AN INVESTIGATION INTO CONTROL STRATEGIES FOR ACTIVATED SLUDGE WASTEWATER TREATMENT PLANTS

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THE FOLLOWING APPENDIX AND FIGURES HAVE BEEN EXCLUDED ON INSTRUCTION FROM THE UNIVERSITY

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ABSTRACT

The activated sludge process is widely used throughout the world for the treatment of wastewater from domestic and industrial users. This process is not normally efficiently controlled and hence increasingly important financial incentives and environmental considerations exist for improving the efficiency and quality of the treatment before releasing the treated water into the environment.

This thesis presents the development of MATLAB computer simulation models for activated sludge wastewater treatment plants. A comparison of control systems has been made using these models for typical operating conditions of wastewater treatment processes, such as influent flow pattern and temperature.

The investigation identified the control of dissolved oxygen as an important area to study because insufficient levels of dissolved oxygen in the wastewater prevent the successful degradation of organic matter present, whereas too high a level causes settling problems and inefficiencies. Three dissolved oxygen control methods, namely PID, Fuzzy logic and self-tuning control have been investigated, applied and their performances compared. As in most other processes, the number and location of sensors and actuators within a water treatment plant can have large implications for successful process control. Therefore, the model developed was used with real plant data to test different designs and investigate the best location of sensors and actuators for a specific North West Water plant to improve control of the process. Optimisation of process operation has also been investigated with the objective of improving effluent quality and reducing operation costs.

Simulations suggest that all three dissolved oxygen control methods investigated are able to control the process satisfactorily with relatively little deviation from the set-point. The PID and fuzzy logic controllers needed retuning for changing process conditions, but the adaptive nature of the self-tuner makes it more robust. Optimal sensor and actuator placements have been identified and a cost/quality benefit analysis performed. Significant cost reductions and effluent quality improvements may be achieved by applying optimisation techniques to regulating the concentration of the solids within the aeration stage. These objectives are conflicting and therefore simultaneous improvement is not always achievable.

The project has demonstrated the potential benefits of employing models to simulate the process, subject to availability of data to parameterise them. Process operation can be significantly improved with the application of well-tuned controllers and optimisation techniques.

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NOMENCLATURE

α	Variable used to weight the objective function used by the optimisation algorithm
$\hat{\mu}_A$	Maximum specific growth rate for autotrophic biomass (day^{-1})
$\hat{\mu}_H$	Maximum specific growth rate for heterotrophic biomass (day^{-1})
aeration	Aeration rate in grams of O_2 per hour
Asc	Final clarifier area (m^2)
b_A	Decay coefficient for autotrophic biomass (day^{-1})
b_H	Decay coefficient for heterotrophic biomass (day^{-1})
BOD	Biochemical Oxygen Demand (g oxygen / m^3)
costkWh	Electricity cost in £ / kilo Watt hour
cost WAS disposal	disposal cost of one cubic meter of surplus sludge (£/m^3)
C_S	Concentration of sludge in secondary clarifier model (g/m^3)
COD	Chemical Oxygen Demand (g oxygen / m^3)
DO	Dissolved Oxygen concentration (g/m^3)
$e(t)$	control error
f_p	Fraction of biomass leading to particulate products
η_h	Correction factor for hydrolysis under anoxic conditions
η_g	Correction factor for μ_H under anoxic conditions
i_{XB}	Mass nitrogen / mass COD in biomass
i_{XP}	Mass nitrogen / mass COD in products from biomass
k_a	Ammonification rate ($m^3\ g^{-1} day^{-1}$)
k_h	Maximum specific hydrolysis rate ($m^3\ g^{-1} day^{-1}$)
K_{hyd}	Monod constant for load ($m^3 d^{-1} m^{-2}$)
K_{NH}	Ammonia half-saturation coefficient for autotrophic biomass (g m^{-3})
K_{NO}	Nitrate half-saturation coefficient for denitrifying heterotrophic biomass (g m^{-3})
K_{NO3}	Monod constant for nitrate (g m^{-3})
$K_{O,A}$	Oxygen half-saturation coefficient for autotrophic biomass (g m^{-3})
$K_{O,H}$	Oxygen half-saturation coefficient for heterotrophic biomass (g m^{-3})
Kp_1	Proportional gain of PI controller in tank 1

Kp_2	Proportional gain of PI controller in tank 2
K_S	Half-saturation coefficient for heterotrophic biomass
K_X	Half-saturation coefficient for hydrolysis of slowly biodegradable substrate
New $MLSS_{SP}$	New value of the mixed liquor suspended solids as determined by the optimisation algorithm (g/m^3)
$MLSS_{SP}$	Mixed liquor suspended solids set-point (g/m^3)
OUR	Oxygen Uptake Rate (g/m^3/day)
pumping costm^3	cost of pumping a cubic metre of liquid (£)
$\frac{Q_0}{A}$	Hydraulic load to the clarifier {≅ (QinI-Qwas)/Area} (m/day)
Q_{inI}	Influent wastewater flow rate (m^3/day)
Q_{ras}	Recycled activated sludge flow rate (m^3/day)
Q_{was}	Wasted, or surplus, activated sludge flow rate (m^3/day)
RAS	Recycled Activated Sludge (m^3/day)
$r(t)$	control set-point
S_{ALK}	Alkalinity (mol)
S_I	Soluble inert elements (g/m^3)
S_S	Readily biodegradable substrate (g/m^3)
SS_{EFF}	Suspended solids in the effluent (g/m^3)
SS_F	Concentration of particles in the feed to the clarifier which will not settle (g/m^3)
SVI	Sludge Volume Index
SS_{init}	Constant SS concentration which will always be non-settleable (g/m^3)
S_{ND}	Soluble biodegradable organic nitrogen (g/m^3)
S_{NH}	Ammonia nitrogen (g/m^3)
S_{NO}	Nitrate and nitrite nitrogen (g/m^3)
S_{NO3}	Concentration of nitrate in inlet to clarifier {≅ S_{NO} inASM1} (g/m^3)
S_O	Dissolved oxygen (negative COD in aeration model) (g/m^3)
SS_{hyd}	Maximum concentration of suspended solids in the inlet which will not settle due to hydraulic and suspended solids load (g/m^3)
SS_{NO3}	Maximum concentration of suspended solids in the inlet which will not settle due to nitrate in the inlet (g/m^3)
Ti_1	Integral action time constant for PI controller in tank 1

Ti_2	Integral action time constant for PI controller in tank 2
Time unit	Day
$u(t)$	control variable
V_S	gravity settling of sludge in final settling tank
V_U	Downward velocity of settling sludge
WAS	Wasted or Surplus Activated Sludge (m^3/day)
X_0	Concentration of SS in the feed to the clarifier($\cong$ MLSS in tank 2) (g/m^3)
X_{BA}	Active autotrophic biomass (g/m^3)
X_{BH}	Active heterotrophic biomass (g/m^3)
X_I	Particulate inorganic matter (g/m^3)
X_{ND}	Particulate biodegradable organic nitrogen (g/m^3)
X_P	Particulate products arising from biomass decay (g/m^3)
X_S	Slowly biodegradable substrate (g/m^3)
Y_A	Yield for autotrophic biomass
Y_H	Yield for heterotrophic biomass
$y(t)$	measured value

GLOSSARY

Activated sludge: A sewage sludge made by continuous recirculation of the sludge from the secondary sedimentation tank to the aeration tank, thus acquiring many useful active aerobic bacteria.

Aerobe (adj: **aerobic**): A micro-organism that needs free oxygen or dissolved oxygen to develop.

Ammonia: NH_3; bacteria readily decompose urea and proteins in sewage to form ammonia which may later be oxidised to nitrites and nitrates, as in the nitrogen cycle.

Anaerobe (adj: **anaerobic**): A micro-organism that needs no free oxygen to develop.

Anoxic: Description of conditions without free oxygen. Oxygen is available for respiration only from dissolved inorganic substances such as nitrate ions.

Autotrophic organism: An organism that uses carbon dioxide as a source of the carbon it needs for building new cells.

BOD (Biochemical Oxygen Demand): Measure of the amount of pollution by organic substances in water, expressed as the number of mg of oxygen required by the micro-organisms to oxidise the organics in a litre of water. In the standard test a sample of water is incubated at 20°C for 5 days (BOD_5).

Coagulation: The addition of a chemical to water or sewage so as to precipitate and so removes from the water most of the tiny particles.

Colloids (adj: colloidal): Particles smaller than 2×10^{-6} m and larger than 1×10^{-9} meters. Colloids may be removed from water by coagulation.

Clarifier: Synonymous with sedimentation tank in the United States. In the United Kingdom the term is often used for removing solids after chemical coagulation.

COD (Chemical Oxygen Demand): Measured by a test involving a strong oxidising agent (typically a boiling mixture of sulphuric acid and potassium dichromate). The COD value is normaly higher than the BOD value because more organics can be oxidised chemically than are biodegradable in a BOD test. The test can be completed in 2 hours, instead of 5 days for BOD_5.

Denitrification: The removal of oxygen from nitrates in anoxic or anaerobic conditions, resulting eventually in gaseous nitrogen, which bubbles off and is thus removed.

Endogenous phase of growth: A growth phase of a population of micro-organisms in which there is no new input of food from outside. Individual microbes use the nutrients from dead cells and the number of living cells decreases.

Heterotrophic organism: Any organism that needs organic matter as an energy source.

Hydrolysis: The formation of compounds by combination with water. Bacteria can often hydrolyse insoluble or long-chain organic compounds to simpler soluble ones.

Lysis: Disintegration; the word describes the death and break-up of a bacterial cell, making its protoplasm available as food for its neighbours.

Metabolism: The changes, biochemical, chemical and physical, in living matter needed for life to continue, involving the building of complex from simple substances.

Mixed liquor: Mixed activated sludge and settled sewage in the aeration tank.

MLSS (mixed liquor suspended solids): The dry suspended solids in the mixed liquor.

MLVSS (mixed liquor volatile suspended solids): The dry volatile suspended solids in the mixed liquor. It is often considered to be 70% of the MLSS.

Nitrates: Substances whose chemical formula ends in $-NO_3$ are derived in domestic sewage from the oxidation of ammonia.

Nitrification: Conversion of the ammoniacal nitrogen in sewage to nitrites and eventually nitrates, reducing the oxygen demand in the receiving water, since the oxidation of ammonia to nitrite requires 4 to 5 kg oxygen per kg of ammonia oxidised

Nitrites: Compounds whose formula ends in $-NO_2$ are an interim stage of nitrification and readily oxidise to nitrates $-NO_3$.

Oxidation: The addition of oxygen, or the loss of electrons.

Population equivalent: Wastewaters, especially of industrial origin, are often expressed in terms of population equivalent. In the UK the assumption is that the average person release a BOD_5 load of 60g per day. In the US, 80g per day is often used.

Sedimentation or **settling tanks**: Tanks for the settling of solids out of sewage, or water, without the help of chemicals. Can be used for primary sedimentation immediately after the grit chambers or for secondary sedimentation.

Settleability: Ease of settling. An indication of the ability of a secondary sludge to settle in a sedimentation tank can be obtained by a settling column analysis or the sludge volume index or the stirred specific volume of the sludge density index.

Settled sewage: The effluent from primary sedimentation tanks.

Sludge volume index (SVI): A measurement of the settleability of activated sludge. It is dependant upon the proportion of the sludge which has settled after 30 minutes and the mixed liquor suspended solids concentration.

Trickling filter: Basic biological treatment where the effluent trickle down over coarse stones or plastic cubes that fill a tank approximately 2 meters deep. Biological film develop on the filter medium.

Based on Scott and Smith (1980).

Chapter 1

1 INTRODUCTION

Water is increasingly recognised as a precious resource. The growth in population requires an increasing quantity of water which needs to be treated before being released into the natural environment (river, sea etc) or being reused for industrial, agricultural or direct human use. Water usage varies from 100 to 400 litres per person per day in developed countries. In 1991 in the UK, the domestic water use was 147 litres per person per day, and this is expected to increase by over 20% before 2021 (Herrington, 1996). Most of the water used for domestic purposes needs to be treated after use, as does the rainwater collected in sewer systems. The water treatment problem can no longer be ignored, as it largely has been in past centuries, owing to increased urbanisation and the negative impact untreated sewage has over natural ecosystems and human health.

1.1 WASTEWATER TREATMENT

Until the beginning of the 20^{th} century, the normal way of treating sewage was to landspread it. Increasing amounts of sewage, containing higher levels of organics, nitrogen, phosphate and micro-pollutants, imposed the development of more intensive treatment systems. Nowadays, wastewater treatment has become a highly technological process, often comprising primary, secondary and tertiary treatment steps (Lens & Verstraete, 1992).

It has been estimated that the organic load produced in the European Community in 1988 was 300 million 'population equivalent'. Treatment in municipal sewage treatment plants removes around $^2/_3$ of this load, even though the treatment performance in several countries is less. In some countries an important portion of the produced organic load is discharged untreated into the environment. This is mainly due to an incomplete sewage collection system for transportation of the produced sewage to the treatment plants and unsuitable operation of the treatment facilities (Lens & Verstraete, 1992). In a study by Berthouex & Fan (1986) it was shown that even well attended wastewater treatment plants, facing no major shocks or toxic pulses, do not meet the discharge standards for about 20% of the time.

At present, treatment of municipal sewage relies mainly on aerobic treatment processes such as the activated sludge process. A survey of 976 small plants in the Loire-Bretagne basin in France by Racault & Vachon (1989) showed that municipal biological wastewater treatment plants consisted of 49.7% activated sludge, 26.9% lagoons, 10.6% trickling filters, 4.3% biological disks and 8.5% other methods.

1.2 ACTIVATED SLUDGE PROCESS

Municipal wastewater is characterised by strong fluctuations in flow rate. Flow rate variations usually follow a daily, weekly and seasonal pattern (Metcalf & Eddy, 1991) and depend mainly on population size (the larger the population, the smaller the variation) and the sewer type (combined sewers where domestic sewage is mixed with rain and run-off water have much higher fluctuations).

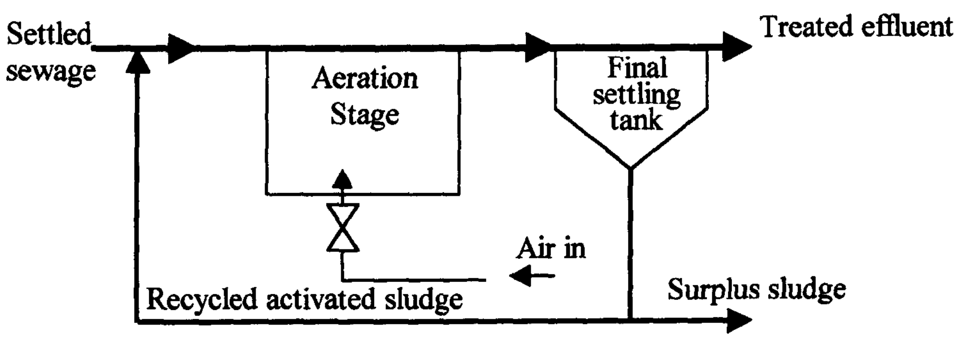


Figure 1.1: Activated sludge plant

In the activated sludge process (Figure 1.1), raw or settled wastewater is blended with micro-organisms that are recycled from the final settling tank (also called final clarifier). The organic matter in the wastewater is used by the micro-organisms for respiration and synthesis of new cells. Soluble and particulate (colloidal) organic matter are thus transformed into gaseous form and cell material settling into the secondary clarifier which must then be removed from the process. In good operating conditions, 90% of the organic load, expressed in terms of BOD, can be removed. However, Tracy &

Keinath (1973) found that the overall efficiency of the wastewater treatment process is largely dependent on the satisfactory performance of the final settling tank. An important parameter of an activated sludge wastewater treatment plant is the operating temperature. In the temperate regions of the world, sewage temperature ranges from 4 to 20°C, depending on the place and time of sampling, and generally exceeds 12°C for only about 6 months per year (Lens & Verstraete, 1992).

1.3 CONTROL AND INSTRUMENTATION

There are a number of reasons to increase the performance of control systems on wastewater treatment plants. However, control systems rely heavily on measurements and this aspect should not be neglected; advances in control and regulation of processes are dependent on the availability of suitable data; therefore instrumentation systems need to be installed and operated successfully.

A number of issues combine to make an increase in control and instrumentation in wastewater treatment plants desirable:

Effluent quality standards

This is a clear driving force for increasing control and instrumentation. In Sweden and Denmark, for example, there is a significant increase in the quality demands on the effluent (Olsson, 1992) because of regulations which impose a tax proportional to the concentration of water pollutants released in the effluent water whatever the level of pollution. Stricter European Commission (EC) directives regarding the release of different pollutants, are also being introduced within the European Union.

Economy

The goal of instrumentation, control and automation has been to achieve a better resource utilisation. This has been summarised for wastewater treatment by Olsson *et al* (1997) as:

- Better energy use by dissolved oxygen control,
- More efficient use of chemical precipitation control,

- Better use of internal carbon in sewage for biological nitrogen and phosphorus removal,
- Better energy use by process development, such as denitrification,
- Interaction between design and operation, such as combined sewer control and plant flow control,
- Unmanned operation during nights and weekends.

The extension of a large plant to a larger capacity by traditional design methods is very expensive. Process dynamics and operational methods should be included in the design procedure in order to make the best use of the financial investment. As a result of such integration, the safety and capacity margins can be decreased, but this requires reliable operation (Olsson, 1992). However, the increase in control and instrumentation is hampered by a number of constraints.

Legislation

In an international survey, Olsson (1993) highlighted that legislation does not favour the widespread implementation of control systems. Olsson identified that the design of improved control systems is not of major importance to wastewater companies owing to a lack of sufficiently rigorous regulatory standards. Moreover, existing legislation is often not enforced adequately and is not adjusted to the actual needs of the receiving water courses because dynamic variations are neglected to the exclusive consideration of steady-state conditions. Geographical differences are also often ignored, resulting in inconsistent rules for effluent water quality. Also, current legislation requires off-line data, and on-line data is not yet acceptable for quality control, reducing the interest of advanced control and instrumentation and the use of on-line measurements to meet the regulatory demands.

Economy

Even though this no longer the case in the UK, in many countries the wastewater treatment industry is often considered as a non-profit activity undertaken by municipal or regional organisations. As a result, the aims assigned to control and instrumentation are often unclear. Automation has been considered expensive and has often been added as an after thought once the original design phase has been completed resulting in higher installation cost and less than optimal control systems. Accordingly, proper analysis between construction and operation costs is often not performed (Olsson, 1993).

Plant constraints

Efficiency and reliability of advanced control and instrumentation systems is still of some concern. There are few complex systems installed on full-scale systems leading to conservative designs with large safety margins to be used even though that means that too little flexibility and controllability is built into most plants (Olsson, 1993) and that too few variables can effectively be manipulated (Zhao *et al*, 1994). Another point is that in most countries, the majority of the plants are quite small. In small-scale installations, it is even more difficult to justify the installation of any advanced instrumentation and control system (Olsson, 1993). There are difficulties in controlling the activated sludge process owing to its inherent non-linearity, time varying dynamics, large variations in effluent concentration and hydraulic loading (Zhao *et al*, 1994).

1.4 MODELLING

The on-line investigation of control approaches is not practical for a number of reasons, ranging from regulatory authorisation to non-reproducibility of results since conditions are always changing. Work in pilot plants of small volumes or even laboratory work sometimes using synthetic sludges (Tsai *et al*, 1996) has been carried out but the portability of such investigations to full-scale operation is not always obvious.

1.4.1 Aeration stage modelling

The activated sludge wastewater treatment process was developed in England during the early 1900's. Early work in the 1910's was aimed at dispensing the treatment process from the use of filters. However, it was not until the 1950's that the activated sludge fundamentals came under close scientific study when Helmers *et al* (1951) reported that the rate of activated sludge growth was proportional to the biochemical oxygen demand (BOD) reduction as long as nutritional deficiencies were not present. Also in 1951, Heukelekian *et al* proposed the evaluation of activated sludge volatile suspended solids (VSS) accumulation rate through the use of a linear mathematical relationship linking it to the BOD in the feed and the mixed liquor volatile suspended solids (MLVSS). In 1955, Eckenfelder & O'Connor proposed a mathematical model for activated sludge wastewater treatment, which was later modified and expanded. In 1963, McKinney proposed another mathematical model for completely mixed activated sludge processes. These publications established a nomenclature widely used at the time. However, confusion between the two models limited their application until a detailed study by Goodman and Englande (1974) showed that the two models were intrinsically identical, and thus developed a unifying model between the two approaches.

In 1975, Busby and Andrews developed a dynamic model in order to address some of the main problems found in the existing models namely:

- Most models usually use only one completely mixed reactor, whereas the hydraulic regimes, for most activated sludge plants, lies between perfect mixing and plug flow.
- In general there was no provision for considering the contribution of suspended solids (SS) to the effluent biochemical oxygen demand (BOD) even though SS are often a major contributor to the effluent BOD.
- The thickening capability of the solids-liquid separator frequently determines the mixed liquor suspended solids (MLSS) level that may be achieved in the aeration basin. This important interaction was often neglected.
- Time-varying inputs may frequently cause the expected performance of a system to be completely different from that predicted by a steady-state model. Provision for prediction of the dynamic response should therefore be included in process models.
- The kinetic expression used most frequently at the time to express the growth rate of the micro-organisms was first order with respect to substrate, instead of the more widely accepted expression presented by Monod (1942) which allows the order of the reaction to vary with substrate concentration.

To overcome these difficulties Busby and Andrews (1975) separated the biomass into three separate components, and coupled the aeration stage model with a dynamic model of the secondary settler.

Since the early 1970's the modelling of the aeration stage of the activated sludge process has become more complex due to new design and operating configurations such as partial re-circulation of mixed liquor, distribution of the settled sewage among several of the tanks in series etc. Also the number of biological processes and elements considered has increased progressively to take into account nitrification, denitrification and phosphorus removal in addition to the biodegradation of carbonaceous matter (Wentzel *et al*, 1992).

In 1980, Dold *et al* developed a dynamic model which divided into two fractions the influent biodegradable chemical oxygen demand (COD); namely readily biodegradable COD and slowly biodegradable COD, thus allowing their model to explain experimental observations which did not fit current models at the time. Dold *et al* incorporated the two fractions COD model into an aerobic nitrification model that gave very good predictions of the observed behaviour of oxygen uptake rate, COD and nitrogen in various aerobic systems under cyclic flow and load conditions.

The International Association on Water Pollution Research and Control (IAWPRC) recognised the requirements for a mathematical model describing the complex interactions needed to accurately describe carbonaceous matter removal, nitrification and denitrification, in a way which would promote the use of modelling in order to improve wastewater treatment practice. The IAWPRC formed a task group in 1983 to promote the development of, and facilitate the application of, practical models to the design and operation of biological wastewater treatment. This led to the publication of a state-of-the-art model generally referred to as "Activated sludge model No. 1" (ASM1) in 1986 (Henze *et al*). ASM1 has been introduced in a number of computer programs; one notably, the Single Sludge Simulation Program (SSSP) developed by Bistrup & Grady (1988) to allow detailed evaluation and design of a variety of suspended growth reactor options by configuring the biological reactor as a series of completely mixed reactors in series. Other dynamic modelling platforms using ASM1 are ASIM (Gujer & Henze, 1991) and GPS-X (Patry & Takács, 1991), which incorporates ASM1 as one of its biological process modelling options.

ASM1 has opened the way to further research into modelling and characterisation, as the many papers using it directly or in a reduced version testify. For example, Jeppsson and Olsson (1993) developed a simplified model based on ASM1 for simulating the activated sludge process capable of modelling carbonaceous and nitrogen activities. Other researchers (Larrea *et al*, 1992; Tenno & Uronen, 1995) have approached the on-line identification / state estimation problem, by developing other simplified forms of ASM1, excluding denitrification.

Daigger and Nolasco (1995) evaluated thirteen full-scale wastewater treatment plants using dynamic models based on ASM1 with the addition of the phosphorus removal model of Dold (1990) where necessary. As far as nitrogen is concerned the models have proved to be able to accurately predict full-scale plant performance, even using default model parameters. Default values of model stoichiometric and kinetic parameters have been found in their study to often provide satisfactory prediction of process performance and when identification of the kinetic and stoichiometric parameters is performed, the resulting values are close to the default values (Couillard and Zhu, 1992; Sorour *et al*, 1993; Stokes *et al*, 1993).

Wentzel *et al* (1989) introduced a more complex model to deal with phosphorus removal which was used extensively for this purpose until the International Association on Water Quality (IAWQ), formerly IAWPRC, task group on mathematical modelling for design and operation of biological wastewater treatment processes, produced "Activated sludge model No. 2" or ASM2 (Henze *et al*, 1995) which is an extension of ASM1 and uses the concepts incorporated in it. The main advantage of ASM2 over ASM1 was the incorporation of phosphorus removal. However, this resulted in an even more complex model which requires many more components in order to characterise the wastewater, as well as the activated sludge. In addition to the biological processes ASM2 incorporates two chemical processes needed to model the chemical precipitation of phosphorus.

In addition to the development of deterministic models, a few attempts at grey-box and black-box models have been made. Time series models have been developed to describe dynamic input-output relations between flow rates and suspended solids, aeration rate and dissolved oxygen, carbon source dosage and denitrification rate (Berthouex *et al*, 1978; Novotny *et al*, 1990). The main advantage of a time series model is that no knowledge of the actual process is needed as long as the inputs applied result in a noticeable output. More recent developments using Neural Networks (Tyagi & Du, 1992) and fuzzy logic approaches (Fu & Poch, 1995) have also been studied in order to identify patterns in the process in order to improve control efficiency. However, it has to be recognised that deterministic models have found a wider acceptance.

Models such as ASM1, even though considered as a reference for carbon removal, nitrification and denitrification, have been deemed too complex for many control applications leading to the development of reduced order models which try to retain the main characteristics of the process by limiting the validity of the reduced model to a narrow range of operating conditions for example (Kabouris & Georgakakos, 1992; Jeppsson & Olsson, 1993).

1.4.2 Final settling tank modelling

The name clarifier for the final separation stage tends to be misleading in the sense that it also serves as a thickener to concentrate biological solids, which must be recycled to sustain the microbial processes in the aeration basin. Furthermore, the clarifier is the only location where solids can be stored in the conventional activated sludge process. This function is significant when control strategies for activated sludge process are considered (Tracy & Keinath, 1973).

Early research on the subject of thickening was concerned with the development of design equations which would allow the prediction performance of continuous thickening from batch settling tests. The earliest work in this area was performed by Coe & Clevenger (1916). They developed an empirical relation, which predicts the ability of a layer of solids of a given concentration to transmit solids in a continuous thickener. They also first described the phenomenon of compression involved in settling, compression being the point where floc particles rest on one another.

Kynch (1952) developed the theory of flocculent suspensions which laid the basis for the first models describing flux theory (Dick & Young, 1972). Another formulation of flux theory that is widely used was published by Vesilind (1979). The partial differential equations needed to describe the phenomena involved have often been neglected in favour of empirical rules, as used by Lech *et al* (1978) and Marsili-Libelli (1989). Another method, pioneered by Tracy and Keinath (1973), is to use an approximation based on the division of the clarifier in a number of layers, typically 10, through which the suspended solids thicken. It has proved a popular approach, being adopted by many researchers (Takács *et al*, 1990, Diehl *et al*, 1990). Hill (1985) also based his model on the multi-layered approximation but introduced considerations for the typical conical shape of the final settling tank.

Dick (1970) emphasised the thickening function over the clarification which was the main concern in those days, and showed that the sludge volume index (SVI) does not always have an effect on the return sludge concentration. Therefore, the use of the sludge volume index could be misleading as an indicator of sludge zone settling velocity measurement (Bye & Dold, 1998), and caution should be exerted if it is used to regulate the return activated sludge flow rate. In addition to the two zones of clarification and thickening, Tanthapanichakoon & Himmelblau (1981) introduced a third zone, the dilute zone, located between the first two. However, Keinath (1985) has stated that the dilute zone may not actually exist. Based on this, Lessard (1989) developed a reasonably simple model, which can be coupled relatively easily to an aeration stage model. At the same time as dynamic models became more complex, the need for simpler models was recognised for the design of control systems, as Stehfest (1984) observed. He developed a lumped parameter model consisting of two variable volume continuous stirred tank reactors separated by a discontinuity.

More recent work on the final settling tank has been concerned with the behaviour of the sludge blanket (Göhle *et al*, 1996), the biomass storage function and the coupling with the aeration stage (Marsili-Libelli, 1993) and even two dimensional hydrodynamic solids transport models for the thickening function (Ji *et al*, 1996). It is difficult to determine what the state-of the art for dynamic models for the clarification and thickening is. There is still no admitted universal reference model even though an IAWQ task group is working towards producing such a reference document, as done with the aeration stage of the activated sludge process with ASM1 (Henze *et al*, 1986) and ASM2 (Henze *et al*, 1995). Generally, the final settling tanks are represented as two different processes: clarification and thickening. Most models have not been evaluated thoroughly against experimental work at plant scale, especially for the thickener models. Finally, clarifier models are mostly based on empirical relationship and are therefore largely related to the particular plant used to determine the parameters (Lessard, 1989).

1.4.3 Integration of the models

It has been noted (Lessard & Beck, 1991) that there have been few studies on the integration of the constituent unit process models into a description of the plant as a whole due to the complexity of the task and the relatively focused interest upon the activated sludge itself. Primary sedimentation and the sludge disposal problem were not seen as matters of urgent concern until recently.

Since it is not possible to mathematically model an activated sludge plant without considering the function of the clarifier, most models include a very simple representation of the final clarifier or assume that the secondary clarifier is always able to concentrate the sludge adequately. Dupont & Henze (1992) combined ASM1 with a more complex model of the final settling tank even though it is purely empirical.

1.4.4 Parameter estimation and characterisation

The high complexity of the models causes a severe problem of identification and verifiability. Often the models are derived from simpler unit operations and later combined into large plant models. The parameter values consequently may not be the same. Several parameter combinations can often explain the same dynamic behaviour. This is further accentuated when the influent wastewater composition is taken into consideration; a change in its characteristics can quite often be explained by kinetic parameter changes (Jeppsson & Olsson, 1993).

As a result, a lot of effort has been devoted to the parameter identification of the activated sludge model No. 1. An important problem is the fractionation of the organic matter in the model. Henze (1992) noted that the methods for measuring the fractionation of the organic matter are only partly developed. However, he also showed that the proportions of COD, biomass and nitrogen found in a specific wastewater seem to be constant even when concentrations vary. The other important model parameters are the kinetic parameters. Kappeler and Gujer (1992) presented a relatively simple method to identify the model kinetic parameters and the COD wastewater fractions. Larrea *et al* (1992), Vanrolleghem *et al* (1992 and 1995), Spanjers & Keesman (1994) and Von Sperling (1994a) also presented methods to identify model parameters using a combination of on-line data, laboratory batch tests and classical error function minimisation.

1.4.5 Different time scales

The activated sludge process dynamics are classified as stiff in that they are characterised by fast and slow response components (Kabouris & Georgakakos, 1992). For example, the IAWQ task group for mathematical modelling of the ASP (Henze *et al*, 1986) assessed the time constants associated with particulate substrates in the order of hours, those associated with dissolved oxygen in the order of seconds, and for other soluble components in the order of minutes. In their implementation of the IAWQ model, Bidstrup & Grady (1988) adopted integration steps of 15 min, 0.15 min and 1.5 min respectively. During a slower first multi-rate integration, missing values for slower variables during faster time steps are linearly interpolated from the slower step boundary values. In this way the computationally expensive evaluation of time derivatives for the slower variables during the faster time steps is avoided.

A simulation model based on IAWQ model No.1 (Henze et al, 1986) with the addition of a relatively simple secondary settler based on the work of Lessard and Beck (1991), modified to give a better indication of the water quality, was used in this work.

1.5 PROCESS CONTROL

A biological wastewater treatment plant is a complex dynamic system, including biological, chemical and physical phenomena. Its dynamic nature is highlighted by the time varying flow rates, concentrations and compositions that can be quite significant and very sudden. Control actions have to be related to the dynamics of the process since the result of such action cannot generally be observed on a few samples. It is often not trivial to find the right cause-effect relationship and there are strong links between the different elements of the process such as sludge recycling, aeration, and so on (Olsson *et al*, 1989).

Early attempts at control in wastewater treatment plants date from the 1950's, and involved the use of individual analogue controllers located at or near the control devices associated with them, in what were effectively fully distributed analogue control systems. The plant operators had to go out to the site of each controller to adjust the settings. However, the overall plant operation was improved by this early approach to process control. Pneumatic control was used in some cases but the majority of plants used mechanical and electrical control. Centralisation of the control system in a reduced number of locations within the plant, one or more depending on the plant size and complexity, improved this situation (Walker, 1977).

Control strategies currently used in wastewater treatment plants are mostly conventional controllers based around on-off and simple PID-based feedback control systems. Advanced control strategies have generally only been evaluated on pilot-scale wastewater treatment processes or for short periods on full-scale systems.

1.5.1 Conventional feedback

The widespread use in industry of PID and on-off controllers and the resulting familiarity with their properties and design characteristics, have made these regulators the most popular control method in wastewater treatment processes. However, the performances of these controllers cannot be expected to be optimal owing to the time-varying and non-linear nature of the processes involved (Andrews, 1974; Heinzle *et al*, 1993). The controllers have to be tuned for optimal performance of the regulator. Tuning requires that either experimentation on the plant or simulation with an accurate process model be carried out (Vaccari *et al*, 1988; Heinzle *et al*, 1993). The value of the controller parameters depends upon process characteristics which change for a non steady-state process. Therefore, these tuned parameters become non-optimal when the plant characteristics are modified.

Multi-input, multi-output systems should be considered to describe and develop control systems for the activated sludge process. However, the wide range of response time involved in the process enables the decoupling of many process units (Lessard & Beck, 1993). Separate local controllers can provide reasonable control performances.

1.5.2 Optimal control

There are design techniques available that allow the development of an optimal controller for a given process model and performance index. Optimal feedback control design has become a generally accepted technique when linear models are used (Marsili-Libelli, 1989). Examples of linearisation around the operating point for sludge recycle and dissolved oxygen control have also been reported by Marsili-Libelli (1984). Few results of analytical solution of the optimal control law have been published for non-linear models, most results having been obtained by numerical solution of the optimisation problem (Sincic & Bailey, 1978; Yeung *et al*, 1980; Kabouris & Geogakakos, 1990; Zhao *et al*, 1994). One problem with some of the resulting control systems is that they rely on a perfect process model with fixed model structure and known parameters. The results of Yeung *et al* (1980) are an example of this dependence of optimal control actions on the model structure. It is therefore difficult to rely on such a control strategy for a process whose inherent non-linear dynamic and changing nature is well known. Also, Marsili-Libelli (1984) found that the effectiveness of a control scheme depends greatly upon a proper choice of the cost function.

1.5.3 Adaptive control

From the early 1960's, an important research area has been the development of adaptive regulators. Adaptation of the controller may be required for two main reasons:

- In the case of a linearised model, the linearisation takes place at a particular operating point, if this operating point is changed, the parameters of the control system need adjustment to provide an optimal performance in the new conditions.
- If the process is time varying, such as a biological process. The regulator being based on nominal values of the process model, the controller parameters also need to be adapted.

A newer approach to deal with time-varying and uncertain dynamics has been developed called H_∞ or robust control theory (Doyle, 1983; Kwakernaak, 1988). Model uncertainty is taken into account and fixed, linear time-invariant designs based on the minimisation of infinite norm of a sensitivity function are used. The main problem with this technique is that to ensure robustness the controller performance, in terms of conventional criteria, is generally degraded (Gendron *et al*, 1993).

The main functions needed by an adaptive control loop are identification of the process dynamics and update of the control parameters. When the process is being linearised, adaptivity is produced by estimating, generally recursively, the model parameters used by the control law. Examples of applications of adaptive linearising control can be found for anaerobic digestion and activated sludge systems (Ko *et al*, 1982; Renard *et al*, 1988; Dochain & Perrier, 1995).

Predictive control methods have also been applied to the aeration stage of an activated sludge process to determine the sequence of motor on/off switches needed to regulate dissolved oxygen (Moreno *et al*, 1992) and to the control of an aerated lagoon (Ben Youssef & Dahhou, 1996) which is another type of biological wastewater treatment process.

In situations where the process changes cannot be measured or predicted, the adaptive control strategy has to be implemented in a feedback manner. An important class of controller systems called self-tuning regulators has been developed (Åström & Wittenmark, 1973). Originally, the regulator was based on a recursive least-squares estimator of the parameters of a feedback control law from on-line process data, followed by the use of these estimated parameters in the control law itself. Later modifications to the self-tuning controller (Clarke & Gawthrop, 1975) and the generalised predictive controller (Clarke *et al*, 1987) were developed and implemented successfully on industrial applications in general. The self-tuning regulator and controller are usually based on a minimum variance criterion to reduce the error in the controlled variable, they are well adapted for applications where process disturbances are stochastic in nature, rather than deterministic (Seborg *et al*, 1989). Self-tuning controllers have been shown to be able to deal with changes in mass transfer efficiencies and large variations in oxygen demand (Olsson *et al*, 1985; Marsili-Libelli, 1990).

1.5.4 Expert systems

Among artificial intelligence techniques, Expert Systems have a role to play in an industry where the main actors (water companies) are sometimes fearful of having complex control systems running the plant. Expert systems give plant operators either on-line or off-line advice for a variety of situations, from day to day control problems to explaining more serious plant failure. They can also provide possible solutions (Maeda, 1984; Stimson, 1993; Ladiges & Kayser, 1993). However, it seems that these promising guidance systems have yet to make an impact with the water utilities for use in wastewater treatment plants, even though Ladiges & Kayser (1994) have actually evaluated an off-line version of their Expert System on a full-scale plant and expert systems techniques are being used in other areas of the water industry (clean water treatment, leak reduction in the piping network etc).

1.5.5 Fuzzy logic control

Fuzzy logic control theory was first proposed by Mamdani & Assilian (1975) from the fuzzy set theory originated from Zadeh (1973). Fuzzy sets are a way of representing qualitative knowledge in mathematical terms. Fuzzy logic has attracted increasing attention in the wastewater treatment field which seems well suited with all the uncertainties associated with the operation of water treatment processes. Early work (Tong *et al*, 1980) was mainly based on incorporating the knowledge of human operators and control engineers through a linguistic approach. However, when a problem is complex it might become necessary to build a fuzzy relational equation from operational and experimental data to derive control rules using fuzzy identification techniques. These two approaches can be combined to develop models of more complex systems (Babuska & Verbruggen, 1996).

Fuzzy logic control systems have been developed for operation with a wastewater treatment process. Tsai *et al* (1993) developed a system for the control and forecast of the suspended solids concentration in the effluent, and presented experimental results on a laboratory scale wastewater treatment plant replica using artificial wastewater (Tsai *et al*, 1996). Fuzzy feedback controllers have been used to control the chemical removal of phosphorus, which could not be controlled adequately by conventional feedback methods because of the long and varying dead-time in the process (Hou & Lauer, 1993). In addition, partial knowledge of the process can be incorporated into a FLC so that better performance of the system is obtained (Yin & Stenstrom, 1996). Fuzzy control of intermittent aeration has also been investigated (Alex *et al*, 1994) as well as the real time control of sewer systems (Fuchs *et al*, 1997). The supervisory level of hierarchical control systems whose lower level were PID controllers have also been developed with the help of fuzzy control (Couillard & Zhu, 1992).

1.5.6 Neural network control

Artificial neural networks are based on a 'black-box' approach, but unlike time series analysis, their structure makes them particularly suited to deal with non-linear systems. Before being used, neural networks need to be trained, that is to say they need to be presented with examples of the desired behaviour so that their parameters can be adjusted. Neural networks can be applied to different tasks, including process control (Hunt, 1992). While neural network control is being used in other applications it seems it has not yet been implemented on full-scale wastewater treatment plants. Capodaglio *et al* (1991) developed a neural network for pattern recognition in order to forecast sludge bulking problems. Tyagi & Du (1992) applied a neural network for operational prediction, and Tyagi *et al* (1993) developed a neural network to control activated sludge flows using these predictions. Another promising field is the application of neural networks for improving the modelling of the activated sludge process, by either developing neural network models (Cote *et al*, 1995) or even creating hybrid models using both artificial neural networks and first principle techniques (Zhao & McAvoy, 1996).

1.6 OPTIMISATION OF THE ACTIVATED SLUDGE PROCESS

Optimisation can be defined as the science of determining the 'best' solution to certain mathematical problems, such as models of a physical reality. This means finding the minimum or maximum of a function of one or more variables. Until 1940 little was known about methods for numerical optimisations of functions of many variables. Least square calculations were carried out, steepest descent type methods had been applied and Newton's methods in many variables were used. However, the introduction of the computer was primordial in the development of optimisation methods. The 1940s and 1950s saw the introduction of linear programming, where 'programming' is understood as optimisation. Hill-climbing methods were developed at approximately the same time. In the 1960's non-linear and multivariable methods were developed and optimisation methods were applied successfully to industrial processes (Fletcher, 1987; Beale, 1988).

In many practical optimisation problems there are constraints on the values of some parameters, which restrict the region of search for the minimum (or maximum). The region of search in which the constraints are satisfied is often called the *feasible* region, while the region in which constraints are not satisfied is termed the *non-feasible* or *infeasible* region.

In practice it is very difficult to determine if the minimum obtained by a numerical process is a global optimum or not. In most circumstances it can only be said that the optimum obtained is an optimum within the local area of search. A particular function may have several local optima but it is usually impossible to determine if a local optimum is the global optima unless all optima are found and evaluated. A number of numerical methods exist for the solution of optimisation problems. The applicability of each method for a particular optimisation problem depends on the various properties of the function that is to be optimised such as continuity, derivative existence, convexity, etc.

Linear Programming

The Simplex search technique determines the direction of movement in a two dimensional search problem using only three observations. The input information for a Simplex search is the same as that required for all search methods of optimisation. The function given by $E = f(x)$ and a first approximation x_0 must be specified. Search techniques that take steps towards the minimum usually require that the step size be specified. As the minimum of the function is approached the step size is reduced to improve the resolution of the search. The search is finished when the step size falls below a specified minimum value. For the Simplex search the step size is replaced by a single value which gives the length of one side of the simplex. The use of equal units in each dimension, points to the importance of correct scaling for this search method. A lower limit to the length of a simplex side is also required so that the search can be terminated (Adby & Dempster, 1974).

Several improvements to the simplex search are available. The most useful of these is due to Nelder and Mead (1965) which incorporates expansion as well as contraction of simplex so that movement towards the minimum can be accelerated. Also the simplex can be arranged to incorporate some form of linear search in the direction of the reflected vertex. It has the advantage of not requiring the derivatives of the function to operate but suffers from slow convergence and can easily converge to local optima.

Non-Linear Programming

Gradients methods require that the function is differentiable that is to say continuous. Direct gradient based methods restrict the search space to the points where the partial derivatives are zero in all directions. The indirect gradient based methods use the partial derivatives of the function at a given starting point to guide the search towards the point in the neighbourhood of the starting point where all partial derivatives are zero. These are called *hill-climbing* methods and can be traced back to Cauchy in the 19th Century. The application of such methods is limited because of their dependence on the existence of derivatives; also they easily converge to local optima in case of multimodal functions.

Randomised algorithms such as random walk can be used in any search space but they are extremely inefficient because they do not exploit the search space and an extremely large number of functions evaluations is usually required in order for them to converge with reasonable accuracy.

Differential calculus

Differential calculus is useful for unconstrained optimisation of functions of continuous variables. To minimise a function of n variables $f(x_1..x_n)$, the n simultaneous equations 1.1 have to be satisfied.

$$\frac{\partial f}{\partial x_j}(x_1, x_2, \ldots, x_n) = 0 \qquad (j = 1, \ldots, n) \tag{1.1}$$

The calculus approach is useful if the equations can be solved directly (for example if they are linear) or if it enables the dimension of the problem to be reduced since it does not provide a method for solving such equations if they have no exploitable structure.

There is a trade-off to be made with the different algorithms between the degree of exploration of the search space and the degree of exploitation of the available information about it. The gradient based methods have a high degree of exploitation by using the derivatives of the function to guide the search, but can very easily converge to local optima, because of their lack of exploration of the search space. On the other hand, randomised methods have a high degree of exploration of the search space. It is theoretically guaranteed that given a sufficiently large number of function evaluations a near optimal solution will be found by randomised methods. However, they do not exploit the available information at all, so even if they reach a point in the neighbourhood of the optimal solution, they may easily diverge to other sub-optimal point.

Genetic algorithms

Genetic algorithms (GA) are a stochastic search method which can be used for the numerical optimisation of difficult functions. GAs operate on a population of potential solutions applying the principle of survival of the fittest to produce better and better approximations to a solution. At each generation a new set of approximations is created by the process of selecting individuals according to their level of fitness in the problem domain and breeding them together using operators borrowed from natural genetics such as recombination, crossover and mutations. The fitness of individual members of a population is assessed through an objective function characterising its performance in the problem domain. The fittest individuals are mated together in order to produce new individuals, low fitness individuals are discarded. Genetic operators are applied on the new population. The new population fitness is tested and an iterative process takes place. The GA is terminated when some criteria are satisfied, for example a certain number of generations, a mean deviation in the population, or when a particular point in the search space is encountered (Chipperfield *et al*, 1994)

GAs do not require derivative information or other additional knowledge, only the objective function and corresponding fitness level influence the direction of search. GAs use probabilistic transition rules, not deterministic ones. GAs provide a number of potential solutions to a given problem and the choice of final solution is left eventually to the user. In the case of multi-objective functions, GAs can be useful to identify the different alternative solutions simultaneously.

Studies of Holland (1975), De Jong (1975), Goldberg (1989) and others have demonstrated both theoretically and experimentally, the superior performance of GAs over traditional optimisation techniques. The genetic algorithm approach is well suited to the optimisation of complex systems where noisy, highly non-linear, multimodal and discontinuous functions of many dimensions needs to be optimised. GA should therefore be a natural optimisation tool for the activated sludge process. However, it has to be noted that it is not because the process itself is non-linear that the optimisation algorithm will have to minimise a highly non-linear objective function.

Most of the optimisation methods briefly described here have limitations in that they require the objective function to optimise to have particular properties such as being continuous or derivable. The choice of the optimisation techniques employed is dependant on the characteristics of the objective function to optimise and not on the process itself. Nevertheless, a complex non-linear system will usually lead to the definition of an objective function which is also complex and non-linear.

Optimisation in water treatment

Biological wastewater treatment is a complex process, with many different elements: primary sedimentation, aeration, secondary sedimentation, anaerobic fermentation of sludge, and so on. Often, each of these elements can be operated more efficiently from economic and environmental considerations. Some work has been performed on: improving the management of the solids within the different parts of the plant (Von Sperling, 1994b); the effect of the use of chemicals on the biological treatment stage (Robson *et al*, 1972); the anaerobic digestion of surplus sludge (Renard *et al*, 1988). However, the main research effort, in this domain, is concentrated on increasing the effluent quality and/or minimising the operation costs. The impact of return sludge flows on the water quality has been considered (Grulois *et al*, 1993) and operating cycle optimisation applied to pilot plants (Dupont & Sinkjaer, 1994) even though model calibration is important for such tasks. The research into cost minimisation is concentrated on the clean water side by the reduction of chemical use, and on the wastewater side as the reduction in energy consumption since it is the main operating cost for an activated sludge plant. Short of modifying the plant design (Bischoff *et al*, 1996), control strategies making better use of the energy used for aeration, have been developed (Clifft & Andrews, 1981; Cantwell, 1987; Garret *et al*, 1990). However, Prindle *et al* (1983) pointed out that energy cost control is not synonymous with energy use reduction because energy savings in one process unit can lead to increased expenses in another. Also, prices of electricity, which is the main form of energy used in wastewater treatment works, have a pattern fluctuating daily, weekly and annually.

Much work remains to be done on the process optimisation side and especially implementing successful strategies on full-scale wastewater treatment plants.

1.7 AIM OF THE RESEARCH

This research program was partly funded by North West Water Limited, the second largest water company in the UK. Care has been taken to make this work as transposable as possible to full-scale plant operation.

1.7.1 Objective

The objective of this research project was to investigate different control strategies for the activated sludge process in order to identify the best options faced by the water industry in the medium term. This includes both developing new control solutions but also optimising, if possible, the existing situation and practice.

1.7.2 Investigation approach

a) Evaluation of three controllers for the control of dissolved oxygen

PID control is industry's solution to most control problems. Most water treatment processes are being regulated by programmable logic controllers (PLCs) with built-in PID control capacity. Thus it seems only natural to use PID control as the control reference since it is readily available and used, in most wastewater treatment plants.

Fuzzy logic controllers (FLC) have been used successfully in a wide range of applications, including water treatment where a number of studies have been carried out (Tong *et al*,1980; Tsai *et al*, 1993; Alex *et al*, 1994). PLCs with fuzzy logic capability have started to appear on the market, making fuzzy control a viable alternative in the short-term future. These PLCs will probably operate with simple fuzzy logic algorithms and therefore these algorithms for fuzzy control became of interest to this research.

Last but not least, it has been seen that self-tuning controllers have been effective in dealing with the large and relatively unpredictable variations of oxygen demand making it a useful tool for dissolved oxygen control. In the medium term, self-tuning systems could be implemented on wastewater treatment plants if the benefits were great enough to justify the higher level of complexity required.

b) **Investigation of the effectiveness of PID-based control strategies,** employing different locations for a limited number of sensors and actuators. This is a problem faced in industry when only partial instrumentation is performed for economic or technical reasons. Simulations were developed for different scenarios and the resulting control performances compared.

c) **Process optimisation**, accounting for both operating costs and effluent quality. A cost function has been defined with available data and optimisation performed by conventional and genetic algorithms techniques for minimising plant operation cost and/or maximising effluent water quality.

1.7.3 Originality of research

Few models used for control purposes integrate the different key elements of a wastewater treatment plant. Most schemes dealing with dissolved oxygen control only consider the aeration stage while assuming a near perfect settling stage and therefore do not include the interactions between the two elements. In this project however, a state-of-the-art model has been used for the aeration stage and a relatively complex model, even though not too demanding mathematically, has been employed for the clarification stage. The effluent quality is also modelled more realistically than is normally found in publications.

In this study, the comparisons between the different controller schemes are performed over a period of 14 days, giving a much more realistic picture of the controller behaviour than the usual tests performed over at most two days. Typical daily and weekly sewage flow and loading pattern are used, as well as storm conditions which are putting stress on the water treatment system.

The costs taken into account in order to perform process optimisation are as thorough as possible in this work and include indirect costs, such as sludge disposal, which are often neglected in optimisation studies of the operation of the activated sludge. These added costs are generally ignored, either because they are treated as constant overheads or even assumed to be non-existent even though large sums of capital might be required to deal with the problems, such as building sludge digesters.

Finally, the optimisation algorithm works by modifying the MLSS set-point rather than modifying directly the recycled and surplus sludge flow rates. This approach has not been encountered so far in the literature.

1.8 THESIS OUTLINE

It has been recognised that on-line work is impractical for a full comparative evaluation due to the non-repeatable nature of experimental work on a time-varying non-linear process industrial process. Simulation of the activated sludge wastewater treatment process was therefore required. In Chapter 2, a suitable computer model based on ASM1 is described and its implementation explained. The development and the comparison of different control strategies namely PID, fuzzy logic and self-tuning control are described in Chapter 3. A control scheme is not just a control algorithm, since the number and location of the sensors and actuators also play an important part and can hinder the ability to develop a suitable control system. The placement of sensors and actuators in a particular North West Water plant is investigated in Chapter 4 using the simulation of the process. The optimisation of the process in terms of effluent water quality and operating cost over the overall plant, and not only a single process unit, is investigated in Chapter 5. Finally, the conclusions of the work undertaken are presented in Chapter 6.

Chapter 2

2 ACTIVATED SLUDGE PROCESS MODEL

The treatment of human and industrial wastes by micro-organisms called the activated sludge wastewater treatment method is described by the Encyclopaedia Britannica as:

> "Activated sludge method: sewage treatment process in which sludge, the accumulated, bacteria-rich deposits of settling tanks and basins, is seeded into incoming waste water and the mixture agitated for several hours in the presence of an ample air supply. Suspended solids and many organic solids are absorbed or adsorbed by the sludge, while organic matter is oxidised by the micro-organisms. The sludge is then separated out in a settling tank."

2.1 PROCESS DESCRIPTION AND MODEL

The operation of the activated sludge process consists of blending sewage and recycled activated sludge from the process into a liquid termed *mixed liquor* which is oxidised in the presence of oxygen in order to degrade the organic elements. The oxidation stage is also termed the *aeration stage*. Frequently, denitrification precedes this oxidation stage to release nitrogen in its gaseous form. Following the aeration stage, the liquor is clarified to allow the release of clean water into the environment, while the sludge is thickened for recycling or disposal.

2.1.1 Description of process operation

The influent sewage water is first screened in order to remove the numerous objects that can be found in wastewater (such as plastic, wood etc), the raw sewage is then settled in primary settling tanks where large particles settle by gravitation, prior to transfer toward the aeration stage. The series of communicating tanks (or aeration lane) of the aeration stage can be represented by three continuous stirred tank reactors (Figure 2.1). The first tank is anaerobic and represents typically one tenth of the total aeration stage volume. In the plug flow configuration used here, this tank receives the influent water to be treated and any recycled sludge. No air is added in order to allow an anoxic zone to develop which is needed to allow denitrification, or in other words the release of nitrogen in gaseous form. The output from this first tank flows into two tanks in series, where air is pumped for both aeration and mixing. This succession of tanks is a convenient way of representing the activated sludge plant in which the whole of the aeration stage can be composed of a single lane (typically 50 m long) or of a number of physically distinct tanks. The bacterial activity and the degradation of the organic matter, namely carbon removal (as CO_2 and biomass) and nitrification, primarily takes place in these two tanks. Phosphorus removal is not considered in this work since it requires a more complex model (Henze *et al*, 1995) and is not yet of prime importance to the UK water industry. The output of the last aeration tank is directed towards a secondary sedimentation tank, known as the *final settling tank* or clarifier. This stage separates the suspended solids and organic matter, present in the liquor that settles at the bottom of the tank (thickening into sludge), from the clean water which can then be released, called final effluent (clarification). A large part of the settled sludge is recycled to keep the level of biomass and nutrients within the aeration tanks at an adequate level to maintain process operation (2000-3500g/m^3 of mixed liquor suspended solids), while a smaller proportion, the surplus sludge, is diverted to remove excess biomass and accumulating inert solids from the plant. The surplus sludge can be fermented in order to produce energy, incinerated after dewatering or disposed at sea.

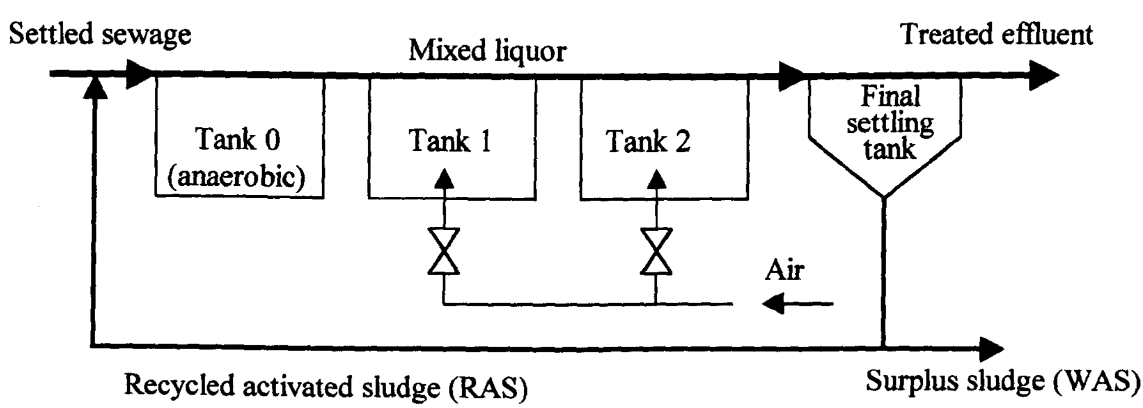


Figure 2.1: Schematic of the activated sludge process

2.1.2 Modelling goals

The aim of this work was to investigate control strategies on this activated sludge process and to optimise process operation. This requires a model which adequately represents the different phenomena involved in the operation of the activated sludge process. There are several problems associated with the investigation of control strategies on a real plant; in addition to implementation problems inherent in developing control systems on such a large scale process, the reliability of the process and the possible environmental and regulatory effects of any reaction of the process have to be taken into consideration.

Another disadvantage of on-line work is the difficulty in implementing reproducible tests. Influent flow rates are not usually directly controlled, except on some small-scale purpose built facilities, and therefore cannot be reproduced exactly. Moreover, the concentration in different substances (load) of the influent sewage is generally highly variable according to rainfall, the time of day, day of week, season of the year, and so on. Last but not least, the time scales involved in the process vary from a few minutes for dissolved oxygen mass transfer to a few hours for the suspended solids concentrations. This would require experiments with a minimum duration of a few days and hence result in many months of activity. All these factors contribute to make the on-line comparison of control techniques impractical. However, simulation offers a less expensive and faster alternative.

An enhanced model has been developed and implemented to allow control strategies to be investigated and compared in identical conditions trying to be as realistic as possible and incorporating real plant parameters when available. Initially, for simple dissolved oxygen control, only the aeration stage was of interest. A state-of-the-art model has been implemented based on the International Association on Water Quality (IAWQ) activated sludge model No.1; often called ASM1 (Henze *et al*, 1986).

However, in order to obtain a more accurate model of the overall plant, a model of the final settling tank (Lessard & Beck, 1993), which is not available in ASM1, has been incorporated. This enables the inclusion of activated sludge flow control (recycled and surplus) which influences directly the aeration stage. The recycling rate determines the concentration of solids and biomass and therefore the oxygen demands, and thus the overall performance of the plant. This model is similar to many of the empirical models developed to model a final settling tank/clarifier (Takács *et al*, 1990, Diehl *et al*, 1990).

In a later stage of the work, to implement the optimisation of the overall plant, a more reliable indicator of the quality of the treated water was needed than the one included in the original clarifier model, requiring an enhanced model for the effluent suspended solids.

Numerical values for physical parameters and plant layout, such as dimensions and number of tanks, average flow rates, different product concentrations, sensitivity and time constants of the sensors, physical limitations of the aeration and pumping, have been taken from real North West Water plants when such data was available.

For a specific part of this study (Chapter 4), the simulation has been based on an existing treatment plant (Runcorn plant A) which does not incorporate denitrification. Its aeration stage is composed of 8 tanks of equal volume and offers only limited control possibilities owing to the design of the aeration system.

2.1.3 Measurement limitations

Activated sludge wastewater treatment plants are a very harsh environment in general, and particularly so for sensors. Bacterial activity can develop on the sensors themselves (fouling) generating false data if regular maintenance is not carried out. Reliability is a major problem for the industry, which explains the small number of sensors which meet the requirements of control systems (Stokes *et al*, 1993).

Most wastewater treatment plants (WWTP) monitor the flow rates of the incoming sewage and returned activated sludge from the clarifier, since flow-meters are relatively robust. Dissolved oxygen measurements can be made available on most plants, however the reliability of the measurement is not always as high as could be expected owing to maintenance problems and the presence of undesirable materials in the raw sewage which can escape screening and obstruct the free flow of liquid around the sensors altering the measurements.

Alkalinity (pH) is monitored on-line in some treatment plants but most rely on off-line measurements, unless a specific problem requiring the addition of chemicals exists. There is generally no such need for domestic sewage.

Equipment exists to measure the suspended solids but again its use is not currently widespread. Technological improvements should make them less expensive and more reliable in the future. The main problem is that most of the suspended solids concentration measurement techniques available at present cannot cope with the high concentrations typically encountered in the returned activated sludge (RAS).

The Oxygen Uptake Rate (OUR) can be measured on-line but requires specialised equipment, called a respirometer. They are generally only available on pilot plants because of the high level of maintenance needed for their satisfactory operation. Biological and chemical oxygen demands (BOD and COD respectively) are measured off-line in a laboratory and therefore cannot be used directly for control purposes. Similarly the Sludge Volume Index (SVI) is measured off-line regularly, however this measure is hard to use for control purposes since the sludge settleability is influenced by many factors such as the composition of the mixed liquor, mixed liquor suspended solids (MLSS) concentration, etc. Suspended solids, MLSS and sludge blanket height are measurable on-line if required. Many other parameters could be measured, at least in the laboratory, if there was a reason important enough to justify the expense and manpower needed to obtain them.

2.2 PROCESS MODELLING

The simulation model of the overall activated sludge process has been developed in stages, starting with the aeration, then clarification/settling, water quality and finally sensor and actuator models.

2.2.1 Modelling the aeration stage

In 1983, the International Association on Water Quality, IAWQ (formerly International Association for Water Pollution Research and Control: IAWPRC), formed a Task Group to promote the development and facilitate the application of practical models to the design and operation of biological wastewater treatment systems. Their goals were first to review existing models, and to reach a consensus concerning the simplest model having the capability of realistic predictions of the performance of single sludge systems carrying out carbon oxidation, nitrification and denitrification. The Task Group's work resulted in a technical publication: Activated Sludge Model No.1 (Henze *et al*, 1986).

2.2.1.1 Aeration model basis

This IAWQ Model No.1 accurately predicts the soluble concentrations of the components under steady-state as well as dynamic conditions, provided that only the activated sludge reactor is of interest, and that there are no limitations to the plant operation introduced by the clarifier.

The basic principles of the model and the assumptions made are as follows:

- The concentration of the organic matter in the wastewater is measured as chemical oxygen demand (COD).
- The organic material is divided into two components: biodegradable, which is itself subdivided into readily biodegradable (S_S) and slowly biodegradable (X_S); non-biodegradable organic matter which is biologically inert, divided into soluble (S_I) and particulate (X_I) components. For modelling purposes, the readily biodegradable substrate is treated as soluble and the slowly biodegradable substrate as particulate. This division provides a lag in the uptake of the electron acceptor, which allows space-time dependent variation in oxygen and nitrate utilisation to be simulated.
- The readily biodegradable substrate is made of simple molecules, which can be taken up directly by heterotrophic bacteria and used for growth of new biomass.
- The slowly biodegradable substrate consists of more complex molecules and must be converted, by hydrolysis, into readily biodegradable substrate before it can be used.

- Heterotrophic biomass is generated by growth on the readily biodegradable substrate under either aerobic or anoxic conditions, but is assumed to cease under anaerobic conditions.
- Some biomass is lost by decay, which incorporates a number of mechanisms including endogenous metabolism, death, predation and lysis. Decay is assumed to result in the conversion of biomass into slowly biodegradable substrate (X_S) and inert particulate products (X_P).
- Nitrogenous matter is divided into two categories: non-biodegradable and biodegradable, which are both further sub-divided. In the non-biodegradable fraction, the particulate portion is that associated with the non-biodegradable particulate COD, the soluble fraction is usually very small and is not incorporated into the model. The biodegradable nitrogenous matter is subdivided into 'ammonia' (S_{NH}) which is both the free compound and its salts; soluble organic nitrogen (S_{ND}) and particulate organic nitrogen (X_{ND}).
- Particulate organic nitrogen is hydrolysed into soluble organic nitrogen in parallel with hydrolysis of the slowly biodegradable organic matter.
- The soluble organic nitrogen is converted to ammonia nitrogen by the heterotrophic bacteria.
- Ammonia nitrogen serves as the nitrogen supply for synthesis of the heterotrophic biomass and as the energy supply for the growth of the autotrophic nitrifying bacteria. For simplicity, the autotrophic conversion of ammonia to nitrate is considered to be a single step process, which requires oxygen. The nitrate formed may serve as terminal electron acceptor for heterotrophic bacteria under anoxic condition, yielding nitrogen gas.

Figure 2.2 presents a schematic of the conceptual model of ASM1 (Lessard, 1989).

Figure 2.2: Schematic of IAWQ conceptual model

2.2.1.2 Aeration model equations

Switching functions are used to turn process rates on and off as environmental conditions are changed (anoxic or aerobic conditions for example). A typical switching function is of the form $\frac{S}{K+S}$ or $\frac{K}{K+S}$ with K significantly smaller than S, dependent on whether the process rate has to be turned on or off when a given condition occurs. This allows for example the use of one equation to describe the processes occurring in both anaerobic and aerobic conditions.

Four main processes are considered: growth of the biomass, decay of the biomass, ammonification of organic nitrogen and "hydrolysis" of particulate products. The details of the aeration model equations are as follows.

- Rate of change of readily biodegradable substrate [g(COD)m^{-3}day^{-1}]

$$\dot{S}_S = -\frac{1}{Y_H}\hat{\mu}_H\left(\frac{S_S}{K_S+S_S}\right)\left[\left(\frac{S_O}{K_{O,H}+S_O}\right)X_{B,H}+\left(\frac{K_{O,H}}{K_{O,H}+S_O}\right)\left(\frac{S_{NO}}{K_{NO}+S_{NO}}\right)\eta_g X_{B,H}\right] + k_h\frac{X_s/X_{B,H}}{K_X+\left(X_S/X_{B,H}\right)}\left[\left(\frac{S_O}{K_{O,H}+S_O}\right)+\eta_h\left(\frac{K_{O,H}}{K_{O,H}+S_O}\right)\left(\frac{S_{NO}}{K_{NO}+S_{NO}}\right)\right]X_{B,H} \quad (2.1)$$

The main processes affecting the readily biodegradable substrate are in the order of equation 2.1: aerobic growth of heterotrophs, anoxic growth of heterotrophs and hydrolysis of entrapped organisms.

- Rate of change of slowly biodegradable substrate [g(COD) m^{-3}day^{-1}]

$$\dot{X}_S = \left(1-f_P\right)\left(b_H X_{B,H}+b_A X_{B,A}\right) - k_h\frac{X_s/X_{B,H}}{K_X+\left(X_S/X_{B,H}\right)}\left[\left(\frac{S_O}{K_{O,H}+S_O}\right)+\eta_h\left(\frac{K_{O,H}}{K_{O,H}+S_O}\right)\left(\frac{S_{NO}}{K_{NO}+S_{NO}}\right)\right]X_{B,H} \quad (2.2)$$

The processes involved are decay of the heterotrophs and autotrophs, and hydrolysis of entrapped organisms.

- Rate of change of active heterotrophic biomass [g(COD) m^{-3}day^{-1}]

$$\dot{X}_{B,H} = \hat{\mu}_H\left(\frac{S_S}{K_S+S_S}\right)\left[\left(\frac{S_O}{K_{O,H}+S_O}\right)X_{B,H}+\left(\frac{K_{O,H}}{K_{O,H}+S_O}\right)\left(\frac{S_{NO}}{K_{NO}+S_{NO}}\right)\eta_g X_{B,H}\right]-b_H X_{B,H} \quad (2.3)$$

The first two terms of equation 2.3 represent aerobic and anoxic growth of heterotrophs respectively, while the last term describes the decay of the heterotrophs.

- Rate of change of active autotrotrophic biomass [g(COD) m^{-3}day^{-1}]

$$\dot{X}_{B,A} = \hat{\mu}_A\left(\frac{S_{NH}}{K_{NH}+S_{NH}}\right)\left(\frac{S_O}{K_{O,A}+S_O}\right)X_{B,A}-b_A X_{B,A} \quad (2.4)$$

The first term denotes the aerobic growth of the autotrophs, the second one their decay.

- Rate of change of particulate product arising from biomass decay [g(COD) m^{-3}day^{-1}]

$$\dot{X}_P = f_p\left(b_H X_{B,H}+b_A X_{B,A}\right) \quad (2.5)$$

The first term within the bracket represents the decay of the heterotrophs, the second term the decay of the autotrophs.

- Rate of change of oxygen (negative COD) [g(COD) $m^{-3}day^{-1}$]

$$\dot{S}_O = -\frac{1-Y_H}{Y_H}\hat{\mu}_H\left(\frac{S_S}{K_S+S_S}\right)\left(\frac{S_O}{K_{O,H}+S_O}\right)X_{B,H} - \frac{4.57-Y_A}{Y_A}\hat{\mu}_A\left(\frac{S_{NH}}{K_{NH}+S_{NH}}\right)\left(\frac{S_O}{K_{O,A}+S_O}\right)X_{B,A} \quad (2.6)$$

The oxygen concentration is affected by the aerobic growth of the heterotrophs (first term) and autotrophs (second term).

- Rate of change of nitrate and nitrite nitrogen [g(N) $m^{-3}day^{-1}$]

$$\begin{aligned}\dot{S}_{NO} = &-\frac{1-Y_H}{2.86Y_H}\hat{\mu}_H\left(\frac{S_S}{K_S+S_S}\right)\left(\frac{K_{O,H}}{K_{O,H}+S_O}\right)\left(\frac{S_{NO}}{K_{NO}+S_{NO}}\right)\eta_g X_{B,H} \\ &+\frac{1}{Y_A}\hat{\mu}_A\left(\frac{S_{NH}}{K_{NH}+S_{NH}}\right)\left(\frac{S_O}{K_{O,A}+S_O}\right)X_{B,A}\end{aligned} \quad (2.7)$$

The first term of the equation is related to the anoxic growth of the heterotrophs, the second to the aerobic growth of the autotrophic biomass.

- Rate of change of $NH_4^+ + NH_3$ nitrogen [g(N) $m^{-3}day^{-1}$]

$$\begin{aligned}\dot{S}_{NH} = &-i_{XB}\hat{\mu}_H\left(\frac{S_S}{K_S+S_S}\right)\left[\left(\frac{S_O}{K_{O,H}+S_O}\right)X_{B,H} + \left(\frac{K_{O,H}}{K_{O,H}+S_O}\right)\left(\frac{S_{NO}}{K_{NO}+S_{NO}}\right)\eta_g X_{B,H}\right] \\ &-\hat{\mu}_A\left(i_{XB}+\frac{1}{Y_A}\right)\left(\frac{S_{NH}}{K_{NH}+S_{NH}}\right)\left(\frac{S_O}{K_{O,A}+S_O}\right)X_{B,A} + k_a S_{ND} X_{B,H}\end{aligned} \quad (2.8)$$

The first term of equation 2.8 represents the aerobic growth of the heterotrophs and the second their anoxic growth. The third term relates to the aerobic growth of the autotrophs, while the last term denotes the action of ammonification of the soluble organic nitrogen (S_{ND}).

- Rate of change of soluble biodegradable organic nitrogen [g(N) $m^{-3}day^{-1}$]

$$\dot{S}_{ND} = -k_a S_{ND} X_{B,H} + k_h \frac{X_s/X_{B,H}}{K_X+\left(X_S/X_{B,H}\right)}\left(\frac{X_{ND}}{X_S}\right)\left[\left(\frac{S_O}{K_{O,H}+S_O}\right) + \eta_h\left(\frac{K_{O,H}}{K_{O,H}+S_O}\right)\left(\frac{S_{NO}}{K_{NO}+S_{NO}}\right)\right]X_{B,H} \quad (2.9)$$

The first term of equation 2.9 represents ammonification, while the second expresses the action of hydrolysis of entrapped organic nitrogen.

- Rate of change of particulate biodegradable organic nitrogen [g(N) $m^{-3}day^{-1}$]

$$\dot{X}_{ND} = \left(i_{XB} - f_P i_{XP}\right)\left(b_H X_{B,H} + b_A X_{B,A}\right) - k_h \frac{X_s/X_{B,H}}{K_X + \left(X_S/X_{B,H}\right)}\left[\left(\frac{S_O}{K_{O,H}+S_O}\right) + \eta_h\left(\frac{K_{O,H}}{K_{O,H}+S_O}\right)\left(\frac{S_{NO}}{K_{NO}+S_{NO}}\right)\right]X_{B,H}\left(\frac{X_{ND}}{X_S}\right) \tag{2.10}$$

The first term of equation 2.10 is a coefficient of proportionality, the second represents the decay of heterotrophic and autotrophic biomass, while the final term denotes the action of hydrolysis of entrapped organic nitrogen.

- Rate of change of alkalinity - Molar units / day

$$\begin{aligned}\dot{S}_{ALK} = &-\frac{i_{XB}}{14}\hat{\mu}_H\left(\frac{S_S}{K_S+S_S}\right)\left(\frac{S_O}{K_{O,H}+S_O}\right)X_{B,H} \\ &+\left(\frac{1-Y_H}{14\cdot 2.86Y_H} - \frac{i_{XB}}{14}\right)\hat{\mu}_H\left(\frac{S_S}{K_S+S_S}\right)\left(\frac{K_{O,H}}{K_{O,H}+S_O}\right)\left(\frac{S_{NO}}{K_{NO}+S_{NO}}\right)\eta_g X_{B,H} \\ &+\left(-\frac{i_{XB}}{14} - \frac{1}{7Y_A}\right)\hat{\mu}_A\left(\frac{S_{NH}}{K_{NH}+S_{NH}}\right)\left(\frac{S_O}{K_{O,A}+S_O}\right)X_{B,A} + \frac{1}{14}k_a S_{ND} X_{B,H}\end{aligned} \tag{2.11}$$

Alkalinity is a complex term, which incorporates many processes; the first line represents the aerobic growth of the heterotrophs, the second line, the anoxic growth of the heterotrophs, the first term of the third line the aerobic growth of the autotrophs and the last term, the hydrolysis of entrapped organic nitrogen. In this work, this term has not been used, the alkalinity of the mixed liquor being assumed constant.

2.2.1.3 Aeration model parameters

The numerical values of the stoichiometric and kinetic parameters used in the simulation are those widely accepted and found in the literature (Henze *et al*, 1986). A few variations of these parameters exist, but they only differ in a couple of the values (Jeppsson & Olsson, 1993) or are very close to the quoted values (Stokes, *et al*, 1993; Sorour *et al*, 1993). Two data sets are provided in Appendix A corresponding to two different temperatures of operation (10°C and 20°C). Appendix A also incorporates three sets of typical characteristics for settled domestic sewage.

2.2.1.4 Assumptions and limitations

There are a number of limitations inherent in IAWQ model No.1:

- The process is assumed to operate at a constant temperature (20°C is generally used) because many coefficients are dependent upon temperature. Values are available for 10°C and 20°C only. The parameters for other temperatures can only be inter- or extrapolated from the two sets available.
- Parameterisation of the model is difficult.
- The pH is assumed constant and near neutrality, because it affects some parameters and there is no feasible way to accurately predict the pH in a bioreactor. Furthermore, there is no known way of expressing the pH influence on the coefficients. When the pH is significantly far from neutrality some chemicals are generally added to the influent water to maintain a near constant value.
- A significant limitation of the model is that no consideration is given to the possible change in the nature of the organic matter, which is the types of bacteria involved in the process. Consideration has been given neither to the possible development of filamentous bacteria, which have a negative effect on the settling of the mixed liquor, nor to the diversity of the bacterial species in time.
- The effects of limitation of nitrogen, phosphorus and other inorganic nutrients on the removal of organic substances and cell growth have not been considered.
- The nitrification rate is assumed constant.
- No mass balance check can be performed due to the lack of representation in the model of the gaseous release of carbon dioxide, nitrogen, etc...

2.2.2 Final settling tank modelling

The final settling tank (or clarifier) is a key component in the activated sludge process, it has two main roles to perform: separation of the solids from the water (clarification) and thickening of the sludge. The IAWQ model assumes that these functions are performed in a perfect manner by a secondary stage which is not described, thus for this work a final settling tank stage model has been added. In large plants, several final settling tanks are used simultaneously in parallel for efficiency reasons; the individual size cannot be expanded as required for the treatment of large volumes of water (the height and diameter are constrained). When dealing with large-scale plants, a number of final settling tanks in parallel are simulated.

Since the aeration stage model stays relatively simple (for example no filamentous bacterial growth is taken into account) the secondary clarifier model should also be simple and able to represent the thickening of the mixed liquor, sludge blanket movement and clarifier effluent behaviour.

2.2.2.1 Final settling tank model

Final settling tank (also called secondary settler) models are often represented by two conceptual zones: clarification and thickening. Some models use a third zone (dilute zone), located between the first two (Tanthapanichakoon & Himmelblau, 1981), even though it has been found that it may not exist in reality (Keinath, 1985). For this work a reasonably simple model composed of four layers was used (Figure 2.3) based on the work by Lessard & Beck (1993). The sludge blanket is composed of two elements: the thickening zone and beneath it a compression zone.

The four layers of the model are:

- Clarification zone of fixed volume where the water is assumed clean.
- Dead zone which occupies the volume left by the thickening zone where no reaction occurs.
- Thickening zone of variable volume where the water is separated from the sludge.
- Compression zone of fixed volume where the sludge has already settled.

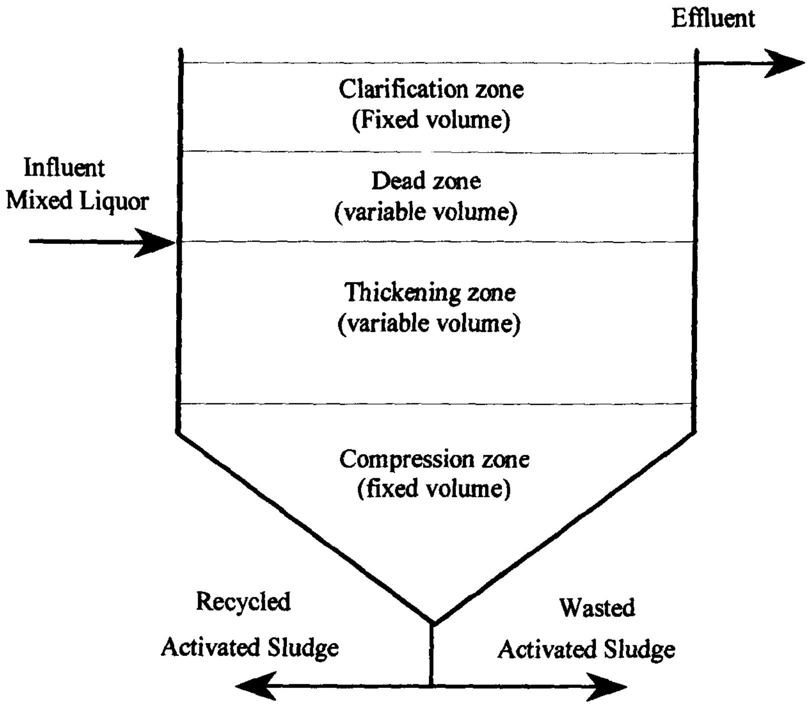


Figure 2.3: Final settling tank

The behaviour of the clarifier is critical for the quality of the effluent. The clarification part of the final settling tank model is based on empirical rules.

The suspended solids in the effluent (SS_{eff}) are assumed directly proportional to the inflow rate (Q_{inI}) and the recycle flow rate (Q_{ras}), with a minimum value (a_1).

$$SSeff = a_1 + a_2(Qin_I + Q_{RAS}) \tag{2.12}$$

Where a_1 and a_2 are constants and represent the minimum suspended solids in the effluent (3.0 g/m^3), and the proportionality constant for effect of flow on SSeff (0.009 g/m^3/day) respectively.

The thickener element of the model is based on flux theory (Dick & Young, 1972). There exists a limiting flux of solids that the settler can absorb for each specific condition (sludge settleability and underflow rate). The total flux of solids, G_T, in a continuous thickener is a function of solids flux due to gravitational settling of the sludge solids relative to the liquid, G_G, and of the solids flux due to the downward movement of the liquid, G_U, caused by the removal of sludge at flow rate Q_U.

$$G_T = G_G + G_U = C_S \cdot V_S + C_S \cdot V_U \tag{2.13}$$

With C_S = concentration of sludge

V_S = gravity settling of sludge

V_U = downward velocity = Q_U/Asc

Asc = clarifier area

The thickening zone is modelled as a sequence of two completely mixed reactors: one of variable volume representing the sludge blanket and one of fixed volume representing the compression zone. Five state variables are simulated by the model: biodegradable and non-biodegradable soluble Chemical Oxygen Demand (COD), Ammonia (NH_4), Nitrates (NO_3) and Mixed Liquor Volatile Suspended Solids (MLVSS). These substances are routed through the sludge blanket and the compression zone. It is assumed that the feed-point is located near the surface of the unit, and the solids stream behaves as a submerged waterfall that enters at the top of the sludge blanket. The concentration of MLVSS in the sludge blanket is then evaluated by closing a mass balance around the blanket, according to the flux theory (equation 2.14).

The variation of the volatile suspended solids concentration in the sludge blanket (VSSsb) is a function of:

- the influent sewage (Q_{in_l})
- the recycled and wasted sludge flows (Q_{ras} and Q_{was} respectively)
- the sludge blanket height (SBHT) and the volatile suspended solids concentration in the mixed liquor (MLVSS)
- the liquid inside the aeration tank
- the downward velocity (V_u)
- the gravity settling velocity (V_s).

$$\dot{VSSsb} = \frac{MLVSS(Qin_I + Q_{RAS}) - VSSeff(Qin_I - Q_{WAS})}{Asc} - \frac{VSSsb(V_S + V_u)}{\dot{SBHT}} \tag{2.14}$$

The gravity settling velocity is approximated by an exponential function:

$$V_S = a_3 \cdot e^{-b \cdot MLVSS} \tag{2.15}$$

Settling parameters a_3 and b are assumed constant, at 4.57 and 0.55 respectively (Lessard, 1993).

In the simulation, after each iteration of the integration routine of the overall process, the resulting concentration of the sludge blanket is checked against the flux theory. If the sludge blanket concentration exceeds the limits given by the flux theory, the sludge blanket height is then altered accordingly (lowered if the actual solids flux is higher than the flux theory, increased if the solids flux is lower than the flux theory).

The variations of the volatile suspended solids concentration in the underflow (VSS_{un}) is dependent primarily upon the concentration of the volatile suspended solids in the sludge blanket (VSS_{sb}) since there is no gravity settling taking place:

$$\dot{VSSun} = \frac{VSS_{sb}(V_S + V_u) - VSS_{un}V_u}{Hcz} \tag{2.16}$$

Where Hcz is the height of the compression zone and is invariant in the model. Typical values found in the literature (Tracy & Keinath, 1974 and Attir *et al*, 1976) range from 0.1 to 0.4 meters. The value used here was 0.3 m.

A time lag of 20 minutes has been added in the concentrations of the return activated sludge to account for the hydraulic retention time to include the time required for fluids flow through the pipes (See Chapter 3). This time delay has been added in order to make the behaviour of the solids more realistic in the model

The International Association on Water Quality has formed a task group to look at the problem of final settling tank (FST) modelling. However, the approach to FST design and operation is very different in philosophy for example between Europe and the United States. A unified model has not yet been published as in the case of the aeration stage. However, an *ad hoc* technical report is expected to be published in 1998 offering a wide range of models dealing with specific problems.

2.2.2.2 Final settling tank model limitations

There is a need to limit the range of values of the concentrations of solids in the clarifier because this is not performed directly in the settler model. Maximum values must be fixed since it is not physically possible to pump sludge which is too thick and the concentration must not be allowed to become negative.

Flows must also be restricted: negative flows are not physically possible since many pumps can act in only one direction, maximum pumping rates exist and also have to be simulated.

The concentration of suspended solids which passes into the clean effluent water is a crude linear approximation related only to the total plant throughput. The effects of solids concentration in the aeration and settling stages as well as the nitrate concentrations are ignored although significant.

This four layer model is not a physical representation of the real process since in a real tank the concentrations would increase gradually. It is however easier to handle than the available models with 10 or 20 layers and is adequate for our purposes.

2.2.3 Effluent suspended solids model

A model providing realistic suspended solids prediction, according to the state of the plant and the disturbances applied to it, is included in order to allow some process optimisation to take place. However, it is difficult to define a quality indicator which can be inferred from the process states and which is related to physical realities.

2.2.3.1 Model equations

Dupont & Henze (1992) have determined a model for the portion of sludge which will not settle in the effluent. Non-settled sludge means the particles which are found in the effluent, either because they have a low mass weight, or because they are floated by the release of nitrogen or by turbulence in the water due to non-ideal operation of the clarifier. This empirical model is based partly on Billmeier (1988) and partly based on conceptual ideas. It does not directly predict the effluent concentration of particles from the clarifier but only the contents of particles in the feed to the clarifier which will not settle. However, by applying a time delay, allowing for the hydraulic retention time within the final clarifier, this model can be used to give an indication of the quality of the effluent water.

This model takes into account the main elements influencing the released water quality, namely hydraulic throughput and liquor concentration (plant loading) and nitrate concentration.

$$SS_F = SS_{init} + SS_{NO_3} \cdot \frac{S_{NO_3}}{K_{NO_3} + S_{NO_3}} + SS_{hyd} \cdot \frac{X_0 \cdot SVI \cdot \frac{Q_0}{A}}{K_{hyd} + X_0 \cdot SVI \cdot \frac{Q_0}{A}} \tag{2.17}$$

where:

SS_F Concentration of particles in the feed to the clarifier which will not settle

SS_{init} Constant SS concentration which will always will be non-settleable

SS_{NO3} Maximum concentration of SS at the inlet which will not settle due to nitrate in the inlet

S_{NO3} Concentration of nitrate at inlet to clarifier

K_{NO3} Monod constant for nitrate

SS_{hyd} Maximum concentration of SS in the inlet which will not settle due to hydraulic and SS load

X_0 Concentration of SS in the feed to the clarifier

SVI Sludge Volume Index

$\frac{Q_0}{A}$ Hydraulic load to the clarifier

K_{hyd} Monod constant for load

The first term on the right hand side of equation 2.17 is a constant which introduces a minimum amount of non-settleable suspended solids in the feed to the clarifier. The second term is non-settled suspended solids arising from denitrification. This term consists of a constant which represents a maximum concentration of suspended solids which could arise because of denitrification, multiplied with a Monod term for the nitrate concentration. The third term represents non-settled suspended solids due to hydraulic loading and sludge characteristics. This term increases the concentration of non-settled suspended solids when the load of suspended solids is high, the hydraulic surface load is high, or the SVI is high. The values used are given in Appendix A in Table A.2.

2.2.3.2 Effluent suspended solids model limitations

The maximum concentration of suspended solids in the inlet, which will not settle due to nitrate in the inlet (SS_{NO3}), and the Monod constant for nitrate (K_{NO3}) are both temperature dependent so that there is a higher concentration of particles in the effluent arising from denitrification when the temperature is high.

The estimation of the concentration of suspended solids in the effluent can only be used in simulation because some of the parameters needed, for example nitrate concentration, are generally not available on-line. However, it is technically possible to measure these values on-line with suitable instrumentation. The calculated value is only an approximation and all the phenomena involved are not accurately represented.

2.2.4 Actuators and sensors models

Sensing devices as well as actuators are essential to the development of control systems. They are integral part of the control loop and as such should be modelled in a process simulation. Therefore, care has been taken to use realistic characteristics for the sensors and actuators.

2.2.4.1 Dissolved oxygen probes

The measurement of dissolved oxygen is very important for the control of aeration. The dissolved oxygen measurements are composed of the 'true' value given by the model, to which 1% normally distributed white noise is added in the simulation. Measurement noise is inherent to the system owing to the nature of the aeration systems generally employed such as surface aerators. This signal is then filtered with a first order filter with a 3 minute time constant which simulates the action of a commonly used dissolved oxygen probe (based on data from North West Water on the "Endress+Hauser" *COS 3* DO probe as used in real wastewater treatment plants). The dissolved oxygen concentration so measured is then made available to the control system.

2.2.4.2 Aerators

The characteristics of the aerators used are based on specification of aerators used by North West Water Ltd. The oxygen transfer rate is specified in the manufacturer's literature as being between 1.2 kg O_2/kWh and 2.4 kg O_2/kWh. Data available did not allow a reduction of that range therefore the value used in this work has been fixed conservatively at 1.3 kg oxygen/kWh, as used by Kruger (1995). The aerators are assumed to be controllable independently. No time delay in their action has been considered.

2.3 SIMULATION IMPLEMENTATION

Many details of the actual implementation of the model can play an important part on the results of the overall simulation. Sample time and initial conditions, for example, are critical parameters determining the behaviour of the model.

2.3.1 Determination of the sample time

The computer model has to simulate at least a few days of process operation to be of significant use since there are very slow time constants in the activated sludge process. Appendix B explains the choice of the Euler integration method used for the model implementation instead of the more standard fourth order Runge-Kutta integration method. The shorter the integration time step, the more accurate the simulation, but the simulation time is longer. Therefore, a compromise has to be reached. In this work an integration time step corresponding to 30 seconds has been used. It has been found to provide a good compromise between accuracy and computational time required. It also seems a reasonable choice for industrial implementation.

The dissolved oxygen control interval encountered in literature varied from 15 seconds to 2 minutes with Stephenson *et al* (1981) using 60 seconds, Yust & Howell (1988) 100 seconds etc. For this work, the aeration rate was updated every two minutes, which has been found to give adequate results. Shorter values have been shown to bring no significant performance improvement.

2.3.2 Time delays

A time delay equivalent to twenty minutes has been introduced in the recycle flow to simulate the hydraulic retention time of the piping and pumping system. This is needed to allow for transportation time and hydraulic damping of the overall plant.

A further delay is needed to transform the suspended solids arriving in the final settling tank which will not settle into the final effluent suspended solids concentration. This time delay which in practice is variable with the sewage flow rate, has been fixed to 3 hours corresponding to the average flow rate to the plant.

It should be noted that most time delays within the plant are variable in reality, according to the different flow rates and temperatures within the plant.

2.3.3 Plant characteristics

Unless otherwise stated, the plant simulated is composed of an aeration lane represented by 3 tanks in series, the first one of 450 m^3 being anaerobic followed by 2 tanks of 2,250 m^3 each, which are aerated. Six final settling tanks with a volume 1,560 m^3 and surface area of 1,040 m^2 each, receive the activated sludge from the aeration stage. The average influent sewage flow received by the simulated plant was 20,000 m^3/ day.

2.3.4 Initial conditions

The initial conditions have been chosen as the numerical values found after two days of steady-state process operation: constant influent flow rate and influent product concentrations are applied. The controllers, where fitted, are left with the parameter values found after this particular simulation. The aeration and final settling tanks are given the concentrations found after this simulation as initial conditions.

2.3.5 Miscellaneous assumptions

Mixed liquor volatile suspended solids (MLVSS) are assumed to be equal to 70% of the mixed liquor suspended solids (MLSS) which is a standard assumption (Scott, 1980) since this is not directly available and cannot be inferred easily from the model.

The dissolved oxygen saturation constant (solubility) is assumed constant, equal to 10 mg/l. In reality this value is variable with temperature, atmospheric pressure, chlorides concentration, etc, which are difficult to simulate.

2.3.6 Computer simulation development environment

The simulation has been developed extensively using Matlab® and some of its toolboxes, mainly Fuzzy Logic, System Identification, Genetic Algorithms and Model Predictive Control from Mathworks® and the Self-Tuning Friend for Matlab from the Control Systems Centre of UMIST. Process data are logged the equivalent of every 2 minutes of operation.

Chapter 3

3 Dissolved oxygen control

This chapter describes three different control schemes; PID, fuzzy logic and self-tuning control, which represent different stages of controller implementation in industry. Test conditions are described and put in perspective with the actual disturbances encountered in the activated sludge process by controllers. They include a composite pattern for the influent sewage flow and composition and another data set based on real data. Both data sets contain events exciting the process sufficiently to compare the performances of the controllers. Responses for the three controllers for different conditions of temperature and plant loading are shown extensively. Finally the controller performances are compared and discussed.

3.1 Introduction

Changes in European and national legislation in recent years, added to the pressure of market forces, emphasised the need for process efficiency, leading directly to increased use of process monitoring and control in the water industry. Aeration forms a major part of the running costs of an activated sludge wastewater treatment plant and thus is a particularly attractive target for cost cutting exercises.

The activated sludge process has unpredictable behaviour due to the non-linear, time variant nature of the process and changes in the influent sewage. Keeping the dissolved oxygen (DO) concentration at a suitable value is of prime importance. This value or set-point is dependent on a number of factors which are difficult to evaluate. A plant with the only objective to remove carbon would operate correctly with DO concentrations of 1 mg/l at the beginning of the aeration stage and 1.5 mg/l at the end. A plant also performing denitrification would need to maintain 2 mg/l throughout unless knowledge of the nitrification rate is known in which case, assuming it is sufficient to assure full nitrification by the end of the aeration stage, the DO set-point could be reduced.

Improved aeration control has been on the agenda for a long time, sensors for dissolved oxygen having been available since the 1970s. However, at first many doubted their reliability and highlighted the difficulty in obtaining a true measurement due to the hostile environment for sensing equipment offered by the process itself. The most common problems are sensor fouling by bacterial growth and 'ragging' that is to say the obstruction of free liquid flow around the sensor by floating material.

For a particular aeration tank, the aeration rate required to maintain a given dissolved oxygen concentration is dependent upon the following:

- Dimensions of the tank,
- Composition of the mixed liquor within the tank (proportion of the different constitutive elements),
- Concentration of suspended solids of the mixed liquor,
- Flow rate of incoming tank influent,
- Dissolved oxygen concentration of the incoming flow,
- Load of the influent flow to the tank.

In an aeration lane the oxygen requirement will vary along its length because the exact composition of the mixed liquor also varies along the length. The mathematical model used in this work assumes a series of continuous stirred tanks, so that the aeration rate can be different in every tank even when the same set-point is used for all tanks.

3.2 Dissolved oxygen control strategies

Choosing a control scheme for the activated sludge process aeration is a delicate task. Sensor availability, the type of process disturbance expected (domestic sewage only or combined with rainwater and/or industrial sewage), installation cost, human plant operator experience and training, and so on have all to be taken into consideration. For these reasons three types of controller have been investigated for aeration control: a simple PID controller since it is an industry standard, widely available and is the most likely system to be implemented on a real plant for the foreseeable future. A Fuzzy Logic Controller has also been developed owing to the increasing interest in industry, PLC's with fuzzy capabilities are available even if not yet widely used. Finally, a self-tuning controller was implemented for comparison because it is a technique that is likely to have an impact in the future and has an ability to accommodate non-linearity and time variance.

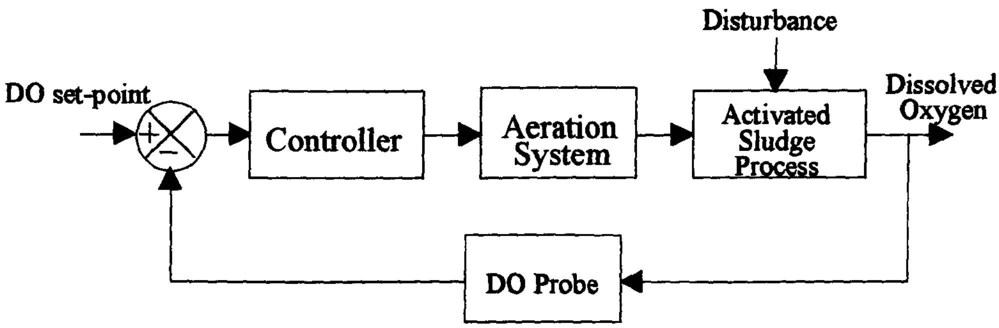


Figure 3.1: The dissolved oxygen control loop

The variations within the activated sludge process can consist of actual process disturbance (variation of the total flow rate through the plant and/or variation of the load that is to say concentration of pollutants considered), changes within the process itself (change of the nature of the biomass, change of temperature, etc) and measurement noise (Figure 3.1). Some of these changes can be predicted using, for example, the flow measurements generally taken at the inlet of the plant, temperature could also be crudely estimated in advance. However, the main sources of process disturbance, that is to say the sewage flow rate and the concentration of its different constitutive elements, are not controllable. Rainfalls are also not accurately predictable and non-controllable. The case in favour of a form of regulation of the process is therefore straightforward even if the method to achieve this is not.

3.2.1 PID Control

PID controllers are the basic tools of control engineering. Generally, in industry most feedback loops are controlled by the PID algorithm or minor variations of it (Åström & Hagglund, 1988). It provides feedback, has the ability to remove steady-state offsets through integral action, and can anticipate the future through derivative action. It also offers a certain flexibility by being implemented in different forms, as stand-alone regulators or hierarchical distributed process control systems.

There is a well-established practice of installing and tuning PID controllers based on empirical rules such as those defined by Ziegler & Nichols (1942). Although these methods are well known, the parameters they provide often result in poor performance and they should be used only as a first approximation. The derivative action is frequently switched off simply because it is difficult to tune properly due to its noise amplification action which causes erratic actuator signals.

3.2.1.1 PID algorithm

The classical PID algorithm has the following form:

$$u(t) = K \cdot \left(e(t) + \frac{1}{T_i}\int_0^t e(t)\cdot dt + T_d \frac{de(t)}{dt} \right) \tag{3.1}$$

Where $u(t)$ is the control variable and $e(t)$ the control error, which is the difference between the set-point, $r(t)$, and the measured value, $y(t)$. The control variable is the sum of three terms: the P term which is proportional to the error, the I term which is proportional to the integral of the error, and the D term which is proportional to the derivative of the error. The controller parameters are proportional gain K, integral action time T_i and derivative action time T_d.

However, nowadays a digital form of the PID is often used:

$$u_n = K \cdot \left(e_n + \frac{\Delta t}{T_i}\sum_{k=1}^{n} e_k + \frac{T_d}{\Delta t}(e_n - e_{n-1}) \right) \tag{3.2}$$

With n the sample number and Δt the time step. Equation 3.2 provides an algorithm easily implemented in a digital computer and shows the form used in this work.

3.2.1.2 PID implementation

All actuators have limitations, in the aeration case the limitations are the maximum aeration rate and the fact that dissolved oxygen cannot be removed (it is not practically possible to have a negative aeration rate that is to say to remove dissolved oxygen even though it is technically possible). When a control system operates over a wide range of operating conditions, it may happen that the control variable reaches the actuator limits. When this happens, the feedback loop is effectively broken because the actuator will remain at its limit independently of the process output. If a regulator with integration action is used, the error will continue to be integrated. This means that the integral term may become very large, it is then required that the error changes sign for a long period before things return to normal. The consequence is that any controller with integral action may have a large transient when the actuator saturates. To overcome this problem, a simple anti 'wind-up' mechanism has been used in this work successfully. It consists of resetting the integrated error value, if the integrated error is very large and a change of sign of the error occurs.

Relatively large measurement noise is present in the process; this prevents the accurate calculation of the derivative of the dissolved oxygen concentration. As a result only the proportional and integral terms have been implemented for the controllers. If a large proportional term is used, the measurement noise may be of an amplitude close to the actual change of DO concentration taking place in the process between two time steps, reducing the effectiveness of the control signal generated. If the measurement noise was smaller (or altogether absent), a derivative term for the controller would be welcome, adding to the overall stability of the controller.

3.2.1.3 Importance of controller parameters

A PID controller manually tuned first using Ziegler-Nichols and then adjusted by trial and error has been compared against a PID controller with different parameters, changing successively the original gain (K_{p1}=35.25, K_{p2}=18.75 for tank 1 and tank 2 respectively) and integral action constant (T_{i1}=0.002, T_{i2}=0.002) to values of twice and half the original controller values.

The test was based on a one-day period with a sinusoidal input flow rate of mean value of 20 000 m^3/day and variations of ±50%, which could be used as a crude approximation of the diurnal cycle. The original manually tuned PID controller managed to keep the DO concentration within 2% of the set-point of 2g/m^3 at all times even in the presence of noise (Figure 3.2).

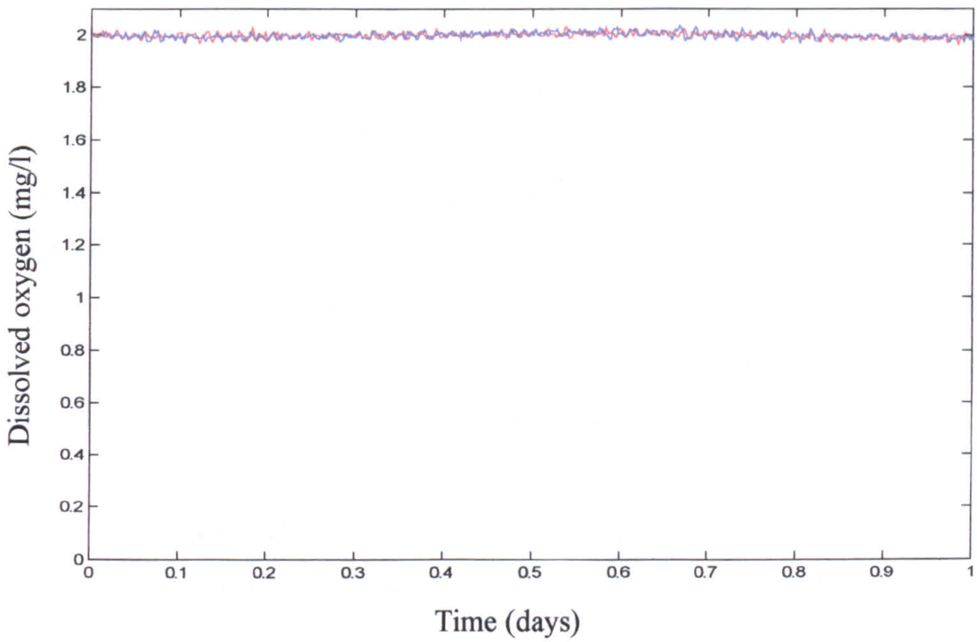


Figure 3.2: Dissolved oxygen concentration with original PID parameters.

In order to test the influence of the individual PID parameters, the controller gain, K_p, and integration action time, T_i, from the original PID controller were modified alternately. The new controllers have been tested with the same initial conditions and process input used for the test of the original controller. In order to obtain a perceivable difference between the controllers' responses, controller gains of twice and half the original value were tested, followed by integral action times also of twice and half the original value.

The Ziegler-Nichols closed loop method was used to determine a standard set of parameters. The controllers have been set to deliver only proportional control ($Ti = \infty$ and $Td = 0$), and the gain gradually increased until the controlled variable (DO concentration) oscillated continuously with constant amplitude. From this point, corresponding to the intersection of the Nyquist curve with the negative real axis, was determined the critical Gain (K_c) and ultimate period (T_u). Ziegler-Nichols recommend that for a PI controller the parameters be set to $K_p = 0.45 \times K_c$ and $T_i = 0.8333 \times T_u$. This results in $K_{p1zn} = 135$, $T_{i1zn} = 0.004$, $K_{p2zn} = 125$ and $T_{i2zn} = 0.0033$.

Different cost functions were used to test the performances of the controllers, the root mean square error (RMS) which reflects the average amplitude of the error, and the integrated error over the test period (IE) which shows if the plant has been primarily over- or under-aerated (or equally over- and under-aerated) which can be important for economic and quality considerations. In each test, two controllers were involved, one for each of the two aeration tanks of the wastewater treatment plant simulated (tank 1 & tank 2 in Figure 2.1) the process behaviours being slightly different as explained in chapter 2. The methods used to calculate the RMS and IE error functions are explained in Appendix C. The results are summarised in Table 3.1.

Table 3.1: Error functions for different PID parameters

TEST	Tank	RMS ($x10^{-2}$)	IE ($x10^{-4}$)
PI (K_p, T_i)	1	4.02	5.27
	2	4.44	6.38
$K_p \times 2$, T_i	1	4.58	2.19
	2	4.39	3.11
$K_p / 2$, T_i	1	5.29	9.57
	2	6.27	12.3
K_p, $T_i \times 2$	1	5.28	8.29
	2	6.08	12.8
K_p, $T_i / 2$	1	7.30	3.08
	2	7.90	2.11
Closed-loop	1	13.2	12.3
Ziegler-Nichols	2	13.8	10.4

The RMS errors for the different PID parameters are presented in Figure 3.3, which shows that the original set of controller parameters was close to optimum to control the process for these particular test conditions (sinusoidal influent flow rate). The only improvement that seems possible is to increase the gain (K_p) of the original PID controller for the control of the aeration but only in the second tank. All the other parameter changes show a detrimental effect on the controlled variable.

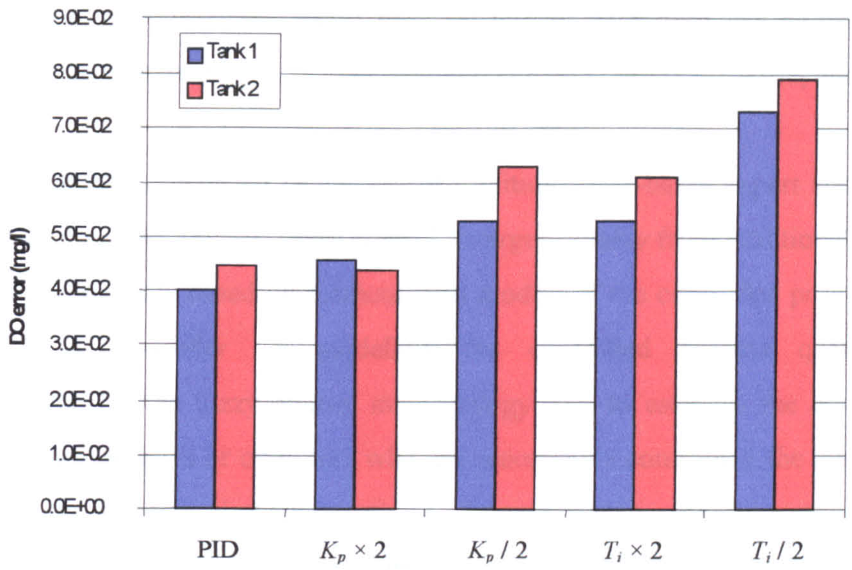


Figure 3.3: RMS error for different PID controller parameters.

From this practical example it is clear that the fine tuning of a PID controller is a delicate operation. In this test, the different values of the parameters have a factor 2, fine-tuning requires more experiments of this sort to be carried out which is a long procedure. It is also obvious that it cannot be carried out on the on-line process since the test procedure would not be reproducible. This test shows that the PID parameters employed in this work are near optimal.

3.2.2 Fuzzy Logic Control

A growing technique in the control engineering field is fuzzy logic control. Fuzzy logic opens a new way of mapping input and output spaces. It can therefore be used to develop controllers which can more effectively deal with some process problems than usual conventional techniques.

Since Mamdani's (1974) pioneering work, rule-based fuzzy control has been and continues to be an attractive and fruitful research field, based on Zadeh's novel approach formulated in his original paper (Zadeh, 1973). The drive behind these developments lies largely in the fact that numerous applications of fuzzy control have emerged, covering a wide range of practical areas, and that many software and hardware products for fuzzy control are now available. Fuzzy logic techniques have been incorporated in everyday products such as washing machines, vacuum cleaners, air conditioners, and so on.

As a result of merging the techniques of traditional rule-based expert systems, fuzzy set theory and control theory, fuzzy control diverges notably from traditional control theory which is essentially based on mathematical models of the controlled process. Instead of deriving a controller via modelling the controlled process quantitatively and mathematically, the fuzzy control methodology tries to establish the controller directly from domain experts or operators who are successfully controlling the process manually. Clearly, this is a typical characteristic of an expert system where the attention is focused on the human's behaviour and experience, rather than on the process being controlled. It is this distinctive feature that makes fuzzy control attractive for dealing with problems where the process is complex and ill-defined, making it either impossible or too expensive to derive a mathematical model which is accurate and simple enough to be used by traditional control methods, but the process may be controlled satisfactorily by human operators. However, caution must be exerted when assuming that fuzzy control does not need a process model, because that leads to a misunderstanding about fuzzy control. It would be impossible to control a process by either a human or machine without knowing something about the process. In fact, all the knowledge about the process has been incorporated implicitly into the fuzzy controller by the domain expert or operators.

3.2.2.1 Principle of operation

In recognising that human control behaviour is the basis for implementing fuzzy control, it is necessary to express the human knowledge in an easy and effective way. The deterministic IF-THEN rule format is one of the easiest representations for control applications because it follows the standard human reasoning pattern. The control knowledge can be expressed by a set of linguistic rules with the form of IF *situation* THEN *action*. It is noted that this kind of statement possesses two distinct features: it is qualitative rather than quantitative; it is a local knowledge associating a local situation with an appropriate action. This qualitative nature can be characterised by fuzzy subsets, whereas the actual knowledge can be expressed by a fuzzy implication or relation.

However, the final output of a fuzzy controller has to be in a 'crisp' numerical form to be able to relate with the rest of the control system. For this purpose, membership functions and approximate reasoning provide powerful means to characterise numerically fuzzy sets and fuzzy implication. It is the rule-based structure combined with fuzzy set theory that makes the implication of the fuzzy control possible (Nie, 1995).

3.2.2.2 Implementation

The basic structure of a fuzzy logic control scheme is shown in figure 3.4. In this example, the inputs have been chosen as the error, *e*, determined by subtracting the process output from the target value, and the change of error, *ce*, determined by subtracting the error at the last sample from the current error. The control action, *u*, is the input applied to the controlled process. The measured variables, *e*, and, *ce*, are mapped into the fuzzy domain by a fuzzification operation. Similarly, the deterministic output, *u*, is obtained through 'defuzzification' which converts the fuzzy output of the controller into a crisp value.

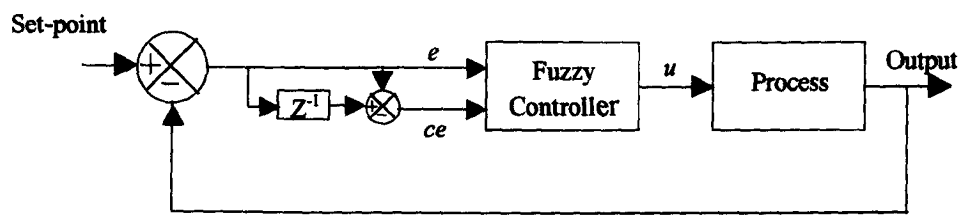


Figure 3.4: Simple fuzzy logic controller.

The fuzzy logic controller developed in this work uses the error signal and the change of error as inputs (Figure 3.5). These numerical values are then translated into a degree of membership of membership functions defining the universe of discourse (or input space) of each of the two variables; four membership functions have been used to describe the universe of discourse of the error signal and three for the change of error. An incremental control method was used, which means that the controller output is not directly the manipulated variable value, but the change in its value. A number of basic rules are then employed to determine if, and by how much, the aeration rate has to be modified according to the linguistic rules displayed in matrix form in Table 3.2.

The fuzzy operators used are the product of the subsets for AND and the probabilistic OR (probor) for the OR operator. probor (a, b) = a + b - ab

The fuzzy implication method employed is the product of the terms.

The aggregation method producing the output is the probabilistic OR.

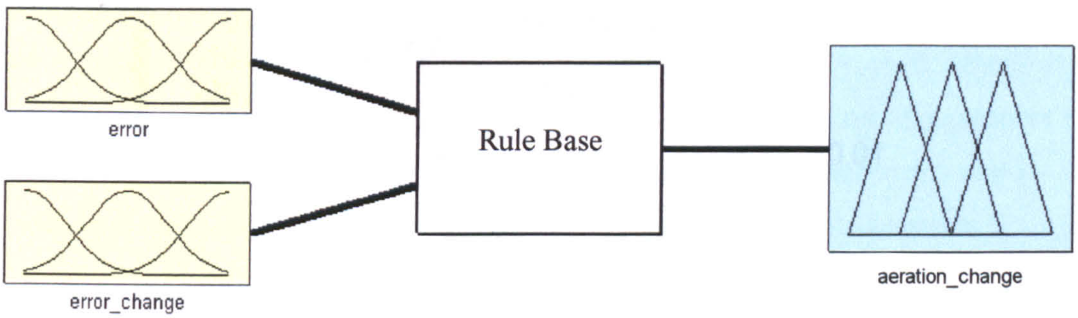


Figure 3.5: Fuzzy logic controller structure

The membership function types selected are Gaussian for the inputs (error and change or error) and triangular for the output (change in aeration rate). In order to keep the rule base simple and consistent with process knowledge, the error input space has been defined using 4 Gaussian membership functions, while the change of error universe of discourse employs 3 triangular membership functions. Increasing this number results in an increased number of rules which is not necessary to reflect the expected controller behaviour.

A relatively simple rule base was used formed of 12 rules such as:

If (error is nb) and (error_change is z) then (aeration_change is ps)

Table 3.2 shows the rules used in a compact form.

Table 3.2: Change of aeration rate linguistic performance index

Change of error \ **Error**	nb	ns	ps	pb
n	pb	z	ns	ns
z	ps	ps	ns	ns
p	ps	ps	z	nb

n=negative, nb=n big, ns=n small, z=zero, p=positive, ps=p small, pb=p big

After centroid defuzzification, the output of the fuzzy controller can be represented by the surface shown in figure 3.6.

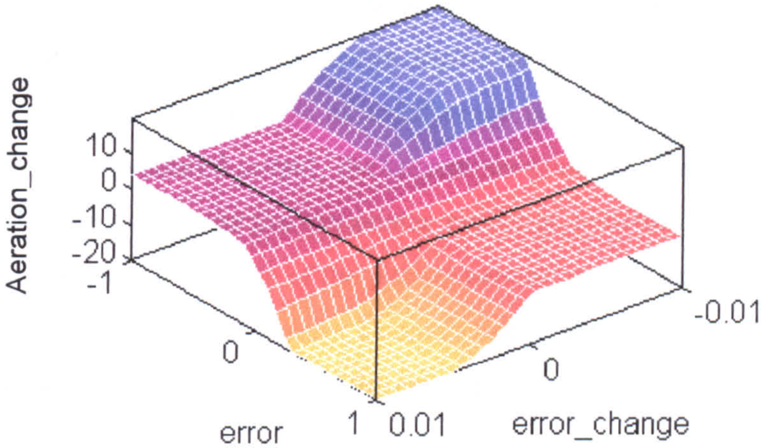


Figure 3.6: Controller output surface

It has to be recognised that in the absence of well defined linguistic rules and obvious membership function definition, the tuning of a fuzzy controller is not easy. Unlike PID control, there are few rules and the 'tuning' is mainly based on common sense and heuristics.

3.2.3 Self-tuning control

Providing control on a real process using only a pre-determined process model leads to inaccuracy in the response and in the worst case the system can become unstable because of modelling errors. An alternative approach to the use of a fixed model for the system, is to configure the control system so that it can adapt its control parameters to achieve the closest match to a defined performance criterion. An on-line identification technique is used to estimate and update the parameters of a model and these model parameters are then used to calculate the parameters of the controller.

3.2.3.1 Principle of operation

A self-tuning controller has three main elements: a feedback controller, a recursive model parameter estimator and a control design algorithm (Figure 3.7). Usually, there is a standard feedback law in the form of a difference equation which acts upon a set of values such as the measured output, the current set-point, etc, and which produces the new control action. A recursive parameter estimator monitors the plant's input and output and computes an estimate of the plant dynamics in terms of a set of parameters in a prescribed structured model. Finally, a control design algorithm calculates a new set of coefficients for the feedback law using the estimated parameters from the model.

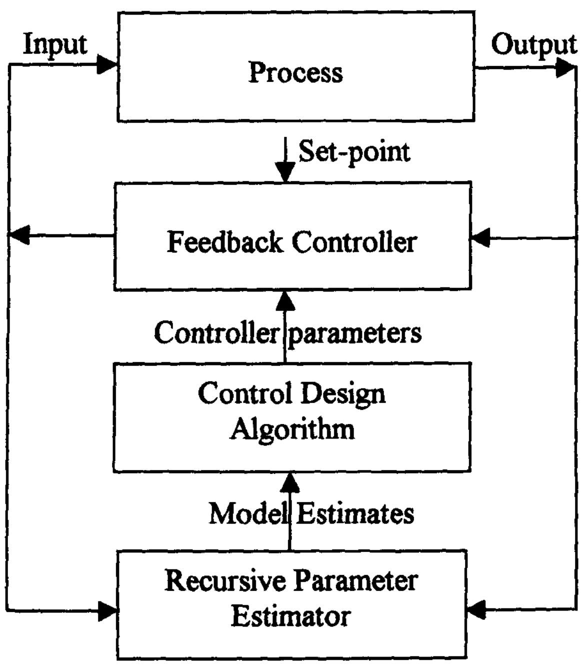


Figure 3.7: Structure of a self-tuning controller.

On-line determination of the process model parameters is an important part of a self-tuning controller. The parameters of the process may change continuously owing to non-linearity or time variance hence it is a necessity to have an estimation method that updates the parameters of the process.

The least squares method, formulated at the end of the 18th century by Gauss, is a basic technique for parameter estimation (Aström & Wittenmark, 1989). However, it is desirable to make the computations recursive in order save computation time; the computations can be arranged in such a way that the results obtained at time t-1 can be used in order to get the estimates at time t.

However, to be able to apply least squares to a non-linear model, it is essential that the model is linear in the parameters so that it can be written as a regression model (Aström & Wittenmark, 1989). The least-squares estimate is biased when the errors are correlated. One way to avoid this difficulty is to model the correlation of the disturbance and to estimate the parameters describing the correlation. Considering:

$$Ay(t) = Bu(t-1) + Ce(t) \tag{3.3}$$

where A, B and C are polynomials and e(t) is white noise. The parameters of C describe the correlation of the disturbance.

The model of equation 3.3 cannot be converted directly into a regression model since the variable e(t) is not known. Several estimation methods exit, which replace e(t), but generally the prediction error ε(t) or the residual η(t) can be used.

To describe these, defining the parameter vector θ and the regression vector φ:

$$\hat{\theta} = \left[-\hat{a}_1 \ldots -\hat{a}_{na} \quad \hat{b}_0 \ldots \hat{b}_{nb} \quad \hat{c}_1 \ldots \hat{c}_{nc} \right] \tag{3.4}$$

$$\varphi^T(t) = \left[y(t-1) \ldots y(t-na) \quad u(t-1) \ldots + u(t-nb-1) \quad \varepsilon(t-1) \ldots + \varepsilon(t-nc) \right] \tag{3.5}$$

where,

$$\varepsilon(t) = y(t) - \varphi^T(t)\hat{\theta}(t-1) \tag{3.6}$$

is the prediction error using output prediction based on information up to the time t - 1. The variables e(t) are thus approximated by the prediction errors. The model can then be approximated by:

$$y(t) = \varphi^T(t-1)\theta \tag{3.7}$$

A method of estimating the parameters in Equation 3.3 is to make a recursive approximation of the maximum likelihood estimate. The estimate is then given by:

$$\begin{aligned}\hat{\theta}(t+1) &= \hat{\theta}(t) + P(t+1)\varphi(t+1)\varepsilon(t+1) \\ P^{-1}(t+1) &= P^{-1}(t) + \varphi(t)\varphi^{T}(t)\end{aligned} \tag{3.8}$$

with residual

$$\hat{C}\varepsilon(t) = \hat{A}y(t) - \hat{B}u(t) \tag{3.9}$$

and regression vector φ replaced by φ_f, where

$$\hat{C}\varphi_f(t) = \varphi(t) \tag{3.10}$$

The algorithm obtained is then called recursive maximum likelihood method (RML).

Generalised predictive control

The unknown polynomials A, B and C of the CARIMA (Controlled Auto-Regressive Integrating Moving Average) model are replaced by the estimates $\hat{A}$, $\hat{B}$ and $\hat{C}$ in the following form for incremental control:

$$\hat{A}\,\Delta y(t) = \hat{B}\,\Delta u(t-1) + \hat{C}\,e(t) \tag{3.11}$$

The generalised predictive control algorithm minimises the following cost function:

$$J = E\left\{\left[\sum_{i=1}^{Ny}\frac{Pn}{Pd}\big(y(t+i) - r(t+i)\big)\right]^2 + \sum_{i=1}^{Nu}\lambda\big(\Delta u(t+i-1)\big)^2\right\} \tag{3.12}$$

where $E\{\ \}$ denotes expectations conditioned on data up to time t, with Pn and Pd being equal to unity.

3.2.3.2 Implementation

An ARMAX (Auto-Regressive Moving Average eXogenous) model was computed on-line using the Recursive Maximum Likelihood method as described earlier. The structure of the process was previously identified by standard identification techniques using process simulation data, resulting in the determination of the orders of the model n_a, n_b and n_c. In this case, analysing the loss function for a family of ARX models and then extrapolating to an ARMAX structure and comparing different values, $n_a = 2$, $n_b = 3$, $n_c = 2$ and the delay $k = 1$ was selected. The generalised predictive coefficients were then determined for a CARIMA model. It minimises the loss function shown on equation 3.12, giving a sequence of future control signals for given future desired outputs. Only the first element of the control sequence was used, the calculation being repeated when a new measurement was obtained. The generalised predictive controller polynomials are then used to generate the controller output. This procedure was then repeated at the next step.

The output horizon (*Ny*) corresponds to the number of future outputs considered in the cost function. An increase in the value of *Ny* is normally associated with a smoother system response and reduced control signal variation for set-point change. The increase in the value of *Ny* corresponds to an increase in computational effort and in the case of servo control the increase in *Ny* does not influence the strength of the control signal (Welltstead and Zarrop, 1991).

The control horizon of the predictive controller (*Nu*) was fixed after trial and error. *Nu* is generally used to influence indirectly the set-point tracking and transient behaviour. In some case performance improvement is noted when *Nu* is increased from 1 to 2 but not much beyond (Welltstead and Zarrop, 1991).

In this work $Ny = 2$ and $Nu = 1$. The control weighting factor λ has been set to 1.5. Simulation results show that smaller values result in large variations of the control signal and larger values in a degradation of the set-point tracking performances, leading to the choice of 1.5 as a compromise.

The data used for parameter estimation are the raw dissolved oxygen concentration and aeration rate. The generalised predictive controller provides the value of the change needed to the control action value, that is to say the change of aeration rate.

The Self-Tuning Friend[1] for Matlab was used for the implementation of the self-tuning controller.

3.2.3.3 Demonstration of parameter update

At each iteration, the parameters of the ARMAX model is updated. Figure 3.8 illustrates some of the parameters for the self-tuning controller in the first aeration tank for one particular test which included major disturbances in the form of two storm events. The parameter values were normalised by statistical scaling for display in Figure 3.8. In the first period (beginning of the first day) the parameters are changing significantly, however, the estimator actually 'locked' quickly, within a few samples on to the correct parameter value as experiments have proved. The drifts of the parameters shown on Figure 3.8 (the 7 significant parameters of the model) are possibly due to qualitative changes occurring within the process such as a change of the ratio between the two kind of biomass, and so on.

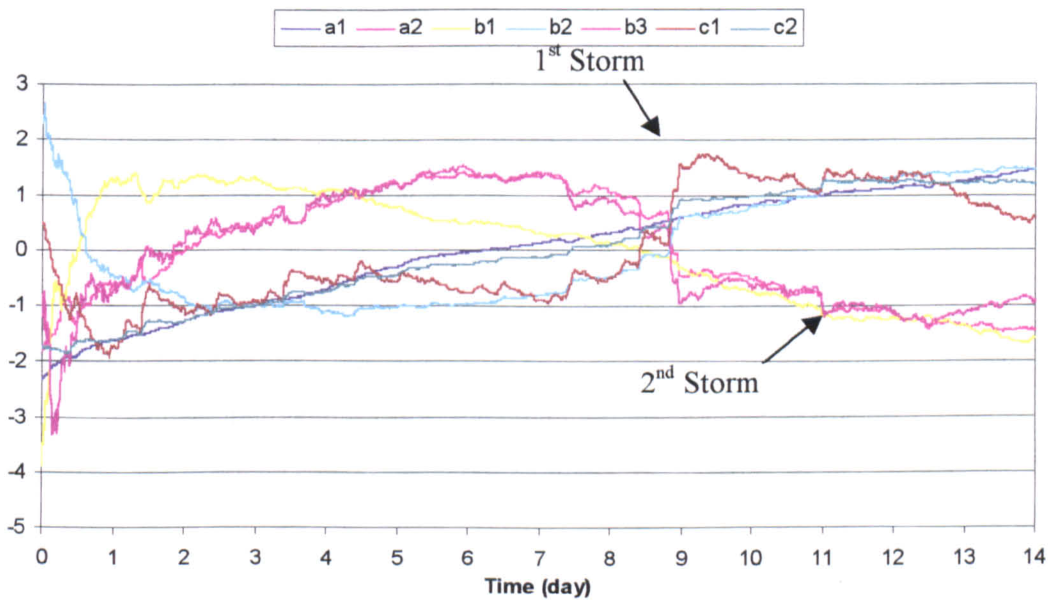


Figure 3.8: Normalised model parameters over test period.

It can also be seen that the first storm caused a large variation in the model parameters, when the system had to adapt to the new conditions. The second storm also showed

[1] Developed by the Control Systems Centre of UMIST (UK).

some model adjustments even though they have a more limited impact. The adaptation of the model is required to deal with changes within the process.

3.3 Comparison methods

The objective of the tests was to enable the examination of the behaviour of the different controllers in a range of representative situations, for a reasonable length of time in order to test stability and adequate response to the process and associated disturbances. The tests have to be reproducible, representative of reality and excite the process sufficiently. The last two conditions are clearly contradictory but can be simulated by some unusual event such as storm flow rates, for example.

When considering dissolved oxygen consumption, a change of concentration of the influent sewage (change of load) is approximately equivalent to a change of flow rate from a process point of view.

Temperature changes modify the time constants of the process and therefore have an important effect on the controller performances. Comparison should therefore be performed using different operating temperatures.

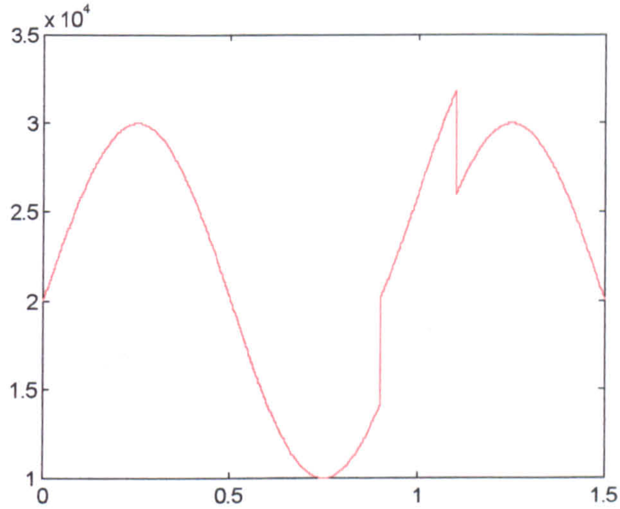
The tests which have been performed include a combination of variations of:

- Flow pattern including a step change.
- Change of operating temperature, and therefore process characteristics.
- Change of suspended solids concentration within the aeration stage.

3.3.1 Flow and load changes

Flow rate and influent flow concentrations are the normal major changes affecting a wastewater treatment plant, therefore the activity of a suitable control system would concentrate on overcoming such disturbances.

A first assumption of an influent sewage flow can be of a sinusoid signal, which is a reasonable approximation of the diurnal pattern obtained in many domestic wastewater systems. A storm event can be associated by adding a square signal to the sinusoid as performed by Vitasovic (1986). Such a flow is shown in Figure 3.9.



Time (days)

Figure 3.9: Sinusoidal influent flow pattern with 'storm event'

Input data representing two weeks of measurements (including substrate, nitrogen compounds, biomass, DO, etc) obtained from Spanjers *et al* (1997) has also been used. It incorporates weekly and diurnal flow and concentration variations as can be seen in Figures 3.10 and 3.11. It is based on real data which have been normalised, and in addition incorporates two storm events. The average flow is 20,000 m^3/day and total Chemical Oxygen Demand (COD) is 300 mg/l for a population equivalent of 100,000. Influent sewage flows and solids concentrations are reduced during days 6 and 7, as well as days 13 and 14 as naturally happen during weekends. The two storms behave differently, even though, in both cases, the flow increases 3 fold to 60,000 m^3/day which is assumed to be the maximum capacity of the plant. In the first storm, the soluble substrate decreases by 15 % while the particulate increases 4 fold. In the second storm event, the soluble substrate decreases again by 15% but the particulate substrate is reduced to half its dry weather value, simulating the wash out that happened during the first storm.

Two weeks worth of data, measured every 15 minutes, were available. This data has been interpolated linearly in order to provide input data for each simulation model integration step, that is every 30 seconds.

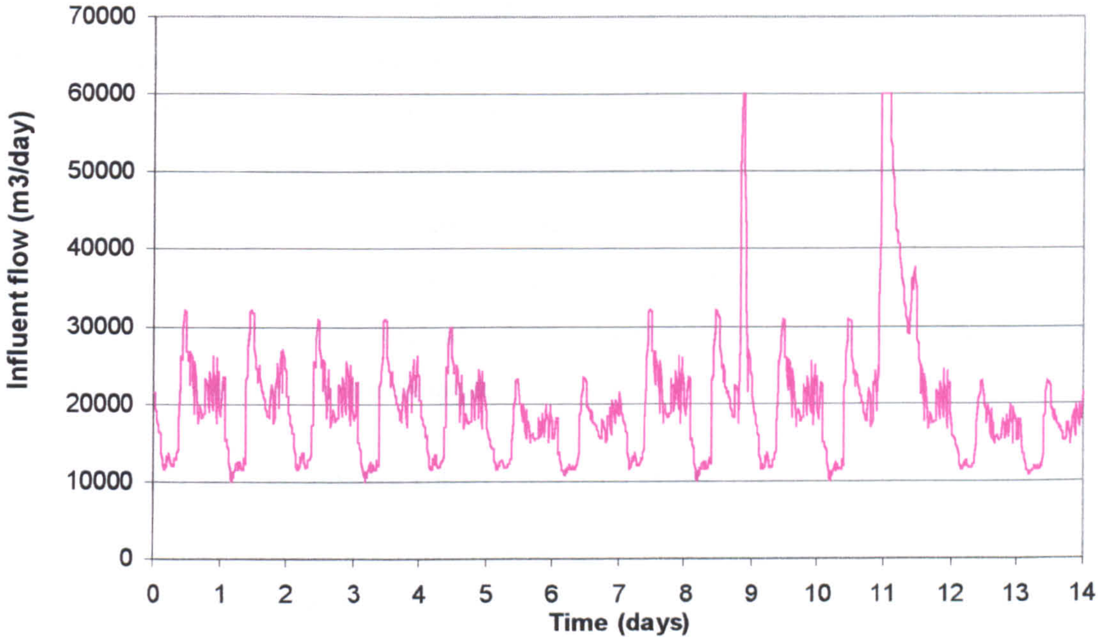


Figure 3.10: Influent flow rate of realistic data set

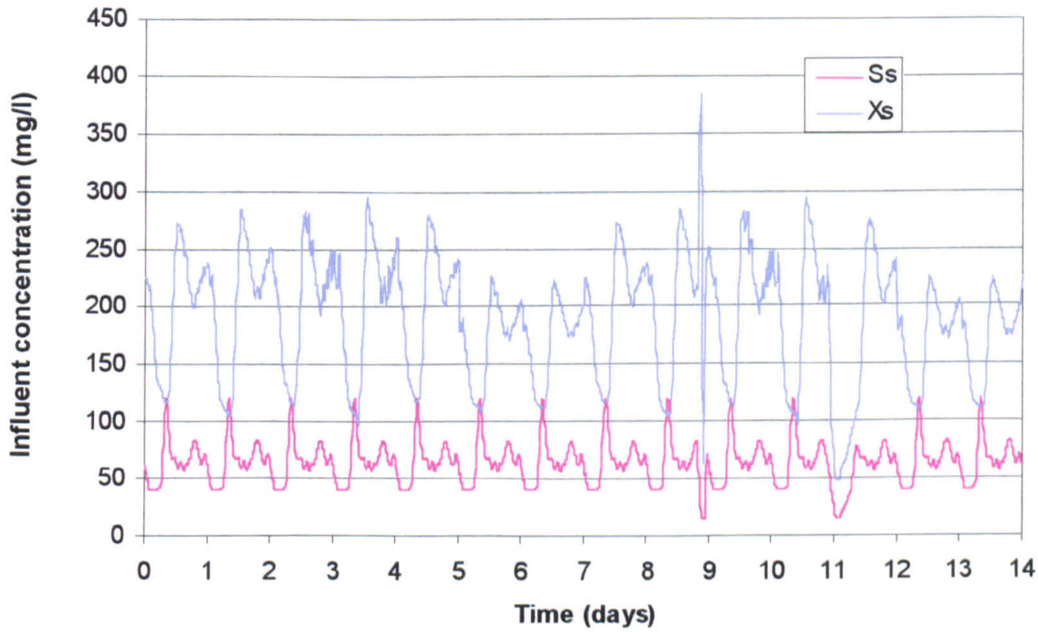


Figure 3.11: Soluble (S_S) and particulate (X_S) substrates concentration in realistic data.

3.3.2 Change of temperature

The operating temperature of the process is important since the values of the kinetic parameters are dependent upon it. Changing the temperature modifies the characteristics of the process (non-linearity and time constants). The normal operating temperature for this study is 20°C, however the plant behaves differently at 10°C because the bacterial activity is reduced; kinetic parameter values are presented in Appendix A for both temperatures. Also affected at lower temperatures are the Dissolved Oxygen Uptake Rate (OUR), the biomass growth and substrate oxidation because they are related to the biomass activity. This test corresponds to the natural change of behaviour of the process between summer and winter for example.

3.3.3 Change of suspended solids concentration

It can be decided to change the suspended solids concentration within the aeration stage of a plant for operational reasons or to optimise process efficiency. This in turn will affect the recycle flow rate of activated sludge necessary to maintain this new concentration and of course the aeration rate required to maintain the dissolved oxygen concentration will need to vary accordingly.

3.4 Controller Comparisons

The comparisons of the response of the different controllers to various conditions (change of wastewater treatment plant characteristics, such as temperature, nature and flow-rate of the wastewater, loading of the plant, etc.) have been carried out using the same controller settings and initial conditions.

3.4.1 Flow and load changes

The usual daily control problem in an activated sludge process is to accommodate the variability of the influent flow-rate and the concentration of its different constituents which usually peak at the same time. Any suitable control system has to be able to handle these disturbances with a minimum deviation from the set-point. A simple evaluation of the different controllers was first being performed on a relatively simple composite flow pattern (Figure 3.9) derived from the pattern used by Vitasovic (1986).

The same controllers were then tested over a longer period, using realistic influent sewage data (Figures 3.10 & 3.11).

3.4.1.1 Composite flow pattern at 20°C

This test was performed over a duration of 1½ days. The operating temperature was assumed to be 20°C and the mixed liquor suspended solids concentration in the aeration stage was 2,000g/m^3.

The PID controller described in section 3.2.1 was implemented and tested with the composite flow pattern. The resulting controlled variable (DO) and manipulated variable values (aeration) are shown in Figure 3.12. The maximum deviation for the DO concentration in tank 1 is less than 3% and occurs when a step change is added to the sinusoid to simulate a storm event at time t = 0.9 and is of a lower amplitude in tank 2. The control action in tank 2 is nearly completely smoothed by the action on the controller in tank 1 and no great variation can be noted.

The step change in the sinusoid has a greater effect on the response delivered by the Fuzzy Logic Controller (Figure 3.13) but the maximum error is only 3.5% in tank 1 and less than 3% in tank 2. The step change has a small influence on the response of the self-tuning controller (Figure 3.14) with a maximum error of 2% shown in tank 1. The manipulated variable (aeration) also shows the influence of the measurement noise in the control action taken, these relatively high frequency signals are usually not suitable in a control system; however the time scale is in days and therefore the variations are not as oscillatory as they appear and would not damage the aeration system.

The performances of the controllers are compared in term of error functions in Table 3.3 which contains the Root Means Square error (RMS), Integrated Error (IE), and gives an indication of the wasted energy or detrimental process performance depending on the sign, over the test period.

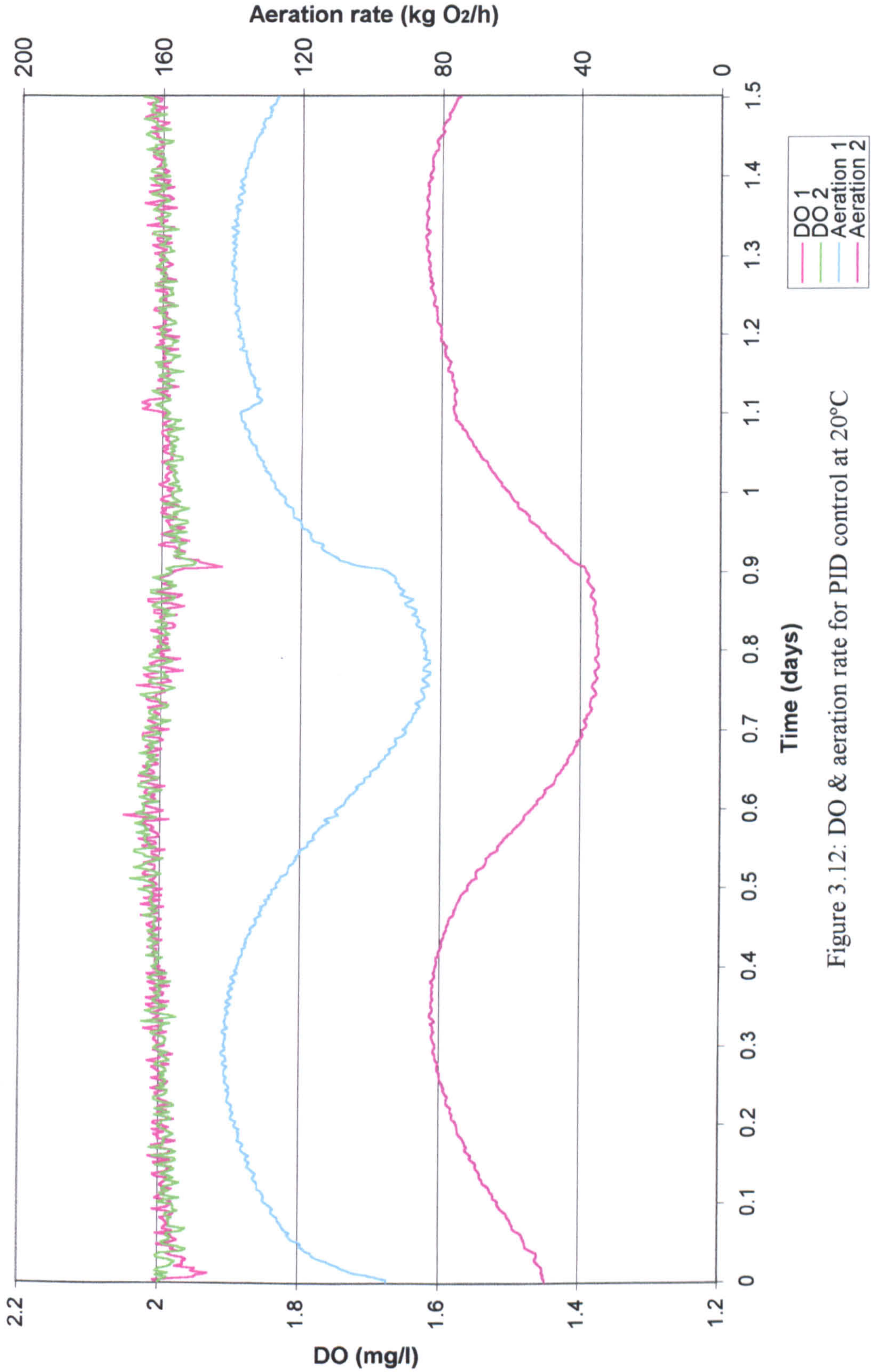


Figure 3.12: DO & aeration rate for PID control at 20°C

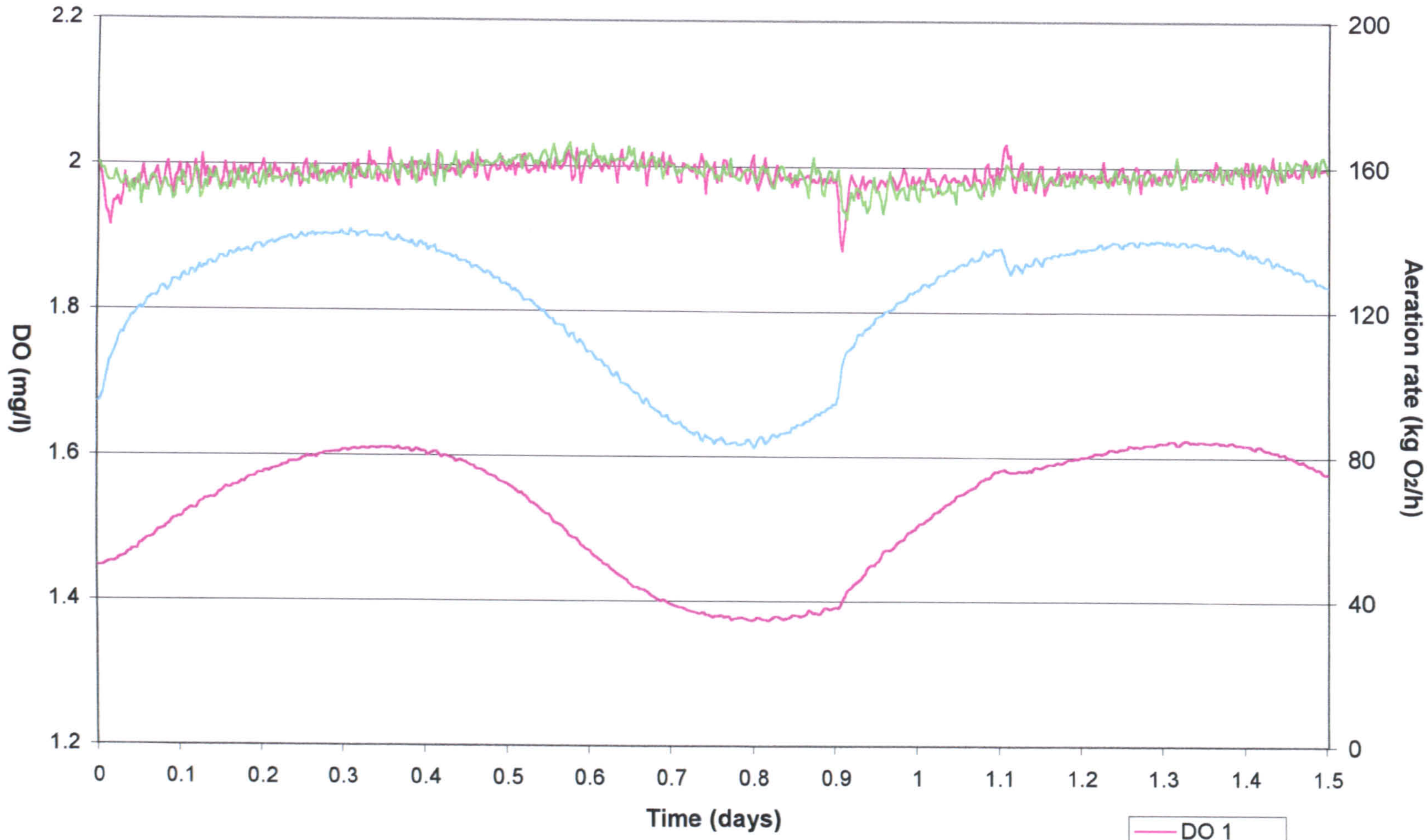


Figure 3.13: DO & aeration rate for fuzzy logic control at 20°C

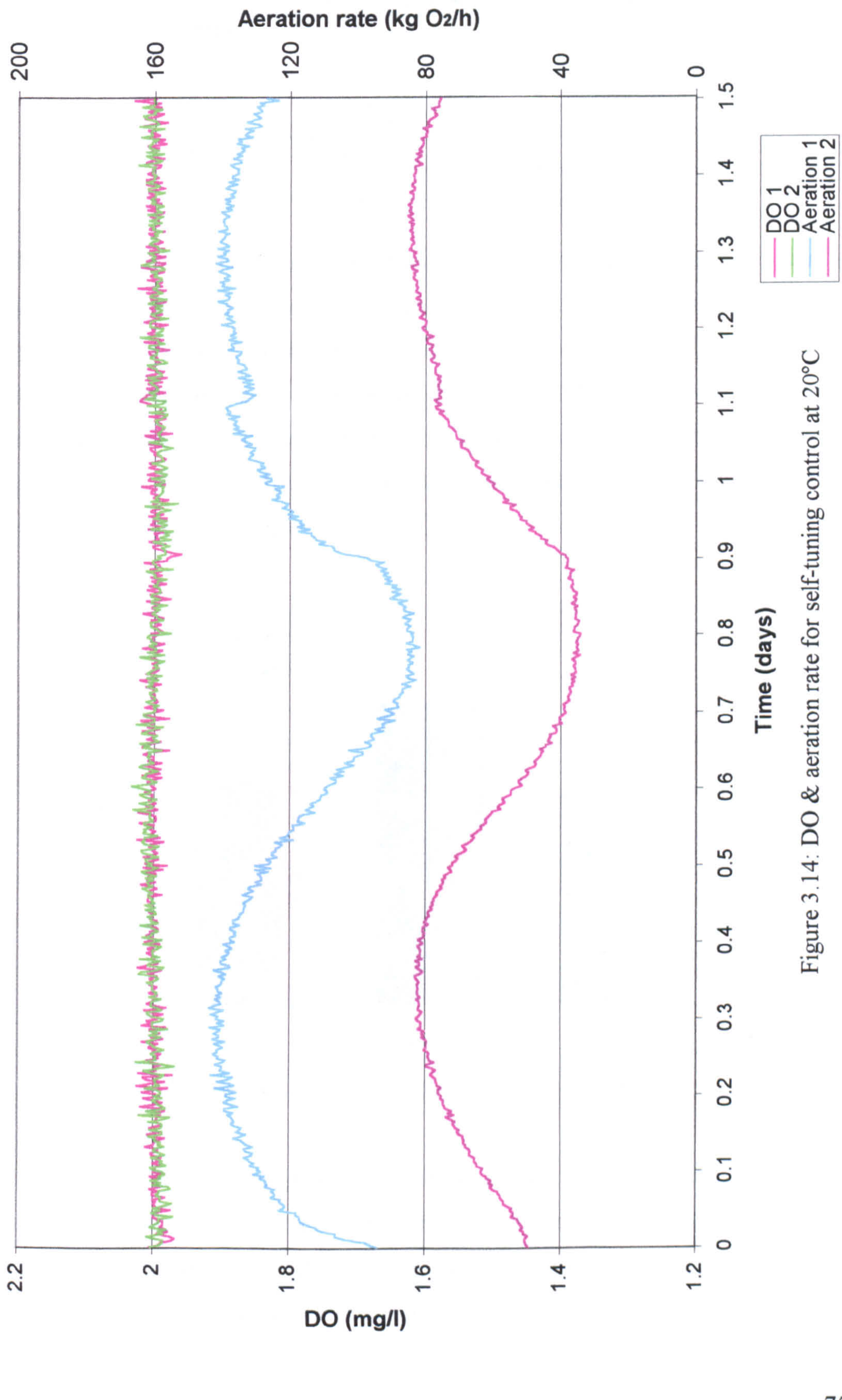


Figure 3.14: DO & aeration rate for self-tuning control at 20°C

Table 3.3: Table of error with respect to the set-point for composite flow at 20°C.

TEST	Tank	RMS($x10^{-2}$)	IE ($x10^{-4}$)
PID	1	3.54	-3.24
	2	3.65	-6.77
Fuzzy	1	4.65	-146
	2	5.12	-158
STC	1	3.18	-8.90
	2	3.26	-13.2

It has to be noted that in this test there is under-aeration with all the controllers, that is to say the treatment process was, on average over the test period, presenting a dissolved oxygen concentration below the optimal dissolved oxygen set-point for nitrification on the organic matter as the integrated error shows. The PID controller has the average dissolved oxygen concentration which is the closest to the set-point, while the fuzzy logic controller shows the largest deviation, the self-tuning controller does not perform as well as the PID for this criterion.

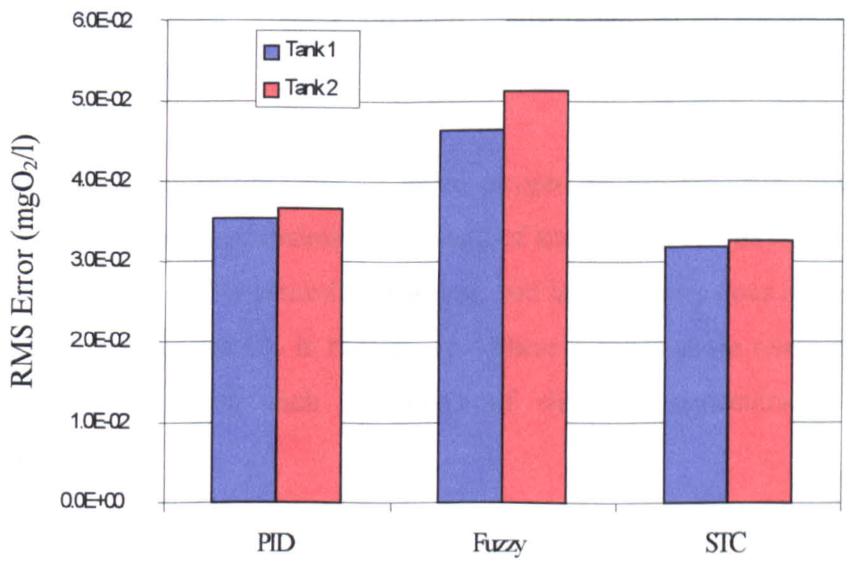


Figure 3.15: RMS errors for composite flow at 20°C.

In Figure 3.15, the self-tuning controller shows a RMS error more than 10 % smaller than the PID. However, this has to be balanced by the smoother control action delivered by the PID controller. Finally the fuzzy logic controller does not performs as well as the other two controllers with RMS errors approximately 30 % higher than the PID.

3.4.1.2 Real influent data at 20°C

This data was chosen to test the robustness and stability of the controllers by: the variability of the influent; two storm events occurring and a longer duration of the test (two weeks of operation). The controller performances under these conditions, as realistic to real operation as possible, should reflect closely the actual performances expected on a real plant.

The dissolved oxygen concentrations and aeration rates over the overall test period for the PID controller are presented in Figure 3.16. Also presented, are expanded time scales for two particular days for closer analysis (Figure 3.17), day 2 of the test as a "normal" day and day 9 where the first storm takes place as a "stress" condition for the control system.

It can be seen that the aeration rate has to adjust rapidly to the change of influent arriving at the treatment plant.

Significant deviation from the dissolved oxygen set-point occurs only during the two storm conditions at approximately the end of the 9th and 11th days. In Figure 3.17, the actual deviation of DO caused by the first, and larger, storm does not exceed 4 % in the first aeration tank and 6% in the second. These deviations are relatively small since the process can support such variations of the DO concentration without major consequences.

Only a detailed portion of the test period (day 2 and 9) for the fuzzy logic controller is presented in Figure 3.18 since the response over the complete test period is very similar to that obtained for the PID controller. The maximum deviations are 3.5% for tank 1 and just over 7% for tank 2.

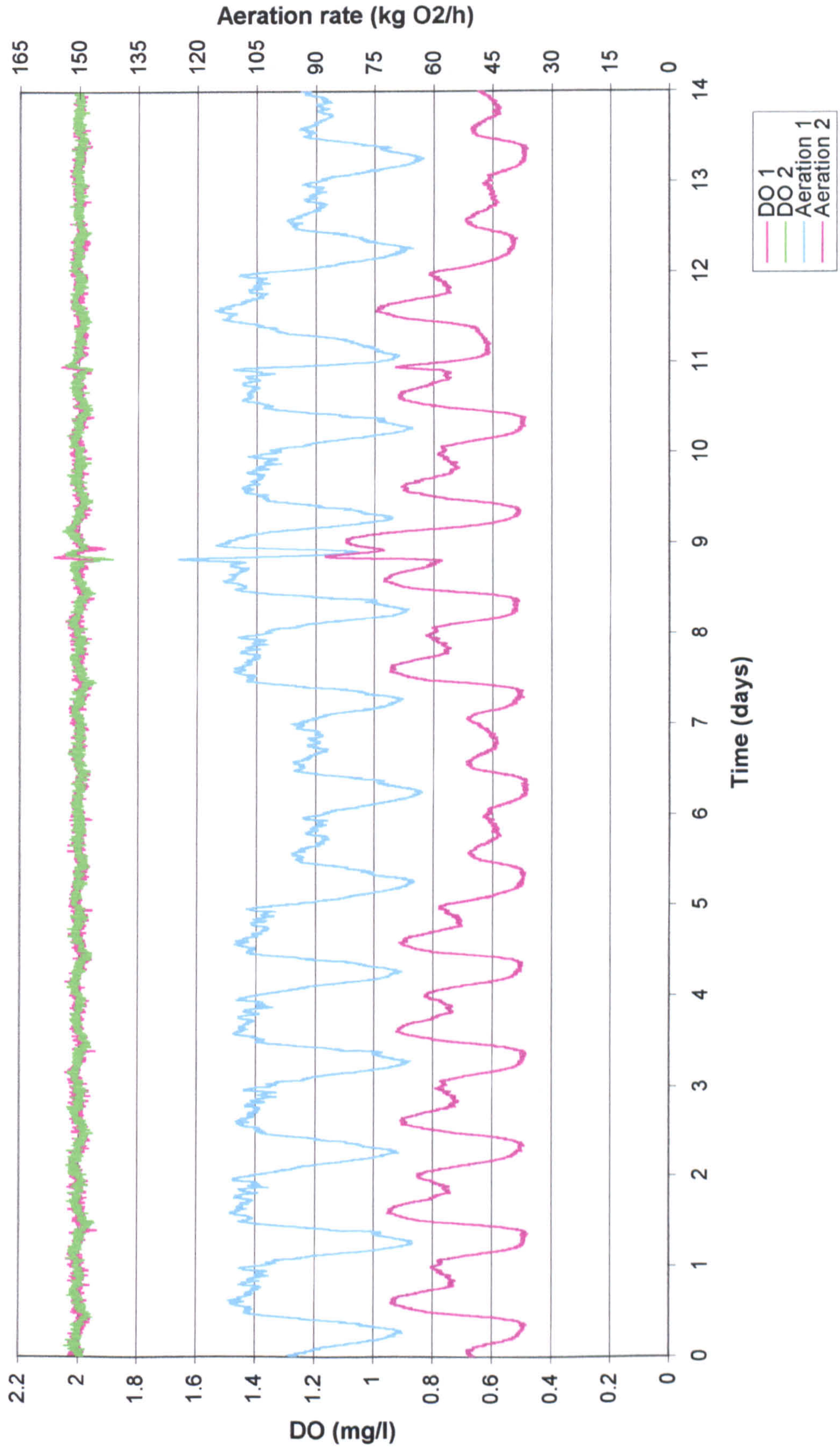


Figure 3.16: DO & aeration rate for PID control at 20°C

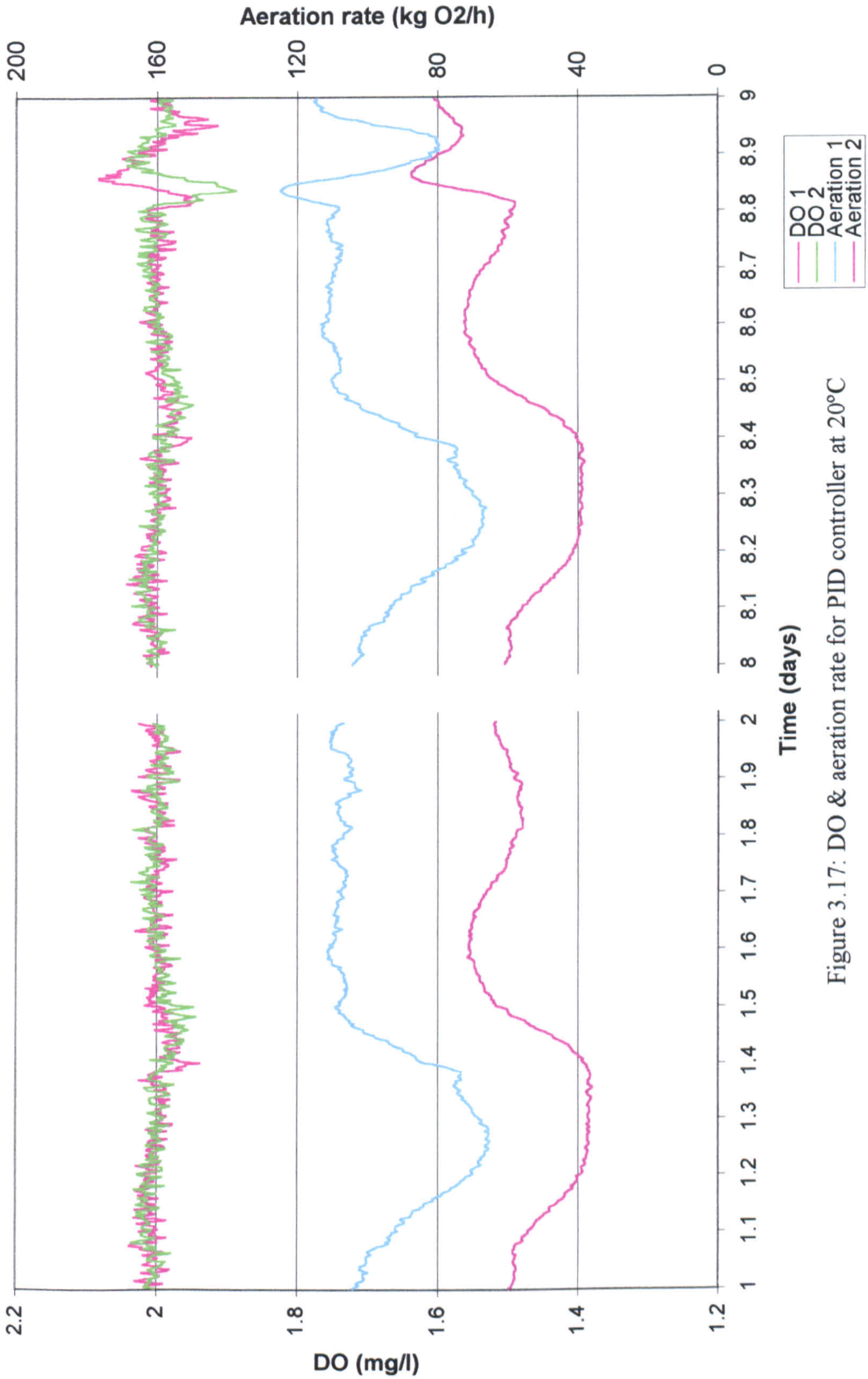


Figure 3.17: DO & aeration rate for PID controller at 20°C

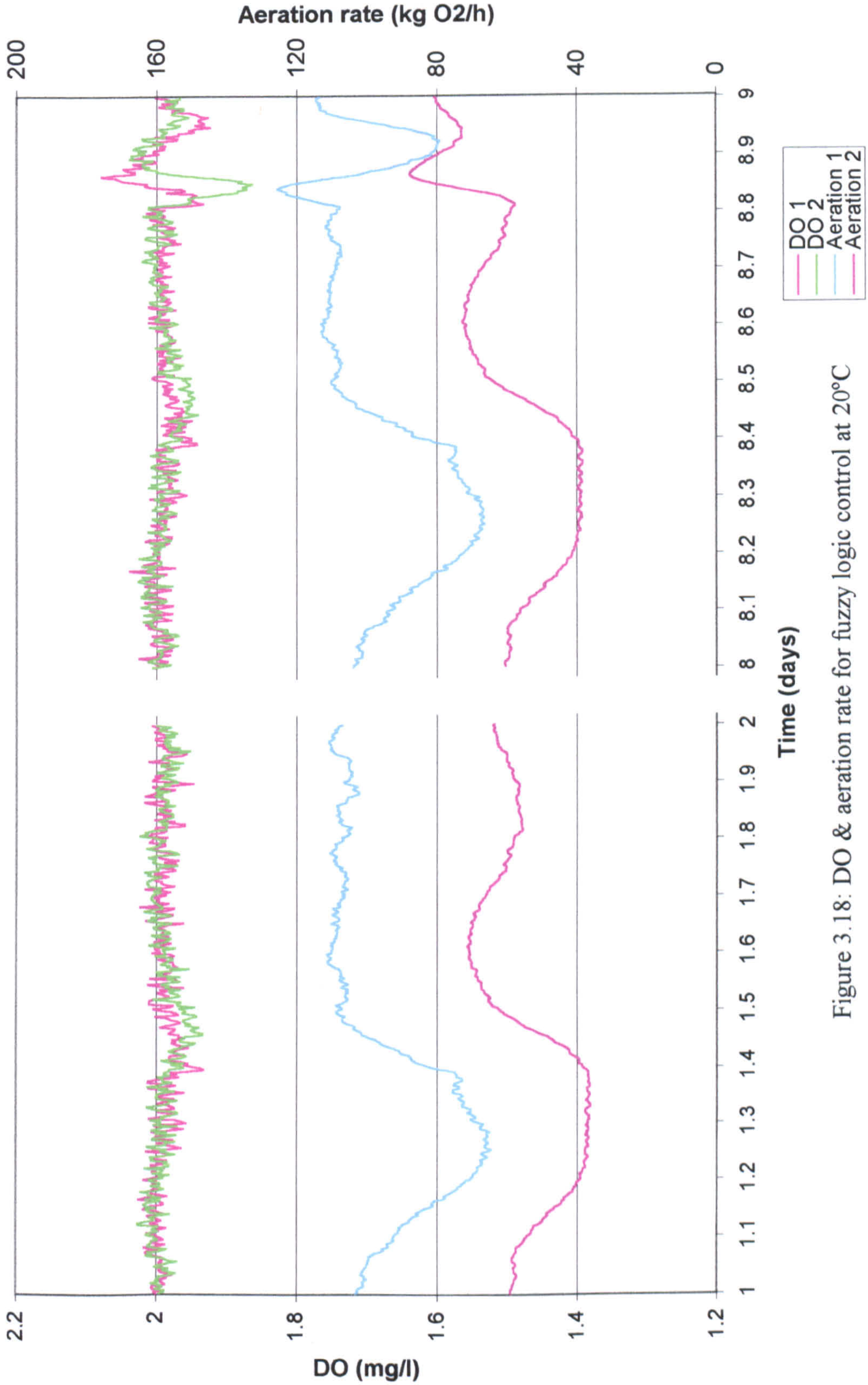


Figure 3.18: DO & aeration rate for fuzzy logic control at 20°C

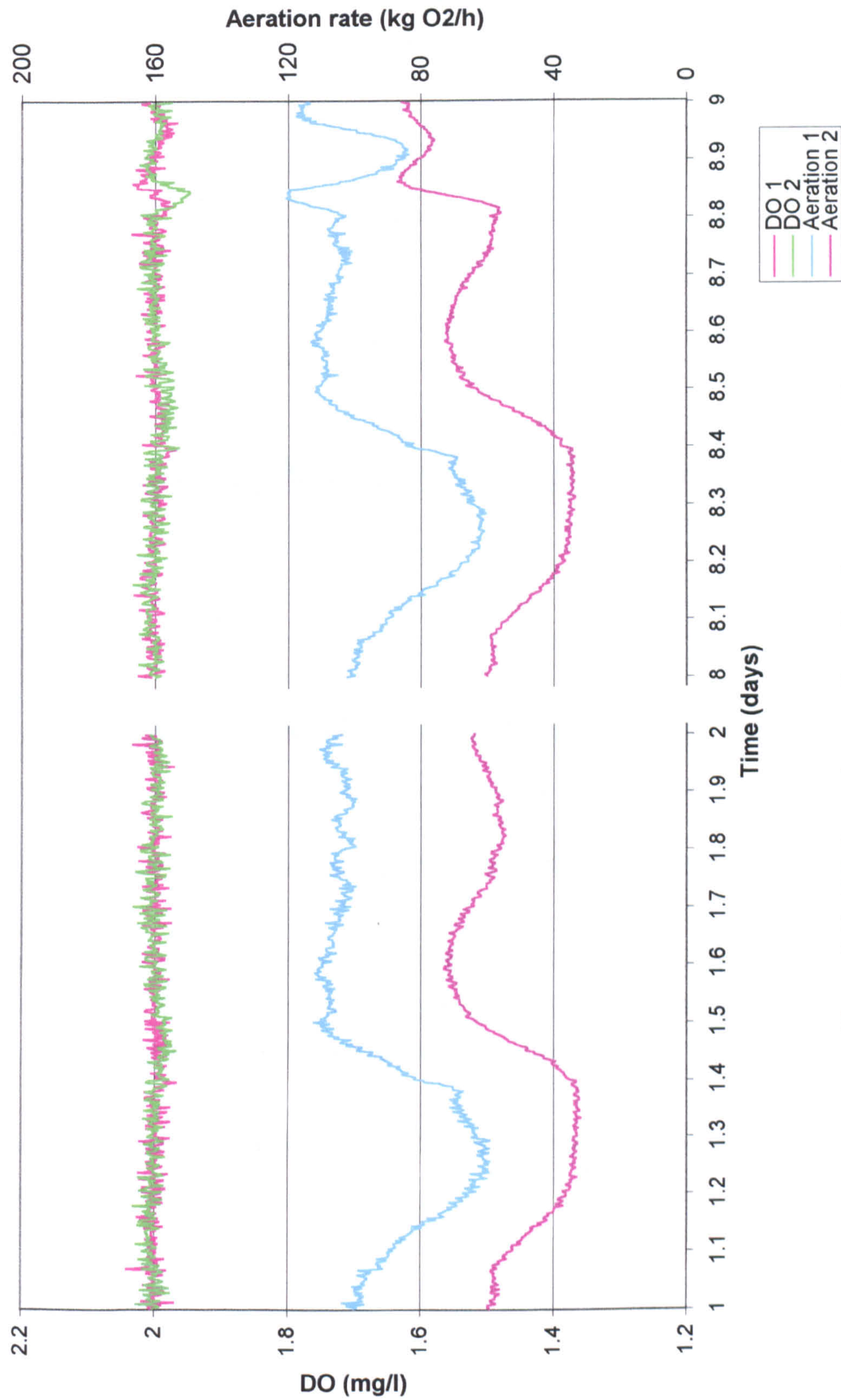


Figure 3.19: DO & aeration rate for self-tuning control at 20°C

Figure 3.19 shows that the Self-tuning controller presents a very small deviation from the set-point; even during the storm with maximum errors of 2% and 3% in tanks 1 and 2 respectively. However, the aeration rate presents continually small amplitude changes.

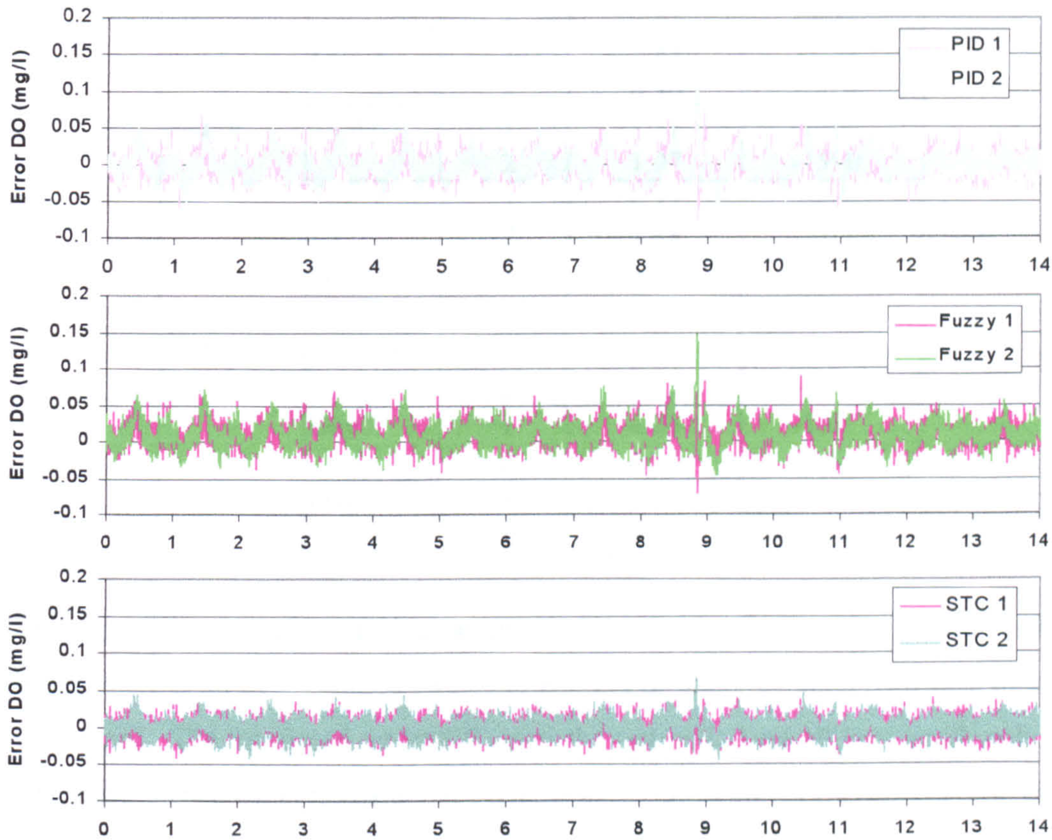


Figure 3.20: DO deviations for the three controllers for real data at 20°C

The errors for the three different controllers are presented in figure 3.20. The error pattern for the PID and fuzzy logic controller are very similar, although the amplitude of the error is slightly greater for the fuzzy logic controller.

Table 3.4 presents comparison for both the entire test period (14 days of operation) and specifically day 2 and day 9.

Table 3.4: Error function values for real data at 20°C

TEST	period	Tank	RMS ($x10^{-2}$)	IE ($x10^{-4}$)
PID	14 days	1	1.46	2.35
		2	1.54	-1.71
	Day 2	1	5.64	-4.85
		2	6.21	-5.51
	Day 9	1	7.83	-7.30
		2	8.36	-26.0
Fuzzy	14 days	1	1.77	-1360
		2	1.97	-1390
	Day 2	1	6.72	-992
		2	7.88	-105
	Day 9	1	6.87	-108
		2	11.49	-137
STC	14 days	1	1.04	1.23
		2	1.13	4.99
	Day 2	1	4.06	-1.61
		2	4.34	-1.51
	Day 9	1	4.37	-1.69
		2	5.28	-12.4

The integrated error gives an indication of the overall effect of the control action, whether there is an over-aeration (waste of energy) or under-aeration (less than optimal nitrification). The integrated errors (IE) over the test period are all very small, only the fuzzy logic controller presents a relatively large IE of about -14 over fourteen days, about 200 times more than the other two control methods.

The RMS errors are presented in Figure 3.21. The superiority of the self-tuning controller over the other methods is clearly shown whether the results are over the overall test period or individual days are considered.

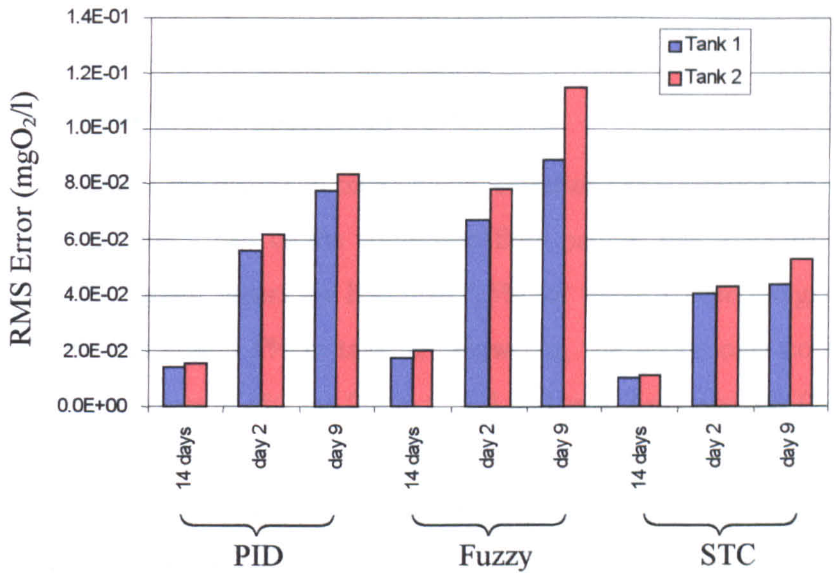


Figure 3.21: RMS error for real influent data at 20°C

The self-tuning controller appears to deliver the best overall response, performing only marginally worse than the PID controller for Integrated Error. The only drawback is the fast and nearly continuous variation of the aeration rate which can be detrimental to the life-time of the aeration system employed, that is the motor or pump.

3.4.2 Change of temperature

Temperature changes occur continuously in a water treatment process, for example, nights are cooler than days. This in turn affects the growth parameters of the biomass and therefore the way in which dissolved oxygen is used.

The two flow and load patterns presented earlier (section 3.3.1) were also used to test at 10°C the same controllers (tuned at 20°C), with unchanged parameters. The initial concentrations of the different constitutive elements of the mixed liquor in the different tanks were modified to reflect the new growth conditions. In a real plant the mixed liquor temperature would change gradually and not suddenly and uniformly as a step change as simulated in this test. This test reflects another aspect of the robustness expected of control systems for water treatment applications. It would not be very satisfactory from a maintenance aspect to have to retune the controllers when the temperature changes significantly.

3.4.2.1 Composite flow pattern at 10°C

Figure 3.22 shows the dissolved oxygen concentrations and aeration rates in tank 1 and 2, over the day and a half of the composite flow pattern test, obtained using the PID controller. The largest errors are less than 2.5% for the dissolved oxygen concentration in tank 1 and less than 1.5% in tank 2. However, the fuzzy logic controller presents larger maximum errors of 3% and 2% in tank 1 and tank 2 respectively (Figure 3.23).

Figure 3.24 shows the responses for the self-tuning controller. The maximum deviations from the set-point are of 2.5% for tank 1 and 2% for tank 2. A point to note is that the maximum deviation for tank 2 is not caused, as expected, by the addition of the square signal to the sinusoid but earlier at approximately time T = 0.6 days without a particular cause being identifiable.

Table 3.5 presents the error function values over the test period of 1 ½ days for the three control methods employed.

Table 3.5: Error function values for composite flow at 10°C.

TEST	Tank	RMS ($x10^{-2}$)	IE ($x10^{-4}$)
PID	1	3.47	0.127
	2	3.05	-1.85
Fuzzy	1	4.60	-143
	2	4.44	-149
STC	1	3.16	-4.53
	2	3.00	2.26

The RMS errors of the fuzzy logic controller are only slightly larger than those of the PID and self-tuning controllers as can be seen in Figure 3.25. The PID and self-tuning controllers also have a smaller integrated error over the test period than the fuzzy logic controller, which is under-aerating as in the previous series of tests at 20°C. The PID controller presents a smaller IE than the self-tuning controller even though its RMS error is marginally greater.

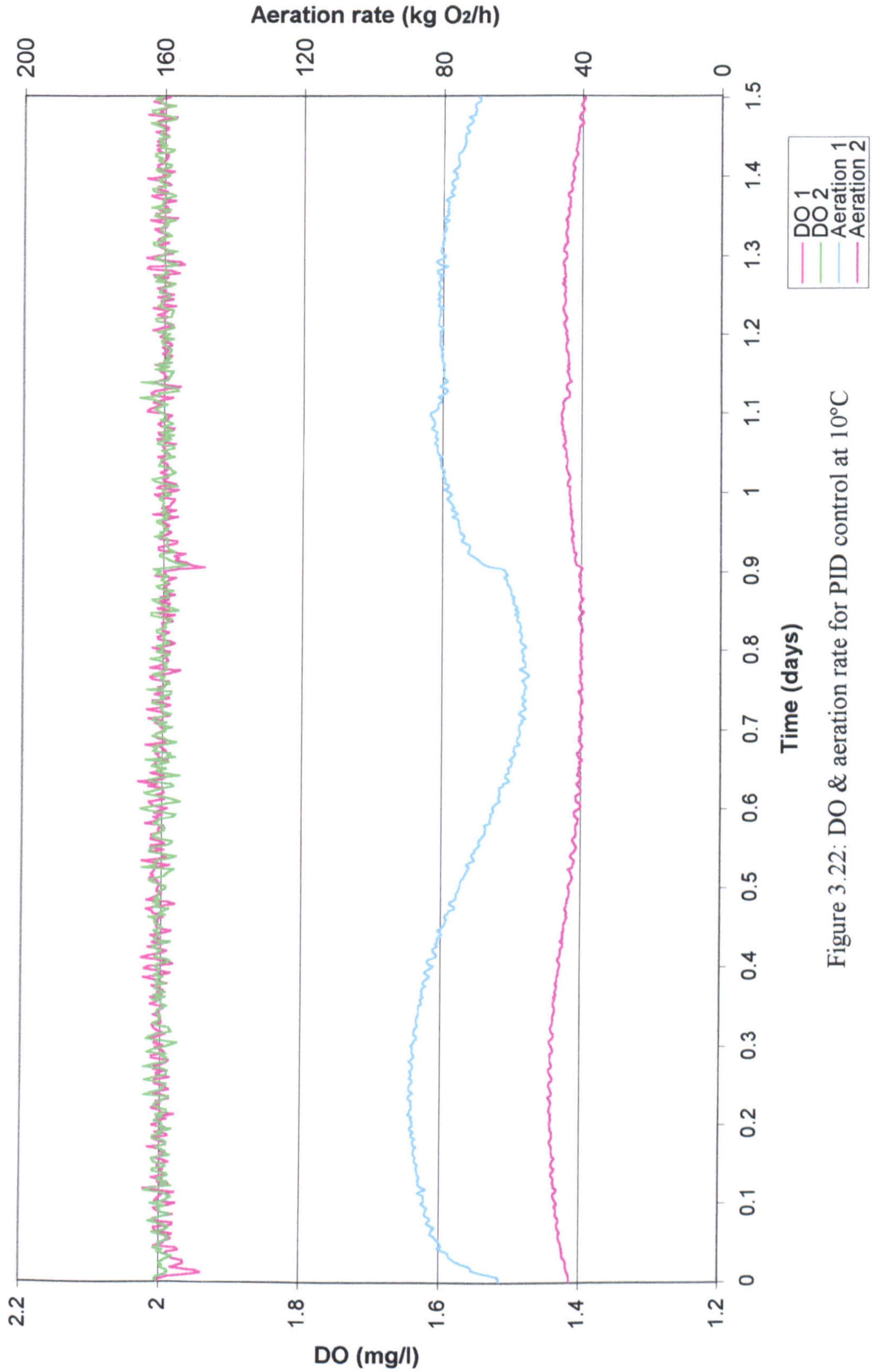


Figure 3.22: DO & aeration rate for PID control at 10°C

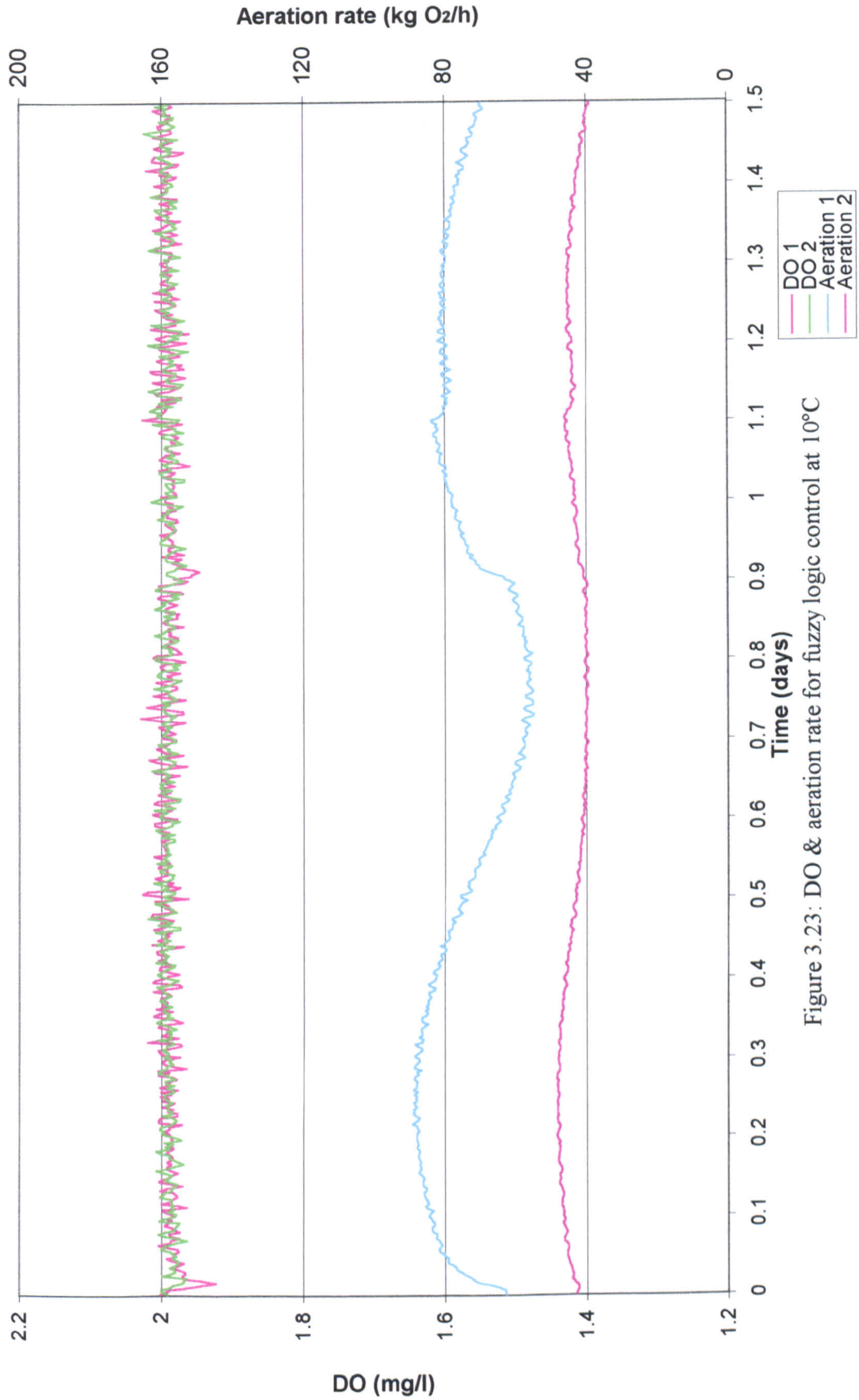


Figure 3.23: DO & aeration rate for fuzzy logic control at 10°C

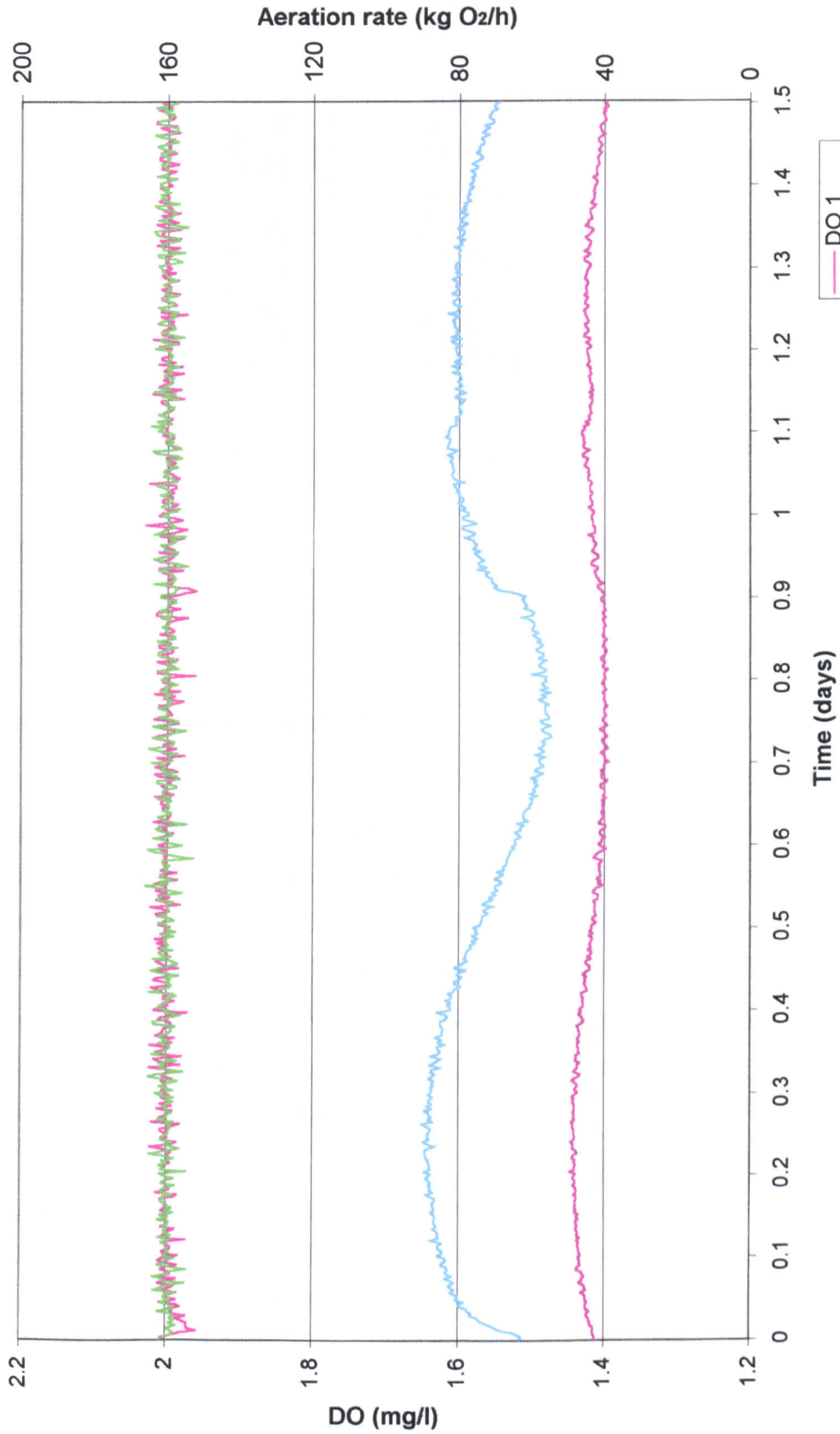


Figure 3.24: DO & aeration rate for self-tuning control at 10°C

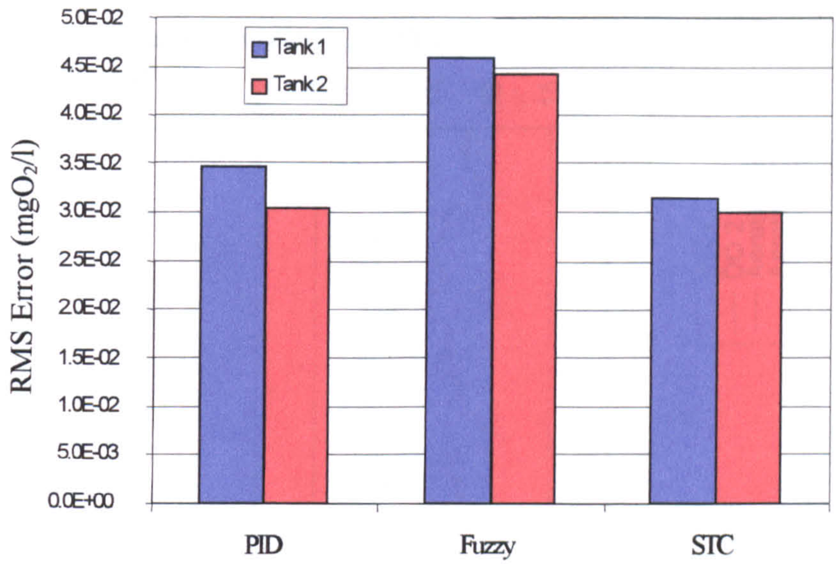


Figure 3.25: RMS error for composite flow pattern at 10°C.

For this test the PID and self-tuning controllers are performing nearly equally well, the fuzzy logic controller having larger errors which is clearly reflected in the dissolved oxygen concentration graphs.

3.4.2.2 Real influent data at 10°C

A graph of the dissolved oxygen concentration and aeration rate over the full test period is presented only for the fuzzy controller (Figure 3.26) the corresponding figures for the PID and Self-tuning controller being very similar. However, results for day 2 and 9 are presented for the three control methods under study (Figures 27, 28 & 29). The first point to note is that the aeration rate needed to sustain process operations at 10°C is considerably reduced compared with process operations at 20°C. This is due to the reduced biomass growth and activity. This in turns reduces the amplitude of the control action needed to respond to the disturbances.

Figure 3.27 shows the dissolved oxygen concentrations and aeration rates in the two aeration tanks for the PID controller. The maximum deviations observed are of 3.5% in the first aeration tank and 2.5% in the second.

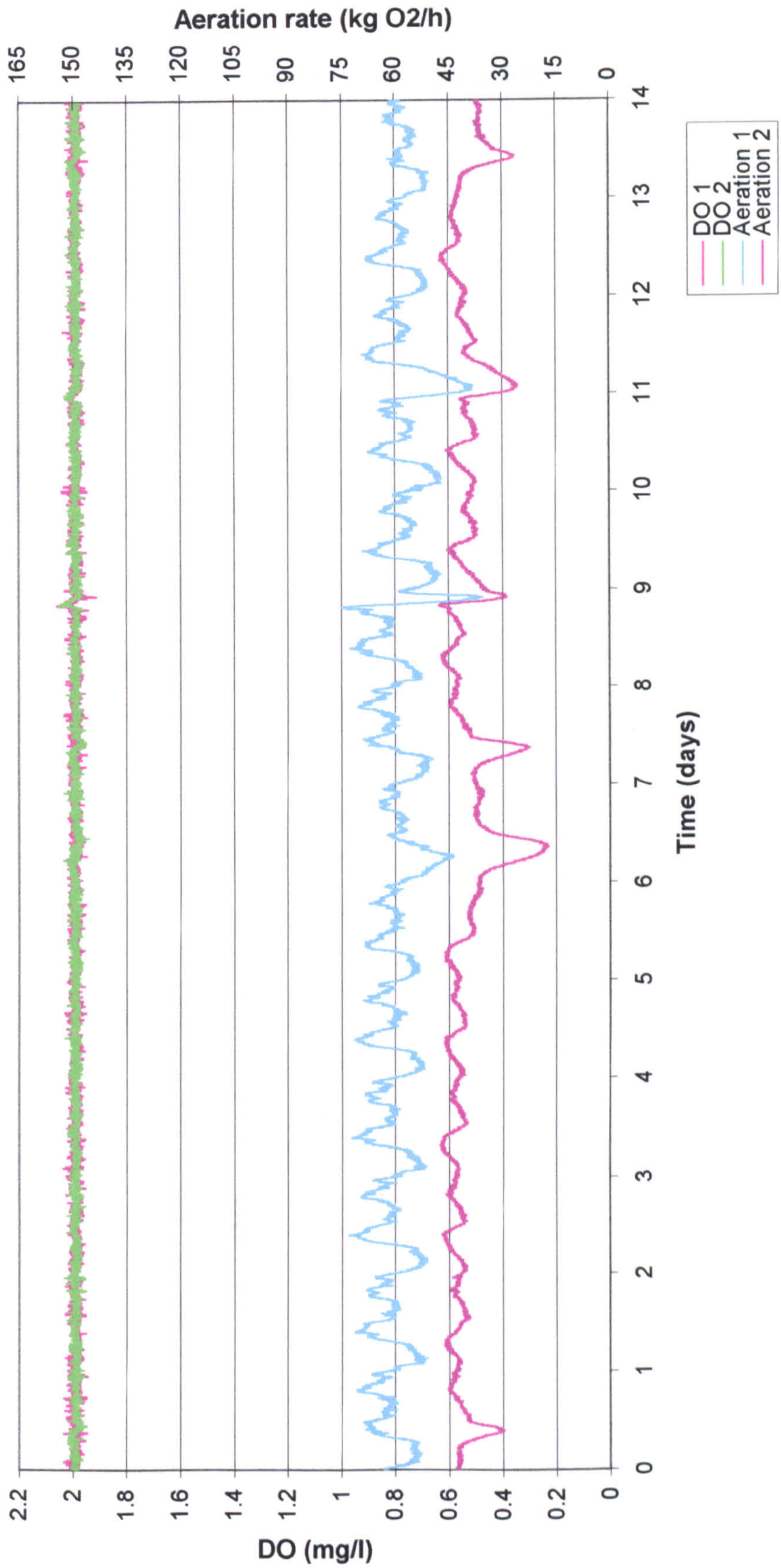


Figure 3.26: DO & aeration rate for fuzzy logic control at 10°C

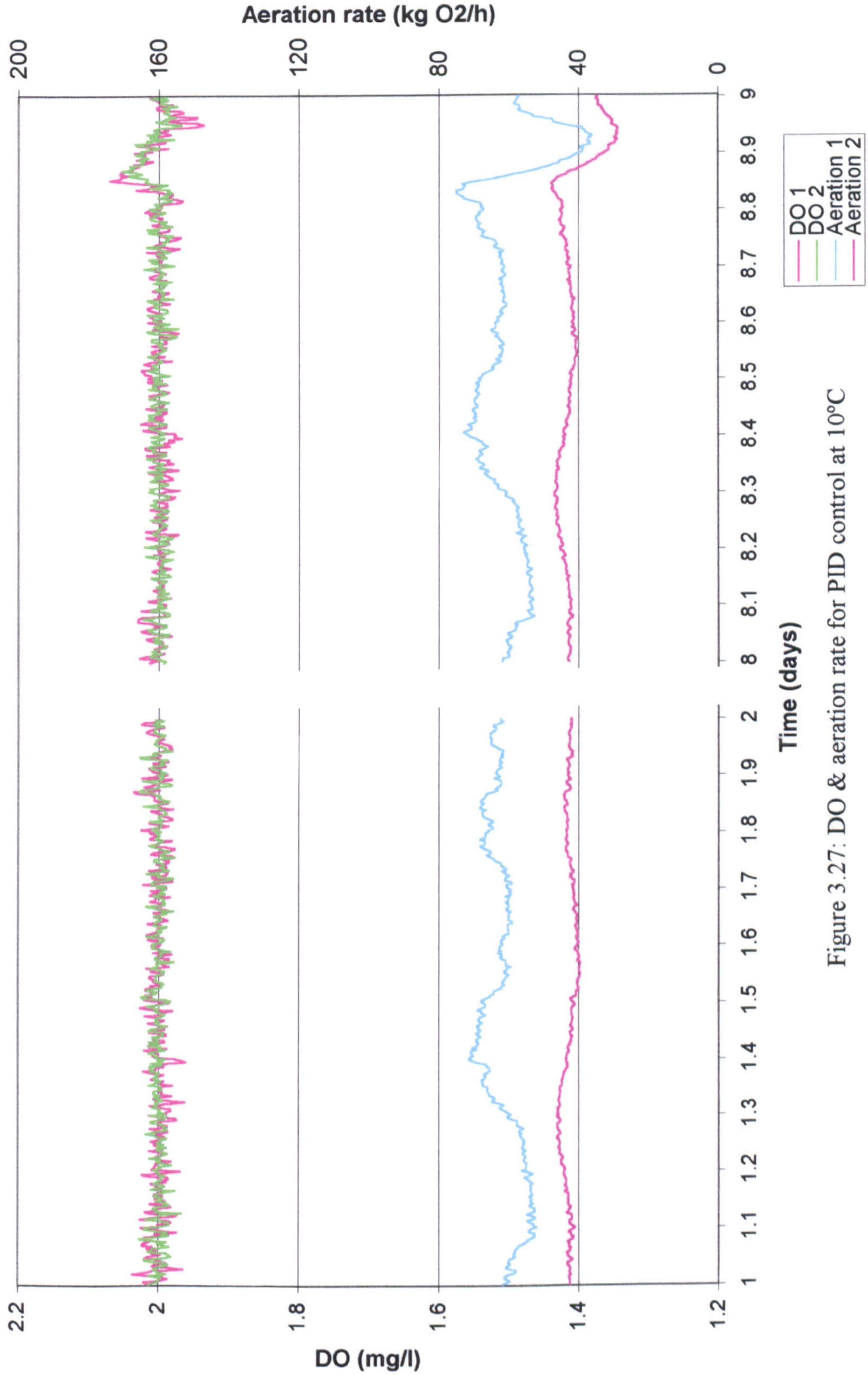


Figure 3.27: DO & aeration rate for PID control at 10°C

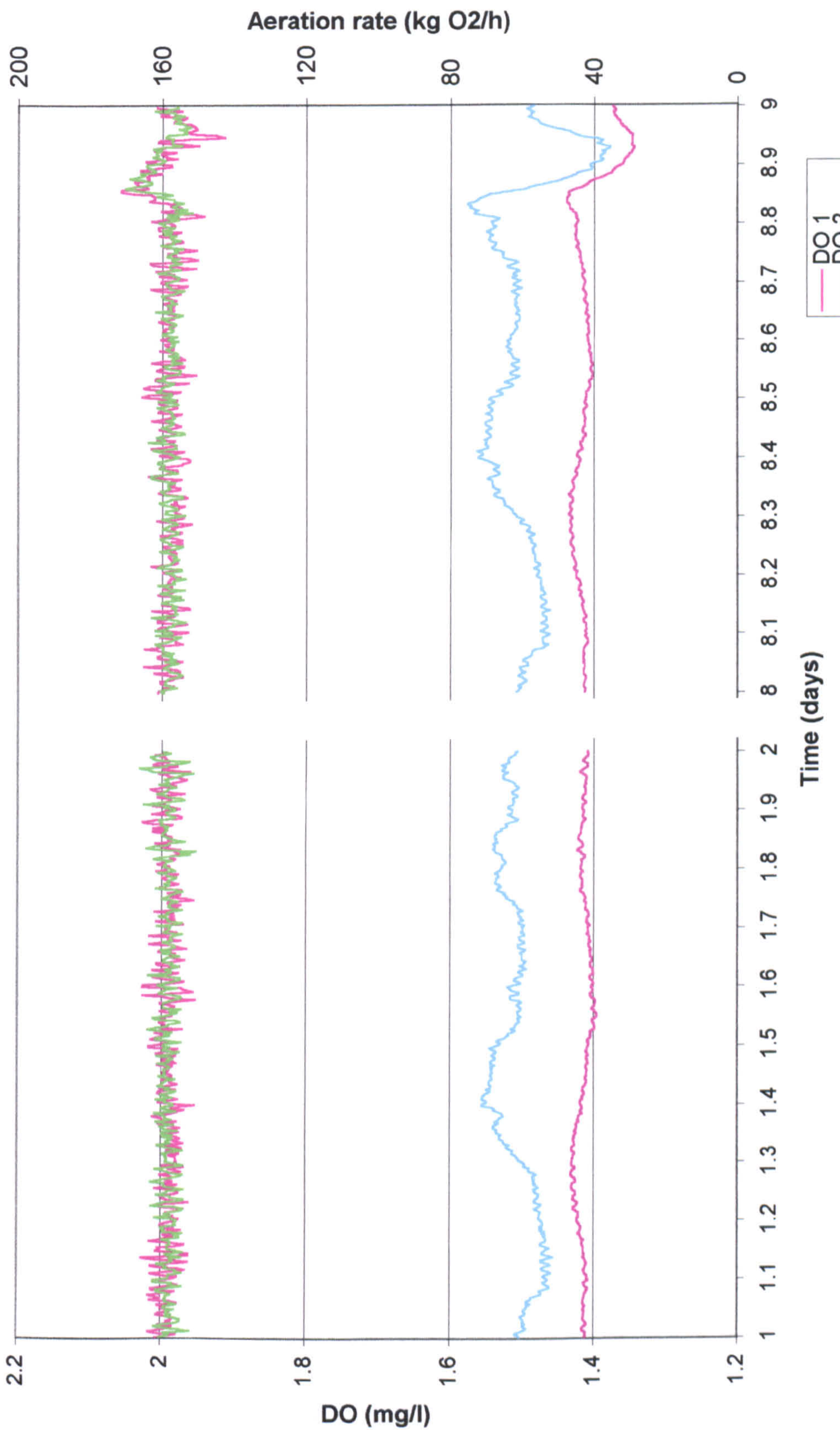


Figure 3.28: DO & aeration rate for fuzzy logic control at 10°C

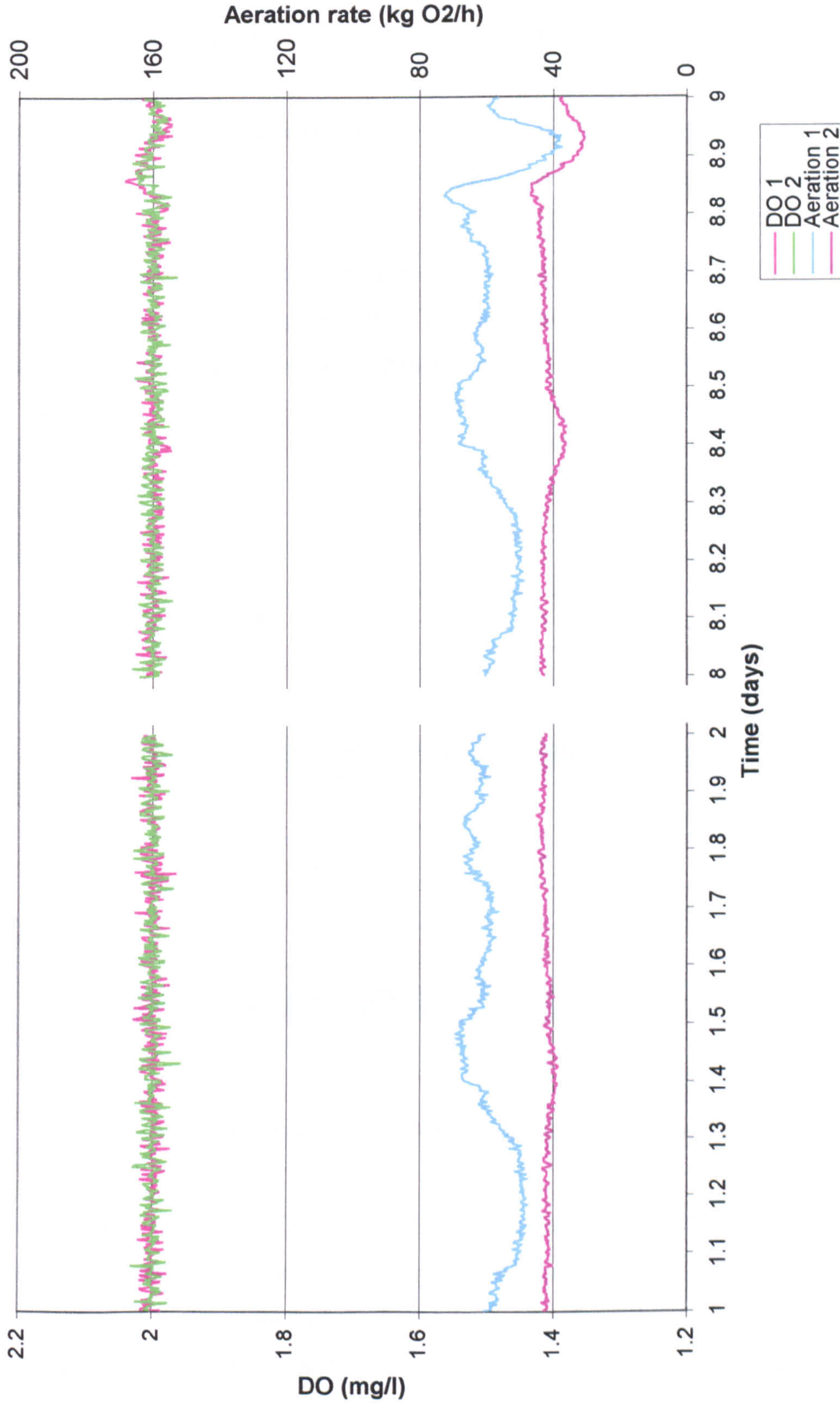


Figure 3.29: DO & aeration rate for self-tuning control at 10°C

Figure 3.26 shows the DO concentrations and aeration rates for the whole test period for the fuzzy logic controllers whereas Figure 3.28 only shows days 2 and 9. The maximum deviations found are approximately 3 % in both aeration tanks.

The self-tuning controlled variables and control action for days 2 and 9 are shown in Figure 3.29. The maximum errors are 2% of the target value in tank 1 and 3% in tank 2.

The deviations of the dissolved oxygen concentration from the set-point are shown for the three controllers in Figure 3.30. The amplitude of these deviations is reduced compared with the equivalent figure obtained while operating at 20°C (Figure 3.20).

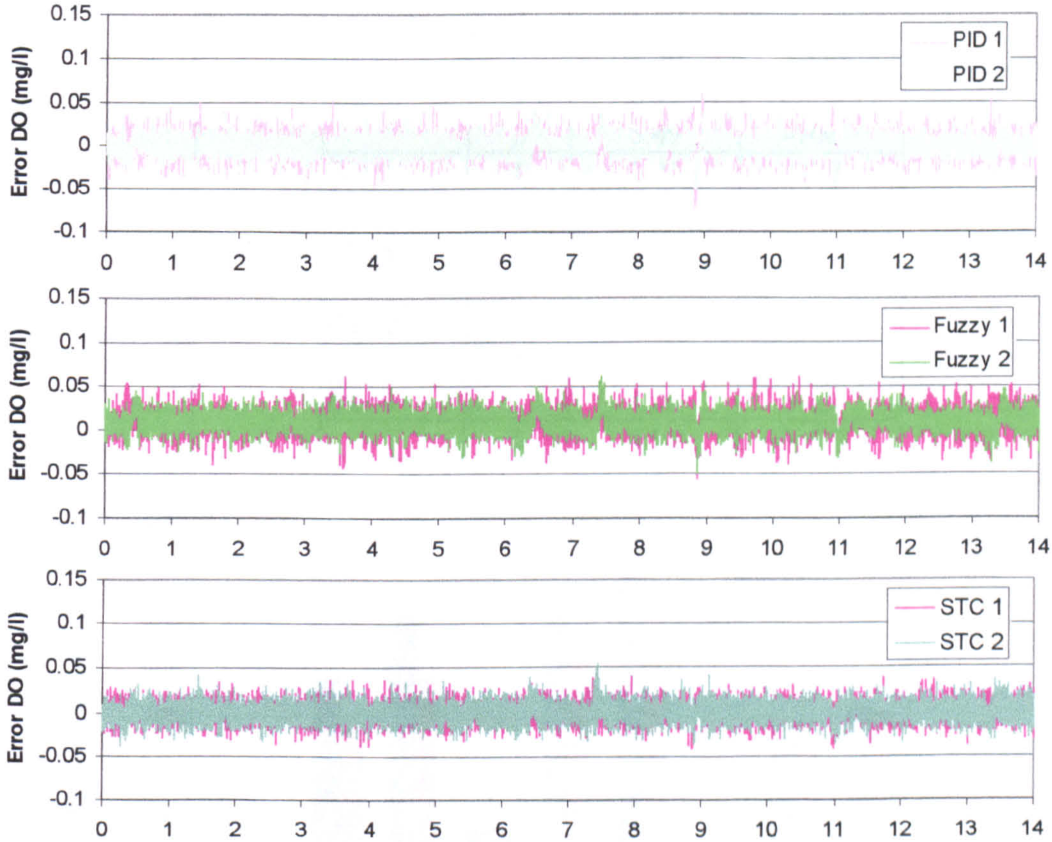


Figure 3.30: DO deviations for the three controllers for real data at 10°C

The integrated error for the fuzzy logic controller remains nearly identical and far greater than for the other two control methods (approximately one hundred times) as can be seen in Table 3.6, this is due to a persistent small offset from the set-point. The IE of the PID controllers is larger in absolute value, whereas the self-tuning controller IE remains unchanged in absolute value even if some of the signs have changed. The RMS errors for the three controllers are very similar to those obtained in the same test at 20°C. The self-tuning controller offers the smallest RMS error of all control methods tested as shown in Figure 3.31.

Table 3.6: Error function values for real data at 10°C.

TEST	Period	Tank	RMS ($x10^{-2}$)	IE ($x10^{-4}$)
PID	14 days	1	1.28	3.85
		2	1.09	8.37
	Day 2	1	4.78	-3.01
		2	3.76	1.85
	Day 9	1	6.14	0.496
		2	4.8	7.42
Fuzzy	14 days	1	1.69	-1340
		2	1.50	-1350
	Day 2	1	6.35	-94.6
		2	5.49	-100
	Day 9	1	7.09	-95.2
		2	6.10	-90.0
STC	14 days	1	1.05	1.87
		2	1.05	-3.19
	Day 2	1	3.88	-1.22
		2	3.90	-1.64
	Day 9	1	4.20	3.15
		2	4.13	3.67

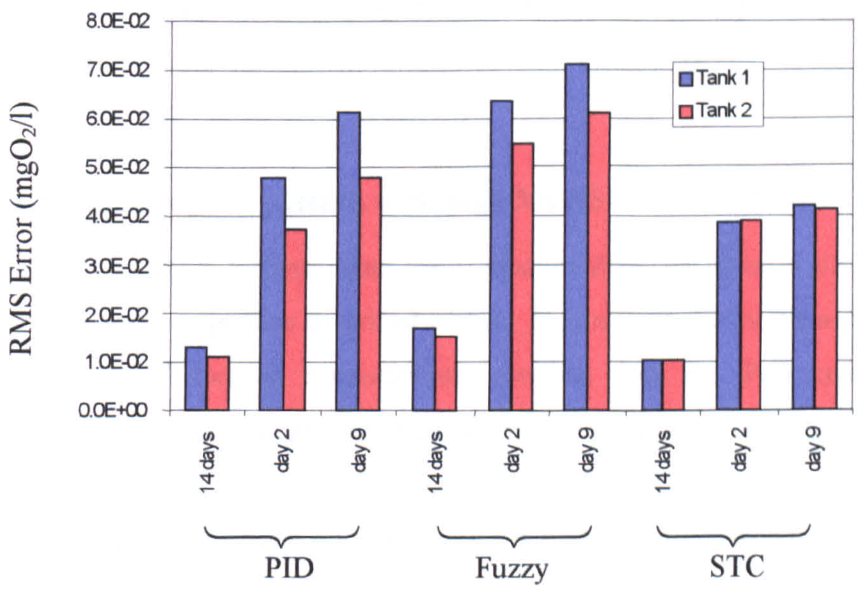


Figure 3.31: RMS error for real influent data at 10°C.

The self-tuning controller has proved to be resilient to temperature changes in these two tests. Very little change in the error function values has been seen, which seems to indicate a good degree of robustness for this controller. The PID controller is coming very close to the self-tuning controller in terms of performances. However, the integrated errors seem to have increased with the change of operating temperature. The fuzzy logic controller, while still the control method with the highest deviations, RMS and integrated errors has not shown any significant degradation of its performances.

3.4.3 Change of suspended solids concentration

This test tries to represent a modification of the plant operation. A change in the concentration of suspended solids, in the mixed liquor, can be required for a number of reasons for example, environmental considerations, operating requirement, cost and/or quality efficiency. Increasing the suspended solids concentration affects the settling in the final sedimentation tanks. It also increases the quantity of biomass available and tends to decrease the available substrate for growth. This increase in biomass requires more oxygen to allow for respiration, which means an increased aeration rate.

In this series of test, the normal operating temperature used is 20°C and the mixed liquor suspended solids (MLSS) concentration is increased by 25% from 2,000 g/m^3 to 2 500 g/m^3 as previously applied.

3.4.3.1 Composite flow pattern with high MLSS concentration

This test is run over 1 ½ days using the composite flow, based on a sinusoid with the addition of a square signal as described earlier. Figure 3.32 shows the aeration rate and resulting dissolved oxygen concentration obtained with the PID controller. The maximum DO errors are of approximately 5% and 7% in tanks 1 and 2 respectively.

Figure 3.33 shows the results obtained with the fuzzy logic controller. In this case the maximum errors are of 5.5% and 9% in tank 1 and 2 respectively.

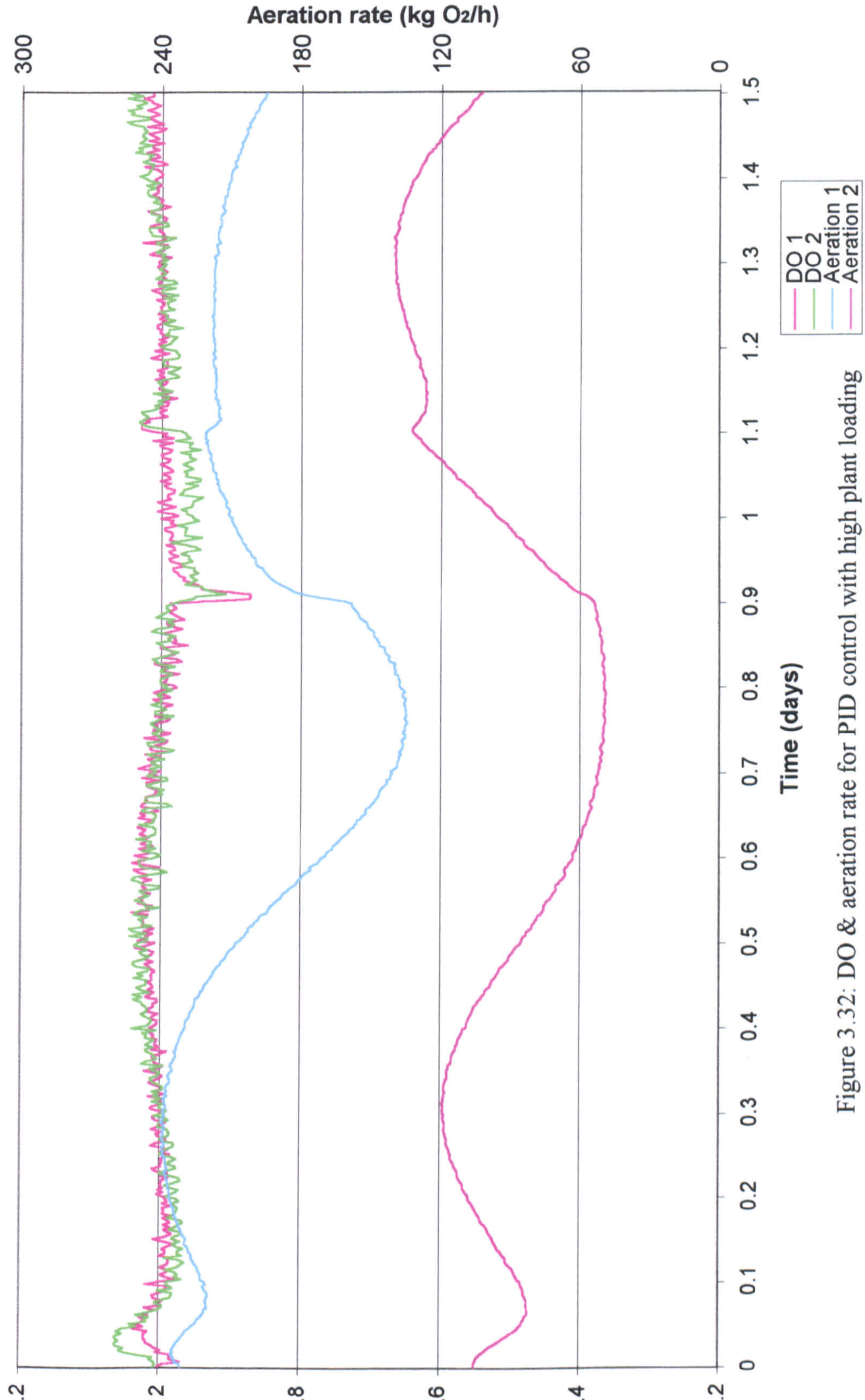


Figure 3.32: DO & aeration rate for PID control with high plant loading

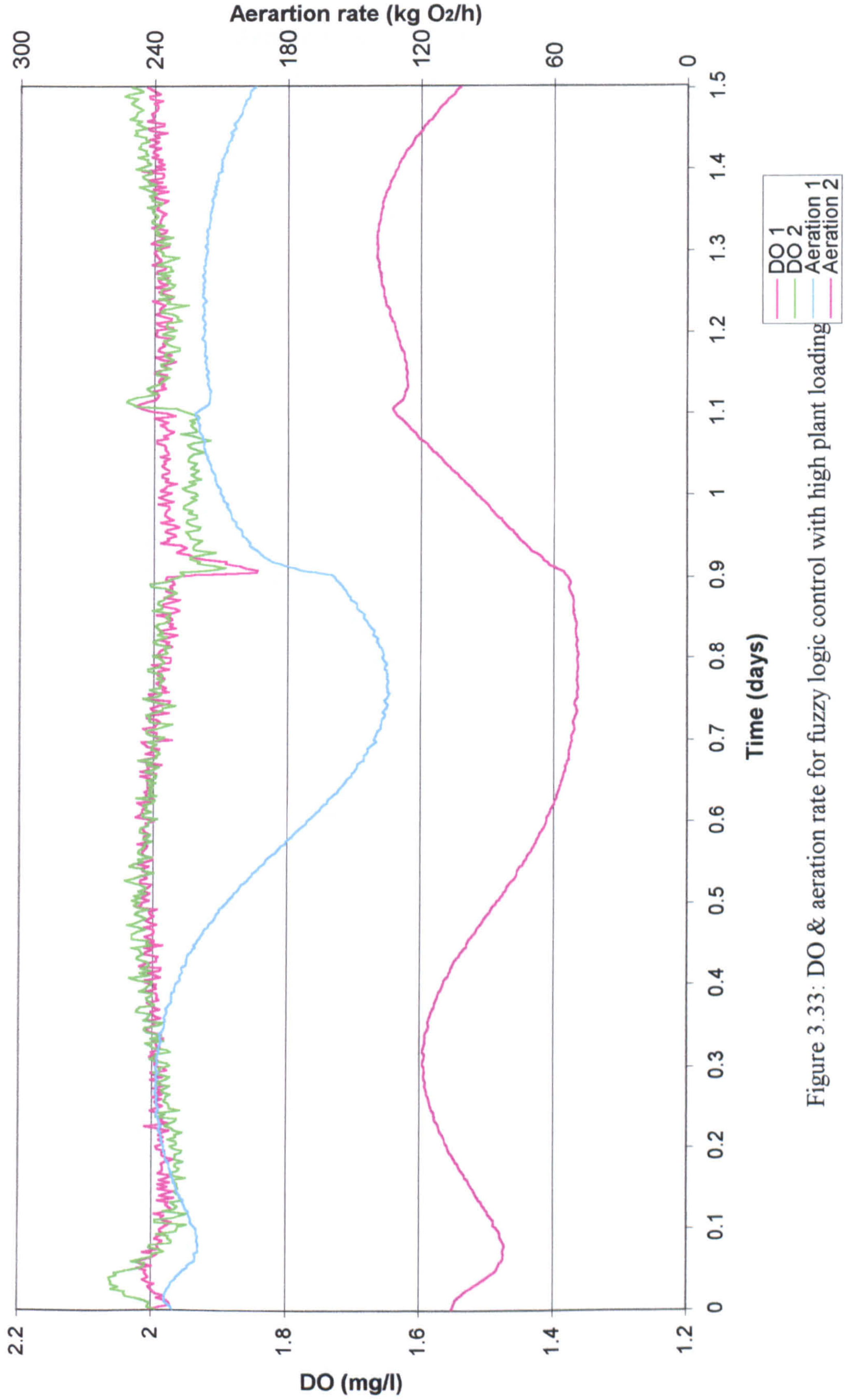


Figure 3.33: DO & aeration rate for fuzzy logic control with high plant loading

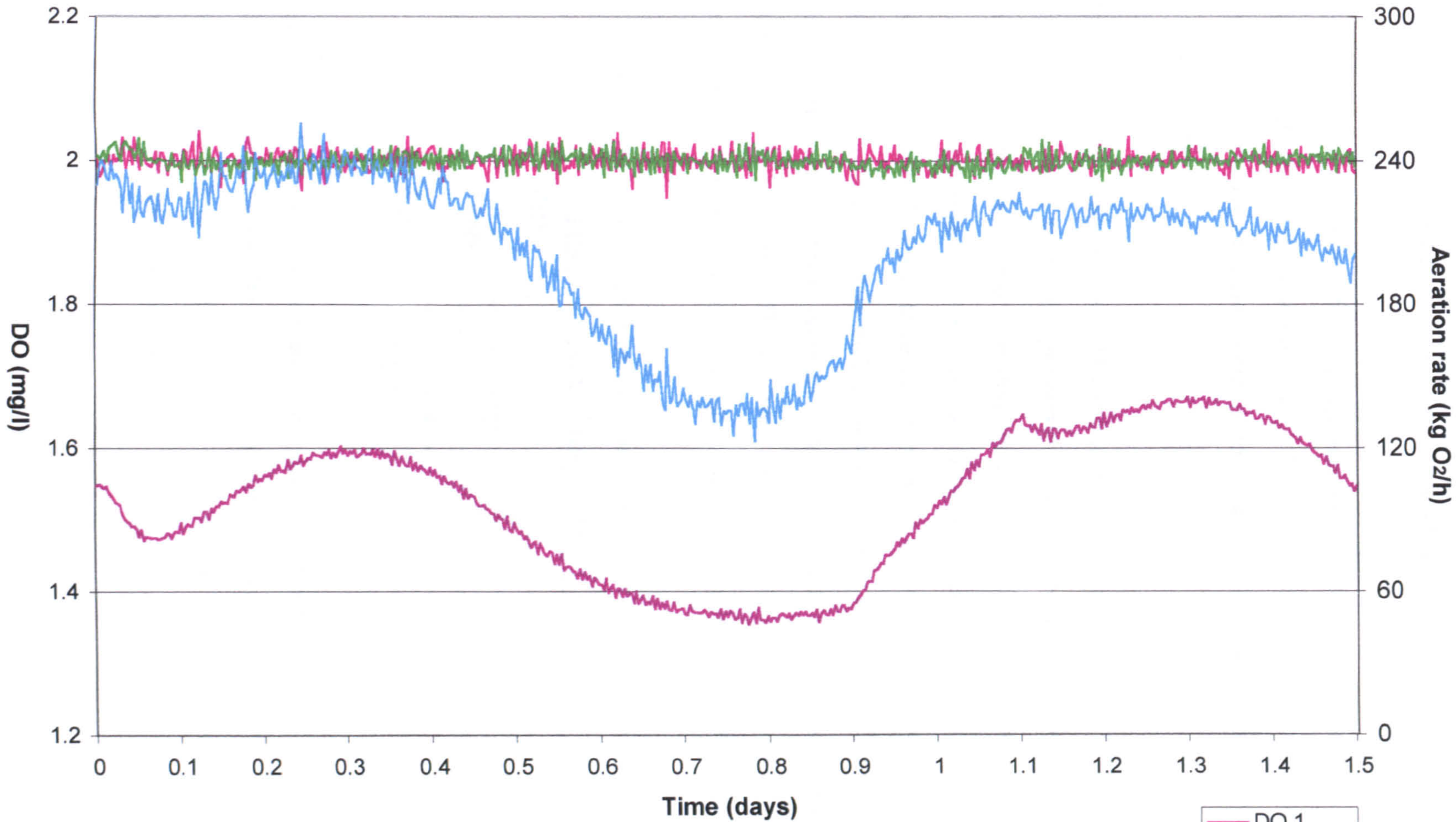


Figure 3.34: DO & aeration rate for self-tuning control with high plant loading

The response with the self-tuning controller is presented in Figure 3.34. The maximum deviations are 2.5% and 2% in tank 1 and 2 respectively.

The increase of 25% in MLSS concentration results in an increase in demand of approximately 50% in aeration rate. The same error in the dissolved oxygen concentration requires a larger control action (that is to say a larger aeration rate change) to be corrected.

As a result, the values of the RMS and integrated errors (Table 3.7) for this test are degraded compared with tests performed previously which incorporated a change of influent flow rate and load or operating temperature. Significantly, the errors are larger in the second tank than in the first for the non-adaptive control methods; the first aerated tank is designed to deal with large variations of the dissolved oxygen which are changing according to many parameters such as biomass concentration, initial DO concentrations, etc, whereas the second tank normally only has to provide the aeration needed to sustain oxidation of the substrate. The relatively large negative integrated error for the fuzzy controller shows that it does under aerate compared with the other two control methods.

Table 3.7: Error function values for composite flow with high MLSS concentration.

TEST	Tank	RMS ($x10^{-2}$)	IE ($x10^{-4}$)
PID	1	4.95	-6.86
	2	12.25	-34.1
Fuzzy	1	5.78	-150
	2	15.84	-227
STC	1	4.15	1.39
	2	3.47	2.80

Figure 3.35 shows that only the self-tuning controller has the capacity to adapt to such a different situation for the DO control system in the second aeration tank. The gain of the other two controllers would need to be increased in order to achieve a comparable performance as shown in the earlier tests.

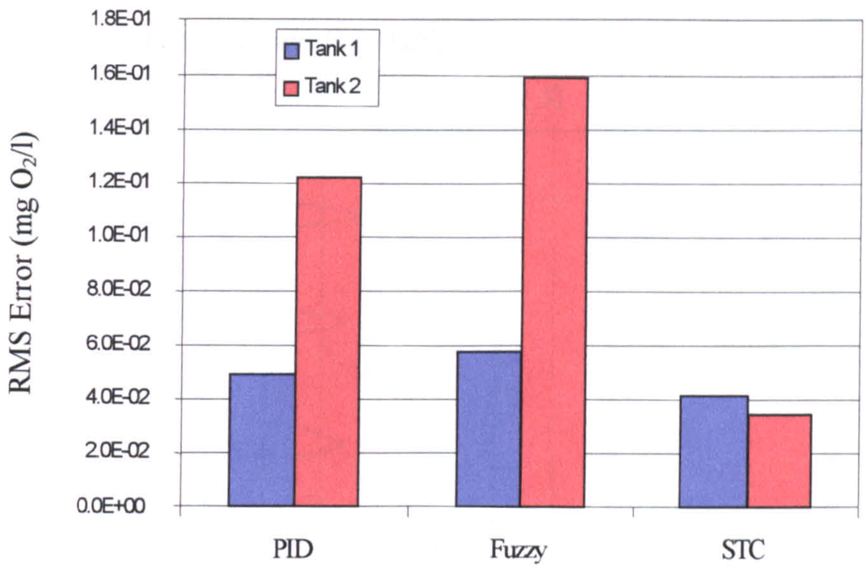


Figure 3.35: RMS error for composite flow with high MLSS concentration.

3.4.3.2 Real influent data with high MLSS concentration

When using real influent data, a situation similar to the composite influent flow pattern is encountered. The aeration rate and resulting DO concentration using PID controllers over the 14 days of the test is shown in Figure 3.36. The increase in MLSS concentration from 2,000 g/m^3 to 2,500 g/m^3 has also resulted in an increase of aeration rate of over 50%. Details for days 1 and 9 for the three controllers are presented.

The rate response for days 1 and 8 using PID controllers is shown in Figure 3.37. Overall, the maximum deviations encountered are 5% in tank 1 and 10% in tank 2 (Figure 3.40). The response obtained with fuzzy logic control is presented in Figure 3.38. The maximum errors observed are of 5% and 12% in tank 1 and 2 respectively. The self-tuning controller response for days 1 and 8 is presented in Figure 3.39. The maximum errors encountered are of approximately 3 % in both aeration tanks.

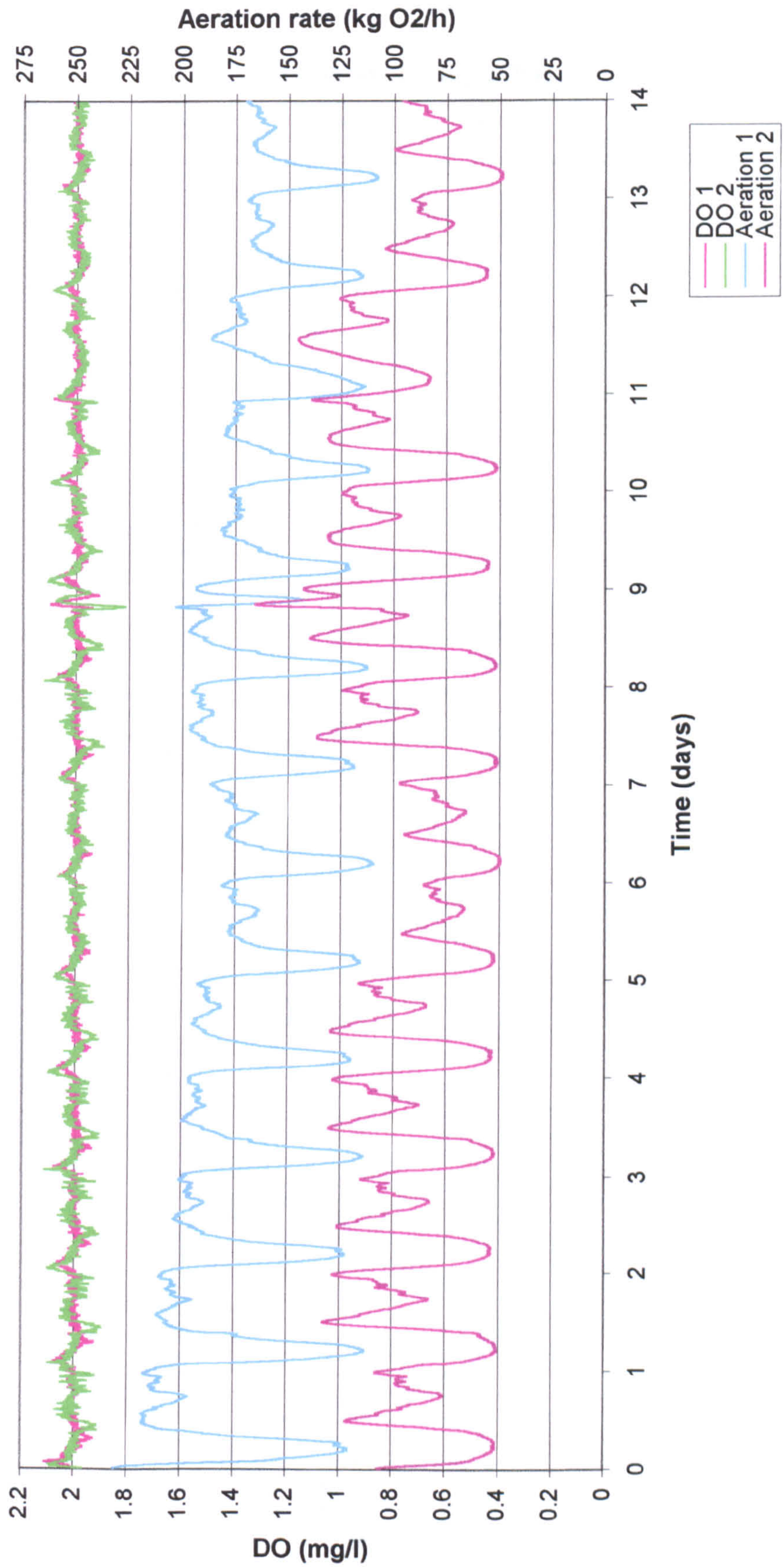


Figure 3.36: DO & aeration rate for PID control with high plant loading

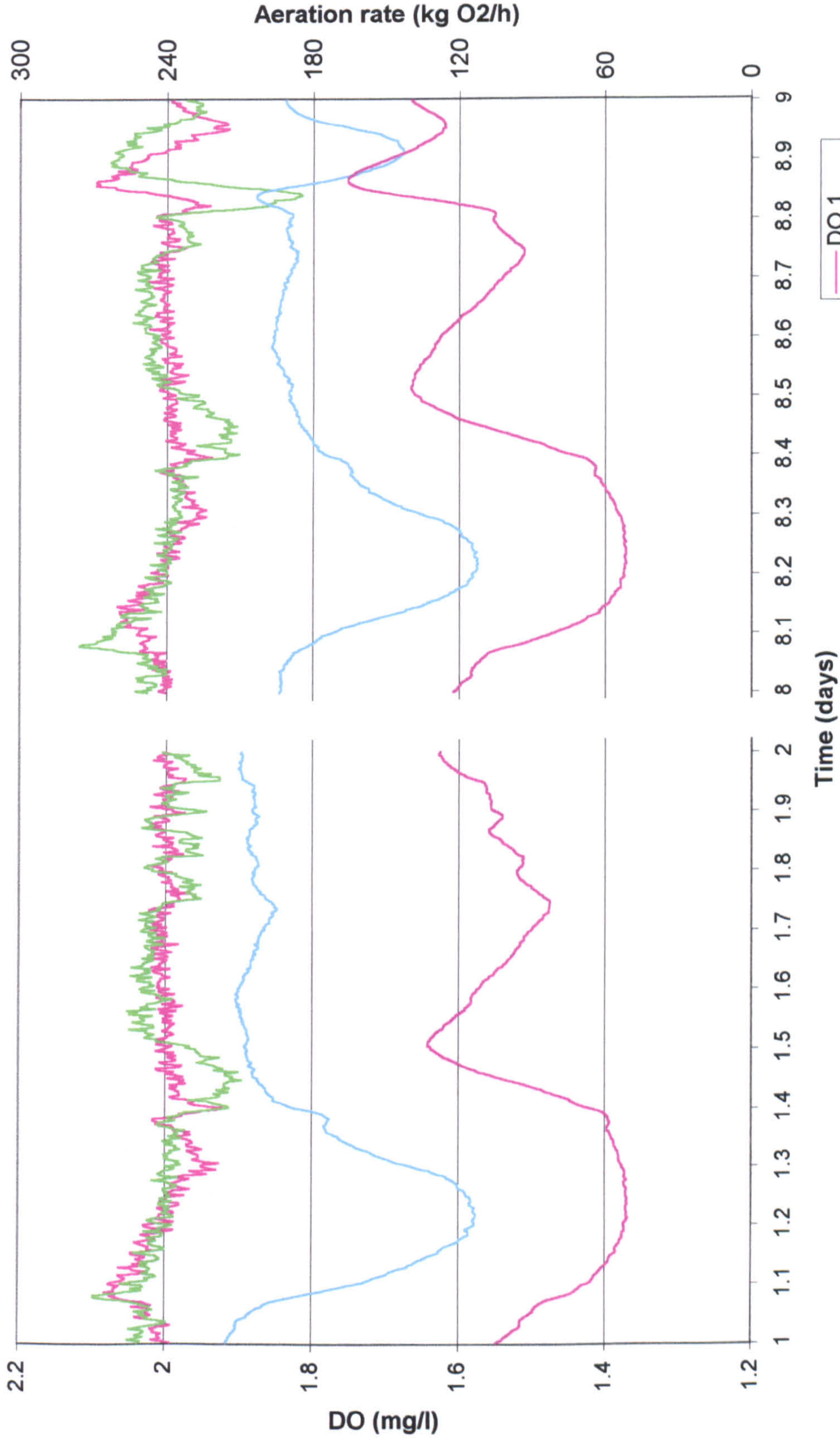


Figure 3.37: DO & aeration rate for PID control with high plant loading

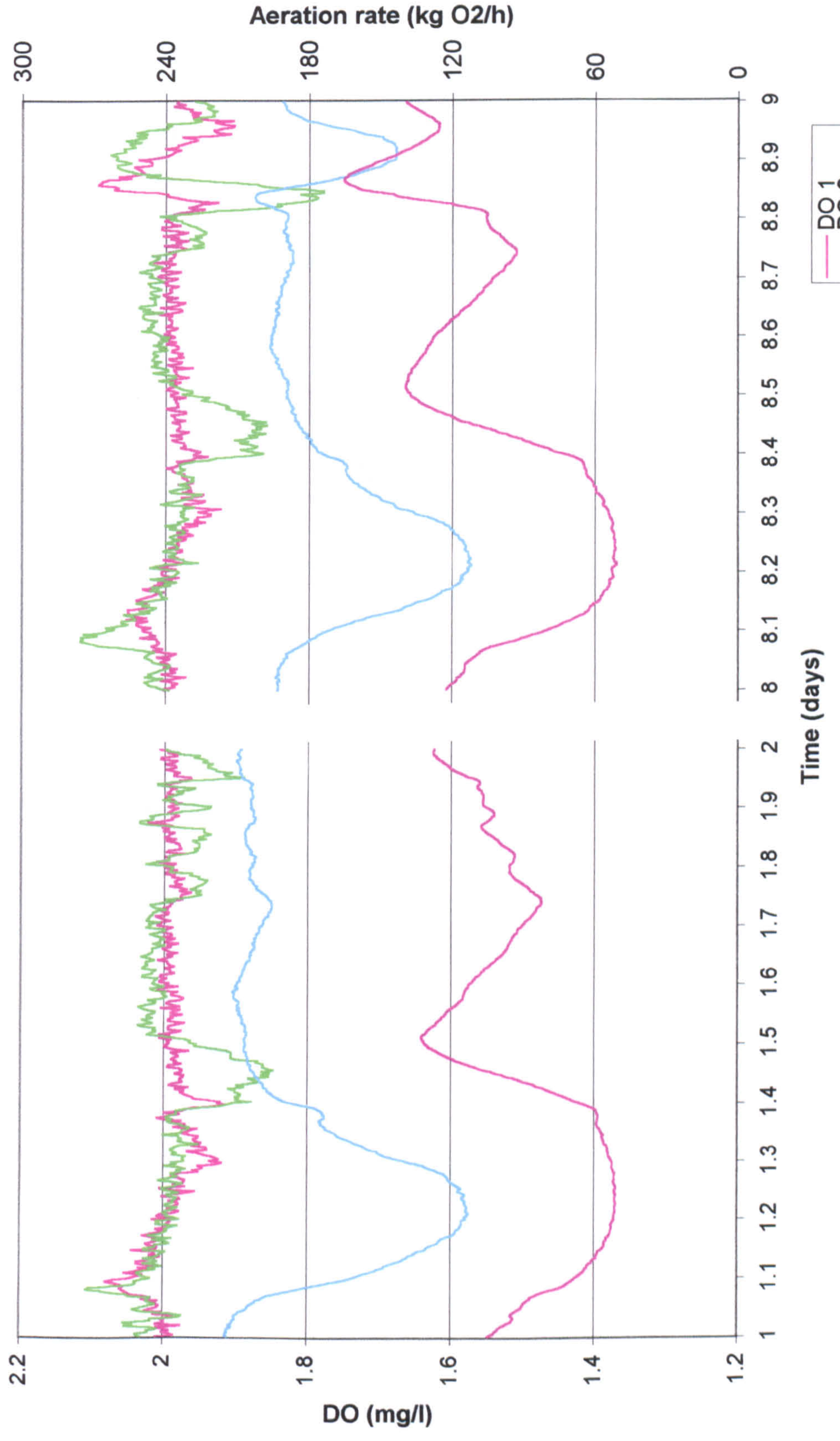


Figure 3.38: DO & aeration rate for fuzzy logic control with high plant loading

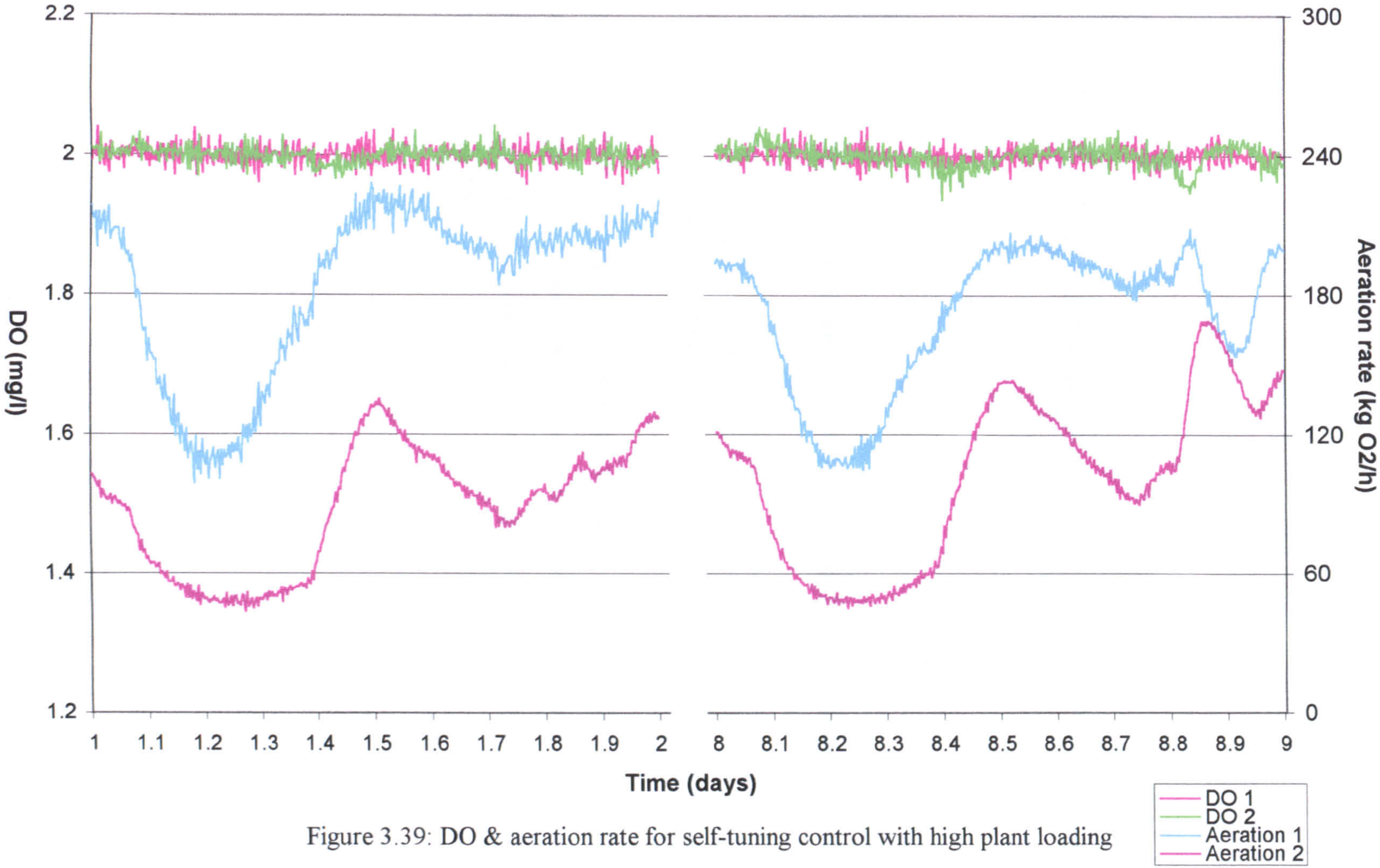


Figure 3.39: DO & aeration rate for self-tuning control with high plant loading

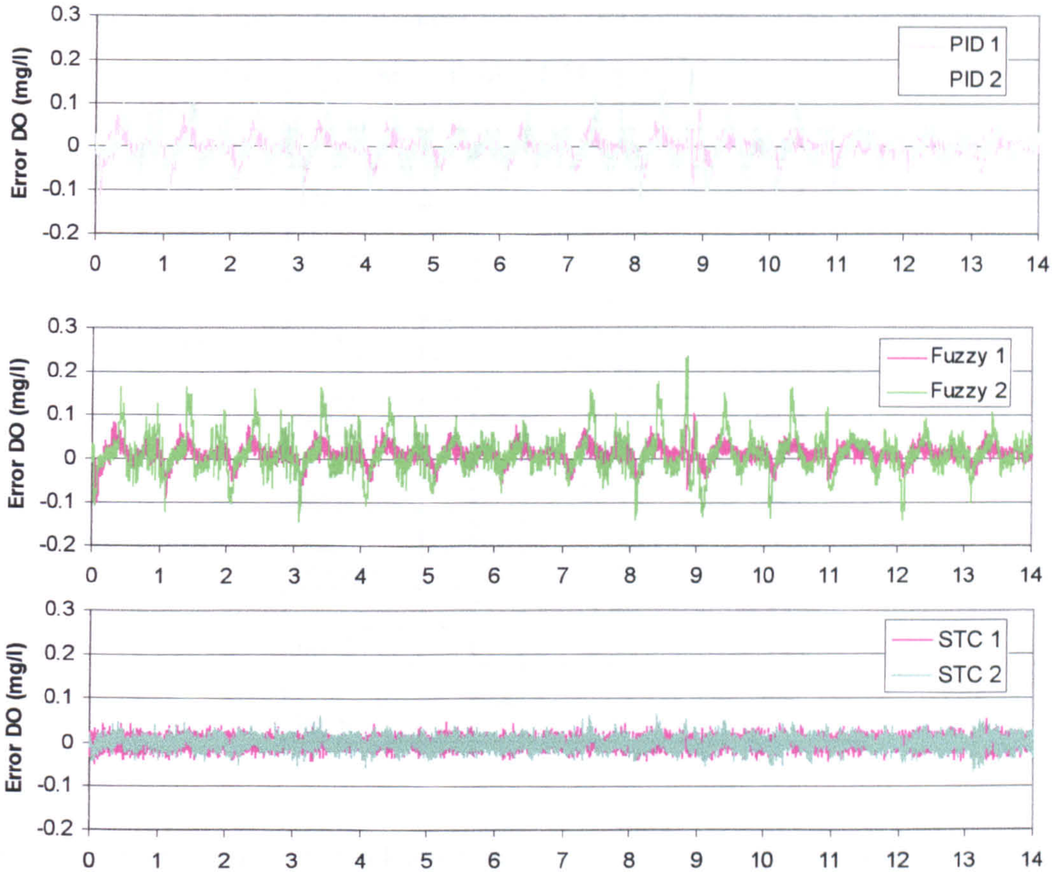


Figure 3.40: DO deviations for real data with high MLSS concentration

Figure 3.40 shows the benefit of having an adaptable system. Unlike the other two control methods, there is nearly no degradation of the performances with the STC whether in term of RMS or integrated errors compared with the other tests as can be noted from Table 3.8.

Table 3.8: Error function values for real data with high MLSS concentration

TEST	Period	Tank	RMS ($x10^{-2}$)	IE ($x10^{-4}$)
PID	14 days	1	2.16	35.6
		2	3.55	8.50
	day 2	1	10.05	2.29
		2	14.29	-24.0
	day 9	1	10.68	-3.05
		2	19.56	-23.4
Fuzzy	14 days	1	2.28	-1350
		2	4.52	-1570
	day 2	1	10.25	-96.3
		2	19.25	-158
	day 9	1	11.07	-104
		2	25.13	-161
STC	14 days	1	1.26	3.77
		2	1.44	0.330
	day 2	1	5.23	0.995
		2	5.05	-4.88
	day 9	1	4.69	0.195
		2	6.02	-5.93

The performances of the non-adaptive methods are degraded as clearly shown in Figure 3.41, for the controller in the first aeration tank but especially the second tank controller which requires a greater 'effort' to perform in these conditions.

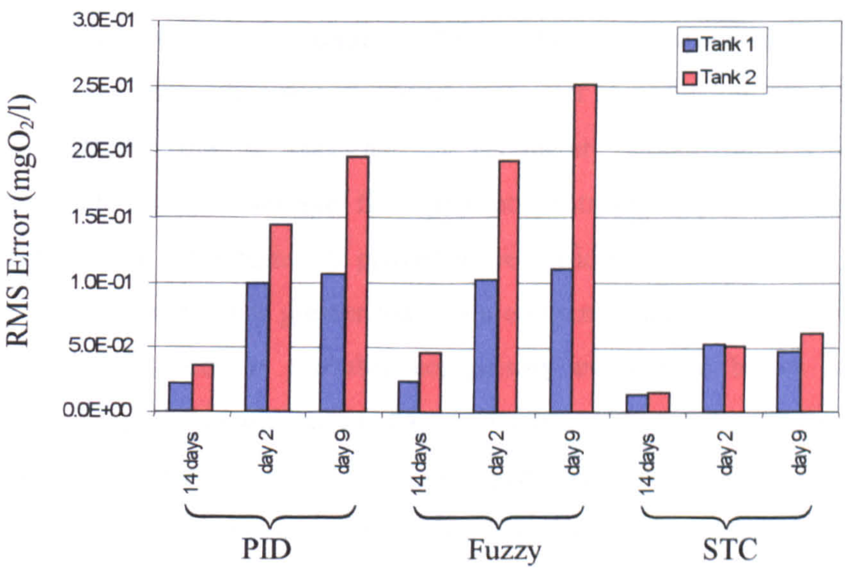


Figure 3.41: RMS error for real influent data with high MLSS concentration.

3.5 Discussion

The main problem for controlling dissolved oxygen is the lack of instrumentation available. Dissolved oxygen sensors need maintenance and are prone to 'ragging' if the screening of the sewage is not done thoroughly. The restricted control action is also a limiting factor. Aeration systems are not always controllable apart from switching aerators off, which is often not a desirable solution since unmixed sludge tends to settle. A control system needs three main elements, the controller algorithm being only one of them, sensor and actuators are also very important.

The results presented here, show that all the controllers successfully regulate dissolved oxygen even in the presence of 1 % measurement noise. The regulation consists mainly of rejecting the disturbances present in the process, which are caused mostly by the sewage variations in concentration and flow, and the dissolved oxygen measurement noise, usually not negligible because the most common aeration process is surface aeration.

The self-tuning controller appears to be the better control system in nearly all the tests. This is not totally unexpected, being the only controller of the three with adaptability. Nevertheless, the self-tuning controller requires good design; there is a need for determining the initial model parameters before the control system is activated. In the simulation presented, only one such model parameter identification has been performed for each controller (one per tank) and the parameters obtained after a certain time of operation with constant sewage flow and concentration have been used as initial parameters for the other tests. It proved to be sufficient, however on a real plant the variance of the conditions is greater than on a computer simulation and a proper model parameters identification is probably compulsory every time before a self-tuner is switched on-line, otherwise initial oscillation may occur. From the results presented, the compensation for measurement noise may appear insufficient. However, reducing the effect of the noise results in reduced capacity for the controller to reject process disturbances.

The PID controller offers performances often close to the self-tuning controller in terms of the RMS error. However, close inspection of the results, accentuates the differences unfavourably for the PID. The main problem with PID control is the tuning which is difficult and time consuming but it has the advantage of simplicity and widespread use.

The fuzzy logic controller used does not need complex initial conditions to be configured prior to being switched on; the only requirement is to know the original aeration rate used when the controller is put on-line. However, determining the rule base and defining the limits of the membership functions can be compared with the tuning of a conventional controller. Unlike PID control, there is no clear set of rules available to determine the parameters making this "tuning" difficult. Despite the relatively poor performance of the fuzzy logic controller tested here, it has to be said that it is a relatively simple system. Further detailed investigations using a more complex structure are necessary to improve performances, the FLC used being only a simple implementation.

From this study, it can be said that even if the self-tuning controller seems to be the method delivering the best all-round performances, the choice of a control system is not obvious. All the deviations seen would be acceptable if obtained in a real plant. A fuzzy controller is harder to put in place than a PID because of a general lack of expertise in the technique and possible difficulty in determining the adequate parameters (type, number and limits of membership functions, rule base, etc). Also, a limited choice of hardware supporting FLC is available even though it is becoming more common.

The fuzzy logic controller developed here is relatively basic and this new technique offers much scope for improvement, which is not the case with the conventional PID control method. The results obtained for the fuzzy logic controller could appear quite uninspiring but it would be wrong to assume so. In most cases, it has been able to compare satisfactorily with the PID controller. An improved design such as a self-organising fuzzy logic controller would add the needed adaptive capability to compete with self-tuning techniques.

Chapter 4

4 PROCESS DESIGN USING SIMULATION

In chapter 3, the layout of the plant investigated was simple in that the aeration stage was assumed to be composed of only three tanks: one anaerobic and two aerated ones. Most wastewater treatment plants have a more complex structure, for example an aeration stage composed of 8 tanks in series. Also, the instruments and actuators available in most plants are not as numerous as could be desired to perform accurate control. However, the influence of the location of sensors and actuators in a plant is of prime importance for any control system. In collaboration with the Technology Development Team of North West Water Limited (NWW), the process model developed in Chapter 2 was used to determine suitable sensor and actuator placements for a specific wastewater treatment plant. This chapter shows the benefits of utilising a simulation of the process to solve a practical problem.

4.1 PROBLEM DEFINITION

4.1.1 Runcorn wastewater treatment plant

The Runcorn wastewater treatment works comprises two independent activated sludge plants called Runcorn A and B. This study has focused on Runcorn A which consists of two parallel lanes, each of 8 aeration tanks in series. The sludge from the two parallel aeration stages is then mixed and distributed into 4 final settling tanks, from which activated sludge is recycled to the first tank of each of the two parallel aeration lanes (Figure 4.1).

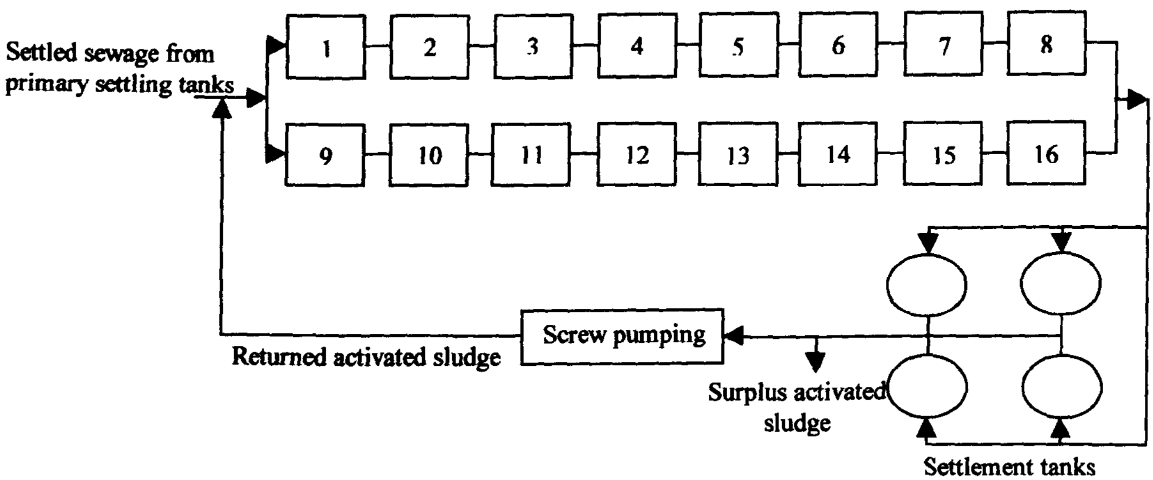


Figure 4.1: Runcorn A schematic diagram

The two primary settlers, which receive the raw sewage, have not been included in Figure 4.1. They have a volume of 5840 m^3 and provide 5.18 hours retention time at the maximum flow of 27,000 m^3/day. If the influent flow rate is greater than the maximum flow, the excess is diverted into storm tanks, and is then pumped into the treatment process at an appropriate time. The dry weather flow of Runcorn A is 9,000 m^3/day, and the average influent flow is 10,000 m^3/day.

The aeration stage is made of two lanes composed of 8 tanks of 192 m^3 each, providing a total volume of 3,072 m^3. Aeration in each of the 16 tanks, is provided by surface aerators, with nominal power consumption 9.4 kWh, rotating at up to 960 rpm. The ammeters connected to the aerators indicate an average current of 10 to 12 A (Kruger, 1995). The power drawn by each aerator is therefore approximately 5 kW.

The four secondary settlers have a diameter of 19.6 m, a surface area of 301.7 m^2, and a minimum water depth (at the side) of 1.5 m, a maximum water depth of 6.8 m and a volume of 993 m^3 each. The recycled sludge is pumped back into the aeration stage by two screw pumps in parallel, each of nominal capacity 11.25 kW.

4.1.2 Sensor and actuator placement proposed by NWW

Originally the aeration system was composed of fixed speed aerators, with the aeration rate controlled by switching the aerators on or off. There was only one dissolved oxygen sensor (DO probe), for the two aeration lanes, placed in the effluent of the aeration stage (prior to the final settling tanks). This led to problems of sludge sedimentation within the aeration stage when the aerators were switched off. To remedy this problem, it was decided by North West Water to implement a new control strategy, constrained by the addition of only two dissolved oxygen (DO) probes and three variable speed drives (VSD) per aeration lane. The existing DO probes were removed during the installation of the new equipment. As part of the collaborative research with North West Water, an investigation was undertaken to determine a suitable strategy using the simulation model previously developed (Chapter 2).

A specific condition was that one of the two DO probes had to be placed in the final tank of the lane (i.e. tanks 8 and 16 in Figure 4.1), so that the DO concentration of the mixed liquor flowing to the final settling tanks was known, in line with current practice. It was assumed that the aeration tanks without variable speed drives were maintained in operation by continuous fixed speed aerators to prevent sedimentation of the activated sludge.

Two designs had been suggested within NWW. The first submitted design had variable speed drives fitted to the aerators in tanks 3, 6 and 7, while DO probes were placed in tank 5 and 8 (Figure 4.2).

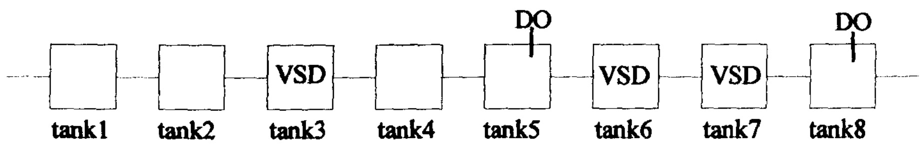


Figure 4.2: First NWW submitted design.

Following detailed analysis, it was determined that the first NWW design proposal (Figure 4.2) was not practical for control purposes. The control of the first variable speed drive (in the third tank) is difficult since the nearest dissolved oxygen measurement is in tank 5 which is after two tanks where the aeration is fully on. This VSD is therefore 'wasted' since it cannot be used to control the dissolved oxygen in a proper way as there is no information which can be used to regulate its action. Also, if there is an important need for aeration (high load and or high throughput flow within the plant), the DO set-point might not yet be attained at that stage in the aeration lane forcing this aerator to full power. The last two VSDs in tanks 6 and 7 are also very hard to control accurately since the DO probes are placed within tanks 5 and 8 where the aerators are fully on, therefore the DO concentration within the controlled tanks can only be estimated crudely. The presence of a non-controllable aerator in tank 8 would result in a disturbance of the DO concentration previously obtained.

The second submitted design, had VSDs located in tanks 5, 6 and 7 and DO probes placed in tank 7 and 8 (Figure 4.3).

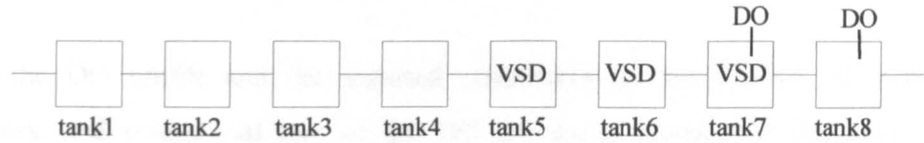


Figure 4.3: Second NWW submitted design.

This design is more practical than the previous, with at least one DO probe in the controlled tanks but it is always difficult to perform accurate control when there is no direct measurement on the controlled variable. DO control can be accurate only in tank 7. The last problem encountered in the first design still remains, namely the disturbance of the DO concentration before release into the final settling tank.

4.2 INVESTIGATION USING SIMULATION

Figure 4.4 shows the actual measured dissolved oxygen concentration profile in the wastewater treatment plant of interest during one particular 24 hour period with all 8 aerators continuously at full power. Only results in the last four tanks in one of the lane are presented. It is clear that the DO concentration increases along the lanes, which means that there is over-aeration, thus more oxygen is 'wasted', in the last tanks than in the first tanks.

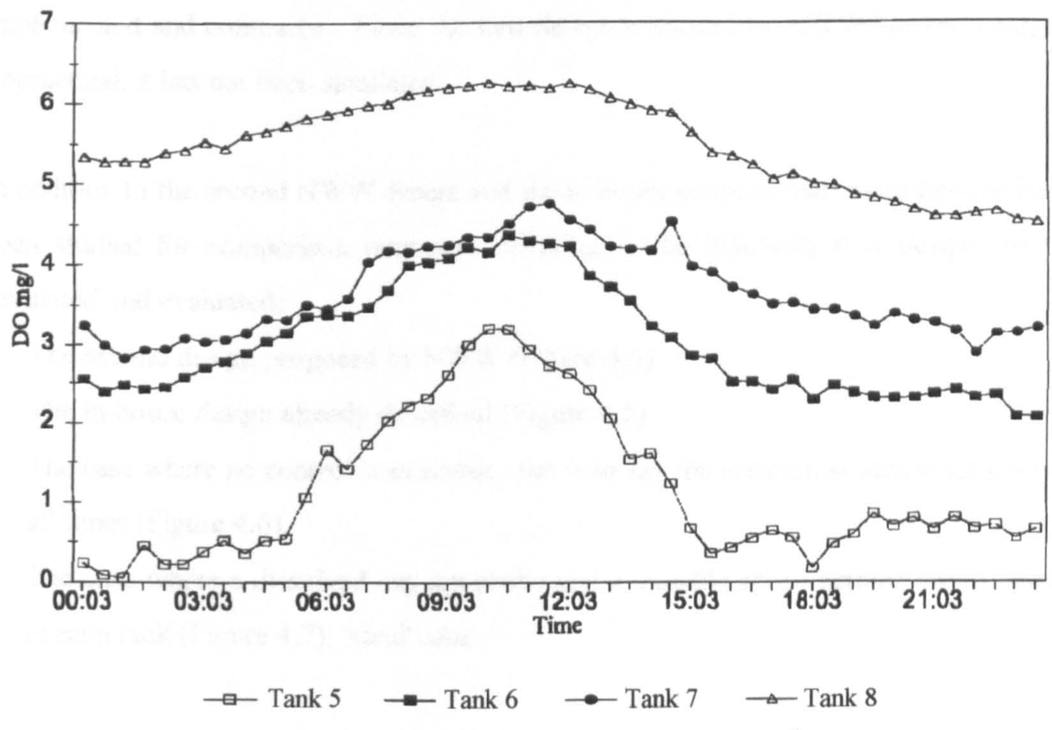


Figure 4.4: DO concentrations profile in Runcorn A on 17th August 1996

From the DO profile and the imposed constraints on the number of transducers, actuators, and position of one of the DO probes, it seems that the most suitable placement possible for control purposes is to position the three variable speed drives in the last three tanks of the aeration lane and to position the second DO probe in the first controlled tank, which is tank 6 (Figure 4.5). This has the advantage of providing the possibility of reducing aeration where it is the more useful, and to give accurate DO control in three tanks out of eight.

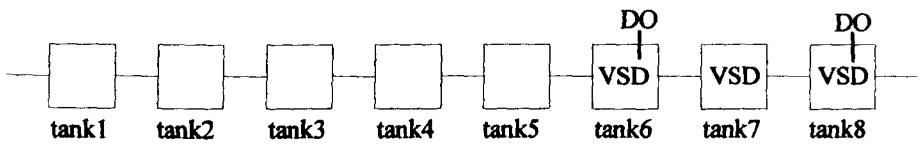


Figure 4.5: In-house design proposed.

4.3 SIMULATION OF PLACEMENT DESIGNS

In order to investigate the different designs, a computer simulation of the plant has been developed based on the model detailed in Chapter 2; the main difference being the number of tanks (eight) and the absence of an anaerobic zone since Runcorn A does not include denitrification. The position of the transducers for the various designs has been implemented and compared. Since the first design proposed by NWW has been judged impractical, it has not been simulated.

In addition to the second NWW design and the in-house proposal two more designs have been studied for comparison purposes, resulting in the following four designs to be simulated and evaluated:

- The second design proposed by NWW (Figure 4.3)
- The in-house design already described (Figure 4.5)
- The case where no control is available, that is to say the aeration system is fully on at all times (Figure 4.6),
- The case where a dissolved oxygen probe and a variable speed aerator are available in each tank (Figure 4.7): 'ideal' case.

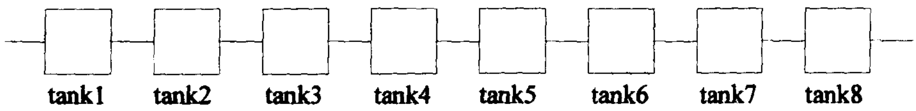


Figure 4.6: Design without controlled aeration.

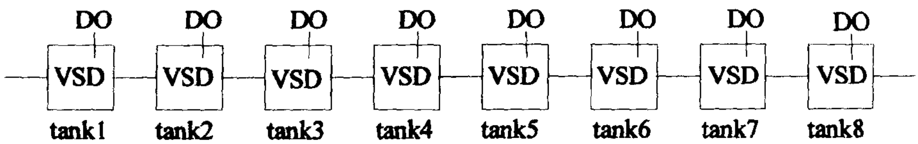


Figure 4.7: 'Ideal' design with complete instrumentation.

The uncontrolled design is not suitable for obvious reasons: the negative impact on the process operation of over aeration and also the cost of the energy wasted by aerating when it is not necessary. The 'ideal' design is ideal only from the point of view of a control system and requires more than twice the instrumentation of the other designs, requiring a higher level of financial investment initially and higher maintenance costs. These costs would need to be justified, either for cost effectiveness or for process efficiency reasons.

4.3.1 Assumptions

The actual concentrations of the different constituents of the plants mixed liquor are varying and not precisely known. A relatively high suspended solids concentration in the aeration stage is assumed in order to give a certain advantage to the designs without adequate control of the dissolved oxygen concentration; a higher load and suspended solids concentration will require more oxygen and the over aeration, if any, will be of less importance and will occur further along the aeration lane.

The oxygen transfer efficiency is assumed, in internal NWW documents, to be 1.3 kg oxygen / kWh and the power drawn by each aerator 5kW (Kruger, 1995). These parameters were used during the investigation, giving a maximum oxygenation capacity for each aerator of 6.5 kg oxygen/hour per aeration tank.

The financial cost of energy needed by the aeration systems is calculated on the basis of an average electricity price of £0.05/kWh.

4.3.2 Implementation

When controlled, the dissolved oxygen concentration has been regulated with PID controllers similar to those described in chapter 3.

Since only half of the plant has been simulated (one aeration lane composed of 8 tanks associated with 2 final settling tanks), the average flow to the plant has also been halved resulting in an inflow of 5,000 m^3/day.

Since actual parameter values for the Runcorn plant are not available, the model parameters chosen correspond to an operating temperature of 10°C, which is closer to natural temperature conditions in the UK.

The load of the influent sewage was chosen to be similar to those of the sludge characteristics found in an activated sludge wastewater treatment plant in Denmark (Henze, 1986), which is the one with the highest load from the three data sets presented in Appendix A, when data was not available from the test pattern used. Influent sewage load data are not easily available, since at the moment there is little interest in knowing the exact nature of the sewage, predictive control techniques having not yet been fully implemented in the wastewater treatment industry. Exceptions exist when an industrial customer is charged according to the load of its effluent. However, by the industrial nature of the effluent, the data gathered is not representative of the domestic sewage for which the IAWQ model has been developed.

The mixed liquor volatile suspended solids concentration (MLVSS) was maintained around the set-point of 2,000 g/m^3 by a basic PID control system acting on the recycling and surplus activated sludge flow rates.

The results presented in section 4.4 for all the simulations were obtained using identical independent controllers with a PID structure and fixed tuning parameters for the control of the aeration in the tanks fitted with variable speed aeration systems.

4.3.3 Test patterns used

Two influent sewage flow patterns were implemented to compare the influence of the position of dissolved oxygen sensors and variable speed aerators on the control systems. The first pattern (Figure 4.8) was composed of a sinusoid of period 12 hours, a constant flow for 6 hours and then a step change maintained for another 6 hours. The second influent pattern (Figure 4.9) was based on the data of the first two days of the realistic data set, including the variations of the influent load described in Chapter 3. Both influent sewage flow patterns present important variability and offer the advantage of providing a consistent controller test for the first one, and of realism for the second.

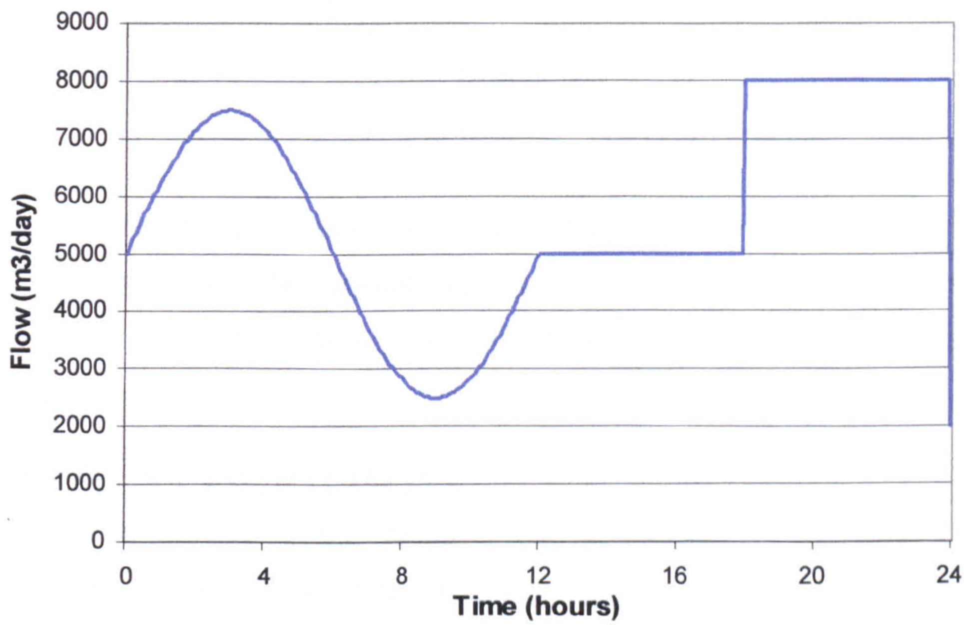


Figure 4.8: Composite influent flow rate (Test pattern A)

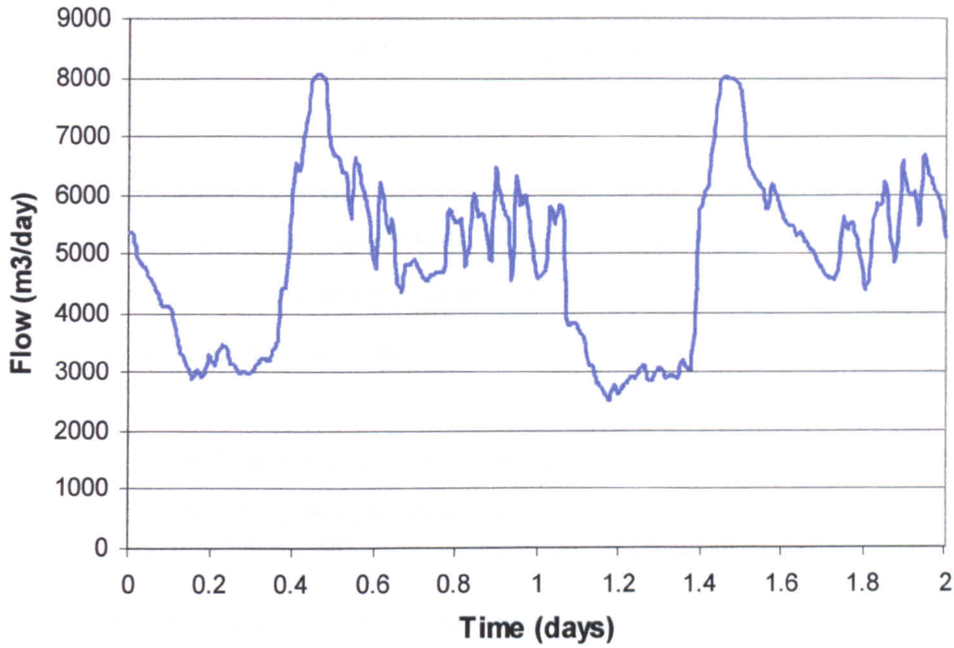


Figure 4.9: Realistic influent flow rate (Test pattern B)

It can be assumed that the most appropriate configuration of DO probes and variable speed drives is the one which maintains the dissolved oxygen concentration closest to the set-point of 2 mg/l, while using as little energy as possible. The energy used for aeration is expressed as financial cost.

4.4 DESIGN COMPARISONS

The results for the four designs presented (no aeration control, the 'ideal' case, 2[nd] NWW design and in-house proposed design) have been obtained using strictly identical initial conditions for each test pattern.

Switching off completely an aerator causes operational problems due to the default of mixing in the tanks not aerated which leads to sludge settlement and build up. Therefore it had been decided by the water company not to stop the aerators which have no regulation capability. Thus, when the aeration system is not variable, it is assumed to be continuously operating at maximum power.

The dissolved oxygen solubility is assumed to be 10 mg/l in all simulations, even though the actual value varies according to many parameters including temperature, mixed liquor composition, etc.

4.4.1 No aeration control

This design represents the original state of the plant, where the aeration was originally controlled by timers switching aeration on and off. In this configuration, the aerators are operating at full capacity at all times.

Figure 4.10 shows that the DO concentration almost reaches the DO saturation value (solubility) using test pattern A, proof of excessive aeration.

However, the DO concentration in tank 1 never reaches the desired value of 2 mg/l and occasionally goes below the desired set-point in tanks 2 and 3. This demonstrates the limit in the capacity of the aeration system. Therefore, the possible improvement for the reduction of energy used is nil in tank 1 and small in tank 2 for this particular influent sewage with high load. This is still true with the influent test pattern B (Figure 4.11), but here a control system would be useful as early as the second tank of the aeration stage. A high level of oxygen is detrimental to good process operation because it favours the growth of filamentous bacteria leading to the release of sludge in the treated effluent, in addition to wasting energy.

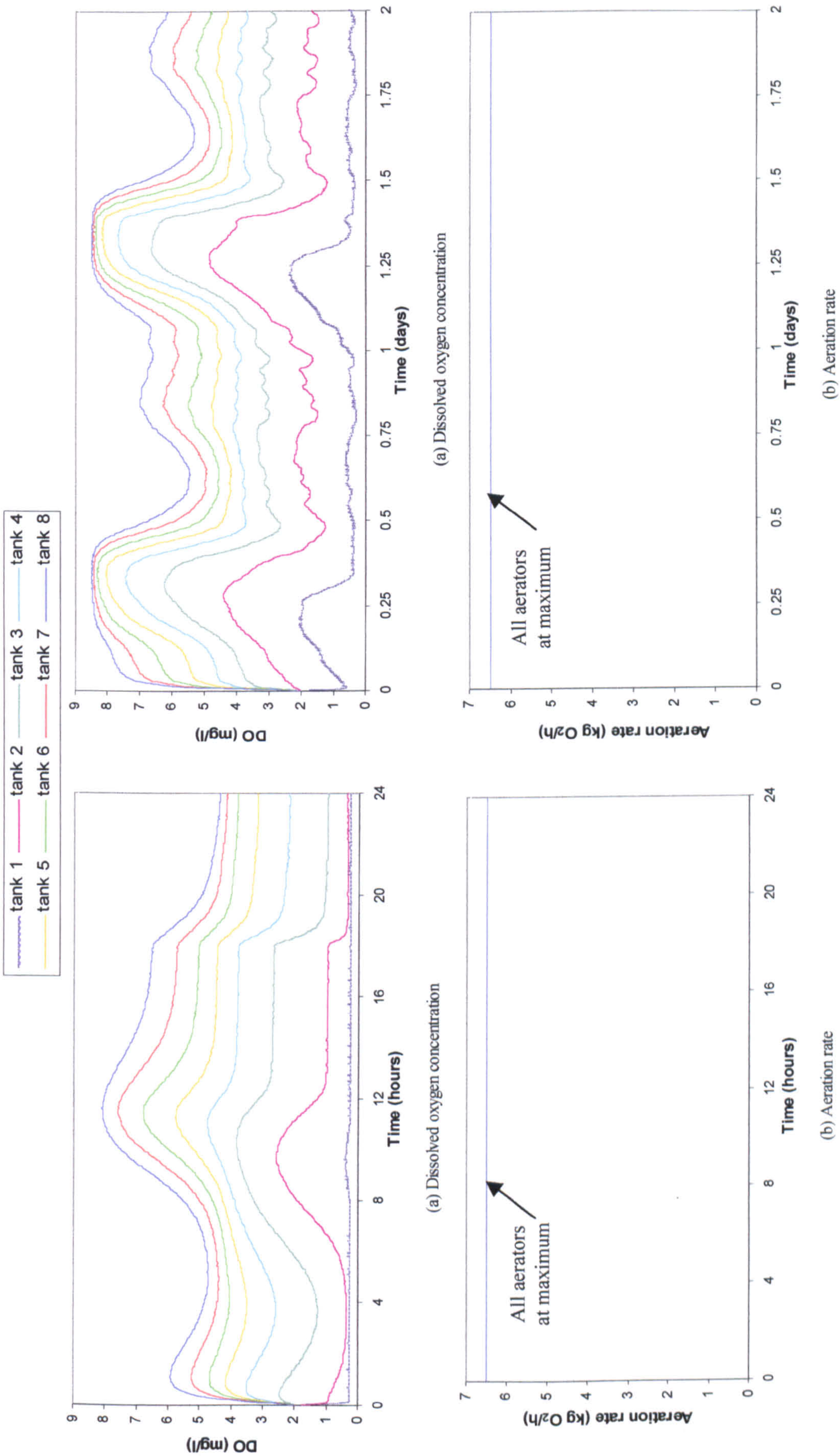
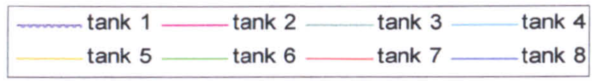
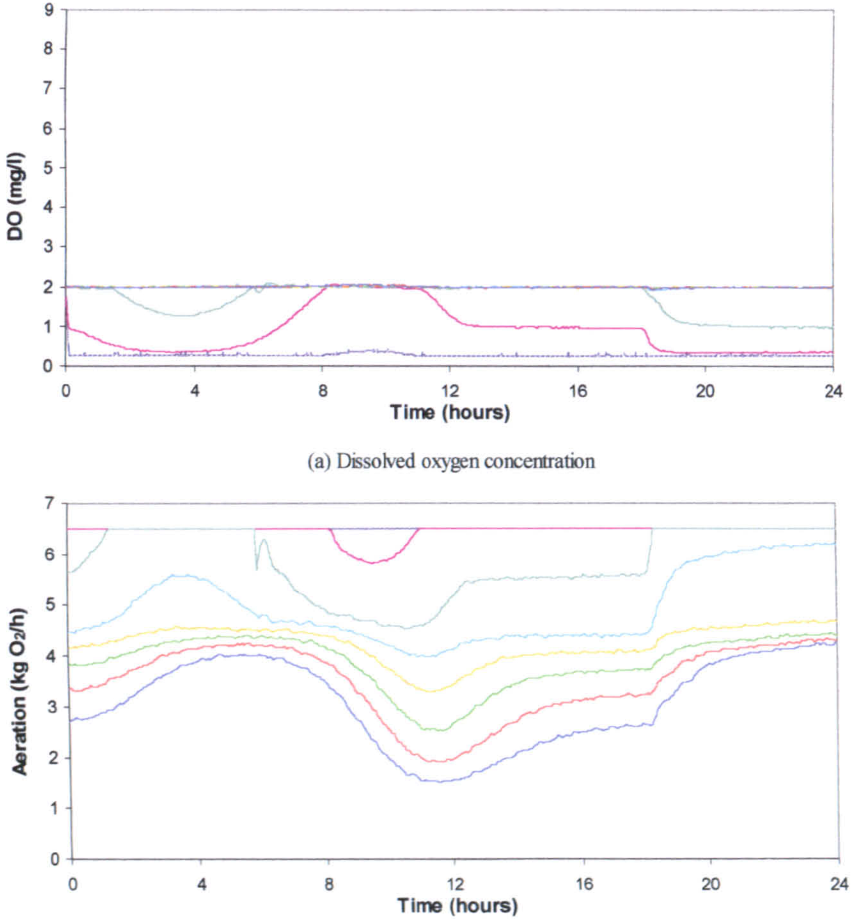


Figure 4.10: Test pattern A, no control

Figure 4.11: Test pattern B, no control

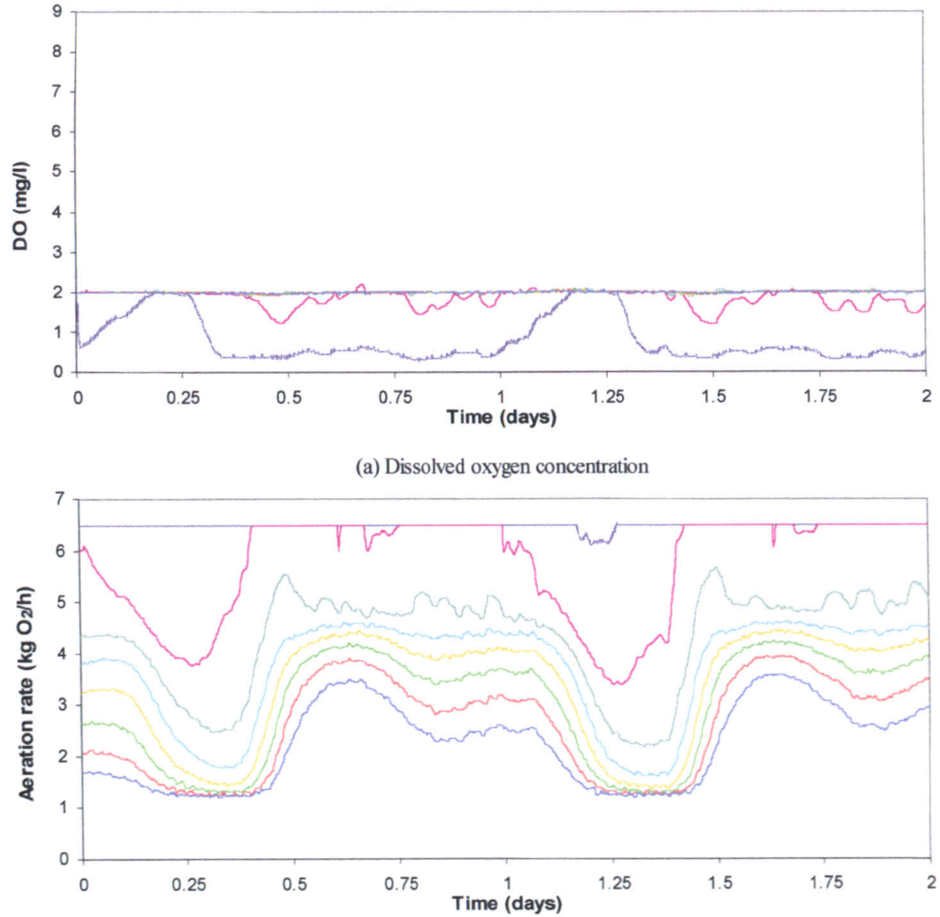




(a) Dissolved oxygen concentration

(b) Aeration rate

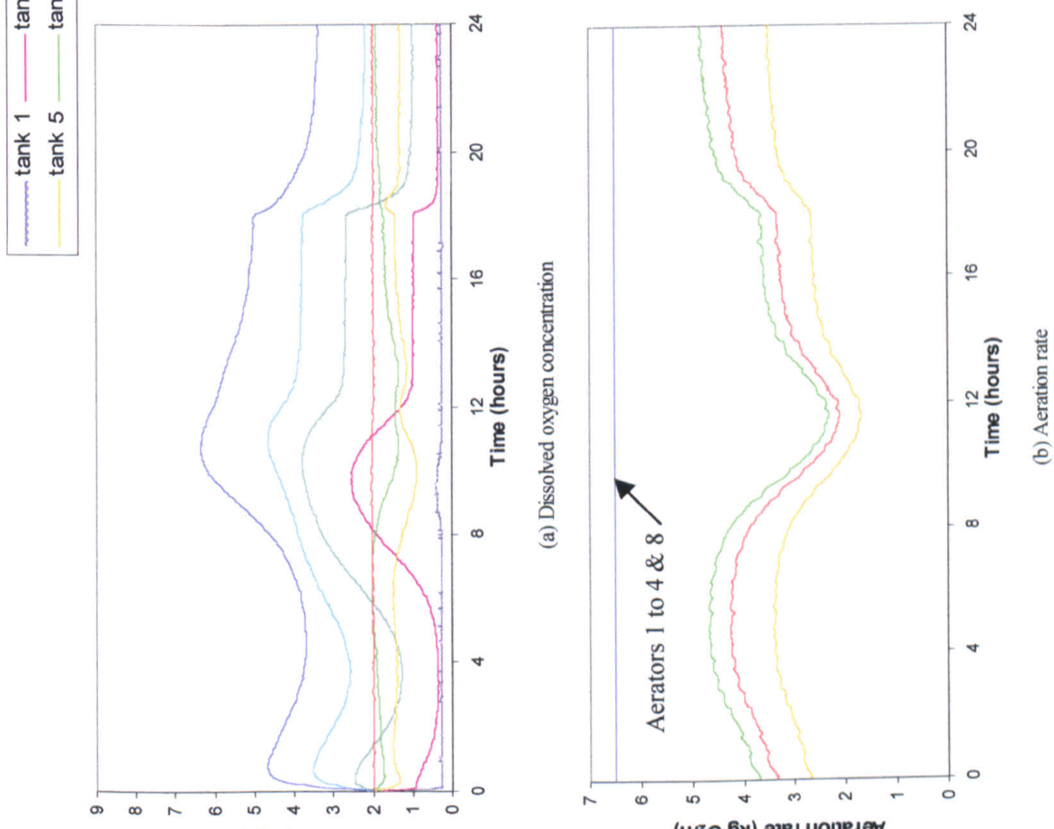
Figure 4.12: Test pattern A, 'ideal' design



(a) Dissolved oxygen concentration

(b) Aeration rate

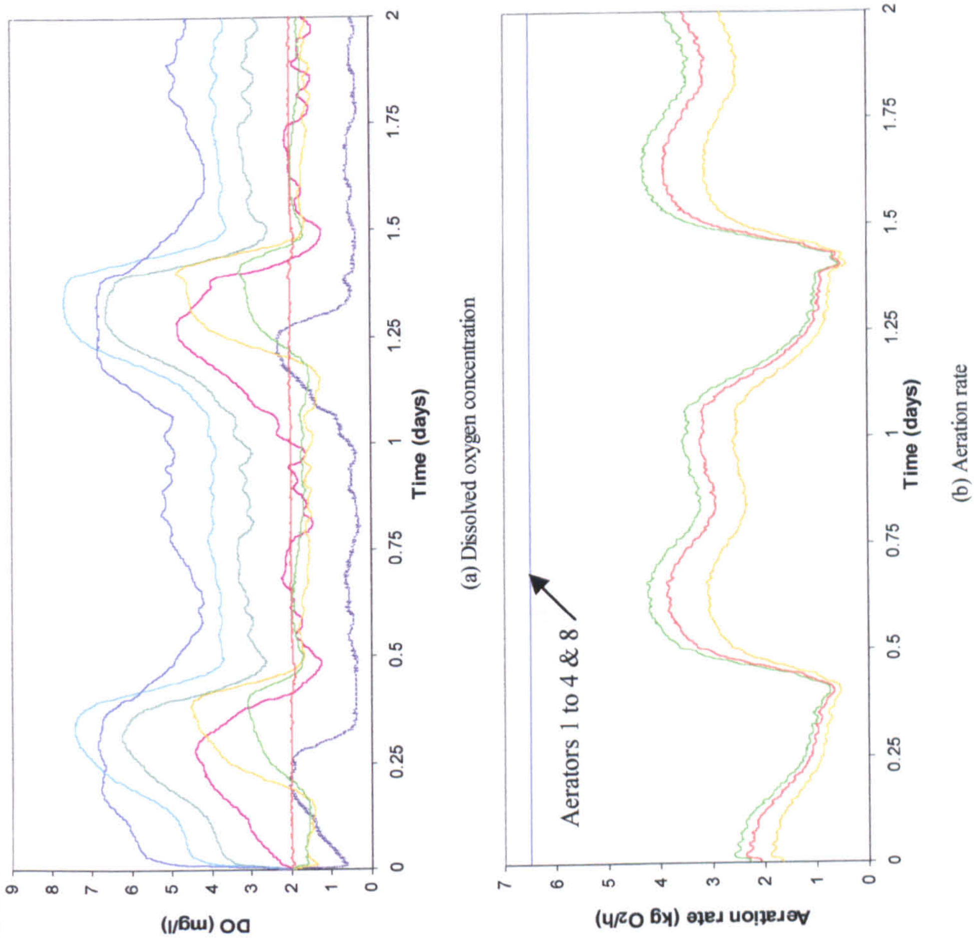
Figure 4.13: Test pattern B, 'ideal' design



(a) Dissolved oxygen concentration

(b) Aeration rate

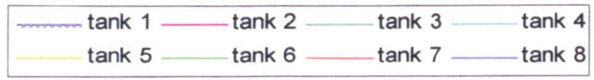
Figure 4.14: Test pattern A, NWW design



(a) Dissolved oxygen concentration

(b) Aeration rate

Figure 4.15: Test pattern B, NWW design



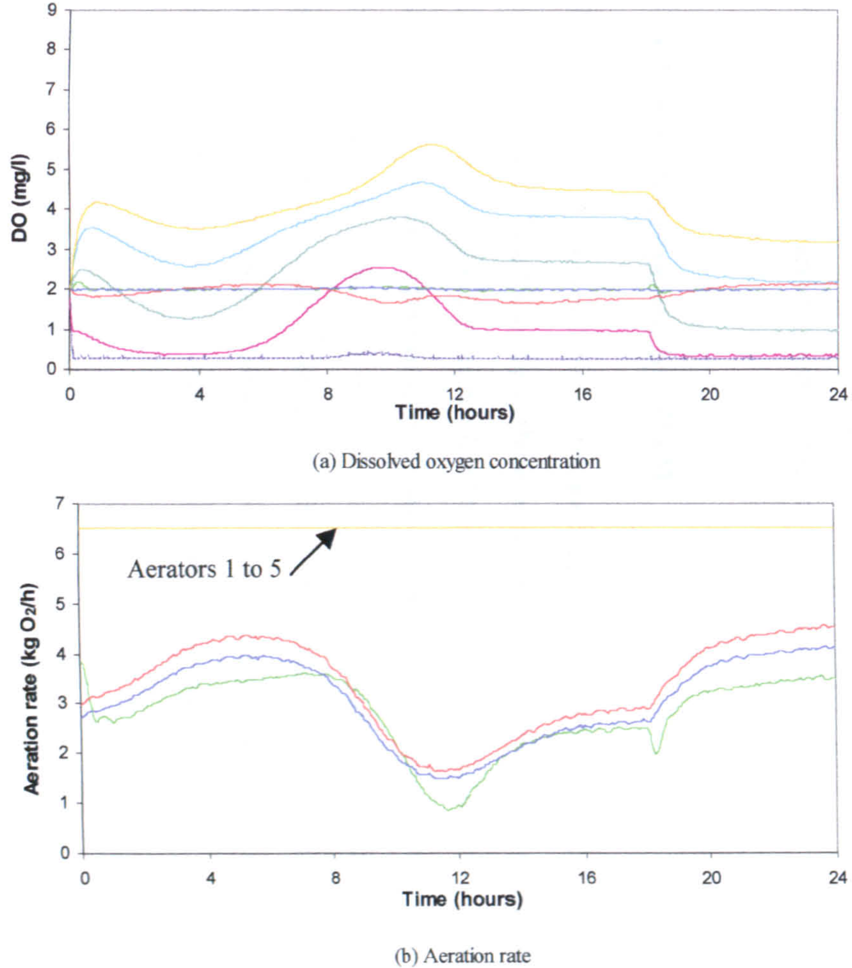


Figure 4.16: Test pattern A, suggested design

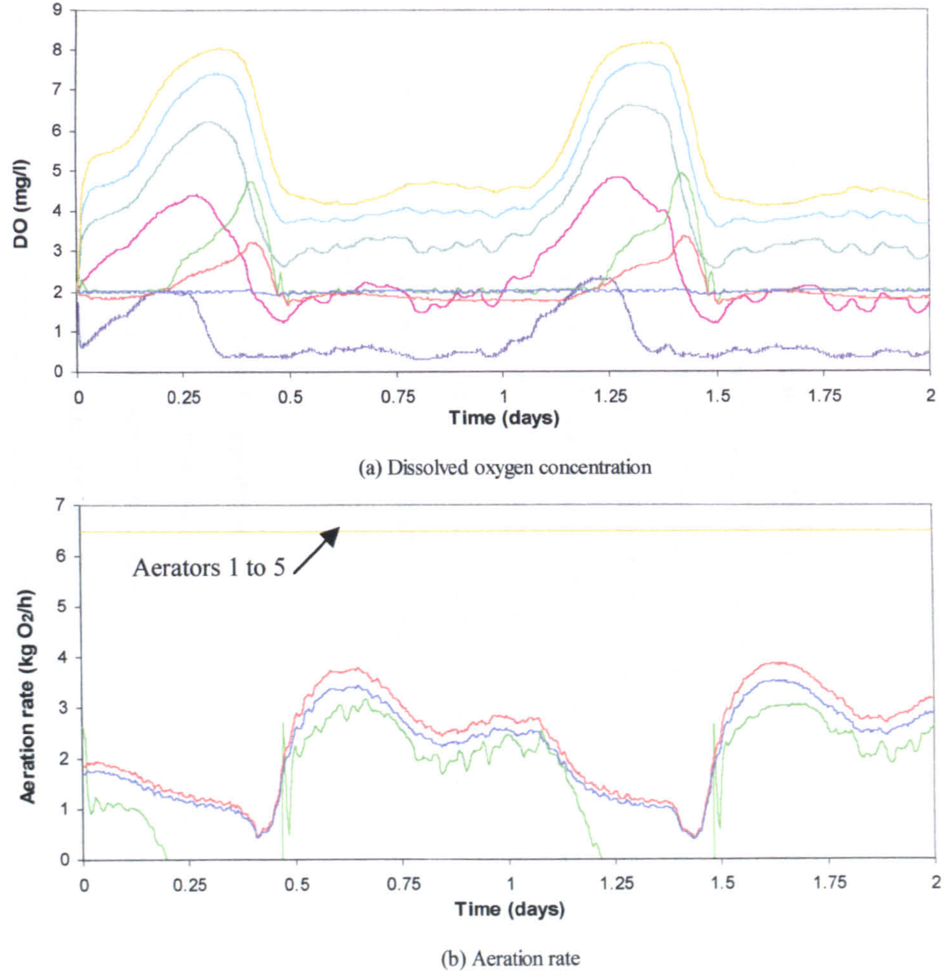


Figure 4.17: Test pattern B, suggested design

4.4.2 'Ideal case'

This design represents the ideal case from the point of view of a control engineer, as it provides the most data and possibilities of control action on the aeration rate within the plant. In this case, although the aerator in tank 1 is constantly fully on, it does not manage to raise the dissolved oxygen level to the desired concentration as observed in the previous case (Figures 4.12 and 4.13). Therefore, it seems unnecessary to regulate the aeration in tank 1 for the two effluent flows and loads used in this test. This is only true for high concentrations of MLSS in the aeration stage and the high load of the influent wastewater, as used in this simulation. In other conditions control of the first aerator may be necessary.

Most of the control error, which appears in the dissolved oxygen concentration (Figures 4.12a and 4.13a), is due to the controller anti-windup mechanisms that are used to reduce the effects of the limitations in the maximum aeration rate. During long periods in which the aeration is set at the maximum value, the integration term of the PID is increasing. The integral term takes a large value that needs to be 'reset' when the error changes sign (i.e. when the DO concentration is above the set-point). This case is the best from a control and process operations point of view.

4.4.3 Design proposed by NWW

The 2nd approach proposed by the Technology Development Team of North West Water presents a control problem, since there is only one dissolved oxygen sensor available for control purposes in the last "controlled" tank (tank 7), while the second probe is installed in tank 8. The fine control of tanks 5 and 6 is impossible because the dissolved oxygen concentrations in tanks 1 to 6 are unknown. The dissolved oxygen set-point can be achieved accurately only in tank 7. The DO concentration in tank 8 will be higher because aeration is not variable and since it is at maximum power. The dissolved oxygen measurement in tank 8 is not exploited for control purposes.

The aeration in tanks 5 and 6 is controlled by assuming that the dissolved oxygen requirement in tank 5 is higher than in tank 6 which is itself higher than in tank 7 as the standard DO distribution profile suggests; the substrate available at the end of the aeration lane being less than at the beginning. However, the first controlled tank has to correct any DO concentration excess present in the earlier stage of the aeration lane, which means aerating less than would normally be necessary if the aeration lane was controlled on its entire length, assuming the system is over-aerated with the previous aerators constantly operating.

For this design, the aeration rate in tank 7 is controlled according to the local DO measurement. Aeration rate in tank 6 is set equal to 110% of the aeration rate of tank 7 to allow for the normal aeration profile. The aeration in tank 5 has to be lower to correct the high DO concentration probably present in tanks 3 and 4, while still providing adequate aeration rate to prevent the DO concentration dropping below the set-point. The ratio of the aeration rate changes according to different parameters (MLSS, flow etc) and are not constant in time. The aeration rate in tank 5 has been set arbitrarily to 80% of tank 7 aeration rate.

Figure 4.14 shows that the fixed ratio between the aeration rates does not provide an ideal solution. The aeration in tanks 5 and 6 is insufficient since the dissolved oxygen concentration is always at or below the set-point which would suggest the aeration ratios between aeration in tank 5 and tank 6 to aeration 7 are too small. However, the same control system submitted to the second flow pattern (Figure 4.15) creates periods of over- and under-aeration according to the influent flow and load, in the same tanks, using the same aeration ratio. The DO in the last tank is significantly higher than the desired value since the aerator is working at maximum capacity.

The ratio between the aeration rates in the different tanks is variable in time in an accurate control system because it is dependent upon the flow, the concentrations of the different substrates, biomass etc. A single ratio between the different aeration rates cannot be used in a satisfactory manner with this design. It is however the most appropriate solution possible with the limited instrumentation available.

4.4.4 In-house proposal

In this design, two dissolved oxygen measurements are used to control 3 consecutive tanks. Aeration rates in tank 6 and 8 are set independently, according to the value of the dissolved oxygen level measured locally. The aeration rate in tank 7 is set 10% higher than the aeration rate of tank 8 to take into account the normal dissolved oxygen profile.

It can be seen in Figure 4.16 that the dissolved oxygen set-point is achieved in the controlled tanks fitted with a DO probe (tanks 6 & 8) and the DO concentration in tank 7 is very close to the desired value. Figure 4.17 shows different features; the control system in tank 6 cannot completely correct the over-aeration occurring in the previous part of the aeration stage, even by stopping the aerator completely. During these periods, the DO concentration in tank 7 is also above the set-point since the system assumes that the DO concentration in tank 6 is at the set-point. Therefore, this design allows the control system to perform a regulation close to the set-point only if the DO concentration correction has been effective in tank 6.

This design also ensures that the effluent to the final settling tanks has the desired DO concentration, which is not possible with the other layouts seen so far. This reduces the possibility of settling problems due to over aeration.

Using a more advanced control algorithm, it would be possible to reduce the error in tank 7, using the information delivered by the DO probe in tank 6 as well as the one from tank 8 to allow corrections of the DO concentration to take place in tank 7 when this correction is not performed fully in tank 6. However further investigation would be needed to implement such a system.

4.5 DISCUSSION

Four control schemes have been compared for a real plant: the North West Water proposal, a suggestion based from simulation experience requiring only minor position changes from the NWW proposal, the original arrangement which does not include any control possibility and finally a design incorporating maximum instrumentation of the plant.

The original aeration system of Runcorn Wastewater Treatment Works plant A is not optimal, and can be greatly improved. The complete instrumentation of the plant (as in the 'ideal' case) does not seem necessary from the tests performed; however, it offers additional flexibility which might be useful depending on the load of the effluent sewage and the way the plant is operated (especially MLSS, the concentration of suspended solids maintained within the aeration stage). A satisfactory control scheme could be developed from the in-house suggested design. Maximum cost improvement could be obtained by adding just a few more variable speed drives and dissolved oxygen probes in the system but without going to the extreme of the 'ideal' case which would probably not justify the expense of the extra equipment required. A reasonable aeration control scheme would probably require 6 variable aerators and 3 dissolved oxygen probes per aeration lane, leaving the first two aerators fully on.

Table 4.1 shows the total energy cost incurred, for the aeration system for the test day, for the 4 designs as well as the average dissolved oxygen level in tanks for which the aeration rate is controlled, with the first composite influent sewage pattern. Table 4.2 shows the same data measured using the second influent sewage pattern.

Table 4.1: Comparisons of costs in one aeration lane (8 tanks) and DO concentrations for test pattern A

	Aeration cost for Test Day	Average DO concentration (8 tanks)	Average DO in controlled tanks
NWW proposal	£39.60	2.06 mg/l	1.69 mg/l
Proposed design	£38.46	2.10 mg/l	1.97 mg/l
No control	£48.00	3.38 mg/l	N/A
Ideal	£35.42	1.61 mg/l	2.00 mg/l

Table 4.2: Comparisons of costs in one aeration lane (8 tanks) and DO concentrations for test pattern B

	Aeration cost for Test Day	Average DO concentration (8 tanks)	Average DO in controlled tanks
NWW proposal	£36.83	2.95 mg/l	2.08 mg/l
Proposed design	£35.54	2.99 mg/l	2.15 mg/l
No control	£48.00	4.65 mg/l	N/A
Ideal	£28.98	1.83 mg/l	2.00 mg/l

According to the above tables, the average dissolved oxygen concentration seems to be high but one must bear in mind that only 3 of the 8 tanks include a control system for the aeration, except the ideal case which is used as a reference. The possible cost savings are 26% with the composite flow pattern, and 40% with the realistic influent. The implementation of the suggested design achieves 76% / 65% of the possible cost savings for a third of the equipment cost for the influent sewage characteristics used. However, it would bring more stability in the plant to reduce the over aeration within a larger volume: with the current limit on the number of variable speed drives and dissolved oxygen probes only 3 out of the 8 tanks can be maintained close to the desired dissolved oxygen concentration.

It can be noted that the lower average for dissolved oxygen concentration in the second design proposed by NWW is due to the fact that the DO level in tanks 6 and 7 often falls well below the desired value, bringing the average down, even though this is exerting a detrimental action on process operation.

The implementation of the suggested design would provide a saving of over £9,000 per year if implemented on both halves of plant A. This saving is theoretical and based on the assumption made for the simulation of the plant with realistic influent sewage flow and load and will vary according to the influent flow rate and the loading of the plant itself (MLSS concentration). The lower the loading and the flow, the higher is the potential saving.

A real engineering problem has been solved by the use of a computer simulation of a real plant, even though all characteristics and parameters of the plant and influent are not known. Simulation can be used to address a wide range of issues, even if the results do not totally reflect the real process, it provides a better knowledge of the process and enables the engineer to adopt better solutions that might otherwise be overlooked.

Chapter 5

5 PROCESS OPTIMISATION

Optimisation of the activated sludge wastewater treatment process is desirable in two aspects: improving the effluent water quality and reducing the cost of treatment. This chapter will introduce the specificity of the process and will see whether these two optimisation aspects can be combined to produce an optimal operating condition for the complete system.

The optimisation algorithm has to take the form of a hierarchical control system which gives optimal set-points to the local control loops according to the conditions of the plant and the desired outcome in terms of cost reduction and/or effluent quality improvement.

5.1 OPTIMISATION PROBLEMS

In practical terms, the optimisation of a process consists of improving the quality of its output and/or reducing the running costs of the process. In the case of a wastewater plant, this can relate to increasing the quality of the released effluent while reducing operation costs. It could also be advantageous in some circumstances to be able to trade-off between the two parameters; for example if the released water quality is particularly poor, improving it regardless of cost is probably the most logical thing to do to avoid possible environmental regulatory problems. On the other hand it might be possible to reduce the treatment costs substantially while degrading the quality of the effluent only slightly while keeping within legal limits.

Traditionally, wastewater treatment plants have been designed by civil engineers with the result that control and instrumentation issues were often an afterthought or at least were not given enough consideration. This results in plants which are 'robust' in terms of dealing with events such as storms and so on, but with little flexibility regarding control and instrumentation and improved performance. Few variables are measured on-line and even fewer controllable since very few actuators exist within the plant. A quick review of available measurements and actuators/control actions is therefore needed.

Firstly, water quality has to be defined. A number of parameters can be considered including: concentration of suspended solids, ammonia or other forms of nitrogen, carbon, oxygen demand, presence of pathogenic bacteria, etc. In this study it is assumed that 'water quality' is related to the concentration of suspended solids present in the released 'clean' water, this being one of the few variables measurable on-line. The mathematical model developed in Chapter 2 incorporates the effluent suspended solids concentration as a variable. Secondly, cost is defined as the financial cost incurred to run the plant without the overheads or personnel costs included, it is therefore reduced to the energy used for aeration and pumping and the cost of disposal of surplus sludge.

In Chapter 2 it was explained that the available on-line measurements are limited mostly to dissolved oxygen concentration (DO), mixed liquor suspended solids concentration (MLSS), height of the sludge blanket within the final settling tank and flow measurements. The variables which can be manipulated are assumed to be limited to the aeration rates (in the different aeration tanks), recycled activated sludge flow rate and surplus sludge wastage flow rate. Table 5.1 shows the main results of changing the magnitude of the manipulable variables.

Table 5.1: Variable interactions (assuming the process is in steady state)

	Dissolved Oxygen	MLSS	Solids in recycled AS	Effluent quality	Cost
Aeration +	+ + +	-	0	0	+ +
-	- - -	+	0	0	- -
Qras +	- -	+ + +	- -	- -	+
-	+ +	- - -	+ +	+ +	-
Qwas +	-	-	- - -	- -	+ + +
-	+	+	+ + +	+ +	- - -

In this table, '+' denotes an increase, '-' a decrease, in flow rate or concentration according to the variable. A '0' signifies that there is no direct effect even though if, for example, the aeration rate is reduced below a certain level, this will have a detrimental impact on the effluent water quality. Multiple signs indicate the relative strength of the process response.

Clearly, it is seen from Table 5.1 that there are a number of interactions taking place. The action of each manipulated variable results in opposite variations between effluent quality and cost improvement in every case, leading to difficulty in achieving both objectives simultaneously. Independent consideration of a single variable does not lead to overall process optimisation. Direct control action on some of the variables is also not suitable since they interact with a number of other parameters and variables within the plant which need to stay within limits so that the treatment process is performed satisfactorily. Reduced control efficiency or even instability in one part of the process could result from undue manipulation of a key process variable such as recycled activated sludge flow rate.

The obvious measure to reduce costs, without affecting the quality of the released water, would be to reduce aeration. Unfortunately, the dissolved oxygen (DO) concentration set-point is fixed at 2 mg/l in this study, as in most plants, in order to maximise the nitrification rate within the aeration stage. Reducing the value of the DO set-point without affecting the plant performance would require on-line measurement of the nitrification rate to ensure that the value obtained is compatible with plant operation. This equipment is not widely available and on-line nitrification rate measurements are experimental, thus preventing this obvious cost-reducing measure to be taken.

5.2 OPTIMISATION TECHNIQUES

In this work the most suitable mixed liquor suspended solids set-point has been determined using two optimisation techniques, one 'conventional technique' based on mathematical reasoning and another based on genetic algorithms.

5.2.1 Conventional technique

A constrained non-linear optimisation method using a Sequential Quadratic Programming (SQP) method has been implemented and used. SQP represents state of the art in non-linear programming methods and has been shown (Schittowski, 1995) to outperform all the other methods tested on a large number of problems. It replicates Newton's method for constrained optimisation. At each iteration the Hessian of the Lagrangian function is approximated using a quasi Newton updating method, which is then used to generate a Quadratic Programming (QP) sub-problem. The Hessian is updated according to the Broyden, Fletcher, Goldfarb and Shanno (BFGS) method published in 1970. This optimisation method is extensively described in Fletcher (1987) and Chapter 2 of Matlab Optimisation Toolbox User's guide (MathWorks, 1996).

5.2.2 Genetic Algorithms

Genetic algorithms represent a search technique which aims at emulating the biological diversity brought by natural genetic operations such as mutation, cross-over, and natural selection. Potential solutions of the problem are initially generated, sometimes at random. The best solutions (i.e. the fittest) are then kept, inbred with the use of operators similar to biological genetic operators in order to have a statistical chance of covering the complete search space for the solution. Random factors are introduced to increase diversity and thus avoid being locked in local minima.

The groupings of variables to identify are called *individuals*. They are coded as strings (*chromosomes*) composed in an 'alphabet', often but not necessarily in binary coding.

A problem with several variables can be mapped into a single binary chromosome structure. The length of the representation of a variable should depend upon the accuracy required and/or the range to cover. The length of each variable (*gene*) present on a chromosome is independent of the length of the other variables carried by the chromosome.

The chromosome string in isolation does not yield information about the problem to be solved. The values it carries can only be extracted by decoding the string. However, the search process operates on the string representing the value rather than on the value itself (except in the case where real valued 'genes' are used instead of a binary or other representation).

Once the chromosome is decoded into real value(s), an objective function can be used to measure the performance, or *fitness*, of all the individuals composing the population. It is a single valued, problem dependent function of the parameters to be optimised. The objective function establishes the basis for selecting the individuals that will reproduce to form the next generation.

In a proportionate selection, the fittest individuals have a high probability of being selected for mating whereas less fit individuals have a lower probability of being selected. Other selection schemes exist including tournament selection, truncation selection, etc. (Chipperfield *et al*, 1994).

The next generation is produced by recombination of the individuals selected for mating. Genetic operators are applied on the genes of the chromosome under the assumption that a certain individual's gene produces on average fitter individuals. The recombination operator is used to exchange genetic information between pairs, or larger groups, of individuals. The simplest recombination operator is the single point crossover, which is the exchange of a part of the strings containing the information between two chromosomes from a common random position.

This operation is not performed on all the population but only on a defined percentage. Other crossover operators exist, including multipoint crossover, uniform crossover, shuffle crossover, etc. An additional genetic operator, called *mutation*, is then applied to another pre-defined percentage of the new population. Mutation causes the individual gene to be changed according to some probabilistic rule. In a binary string representation, mutation will cause a bit to change its state from 0 to 1 or from 1 to 0. This simple bit mutation can affect the value the gene represents considerably.

Mutation is often considered to be a background operator that ensures the probability of searching a particular subspace of the problem is never zero. This has the effect of preventing the convergence to a local rather than the global optimum.

After recombination (crossover) and mutation, the new individual strings are decoded, the objective function evaluated and a fitness value assigned to each individual. According to their fitness, some individuals are selected for mating and so on. The process continues through subsequent generations until it is stopped. Generally the process carries on until a maximum number of generations is attained or a minimum error criterion for the objective function is met. The average performance of individuals in a population is expected to increase, as good individuals are preserved and bred with one another and the less fit individuals die out.

In some GA schemes the entire population is replaced at each generation whereas in others only a percentage of the population is replaced at each generation. This is controlled by the *generation gap*. The individuals propagated without change to the next generation can be chosen at random (random reinsertion) or according to their fitness values (fitness based reinsertion). The latter method is also called an elitist strategy because the best individuals in the population always propagate to the following generation. This ensures that the best solution in a generation can only be replaced by a better solution.

In this study, a fitness based reinsertion algorithm is used and the 2 fittest individuals are kept in the following generation. The probability of mutation is 0.7 and the probability of recombination between two individuals of a pair 0.8.

5.3 FINANCIAL COST OF PROCESS OPERATION DEFINITION

5.3.1 Aeration cost

A study by Fujie and Kubota (1986) on only the aeration stage of activated sludge wastewater treatment plants showed that the relationship between costs and aeration depends upon many factors including mixed liquor suspended solids concentration (MLSS), liquid depth, type of the air diffusers, temperature, atmospheric pressure, etc. However, the cost of the aeration of the process can be estimated in a straightforward manner, assuming that the oxygen transfer rate is known, according to equation 5.2.

$$\text{Aeration cost} = \frac{\text{oxygen transfered (kgO}_2\text{)}}{\text{oxygen transfer rate (kgO}_2\text{/kWh)}} \times \text{Electricity cost (£/kWh)} \qquad (5.2)$$

In Chapter 2, the oxygen transfer rate was fixed conservatively at 1.3 kg oxygen/kWh. In the same manner the price of electricity has been assumed in North West Water's own data (Kruger, 1995) to be £0.05/kWh.

5.3.2 Recycle flow cost

The direct operational cost associated with the recycled activated sludge flow rate is only composed of the pumping cost and therefore can be easily determined. Although the nominal power of the pump is easily found in the documentation consulted, it is not the case for the maximum flow rate attainable. In this work the pumping of 1 m^3 of activated sludge is assumed to require 0.1 kWh. This value seems to be low but has been calculated conservatively according to North West Water plant data (*personal communication*) based on the pump nominal power and recycled flow rate.

Therefore,

$$\text{recycled activated sludge cost} = 0.1\ \text{kWh/m}^3 \times \text{cost/kWh} \times \text{surplus sludge flow rate} \qquad (5.3)$$

5.3.3 Surplus sludge disposal cost

This variable is even more difficult to fix than the recycled sludge pumping cost. This cost is composed of two parts: the cost of pumping the activated sludge to be disposed of, and the actual cost of disposal. The pumping cost of surplus sludge is assumed equivalent to the pumping cost of the recycled sludge. However, depending on the source of the information, the cost of disposal of surplus sludge varies from zero to a large value. In most wastewater treatment plants the surplus sludge is subject to a number of operations before being disposed of. Dewatering is a complex and relatively costly operation. The surplus sludge may be fermented in order to obtain methane gas, which is subsequently converted into electricity and/or heat which can be reused within the plant. With this approach it can even be considered that the sludge is a free raw material, however the infrastructure needed to convert it is costly and it might not have been worthwhile to build sludge fermenters unless there was originally a problem of disposal of the sludge. The residues of fermentation must eventually be disposed of. The favoured method of disposal of surplus sludge, or its residue, in the UK has been disposal at sea, which will be prohibited in the near future. The preferred alternative is incineration of the sludge, which is even more expensive.

The pricing information is variable from one plant to another according to the infrastructure, design etc. A cost of £0.25/m^3 of raw surplus sludge has been used, which would be characteristic of transport costs for a relatively small distance, but the actual figure could be quite different according to the plant design, its geographic location, the characteristics of the sludge, the favoured method of disposal, etc. This value does, however, provide a basis for comparisons.

The resulting cost equation is of the form:

Surplus sludge disposal cost = (unit disposal cost + 0.1 kWh/m^3 × cost/kWh) × flow rate of surplus sludge (5.4)

5.3.4 Effluent quality

The effluent quality is measured by the suspended solids in the effluent because of a lack of available and reliable measurements. This quantity is available in the developed model, however it is not possible to attribute an accurate financial cost to effluent quality. The actual financial cost of releasing solids into the effluent water is nil until the discharge consent value fixed by the regulator is reached, after which legal problems arise which can lead to a fine or even a prison sentence in some countries. Therefore, it is difficult to translate the effluent quality in financial terms.

As described in Chapter 2 the suspended solids in the effluent can be approximated by function (2.17) and a time delay:

$$SS_F = SS_{init} + SS_{NO_3} \cdot \frac{S_{NO_3}}{K_{NO_3} + S_{NO_3}} + SS_{hyd} \cdot \frac{X_0 \cdot SVI \cdot \frac{Q_0}{A}}{K_{hyd} + X_0 \cdot SVI \cdot \frac{Q_0}{A}} \tag{2.17}$$

Where:

SS_F Concentration of particles in the feed to the clarifier which will not settle

SS_{init} Constant SS concentration which will always will be non-settleable

SS_{NO3} Maximum concentration of SS at the inlet which will not settle due to nitrate in the inlet

S_{NO3} Concentration of nitrate at inlet to clarifier

K_{NO3} Monod constant for nitrate

SS_{hyd} Maximum concentration of SS in the inlet which will not settle due to hydraulic and SS load

X_0 Concentration of SS in the feed to the clarifier

SVI Sludge Volume Index

$\frac{Q_0}{A}$ Hydraulic load to the clarifier

K_{hyd} Monod constant for load

From equation (2.17) it can be seen that the variables that can theoretically be acted upon, in order to reduce the solids in the effluent, are X_0 and $\frac{Q_0}{A}$.

In practical terms this means maintaining a mixed liquor with as weak a concentration as possible and, since the area of the final settling tanks is not variable for a given plant, reducing the flow rate of mixed liquor through the plant. Since the flow rate of the sewage coming into a plant is generally not controllable, the only way of reducing the flow through the plant is therefore to reduce the recycled sludge flow which has for direct effect to reduce the mixed liquor suspended solids concentration. Therefore an optimisation algorithm based on this would systematically set the mixed liquor suspended solids concentration to the minimum value allowed.

5.4 OBJECTIVE FUNCTION DEFINITION

The aim of all optimisation techniques is to minimise (or maximise) an objective function which reflects how the process is performing according to some criteria, using available variables. An objective function used in order to optimise the operation of the activated sludge process requires two components: one for the operational cost based from equations (5.2), (5.3), (5.4) and another one representing the effluent water quality based on (2.17).

It is clear that these two components have different units and therefore a scaling factor is needed since the effluent suspended solids are typically in the region of 20 (g/l) while the operating cost as defined above are in the region of 500 (£/day) for the typical plant modelled, both varying considerably according to the design and size of the treatment plant and its conditions.

A solution is to calculate both terms independently and combine them with the inclusion of a scaling factor, α, which varies according to the optimisation system priority (increasing water quality or reducing costs).

$$\text{Objective function} = \text{cost} + \alpha \times SS_{EFF} \tag{5.5}$$

The objective function that includes all the cost elements can be expressed as:

$$\text{cost} = (\text{aeration}_1 + \text{aeration}_2) \times \frac{\text{costkWh}}{\text{kgO}_2\text{pkWh}} + (\text{Qras}+\text{Qwas}) \times \text{pumping cost/m}^3$$
$$+ \text{Qwas} \times \text{WAS cost disposal} \tag{5.6}$$

However, it can been seen from Table 5.1 that to reduce the aeration rate (apart from changing the dissolved oxygen set-point which is not possible as explained earlier) the solution is to reduce the recycled flow rate.

Following this reasoning, to reduce cost and increase quality, the solution is to operate the plant with as minimum values of Qras and Qwas as possible. This would reduce the plant loading in the clarifier and also the aeration needed to sustain the oxidation of the influent sewage. Unfortunately, in practice this is not possible. To maintain good operation of the plant, a number of parameters have to lie within strict limits, otherwise the assumptions used in the model are not permissible. For example if the mixed liquor is not concentrated enough, then settling will not occur properly and more solids will be released in the effluent. The process is a wastewater treatment plant whose aim is to degrade organic matter as much as possible; the IAWQ activated sludge model incorporates many assumptions and even the addition of a final settling tank and water quality model does not remove these limitations completely, therefore the error function has to be reformulated in a more appropriate manner.

First of all, direct control of the recycled and surplus activated sludge flow rates (Qras and Qwas) is not suitable. The ASP is a slow process as far as solids are concerned. Also a strong interaction exists between the concentrations of Qwas and Qras. Direct control of the solid flows might result in instability in the overall process caused by large and repeated changes in solids flow rates. Two PID control loops have been developed to deal with this. The time constants are quite slow and the gains have also been set low in order to prevent any instability being introduced by the controller actions. The recycled activated sludge flow rate is set by a PID loop acting upon the MLSS concentration in the first aeration tank. The surplus sludge flow rate is controlled by another PID loop acting upon measurement of the suspended solids in the underflow, that is to say the recycled or wasted sludge. More details of the method used to control sludge flows are presented in section 5.5.1.

The optimisation required has to operate at a supervisory level by adjusting the set-points of the two sludge flow controllers.

The main variables that the optimisation system can manipulate are the mixed liquor suspended solids and the underflow suspended solids concentrations. However, the action will be indirect, leaving the local control loops modifying the sludge flows. As a result the main variable considered by the error function is the MLSS set-point ($MLSS_{sp}$) and therefore it would also seem logical to manipulate the underflow suspended solids concentration ($SSun_{sp}$). However, the maximum allowable value for the set-point would be automatically adopted since there is no moderating element present in the available equations. There is also a strong coupling between recycled and wasted sludge flows which is important not to over-stress. The problem in determining the most suitable value of $SSun_{sp}$ is mainly due to the failure of models, particularly the water quality one, to represent accurately all the phenomena involved in the process.

The suspended solids concentration set-point ($SSun_{sp}$) for the underflow (recycled and surplus sludges) is fixed by the plant operator. It is a variable which could be controlled by the optimisation system. However, this solution has not been retained owing to the large interactions with the control of recycled sludge and the possible risk of plant upset resulting in undue variations.

In order to allow optimisation using the mixed liquor suspended solids set-point ($MLSS_{sp}$) as the manipulated variable, the objective function has to reflect the resulting changes that might occur on both water quality and costs when $MLSS_{sp}$ is modified. The exact influence of a change of $MLSS_{sp}$ is not easily quantifiable, a linear relation is therefore assumed. A term $\frac{\text{New MLSS}_{SP}}{\text{MLSS}_{sp}}$ is added to each term of (5.5) which increases when MLSS_{sp} increases (according to Table 5.2) and $\frac{\text{MLSS}_{sp}}{\text{New MLSS}_{sp}}$ for the terms comprising Qwas, which decreases when MLSS_{sp} increases.

In equation (2.17), the concentration of SS in the feed to the clarifier (X_0) is replaced by the value of the New MLSS_{sp}.

Table 5.2: Interactions between set-points and key variables, assuming a control system is present to maintain DO and MLSS concentrations

	Aeration	Qras	Qwas	SS_{EFF}	Cost
MLSS set-point +	+ +	+ +	-	+ +	+ +
-	- -	- -	+	- -	- -
SSun set-point +	0	-	- - -	0	- -
-	0	+	+ + +	0	+ +

See table 5.1 page 132 for explanation of signs.

From Table 5.2 it is obvious that a compromise between the effluent quality and the cost of the wastewater treatment has to be achieved.

The terms $\frac{\text{MLSS}_{sp}}{\text{New MLSS}_{sp}}$ and $\frac{\text{New MLSS}_{SP}}{\text{MLSS}_{sp}}$ will be close to 1 except in exceptional circumstances (manual change of MLSS set-point by the operator). The strong influence of SSun_{sp} on the recycled sludge flow rate (Qwas) has been represented by squaring the term $\frac{\text{MLSS}_{sp}}{\text{New MLSS}_{sp}}$ associated with the surplus sludge flow rate. The resulting new cost function is therefore as follows:

$$cost = (\text{aeration1}+\text{aeration2}) \times \frac{\text{costkWh}}{\text{kgo2pkWh}} \frac{\text{New MLSS}_{SP}}{\text{MLSS}_{sp}} + \ldots \tag{5.7}$$

$$(\text{Qras}\frac{\text{New MLSS}_{SP}}{\text{MLSS}_{sp}} + \text{Qwas}\frac{\text{MLSS}_{sp}}{\text{New MLSS}_{sp}}) \times \text{costm}^3 + \text{Qwas}\times\text{costwas}\left(\frac{\text{MLSS}_{sp}}{\text{New MLSS}_{sp}}\right)^2$$

also,

$$SS_F = SS_{init} + SS_{NO3}\frac{S_{NO3}}{K_{NO3} + S_{NO3}} + SShyd\frac{\text{New MLSS}_{sp} \cdot SVI \cdot \frac{Q_0}{A}}{K_{hyd} + \text{New MLSS}_{sp} \cdot SVI \cdot \frac{Q_0}{A}} \tag{5.8}$$

Resulting in the final function to minimise:

$$\text{Objective function} = cost + \alpha \times SS_F \tag{5.9}$$

To summarise, the definition of an objective function which represents accurately the behaviour of the process is difficult because the process reacts to a large number of factors whose actions are ill defined and are themselves difficult to measure. Moreover few variables can be manipulated by an optimisation algorithm and the objective function has to be expressed using these variables.

5.5 OPTIMISATION METHODS EMPLOYED

The aim of reducing the suspended solids in the effluent results in the need to decrease both the recycled activated sludge flow rate and the mixed liquor suspended solids concentration. The surplus activated sludge (WAS) is dependent upon the composition of the effluent and to a small extent on the total plant throughput, that is to say the influent and recycled flow rates.

In this study, a scaling factor has been used in order to put effluent quality and operation cost at the same level of importance (Equation 5.5).

The optimisation system cannot act directly on the manipulated variables (recycled and surplus activated sludge flow rates) because direct action could lead to instability in the process. The variation of the mixed liquor suspended solids set point in the first aeration tank (tank 0) is a viable alternative. The actual MLSS in the following tanks is slightly lower than in the previous one due to degradation of the organic matter in the process, but the concentration values are strongly correlated. Therefore, a modification in the first tank will result in a proportional change in the following tanks after a time delay.

As seen previously, the optimisation of operating cost and effluent quality is difficult to combine, and can be achieved only if the initial state of the plant allows it by a combination of particular circumstances and high or low costs, influent flow rate, influent loading etc.

In most 'normal' conditions, the optimisation system can be used to increase the effluent quality in periods when it approaches the discharge consent limits, regardless of the exploitation costs involved, or on the contrary, to partly reduce costs while maintaining only a slightly degraded effluent water quality. It is also possible to minimise operational costs as much as possible while degrading more significantly the effluent water quality, which can be thought desirable in periods of relative high quality. The switching between these different modes is achieved by modifying the value of α. A value of $\alpha = 0$ results in maximum cost optimisation while, $\alpha \rightarrow \infty$ results in a maximum released water quality optimisation (for this work the maximum value is $\alpha = 100$). Values between 0 and 100 allow for a compromise where one of the parameters is optimised while keeping a relative importance to the other parameter optimisation requirement.

5.5.1 Flow control

5.5.1.1 Recycled sludge flow

The recycled sludge flow is controlled using a standard PID controller. The sludge is recycled in order to maintain the concentration of suspended solids within the aeration stage. Therefore it seems natural to control the recycled activated sludge flow rate (Qras) to maintain the solids, measured in terms of MLSS at the desired set-point. Ideally the solids concentration should be controlled in the last aeration tank, providing the feed into the sedimentation stage, however due to the large size of the plant, a long time delay exists making accurate control difficult. To get around this problem, it has been decided to control the solids concentration in the first aeration tank (tank 0), reducing the time delay. The solids concentration set-point has to be slightly higher than the desired value in the final tank to account for the degradation of part of the solid content during the biological degradation which occurs in the aeration stage.

5.5.1.2 Surplus sludge flow

Theoretically the surplus sludge flow is dependent only on the quantity of solids entering the plant in the form of raw sewage and the actual concentration attained in the sedimentation stage. However, a small part of the solids is lost in the effluent clean water, depending on the efficiency of the sedimentation stage, which is influenced by several factors such as plant through flow rate (influent sewage flow rate plus recycled activated sludge flow rate).

5.5.2 Traditional optimisation technique

The optimisation is constrained by boundaries since the mixed liquor suspended solids (MLSS) concentration has a limited range of acceptable values for successful process operation. This range is between 2,000 and 4,000 g/m^3, because lower concentrations bring sedimentation problems, and higher concentrations might also bring sedimentation and clarification difficulties. The Sequential Quadratic Programming (SQP) method is the state-of-the-art method in non-linear programming. It is particularly adapted to solve constrained problems and although this problem is not strictly speaking constrained, it offers advantages in term of convergence speed and ease of implementation. One of its requirements is that the objective function is continuous, which is the case here.

The optimisation sample time has been determined in a heuristic manner. One change of MLSS set-point per hour has been found to give adequate results with fixed electricity prices; reducing the interval further does not bring any further improvement, while increasing this period, degrades performance.

In the UK, electricity prices are set every half hour, roughly one day in advance. Therefore, changing electricity prices can be made available to an optimisation algorithm. With this new set of data it becomes necessary to run the optimisation algorithm every half hour using the electricty price that is correct for the next half hour of operation. The optimisation algorithnm is therefore called every 30 minutes of simulated operation.

5.5.3 Genetic algorithms

A population of 40 individuals has been used to implement the genetic algorithm. It has been found to be an acceptable compromise between computational time at each iteration and overall convergence. The generation gap which controls the percentage of the population to be kept at the next generation, has been fixed at 0.95 which means that for a population of 40 the best 2 individuals of each generation are reinserted into the next. Mutation and recombination (crossover) operators are applied on the population at each generation to ensure that the search is performed over the entire problem space with probabilities of .035 and 1 respectively. The variable manipulated is the same as in the case of the linear optimisation technique, the mixed liquor suspended solids concentration set-point (MLSSsp). The actual value of the MLSSsp is carried by each individual in the form of a binary string, also called a chromosome, coded with a precision of 20 bits which is sufficient to cover the problem space (range of 2,000 - 4,000 g/m^3) accurately. The maximum of generations or iterations of the algorithm has been limited to 80 because it has been found that convergence is generally attained before that stage.

5.6 OPTIMISATION RESULTS

Optimisation of the operation of the activated sludge process has been investigated relative to operating cost and effluent water quality as defined previously, subject to conditions aimed at representing real situations. In order to represent the different conditions which can be met by the process in operation, three scenarios have been developed. In the first scenario, the electricity price is fixed over the period of interest, while in the others the prices used are those encountered during the second week of July 1997 and the third week of December 1997 as provided by North West Water Ltd. To represent typical summer and winter operating conditions, the temperature of operation of the wastewater treatment plant has also been adjusted to reflect the ambient conditions (20°C in July, 10°C in December). The influent flow rates and sewage composition used are those of the first week of realistic influent sewage data presented in Chapter 3 (Figures 3.10 and 3.11).

5.6.1 Fixed electricity price

In many cases, the price of electricity is, or can be considered, to be constant over a given period of time. Estimates of electricity costs at the plant previously used in Chapter 4 were £0.05 per kilowatt-hour. This price has been used as a reference in the first part of this study.

Figures 5.1 and 5.2 show the actual suspended solids concentration obtained in the effluent and the cost of treatment for $\alpha = 0$ and $\alpha = 100$ respectively with an operational temperature of 20°C; the case with no optimisation is used as a reference.

The first observation is that the effect of optimisation takes a few hours before being noticeable. This is because the optimisation is acting indirectly on the mixed liquor concentration, which is a relatively slow process. The second observation is that the optimisation of cost is achieved to the detriment of the water quality and the improvement of quality results in higher operating costs. Neiva *et al* (1996) have also observed a slight degradation of the effluent water quality as a result of their energy reduction control strategy. In both Figures 5.1 and 5.2, the characteristic changes in the effluent suspended solids largely remain, the main difference being due to an 'offset' in the mean value, but not a significant alteration of the pattern. The operating cost patterns are fundamentally affected by the optimisation.

In figure 5.1 ($\alpha = 0$, cost optimisation), the peak in cost, over £900/day, occurring in day 2 has disappeared. The cycles associated with financial costs, which is roughly a daily cycle in the case of a non-optimised system, becomes twice daily while implementing the optimisation algorithm, one with a larger amplitude than the other. The cost optimisation is disappointing in this case with a reduction of costs of only 2% on average. The effect of the optimisation on cost is to remove the peaks, and to relate more closely the operations cost with the actual influent sewage flow into the plant. This is achieved with only a minimal increase (0.7%) of released suspended solids in the effluent.

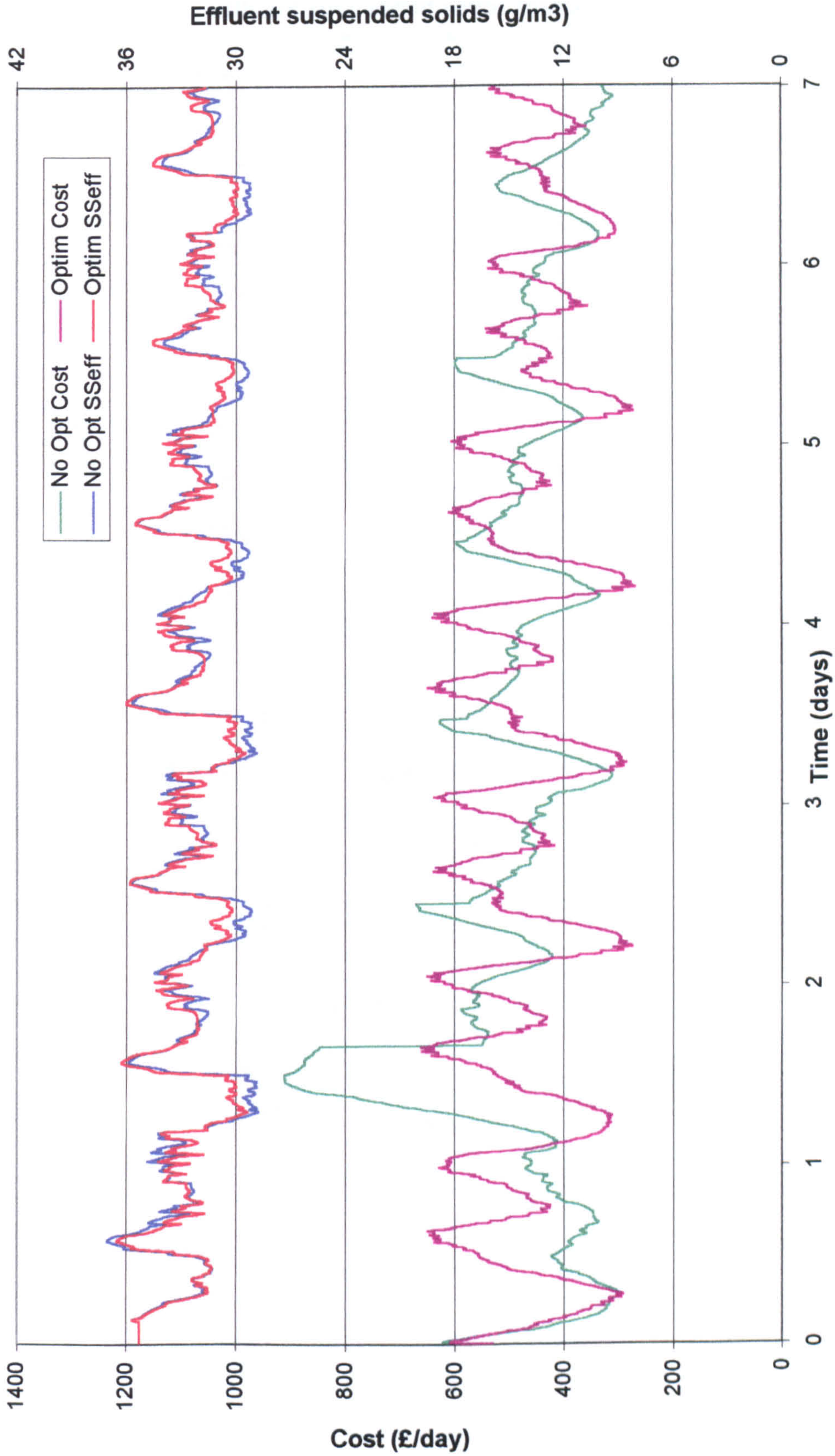


Figure 5.1: Cost & suspended solids at fixed electricity price and α=0

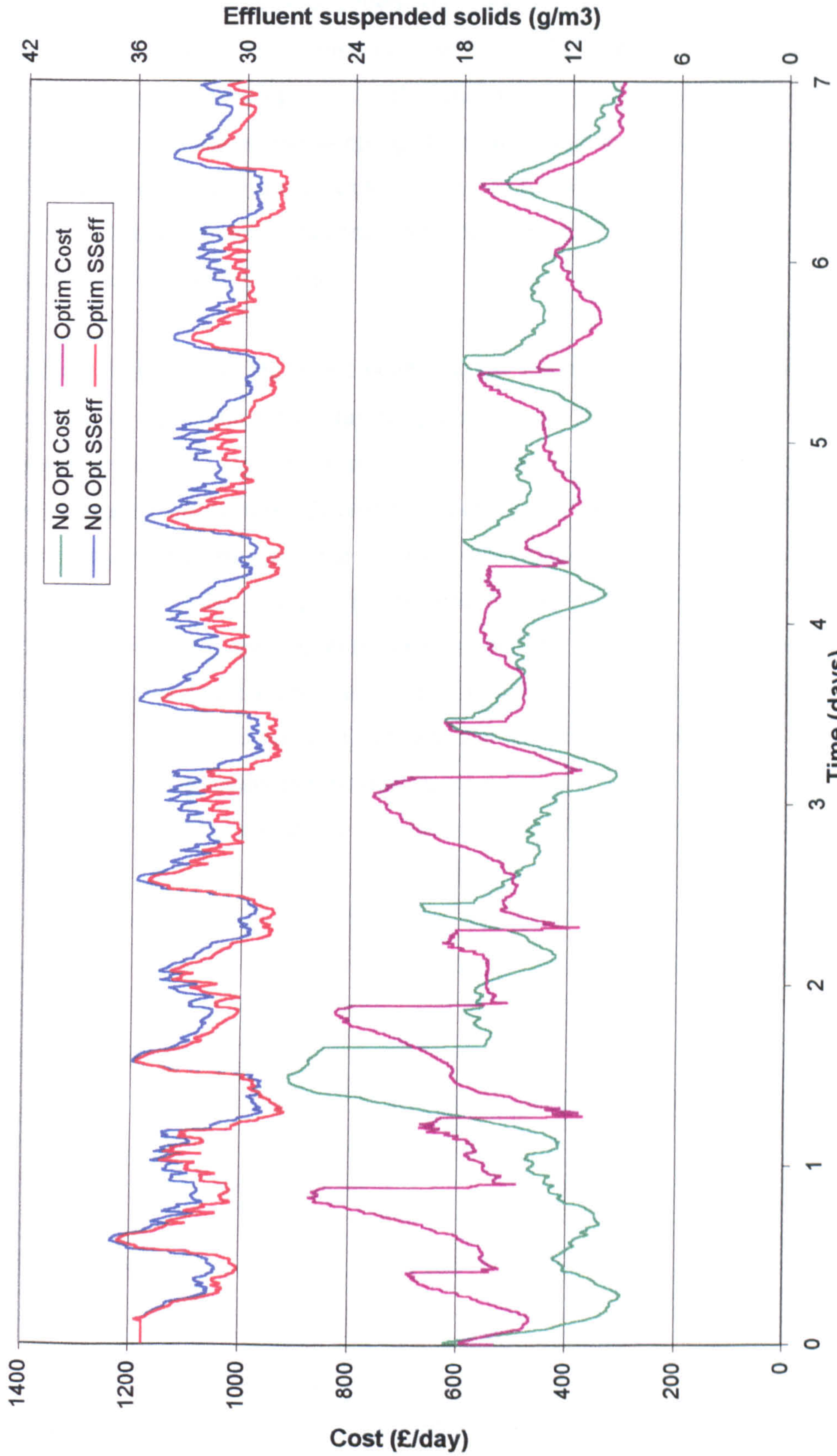


Figure 5.2: Cost & suspended solids at fixed electricity price and α=100

Figure 5.2 shows that the cost pattern keeps its daily cycle when the effluent quality is the main concern of the optimisation routine ($\alpha = 100$), where the modest reduction of 3.7% is being achieved by an 'offset' in the pattern. The steep drops in operating cost are caused by the occasional stopping of surplus sludge disposal when the concentration of the activated sludge decreases too much due to the combined recycling and disposal actions. It is to be noted that the operation cost has increased by 9% to achieve this improvement in effluent quality.

Figure 5.3 shows the MLSS set point and the resulting concentration obtained in the first tank of the aeration stage during optimisation with $\alpha=20$. This value of α has been chosen because it presents a more regular pattern than when the optimisation is predominantly biased towards cost reduction or quality improvement. The MLSS set point actually changes according to a twice-daily pattern explaining the results observed in Figure 5.1. These changes are dictated by the state of the plant and notably the influent flow rate and aeration rate needed to maintain the dissolved oxygen concentration as described by the objective function used by the optimisation system. It can also be noted that most of the time the actual MLSS value does not reach the minimum, and especially the maximum, set-point values. This is due to the limitation in the control of Qras caused by the effect of the response time and maximum possible flow rate.

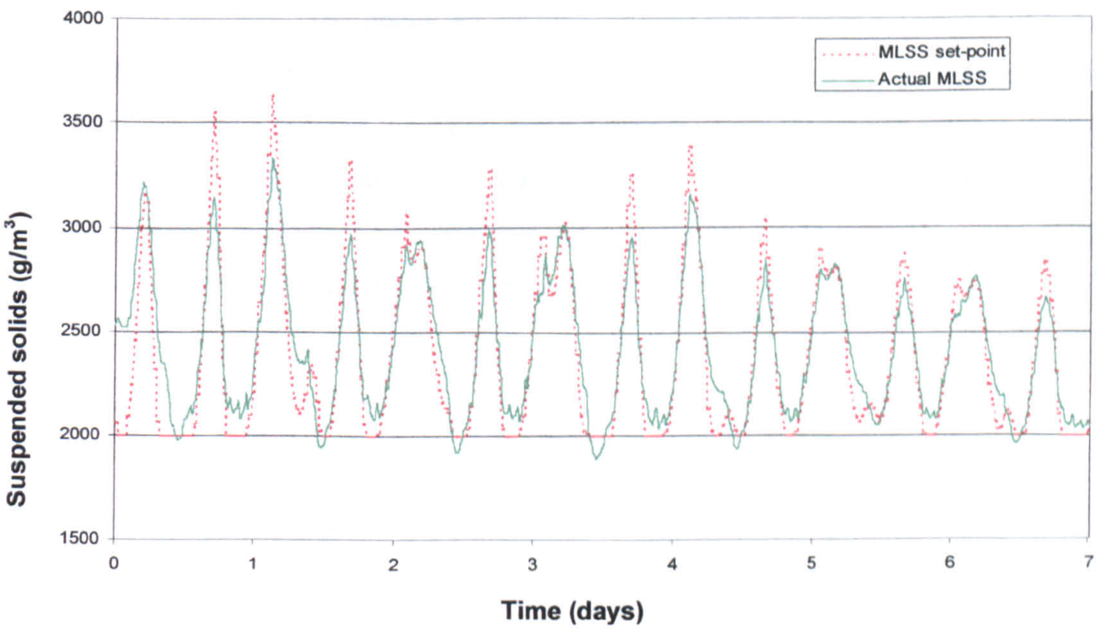


Figure 5.3: Change of MLSS set-point during optimisation.

Table 5.3 shows the average values of costs and suspended solids in the effluent obtained over the seven day test period at 20°C and 10°C for various values of α. It shows that at 10°C, the process presents a greater flexibility than at 20°C, allowing both greater cost savings and higher improvement in effluent quality to be achieved.

Table 5.3: Comparison of cost and effluent quality with fixed electricity price

Temperature	**20°C**		**10°C**	
	Cost (£/day)	**SS effluent (g/m^3)**	**Cost (£/day)**	**SS effluent (g/m^3)**
No optimisation	477.18	32.15	368.05	15.61
$\alpha = 0$	467.90	32.39	300.52	16.92
$\alpha = 10$	482.23	32.14	317.47	16.69
$\alpha = 20$	496.56	31.90	334.07	16.45
$\alpha = 50$	517.81	31.36	378.10	15.65
$\alpha = 100$	520.34	30.97	419.04	14.75

5.6.2 Variation in electricity prices

In the UK, the electricity market is open to competition. As a result the electricity demand is forecasted in advance and prices set the previous day according to the laws of supply and demand. The prices are set for half-hour periods with potential half-hourly step changes. Figure 5.4 presents the electricity pool prices for the week starting Monday 7th July 1997 and the week starting Monday 22nd December 1997 as used by North West Water Limited. Electricity prices are higher in winter than during the summer, which is a period of lower demand. The average price over the test period is £0.0163/kWh in July and £0.0275/kWh in December.

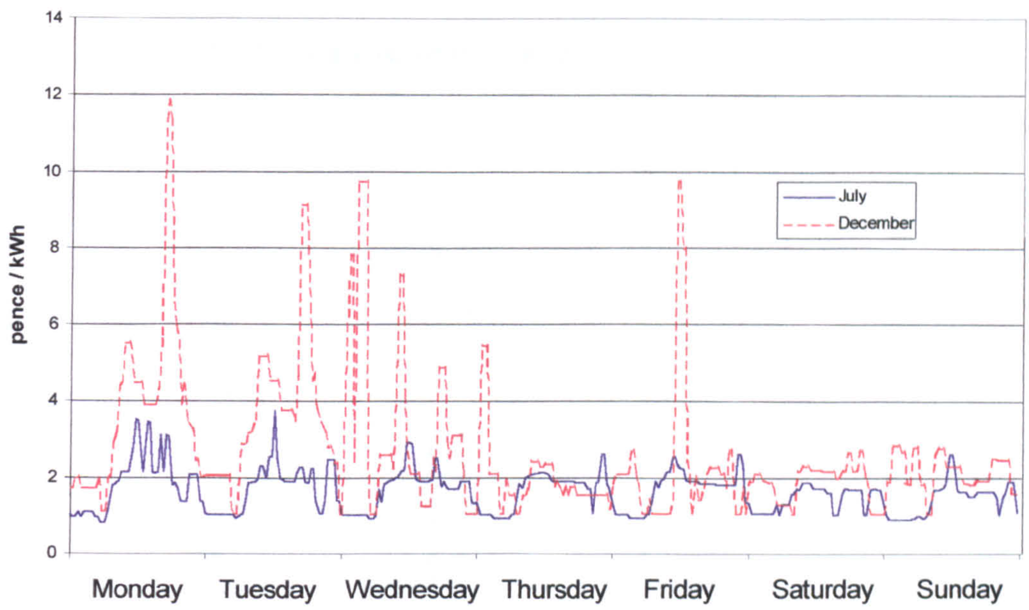


Figure 5.4: Electricity prices

A point to be noted is some similarity between the electricity prices pattern (Figure 5.4) with the real influent sewage flow pattern (Figure 3.10). In both cases, a reduced value is noted during nights and weekends. The December pattern is perturbed by the presence of Christmas (Wednesday), which presents a much lower average price than could be expected for a normal December week day owing to the reduced activity on that day; as well as on Thursday, Boxing day, also a bank holiday in the UK.

5.6.2.1 July electricity prices

Optimisation has been performed using the electricity prices for a particular week of July 1997 and an operating temperature of 20°C, representative of the sewage temperature at this period of the year. Table 5.4 shows the average daily operating cost and suspended solids in the effluent over the test period for different weightings of the objective functions (α varying from 0 to 100).

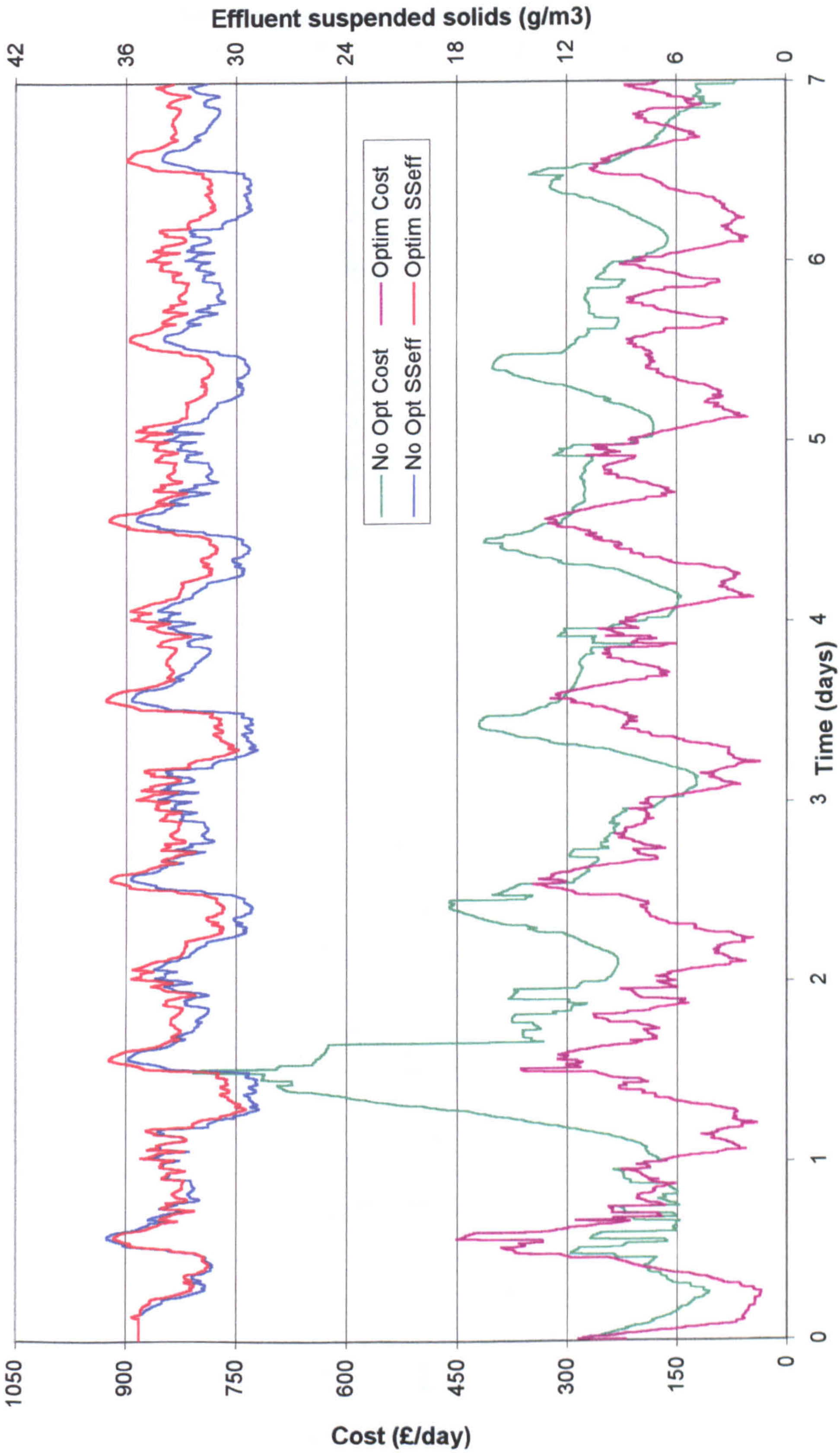


Figure 5.5: Cost & suspended solids at July electricity price and $\alpha=0$

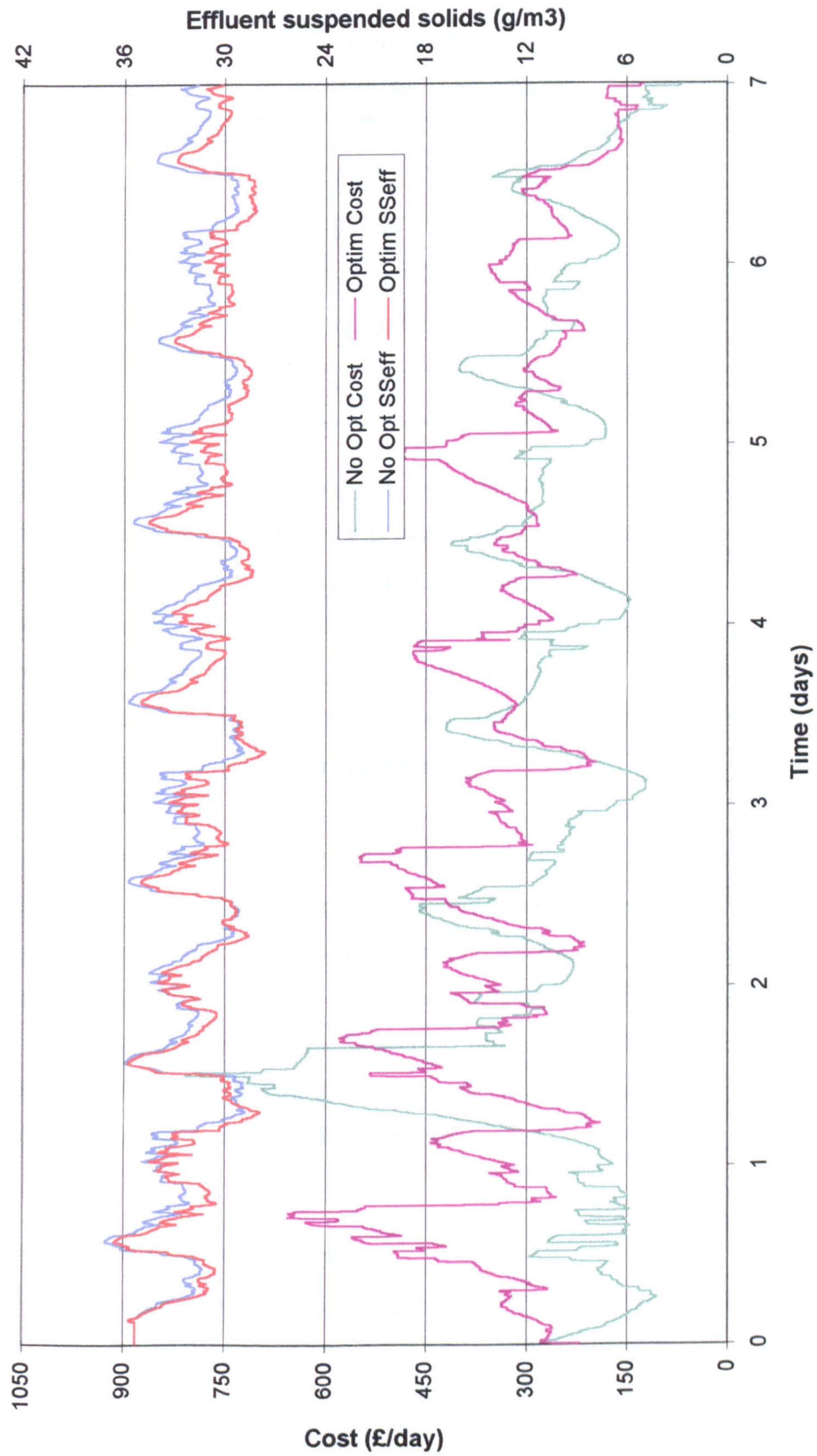


Figure 5.6: Cost & suspended solids at July electricity price and α=100

Table 5.4: Comparison of cost and effluent quality with July electricity price

Method	Non-linear optimisation		Genetic Algorithms	
	Cost (£/day)	SS effluent	Cost (£/day)	SS effluent
No optimisation	272.92	32.16	272.92	32.16
$\alpha = 0$	176.46	33.38	176.45	33.39
$\alpha = 10$	197.43	33.15	197.43	33.15
$\alpha = 20$	219.80	32.91	219.80	32.91
$\alpha = 50$	280.91	32.11	280.89	32.11
$\alpha = 100$	335.03	31.20	335.03	31.20

Figure 5.5 shows the resulting cost and suspended solids in the effluent when the objective function is biased towards maximum cost savings (α=0). During the first day of operation the cost savings are far from being obvious even though on average over the seven days of the test, cost reductions of 35% over non-optimised equivalent operation is achieved. The corresponding increase in effluent suspended solids is less than 4%. The peaks of cost are reduced in intensity, especially the first one (on day two), and are also slightly delayed in time.

Figure 5.6 shows the results of optimisation with a strong water quality bias (α = 100). The quality of the effluent water is increased by slightly less than 5% for an increase in operating costs of nearly 20%. The step changes in electricity prices are more pronounced than in Figure 5.5 where the emphasis is put on cost reduction. The peaks in operating costs are slightly delayed in time compared with the normal operation, without optimisation, but the dual daily cycle is still present even if the first peak of the day is of a much smaller amplitude than the second.

5.6.2.2 December electricity prices

A similar investigation was undertaken with the December electricity price data set, but this time with an operating temperature of only 10°C, being closer to reality at this time of the year: sewage is usually warmer than the outside temperature in winter because it is transported in underground pipes.

Table 5.5 shows the results obtained with different values of α, the weighting factor of the objective function used for the optimisation for non-linear and genetic algorithm methods.

Table 5.5: Comparison of cost and effluent quality with December electricity price

Method	Non-linear		Genetic Algorithms	
	Cost (£/day)	SS effluent	Cost (£/day)	SS effluent
No optimisation	295.11	15.61	295.11	15.61
$\alpha = 0$	176.41	17.28	176.37	17.28
$\alpha = 10$	196.01	17.06	196.00	17.06
$\alpha = 20$	215.53	16.85	215.55	16.85
$\alpha = 50$	271.32	16.11	271.30	16.11
$\alpha = 100$	351.26	14.86	351.26	14.86

The results obtained with α=0 and the non-linear method are shown in Figure 5.7. The December electricity price data set presents some high 'peaks' which are directly reflected in the operating costs, the optimisation algorithm having no possibility to smooth them out due to their sudden and generally short lived nature. Still, a substantial cost saving of 40% is achieved for an increase of suspended solids, that is to say a reduction of effluent water quality, of 10%. The percentage change in the suspended solids in the effluent is misleading since the actual reduction in this case of 1.6 g/m^3 represents 10%, whereas it would be only half that percentage if the operating temperature was increased to 20°C, the water quality being strongly dependent upon process parameters which are themselves dependent on temperature.

With α=100, the operating cost peaks provoked by the peaks in electricity prices are increased as shown in Figure 5.8. A reduction of 8% of the suspended solids concentration in the effluent is achieved, on average over the seven day test period, for an operating cost increase of 15%.

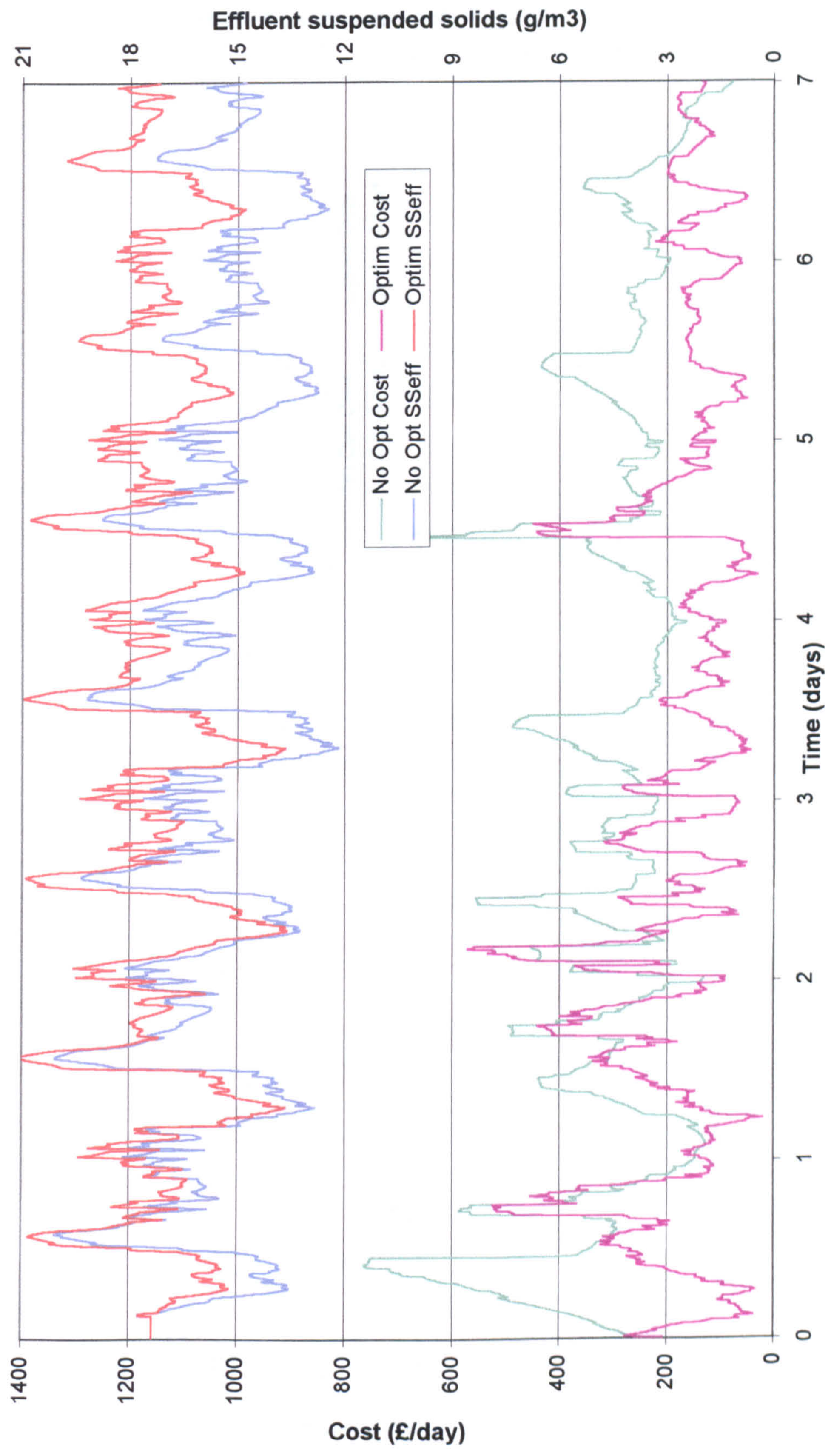


Figure 5.7: Cost & suspended solids at December electricity price and α=0

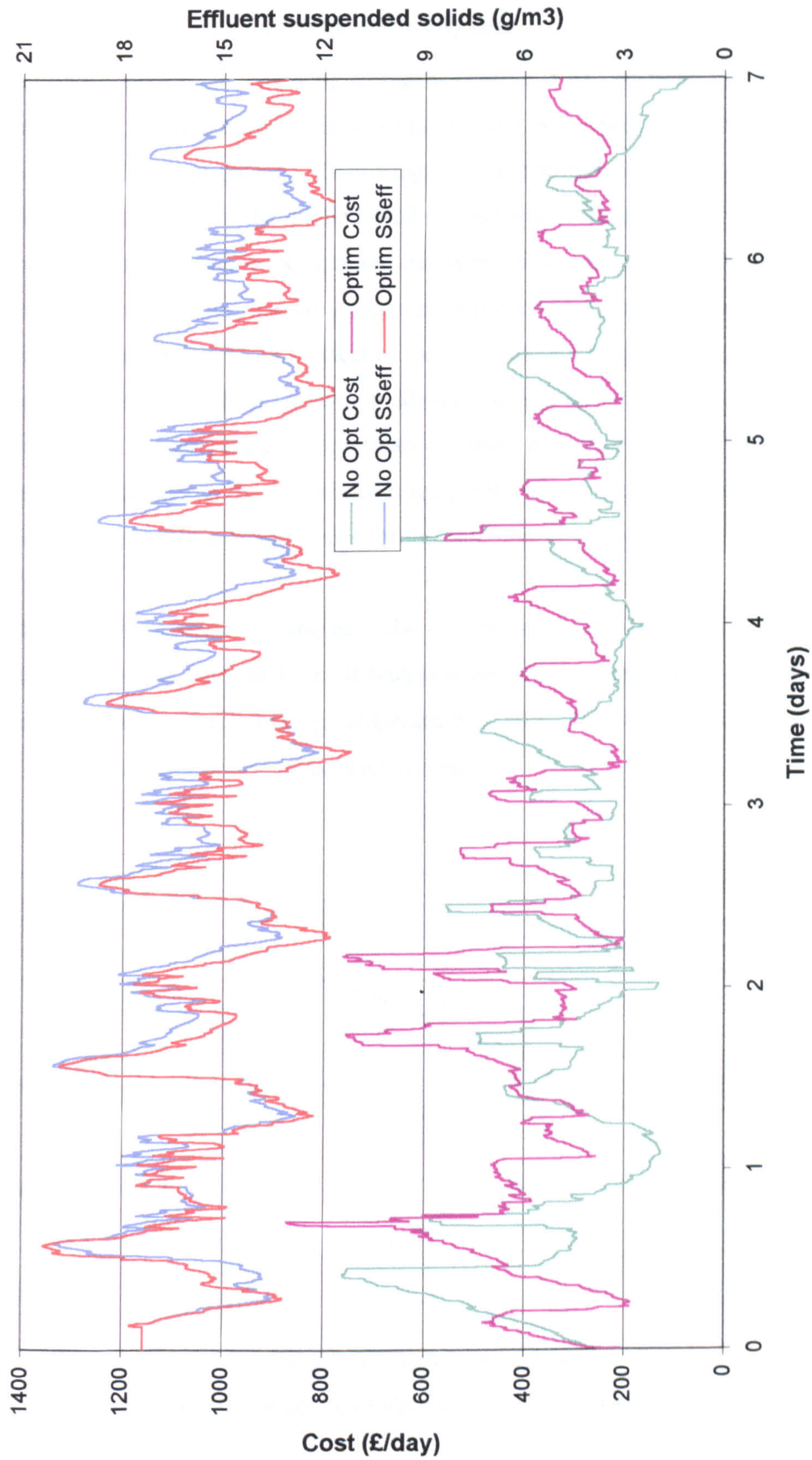


Figure 5.8: Cost & suspended solids at December electricity price and α=100

5.6.2.3 Effects of using average electricity cost

Electricity prices are changing abruptly (Figure 5.4), whereas the activated sludge wastewater treatment process is continuous and it is not possible to change radically the operation pattern so quickly. The change of concentration of the suspended solids in the mixed liquor, which is the method used in this work to optimise process efficiency, does not occur instantly once the decision has been taken. Since the optimisation algorithm is run every half-hour, the slow response could lead to a new optimum operating point being decided before the full effect of the previous one has fully taken effect. However, the electricity prices being known in advance, it is possible to use the average electricity prices for a longer period of time than the fixed half hour period. This should lead to smoother changes in the optimisation set-point. The potential of this method has been evaluated using the average prices for the next one, two, four and six hours.

These results, compared using only the current price, are shown on Figure 5.9 for July electricity prices with an ambient temperature of 20°C, and Figure 5.10 for December electricity prices and operating temperature of 10°C, for different values of α resulting in varying concentrations of suspended solids.

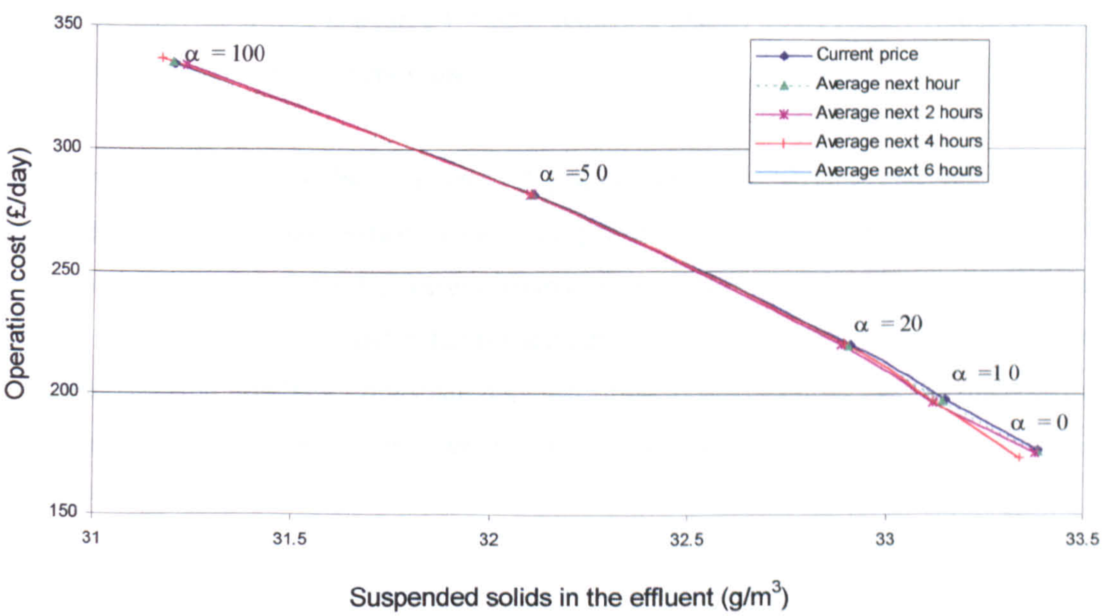


Figure 5.9: Influence of electricity prices averaging (July prices)

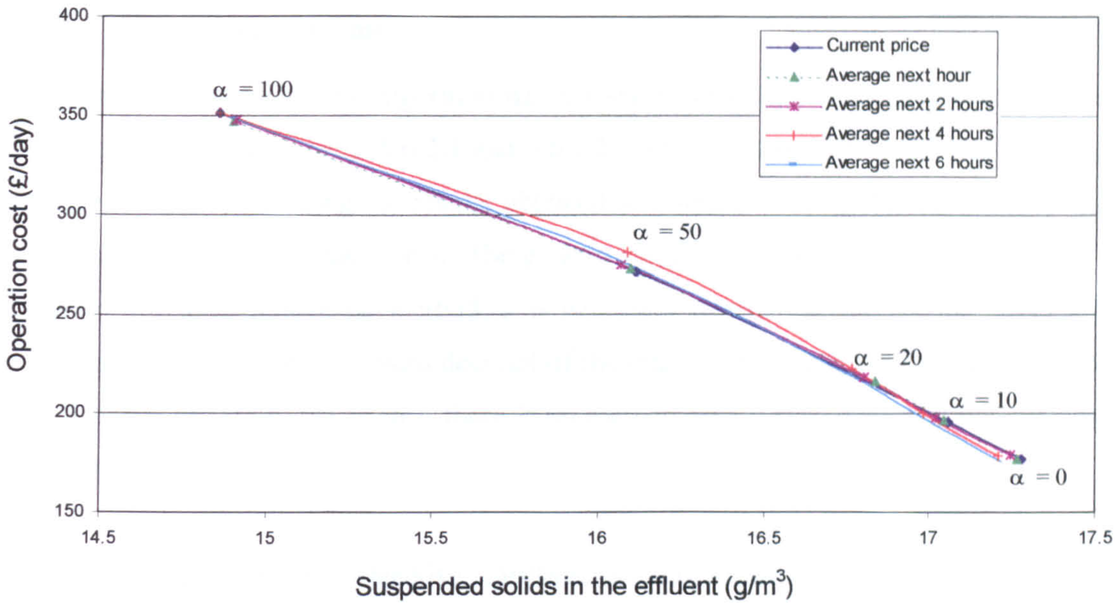


Figure 5.10: Influence of electricity prices averaging (December prices)

The most suitable solution is the one resulting in the lowest suspended solids concentration in the effluent with the lowest operating costs (that is to say as close as possible to the bottom left corner of the graph).

Figure 5.9 seems to give an advantage to longer averages (4 and 6 hours) when the optimisation algorithm is geared towards reducing mainly costs (small values of α) but otherwise, the results are very close.

Figure 5.10, confirms that averages of prices over long periods give slightly better results when one is concerned of reducing prices, by achieving the same cost benefits but with delivering a slightly better effluent quality. However, in the 'mid-range' these same longer averages (4 and 6 hours) are performing less well. There is no clear-cut 'ideal' solution, the 'best' one changing according to the objectives of the optimisation. Therefore it seems reasonable to use only the current electricity prices.

5.6.3 Genetic Algorithms

Optimisation using genetic algorithm has not shown any significant difference with the results obtained in sections 5.6.2.1 and 5.6.2.2 with the conventional non-linear method as can be seen comparing the results obtained for summer and winter electricity prices on Table 5.4 and 5.5 respectively. The genetic algorithm delivers results very similar to the conventional non-linear method; it is necessary to examine the second decimal of the operating costs and the third decimal of the released suspended solids concentration to notice a variation. Even then there is no method which systematically out-performs the other.

It is believed that the objective function is 'too simple', with the non-linearity introduced only by the squaring element on the MLSSsp associated with the surplus activated sludge flow rate. If GAs have not been shown to perform better, their performances are in no way inferior to the other method used. Their only disadvantage is that there are more computations involved, but this should not be a deterrent to their possible use on this process, modern computers coping easily with the computational requirement.

5.7 DISCUSSION

Optimisation has been performed on simulation of the activated sludge process in diverse conditions (electricity cost, temperature, etc). The change of other parameters such as surplus sludge disposal cost, etc, have only a limited impact on the optimisation performance, even though the impact on costs can be important.

From this study it has been seen that it is possible to improve process operation of an activated sludge wastewater treatment plant according to different criteria. The definition of a suitable objective function is the key to successful optimisation, but is a difficult exercise. Many of the parameters needed to determine the objective function are badly defined and are plant specific, such as operating costs of different parts of the process (pumping, disposal of surplus sludge and so on).

Only a few of the elements that are needed to define the objective function required for optimisation are measurable on the real process. Also, it has been seen that in this example different elements first considered tended to minimise the suspended solids concentration in the mixed liquor. This was not desirable for process operation but no mathematical relationship had been developed to take all the process limitations into account. In this case, limits concerning the permissible values of process variables have been set, but such a solution is not always possible when more complex interactions occur. For example, the cost of surplus sludge disposal is for some part dependant upon the initial concentration of the surplus sludge. Such interactions have not been considered since even simple pricing information was difficult to establish.

The control of the mixed liquor suspended solid (MLSS) has been performed successfully; as a result optimisation for cost and quality have been accomplished. However, except in particular circumstances such as badly chosen original set-points it was difficult to improve both the effluent water quality and operation costs simultaneously, and a compromise choice had to be made. A faster response of the control system might be desirable for improved optimisation of cost and quality but is not easily achievable without extra sensors and actuators. The displacement of solids (suspended or settled as sludge) is a relatively slow process compared with dissolved oxygen and sudden variations would have a detrimental effect on the overall process operation leading to the compromise obtained in this study.

It seems possible to define a hierarchical system which would move the priorities between high water quality and low operation cost by manipulating the weighting factor α in the objective function which has been defined in this study according to the state in which the water treatment plant operates and its consent limits.

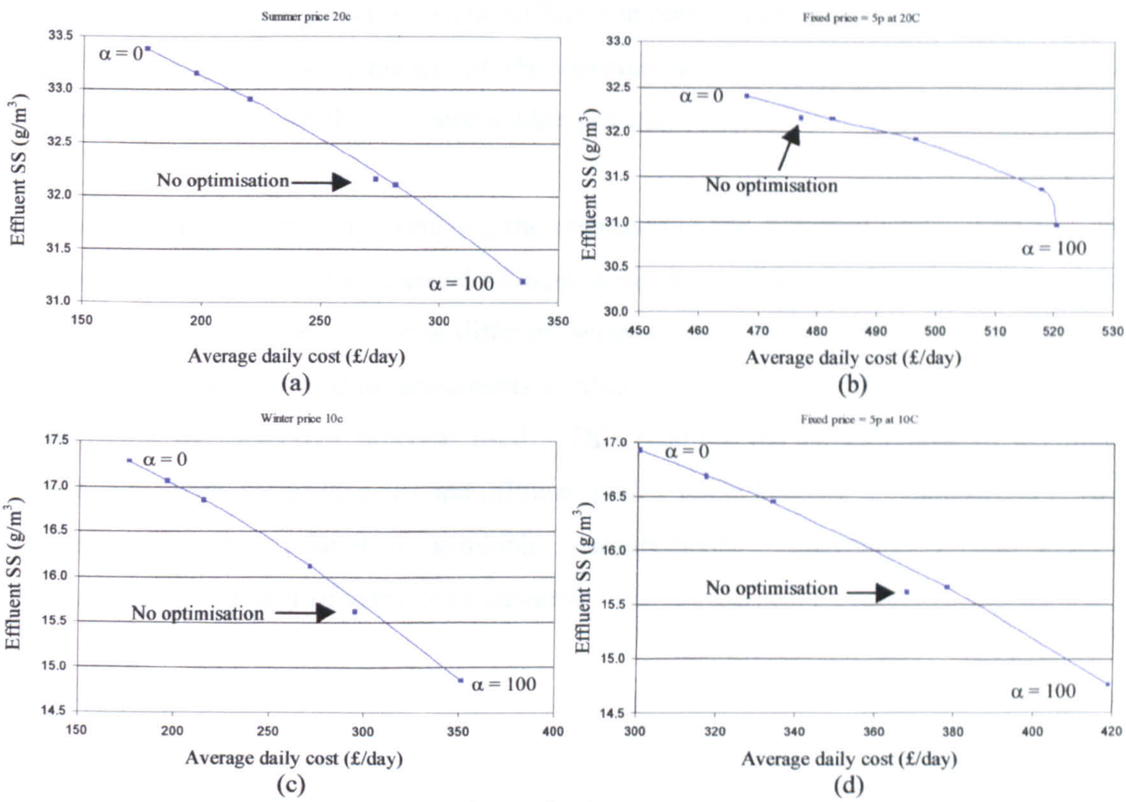


Figure 5.11: Comparison of achieved operating conditions

Figure 5.11 presents the average operating points achieved over the 7 day period of each test. The non-linearity of the process is clearly shown in Figure 5.11(b) where a reduction of released suspended solids of 0.4 g/m^3 is achieved for an extra cost of only £2.5/day. Ideally, the non optimised case should lie above, on the right hand side of the curve linking the different conditions meaning that it has been possible to achieve the same water quality at a lower cost or alternatively a better quality for identical operating cost. Unfortunately, this is not the case even if it is relatively close except for 5.11(d).

These discrepancies are due to the fact that the objective function does not model perfectly the actual modification in process parameters related with change of MLSS concentration, and as a result less than optimal MLSS set-points are devised. This is also why the choice of the actual method employed to determine the mixed liquor suspended solids set-point, $MLSS_{sp}$, (conventional technique or GA) is not of prime importance.

The fact that the actual MLSS value differs sometimes substantially from its set-point also decreases the performance of the optimisation in terms of finding the ideal operating condition for the activated sludge process.

This work has shown that optimising the operation of the activated sludge with respect to costs and quality of the released effluent water is possible. It also showed that it is possible to operate the process at different set-points despite the limitations in terms of controllable variables and measurements available. Further work should concentrate on improving the objective function used. This requires the development of accurate models for both operation costs and effluent quality while keeping the parameters of the developed models related to available measurements. Therefore, it also means increasing the number of variables measured.

Chapter 6

6 CONCLUSIONS AND FURTHER WORK

6.1 CONCLUSIONS

The main elements of an activated sludge wastewater treatment plant have been modelled by combining a state-of-the-art model for the aeration stage with models for secondary settling and separation of the mixed liquor, and quality of the final effluent. The enhancement of the aeration stage model was necessary for control of the plant over a long period of time because of the assumptions made in the original model. For example, perfect separation of solids and liquid in the final settling tank and no release of solids in the effluent were assumed in the original aeration stage model.

The computer simulation developed has been used to investigate three different control problems encountered with the activated sludge process. Control methods for dissolved oxygen in the aeration stage have been developed and compared, the recommended position of a limited number of sensors and actuators for control purposes has been studied and finally the possibility of improving process efficiency has been evaluated. All these problems are of interest to water utilities.

The dissolved oxygen control methods investigated (PID, fuzzy logic and self-tuning control) all present responses which would be suitable for implementation on a real plant. The PID would be the favoured method in many cases, because of the familiarity most control engineers have with this well known and proven technique, it is therefore the easiest technique to implement. However, the tuning of a PID controller for a non-linear, time-varying process is not an easy task. In a wastewater treatment process, the influent flow and sewage characteristics are not easily controllable, this does not permit a repeatable test procedure which is needed for the use of standard tuning methods. This often results in badly or not tuned control loops which would present a worse response than presented for the PID in this work, where tuning has been performed. Fuzzy logic provides an alternative, with similar performance, but offering more flexibility and portability with fewer tuning problems. Although fuzzy logic software is becoming more and more available, the knowledge necessary for the support of fuzzy logic techniques is still not widespread. Moreover, there is no recognised set of empirical rules to give a basic set of parameters for a fuzzy logic controller that is equivalent to PID tuning by a method such as Ziegler-Nichols open-loop (1942). Finally, it is perceived that adaptive methods offer a more practical alternative to conventional methods such as PID, even though they increase the complexity of the control systems. The adaptive nature of a self-tuning controller would allow the update of the controller parameters as the characteristics of the process vary, delivering the most effective control action possible. However, it is undeniable that practical implementation of self-tuning control techniques would not be as simple as PID.

From this study, it can be said that even if the self-tuning controller seems to be the option delivering the best all-round performance, the choice of a control system is not obvious. Except in some applications where controller response is critical, problems of implementation and maintenance of the control system cannot be neglected for pure performances. In the test conducted, all the deviations from the set-point encountered in the simulations performed would be acceptable on a real plant.

However, a control system needs three main elements, the controller being only one of them. Sensors and actuators are also very important. The main problem for controlling dissolved oxygen on an activated sludge wastewater treatment plant is the lack of reliable instrumentation available. Dissolved oxygen sensors need maintenance and are prone to 'ragging' if the screening of the sewage is not done thoroughly. Furthermore, aeration systems are also not always controllable apart from switching aerators on or off, with a timer for example, which is not always a desirable solution since unmixed sludge tends to settle. Additional mixing is therefore required during the phase where the aerators are switched off to prevent sedimentation from occurring in the aeration tanks.

The simulation model of an activated sludge wastewater treatment process also allows the investigation of a variety of possible scenarios, for example to determine where in the plant to install a limited number of sensors and actuators for maximum process operation benefit. In this work, it has been possible to achieve this objective by optimally locating a combination of dissolved oxygen sensors and variable speed aerators. Even though all characteristics and parameters of the plant and influent were not known, the use of a computer simulation based on known data from a real plant has enabled the solution of a real engineering design problem. Simulation can be used to address a wide range of issues, even if the results do not completely reflect the real process, it provides a better knowledge of the process and permits the adoption of better solutions that might otherwise be overlooked. In this example the actual financial advantage of the suggested design over the original NWW proposal cannot precisely be determined because of the uncertainties in the influent data and the lack of measurements prior to installing the new sensors, but nevertheless it seems to be a better solution than the original situation in financial terms and effluent quality.

Improved process operation of an activated sludge wastewater treatment plant according to different criteria, without modifying its design or adding sensors and/or actuators, has also been studied. Improvements in effluent quality have been possible to achieve, as well as reduction of the operating cost, but not simultaneously in the general case. The definition of a suitable objective function seems to be the key to successful optimisation. It is a demanding exercise, especially since the number of measurements available for such an objective function are limited. Improved optimisation performances should be achievable with a more accurate objective function than the one used here. However, this would require in-depth knowledge of the dynamic physical and biological processes involved and much research is still needed in this area. Except in particular circumstances such as badly chosen original set-points, it is difficult to improve both the effluent water quality and operation costs, a choice of one over the other or a compromise between the two objectives has to be made.

It seems possible to define a hierarchical system which would move the priorities between high water quality and low operation cost by manipulating the weighting factor in the objective function, which has been defined in this study, according to the state in which the water treatment plant operates and its discharge consent limits.

6.2 FURTHER WORK

6.2.1 Model improvement

The model used in this work suffers from some limitations which could be reduced. In the aeration stage for example the phosphorus removal function has not been considered since it is not yet of prime importance to the UK water industry. Implementing 'activated sludge model No.2' (Henze *et al*, 1995), from the same IAWQ task group which developed the aeration stage model used in this work, would remedy this problem. However, the extra complexity added and the new sub-classification of the organic elements in the wastewater, reduces its applicability due to a lack of identification of the increased number of model parameters.

The functions of clarification and sludge thickening are of prime importance to the overall process. A more accurate simulation of the behaviour of the final settling tank, including the quality of the released effluent would allow improvement in the optimisation of the process by being able to describe better the interactions between the different units of the process and to develop a more accurate objective function for minimisation. The results of the work of an ad hoc IAWQ task group to that effect are still awaited but are not expected to yield a universally applicable model easily identifiable.

The effluent quality is a concept which can incorporate many different aspects: BOD_5, COD, suspended solids concentrations, colour, odour, etc. Ideally all of the above parameters should be considered. A true optimisation of process operation should encompass and give relative importance to all of the above parameters.

The integration of a complete dynamic model of the activated sludge process would be very desirable. The main problem faced to achieve it is the variability of the process according to both the time variance of a given plant and the difference between plants.

Financial data has proved to be scarce and unreliable. A truly economic approach is difficult because many of the costs are hidden, such as cost of failure of meeting legal discharge limits, and appears only when extending the approach to other parts of the process. For example the cost of dewatering/thickening the surplus sludge for disposal would be modified by changing its concentration but such relationships are difficult to establish. However, detailed knowledge of financial data as well as an accurate model of the released water quality are necessary if efficient optimisation of process operation is to be carried out.

6.2.2 Development of other control methods

The fuzzy logic controller developed here is relatively basic and this approach offers much scope for improvement which is not the case with the conventional PID control method. In most cases it has been possible to compare satisfactorily with the PID controller. An improved design such as a self-learning fuzzy logic controller (Ghwanmeh, 1996) would add the needed adaptive capability to compete with self-tuning techniques. Self-learning fuzzy logic is a field which appears promising because it combines the flexibility of the fuzzy approach to the adjustable nature of adaptive methods.

6.2.3 Including other plant measurements

The use of respirometry within the plant would allow one to perform the most obvious optimisation, that is to say adjustment of the dissolved oxygen set-point. To date the use of respirometers is limited to specific sites such as pilot plants and no respirometer simulation model has so far been incorporated in activated sludge process models.

The use of oxydation-reduction potential (ORP) seems to offer some potential for real-time control of the activated sludge process. Using either the actual ORP value or its change over time (bending point), often associated with dissolved oxygen concentration measurement, has allowed several research teams to develop models which monitor aerobic, anoxic and anaerobic phases in alternate aeration systems (De la Menardiere *et al*, 1991; Wareham *et al*, 1993). Long term testing of such an alternate aeration control system on full-scale plants has been successfully performed recently (Caulet *et al*, 1997). ORP shows a net change in value as the concentration of nitrate decreases (Wareham *et al*, 1993). Control strategies for dissolved oxygen could be developed to take this data into account, allowing one to reduce the DO set-point when total nitrification is achieved.

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Appendices

Appendix A: Typical parameters and characteristic values for the aeration stage model

Stoichiometric parameters

Stoichiometric parameters are not temperature dependent.

Y_H	yield for heterotrophic biomass **[g cell COD formed (g N oxidised)$^{-1}$]**	0.67
Y_A	yield for autotrophic biomass **[g cell COD formed (g COD oxidised)$^{-1}$]**	0.24
f_p	fraction of biomass leading to particulate products **[dimensionless]**	0.08
i_{XB}	mass N / mass COD in biomass **[g N (g COD)$^{-1}$ in biomass]**	0.086
i_{XP}	mass N / mass COD in products from biomass **[g N (g COD)$^{-1}$ in endogenous mass]**	0.06

Kinetic parameters at 20°C

$\hat{\mu}_H$	maximum specific growth rate for heterotrophic biomass **[day^{-1}]**	6.0
K_S	half-saturation coefficient for heterotrophic biomass **[g COD m^{-3}]**	20.0
$K_{O,H}$	oxygen half-saturation coefficient for heterotrophic biomass **[g O_2 m^{-3}]**	0.20
K_{NO}	nitrate half-saturation coefficient for denitrifying heterotrophic biomass **[g NO_3-N m^{-3}]**	0.50
b_H	decay coefficient for heterotrophic biomass **[day^{-1}]**	0.62
$\hat{\mu}_A$	maximum specific growth rate for autotrophic biomass **[day^{-1}]**	0.8
K_{NH}	ammonia half-saturation coefficient for autotrophic biomass **[g NH_3-N m^{-3}]**	1.0
$K_{O,A}$	oxygen half-saturation coefficient for autotrophic biomass **[g O_2 m^{-3}]**	0.4
b_A	decay coefficient for autotrophic biomass **[day^{-1}]**	$0.05<b_a<0.15$
η_g	correction factor for μ_H under anoxic conditions **[dimensionless]**	0.8
k_a	ammonification rate **[m^3 COD (g day)$^{-1}$]**	0.08
k_h	maximum specific hydrolysis rate **[g slowly biodegradable COD (g cell COD day)$^{-1}$]**	3.0
K_X	half-saturation coef for hydrolysis of slowly biodegradable substrate **[g slowly biodegradable COD (g cell COD)$^{-1}$]**	0.03
η_h	correction factor for hydrolysis under anoxic conditions **[dimensionless]**	0.4

Kinetic parameters changing at 10°C

At 10°C the kinetic parameters are identical to those at 20°C except the following:

$\hat{\mu}_H$	maximum specific growth rate for heterotrophic biomass **[day^{-1}]**	3.0
b_H	decay coefficient for heterotrophic biomass **[day^{-1}]**	0.2
$\hat{\mu}_A$	maximum specific growth rate for autotrophic biomass **[day^{-1}]**	0.3
k_a	ammonification rate **[m^3 COD (g day)$^{-1}$]**	0.04
k_h	maximum specific hydrolysis rate **[g slowly biodegradable COD (g cell COD day)$^{-1}$]**	1.0
K_X	half-saturation coef for hydrolysis of slowly biodegradable substrate **[g slowly biodegradable COD (g cell COD)$^{-1}$]**	0.01

Different influent flow concentrations provided

Data are available for average concentration of the influent settled sewage in 3 different treatment plants based respectively in Switzerland, Denmark and Hungary.

Table A.1: Influent sewage concentrations

		Hungary	Denmark	Switzerland
S_S	Concentration of readily biodegradable COD in wastewater [g COD m-3]	100	125	70
S_I	Soluble inert elements[g COD m-3]	30	40	25
X_S	Slowly biodegradable organic matter concentration in wastewater [g COD m^{-3}]	150	250	100
X_I	Particulate inert elements[g COD m^{-3}]	70	100	25
S_{ND}	Concentration of readily biodegradable nitrogen in wastewater [g N m^{-3}]	10	8	5
X_{ND}	Slowly biodegradable organic nitrogen concentration in wastewater [g N m^{-3}]	15	10	10
S_{NH}	Soluble 'ammonia' nitrogen concentration in wastewater [g NH_3-N m^{-3}]	30	30	10
S_{NI}	Soluble inert nitrogen [g N m^{-3}]	3	2	2
S_{NO}	Soluble nitrate nitrogen concentration in wastewater [g NO_3-N m^{-3}]	1	0.5	1

Parameters of the effluent quality model

Table A.2: Influent sewage concentrations

$SS_{init} = 5$ g/m^3	$X_0 \cong$ MLSS in tank 2
$SS_{NO3} = 25$ g/m^3	$SVI = 150$ ml/g
$S_{NO3} \cong S_{NO}$ in IAWQ model 1 (g/m^3)	$\frac{Q_0}{A} \cong$ (Qin$_I$-Qwas)/Area (m/day)
$K_{NO3} = 12$ g/m^3	$K_{hyd} = 1.5$ m^3/d/m^2
$SS_{hyd} = 25$ g/m^3	

Appendix B: Comparison of Euler and Runge-Kutta 4^{th} order integration methods.

Runge-Kutta 4^{th} order and Euler integration methods have been evaluated and compared to determine which method was best suited to perform the integration calculations used in this work. A standard Runge-Kutta (RK) 4^{th} order method has been implemented in the simulation program, in parallel with the Euler method implementation. Both methods were running concurrently and independently (Euler results were feeding the next Euler integration and RK results feeding the next RK integration) in order to be able to observe any discrepancy or a possible drift in the results given by the two methods. The sample time used for the integration is the same for both methods.

Seven days of operation with real data have been simulated even though the results presented here are only related to the first two days of this simulation.

The discrepancy between the two methods (error) is further defined as:

$$Error = Value_{Runge-Kutta} - Value_{Euler}$$

Tank 0 (anaerobic tank)

In the standard three tanks configuration described and used previously, the first tank (called tank 0) is anaerobic. The very small value of oxygen present allows for very large differences as a percentage of total value for the oxygen concentration. Figure B.1 shows the percentage Error with respect to the numerical values obtained with RK4, omitting the oxygen concentration. The discrepancies between the values calculated by the two methods do not diverge by more than 1% if one omits the initial period, and the main point is that there is no persistent variable drift.

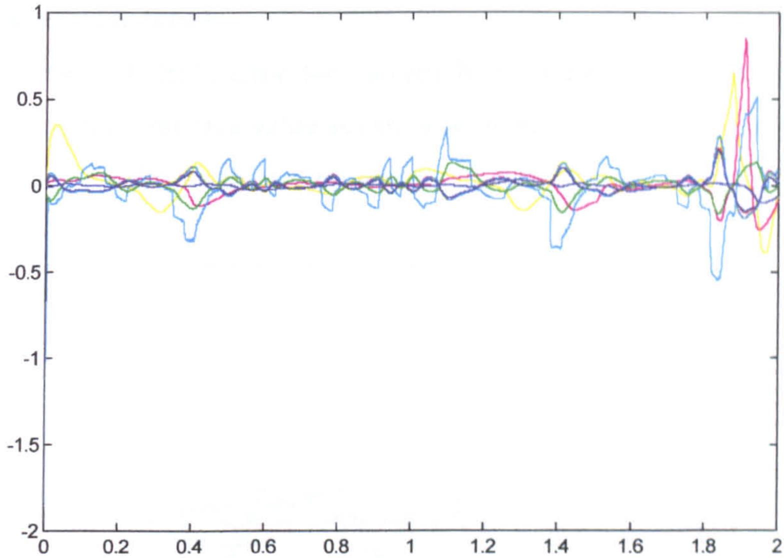

Figure B.1: % Error wrt Runge-Kutta 4 values in Tank 0

Figure B.2 shows the oxygen concentration in Tank 0 for both the RK4 and Euler methods. The scale is in 10^{-4} mg/l, which is not significant for the biological process as such level cannot play any role and cannot be measured accurately. However, the Result given by the RK4 method seems to be more realistic than the Euler method but only in a numerical way not as far as the process representation is concerned.

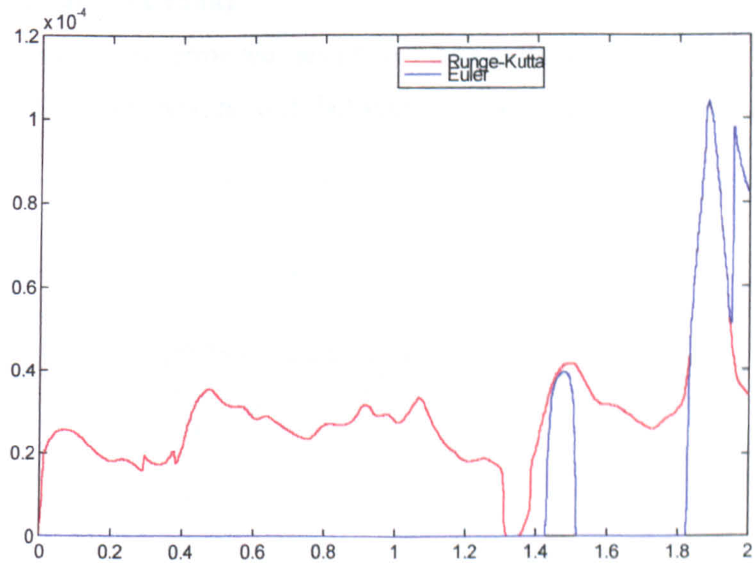

Figure B.2: O_2 concentration in Tank 0

Tank 1 (First aerobic tank)

In the first aerobic tank the % error does not reach 1% at any time, including the dissolved oxygen concentration value as can be seen on Figure B.3. No increasing drift between the Euler and RK4 values is present.

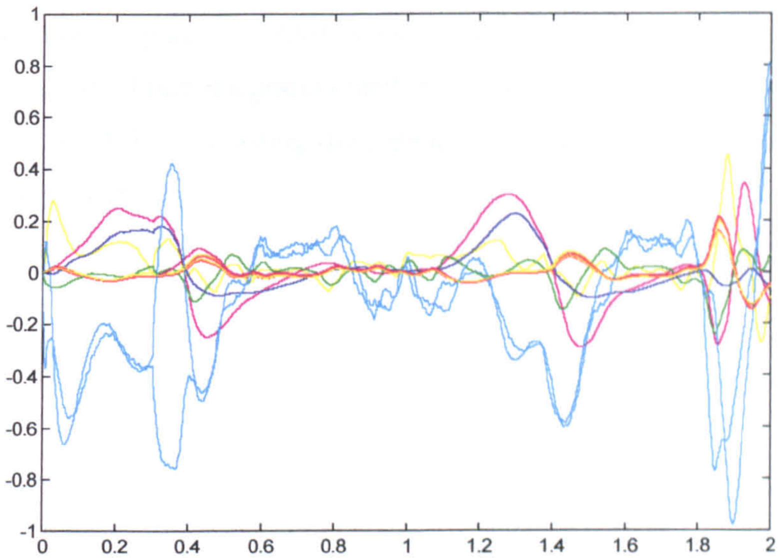

Figure B.3: % Error wrt Runge-Kutta 4 values in Tank 1.

Tank 2 (Second aerobic tank)

Figure B.4 shows that the error reaches up to 1.2 % in the second aerobic tank of the simulated process. However, no drift between the Euler and RK4 data is present.

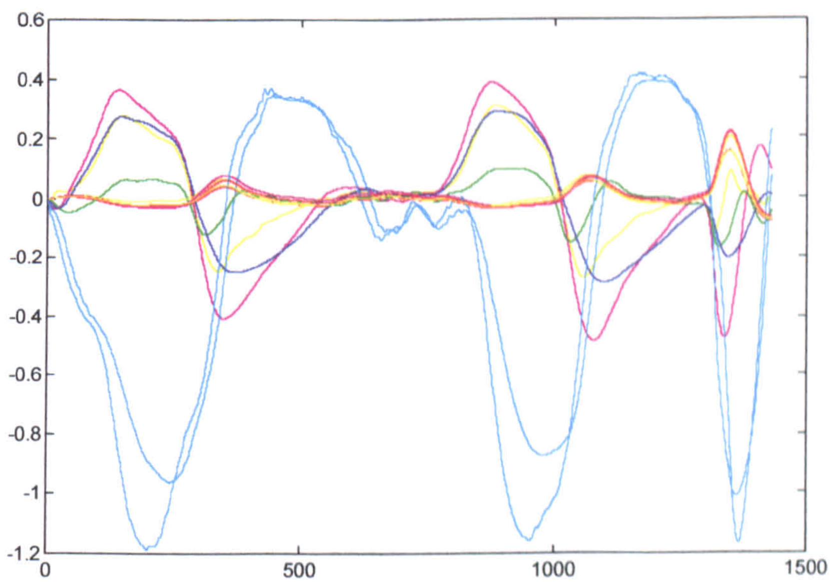

Figure B.4: % Error wrt Runge-Kutta 4 values in Tank 2.

Conclusion:

Both integration methods seem to give equally valid results. Runge-Kutta might be a bit more accurate as the dissolved oxygen concentration values for the anaerobic tank suggest. However, this is not significant for the simulation of the process. The computational time required by RK4 is more than 4 times greater than Euler. It is reasonable to use the Euler integration method for the model implementation since the end result will not differ, no lasting discrepancy between the values obtained by both methods being present.

Appendix C: Root Means Square and Integrated Errors functions

The two main error criteria used for the dissolved oxygen control are Root mean squared (RMS) Error and Integrated Error (IE). These indicators reflect different physical realities.

RMS and IE are defined as:

$$\text{RMS} = \frac{\sqrt{\sum_1^n e(n)^2}}{n}$$

$$\text{IE} = \int e(n)$$

with $e = DO_{measured} - DO_{set\text{-}point}$
and n = number of data samples

RMS is an indicator of the amplitude of the average error whereas IE is an indicator of the cumulated error over time. IE will show if the system is over or under aerated systematically.

Appendix D: Matlab program listing

Initialisations

```
% INWTW6.m: initialisation of WTW7.m
% 3 tanks + clarifier
% DO control + aeration delay
%
% Vincent Turmel
% Control Systems Research Group
% Liverpool John Moores university

%Initialisations
format compact;
%-----------------------------influent parameters
QinI=20000.0;

%-----------------------------Tank0 parameters
V0=500.0;        %Volume of 1st aeration tank
V1=2250.0;       %Volume of 2nd aeration tank
V2=2250.0;       %Volume of 3rd aeration tank

%-----------------------------clarifier parameters
Vc=1560;         %Volume of Secondary Clarifier
a1=3.0;          %min SS in secondary clarifier eff
a2=0.009;        %prop cst for effect of flow on SSeff
a3=4.57;         %setlling parameter
b=0.55;          %setlling parameter
Vu=4.0;          %???NO VALUE GIVEN Underflow velocity
%Asc=490.87;         %Area of secondary clarifier
Asc=1040;        %Area of secondary clarifier
SBHT=1;        %sludge blanket height
SBHmax=2.17;
sbhtt1=SBHT;
sbhtt2=SBHT;
Hcz=0.3;       %compression zone height

%------------------------effluent suspended solids
global NBclar SSinitial SSno3 Kno3 SShyd SVI Khyd Qoutc Sno3 Asc aeration1
               aeration2 QinI Qras Qwas mlvss1sp MLVSS2

NBclar=6;     %number of clarifiers

SSinitial=5; % g/m3
SSno3=25;    % g/m3
Kno3=12;     % g/m3
SShyd=25;    % g/m3
SVI=1.5e-4;  % m3/g !  %150;% ml/g
Khyd=1.5;    % m3/d/m2

%-----------------------------Control parameters
vsunsp=5000; %VSSun setpoint
vssbmx=vsunsp+250;
vssbmn=vsunsp-250;
vsunmx=12000;%VSSun max

so1sp=2.0;
so2sp=2.0;

DO1=so1sp;
DO2=so2sp;
```

```
%---------------------initial conditions tanks,
%                    controllers initial parameters, etc...
%icreal20;   %NORMAL ic for real storm data at 20c (2000 4000)
ic2real2;    %  (2500 5500)

%================================control technique choice:
fuzzy=0
PI=1
STC=0

%-------------------------Self tuning parameters and initialisations
% set estimator initial conditions and model structure
A1=[1 -1.86 .895];B1=[0 .2 -0.058 -0.158];C1=[1 -0.3 -0.0339];
[th1,nn1,phi1] = polyth(A1,B1,C1);
P1=40*eye(length(th1));
lambda1 = .999;
method1 = 'df';
Pn1=[1 0];
Pd1=[1];
Pn1= Pn1/sum(Pn1);
%zcon1=[-0.0272;-0.0335;-0.0412;-0.0439;1.9714;1.9747;1.9825;2;2];

A2=[1 -1.92 .921];B2=[0 .1285 -0.024 -0.105];C2=[1 -0.49 -0.002];
[th2,nn2,phi2] = polyth(A2,B2,C2);
P2=40*eye(length(th2));
lambda2 = .999;
method2 = 'df';
%zcon2=[-0.0377;-0.0453;-0.0426;-0.0945;1.9802;1.9779;1.9763;2;2;2];

%---------------Load fuzzy inference system for Do control in tank 1
contint=readfis('instmc1');
eso11=0;
eso21=0;

%-----------------PI control for oxygen
aerref1=aeration1;
Kaer1=-50/2*1.25;
Tiaer1=.002;

aerref2=aeration2;
Kaer2=-30/2*1.25;
Tiaer2=.002;

aermax=800e3;

% Recycled and wasted sludge flow rate control parameters
evssun=0;
Kwas=2;
Tiwas=.5;
qwasmax=8000;

emlvss1=0;
Kras=-15; %30
Tiras=.02; %.2
iemlvss1=iemlvss1/10;
qrasmin=50;
qrasmax=30e3;

Qoutcmin=500;%minimum output flow rate

%----------------influent waste water parameters

denmark;      %high concentration
%switzerl;    %low
%hungary;     %medium

% ---------------aeration model parameters
```

```
global fp mua muh nug nuh Ya Yh ba bh ka kh Kx Knh Ks Koa Koh Kno ixb ixp
aerat20c; % aeration model parameters at 20 degree C
%aerat10c; % at 10 degree C

DOmax=10;

%----process rate init
% rates([rSs rXs rSno rSnh rSnd rXnd rXbh rXba rSo rXp rSi rSni rXi])
rates=[0 0 0 0 0 0 0 0 0 0 0 0 0];

IEso1=0;ISEso1=0;
IEso2=0;ISEso2=0;

needsox1=0;
needsox2=0;

donoise=0.01;
index1=1;
%tsamp=0.00035; % = 30sec
tsamp=30/86400;
tlog=4; %4;  *tsamp
index2=tlog;
dosamp=4; %*tsamp
index4=dosamp;
slsamp=12;   %12;
index3=slsamp;

%---------------------Financial Cost
global kgO2pkWh costkWh costm3 costwas
kgO2pkWh=1.3;
costkWh=.05;
costm3=0.005;
costwas=.15;

%-------optimisation
%toptim=240; % *tsamp ==2 hours
toptim=60;   % *tsamp ==30 minutes
index5=0;

if exist('timestop')==0
     timestop=0.1;
elseif size(timestop,1)==0
     timestop=0.1;
end  %endif

t=0.0;

ProdI=prodI;
%--------------cost function initialisation
intaerat1=0;
intaerat2=0;
intqwas=0;
intqras=0;

%-------------transport delay
%delay1=0.08333;  %delay in days
delay1=1/3/24;  %delay in days
delay1samp=round(delay1/tsamp);
for i=1:delay1samp
     delayprodc(i,:)=prodc;
end

delay2=3/24;  %delay in days (Effluent SS)
delay2samp=round(delay2/tsamp);
```

```
initSSf=SSinitial + SSno3*prod2(3)/(Kno3+prod2(3)) + SShyd*MLSS2*SVI*(((QinI-
              Qwas)/NBclar)/Asc)/(Khyd+MLSS2*SVI*(((QinI-
              Qwas)/NBclar)/Asc));
for i=1:delay2samp
    delaySSf(i)=initSSf;
end


%load realdata.dat
%plantdata=interp1(realdata(:,1),realdata(:,2:4),0:tsamp:.5,'linear');
%load inf_strm.dat
%plantdata=interp1(inf_strm(:,1),inf_strm(:,2:10),0:tsamp:14,'linear');
load strmdata
```

Main program

```
% WTW7, Change in clarifier model with noise and delay
% +GA
% 3 tanks + clarifier
% DO control + do reading delay + cost function
%
% inwtw6 and 7 should be run first
% use dataw6 to display results
%
% Vincent Turmel
% Control Systems Research Group
% Liverpool John Moores university

tic;

for t=t:tsamp:timestop

QinI=flowth1(t);

%QinI=plantdata(t/tsamp+1,9);          %real data
%prodI=[plantdata(t/tsamp+1,1) plantdata(t/tsamp+1,3) 1 plantdata(t/tsamp+1,5)
              plantdata(t/tsamp+1,7) plantdata(t/tsamp+1,8)
              plantdata(t/tsamp+1,2) 0 0 0 plantdata(t/tsamp+1,6) 2
              plantdata(t/tsamp+1,4)];

Qin0=Qras+QinI;
Qout0=Qin0;
Qin1=Qout0;
Qout1=Qin1;
Qin2=Qout1;
Qout2=Qin2;
Qoutc=QinI-Qwas;

% tank0
rates=update4(prod0);
prod0=positiv(prod0+((Qras*prodc+QinI*prodI-Qout0*prod0)/V0+rates)*tsamp);
prod0(9)=0.01;  % So0
MLSS0=mlss(prod0);
MLVSS0=MLSS0*.7;

% tank 1
rates=update4(prod1);
prod1=positiv(prod1+((Qout0*prod0-Qout1*prod1)/V1+rates)*tsamp);
prod1(9)=prod1(9)+aeration1*24000/V1*tsamp*(DOmax-prod1(9))/DOmax;   % So1
MLSS1=mlss(prod1);
MLVSS1=MLSS1*.7;

% tank 2
rates=update4(prod2);
prod2=positiv(prod2+((Qout1*prod1-Qout2*prod2)/V2+rates)*tsamp);
prod2(9)=prod2(9)+aeration2*24000/V2*tsamp*(DOmax-prod2(9))/DOmax;   % So2
MLSS2=mlss(prod2);
MLVSS2=MLSS2*.7;

%----------------------------Clarifier
SSeff=a1+a2*(QinI+Qras)/NBclar;

Sno3=prod2(3);
%X0=MLSS2;
SSfd=SSinitial + SSno3*Sno3/(Kno3+Sno3) +
              SShyd*MLSS2*SVI*(Qoutc/NBclar/Asc)/(Khyd+MLSS2*SVI*(Qoutc/NBcl
              ar/Asc));

VSSfd=SSfd*0.7;
VSSeff=SSeff*0.7;
```

```
Vs=a3*exp(-b*MLSS2*.7/1000);
Vu=(Qras+Qwas)/(Asc*NBclar);
%VSSsb=positiv(VSSsb+(MLSS2*.7*(QinI+Qras)-VSSfd*(QinI-Qwas)-
                VSSsb*(Qwas+Qras))/(Asc*SBHT)/NBclar*tsamp);
VSSsb=positiv(VSSsb+((MLSS2*.7*(QinI+Qras)-VSSfd*(QinI-Qwas))/NBclar/Asc-
                VSSsb*(Vs+Vu))/SBHT*tsamp);

Gt=(MLSS2*Vs+MLSS2*Vu);
Ga=(Qras+QinI)/(Asc*NBclar)*MLSS2;

if VSSsb >= 12000
     VSSsb=12000;
     end %if
if Ga>=Gt
     SBHT=SBHT+.0005;
%    SBHT=SBHT*1.001;
     end

if Ga<=Gt
     SBHT=SBHT-.0005;
%    SBHT=SBHT*.999;
     end
if SBHT >= SBHmax
     SBHT=SBHmax;
     end %if
if SBHT <= 0.1
     SBHT=0.1;
     end %if
sbhtt2=sbhtt1;
sbhtt1=SBHT;
VSSun=positiv(VSSun+((VSSsb*(Vs+Vu)-VSSun*Vu)/Hcz)*tsamp);
if VSSun >= vsunmx
      VSSun=vsunmx;
     end %if
concun=VSSun/(MLSS2*.7);

% delayed prodc
prodc=delayprodc(1,:);
delayprodc(1:delay1samp-1,:)=delayprodc(2:delay1samp,:);
delayprodc(delay1samp,:)=prod2.*[1 concun 1 1 1 concun concun concun .1 concun
            1 1 concun];

SSf=delaySSf(1);
delaySSf(1:delay2samp-1)=delaySSf(2:delay2samp);
delaySSf(delay2samp)=SSfd;

%----------------------Integrated Errors
IEso1=IEso1+(prod1(9)-so1sp)*tsamp;
ISEso1=ISEso1+(prod1(9)-so1sp)^2*tsamp;
IEso2=IEso2+(prod2(9)-so2sp)*tsamp;
ISEso2=ISEso2+(prod2(9)-so2sp)^2*tsamp;

%-----------------------Cost function
intaerat1=intaerat1+aeration1*tsamp;
intaerat2=intaerat2+aeration2*tsamp;
intqwas=intqwas+Qwas*tsamp;
intqras=intqras+Qras*tsamp;

%========================================O2 control

DO1=positiv(DO1+(prod1(9)+randn*donoise*so1sp-DO1)*(1-1/exp(720*tsamp)));
DO2=positiv(DO2+(prod2(9)+randn*donoise*so2sp-DO2)*(1-1/exp(720*tsamp)));

if index4>=dosamp

eso1=DO1-so1sp;
```

```
eso2=DO2-so2sp;
ieso1=ieso1+eso1*tsamp*dosamp;
ieso2=ieso2+eso2*tsamp*dosamp;

 if fuzzy==1
     %aerrate1=evalfis(eso1,cont1);
     %aeration1=aeration1*aerrate1;
     aerrate1=evalfis([eso1 eso1-eso11],contint);
     aeration1=aeration1+aerrate1/2.5*1.25; %stability pb at low flow

     %aerrate2=evalfis(eso2,cont1);
     %aeration2=aeration2*aerrate2;
     aerrate2=evalfis([eso2 eso2-eso21],contint);
     aeration2=aeration2+aerrate2/5*1.25;    %stability pb at low flow

eso11=eso1;
eso21=eso2;

  end

 if PI==1
     if ieso1<-.05 & eso1>0
             ieso1=0;
     end
     aeration1=positiv(Kaer1*(eso1+ieso1/Tiaer1));

     if ieso2<-.05 & eso2>0
             ieso2=0;
     end
     aeration2=positiv(Kaer2*(eso2+ieso2/Tiaer2));
 end

 if STC==1
     %[F1,G1,H1]=gpc(A1,B1,C1,Pn1,Pd1,5,1,1.5,1);    %predictive control
     [F1,G1,H1]=gpc(A1,B1,C1,Pn1,Pd1,2,1,1.5,1);     %predictive control
     if exist('zcon1')==0
             [aercon1,zcon1]=cntrl(F1,G1,H1,DO1,so1sp);
     else
             [aercon1,zcon1]=cntrl(F1,G1,H1,DO1,so1sp,zcon1);
     end
     aeration1=positiv(aercon1*aerref1+aerref1);
     [th1,eta1,P1,phi1] = rmlk([(DO1-so1sp)/so1sp (aeration1-
                  aerref1)/aerref1],nn1,method1,lambda1,P1,th1,phi1);
     %P1=4/trace(P1)*P1;
     [A1,B1,C1] = thpoly(th1,nn1);

     [F2,G2,H2]=gpc(A2,B2,C2,1,1,2,1,1.5,1); %predictive control
     if exist('zcon2')==0
             [aercon2,zcon2]=cntrl(F2,G2,H2,DO2,so2sp);
     else
             [aercon2,zcon2]=cntrl(F2,G2,H2,DO2,so2sp,zcon2);
     end
     aeration2=positiv(aercon2*aerref2+aerref2);     %positional control
     [th2,eta2,P2,phi2] = rmlk([(DO2-so2sp)/so2sp (aeration2-
                  aerref2)/aerref2],nn2,method2,lambda2,P2,th2,phi2);
     %P2=450/trace(P2)*P2;
     [A2,B2,C2] = thpoly(th2,nn2);
 end


 if aeration1>aermax
    aeration1=aermax;
 end
 if aeration2>aermax
    aeration2=aermax;
 end
```

```
%-------------calculate instantaneous daily running cost
%   cost=(aeration1+aeration2)*24/kgO2pkWh*costkWh+Qras*costm3+Qwas*costwas;

index4=0;
end %if
index4=index4+1;

%=====================================   OPTIMISATION
if index5>=toptim

%optimga2;   % GA's optimisation %optimga1
optim3;      % Linear optim constrained  %optim2

index5=0;
end
index5=index5+1;


%------------------------------Flow control
if index3>=slsamp
      evssun=VSSun-vssunsp;
      ievssun=ievssun+evssun*tsamp*slsamp;
      if evssun>0 & ievssun<0
              ievssun=0;
      end
      if evssun<0 & ievssun>400
              ievssun=0;
      end
      Qwas=positiv(Kwas*(evssun+ievssun/Tiwas));
      if Qwas>qwasmax
              Qwas=qwasmax;
      end

      emlvss1=mlss(prod0)*.7-mlvss1sp;
      iemlvss1=iemlvss1+emlvss1*tsamp*slsamp;
      if emlvss1<0 & iemlvss1>0
              ievssun=0;
      end
      Qras=positiv(Kras*(emlvss1+iemlvss1/Tiras));

      if Qras>qrasmax
              Qras=qrasmax;
      end
      if Qras<qrasmin
              Qras=qrasmin;
      end

      home;
      disp('Calculated days =');disp(t);
      toc;
index3=0;
end
index3=index3+1;


%------------------------------------ plotable variables
if index2>=tlog
      time(index1)=t;
      PROD0(index1,:)=prod0;
      PROD1(index1,:)=prod1;
      PROD2(index1,:)=prod2;
      PRODc(index1,:)=prodc;
      PRODI(index1,:)=prodI;
      dom(index1,:)=[DO1,DO2];
      aerat(index1,:)=[aeration1,aeration2];
      mlvsssp(index1,:)=mlvss1sp;
      vssun(index1)=VSSun;
```

```
     flow(index1,:)=[QinI,Qras,Qwas];
%
                    ssf(index1,:)=[SSeff,SSf,SSno3*Sno3/(Kno3+Sno3),SShyd*MLSS2
              *SVI*((Qoutc/NBclar)/Asc)/(Khyd+MLSS2*SVI*((Qoutc/NBclar)/Asc)
              )];
     ssf(index1,:)=[SSeff,SSf];
     sbht(index1)=SBHT;
     flux(index1,:)=[Gt,Ga];
     vsssb(index1)=VSSsb;
     index1=index1+1;
     index2=0;
end  %endif datastorage

index2=index2+1;
end     % of for loop used for time
```

Aeration stage process rates updating

```
function rates=update4(prodx)

% process rate for the dissolved matter in
% aeration stage of a Activated Sludge Process
%
% Vincent Turmel
% Control Systems Research Group
% Liverpool John Moores university

global fp mua muh nug nuh Ya Yh ba bh ka kh Kx Knh Ks Koa Koh Kno ixb ixp

%Ss=prodx(1);
%Xs=prodx(2);
%Sno=prodx(3);
%Snh=prodx(4);
%Snd=prodx(5);
%Xnd=prodx(6);
%Xbh=prodx(7);
%Xba=prodx(8);
%So=prodx(9);
%Xp=prodx(10);

%----------Readily biodegradable substrate
% rSs=(-
muh*Ss*Xbh/(Yh*(Ks+Ss))*(So+Koh*Sno/(Kno+Sno)*nug)+kh*Xs/(Kx+(Xs/Xbh))*(So+nuh
*Koh*Sno/(Kno+Sno)))/(Koh+So);
rates(1)=(-
muh*prodx(1)*prodx(7)/(Yh*(Ks+prodx(1)))*(prodx(9)+Koh*prodx(3)/(Kno+prodx(3))
*nug)+kh*prodx(2)/(Kx+(prodx(2)/prodx(7)))*(prodx(9)+nuh*Koh*prodx(3)/(Kno+pro
dx(3))))/(Koh+prodx(9));

%----------Slowly biodegradable substrate
% rXs=(1-fp)*(bh*Xbh+ba*Xba)-kh*Xs/( (Kx+(Xs/Xbh))*(Koh+So) )*(
So+nuh*Koh*Sno/(Kno+Sno) );
rates(2)=(1-fp)*(bh*prodx(7)+ba*prodx(8)) -kh*prodx(2)/(
(Kx+(prodx(2)/prodx(7)))*(Koh+prodx(9)) )*(
prodx(9)+nuh*Koh*prodx(3)/(Kno+prodx(3)) );

%----------Active heterotrophic biomass
% rXbh=( muh*Ss/( (Ks+Ss)*(Koh+So) )*(So+Koh*Sno/(Kno+Sno)*nug ) -bh )*Xbh;
rates(7)=( muh*prodx(1)/( (Ks+prodx(1))*(Koh+prodx(9))
)*(prodx(9)+Koh*prodx(3)/(Kno+prodx(3))*nug ) -bh )*prodx(7);

%----------Oxygen (negative COD)
% rSo=So*( (Yh-1)/Yh*muh*(Ss/(Ks+Ss))/(Koh+So)*Xbh-(4.57-
Ya)/Ya*mua*(Snh/(Knh+Snh))/(Koa+So)*Xba );
rates(9)=prodx(9)*( (Yh-
1)/Yh*muh*(prodx(1)/(Ks+prodx(1)))/(Koh+prodx(9))*prodx(7)-(4.57-
Ya)/Ya*mua*(prodx(4)/(Knh+prodx(4)))/(Koa+prodx(9))*prodx(8) );

%----------Nitrate and nitrite nitrogen
% rSno=(Yh-
1)/(2.86*Yh)*muh*(Ss/(Ks+Ss))*(Koh/(Koh+So))*(Sno/(Kno+Sno))*nug*Xbh+1/Ya*mua*
(Snh/(Knh+Snh))*(So/(Koa+So))*Xba;
rates(3)=(Yh-
1)/(2.86*Yh)*muh*(prodx(1)/(Ks+prodx(1)))*(Koh/(Koh+prodx(9)))*(prodx(3)/(Kno+
prodx(3)))*nug*prodx(7)+1/Ya*mua*(prodx(4)/(Knh+prodx(4)))*(prodx(9)/(Koa+prod
x(9)))*prodx(8);

%----------NH4+ and NH3 nitrogen
% rSnh=Xbh*( -ixb*muh*Ss/((Ks+Ss)*(Koh+So))*( So+Koh*Sno/(Kno+Sno)*nug
)+ka*Snd ) -mua*(ixb+1/Ya)*Snh/(Knh+Snh)*So/(Koa+So)*Xba;
```

```
rates(4)=prodx(7)*(-ixb*muh*prodx(1)/((Ks+prodx(1))*(Koh+prodx(9)))*(
prodx(9)+Koh*prodx(3)/(Kno+prodx(3))*nug )+ka*prodx(5) ) -
mua*(ixb+1/Ya)*prodx(4)/(Knh+prodx(4))*prodx(9)/(Koa+prodx(9))*prodx(8);

%----------Soluble biodegradable organic nitrogen
% rSnd=-ka*Snd*Xbh+kh*Xnd/( (Kx+(Xs/Xbh))*(Koh+So) )*(
So+nuh*Koh*Sno/(Kno+Sno) );
rates(5)=-ka*prodx(5)*prodx(7)+kh*prodx(6)/(
(Kx+(prodx(2)/prodx(7)))*(Koh+prodx(9)) )*(
prodx(9)+nuh*Koh*prodx(3)/(Kno+prodx(3)) );

%----------Particulate biodegradable organic nitrogen;
% rXnd=(ixb-fp*ixp)*(bh*Xbh+ba*Xba)-kh*Xnd/( (Kx+(Xs/Xbh))*(Koh+So) )*(
So+nuh*Koh*Sno/(Kno+Sno) );
rates(6)=(ixb-fp*ixp)*(bh*prodx(7)+ba*prodx(8))-kh*prodx(6)/(
(Kx+(prodx(2)/prodx(7)))*(Koh+prodx(9)) )*(
prodx(9)+nuh*Koh*prodx(3)/(Kno+prodx(3)) );

%----------Active autotrophic biomass
% rXba=( mua*(Snh/(Knh+Snh))*(So/(Koa+So)) -ba )*Xba;
rates(8)=( mua*(prodx(4)/(Knh+prodx(4)))*(prodx(9)/(Koa+prodx(9))) -ba
)*prodx(8);

%----------Particulate products arising from biomass decay
% rXp=fp*(bh*Xbh+ba*Xba);
rates(10)=fp*(bh*prodx(7)+ba*prodx(8));

%rSi=0;
rates(11)=0;
%rSni=0;
rates(12)=0;
%rXi=0;
rates(13)=0;
```

Aeration stage model parameters at 20c definition

```
% aeration model parameters at 20 degree C
%
% Vincent Turmel
% Control Systems Research Group
% Liverpool John Moores university

global fp mua muh nug nuh Ya Yh ba bh ka kh Kx Knh Ks Koa Koh Kno ixb ixp

fp=0.08;
mua=0.8;
muh=6.0;
nug=0.8;
nuh=0.4;
Ya=0.24;
Yh=0.67;
ba=0.05;
bh=0.62;
ka=0.08;
kh=3.0;
Kx=0.03;
Knh=1.0;
Ks=20.0;
Koa=0.4;
Koh=0.2;
Kno=0.5;
ixb=0.086;
ixp=0.06;
```