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Application of Adaptive Controller Neural Network Based on RBF NN for Temperature Control Electrical Resistance Furnace

***Abstract**. In order to solve the problem for temperature electrical resistance furnace. Characterized by their large inertia, nonlinear, long time delay and time-varying property it is rather difficult to obtain satisfactory control results with Performances of conventional PI control cannot achieve good control effect. In this paper a neural network-based adaptive control approach (ACNN) for electrical furnace is developed .using RBF NN to estimate the unknown functions by neural networks and from good choice of the law of adaptation. Based on the resolution of the lyapunov equation. Taking account of all possible parameter variations the adaptive control is designed so that it has the ability to improve the performance of the closed loop system, producing the control signal by using the information from the system. In this case we use a coping mechanism that observes the signal to control and adjust the synaptic weights of neural networks when system parameters change over time. Result shows that the proposed algorithm (ACNN) performs very well when furnace parameter varies the latter allow the neural model to be identified online and, if necessary its parameters to be stabilized and it is very easy to program it online.*

Streszczenie.** Piec elektryczny charakteryzuje się nieliniowością, dużym czasem opóźnienia co utrudnia sterowanie nime. W pracy zaproponowano system sterowania piecem z wykorzystaniem sieci neuronowej System jest zaprojektowany tak, że uwzględnia zmiany parametrów. **Zastosowanie sterowania adaptacyjnego bazującego na sieci neuronowej do kontroli temperatury pieca elektrycznego.

Keywords: Electric Resistance Furnace, Integral Control with Compensation Poles and Zeros, Online Learning, Inverse Neural Model Control, Model Reference Adaptive Control and Neural Network
Słowakluczowe: piec elektryczny, sieć neuronowa, sterowanie temperaturą .

Introduction

Conventional controllers Integral (PI) are not suitable for thermal processes. They are designed for linear processes without delay. And the rise in consecutive temperature of the load makes the furnace Almost nonlinear system. For this reason. New methods have recently appeared to furnace temperature control of different kinds of furnace, for example [1, 2, 3, 4, 5, 6, 7, 8, and 9].These methods, which are oriented towards identification and regulation, are based on neural network theory. The progress of research in the field of neural networks has proven the capacity and power of the neural model in neural identification (learning) complex processes. Several researchers use this learning power to represent the dynamics of these processes. Indeed, neural networks are capable of to approximate, with a fixed arbitrary degree of precision, any dynamic of a process to. The construction of electric furnace temperature control system is shown in Figure 1.The heat [1 2] inside the furnace ventilated model, is produced by resistance heating, controlled by a voltage V_c power amplifier Measuring The temperature measurement is made from a thermocouple placed in a cavity measurement and instrumentation amplifier producing a voltage V_m image of the θ_m . Overall +sensor instrumentation amplifier are supposed linear in the range of temperature oven power.

$Q = k_1 v_c$: Quantity of heat produced

θ_m : Temperature measured his image is tension V_m ($V_m = k_2\theta_m$).

In this paper, adaptive control approach (NNAC) for electrical furnace is proposed .A Simulations indicate that it is more steady and strong applicability than traditional PI.

Advanced searches in the area of neural networks have proven the capacity and power of these new approaches in the control systems whose dynamics are unknown or poorly modelled through identification techniques (learning).Many researchers[10, 11, 12, 13 14] using this learning power to represent the system dynamics. The problem of neural control is based on the result that neural networks are universal approximators.

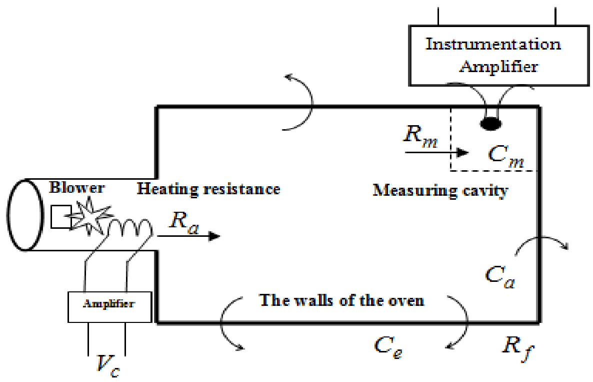

Fig.1. Process of electric furnace-ventilated [1]

In this article, we develop an adaptive neural control (NNAC)using RBF NN-based Adaptive to identifiers the unknown nonlinearities in order to get a high adaptive control performance capable of ensuring robustness in the presence of disturbance, stability and stabilization of parameters used in the control structures. Knowing that this command is synthesized from a neuronal model to represent the dynamics of the system to control where parameters are assumed unknown. [1]

In the presence of disturbances, the stabilization problem (convergence) parameters become paramount. This is a learning problem where the neural model and its associated controller must be learned. If at first, the neural model of the system is assumed unknown, adaptive control is proposed. The latter can identify the neural model online and eventually stabilize its parameters.

Mathematical Modelling of Electrical Furnace

The Figure 2 shows the circuit diagram of a electrical oven. This is resistive-capacitive:

By identification between the parameters of the furnace and the electrical diagram and considering the amount of heat Q as the current, the following equations are:

(1) $$Q = C_a \frac{d\theta_a}{dt} + C \frac{d\theta_m}{dt} + \frac{\theta_a - \theta_e}{R_f}$$

$C\frac{d\theta}{dt}$ as the current crossing capacity. The temperature is expressed by (2) as follows:

(2) $$\theta_m = \theta_a - R_m C_m \frac{d\theta_m}{dt}$$

The parameters θ_a, θ_m and θ_e were chosen as the voltages (images temperatures) of capacity C_a, C_m and C_e

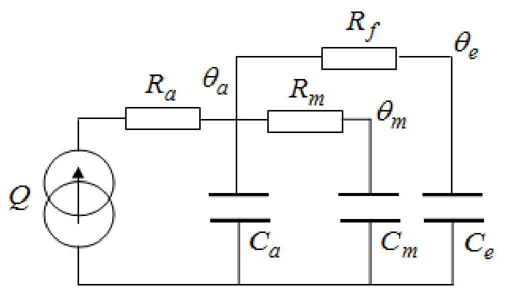

Fig.2 Electric Furnace [1].

Control of Furnace Equations

Control with Integral Compensation Poles and Zeros

Using the Laplace transforms of expression (1) and (2) we obtain the following equations:

(3) $$\theta_a = \left(Q + \frac{\theta_e}{R_f}\right) \cdot \left(\frac{R_f(1+R_m C_m p)}{1+(R_m C_m + R_f C_m + R_f C_a)p + R_f R_m C_m C_a p^2}\right)$$

(4) $$\frac{\theta_m}{\theta_a} = \frac{1}{1+R_m C_m p}$$

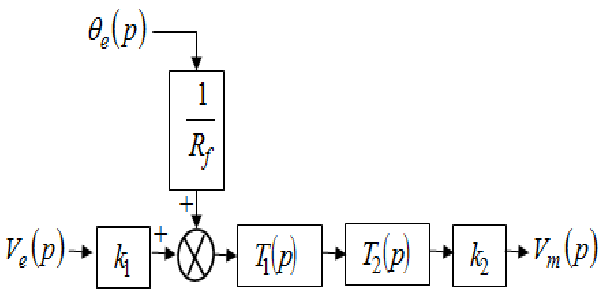

Fig.3. Block diagram of the electric furnace [1]

Given the equations (3) and (4), the simulation scheme of the whole process can be described as follows:

(5) $$T_1(p) = \frac{R_f(1+R_m C_m p)}{1+(R_m C_m + R_f C_m + R_f C_a)p + R_f R_m C_m C_a p^2}$$

(6) $$T_2(p) = \frac{1}{1+R_m C_m p}$$

The model parameters of the furnace [1] are prepared in Table 1. The simulation was performed in the MATLAB 7 / SIMILINK 6.

Figures 4 and 5 show the responses V_m and θ_m the levels of the reference voltage V_c and the oven temperature θ_a respectively. The Analog control shows that the measured voltage V_m is the image of the oven temperature θ_m (Figures 4 and 5).

Table 1.Parameter of the Furnace[1]

R_a	0.01 °C / W	C_a	5000 J / °C
R_m	0.1 °C / W	C_m	10 J / °C
R_f	0.1 °C / W	C_e	∞
$Q_{\max}$	5000 W	k_1	100 W / V
θ_e	20 °C	k_2	0.1 V / °C

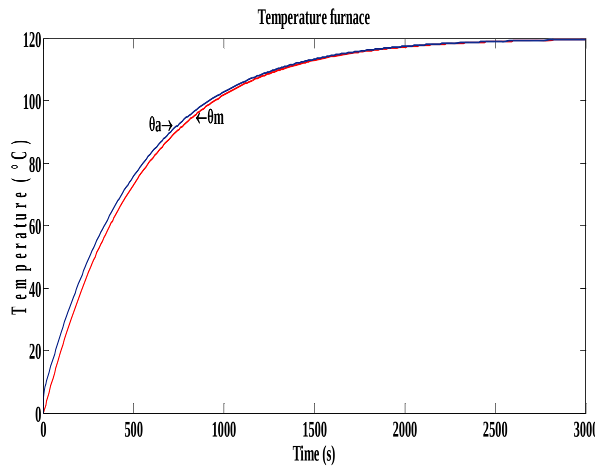

Fig.4. Response from the electric furnace to a temperature step

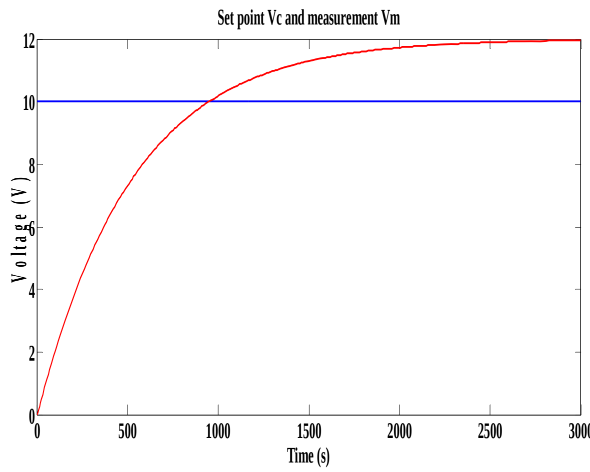

Fig.5. Response from the electric furnace to a voltage step performance

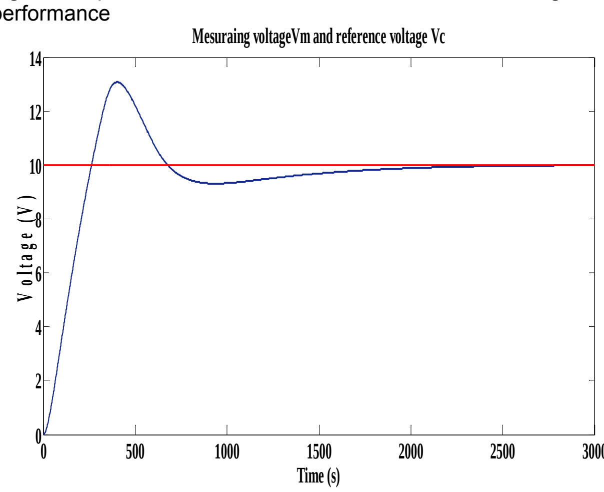

Fig.6. Response of the electric furnace with improved response time.

We also note that the response is quite slow oven (Figure 4) and the system response is damped to a value other than the excitation (Figure 5).

The corrector synthesized by the control integral with compensation poles and zeros (PI) allows both to cancel the static error and obtain stable process with satisfactory dynamic. From Figure 6 it can seen that the control system has a fast dynamical response

It is clear that the response time has been improved but there is a fairly significant overshoot in the transitional regime.

Adaptive Neural Control for Electrical Furnace

Neural networks and universal approximation theorem

Our study [12 13 14] considers the use of neural networks in which one or two hidden layers of radial basis functions are used (Figure7) shows the two types of neural networks.

With a single hidden layer of radial basis function, the output neuron network is given by:

(7) $$\tilde{y} = c^T \varsigma$$

Which $\varsigma \in R^p$ *are* radial basis functions (eg, functions characterized by Gaussian functions) and c^T is a vector of synaptic weights.

A second type of neural networks considered in this study is one in which there are two hidden layers, the output of the first hidden layer produces a vector functions

(8) $$\bar{z} = [\theta_1 .. \theta_m]$$

The node which make up the first hidden layer may be normalized radial basis functions, squashing functions, or any other standard neural basis function[12]. Here we allow both the output of the first hidden layer and the original input to be passed to the second hidden layer (see Figure 7). The output of the i^th node of the second hidden layer is given by:

(9) $$\xi_i = \zeta_i(\bar{z}, X)\left(b_{i,0} + \sum_{j=1}^{m} b_{i,j}\theta_j + \sum_{j=1}^{n} b_{i,j+m} x_j\right)$$

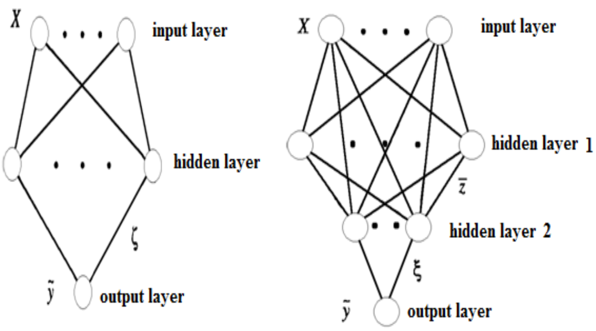

Fig.7. Two type of neural networks which may be used witch the adaptive techniques

Where $\varsigma_i(\bar{z}, X)$ are squashing[12] functions, or radial basis functions which may be normalized and $b_{i,0}$ the basis for i^th node. The output of the neural network is taken as linear combination of the output of the second hidden layer that is

(10) $$\tilde{y} = \sum_{i=1}^{p} c_i \xi_i$$

We may combine (9) and (10) to obtain:

(11) $$\tilde{y} = \sum_{j=1}^{p} \zeta_i(z, X)\left(a_{i,0} + \sum_{j=1}^{m} a_{i,j}\theta_j + \sum_{j=1}^{n} a_{i,j+m} x_j\right)$$

Which may be expressed in the form of with $z = \begin{bmatrix} 1 & \theta_1 \cdots \theta_m & x_1 \cdots x_n \end{bmatrix}^T$ $A = [a_{i,j}]$ with $a_{i,j} = c_i b_{i,j}$

Note that, z may, or may not, include any θ_i or x_i

From a mathematical point of view, the construction of a approximators, based on neural networks, is to find a correspondence relationship between the input space and the output space to approximate, with a degree of precision given the desired function or dynamic

Let f an unknown function defined on a compact S_X. For any positive constant ε, there is a neural approximator Σ_f of the form (7) such that:

(12) $$\sup_{X \in S_X} \left| \tilde{f}(x) - f(X) \right| < \varepsilon$$

The universal approximation theory provides the ability to model the dynamics of an unknown system by neural networks. These are used to develop neural controllers. Remains one of the fundamental properties of the order, namely stability, must be ensured. It is therefore necessary to analyze the problem of stability [12 13 14 15].

We study "an adaptive neural controller" as shown in Figure 8.

The approximators (identifiers) are introduced to approximate the dynamics of the system and use this dynamic to adjust the settings of the controller so that the tracking error tends to 0. In the design of adaptive controller, it is proposed to estimate the unknown functions by neural networks and from good choice of the law of adaptation.

Write the equations of the oven as follows by:

(12) $$\dot{x} = f(x) + g(x)\,u$$
$$y = h(x)$$

$\boldsymbol{f(x)}$ and $\mathbf{g(x)}$ Are functions that depend on the settings of the furnace. They are supposed to be unknown and take account of any variation of these parameters.The aim of the work is to solve the trajectory tracking problem, the control law is derived from a neuronal model representing these functions. The proposed solution is to use an adaptive control to ensure the robustness of parametric variations.

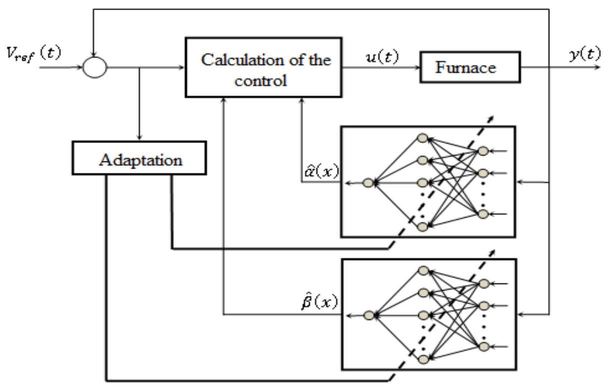

Fig.8. Adaptive neural controller

Change of coordinates

Define the new change of coordinates y is:

(13) $$y_1 = h(x)$$
$$y_2 = L_f h(x)$$

Write the system (9) in the y coordinates defined by (10):

(14)
$$\dot{y}_1 = y_2 = L_f h(x)$$
$$\dot{y}_2 = L_f^2 h(x) + L_g L_f h(x).u$$

To ease the notation, let:

(15)
$$\alpha(x) = L_f^2 h(x)$$
$$\beta(x) = L_g L_f h(x)$$

Note that α and β the functions are modeling the unknown part of the model, they depend on the settings of the oven. In this case, the system (11) becomes:

(16)
$$\begin{cases} \dot{y}_1 = y_2 \\ \dot{y}_2 = \alpha(x) + \beta(x).u \end{cases}$$

Neural networks are adopted to represent the dynamics of unknown functions α and β such as.

(17)
$$\alpha = f_\alpha(x) = W_\alpha^T \theta_\alpha$$
$$\beta = f_\beta(x) = W_\beta^T \theta_\beta$$

We can write:

(18)
$$\alpha = W_\alpha^T \theta_\alpha^*$$
$$\beta = W_{\beta_i}^T \theta_{\beta_i}^*$$

Where: θ_α^*, and θ_β^* are the optimal parameter vectors when is the unknown part of the furnace model by neural networks.

Suppose that estimates of unknown functions by neural networks are given by

(19)
$$\hat{\alpha} = W_\alpha^T \theta_\alpha$$
$$\hat{\beta} = W_\beta^T \theta_\beta$$

Error matrices of these parameters are:

(20)
$$\Delta\theta_\alpha = \theta_\alpha^* - \theta_\alpha$$
$$\Delta\theta_\beta = \theta_\beta^* - \theta_\beta$$

Now we introduce the parameter estimates $\hat{\alpha}$ and $\hat{\beta}$:

The systems (13) become:

(21)
$$\begin{cases} \dot{y}_1 = y_2 \\ \dot{y}_2 = \hat{\alpha}(x) + \hat{\beta}(x).u \end{cases}$$

The following neural control law as shown in:

(22)
$$u = \frac{v - \hat{\alpha}(x)}{\hat{\beta}(x)}$$

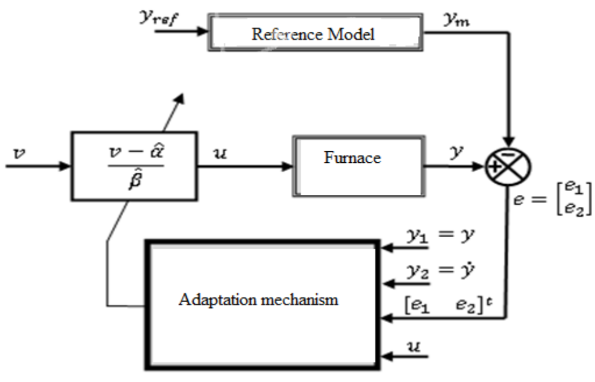

Fig.9. Neural control law

Fully offset parts of the system, that is to say,

$$\ddot{y}_1 = v$$

The new control stabilizing v is given by:

(23)
$$v = -k_1 y_1 - k_2 y_2 + v_{a\,ref}$$

where:

(24)
$$v_{ref} = k_1 V_{m\,ref}(t) + k_2 \dot{V}_{m\,ref}(t) + \ddot{V}_{m\,ref}(t)$$

The control parameters (k_1, k_2) are selected such that;

(25)
$$K = \begin{bmatrix} 0 & 1 \\ -k_1 & -k_2 \end{bmatrix}$$

It is asymptotically stable.

We now define the reference model as follows:

(26)
$$\begin{pmatrix} \dot{y}_{1m} \\ \dot{y}_{2m} \end{pmatrix} = \begin{bmatrix} 0 & 1 \\ -k_1 & -k_2 \end{bmatrix} \begin{pmatrix} y_{1m} \\ y_{2m} \end{pmatrix} + \begin{pmatrix} 0 \\ v_{ref} \end{pmatrix}$$

While the tracking error is given by:

(27)
$$e = \begin{bmatrix} e_1 \\ e_2 \end{bmatrix} = \begin{bmatrix} y_1 - y_{1m} \\ y_2 - y_{2m} \end{bmatrix}$$

The dynamics of these errors are calculated as follows:

(28)
$$\dot{e}_1 = \dot{y}_1 - \dot{y}_{1m} = y_2 - y_{2m}$$
$$= e_2$$

From where:

(29)
$$\dot{e}_1 = e_2$$

For the second error, we have:

$$\dot{e}_2 = \dot{y}_2 - \dot{y}_{2m}$$
$$= \alpha(x) + \beta(x)u + K_1 y_{1m} + K_2 y_{2m} - K_1 y_1 - K_2 y_2 - v$$

as:

(30)
$$v = \hat{\alpha}(x) + \hat{\beta}(x).u$$

We will then:

(31)
$$\dot{e}_2 = [\alpha(x) - \hat{\alpha}(x)] + [\beta(x) - \hat{\beta}(x)]u - K_1(y_1 - y_{1m}) - K_2(y_2 - y_{2m})$$

From where:

(32)
$$\dot{e}_2 = -K_1 e_1 - K_2 e_2 + W_\alpha^T \Delta\theta_\alpha + W_\beta^T \Delta\theta_\beta u$$

We can group equations (27-30) in a matrix form:

(33)
$$\begin{bmatrix} \dot{e}_1 \\ \dot{e}_2 \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ -K_1 & -K_2 \end{bmatrix} \begin{bmatrix} e_1 \\ e_2 \end{bmatrix} + \begin{bmatrix} 0 \\ W_\alpha^T \Delta\theta_\alpha + W_\beta^T \Delta\theta_\beta u \end{bmatrix}$$

Law adaptation of synaptic weights

Consider the quadratic Lyapunov function:

(34)
$$V = e^T P e + tr(\Delta\theta_\alpha^T \Gamma_\alpha \Delta\theta_\alpha) + tr(\Delta\theta_\beta^T \Gamma_\beta \Delta\theta_\beta)$$

P is a symmetric positive definite matrix and that is the solution of the Lyapunov equation

Γ_α and Γ_β are symmetric positive definite matrices.

The derivative of the Lyapunov function V is:

$$\dot{V} = e^T (K^T P + PK) e$$
$$+ 2tr(\Delta\theta_\alpha^T)\left(\Gamma_\alpha \Delta\dot{\theta}_\alpha + W_\alpha^T P e\right) + 2tr(\Delta\theta_\beta^T)$$
$$\left(\Gamma_\beta \Delta\dot{\theta}_\beta + W_\beta^T P e u\right)$$

(35)

if we now define the laws of adaptation of the synaptic weights as follows Figure 10:

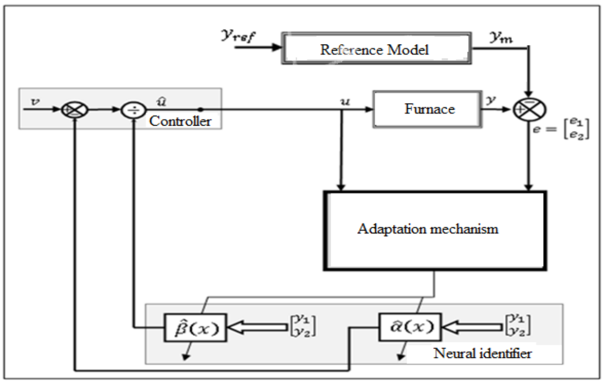

Fig.10. Laws of adaptation of the synaptic weights as follows

(36)
$$\begin{cases}\Delta\dot{\theta}_\alpha = -\Gamma_\alpha^{-1} W_\alpha^T Pe \\ \Delta\dot{\theta}_\beta = -\Gamma_\beta^{-1} W_\beta^T Peu\end{cases}$$

(37)
$$\begin{cases}\dot{\hat{\theta}}_\alpha = -\Delta\dot{\theta}_\alpha = \Gamma_\alpha^{-1} W_\alpha^T Pe \\ \dot{\hat{\theta}}_\beta = -\Delta\dot{\theta}_\beta = \Gamma_\beta^{-1} W_\beta^T Peu\end{cases}$$

These adaptation laws (34) define the update weights $\hat{\theta}_\alpha(t)$ and $\hat{\theta}_\beta(t)$ for neural networks which model the dynamics of the oven

Replacing the adaptation law (36) in (35) using (34) we find:

(38)
$$\dot{V} = -e^T Q\, e \leq \; 0$$

The inequality $\dot{V} \leq 0$ ensures stability of the control structure. And, according to the lemma Barbalat [12], the tracking error $e(t)$ and errors $\Delta\theta_\alpha$ and $\Delta\theta_\beta$ on the estimated parameters tend to 0 when $t \to \infty$

Simulation Results and Discussions

The software used is the MATLAB 7. The schematic diagram of the furnace was made from SIMULINK6. The performance of the adaptive neuronal command applied to the ventilated furnace is evaluated after the numerical simulation study. To better show the robustness of this control technique with the proposed techniques. [1, 2, 3, 4, 5]. We varied the resistance t = 3500 s.

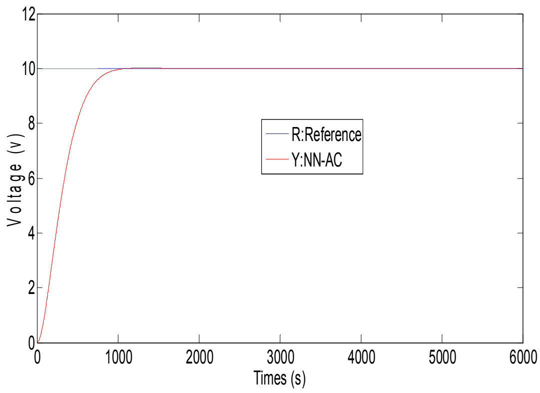

Fig.11. System response of NN-AC

At t = 3500s, increasing the resistor R_f 50% of its nominal value, there is, according to Figure 8. That the temperature returns to its initial value with a much improved trajectory.

The adaptation functions $\hat{\alpha}(x)$ and $\hat{\beta}(x)$ estimated by the neural network. Reinforces the robustness of the control structure.

These functions, which are illustrated by Figures 13 and 14 rapidly converge to the actual values $\alpha(x)$ and $\beta(x)$ that represent the dynamics of the furnace.

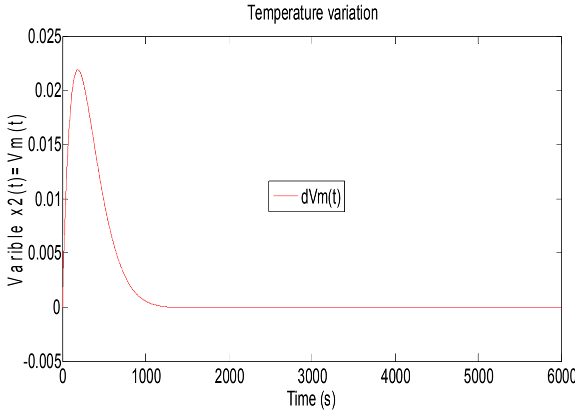

Fig.12. Temperature variation

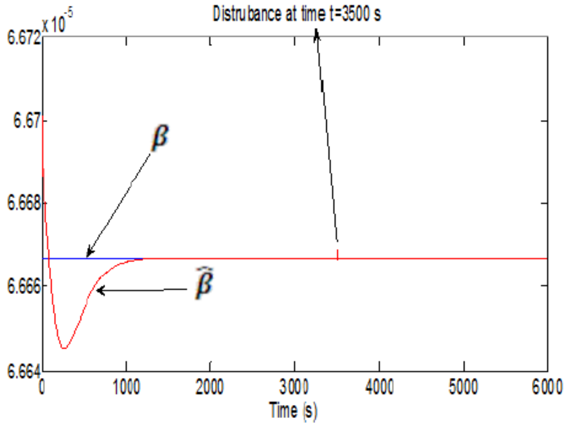

Fig.13.Real functions $\beta(x)$ and estimated $\hat{\beta}(x)$

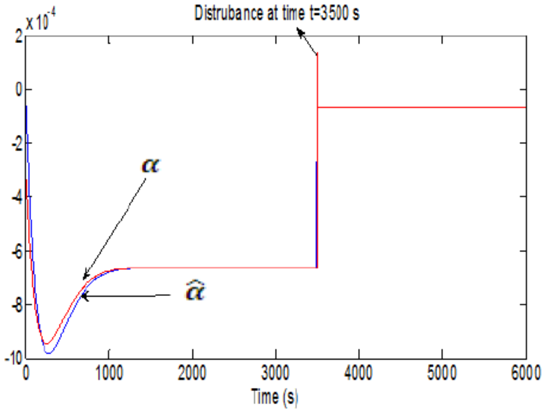

Fig.14. Real functions $\alpha(x)$ and estimated $\hat{\alpha}(x)$

Conclusion

In this article, we proposed a technique adaptive control neural network *ACNN using RBFNN*. to control the temperature of Electrical Resistance Furnace. When system parameters change over time. This technique solves the problem of convergence exploiting both the tracking error and modeling error It ensures also the stabilization of the neuronal model parameters while ensuring satisfactory tracking performance .We proved the stability of this method of control and we showed it guarantees convergence to zero tracking error. The synthesis of adaptation laws are based on the resolution of the Lyapunov equation. Thus, the simulation results show the advantages that the control technique proposed in this article, compared with other used control methods. [1, 2, 3, 4, 5]. This algorithm allows the furnace temperature to be regulated, taking into account any possible parametric variation.and *has good robustness*

Nomenclature

Q: Quantity of heat produced

R_a: Thermal resistance hindering the movement of heat led to the oven

R_m: Thermal resistance hindering the movement of heat from the oven inside the cavity of measurement

R_f: Resistance leak slowing the flow of heat outwards from the oven

C_a: Calorific capacity of the cavity extent

C_e: Calorific capacity outside the oven regarded as infinite

θ_a: Temperature of the cooking chamber

θ_m: Temperature measuring cavity

θ_e: Temperatures outside the furnace

V_m: Voltage measurement

p: Laplace operator

V_e: Control voltage

k_1: Watt/volt

k_2: Volt/degree

$Q_{\max}$: Maximum amount of heat produced coefficient

T_e: Sampling period

W_{ij}: Is the synaptic weight from neuronj.

$J(\theta)$: Criterion

$\hat{y}(t)$: The estimated output

$y(k)$: The output actually provided by the neuron

$u(t)$: Command

$H(z)$: ARMA model

W: Weights

b: Bias

W and Z: The Matrix Weight

W_0 and Z_0: Bias vectors

$u(k)$: The sequence is control inputs

$u(t)$, $y(t)$, $\Delta u(t)$ et $\Delta y(t)$: Different signals

n: Number of examples

N and DN: Normalization and denormalization

N: Neutral

$r(t)$: The reference signal resistance.

$\varsigma \in R^p$: *are* radial basis functions.

$\varsigma_i(\bar{z}, X)$: are squashing functions, or radial basis functions which

$b_{i,0}$: the basis for i^th node

Σ_f: is a vector of synaptic weights

c^T: is a vector of synaptic weights

AC NN: Adaptive Control Neural Networks

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