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STOCHASTIC MODELING AND COMPUTER CONTROL OF A FULL SCALE WASTEWATER TREATMENT PLANT

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Modeling, identification and control of an activated sludge process has been considered. Dynamical experiments have been performed on a full scale municipal wastewater treatment plant at Käppala, Stockholm, Sweden. The air flow rate, influent water flow rate and the return sludge flow rate have been manipulated. Models for dissolved oxygen and the separator have been identified with the Maximum Likelihood method. The parameters have been compared with physical parameters. Control of the dissolved oxygen concentration is demonstrated.

INTRODUCTION

The activated sludge process is the major part of most wastewater treatment plants. In this process microorganisms react with organic pollutants in the wastewater and with oxygen dissolved in the water to produce more cell mass, carbon dioxide and water. Diffused air, mechanical aeration or even pure oxygen is used to achieve the aerobic environment in the reactor. The effluent of the reactor flows to a settler, where the activated sludge is separated from the liquid phase, Fig. 1. A portion of the concentrated sludge is recycled in order to maintain enough mass of viable organisms in the system and a reasonable ratio of food to microorganisms. Part of the settled sludge is wasted. The process effluent consists of the clarified overflow from the settler tank.

Dynamical modeling of the activated sludge process has been studied extensively during the last few years. Surveys can be found in Andrews [1], Buhr et al [2] and Olsson [3]. Particularly the biological models have reached quite a structured status. They are generally deterministic and contain many parameters such as kinetic rate and mass transfer coefficients. Hitherto hardly any of these models have been verified in any full scale plant more than in a semi-quantitative way (responses in the right direction and right order of magnitude).

System identification has been proved to be a useful tool in water quality and wastewater treatment systems modeling. Many ideas from industrial process identification are directly applicable to the sewage treatment field. Some specific problems, however, should be mentioned:

- the flow rate, composition or concentration of the influent stream can seldom or never be manipulated
- adequate instrumentation is a major obstacle
- the level of understanding the underlying phenomena is often poor
- it is difficult to reproduce experiments

Some of these problems are discussed in more detail in [3] and in Beck [4].

In this paper Maximum Likelihood identification technique has been applied to achieve models and internal parameters of a full scale activated sludge process. By this type of method a possibility is found to approach the structured mechanistic models piecewize. Previous results are presented in Olsson and Hansson [5].

The paper is organized as follows. Dissolved oxygen (DO) dynamics is discussed and the significant disturbances are described. The plant and the identification experiments as well as the data handling and analysis are briefly summarized. The

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identification results of the oxygen transfer models are presented and some DO control experiments are discussed. Some hydraulic experiments are described and physical interpretations are made. In particular it is shown how the settler dynamics are examined with stochastic methods.

DISSOLVED OXYGEN DYNAMICS

The DO dynamics are important to know of two major reasons. Firstly, the DO concentration has to be kept above a certain critical level, some 1-2 mg/l, in order to supply the synthesis and endogeneous respiration with enough oxygen. For higher concentrations, the metabolism is independent of the DO level. To save power costs the DO concentration therefore should be minimized. Secondly, the DO concentration is closely related to the biological activity of the reactor. Therefore it is a useful indicator of load changes or other disturbances of the metabolism activity. The basic theory of oxygen transfer and comsumption is found e.g. in Eckenfelder et al [6]. Four basic mechanisms determine the DO mass balance in a biological reactor,

(a) the hydraulic transportation or dispersion of DO in the reactor,
(b) the oxygen transfer from gaseous to liquid phase,
(c) the oxygen uptake due to cell synthesis,
(d) the endogeneous respiration.

A complete mix reactor mass balance equation describes these mechanisms,

$$\frac{dc}{dt} = \underset{(a)}{\frac{Q}{V}\, c_i} - \underset{(b)}{\frac{Q+Q_R}{V}\, c} + \underset{(b)}{k_1 u (c_s - c)} - \underset{(c)}{k_2 \frac{c}{K_c + c} \cdot \frac{s}{K_s + s}\, x} - \underset{(d)}{k_3 x} \qquad (1)$$

where
c = DO concentration
c_s = DO saturation concentration
c_i = influent wastewater DO
V = reactor volume
Q = influent flow rate
Q_R = return sludge flow rate
k_i = constants
s = substrate concentration
x = microorganism concentration
K_c, K_s = rate limiting constants
$k_1 u$ = overall oxygen transfer coefficient
u = air flow rate

The overall oxygen transfer coefficient is assumed to be proportional to the air flow rate. This assumption is reasonable over a small operating range, see [6]. The coefficient k_1 is also depending on the water quality and the operating conditions. The cell synthesis oxygen uptake rate is limited both by the substrate and oxygen concentrations. It is assumed that the endogeneous respiration is not limited by the DO concentration.

In many plants (also in the Käppala plant) the concentrations are spatially dependent. Suitable changes of Eq. (1) then have to be made, see further Olsson [7].

The natural control variable of the DO concentration is the air flow rate. Several different disturbances can change the DO concentration, such as

- changes in substrate concentration of the influent wastewater
- toxic content of the influent wastewater
- changes of the raw wastewater flow rate
- changes of the return sludge flow rate.

Here the interesting time scale is limited to a few hours. The change of total cell mass due to metabolism or endogeneous respiration therefore can be neglected.

A substrate change of the influent wastewater will cause a dilution change of substrate in the reactor. This in turn will influence the metabolism rate and is directly reflected into the oxygen uptake rate. Therefore a DO concentration change is a useful detector of substrate disturbances. Toxic disturbances are also reflected in the oxygen uptake rate but in opposite direction. Generally the toxic substance can either change the specific growth rate or the number of micro-organisms.

Hydraulic changes in the raw wastewater have different consequences on the DO concentration. The hydraulic transport of oxygen into and out of the reactor will change, but this effect is of little importance. Substrate and suspended solids concentration changes are more significant consequences, causing the oxygen uptake rate to change. Also the settler will be affected by a flow disturbance. The clarifier part of the separator is sensitive to flow disturbances. Already at normal operating conditions a significant part of the wasted suspended solids are

lost unpurposefully in the clarified water. For a major flow increase the effluent suspended solids content can increase dramatically. This results in a significant loss of microorganisms and consequently a decrease of the oxygen uptake rate.

Changes in return sludge flow rate will have two major effects on the DO concentration. Firstly the hydraulic change in principle gives the same consequence as the previous hydraulic disturbances, but generally the amplitudes are smaller. Secondly, the suspended solids concentration in the aerator will change, which in turn changes the oxygen uptake rate in the reactor.

A steady state gain due to different disturbances are derived from Eq. (1). For small disturbances the static change of the DO concentration can be written,

$$\Delta c = G_1 \frac{\Delta u}{\bar{u}} - G_2 \cdot \frac{\Delta Q_R}{\bar{Q}_R} - G_3 \cdot \frac{\Delta Q}{\bar{Q}} - G_4 \cdot \frac{\Delta s}{\bar{s}} - G_5 \cdot \frac{\Delta x}{\bar{x}} \qquad (2)$$

where all $G_i > 0$. The details are found in [8]. The values of G_1, G_4 and G_5 are of the same order of magnitude, about 5. G_3 is an order of magnitude smaller, about 0.5 and G_2 even smaller. It should however, be emphasized, that changes in Q or Q_R will change s and x. Therefore the DO concentration is indirectly influenced by the flow rates to quite a large extent.

EXPERIMENTS

The dynamical studies have been performed at the underground municipal wastewater treatment plant at Käppala, Lidingö, outside Stockholm. The plant serves some 300 000 - 400 000 people in the northern suburbs of Stockholm and was completed in 1969. The average dry weather flow is about 1.3 m^3/sec. The biological treatment in the plant is made in six parallel activated sludge units. Each aerator has a volume of 6000 m^3 and a length of 100 m. Air is supplied by diffusers uniformly along the tanks. The primary sedimentation effluent is fed at four positions along the aerators, between 30 and 60 m from the head end, a so called step loading, Fig. 1. The settlers are lamella sedimentation units. Because of their small volume they hold a relatively small amount of buffer volume of sludge. The plant has also chemical precipitation for phosphorus removal, but these units are not considered here.

In a series of experiments the air flow rate and the return sludge flow rate have been manipulated. Also the influent wastewater flow rate has been manipulated by redirecting the flow to other aeration basins. The inputs are changed both separately and simultaneously and independently.

DATA HANDLING AND IDENTIFICATIONS

The measurement data were acquired in the Siemens 304 computer installed at the plant. The paper tape output has been brought to the PDP 15/35 computer at the Department of Automatic Control, Lund, where the data has been analyzed and identified. For this purpose a program package IDPAC (see Wieslander [9]) has been used. The program package is interactive, which offers a great flexibility, especially for relatively poorly known systems like a wastewater treatment system. Many relationships can be tested, data can easily be manipulated and models be simulated and tested to different accuracy criteria.

It is assumed that the different relationships can be described by linear difference equations with constant coefficients. The canonical Åström [10] structure, has been proved to describe a large class of stochastic systems with one output y and several input signals u_i,

$$A(q^{-1})\, y(t) = \sum_{i=1}^{p} B_i(q^{-1})\, u(t-k) + \lambda C(q^{-1})\, e(t) \qquad (3)$$

where A, B and C are polynomials of the backward shift operator q^{-1},

$$\begin{aligned} A(q^{-1}) &= 1 + a_1 q^{-1} + \ldots + a_n q^{-n} \\ B_i(q^{-1}) &= b_{i0} + b_{i1} q^{-1} + \ldots + b_{in} q^{-n} \\ C(q^{-1}) &= 1 + c_1 q^{-1} + \ldots + c_n q^{-n} \end{aligned} \qquad (4)$$

The unknown disturbances are described by a moving average process, where e(t) is a sequence of independent, normal stochastic variables with zero mean and unit

variance, while λ is an amplitude factor. A system described by (3) can be identified with the Maximum Likelihood (ML) method, see Åström [10]. The parameter estimates are consistent, asymptotically normal and efficient under quite mild conditions. The parameter λ can be interpreted as the standard deviation of the one step prediction error. The techniques give not only the estimates but also their standard deviations from the Cramer-Rao inequality.

The ML method has been used in many industrial applications and surveys can be found in Åström-Eykhoff [11] and Gustavsson [12].

IDENTIFICATION OF THE OXYGEN TRANSFER DYNAMICS

The oxygen transfer dynamics can be examined by manipulation of the air flow rate. The value of the mass transfer coefficient $k_1 u$ corresponds to a time constant of 10 - 20 minutes for a nominal air flow rate. The mass transfer parameter varies due to e.g.

- the water quality
- the *real* air flow in different parts of the aerator
- the efficiency of the diffusers
- the location of the DO probe

Some identification results are shown in Table 1. All of the models are of first order. From experiment 1 the time constant for the two sensor locations are compared, 14 and 28.7 minutes respectively. They correspond to overall oxygen transfer coefficients of 4.3 (h^{-1}) and 2.1 (h^{-1}) respectively. The latter value is too small and indicates that the real air flow is lower than expected near the tail end. One reason for this may be clogging of the diffusers. Another one can be a vertical position error of the diffusers. This causes a different pressure resistance in the air tube. The air flow rate is extremely sensitive to this type of position error.

TABLE 1 - DO Model Parameters for Air Flow Input

Expt	1	1	2	2	3	3
Output	DO (60 m)	DO (84 m)	DO (90 m)	DO (80 m)	DO (90 m)	DO (90 m)
N	405	405	144	144	205	99
a_1	-0.977±0.003	-0.988±0.002	-0.962±0.007	-0.947±0.009	-0.961±0.008	-0.928±0.013
b_{11}*100	1.272±0.104	1.017±0.086	1.901±0.153	1.929±0.189	1.988±0.190	3.646±0.329
b_{21}	-	-	-	-	-	-0.915±0.359
c_1	-0.527±0.036	-0.244±0.046	0	0.096±0.082	-0.153±0.080	-0.235±0.106
λ	0.380±0.013	0.256±0.009	0.268±0.016	0.302±0.018	0.251±0.012	0.324±0.023
Δt (s)	20	20	60	60	60	120
T (min)	14.0	28.7	25.1	18.5	24.8	26.6

N = number of samples; Δt = sampling time; T = time constant; input 1 = air flow (N m^3/min); input 2 = water flow (m^3/sec); DO is measured in % (100 % = 12 mg/l).

The conclusion is confirmed by Expt 2, performed more than one year later. The sensor at 80 m from the head end has a shorter time constant (18.5 min) than the one at 90 m (25.1 min). A λ value of 0.3 corresponds to a standard deviation of the 2 minute prediction error of about 0.03 mg/l of the DO concentration. A further discussion of the DO mass transfer dynamics is found in [5] and [8].

In Expt 3 not only the manipulated variable but also the influent flow rate has been changed unpurposefully. Column 5, Table 1, shows the model where only air flow is assumed to be the input. The water flow was recorded every 2 minutes, and was included as an input in column 6. This improves the model.

The static gains are compared with the assumption of Equation (2). In columns 3-6 the normalized static gain with respect to air flow is 4 (cf. G_1 in Eq. (2)). The corresponding static gain for the water flow (G_3) is found to be -0.6 in column 6. The model outputs of the models in column 3 and 6 are compared with the experimental data in the Figures 2 and 3 respectively. The relatively large model error between 60 and 80 minutes in Fig. 3C depends probably on incomplete mixing due to the water flow disturbance (Fig. 3B).

CONTROL OF THE DISSOLVED OXYGEN CONCENTRATION

The control of DO as a physical variable is not a complex problem as long as suitable sensors and actuators are available. This has been performed earlier in complete mix reactors and implementations are reported e.g. by Brouzes [13], Stepner et al [14], Petersack et al [15] and Roesler [16]. Digital or analog PI controllers have been used. In the Käppala plant two control algorithms have been implemented in the computer, one PI controller and one self-tuning regulator. Here we describe some experiences of the PI control. The self-tuning controller is described by Aström et al [17,18]. Operating experiences of the self-tuning regulator in the plant will be reported later.

The DO concentration is measured in two points. Typically the sampling interval is 30 seconds. The DO signals are weighted together and filtered in an exponential filter. A new desired control signal is calculated each n:th sampling interval, where n has been typically 10 or 20. The control signal will adjust a valve in the air tube system. Because of pressure constraints in the air tube it is often impossible to realize the whole desired control signal in one sampling interval. The pressure must be kept within 0.58 and 0.62 kp/cm^2 (57 and 61 kPa). At the high pressure limit the air flow can only be increased and at the low limit it can only be decreased. Moreover, the air flow rate change must not exceed 2 Nm^3/min in one sampling interval. Therefore the controller often has to actuate the desired control signal during several sampling intervals. If the whole desired control signal cannot be realized before the next signal is calculated the real control signal is stored. This is adequate only for the self-tuning regulator.

A pressure control loop is closed outside the DO control loop. The main tube pressure is controlled by a throttle valve of the compressor. By the pressure control the air flow rate can be adjusted 20-30 % of the total blower capacity.

In the Figure 4 a sequence of the test period is shown. The DO concentration at 60 m downstream is controlled. The air flow rate is a good measure of the load variations. During the weekend the air flow rate is kept at its lower limit. Consequently the desired DO concentration can not be maintained.

HYDRAULIC DISTURBANCES

In this section if will be discussed how disturbances in the influent flow rate will affect the DO concentration as well as the separator effluent concentrations.

Influence on DO Concentration

The influent flow rate has been disturbed in Expt 4 according to Fig. 5. The flow rate change results in an MLSS (Mixed Liquor Suspended Solids) concentration variation, Fig. 5. First order models have been found relating the water flow rate and the MLSS to the DO concentration, Table 2. The MLSS input parameter is quite inaccurate but improves to the model. A physical interpretation of the time constant has been given in [4]. The normalized static gain for the flow input (G_3 in (2)) is found to be 0.5. If it is assumed that the MLSS consists of 20 % living microorganisms, then the static gain for the MLSS input (G_5 in (2)) is 6.

Fig. 6 shows the comparison between the model output and the real data in Expt 4.

TABLE 2 - DO Model Parameters for Hydraulic Disturbances

Expt	4	4
Output	DO (66 m)	DO (66 m)
N	424	424
a_1	-0.969±0.005	-0.967±0.005
$b_{11}\cdot 10$	-0.344±0.031	-0.349±0.030
$b_{21} * 10^3$	-	-0.101±0.046
c_1	-0.453±0.042	-0.469±0.042
$\lambda \cdot 10$	0.113±0.004	0.112±0.004
Δt (min)	1	1
T (min)	32.1	30.0

input 1 = influent water flow rate (m^3/s)
input 2 = MLSS (g/m^3)
DO is measured in g/m^3

Clarifier dynamics

Very little progress has been made on structured dynamical models for clarifiers. In such a model the effluent suspended solids concentration should be related to the flow rate and concentration variations surrounding the clarifier. Static models are used sometimes, and a common approach is the empirical static relationship found by Pflanz [19]. This formula says that the effluent suspended solids content is approximately proportional to the solids flux to the solids-liquid separator,

$$x_e = K \frac{Q + Q_R}{A} x \qquad (5)$$

where x_e = effluent suspended solids concentration
A = clarifier area (= 210 m^2 at Käppala)
K = constant.

In the actual experiments the load change has been large. Therefore it is not à priori clear, that linear models could predict the sludge concentration of the effluent. The results of two different experiments are presented here.

TABLE 3 - Clarifier Parameters

Expt	4	4	5	5
Output	x_e (g/m^3)	x_e (g/m^3)	x_e (g/m^3)	x_e (g/m^3)
N	424	424	247	247
a_1	-0.982±0.005	-0.977±0.006	-0.967±0.008	-0.978±0.010
b_{11}	21.5±2.5	16.4±3.9	29.4±7.0	26.7±7.0
$b_{21} * 10$	-	-	-	0.12±0.06
$b_{31} * 10^{-3}$	-	1.11±0.66	-	-
c_1	-0.312±0.041	-0.312±0.041	0	0
λ	8.67±0.30	8.64±0.30	4.85±0.22	4.81±0.22
Δt (min)	1	1	2	2
T (min)	56	43	59	90

input 1 = influent water flow (m^3/s)
input 2 = MLSS (g/m^3)
input 3 = underflow rate (m^3/s)

In Fig. 7 and 8 the essential signals are shown from the experiments 4 and 5 respectively. The influent flow rate is an essential input signal to the clarifier system. Moreover, as the flow rate is manipulated it is possible to get a relatively good accuracy of the model. In Fig. 8 it is also demonstrated, how the MLSS concentration is changed because of the flow rate change. Fig. 8 shows, that the system is not linear. The effluent concentration does not decrease for a flow rate decrease (at t ≈ 55). For a flow rate increase, however, the response is very clear.

Column 1 and 3 of Table 3 show, that a system with a time constant close to one hour can describe the relationship. From the static gain of the models the constant K can in Eq. (5) be determined to 0.06. With respect to the large flow disturbances this value is favourable compared to values found in the literature (0.08 - 0.10 during static conditions).

It is possible to achieve improvement of the models by incorporating either the MLSS concentration or the settler underflow rate as inputs. In Expt 4 the underflow rate was improving the model (column 2) while in Expt 5 the MLSS concentration instead made the model somewhat better (column 4). The parameter accuracy is quite poor, however. The major reason is, that the MLSS concentration can not be manipulated and depends on the flow rate input. The underflow rate is small compared to the influent water flow rate, which causes the poor accuracy. It has also been tested if a more accurate model could be achieved with the total solids flux $(Q+Q_R)x$ entering the settler as an input. The model accuracy, however, is not better compared to only the flow rate as input.

In the Figs 9 and 10 the models outputs are compared with the experimental data. It should be remarked, that the purpose of the present model is not to predict an overflow of the clarifier. Such a model should incorporate the sludge blanket level. Tracy and Keinath [20] have derived and tested such a model in laboratory scale.

Thickener Dynamics

Dynamical models of the thickener have not yet attained the same level of development and structure as the aerator models. Further, none of the existing models have been used as a part of a control system in any full scale system. A dynamical model should predict the underflow concentration or the recycle flow sludge concentration. This is related in a complex way to the settling characteristics of the sludge, physical features of the separator, temperature, recycle flow rate, and the solids flux to the separator.

Most of the available dynamical models are based on the Kynch [21] analysis of

zone settling. It is assumed that solids are transported to the bottom of a settler by bulk flow and gravitational sedimentation. An excellent survey of the state of the art in thickener design is found in Fitch [22].

From the hydraulic experiments it has been attempted to establish dynamic models for the thickener. The Kynch theory states that the underflow concentration depends primarily on the underflow rate. When the flow rate increases the concentration would decrease. A first order model is presented in Table 4, column 1. It has a relatively long time constant, 78 minutes. The accuracy of the b_{11} parameter is not good but adequate. Also the MLSS can be related to the underflow concentration, column 2, but this model is somewhat less accurate. With the two inputs combined the model accuracy can be increased, even if the b_{21} parameter accuracy is relatively poor. Observe, however, that the time constant now is only 42 minutes.

In particular it has been verified that the influent water flow rate has a negligible influence on the underflow concentration. Neither is the total solids flux $(Q-Q_R)x$ entering the settler any adequate input signal.

The models from columns 1 and 3 in Table 4 are simulated in Fig. 11. The experimental data are compared with the two model outputs. The recycle flow rate is also shown, while the other inputs from Expt 5 are shown in Fig. 8.

TABLE 4 - Thickener Parameters

Expt	5	5	5
Output	x_r (g/m^3)	x_r (g/m^3)	x_r (g/m^3)
N	247	247	247
a_1	-0.975±0.009	-0.953±0.019	-0.954±0.017
$b_{11} * 10^{-3}$	-0.999±0.258	-	-0.907±0.274
b_{21}	-	-0.152±0.063	-0.086±0.059
c_1	-0.484±0.076	-0.390±0.076	-0.459±0.081
$\lambda \cdot 10^{-2}$	0.523±0.023	0.532±0.024	0.521±0.023
Δt (min)	2	2	2
T (min)	78	42	42

input 1 = underflow (return flow) rate (m^3/s)

input 2 = MLSS (g/m^3)

x_r = underflow concentration (g/m^3)

CONCLUSIONS

Identification techniques offer good possibilities to examine not only dynamical models for control purposes but also internal parameters of structured models of a wastewater treatment plant. Oxygen transfer identification has been demonstrated. Several spin-off results are obtained. Control of DO has been tested for a long period. The load variations to the plant are clearly reflected in the control signal. Even if a great modeling changelle still exists for the biological reactor as well as for the separator, model identification can provide the model builder with insight into the proper cause-effect relationships.

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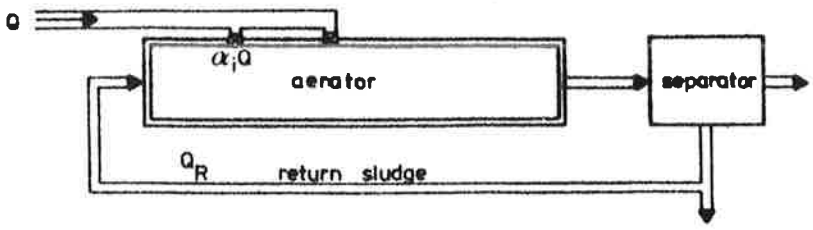

Figure 1. The activated sludge process.

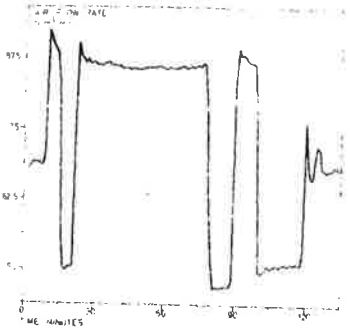

Figure 2A. The air flow rate input of Expt 2.

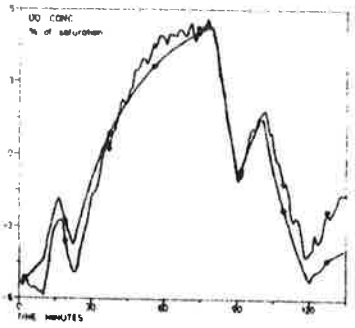

Figure 2B. Experimental DO output from Expt 2 compared with a first order model output. The DO probe is located at 90 m from the head end.

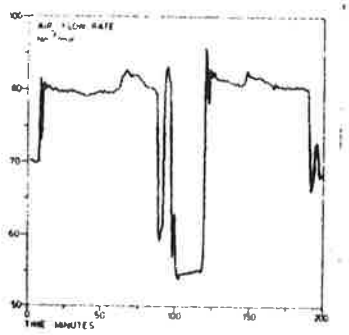

Figure 3A. The air flow rate input of Expt 3.

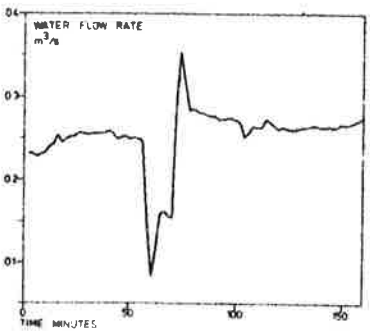

Figure 3B. The water flow rate input (unpurposefully disturbed) in Expt 3.

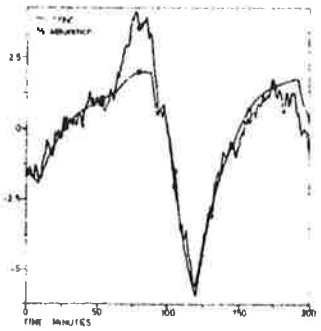

Figure 3C. Experimental DO output from Expt 3 compared with a first order model output. The air and water flow rates are considered inputs. The DO probe is located at 90 m from the head end.

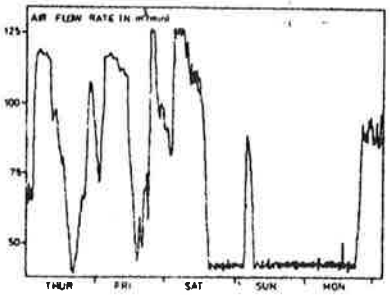

Fig. 4A

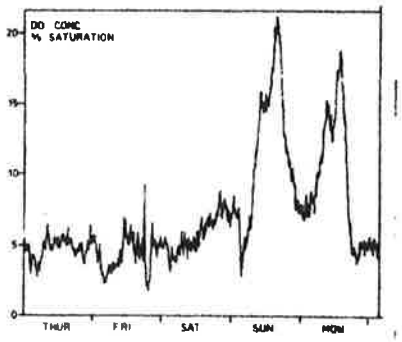

Fig. 4B

Figure 4 A-B. Part of DO control experiments, April 21-27, 1975. The air flow rate reflects the diurnal load variations to the plant. The air flow is not permitted to be smaller than 40 N m^3/min. Therefore the two peaks of the DO concentration appear during the weekend low loading. The upper limit of the air flow rate is reached during early Saturday. No rainstorm occurred during the actual test period.

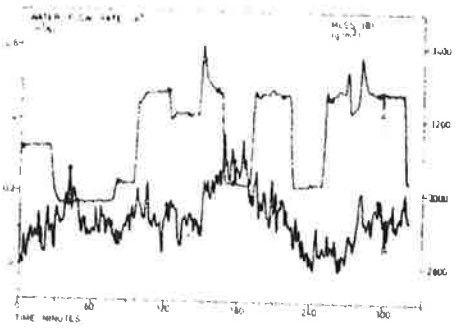

Figure 5. Disturbance signals in Expt 4. The water flow rate has been manipulated, causing the Mixed Liquour Suspended Solids Concentration to vary.

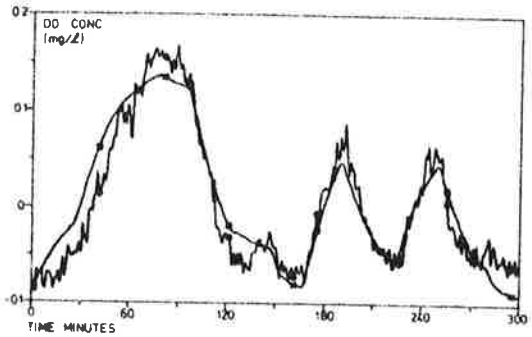

Figure 6. Experimental DO output from Expt 4 compared with a first order model output. The water flow rate and the MLSS concentration (fig. 5) are the inputs. The DO probe is located at 66 m from the head end.

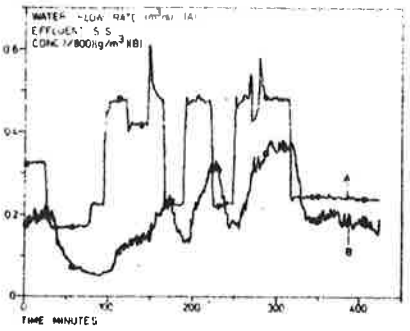

Figure 7. The manipulated flow rate input of Expt 4 and the resulting effluent suspended solids concentration variation.

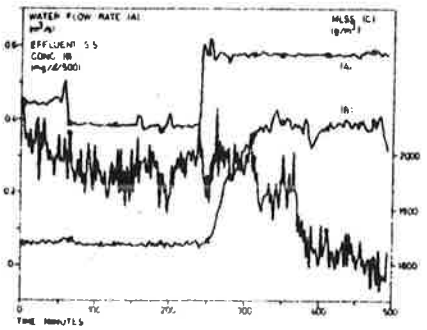

Fig.8

Figure 8, Input and output signals of Expt 5. The water flow rate (A) has been manipulated, causing the effluent suspended solids concentration to vary (B). The MLSS concentration (C) is also affected by the water flow change, but here considered as the second input.

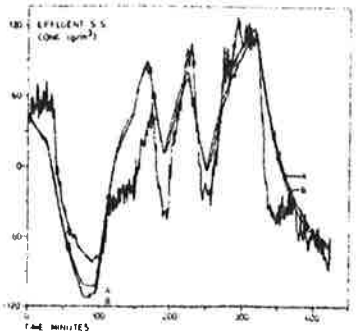

Figure 9. Experimental data from Expt 4 of the effluent suspended solids concentration compared with model outputs. Curve B is the model output for only water flow input. In curve A also the underflow rate is an input.

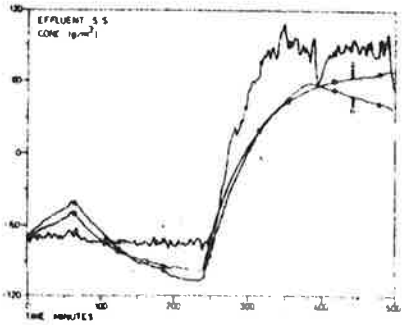

Figure 10. Experimental data of the effluent suspended solids concentration compared with model outputs of Expt 5. In curve A only the water flow rate is an input, in curve B also the MLSS is considered an input.

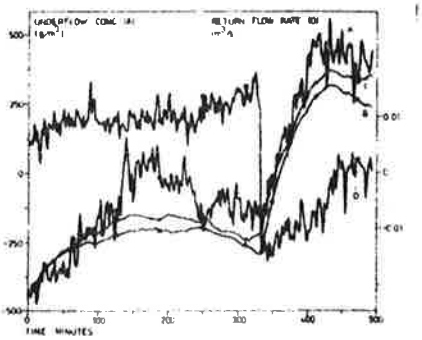

Figure 11. Input and output signals of Expt 5 for the thickener identification. The return flow rate (D) has been manipulated (as well as the water flow rate, cf. fig. 8). The underflow concentration output is compared with two model outputs, only return flow rate as input (B), also MLSS as input (C).