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From complex real-world data to process understanding and monitoring, a use case in the chemical industry

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1 Introduction

Process analytics using all kinds of data collected along the production line, from process parameters, univariate sensors, to more complex process analyzers, such as in-line NIR or Raman probes, is now of a great importance within Operational Excellence and Continuous Improvement in different process industries, for both continuous and batch processes. Within a pilot plant or production line and using the same initial database, several goals can be achieved by choosing the appropriate data analytics/chemometrics tools: process understanding, process optimization, real-time process monitoring and troubleshooting, forecasting and control, and even predictive maintenance.

This use case will show how complex real-world industrial data has been handled to get insight into a chemical process for understanding, monitoring and troubleshooting. The singularity of this study lies in the different data analysis challenges arising from the complex nature of the process studied.

2 Material and methods

Spectra were collected on production line during one year from an in-line Kaiser Raman probe RXN4 located between two steps of a complex process (reactor and treatment) for silicone polymer manufacturing. Two different quality parameters were measured on final product.

A well-known Multivariate Statistical Process Control (MSPC) approach was implemented ([1], [2] and [3]). However, different challenges had to be addressed in order to be able to deploy the methodology:

- Massive data due to a high frequency and high resolution measurement
- High level of noise due to starts and ends of production lots
- Weak correlation between the intermediate product measured and the averaged end-product quality, since spectra acquisition was done in the middle of the whole process course
- High process variability due to solvent recycling.

3 Results and discussion

Handling of massive data was resolved by tuning an optimal data compression rate. Iterative specific data cleaning for starts and ends of production lots was performed using different chemometrics diagnostic tools. Despite weak correlation with end-product quality, end-product information was used to refine NOC (Normal Operating Conditions) dataset. And high variability of the process has been modeled within the monitoring model.

Thus, specific data cleaning, preprocessing, and modeling strategy have been the key to achieve a new insight into the process and to build a real-time monitoring tool bringing added value for process understanding, monitoring, and chemical interpretation.

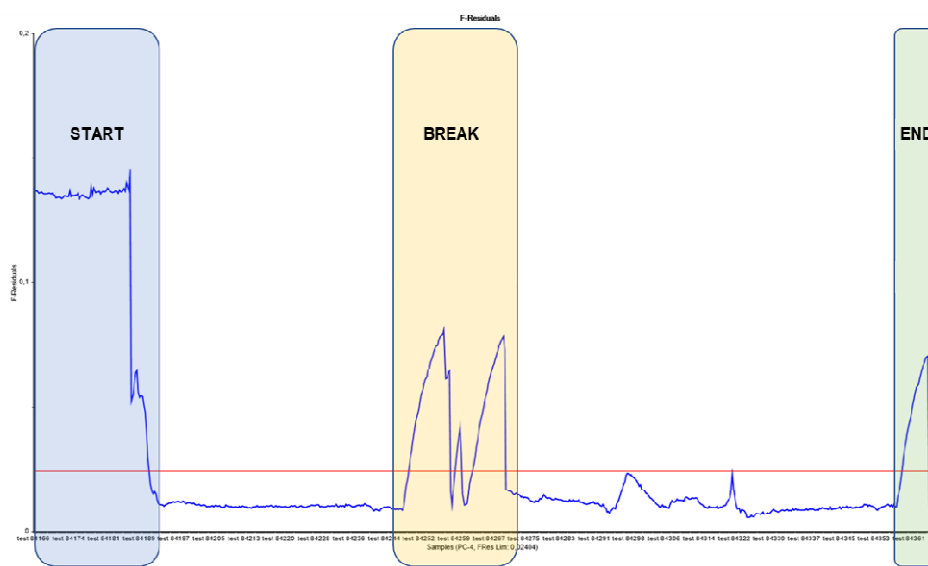


Figure 1 – Real-time monitoring tool (F-Residuals vs. time).

4 Conclusion

Multivariate data analytics has brought high value in this work for extracting useful information from on-line analyzer and for building a real-time monitoring tool of the process, despite the numerous challenges due to this complex process. Relevant dashboards useful for the operators were implemented for real-time monitoring and troubleshooting.

5 References

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