Improvement of Cold Mill Precalculation Accuracy Using a Corrective Neural Network

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Abstract

Cold rolling mill process in steel works uses stands of rolls to flatten a strip to a desired thickness. At Pohang Iron and Steel Company (POSCO) in Pohang, Korea, precalculation determines the mill settings before a strip actually enters the mill and is done by an outdated mathematical model. A corrective neural network model is proposed to improve the accuracy of the roll force prediction. Additional variables to be fed to the network include the chemical composition of the coil, its coiling temperature and the aggregated amount of processed strips of each roll. The network was trained using a standard backpropagation with 2,277 process data collected from POSCO from March 1995 through December 1995, then was tested on the unseen 200 data from the same period. The combined model reduced the prediction error by 55.4% on average.

1 Introduction

Cold rolling mill process in steel works uses stands of rolls to flatten a steel strip to a desired thickness. As passing through the stands of rolls, source strip coils are pressed. At this time, roll gap and rolling force which are the most important variables in the process are determined by a mathematical model in precalculation [4, 1, 5].

Cold mill process control(Figure 1) at Pohang Iron and Steel Company(POSCO) is divided into three phases, precalculation, real time control and postcalculation. Precalculation determines initial settings of the mill before a source strip coil is up-loaded into the mill. Real time control consists of four different kinds of control systems (see Figure 1) which, based on the preset values determined by precalculation, continuously update the control commands. In particular, automatic gauge control system issues commands in order to meet the desired thickness of the strip. Thus, errors made in precalculation can be compensated if it's within a certain range. However, large errors can not be handled by the real time control

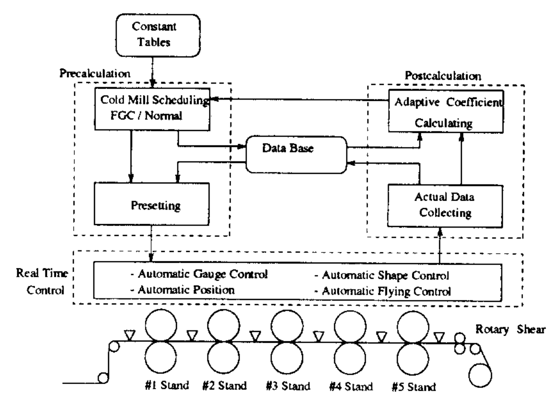


Figure 1: Cold mill process at POSCO

system. Postcalculation adjusts certain parameter values used in the mathematical model for precalculation of future strips [5].

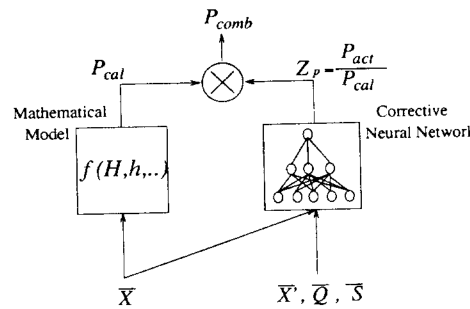
The goal of precalculation is a precise control of roll gap. This depends on the rolling force predicted by the mathematical model. The difficulty of rolling force calculation stems from not knowing the exact values of variables in the mathematical model, such as friction coefficients and deformation resistance of the coil. Because the exact values of variables cannot be measured during processing of the coil, it is impossible to mathematically calculate the rolling force in the cold mill process. We can only "predict" the rolling force by approximating from the historical information. The information consists in a number of tables specified according to the steel class of a coil. By referring the tables, mathematical model gets values of variables and coefficients. But values in the tables are very discrete and even sparse at some ranges, thus the predicted rolling force cannot but be poorly approximated. Another problem in the mathematical model is the fact that it is missing some important variables in rolling force precalculation, such as the coiling temperature at hot mill, the chemical compositions of the coil, the aggregated amount of processed strip at each stand and the roll type. These factors are well known to influence the rolling force prediction, but it is not clear how these factors could be incorporated in the present mathematical model [6].

What we propose here is to use a corrective neural network alongside with the mathematical model. Since there are a plenty of cold mill data available, the network can be trained to adjust the rolling force values calculated by the mathematical model.

The combined math/NN model is described in the next section, followed by simulation results based on the real data from POSCO cold mill plant. Then we conclude with a summary and future work.

2 Combined Model using a Corrective Neural Network

Figure 2 shows a combination of mathematical model and a corrective neural network, originally proposed in [6]. The mathematical model on the left side calculates its prediction of rolling force P_{cal} based on input variables $\bar{X}$ as before. The neural network on the right side is a multilayer perceptron which is trained on the ($\bar{X}$, $\bar{X}'$, $\bar{Q}$, $\bar{S}$) and Z_P pairs. The corrective coefficient(Z_P) from the neural network is multiplied to the rolling force P_{cal} calculated by the mathematical model, to produce the combined rolling force P_{comb}.



$\bar{X}$={roll diameter(D_i), forward tension(T_f), backward tension(T_b), initial thickness(H), target thickness(h), coil width(W) }
$\bar{X}'$={aggegrated amount of coil processed, roll type }
$\bar{Q}$={chemical composition (C, Mn, Si) }
$\bar{S}$={average coiling temperature at hot rolling mill }

Figure 2: Combined model of math/NN

The input variables to the neural network have four parts. First, $\bar{X}$ contains the same inputs to the mathematical model. Second, $\bar{X}'$ consists of two stand-oriented variables, the aggregated amount of processed coil in length and the roll type. Third, $\bar{Q}$ represents the composition of C, Mn and Si in the coil. The chemical compositions are known to have to do with the deformation resistance. Lastly, $\bar{S}$ is the average coiling temperature from hot rolling mill, known to play an important role in determining deformation resistance.

Figure 3 shows the corrective neural network with 12 input units and one output one. The output of the neural network is the corrective coefficient Z_P, the ratio of the actual measured rolling force (P_{act}) to the predicted rolling force (P_{cal}) by the mathematical model. This corrective coefficient is multiplied to the rolling force calculated by the mathematical model to result in the combined rolling force (P_{comb}). A corrective neural network is built for each of the five milling stands.

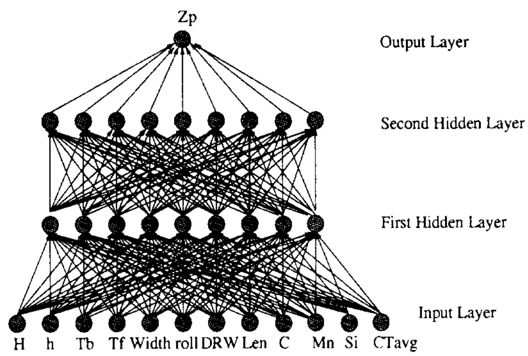


Figure 3: Corrective neural network

3 Simulation Results

A total of 2477 coil data with the yielding point ranging from 30 to 33 were collected at POSCO from March 1995 through December 1995. Each input variable was normalized as

$$x_{norm} = \frac{x - avg(x)}{sdv(x)}, \quad (1)$$

where $avg(x)$ and $sdv(x)$ denote the average and standard deviation of variable x, respectively.

A multilayer perceptron with two hidden layers of ten hidden nodes each was trained with 90% of the coil data using a standard backpropagation algorithm. Each network took less than 2 hours for learning on a SPARC 20 workstation.

To evaluate the performance of the combined model, the unseen 10% of the coil data was used for testing. The prediction error (E) was defined as the difference in ton between the actual (P_{act}) and calculated (P_{cal}) or combined (P_{comb}) rolling forces. Formally, they are defined as

$$\begin{aligned} E_{math} &= |P_{act} - P_{cal}| \\ E_{comb} &= |P_{act} - P_{comb}|, \end{aligned} \quad (2)$$

where E_{math} and E_{comb} are prediction errors of mathematical model and combined model, respectively.

Table 1 shows the average prediction error of the two models. The combined model using the corrective neural network reduced the error 55.4% on average and up to 72% in stand No. 2. Also, average maximum and standard deviation of prediction error were reduced from 236.4 to 163.3 and from 52.2 to 29.4, respectively.

Figure 4 shows how well the two models can predict the rolling force at stand No. 5. If the predicted rolling force (P_{cal} or P_{comb}) is same to the actual rolling force(P_{act}), the model's prediction is perfect and the dot will be placed on the line ($y = x$). The less perfect the model is, the farther the dot is placed from the line. The figure clearly shows that the combined model's predictions are placed more closely to the line than those of the mathematical model.

Table 1: Comparison of the rolling force prediction error both the mathematical and combined model.

Stand number	average E_{math} (ton)	average E_{comb} (ton)	average error reduction(%)
1	118.82	41.48	65.1
2	98.09	27.17	72.3
3	116.83	36.85	68.5
4	35.64	30.37	14.8
5	41.08	17.97	56.2
Average	82.09	30.77	55.4

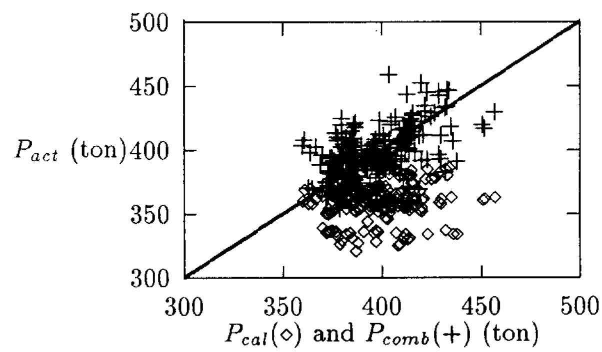


Figure 4: Comparison of the combined with mathematical models at stand No. 5. Dots shaped as + and $\diamond$ are the rolling force predictions of the combined model and mathematical model, respectively.

4 Conclusions

We propose a math/Neural Network combined model for rolling force prediction in cold rolling mill process. Addition of a corrective neural network is especially advantageous in that it enables the model to take into account those variables which are known to be influential, but whose mechanism not explicitly understood. In particular, we have incorporated such additional factors as the chemical composition of the coil, its hot coiling temperature, the aggregated amount of processed strips for each roll and the roll type. On average, the new proposed model reduced the prediction error by 55.4%.

Here, we only reported results from experiments with one class of coil. But there are a total of 11 classes of coils determined by the yielding point. As additional data for other classes are being gathered from an on-line computer, the combined models for other classes of coils will be implemented. Also, various preprocessing techniques are being investigated to reduce the network input dimension.

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