PLS-based FDI of a Three-Tank Laboratory System

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Abstract—The problems of fault detection and isolation of dynamic systems has been studied intensively in the recent years and many successful industrial applications have been reported. In the main these studies have been restricted to model based techniques, with few reports of successful implementation of data driven approaches. These data driven approaches have been range from the application of linear regression techniques, to neuro-fuzzy systems. This paper reports on application of, Multivariate Statistical Process Control (MSPC) methodologies, which can provide a diagnostic tool for the on-line or real time monitoring and detection of the process malfunction is proposed. Finally the effectiveness of Partial Least Squares (PLS) in FDI of the Three-Tank system are represented and discussed through simulation results.

I. INTRODUCTION

During the last two decades, there have been immense advances in the areas of advanced process control, specifically dealing with fault detection and isolation (FDI). The objective of these developments is to be able to detect and distinguish not only sudden faults (step faults) but also incipient faults (including drift faults) occurring in the process. The ability to detect and isolate these faults is crucial in order to avoid loss of product and reduced profitability and eventual inappropriate shut-down. In addition FDI methods enhance the safe operability of the processes, lack of attention to a suitable level of process monitoring and FDI will obviously lead to environmental processes, lack of attention to a suitable level of process performance monitoring (allied to FDI) through the PLS based FDI simulation results are reported and analyzed.

II. MULTIVARIATE STATISTICAL PROCESS CONTROL

MSPC is based on statistical projection techniques, namely Principal Component Analysis (PCA), [11] and Projection to Partial Least Squares, [12]. These two methods are employed extensively for on-line or real time multivariate monitoring and detection schemes of the process malfunction. PLS offers certain attractive features, both in MSPC applications and control system applications. The basic approach of the algorithm is to identify the principal features in the data by dividing the variable space in to cause and effect, and performing a dimensionality reduction on them. In a sense, PLS provides a method for compressing the dimensionality of the data space. It then identifies the primary features in the cause variables that are able to describe the variation in the effect variables. A major feature of PLS is that it will deal with correlated data and will produce answers when Ordinary Least Squares cannot [12] and [13]. This property is not unique to PLS as there are alternative algorithms that can also cope with correlated data, such as recursive least squares and ridge regression [14]. A significant benefit that PLS offers over these approaches is that once the model is developed it can be used for both monitoring the condition of a plant, but also to control it.

The PLS approach relies on decomposing the input matrix, \( X \in \mathbb{R}^{K \times M} \) and the output matrix, \( Y \in \mathbb{R}^{K \times N} \), to sum of rank one component matrices, [15]. Here \( K \) is the number of measurements or data sizes, \( M \) is the number of output variables and \( N \) is the number of input variables.

Typically, the PLS decomposition of \( X \) and \( Y \) are given is carried out in the following manner [14]:

\[
X = T P' + E \\
Y = U Q' + F
\]

where \( T \) and \( U \) are the score matrices and \( P \) and \( Q \) are the weight matrices, respectively.
where \( n \) is the number of rank one component matrices, 
\( \tilde{X}_i = t_i p_i^T \) and \( \tilde{Y}_i = \hat{u}_i q_i^T \), retained in the decomposition.

The vectors \( t_i \) and \( \hat{u}_i \) are referred to as the t-score vector
and u-score vector, the vectors \( p_i \) and \( q_i \) are loading
vectors, \( X_n \) and \( \hat{Y}_n \) represent the sum of \( n \) the rank one
component matrices to reconstruct the input matrix and
predict the output matrix, respectively, \( E_n \) and \( F_n \) are
residual matrices. The u-score vectors, \( \hat{u}_i \), can be estimated from the t-score vectors as follows:

\[
\hat{U}_i = [\hat{u}_1, \ldots, \hat{u}_i] = [t_1 b_1, \ldots, t_i b_n] = T_n B_n
\]

where \( B_n \) represents a diagonal matrix containing the
regression coefficients of the score model, \( b_i \), determined
by PLS algorithm.

The loading vectors are identified using a technique known
as singular value decomposition (SVD), which calculates the
loadings such that the first score explains the greatest
variation in the data, the second score the next and so on.
Each of the scores is uncorrelated to one another.
However, it should be noted that the scores are often
referred to as latent variables, i.e. each score vector
represents an instance of a particular latent variable or LV
[14].

Another way of looking at PLS is that it creates a new set
of variables (latent variables) which are reflective of true
dimensionality of the system. This new set of variables, are
a set of strongly correlated variables and often only a few
score vectors are needed to describe the process variation
or process performance [12]. The number of retained
score vectors is typically determined by cross-validation or
the analysis of variance, etc as demonstrated for example
by [3] and [10].

Fig. 1 shows the example of PLS algorithms the system
which contains original input (I) and original output (O),
respectively. PLS provides the \( T_{PLS} \)-transformation
which can reduce the dimensionality of the original input
(I) and output (O) with the relationship \( I = f_p(O) \) to the
new dimensionality of X and Y which can reserve the
relationship between input and output to the term of
\( Y = f_m(X) \).

In this case, it should be noted that the \( T_{PLS} \)-
transformation is not invertible, the dimensionality of X is
less than the dimensionality of I (DIM X < DIM I) and
the dimensionality of Y is less than the dimensionality of O
(DIM Y < DIM O). Namely, this has two implications:
(a) the relationship between X & Y need not have the same
characteristics as that between I & O (b) there need not be
a direct one to one relationship between the variables in
the space X and those in the space I on one hand and the
space Y and the space O on the other. In addition,
numerical analysis carried out in the transformed space
cannot be translated back to the original space.

III. THE NECST THREE-TANK BENCHMARK SIMULATION

The NECST 3-Tank Bench Mark Simulation [16] and [17]
has been selected for both testing and verifying the ideas
developed in this paper. The model represents a real 3-tank
system (Fig 2) from the Research Centre for Automatic
Control in CRAN-UHP, Nancy, FRANCE. The concepts
presented will be later tested on this bench mark system.

It can be seen that Fig. 2 shows the subsystem-1 has 3
inputs (\( Q_{01}, P_w \) and \( Q_{12} \)) and 3 states (\( x_1 = [L_4, T_1, V_{12}] \))
with the following dynamics:

\[
\begin{align*}
S_1 L_4 &= Q_{01} - Q_{12} - Q_{10} \\
S_1 L_4 T_1 &= Q_{01} (T_0 - T_1) + \frac{P_w}{\rho c} \\
V_{12} &= Q_{12}
\end{align*}
\]

Subsystem-2 has 2 inputs (\( Q_{02} \) and \( Q_{20} \)) and 3 states
\( x_2 = [L_2, T_2, V_{20}] \) with the following dynamics;

\[
\begin{align*}
S_2 L_2 &= Q_{12} + Q_{02} - Q_{20} + (Q_{32} + Q_{32}^*) - Q_{\text{leak}_2} \\
S_2 L_2 T_2 &= Q_{12} (T_1 - T_2) + Q_{02} (T_0 - T_2) + (Q_{32} + Q_{32}^*) (T_0 - T_2) \\
V_{20} &= Q_{20}
\end{align*}
\]

Subsystem-3 has 2 inputs (\( Q_{03} \) and \( Q_{32} \)) and 2 states
\( x_3 = [L_3, V_{32}] \) with following dynamics:

\[
\begin{align*}
S_3 L_3 &= Q_{03} - (Q_{32} + Q_{32}^*) - Q_{30} - Q_{\text{leak}_3} \\
V_{32} &= Q_{32}
\end{align*}
\]

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where $S_i, L_i, T_i, V_j, Q_{ij}, Q_{leak}$; $i=0,1,2,3$ are the cross-sectional areas of each tank, the level of liquid in tank-$i$, the temperature of liquid at the centre of the tank-$i$, the volume of liquid passing from tank-$i$ to tank-$j$, the liquid flow rates between tank-$i$ to tank-$j$, and the leak from tank-$i$, respectively. $ij=0$ means the buffer tank. $P_w$ is the power input. $\rho$ and $c$ are the density and the specific heat capacity of the liquid inside the tank.

It should be noted that the flow-rates on the system are controlled by either pumps or valves. The system working as follows:

- **Pump_1** is kept constant at 0.75 m$^3$/sec.
- Tank-1 is fed by Valve01 ($Q_{01}$).
- Tank-2 is fed by Valve02 ($Q_{02}$) and **Pump_2** ($Q_{12}$).
- Tank-3 is fed by **Pump_3** ($Q_{03}$).

The liquid inside the Tank-1 is heated by an electrical heater. The Tank-2 is taking preheated liquid from the Tank-1 ($Q_{12}$) and mix it with a solution coming from the Tank-3 ($Q_{32}$). Valve32, Valve_leak_1, Valve_leak_2, and Valve_leak_3 are totally closed ($Q_{32} = Q_{0} = Q_{02} = Q_{03} = 0$) and Valve30 is totally opened during the simulation.

The performance objectives for the system are as follows:

- Maintain the levels of each tank, $L_1$ at 0.75 m, $L_2$ at 0.3 m and $L_3$ at 0.5 m.
- Maintain the temperature of 1$^{st}$ and 2$^{nd}$ tank, $T_1$ at $30^\circ$C and $T_2$ at $28^\circ$C.

The system is simulated initially without any faults and from Fig. 3 it can be seen that the outputs track the reference signal. The desired values (reference) for each control objective are shown in the dashed lines [18].

This example system constitutes a distributed control problem under autonomous learning supervision with each tank represented as one subsystem in the inter-connected structure. This involves the use of two-level constrained optimal control, fitting to the structure of a receding horizon control problem with an added supervision layer to compensate the inter-connection disturbance (states) yielding good fault-tolerance properties. However, in this study the fault information is not actually used for improving the fault-tolerant control performance. Details of this approach can be found in [21]. Further studies have involved fault compensation within this distributed system structure [22].

![Fig. 2. Schematic diagram of NeCST Three-Tank Benchmark System](image)

![Fig. 3. System outputs without fault](image)

IV. FDI FOR EXPERIMENTAL PLATFORM

In order to study and develop FDI for the system when subjected to different types of faults, the experiment platform has been enhanced with the addition of 3 new software modules, as shown in Fig. 4. This modification allows for real-time /on-line FDI. It should be noted that the simulation is running in real-time.

![Fig. 4. On-line FDI scheme for Three-Tank System](image)
developed using LabVIEW© (National Instruments, http://www.ni.com) running as a real-time parallel with the three-tank simulation. Namely, the both input and output variables from the Three-tank simulation (using MATLAB) have been send to Data collection module (using LabVIEW) every time interval (second) and such data will be collected and saved into the buffer within this module in term of the input and output matrices with the matrix sizes $K \times N$ and $K \times M$, respectively, and then transfer these matrices to the next module.

Second module is the PLS module, which takes the data, collates them into the relevant matrices, and performs the dimensionality reduction, and also determines the other values required for the FDI. However, as discussed in Section II, it should be noted that the dimensionality of original inputs and outputs are less than the dimensionality of the new ones and these new variables are linear combinations of the original measured variables.

In the simulation, 44 input variables (I) were measured along with 22 output variables (O). The results from the PLS module using these variables are presented in Tables 1, and 2. Fig.5 shows the results after processing the PLS shows the score and the corresponding explanations for the variances.

From the results, it can be seen that the first three scores of the new dimensionality (X and Y) have captured the major features in the data. In other words only three score/latent variables (1st, 2nd and 3rd) are sufficient to describe the process performance while the 4th score contains very little variation and it can be assumed that this value explains the measurement noise in the system. Table 1 & 2 below list the variance of each of these scores:

<table>
<thead>
<tr>
<th>Score</th>
<th>% Variance</th>
<th>Cumulative Variance</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>68.26</td>
<td>68.26</td>
</tr>
<tr>
<td>2</td>
<td>20.272</td>
<td>88.532</td>
</tr>
<tr>
<td>3</td>
<td>11.118</td>
<td>99.65</td>
</tr>
<tr>
<td>4</td>
<td>0.35</td>
<td>100</td>
</tr>
</tbody>
</table>

Table 1: Variance information of the input variables

<table>
<thead>
<tr>
<th>Score</th>
<th>% Variance</th>
<th>Cumulative Variance</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>75.331</td>
<td>75.331</td>
</tr>
<tr>
<td>2</td>
<td>15.3</td>
<td>90.631</td>
</tr>
<tr>
<td>3</td>
<td>7.569</td>
<td>98.2</td>
</tr>
<tr>
<td>4</td>
<td>1.8</td>
<td>100</td>
</tr>
</tbody>
</table>

Table 2: Variance information of the output variables

Fig.5 also shows that the first three latent values of X and Y can describe over 99.65% and 98.2% of the variation. However, as has been pointed out in [1] and [2], it is very important that the lower scores are not to ignored since they can provide additional information to aid process fault detection.

V. FAULT ANALYSIS MODULE

As discussed in Section IV, the fault-detection abilities of the FDI systems were evaluated using the simulation datasets, for period of 5,000 seconds under fault condition. Fig. 6 shows the FDI system for three-tank system in case of fault free.

Definition 1: $dU_i = U_i(t + 1) - U_i(t), \forall t$

where $U_i$ is output score/latent value-l of tank-i, respectively.
The next sets of simulation results were carried out with bias faults (20%, 40% and 60%) of the electrical heater operating point after $t = 2500$ seconds. The results of these simulations are shown in Figs. 7, 8 and 9.

Fig. 7. The example of the FDI system for three-tank simulation: (a) the fault detection (Fault in tank-1 is detected only) and (b) the relationship between the process and/or quality variables between output latent variable #1 and #4 due to bias fault (20% of heater operating point).

Fig. 8. The example of the FDI system for three-tank simulation: (a) the fault detection (Fault in tank-1 is detected only) and (b) the relationship between the process and/or quality variables between output latent variable #1 and #4 due to bias fault (40% of heater operating point).

Fig. 9. The example of the FDI system for three-tank simulation: (a) the fault detection (Fault in tank-1 is detected only) and (b) the relationship between the process and/or quality variables between output latent variable #1 and #4 due to bias fault (60% of heater operating point).

Fig. 7(a), 8(a) and 9(a) show the faults with 20%, 40% and 60% bias of heater operating point in tank-1 are detected (only detected).
Fig. 7(b), 8(b) and 9(b) present \((x_i, y_i)\) pair with the particular pattern of clusters (fault information) depending upon; fault types, fault sizes, etc.

It should be noted that in this study, the only the electrical heater fault with the various magnitudes (e.g., the magnitudes of bias faults: 20\%, 40\% and 60\% of heater operating point, respectively) are presented.

Throughout the simulation results it can be seen that the FDI units using PLS algorithm is able to detect faults and also identify the subsystem where the fault is occurred.

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VI. CONCLUSION

There have been numerous studies on the utility of MSPC in general and PLS in particular. These results and studies have shown that PLS is a useful tool for both modeling, and controlling process plants as well as for an integrated condition monitoring system. All of these studies indicate that the MSPC based methods are able to handle the high dimensionality of the data, which is a given in process plants, and also extract relevant information from this data. It is this property which is attractive, and has been used here. This paper presented ideas for the development of an FDI methods based on PLS and clustering. However, the concepts though are generic; they require fine tuning and are application dependent. The results obtained from the test platform used, namely three-tank system using “primary” process data indicates promising results. Currently work is underway to make the FDI method more efficient and less process specific.

REFERENCES