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# Dynamic Modeling of the Efficiency in a Uasb Reactor for Milk Wastewater Treatment

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Abstract: - There is a need to develop methodologies enabling one to determine UASB reactor performance, not only for designing more efficient UASB reactors but also for predicting the performance of existing reactors under various conditions of influent wastewater flows and characteristics. In this work dynamic mathematical models for the prediction of the efficiency of a UASB reactor were developed. The dynamic modeling technique was applied successfully to a three-month data record from a laboratory milk wastewater treatment UASB reactor. The technique used included regression analysis by residuals. 11 parameters were examined including the following: % COD efficiency, influent COD, COD reduction, biomass produced, biogas production rate, % methane in biogas, alkalinity, reactor's temperature and RedOx, recirculation vessel's temperature and pH, and each parameter with a time lag of up to 3 days. Finally, after all parameters and all time lag trials two were the best fitted models that were developed. The models' adequacy was checked by $X^2$ test and F test for a data record of the same UASB reactor but at a different time period and proved to be very satisfactory. Additionally, the model's ability to predict and to control the plant's operation was examined. Simulation results thus obtained were carefully analyzed based on qualitative understanding of UASB process and were found to provide important insights into key variables that were responsible for influencing the working of the UASB reactor under varying input conditions.

Key-Words: -anaerobic digestion, dynamic model, milk wastewater, efficiency, Upflow Anaerobic Sludge Blanket

## 1 INTRODUCTION

Anaerobic treatment is a popular choice for removing biologically degradable organic matter in domestic and industrial wastewater. This is due to the economic advantages of anaerobic processes and the low generation of surplus sludge [1,2]. One of the most popular anaerobic treatment technique is the upflow anaerobic sludge blanket (UASB) process, developed in the 1970s by Lettinga and co-workers in the Netherlands [3].

Several researchers have enhanced the state-of-the-art on design, operating procedures, and performance characteristics of such reactors. Through these efforts, a large volume of data on UASB reactor performance under various operating conditions has been generated. Interpretation of this data has undoubtedly enhanced the qualitative understanding of the UASB process. Based on the qualitative understanding of the UASB process gained over the years, several attempts have been made to develop mechanistic models for quantitative description of UASB reactor performance under various operating conditions. However, none of the mechanistic models are able to completely explain or predict the performance of a UASB reactor treating wastewater from industrial or domestic sources under various input conditions. The deficiencies in mechanistic model formulation are primarily due to insufficient qualitative understanding of the process dynamics in the UASB reactor under various input conditions, and may only be overcome through additional empirical observation and analysis of experimental data on UASB reactor performance [4].

Given the scenario described above, developed of an empirical model for predicting UASB reactor performance seems to be an attractive proposition. Simulation studies using a validated empirical model and subsequent analysis of the simulation results may provide valuable information regarding behavior of UASB reactor under a variety of conditions. This may result in deeper understanding of the UASB process and thus provide valuable input for "fine-tuning" of mechanistic models for UASB reactors [5,6] .

The aim of this work is the application of a suitable methodology, so as to derive a dynamic mathematical model for the control of an operating anaerobic plant, either laboratory or industrial. The methodology chosen is the regression analysis by residuals, whose main advantages are:

- The model's construction only needs data of routine determinations usually performed in any plant.

- The derived model takes into account all the particularities of the specific plant thus can successfully control plant's operation.

# 2 METHODOLOGY

## 2.1 Dynamic model

The dynamic model used in this study was developed from measurements recorded at equally spaced time intervals. If the response at time t is denoted by $Y_t$, the model will contain terms of the form:

$Y_{t-1}$, $Y_{t-2}$ , …, $Y_{t-n}$

where $Y_{t-1}$ = response one sampling period in the past

$Y_{t-2}$ = response two sampling periods in the past, and so on

Additionally, for variables, $X_j$, which act as inputs, terms of the following type will appear in the model:

$X_{j,t}$, $X_{j,t-1}$, $X_{j,t-2}$,…, $X_{j,t-m}$

where $X_{j,t}$ = current measurement of variable j at time t

The model form, which is linear in the coefficients, is:

$$Y_t = k_o + A_1Y_{t-1} + A_2Y_{t-2} + \dots + A_nY_n + k_{10}X_{1,t} + \dots + k_{1m}X_{1,t-m} + k_{20}X_{2,t} + \dots + k_{2n}X_{2,t-n} + \dots$$

This model is called a lagged regression model because the variables that are the "independent variables" are current values or values at previous times or "lags"[7].

## 2.2 Residual analysis

Building the regression models by residual analysis will be presented in this article. The method consists of the following steps:

Step 1: Choose the variable best correlated with the Y-variable, transform it as necessary to produce a straight line, and perform a least-squares regression with the dependent variable (Y-variable to be predicted with a correlation coefficient $R_0$). The result will be an equation of the form:

$$\hat{Y} = b_0 + b_1 f(X_1)$$

where $\hat{Y}$ = predicted value of Y-variable, $b_0$ and $b_1$ are constants and $X_1$ = variable

Step 2: Calculate "residuals" as follows:

$Z_i = Y_i - [b_0 + b_1 f(X_{1,i})]$

where $Z_i$ = residuals, $Y_i$ = data for variable to be predicted and $X_{1,i}$ = data for variable $X_1$.

Step 3: Choose the best-correlated X-variable. Transform the X-variable, if necessary, to yield a linear plot.

Step 4: Add the new, transformed variable to the regression model, and perform a least-squares fit by computer, resulting in:

$$\hat{Y} = b_0 + b_1 f(X_1) + b_2 g(X_2)$$

Step 5: Calculate residuals and repeat the process until all variables have been added. Each time the correlation coefficient R of the model is:

$R = R_0 + R_1(1-R_0) + \dots\dots$

Each term of the equation expresses the participation of each variable in the final correlation coefficient.

Step 6: Check the goodness-of-fit of the model. Moderate deviations from a straight line may not be serious [8]. The adequacy of a theoretical model implies the difference between the observed and the expected results. This was checked by and $X^2$ test.

# 3. CASE STUDY

In this study, multiple linear regression was used to develop a discrete dynamic model for a UASB reactor. For the construction of the dynamic model a three-month data record from a UASB reactor treating milk wastewater was used. The reactor's volume was 22L and the mean hydraulic retention time of the wastewater was about 1 day (Figure 1).

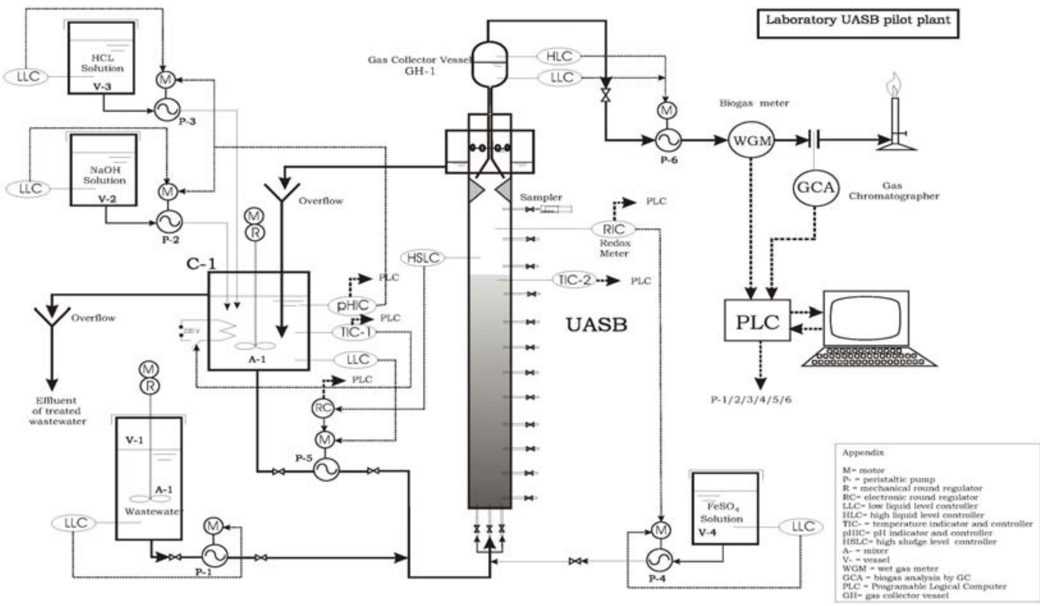


Figure1: Laboratory Pilot UASB Plant

In order to control the reactor's operation and efficacy, various parameters such as recycle vessel's temperature and pH, UASB reactor's temperature and RedOx and biogas production rate are on-line measured and so daily measurements of these parameters are available. Apart from these, % COD efficiency, influent COD rate (g COD/d), COD reduction (g COD/d), biomass produced as Volatile Suspended Solids (g VSS/d), biogas production rate (L/d), % methane in biogas, bicarbonate alkalinity (g $CaCO_3$/L) are almost daily measured in the laboratory. Subsequently, a data record of 11 variables (Figure 2) was accessible so as to build a prediction model.

Thus, this study's main objective was to correlate the % COD efficiency with the variables of the data record with a time lag up to 10 days. The correlation was achieved using the technique mentioned above, regression by residual analysis.

The correlation attempt included the equations:

$Y = A + B X$

$Y = A e^{BX}$

$Y = A + B \ln X$

$Y = A + B \sqrt{X}$

$Y = A + \dfrac{B}{X}$

$Y = A X^B$

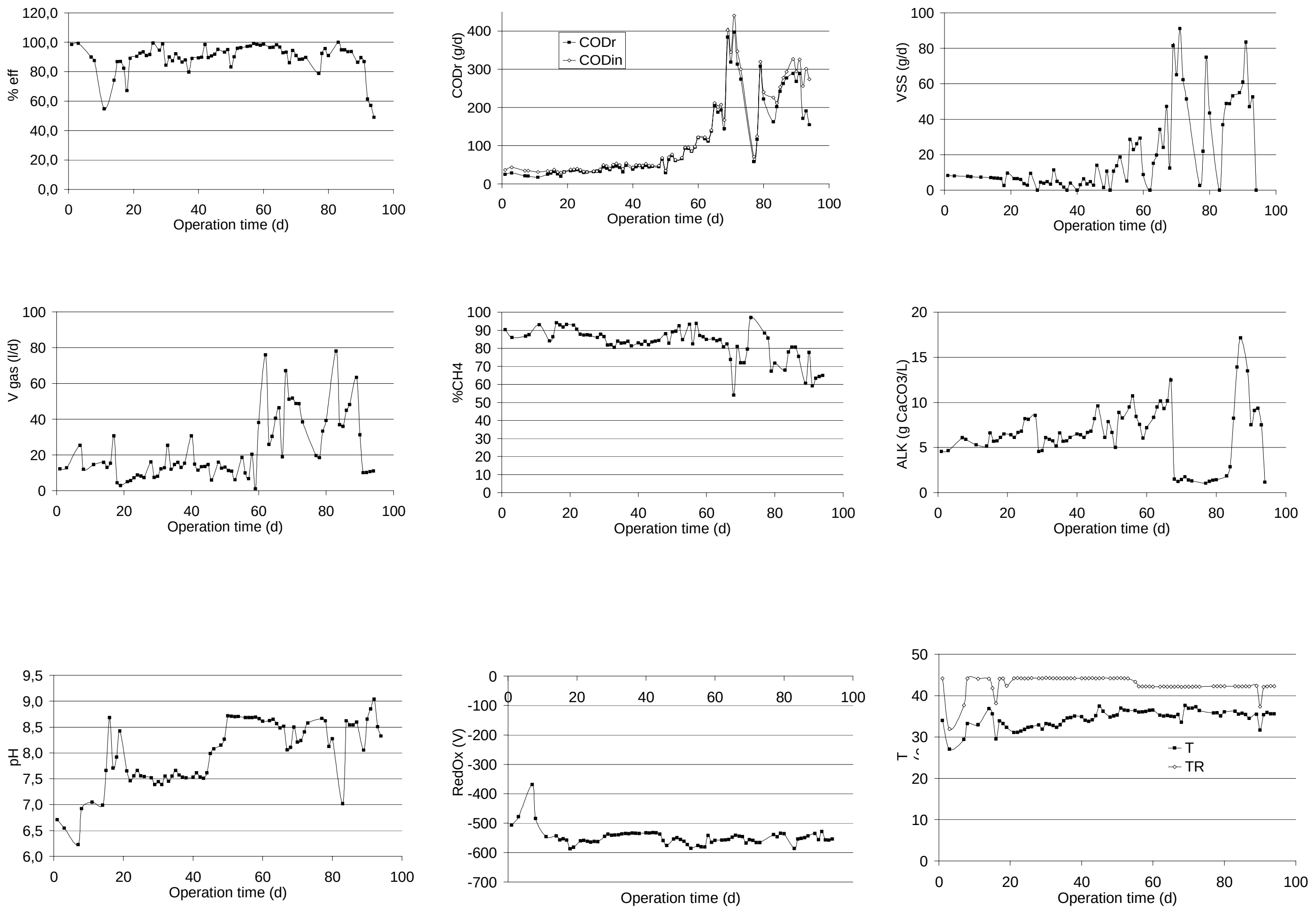


Figure 2. Fluctuation of wastewater's and reactor's characteristics

## 4. RESULTS AND DISCUSSION

Using the methodology mentioned above and the data of Figure 2, the following models were developed.

*Model 1*

The variables that were strongly correlated with the % COD efficiency were:

- % COD efficiency (%eff), with time lag t=1d
- % methane in biogas ($CH_4$), with time lag t=3d
- Recycle vessel's temperature ($T_R$) with time lag t=2d
- Influent COD mass flow, $COD_{in}$, with time lag t=0d

The dynamic model developed to relate % COD efficiency to these variables was:

$$\%Efficiency = -5836{,}1\cdot\left(\frac{1}{\%eff}\right)_{t=1} - 1421{,}5\left(\frac{1}{CH_4}\right)_{t=3}$$

$$-3965{,}8\left(\frac{1}{T_R}\right)_{t=2} + 0{,}0214(gCODin)_{t=0} + 261{,}04$$

(R =0,975) Equation 1

The variables of the consecutive levels of regression analysis are shown in Table 1.

Table 1: Levels of the regression by residual analysis of the model

| Level | Best-fitted Variable | Variable's participation % in the final R |
|---|---|---|
| 1st | $(\%eff)_{t=1}$ | 78,9 |
| 2nd | $(CH_4)_{t=3}$ | 8,8 |
| 3rd | $(T_R)_{t=2}$ | 9,1 |
| 4th | $COD_{in,t=0}$ | 3,2 |

*Model 2*

The variables that were strongly correlated with % COD efficiency were:

- % COD efficiency (%eff), with time lag t=1d
- RedOx, with time lag t=3d
- Recycle vessel's temperature ($T_R$) with time lag t=2d

The dynamic model developed to relate biogas production rate to these variables was:

$$\%Efficiency = -5331{,}6\cdot\left(\frac{1}{\%eff}\right)_{t=1} + 94214\left(\frac{1}{RedOx}\right)_{t=3}$$

$$-5924{,}2\left(\frac{1}{T_R}\right)_{t=2} + 458{,}11$$

(R=0,975) Equation 2

The variables of the consecutive levels of regression analysis of the third model are shown in Table 2.

Table 2: Levels of the regression by residual analysis of model 2

| Level | Best-fitted Variable | Variable's participation % in the final $R^2$ |
|---|---|---|
| 1st | $RedOx_{t=3}$ | 52,8 |
| 2nd | $(\%eff)_{t=1}$ | 37,0 |
| 3rd | $(T_R)_{t=2}$ | 10,2 |

**4.1 Goodness-of-fit test**

The correlation coefficient R that was calculated for the resultant model cannot give sufficient information for its adequacy. In other words, it cannot predict how the model will react in an unknown data range. In order to check the model, F and $X^2$ tests were conducted for a data record of the same UASB reactor but at a different time period.

Figures 3 and 4 compare the observed values to the predicted values of models 1 and 2 respectively for the new study period.

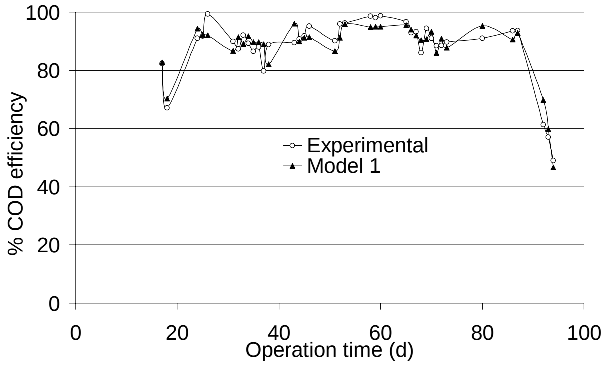


Figure 3: % COD efficiency, predictions and observed values for the new time period for model 1

They are plots of the predicted % COD efficiency based on previous actual waste and system operating data. Both models predict the ratio adequately well.

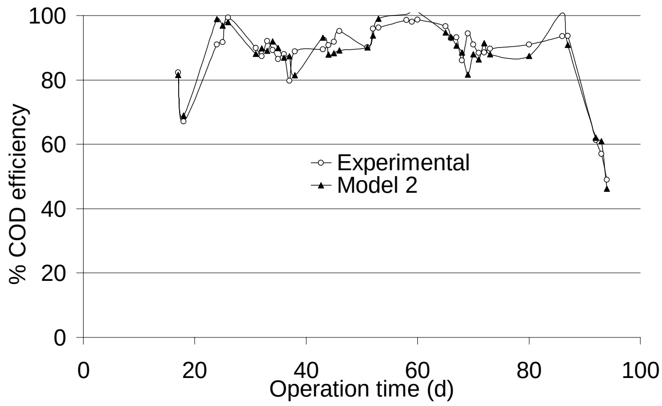


Figure 4: % COD efficiency, predictions and observed values for the new time period for model 2

The results of $X^2$ and F tests that are shown in Tables 3 and 4 reveal that the models can be a satisfactory prediction tool for the specific plant.

Table 3: Goodness-of-fit using $x^2$ test

| Model | Degrees of freedom | $x^2$ | Results |
|---|---|---|---|
| 1 | 4 | 0,978 | Perfect |
| 2 | 4 | 2,158 | Perfect |

Table 4. Goodness-of-fit using F test

| Model | Degrees of freedom | F | Results |
|---|---|---|---|
| 1 | (71, 31) | 0,170 | Perfect |
| 2 | (71, 33) | 0,184 | Perfect |

# 5 CONCLUSIONS

The methodology of regression analysis by residuals for the construction of a dynamic model proved to be very satisfactory. It is worth noticing that for this kind of model construction it is not necessary to conduct tedious factorial experiments, but routine determinations in a plant are sufficient. The models that arise from this data can be used as a powerful tool for the plant's control.

An important aspect that has to be examined is the model's ability to predict and control the plant's operation. This ability is based on how handlable the parameters are and how long is their time lag. The derived models have a satisfactory ability for prediction and thus control due to the fact that most parameters (model 1: three out of four, model 2:all) have time lag over t=1day.

Despite the fact that the three models have the same effectiveness to estimate the % COD efficiency, the results of the goodness-of-fit tests reveal a slight superiority of model 1. On the other hand, model 2 includes just 3 parameters that can be easily measured. Besides this, all parameters of model 2 have a time lag of more than one day and thus, model 2 can also be considered very useful.

# 6 APPENDIX

| | |
|---|---|
| $T_R$ | Recycle vessel's temperature |
| pH | Recycle vessel's pH |
| T | Reactor's temperature, °C |
| RedOx | Reactor's RedOx, mV |
| $Q_B$ | Biogas production rate, L/d |
| %eff | % COD efficiency |
| $COD_{in}$ | Influent COD mass flow, g COD/d |
| Biomass | Biomass produced as Volatile Suspended Solids, g VSS/d |
| $CH_4$ | % methane in biogas |
| ALK | Bicarbonate alkalinity, g $CaCO_3$/L |
| $COD_r$ | COD reduction, g COD/d |
| $A_{t=I}$ | Parameter A with time lag t=i days |
| $R^2$ | Correlation coefficient |
| Res | %eff - $\%\hat{eff}$, residuals are calculated by substituting data-set values into the regression equation of the previous stage and subtracting them from the corresponding measurement of efficiency |
| UASB | Up-Flow Anaerobic Sludge Blanket |
| VSS | Volatile Suspended Solids, mg/L |

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