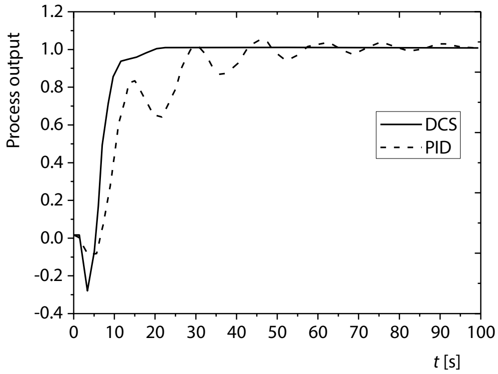

Figure 5. Comparison of prediction system performance based on two control algorithms

Results of stability and robustness tests of DCS control system

The dual stability of internal model control is obtained under the assumption that the object model $G(z)$ is accurate, which is difficult to guarantee in practice. Therefore, when the model and the object are mismatched, even if the object and the internal model controller are stable, the closed-loop system may be unstable. Therefore, how to make the control system robust enough needs to be considered. In the internal model control system, it is realized by adding a filter in front of the controller. When α is zero, *i. e.*, the reference trajectory $y_r = y_{sp}$, the temperature Y in electric heating shows a constant amplitude oscillation at this time, as shown

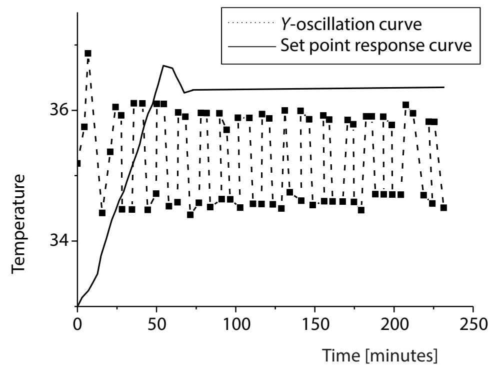

Figure 6. Temperature *Y* oscillation and response curve

in fig. 5 (dotted line). As α increases, the system gradually stabilizes, when α = 0.8, the set-point response curve of the system is shown in fig. 6 (solid line). Therefore, the selection of the reference model plays an essential role in the stability and robustness of the predictive control system. A reasonable selection directly affects the resistance of the system to environmental uncertainty. Generally, a slow response reference trajectory will enhance the robustness of the system.

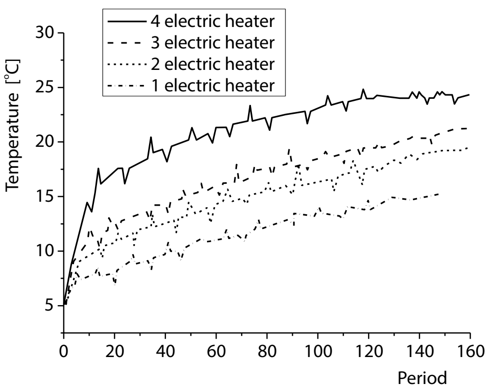

Figure 7. The internal model curve of the temperature controller controlling different numbers of electric heaters

Data collection and model application results

The N temperature values collected at time N constitute the internal model of the electric heater, and the internal model is stored in the form of a table in the database of the industrial controlling computer. In the online state, the industrial controlling computer automatically completes the aforementioned acquisition through a sampling program. The internal model of each electric heater is obtained under the conditions that the test conditions are almost consistent, which can reduce the error of the fault prediction model. Figure 7 illustrates the internal model curve of the temperature controller controlling different numbers of electric heaters.

When a failure occurs in the electric heater or the data transmission channel between the electric heater and the temperature controller in the temperature-controlled room, the control failure increases the temperature given value of the normal supply channel in the temperature-controlled room based on the number of failed execution channels. If all of the execution channels in the temperature-controlled room are faulty, the temperature set-point of the temperature-controlled room adjacent to the temperature-controlled room is increased to increase the temperature of the failure point or the ambient temperature in the temperature-controlled room.

Conclusion

For complex control problems, predictive control technology can provide better control performance than PID control technology. Based on the idea of predictive control, the internal model of step response for each room is obtained online or offline. Then, a prediction model is constructed. The difference between the output variations of the prediction model and the actual output variations is calculated. Compared with the threshold, the working status of the system is determined. In addition the comprehensive analysis of other fault information, the type of faults is determined. Finally, different control strategies are adopted according to the fault types. Furthermore, based on the difference between the output variations of the prediction model and the actual output variations, the number of faults in the execution channel is estimated. For actuator and execution channel failures, the control method based on environmental temperature optimization is adopted to realize failure diagnosis and fault tolerant control, which achieves the reliability and economy of heating through software without adding any hardware resources.

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