Prediction of Chamber Leak Pattern Using Time-Series Neural Network

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Abstract: A leak of plasma chamber should be strictly monitored to maintain process quality as well as device yield. Using an Auto-Correlated Time Series Neural Network (A-NTS), a prediction model of chamber leak was developed. A total of 47 leak patterns were used to construct and test the monitoring efficacy of model. The validation errors for normal and abnormal data ranged between 51.9 and 61.7, and between 126.0 and 163.8, respectively. The validation errors for the abnormal data were more than two times larger than those for the normal data. This clearly indicates that the A-NTS model can accurately detect a leak from the chamber of plasma equipment.

Key-Words: Plasma; Leak; Prediction; Time-series neural network; Monitoring; Detection; Diagnosis; Optical emission spectroscopy

1 Introduction

To main device yield and equipment throughput, plasma processes need to be stringently monitored, diagnosed, and controlled. With the introduction a nano-scaled patterning and deposition technologies, the issue of chamber monitoring is an important issue in actual manufacturing sites. For this purpose, a huge number of in-situ diagnostic instruments have been applied to monitor certain variation in plasma. These may include an optical emission spectroscopy (OES) [1-3], a radio-frequency (rf) impedance sensor [4-6], or a rf matching network monitor [7]. Currently, the OED is being applied to monitor a leak in the chamber of plasma equipment. For real-time detection of chamber leak, a prediction model needs to be developed.

In this study, a prediction model is constructed by using an auto-correlated neural time-series (A-NTS) model. Leak patterns were collected from a plasma-enhanced chemical vapor deposition system (PECVD).

2 Experiments and Neural Network

2.1 Experimental Data

A total of 47 sets of OES leak patterns were collected from a PECVD system operating in an actual manufacturing site. Among them, 42 and 5 sets correspond to normal and abnormal equipment operations, respectively. One normal pattern was used to construct A-NTS model. The remaining 46 patterns were used to evaluate the monitoring efficacy of constructed model. An example of OES leak patterns is shown in Fig. 1. The experimental range of OES is 178.2 - 887.77 nm and sampling interval is 0.17 nm. As shown in Fig. 1, the abnormal leak pattern is clearly differentiated from the normal one. In considerable parts of the overall pattern, the peak intensities for the abnormal pattern are much larger than that for the normal one.

![Fig. 1. Normal and abnormal patterns of leak OES patterns](image-url)

2.2 Time Series Neural Network

In constructing A-NTS model, the backpropagation neural network [8] was used. Its schematic is shown in Fig. 2. As shown in Fig. 2, the...
output of the hidden layer is determined by a bipolar sigmoid function.

\[ \text{out}_{i,k} = \frac{1 - \exp(-\frac{\text{in}_{i,k}}{g_b})}{1 + \exp(-\frac{\text{in}_{i,k}}{g_b})} \]  \hspace{1cm} (1)

where \( \text{in}_{i,k} \) and \( \text{out}_{i,k} \) are the weighted input and output to the \( i \)th neuron in the \( k \)th layer, respectively. \( g_b \) is the gradient of the bipolar sigmoid function.

The output of the output layer is determined by a linear function, which is expressed as

\[ \text{out}_{i,k} = \text{in}_{i,k} g_t \]  \hspace{1cm} (2)

where \( g_t \) is the gradient of the linear function. A weight update equation, commonly known as the generalized delta rule, is expressed as

\[ W_{i,j,k}(m+1) = W_{i,j,k}(m) + \eta \Delta W_{i,j,k}(m) \]  \hspace{1cm} (3)

where \( W_{i,j,k} \) is the connection strength between the \( j \)th neuron in the layer \( (k-1) \) and the \( i \)th neuron in the layer \( k \). \( \Delta W_{i,j,k} \) is the calculated change in the weight to minimize error \( (E) \) of all the input-output pairs.

As seen in Fig. 2, the prediction performance of A-NTS model can be affected by the various combinations of \((k, m)\). For convenience, both \( k \) and \( m \) were set to the same 1. Apart from this, other training factors are typically involved in BPNN training [9]. The training factors employed here are shown in Table 1.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Ranges</th>
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<tbody>
<tr>
<td>Error tolerance</td>
<td>0.1</td>
</tr>
<tr>
<td>Learning rate</td>
<td>0.01</td>
</tr>
<tr>
<td>Magnitude of weight dist</td>
<td>\pm1</td>
</tr>
<tr>
<td>Gradient of slope</td>
<td>1</td>
</tr>
<tr>
<td>Number of hidden neuron</td>
<td>2</td>
</tr>
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</table>

3 Results

Each leak pattern was composed of 3648 elements. Using the first normal leak pattern represented as \#1, A-NTS model was constructed. For this, the pattern was divided into two training and testing data. Each data were comprised of 1823 patterns. The performance of A-NTS model was measured by the root mean square error (RMSE), defined as

\[ \text{RMSE} = \sqrt{\frac{\sum_{j=1}^{q} (d_j - \text{out}_j)^2}{q}} \]  \hspace{1cm} (4)

where \( q \) is the total number of test data, and \( d_j \) and \( \text{out}_j \) are the desired output and the calculated output of the \( i \)th neuron in the output layer, respectively. The RMSE training and testing errors of the constructed A-NTS model are 45.54 and 66.37, respectively. For each of training and testing data, the predictions are also plotted in Figs 3 and 4. As seen in both Figs. 3-4, the model predictions closely match the actual measurements. Then, the model was validated by using the remaining 46 patterns. For the 41 normal patterns, the predictions were calculated and they are plotted in Fig. 5. For the comparison purpose, the predictions for the whole first leak pattern were calculated from the A-NTS model and they are included in Fig. 5. As seen in Fig. 5, the pattern of model predictions are very close to other predicted patterns. Meanwhile, those predictions for 5 abnormal leak patterns are shown in Fig. 6. As seen in Fig. 6, they are much different from the pattern predicted from the model. This indicates that those anomalies
hidden in the abnormal patterns can accurately be detected by using the A-NTS model.

Fig 3. Actual and prediction values for the training data of A-NTS model

Lastly, the RMSEs obtained from the A-NTS model were plotted in Fig. 7. As shown in Fig. 7, the RMSEs for the normal data ranged between 51.9 and 61.7. For the abnormal data, the RMSEs ranged between 126.0 and 163.8. Therefore, the RMSEs for the abnormal data are more than two times larger than those for the normal data. This indicates that a leak from the chamber could be detected.

Fig 4. Actual and prediction value for the testing data of A-NTS model

Fig 5. Predicted patterns for normal data

Fig 6. Predicted patterns for abnormal data

Fig 7. RMSE of normal and abnormal error.
4 Conclusion

In this study, a leak detector was developed by using a time-series neural network. The proposed detector could successfully detect several leaks in plasma chamber. The presented detection scenario can be implemented during or after the process for real-time and run-to-run monitoring of chamber leaks.

Acknowledgements

This research was supported by the Ministry of Knowledge Economy, Korea, under the ITRC (Information Technology Research Center) support program supervised by the IITA (Institute of Information Technology Advancement) (IITA-2008-C109008010030).

References:


