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Improved shape control performance of a Sendzimir mill using wavelet radial basis function network and fuzzy logic actuator

Jeon Hyun Park¹, Jong Shik Kim¹ and Seong Ik Han²

Abstract
A shape control system based on a wavelet radial basis function network for a Sendzimir mill (ZRM) and fuzzy control are developed to improve the shape control performance of a conventional ZRM system. The conventional shape recognition system for a ZRM adopted an incomplete multi-layer perceptron neural network system that was constructed two decades ago. The poor shape recognition of this system leads to actuator saturation and shape control performance deterioration. Therefore, the full automatic operation of a ZRM is often stopped, and manual input need to be performed. This affects the quality, causes a decline in the productivity of the steel strip and an unnecessary waste of manpower. In this paper, a wavelet radial basis network is developed to replace the multi-layer perceptron network and consequently improve shape recognition performance. A modified fuzzy controller is also constructed to prevent actuator saturation that occurs in a conventional shape control system owing to the use of a fixed gain-based fuzzy controller. A comparative simulation based on the data measured from an actual ZRM plant demonstrates the efficacy of the proposed shape control system.

Keywords
Sendzimir mill, shape control, multi-layer perceptron neural network, wavelet radial basis function network, fuzzy controller

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Introduction
Rolling work using the general four stands or 65 stands for an electrical sheet and a stainless cold-rolled steel, respectively, is very difficult because the deformation resistances of the electrical sheet and stainless cold-rolled steel are greater than that of general carbon steel. Therefore, a Sendzimir mill (ZRM) with a small-diameter work roll is used to roll high strength steel because the reduction ratio in a ZRM is very high. A thin steel plate can be obtained by using a ZRM using a small amount of acting force owing to the small diameter of the working roll. However, the working roll is apt to be bent because its diameter is very small compared to its length. This roll bending causes a waved shape in the steel plate, which reduces its flatness. In particular, when tension is applied to a brittle material such as an electroplated steel sheet due to the movement of the plate, a rupture of the plate can occur in the welded part during the subsequent heat treatment process owing to the nonuniform distribution of tension in the plate. Therefore, shape control is required because the generation of a rupture in the plate reduces the rolling speed and causes lower productivity in manufacturing steel. Shape control is accomplished by regulating the bending of the working roll. This regulation is achieved by applying an appropriate load, which is generated using a vertically moving AS-U roll and a horizontally moving the 1st intermediate roll (IMR). Strip shape control in ZRMs has been actively studied since the work of Gunawardene in 1981.¹–⁴ On the other hand, multi-layered perceptron (MLP) neural networks (NNs)⁵,⁶ and fuzzy logic control (FLC)⁷,⁸ have been adopted in the shape control system owing to the complexity, nonlinearity, multi-input, and multi-output properties of the roller structure.

In 1992, NN-FLC was first applied to a ZRM by Hattori.⁹,¹⁰ In this system, an NN was used to...
recognize a shape pattern and FLC was used in the shape controller by creating a working rule for an operator from the recognized shape pattern. Although NN-FLC algorithms have been applied, a fully automatic shape control system cannot be constructed in the present ZRM shape control system, and manual input is frequently necessary. For a fully automatic shape control system, actuator saturation in an AS-U rack often occurs. Thus, operators must intervene manually in an AS-U actuator to prevent saturation because the saturation causes a reduction in the quality and productivity of the steel plate. NN and FLC algorithms applied in a ZRM were developed relatively early on, and they consequently exhibit lower shape recognition performance and inappropriate fuzzy rules that cause actuator saturation. In addition, improper shape pattern recognition and fuzzy control degrade the shape control performance. Therefore, improvement of the shape pattern performance and fuzzy rule is required to avoid actuator saturation and obtain advanced performance for the shape control. A wavelet NN has been developed to improve the performance of a conventional NN.\textsuperscript{11,12}

In this paper, a wavelet radial basis function (RBF) NN method (WNN) is developed to improve the performance of the shape pattern recognition instead of the conventional MLP that is equipped in an actual ZRM plant. An RBF NN\textsuperscript{13,14} was also considered for comparative NN performance. In addition, an improper fuzzy rule was analyzed and a modified fuzzy rule was proposed. The performance of the shape control system was evaluated through simulation on the basis of data obtained from the actual ZRM plant.

**Structure of the ZRM and the shape-detection device**

A ZRM is a 20-stand roller that has separated upper and lower parts, where 10 rollers are symmetrically placed in each part. Figure 1 shows the inner mill housing of a ZRM. As shown in Figure 2, the rolls of a ZRM consist of four AS-U rolls, three 2\textsuperscript{nd} IMR rolls, two 1\textsuperscript{st} IMR rolls, and one work roll. The diameter of the work roll is approximately 65–85 mm, and the length of roll is 1677 mm. The 1\textsuperscript{st} IMR rolls are used for shape control because they can move along the width of the steel plate, allowing for one side of the plate to be manufactured as a tapered shape. The two rolls of the 2\textsuperscript{nd} IMR are operated with connection to motors. In Figure 3, the upper part of the AS-U roll is described, where the AS-U rack on which the input and output sides are distributed symmetrically and pinion gears that rotate the eccentric rings are installed. The actuator of the AS-U rack can be moved up to 100 mm and generates the relative vertical displacement of the AS-U roll. This effect provides the bending of a work roll that is used in shape control. When the steel strip is rolled, the distribution of the elongation rate cannot be measured directly in the rolling process. This distribution of the elongation is called as the shape. Tension is generated in wrapping the steel strip and its magnitude varies with the elongation distribution. Thus, the tension distribution can be measured by a shape-detecting device installed between roller and wraper. The shape-detecting roll has tension sensors located on the plate in the width direction at regular intervals. The shape can be expressed using 38 tension sensors located along the width. The elongation rate is calculated indirectly from the measured unit tension distribution using Hooke’s law in equations (1) to (4). This unit tension distribution or elongation distribution is called its shape and is generally represented in I-Unit, which denotes that the steel is elongated to 1 mm per 100 m.\textsuperscript{15} A positive I-Unit indicates that a steel strip of a specific interval is significantly more elongated than the entire mean elongation and a negative I-Unit indicates the opposite case.

$$\sigma_0 = \frac{T}{A} = \frac{T}{t \times w}$$  \hspace{1cm} (1)

$$\bar{F} = \frac{1}{n} \sum_{i=1}^{n} F_i$$  \hspace{1cm} (2)

$$\sigma_i = \frac{F_i - \bar{F}}{F} \times \sigma_0$$  \hspace{1cm} (3)

$$I - Unit = - \frac{\sigma_i}{E} \times 10^5$$  \hspace{1cm} (4)

In equations (1) to (4), $\sigma_0$ is the stress acting on the strip, $T$ is the tension of the strip, $t$ is the thickness of the strip, $w$ is the width of the strip, $F_i$ is the vertical force acting on the measurement roll, $\bar{F}$ is the average vertical force, $\sigma_i$ is the stress deviation, and $n$ is the interval of the strip. Figure 4 shows the relationship between the elongation of the steel strip and the measured acting force of the shape-detecting roll. We find...
that as the measured tension increases, the elongation of the strip decreases, i.e., the shape curve that denotes the elongation is vertically symmetric to the tension distribution in the shape meter. Figure 5 represents the detecting section of the shape. The shape-detecting roll has stress sensors arranged at regular intervals between −663 mm and 663 mm along the strip width. 14 sensors arranged at 52-mm intervals in the center section, and 12 sensors on both sides arranged at 26-mm intervals in the edge section. The shape is therefore measured using 38 tension sensors arranged along the strip width.
Figure 4. The relation between elongation and the tension of a steel plate.

Figure 5. Layout and zone classification of shape-detecting roll: (a) layout of shape-detecting roll; (b) zone classification of shape-detecting roll.
Neural network-based shape pattern recognition of a ZRM

The faulty shapes in rolled steel plates are caused by various reasons such as a disproportion between the rolling load and the roll bending and surface damage of roll. Nonlinear control considering many related variables is therefore required to properly control the shape of the cold-rolled steel plates. On the other hand, satisfactory shape control is challenging to create because constructing a nonlinear model is very difficult for shape control, and many parameters should be obtained through many repeated experiments. To overcome this problem, intelligent shape control methods such as an NN and FLC have been applied frequently to shape control systems in many industrial fields.10

A block diagram of the automatic shape control system in a ZRM is represented in Figure 6. The shape signals are measured from 38 sections according to the width of a steel plate because the width of a steel plate varies with the types of a steel plate. The measured 38 shape signals are transformed into 32 signals using the linear interpolation because the maximum input channels of the shape control system are limited as 32, and in next are normalized by dividing them the maximum signal value. The error shape is constructed by the differences between 38 corresponding shapedata points measured from a shape-detecting roll and target shapes. The error shape signal is used as the input signal of an NN algorithm through several transformations because an NN system applied in a ZRM receives 32 input signals that have values between 0 and 1. Once the 32 input signals are applied to the trained NNs, 14 output patterns of shape recognition results are obtained. These results are applied to the input of the fuzzy controller, where the positions of the actuators are determined. The positions of the actuators are used as the control input signal of the shape plant. The 38 shape data points can be extracted through the shape plant. However, at this time, a manual input is introduced into automatic shape control because saturation in the actuator may occur if the shape control of a ZRM is operated only fully automatically.

Shape pattern recognition using an MLP

In current ZRM mills, the applied NN is an MLP, which is used to recognize a shape pattern. Figure 7 shows the input and output channels of the NN for shape recognition. The 38 shape data points measured by the shape-detecting roll are converted into 32 signals through signal conversion. These 32 signals are used as the input signals and the 14 pattern outputs are selected. This MLP has an input layer with 32 nodes, one hidden layer, and an output layer with 14 nodes. The weights connecting each node and the bias contained in each node are trained off-line on the basis of the representative shapes, as shown in Figure 8, where the $x$-axis of the representative shape represents the normalized strip width, and the $y$-axis represents the normalized magnitude. Figure 9 shows the structure of the MLP for shape recognition in a ZRM where $i$, $r$, and $j$ represent the input layer, hidden layer, and output layer, respectively; $w_{ij}$ and $W_{ij}$ denote the weights between the hidden layer and the input layer and the weights between the output layer and the hidden layer, respectively.
Figure 8. Learning results for the representative shapes.
The MLP process is described as follows:

Forward propagation:

- For each hidden node, the net and z values are calculated as:

\[
net_r = \sum_{i=1}^{n} w_{ri}x_i, \quad z_r = f_1(net_r)
\]  

where \( f_1 \) is the activation function.

- For each output node, \( net_j \) and \( y_j \) are calculated as:

\[
net_j = \sum_{r=1}^{m} W_{jr}z_r, \quad y_j = f_2(net_j)
\]  

where \( f_2 \) is the activation function.

Figure 8. Continued.
Backward propagation:
The cost function is defined as follows
\[ E = \frac{1}{2} \sum_{j=1}^{m} (t_j - y_j)^2 \]  
(7)

The connection strength in the direction of the hidden layer from the output layer is calculated as follows
\[
\frac{\partial E}{\partial W_{jr}} = \frac{\partial E}{\partial y_j} \frac{\partial y_j}{\partial W_{jr}} = -(t_j - y_j) \cdot f'_j(\text{net}_j) z_r
\]
(8)

where \( \delta_{wj} = (t_j - y_j) \cdot f'_j(\text{net}_j) \) and \( f'_j(\text{net}_j) = \frac{dy_j}{dW_{jr}} \). The new weights are calculated as follows
\[
W_{jr}(\text{new}) = W_{jr}(\text{old}) - \mu \frac{\partial E}{\partial W_{jr}}
\]
(10)
\[
w_{ri}(\text{new}) = w_{ri}(\text{old}) - \mu \frac{\partial E}{\partial w_{ri}}
\]
(11)

where \( \mu \) denotes the learning rate.

The measured error shape in a real plant through the shape meter and the recognized error shape using the MLP are displayed in Figure 10, where the recognized performance of the error shape using the MLP was poor. This poor recognition performance causes erroneous fuzzy rule application because each gain of the fuzzy rule has a fixed value, and the outputs of the fuzzy control are only determined by the recognized shape pattern ratio. In addition, the information for the error shape magnitude disappears because the shape information used for the NN inputs is normalized. Therefore, the fuzzy controller provides the same movement in the actuator if the same pattern is entered regardless of the magnitude of the error shape. This phenomenon can cause an excessive control input in the actuator even though the error size is...
reduced to be satisfactorily small. The recognition performance of the NN must therefore be improved to solve this problem.

There are two methods to enhance the performance of the shape pattern recognition. The first increases the number of neuron in the hidden layer. The second selects a more efficient NN algorithm that is suitable for pattern recognition. The first method is not plausible because the basic information of the MLP applied in the real ZRM plant, such as neuron numbers and weighting values, is known to be difficult a priori. In this paper, the WNN method is therefore applied to obtain further improved performance for the pattern recognition. The RBF method is also considered for comparison with the proposed WNN method.

Radial Basis Function Network Design for the Improvement of the Shape Recognition Performance

An RBF network is considered for comparison with the proposed WNN recognition method. An RBF network has a feedforward structure including one hidden layer, as shown in Figure 11. In the hidden layer, each RBF neuron uses a Gaussian function, where the center of the covered domain and activated domain represent the input domain in which the local neurons are activated. The Gaussian transfer function is defined as

$$Z_j(x) = \exp\left(-\frac{\|x - \mu_j\|^2}{2\sigma_j^2}\right), \text{ for } j = 1, 2, \ldots, J$$  

(12)

where \(x\) is the input, \(\mu_j\) is the center of covered domain, \(\sigma_j\) is the width of the covered domain, \(J\) is the number of the hidden layer, and \(Z_j(x)\) is the output of the \(j\)th neuron. The output of the RBF network is expressed as

$$y_l(x) = \sum_{j=1}^{J} w_{lj}Z_j(x), \text{ for } l = 1, 2, \ldots, L$$  

(13)

where \(w_{lj}\) is the weight, \(L\) is the neuron number of the output layer, and \(y_l(x)\) is the \(l\)th output. \(\mu_j, \sigma_j, \text{ and } w_{lj}\) are trained using the representative shape pattern. A performance index for the training parameters is defined as

$$E = \frac{1}{2} \sum_{k=1}^{B} (t_{lk} - y_{lk})^2, \text{ for } k = 1, 2, \ldots, B$$  

(14)

where \(t_{lk}\) is the desired output and \(B\) is the number of the representative shape pattern. The interconnected strength between the hidden and output layers is expressed as

$$\frac{\partial E}{\partial w_{lj}} = \frac{\partial E}{\partial y_{lk}} \times \frac{\partial y_{lk}}{\partial w_{lj}} = \frac{\partial E}{\partial y_{lk}} \times Z_j$$  

$$= -(t_{lk} - y_{lk}) \times Z_j$$  

$$= -\delta_{lk} Z_j$$

where \(\delta_{lk} = (t_{lk} - y_{lk})\). The new weight is calculated as

$$w_{lj}(\text{new}) = w_{lj}(\text{old}) - \eta_w \frac{\partial E}{\partial w_{lj}}$$

(16)

where \(\eta_w\) is the learning rate. The new innovations for \(\sigma_j\) and \(\mu_j\) are calculated as

$$\delta\sigma_j = -\eta_{\sigma} \times \frac{\partial E}{\partial \sigma_j}$$  

(17)

$$\delta\mu_j = -\eta_{\mu} \times \frac{\partial E}{\partial \mu_j}$$  

(18)

$$\sigma_j(\text{new}) = \sigma_j(\text{old}) + \delta\sigma_j$$  

(19)

$$\mu_j(\text{new}) = \mu_j(\text{old}) + \delta\mu_j$$  

(20)

where \(\eta_{\sigma}\) and \(\eta_{\mu}\) are the learning rates of \(\sigma_j\) and \(\mu_j\), respectively. The interconnection innovations of \(\mu_j\) and \(\sigma_j\) are calculated as

$$\frac{\partial E}{\partial \mu_j} = \frac{\partial E}{\partial Z_j} \times \frac{\partial Z_j}{\partial \mu_j} = \frac{\partial E}{\partial Z_j} \times \left(\frac{\|x - \mu_j\|^2}{\sigma_j^2}\right) \times Z_j$$  

(23)

$$\frac{\partial E}{\partial \sigma_j} = \frac{\partial E}{\partial Z_j} \times \frac{\partial Z_j}{\partial \sigma_j} = \frac{\partial E}{\partial Z_j} \times Z_j$$  

(24)

WNN Design for the Improvement of the Shape Recognition Performance

The proposed WNN is a feedforward NN and has input, hidden, and output layers, as shown
in Figure 12. The adopted wavelet is a Morlet wavelet\(^1\) composed of a cosine function and a Gaussian function as follows

\[
\phi(x) = \cos(\omega x) \exp(-x^2) \tag{25}
\]

where \(\omega\) is the frequency.

The outputs of the hidden layer and output layer are expressed as follows

\[
\psi_j = \cos\left(\omega \frac{x_j - t_j}{d_j}\right) \exp\left[-\frac{1}{2} \left(\frac{x_j - t_j}{d_j}\right)^2\right],
\]

for \(i = 1, \ldots, I, j = 1, \ldots, J\)

\[
O_k = \sum_{k=1}^{K} w_k \psi_j, j = 1, \ldots, J
\]

where \(I, J,\) and \(K\) denote the number of input, hidden, and output layers, respectively, \(t_j\) is the translation, \(d_j\) is the dilation, and \(w_k\) is the output strength. The performance index for parameter training is defined as

\[
C = \frac{1}{2} (y_d - O_k)^2 \tag{28}
\]

The training process is given as follows

\[
\frac{\partial C}{\partial w_k} = \frac{\partial C}{\partial O_k} \frac{\partial O_k}{\partial w_k} = -(y_d - O_k) \psi_j \tag{29}
\]

\[
\frac{\partial O_k}{\partial \psi_j} = w_k \tag{30}
\]

\[
\frac{\partial \psi_j}{\partial y} = -\sin\left(\omega \frac{x - t}{d}\right) \cdot \left(-\frac{\omega y}{d}\right) \cdot \exp\left[-\frac{1}{2} \left(\frac{x - t}{d}\right)^2\right]
\]

\[
+ \cos\left(\omega \frac{x - t}{d}\right) \exp\left[-\frac{1}{2} \left(\frac{x - t}{d}\right)^2\right] \cdot \frac{x - t}{d^2}
\]

\[
= -\sin\left(\omega \frac{x - t}{d}\right) \cdot \frac{\omega y}{d} \cdot \exp\left[-\frac{1}{2} \left(\frac{x - t}{d}\right)^2\right]
\]

\[
+ \psi_j \cdot \frac{x - t}{d^2} \tag{31}
\]

Figure 12. The structure of wavelet RBF neural network.

\[
\frac{\partial C}{\partial t} = \frac{\partial C}{\partial y} \frac{\partial y}{\partial t} \tag{32}
\]

\[
\frac{\partial \psi_j}{\partial t} = -\sin\left(\omega \frac{x - t}{d}\right) \cdot \left(-\frac{\omega y}{d}\right) \cdot \exp\left[-\frac{1}{2} \left(\frac{x - t}{d}\right)^2\right]
\]

\[
+ \cos\left(\omega \frac{x - t}{d}\right) \exp\left[-\frac{1}{2} \left(\frac{x - t}{d}\right)^2\right] \cdot \frac{x - t}{d^2}
\]

\[
= -\sin\left(\omega \frac{x - t}{d}\right) \cdot \frac{\omega y}{d} \cdot \exp\left[-\frac{1}{2} \left(\frac{x - t}{d}\right)^2\right]
\]

\[
+ \psi_j \cdot \frac{x - t}{d^2} \tag{33}
\]

\[
\frac{\partial C}{\partial d} = \frac{\partial C}{\partial t} \frac{\partial t}{\partial d} \tag{34}
\]

\[
\frac{\partial O_k}{\partial \psi_j} = w_k \tag{35}
\]

\[
\frac{\partial t}{\partial new} = t_{old} - \mu_t \frac{\partial C}{\partial t} \tag{36}
\]

\[
\frac{\partial d}{\partial new} = d_{old} - \mu_d \frac{\partial C}{\partial d} \tag{37}
\]

where \(\mu_t, \mu_d\) are the learning rates of \(w, t,\) and \(d,\) respectively.

**Fuzzy controller**

**Conventional fuzzy control of a ZRM**

A fuzzy control in the steel process means that this controller uses a fuzzy rule that is constructed from the experience of an operator and the analysis of the process data. The fuzzy rule of the fuzzy controller applied in a ZRM plant is set according to the steel type and width. There are 14 constructed fuzzy rules-based on the recognized shapes. Thus, the fuzzy control used in the shape control differs from a general fuzzy control. The fuzzy control in the ZRM process does not have a full property, such as fuzzy input, membership function, fuzzifier, fuzzy operation, and defuzzifier of a general fuzzy logic system because the shape information of the steel strip has two-dimensional properties, making it difficult to define two-dimensional relations for the shape information. Instead of the full fuzzy system, the partial fuzzy system that has the properties with the fuzzy input, fuzzy reasoning, and fuzzy output was considered. Therefore, in most ZRM processes, the fuzzy control laws of this type have been adopted from the usually recognized shape patterns and the corresponding manual operating values-based on the experience of a skillful operator in a real plant. Table 1 summarizes the fuzzy rule of an HGO steel strip that is 1200-mm-wide. For the 14 patterns, the movable displacements of seven actuators are prescribed and the displacement of each actuator is a fuzzy output. If the fuzzy output has a positive value, the AS-U actuator moves against the direction of the AS-U roll movement. If the AS-U actuator moves in the reverse direction of the AS-U roll, the loads of the work roll increase by...
the eccentric ring. If the AS-U actuator moves in the direction of the AS-U roll, the load of the work roll decreases. The control laws for a recognized shape are given as follows:

If pattern recognition result = shape pattern\#1, then control rule \#1,
Else if pattern recognition result = shape pattern\#2, then control rule \#2,
...
Else if pattern recognition result = shape pattern\#14, then control rule \#14.

Because a WNN provides 14 representative patterns as values between 0 and 1, the actuator movement for each recognized pattern in the fuzzy controller must be combined as follows:

Position_{fz} = \sum_{i=1}^{14} P_i \times R_i \tag{38}

where \( P_i \) is the shape pattern that is the output of a NN system, and \( R_i \) are the fuzzy control outputs that determine the value of the moving distance of the AS-U actuator. The final actuator position is determined as

Position(t + 1) = Position(t) + Position_{fz} \tag{39}

### Improvement of fuzzy control

The fuzzy gain can be regulated according to the magnitude of the shape error by adding the following gain shown in Figure 13. The fuzzy gain is regulated by the following error variation rate because the shaper errors have 32 data points

\[ \dot{R}_i = R_i \times \frac{E_{s, \text{current}}}{E_{s, \text{initial}}} \tag{40} \]

Table 2. Improved fuzzy control rule.

<table>
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Figure 13. An improved fuzzy controller with Es-gain.
Esp = \frac{\max(E_{sp}(i))}{\min(E_{sp}(i))} \quad (41)

where \( \hat{R}_i \) is the regulated fuzzy gain according to the error variation rate, \( R_i \) is the existing fuzzy gain, \( E_{sp} \) is the error variation rate constructed from \( E_{sp,\text{current}} \) and \( E_{sp,\text{initial}} \), \( E_{sp} \) is the scale parameter of the error shape, and \( E_{s} \) is the shape error. Finally, the actuator position is fixed to avoid actuator saturation when the actuator approaches saturation (Table 2).

**Simulation**

A simulation was executed to compare the performance of the proposed shape control method with conventional systems. The MLP applied to the actual ZRM plant adopted an NN method that was developed in the past and its number of neurons, optimal weights, and learning rate are not well known. Because it is impossible to realize an MLP that is

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**Table 3. Simulation parameter.**

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
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<tbody>
<tr>
<td>Magnitude of target shape</td>
<td>[0(1), 0(2), ..., 0(38)]</td>
</tr>
<tr>
<td>AS-U rack initial position</td>
<td>50-50-50-50-50-50-50 mm</td>
</tr>
<tr>
<td>Input thickness</td>
<td>2.258 mm</td>
</tr>
<tr>
<td>Output thickness</td>
<td>1.47 mm</td>
</tr>
<tr>
<td>Sheet width</td>
<td>1257 mm</td>
</tr>
<tr>
<td>Time</td>
<td>50 s</td>
</tr>
<tr>
<td>Steel sheet type</td>
<td>HGO</td>
</tr>
</tbody>
</table>

**Figure 14.** Measured error shape and recognized error shape at each NN.

WNN: wavelet neural network; RBF: radial basis function; MLP: multi-layered perceptron.

**Figure 15.** The RMSE values of the normalized error shape based on the MLP, RBF, and WNN.

WNN: wavelet neural network; RBF: radial basis function; MLP: multi-layered perceptron.
Figure 16. Shape variation as time progresses: (a) output shape using MLP; (b) output shape using RBF; (c) output shape using WNN.
completely equivalent to that operating in a real ZRM via simulation, the simulated result in Figure 14 were realized using an MLP training that is similar to an MLP applied to an actual ZRM plant. In Figure 14, the simulated results of the MLP, RBF, and WNN methods with the measured shape in an actual ZRM plant are shown. The initial weights and bias were selected as random values and 14 representative shapes were used to train the weights. The number of neurons in the hidden layer was 50, the learning rate was 0.01, and the activation function was selected to be log-sigmoid function. The reconstructed shape was created using the following expression

\[
\text{reconstituted shape} = \sum_{n=1}^{14} \left( \text{nth output of neural network} \right) \times \left( \text{nth representative shapes} \right)
\]

The number of neurons in the hidden layer of the RBF and WNN was 50, which was equal to the number in the MLP, and learning rates of each method were similarly selected as those of the MLP. Figure 14 shows the recognized shapes using an NN for the normalized shapes measured by the shape meter.

In Figure 14, the shape recognition performance of the WNN was higher than the other two methods and the MLP had the worst performance. The normalized RMSE values of each system as time progresses are shown in Figure 15. The average RMSE of the MLP was 0.22, whereas the RBF and WNN had RMSE values of 0.127 and 0.1, respectively. Therefore, the shape recognition of the WNN was 54% better than that of the MLP. Next, the proposed shape control system was implemented to evaluate the performance of the shape controller designed by each NN method. In order to choose a quartered wave, which appears frequently in actual plant, a sine-wave shape that had a positive I-Unit was chosen as the initial shape of the steel strip. The target shape was chosen with zero I-Unit. The simulation parameters are listed in Table 3. The calculations of the shape model included the handling of the input/output data, calculation of the roll coordinates, components, roll load, effect coefficients, roll bending, flatness, and output thickness. The plate shape \( S(i) \) from the input/output thickness profile is expressed as follows

\[
s(i) = \beta \times \frac{h(i) \times H_m}{H(i) \times h_m - 1} \times 10^5 \tag{43}
\]

where \( s(i) \) is the strip shape, \( \beta \) is the scale factor, \( H(i) \) is the thickness profile of the input direction, \( h(i) \) is the thickness profile of the output direction, \( H_m \) is the average thickness of the input direction, and \( h_m \) is the average thickness of the output direction. The simulated results of each shape control system are shown in Figure 16. Actuator saturation occurred at 26.8 s, 15.1 s, and 8.9 s, respectively, for each control system. Figure 17 shows the RMSE of the output shapes versus the target shapes as time progresses. Although the RMSE of the WNN was quickly reduced by virtue of the improved shape recognition performance, vibration of the controlled shape appeared owing to the fixed fuzzy gain. The improved fuzzy controller combined with three NNs was applied to compare it with the conventional fuzzy controller. Figure 18 shows the shape variation as time goes on and the RMSE for the target shape is shown
Figure 18. Shape variation as time progresses for the improved fuzzy control: (a) output shape using MLP; (b) output shape using RBF; (c) output shape using WNN.
Figure 19. RMSE of the output shape for the improved fuzzy control.
RMSE: root mean square error.

Table 4. Simulation result.

<table>
<thead>
<tr>
<th></th>
<th>Conventional system</th>
<th>Improved system</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Using MLP</td>
<td>Using MLP</td>
</tr>
<tr>
<td>Actuator saturation</td>
<td>O</td>
<td>X</td>
</tr>
<tr>
<td>Total average RMSE</td>
<td>11.1 l-Unit</td>
<td>8.1 l-Unit</td>
</tr>
<tr>
<td>Performance improvement</td>
<td>37%</td>
<td>41%</td>
</tr>
</tbody>
</table>

RMSE: root mean square error; WNN: wavelet neural network; RBF: radial basis function; MLP: multi-layered perceptron.
in Figure 19. In simulation results, actuator saturation did not occur, but the vibration of the shape output always appeared in the shape control system with the MLP. For the shape control system with the RBF, the shape stabilized after 30 s, and the average RMSE value decreased to within 4.3 $I$-Unit. The output shape of the shape control system with the WNN stabilized after 20 s and the average RMSE remained within 2.9 $I$-Unit. Figure 20 shows the graph of the actuator position for the conventional and improved fuzzy control systems. In the conventional fuzzy control system, the actuator position quickly varied, and thus, saturation appeared. On the other hand, saturation did not appear in the proposed control system, where the actuator position was never below 5 mm. The simulated results are summarized in Table 4.

Therefore, if the improved fuzzy control system with the WNN-based shape recognition is applied to the ZRM shape control system instead of the MLP and conventional fuzzy control system, actuator saturation can be avoided and the shape recognition performance can also increase to 62%. Furthermore, a steel strip with better quality will then be produced.

**Conclusion**

A conventional shape control system has low shape recognition performance and an actuator saturation problem. These problems disturb the automatic control of the ZRM apparatus, which necessitates manual intervention. To achieve full automatic shape control, a WNN and an improved fuzzy rule were developed to improve the shape recognition performance and remove the actuator saturation problem. A comparative simulation was carried out to evaluate the proposed method with a conventional shape control system. As a result, actuator saturation could be avoided, and the shape control performance was improved by 65%. Therefore, fully automatic shape control that produces steel strip with better quality will then be produced.

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**Conflict of interest**

None declared.

**References**