Indonesian Journal of Electrical Engineering and Computer Science
Vol. 2, No. 1, April 2016, pp. 32 ~ 39
DOI: 10.11591/ijeecs.v2.i1.pp32-39

A New Electrode Regulator System Identification of Arc Furnace Based on Time-Variant Nonlinear-Linear-Nonlinear Model

Jinfeng Wang*[1], Shoulin Yin[2], Xueying Wang[3]
Shenyang Normal University
No.253, Huang He Bei Street, Huang Gu District, Shenyang, P.C 110034 - China
*Corresponding author, e-mail: 1057417325@qq.com[1], 352720214@qq.com[2], 751661713@qq.com[3]

Abstract

In this paper, we express arc furnace electrode regulator system as a time-variant nonlinear-linear-nonlinear model. On this basis, we propose an online identification method based on nonlinear-linear-nonlinear model system. This new scheme solves the problem of model variation and prediction precision decline causing by time-varying of arc characteristic. In order to dispose the difficulty of parameters separation in the online identification process, this new method adopts the mind of update the parameters of linear parts and nonlinear parts respectively. It realizes the parameters separation of system effectively. Simulation results show that this method can track the changes of arc characteristics effectively. That it achieves the aim of real-time monitoring and controlling system parameters.

Keywords*: Arc furnace electrode regulator, online identification, time-varying, nonlinear-linear-nonlinear model system*

1. Introduction

Arc furnace electrode regulator system remains a constant arc resistance by adjusting the length of the arc between the electrodes and the burden to optimize output power and reduce energy consumption. When designing electrode regulator system, an accurate system model can provide the basis for the calculation of the controlled quantity and lay the foundation for realizing the control goals. However, the non-linear of electrode regulator system and time-varying of electric arc have increased the difficulty in modeling. Reference [1] proposes a neural adaptive PSD dispersive decoupling controller which combining neural adaptive PSD algorithm with dispersive decoupling network. Yu F etc [2] show a new IMC controller including two RBF neural networks. It adjusts center vectors and the shape parameters of the networks online. P Guan [3] represents electrode regulator systems of industrial arc furnace with genetic algorithm predictive control and designs a detailed dynamic matrix controller to diminish the predictive error and get a desired system output. However, they don't take time-varying characteristics of electric arc into consideration. The established model of the electric arc furnace does not reflect system characteristics accurately.

We propose the online identification method based on nonlinear-linear-nonlinear (N-L-N) model system for the first time. In this paper, we express the arc furnace electrode regulator system as N-L-N model of parameters time-varying in linear parts for time-varying arc. And we propose a online identification method to identify time-varying parameter of system. To handle the difficulty on parameters separation within identification process [4, 5], this paper draws the identification idea of relaxation iterative method [6] and combines N-L-N system structure characteristic to divide every moment iterative calculation into three steps. Then this scheme updates linear parts and nonlinear parts in turn. It achieves the effective separation of system parameters and realizes online identification N-L-N system time-varying parameters.

2. Electrode Regulating System Statement

Electric arc furnace electrode adjustment system consists of two parts, hydraulic system and electric arc. Its structure frame is as figure 1.

Received January 23, 2015; Revised March 9, 2016; Accepted March 20, 2016

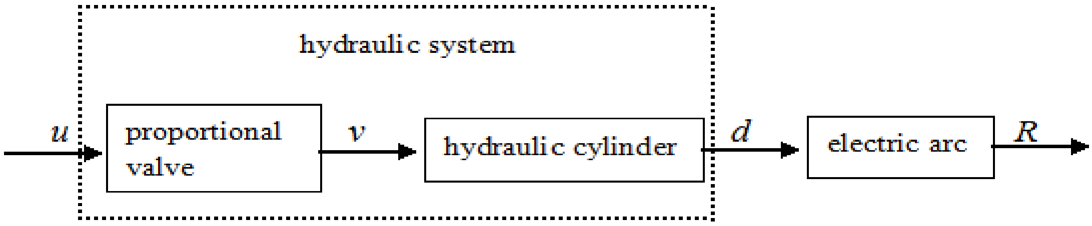

Figure 1. Electric arc furnace electrode adjustment system structure

In figure 1, *u* is input controlled quantity. *v* is proportional input value. *d* is electrode position. *R* is arc resistance. Its unit is Ω.

2.1 Hydraulic System Model

The hydraulic system consists of a proportional valve and hydraulic cylinder series. Because proportional valve has dead zone features. At the same time the restriction of spool displacement results in upper and lower of valve output. So the proportional valve characteristic can be expressed as a proportional component between dead zone and saturation characteristics.

The hydraulic cylinder features can be expressed by 3-order transfer function. After discretizing, it can be obtained by:

$$\frac{l(z^{-1})}{v(z^{-1})}=\frac{b_{y1}z^{-1}+b_{y2}z^{-2}+b_{y3}z^{-3}}{1-a_1z^{-1}-a_2z^{-2}-a_3z^{-3}} \tag{1}$$

2.2 Electric Arc Model

Arc and power system model are static nonlinear variable characteristics, so arc voltage characteristics can be expressed as the following approximate relation:

$$U_{arc}=a+bl \tag{2}$$

Where U_{arc} is arc voltage, its unit is *V*. *l* is arc length, its unit is *cm*. *a* is arc cathode and anode voltage drop, its unit is *V*. We can consider it as a constant. *b* is electric arc drop gradient, its unit is *V/cm*. In the beginning of smelting, *b≈8*. *b* will decrease as temperature rise. Electric arc furnace temperature drop gradient changes over furnace temperature which reflects the system time variability.
Power system model is equivalent to R-L circuit.

$$U_p^2=(R_d I_{arc}+U_{arc})^2+(X_d I_{arc})^2 \tag{3}$$

Where U_p is transformer secondary voltage, its unit is *V*. R_d is short-net resistance, its unit is Ω.X_d is short-net impedance.I_{arc} is arc current,its unit is *A*. U_{arc} is arc voltage, its unit is *V*.

2.3 Electrode Regulating System Model

Because electric arc furnace electrode adjustment system consists two parts, hydraulic system and electric arc; electric arc furnace electrode regulator system can consist of three parts, dead zone nonlinear characteristic, 3-order linear characteristic and arc nonlinear characteristic in series. It matches the N-L-N model.

In the identification process, it uses polynomial function to approximate and replace the nonlinear characteristics caused by arc and power supply system. Time-varying parameters of arc characteristics increase the difficulty of identification in the polynomial function coefficients. To simplify the identification method, the system is transformed as follows.

Let U_d=*bl* be arc column voltage drop. Putting it into (1) and (3) and combining (2), it can get:

$$\frac{U_b(z^{-1})}{v(z^{-1})} = b\frac{b_{y1}z^{-1} + b_{y2}z^{-2} + b_{y3}z^{-3}}{1 - a_1z^{-1} - a_2z^{-2} - a_3z^{-3}} = \frac{b_1z^{-1} + b_2z^{-2} + b_3z^{-3}}{1 - a_1z^{-1} - a_2z^{-2} - a_3z^{-3}} \tag{4}$$

$$U_p^2 = F(l) = (R_d I_{arc} + a + bl)^2 + (X_d I_{arc})^2 \tag{5}$$

From formula (4) and (5) we can know that the equivalent transformation merges time-varying parameters into linear model part. So the arc furnace electrode regulator system is equivalent to N-L-N model of linear part parameters time-varying. It simplifies the identification process during the arc time-varying. The new model structure is as figure 2.

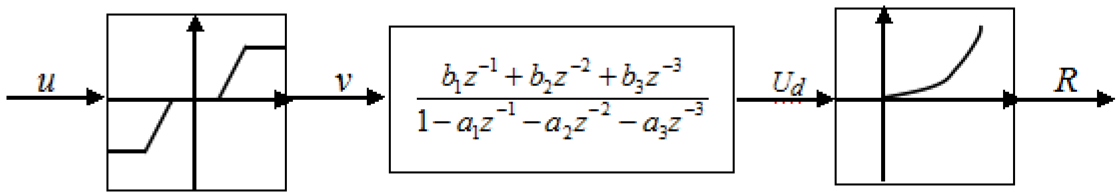

Figure 2. Electric arc furnace electrode adjustment system model

3. N-L-N Model Parameter Identification

3.1 N-L-N System Parameterization

Before system identification, we must make parameterization for N-L-N system [7, 8]. The dead zone saturation nonlinear characteristics can be expressed as the following equation:

$$v(k) = G(u(k)) = \sum_{i=1}^{p} c_i g_i(u(k)) \tag{6}$$

Where $u(k)$ is input controlled quantity at k time. $v(k)$ is proportional valve output at k time. c_i is undetermined parameter. $g_i(\cdot)$ is polynomial function.

From formula (5), we know that $F(l)$ is invertible function. The invertible function is as follows [14-16].

$$l(k) = F^{-1}(R(k)) = \sum_{i=1}^{q} d_i f_i^{-1}(R(k)) \tag{7}$$

Where $l(k)$ is arc length at k time. $R(k)$ is arc resistance at k time. $f_i^{-1}(\cdot)$ is polynomial function. The linear part can be obtained by formula (4). Combining (4), (6) and (7) gets:

$$\sum_{n=0}^{3} a^n(z) \sum_{j=1}^{q} d_j f_j^{-1}(R(k)) = \sum_{m=1}^{3} b^m(z) \sum_{i=1}^{p} c_i g_i(u(k)) \tag{8}$$

Where $a^0=1$, $a^1=a_1z^{-1}$, $a^2=a_2z^{-2}$,……; $b^1=b_1z^{-1}$, $b^2=b_2z^{-2}$,……

So, we can identify the parameters a_i, b_i, c_i, d_i in formula (8) only by input-output data. Finally we obtain the system model.

3.2 N-L-N System Parameters Identification

In the smelting process, electric arc exists time-varying characteristics. In order to real-time control system changes and get the best control signal, we must study the N-L-N system's online identification method. (8) is abbreviated to:

$$\theta \bullet \phi(k) = 0 \tag{9}$$

Where θ=[$d_1,\dots,d_q,a_1d_1,\dots,a_1d_q,\dots,a_3d_1,\dots,a_3d_q,\dots,b_1c_1,\dots,b_1c_p,\dots,b_3c_1,\dots,b_3c_p$].

$$\phi(k) = [\, f_1^{-1}(R(k-1)),\dots,\, f_q^{-1}(R(k-1)),\dots,\, f_1^{-1}(R(k-3)),\dots,\, f_q^{-1}(R(k-3)),\dots,$$
$$g_1(u(k)),\dots,g_p(u(k)),\dots,g_1(u(k-3)),\dots,g_p(u(k-3))]$$

The formula (9) shows that using existing mature online identification methods, such as recursive least squares method (RLSM), can get vector θ online. However, θ is composed of product of a_i, b_i, c_i and d_i, it cannot get separate parameters of a_i, b_i, c_i and d_i. Papers [9] use singular value decomposition (SVD) method to offline separate four sets of parameters. That is not suitable for the online identification of time-varying N-L-N system.

Because it is difficult to separate parameters.This paper draws the identification idea of relaxation iterative method. According to N-L-N system specific 3-parts structure characteristic, it first fixes two parts parameters and then adjusts the parameters of the other parts to achieve parameter separation.

Model error is:

$$\varepsilon(k,\theta) = \sum_{n=0}^{3} a^n(z) \sum_{j=1}^{q} d_j f_j^{-1}(R(k)) - \sum_{m=1}^{3} b^m(z) \sum_{i=1}^{p} c_i g_i(u(k)) \tag{10}$$

Error function is defined as:

$$E(E,\theta) = \frac{1}{2}\varepsilon(k,\theta)^2 \tag{11}$$

We conclude the identification procedure within a sampling period. Firstly, the initial iteration values are given: $\hat{A}(1)$, $\hat{B}(1)$, $\hat{C}(1)$, $\hat{D}(1)$. Setting $\hat{A}(k)$, $\hat{B}(k)$, $\hat{C}(k)$, $\hat{D}(k)$ as the estimation value of parameters at *k* sampling time.So

$$\hat{A}(k) = [\hat{a}_0(k), \hat{a}_1(k), \hat{a}_2(k), \hat{a}_3(k)] \quad \hat{B}(k) = [\hat{b}_1(k), \hat{b}_2(k), \hat{b}_3(k)]$$
$$\hat{C}(k) = [\hat{c}_1(k), \hat{c}_2(k), \dots, \hat{c}_p(k)] \quad \hat{D}(k) = [\hat{d}_1(k), \hat{d}_2(k), \dots, \hat{d}_q(k)]$$

Step 1. Selecting input-output data *R(k)*, *R(k-1)*, *R(k-2)*, *R(k-3)*, *u(k-1)*, *u(k-2)*, *u(k-3)*.

Step 2. Using $\hat{A}(k)$, $\hat{B}(k)$, $\hat{C}(k)$, $\hat{D}(k)$ as model parameters. Calculating error function value based on formula (10).

Step 3. Fixing parameters $\hat{A}(k)$, $\hat{B}(k)$, $\hat{C}(k)$ and adjusting $\hat{D}(k)$ to make the error function minimum. Then we can get the new parameter $\hat{D}(k+1)$.

Step 4. Using $\hat{A}(k)$, $\hat{B}(k)$, $\hat{C}(k)$, $\hat{D}(k+1)$ as model parameters. Calculating error function value based on formula (10).

Step 5. Fixing parameters $\hat{A}(k)$, $\hat{B}(k)$, $\hat{D}(k+1)$ and adjusting $\hat{C}(k)$ to make the error function minimum. Then we can get the new parameter $\hat{C}(k+1)$.

Step 6. Using $\hat{A}(k)$, $\hat{B}(k)$, $\hat{C}(k+1)$, $\hat{D}(k+1)$ as model parameters. Calculating error function value based on formula (10).

Step 7. Fixing parameters $\hat{C}(k+1)$, $\hat{D}(k+1)$ and adjusting $\hat{A}(k)$, $\hat{B}(k)$ to make the error function minimum. Then we can get the new parameter $\hat{A}(k+1)$, $\hat{B}(k+1)$.

Step 8. Giving the new input signal *u(k+1)*, let *k=k+1*, return step1.

Therefore, according to the N-L-N system structure, each iteration can be divided into three steps. It updates parameters of 1-linear part and 2-nonlinear parts in turn, finally, we can get the purpose of parameters separation. Some parameters adjustment optimization methods can be used in step 3, 5, 7, such as gradient algorithm or least square method.

4. Simulation Results and Analysis

As mentioned earlier, we take electric arc furnace of one factory as an example and conduct online identification simulation for arc furnace electrode adjustment system.

The proportional valve dead zone length of arc furnace electrode adjustment system is 1. Its output upper and lower bounds is ±10. Sampling period T=0.02s. The discretization transfer function of hydraulic cylinder can be expressed by:

$$P(z^{-1}) = \frac{0.0082z^{-1} + 0.0254z^{-2} + 0.0043z^{-3}}{1 - 2.251z^{-1} + 1.552z^{-2} - 0.3011z^{-3}} \tag{12}$$

In the beginning of the smelting, arc pressure drop gradient is 8. At the end of smelting, arc pressure drop gradient is 1.

In step 3, 5, 7, we use gradient algorithm to adjust each parameter. Adjusting parameters are as follows.

$$\begin{aligned} \hat{d}_i(k+1) &= \hat{d}_i(k) - \lambda_d \frac{\partial \varepsilon(k)}{\partial \hat{d}_i(k)} \\ &= \hat{d}_i(k) - \lambda_d \sum_{j=0}^{3} a_j(k) f_i^{-1}(y(k-j))\varepsilon(k,\theta) \end{aligned} \tag{13}$$

$$\begin{aligned} \hat{c}_i(k+1) &= \hat{c}_i(k) - \lambda_c \frac{\partial \varepsilon(k)}{\partial \hat{c}_i(k)} \\ &= \hat{c}_i(k) - \lambda_c \sum_{j=0}^{3} a_j(k) g_j(u(k-j))\varepsilon(k,\theta) \end{aligned} \tag{14}$$

$$\begin{aligned} \hat{a}_i(k+1) &= \hat{a}_i(k) - \lambda_a \frac{\partial \varepsilon(k)}{\partial \hat{a}_i(k)} \\ &= \hat{a}_i(k) - \lambda_a \sum_{j=1}^{p} d_j(k+1) f_i^{-1}(u(k-j))\varepsilon(k,\theta) \end{aligned} \tag{15}$$

$$\begin{aligned} \hat{b}_i(k+1) &= \hat{b}_i(k) - \lambda_b \frac{\partial \varepsilon(k)}{\partial \hat{b}_i(k)} \\ &= \hat{b}_i(k) - \lambda_b \sum_{j=1}^{q} c_j(k+1) g_j(y(k-j))\varepsilon(k,\theta) \end{aligned} \tag{16}$$

Where λ_a, λ_b, λ_c and λ_d is step length of parameter adjustment. Set $\lambda_a = \lambda_b = \lambda_c = \lambda_d = 10^{-3}$.

System ignite signal is sinusoidal signal. Each initial parameter value is 0.9 times as the true value of initial simulation parameters. After 40000 steps (i.e.800s) simulation identification, the true value and estimation value of each parameter are as figure 3, 4.

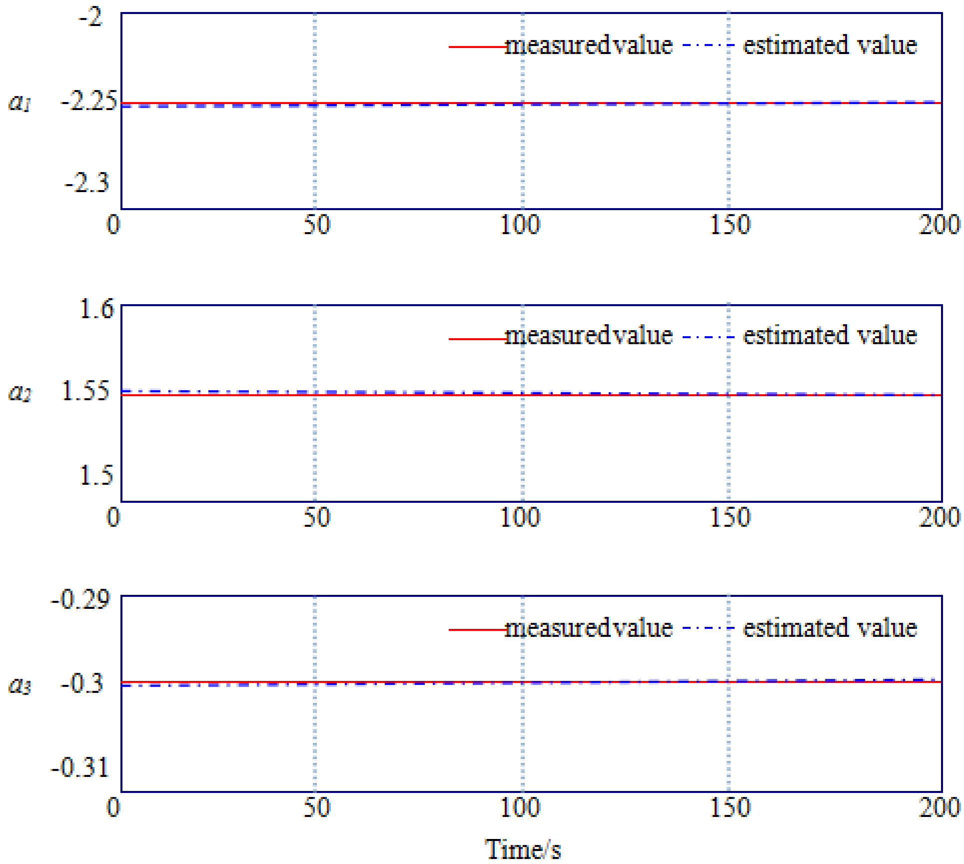

Figure 3. True value and estimated value of parameter A comparison

Figure 3 shows that model parameter A dose not change during identification process. Its estimated value $\hat{A}$ converges to a true value rapidly. As $\hat{A}$ has a fast convergence speed, we gives the identification result within 200s. Figure 4 shows that the parameter B changes with time in the identification process. The estimated value $\hat{B}$ appears some deviation at the beginning of identification. But it tracks the true value in a short time. The simulation takes 60. 3219s less than the simulation time 800s. Thus we can draw a conclusion that this new scheme can be applied for online identification of parameters of the electric arc furnace systems.

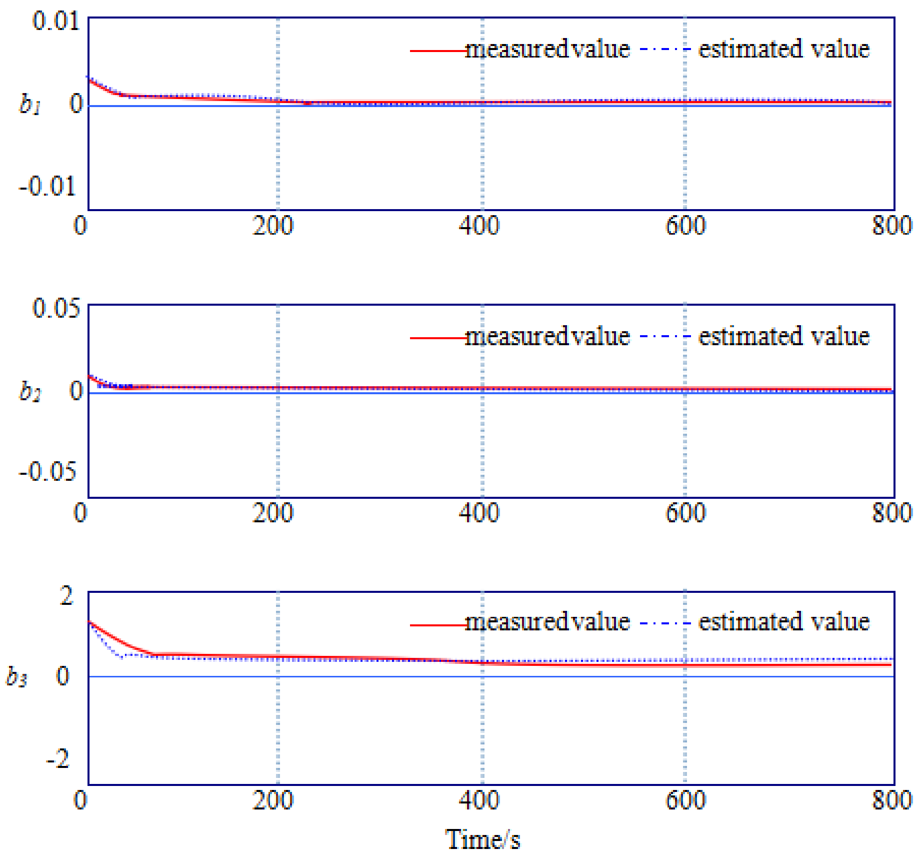

Figure 4. True value and estimated value of parameter B comparison

5. Conclusions

This paper classifies arc furnace electrode regulator system as parameter time-varying N-L-N system of linear part. And N-L-N model is parameterized based on arc furnace electrode regulator system. In order to solve the difficult problem of online identification N-L-N system parameter separation, we use the relaxation iterative identification method realizing parameter separation in N-L-N system identification process. So we achieve the purpose of system online identification. The simulation results show that the new method can identify the electric arc furnace electrode adjustment system with parameter time-varying effectively and ensure the accuracy of system model in the smelting process.

Acknowledgment

This work is partially supported by the National Natural Science Foundation of China (60970112).

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