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PREDICTION OF WORK PARAMETERS IN A FIVE STAND COLD MILL

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ABSTRACT

The accurate prediction of work parameters is essential for a quality product. A mathematical model is used for parameters calculus. It is important to directly predict the roll force and the other parameters and to compute a corrective coefficient. Combining the network of work parameters and the mathematical model grove up the possibility to obtain parameter who give a new quality for laminates strip.

KEYWORDS: *cold rolling mill, stand, work parameters.*

1. Introduction

A rolling mill process for sheet processed consists in five stands where the force and the thickness tension between each stands is measured.

The roll gap is the distance between two working rolls, most important variable to affect the actual output thickness of the strip. The set parameter values are dynamically adjusted as the strip thickness and tension are measured during milling. After milling finishes, certain parameter adjustments are made in post calculation.

The initial setting produced by the mathematical model give errors that can usually be compensated by the real – time controller, but large errors lead to quality decline and cost increase.

The installed system produces the initial settings on the tension roll and the force prediction values with the settings from the mathematical model. The human operator is monitoring and comparing both settings.

Using a mathematical model, the mill settings are determined before a strip enters in the mill, like the work load, the roll gap for each stand is calculated, the speed in each stand (from the first stand to the four stand).

It is known to be a function of many variables, with an exception of the roll force. It is essential to predict the roll force. In most steel works, it is calculated using mathematical formula based on the metallurgical and mechanical knowledge:

$$F_m = f(H_i , H_o , T_b , R_{p\,0,2} , \mu , v_e , n_r) \qquad (1)$$

where F_m - the roll force produced by the mathematical model.

Those factors which affect the roll force include the incoming and target thickness (H_i and H_o), backward and forward tension (T_b and T_f), deformation resistance ($R_{p\,0,2}$), friction coefficient (μ), and other constants. The first four factors (thickness and tension) are constant and impose.

The rolling stands press a strip of steel using upper/lower rolls to a desired thickness. The gap between upper/ lower rolls determines how much pressure or force is applied. Thickness and tension is measured while the strip is processed, and then for real – time control like in the figure 1.

The mathematical model does not take all the factors into account. The friction coefficient is known to be affected by working roll parameters such as the rolling speed, the roll surface, the oil used, etc. [1]. However, the mathematical model employs only the rolling speed in calculating the friction coefficient. The mathematical model's prediction values (F_m), against the target values (F) are selected in the time of coil processed. The parameters predictions involve many other factors whose exact relations are not well understood and the mathematical model is far from perfect.

Recent studies [1] about the roll force tension and coil width prediction were made in two directions, first in improving the mathematical model and second in employing the network of parameters.

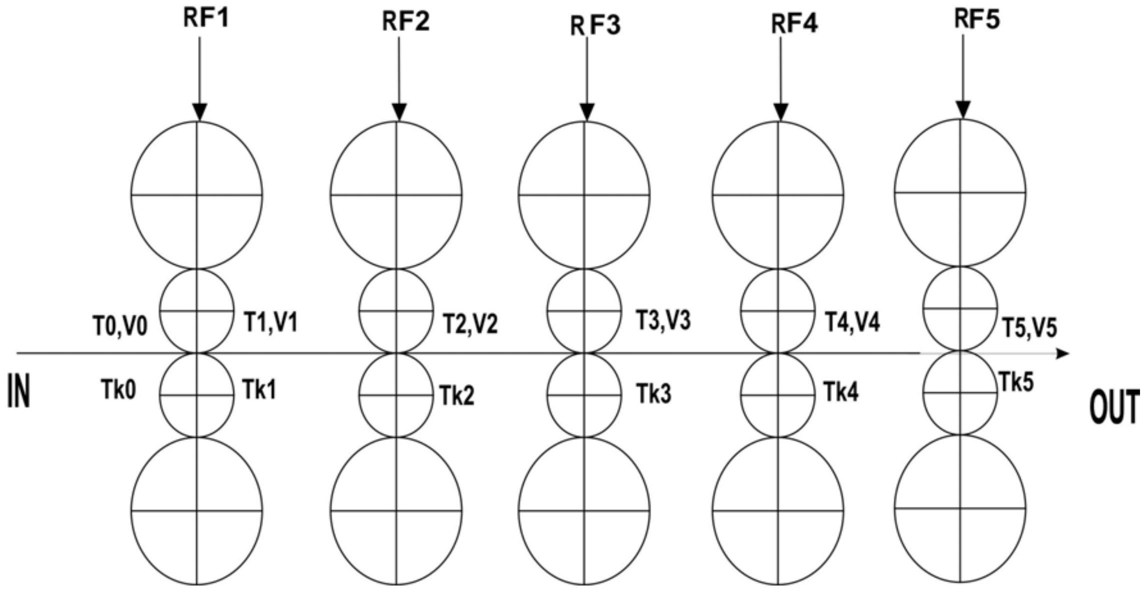

Fig.1. *Control of cold rolling mill process, with presetting in precalculation, which is related to thickness control.*

The networks of work parameters were used to calculate the roll force with the improved prediction accuracy in cold rolling process.

Many factors not considered in the mathematical model can be incorporated in networks of work parameters.

It can predict the tension, coil with roll force or produce a corrective coefficient to be multiplied to the prediction of the mathematical model.

2. Prediction by neural networks

The selected input variables are shown in the figure no.1. The first six came from the mathematical model. The roll force values were obtained from measurement.

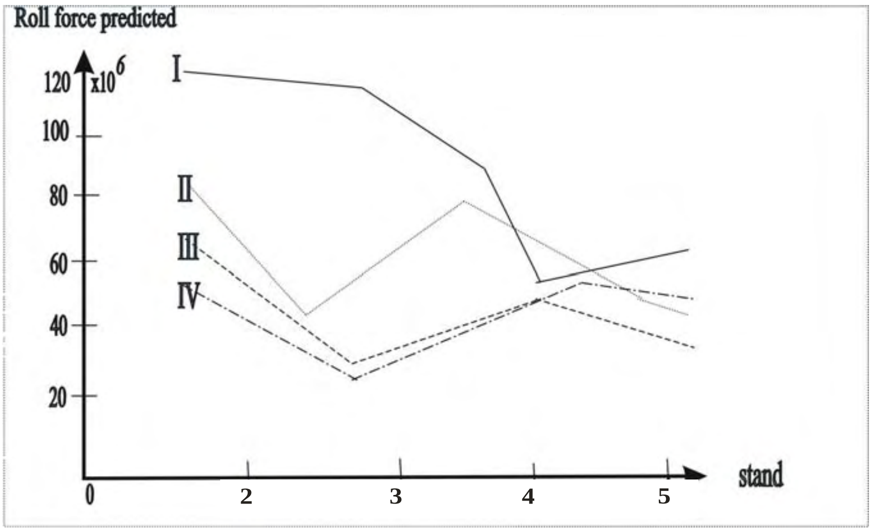

Fig.2. *The predicted values of roll force.*

This model is the mathematical model's predictions to the target values for the training data set with a constant scaling factor and a mathematical model's predictions.

The model of roll force prediction are given in figure no.2. The only exception was stand no.5, where the mathematical model is exactly.

The networks of work parameters, the multilayer perceptions, are unpredictable behavior in a novel environment. Improvement in average performance is not sufficient enough to convince a factory manager who is usually willing to keep a more reliable even if less accurate, old model.

When the single networks of work parameters were tested they reduced the errors on average by 60%.. A large error in roll force prediction causes a large error in roll gap which in turn could lead to the coil rupture. A single incident of operation interruption could wipe out the advantages that model. The average prediction for coil tension is shown in figure 3.

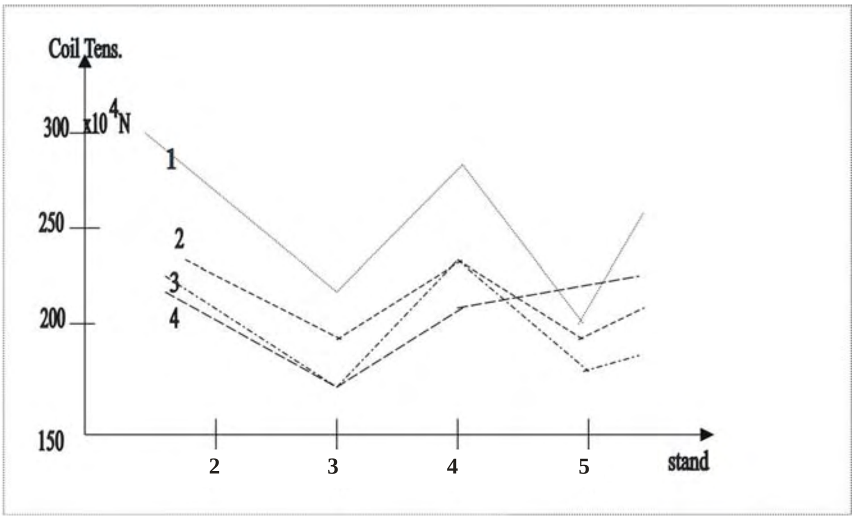

Fig. 3. *Average prediction of coil tension*

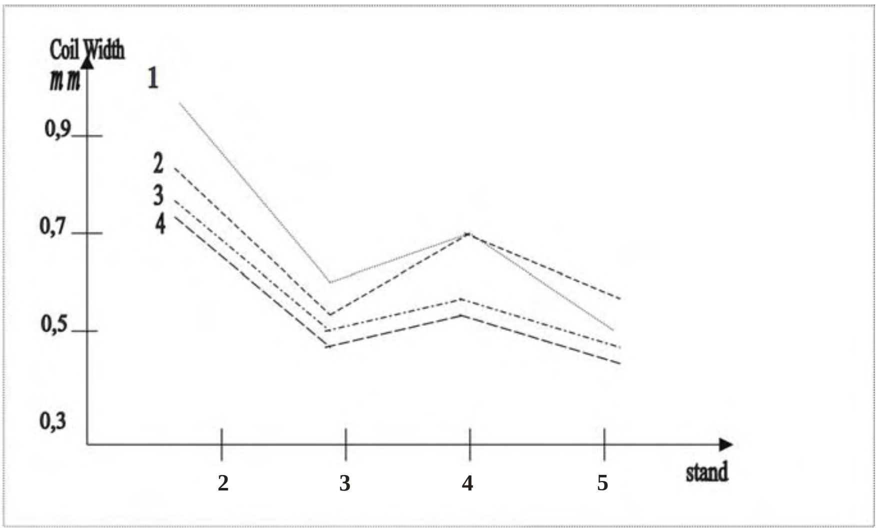

Fig.4. *Average prediction of coil width*

Reliability breakdown seems to result from the following causes: first, the distribution of the training patterns. I tried to collect as many coil data as possible, the twelve months worth of data my not be sufficient, given that many of which were discarded due to noise. It is difficult to even test if the training data have the same distribution as future data.

Transmission error is introduced when a large amount of data is passed from one computer to another. It appears in the form of irregular characters, missing values, or nonsense values such as zero temperature or zero roll force. The data with this type of noise are relatively easy to identify.

However, sensor noise is difficult to detect because it is not clear what the "correct" value range is for some variables. The average prediction for coil width is shown in figure no. 4.

One can improve the network reliability by estimating the network’s error and ignoring the network output when it is to large [2]. Given the same input variables. The network of parameters could not correctly estimate the prediction error.

Another approach is to detect the novelty of a test pattern’s input. If it is novel, the reasoning goes, the network is not likely to make a reliable prediction. We analyzed the correlation with the prediction error in order to identify the default domain. If a new coil’s input came from the aberrant domain, the mathematical model was instead used for prediction.

3. Conclusions

Using the roll force –prediction models we can show that the prediction errors of the currently used mathematical model reduced by 30-50%. The substitutive model directly predicts the roll force, while the corrective model produces a correct coefficient, which is then multiplied to the mathematical models prediction. Additional variables which were not used in the mathematical model were found to be necessary for the substitutive model only. The networks of parameters can be easily retrained if necessary. The retraining period does not have to be fixed such as monthly or yearly .It will be more proper to determine it dynamically by monitoring the trend of prediction error.

The network of parameters are planned to be used in daily operation. One difficulty is to estimate the financially savings resulting from the improved quality.

The using of network of work parameters have a potential to improve the accuracy of dimensions and too the quality of laminated strip.

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