



Acoustical characteristics based predictive diagnostics of individual dry pump for semiconductor manufacturing process

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ABSTRACT

This paper addressed the acoustical characteristics of dry vacuum pumps and predictive diagnostics of dry vacuum pumps with these characteristics. The dry pump system designed for the semiconductor manufacturing is used to maintain the cleanliness by exhaust the purge gas. The semiconductor process can be divided two separable state segments, the one is gas loaded state batch when pump exhaust the purge gas and the other is idle state batch when the valve is closed during pump operation. As the physical attributions of gas loaded state and idle state are different, the corresponding noise characteristic is different, too. With the Linearized Adaptive Parameter Model (APM), the parameters indicate each batch can be obtained. These parameters contain the characteristics of pump noise and can be used for predictive diagnostic of individual dry pump by observing the trend of parameters.

1. INTRODUCTION

In semiconductor manufacturing process, the need for predictive diagnostic technique for dry vacuum pump has been one of the “hot” technical issues since R. Bahren and M. Kuhn [1] pointed out its significance. One of main applications of the dry vacuum pump system has focused on the semiconductor manufacturing processes that require much improved cleanliness [2]. So, diagnostic technique for dry vacuum pump system has strong relationship with an error rate of semiconductor.

The test result, carried out in the Centre of Vacuum Technologies of KRISS, indicate that state variables such as exhaust pressure and supply currents to booster and dry pump motor are monitored only as static properties. Lim et al.[3] proposed the use of vibration accelerometers to monitor the dynamic running conditions of the gears and bearing of vacuum pumps, including the unbalance of rotors. A common idea for predictive diagnostics, as described by Robert et al.[4], is to extract extraordinary features from the recorded signals of state variables using multiple principal component analysis (PCA). These principal components are converted to one value, Hotelling’s T^2 . However, much difficulty in using PCA is encountered when the sizes of the collected batch data are different each others. Unfortunately, the semiconductor process period is time-varying, so the sizes of the collected state variables batch are different. D. Sung [5] reported that the dynamic time warping algorithm[6,7] worked well for predictive diagnosis of dry vacuum pumps by warping collected state variables batch data. To overcome that DTW take number of computation resources, W. Chueng [8] proposed linear adaptive parameter modeling (APM) algorithm and K. Lee [9] applied APM to pump diagnosis.

To use adaptive parameter modeling, the characteristics of collected state variable batch data have to be considered first. K. Lee [9] divided semiconductor manufacturing processes into

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gas-loaded state process and idle state process, and used batch data from gas-loaded state process to diagnose vacuum pump. Batch data signals from gas-loaded state process has large displacement variance, however, Batch data signals are affected by purge gas. On the other hand, the batch data from idle state process are only affected by state of vacuum pump. In this study, we diagnosed vacuum pump with APM algorithm using idle state process data.

In section II, the measurement setup of multiple state variables and their statistical features are introduced. In Section III, the preprocessing scheme (APM) required for predictive diagnostics are introduced and their resultant batch data are illustrated. In Section IV, our diagnostic results and discussion are presented. Finally, our main results are summarized in Section V.

2. MEASUREMENT SETUP AND STATISTICAL FEATURE

2.1 Measurement setup of state variables

In this study, Inlet pressure, exhaust pressure and the supply currents, acceleration for vibration, and acoustic pressure are chosen as the state variables. Inlet pressure and exhaust pressure represent the condition of chemical reacting process and performance of vacuum pump. There are correlations between the supply current to dynamic behavior of load torque of pump motor. As mentioned before, vibration accelerometers were proposed to monitor the dynamic running conditions of vacuum pump. W. S. Cheung [10] addressed that dry pumps designed for semiconductor processes has own acoustical characteristics.

Most of dry vacuum pump systems for semiconductor processes are composed of booster pump parts and dry pump parts. Fig. 1 shows the experimental setup for measurement of the state variables of the dry vacuum pump system. The accelerometer signals measured from the body of the dry vacuum pump are vector-summed and converted into a scalar value. The signal sampling rate of 40.96 KHz was chosen, which is sufficient to cover the 10 kHz bandwidth of vibration signals. Collected digital signals are used to calculate in every 0.1 second the mean values of two pressure signals and the root mean squared (RMS) values of two supply current signals and two vibration signals.

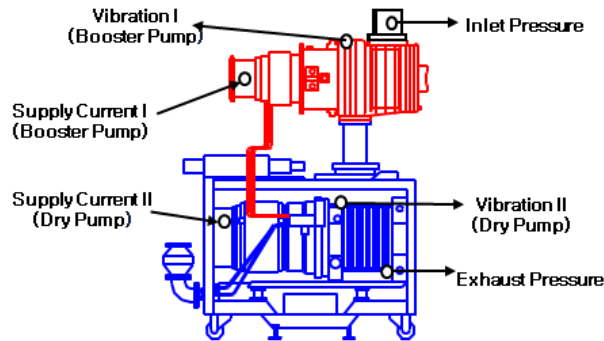


Figure 1 - Experimental setup for measurement of the state variables of the dry vacuum pump system

2.2 Statistical analysis of measured state variables

Fig.2 shows time series signals measured during 6 hours and their amplitude distributions. The inlet pressure and booster supply pump current signals (Fig. 2 (a) and (c)) are seen to have three segmented amplitude distributions. Two upper distributions are related to the gas-loaded state of the vacuum pump and the lowest one is related to the idle state of the vacuum pump, respectively. These separable states are obviously observed from the distributions of the exhaust pressure and dry pump supply current signals (Fig. 2 (b) and (d)). This work proposes to separate all the collected process data into the gas-loaded and idle groups. As shown in Fig. 2, the segments of $G_1 \sim G_4$ correspond to the gas-loaded state group and those of $I_1 \sim I_3$ to the idle state group. Each segment is assigned to each batch in this work. Of course, the series of gas-loaded batches as well as those of idle batches are separately used for predictive diagnostics. A reference signal suitable to divide both batch data is seen to be one of four signals (inlet pressure, exhaust pressure, booster and dry pump current signals). It is interesting to note that the vibration acceleration signals shown Fig. 2 (e) and (f) have a single peaked distribution similar to the normal distribution. It may mean that the vibration signals

are generated by the running conditions of rotating elements of the vacuum pump system, not the gas-loading conditions. It is the reason to use the vibration accelerometers to monitor the running conditions of rotating elements (e.g. bearings, gears and rotors). As shown Fig. 2(g), acoustic pressure data of gas loaded state and idle state have different shapes.

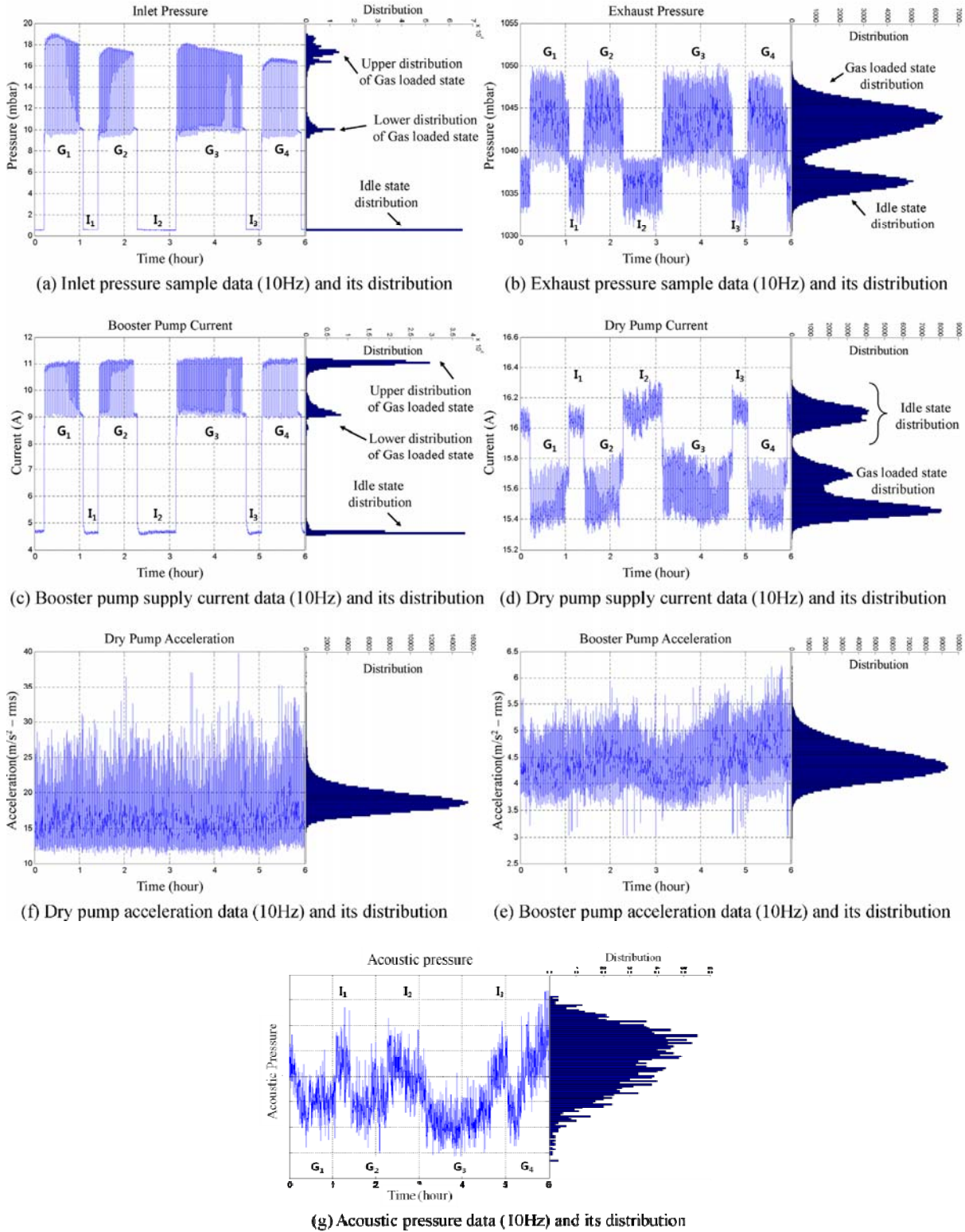


Figure 2 - Measured sample data and their distribution characteristics calculated every 0.1 seconds

3. PROCEDURE OF PREDICTIVE DIAGNOSTICS

3.1 Preprocessing scheme for Hotelling's T^2

The main idea of predictive diagnostic algorithm is that compare the monitored batch data from present processing with the reference batch data under the normal operating condition. Therefore, the first step is to collect the reference batch (or historical data set, HDS) including all possible normal running conditions, which are obtained from the initially repeated 20~50 processes. In this study, we selected the pumping speed decreased case data and collected batch data during first 4 days (46 processes) are decided as the reference batch.

Next step is to calculate T^2 values from each batch data. T^2 means the statistical distance of batch data, so, the sizes of each batch data should be equal for valid comparison. However, the size of batch data is depending on processing time, and processing times is irregular as shown Figure 2. It is the reason why preprocessing scheme is needed for Hotelling's T^2 to apply the vacuum pump diagnostics.

3.2 Adaptive parameter modeling (APM)

As shown previously in section 2.2, batch data of gas loaded states were separately decentralized into the upper and the lower bounds, and batch data of idle states were centralized. The trend and distribution of idle state process data indicates how well the processes were maintained stable. We assumed that one asymptotic curve can express trend of data. To model their linear trend, a simple linear model was chosen as described by Eq. 1

$$y_n = \alpha \cdot n + \beta \quad (1)$$

Where y_n is the n-th mean value, α is the slope coefficient of the asymptotic curve, and β is each initial value asymptotic curve (i.e. at $n=0$). The linear model parameters $\{\alpha, \beta\}$ are obtained from the least squares methods using equation (2). Also, the standard deviation for fitted asymptotic curve was calculated using equation (3).

$$\alpha = \frac{N \cdot \sum_{n=1}^N n \cdot y_n - \sum_{n=1}^N n \cdot \sum_{n=1}^N y_n}{N \cdot \sum_{n=1}^N n^2 - \left(\sum_{n=1}^N n \right)^2}, \quad \beta = \frac{\sum_{n=1}^N n^2 \cdot \sum_{n=1}^N y_{k,n} - \sum_{n=1}^N n \cdot \sum_{n=1}^N n \cdot y_{k,n}}{N \cdot \sum_{n=1}^N n^2 - \left(\sum_{n=1}^N n \right)^2} \quad (2)$$

$$\sqrt{\frac{1}{N-1} \sum_{n=1}^N (y_n - \alpha \cdot n - \beta)^2} \quad (3)$$

We note that the three parameters in Equations (2) and (3) were obtained from each idle state batch data. As a result, the idle state batch was represented with 21 parameters (i.e., 7 state variables multiplied by 3 parameters per state variable) from the mean value. We note that the parametric model is adaptive even with respect to the time-varying processes and the statistically different measurement signals. These model parameters actually embed the major features of each batch such that they enable the restoration of the 'representative' trend of the measured data. The evaluated standard deviation corresponding to each model was used to add the randomly disturbed values. This series of step is called adaptive parameter modeling (APM), and one process batch data is converted to one row vector consisted of 21 parameters by APM. As mentioned section 3.1, reference batch data were selected first 46 processes for this study. As a result, the reference data matrix (46 by 21) was recorded.

3.3 PCA and Hotelling's T^2

Principal component analysis (PCA), which is well known as a measurement data-driven predictive diagnostic approach, has proven to be an effective method. For PCA, the reference data are expressed as a matrix in the following form

$$X = T \cdot V^T + E \quad (4)$$

where T and V^T denote the score matrix and the transposed loading matrix, and E represents the residual matrix. Each column of the reference matrix X was mean-centered and normalized to unit variance. In the singular value decomposition, the score matrix is equivalent to the production of the

normalized column-orthogonal matrix U and the diagonal matrix Λ of singular values and the loading matrix V to the normalized column-orthogonal matrix. The residual matrix E indicates the unselected signal components of the reference batch data that depend on the number of selected singular values chosen to construct the score matrix. In this work, 95 % ascending ordered singular values were selected.

A major advantage of PCA is its ability to quantitatively compare new batch data X_n to the reference batch. This comparison is made by projecting the new batch data onto the principal component model of the reference batch defined in Eq. (5), which allows to evaluate a new score Y_n

$$Y_n = X_n \cdot V \quad (5)$$

This score (row vector) is used to calculate the statistical value of Hotelling's T^2 which allows us to monitor disparities between the newly collected batches and the reference batch. The current value (n-th process) of Hotelling's T^2 is calculated as (6)

$$(T^2)_n = \sum_{k=1}^{N_S} \frac{Y_{n,k}^2}{\lambda_k^2} \quad (6)$$

where N_S is the number of selected singular values and symbols $Y_{n,k}$ and λ_k denote the k -th elements of the current score vector and the singular values, respectively.

4. Result and discussion

To validate diagnostic algorithm proposed in this study, we applied this algorithm to pump data from reference paper [9]. Used pump data included 201 processes data and replaced by performance degradation. The algorithm of reference [9] used six gas-loaded signal data, and the algorithm of this study used 7 idle state signal data. T^2 value were recorded every process, T^2 chart well represented the status of dry pump. If trends of T^2 value observed, we could diagnose the state of vacuum pump qualitatively. By extension, the *upper critical limit* (UCL) is widely used to diagnose quantitatively. UCL is

$$T^2_{UCL} = m_{ref} + k \times \sigma_{ref} \quad (5)$$

where m_{ref} is average of T^2 calculated from reference data, σ_{ref} is standard deviation of T^2 from reference data, and k is factor.

As shown Figure 3 (a), T^2 value passed the UCL at 187th process. In Figure 3(b), continuous rising trend was observed and it was evidence of to setup the warning section. With warning section considered, Figure 3 (b) means, that performance of vacuum pump were decreased since 129th process and vacuum pump was dead at 187th process.

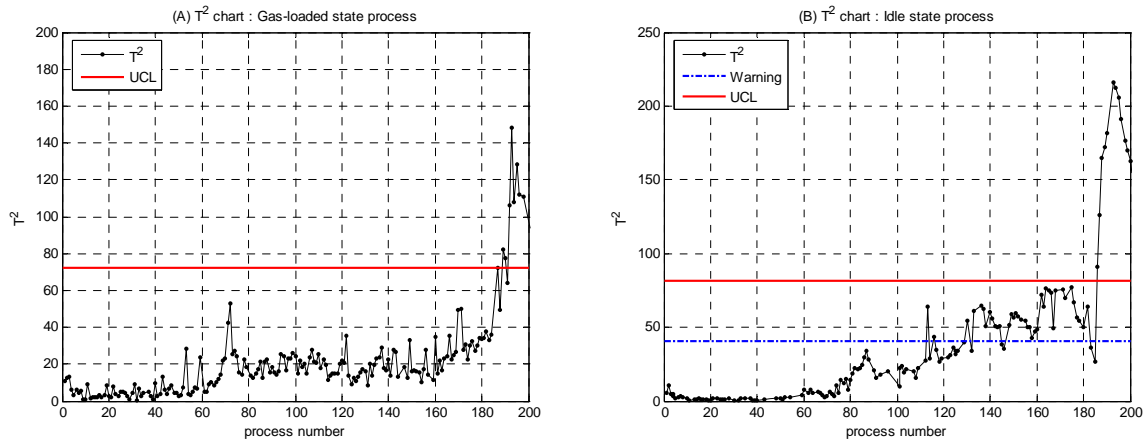


Figure 3 – APM-based T^2 chart. (a) is result of six gas-loaded state signal data.

(b) is result of seven idle state signal data.

In summary, chart of Figure 3 (a) was diagnosed fault point correctly with gas-loaded state process data except acoustic pressure data. Chart of Figure 3 (b) was predictive diagnosed fault with idle state process data with acoustic pressure added seven signal data.

5. Concluding remarks

We proposed two refinements to predictive diagnose of vacuum pump, one is that idle state process data were selected instead of gas-loaded state data, the other is that collected signal is six previously used data and added acoustic pressure data. Collected raw data converted to parameter matrix with APM algorithm, dimensional reduced by PCA, and calculated Hotelling's T^2 value. The trend of T^2 value well represented the performance state of vacuum pump, and detected fault point. The improvement of added acoustic pressure data was that the available of setting up the warning section, and it means that predictive diagnose of vacuum pump for semiconductor manufacturing process is possible.

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