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# PREDICTION OF HOT STRIP MILL ROLL WEAR

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*Preliminary Note - Prethodno priopćenje*

Wear of work rolls has significant influence on the flatness of hot rolled strip and therefore it is a technological parameter, which should be considered in planning and realization of the rolling technology. The relationship between the rolling program, pass schedule, and the work roll wear profile will be presented with the CAE neural network. The same method is applied in the program for prediction of the optimal shape and prediction of wear progress during the rolling process on one pair of work rolls. This study of the wear of work rolls refers to the Steckel rolling strip technology.

***Key words:*** *neuronal networks, wear prediction, hot strip rolling*

**Predviđanje trošenja valjaka za toplo valjanje traka.** Trošenje valjaka ima velik utjecaj na ravnoću toplo valjanih traka i parametar je kojeg treba imati u vidu kod planiranja i realiziranja tehnologije valjanja. U ovom članku prikazana je korelacija između asortimana valjanja, programa valjanja i opisa trošenja profila valjaka pomoću CAE neuronskih mreža. Istom metodom (CAE) služi se za predviđanje optimalnog oblika i razvoja trošenja radnih valjaka. Ova studija odnosi se na trošenje valjaka pri vrućem valjanju na Steckel valjačkom stanu.

***Ključne riječi:*** *neuronske mreže, predviđanje trošenja, toplo valjanje traka*

## INTRODUCTION

Rolling of steel at elevated temperatures is one of the most imported industrial processes, since greater volume of materials is worked by rolling than by any other technique. Key tools in the rolling processes are the rolls themselves. They have to withstand severe extremes of temperature and load. Wear resistance is very important for the economy of production and the geometrical tolerances of rolled products. The wear of work and backup rolls have the major influence on final product quality by changing their geometry and surface roughness. Experience has shown that roll wear rate increases rapidly after manufacturing a specific amount of rolled steel. In order to avoid catastrophic wear, the rolls have to be changed after rolling a particular tonnage of material.

Generally, rolls contribute some 5 - 15% of overall productions cost. Considering the relatively high proportions of roll costs in overall productions costs, the ability to predict roll performance, especially in the domain of wear, becomes more important.

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The principal aim of this presentation is focused to the relationship between the rolling program, the pass schedule, and the work roll wear profile, which is presented with the neural net method. The same method is applied in the program for prediction of the shape and the wear progress during the rolling process on one pair of work rolls. Results can be applied later in the optimization of the rolling program and in the schedule for the axial roll shifting. This study of the wear of work rolls refers to the Steckel rolling strip technology.

## FACTORS, VARIABLES AND MODELS OF HOT ROLL WEAR

Wear prediction is based on identification and quantification of the phenomena which control this process. Due to the complexity of tribological system and the simultaneous presence of different mechanisms causing the wear, the phenomenological approaches for prediction of wear are still imperfect and too complicated for a practical use.

Many outstanding papers are found in published references for parameters controlling the wear progress. The same is true for their mathematical linkage for the purpose of wear prediction. Main restrictions which occur here are the number of the included influence parameters or variables, their weight, and the consideration of their mutual space interactions.

Different mechanisms can be identified that relate to the phenomenon of roll wear:

- surface adhesion and abrasion due to friction between the work roll and rolled strip;
- fatigue of the roll surface layers due to cyclic mechanical stress that normally occur during the rolling process;
- thermal fatigue of the toll surface due to the thermal cycles created by contact with hot strip and roll cooling water;
- tribochemical reaction.

For each of the major wear mechanism wear rate can be expressed, e.g. [1], in terms of

$$w_i = f_i\,(F, v, T_0, M) \tag{1}$$

where $w_i$ is the wear rate (m$^3$/m), F the normal force (N), $v$ the sliding velocity (m/s), $T_0$ the initial temperature (°C) and $M$ material properties e.g. (yield strength, etc.). Each factors from the Eq. (1) can be expressed approximately as a vector with n components:

$$v_i = (v_{i1}, ..., v_{in}) \tag{2}$$

and each component can be considered as a variable. There is an obvious necessity to reduce the number of variables

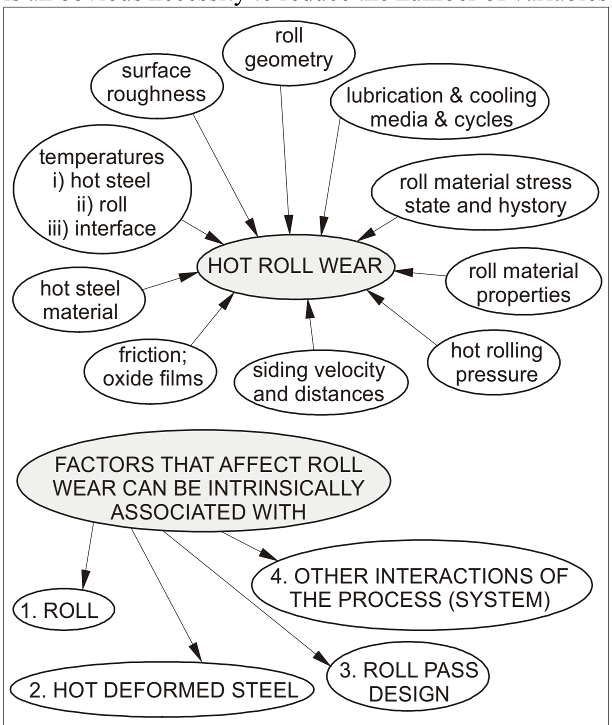


Figure 1. **Parameters influencing the hot roll wear**
Slika 1. **Utjecajni parametri na trošenje valjka za toplo valjanje**

in Eqs. (1) and (2). Theoretical disciplines contain relations involving some of above variables. Some of the components can be considered as discrete variable, while other s can be assumed as approximately constant value. Figure 1. summarizes the factors affecting roll wear. In the open literature can be found more comprehensive attempts to model special cases of hot roll wear [2-4].

Recent publications report an increasing number of applications of expert systems and neural networks in the research of physical alike complex systems. In predicting tool life, Engel, Cser and Geiger [5], have combined the expert knowledge and data from numerical simulation. Falk and Engel [6] proposed a combined use of numeric simulation and neural networks in solving similar problems. The used CAE neural network was successful in predicting wear [7] on the basis of experimental data of physical simulation of hick - temperature forging combined with FEM.

## DESCRIPTION OF METHOD - CAE NEURAL NETWORK

The problem addressed in this paper is how to estimate the unknown parameters as a function of known data. The first and second sets of variables are called the output and input variables, respectively. In order to determine unknown output variables from known input variables, a data base containing sufficient well-distributed and reliable empirical data is needed.

The data base should include both, measured values of output variables and the corresponding input variables. Single particular observation, which is included in the data base, can be described by a sample vector $x_n$. The input variables $p_{ni}$ and output variables $r_{nk}$ correspond to the components of this vector

$$\mathbf{x}_n = \left(p_{n1}, ..., p_{ni}, ..., p_{nL}, r_{n1}, ..., r_{nk}, ...\right)^T \tag{3}$$

The data base consists of a finite set of sample vectors. According to the presented CAE neural network, each of the output variables corresponding to the vector under consideration $\hat{\mathbf{x}}$ (i.e. a vector with known input variables $p_i$ and output variables $\hat{r}_k$ to be predicted)

$$\hat{\mathbf{x}} = \left(p_1, ..., p_i, ..., p_L, \hat{r}_1, ..., \hat{r}_k, ...\right)^T \tag{4}$$

can be estimated by the equation

$$\hat{r}_k = \sum_{n=1}^{N} C_n \cdot r_{nk} \tag{5}$$

where

$$C_n = \frac{c_n}{\sum_{j=1}^{N} c_j} \tag{6}$$

and

$$c_n = \exp\left[\frac{-\sum_{i=1}^{L}\left(p_i - p_{ni}\right)^2}{2w^2}\right] \tag{7}$$

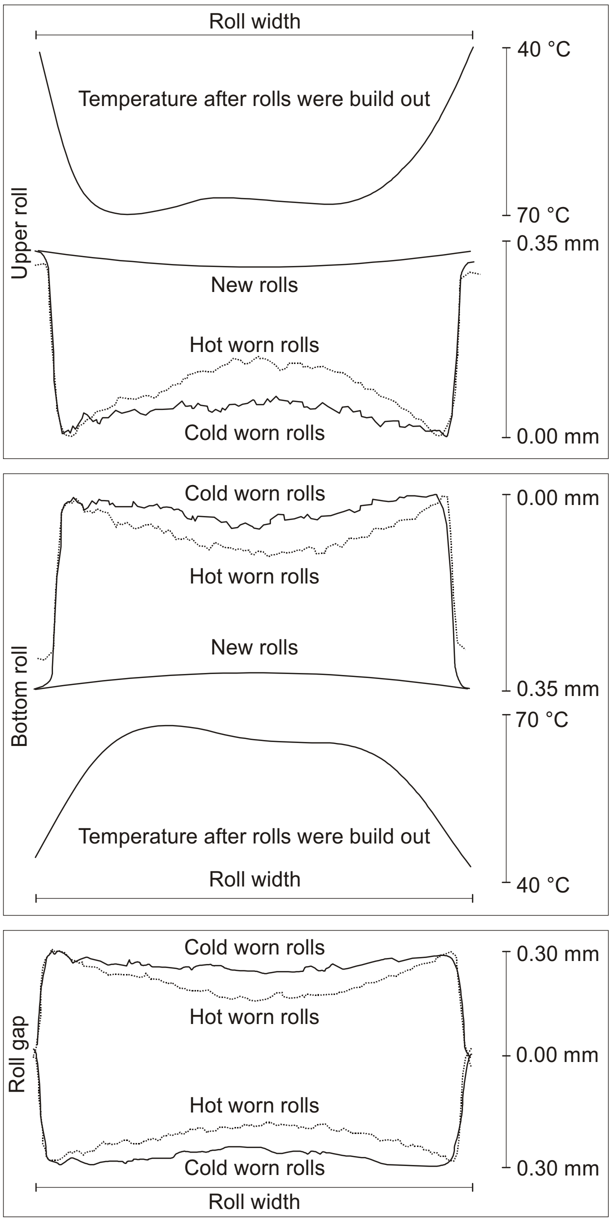


Figure 2. **Typical measured roll wear and temperature profile**
Slika 2. **Tipični izmjereni profil trošenja i temperature**

Here $\hat{r}_k$ is the $k$-th output variable to be predicted (corresponding to the vector $\hat{\mathbf{x}}$; in our case tool wear), $r_{nk}$ is the same output variable corresponding to the $n$-th vector in the data base, $p_{ni}$ is the $i$-th input variable of $\mathbf{x}_n$ (parameters that influence tool wear), $p_i$ is the $i$-th input variable of $\hat{\mathbf{x}}$, $N$ is the number of vectors in the data base, and $L$ is the number of input variables.

Equation (5) suggests that the estimate of an output variable $\hat{r}_k$ is computed as a combination of all the output variables $r_{nk}$ in the data base. Their weights $C_n$ depend on the similarity between the input variables $p_i$ of the vector $\hat{\mathbf{x}}$ and the corresponding input variables $p_{ni}$ pertinent to the sample vectors $\mathrm{x}_n$ stored in the data base. $C_n$ is a measure of similarity. Consequently, the unknown output variable is determined in such a way that the computed vector $\hat{\mathbf{x}}$ composed of given and estimated data is most consistent with the sample vectors $\mathrm{x}_n$ in the data base.

Table 1. **Input data base for strip rolling programs using in CAE neural network analyses**
Tablica 1. **Ulazni podaci za program valjanja koje koristi CAE neuronsku mrežu za analize**

| Rolling program | Steel gradient | Heat No | Quantity Amount of slabs |
|---|---|---|---|
| 1 | O | 231 | 1 |
| | A | 291 | 10 |
| | B | 284 | 9 |
| 2 | O | 267 | 1 |
| | C | 340 | 11 |
| | A | 338 | 10 |
| 3 | P | 325 | 1 |
| | C | 451 | 9 |
| | A | 442 | 9 |
| 4 | R | 479 | 3 |
| | A | 529 | 4 |
| | A | 530 | 10 |
| 5 | R | 480 | 3 |
| | C | 539 | 9 |
| | A | 532 | 4 |
| | A | 530 | 1 |
| 6 | O | 551 | 3 |
| | A | 639 | 9 |
| | A | 640 | 5 |

The parameter $w$ is the width of Gaussian function which will be called the smoothness parameter. It determines how fast the influence of data in the sample space decreases with increasing distance from the point which coordinates are determined by the components (input variables) of the vector under consideration. The larger is the value of $w$ is, the more slowly decreases this influence. Large $w$ values exhibit an averaging effect. In principle, a proper value of $w$ should correspond to a typical distance between data points. In this case the CAE method yields a smooth interpolation of functional relation between the input and output variables.

The choice of an appropriate value of $w$ depends on the distribution of data, on the accuracy of the latter and on the sensitivity of the output variables to changes in the input variables. Usually, engineering judgment, based on knowledge of the investigated phenomenon, and a trial and error procedure are needed to determine appropriate value(s) for *w*. The reader interested can find more details about CAE neural network in [8-10].

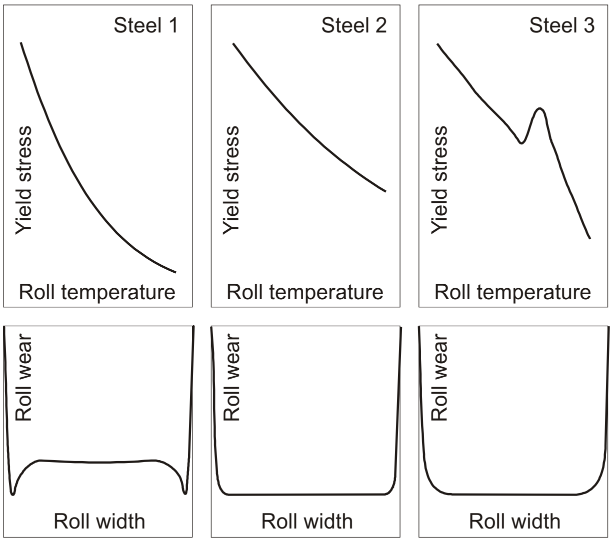


Figure 3. **Ideal correlation between the flow and the roll wear profile at unstable temperature condition across the roll width**
Slika 3. **Idealna korelacija između krivulja tečenja i profila trošenja valjaka pri nestacionarnoj temperaturi**

## PRELIMINARY EXPERIMENTS AND RESULTS

Table 1. gives the input data base for the predicting of the roll wear carried out with a CAE neural network and includes:

- the rolling program with chemical composition of each steel heat;
- always the same pass schedule for each steel grade;
- dimension;
- quantity of hot strip selected steel grade.

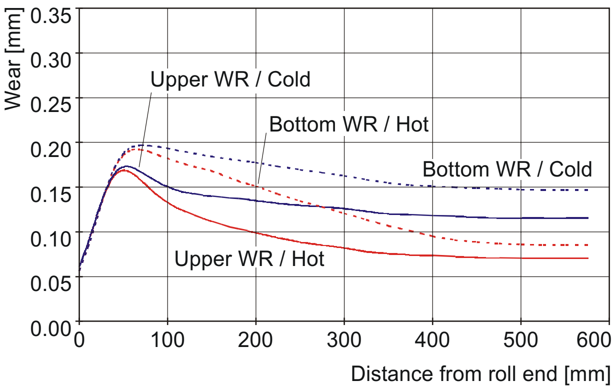


Figure 4. **CAE neural network predicted roll wear for EV 15**
Slika 4. **Predviđeno trošenje valjaka sa uporabom CAE neuronske mreže za material EV 15**

Roll wear profile for the top and the bottom roll was registered as geometrical change of roll contour. Wear profiles of hot, as well as cold rolls, were registered. Gap between rolls with wear profiles in unloaded state and without mechanical profile completed the input base (Figure 2.).

For the CAE neural network analyses the rolling of strips, which rolling technology (heating of slabs and strip pass schedule) where in agreement with the technological standards, were chosen. CAE neural network analyze has verified expected tends on strip edge shape forming (Figure 3.). For arbitrary pass schedule including the same steel grade (Table 2.) such as input data base, roll wear where predicted using CAE neural network, as shown on Figure 4., 5..

Table 2. **Input data base for arbitrary strip rolling programs using in CAE neural network prediction**
Tablica 2. **Ulazni podaci za kontrolni program valjanja traka koje koristi CAE neuronska mreža kod predviđanja**

| Rolling program | Steel grade | Heat | Quantity Amount of slabs |
|---|---|---|---|
| EAC neural network illustration for prediction of roll wear | R | Chemical composition R | 3 |
| | B | Chemical composition B | 2 |
| | C | Chemical composition C | 5 |
| | A | Chemical composition A | 7 |

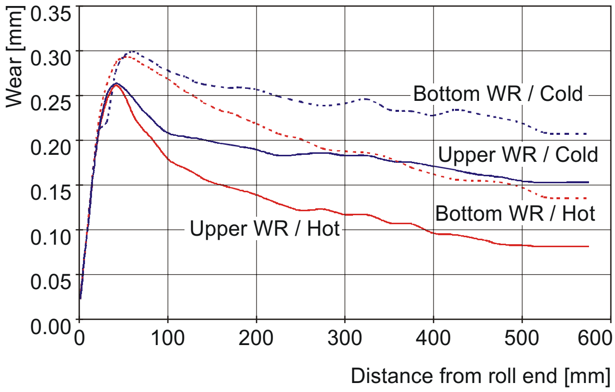


Figure 5. **CAE neural network predicted roll wear for EV 18**
Slika 5. **Predviđeno trošenje valjaka sa uporabom CAE neuronske mreže za material EV 18**

## CONCLUSION

The used CAE neural network was successful by implemented in predicting wear profile of work strip rolls based of experimental data from industrial measurement of plant production.

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