

Supply chain monitoring: a statistical approach

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Abstract

Although the nodes of a supply chain (SC) network generate a huge amount of data along their operation, extracting useful information from them is not straightforward. Within the Supply Chain Management (SCM) scope, monitoring reveals as a key task that is currently waiting for further study. It is necessary to minimize risks of undesired situations and administrative efforts to manage material flows. Supply Chain Monitoring (SCMo) techniques should support manager decisions warning of the abnormal situation telling what have gone wrong and suggesting solutions. Additionally, they should be able to store the causes and consequences in order to help in the decision making onto future similar situations. This work presents an extension of multivariate statistical methods to SCMo that consists in a wavelet based multi-scale Principal Component Analysis (PCA) technique accounting for time delays. The proposed approach has been tested using data generated through an event discrete simulation model running in several scenarios. Results have revealed that statistical multivariate techniques are very useful for SCMo.

Keywords: SCM, SCMo, PCA.

1. Introduction

A company's supply chain (SC) comprises both geographically dispersed facilities where raw materials, intermediate products, or finished products are acquired, transformed, stored, or sold, and transportation links that connect these facilities among them (Simchi-Levi et al. 2000). Within a SC there is an actual agreement among the different partners so as to award the general coordination task to a central entity. The central entity has a global view and tries to equilibrate the stresses that each SC nodes creates. In this point, Supply Chain Monitoring (SCMo) plays its essential role offering the information in a suitable way to the central entity's disposal. It is as the halfway between the transactional and analytical tools on which Supply Chain Management (SCM) is often supported.

In recent years, astonishing gains in personal computer speed, e-commerce, and the power and flexibility of data management software have promoted a range of applications. Widespread implementation of transactional tools or backend-systems as Enterprise Resource Planning (ERP), Material Requirement Planning (MRP) or Distribution Resource Planning (DRP) systems offer the promise of homogeneous,

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transactional databases that will facilitate integration of SC activities. In many companies, however, the scope and flexibility of these systems have been less than expected or desired, and their contribution to integrated SCM has yet to be fully realised. Moreover, competitive advantage in SCM is not gained simply through faster and cheaper communication of data. Companies are seeking to utilise systems that automatically analyse their corporate databases to identify plans for redesigning their SCs and operating them more efficiently. Nevertheless, extracting useful information from data is not straightforward. These data are disparate in nature and, additionally they are collected at different frequency and even saved occasionally. Thus, within the SCM scope, monitoring reveals as a key task that has received little attention up to now and it is currently waiting for further study.

In this work, monitoring is proposed as an intermediate technique that provides an initial analysis over the large amount of data saved in the aforementioned databases, which enables to characterise the normal operation of the system. This is very useful in order to visualise the operation of the SC to control whether it is kept between the normality boundaries. Otherwise the traditional fault detection for chemical processes, in SCM it is not necessary to detect the occurrence of a fault but to obtain a pattern indicating how this event, whose occurrence is known, affects the value of the measured variables in the system, e.g. inventory levels. The idea is to store in a database a model that could give notion about the variations or changes in the variables when the event is repeated in such a way to be able to study and anticipate corrective actions. This work is based on multivariate statistical methods usually applied to process monitoring.

2. Monitoring Methodology

2.1 Principal components analysis

PCA (MacGregor et al. 1995) is a statistical method for process monitoring based on data correlation. Consider a matrix $\bar{\mathbf{X}}$ (of dimension $m \times n$) containing data corresponding to m samples of n variables. Each column of $\bar{\mathbf{X}}$ is supposed to follow a normal probability distribution and is normalized with zero mean and unit variance. Let $\mathbf{R}$ be its corresponding correlation matrix. Then, performing singular value decomposition on $\mathbf{R}$, a diagonal matrix $\mathbf{D}_\lambda = \text{diag}(\lambda_1, \lambda_2, \dots, \lambda_n)$ where λ_i are the eigenvalues of $\mathbf{R}$ sorted in decreasing order $\lambda_1 > \lambda_2 > \dots > \lambda_n$, is obtained. The corresponding eigenvectors $\mathbf{p}_i$ are the principal components (PCs) and form an orthonormal base in $\mathbb{R}^n$. It is possible to divide the PCs in two orthogonal sets, $\mathbf{P} = [\mathbf{p}_1, \mathbf{p}_2, \dots, \mathbf{p}_A]$ and $\tilde{\mathbf{P}} = [\mathbf{p}_{A+1}, \mathbf{p}_{A+2}, \dots, \mathbf{p}_n]$. The first containing most of the common cause variation and the second describing the variation due to the noise (called the residual subspace). A reduction of dimensionality is made by projecting every normalized sample vector $\mathbf{x}'$ in the subspace generated by $\mathbf{P}$, obtaining $\mathbf{t} = \mathbf{P}^T \mathbf{x}'$, which is called the principal score vector. Then, the state of the process can be monitored using two statistics, the Hotelling's statistic (T^2) and the Squared Prediction Error statistic (SPE). The first describing common cause deviations and the second describing deviations in the residual subspace.

2.2 Genetic algorithm-based delay adjusted PCA (DAPCA)

One main drawback of PCA is that it does not account for time-delays present in data. Those delays can cause that the percentage of variance contained in the first few PCs is low and the difference between the variance contained in the last significant PC (λ_A) and the next one (λ_{A+1}) is not accentuated. Therefore, there exists a trade-off between the number of linear relations considered (A) and the embedded errors that is introduced in the model, causing an inefficient reduction of dimension and a bad performance to filter the noise and to detect disturbances and changes in the process correlation (faults).

If one want to deal with all the complete adjustment problem, without additional assumptions, $(d_{\max})^n$ singular value decompositions have to be evaluated (Wachs and Lewin, 1999), where $d_{\max}$ is the maximum delay considered. In this work, a Genetic Algorithm (GA) has been developed to solve this high combinatorial optimization problem. In this approach, each chromosome represents a backward shift vector ($\mathbf{DV} = [d_1, d_2, \dots, d_{n-1}]$, with d_j in the range $0 < d_j < d_{\max}$ for $j = 1, 2, \dots, n-1$) and contains the delays present in the process signals with respect to a reference signal. This reference signal can be in general any input.

The optimization is performed in two loops. The first one, find $\mathbf{DV}$ that minimize the number of PCs that are selected by a parallel analysis (Himes et al. 1994). The fitness function is simply $\Phi_1 = -A$. The second loop searches $\mathbf{DV}$ that maximize the variance contained in the first A PCs (selected in the loop 1) (i.e. $\Phi_2 = \sum_{i=1}^A \lambda_i$), which is considered as the true system variation. As a consequence, λ_A results greater than λ_{A+1} , making easier the distinction between spurious and system variance. Additionally, the model explains the most of the true process variance in the smallest number of PCs.

2.3. Multiscale DAPCA (MS-DAPCA):

The capacity of PCA to eliminate the noise heavily relies on the assumption of the normality of data. Therefore, sometimes measurement and process noise can difficult the detection of small faults and disturbances. MS-DAPCA aims to join the properties of DAPCA to those of Multi-scale PCA (MSPCA, Bakshi, 1998). MSPCA is an approach that handles multi-scale data by using wavelets. PCA is then applied to generate independent latent variables at each scale. In addition, wavelets act as a multi-scale filter by thresholding the coefficient of the more detailed scales. MSDAPCA performs similar to MSPCA, but DAPCA is applied instead of PCA, at each scale of the wavelet decomposition.

One main advantage of this method is that two stages of dimension reduction are performed. First the MSPCA decomposition reduce the length of the coefficient matrixes from m to $m/(2^l)$, and the maximum delay considered results $d_{\max l} = d_{\max}/(2^l)$ were l is the decomposition level. This situation reduces the computation time of DAPCA several times, especially in the approximation scale, sometimes allowing the use of exhaustive delay adjustment. Finally, delays can be estimated and compensated independently at different scales. The Matlab® genetic algorithm Toolbox developed by the University of Sheffield has been used in the following case study, which has been solved using an AMD XP2500 processor with 512MB RAM.

4. Case Study

An event-driven simulation model has been constructed using two toolboxes of Matlab®: Stateflow and Simulink. The case study is a SC network involving six entities: one raw material supplier (S), a manufacturing plant (P), two distribution centres (D_A, D_B), and two retailers (R_A, R_B) (Figure 1). The raw material that enters P is designed by W and the products manufactured by the plant are A and B . In this case, customer orders for A and B arrive to R_A and R_B , respectively, which, in turns, send orders to D_A and D_B . The plant P supplies the distribution centres whilst S provides the raw material to the plant. Furthermore, the study is addressed to variables belonging to the operational and tactical level.

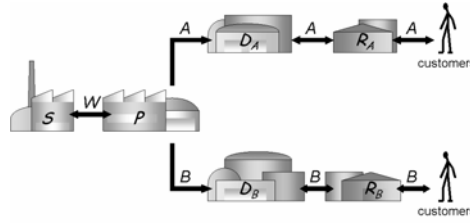


Figure 1: Supply Chain case study.

The nineteen monitored variables are of two kinds: flows that involve material (inputs and outputs of materials at each node) and information (inputs and outputs of orders at each node), and cumulated variables that also involve material (inventory level at each location) and information (cumulated orders level at each node).

Two different abnormal situations have been programmed. The first one is related to a machine breakdown in the production line of product B at the factory P . This causes a delay in the production response. The second one is due to a transport fault between P and D_B . Then, during a certain time period D_B cannot replenish its inventory.

5. Results

Firstly, a standard PCA model has been built using simulated data from normal operation condition. Seven PCs has been selected using parallel analysis ($A = 7$). The variance contained in each PC is presented in Table 1. Note that $\lambda_7 \approx \lambda_8$, making difficult the distinction between the common cause and residual subspaces.

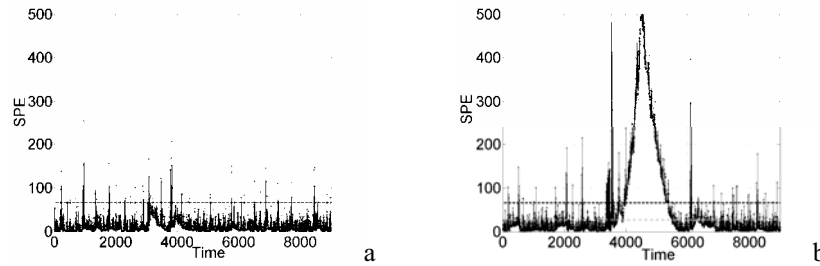


Figure 2. PCA results. SPE statistic for: a) Event I at $t=3000$ b) Event II at $t=3500$. The dashed line represents the detection limit of 99%

With this model, Event II is easily detected. However, Event I cannot be detected (see Fig 2). In addition several false alarms (3 consecutive points out of limit) occur.

Table 1: Variance percentage contained in the first ten PC dimensions.
Gray cells correspond to the selected PCs in each case.

	λ_1	λ_2	λ_3	λ_4	λ_5	λ_6	λ_7	λ_8	λ_9	λ_{10}	CPU time
PCA	10.13	9.21	7.23	6.42	6.28	5.93	5.56	5.36	5.21	4.96	-
DAPCA	12.25	11.12	8.91	5.78	5.51	5.24	5.09	5.00	4.79	4.66	836s
MSPCA	17.73	13.94	11.67	8.53	7.95	5.76	5.27	4.69	4.19	3.92	-
MS-DAPCA	22.23	16.57	11.50	5.85	5.51	5.08	4.94	4.27	3.71	3.53	32s
MS-DAPCA*	35.30	19.94	14.54	13.93	9.62	6.67	-	-	-	-	5s

Therefore, DAPCA has been implemented to reduce the model dimension and to look for a better detection of Event I. In this case only three PCs has been selected ($A = 3$) and λ_A results significantly greater than λ_{A+1} (see Table 1). However, the detection performance has not improved (Fig. 3a). Then, to improve the monitoring performance the MSPCA has been applied. Five PCs are chosen. Results corresponding to the approximation scale of MSPCA are presented in Figure 3. The Event I is clearly detected without false alarms.

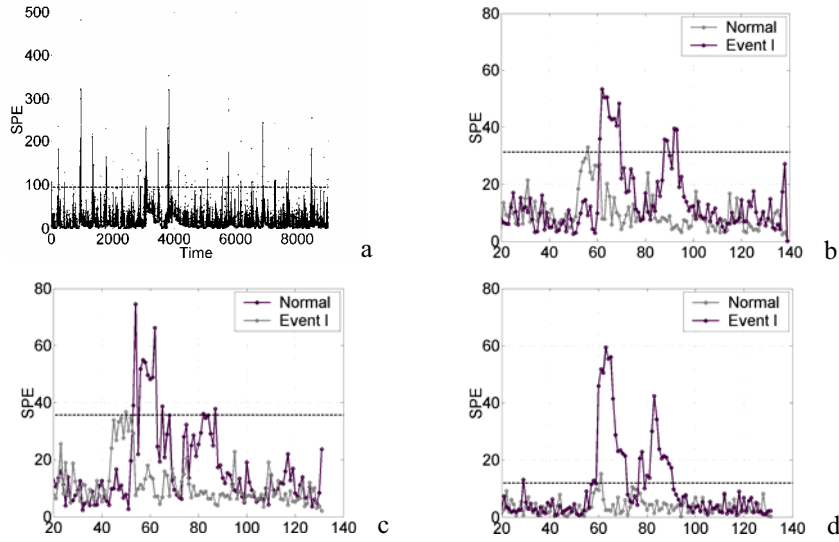


Figure 3. SPE statistic for Event I: a)DAPCA b)MSPCA c)MS-DAPCA d)MS-DAPCA using only inventory signals. The dashed line represents the detection limit of 99%

Applying MS-DAPCA similar results are obtained, but using only three PCs (Figure 3c). Finally, MS-DAPCA has been applied but only on the six inventory signals because they are variables that are registered in an almost continuous manner. Then, data processing is easier than in case that the register is eventual, such as material flows transported by the lorries or the orders sent out by the customers. Now, only one PC is enough to describe the system variance contained in data. Figure 3d shows that the detection limit can be placed lower leading to a faster and more reliable detection. Once the deviation is detected, the causes and consequences of the abnormal events can be investigated. Figure 4 shows the statistics corresponding to Event I using the last implemented DA-MSPCA model. One can observe that the *SPE* is first deviated,

showing a broke in the system correlation, and then the T^2 statistic. Figure 5a shows that the DB is the inventories that cause the deviation in SPE , and then the disturbance in P due to accumulation of orders (Figure 5b).

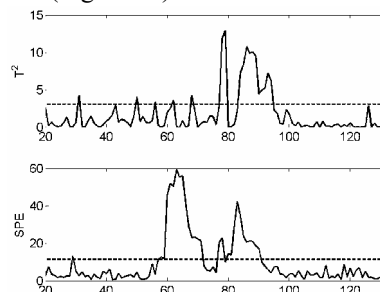


Figure 4: MS-DAPCA using only inventory signals: T^2 and SPE statistic for Event I

5 Conclusions

Several statistical techniques usually applied in Chemical Engineering for process monitoring has been tested in a new environment, the SCM network. Results so far obtained are very promising. This study reveals that the standard PCA algorithm is not able to deal with the noise and non-gaussianity featuring of this kind of signals. Nevertheless, multiscale and the novel delay adjusted techniques can strongly improve the monitoring performance. Research tasks in this direction will continue.

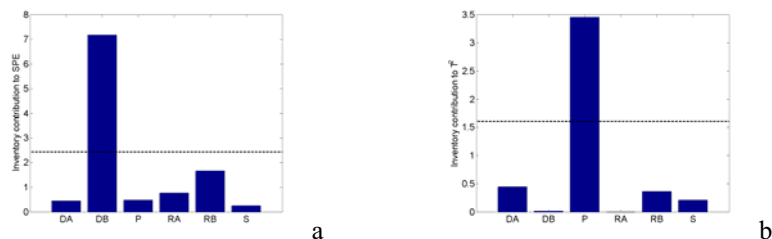


Figure 5: MS-DAPCA. Inventory contributions to the statistics deviations a) absolute contribution to the SPE in the 64th coefficient b) absolute contribution to T^2 in the 86th coefficient

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