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Real-time application of multivariate statistical methods for early event detection in an industrial slurry stripper

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Abstract: Multivariate data analysis (MDA) is a well-established technique for abnormal situation management and early event detection (EED). This paper presents the development and on-line deployment of a Principle Component Analysis (PCA) model based EED system for an industrial-scale slurry stripper processing a solid state particle suspension. The developed solution was designed to detect plugging or blockage of the stripping column trays earlier than it is possible using traditional monitoring techniques and to avoid process disruption and production losses. The paper describes the project steps from data selection and preparation to the online implementation and utilization by operators and plant personnel. It was developed within a close collaboration between university and industry.

1. INTRODUCTION

Due to an Abnormal Situation Management Consortium (www.asmconsortium.com) study, the cost of lost production due to abnormal situations is at least $10 billion annually in the U.S. petrochemical industry. While 40% of it is related to equipment failures such as sensor, actuator or rotating machinery faults, and another 40% is due to people and work context factors, about 20% of the losses can be explained by process factors (Nimmo,1995). Real-time performance monitoring and early event detection can prevent undesirable operation and help to operate plants at full capacity while meeting product quality specs.

There is a huge amount of literature on fault detection and diagnosis ranging from analytical, rigorous model-based to artificial intelligence approaches and historical data-based methods (Venkatasubramanian et al., 2003). In last two decades, the application of multivariate statistical methods (and in particular Principal Components Analysis (PCA) and Partial Least Squares (PLS)) has been demonstrated to be a powerful approach for the detection and isolation of abnormal conditions in an industrial environment. These methods are able to cope with large amounts of multivariate, collinear, noisy and incomplete historical data which are routinely collected in automation systems and stored in historians. In comparison with other approaches based on systems theory and rigorous process models, PCA/PLS methods are in many cases easier to apply in an industrial environment.

The first applications of MDA methods for abnormal situation detection and diagnosis have been reported in the early 1990s (e.g. Kresta, MacGregor and Marlin, 1991; Kourti and MacGregor, 1995). Since then, these methods have been extended and enhanced rapidly. Examples are extensions to monitor batch processes and grade transitions, to deal with multiple process modes, to include process dynamics and nonlinearities, or multivariate image analysis. A number of recently published surveys and books provide an excellent overview of the state of the art and ongoing developments (Kourti, 2002; Qin 2003 and 2012; Miletic et al., 2004; Ge, Song and Gao, 2013, Kruger and Xie, 2012).

AlGhazzawi and Lennox (2008) mentioned that although many papers on MDA refer to industrial applications, there is only a limited number of documented cases of real-time applications with results interpreted by operators rather than advanced control or multivariate statistics experts. This coincides with the statement of the NAMUR organization (www.namur.de) that there is a remarkable gap between available MDA methods and the small number of applications in the NAMUR member companies (NAMUR, 2002).

Successful industrial-scale on-line applications include the detection of abnormal conditions in the fuel gas system of a condensate fractionation process in a Saudi Aramco refinery (AlGhazzawi and Lennox, 2008), breakout prevention in a continuous steel-casting process at Dofasco (Zhang and Dudzic, 2006), the supervision of batch sulfite pulp digester at Tembec (Miletic et al. 2004), early detection of anode faults in aluminium smelter at Aluminium Delfzijl (Majid et al. 2011), and furnace caking detection in a Hydrofluoric Acid Plant at Honeywell Geismar (Yoon et al., 2003).

The objective of this paper is to describe the development of a real-time early event detection system based on PCA for a slurry stripper in one of the plants at Sasol Germany

Brunsbüttel. The abnormal situation to be detected is plugging or blockage of the stripping column trays by solid state particles leading to process disruption and consequent production losses.

The paper is organized as follows. Section 2 provides a brief introduction into the MDA concepts used and the commercial tool selected for the development. Section 3 presents a process description. In Section 4, the development and validation steps for the off-line PCA model are described. Section 5 presents the architecture of the real-time application including the integration with the existing IT infrastructure and the human-machine interface. Finally, Section 6 gives experiences and conclusions.

2. METHODOLOGY AND TOOLS

PCA is a data-based multivariate statistical method that is widely used in science and engineering. For process monitoring, the usual approach is to build a PCA model for the "normal-case" operation using normal process data which span the operating region. When new data become available, this model is used to detect faults that deviate from the normal case. At the same time PCA is used as a data reduction method. High dimensional data are projected onto a lower dimensional model which is easier to visualize and analyse. Often, a few so-called latent variables are able to uncover hidden information in the original multivariate data set.

The principal components or latent variables are the result of decomposing a $(n \times k)$ normalized data matrix $\boldsymbol{X}$ as follows:

$$\boldsymbol{X} = \boldsymbol{T}\,\boldsymbol{P}^{\boldsymbol{T}} + \boldsymbol{E} = \sum_{i=1}^{A} \boldsymbol{t}_i \boldsymbol{p}_i^T + \boldsymbol{E} \qquad (1)$$

Here, n denotes the number of observations and k the number of sensors, i.e. each row of $\boldsymbol{X}$ contains a snapshot of the measured process variables at a certain time instant, and each column represents the temporal development of a process variable. $\boldsymbol{T}$ $(n \times A)$ and $\boldsymbol{P}$ $(k \times A)$ denote the scores and loading matrices, and $\boldsymbol{E}$ a matrix of residuals. Note that the dimension A of the latent variable space is usually quite small and less than the number k of the original process variables. $\boldsymbol{t}_i$ and $\boldsymbol{p}_i$ denote the scores and loadings vectors, respectively. The loading vectors which are orthogonal to each other provide the directions of maximum variability in the process. The scores represent the coordinates of the data in the new coordinate system defined by the loading vectors. The PCA model can either be calculated by singular value decomposition of $\boldsymbol{X}$ or by the NIPALS algorithm (Wold, 1966).

If new data become available, they are first normalized and then transformed into the new coordinate system:

$$t_{i,new} = \boldsymbol{p}_i^T \boldsymbol{x}_{new}^T \quad i = 1 \ldots A \qquad (2)$$

Usually, univariate Hotelling's T^2 or Squared Prediction Error (SPE) charts are used for the detection of abnormal situations. The Hotelling's T^2 value for the i-th observation

$$T_i^2 = \sum_{j=1}^{A} \frac{\boldsymbol{t}_j \boldsymbol{t}_j^T}{s_{\boldsymbol{t}_j}^2} = \sum_{j=1}^{A} \frac{\boldsymbol{t}_j \boldsymbol{t}_j^T}{\lambda_j} \qquad (3)$$

is calculated from the score vectors and their variance $s_{\boldsymbol{t}_j}^2$ which is equal to the eigenvalue λ_j of the data covariance matrix $\boldsymbol{S} = \operatorname{cov}(\boldsymbol{X}) = \dfrac{\boldsymbol{X}^T \boldsymbol{X}}{N-1}$. The SPE statistic is

$$SPE = \sum_{i=1}^{m} \left(x_{neu,i} - \hat{x}_{neu,i} \right)^2 \qquad (4).$$

It represents the average distance between the new measurements and their predictions based on the normal PCA model loading matrix and the new observation scores $\hat{\boldsymbol{x}}_{neu}^T = \boldsymbol{P}\,\boldsymbol{t}_{new}$. The SPE statistic is also known as Q statistic and similar to the DModX value (Distance to the model in the $\boldsymbol{X}$ space, (Eriksson et al., 2006)). For both statistics, upper control limits can also be defined (Kourti and MacGregor, 1995).

While the Hotelling's T^2 and SPE (or DModX) charts allow to detect the existence of a deviation from normal process variability and its size, contribution plots show how much individual process variables contribute to one of the statistical metrics. However, they do not directly provide information about the root cause of the deviation. In most cases, the root cause diagnosis cannot be fully automated but needs the involvement of process and advanced control personnel (Venkatasubramanian et al., 2003).

Based on a separate evaluation study at the beginning of the project, a commercial MDA software (SIMCA/SIMCA online from Umetrics AB, Sweden (Eriksson et al., 2006)) was selected for several reasons including the number of available interfaces to automation systems, the possible application to continuous as well as batch process data, and available references in the process industries. Due to limited resources, the in-house development of an application-specific software was not further considered.

3. PROCESS DESCRIPTION

Sasol Germany Brunsbüttel is a manufacturer of fatty alcohols and pure alumina (Al_2O_3) powder which is further processed in different branches of industry. In particular sections of the plant, slurry must be stripped to remove organic side products. This is done in stripping columns (see Fig. 1) where the slurry is fed in the top section, and the stripping medium in the bottom section of the tower. The stripping medium together with the highly volatile organic compounds is removed as overhead product, and the purified slurry is the bottoms product sent to the downstream processing stages of the process.

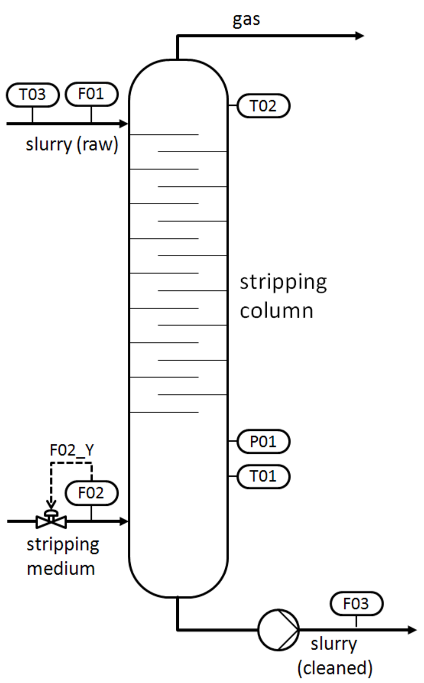

Fig. 1: Simplified P&I diagram of the slurry stripper

Due to the solids contained in the slurry, the column trays may be plugged or even blocked which leads to a disruption of the process. In the past, those process faults occurred twice a year per column in average. It can take hours to remove the blockage by either adding water to the top section (flushing), by executing a boiling up process, or – in extreme cases – by opening the tower and remove the solids mechanically.

The instrumentation includes sensors for the raw/cleaned slurry and stripping medium flow rates F01 to F03, the temperatures in the stripper bottoms and overhead section T01/T02 as well as at the slurry inlet T03, and stripper bottoms pressure P01. The stripping medium to feed rate ratio is controlled. F02_Y denotes the output of the stripping medium flow controller. Traditionally, operators try to identify plugging by observing the individual trends of those variables. Fig. 2 shows the trend of the bottoms pressure as one of the most indicative variables before and during a process upset. Note that the pressure moves within the normal operating range just until the plugging occurs. The individual trends of other variables show a similar characteristic making it impossible for the operators to recognise the disturbance early enough and to initiate counteraction. The time scale selected for Fig. 2 and the subsequent trends is two months, since operational experience and the PCA models indicate that there is a (relatively long) time span of one to two months from the start of plugging to a complete blockage of the stripper.

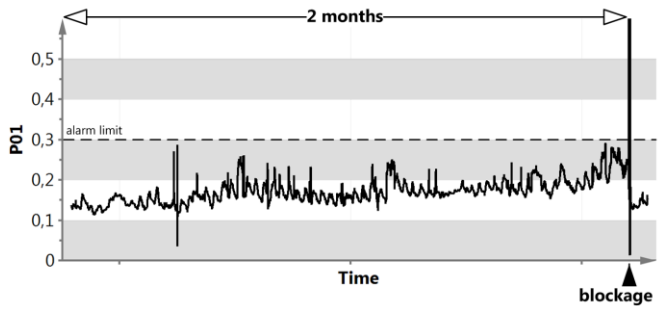

Fig. 2: Bottoms pressure before and during a process upset

4. DEVELOPMENT OF THE EED SYSTEM

As mentioned in Section 2, the PCA model is developed with historical process data in "normal" operation mode. The data is obtained from a process information and management system (PIMS). Archiving parameters of the system ensure that the recorded data is almost kept free from noise and only contains changes due to process variability. The PIMS also allows to extract interpolated data in selectable time intervals.

Based on several dialogues with the plant personnel, seven process variables shown in Fig, 1 were initially chosen to create a first (prototype) PCA model An imminent blockage is indicated by

- a bottom pressure increase due to a higher pressure loss in the trays if they are increasingly clogged by solids,
- a bottom temperature increase together with a top temperature decrease, because less stripping medium arrives at the top section,
- an increased valve opening necessary to achieve the required stripping medium flow rate caused by the higher bottoms pressure.

To select a data set for building the PCA model, the plant's operation journals were carefully reviewed to ensure that the process unit was running under normal conditions. The chosen time span included 75 days of data recorded in five minute time intervals on the plant historian, resulting in ~21,000 observations. The sampling time for data collection is the same as planned for the online application. Although a larger sampling time might be sufficient due to the slow development of the fault, a value of 5 minutes was selected for two reasons: a) the operators should see the effect of flushing immediately in the DModX trend, and b) the much higher number of observations provided for model building.

The data pre-processing included the rejection of univariate outliers by visual inspection, mean centering and scaling to unit variance (normalization).

Figures 3 to 5 show some of the modelling results. Four principle components (PC) explain 98% of variable variances. The number of PCs was chosen by cross validation (CV) shown in grey bars in Fig. 3 and by the model's capability to detect the abnormal situation as soon as possible.

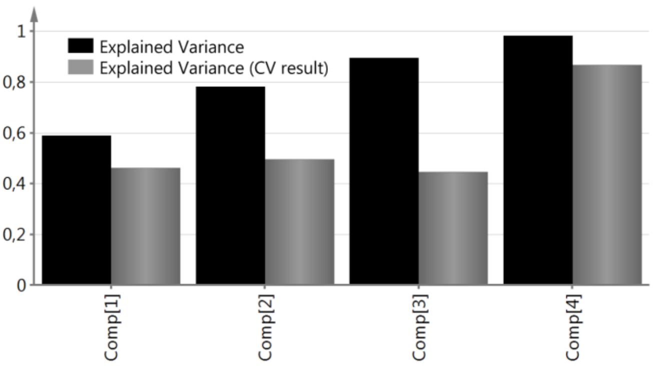

Fig. 3: Cumulated explained variance and cross validation result

Fig. 4 shows the principle components' loadings. PC1 is highly influenced by all throughput related process variables, like flow rates and the stripping medium valve opening. The bottom temperature also affects the first component. It's mainly the top temperature which affects the second PC, and the third component is primarily dependent on the bottom pressure. The last component is affected by several process variables, describing variance which has not been captured by the first three components. Note that the cross validation result is significantly affected by the fourth PC (see Fig. 3).

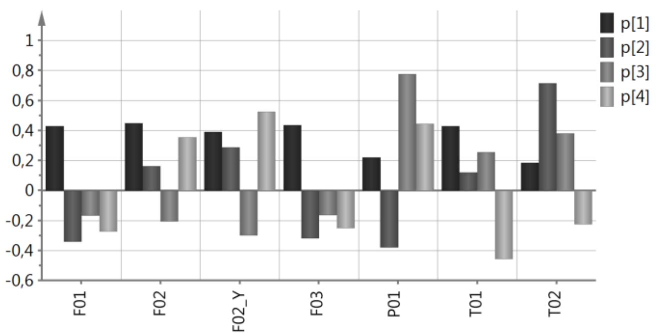

Fig. 4: Loadings of the PCA model

The impact of different column feed rates on the PCA model scores are visible in Fig. 5. The scores move from lower feed rates at the top left corner of the scores plot to higher feed rates at the bottom right corner.

In the data set selected for building the PCA model, the ratio between the maximum and minimum feed flow rates was approximately 3:1. Since the Hotelling's T^2 chart is obtained by calculating the distance from the model center, and the feed rate variation only causes a certain distance from the center without any relation to an imminent blockage, the DModX chart was chosen to detect the process upset.

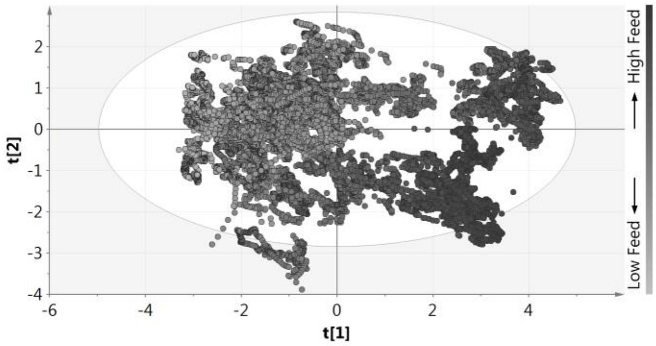

Fig. 5: Scores of the PCA model

Monitoring the model residuals of observations using the DModX provides a test whether the correlations between the variables remain the same for observations before an upset as compared to normal operation. This enables a more reliable approach to detect the column tray blockage.

The ability to detect an imminent blockage is demonstrated in the DModX trend shown in Fig. 6. Upper control limits for DModX were set after the refinement of the model which is the subsequent step described in the next paragraphs.

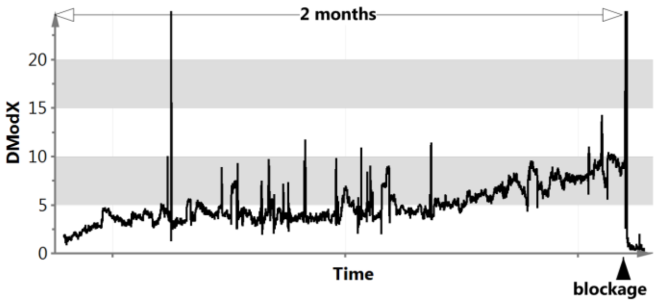

Fig. 6: DModX chart before a stripper column blockage (initial prototype model)

Two additional steps substantially increased the model's sensitivity for early event detection. First, the model data set was reviewed for possible multivariate outliers. These outliers were captured using the DModX trend. Each deviation in the trend could be assigned to events such as stripper flushing recorded in the operation journal; and all those deviations were excluded from the model data set.

Second, the model data set was extended by some intermediate variables. As mentioned in the enumeration at the beginning of this section, there are three possible indications for an upcoming blockage. According to the second and third of them, the data set was extended by the temperature difference across the column (denoted as TempDiff) and the ratio between the control loop manipulated variable and the steam input flow rate (denoted as F02_Y_F). The feed temperature (T03) was added too. In Fig. 7, the DModX trends based on the prototype and extended models are compared with each other.

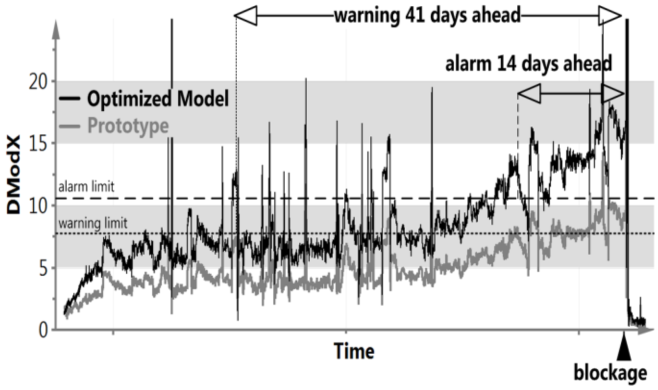

Fig. 7: DModX trend: prototype vs. optimized model

Due to the different feed rates processed in normal operation, it was impossible to select data for modelling which were approximately normally distributed. Hence, the statistical control limits for DModX calculated by SIMCA had to be checked for adequacy in order to detect faults reliably and, at the same time, avoid false alarms. Therefore, data sets from three previous blockages between 10/2010 and 01/2012 were used to analyze the DModX charts. It was found that the statistical control limits calculated by SIMCA (based on the normal distribution assumption) were too low which would have caused false alarms. Thus new limits were set which allowed an optimal detection of those historical blockages. Two different levels of operator notification were defined: a warning and an alarm level. When the warning limit is exceeded, operators are notified early enough to take corrective actions. If this is not possible for some reason, and the alarm limit is violated, the operators are alerted that the process may reach a critical state. In all historical blockage situations examined, this strategy would have provided suitable results. Based on the experience gained in the long term operation of the real-time EED system, these limits may be adjusted on-line.

At irregular time instants, spikes may occur in the DModX trends (see Figs. 6 and 7). They are caused, for example, by regular flushing of separators next to the strippers, or by sporadic partial clogging of the trays. Therefore, special means are provided to prevent alarm chattering: the warning and alarm flags are not triggered until there is an enduring limit violation of more than a pre-specified time. In case of the event shown in Fig. 7, the operators would have been warned 41 days and alarmed 14 days before the stripping column gets actually blocked. Compared to the pressure trend in Fig. 2, the monitoring via PCA leads to a much more effective detection of an imminent blockage.

In order to prevent false alarms, two exceptions were set in the monitoring system. Model execution is interrupted when the manipulated variable decreases to a value of less than 10% which means that almost no stripping medium is injected. This may happen when the plant is in shut-down mode or running its feed in a loop. The second exception is a temperature difference across the column of less than 2.2K indicating that a lot of condensed stripping medium is inject-ted.

5. REAL-TIME IMPLEMENTATION

For the online monitoring of the stripping column with the PCA model developed in section 4, the SIMCA project file has to be imported into the SIMCA-online application. SIMCA-online has a client-server architecture. The clients communicate with the server over one selectable port. That allows the installation of the server and the clients in different networks. The integration of SIMCA-online with the existing IT infrastructure at Sasol Brunsbüttel is shown in Fig. 8. The SIMCA-online server reads process variables from the PIMS via OPC-DA and writes back model outputs using the same interface. Both (PIMS and SIMCA-online) servers are located in an intermediate network between the office network and the distributed control systems (DCS). The PIMS forwards the outputs to the DCS. In the office network, additional SIMCA-online clients are available for the plant staff.

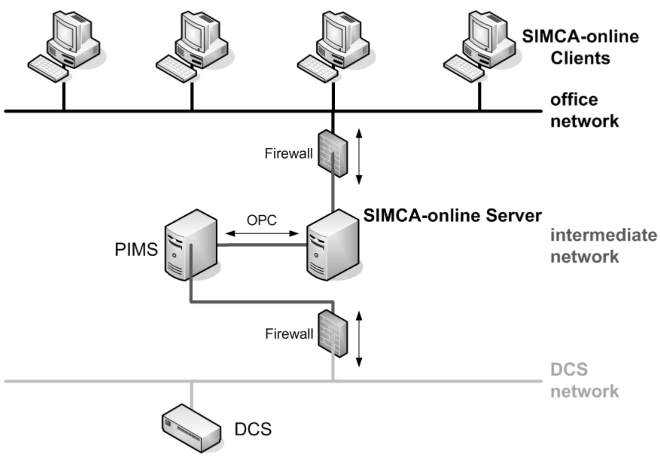

Fig. 8: Integration of the real-time application

The model calculations are executed with a sampling interval of five minutes. In order to define the server's online data source, tag numbers in the PIMS are assigned to model variables in SIMCA. A watch dog signal is provided for the detection of communication errors between the server and the DCS. All parameters necessary for the online execution are defined in the project file mentioned above.

Using the write-back function, warnings and alarms triggered by the SIMCA-online server finally show up in the DCS alarm and event system with clear recommendations for operator actions. The DModX value is also transferred to the DCS and can be displayed as a trend on the operator screens.

The SIMCA-online client provides additional functions to analyze a recent or upcoming upset. For example, contribution plots shown in the SIMCA-online client are a powerful tool for the engineers to figure out which process variables contribute most to the current deviation from normal operation. Fig. 9 shows a typical contribution plot. The variables marked with an arrow (bottoms pressure and temperature, and temperature difference across the stripper) have the largest influence. As described in section 4, this clearly supports the diagnosis of an upcoming blockage, while other possible causes of deviation from normal operation can be excluded.

For a smooth long-term operation of the monitoring system, documentation and training for different user groups have been provided.

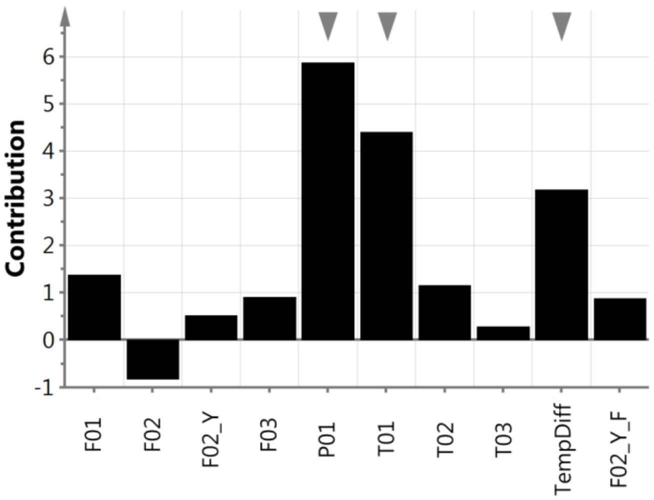

Fig 9: Contribution plot showing an imminent blockage

6. CONCLUSION

The paper describes the development and real-time implementation of an early event detection system for an industrial-scale slurry stripper based on MDA methods. Compared to traditional single-signal based monitoring, operators can be alerted far earlier and avoid production losses due to possible unit shut downs. The system is in permanent operation since August 2013 and works well for a wide range of plant throughputs. In January 2014, the EED system successfully detected an upcoming blockage which could presumably be avoided by flushing the stripper.

Keys to success of the project included the careful selection and pre-processing of process data, the use of process knowledge in defining the variables for building the PCA model and the development of an easy-to-understand interface for different user groups. The involvement of plant and DCS/IT personnel beginning with the early project stages, and the backup from the site's management allowed to gain a good understanding of the process and increased the acceptance of the new monitoring system. Since the application has shown very promising results, Sasol Germany currently considers to set up similar systems for the monitoring of other slurry strippers as well as for other process units at their Brunsbüttel site.

Acknowledgements

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