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IDENTIFICATION OF ANALYTICAL REDUNDANCY RELATIONS DESIGN FOR SENSOR FAULT DIAGNOSIS OF A WASTEWATER TREATMENT STATION

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Abstract: This article deals with identification design for sensor fault diagnosis of a wastewater treatment station. First, we established a physical model of this station by simplifying and linearizing the model ASM1 (Henze et al., 1987). Then, we study the measurement values in order to find other redundancy equations. Multiple linear regression allowed the determination of a static black box type model, coherent with the physical model. The addition of temporal lags between the signals makes possible to improve the performances of this model. We show finally the use of this model for detection-localization of faults measurements.

Keywords: Diagnostic, ASM1, Data validation, Identification.

1. INTRODUCTION

In the case of an activated sludge wastewater treatment station, the complexity of the biological mechanisms (non-linear kinetics, parameters varying in time, ...) imposes the development and the use of advanced techniques of automatic control to develop a strategy of real time fault diagnosis. In our work, we use the model-based diagnosis methods based on analytical redundancy, that correspond to execute a test of coherence between measurement and the estimate provided by a model.

In a first part, we present the wastewater treatment station of Bleesbrück. To highlight the existing relations between the variables characterizing the activated sludge process of the biology, the second part of the talk is devoted to the application of the Activated Sludge Model 1 (ASM1) (Henze et al., 1987) to this station. Initially, we seek a linear model which depends on the available measurements; it was then necessary to reduce the complexity and to linearize the ASM1 model. Next we search the relations between the variables of the station by multiple linear regression. This analysis allows us, at the same time, to check in the data the relations of the second part and to underscore the redundancy relations used to determine a black box type model. We show then that this approach is useful for fault localization. In the last part, we conclude on the current results of the study.
2. BLEESBRÜCK STATION

The station has a maximum capacity of treatment of 100 000 equivalent inhabitants and it treats wastewater of urban and industrial origins. It is located near the Sûre, river which collects purified water.

2.1 Description of operation

In the purification procedure of water, we can distinguish three phases, the pretreatment, the primary treatment and the secondary treatment. The pretreatment operation consists in the elimination of all the components which could block or cause an abrasion of the conduits and pumps or disturb the treatments of decontamination. The primary treatment is composed of a rectangular aeration tank called the first biology which is an activated sludge biology and two settling tanks. The sludges in the settling tanks are recirculated in the biology. The goal of this biology is to eliminate mainly organic pollution. Phosphorus is eliminated chemically by the addition of a product. The secondary treatment is composed of a second biology split into two aeration tanks (Bio 2.1 and Bio 2.2) and two settling tanks. The aim of this treatment is to eliminate ammonium by nitrification. An overflow, limits the input flow of the second biology.

### Table 1. Available sensors

<table>
<thead>
<tr>
<th>No</th>
<th>Position</th>
<th>Name</th>
<th>Measure type</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Before</td>
<td>$Q_{in}$</td>
<td>Flow</td>
</tr>
<tr>
<td>2</td>
<td>T</td>
<td>$T$</td>
<td>Temperature</td>
</tr>
<tr>
<td>3</td>
<td>$\sigma$</td>
<td>Conductivity</td>
<td>UV absorption</td>
</tr>
<tr>
<td>4</td>
<td>$A$</td>
<td>PH</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>$O_1$</td>
<td>Dissolved oxygen</td>
<td>Suspended matter</td>
</tr>
<tr>
<td>6</td>
<td>After</td>
<td>NH1</td>
<td>Ammonium</td>
</tr>
<tr>
<td>7</td>
<td>biology 1</td>
<td>NO1</td>
<td>Nitrate</td>
</tr>
<tr>
<td>8</td>
<td>OP1</td>
<td>Orthophosphate</td>
<td></td>
</tr>
<tr>
<td>9</td>
<td>Before</td>
<td>$H$</td>
<td>Height of wastewater before the overflow</td>
</tr>
<tr>
<td>10</td>
<td>$Q_{eff}$</td>
<td>Suspended matter</td>
<td></td>
</tr>
<tr>
<td>11</td>
<td>biology 2</td>
<td>O21</td>
<td>Dissolved oxygen</td>
</tr>
<tr>
<td>12</td>
<td>$O_{22}$</td>
<td>Suspended matter</td>
<td></td>
</tr>
<tr>
<td>13</td>
<td>$O_{21}$</td>
<td>Suspended matter</td>
<td></td>
</tr>
<tr>
<td>14</td>
<td>$O_{22}$</td>
<td>Suspended matter</td>
<td></td>
</tr>
<tr>
<td>15</td>
<td>$O_{21}$</td>
<td>Suspended matter</td>
<td></td>
</tr>
<tr>
<td>16</td>
<td>After</td>
<td>NH2</td>
<td>Ammonium</td>
</tr>
<tr>
<td>17</td>
<td>$O_{22}$</td>
<td>Suspended matter</td>
<td></td>
</tr>
<tr>
<td>18</td>
<td>$O_{22}$</td>
<td>Suspended matter</td>
<td></td>
</tr>
</tbody>
</table>

### 3. MODEL OF KNOWLEDGE

With an aim of determining the relations between the variables and their structures, we model a system made up of a biology (activated sludge process) and of a settling tank. In the literature, there are various types of models which describe the mechanisms of biological degradation in wastewater treatment stations, as the ASM1, the AMS2, ASM2d, and the ASM3 (Gernaey et al., 2004). In our case we will use ASM1, which describes the biological mechanisms of degradation of the organic matter, nitrification and denitrification.

The objective is to simplify model ASM1 in order to as much as possible remove the unmeasured variables. For that we will use assumptions generally allowed in the literature and validated by the practice.

![Fig. 1. Aeration tank and settling tank](#)

The figure 1 presents the biology and the settling tank. We call $Q_e$ the flow entering the station, $Q_r$ the flow of recirculation of sludges, $Q_{out}$ the flow of extraction of sludges in excess and $Q_{eff}$ the
flow on the outlet side of the settling tank. Next, we consider, because of absence of measurement in the settling tank, that this one is perfect, i.e. no sludge leaves by the overflow the settling tank. This assumption leads to the two following equations:

\[ S = S' \]
\[(Q_s + Q_r)X = (Q_r + Q_{wa})X' \]  

where \(X\) and \(S\) are the respective concentrations of particle and substrate in the aeration tank, and \(X'\) and \(S'\) the concentrations of particle and substrate in the circuit of sludge recirculation.

### 3.1 ASM1 Modeling

In this study two traditional simplifications are applied to the original model (Julien, 1997) (the alkalinity \(S_{ALK}\) is omitted and the particulate compound interns \(X_I\) and \(X_P\) are not distinguished). Then ASM1 model includes 11 variables of states. It is a general model, which can be used to model the first or the second biology. The figure 1 represents the biological engine. The equations of mass balances are written:

\[ \dot{\xi}_\alpha = D_s \xi^{in}_\alpha + D_r \xi^{r}_\alpha - (D_s + D_r) \xi_\alpha + R_\alpha \]  

where \(D_s = \frac{Q_s}{V}\), \(D_r = \frac{Q_r}{V}\), \(V\) is the volume of the aeration tank and \(R_\alpha\) correspond to the degradation of the compound \(\alpha\) and \(\xi^{in}_\alpha\), \(\xi^{r}_\alpha\), \(\xi_\alpha\) indicate the concentration of the compound \(\alpha\) in the influent, the recycling and the aeration tank, i.e.:

\[ \xi = [S_1, S_2, S_3, S_4, S_5, S_6, S_7, S_8, X_I, X_5, X_6, X_7, X_8]^{T} \]

The various values of \(R_\alpha\) are explicitized in table 2 and table 3. The parameters \(Y_A, Y_H, f_{X_I}, i_{NBM}\), according to time. The \(k_{LA} (S_i^{out} - S_i)\) term corresponds to the supplying of air in biology, i.e. with the operation of the aerators of biology. The terms in \(p_j\) with \(j=1...8\), correspond to the kinetics of the degradation model and are explicit in table 3.

To be able to apply model ASM1 to our situation, it should be reduced for taking into account only the measured variables.

### 3.2 Reduction of model ASM1

The simplifying assumptions used are inspired by (Chachuat, 2001) and (Gomez-Quintero, 2002):

- **Absence of anoxic growth of heterotrophs.** Indeed, the wastewater treatment station does not have a period of significant anoxia, therefore the term \(p_2\) is removed from the various values of degradation \(R_\alpha\) (table 2).
- **Independence of \(S_I\).** The variations of the inert soluble organic matter concentration \(S_I\) do not have any influence on the others composed and conversely, we then omit this compound in the model, by removing the state variable of the equation (3) with \(\alpha = 1\).
- **Simplification of model dynamic.** Theory of the singular disturbances makes possible to consider that \(X_I, X_A,\) and \(X_H\) have slow dynamic. Thus these variables are considered constant over a few hours.

The corresponding states variables are removed from the equation (3) corresponding to \(\alpha = 7, 9\) and 10.

- **Simplification of the organic compounds.** The measurement of the chemical oxygen demand (COD), does not make possible to distinguish the soluble part \((S_5)\) and the particulate part \((X_5)\) (Smets et al., 2003). A single organic compound then is considered: \(X_{COD} = S_5 + X_5\)
- **Simplification of the nitrogenized compounds.** Model ASM1 distinguishes four nitrogenized fractions \(S_6, S_7, S_8\) and \(X_8\). The process of ammonification of soluble organic nitrogen (kinetic \(p_8\)) is assumed constant. The concentration \(S_{ND}\) being constant, the modeling of \(X_{ND}\) is then useless, because this concentration is only used in the estimate of \(S_{ND}\). With this assumption, the ammonium internal formation is also considered constant.

In the station, the flow of recirculation is higher than the flow of extraction of sludges, one supposes that \(\frac{D_{wa}}{D_r + D_{wa}} \ll 1\). Thus the \(X_8\) term is neglected from the equation \(X_{COD} = S_5 + X_5\). Next one defines the soluble fraction of the organic compounds by \(f_{SS} = \frac{S_5}{X_{COD}}\). \(X_{COD}\) can be written:

\[ f_{SS} = \frac{S_5}{X_{COD}} = \frac{S_5}{S_5 + X_5} \]

\[ X_{COD} = S_5 + X_5 \]

\[ f_{SS} = \frac{S_5}{S_5 + X_5} \]

\[ S_5 + X_5 = X_{COD} \]

\[ f_{SS} = \frac{S_5}{X_{COD}} \]

\[ X_{COD} = S_5 + X_5 \]

\[ f_{SS} = \frac{S_5}{S_5 + X_5} \]

\[ S_5 + X_5 = X_{COD} \]

\[ f_{SS} = \frac{S_5}{X_{COD}} \]
We linearize the model (6) with the following variables:

\[ X_{\text{COD}} = D_s (X_{\text{COD}}^n - f_{\text{SS}}X_{\text{COD}}) - \frac{1}{Y_H} \rho_1 \]
\[ + (1 - f_{X1})(\rho_4 + \rho_5) \]  

(5)

It is also supposed that the concentration, at the input of the station, of dissolved oxygen is negligible in front of the concentration in the tank \((S_{\text{O2}}^n = 0)\). Then, starting from the equations (3, 5), the following reduced model is as follows:

\[
\begin{align*}
X_{\text{COD}} &= D_s \left( X_{\text{COD}}^n - f_{\text{SS}}X_{\text{COD}} \right) - \frac{1}{Y_H} \theta_1 \\
&+ (1 - f_{X1})(\rho_4 + \rho_5) \\
\dot{S}_{\text{NO}} &= D_s \left( S_{\text{NO}}^n - S_{\text{NO}} \right) - i_{\text{NBM}} \theta_1 \\
\dot{S}_{\text{NH}} &= D_s \left( S_{\text{NH}}^n - S_{\text{NH}} \right) - i_{\text{NBM}} \theta_1 \\
\dot{S}_{\text{O2}} &= -D_s S_{\text{O2}} - \frac{1}{Y_H} \theta_1 \\
\end{align*}
\]

(6)

with constants:

\[
\begin{align*}
D_s &= \frac{Q_S}{V} \\
\theta_1 &= \mu_H X_H \\
\theta_2 &= (1 - f_{X1})(\rho_4 + \rho_5) \\
\theta_3 &= \rho_A X_A \\
\theta_4 &= k_{A,N} S_{\text{NO}}^n \\
\end{align*}
\]

Hence the model obtained depends only on nine variables: \(D_s, X_{\text{COD}}^n, X_{\text{COD}}, S_{\text{NO}}, S_{\text{NO}}^n, S_{\text{NH}}^n, S_{\text{NH}}, S_{\text{O2}}\) and of the aerators working. For simplicity, one tries now to find linear relations.

### 3.3 Linearization of the reduced model

We linearize the model (6) with the following considerations:

- In our case, biology 1 does not have an anoxia period, then it is supposed that the dissolved oxygen concentration is important, i.e. \(S_{\text{O2}} >> K_{\text{O2,H}}\) and thus \(\frac{S_{\text{O2}}}{S_{\text{O2}} + K_{\text{O2,H}}} \approx 1\); one uses the same assumption with \(K_{\text{O2,A}}\), thus \(\frac{S_{\text{O2}}}{S_{\text{O2}} + K_{\text{O2,A}}} \approx 1\).

- To linearize the equations (6) compared to the state variables \(X_{\text{COD}}, S_{\text{NH}}\) et \(S_{\text{NO}}\), one simplifies:

\[
\begin{align*}
X_{\text{COD}} &= a_{\text{COD}} X_{\text{COD}} + b_{\text{COD}} \\
\end{align*}
\]

where \(a_{\text{COD}}\) and \(b_{\text{COD}}\) are constants.

\[
\begin{align*}
S_{\text{NH}} &= a_{\text{NH}} S_{\text{NH}} + b_{\text{NH}} \\
S_{\text{NO}} &= a_{\text{NO}} S_{\text{NO}} + b_{\text{NO}} \\
\end{align*}
\]

where \(a_{\text{NH}}\) and \(b_{\text{NH}}\) are constants.

- Moreover, the products of state variables are also replaced by terms of type \(S_{\text{S}} S_{\text{y}} = S_{\text{S}} S_{\text{y}} + S_{\text{S}} S_{\text{y}}\) with \(S_{\text{S}}\) and \(S_{\text{y}}\) constant average values of the variables \(S_{\text{S}}\) and \(S_{\text{y}}\).

Then one finds a linear system with variable parameters, however the dilution ratio relating to the input flow \((D_s(t))\) and the operation of the aerators \((k_{\text{LA}}(t) = S_{\text{O2}} - S_{\text{O2}}(t))\) depend on time.

Discretization of the linear model from a numerical point of view gives with a sampling step of \(\Delta\):

\[
\begin{align*}
X_{\text{COD}}(k + 1) &= \Delta \left( D_s(k) X_{\text{COD}}^n(k) + A_{\text{COD}}(k) X_{\text{COD}}(k) + B_{\text{NH}} S_{\text{NH}}(k) + k_1 \right) \\
S_{\text{NO}}(k + 1) &= \Delta \left( D_s(k) S_{\text{NO}}^n(k) + C_{\text{NO}}(k) S_{\text{NO}}(k) + D_{\text{NH}} S_{\text{NH}}(k) + k_2 \right) \\
S_{\text{NH}}(k + 1) &= \Delta \left( G_{\text{NH}}(k) S_{\text{NO}}(k) + R_{\text{NH}} S_{\text{NH}}(k) + E_{\text{NH}}(k) S_{\text{NH}}(k) + F_{\text{COD}} X_{\text{COD}}(k) + k_3 \right) \\
S_{\text{O2}}(k + 1) &= \Delta \left( G_{\text{O2}}(k) S_{\text{O2}}(k) + H_{\text{NH}} S_{\text{NH}}(k) + I_{\text{COD}} X_{\text{COD}}(k) + k_4 \right) \\
\end{align*}
\]

(8)

where parameters \(A_{\text{COD}}(k), B_{\text{NH}}, C_{\text{NO}}(k), D_{\text{NH}}, E_{\text{NH}}(k), F_{\text{COD}}, G_{\text{O2}}(k), H_{\text{NH}}, I_{\text{COD}}, k_1, k_2, k_3\) and \(k_4\) are identified according to the linear model, for example \(G_{\text{O2}}(k) = \frac{1}{k} - D_s(k) - k_{\text{LA}}(k)\).
To extract the relationship between the variables of biologies and obtaining redundancy relations connecting the variables of the two biology sets, we will now used multiple linear regression.

4. BLACK BOX MODEL

To build a black box model by multiple linear regression, we choose a period where the water temperature is varying a bit thus allowing to free itself from this disturbance. The period include variations of pollutant because of the week-end (close of industries).

4.1 Static model

Initially, explained variables (table 4) are determined by multiple linear regression by adding the most explanatory variables in first (variable 55 corresponds to a constant). If one calls $y_i(t)$ the explained variable, $u_j(t)$ the explanatory variables and $\theta_j$ the parameters associated with the explanatory variables, then one finds a linear model of the form:

$$y_i(t) = \sum_{j=1}^{p} \hat{\theta}_j u_j(t)$$

where $p$ represent the number of explanatory variable.

The estimates $\hat{\theta}_j$ of the parameters and $\hat{y}_i(t)$ of the measurement are determined by minimization of the quadratic criterion corresponding to the sum of the squares of the differences between measurement and estimate.

The table 4 specifies the coefficient of correlation of each estimated variable $\hat{y}_i(t)$ towards its measurement $y_i(t)$. Let us note that these calculations were carried out on a data set not used for the identification.

One notices that in the case of the measurement of the pH (5), it is not possible to build a model, because of weak correlations with the other variables. Whereas the flow (1) is explained only from the height measure of the overflow (11) and vice-versa, which translates a strong correlation between these two measurements.

4.2 Dynamic model

By putting back certain parameters, one can improve the quality of modeling. One considers, moreover, the same delay of 120 points (signal number from 19 to 36) and 240 points (signal number from 37 to 54), i.e. a lag of 1h and 2h, which corresponds roughly to the residence times of the water used in the first and the second biology. The table 5 presents the same information as in the table 4 but in the dynamic case. The constructed models are, when the redundancy are near direct (like parameters 12 and 14 or 13 and 15), good. The other model must be improved.

The determined model for NO1 is then:

$$NO1(k) = 0.38 \cdot NO1(k - 120) - 0.03 \cdot O1(k - 120) - 0.01 \cdot O1(k) + 0.02 \cdot N11(k - 120) + 0.75 \cdot N11(k) + 0.23$$

The figure 2 represents the estimate of the concentration of NO1 with the static model and the difference between its estimate and its measurement, this difference is named residual. The figure 3 shows the estimate and the residual of this same variable but with the dynamic model. These two estimates are carried out on validation data, one notices an better estimation in the dynamic case. For the residual determined with the dynamic model, it is necessary to adapt the test of fault detection according to the nature and the amplitude of the defect.
4.3 Use of the models for the diagnosis

The construction of the incidence matrix of the various variables for the dynamic models makes possible to highlight the ability of locating the sensors faults. Indeed, this matrix shows the relationship between two classes of objects. If we consider two classes, X for the residual and Y for the parameters, the matrix has one row for each element of X and one column for each element of Y. The entry in row x and column y is 1 if x and y are related (called incident in this context) and 0 if they are not.

For example, if a fault appears on the temperature measurement (2), then the tests of fault detection of residuals 3, 4, 7, 8 and 10 must be positive, one can thus locate the defect. This table also makes it possible to highlight impossibility of dissociating a defect on the sensor MES21 (13) and on the sensor MES22 (15), because in both cases the tests of fault detection of residuals 13 and 15 must be positive, it is then necessary to have additional information to locate the defect. One is in the same case to locate a defect appearing on the sensor O21 (12) and that P22 (14).

5. CONCLUSION

To build models for fault diagnosis, the first stage is the comprehension of the system in order to release the relationship between the measured variables. In optics to highlight linear redundancy relations between the variables, we used ASM1 model. But not having measurements of all the variables of this model, it should initially have been reduced by assuming realistic and commonly accepted assumptions. To determine the simplest possible relations, we linearized it. We thus determined the structure of the relations between the variables.

After having found the structure of the relations between the variables describing the operation of biologies, we were then interested in the determination of the redundancy relations between the variables of the station, by multiple linear regression. This regression allowed, by adding the most explanatory variables successively, to build black box models. It is however necessary to take into account, in modeling, the need for locating a fault when it is detected. The last part of this article approaches this problem.

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