

# Development of AI for Tandem Cold Mill Pass Schedule Setup

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## Abstract:

*In a Tandem Cold Mill (TCM) consisting of multiple rolling stands, there is flexibility in setting the reduction rate at each stand and the tension between stands, which is referred to as the pass schedule. The quality of the pass schedule affects productivity and quality, leading to frequent manual adjustments by operators. To address this, we introduced an AI-based automatic pass schedule setting system at the cold rolling mill in our West Japan Works (Fukuyama District). By considering the cooperation with manual interventions by operators, we achieved a smooth transition to the automated system. Additionally, the system contributes to improved efficiency by allowing the AI to select the data used for learning.*

## 1. Introduction

The Tandem Cold Mill (TCM) is used to build the aimed product thickness into cold-rolled steel strips. Although the thickness of the substrate and the target thickness of the product dimensions are specified, as a distinctive feature of the TCM, there is considerable flexibility in setting the thickness at each stand, and the tension between the rolling stands can also be set flexibly within the range that will not adversely affect operation. In this paper, the process of setting the strip thickness at each stand of the TCM (setting of reduction rate) and the tension between the stands is referred to as pass schedule setting.

Since there is a high degree of freedom in setting the pass schedule of a TCM, as above, and pass schedule setting directly affects the rolling load and rolling torque at each stand, the pass schedule setting inevitably has a large impact on the productivity of the TCM

and the quality of the steel strip product in terms of the off-gauge length of the product thickness. To address this problem, various methods for determining the pass schedule settings of the TCM have been proposed.

Historically, the most widely used method is to provide a pass schedule setting table, which is subdivided by steel grade and product dimensions, in the process computer. In this method, the values in the table are adjusted by a trial-and-error process, and finer pass schedule setting for operational improvement is possible by further subdivision of the setting table, but conversely, the load of table maintenance work increases as the table becomes more complex. Moreover, it is also difficult to reflect constantly-changing operational performance indicators, such as the rolling length between roll changes and the concentration of the rolling oil, in pass schedule setting.

An another publicly-known pass schedule setting method, the pass schedule is set so as to minimize certain evaluation functions, which are designed in consideration of the rolling load, current of the rolling mill motors and other parameters<sup>1)</sup>. Provided that the design of the evaluation functions and constraint conditions is appropriate, this method enables us to perform pass schedule setting that achieves high productivity with little risk of operational trouble, as well as excellent product quality. On the other hand, as issues of this method, setting of the evaluation functions themselves is difficult due to the high degree of freedom in setting the functions, and the load of parameter maintenance is high, for example, as it is necessary to set the upper and lower limits of the various constraint conditions and adjust the weights of the evaluation functions.

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Based on the issues described above, JFE Steel introduced a pass schedule setting model trained with actual past rolling data using a neural network<sup>2)</sup>. As one superior feature of this method, the model does not include adjustable parameters, such as the values of the pass schedule setting table and operating conditions, which require maintenance by individual human intervention. However, although the method of using a setting table is the same, as one problem, this method unavoidably depends on human intervention by the operator to revise the table when rolling new steel grades without adequate actual rolling data. As an additional problem, in terms of system implementation, the model may easily become obsolete because human intervention is necessary when retraining the neural network model.

To solve the above-mentioned problems, we developed an AI-based pass schedule setting system with the following features, which is trained with actual past rolling data using a neural network in a same manner described above. The details of this development are reported in this paper.

- (1) Maintenance-free parameters that eliminate subdivision by steel grade and product dimensions as much as possible.
- (2) Achievement of automatic retraining of the AI model itself, without relying on human intervention, based on the accumulation of actual rolling data.
- (3) Use of AI setting even when the accumulation of actual rolling data is inadequate by construction of a model that allows cooperation with manual interventions by operators
- (4) System configuration that enables learning of improved settings by providing a step where the AI selects the data to be used in training for training of the AI model itself

## 2. TCM Schedule Calculation

### 2.1 Pass Schedule Setting and Schedule Calculation

This section presents an outline of pass schedule setting in the TCM, setting of the reduction positions among the TCM mill stands, which is referred to as schedule calculation, and setup of rolling speed setting. The general flow of schedule calculation is shown in Fig. 1.

Pass schedule setting, which is the main subject of this paper, corresponds to ① at the top of the flow, and is performed by various methods based on the rolling material specifications (strip width, strip thickness, steel grade), roll specifications, etc.

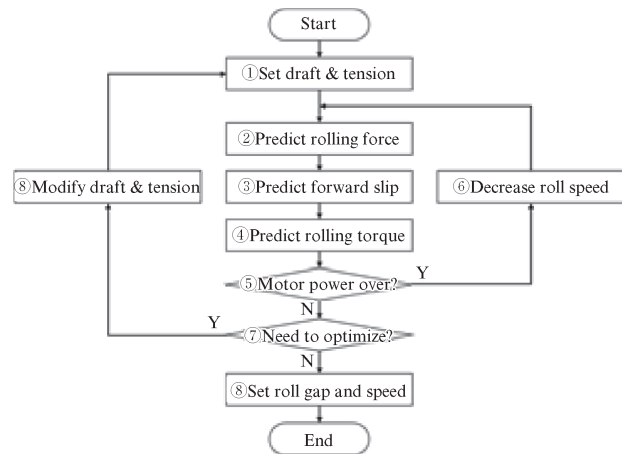


Fig. 1 TCM setup procedure

Table 1 An example of pass schedule

	Entry	1STD	2STD	3STD	4STD	5STD
Thickness mm	<u>3.1</u>	2.5	1.9	1.44	1.11	<u>1.00</u>
Tension kgf/mm <sup>2</sup>	0	11.9	15.6	20.6	21.8	5.4

Kamata et al. showed the pass schedule for low carbon steel in **Table 1** as a concrete example of pass schedule setting at a TCM consisting of 5 stands<sup>3)</sup>. As described in the previous chapter, the thickness of the original (entry-side) strip and the thickness at the exit side of No. 5 stand (numbers underlined in Table 1) are set as the rolling material specifications. However, this is a setting process with an extremely high degree of freedom, as all the other items can be set arbitrarily.

At the TCM of JFE Steel's West Japan Works (Fukuyama District), adequate maintenance of the pass schedule setting table was not being performed, and manual intervention in pass schedule setting by the operators, corresponding to the condition of the rolling operation, had been a daily occurrence. Since pass schedule setting is directly related to the productivity of the TCM, as described in the previous chapter, there were significant differences in the maximum line speed between operator groups, as can be seen in Fig. 2. Fig. 2 shows a relative evaluation, where the operator group with the lowest maximum speed is defined as 1.

### 2.2 Configuration of AI-Based Schedule Setting Calculation System

This section describes the configuration of the developed AI system for schedule calculation. Here, the total system, including the AI-based pass schedule setting system, is referred to as the AI-based schedule calculation system.

First, Fig. 3 shows the system configuration of the

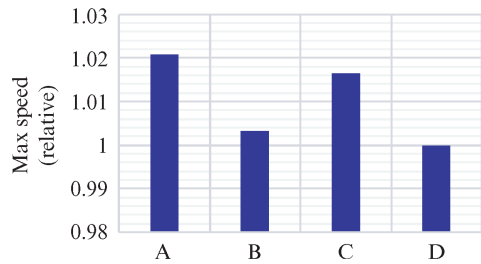


Fig. 2 Max speed differences between operator groups

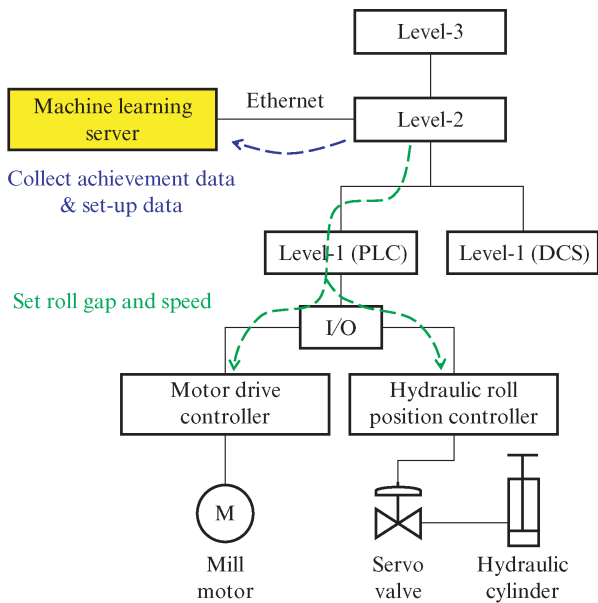


Fig. 3 System configuration diagram

system. The schedule calculation training server (machine learning server) collects process data beginning with the rolling load obtained from the Level-1 computer (PLC: Programmable Logic Controller and DCS: Distributed Control System), schedule calculation data obtained from the Level-2 computer (process computer), and instruction data (set-up data) such as the rolling material specifications, roll specifications, etc. transmitted from the Level-3 computer (business computer), by way of the Level-2 computer, and stores those data in the training database per coil.

The Level-2 computer not only performs pass schedule setting, which is the main subject of this paper, but also calculates the rolling load, rolling torque and forward slip using an AI model.

The training server automatically executes model retraining using the data accumulated in the database, and transmits the completed model parameters to the Level-2 computer when training is completed. Automatic reloading of the parameters by the Level-2 computer achieves parameter updating without human intervention, in other words, automatic retraining.

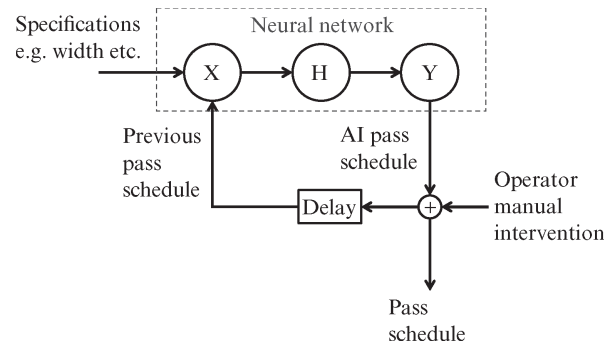


Fig. 4 AI pass schedule model

### 3. AI Pass Schedule Setting System

#### 3.1 AI Model for Pass Schedule Setting

This section explains the configuration of the neural network model used in the developed AI pass schedule setting. The configuration of the AI pass schedule setting system is shown in Fig. 4.

Here, Layer “X” is the input layer, Layer “H” is a hidden layer, and Layer “Y” is the output layer. Multiple variables are used as explanatory variables, which corresponds to the input layer, including the rolling material specifications, that is, the original strip thickness and mill exit-side strip thickness settings, the strip width and the deformation resistance, and roll specifications such as the work roll diameter and the rolling length after a work roll change.

On the other hand, as the objective values corresponding to the output layer, the reduction rate setting at each stand and the inter-stand tension are used. However, because the strip thickness at entry side and exit side of the mill stand are specified, the degree of freedom in this process does not necessarily correspond to the number of stands. That is, in the case of a TCM consisting of 5 rolling stands, if the reduction rate of stands No. 1 to 4 is decided, the reduction rate at No. 5 stand is uniquely determined so that the strip thickness at the exit side of that mill stand is equal to the target value. To avoid this problem, the authors constructed a model that predicts the ratio of the reduction rate of each stand to the reduction rate at the stand selected as the reference stand, rather than predicting the actual reduction rate settings.

As shown in Fig. 4, the pass schedule settings used in actual rolling are the results obtained by manual intervention by the operators in the output from the neural network (i.e., the AI pass schedule settings). This approach was adopted considering the need for operator intervention, based on the AI pass schedule settings obtained by extrapolation from the past actual rolling data, particularly under the conditions of test

rolling of new steel grades for which adequate actual rolling data are not necessarily available.

Also as shown in Fig. 4, an irregular output recursive-type recurrent neural network was adopted, using the pass schedule settings after operator intervention as the explanatory variables in the pass schedule prediction for the next material. This reflects the fact that significant variability could be seen in the pass schedule settings by individual operators under similar rolling conditions, because conventional operator interventions had been performed based on the know-how of individual personnel. In other words, the aim of this approach is cooperation of AI with the operators in modifying AI setting values corresponding to human operator intervention, by providing a recursive structure for ensuring that the outputs of AI setting values are always the same under the same rolling conditions, in the case of AI pass schedule setting without recursive coupling.

Although the results of application to the actual TCM will be presented in the following chapter, the adoption of this type of configuration is steadily improving the usage rate of the AI pass schedule setting system.

### 3.2 Selection of Training Data by AI

This section describes the method of selecting the data to be used in training, which is an innovative feature of the model training in this AI pass schedule setting system. In the AI pass schedule setting system, training is performed on-line, without human intervention, in following three steps in this section.

First, in developing the AI pass schedule setting system, the authors considering that, even if it is possible to develop a model configuration that learns pass schedule setting based on the past actual rolling data and reproduces it with good accuracy, this would be no more than reproducing the results of the average operator. In other words, with that kind of simplistic training method, it was thought that the competence of human intervention by experienced operators as “craftsmanship” would be lost from the AI pass schedule setting system. This is very different from reproducing the actual values as accurately as possible, as in the case, for example, of a rolling load AI that predicts the actual values of the rolling load measured by a load cell. This is a problem specific to the application, as seen in pass schedule setting, where it is difficult to evaluate the relative quality of the settings.

Therefore, we attempted to solve this problem, not by a method that evaluates the relative quality of pass schedule settings by providing some type of evaluation function, but by eliminating data associated with “poor operation” from the data used to train the AI pass

Data in database of learning server

Thickness	Width	...	Reduction 1	...	Tension 1	...	Max speed
3.1	930	...	0.193	...	11.9	...	1 000
3.1	900	...	0.190	...	12.5	...	1 050

Explanatory variables of Step.1

Objective variable of Step.1



Step.1: Add Step.1 AI's predicted maximum speed.

Thickness	Width	...	Reduction 1	...	Tension 1	...	Max speed	Speed AI predict
3.1	930	...	0.193	...	11.9	...	1 000	1 010
3.1	900	...	0.190	...	12.5	...	1 050	1 030



Step.2: Keep only the rows where maximum speed is higher than the predicted value.

Thickness	Width	...	Reduction 1	...	Tension 1	...	Max speed	Speed AI predict
3.1	900	...	0.190	...	12.5	...	1 050	1 030

Explanatory variables of Step.3

Objective variable of Step.3



Step.3: Train AI pass schedule using the remaining data.

We had pre-trained AI pass schedule.

Fig. 5 Training flow of AI pass schedule

schedule setting system.

Concretely, focusing on the fact that the pass schedule settings have a direct effect on rolling power, that is, on productivity, as described in Chapter 1, we defined “poor operation” as operating data with a poor allocation of rolling power and low maximum speed of the mill stands. Based on this concept, training of the AI pass schedule setting system was carried out, divided into the following three steps, as shown in Fig. 5. By adopting this training process, which includes a data selection step, it is assumed that the AI pass schedule setting system will gradually converge on setting values that lead to high productivity. The following explains each of the steps.

#### Step 1 Prediction of mill stand maximum speed by AI

First, the maximum speed of the mill stands based on all the data in the database is predicted by the AI using the rolling material specifications, etc. as the explanatory values. The database contains the actual values of the maximum speed for the coils concerned. However, in this step, the pass schedule settings are not included in the explanatory values of the maximum speed predictions by AI.

In other words, by intentionally not including the pass schedule settings, the AI model is expected to function as a model that predicts the “average maximum speed,” independent of the pass schedule settings of the coils concerned.

#### Step 2 Extraction of high productivity data

The AI prediction of the maximum speed obtained in Step 1 is compared with the actual maximum rolling speed. When the actual value is larger

than the AI prediction based on an appropriate threshold, those values are kept, and conversely, when the actual values are smaller than the AI prediction, those values are discarded.

Since the AI predictions were intentionally the “average maximum speed” independent of the pass schedule settings, it was thought that the selected data have high maximum speeds because the pass schedule setting was favorable for higher speeds.

### Step 3 Training of AI pass schedule setting system using remaining data

In this step, the AI pass schedule setting system is trained using the data extracted in Step 2. The AI pass schedule setting system trained in this way is expected to tend to predict pass schedule settings with high maximum speeds.

Adoption of this multi-step model training method results in gradual improvement of the actual values of the maximum speed when the AI pass schedule setting system is used.

## 4. Results of Application to Actual TCM

### 4.1 Condition of Usage of AI Pass Schedule Setting System

This section describes the results when the AI pass schedule setting system was implemented in the control system of an actual TCM and operated over a long-term period.

First, the graphs in Fig. 6 show the usage rate for each fiscal year after introduction of the AI pass schedule setting system for representative steel grades. The final decision of whether the AI is to be used or not is left to the judgment of the operator. However, as can be seen in Fig. 6, the usage rate of AI pass schedule setting gradually increased and reached 73 % in the 3<sup>rd</sup> year. Figure 7 shows the usage rate by operator group in each fiscal year. From Fig. 7, it is clear that whether the AI settings are actively used depends on the indi-

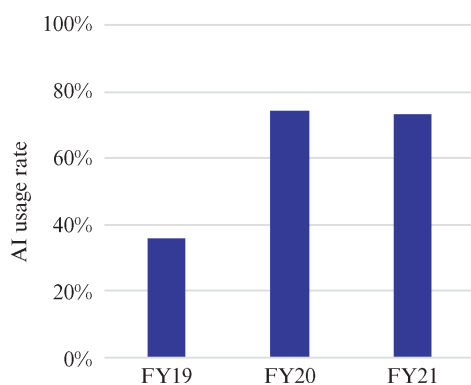


Fig. 6 Usage rate of AI pass schedule

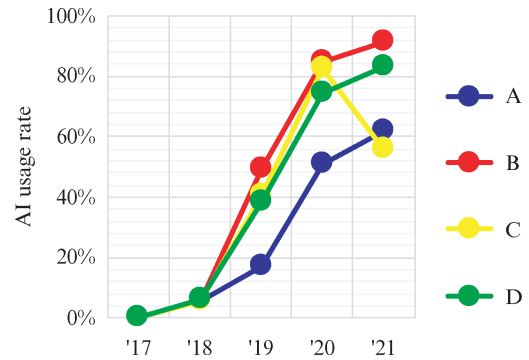


Fig. 7 Usage rate of AI by operator group

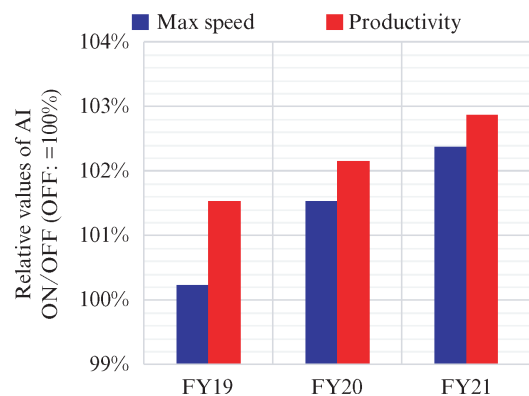


Fig. 8 Productivity improvement using AI

vidual judgments of the operators. Here, it should be noted that, in both of these evaluations, when the automatic setting function by AI was set to the ON condition, this was counted as “AI usage,” even when operators intervened for multiple pass schedule setting items.

### 4.2 Productivity Improvement by AI Usage

Section 3.2 described the method of automatically selecting data associated with high maximum speeds and training the AI model using only the selected data as an innovation in the training of the AI pass schedule setting system. As verification of the effect of this type of training, the present section describes the effects of the AI pass schedule setting system on the maximum speed and productivity (production per unit time).

Figure 8 shows the relationship of use/non-use of the AI pass schedule setting system and the maximum speed and productivity by fiscal year for representative steel grades. As a relative evaluation of the improvement when the AI function is ON, the y-axis in Fig. 8 shows the relative values of AI use/non-use for each fiscal year, where the average value of the maximum speed with the AI function OFF is defined as 100%.

First, the difference between the maximum speed when the AI function for pass schedule setting is ON and OFF expands in each fiscal year, reaching a differ-

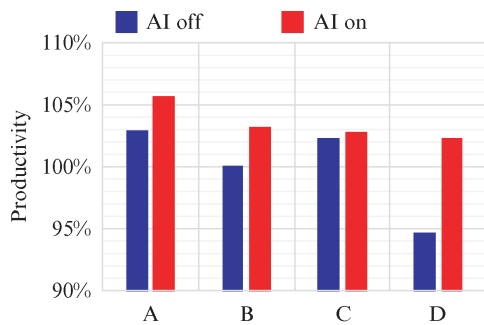


Fig. 9 Productivity variability by operator group

ence of 2.4% in the 3<sup>rd</sup> year. This is thought to occur because the training algorithm that automatically selects data associated with high maximum speeds is operating as expected, and the pass schedule settings are continuing to converge on high productivity setting values.

Similarly, as in the difference in the maximum speed, the difference in productivity when the AI function is OFF and ON expanded in each fiscal year and was 2.9% in the 3<sup>rd</sup> year. The fact that the improvement in productivity was larger than the improvement in the maximum speed is thought to be a result of realizing stable operation with little risk of trouble, even when the maximum speed is raised, by reducing the individual variability between the operators in pass schedule setting by using AI setting.

Next, **Fig. 9** shows the results of an evaluation of productivity variability by operator group using the data for fiscal year 2021. In Fig. 9, “Average value of production per unit time with AI function OFF,” which is assumed to be the same as before introduction of the AI pass schedule setting function, is defined as 100%, and a relative evaluation of the variability of productivity between operator groups is carried out.

First, the fact that productivity when the AI func-

tion is ON is 2.9% superior to productivity when the AI function is OFF is as described above. However, the largest difference between the operators group with the AI function OFF was 8.2%, but this difference decreases to 3.3% with the AI function is ON. Thus, in addition to improvement of productivity by use of the AI pass schedule setting system, use of the AI function also reduces the differences in productivity between operator groups.

## 5. Conclusion

This article has described the development of an AI pass schedule setting system as part of the AI schedule calculation system of the Tandem Cold Mill (TCM) in standard operation at the cold rolling mill of JFE Steel’s West Japan Works (Fukuyama District).

- (1) This system has been in continuous long-term operation since 2018, and has achieved pass schedule setting in cooperation with the operators, including when rolling new steel grades.
- (2) The system is also contributing to maintenance-free system operation and gradual productivity improvement by automatic training, including automatic selection of the data to be used in model training.
- (3) The effect of the system in reducing variations in productivity between operators has also been confirmed.

## References

- 1) Murakimi, A.; Nakayama, M.; Okamoto, M.; Abiko, Y.; Sano, K.; Tsuchihashi, T. Optimization of Pass Schedules for a Tandem Cold Mill. *Tetsu-to-Hagané*. 2004, vol. 90, no. 11, p. 953–957.
- 2) Toyofuku, T.; Takegoshi, A.; Yamamoto, M.; Tanaka, H. Determination of Drafting Schedule for Tandem Cold Mills Using Neural Network. *CAMP-ISIJ*. 1991, vol. 4, no. 5, p. 1496.
- 3) Kamata, M.; Fujita, F. Theory and Practice of Strip Rolling (Revised), chapter 5. *ISIJ*, 2000, 350p (p. 115).