UNLOADING ARM MOVEMENT MODELING USING NEURAL NETWORKS FOR A ROTARY HEARTH FURNACE

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ABSTRACT

Neural networks are being applied in many fields of engineering having nowadays a wide range of application. Neural networks are very useful for modeling dynamic processes for which the mathematical modeling is hard to obtain, or for processes that can't be modeled using mathematical equations. This paper describes the modeling process for the unloading arm movement from a rotary hearth furnace using neural networks with back propagation algorithm. In this case the designed network was trained using the simulation results from a previous calculated mathematical model.

Keywords: Rotary hearth furnace, unloading machine, neural network, back propagation algorithm, parallel structure

1. Introduction

The hot rolling process is one of the main processes for manufacturing seamless pipes. In the technological flow of hot rolling the first aggregate is the rotary hearth furnace [1]. The role of the furnace is to heat up the billet blocks from the ambient temperature to the rolling temperature, which is about 1250°C. Before the heating process begins the billets are cut at the required lengths. The billets heating process makes the material change from the elastic domain to the plastic one, and prepares the billet for manufacturing.

The heating process is slow and the furnace consists of five regulating temperature sectors which have a total of 48 burners, a sector for preheating and a sector for loading and unloading billets.

The furnace's hearth is rotated by two mechanisms for action located at the furnace exterior on opposite directions. The furnace has two machines, and when the hearth stops one is used for the loading and the other for unloading the billets from the furnace. Figure 1 presents the loading and the unloading machines principle scheme.

The unloading machine consists of a trolley moving on a rail way track and a robotic arm that has a clamp at the furnace end [2]. The clamp is design to catch the billet and has one fixed and one movable jaw, according to fig. 2. The robotic arm has to be positioned over a billet so that the clamp catches the block right in the middle according to its length. Driving the machine and the clamp opening is done hydraulically.

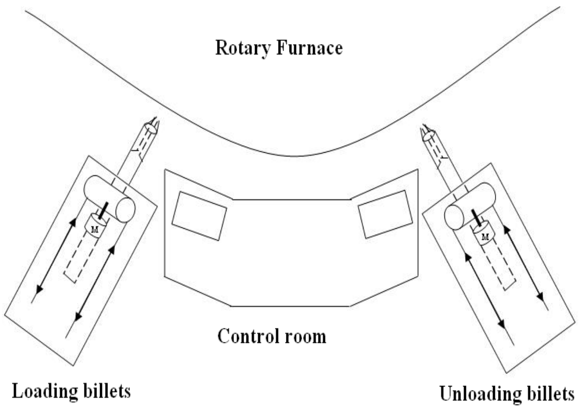

Fig. 1 – The principle scheme of loading and unloading machines

The billets charging and discharging is being done according to the billet length and the rhythm of rolling [3]. The charging of the hearth can be made on one row, or on two rows, depending on the billets length. Billets that are longer than 2000 mm should be charged on one row.

According to the loading scheme we know the distance from the initial position of the loading or unloading machine and the position of the billet on the furnace hearth.

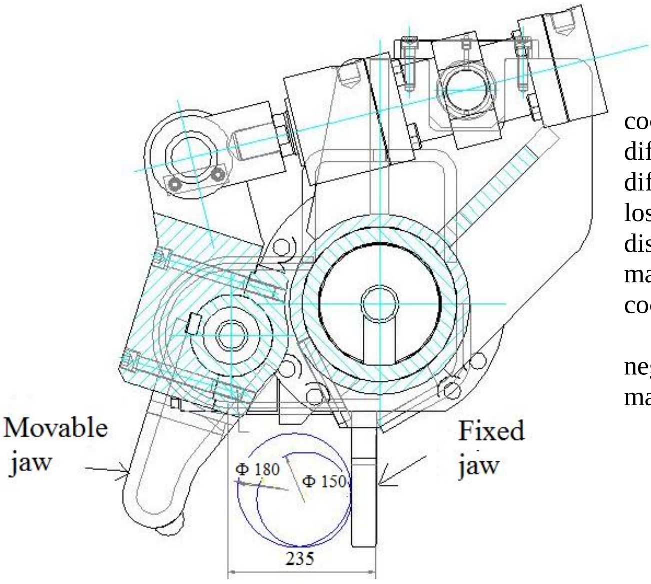

Fig. 2 - Transverse image of the unloading clamp

When the unloading or the loading machine moves from front to back, in order to unload or to load the billet block, the machine distance from its initial position it is measured by using an incremental encoder placed behind the machine. At the unloading door the billet block has a small displacement from the rail way axis position. To achieve the left-right positioning inside de furnace the arm is able to rotate around a static point. The maximum distance that results from the rotation of the arm is about 300–400 mm, and it is approximated by a linear motion.

To achieve the clamp positioning for the correct grip, it is required to use a control loop and for that we need to determine the mathematical model for the unloading arm movement.

The billet displacement from the rail way axis is calculated using a video camera. In the pictures taken from the camera the billet is detected as a circle and a computer calculates the distance between the billet circle centre and the rail way axis, considered as the point zero. This distance is going to be the reference for the control loop, and the output for the control loop will be the arm movement.

2. Mathematical model for the unloading machine's positioning system

The mathematical model for the left-right arm movement process starts with the assumption that the arm is an electro-hydraulic axis and the dynamic of the electrical part is neglected for consideration of time constants [4]. Dynamics of the hydraulic part are described by the following equations.

Linear equation of servo valves:

$$\Delta Q = K_Q \Delta x - K_C \Delta p_m \tag{1}$$

Equation of flow conservation:

$$\Delta Q = S\frac{d(\Delta y)}{dt} + \alpha \Delta p_m + \frac{V_T}{4E}\frac{d(\Delta p_m)}{dt} \tag{2}$$

Mechanical equation of motion:

$$S\Delta p_m = m\frac{d^2(\Delta y)}{dt^2} + f\,\frac{d(\Delta y)}{dt} + F_R \tag{3}$$

Where: K_Q – flow gain, K_c – flow-pressure coefficient of the proportional valve, ΔQ – flow differential, Δx – billet displacement, Δp_m – pressure differential, S – piston area, α – overall rate of oil loss, V_T – total oil volume, Δy – output size (arm displacement), E – coefficient of oil elasticity, m – mass of the piston and the load, f – viscous damping coefficient, F_R – static force strength.

The Laplace transformation to (1) - (3), and by neglecting the parameters α, K_c, and F_R the mathematical model (4) was obtained:

$$\begin{aligned} \dot{x}_1 &= \omega(u - x_2) \\ \dot{x}_2 &= \omega(x_1 - 2\xi x_2) \\ y &= kx_2 \end{aligned} \tag{4}$$

The state space model parameters are defined as follows:

$$\begin{aligned} k &= \frac{K_Q}{S} \\ \omega &= \sqrt{\frac{4ES^2}{V_T m}} \\ \xi &= \frac{V_T f}{8ES^2}\cdot\sqrt{\frac{4ES^2}{V_T m}} \end{aligned} \tag{5}$$

The model parameters have the following values:

$$\begin{aligned} k &= 13.281 \\ \omega &= 797.1495 \\ \xi &= 3.0355\cdot 10^{-7} \end{aligned} \tag{6}$$

3. Neural network design

Neural networks are being applied nowadays in many fields of engineering even if there is no general procedure through which we can select the appropriate neural network design for a specific task [5]. Neural network have a wide range of application, especially after the back propagation algorithm was developed, in fields like modeling, pattern recognition or signal processing. In the modeling field neural networks are used to model processes for which the mathematical model is hard to obtain, or for processes that can't be described using mathematical equations. These networks are also used for estimating the values of parameters for which no analytical method has been developed.

An important element in network design is the network structure and structurally networks are composed of single or multi layers that include a finite number of neural cells [6]. In order to shape a dynamic process the neural network should take into account the past values of input and output. For a neural network to reproduce the dynamic behaviour of a system it has to be trained using the same input signal as the system, and the purpose is to minimize the network errors, the difference between the exact value of the systems output and the value predicted by the network.

For the dynamic systems modeling we can highlight two typical structures for the neural network: a parallel structure, presented in fig. 3, and a series-parallel structure, presented in fig. 4.

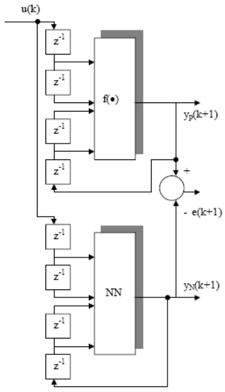

Fig. 3 - Neural network parallel structure

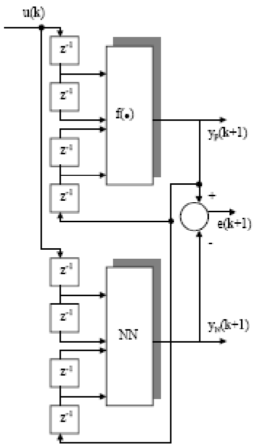

Fig. 4 - Neural network series-parallel structure

In the series-parallel structure the neural network and the dynamic system have the same input signals, but in this case, the output signals (and the past values of it) are applied to the neural network inputs. In this case the neural network and the system are not independent entities, like in the case of parallel structured network. For this case the system output is affecting the behaviour of the network.

From the point of learning algorithms the neural networks are divided into various groups. In this paper we use the back propagation algorithm. A multilayered network with back propagation algorithm is very useful for mapping nonlinear functions.

To train the designed network we can use the experimental data from the process or the simulation results. As input signals used to identify a system on which no knowledge exists, or they are in a limited quantity, we can use persistent signals. Persistent signals will excite all the system modes under identification, in fig. 5 we have an example of a persistent signal. This persistent signal is generally a white noise.

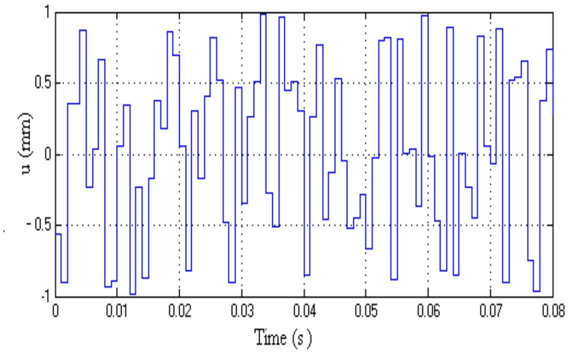

Fig. 5 - Persistent signal

4. Simulation results for the movement modeling using neural networks

Using MATLAB 7.6 we designed a neural network with a series-parallel structure and we simulated the step response obtained for the trained network.

The network is built with a single hidden layer containing 10 linear neurons and one linear neuron on the output layer. The training algorithm is a back propagation algorithm with variable learning rate.

Because we have information about the dynamic system, in this case from the mathematical model, we use four delay elements for the input and four delay elements for the output data.

In order to obtain the input-output pairs for training the network we apply a noise input signal, like the one in fig. 4, to the mathematical model (4) with the parameters values (6).

The simulation time is 0.5 s, and the sampling period is 0.001 s, so we obtain 501 input-output pairs to train the network. In Fig. 6 we have represented the applied input signal sequence and the corresponding mathematical model outputs.

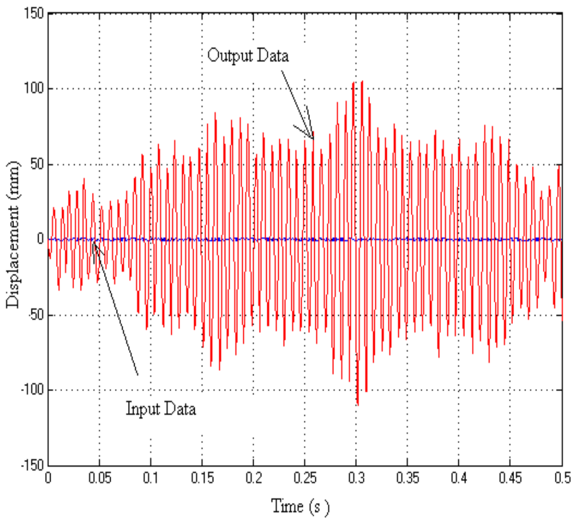

Fig. 6 - Data signals used for training the network

A unitary step signal was used for the trained network in order to compare it to the mathematical model response at the same reference. Figure 7 shows the two step responses on the same plot for a time period of 0.08 sec, and we can observe that the signals are overlapped.

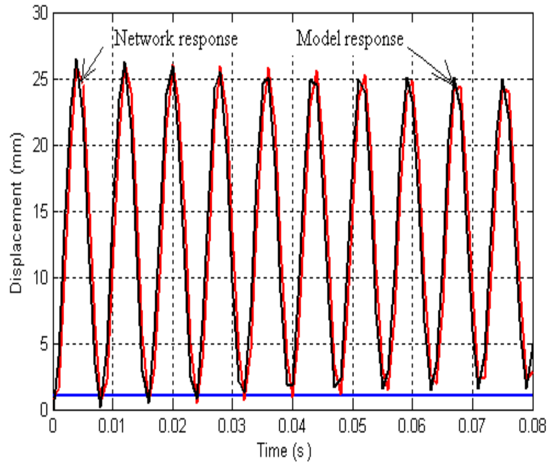

Fig. 7 -Trained network and the mathematical model step response for the simulation period of 0.08 seconds

We simulated the trained network step response for a longer period of time, 3 sec, in order to observe if the network behavior is the same as the model behavior. In fig. 8 we have the two responses and they are overlapped meaning that the trained network behavior is the same as the mathematical model behavior. From this figure we can determine that the dynamic systems settling time is about 2.5 seconds.

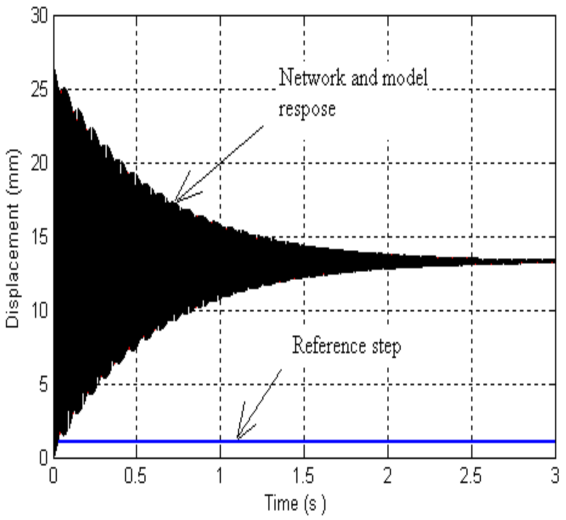

Fig. 8 - Trained network and the mathematical model step response for the simulation period of 3 seconds

For this network the error reaches the allowed value after 4 training epochs as can be seen in fig. 9. Other training performances such as the gradient evolution can be seen in fig. 10.

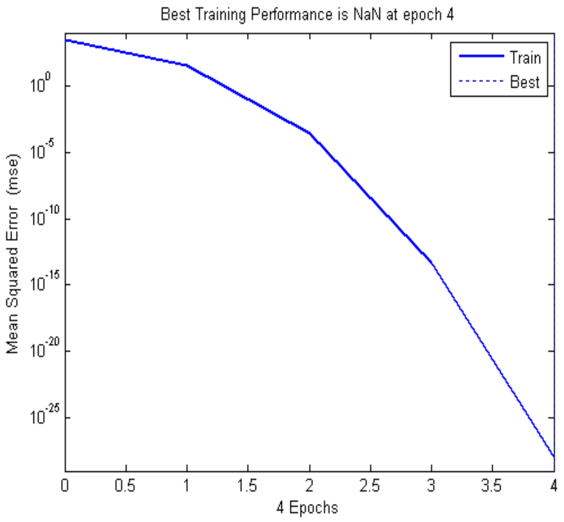

Fig. 9 - Mean squared error evolution for the network training

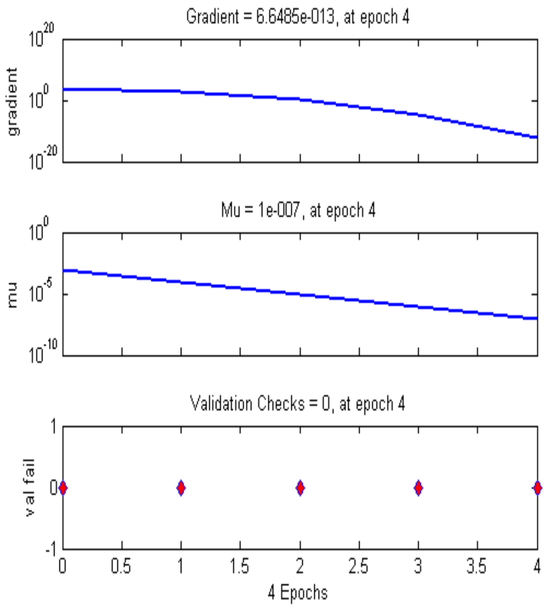

Fig. 10 - Training performances

5. Conclusion

In this paper the designed neural network was trained using the simulation results from a previous calculated mathematical model.

Neural networks are very useful in modeling dynamic systems. For the movement model of the unloading arm we can retrain the network when we have the experimental data and we will obtain the real behaviour of the robotic arm. For the experimental data the same input signal will be use.

In order for the neural network to learn the true behaviour of the system it must be properly constructed. If for example we choose for the above process only one input element delay and two output element delays instead of four, we obtain the step response from fig. 11. As we can see from this figure it is recommended that the number of delay elements for the input and the output signal to be given as accurately as possible. If we do not have information about the process we will use more delay elements.

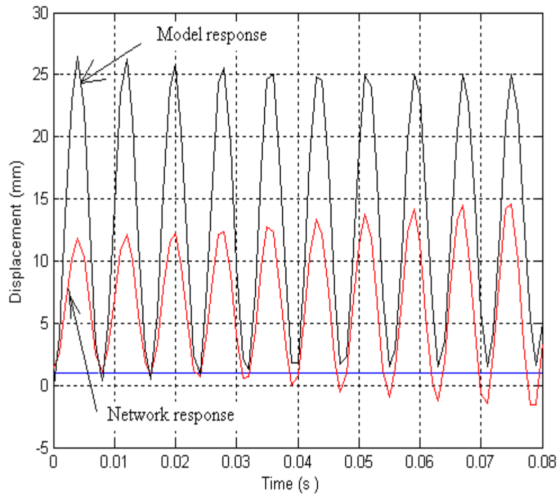

Fig. 11 - Network and model step response

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References

[1] Roberts, W.L. - *Hot Rolling of Steel - Manufacturing Engineering and Materials Processing*, Marcel Dekker, Inc., New York, 1983.

[2] Brunklaus, J.H. - *Cuptoare industriale – Calcul, construcţie şi utilizare*, Editura Tehnică, Bucureşti, 1977.

[3] Muresan, V. and Abrudean, M. - *Temperature Control in the Furnace with Rotary Hearth*, 2010 IEEE International Conference on Automation, Quality and Testing, Robotics (AQTR), Cluj–Napoca, România, May 28-30, 2010, pp. 225-230.

[4] Inoan, I. - *Movement control of an unloading machine from a rotary furnace*, 2010 IEEE International Conference on Automation, Quality and Testing, Robotics (AQTR), Cluj–Napoca, România, May 28-30, 2010, pp.131-134.

[5] Mureşan, V.and Abrudean, M. -*Control System Optimization of Rotary Hearth Furnace Charging/Discharging*, IEEE 5th International Symposium on Applied Computational Intelligence and Informatics, Timişoara, România, May 28-29, 2009, pp. 267-270.

[6] Lazea, G., Lupu, E., Dobra, P. – *Echipamente de automatizare pneumatice şi hidraulice. Îndrumător, Partea I*, Mediamira, Cluj-Napoca, 1998.

[7] Zhang, L., Zhang, L. Jr., Wang, J. and Ma, F. - *Prediction of Rolling Load in Hot Strip Mill by Innovations Feedback Neural Networks*, Journal of Iron and Steel Research, International, 14(2), 2007, pp. 42 – 45.

[8] Pham, D.T., Liu, X. – *Neural networks for identification, prediction and control*, Berlin, 1997.

[9] Shahani, A.R., Setayeshi, S., Nodamaie, S.A., Asadi, M.A., Rezaie, S. - *Prediction of influence parameters on the hot rolling process using finite element method and neural network*, Journal of Materials Processing Technology 209, 2009, pp. 1920 –1935.

[10] Demuth, H., Beale, M. – *Neural network Toolbox: for use with Matlab*, Natick, Massachusetts, 1995.