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# On-line process monitoring using local measures of association. Part II: Design issues and fault diagnosis

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ABSTRACT

Control charts based on partial correlations have proved to be an effective approach to detect fine deviations on the underlying structure of process data. The prompt detection of such faults is dependent on the proper selection of the control chart design parameters, namely their control limits, subgroup size (off-line case) and forgetting factor (on-line case). In this article, specific guidelines are provided to attain the desired detection power while maintaining the intended false alarm rate. A formal relationship that relates the on-line monitoring approach with the simpler off-line implementation is also derived. This relationship can then be used to design on-line control charts based on insights and results obtained with the more interpretable off-line version. A new fault diagnosis procedure is also introduced in order to take advantage of the partial correlations ability to remove the effects of faulty variables in the data, and thus obtain higher identification accuracy and decrease the total time invested in diagnosis activities and troubleshooting.



## 1. Introduction

When a critical fault is detected in an industrial process, the next step regards the isolation of its root cause in order to fix it and return to normal operation conditions as quick as possible. From the total time elapsed since the occurrence of the abnormality, fault diagnosis takes the highest share, especially when compared to the fault detection time. Therefore, the existence of effective and efficient fault diagnosis and isolation methodologies is of special importance for the reduction of the total downtime due to process upsets. For large scale systems, a common approach adopted in practice is to implement PCA-MSPC [1,2] to detect process upsets, and then analyze the associated contribution plots [3,4], to diagnose them once they occur. However, it is now well-established that PCA-MSPC has a relatively low ability to detect structural changes in the process. For instance, a variation in the eigenvalues of the process' variance–covariance matrix may pass completely unnoticed [5] to this technique. Similarly, some incipient perturbations on the variables causal relationships that slowly drift the in-control process mean, may pass undetected at their early stages of development. Therefore, a PCA-MSPC based approach is ineffective for detecting and diagnosing structural changes, since the fault is generally not even detected in the first place. A more detailed picture of the state of the art is provided in the first article of this sequel [6].

On the other hand, structural changes are more easily detected by monitoring statistics dedicated to follow the process variables' correlation. These approaches are mostly based on some measurement of the marginal variance–covariance matrix, which in turn is rather uninformative regarding the exact fault's location. In fact, the whole chain of causally related variables might experience a change in correlation, leading to a wide range of possible root causes and consequently to an increase of time consuming inspections. To avoid such fault's smearing effect, some diagnosis procedures have been developed based on transfer entropy [7], time delay analysis [8] and Granger causality [9] in order to identify the directionality of the fault's propagation path and thus focus the analysis on a module that, with high probability, may contain the fault root cause. Knowledge about the process causal map has also been considered to supplement data-driven approaches for fault diagnosis [10,11]. Another solution encompasses the use of local measures of association, such as partial-correlations.

Even though partial correlations do not provide information about the variables causality direction, they are still able to discern if such connectivity does exist and in what degree it has changed. This characteristic, coupled with their easy computation, makes them suitable for fault detection and diagnosis purposes at the structural level. On the first article of this sequel [6], the use of partial correlations in fault detection was proposed and tested for the case of on-line monitoring and proved to lead to monitoring statistics with a consistently higher detection performance than their current counterparts based on the (marginal) correlation and covariance. Therefore, in this article, partial correlations are employed to implement fault diagnosis and complete the Fault Detection and Diagnosis (FDD) approach initiated in the first reference. The purpose now is to robustly identify a reduced set of variables closely related with the actual root cause. The application of the FDD scheme based on partial correlations has thus the ability to decrease the total downtime due to process upsets, by reducing the

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detection time and, more importantly, the time dispended in diagnosis, which is the dominant time consuming task.

The rest of the paper is organized as follows. In the next section we discuss several issues with practical interest regarding the design of control charts based on partial correlations, including the rigorous definition of the control limits. We also demonstrate a formal equivalence between the EWMA forgetting factor and the size of a moving window, and discuss its practical consequences and applications. Then, in the following section, a fault diagnosis method based on partial correlations is introduced. This approach is applied to two cases studies in order to assess its validity and robustness. Finally, we discuss the results obtained and summarize the contributions of this article, as well as its main conclusions.

## 2. Practical issues on the design of control charts based on partial correlations

In reference [6], two monitoring statistics based on partial correlations are proposed. These are the *RMAX* statistic (for monitoring the partial correlation coefficients) and the *VnMAX* statistic (for monitoring the variables' variance). Both monitoring statistics are implemented as successive hypothesis tests in order to verify if the variables' partial correlation coefficients and variances remain close to their in-control values. In order to avoid the use of multiple parallel control charts, each of these vectors of monitored quantities is summarized through the maximum norm (i.e., the maximum in absolute value). This is equivalent to monitor all parameters in simultaneous and issue an alarm if at least one of them exceeds the control limits. A key step in this procedure is the proper normalization of the sample partial correlation coefficients and sample variances so that all of them follow the same symmetric distribution (in this case the standard normal distribution). By doing so, all monitored values have the same importance and the resultant monitoring procedure has the same sensitivity to increases and decreases in the monitored parameters. For the case of the sample partial correlation coefficients of uncorrelated variables, this normalization can be done based on the following expression ([12] pp. 133–134 and pp. 143–144),

$$w_r = r\sqrt{n-q-1} \tag{1}$$

which tends to be normally distributed with zero mean and unit variance. In Eq. (1) $n$ stands for the number of observations used to estimate the sample variance-covariance matrix and $q$ is the order of the partial correlation coefficients. Similarly, the sample variances ($s^2$) is normalized by [13],

$$w_s = \frac{\left(\frac{s^2}{\sigma_0^2}\right)^{1/3} - \left(1 - \frac{2}{9(n-1)}\right)}{\sqrt{\frac{2}{9(n-1)}}} \tag{2}$$

where $\sigma_0^2$ is the in-control variance, and the resulting transformed variable follows a normal distribution with zero mean and unit variance.

After application of the normalization functions to the sample partial correlation coefficients and sample variances, the monitoring statistics can be defined as,

$$R0MAX = \max\{|w_r(\mathbf{r}_0)|\} \tag{3}$$

$$R1MAX = \max\{|w_r(\mathbf{r}_1)|\} \tag{4}$$

$$VnMAX = \max\{|w_s(\mathbf{v})|\} \tag{5}$$

where $\mathbf{r}_0$ is the $[m(m-1)/2] \times 1$ column vector of sample correlation coefficients (0th order partial correlations), $\mathbf{r}_1$ is the $[m(m-1)(m-2)/2] \times 1$ column vector of 1st order sample partial correlation coefficients and $\mathbf{v}$ is a $(m \times 1)$ column vector containing the variables' sample variances of a $m$-dimensional process. All these values can be computed based on the estimated sample variance — covariance matrix (either using moving windows or an EWMA recursion). The formulas are:

$$r_{xy} = \frac{\operatorname{cov}(x,y)}{\sqrt{\operatorname{var}(x)\operatorname{var}(y)}} \tag{6}$$

for the case of 0th order partial correlation, and,

$$r_{xy\cdot z} = \frac{r_{xy} - r_{xz}r_{yz}}{\sqrt{\left(1-r_{xz}^2\right)\left(1-r_{yz}^2\right)}} \tag{7}$$

for the case of 1st order partial correlation.

This monitoring scheme assumes that variables are previously transformed to be decorrelated, by the application of a proper sensitivity enhancing transformation (SET) that makes use of the inner network of associations among the variables. As a result, the transformed variables are uncorrelated by design and the detection of structural changes is maximized under such conditions. The advantages and properties of SET are well documented elsewhere [13] and are briefly discussed again in the previous paper of this series [6]. Thus, the behavior of the proposed monitoring statistics will be here assessed for the general case of uncorrelated variables, since it is for this situation that the proposed procedure was designed to operate and where it shows its best performance.

The formulation of Eqs. (1) and (2) can be directly applied to any window based procedure, namely for non-overlapping windows (off-line) or receding horizon (overlapping) moving windows (on-line). Since the normalization functions have the same structure and, moreover, the same uncertainty on the estimates, both approaches have similar detection properties. In the following subsections it will be demonstrated that the same is also valid for variance — covariance matrix estimates based on EWMA recursion. This will be done through the derivation of a formal relationship between the window size ($n$) and forgetting factor ($\lambda$) of the EWMA updating scheme. For presentation purposes, we recall that the variance — covariance matrix can be recursively updated at each new observation ($\mathbf{x}_t$) as [14],

$$\mathbf{S}_t = \lambda \mathbf{x}_t \mathbf{x}_t^{\mathrm{T}} + (1-\lambda)\mathbf{S}_{t-1} \tag{8}$$

where $0 < \lambda < 1$. $\mathbf{S}_t$ is positive definite matrix when $t \geq m$. The advantages of such relationship will be explored for the purpose of designing on-line control charts based on insights and results from the off-line implementation, which are easy to obtain and interpret. Furthermore, an approach to select appropriate control limits for these monitoring statistics will also be provided.

### *2.1. Equivalence between the forgetting factor and the number of observations in a moving window approach*

In the case of monitoring statistics based on non-overlapping moving windows, the required design parameter is the number of observations forming the window ($n$), from which the sample variance — covariance matrix is calculated and subsequently the partial correlations are obtained. This parameter affects not only the correlation coefficients and variance distributions, but also the monitoring statistics performance. The same effects are observed in the EWMA recursion approaches for the forgetting factor $\lambda$, which is the design parameter of this class of techniques.

The forgetting factor, $\lambda$, acts as a weighting parameter that is used to balance the importance of recent observations regarding the older ones. However, from its sole analysis, it is not easy to grasp which observations are more significantly contributing to the variance — covariance