

Kernel principal component analysis (KPCA) is a well-established data-driven process modeling and monitoring framework that has long been praised for its performances. However, it is still not optimal for large-scale and uncertain systems. Applying KPCA usually takes a long time and a significant storage space when big data are utilized. In addition, it leads to a serious loss of information and ignores uncertainties in the processes. Consequently, in this paper, two uncertain nonlinear statistical fault detection methods using an interval reduced kernel principal component analysis (IRKPCA) are proposed. The main objective of the proposed methods is twofold. Firstly, reduce the number of observations in the data matrix through two techniques: a method, called IRKPCAED, is based on Euclidean distance between samples as dissimilarity metric such that only one observation is kept in case of redundancy to build the reduced reference KPCA model, and another method, called IRKPCAPCA, is established on the PCA algorithm to treat the hybrid correlations between process variables and extract a reduced number of observations from the training data matrix. Secondly, address the problem of uncertainties in systems using a latent-driven technique based on interval-valued data. Taking into account sensors uncertainties via IRKPCA ensures better monitoring by reducing the computational and storage costs. The study demonstrated the feasibility and effectiveness of the proposed approaches for faults detection in two real world applications: Tennessee Eastman (TE) process and real air quality monitoring network (AIRLOR) data