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# Data-driven Fault Detection and Diagnosis of Industrial Scale Steam Methane Reformers via Dynamic External Analysis

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## 1. EXTENDED ABSTRACT

Steam methane reformers are key process units which form an integral part of every syngas plant. Fault-free reformer operation helps to keep plant reliability high and product yield optimal; however, reformers, being complex, large-scale, and high-temperature units, undergo various failures. Rapid detection of such failures is crucial to minimize failure costs (due to product loss, equipment repair) and prevention of unplanned shutdowns. Practical constraints on continuous manual monitoring of reformers by plant engineers necessitates the usage of automatic fault detection (FD) methodologies. The easy availability of process measurements and the difficulty of development of high-fidelity first-principle models of complex systems like reformers have motivated development of expert systems based on data-driven process monitoring methodologies. However, implementation of the plant-wide FD tools in chemical process industry has been low - lack of published work from industry on industrial FD applications and the subsequent dearth of industry-relevant practical guidelines can be attributed to the low industrial adoption. In this work, the capabilities of the FD methodologies are studied for real industrial steam methane reformers operating in hydrogen manufacturing plants. The methodologies are evaluated on 2 important aspects, frequency of false alarms and fault sensitivity (minimum fault magnitude that leads to alarms). An ideal FD methodology has low false alarm frequency and high fault sensitivity (an abnormal change of small magnitude in any process variable causes alarm). Fault detection performance is tested on simulated faults by imposing a 5% abnormal increase in three crucial temperature variables.

For FD model development, 3 years of data with 1-minute sampling period is taken. A total of 36 variables/sensor-measurements are used to build the monitoring expert system. Out of the 36 variables, 27 variables are temperature or pressure measurements of several high-temperature process streams around and within the reformer box. Some of these include, amongst others, temperatures of flue gas at several locations within the reformer, temperatures at several locations in the flue gas-heat recovery section, and plant production rate. The rest of the variables include fuel flow, PSA recycle flow, combustion air flow into the burners, process feed flow, steam flow into the reformer tubes, heat content of natural gas, and temperatures of a few reformer input streams. During pre-processing, steady-state data are extracted from the plant data for implementation of steady-state-based methods.

PCA-based FD methodology failed to provide desirable performance on test dataset as the faults in 2 of the 3 variables went undetected. Consequently, external analysis methodology was attempted. Kano et. al. proposed external analysis for multivariate statistical process monitoring to explicitly consider the changes in operating conditions of ‘main’ or output variables due to changes in ‘external variables’ or input variables. Figure (1) gives an overview of the method. A PLS model between main variables (reformer outputs) and external variables (reformer inputs) is developed to decompose main variables into two parts: one part is explained by external variables and the other part is not explained. PCA is then performed on the unexplained part (output residuals) and (99.5%) control limits for SPE and $T^2$ are determined.

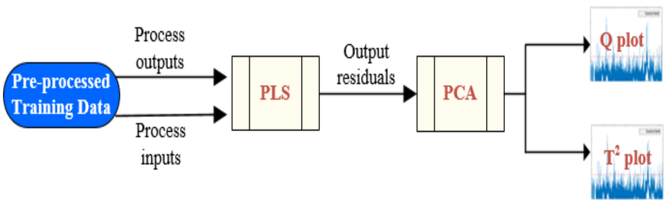


Fig. 1. Steps involved in external analysis method

The fault-detection capability of steady-state external analysis for reformer unit was found superior to PCA-based approach as only ~2% faults caused the breach of SPE control limit for all the three test variables. A problem associated with training models with steady-state operation data is that such models can be used for fault detection only when the input variables are steady. While it seems reasonable to selectively monitor a process for faults only when inputs are steady, fault scenarios where abnormality in process output leads to changes in process inputs (for example, unexpected changes in flue gas temperature can affect the reformed gas temperature and the control system will manipulate fuel flow to burners to keep the reformed gas temperature steady) will not be monitored and the faults will remain undetected. When the inputs are undergoing normal change and the whole plant is moving from one operation state to another, steady-state models, if used, can report high percentage of false fault-alarms; this happens because process variables do not maintain steady-state correlations during the transient phase when moving from one steady-state condition to the other, leading to high SPE values. one such instance where the plant experiences normal dynamic changes leading to ~10% variations in output temperatures within a few hours is shown in Figure (2). Q statistic, however, flags this normal transient period as faulty period.

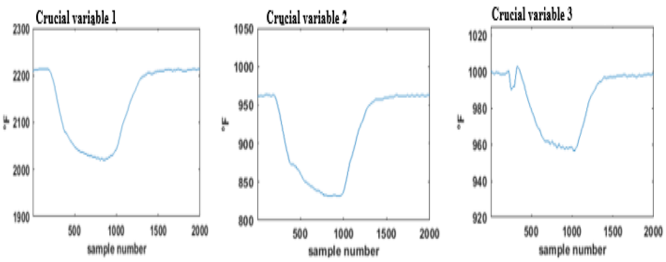


Fig. 2(a). Normal dynamic changes in crucial variables

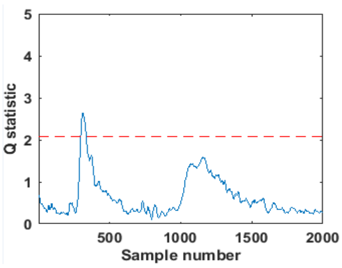


Fig. 2(b). Q statistic from steady-state external-analysis model for data during normal process changes

To account for the temporal correlations among reformer variables, dynamic external analysis was implemented. The procedure is similar to that of steady-state external analysis except that the input data matrix is replaced by its augmented version where past or lagged measurements are treated as additional process variables. Dynamic PLS is followed by a PCA on output residuals and the 99.5% control limits are determined. For the test dataset, ~ 3% faults in crucial variables caused the threshold breaches. Thus, the fault sensitivity, slightly worse than that of steady-state external analysis method, is adequate for reformer unit monitoring. The primary motivation for using dynamic variation of the external analysis method was to avoid false alarms during normal process transients. Figure (3) gives the plots of the fault-detection metrics for the normal process data from Figure (2b). It can be seen that unlike steady-state external analysis, dynamic external analysis results in Q and $T^2$ values that are well below the threshold value. Note that this period of process data was removed from the training dataset.

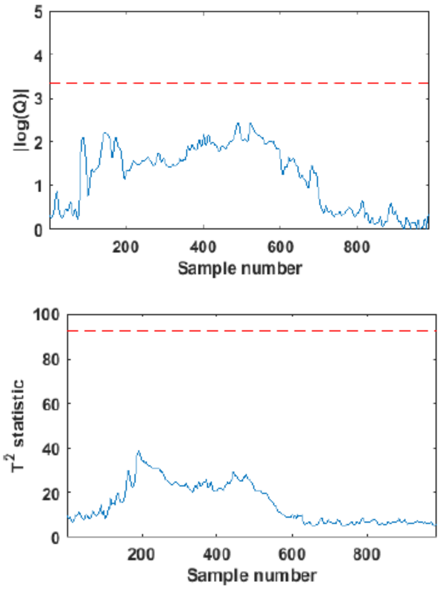


Fig. 3. Monitoring metrics from testing dynamic external-analysis model for data during normal process changes

In this work, it has been shown that external analysis - a combination of partial least squares regression and principal components analysis - can be effectively used for monitoring large-scale industrial steam methane reformers. Emphasis has added on the need for the FD methodology to be robust to dynamic process transients; in this work this is achieved through employment of dynamic variation of the external analysis method.

## REFERENCES

Kano, M., Hasabe, S., Hashimoto, I., and Ohno, H. (2004). Evolution of multivariate statistical control: application of independent component analysis and external analysis. *Computers & Chemical Engineering,* 28(6-7), 1157-1166.