T08. Statistical methods of process monitoring and diagnostics

L.A. Rusinov, I.V. Rudakova
Saint-Petersburg State Technological Institute, Russia

Many processes in the chemical industry are potentially dangerous and require a permanent monitoring of their conditions. In case of an abnormal situation, it is highly important to determine its origin, and provide control engineers with all the necessary instructions on the recovery operation. The process monitoring and diagnostics is carried out on the basis of diagnostic models, which are able to detect the faults based on symptoms. Taking into account, that most of the processes have no analytical model describing their behaviour, especially in abnormal situations, the statistical modelling becomes important, as it does not need any knowledge of process chemistry.

The processes data is commonly multivariate, so the application of Principal Component Analysis (PCA) becomes effective. It allows not only reducing the dimensionality of a monitoring problem, but also the use of Q and T2 statistics to carry it out. There are a number of method modifications, e.g. "moving" PCA. With their help, it is possible to monitor fault processes with significant speed differences, like batch processes.

Furthermore, many production processes in the chemical industry are essentially non-linear. Therefore, the use of conventional linear PCA for their control may lead to monitoring errors. At the same time, the application of non-linear PCA methods, including kernel PCA, may result in significant computational difficulties and still cannot guarantee a sufficient sensitivity for exact detection of abnormal situations.

The origin identification of an abnormal situation in the space of principal components is a complicated task. Usually, it is executed by the estimation of variable contributions in the fault statistics. However, it is quite difficult to determine the fault, especially if it involves changes in many variables, as it frequently happens in practice. In this situation combined diagnostics methods are of use. Thus, attracting an expert information allows more effective identification. For this purpose, the two-level frame-based production diagnostic model, connecting symptoms with faults by means of fuzzy production rules can be constructed. The root frames on the upper level of the model contain information on the faults in the structural units that are selected during the decomposition of the controlled process. The daughter frames of the model contain fuzzy production rules, which determine certain faults in the actual structural unit. The origin of the fault depends on the situation similarity degree that can be determined according to some criterion.

If the expert data, connected to an actual structural unit, appears to have a lack of information, there comes the fuzzy clustering of the data for the benefit of the diagnostics. Using the clusters, the fuzzy diagnostic model, for example, the one with production rules of the Takagi-Sugeno type, can be built.

The two-level neural network diagnostic model, constructed and trained on expert analysis results can be a good choice. The upper-level network serves for the faults isolation, while the bottom-level networks determine the origin of the faults. The PCA is used for significant dimensionality reduction of the upper-level network. It allows a considerable reduction of the networks retraining time and to keep the main benefits of the expert system without inserting it into the structure.