

ADVANCED CONTROL DESIGN FOR A HIGH-PRECISION HEATING FURNACE USING COMBINATION OF PI/NEURAL NETWORK

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ABSTRACT

Nowadays, thermal energy plays a very important role in manufacturing as well as daily activities, such as: steaming, drying, pasteurization, sterilization, steel refining, cooking, heating. Day by day, high-accuracy control is required to increase the performance of the thermal applications. However, nonlinear characteristics and high-inertial property are main obstacles in the development of precise controllers. In this paper, we propose an intelligent control scheme to improve the performance of a typical heat furnace. The mathematical model of the plant is first identified based on the experimental data acquired. The controller is then designed with a proportional-integral (PI) regulator and a neural-network-based adjustor. The linear control term is employed to ensure the excellent steady-state behavior while the intelligent control signal is worked as a feed-forward predictor to maintain the acceptable transient performance. The PI control gains are obtained using an auto-tuning toolbox. A nonlinear updating method is developed to increase the learning speed of the network. Effectiveness and feasibility of the proposed controller are confirmed both by simulation and real-time experimental results.

Keywords: Heating System; PI; Feed-Forward Control; Neural Network; Nonlinear Learning.

1. INTRODUCTION AND MAP OF CONTROL

The temperature of heating furnaces is a key control parameter in many industrial applications, such as processes of food, pharmacy, and chemical manufacturing. In fact, it is not easy to obtain high-product values because of the existence of nonlinearities, interferences and dead-time phenomena inside the system dynamics. So far, there are many control methods employed for temperature control. One of them, the basic technique is the ON-OFF controller [1] which could be set up easily by simple hardware such as relay systems. Optimal approaches [1]-[2] were then considered to improve the control quality of the ON-OFF controllers. However, oscillation on the control result is the main problem of such control technologies. Nowadays, Proportional-Integral-Derivative (PID) controllers are widely used in the industry. Obviously, it is also applied for

temperature control from simple applications to complex systems [3]-[5]. There are different techniques that have been combined with the PID controller to yield better results like fuzzy based [4] and neural-network-based PID [5], etc. Moreover, several advanced research have been studied to increase the applicability of the PID control using adaptive approaches [6], [7]. The core advantage of these controllers is model-free and strong robustness. Since their working principles are mainly based on the control error accumulated, the transient performance might be difficult to maintain.

As a result, in this paper, we propose a predictor-based controller to effectively provide good control quality in both transient and steady-state performance. The controller is structured from a PI control term and neural-network-based feedforward control term that is trained offline from an experimental data set. The neural network is used to predict the equivalent control signals

based on setpoint values given while the PI signal is used to refine the control accuracy in the steady-state phase. Effectiveness of the proposed controller was successfully validated in a real-time system.

Remaining of the paper is organized as follows: the experimental test-rig and procedure to determine its transfer function is presented in Section 2; the proposed controller is designed in Section 3 while the experimental validation is discussed in Section 4; finally, the paper is concluded in Section 5.

2. DESCRIPTION OF THE EXPERIMENTAL SYSTEM

In this section, the setup of the testing system is introduced, and its transfer function is identified to provide the material for the controller design.

2.1 Experimental Setup

The thermal furnace used is a closed system consisting of three main components: Outside of the furnace was built up by heat-resistant bricks that could work well up to more than 1000 Celsius degrees; the inside was heated by a thermistor wire with a small resistor of about 40 Ohm. A three-wire PT100 sensor was set up to measure the working temperature. The system also contains a power system (single-phase SSR, 4-20mA transmitter) and electrical controller (PLC S7-1200). Schematics of the control system is illustrated in Fig. 1.

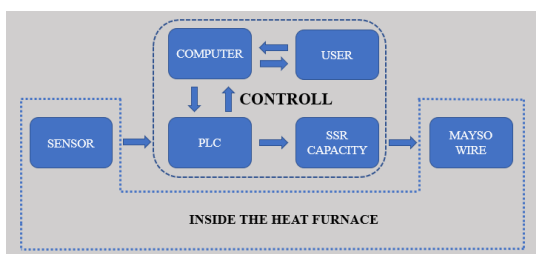


Fig. 1 Configuration of the experimental system

2.2 Transfer Function of the Furnace

Behavior of the furnace could be represented by an approximation transfer function that is possible to be determined by experimental methods. The procedure was

that supplying the maximum heat to the system (input power $P = 100\%$) [8]-[11], its temperature gradually increases and reaches a certain value after a certain time. The real-time data were collected through OPC toolbox on Matlab and PLC using the diagram depicted in Fig. 2.

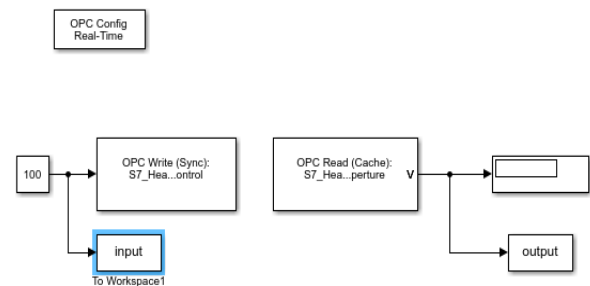


Fig.2 Data-acquisition model in Matlab

An identification toolbox in Matlab was then adopted to explore the system characteristics. The transfer function obtained is presented in Eq. (1) while the identification results are shown in Fig. 3.

$$G(s) = \frac{Y(s)}{U(s)} = \frac{0.7554s + 0.02502}{s^2 + 0.03249s + 4.975 \times 10^{-5}} \quad (1)$$

where $y(t)$ is the temperature ($^{\circ}\text{C}$) inside the furnace and u is a percentage (%) of the input power.

The identification performance is provided in Fig. 3. The result showed that the approximation was well carried out in which the fitness between the acquisition and identified data was accomplished up to 95.57%.

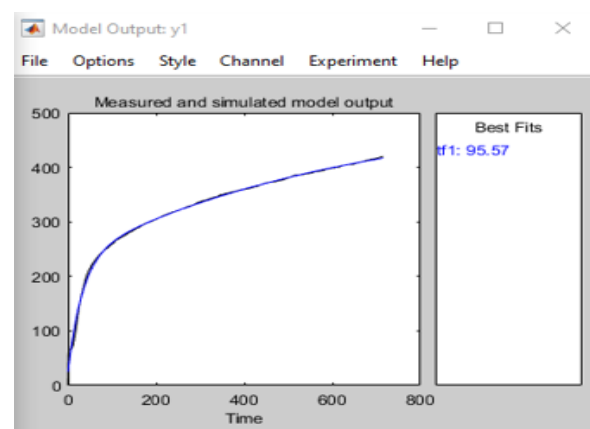


Fig.3 Best fits between real-time data and simulation data of transfer function estimated

3. CONTROLLER DESIGN

The controller proposed includes a PI control term and feed-forward neural-network term to ensure the control performance both in transient and steady-state phases.

3.1 Sub-optimal PI Control

The PI controller is a special case of the PID controller. It is applied a lot in automatic control systems thanks to the easy programming, and acceptable performance obtained [12]-[13], Mathematical description of the PI controller is expressed as:

$$u = K_p e + K_i \int_0^t e d\tau \quad (2)$$

where $e = y_d - y$ is the control error between the desired signal (y_d) and the system output (y). The K_p and K_i parameters could be tuned through the operation of the system based on the operator's experience.

However, for a system that is defined by an explicit transfer function such as the heat furnace used, it is possible to use a PI tuning Toolbox in Matlab to detect the K_p and K_i parameters. The tuning system is set up as displayed in Fig. 4. By manually choosing set time and overshoot as the desired criterions for the closed-loop system, the most appropriate tuning result obtained is plotted in Fig. 5. The best parameters are $K_p = 0.0005600673983$; $K_i = 3.9323499398e-05$.



Fig.4 Tuning model for PI controller

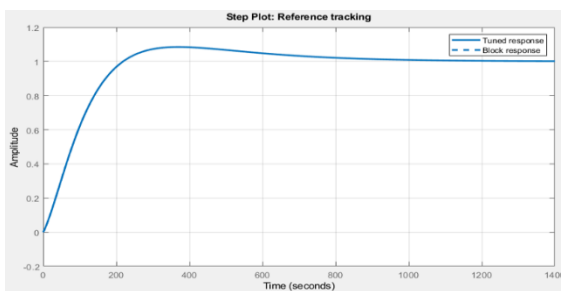


Fig.5 Tuning data obtained using an automatic tuning PID Toolbox in Matlab

The tuning process of the PI controller is constrained by a trade-off between a small steady-state control error, settling time, and reasonable overshoot. The high control accuracy is chosen to be the most priority in this adjustment phase.

It means that an optimal control signal is required to combine with the PI signal for enhancing the other two indicators.

3.2 Feedforward Neural-network Control

We propose a feed-forward predictor that generates an equivalent control signal relying on setpoint information. The signal would drive the system to the desired position as fast as possible. Obviously, we can consider the feed-forward term as the inverse model of the furnace system. However, in practice, nonlinear models of the system may be difficult to drive or inverse. Therefore, to overcome this drawback, a neural network could be an understandable solution of the feed-forward term based on the transfer function approximated in Section 2.2. Structure of the network is presented in Fig. 6. Its input signal is the set of temperature (y), the previous measurement of the control signal (u_{-1}), and bias, while the output is the current control signal (u). It has one neuron in the hidden layer. Forward propagation of the network is as follows:

$$u = v^T P x \quad (3)$$

where $x = [u_{-1}; y; y_{-1}; y_{-2}; -1]^T$ is the input vector, $P = \text{diag}(p)$ is an input-gain matrix, and $v \in R^5$ is the weight vector of the hidden layer.

The learning law of the weight vector is derived using the back-propagation algorithm [14]-[16] with the following modification:

$$v(k) = v(k-1) - \alpha (e_{NN} + \tanh(e_{NN})) P x \quad (4)$$

where $e_{NN} = u - u_d$ is the estimation error, k is the step learning time, α is a constant.

The neural-network sub-controller needs to be trained before applying to control the

system. Real-time data of several experiments with the PI controller were collected. Note that the more control data is acquired, the higher accuracy of the training is accomplished.

In fact, during operation of the heating furnace we found that the difficulty in controlling the system came not only from the high inertia but also from other nonlinear uncertainties such as the thermal absorption of the furnace wall. To effectively deal with this problem, a combination of the Feed-Forward neural-network and sub-optimal PI control terms is employed. The task of the PI controller is to adjust the control signal more smoothly around the value (u_{NN}) that is generated by the Feed-Forward controller. When working in the control mode, the input vector (x) of the network is synthesized from the desired setpoint (y_d) and the previous total control signal (u_{-1}).

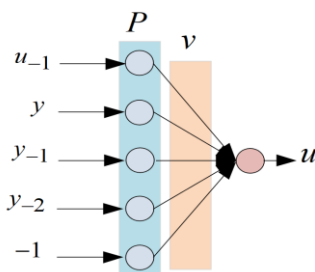


Fig. 6 Structure of the adopted neural network

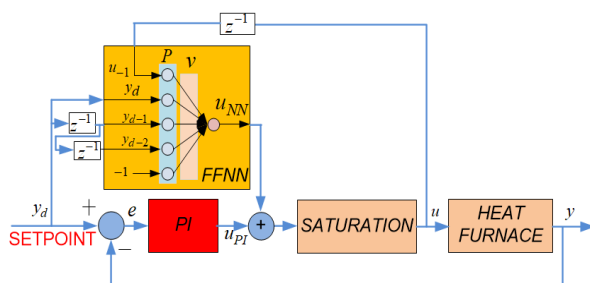


Fig. 7 Control diagram of the PI-Feedforward-Neural-Network controller.

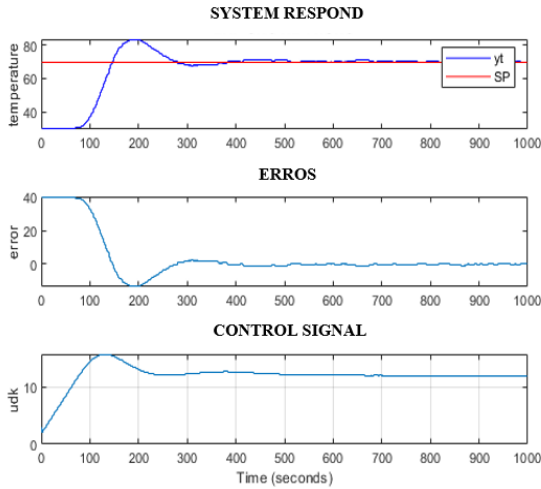
Diagram of the proposed controller is illustrated in **Fig. 7**. The weight vectors of the input and hidden layers were tuned as follows:

$$\begin{cases} p = [0.1; 0.005; 0.005; 0.005; 1] \\ v = [0.9488; 0.2584; 0.2585; 0.2586; 0.6238] \end{cases}$$

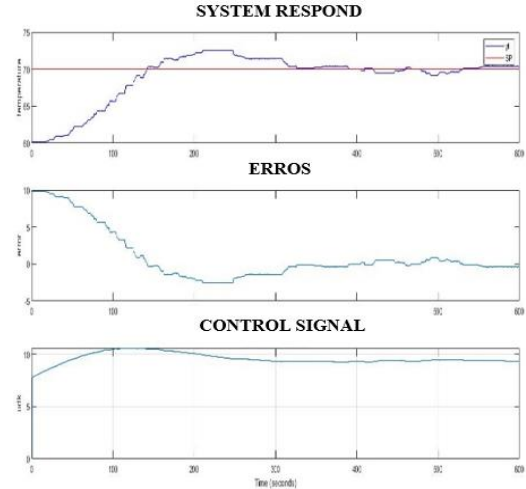
4. EXPERIMENTAL VALIDATION

We performed real-time experiments to verify the performance of the designed controller. To clearly evaluate the effectiveness of the proposed control method, a standalone optimal PI controller that is tuned using the MATLAB Toolbox was applied for the same system under the same working conditions. The system responses of the comparative controllers in the experiments are plotted in **Figs. 8** and **9**.

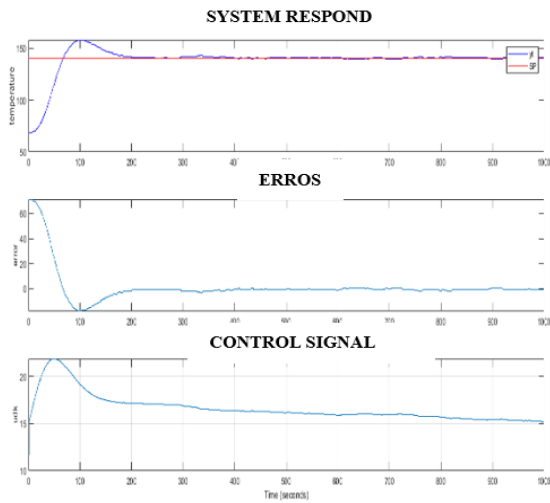
It can be seen that the PI controllers provided high control accuracy (about 1.5°C) in infinite time. However, the overshoot and transient time are still large. Meanwhile, as shown in **Fig. 9**, the performance of the control system is really improved by using the proposed controller. At the setpoint of 70°C degrees, the comparison results show that the overshoot (4.28%) of the designed controller is smaller than that of the PI controller (18.5%). The rise time is relatively equal, but the steady-state time and error variation of the PI-feedforward controller are respectively 100 seconds faster and more stable than those of the PI controller. With the tests of higher temperatures (140°C degrees, 290°C degrees), the results also confirm the superior performance of the proposed control approach over the benchmarking controller. Statistics computation of the control performance provided by the two controllers is summarized in **Table 1**.



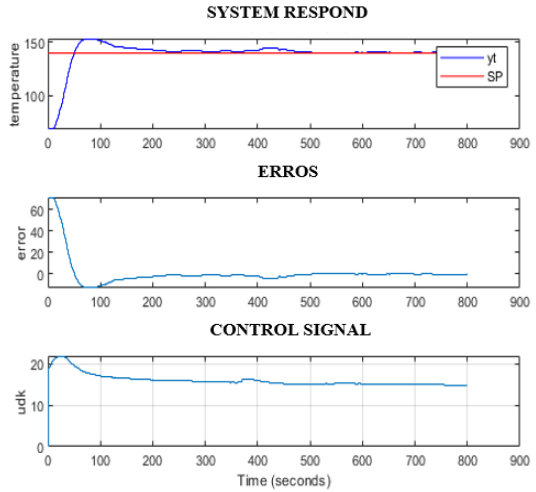
a) Control results for the setpoints of 70°C.



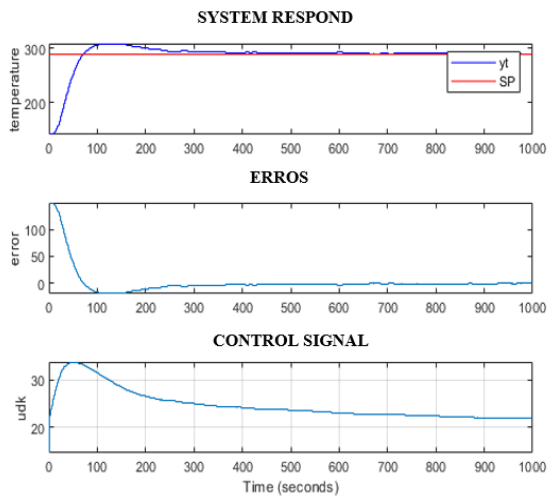
a) Control results for the setpoints of 70°C.



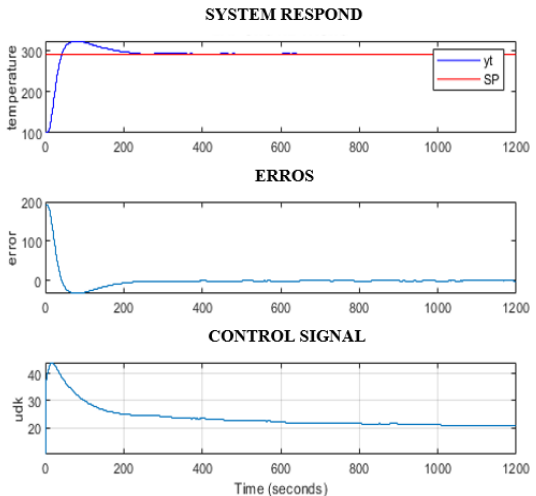
b) Control results for the setpoints of 140°C.



b) Control results for the setpoints of 140°C.



c) Control results for the setpoints of 290°C.



c) Control results for the setpoints of 290°C.

Fig. 8 Performance of the optimal PI controller for three different setpoints.

Fig. 9 Performance of the proposed controller for three different setpoints.

Table 1. Comparison of statistics performance of the two controllers

Criterion	Setpoints					
	70		140		270	
	PI	FF	PI	FF	PI	FF
Overshoot (%)	18.5	4.28	12.8	9.28	11.3	11.5
Time raise (s)	145	140	62	50	70	45
Stability time (s)	360	260	460	470	650	640
Error in percent (%)	1.07	0.92	0.89	0.68	0.43	0.26
Error in medium (%)	0.75	0.65	1.25	0.95	1.25	0.775
Highest error (%)	1.5	0.8	2	1.4	1.5	1.75
Oscillation error (%)	0-1.5	0.5-0.8	0-2	0.5-1.4	0-1.5	0.75-0.8

5. CONCLUSION

This paper presents a new suboptimal intelligent controller for a thermal furnace. The mathematical model of the system is exactly derived using an identification Toolbox supported by Matlab applied to real-

time experimental data. A suboptimal PI controller is employed to maintain excellent steady-state control error while a neural-network is designed as a feed-forward predictor to improve the transient response. The adaptation law of the network is modified to speed up the learning performance. The network is trained offline also based on another series of experimental data. Effectiveness of the proposed controller is validated in real-time tests in comparison with a standalone optimal PI controller. The results obtained reveal that the control performance of the proposed controller is better than that of previous ones in terms of overshoot, rising time, settling time and accuracy.

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