240e Strategy for the Diagnosis of a Biological Nutrient Removal Plant Using Projection Methods

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Wastewater treatment plants (WWTPs) are an important part of the urban water cycle since their objective is to reduce the environmental impact of human usage of water. Nowadays many WWTPs are designed to biologically remove not only organic matter but also nutrients (nitrogen and phosphorus) from wastewaters. Therefore, the complexity of these systems has increased in comparison with those systems designed and operated only to remove organic matter. Moreover, the increasingly severe effluent quality limits imposed by law, makes the on-line monitoring of these processes absolutely essential. However, prior to establishing an on-line monitoring system, it is necessary to determine the trajectories described by the variables when the process is under normal operating conditions, and the possible deviations which can suffer these trajectories when a certain abnormality occurs.

In this work, historical data from a Sequencing Batch Reactor (SBR) operated for enhanced biological phosphorus removal (EBPR) from wastewaters have been analysed to assess the possibility to set up a multivariate statistical control system aimed at monitoring. It is a batch process with three main stages per cycle which take place in the same reactor. In the first stage, which lasts 1.5 hours, the reactor is kept in anaerobic conditions, and phosphorus is released by polyphosphate accumulating organisms (PAOs). Afterwards, the reactor is aerated for 3 hours allowing PAOs to uptake phosphorus and store it intracellularly as polyphosphate. Finally, the activated sludge is settled for 1.5 hours, thus, producing a clarified effluent of treated wastewater. Since the uptake carried out by the PAOs is larger than the release, a net phosphorus uptake is achieved. During the process five variables are collected on-line by means of electronic sensors: electric conductivity, redox potential, dissolved oxygen concentration, pH and temperature. Additionally, samples are taken periodically from the process and analysed in a control quality laboratory to determine if the process operates properly. These analyses are expensive, slow and not suitable to early detect problems in the reactor. Thus, there is a strong interest in taking advantage of the information registered in the process by means of the electronic sensors installed in the reactor in order to establish a system for on-line monitoring.

For this purpose, a historical data set of 70 cycles has been analysed, corresponding to a period of 3 months. As the duration of all cycles is the same, data are structured in a three-way matrix of 70 cycles by 5 variables by 356 instants of time. This matrix has been unfolded into a two-way structure [1]. Carrying out a Principal Component Analysis (PCA) with the variables from stage 1 and projecting the cycles over the first component, a change in the process is detected between cycles 40 and 41 due to a shift in the conductivity. The analysis of the projections over the third component reveals that cycles 41 to 46 have a behaviour different from the rest, due to a shift of pH. Conducting a PCA with the variables of stage 2 and analysing the projections over the first component, a change in the process between cycles 46 and 47 has been detected. With the second component another change appears between cycles 25 and 26. To identify the variables that discriminate among the groups of cycles 1-25, 26-46 and 47-70, a PLS-DA (partial least squares – discriminant analysis) has been carried out [2]. Analysing this model, the trajectory of conductivity is the one that best discriminates the group 47-70, while the concentration of oxygen is the trajectory with highest discriminant capability of cycles 1-25.

With the diagnosis strategies applied, three shifts have been detected. This indicates that the normal operating conditions change, and therefore in order to monitor this SBR process an adaptive approach able to capture the trends in the process should be used. In order to identify the causes that originate those changes it is very useful to compare the weights and the trajectories of the variables in the different models, and to confirm these results with the technical information available from the process.

REFERENCES:

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