

Abnormal plasma detection by non-linear time series analysis

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Plasma processing technology is a key tool in manufacturing LSI. Nevertheless, a well-known flaw in plasma processing is the physical phenomenon of anomalous discharge. Towards fixing this perplexing problem, Yasaka et al. introduced a method to detect the occurrence of anomalous discharge by monitoring acoustic emission associated with a discharge [1]. They utilized power spectral analysis to find the occurrence of anomalous discharge from acoustic data.

In their approach, however, power spectral structure varies with particular materials on the pathway of the acoustic wave, as well as with particular types of environmental noise. As a result, power spectral analysis often misses a signature of anomalous discharge. In this work, we show that nonlinear time series analysis is more useful as an alternative to power spectral analysis. Chaos comes from deterministic dynamics with finite degrees of freedom, while stochastic processes from dynamics with infinite degrees of freedom.

The experimental system utilized in this work is a magnetically enhanced RF RIE system. An ac voltage of 13.56MHz is applied to the lower plate on which semiconductor wafers are set. An etchant gas mixture of C_4F_8 , Ar and O_2 is supplied to the reactor. An acoustic emission sensor is installed on the plasma chamber to measure acoustic emission caused by anomalous discharge.

We observed acoustic emission in the plasma processing system. Figure 1 shows a typical example of acoustic signals. Its initial part ranging from 0 to 0.007 s and the remaining part are labeled as active and quiescent phases, respectively. After the experiment, we checked the silicon wafer and found scars on it, as shown in figure 2. The active and quiescent phases are magnified in figures 3 and 4, respectively.

Frequency power spectra for the active and quiescent phases are depicted in figure 5. The difference in these particular spectra is superficially the relative heights of the peaks lying from 100 to 120 kHz. However, both phases seem to include common oscillatory ingredients. We give a brief description about how to apply the theorem to time series analysis. Given a time series $\{x(t)\}_{t=0}^{N-1}$:

$$x(t) = (x(t), x(t - \Delta t), \dots, x(t - (D-1)\Delta t)),$$

where D is the embedding dimension and t is an appropriate time lag. The diversity of directions of neighboring trajectories can be measured in terms of the translation error:

$$E_{trans} = \frac{1}{K+1} \sum_{k=0}^K \frac{\|v(t_k) - \bar{v}\|}{\bar{v}}, \quad \bar{v} = \frac{1}{K+1} \sum_{k=0}^K v(t_k),$$

$$v(t_k) = x(t_k + T) - x(t_k).$$

The difference vectors $v(t_k)$ approximate tangential vectors of the trajectories. The more visible determinism is the smaller E_{trans} . To reduce stochastic error in estimating E_{trans} , we use the following procedures. We seek the medians of E_{trans} for S sets of M randomly chosen $x(t_0)$ and estimate the mean over the S medians. The mean is taken as a representative of E_{trans} . E_{trans} below 0.1 indicates the visible determinism of the underlying dynamics regardless of how complex a time series appears. In particular, white noise generates $E_{trans} \approx 1$ independently of the embedding dimension.

Results are shown in figure 6. We plot similar estimates for three acoustic signals, where the upper three curves are for the quiescent phase and the lower three curves for the active phase. The translation errors take on almost constant values at $D = 6$ for both the active and the quiescent phases. According to the previous criteria, determinism can be said to be visible at $D = 4$ in the active phase. In contrast, determinism is considerably invisible in the quiescent phase, owing to the relatively large contribution of stochastic ingredients to the signal.

The concept of permutation entropy has been introduced by Bandt et al. as an invariant measure representing the degree of complexity of dynamical behavior [2]. We estimated the normalized permutation entropy for the acoustic time series. Results are shown in figure 7. For $D = 3$, there are considerable differences in the entropy between the active and quiescent phases, where the upper three curves are for the quiescent phase and the lower three curves for the active phase.

In conclusion, anomalous discharge augments specific acoustic ingredients with finite degrees of freedom, and induces a significant lowering of the degree of complexity. On the basis of these findings, a diagnostic method for testing anomalous discharge has been proposed. This method will be applied not only to detecting anomalous discharge but also to detecting various anomalies.

References

- [1] M. Yasaka, M. Takeshita and R. Miyagawa, Jpn. J. Appl. Phys., 42, L157 (2003)
- [2] C. Bandt and B. Pompe, Phys. Rev. Lett., 88, 174102 (2002)

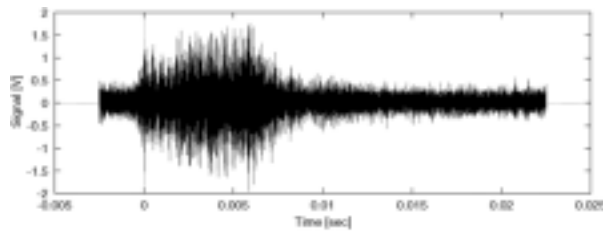


Figure 1. Acoustic signal observed during operation of the plasma system. The initial part ranging from 0 to 0.007 s experienced anomalous discharges, while the remaining part did not.

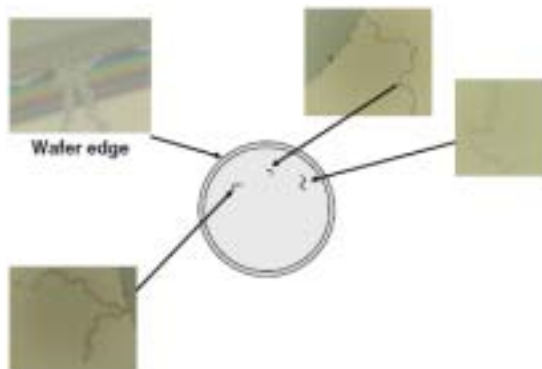


Figure 2. Scars on a silicon wafer caused by anomalous discharge.

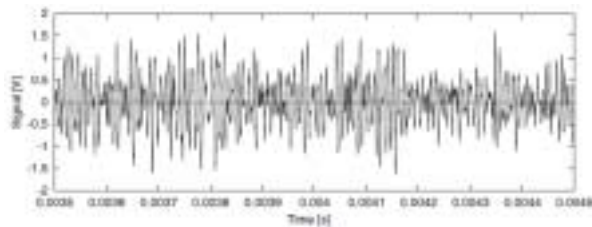


Figure 3. Active phase of acoustic emission.

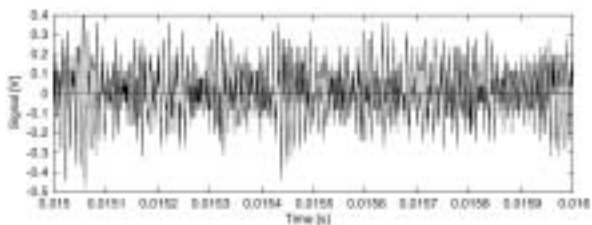


Figure 4. Quiescent phase of acoustic emission.

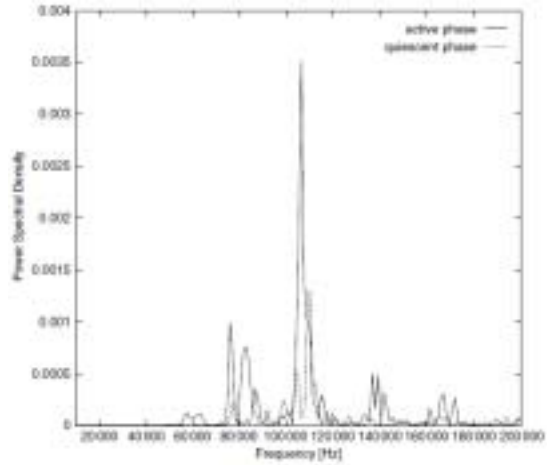


Figure 5. Power spectra of the active phase (—) and the quiescent phase (- - -).

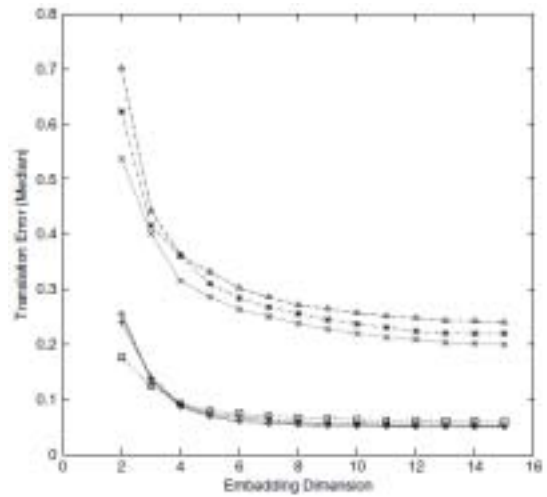


Figure 8. Translation error as a function of embedding dimension for the active phase (lower three curves) and the quiescent phase (upper three curves). The number of data points was $N=10000$ for each curve.

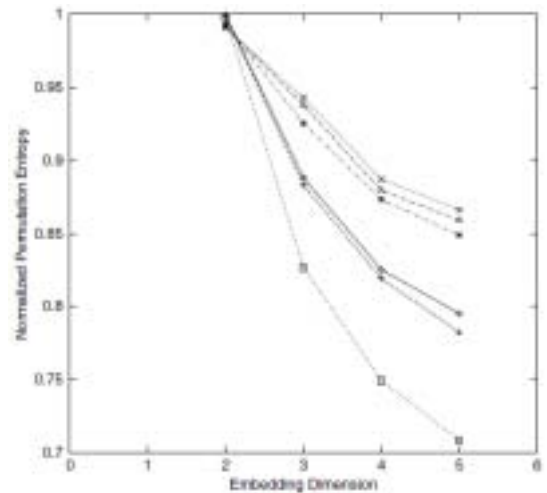


Figure 10. Normalized permutation entropy as a function of embedding dimension for the active phase (lower three curves) and the quiescent phase (upper three curves). The number of data points was $N=10000$ for each curve.