COLD ROLLING NEIGHBORHOOD MODELS WITH A FUZZY HIERARCHICAL STRUCTURE

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ABSTRACT

The paper considers cold rolling simulation during the continuous annealing process. The development of a simulation model of the considered process is relevant as it makes it possible to predict the mechanical properties of steel, such as yield stress, ultimate resistance, tensile strain, without a natural experiment. Dynamic neighborhood models are applied for the simulation of complex distributed production processes and systems. They reflect the dynamics of the considered process and make it possible to control its results at the intermediate production stages. A general definition of dynamic neighborhood models with a fuzzy hierarchical structure is given, the models being characterized by fuzzy neighborhood two-level links between the model nodes of the first and second level. In the paper, linear fuzzy hierarchical dynamic neighborhood models of the cold rolling process for calculating the mechanical properties of steel are developed. The simulated and production data on the basis of relative identification errors are analyzed and conclusions are made.

Keywords: linear dynamic neighborhood models, fuzzy hierarchical structure, mechanical metal properties, cold rolling.

INTRODUCTION

In the production of cold rolled products in the continuous annealing process, it is important to determine, monitor and control such mechanical metal properties as yield stress, ultimate resistance, tensile strain [1 - 3]. The development of the simulation model of the cold rolling process is relevant today as it makes it possible to predict the mechanical steel properties formed during the continuous annealing process without a natural experiment. Static linear regression models were developed for the dependence of the mechanical properties of steel only on its chemical composition [4], and for the dependence of the other technological production parameters: temperature conditions of hot rolling and total reductions during cold rolling [5]. In addition, models of only one specific steel grade are considered [4, 5]. Neural network models of the mechanical properties of steel based on a multilayer perceptron are presented in [6].

However, as cold rolling is a distributed dynamic process, it is important to develop a dynamic simulation model to control the results at the intermediate production stages. Neighborhood models [7 - 11] the main concepts of which are discussed in [12 - 13] are used to simulate these complex distributed manufacturing processes. The aim of this study is to develop a cold rolling simulation model based on linear dynamic neighborhood models with a fuzzy hierarchical structure for the steel gauge of the metallurgical production, to compare the simulation results with the production data. The results in this article are in the course of those presented in [14].

MATHEMATICAL MODEL

The «input-state» dynamic neighborhood model [14] with a fuzzy hierarchical structure can be set by

\[ \dot{\mathbf{N}} \mathcal{S} \mathcal{G} \mathcal{E} = (\dot{\mathbf{N}}, \mathbf{X}, \mathbf{V}, \mathbf{G}, t_0, \mathbf{X}[t_0], t) \],

where:

1. \( \dot{\mathbf{N}} = (A, \mathcal{O}) \) is a two-level fuzzy model structure consisting of many first level nodes \( A = \{a_1, a_2, ..., a_n\} \)
and a set of neighborhoods $\mathcal{O} = \{O_x, O_p, \mathcal{O}_{iter} \}$ which, in their turn, are divided into neighborhoods of nodes by state actions $O_x = \bigcup_{i=1}^{n} O_x[i]$, neighborhoods of nodes by control actions $O_p = \bigcup_{i=1}^{n} O_p[i]$, fuzzy hierarchical neighborhood links between the first and the second levels nodes $\mathcal{O}_{iter}$.

Each first level node $a_i \in A$ is associated with a fuzzy set of the second level nodes $\mathcal{O}_{iter}[i] = \{a_{i}^{1}, ..., a_{i}^{ci}\}$ each of which is a neighborhood model. At the same time, $a_i^b \in \mathcal{O}_{iter}[i]$, $b = 1, ..., c_i$ with some membership function $W_i^b : X_{O_x[i]} \times V_{O_p[i]} \rightarrow R_{[0,1]}$ the values of which depend on the state and control actions on the node $a_i$ at this point in time: $W_i^b(X_i[t], V_i[t]) = W_i^b[t]$.

It means that for each node $a_i$ a membership vector-function is set for the second-level nodes, $W_i : X_{O_x[i]} \times V_{O_p[i]} \rightarrow R_{[0,1]}^{c_i}$.

Thus, each first level node $a_i \in A$ of the neighborhood model is, in its turn, a fuzzy neighborhood model with a set of second level nodes $\mathcal{O}_{iter}[i]$.

For all second level nodes $a_i^b \in \mathcal{O}_{iter}[i]$, neighborhoods $O_x[i^b] = O_x[i]$; $O_p[i^b] = O_p[i]$ are set.

2. $X \in R_{\sum_{i=1}^{n} p_i}$ is the block vector of model states at this point in time.

3. $V \in R_{\sum_{i=1}^{n} m_i}$ is the block vector of control actions at this point in time.

4. $G : X_{O_x} \times V_{O_p} \rightarrow X$ is the stating function of the neighborhood model where $X_{O_x}$ is the set of node states included in the neighborhood $O_x; V_{O_p}$ is the set of node controls included in the neighborhood $O_p$.

5. $t_0$ is the initial time of the model functioning.

6. $X[t_0]$ is the initial state of the model.

7. $t$ is the current time of the model functioning.

For the each second level node $a_i^b$, the stating function $G_i^b$ is set:

$$X[t + 1, i^b] = G_i^b(X_i[t], V_i[t]).$$

In the linear case, for the second level node $a_i^b \in \mathcal{O}_{iter}[i]$, the stating function $G_i^b$ has the form:

$$X[t + 1, i^b] = G_i^b[t] = g_c[i^b] + \sum_{j \in O_x[i^b]} g_x[i^b, j]X[t, j] + \sum_{k \in O_p[i^b]} g_p[i^b, k]V[t, k],$$

where $a_j, a_k \in A \ (j, k = 1, ..., n)$ are the first level nodes of the model; $g_x[i^b, j] \in R_{[0,1]}^{p \times p_j}$, $g_p[i^b, k] \in R_{[0,1]}^{m \times m_k}$, $g_c[i^b] \in R_{[0,1]}^{1 \times 1}$ are the matrices-parameters.

For each first level node $a_i \in A$, the function $G_i$ will have the form:

$$X[t + 1, i] = G_i[t] = \frac{\sum_{b=1}^{c_i} W_i^b[t] \cdot G_i^b[t]}{\sum_{b=1}^{c_i} W_i^b[t]}$$

where $W_i^b[t]$ is the degree of membership of the second level node $a_i^b$ to the first level node $a_i$ at a time $t$.

The identification [14] of the dynamic neighborhood model with a fuzzy hierarchical structure $N_{\mathcal{S}_{iter}}$ is divided into structural and parametric ones which are performed simultaneously until the set limited root mean squared error of identification is reached.

The structural one lies in finding the second-level nodes $c_i$ number for each first level node $a_i \ (i = 1, ..., n)$, as well as the membership functions $W_i^b$ based on fuzzy clustering [15 - 16] for all second level nodes $a_i^b \ (b = 1, ..., c_i)$. Parametric identification determines the parameters of the stating functions $G_i^b$ for all second level nodes $a_i^b (b = 1, ..., c_i)$.

The average relative error of identification (prediction) is calculated using the formula:

$$A = \frac{1}{M \cdot \pi} \sum_{m=1}^{M} \sum_{i=1}^{n} \left( \frac{1}{p_i} \sum_{j=1}^{p_i} \frac{|x_{m}[t + 1, i, j] - x_{m}[t + 1, i, j]|}{x_{m}[t + 1, i, j]} \right) \times 100\%$$

where $n$ is the number of model nodes; $M$ is the volume of the learning (test) sample; $x_{m}[t + 1, i, j]$ is the $j$-th component of the node state vector $a_i$ in the $m$-th row of the learning (test) sample; $x_{m}[t + 1, i, j]$ is the model value of the $j$-th component of the node state vector $a_i \ (j = 1, ..., p_i; i = 1, ..., n)$.
RESULTS AND DISCUSSION

The cold rolled steel treatment involves several steps. The mechanical properties discussed above, i.e. yield stress, ultimate resistance, tensile strain, are most affected by steel smelting in the converter, hot-rolling, cold-rolling, and continuous annealing after cold-rolling. Let us consider the graph of a cold rolling neighborhood structure (Fig. 1), [14]. In Fig. 1, the following nodes are shown: \( \alpha_1 \) - converter, \( \alpha_2 \) - hot-rolling mill, \( \alpha_3 \) - cold-rolling mill, \( \alpha_4 \) - continuous annealing mill.

The neighborhood model nodes correspond to the cold rolling shops, while the control and state actions correspond to the input factors and internal states of the corresponding nodes. The control actions in the model nodes are: chemical composition, hot rolling speed limits, cold rolling speed limits, continuous annealing temperature and speed limits; the state actions are hot rolling temperature limits, cold rolling temperature limits, mechanical properties formed during continuous annealing. The node \( \alpha_4 \) is the output node of the system. In the node \( \alpha_4 \), the condition

\[
X[t, 4] = (x[t, 4, 1] x[t, 4, 2] x[t, 4, 3])^T,
\]

where \( x[t, 4, 1] \) is yield stress, \( x[t, 4, 2] \) is ultimate resistance, \( x[t, 4, 3] \) is tensile strain at this point in time.

Let \( \bar{c}_{iern}[i] = \{a_1^i, \ldots, a_{4i}^i\} \). Then for each second level node \( a_i^b \in \bar{c}_{iern}[i] \) the stating function \( G_{ik} \), given in (4), where \( X[t, i^{b}] \) is the state vector of the \( b \)-th second level node \( a_i^b \) of the \( i \)-th first level node \( a_i \) at a time

\[
\begin{align*}
X[t + 1, 1^b] &= G_1^b[t] = G_1^b \left( V[t, 1] \right); \\
X[t + 2, 2^b] &= G_2^b[t + 1] = G_2^b \left( X[t + 1, 1], V[t + 2, 1] \right); \\
X[t + 3, 3^b] &= G_3^b[t + 2] = G_3^b \left( X[t + 1, 1], X[t + 2, 2], V[t + 3, 2] \right); \\
X[t + 4, 4^b] &= G_4^b[t + 3] = G_4^b \left( X[t + 1, 1], X[t + 2, 2], X[t + 3, 3], V[t + 4, 3] \right)
\end{align*}
\]

(4)

\[
\begin{align*}
X[t + 1, 1^b] &= g_{c1}[1^b] + g_{c2}[1^{b1}], V[t, 1]; \\
X[t + 2, 2^b] &= g_{c1}[2^b] + g_{c2}[2^{b1}] X[t + 1, 1] + g_{c3}[2^b, 2] V[t + 2, 1]; \\
X[t + 3, 3^b] &= g_{c1}[3^b] + g_{c2}[3^{b1}] X[t + 1, 1] + g_{c3}[3^b, 2] X[t + 2, 2] + g_{c4}[3^b, 3] V[t + 2, 3]; \\
X[t + 4, 4^b] &= g_{c1}[4^b] + g_{c2}[4^{b1}] X[t + 1, 1] + g_{c3}[4^b, 2] X[t + 2, 2] + g_{c4}[4^b, 3] V[t + 3, 3] + g_{c5}[4^b, 4] V[t + 3, 4],
\end{align*}
\]

(5)

The data for cold rolling simulation are represented by the values of continuously measured parameters of steel treatment average per each unit, as well as by the results of laboratory tests of selected metal samples.

After identifying the systems (2) and (5), i.e. finding the second level node membership functions and matrixes-parameters, the results presented in Table 1 are obtained. After being identified on the test sample, the simulation results were verified with the help of the relative simulation

\[
\text{Fig. 1. The graph of the first level of the cold rolling neighborhood model structure.}
\]

\[
\text{Fig. 2. Yield stress simulation results.}
\]
TABLE 1. Average relative identification and simulation errors, %

<table>
<thead>
<tr>
<th>NS/LR</th>
<th>Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Identification</td>
<td>4.55</td>
</tr>
<tr>
<td>Test</td>
<td>4.68</td>
</tr>
</tbody>
</table>

errors calculated according to the formula (3). Figs. 2 - 4 show the results of simulating the mechanical properties of steel - yield stress, ultimate resistance, and tensile strain, respectively, for the test sample fragment consisting of 20 measurements for a linear fuzzy hierarchical neighborhood model. Comparing the initial and simulated data for the developed cold rolling model, it is possible to see that the average relative errors of identification and testing do not exceed 4.68%. Thus, a dynamic neighborhood model with a fuzzy hierarchical structure of the discussed process can be recommended for practical application.

CONCLUSIONS

The paper considers the cold rolling simulation during the continuous annealing process based on a dynamic neighborhood model with its nodes corresponding to the shops. According to the steelmaking production data, linear dynamic neighborhood models with a fuzzy hierarchical structure of the considered process were constructed to predict the mechanical properties of steel, the simulation results were compared with the production data. As a result of the comparison, it can be concluded that a dynamic neighborhood model with a fuzzy hierarchical structure gives an acceptable relative error of identification and testing and can be recommended for practical application.

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REFERENCES


