Shape Performance Improvement of a Sendzimir Mill System Using Echo State Neural Networks and Fuzzy Control

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A Sendzimir rolling mill (ZRM) uses a work roll with a small diameter to roll high strength steel. On the other hand, the work roll is often bent because its diameter is very small compared with its length. From roll bending, a complex wave shape appears in the rolled steel plates. In order to solve this problem, an AS-U roll is used to control the vertical rolling load on the plate. A neural-fuzzy control is applied to the shape control system in a ZRM because of the complexity, nonlinearity, and multi-input multi-output (MIMO) characteristics of rolling mills. The current shape control in a ZRM is not a fully automatic shape control. If the shape control were fully automatic, saturation can occur at the AS-U actuator. To solve this problem, the shape recognition performance should be improved and the fuzzy gain should be modified.

In this study, to improve shape control performance, an echo state network (ESN) was applied instead of a multi-layer perceptron (MLP) at the neural network, and the fuzzy gain was set to change depending on error by adding P gain. Finally, the shape control system was evaluated through simulation.

KEY WORDS: Sendzimir; mill system; echo state networks; fuzzy control.

1. Introduction

The deformation resistance of electrical sheet and stainless cold rolled steel is greater than that of general carbon steel. For this reason, A Sendzimir rolling mill (ZRM) uses a work roll with a small diameter to roll the high strength steel. A ZRM can obtain thin steel plates with a small amount of force. On the other hand, the work roll is often bent because its diameter is very small compared with its length. From roll bending, a complex wave shape with quarter and deep-edge waves appears in the rolled steel plates. This adversely affects the flatness of the steel plates. In particular, when tension is applied to a brittle material such as electroplated steel sheet due to the movement of the plate, a rupture of the plate can occur in the welded part during the heat treatment process because of the nonuniform distribution of tension in the plate. In order to solve this problem, an AS-U roll is used to control the vertical rolling load on the plate. In addition, a first intermediate roll (1st IMR) is used to adjust the distribution of the load. In other words, the shape is controlled by the position of the AS-U roll and the movement of the 1st IMR. A neural-fuzzy control is applied to the shape control system in a ZRM because of the complexity, nonlinearity, and multi-input multi-output (MIMO) characteristics of rolling mills. Strip shape control in ZRMs has been actively studied since the work of Gunawardene in 1981.1–5) A neural network-fuzzy control algorithm applied to ZRMs was developed in 1992 by Hattori.6,7) Neural networks are used for shape pattern recognition. Fuzzy control logic that is routinizing driver’s working method for a recognized shape is used for shape control. Therefore, the performance of shape control systems is determined by the degree of shape recognition, and is a reflection of the driver’s experience. The current shape control in a ZRM is not fully automatic shape control. If the shape control is fully automatic, saturation can occur at the AS-U actuator. These problems are caused by incorrect shape recognition and fuzzy gain. To solve these problems, the shape recognition performance should be improved, and fuzzy gain must be modified. In this study, to improve shape control performance, an echo state network (ESN) was applied at the neural network, and the fuzzy gain was set to change depending on error. Simulated results using the real data of a ZRM showed the effectiveness of the proposed control scheme.

2. Configuration of the ZRM and Definition of the Shape

A ZRM is a 20-high rolling mill and its structure is separated by top and bottom parts with ten rolls in each part. Figure 1 shows the inner mill housing of a ZRM. Figure 2 shows the layout of the ZRM rolls. The upper and lower rolls have the same structures. Each part consists of four backing bearing rolls, three 2nd IMRs, two 1st IMRs and one work roll. Two rolls of the 2nd IMR, located on both sides, are connected to a motor. A vertical displacement difference of six backup rolls is realized using seven racks and pinions. This provides the shape control as the work roll is bent. The 1st IMR provides shape control through a shifting operation.
If a reduction ratio of width is not constant at cold rolling, the elongation distribution of the length is not consistent. The elongation distribution should be measured indirectly because direct measurement of the elongation distribution is very difficult. The elongation can be measured indirectly through the value of tension due to elongation. A shape meter that has 38 tension sensors was set between a rolling mill and a down coiler to measure tension. The elongation can be calculated indirectly using Hooke’s law, using the tension distribution. The shape is this tension or elongation distribution. The shape measurement data are represented with the “I-unit.”, typically. The I-unit represents a steel strip that stretches 1 mm in the length direction per 100 m when the steel strip is rolled.\(^8,9\) If the I-unit is a positive number, then a steel sheet of the section stretches in comparison with mean value of the whole section. If the I-unit is a negative number, then the steel sheet of the section shrinks in comparison with the mean value of the whole section. Figure 3 shows the relation between elongation and tension in the steel plate. A larger tension measured by the shape-detecting roll causes smaller elongation in same section. Therefore, a shape curve representing elongation is vertically symmetrical with respect to the tension distribution that affects the shape-detecting roll.

3. Shape Control System in a ZRM

Faulty shapes in rolled steel plates are caused by various reasons such as roll bending, disproportion of the rolling load and surface damage of role, etc. To control properly the shape of cold rolled steel plates, nonlinear control with many variables is necessary. On the other hand, it is very difficult for a nonlinear model to be set up for shape control, and many parameters should be obtained using an experimental method. Therefore, the satisfactory shape control performance is difficult to be obtained. To deal with this problem, a neural network, intelligent shape control method, and fuzzy logic have been applied frequently to the shape control system in general industrial fields.\(^{10}\)

Figure 4 represents a block diagram of the automatic shape control system in a ZRM. The error shape is made by the difference between 38 shape data measured from the shape-detecting roll and from target shapes. The error shape...
signal is used as the input signal of a neural network algorithm through several transformations. Once the input signals are applied to the trained neural networks, the shape recognition results with 14 outputs are obtained. These results are applied to the fuzzy controller that decided the positions of the actuators. At this time, a manual operation is introduced urgently for automatic shape control because a saturation problem in the actuator is occurred if the shape control of a ZRM is performed only depending on fully automatic shape control. The positions of actuators are used as the control input signal of the plant. The 38 shapes information data can be obtained through the shape plant.

3.1. Multilayer Perceptron Neural Networks

The shape control system applied in the current ZRM mills consists of neural networks (NNs) and fuzzy logic. NNs applied in a ZRM mill is a multi-layer perceptron (MLP), and is used to recognize a shape. Figure 5 shows input and output channels of NNs for shape recognition. The 38 shape data points measured by the shape-detecting roll were changed into the 32 signals through signal conversion. These signals were used as the input signals, and the 14 signals were selected as the outputs. Figure 6 shows the structure of MLP for shape recognition in a ZRM. This MLP has one hidden layer. The input layer has 32 nodes and the output layer has 14 nodes. Weights connecting each node and the bias contained in each node were trained based on the representative shapes as shown in Fig. 7. The x axis of the representative shape represents the normalized strip width and the y axis represents the normalized magnitude. Next, the x axis of the learning result represents the 14 shape patterns and the y axis represents the output magnitude of NNs. $w_{ij}$ and $w_{jr}$ denote the weights to the hidden layer $r$ from the input layer $i$, and weights to the output layer $j$ from the hidden layer $r$.

![Fig. 5. Shape recognition procedure using neural networks.](image)

![Fig. 6. Structure of MLP for the shape recognition in a ZRM.](image)

![Fig. 7. Learning result for the representative shape.](image)
New weighting values can be innovated as follows:

$$W_{ij}^{(n+1)} = W_{ij}^{(n)} - \mu \frac{\partial E}{\partial W_{ij}}$$ \hspace{1cm} (10)

$$w_{r}^{(n+1)} = w_{r}^{(n)} - \mu \frac{\partial E}{\partial w_{r}}$$ \hspace{1cm} (11)

where \( n \) and \( \mu \) denote the iteration and learning rate, respectively.

### 3.2. Fuzzy Control

A fuzzy rule was constructed through the experience and knowledge of the operators, and analysis of the actual process data. Based on this information, the fuzzy controller was configured. The fuzzy control system used in this paper for the shape control is an expert knowledge-based one, which is different with a general fuzzy control system that consists of fuzzifier, rule base, fuzzy inference engine and defuzzifier process because it is very difficult to define the relationship of two dimensional relationships between the fuzzy output and information about the width, thickness and material of panel and several shape patterns. Therefore, a fuzzy rule is constructed frequently using the relation of a recognized shape versus a manual driving quantity of the manual operation. Table 1 represents the control table from this expert knowledge-based fuzzy rule for an HGO steel sheet with a width of 1200 mm. Y-axis represents the number of the shape pattern and X-axis represents the AS-U position corresponding to the shape pattern. The values of the intersecting point of XY axises represent the fuzzy outputs, which mean the moving distances of the AS-U actuators. The positive value of the fuzzy output means that the AS-U actuator moves reversely toward to the direction of the AS-U roll and the negative one means that the AS-U actuator moves toward to the direction of the AS-U roll. If the AS-U actuator moves reversely toward to the direction of the AS-U roll, the load of the work roll increases. Otherwise, the load of the work roll decreases.

The inputs of the fuzzy controller are the outputs of the 14 shape patterns, which was decided from NNs and has a value of 0 \( x_i \leq 1 \). These inputs were applied simultaneously to the fuzzy controller because a real shape has the composite shape composed of the 14 representative patterns. Each fuzzy control rule about recognized shape was constructed as follows:

<table>
<thead>
<tr>
<th>Rule (R)</th>
<th>#1</th>
<th>#2</th>
<th>#3</th>
<th>#4</th>
<th>#5</th>
<th>#6</th>
<th>#7</th>
</tr>
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<tbody>
<tr>
<td>1</td>
<td>0.5</td>
<td>0.2</td>
<td>-0.5</td>
<td>-1</td>
<td>-0.5</td>
<td>0.2</td>
<td>0.5</td>
</tr>
<tr>
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<td>-0.5</td>
<td>0.2</td>
<td>0.3</td>
<td>0.2</td>
<td>-0.5</td>
<td>-1</td>
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<tr>
<td>3</td>
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<td>0.2</td>
<td>-0.4</td>
<td>-0.5</td>
<td>-0.4</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>4</td>
<td>0</td>
<td>0</td>
<td>-0.4</td>
<td>-0.5</td>
<td>-0.4</td>
<td>0.2</td>
<td>-0.1</td>
</tr>
<tr>
<td>5</td>
<td>-0.2</td>
<td>0.2</td>
<td>-0.4</td>
<td>-0.5</td>
<td>-0.4</td>
<td>0.2</td>
<td>-0.2</td>
</tr>
<tr>
<td>6</td>
<td>-0.1</td>
<td>-0.3</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>7</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>-0.3</td>
<td>-0.1</td>
</tr>
<tr>
<td>8</td>
<td>0.2</td>
<td>-0.5</td>
<td>0.2</td>
<td>0.3</td>
<td>0.2</td>
<td>-0.5</td>
<td>0.2</td>
</tr>
<tr>
<td>9</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>10</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>11</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>12</td>
<td>-1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>13</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>-1</td>
</tr>
<tr>
<td>14</td>
<td>-1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>-1</td>
</tr>
</tbody>
</table>
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.

For example, if the result of the estimated shape pattern by the MLP system is obtained as the shape pattern #1, the input of the fuzzy system can be selected as the rule #1. The output of the fuzzy control is then selected as the moving distance of the AS-U actuator corresponding to the rule #1. This example is presented graphically in Fig. 8.

On the other hand, because the fuzzy inputs have a combination of several shape patterns, therefore, the control output position of the AS-U actuator could be computed by product of the 14 pattern values and the 14 control rules as follows:

$$\text{Position}_{fz} = \sum_{i=1}^{14} P_i \times R_i$$ \hspace{1cm} (12)

where $P_i$ is the shape patterns that is the output of NN system, $R_i$ is the fuzzy control outputs that determine the value of the moving distance of the AS-U actuator. The final actuator position was determined as

$$\text{Position}(t+1) = \text{Position}(t) + \text{Position}_{fz}. \hspace{1cm} (13)$$

4. Improvement of Shape Control Performance in a ZRM

The current shape control in ZRMs do not carry out fully automatic shape control due to saturation of the AS-U actuator.12) This is caused by incorrect shape recognition and inappropriate fuzzy gain. Figure 9 shows the measured error shape through the shape meter and the recognized error shape using MLP. In this case, the shape information data was lost at center part. Such loss of the shape information causes incorrect shape control, and the shape actuator is saturated.

The fuzzy gain is always constant regardless of error shape size because the fuzzy control input adopts only shape pattern information. Although error shape decreases, a great change of the actuator position by the fuzzy control having fixed gain causes saturation. To tackle this problem, NNs that have high shape recognition performance should be considered. In addition, information regarding the shape size should be also added to the fuzzy input. Therefore, the gain size depending on the error shape size should be adjusted to avoid saturation.

4.1. Echo State Networks

The ESN method13) is recurrent neural networks (RNNs) method that has a relatively simple training structure compared to other RNN methods. The basic idea of ESNs is to use a large “reservoir” RNN as a supplier of interesting dynamics from which the desired output is combined. ESNs consist of an input layer, output layer, and an internal layer as a reservoir. A neuron is connected with a synapse-like RNN with weights that have connection strength. Figure 10 illustrates the structure of ESNs for shape recognition in a ZRM. In this paper, these ESNs have an input layer with 32 nodes, an internal layer with 50 nodes, and an output layer with 14 nodes. $W^{in}$ denotes the input connection weights, $W$ denotes the internal connection weights, $W^{out}$ denotes the output connection weights and $W^{back}$ denotes the internal connection weights at the output layer. The state equations

![Fig. 8. Learning and fuzzy output for the representative shape #1.](image)

![Fig. 9. Normalized error shape and recognized error shape using MLP.](image)

![Fig. 10. Structure of ESNs in a ZRM.](image)
for a renewed value of the internal layer and the output value are defined, respectively, as \(14,15\)

\[
x(n + 1) = f(W^x u(n + 1) + W^x (n) + W^\theta y(n)), \quad \ldots (14)
\]

\[
y(n + 1) = f^{out}(W^{out}(u(n + 1), x(n + 1), y(n))) \quad \ldots (15)
\]

where \(f\) and \(f^{out}\) are the activation functions in the internal and output nodes, respectively. The initial values of \(W^x\) and \(W^\theta\) were randomly selected. \(W\) is defined as follows:

\[
W = \alpha \frac{W_0}{\lambda_{max}} \quad \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots (16)
\]

where \(W_0\) was randomly selected, \(\lambda_{max}\) is the spectral radius of \(W_0\), and \(\alpha\) that is less than 1 is scale of \(W\). \(W^{out}\) was trained by the representative shape pattern, \(f^{out}\) was selected 1, and \(W^{out}\) was trained as follows when \(f^{out}\) is 1:

\[
W^{out} = x^{-1}y_d \quad \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots (17)
\]

where \(y_d\) is the desired value.

### 4.2. Improved Fuzzy Control

The actuator of a ZRM can move physically in a space of 0–100 mm. When the actuator is operated beyond this range, the actuator saturation appears and actuator failure can be occurred. If the actuator position approaches saturation position closely in the field, the actuator is manually adjusted by the operator. Although the shape is well recognized at fully automatic shape control, saturation can occur. This saturation is mainly caused by an incorrect gain setting of the fuzzy control rule. Since the input of the fuzzy controller is the only shape pattern recognized at the neural network, the fuzzy gain is not varied regardless of the magnitude of the error. The fuzzy gain can cause actuator saturation because the actuator position is moved excessively in spite of the small error. Therefore, in this paper, to prevent saturation come from the fixed fuzzy gain, P control was added into the fuzzy input to change the fuzzy gain depending on the error magnitude as shown in Fig. 11. The magnitude of the fuzzy gain could be determined by the size of the shape error if the P control gain is multiplied to the fuzzy gain because the P gain depend on the size of the shape error. Nevertheless, saturation can occur if there are still the shape errors although the actuator arrives at near the position of saturation. In this case, we moved the actuator forcibly to the opposite side against its saturation.

### 5. Simulation

The proposed improved shape control systems were implemented in the computer simulation to evaluate the shape control performance. MLP is a traditional and well-known neural network. On the other hand, this method has the shortage that it is not known in advance how many neurons and layers are needed to train the optimal weights in real application. In addition, the weights are sensitive to input data and learning rate. In this system, selecting optimal MLP parameters to guarantee the desired recognition performance was very difficult. In the steel industry operating ZRM plant, many operators and researchers do not trust the performance of MLP because this method gives severe erroneous shape recognition results frequently. Therefore, we considered ESNs to resolve this problem and the comparative results are shown via simulation. In addition, the improved fuzzy control performance to prevent the actuator saturation caused by selecting the fuzzy rules that are regardless to the variance of the error shape error is evaluated in simulation.

First, MLP with similar recognition performance was implemented in the simulation. For this purpose, weight and bias were trained by the 14 representative shape patterns until the MLP simulation had a similar recognition performance to MLP of the field. The initial weight and bias were set randomly and the train error was set to 0.01. This MLP had 50 nodes at the hidden layer to match the ESN simulation. Figure 12 shows the recognized error shape using MLP in the real field and simulation. It was then assumed that MLP was trained using the measured data of the real ZRM because MLP could be used in the real ZRM directly. Then, ESNs were trained in the simulation under the same operating conditions of MLP. To compare the performance of the shape recognition, the shape data that was measured

![Fig. 11. An improved fuzzy controller with P-gain.](image)

![Fig. 12. Reconstructed error shape from simulation using MLP and recognition shape in a real ZRM.](image)

![Fig. 13. The RMSE values of the error shape based on MLP and ESN.](image)
as time goes during 300 seconds at the real field was recognized using each neural network. Figure 13 shows this root mean square error (RMSE) over time, where the RMSE can be calculated for the measured shape at the real field and the recognized shape. We also trained each NN to recognize the other 16 shape data. The average RMSEs of MLP and ESN were measured 0.217 and 0.075, respectively. This means that the performance of the shape recognition of ESN was improved by 65.4% compared with MLP.

To evaluate shape control performance, the shape control systems using each neural network were implemented for 50 s in the simulation. The P gain was added to fuzzy controller in the shape control system applied ESNs. The motion of the actuator saturates at the ends of its range, 0 mm and 100 mm. Thus, if the actuator position arrived at 5 mm and 95 mm, it was shifted by as much as 5 mm to the opposite side against its saturation. Table 2 shows the improved fuzzy control rule.

The initial shape data was selected as a quarter wave in the shape control simulation because the shape data are almost quarter waves at field. The quarter wave means that the positive I-Unit exists at the quarter section of the panel. Table 3 shows the simulation parameter. The shape model is determined by using handling input data, calculation of roll coordinates, roll elements, rolling loads, the effectiveness coefficient, the matrix, roll bending, flatness quantity, and the profile of the output thickness. From these output thickness profiles, using Eq. (18), the shape model was constructed completely.

\[
s(i) = \beta \times \frac{h(i) \times H_{m}}{H(i) \times h_{m}} - 1\quad \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots (18)
\]

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 shape variation over time is shown in Fig. 14, where the saturation occurred at 25 s in the present shape control system simulation. The RMSE of the output shape and target shape of MLP and ESN are shown in Fig. 15, where a smaller value of RMSE means better shape control performance. The average RMSEs of the improved shape control

**Table 2.** Improved fuzzy control rule.

<table>
<thead>
<tr>
<th>Rule (R)</th>
<th>AS-U Rack (mm)</th>
<th>P=0.025×(max error shape)</th>
</tr>
</thead>
<tbody>
<tr>
<td>#1</td>
<td>0.5P</td>
<td>0.2P –0.5P –P –0.5P 0.2P 0.5P</td>
</tr>
<tr>
<td>#2</td>
<td>–P</td>
<td>–0.5P 0.2P 0.3P 0.2P –0.5P –P</td>
</tr>
<tr>
<td>#3</td>
<td>–0.1P</td>
<td>0.2P –0.4P –0.5P –0.5P 0 0</td>
</tr>
<tr>
<td>#4</td>
<td>0</td>
<td>0 –0.4P –0.5P –0.4P 0.2P –0.1P</td>
</tr>
<tr>
<td>#5</td>
<td>–0.2P</td>
<td>0.2P –0.4P –0.5P –0.4P 0.2P –0.2P</td>
</tr>
<tr>
<td>#6</td>
<td>–0.1P</td>
<td>0 –0.3P 0 0 0 –0.3P –0.1P</td>
</tr>
<tr>
<td>#7</td>
<td>0</td>
<td>0 0 0 0 0 0 –0.3P –0.1P</td>
</tr>
<tr>
<td>#8</td>
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<td>–0.5P 0.2P 0.3P 0.2P –0.5P 0.2P</td>
</tr>
<tr>
<td>#9</td>
<td>P</td>
<td>0 0 0 0 0 0 0 0 P</td>
</tr>
<tr>
<td>#10</td>
<td>0</td>
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</tr>
<tr>
<td>#11</td>
<td>P</td>
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</tr>
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<td>–P</td>
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</tr>
<tr>
<td>#14</td>
<td>–P</td>
<td>0 0 0 0 0 0 0 0 P</td>
</tr>
</tbody>
</table>

**Table 3.** Simulation parameter.

| Magnitude of target shape | [0(1), 0(2), …, 0(38)] (I-Unit) |
| AS-U rack initial position | 50-50-50-50-50-50-50 (mm) |
| Input thickness           | 2.258 (mm) |
| Output thickness          | 1.47 (mm) |
| Sheet width               | 1.257 (mm) |
| Time                      | 50 (sec) |

---

**Fig. 14.** Shape variation as time goes.

**Fig. 15.** The RMSE values of target and output shape of MLP and ESN as time goes.
system were decreased from 17.6 to 14.2 I-units, respectively. The actuator’s final positions were shown in Fig. 16, where the #7 actuator is saturated in the conventional shape control system. Figure 17 shows the position variations of the #1 and #7 actuators in each system as time goes. The actuator positions were maintained below 95 mm in the improved shape control system whereas the conventional ones were saturated. The actuator position is arrived at 95 mm because the fuzzy controller acts the actuator to be transferred in 5 mm to the opposite side against its saturation. Therefore, it could be proved that the proposed shape control system can prevent the actuator from saturating and provide a better shape control performance.

6. Conclusion

The shape recognition performance and fuzzy control are very important in a shape control system because a steel process is very complex. In the conventional ZRM control system, the performance of the shape recognition and shape control using MLP and fixed fuzzy rule gain was not satisfactory due to weakness of MLP and actuator saturation. To improve the shape recognition problem and actuator saturation, ESNs and P controller were adopted in this study. The shape recognition performance using ESNs was improved 65.4% comparing with the conventional MLP. In simulation of the conventional shape control system, saturation occurred and the RMSE of the shape magnitude was reduced into 21% during 20 s. Meanwhile, the saturation did not be occurred in the improved shape control system and the RMSE of the shape magnitude was reduced into 55% during 20 s. Therefore, the proposed shape recognition and control system of a ZRM improved weakness of the conventional control system of a ZRM using ESNs and P control system. Simulated results confirmed the effectiveness of the proposed control scheme.

Acknowledgement

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