# A study on the improvement of thickness accuracy in a plate mill

Duk Man Lee*

* Rolling Technology and Process Control Group, Technical Research Center, POSCO, Pohang, Korea
(Tel : +82-54-220-6295; E-mail: pc554173@posco.co.kr)

**Abstract**: In this paper, two methods are discussed for good rolling force prediction in a plate mill. One is about the development of a long and a short learning scheme using a Neural Network for normal rolling and the other is about a mathematical model improvement by considering microstructural changes for controlled rolling. The research results are implemented in a on-line system of Pohang Works in POSCO and the field tests have showed that the prediction accuracies of rolling force are highly improved.

**Keywords: Rolling force, Neural Network, Grain Size, Microstructure.**

## 1. INTRODUCTION

Recently market demands for high quality products are increasingly severe. Among them, the requirement for thickness precision in a rolling mill process is more strict than any other request. The improvement of the thickness accuracy requires the good prediction ability of a rolling force and a roll gap in pre-calculation stage. Also, a novel control algorithm for gauge control in real-time control stage is absolutely necessary.

The improvement of the prediction ability in the pre-calculation stage requires a good mathematical model and a supporting learning algorithm which is very effective to eliminate the external disturbances. Therefore, the strategies for improving the accuracy of the rolling force prediction are discussed in this paper.

A conventional method for the learning was to compensate the model with a simple corrective term which is obtained from the exponential smoothing of a rolling force ratio. The smoothed rolling force ratio is classified according to sizes and chemical components, and it is saved in a database for later use. However, this method has following drawbacks: The maintenance difficulty of learning parameters grows more and more as the number of classification is increasing; The learning efficiency decreases as lot changing is frequent; Since the sources of prediction errors are various, the compensation ability with only a rolling force ratio is limited by the magnitude of external disturbances.

Also, a recent survey on the accuracy of rolling force prediction showed that the prediction accuracy is decreasing when the controlled rolling is performed. The main reason is that the model only considered the effects of temperature, strain, and strain rate and ignored the rolling force changes due to the effects of microstructural changes during hot rolling.

To solve these problems, two methods are discussed here. One is the development of a long and a short learning algorithm using a Neural Network for normall rolling and the other is a mathematical model improvement by considering microstructural changes for controlled rolling. The research results are implemented in a on-line system of Pohang works in POSCO and the field tests showed that the thickness accuracy is highly improved.

This paper is organized as follows. Section 2 explains the controlled system and its problems. Section 3 describes a Neural Network approach for the correcting the rolling force model discrepancy. Section 4 proposes a new rolling force model by considering microstructural changes. Section 5 concludes this paper with a future work.

## 2. PROBLEM FORMULATION

The process control system of plate mill consists of Pre-calculation stage, Real-time control stag, Post-calculation stage. These sequences are repeated in every rolling passes. Among them, the prediction accuracy in the pre-calculation stage should be guaranteed as good as possible to get a short transient time in a thickness control loop and stable rolling operation. This condition becomes important more and more as the lot change is frequent these days from a various product range and small lot scheduling.

The roll gap setup in the pre-calculation stage is calculated based on a linear gauge meter model such as

$$H = S + \frac{RF}{M} - G_e, \tag{1}$$

where $H$ is the plate thickness, $S$ is the roll gap, $RF$ is the rolling force, $M$ is the mill modulus, and $G_e$ is the model error term.

For a given desired thickness $H$, the correct roll gap setup $S$ is possible when the rolling force $RF$ and the mill modulus $M$ and model error term $G_e$ is exactly estimated. However, since the rolling itself is performed in very nonlinear and time-varying patterns the perfect estimation of those values to cover all the rolling cases is impossible. A lot of research activities had been made by many researchers [1,2,3,4,5,6,7,8,9,10,11,12,13,14]. One of these was to develop a new advanced physical model for the rolling force prediction and the other was to generate an effective learning model to compensate the physical model deficiency. In the following, two studies are introduced for the good rolling force prediction in a plate mill of POSCO.

## 3. Neural Network Learning Model

### 3.1 Conventional learning model

The rolling force model contains many inherent errors caused from a simplified model structure, parameter identification errors, disturbances, etc. To reduce these errors, a short-term learning is performed at every rolling pass in a given plate. The flow of the learning is as follows. After a rolling pass is finished, it calculates the ratio of a measured rolling force $RF_a$ to a rolling force model output $RF_{ma}$ which is calculated from the rolling force model using measured data. Then, this rolling force ratio is filtered and is stored to use for the next pass. New learning coefficient $\xi_{cl}(t)$ of rolling force ratio is determined as the equation (2).

$$\xi_{cl}(t) = (1-\alpha)\cdot\xi_{cl}(t-1) + \alpha\cdot\frac{RF_a}{RF_{ma}}, \qquad (2)$$

where $\xi_{cl}(t-1)$ is the old learning coefficient of rolling force ratio, the subscript $cl$ means the conventional method and $\alpha$ is the real value and $0 \leq \alpha \leq 1$.

Then, this $\xi_{cl}(t)$ is used to correct the model error in a multiplicative form.

$$RF_r = \xi_{cl}(t)\times RF_{md},$$

where $RF_r$ is the rolling force reference, $RF_{md}$ is the rolling force calculated from the mathematical model.

This kind of learning is only effective when the series of same plate are rolled continuously thereby $\xi_{cl}(t-1)$ is tuned well to cover the current model error. However, it has some inherent drawback when lot changes are frequent. Since the compensation term is updated by only a rolling force ratio, the errors from the changes of size, chemical components, temperature, and disturbances can not be effectively handled. This requires more effective learning method which can consider these factors.

### 3.2 Neural Network learning model

To cope with the limitation of conventional learning, this section shows an effective learning method using a Neural Network. Generally, two methods can be considered for the Neural Network application: One is using a static Neural Network of which weights are fixed. The other is using an adaptive Neural Network of which weights are updated after new input is provided. Due to the frequent lot changes, the process drift, the high dimension, and strongly clustered nature of the process data, the rolling force prediction with static Neural Network needs periodic re-training of its weights and this is clearly a time-consuming job for logging, processing, training and verification. Therefore, the on-line adaptable network is considered as a practical alternative.

In this respect, the proposed method adopts a Neural Network compensator as shown in Fig. 1, where the network's weights are updated both in off-line and in on-line. A long-term learning is performed in off-line to initialize the weights and to learn the process characteristics at various rolling conditions whereas a short-term learning is done in on-line to compensate the inherent errors from the current rolling condition within the same lot.

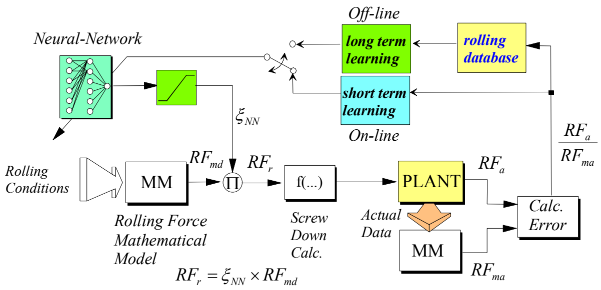


Fig. 1 Block diagram of Neural Network application

The rolling force prediction is determined as the hybrid manner from the Neural Network compensation $\xi_{nn}(t)$ and the model output $RF_{md}$ as follows.

$$RF_r = \xi_{nn}(t)\times RF_{md}.$$

As shown in Fig. 2 a hidden layer with general feed-forward network is selected for the proposed network and a tangential sigmoid function is used for its non-linear transfer function. From several simulation tests, it is confirmed that the proposed structure is good enough for this kind of optimization task.

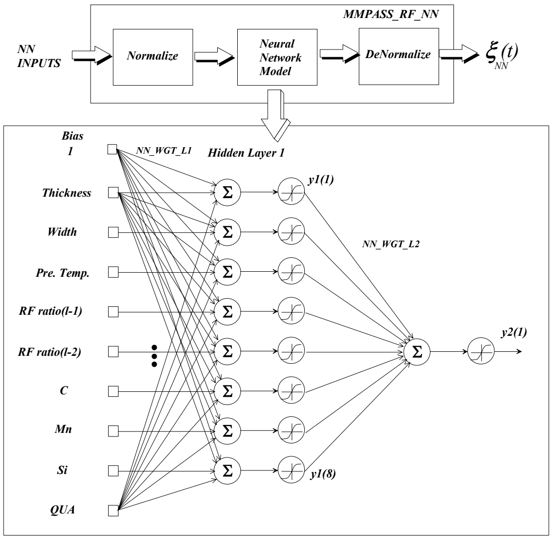


Fig. 2 Internal structure of proposed Neural-Network

As mentioned in previous sections, the conventional learning is not effective to compensate the changes of size, chemical components, temperature, etc. Therefore, thickness, width, temperature, C, Mn, Si, quality code(=QUA) are selected as inputs to network. In addition, since the plate rolling consists of several passes and the model error at current pass is highly correlated with the model error at neighboring passes, the rolling force ratios at lastpass - 1 and lastpass - 2 are added to the network inputs.

All input variables are normalized as follows.

$$\hat{x} = \frac{1.6}{x_{\max} - x_{\min}}(x - x_{\min}) - 0.8,$$

where $x$ is input variable, $x_{max}$ is the maximum value of $x$ and $x_{min}$ is the minimum value of $x$.

The train of Neural Network is done both in off-line, at the laboratory, where the basic knowledge is taught to the system, and in on-line, where the body of knowledge is refined and optimized. The Levenverg-Marquardt back propagation algorithm is used for off-line training and the incremental back propagation with momentum algorithm is used for on-line training.

Fig. 3 shows the development environment for the proposed algorithm. The design procedures consist of three steps. On the first step, the process data gathered in data logging system is transferred to a local development system by the ethernet, where a Neural Network weight is generated in off-line by a batch learning. For the easy of implementation, an automatic fortran code generator transforms the new weight into the form of fortran data file. On the next step, a generated weight file is compiled with a Neural Network engine and the resulting binary image is loaded on the backup system. Then the simulation tests are performed using the actual measured data without applying its output. On the last step, a new network is applied on-line and the test results are stored in process data logger.

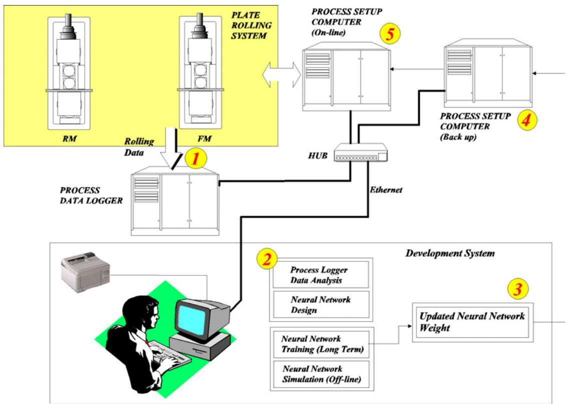


Fig. 3 Neural Network development environment

To verify the performance of the proposed network, field tests are performed in the on-line system. In the tests, the Neural Network output is applied only in the last pass for the plates of which sizes are from 15 mm to 25 mm in thickness. Fig. 4 shows the test results for ten test trials. The horizontal axis represents trial numbers whereas the vertical axis represents the mean and the standard deviation of rolling prediction error, respectively.

As shown in the Fig. 4, the averaged mean and standard deviation of conventional algorithm are 3.13 ton and 154.95 ton, respectively whereas the averaged mean and standard deviation of proposed algorithm are 7.19 ton and 107.52 ton, respectively. The improvement in case of standard deviation is 30.6 %.

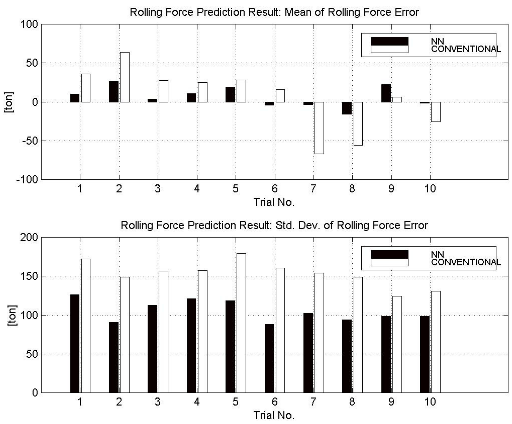


Fig. 4 Neural Network field test result A

In addition, Figure 5 clearly showed that the proposed method has robust characteristics to the lot changes. This is because the network has the multiple inputs which can reflects the change of working conditions whereas the conventional method only uses a rolling force ratio for the model compensation. The averaged mean and standard deviation of conventional algorithm are -7.83 ton and 145.80 ton, respectively whereas the averaged mean and standard deviation of proposed algorithm are 13.16 ton and 113.39 ton, respectively.

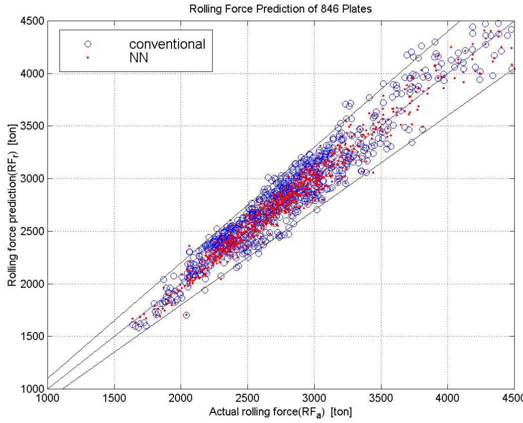


Fig. 5 Comparison of prediction ability in case of lot changes of field test result B

## 4. ROLLNG FORCE PREDICTION WITH AUSTENITE GRAIN SIZE MODEL

Recent development in hot rolling mill have been intended not only to increase productivity, or to improve the gauge or shape control of the rolled products by the use of automated and computerized rolling, but also to improve the various properties of the hot rolled products by means of controlled rolling practice.

A recent survey on the accuracy of rolling force prediction showed that the prediction accuracy is decreasing when the controlled rolling is performed(The temperature range is between 750 degrees ~ 850 degrees). As shown in the Fig. 6, the prediction error of rolling force is bigger in the controlled rolling temperature than in the normal rolling temperature. The main reason is that the model only considered the effects of temperature, strain, and strain rate and ignored the rolling force changes due to the effects of microstructural changes during hot rolling. The basic assumption of conventional model is that the complete restoration of the microstructure would easily occur during the inter-pass time during rolling at high temperature.

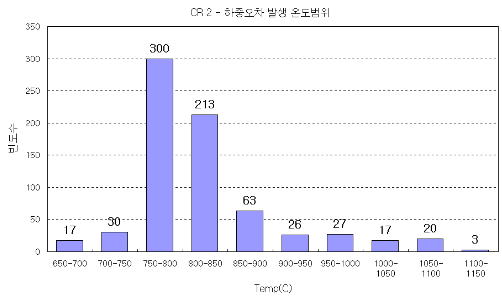


Fig. 6 Histogram of rolling force error according to rolling temperature

Therefore, this section focused on the improvement of rolling force prediction in the controlled rolling by considering the microstructural change. As a first step, a prediction model which predicts the microstructural change is developed. Next, this model is combined to the existing deformation resistance model to make a new rolling force prediction model. Finally, an on-line learning algorithm with RLS is developed to compensate the model discrepancy.

### 4.1 Microstructural change of rolled plates

The microstuctural change of plate rolling is dependant on the strip temperature and the reduction. A slab in the furnace has a big grain size from grain growth during heating procedure, where the grain size is affected by the target temperature, the duration time, the chemical components, etc. In case of common steel, the average grain size after heating is known as above 200 ㎛. Next, the slab is rolled after extracting from the furnace, where the hardening and the softening during or after rolling change the microstructure of plate further.

If a material is deformed above the recrystallization temperature, the deformation of the work piece leads to deformation of the grains and the induction of deformation bands within the grains. After or during deformation the material is recovering by building new grains which leads to the softening of the material. There exists two different kinds of recrystallization effects: Dynamic recrystallization and Static recrystallizatin. The dynamic recrystallization starts and completes during the deformation which is within a pass. It takes place at higher temperature and needs a certain amount strain. The static recrystallization starts and is completed after deformation and needs a certain duration. During rolling this takes place in the inter-pass times.

The amount of the recrystallized fraction X(t) can be described by the Avrami equation:

$$X(t) = 1 - e^{\ln 0.5 \left(\frac{t}{t_{0.5}}\right)^2}.$$

That means that if the pass time is too short the material will not recrystallize completely before the next pass and therefore some strain is accumulated which leads to hardening of the work piece.

The factors involved in controlled rolling are a reduction of the slab reheating temperature, the introduction of holding time during rolling to allow a decrease in the rolling temperature, and a high cumulative rolling reduction in the lower austenite region, with a very low finishing temperature. The effect of the controlled rolling as thermo-mechanical treatment comes about through the transformation from the non-recrystallized austenitic structure. Consequently, the strength of austenite during multi-pass rolling in the non-recrystallized austenitic region is influenced not only by the above factors, but also by the residual strain, which reflects the degree of restoration and is dependant on static recovery and the recrystallization kinetics during the interpass periods during rolling. The noticable increase in the mill load which is commonly experienced during controlled rolling is mainly due to this cumulative residual strain, besides the simple effects of rolling in the lower temperature range [10,11,12,13,14].

The developed microstructural model as shown in Fig 7 consists of several sub-models: a grain growth model after reheating; a recovery model; a recrystallization model; grain growth model; a prediction model of non-recrystallized fraction during rolling.

The model generates an average austenite grain size and a non-recrystallized fraction on every rolling passes from the given rolling conditions. Then, based on this calculation, the new rolling force model is derived in the next sub section.

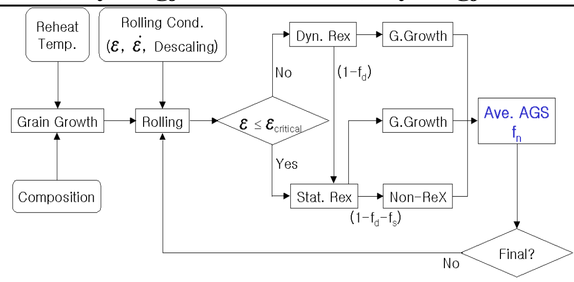


Fig. 7 The schematic diagram of austenite grain size model.

### 4.2 Derivation of new rolling force model

A typical rolling force model has a following form.

$$RF_m = K_m \times B \times L_d \times Q_\pi ,$$

where $RF_m$ is the rolling force computed from a mathematical model, $K_m$ is the mean flow stress, $B$ is the plate width, $L_d$ is the roll contact length and $Q_\pi$ is the geometric term.

Since the flow stress model has very nonlinear characteristics and is difficult to model, an approximated model is generally used.

$$K_m = K_0 \times \varepsilon^n \times \dot{\varepsilon}^m \times \exp(Q / RT) \quad (3)$$

where $K_0$ is the basic flow stress, $\varepsilon$ is the strain, $\dot{\varepsilon}$ is the strain rate, $T$ is the temperature, and the parameters of $n$, $m$, $Q$, $R$ are all constants.

Since Eq. (3) does not contain the microstructural change, the new flow stress model is designed as follows.

$$Ln(K_{mn}) = A_o + A_1 \cdot Ln(K_0) + A_2 \cdot Ln(\varepsilon) + A_3 \cdot Ln\left(\dot{\varepsilon}\right) + A_4 \cdot {}^1\!/_T$$
$$+ A_5 \cdot Ln\left(\frac{1}{\sqrt{AGS_{ave.}}}\right) + A_6 \cdot Ln(1 - f_n),$$

where, $K_{mn}$ is a new mean flow stress, $A_o \sim A_6$ are regression coefficients, $AGS_{ave}$ is the average austenite grain size, and $f_n$ is the non-recrystallized fraction.

The regression coefficients are initially calculated in off-line from least square method using large sum of logged data and they are updated in on-line by RLS(recursive least square) method.

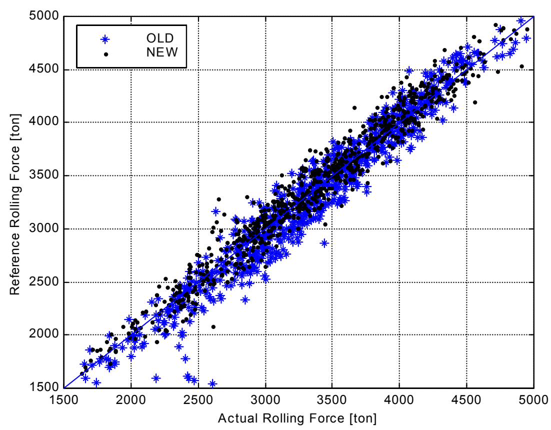


Fig. 8 Comparison of rolling force prediction between new model and old model

Fig. 8 shows the prediction results which is calculated from 752 plates that is gathered during Jan to Mar, 2002. The mean and the standard deviation of prediction error are 40 ton, 175.68 ton, respectively in the existing method whereas -44 ton, 141.65 ton, respectively in the new method. This shows that the new method has improved the prediction by 19.4 % in the standard deviation of prediction error.

## 5. CONCLUSION

In the paper, two approaches to improve rolling force prediction ability in a plate mill were introduced. One was to develop new mathematical model by considering the microstructural change of rolled plate for the controlled rolling and the other was to make a supporting learning method with Neural Network for the normal rolling.

The two approach have showed that both are effective in predicting the correct rolling force in the pre-calculation stage. The model is helpful in designing, scheduling, and understanding the process whereas the Neural Network learning is in compensating the model error by using its MIMO(Multi-Input Multi-Output) mapping capability. The MIMO mapping is very useful in compensating the error from the frequent lot changes due to size, chemical components, etc.

The future research topic is to develop more precise physical model of rolling force with the microstructural model and to expand the Neural Netork applications in the similar steel making plants.

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