Modelling the Technological Part of a Line by Use of Neural Networks

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Abstract. The paper deals with the applications of artificial neural networks in modelling and control of a continuous tinning line's technological part. In the conclusion part of the paper, description of the whole model of the tinning line technological section together with the neural speed estimators is presented, along with an evaluation of the achieved simulation results. Training of individual neural networks was performed off-line and adaptation of the network parameters was done by Levenberg-Marquardt's modification of the back-propagation algorithm. The DC drives were simulated in program Matlab with Simulink toolbox and neural networks were proposed in the Matlab environment by use of Neural Networks Toolbox.

Keywords: Mathematical model, technological line, control, DC motor, neural network.

1 Introduction

Modelling is a method enabling the identification of the characteristics of the system under investigation. Using simulation we can then experiment with the model of the line similarly to the real system, without to need intervene in the real system, eliminating the risk of emergency states. An advantage of neural networks is their ability to learn from examples, the ability of abstraction, so their applications are very useful for complex dynamical system modelling [2-5] and control [2,3,5-12], also.

The continuous process line, the model of which we are going to deal with, is a steel strip tinning line producing tin-plated material used in the packaging industry. It is made up of three autonomous sections [1]:

- the entry section, determined for accumulating a stock of material for the technological section and for reduction of traction in the strip,
- the technological section, where electrolytic tinning of steel sheet takes place, according to the technological formula for particular material options in the Ferrostan process technology,
- the exit section, where coiling of the sheet material takes place.

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The entry section of the process line includes the drive of the decoiler device that provides for the uncoiling of the strip at a required tension, independent from the coil diameter and the strip speed. The material is welded into an endless strip that proceeds into the tower accumulator. The subsequent drives of the entry section traction rolls ensure the required strip speed. The remaining drives are provided with traction control and secure the required strip tension over its entire length. Galvanic tinning of the steel strip is carried out in the middle section of the process line. The treated strip is then, at the exit section of the line, recoiled into coils of the specified diameter and width.

The objective of this paper is the development of the neural model of the line technological section. Designing of the neural model of technological tinning lines is based on the mathematical description (of the line without considering a reel decoiler) because on the running production line was not possible to take measurements, but the description of technology and each devices of the line has been known [1]. Since created mathematical model corresponds to the real process [1], the mathematical model was used for neural networks training sets obtaining and for verification neural model of the line under various conditions without limitation the production.

2 The Line Technological Description and Mathematical Model

Technology part of the continuous line consists of six controlled drives separately excited DC motors that allow independently controlling individual electrical, mechanical and technological quantities so that the production technology would be strictly adhered to. Our intention was to use neural model of the line to observe strip speed at any particular section of the technological line.

Present in the tinning line technology part are six drives:

- drives of traction rolls No.2 (input, middle and output) situated past the tower accumulator and are stretching the strip that enters the middle part of the line,
- drives traction rolls No.3 (input and output) maintain the desired output speed and the desired tension,
- drives of φ rolls, which are used to capture the strip when transiting to the coiler.

The line control allows introducing the strip into the line and supports independent run of each section at desired speed.

During introducing of a new coil, middle part of the line runs at a constant working speed, input part of the line is stopped and the strip is filled from the tower storage. After the input part of the line re-restart-up this part of the line accelerates to a speed about 25% higher than the operating speed of the middle part of the line. Once the tower storage is filled, speeds of them are synchronized.

When designing a neural model of technological tinning lines we used mathematical description of this part of the line.

2.1 Mathematical Model of Middle Part of the Line

Mathematical models of parts of the line along with controls were designed in Simulink, which is part of Matlab, and the line neuron model line was set up using Neural network toolbox of Matlab.

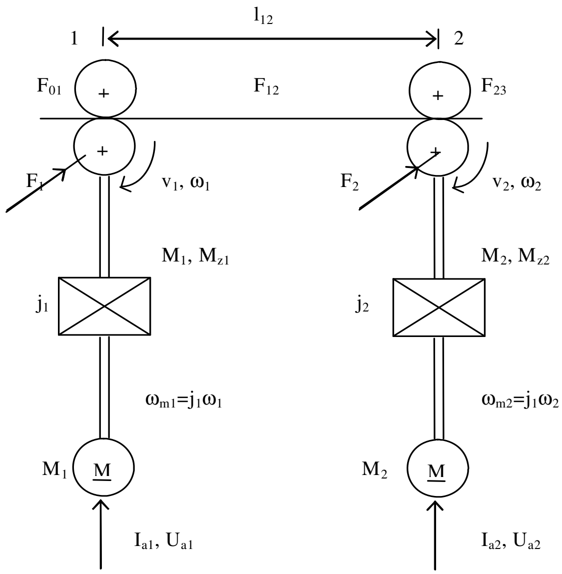

Fig. 1. Part of the continuous line with two motors

To set up an accurate model binding system considered have to be two areas of the model utilization:

- at zero traction, when developing between machines can be material loops,
- at positive tensile stress, when the transportation rollers are mechanically bound together.

In the next section, for more transparent derivation of mathematical expression of the middle part of the line, we are considering only two motors of the line, as illustrated in Fig.1.The part of the continuous line consisting of only two DC separately excited motors 1 and 2, according to Fig.1, can be described by a system of differential equations, in the order for the first drive (equation dynamics as to the driven machine shaft), for the section of the strip between, and the second drive:

$$M_1 + (F_{12} - F_{01})r_1 - M_{z1} = J_1 s.\omega_1 \tag{1}$$

$$\frac{SE}{l_{12}}(r_2\omega_2 - r_1\omega_1) = sF_{12} \tag{2}$$

$$M_2 + (F_{23} - F_{12})r_2 - M_{z2} = J_2 s\omega_2 \tag{3}$$

After supplementing these equations by the equation for the motor armature circuit for the two drives:

$$M_i = j_i C_i \phi_i I_{ai} \tag{4}$$

where i=1,2

$$R_{ai} I_{ai} + L_{ai} \frac{dI_{ai}}{dt} + j_i C_i \phi_i \omega_i = U_{ai} \tag{5}$$

We are obtaining the mathematical model of the simplest continuous line, block diagram of which is illustrated in Fig.2. The constant before the parenthesis in equation (2) presents the strip elasticity constant of the strip for the considered section:

$$K_{p12} = \frac{SE}{l_{12}} \tag{6}$$

Whereas the strip material features besides elasticity also dampening effects that are reflected in K_T dampening constant, expressed in % of constant K_p, equation (2) will take on the following form:

$$K_p(r_2\omega_2 - r_1\omega_1) + sK_T(r_2\omega_2 - r_1\omega_1) = sF_{12} \tag{7}$$

Designed for all of the above-mentioned drives were controllers of the motor armature current and superior speed controllers. Basically, tension control equals controlling the armature current, which determines the motor torque. Direct traction controlling would require the quantity to be precision measured. Yet, the sensors are too expensive and once overloaded they come permanently deformed. Due to the fact, used these days is indirect traction control.

Control is based on equality of mechanical and electrical outputs:

$$P_{mech} = F.v \tag{8}$$

$$P_{el} = U_i.I_a \tag{9}$$

Assuming that the speed of the strip can be observed quantity and value of the induced voltage U_i, and the armature current I_a will be measured, we can determine tension strength from these equations:

$$F = \frac{U_i}{v} I_a \tag{10}$$

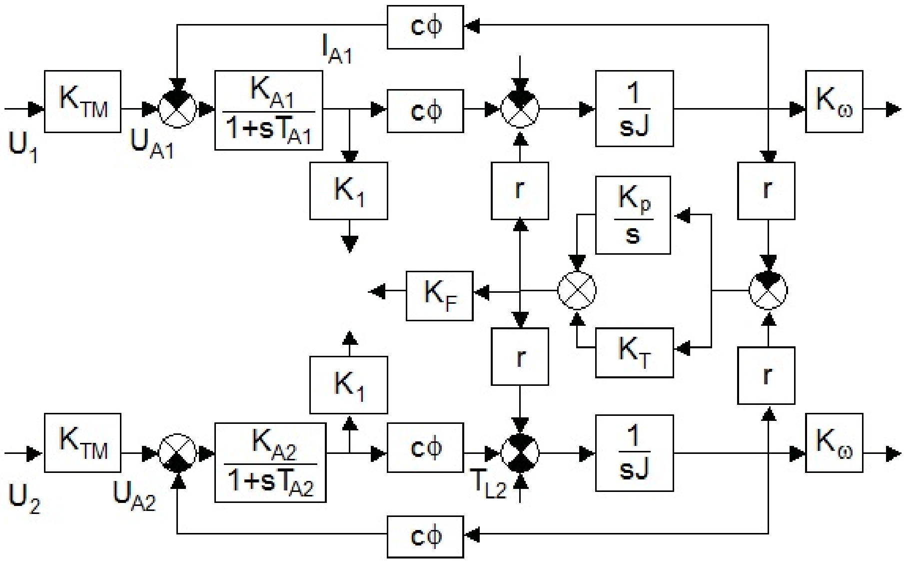

Fig. 2. Block diagram of a part of the continuous line – for two identical drives

The DC motor armature controller maintains the current value I_a proportional to the tension force F and the excitation controller maintains a constant ratio U_i/v. Mathematical models of individual parts of the line along with the control were designed in Simulink.

3 Neural Model of Middle Part of the Line

Neural model of individual parts of the line has been designed as a series-parallel model of drives, shown in Fig. 3.

Whereas to detect speed of the strip, e.g. for determining the tension force, it is necessary to know the speed of the strip in each part of the line, we divided technological line as described above into six parts and for each part of the line a separate neural model was created. Inputs of individual neural models ***u(k)*** present the desired values of the strip speed, armature current in the *k-th*, *(*k-1) and *(k-2)* steps for the drive and the observed value of the speed in the *(k-1)* step.

Basic structure of the neural model of one part of the line approximates speed of the strip based on the following equation:

$$\hat{v}_s(k) = f\left[v_{\check{z}}(k), i_a(k), i_a(k-1), i_a(k-2), \hat{v}_s(k-1), \boldsymbol{w}\right] \tag{11}$$

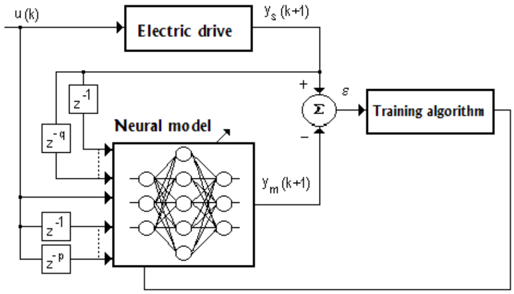

Fig. 3. Block diagram of the series-parallel drive model

Suggested to approximate the relation were two types of neural networks (Figs.4 and 5):

- Multi-layer feed-forward network
- Cascade feed-forward network

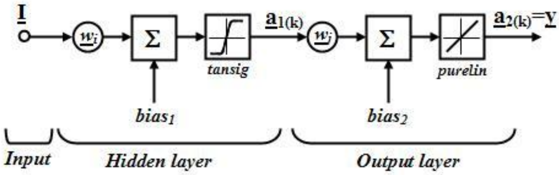

Fig. 4. Neural feed-forward network

Outputs of the first and second layers of the feed-forward network are determined based on relations:

$$\begin{aligned} \underline{a}_1(k) &= tansig\left(\underline{I}\,\underline{w}_i + bias_1\right) \\ \underline{a}_2(k) &= purelin\left(\underline{a}_1(k)\,\underline{w}_j + bias_2\right) \end{aligned} \tag{12}$$

where ***I*** is the input vector and ***w*** is vector of synaptic weights of the network.

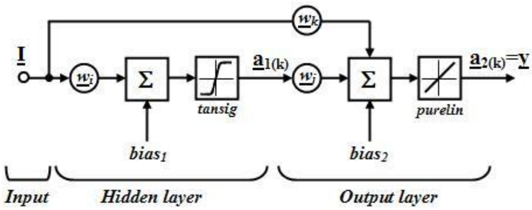

Fig. 5. Cascade feed-forward network

Outputs of the first and second layers of the cascade network are determined based on relations:

$$\underline{a}_1(k) = tansig\left(\underline{I}\,\underline{w}_i + bias_1\right)$$

$$\underline{a}_2(k) = purelin\left(\underline{I}\,\underline{w}_k + \underline{a}_1(k)\underline{w}_j + bias_2\right) \tag{13}$$

For both types of networks, used for the output layer neurons were linear activation functions, and for neurons in the hidden layer tansigmoid activation functions:

$$f(n) = \frac{1}{1+\exp(-an)} \tag{14}$$

where n is the value of the neuron inside activity and a is the slope parameter of the sigmoid. Training of individual networks was carried out off-line, and chosen for adapting the network parameters was the Levenberg-Marquardt modification of back-propagation algorithm.

The optimization objective was seen in minimizing the function (15):

$$e = \frac{1}{Q}\sum\left(v_q - v_q'\right)^2 \tag{15}$$

where: Q - the number of trained samples

v_q - is the q-value of the strip speed based on the given drive model

v_q' - is the q-observed value of the network output.

Synaptic weights adaptation was based on the relation:

$$\Delta\mathbf{w} = \left(\mathbf{J}^T\mathbf{J} + \mu\mathbf{I}\right)^{-1}\mathbf{J}^T\mathbf{e} \tag{16}$$

where:

$\mathbf{J}$	-	is the Jacobian matrix,
$\mathbf{J}^T\mathbf{J}$	-	is the approximated Hessian matrix,
$\mathbf{J}^T\mathbf{e}$	-	is the gradient vector,
$\mathbf{I}$	-	is the unit matrix
μ	-	is the coefficient influencing the rate of adaptation of weights

Neural model of the line middle part was set up using Neural Network Toolbox of Matlab. After comparing the results of testing both types of networks attained by feed-forward and cascade networks, chosen for all six parts was a three-layer cascade feed-forward network with ten neurons in the hidden layer.

4 Results of Simulation and Comparison

Neural models have been tested for a variety of changes in the value of the desired speed and for different load torque changes before and after the tower accumulator.

All tests were conducted under different conditions than they were in the setting up of the training sets of the following desired rates: 1.5 m/ s, 5.1 m/ s, 1.9 m/ s, 2.8 m/ s, 3.6 m/ s; these changes occurred at times: 0s, 10s, 25s, 40s, 45s and at the time 0s, 20s and 35s the load torque changed to the values of 332Nm; 232Nm; 382Nm. Since the results obtained are similar in nature not presented are the testing results of all six neural models but only those of selected models. The following figures show the selected simulation results obtained when testing neural models of the line.

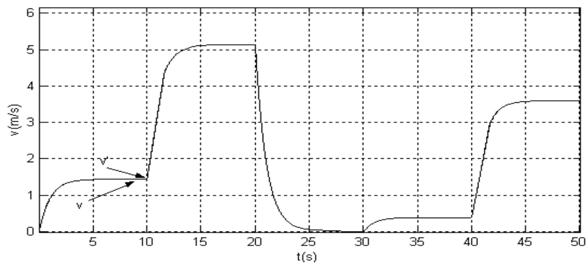

Fig. 6. Traction roll No.1- input, observed and real waveforms of the strip speed

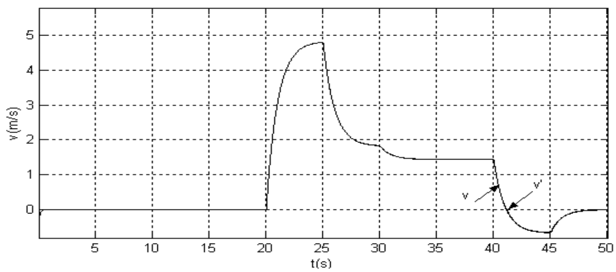

Fig. 7. Observed and real waveform of the strip speed within the tower accumulator

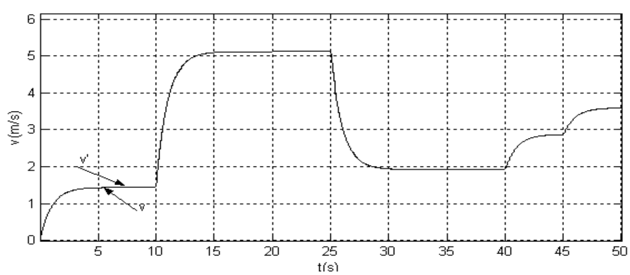

Fig. 8. Traction roll No.2-input: observed and real waveforms of the strip speed

Illustrated in Fig.6 are observed and modeled changes in strip speed at changes in the desired speed in No.1 traction roll.

Waveforms at the identical speed changes in traction rolls No.2, No.3 and φ rolls have the same character (Fig. 8, Fig10). Illustrated in Fig.8 are observed and modeled changes in strip speed within traction roll No. 2.1, corresponding with the waveform shown in Fig. 6.

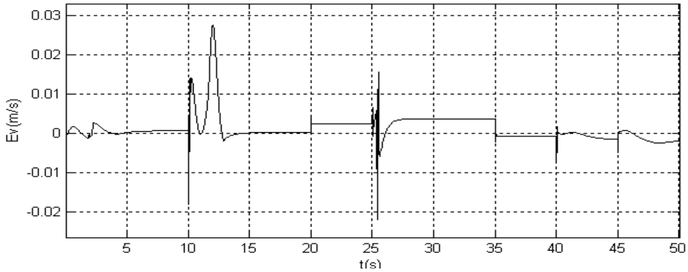

Fig. 9. Detail of the difference in observed and modelled speeds of the strip within traction roll No.2.1

The maximum errors evidenced at dynamic changes fluctuated between 0.5% at the strip speed at φ rolls up to max. 2% at No. 3 traction roll. Max errors at other traction rolls were fluctuating around 1%.Shown in Fig. 9 is the difference between observed and modeled speed zone in the traction rolls No.2.1 corresponding with that shown in Fig.8.

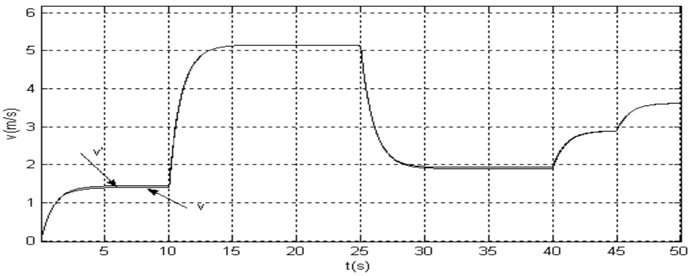

Fig. 10. Traction roll No.3- input: observed and real waveforms of the strip speed

5 Conclusions

Technological lines for treatment of rolled steel or another strip present a significant part of the rolling mill drives. Treatment of rolled strip is based on the longitudinal or transverse divisions or on the surface finish, respectively. The tinning line is intended for producing sheets for packaging. Our objective was to develop a neural model of the line middle part and demonstrate the possibilities of neural networks application.

Mathematical models of parts of the line along with controls were designed in Simulink, and the line neuron model was set up using Neural network toolbox.

Based on easily measurable signals (11) it is possible, using neural model of the line, to observe the strip speed at any particular section of the technological line. Maximum errors that occurred at swift dynamic changes ranged from 0.5% at the strip speed at rolls φ up to maximum of 2% at traction roll No. 3 – the output one. The maximum errors in the other traction rolls and the tower accumulator were around 1%.

As the simulations show, the characteristics of line neural model are similar to standard modeling results. The advantages of neural networks application are mainly in modeling of complex systems, where they allow, the approximation of any continuous function without the precise knowledge of the structure of the modeled system. In our case, the mathematical model of the line was used to obtain the training sets and verification of the proposed neural model without limitation of production process.

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