

# Application of Neural Network to Fault Diagnosis of Electro-Mechanical System

Takashi Torigoe\*  
 Division of Electronic and  
 Information System Engineering  
 Graduate School of Natural Science and Technology  
 Okayama University  
 3-1-1, Tsushima-Naka Okayama, 700-8530

Masami Konishi  
 Dept. of Electrical and Electronic Engineering  
 Okayama University  
 3-1-1, Tsushima-Naka Okayama, 700-8530

Jun Imai  
 Dept. of Electrical and Electronic Engineering  
 Okayama University  
 3-1-1, Tsushima-Naka Okayama, 700-8530

Tatsushi Nishi  
 Dept. of Electrical and Electronic Engineering  
 Okayama University  
 3-1-1, Tsushima-Naka Okayama, 700-8530

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In this paper, neuro based intelligent diagnosis methods for electro-mechanical control system are proposed. A self organizing map neural network (SOM) is used to classify measured data of the target system as a qualitative diagnostic method. Besides of the above procedure, it is expected to attain more efficient maintenance by a quantitative estimation of failure. For the purpose, new method is proposed using a hierarchical neural network (HNN). In the method, classified results by SOM are processed for the quantitative diagnosis. Hierarchical neural network can identify inner structure of the relations between failure causes and its results that enables a quantitative diagnosis.

## 1 Introduction

When some failure occurs in a mechanical system, diagnosis of the system is to be performed. Then, maintenance or repair action is carried out recovering the system performance to its normal state. As it is impossible to acquire whole internal information of the system, it is usual to analyze output data of the system for the estimation of failure causes.

Traditionally, fault diagnosis is governed by human experts with plenty of experiences and know-how. In these days, mechanical systems are becoming more complex and enlarged in its scale together with its control system. So it becomes necessary to develop new technologies for fault diagnosis not only in a qualitative but also a quantitative manner coping with the needs for automatic diagnosis of complex control systems.

In this paper, SOM[3] method is used for qualitative fault diagnosis in a electro-mechanical control system. Measured data of a system is input to SOM, and

classified to particular nodes of SOM. The fault of the system is diagnosed qualitatively from geometrical information of the classified node.

Addition to that, a quantitative diagnosis method using HNN[2, 4] is described. The inputs to HNN are measured data and geometrical information of classification by SOM. The HNN describes correlation between input data and internal fault of the target system. Through learning, the HNN model is updated so as to generate correct value of the internal fault state quantitatively.(Fig. 1)

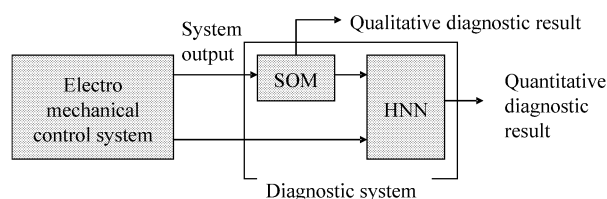


Fig. 1 Diagram of estimation system

\*torigoe@cntr.elec.okayama-u.ac.jp

First, the looper height control system[1, 5, 6] is selected as a target system of the proposed diagnostic method. After that, diagnosis of an induction motor and that of a robot arm control system are made to verify the versatility of the proposed method.

## 2 Diagnosis of looper height control system

### 2.1 The looper height control

The looper height control system consists of looper height detection, PID controller and feedback operation. The block diagram of a looper height control system is shown in Fig. 2.

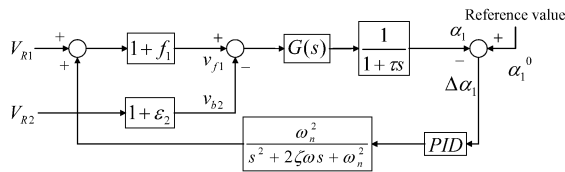


Fig. 2 Block diagram of a looper height control system

Here,  $G(s)$  represents the transfer function of looper dynamics. There is a time delay in measurement after the output of  $G(s)$ . This time delay element is a representation of detection delay. Based on detection of the looper height,  $V_{R1}$  is manipulated by PID control. There are 2nd order time delay element to manipulate  $V_{R1}$ , because of force transmission by torsion.

### 2.2 Waveform of looper angle

Here, the movement of looper height is simulated when the characteristics of looper height control system in the hot strip mills are changed.

In this paper, 3 factors ( $K_P, \tau, \omega_n$ ) are concerned as the characteristics which will be changed.

The looper height is controlled by tuning the proportional gain  $K_P$ . The other two elements are internal values of the looper control system. Time delay  $\tau$  of looper height sensing becomes large with the progression of deterioration in sensing equipment. Natural angular frequency  $\omega_n$  becomes small according to fatigue or deterioration in transmission system. These states are abnormal necessary to be found. Where, normal state means that time delay of the element is short time, and abnormal state means that time delay of the element is long time

The looper height waveforms when the  $K_P$  is changed are shown in Fig. 3(a), and Fig. 3(d). There is an overshoot when the  $K_P$  is large.

The looper height waveforms when the  $K_P$  is changed when  $\omega_n$  is small are shown in Fig. 3(b), and Fig. 3(e). The oscillation of looper height waveform is enlarged by change of  $\omega_n$  or  $\tau$  in comparison with Fig. 3(d). However, By tuning the  $K_P$ , oscillation of the waveform is reduced.

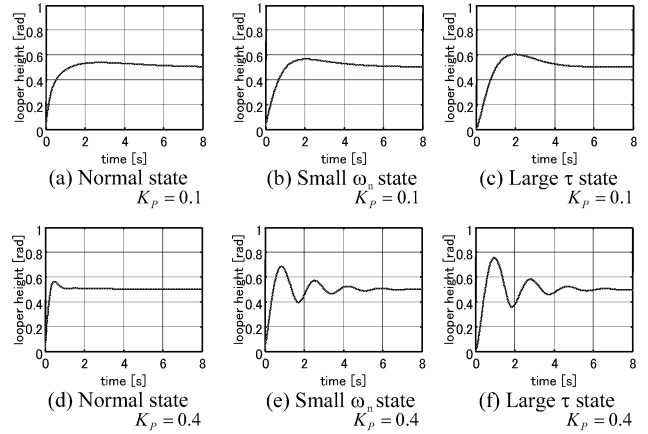


Fig. 3 Waveform of looper angle

## 3 Classification of looper data

When human get data, it is compared with past data, and result of the comparison leads the conclusion. However, it is difficult to execute those procedure automatically. In this section, the classification method by using SOM neural network is proposed.

### 3.1 Self Organizing Maps(SOM) N. N.

SOM[3] is a multidimensional scaling method projecting input data space to lower dimensional output space. Typically, output data space is made as 2-dimension. Thus, input data space is visualized into 2-dimensional plane.

Here, the condition in the application of SOM for the classification of looper height waveforms. The looper height waveform is analyzed by wavelet transform, the feature of the waveform is emphasized to wavelet coefficient which is 2-dimentional matrix.

The wavelet function which used in this paper is written in the following. Eq. (1) is multiplication of gauss function and cosine wave  $e^{-jt}$ .

$$\psi(t) = \frac{1}{2\sqrt{\pi}\sigma} e^{-\frac{t^2}{2\sigma^2}} e^{-jt} \quad (1)$$

where,  $\sigma$  is set to 4 in this paper. The real part of Eq. (1) is shown in Fig. 4.

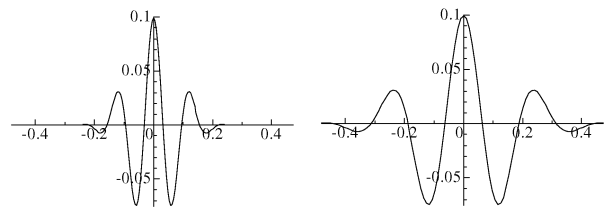


Fig. 4 Real part of  $\psi(t)$  Fig. 5 Real part of  $\psi(\frac{t}{2})$

Using this wavlet  $\psi(t)$ , wavelet transformation of input signal  $x(t)$  is defined as

$$(W_{\psi}f)(b, a) = \int_{-\infty}^{\infty} \frac{1}{\sqrt{a}} \overline{\psi\left(\frac{t-b}{a}\right)} x(t) dt \quad (2)$$

where,  $(W_{\psi}f)(b, a)$  is a wavelet coefficient of the input signal  $x(t)$  and  $\psi\left(\frac{t-b}{a}\right)$  is analyzing wavelet. The  $a$  modifies the frequency of the analyzing wavelet.  $\psi\left(\frac{t}{a}\right)$  is shown in Fig. 5. Fig. 5 is a waveform which is modified by  $a$  only in frequency domain. And  $b$  is a time shift in time domain.

By this equation (2), wavelet coefficient  $(W_{\psi}f)(b, a)$  becomes larger when the input  $x(t)$  is close to the analyzing wavelet determined by  $a, b$ .

The classification method by SOM is applied to the matrix data.

The SOM is trained iteratively. In the training step, the input data vector  $x$  is input, and the distance between the data and all the weight vectors of the SOM is calculated. Where, Euclidean distance is used as distance measure in this paper. The neuron  $c$  whose weight vector is closest to the input vector  $x$  is chosen as the best-matching unit(BMU):

$$\|x - w_c\| = \min_{ij} \{\|x - w_{ij}\|\} \quad (3)$$

where,  $\|\cdot\|$  is the distance measure.

After finding the BMU, the weight vectors of the BMU is updated so that the weight of BMU is moved closer to the input data vector  $x$ . The neighbors of the BMU are also trained by a same way. The neighbors is defined by the distance from the BMU as follows,

$$r(t) = r_0 \left(1 - \frac{t}{T}\right) \quad (4)$$

where,  $t$  is time since the training started.  $T$  is the finishing time of training.  $r_0$  is initial range of neighbors.

The SOM update rule for the weight vector of the node  $(i, j)$  is written as

$$w_{ij}(t+1) = w_{ij}(t) + \alpha(t) [x(t) - w_{ij}(t)] \quad (5)$$

where,  $t$  is time,  $x(t)$  is a input data vector  $x$  at time  $t$ .  $\alpha(t)$  is a learning coefficient at time  $t$ , which is written as

$$\alpha(t) = \alpha_0 \left(1 - \frac{t}{T}\right) \quad (6)$$

where,  $\alpha_0$  is a initial learning coefficient. These parameters:  $\alpha_0, r_0$  and  $T$  is set to appropriate value, according to the problem.

After the above procedure is finished, the nodes of SOM whose weights are close to each other are gathered in topologically restricted area. When certain input  $x_{example}$  chooses certain node  $c_{example}$  as the BMU in the SOM, other input similar to  $x_{example}$  chooses a node nearby the  $c_{example}$  as the BMU. In this paper, this feature of the SOM is used for the classification.

An illustration of the classification is shown in Fig. 6. SOM is trained by a lot of waveforms generated by looper control system in various cases.

Where the input waveforms are analyzed by using wavelet transformation as a pre-processing. The number of training times is set to 10000. The number of

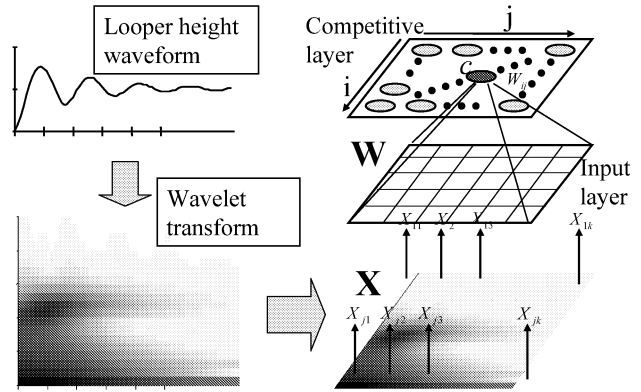


Fig. 6 Qualitative diagnosis by SOM

training data is 250. Where, sampling period is 0.05[s] and sampling time is 5[s]. The size of SOM N. N. in this case is  $15 \times 15$ .

### 3.2 Classified results (Qualitative diagnosis)

The classified ratio of each nodes in the SOM is described. The failure is considered at small  $\omega_n$  value and at large  $\tau$  value. In this case, for failure conditions,  $\omega_n < 13$  and  $\tau > 0.25$  are considered.

Fig. 7 shows classified results for normal conditions. Lines in Fig. 7 are contour lines corresponding to the ratios with which the data is recognized as normal state. The results in failure state are shown in Figs. 8, 10 respectively.

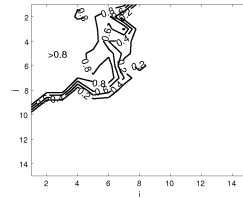


Fig. 7 Classified results of normal state

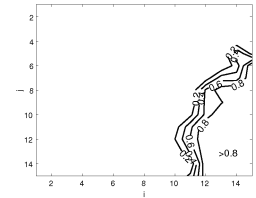


Fig. 8 Classified results of failure state

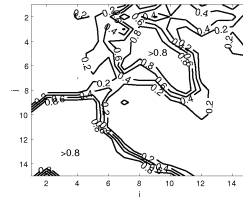


Fig. 9 Classified results of  $\omega_n$  failure

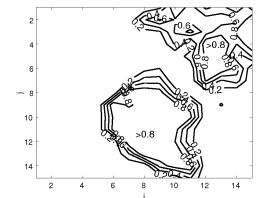


Fig. 10 Classified results of  $\tau$  failure

These figures show that, data are classified in SOM separately according to the fault.

By classifying the wave form, the data is projected to the 2-dimensional plane. From the position of the plane, it is possible that diagnosis of waveform vibrations or estimation of failure causes qualitatively.

## 4 Quantitative diagnosis for hot rolling mills

As described above section, the qualitative estimation is made by using SOM. In this section, quantitative estimation method of failure state is described.

### 4.1 Hierarchical neural network

Neural network is a simplified model of the human brain. It consists of one or more artificial neurons. Therefore, it has the ability to learn and adapt. Also, there are many industrial applications. The hierarchical neural network (HNN) is one of artificial neural networks.[2, 4]

In this paper, the input of HNN is data which contains looper height waveform and classified results described in previous section. And the output of HNN is the parameters in the looper height control system, which provides the fault of the system. Structure of the HNN with the classified results is shown in Fig. 11.

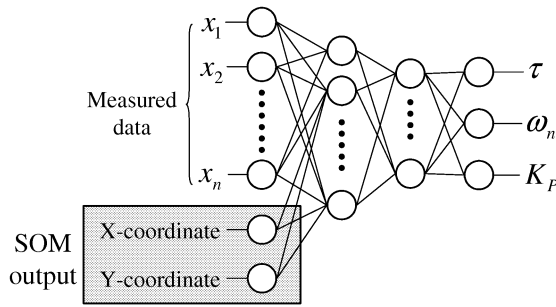


Fig. 11 Quantitative diagnosis by HNN

The HNN model with the classified results (22-40-10-3 4-layer NN) and HNN model without classified results (20-40-10-3 4-layer NN) are trained and compared. These models are trained 5000 times using 500 looper height waveform data which is randomly generated. After the training is finished, another 1500 waveform data is applied to these models.

As described above, In this paper, 3 factors are concerned as the characteristics which will be changed.  $K_P$  is a configurable parameters by human. Although, parameters to be estimated is  $\tau$ ,  $\omega_n$  and  $K_P$  concerning tuning mistake.

### 4.2 Estimated results

Table 1 shows RMSE (Root Mean Square Error) of these estimated results. The results of the estimation

Table 1 Error comparison

	$\tau$	$\omega_n$	$K_P$
without som	0.0089	0.50	0.020
with som	0.0044	0.36	0.0072

are shown in Figs. 12 to 17. The horizontal axis in these figures is actual parameters of looper height control system, And the vertical axis indicates the estimated parameters. If parameters are estimated with no error, dotted points in these figures are on a straight line.

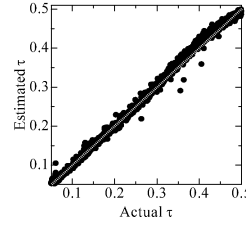


Fig. 12 Estimation result of  $\tau$  without SOM

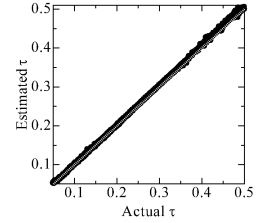


Fig. 13 Estimation result of  $\tau$  with SOM

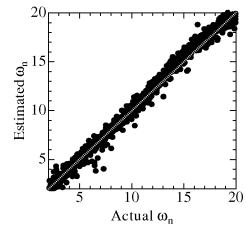


Fig. 14 Estimation result of  $\omega_n$  without SOM

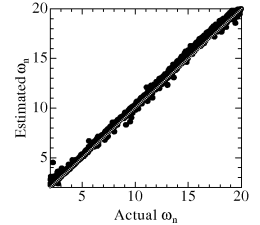


Fig. 15 Estimation result of  $\omega_n$  with SOM

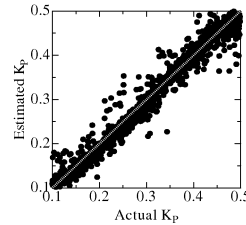


Fig. 16 Estimation result of  $K_P$  without SOM

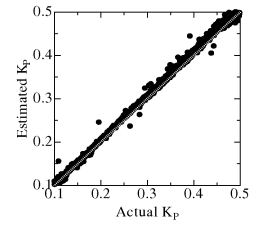


Fig. 17 Estimation result of  $K_P$  with SOM

Figs. 12 to 17 shows that result of estimation using SOM are more accurate. This means that the estimation error is reduced by using SOM.

## 5 Further applications

Neural networks are one of most versatile system. Then, in this section, the proposed diagnostic system based on neural networks is applied to two electro-mechanical control system: induction motor and robot arm control system.

### 5.1 Induction motor

To verify versatility of the proposed diagnostic methods, the estimation system is applied to induction mo-

tor. The physical model of induction motor is shown in Fig. 18

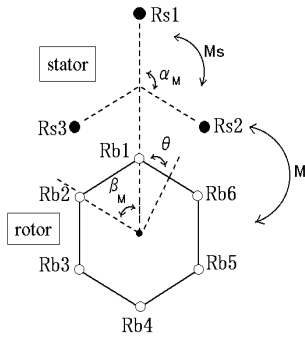


Fig. 18 physical model of induction motor

The induction motor consists of rotor and stator. In this case, fault of rotor bar is considered to diagnose. This time, the motor has six rotor bars ( $R_{B1} \dots R_{B6}$ ), and three of them have possibility of fault. When the fault occurs, the electric resistance of the rotor bar is rise. So, it is intended that detection of the rotor bar resistance from angular velocity. Where, the resistance at normal state is  $R_{B1} = 33.5[\Omega]$  in this time. Fig. 19 shows angular velocity of the induction motor, when the resistance  $R_{B1}$  is changed to  $335[\Omega]$ ,  $3350[\Omega]$ . Fig. 20 shows the angular velocity in the steady state in the same condition.

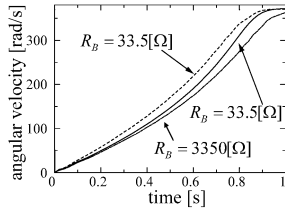


Fig. 19 angular velocity

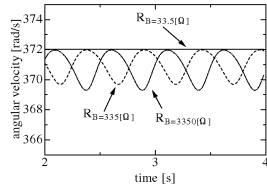


Fig. 20 angular velocity in the steady state

The rotor bar resistance is estimated from the angular velocity waveform shown in Fig. 19 using proposed estimation system consists of neural networks. The angular velocity is input to neural network system, and rotor bar resistance is learned as output of the system. Although, the rotor bar resistance is too large to learn as output of neural network, so the neural network learns the resistance as  $\log R_{Bn}$ . First, the error classification is performed by the SOM method. Classification result is shown in Figs. 21, 22.

Fig. 21 is a classified result of normal state waveform. Fig. 22 is a classified result of abnormal state waveform. These figure shows that, the SOM learned the feature of motor waveform, and is able to classify the waveform to each node individually.

Next, estimation by hierarchical neural network is performed. Table 2 shows RMSE of these estimated results.

Fig. 25 is the result of  $R_{B2}$  estimation using normal neural network. Another estimation result using combined system is shown in Fig. 26.

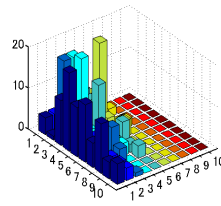


Fig. 21 normal state

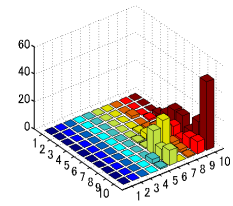


Fig. 22 abnormal state

Table 2 Error comparison

	bar1	bar2	bar3
without som	0.0673	0.0769	0.0670
with som	0.0608	0.0577	0.0597

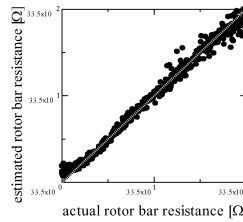


Fig. 23 Resistance of rotor bar #1

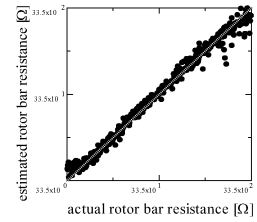


Fig. 24 Resistance of rotor bar #1 with SOM

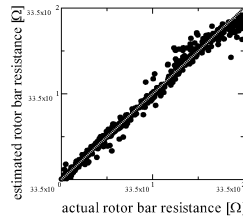


Fig. 25 Resistance of rotor bar #2

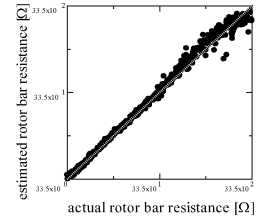


Fig. 26 Resistance of rotor bar #2 with SOM

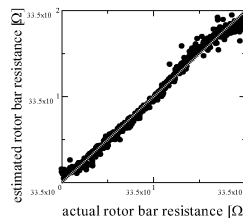


Fig. 27 Resistance of rotor bar #3

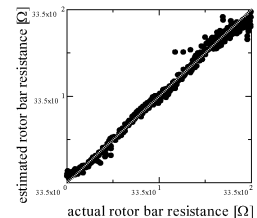


Fig. 28 Resistance of rotor bar #3 with SOM

These results show that estimation error is reduced by neural network combined system, and realized that the neural network system is applicable widely.

## 5.2 Robot arm

Next, the estimation system is applied to robot arm control system. The robot arm control system is shown in Fig. 29.

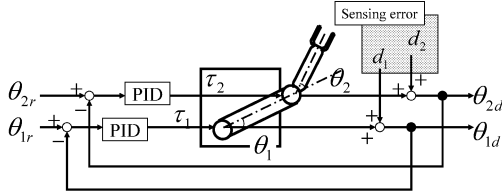


Fig. 29 Robot arm control system

The arm has two motors #1 and #2. The angle  $\theta_n$  of motor # $n$  are controlled to reference angle  $\theta_{nr}$  by PID controller. Although, there are sensing error  $d_n$  in the part of measuring the  $\theta_n$ . So, the measured  $\theta_{nd}$  includes sensing error. This sensing error is defined as Eq. (7).

$$d_n = \alpha(1 - \exp(-\theta_n)) \quad (7)$$

where,  $\alpha$  is constant.  $d_n$  is inverse proportion to the  $\theta_n$ .

Detection of  $d_n$  from  $\theta_{nd}$  is intended. An example waveform of  $\theta_1, \theta_2$  are shown in Fig. 30. Sensing error  $d_1, d_2$  are shown in Fig. 31.

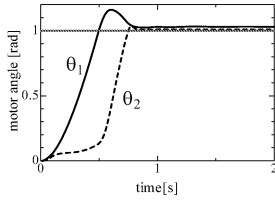


Fig. 30 Angles of arm

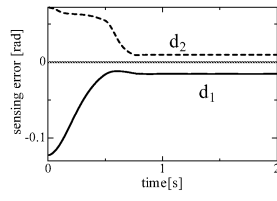


Fig. 31 Disturbances

Two estimation system is applied to  $\theta_{1d}$  and  $\theta_{2d}$ , and output the estimated  $d_1$  and  $d_1$  individually.

First, the error classification is performed by the SOM method. Classification result is shown in Figs. 32, 33.

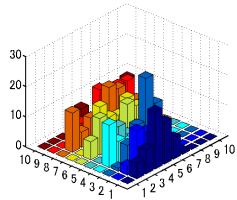


Fig. 32 normal state

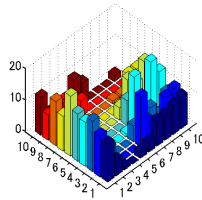


Fig. 33 abnormal state

Fig. 21 is a classified result of normal state waveform. Fig. 22 is a classified result of abnormal state waveform. It seemed that waveforms are not distributed to nodes on SOM completely. Although, waveforms in normal state are collected near the center of SOM, and waveforms in abnormal state are also collected in left or

right side of SOM. It is realized that the SOM could not learn a feature of waveform completely, but it could learn a tendency of the feature.

Next, estimation by hierarchical neural network is performed.

Figs. 34, 36 shows estimated sensing error by using normal neural network. Figs. 35, 37 are results by using proposed estimation system.

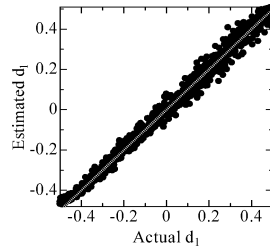


Fig. 34 Estimated  $d_1$

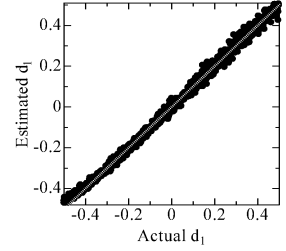


Fig. 35 Estimated  $d_1$  with SOM

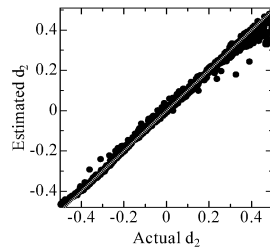


Fig. 36 Estimated  $d_2$

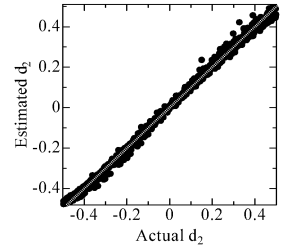


Fig. 37 Estimated  $d_2$  with SOM

Table 3 shows RMSE of these estimated results. It is realized that the estimation system using SOM generates better results.

Table 3 Error comparison

	$d_1$	$d_1$
without som	0.029	0.024
with som	0.019	0.017

## 6 Conclusion

In this paper, a quantitative diagnosis method for electro mechanical control system by using SOM neural network is proposed. It is realized that fault of the looper height control system is detected by classifying the system data using SOM neural network model. Using the model, an accurate quantitative estimation of parameters in a looper controller can be made. Similarly, effective diagnosis could be carried out for induction motor. Thus, not only detection of failure occurrence but also quantitative analysis of fault causes could be realized.

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