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[Maintenance-free Multivariate SPC by Using Correlation-based Just-In-Time Modeling - Tomomi Ino]

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Multivariate SPC (MSPC) is well-known as a powerful method to detect unusual state of equipment. It detects slighter difference in equipment behavior with fewer false alarms compared with univariate SPC. However, the practical use of MSPC is limited in semiconductor mass production lines due to the difficulty in constructing and maintaining multivariate models. In long-term monitoring based on MSPC, false alarms may frequently occur due to drastic changes in equipment state after preventive maintenance (PM) and frequent model maintenance will be required to control alarms. Time-consuming model management is an obstacle to operate MSPC in practice. Although recursive modeling techniques have been developed to adapt models to gradual changes 1), MSPC based on recursive modeling techniques would fail to reduce false alarms right after PM, that is, until the model adapts the new state of equipment. To solve this problem, Just-In-Time (JIT) modeling has been developed 2). However, conventional JIT-MSPC tries to detect abnormalities based only on the distance between the current sample and past samples representing normal operating condition (NOC) and does not take account of the correlation among variables, thus its performance is not always satisfactory in practice. In the present work, a new JIT-MSPC technique is proposed by integrating MSPC and Correlation-based JIT (CoJIT) modeling. CoJIT can realize high-performance soft-sensors (virtual sensors) by selecting samples close to the current sample in the sense of correlation as well as distance 3). CoJIT-based MSPC (CoJIT-MSPC) will be able to eliminate time-consuming work for model maintenance.

Figure 1 shows how CoJIT-MSPC detects unusual state of equipment. The query, which is the latest operation data, is to be monitored. Q statistic of the query is derived from principal component analysis (PCA) of its neighbors.

$$Q = \sum_{m=1}^{M} (x_m - \hat{x}_m)^2 \qquad (1)$$

where $\hat{x}_m$ is the prediction of the *m*-th input variable x_m in the subspace spanned by major principal components and M is the total number of the input variables. Since the Q statistic is a distance between the query and the subspace, it is used as a control indicator of SPC. In conventional JIT-MSPC, Q statistic may become insensitive to faults because generated NOC region becomes unexpectedly broad as shown in Fig. 2(a). To solve this problem, the indicator J is used to select samples by taking account of correlation as well as distance in CoJIT modeling.

$$J = \lambda T^2 + (1-\lambda)Q \quad ,0 < \lambda < 1 \qquad (2)$$

$$T^2 = \sum_{r=1}^{R} \frac{t_r^2}{\sigma_{t_r}^2} \qquad (3)$$

where $\sigma_{t_r}^2$ is the variance of the *r*-th principal component score t_r. In this work, we selected 100 past samples after arranging the neighbors in ascending order of J. As a result, the selected samples are useful to define better NOC region as shown in Fig. 2(b).

We applied the proposed CoJIT-MSPC to lithography equipment. Figure 3 shows the monitoring results. In this case, though the percent defective increases gradually, univariate SPC cannot detect the defectives. Figure 3(b) is the result of CoJIT-MSPC using 13 input variables. Although about 2000 variables are collected from the lithography equipment, not all the variables respond to the fault. The 13 variables are selected by linear discriminant analysis to improve fault sensing capability of the model. The Q statistic in Fig. 3(b) increases in proportion to the percent defective in Fig. 3(a). Although the equipment has been maintained many times during the monitoring period of half a year, the MSPC model has not been rebuilt at all. These results have demonstrated the capability of CoJIT-MSPC. It can detect defectives that univariate SPC fails to detect with less false alarms and without model maintenance.

References

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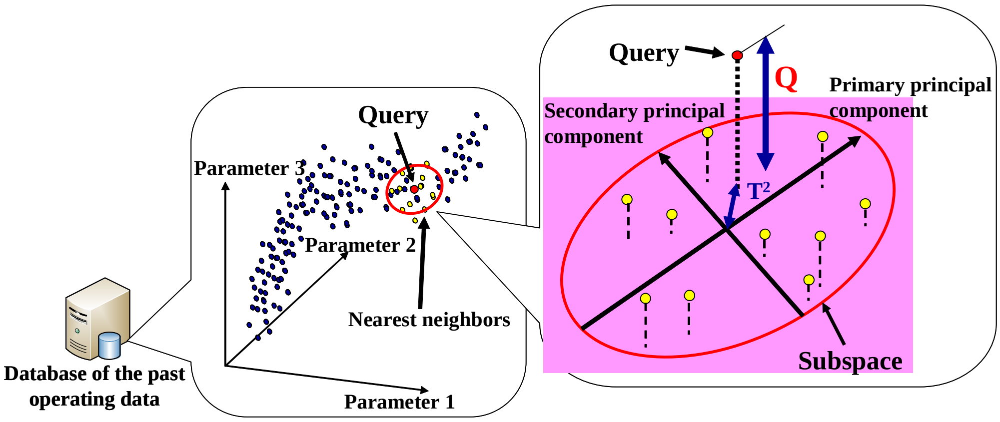

Figure 1: Schematic diagram how to detect unusual state of equipments by MSPC modeled by C-JIT MSPC

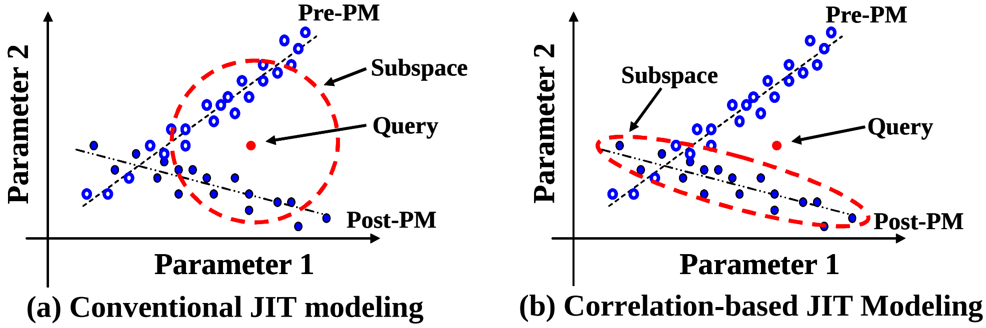

Figure 2: Subspace difference between conventional JIT-MSPC and CoJIT-MSPC in the case of that sample of pre-PM and post-PM intersect. (a) Subspace of conventional JIT-MSPC, (b) Subspace of CoJIT-MSPC.

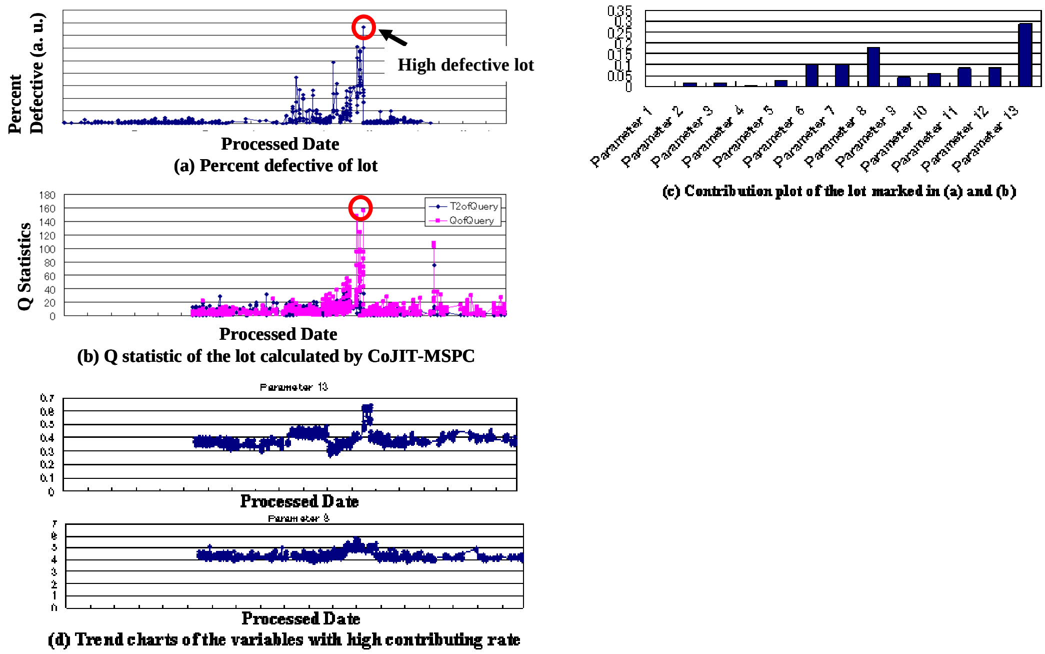

Figure 3: A result of the C-JIT MSPC applied on lithography equipment

(a) Percent defective of lot, (b) Q statistic calculated by C-JIT MSPC, (c) Contribution plot of the lot marked in fig. (a) and (b), (d) Trend charts of the variables with high contributing rate.