

Study of designing regulator for temperature electrical resistance furnace using Kalman stochastic reconstructor

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ABSTRACT

Electric resistance furnaces are the most popular and widely used industrial electro thermal equipment which continues to be the subject of many improvements. The aim of this paper is to control the temperature of electrical furnace for noisy thermocouple sensors. It can be assessed by observing some variables, which are very difficult to observe. Due to limitations, mainly the location of thermal sensors and their noises. In this case, the temperature measurement is trained with centered Gaussian white noise. The problem of accurate temperatures estimation for such sensors is solved using Kalman filter, which is an optimized estimator that provides a computationally efficient way to estimate system state. Thus, variables that are not directly measurable can be reconstructed from the algorithm. Kalman stochastic reconstructor (KSR). We cannot use with fixed parameters to control the temperature. For this reason, this paper comes up with a KSR approach based pole placement (PL) hybrid controller to realize an algorithm for the temperature control electrical furnace. Results based on MATLAB simulation show that the improved algorithm has well produced an optimal estimate of the temperature. Evolving over time from noisy measurements. Hybrid algorithm KSR approach based PL give good performance compared to PL controllers.

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1. INTRODUCTION

In order to Save and manage energy consumption in a rational way, a lot of research is activity is currently focused on energy management systems. Knowledge of the thermal behavior of resistance furnaces is the most well-known and widespread industrial electro thermal equipment. Controlling the electric resistance furnace is a key point [1]-[11]. Most electric resistances furnaces use a thermocouple as a temperature sensor for the controller. The temperature controller then regulates the temperature fixed at the set point. Most of the time these thermocouple sensors are influenced by some issues like: the sensitivity to noise coming from the neighborhood. Such as metrological characteristics (MCs) of measuring instruments (MI) describe the properties that influence a measurand's estimate and the error (uncertainty) of that estimate, including environmental uncertainty, process variance. Also the location of thermal sensors and high level of noise. Are becoming increasingly complex. For resolving complicated problems measuring temperature for electric resistance furnace [1]-[4]. Thus, variables that are not directly measurable can be reconstructed from the algorithm Kalman stochastic reconstructor (KSR).

The KSR algorithm generates an ideal estimate of the temperatures for an electric resistance furnace while reducing the uncertainty in temperature prediction. Some contributions cover the operation of the Kalman stochastic reconstructor (KSR) [12]-[23]. For a wide range of situations and for an even larger class, the KSR is the best (optimal) estimate can be divided into two steps.

The first step in predicting the estimation according to the electrical resistance furnace model. To do this, the Kalman filter takes the previous estimate of parameters and errors and predicts the new parameters and errors based on the electrical resistance furnace model. The second step [24]-[28] will update this prediction with the new measures. These measurements (by definition noisy) will allow obtaining an estimate of the parameters and the error from the prediction made. If there are errors in the electrical resistance furnace model this update step will correct them.

Using KSR algorithm-based pole placement (PL) controller of accurately estimating temperatures, electrical resistance furnace for noisy thermal sensors is solved in this paper the process model is not precisely known and the temperature measurement is trained with centered Gaussian white noise. The estimation of the temperature of the electric resistance furnace is based on the Hybrid intelligent controller algorithm KSR, which method is based on the pole placement finally results demonstrate the performance of the proposed controller designed. The paper is organized in four sections the following section presents the research method. Section 3 algorithm and section 4 draws some conclusions.

2. RESEARCH METHOD

2.1. Furnace system models

As illustrated in Figure 1, the heat inside the electric resistance furnace is produced by a heating resistor controlled via V_c voltage by a power amplifier. The temperature measurement is done from a thermocouple placed in a measuring cavity. An instrumentation amplifier producing a voltage V_m , image of the temperature θ_m . The sensor and instrumentation amplifier set is supposed to be linear in the furnace temperature range. As reported in [1]-[3].

The mathematical modeling of electrical furnace and the model parameters of the furnace. According [1]-[3]. The electric furnace behaves like a first order process with a time constant close to 500 seconds. In open loop the measured temperature θ_m is very close to the furnace temperature θ_a during the transient regime. They are, of course, confused under a permanent regime. Since the time constant of the process is about 500 s large. The electrical furnace is discredited with a sampling period of 0.95 seconds.

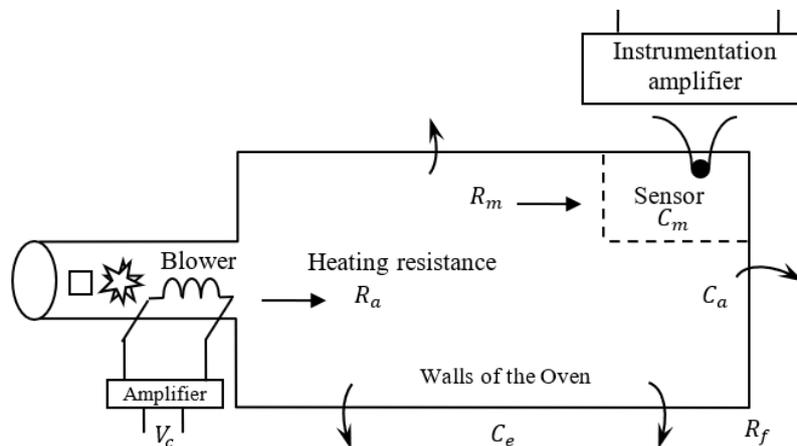


Figure 1. Electrical resistance furnace [1], [2]

2.2. Discrete state representation of the electrical furnace resistance

The mathematical model of electric resistance furnace is being represented in the state space as reported in [1]-[3]:

$$\begin{bmatrix} \dot{x}_1(t) \\ \dot{x}_2(t) \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ -6.6667 \times 10^{-5} & -0.03333 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} + \begin{bmatrix} 0 \\ -6.6667 \times 10^{-5} \end{bmatrix} V_c \tag{1}$$

$$y(t) = V_m = [1 \ 0] \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \tag{2}$$

The pole placement technique is used [1]-[4] to calculate the gains associated with the state vector in this section. For calculating the gains associated with the state vector. Also it is necessary to include a discrete integrator Figure 2. We have chosen for the electric resistance furnace a second order dynamic with ($W_n = 0.005 \text{ rd / s}$ and $\xi = 0.009$). The corrected furnace's functional diagram has changed Figure 2. Where:

$$\begin{cases} u(k) = -Kx(k) + g\varepsilon(k) \\ \varepsilon(k) = \frac{1}{1-z^{-1}}(y_c(k) - y(k)) \end{cases} \tag{3}$$

At a unit step, the system's response becomes.

$$\begin{cases} y_c(t) = 1 \\ y(\infty) = y_c(\infty) = 1 \end{cases} \tag{4}$$

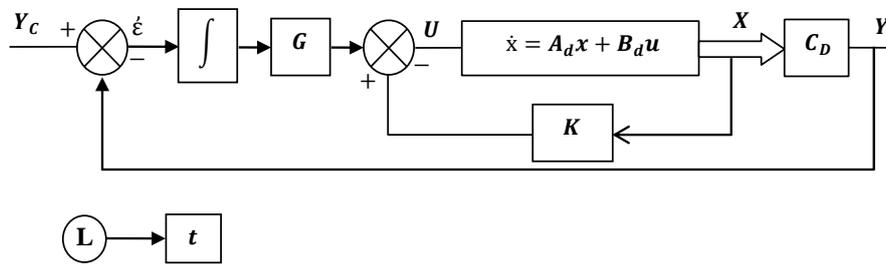


Figure 2. Pole placement control system with integration [1], [2]

The state matrices of the systems are obtained. For the controlled Placement of the poles with the Integrator [1]-[4] for the control electric resistance furnace.

$$A_1 = \begin{bmatrix} A_d & 0 \\ -C_d A_d & 1 \end{bmatrix}, B_1 = \begin{bmatrix} B_d \\ -C_d B_d \end{bmatrix} \text{ and } C_1 = [1 \ 0 \ 0] \tag{5}$$

and the state returns vector with integration.

$$K_1 = [-K \ g] \tag{6}$$

After Somme calculations we obtain.

$$A_1 = \begin{bmatrix} 1.0000 & 0.9351 & 0 \\ -0.0001 & 0.9688 & 0 \\ -1.0000 & -0.9351 & 1.0000 \end{bmatrix}, B_1 = \begin{bmatrix} -0.2977 \times 10^{-4} \\ -0.6234 \times 10^{-4} \\ 0.2977 \times 10^{-4} \end{bmatrix}, D_1 = [0], C_1 = [1 \ 0 \ 0]$$

and

$$K = [-0.0143 \times 10^{-4} \quad -1.5608 \times 10^{-4} \quad 0.0000 \times 10^{-4}]$$

For Figure 3, the applied set point corresponding to a temperature of 100°C followed by a decreasing linear set point. The response to the step is without overshoot and without static error due to the Integrator. Note that the ramp set point deduces tracking error. To cancel the tracking error, a second of integration is required. In the Figure 4 heat quantity for a set point temperature of 100°C.

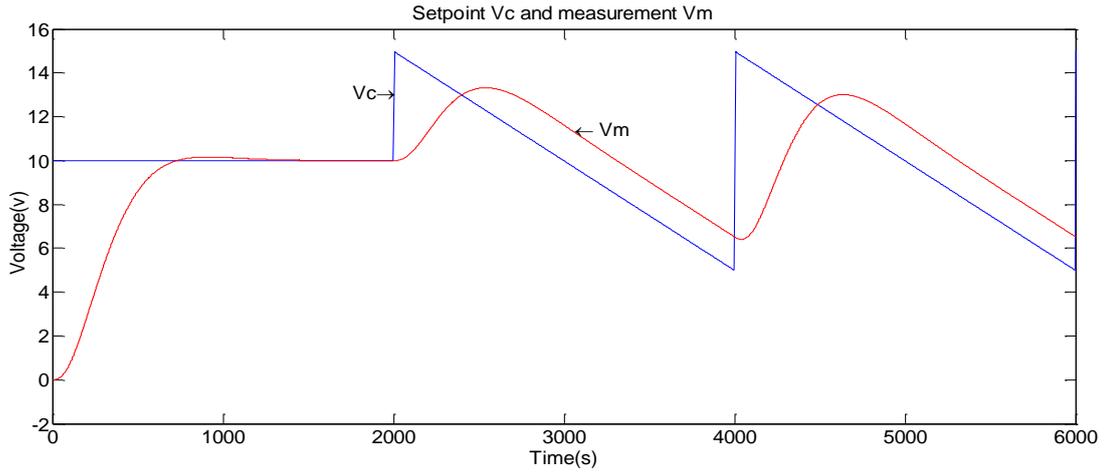


Figure 3. Pole placement with state integration controller for measurement V_m

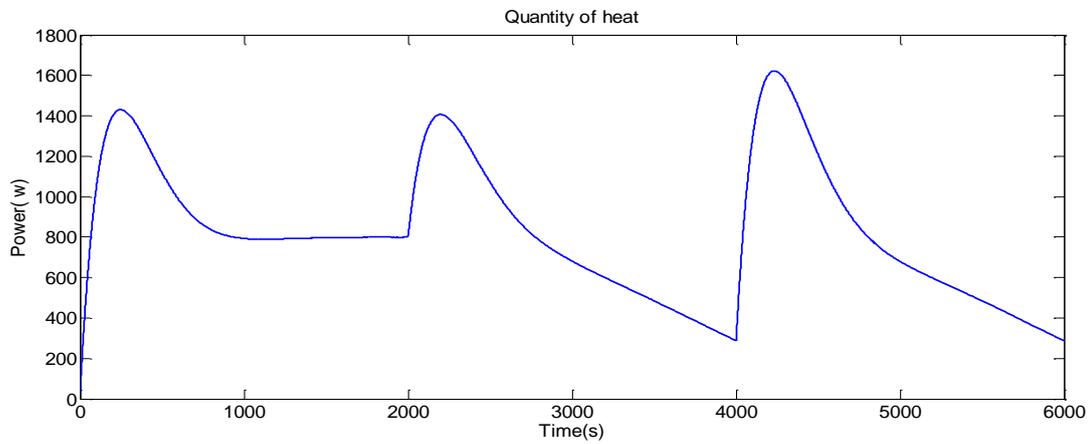


Figure 4. Heat quantity for a set point temperature of 100 °C

3. ALGORITHM

3.1. Development of the discrete kalman filter algorithm

State modeling of the electrical furnace resistance takes into account two random variables Noise of process and measurement [1]-[3]. In this case, the temperature measurement is trained with centered Gaussian white noise. We consider that the system of electrical furnace resistance is stationary. Two equations are used to explain the discrete state model of a resistance electric furnace.

a) The process equation

$$x(k + 1) = A_d x(k) + B_d u(k) + w(k) \tag{7}$$

where $w(k)$ is the modeling noise [1] and [2] related to the uncertainty that we have on the model of the electric resistance furnace.

$$\begin{cases} E[w(k)] = 0 \\ E[w(k)w^T(k + n)] = Q \end{cases} \tag{8}$$

The variance matrix of $w(k)$ is Q [1] and [2].

$$Q = \sigma^2 w = c^{te} \tag{9}$$

b) The measurement equation

$$y(k) = Cx(k) + v(k) \quad (10)$$

where $v(t)$ is the measurement noise [1] and [2].

$$\begin{cases} E[v(k)] = 0 \\ E[v(k)v^T(k+n)] = R \end{cases} \quad (11)$$

The variance matrix of $v(k)$ is R [1] and [2].

$$R = \sigma^2 v = c^{te} \quad (12)$$

c) Estimation of the state of the electric resistance furnace

This estimate is constituted by two following step as the following drawing shows in Figure 5. A step in the evolution of the state of the process between 2 sampling times. This step is called Time Update ("Predict, discrete-time (k-1)"). The state of the process evolves according to the following equation.

$$\hat{x}(k/k-1) = A_d \hat{x}(k-1) + B_d u(k-1) \quad (13)$$

During this phase located between discrete-time $(k-1)T_e$ and discrete-time kT_e , there is an increase in the variance of the estimation error $P(k/k-1)$.

$$P(k/k-1) = E([x(k) - \hat{x}(k/k-1)][x(k) - \hat{x}(k/k-1)]^T) \quad (14)$$

$$P(k/k-1) = A_d P(k-1/k-1) A_d^T + Q \quad (15)$$

A step to update the state of the process at the time t following the acquisition of $y(k)$. This step is called measurement Update ("Correct, discrete-time k"), it is described by the following equations.

$$\hat{x}(k/k) = \hat{x}(k/k-1) + L(k)[y(k) - C_d \hat{x}(k/k-1)] \quad (16)$$

With $L(k)$ is filter adaptation gain matrix.

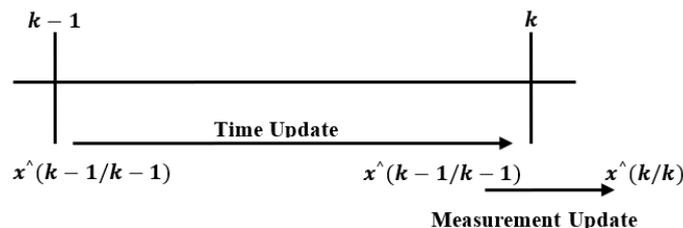


Figure 5. Two following step

During this step, there is a decrease in the variance of the error due to the information provided by the measurement of $y(k)$

$$P(k/k) = P(k/k-1) - P(k/k-1)C_d^T [R + CP(k/k-1)C_d^T]^{-1} CP(k/k-1) \quad (17)$$

The gain is updated using the following formula.

$$L(k) = P(k/k-1)C_d^T + [R + C_d P(k/k-1)C_d^T]^{-1} \quad (18)$$

There are two phases to the Kalman filters. Time update equations, as predictor equations, are responsible for projecting the current state and error covariance estimates forward (in time) in order to obtain an a priori estimate for the next time stage, while measurement update equations, as corrector equations, are responsible for correcting the current state and error covariance estimates [18]-[25], [27]. We can deduce that the final estimation technique in Figure 6 is similar to a hybrid predictor-corrector approach for algorithm for solving complex problems for temperature electrical furnace.

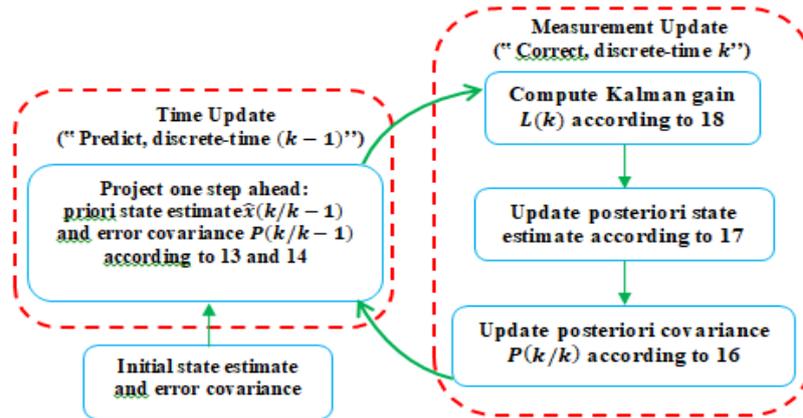


Figure 6. Algorithm with a hybrid predictor-corrector

3.2. Discussion

The Kalman filter algorithm provides [23], [26], [29]. An effective temperature estimate for an electrical furnace thus minimizing the uncertainty in temperature prediction. The temperature measurement is tainted with white Gaussian noise and centered [1]-[3] in this case the state of the Electrical resistance furnace can be reconstructed using KSR. The Kalman function makes it possible to obtain the observer's gain vector from the process description of the variance of the noise of the process Q and the variance of the measurement noise R. We take for our application,

$$\begin{cases} [vv^T] = R = 0.08 \\ [ww^T] = Q = 0.08 \end{cases} \tag{19}$$

In order to determine the gain vector of the Kalman.

$$P = \begin{bmatrix} 0.7778 \times 10^{-4} & 0.0003 \times 10^{-4} \\ 0.0003 \times 10^{-4} & 0.0001 \times 10^{-4} \end{bmatrix} \quad \text{and} \quad L = \begin{bmatrix} 0.7774 \times 10^{-3} \\ 0.0003 \times 10^{-3} \end{bmatrix}$$

The Simulink model of Kalman stochastic reconstructor using P L controller for the temperature electric furnace shown in Figure 7.

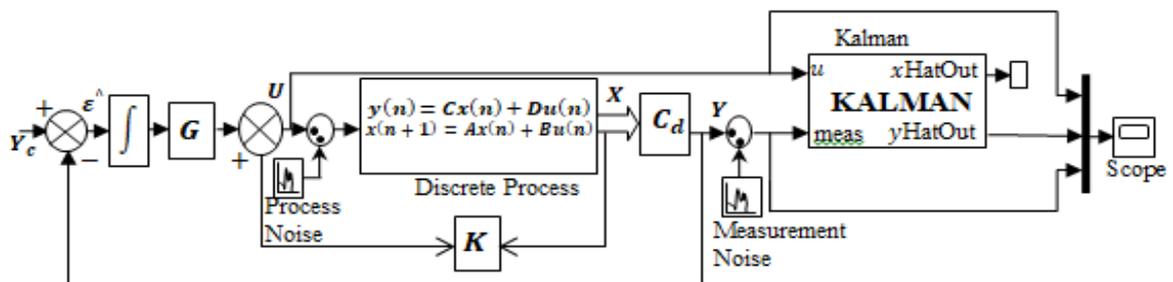


Figure 7. Response of Kalman stochastic reconstructor using PL controller [1], [2]

The efficiency of the stochastic reconstructor appears clearly on the comparison of the estimated variance, cleaned [28]-[30]. Of modeling and measurement noises, with the strongly noisy signal Vm. Figure 8 shows Rebuilt vector stochastic reconstructor without noise for system output. And Figure 9 shows the quantity of heat estimated with Kalman filter with noise. The performance of the estimation of the X1 and X2 states of the temperature of the electric furnace using the KSR has been illustrated by Figure 10. The presented algorithm can provide good performance for estimating the state of the system subjected to Gaussian noise.

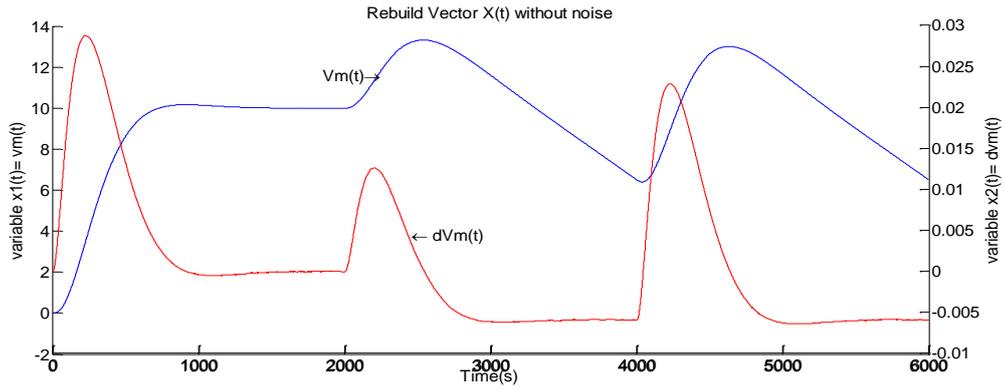


Figure 8. Rebuilt vector kalaman filter without noise

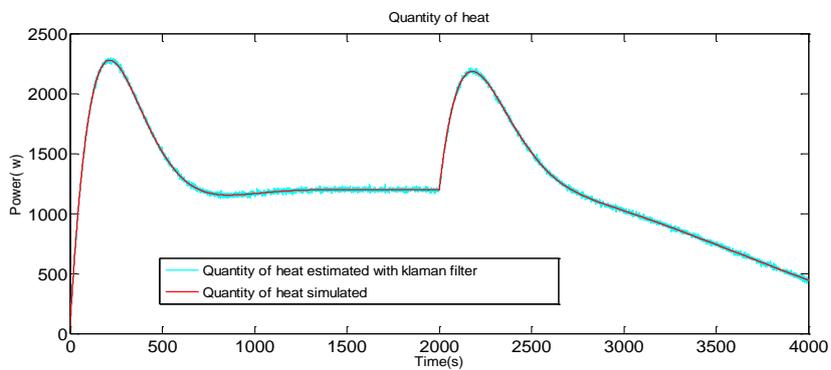


Figure 9. Quantity of heat estimated with Kalaman filter with noise

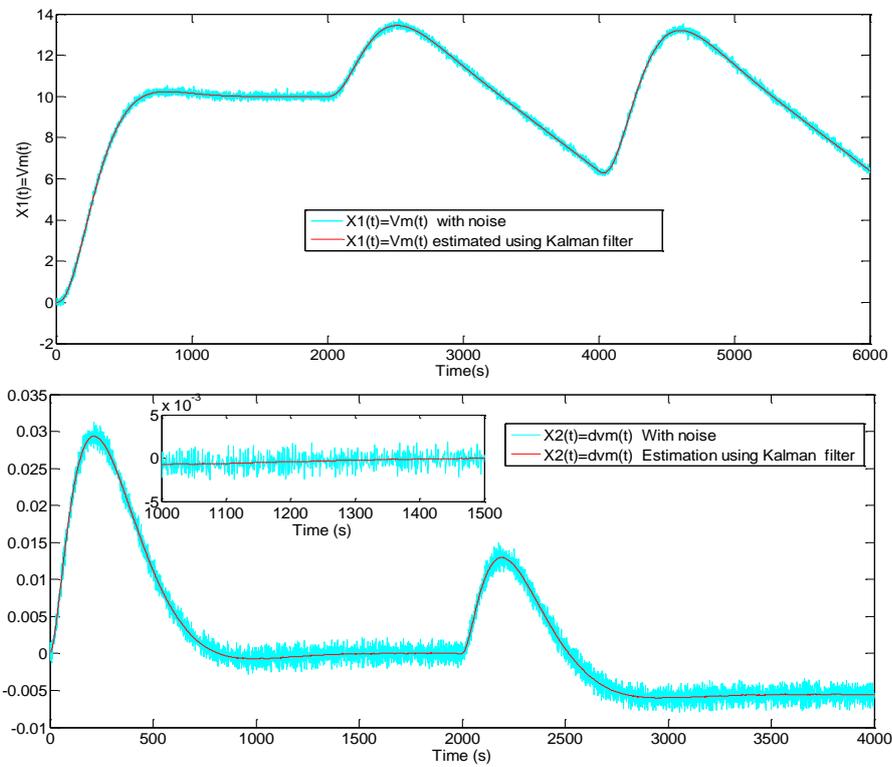


Figure 10. Estimation temperature electrical furnace using Kalman filter

By MATLAB simulation, we can get the response temperature of the PL controller for the temperature electric furnace. Shown as Figure 11 red curve that the overshoot of temperature electrical furnace resistance response curve is large and the adjustment time is longer. In order to reduce the overshoot and to improve the control effect Temperature response. Of electrical resistance furnace, both KSR and P L are combined to control the temperature electrical furnace. Based on simulation MATLAB shown in Figure 11. Blue curve, we see that the performance of the temperature electrical resistance furnace from the point of view overshoot, response time improved, and good robustness. The obtained results by simulation show that this combination between KSR and PL controller possesses better performance compared to the conventional PL controller and which can be a promising solution for such complex system in industrial applications.

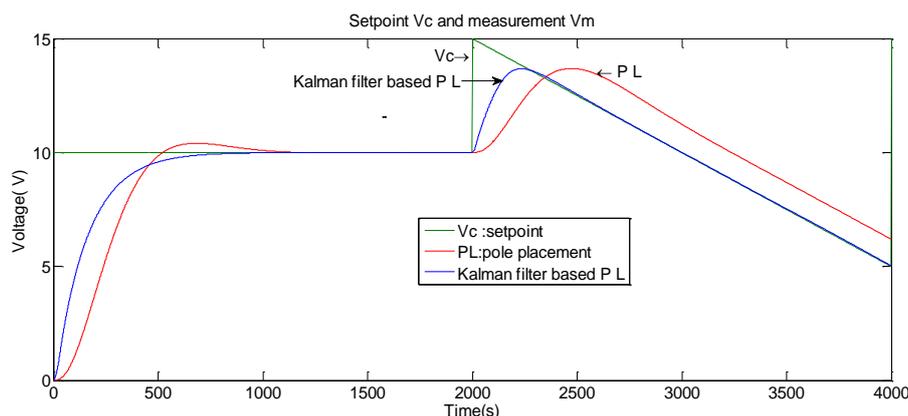


Figure 11. Temperature response curve based KSR using PL controller

4. CONCLUSION

The objective of the proposed work is to ensure the control of the temperature of the electric resistance furnaces. It is obvious that this kind of system has very slow dynamics and most of the time the process model describing this system is not precisely known. On the other side, its temperature measurement is subject to a centered Gaussian white noise. However, to ensure accurate temperature measurements it is necessary to get information of some system states that cannot be obtained by direct measurements which makes the temperature control a complex problem. In this paper, an estimator based on Kalman stochastic reconstructor (KSR) that is capable of delivering the estimation of the unmeasured system state based on the available information is proposed. It is worthy the mention that to ensure the control of the temperature a controller based on PL is used. Furthermore, a hybrid algorithm intelligent controller is proposed and designed in this paper based on the combination of traditional PL approach and KSP technique, where the main aim is to ensure the control the temperature of the studied electric resistance furnaces. The results based on MATLAB simulation show that the KSR based PL controller is better than the PL control method.

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