Asian Journal of Information Technology 5 (9): 1028-1033, 2006

Physical Modeling and Control of Electric Arc Furnace by Neural Inverse Model

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Abstract: In this study, we try to answer a certain number of questions raised in the electric arc furnace control. In this study, we mention the studied choice of the physical model which approaches best the Electric Arc Furnace (E.A.F). The nonlinear model uses the conductance like electric parameter of adjustment, whereas usually one uses the resistance of arc as parameter of adjustment although its accessibility remains implicit. In order to answer the preset objectives, i.e. to control the process of the E.A.F. and this with an acceptable stability in the respect of the constraints and minimization of energy, it is proposed a structure of control by neural inverse model implemented by a Multi-Layer Perceptron network (MLP). The technique of training data base uses the retro propagation of error gradient algorithm. An application on MATLAB SIMULINK made it possible to simulate this structure; convincing results are recorded.

Key words: Electric arc furnace, fusion, neural inverse model, multi-layer neural network, process control

INTRODUCTION

The electric arc furnace takes more and more shares in the field of fusion of metals and mainly in the recycling of scrap. Raising of prices of energy, the constraint of stabilization of the energy systems implying of the rigorous criteria on the process control of fusion. In order to better answer these questions, it is necessary to acquire the broadest knowledge on the phenomena of fusion and its impact on the control devices of the E.A.F.[1]. For this reason we undertook the study of physical models relating to the process of fusion in E.A.F. by indicating that this phenomenon can be compared to a transfer of energy which can bring a solid and disparate metal mass in a liquid state as (t°1600).

Starting from these assumptions, it takes shape that the representative model of this process comprises elements of analogy with the neural networks. After having to delimit the number of inputs and outputs of the physical model and undertaken simulations in open loop and closed loop it will be projected in a Multi-Layer Perceptron model (MLP). A structure of control by neural inverse model is proposed to maintain as exactly as possible, during the fusion and the heating of the liquid bath, the operation point fixed as a preliminary. The retro propagation of error gradient algorithm is used for training neural network parameters and for making the process of fusion self -controlled.

PHYSICAL AND ELECRIC MODEL OF THE E.A.F.

The electric arc furnace is primarily an equipment production of molten steel starting from scrap, those being able to be replaced partially by cast iron or prereduction ores. It is composed of a tank furnished with refractory and energy necessary is provided by electric arcs spouting out between electrodes to graphite and the load. The refining of the crucible cast steel is carried out by reaction of the molten metal with a slag containing lime. The garnishing of the furnace is thus basic. The fusion operation is often accompanied by an operation of decarburization and dephosphorization carried out by addition of iron ores or blowing oxygen in the matte. After complete abolition or partial of the peroxidized slag, metal can be either run out of pocket for refining, or pre-refined with the furnace with powerful deoxidizers, like silicon and aluminium, under a basic slag rich in lime. The precise adjustment of the temperature of metal to run furnace out of pocket is one of the key points for the manufacture of steel of quality. The temperatures aimed to the furnace, before casting, can vary 1550°C with 1750°C. The Fig. 1. represents the physical model of the E.A.F. according to Boulet[2]. The three electrodes, laid out in triangle, move vertically using hydraulic actuators. An electric arc of great power appears between the electrode and scrap. The crucible cast steel, under the effect of its weight, runs out towards the bottom of the tank and slag, lighter, remains on the surface. It should be noted that the distance from the electric arc depends on the amplitude of the applied tensions to the electrodes. Consequently, the difficulty of the regulation of this distance arises. This leads us to represent the E.A.F by an adequate model. The electric diagram are equivalent, which claims to represent more the E.A.F, regards the conductance as electric parameter best adapted to this kind process Fig. 1. It is to be stressed that this figure shows the presence of

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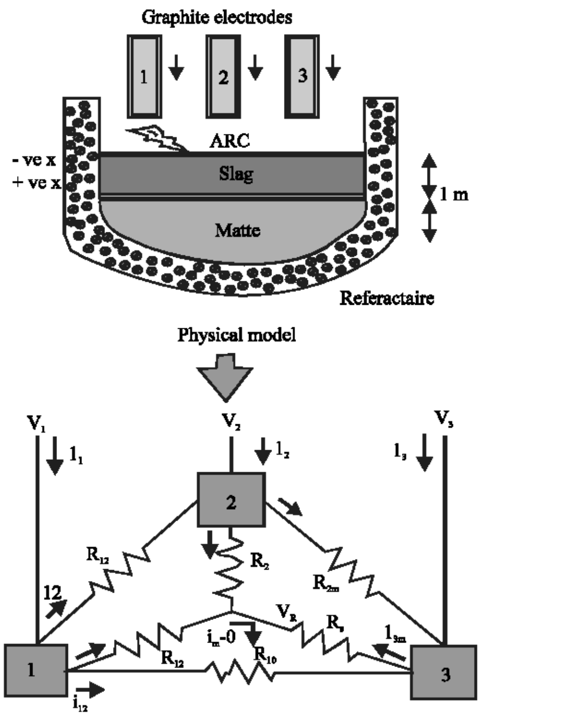

Fig 1: Sturcture and diagram of electric arc furnace

four nodes, a node for each electrode and the fourth node representing the point of the virtual neutral on the level of the Matte (V_m). To solve the electric model, it is necessary to indicate certain assumptions making it possible to apprehend the problem. The law of Kirchoff of the currents makes it possible to determine the intensity of the current in each electrode according to each tension and of the conductance coefficients. The equation of the currents describing the process of the E.A.F is represented by the following currents matrix:

$$[I_i]=[G_{ij}][x_i]+[B_i] \tag{1}$$

where I_I is a currents matrix 3*1 of the electrodes, G_{ij} is the conductance matrix 3*3 and B_I is a constant matrix 3*1. For this model of the E.A.F, we must note that it made up of a circuit with three phases with double configuration. Resistances inter electrodes form a triangle circuit with three nodes. Resistances matte-slag form a star circuit with V_m like neutral point of the circuit. Consequently, it results from this a linear inverse function making it possible to write the conductance G_I slag matte for each electrode I in the sum form:

$$G_i = c_i * x_i + G_s \tag{2}$$

where C_I represents the coefficient of conductance (in siemens/meter), X_I is the length (in meter) of immersion of the electrode in slag and G_S the total conductance of slag (in siemens) when the electrode is in contact with the slag surface. The following equations of the nodes are obtained by applying the law of Kirchoff for each node:

$$\begin{cases} I_1=G_{12}(V_1-V_2)+G_1(V_1-V_m)+G_{13}(V_1-V_3) \\ I_2=-G_{12}(V_1-V_2)+G_2(V_2-V_m)+G_{23}(V_2-V_3) \\ I_3=G_3(V_3-V_m)-G_{13}(V_1-V_3)+G_{23}(V_2-V_3) \\ G_1(V_1-V_m)+G_2(V_2-V_m)+G_3(V_3-V_m)=0 \end{cases} \tag{3}$$

The form of VM is as follows:

$$V_m=\frac{G_1V_1+G_2V_2+G_3V_3}{G_1+G_2+G_3}$$

Let us consider that the currents of the three electrodes will behave in a similar way one will have then the equations of the currents expressed as follows:

$$I_1=\frac{1}{G_{TOT}}\left\{\begin{array}{l} X_1\left[\begin{array}{l}2V_1C_1(G_S+G)-V_2C_1(G_S+G)-V_3C_1(G_S+G)\\ +C_1C_2X_2(V_1-V_2)+C_1C_3X_3(V_1-V_3)\end{array}\right] \\ +X_2\left[V_1C_2(G_S+2G)-V_2C_2(G_S+G)-V_3C_2G\right] \\ +X_3\left[V_1C_3(G_S+2G)-V_2C_3G-V_3C_3(G_S+G)\right] \\ +(2V_1-V_2-V_3)(G_S^2+3GG_S) \end{array}\right\} \tag{4}$$

$$I_2=\frac{1}{G_{TOT}}\left\{\begin{array}{l} X_1\left[-V_1C_1(G_S+G)+V_2C_1(G_S+2G)-V_3C_1G\right] \\ +X_2\left[\begin{array}{l}-V_1C_2(G_S+G)+2V_2C_2(G_S+G)-V_3C_3(G_S+G)\\ +C_2C_3X_3(V_2-V_3)+C_1C_2X_1(V_2-V_1)\end{array}\right] \\ X_3\left[-V_1C_3G-V_2C_3(G_S+2G)-V_3C_3(G_S+G)\right] \\ +(-V_1+2V_2-V_3)(G_S^2+3GG_S) \end{array}\right\} \tag{5}$$

$$I_3=\frac{1}{G_{TOT}}\left\{\begin{array}{l} X_1\left[-V_1C_1(G_S+G)-V_2C_1G-V_3C_1(G_S+2G)\right] \\ +X_2\left[-V_1C_2G-V_2C_2(G_S+G)+V_3C_2(G_S+2G)\right] \\ +X_3\left[\begin{array}{l}-V_1C_3(G_S+G)-V_2C_3(G_S+G)+2V_3C_3(G_S+G)+\\ C_1C_3X_1(V_3-V_1)+C_2C_3X_2(V_3-V_2)\end{array}\right] \\ +(-V_1-V_2+2V_3)(G_S^2+3GG_S) \end{array}\right\} \tag{6}$$

With the total conductance expressed by:

$$G_{TOT} = C_1X_1 + C_2X_2 + C_3X_3 \qquad (7)$$

According to the Eq. (4, 5, 6), one can write the matrix shape of the currents:

$$\begin{bmatrix} I_1 \\ I_2 \\ I_3 \end{bmatrix} = \frac{1}{G_{TOT}} \begin{bmatrix} g_1 & g_2 & g_3 \\ g_4 & g_5 & g_6 \\ g_7 & g_8 & g_9 \end{bmatrix} \begin{bmatrix} X_1 \\ X_2 \\ X_3 \end{bmatrix} + \frac{G_S^2 + 3G_SG}{G_{TOT}} \begin{bmatrix} (2V_1 - V_2 - V_3) \\ (-V_1 + 2V_2 - V_3) \\ (-V_2 - V_1 + 2V_3) \end{bmatrix} \qquad (8)$$

when:

$$g_1 = \left\{ \begin{array}{l} 2V_1C_1(G_S + G) - V_2C1(G_S + G) \\ -V_3C_1(G_S + G) + C_1C_2X_2(V_1 - V_2) \\ +C_1C_3X_3(V_1 - V_3) \end{array} \right\}$$

$$g_2 \left\{ \begin{array}{l} V_1C_2(G_S + 2G) - V_2C_2(G_S + G) \\ -V_3C_2G \end{array} \right\}$$

$$g_3 = \left\{ \begin{array}{l} V_1C_3(G_S + 2G) \\ -V_2C_3G \\ -V_3C_3(G_SG) \end{array} \right\}$$

$$g_4 = \left\{ \begin{array}{l} -V_1C_1(G_S + G) + V_2C_1(G_S + 2G) \\ -V_3C_1G \end{array} \right\}$$

$$g_5 = \left\{ \begin{array}{l} -V_1C_2(G_S + G) + 2V_2C_2(G_S + G) \\ -V_3C_3(G_S + G) + C_2C_3X_3(V_2 - V_3) \\ +C_1C_2X_1(V_2 - V_1) \end{array} \right\}$$

$$g_6 \left\{ \begin{array}{l} -V_1C_3G - V_2C_3 \\ (G_S + 2G) \\ -V_3C_3(G_S + G) \end{array} \right\}$$

$$g_7 \left\{ \begin{array}{l} -V_1C_1(G_S + G) - V_2C_1G \\ -V_3C_1(G_S + 2G) \end{array} \right\}$$

$$g_8 \left\{ \begin{array}{l} -V_1C_2G - V_2C_2(G_S + G) \\ +V_3C_2(G_S + 2G) \end{array} \right\}$$

$$g_9 \left\{ \begin{array}{l} -V_1C_3(G_S + G) \\ -V_2C_3(G_S + G) \\ +2V_3C_3(G_S + G) \\ C_1C_3X_1(V_3 - V_1) \\ C_2C_3X_2(V_3 - V_2) \end{array} \right\}$$

The model thus obtained comprises nonlinearities which appears through a coupling between the parameters in X_I and X_J of immersion intervening in the terms in G_{ij} between the three phases. For the design of control structure around this nonlinear model, one chooses a representation by Multi-Layer Perceptron (MLP)[3].

STRUCTURE OF THE ARTIFICIAL NEURAL NETWORK

The artificial neural networks can be defined as being a whole of strongly connected neurons. The structure of such a network is illustrated by Fig. 2 and whose activity of only one neuron is a nonlinear function of the balanced sum of its input E_I The output noted O of such neuron is thus represented by the following expression:

$$\left\{ \begin{array}{l} net = \sum_{i}^{n} w_i e_i + w_b \\ o = f(net) \end{array} \right. \qquad (9)$$

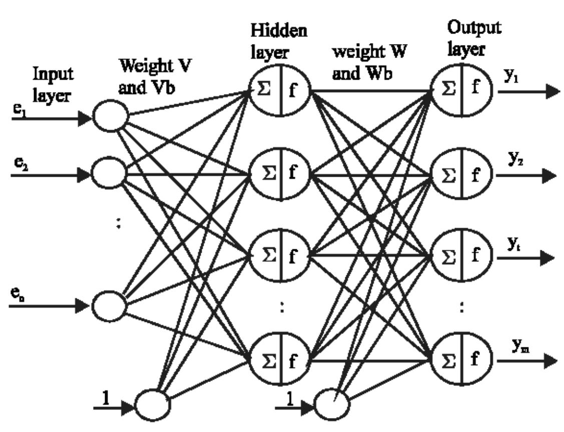

Fig. 2: Diagram of a network of artificial neuron

The term W_B is a skew added to the sum. The activation function used on the neuron output is a onlinear function, for example, the sigmoid function given by:

$$f(\mathrm{net}) = \frac{1}{1+e^{-\mathrm{net}}} \tag{10}$$

The propagation of the signals is done in the following way. For the neuron of the layer of output, the value takes the following form there:

$$y_i = f\left(\sum_{j=1}^{m}\left(w_{ij} f\left(\sum_{k=1}^{n} v_{jk} e_k + v_{bj}\right) + w_{bj}\right)\right) \tag{11}$$

The training of such a network consists in adjusting the value of the weights of connection between the neurons of two successive layers by using a data base S. the strategy of training is based on retro propagation algorithm. The principle is to minimize for each pair (E, y d) of the base S, the quadratic criterion J defined by:

$$J = \frac{1}{2}\varepsilon_{nn}^{T}\varepsilon_{nn} \tag{12}$$

where the vector of error å$_{nn}$ represents the difference between the wished output y_D and the neuron network output y obtained for an input E:

$$\varepsilon_{nn} = y^d - y \tag{13}$$

This representation technique of neural network will enable us to work out a control structure based on the inverse model study.

CONTROL OF ELECTRIC ARC FURNACE BY NEURONAL INVERSE MODEL

One proposes to carry out the neuronal control of thee. E.A.F. by a inverse model. In fact existence of nonlinearities in the operation range of the furnace and i n order to obtain a neuronal model which can be used in any point of operation. For this goal one applies to the process a rich signal (a pseudo sequence binary random, SBPA) to form a data base (input/output) which one will use for the training off line neural network.

The choice thus made of architecture by inverse model according to the diagram of Fig. 3. makes it possible to calculate the input (or signal control) U (t) at discrete moments (T = kT, where T is the period of sampling) starting from the former values input-output. The purpose of this model is to provide at every moment T the command variation Δu (t) :

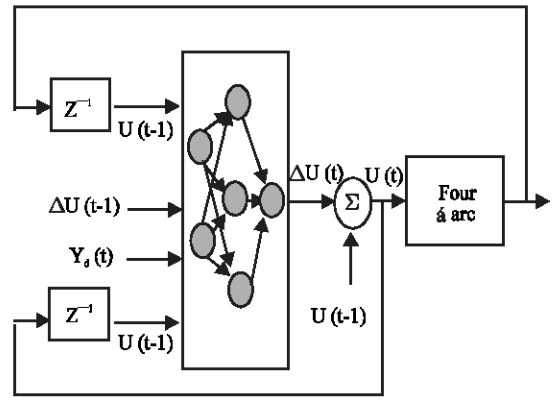

Fig. 3: Structure of control by the neural inverse model for the E.A.F

$$\Delta u(t) = u(t) - u(t-1) \tag{14}$$

Thus the network behaves as an inverse model which will provide in output:

$$u(t) = g^{-1}\left(y(t-1), y_d(t), u(t-1)\right) \tag{15}$$

It is to be stressed that this structure answers the specified objectives and namely to control the E.A.F with flexibility although it comprises nonlinearities.

RESULTS AND DISCUSSION

The data of the variables of the E.A.F are represented by the following Table 1: The tensions V_1 V_2 and V_3 used during simulation are sinusoidal of amplitude equal to 500V with a phase of 120° from each other. Simulations are made with Matlab and Simulink package. According to results' of simulation represented on Fig. 4. one sees that the fluctuations of the intensities and the powers follow almost the input with a transitional stage during the interval [0 1], which corresponds to the opening/closing of the valve.

After the introduction of a noise to the level of the valve, the output running and power according to Fig. 5. This evolution breaks up into three stages:

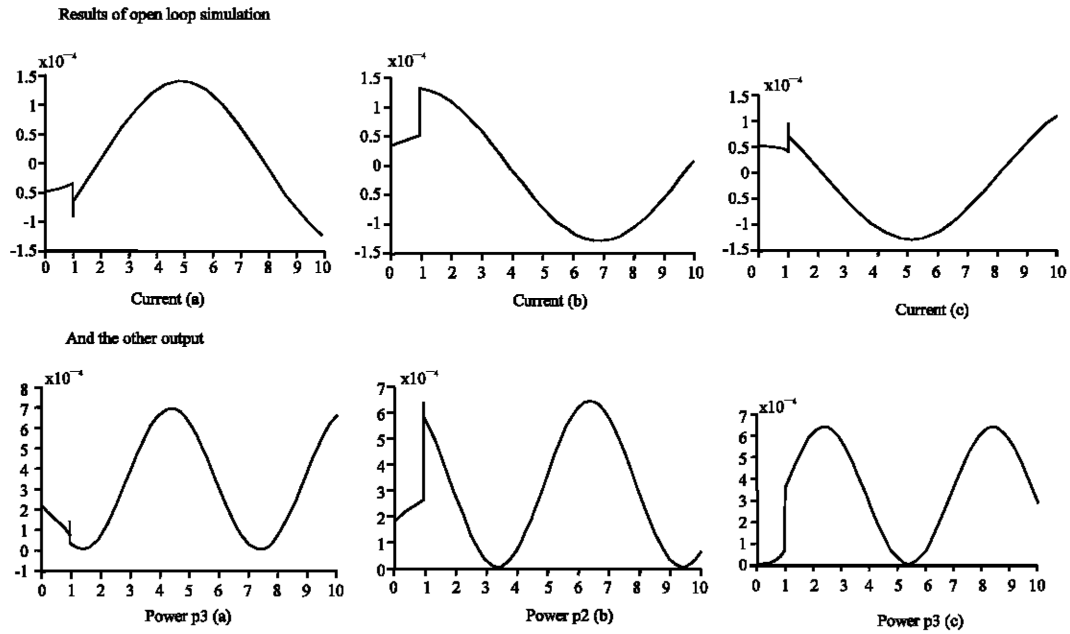

Fig. 4: Results of simulation in open loop

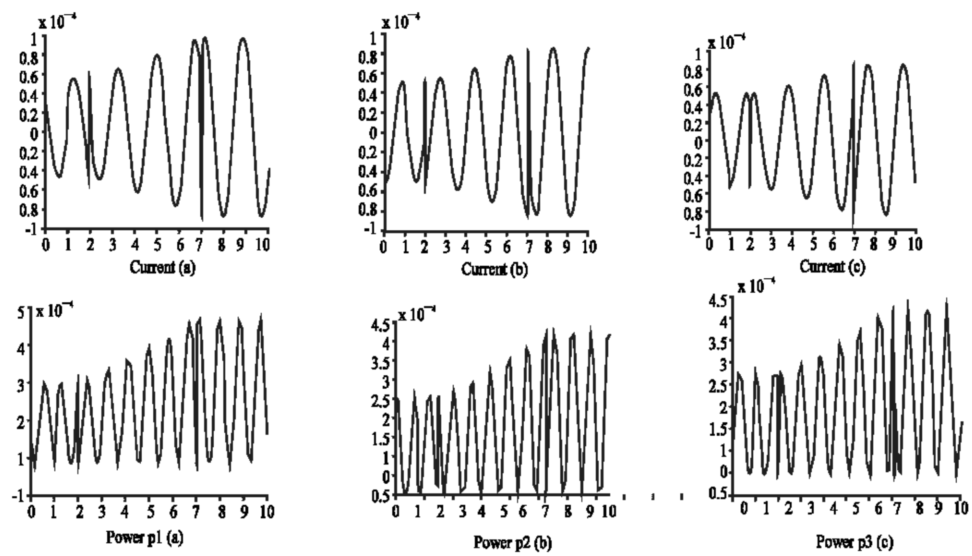

Fig. 5: Results of simulation after use of the value with a noise

[0 1] Opening of the valve.
[1 2] Placement of the electrode.
[2 7] Closing of the valve

Table 1:

Variable	Values
V_1, V_2, V_3	500V
C_1, C_2, C_3	20S/m
G_s	10S
G	0,1S

Of Control By Neural Inverse Model after an iteration count, one arrives in a stationary state of the learning curve with a lower error than 10^{-2}. Indeed the three curves output of the process make it possible to conclude that the structure of control by neural inverses model allows a controllability of the E.A.F with an acceptable degree of stability Fig. 6.

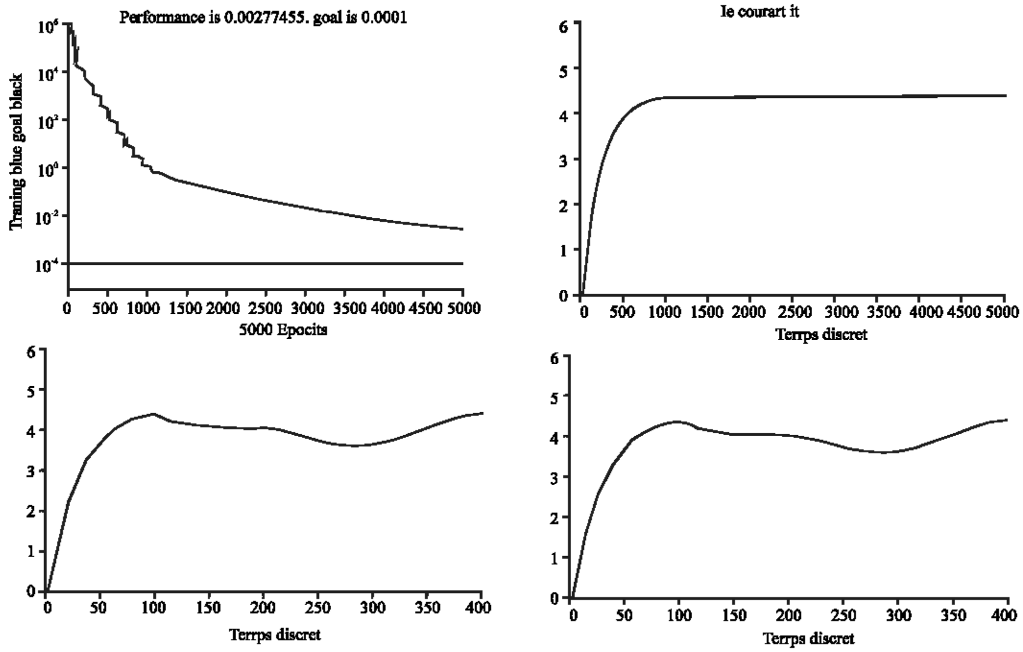

Fig. 6: Results of control simulations by neural reverse model

CONCLUSION

After having to review the models representing the EAF, it is to be stressed that the model, using the conductance like essential physical parameter, makes it possible to represent in a judicious way the phenomenon of electric arc and the transfer of energy which accompanies it.

The analysis of the various physical elements which make this process leading us towards a model containing networks of neurons. Also, it was proposed a structure of control by a neural inverse model implemented by a Multi-Layer Perceptron network (MLP). By this control, the objective was to transform the metal fusion process by the electric arc self-controlled. The results of simulation are encouraging and consolidate the idea of a real implementation on site. Moreover, it is to be noticed that the simplicity of implementation of this technique by specific circuits (FPGA, DSP...) allows a control in real time of the process of fusion.

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