

## **Fault-detection techniques in wastewater treatment processes**

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### **Abstract**

In wastewater treatment plants (WWTPs) management the need to meet the increasingly stringent quality standards and at the same time to minimize the operational costs has prompted the development of efficient fault detection and isolation (FDI) methods to back-up the existing control systems. The aim of this paper is to develop a new fault detection (FDI) algorithm for alternate aerobic\anoxic cycle waste-water processes for nitrogen removal. The proposed FDI algorithm is based on an adaptive version of the principal component analysis (PCA) and monitors the data produced by the ammonia and nitrate probes deployed in the oxidation tank. The adaptation of the reference system is required by the time-varying nature of the WWTP processes and is achieved by means of a moving window updating system.

The method, first developed in Matlab environment, was then ported in LabVIEW and long-time tested on the alternate aerobic\anaerobic nitrogen removal tanks of the municipal wastewater treatment plant of Mantua, Italy.

Considering the alternating process operation the algorithm has been split in two parts, each supervising one phase (aerobic and anoxic). Though they are based on the same principle, they require an individual calibration. First a preliminary screening is performed on the raw signals, in order to detect gross malfunctions such as data interruptions, spikes, anomalous steady measurements and out-of-range duration of the phases. These malfunctions are basically sensor faults and being self-explanatory, are easily detected in this preliminary screening.

The phases that pass this first filtering are examined for process-related anomalies which escape the previous simple checks. To this end a PCA-based method has been developed. For each phase both the ammonia and the nitrate signals are parametrized to

extract four parameters: the two average concentrations and their rates over the phase duration. These parameters are then processed through PCA and projected onto a reference space from which two control charts, based on the Hotelling's  $T^2$  and  $Q$  statistics, are used to identify possible departure from the "normal" conditions. If the scores produced by the tested parameters result greater than the respective thresholds in both statistics, then the corresponding phase is reported as a fault, otherwise it is considered "normal" and its parameters are used to update the reference space. The complete flow-chart of the algorithm is shown in Figure 1.

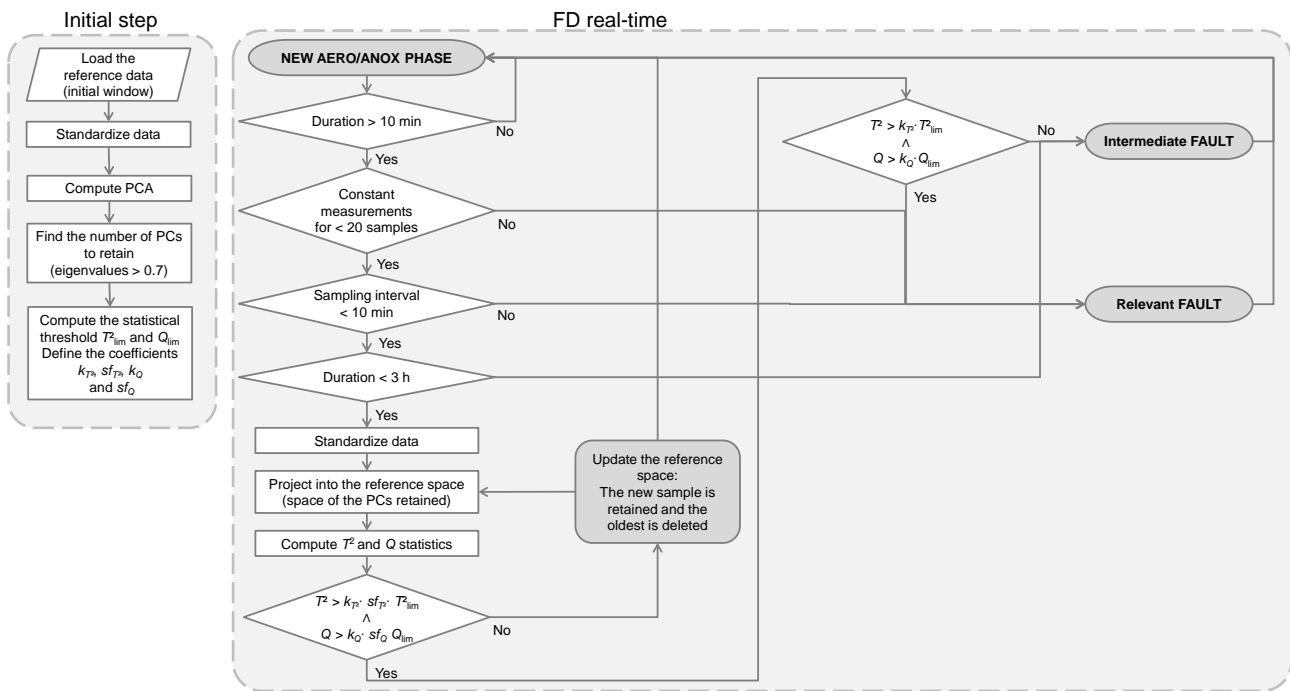


Figure 1 - Block diagram of the FDI algorithm.

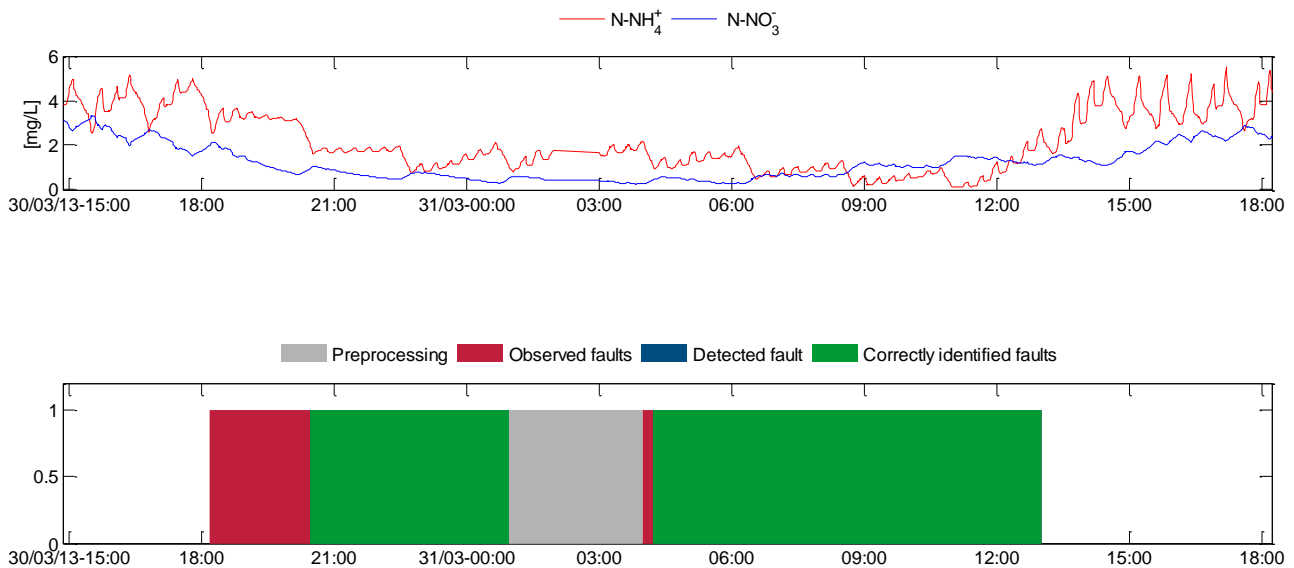
The performance of the algorithm is assessed in Table 1 by comparing the detected anomalies to the fault events actually observed in the historic plant record.

Table 1 – Performance assessment of the complete FDI algorithm.

	<i>PCA Only</i>	<i>Preliminary screening + PCA</i>	<i>Global event characterization</i>
Observed faults	89	396	14
Identified faults	42	349	14
Percentage	47.19 %	88.13 %	100%

The first column present the performance of the algorithm evaluating only the phases that resulted negative to the preliminary screening provided and it is not very satisfactory.

However adding up the performance of the preliminary check on the signal (column 2) the detection success increases dramatically, since the preliminary screening deals with the gross faults, leaving the process anomalies, which typically involve multiple consecutive aerobic and anoxic phases, to be detected by the subsequent PCA analysis. Figure 2 shows an example of a combined fault detection where both the pre-screening and the PCA parts are active at differing times.



**Figure 2 – An example of detection performance of the complete algorithm.**

The time-scale of the algorithm is very fine, investigating one phase at the time, and this is likely to produce differing responses for two consecutive aerobic or anoxic phases, one of which may yield a positive and the other a negative response, however using a more coarse time-scale could lead to a lack of definition in the detection task. Thus it makes sense to combine the phases that are logically connected into a single cycle and analyse this as a whole event. It was observed that considering successfully identified the fault events for which over half of the phases are classified as fault, the algorithm proves to have excellent detection performances raising multiple alarms during long process faults events that lead to the correct identification of all the process anomalies observed in the analysed period. As the third column shows, in this case all the observed (combined) faults are successfully identified.