Ph.D. Thesis

Development of modelling, control and optimization tools for the activated sludge process

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Doktori (PhD) értekezés

Eleveniszapos szennyvíztisztító rendszerek modellezésére, szabályozására és optimalizálására szolgáló módszerek fejlesztése

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Soli deo gloria!

Kivonat

A matematikai modellezés napjainkra a szennyvíztisztító telepek tervezésének és üzemeltetésének fontos részévé vált, mivel segítségével pontosan bemutathatók az üzemeltető részére a telepen lejátszódó folyamatok, felhasználható a tervezési fáziban különböző technológiai megoldások kiértékelésére és a meglevő telepek üzemeletetésének optimalizálásához is. Így dolgozatomban a biológiai szennyvíztisztítás modellezésére és hatékonyabb üzemeltetésére szolgáló módszereket vizsgálok meg. Az előírt határértékeknek megfelelő üzemeltetés érdekében a levegőztetés hatékonyságát javító módszereket dolgoztam ki, majd az irodalomban található modellek alkalmazhatóságával, összehasonlításával foglalkoztam.

Egy optimalizálási módszert fejlesztettem ki, mely a befogadóba kerülő szennyezőanyag-terhelést csökkentő oly módon, hogy az optimális levegőztetési időtartamot meghatározza ciklikus levegőztetésű szennyvíztelepek esetén. A esettanulmány szimulációs eredményei azt mutatják, hogy a elfolyó vízben levő szennyezőanyagok mennyisége akár 10%-al is csökkenthető a hagyományos szabályozási stratégiához képest.

Az oldottoxigén-koncentráció szabályozására egy modell prediktív szabályozási algoritmust vizsgáltam, melynek feladta az oxikus reaktorban az oxigénkoncentráció egy adott szinten tartása. A szimulációs eredmények azt mutatják, hogy a módszer hatékonyan alkalmazható az oxigénkoncentráció szabályozására: a koncentráció maximális eltérése az előírt értéktől 0.2 mg/l alatt maradt a jelentősen változó mennyiségű és összetételű befolyó szennyvíz

ellenére.

A biológiai reaktorrész bármilyen jó hatásfokkal is működhet, ha az ülepítő nem képes megfelelően visszatartani a lebegő részecskéket a telep működésében jelentős zavarok keletkezhetnek. Az utóülepítő modellezésére szolgáló hat matematikai modellt mutattam be és hasonlítottam össze munkámban egy szimulációs protokoll segítségével. A dinamikus szimulációk eredményei azt mutatták, hogy az irodalmi adatok paramétereivel alkalmazott ülepítőmodellek jelentős eltéréseket eredményezhetnek a becsült elfolyó lebegőanyag-koncentráció tekintetében.

Végül a matematikai modellezés alkalmazhatóságát egy esettanulmányon mutatom be. Egy telep működése során jelentős foszforkoncentráció emelkedés volt megfigyelhető bizonyos időszakokban, s ennek a problémának a kivizsgálására és azonosítására alkalmaztunk számítógépes szimulációt. Számítógépes szimuláció alkalmazásával a jelenség okai könnyen azonosíthatók voltak és megoldási javaslatot lehetett adni a probléma kezelésére is.

Abstract

Mathematical modelling is a significant part of wastewater treatment system design since it can enhance the process understanding of the operator, it can be used for process design and it can be used for the optimization of the process. For these reasons, modelling and control tools have been developed and applied to the biological wastewater treatment process in this thesis. In order to comply the industry standards during the operation, different methods have been introduced to enhance the efficiency of the aeration, furthermore, applicability and comparison of wastewater treatment models available in literature have been assessed.

An optimization procedure has been introduced to reduce the effluent pollution load in the receiving body by determining the adequate aeration cycle lengths. It was found that applying this stochastic optimization method on an intermittently aerated activated sludge process using simulated case study approach, the effluent pollution load can be reduced by more than 10% compared to traditional methods.

In another study, model predictive control has been applied to control the dissolved oxygen concentration in an aerobic reactor of a wastewater treatment plant. The results show that this method can be efficiently used for dissolved oxygen control: the maximum deviation of the concentration from the pre-defined setpoint remained under 0.2 g O_2/m^3 in spite of the significantly changing quality and quantity of incoming wastewater.

The biological reactor might be meeting the required effluent standards,

however, by not capturing the suspended solids adequately, could cause a possible failure in the operation of the facility. For this reason, six one-dimensional secondary settler models have been introduced and compared based on a Simulation Benchmark. The results of the dynamic simulations showed that significantly differences suspended solids concentrations can be estimated with the different models using the published model parameters.

Finally, the applicability of the mathematical modelling is introduced by a case-study approach. The phenomenon of a drastic phosphorus concentration increase in the effluent was investigated and identified using computer-aided simulation technique. The practical results justified that wastewater treatment modelling can be efficiently used in the case of operating facilities as well.

Abstrait

Modeler mathématique est une partie significative de systemes de traitement des eaux résiduaires puisqu'il peut augmenter l'arrangement de processus de l'opérateur, il peut être employé pour la conception de processus et il peut être employé pour l'optimisation du processus. Pour ces raisons, modeler et outils de commande ont été développés et appliqués au processus biologique de traitement des eaux résiduaires.

Un procédé d'optimisation a été présenté pour réduire la charge effluente de pollution dans le corps de réception en déterminant à longueurs proportionnées de cycle d'aération. On l'a constaté qu'appliquant cette méthode stochastique d'optimisation à une approche simulée employante de processus par intermittence aérée d'étude de cas de boues activées, la charge effluente de pollution peut être réduite par plus de 10% comparé aux méthodes traditionnelles.

Dans une autre étude, la commande prédictive de modèle a été appliquée pour commander la concentration dissous en oxygène dans un réacteur aérobie d'une usine de traitement des eaux résiduaires. Les résultats prouvent que cette méthode peut être efficacement employée pour la commande dissous d'oxygène : la déviation maximum de la concentration du setpoint prédéfini est demeurée au-dessous de 0.2 g O_2/m^3 malgré la qualité et la quantité changeantes de manière significative d'eau usagée entrante.

Le réacteur biologique pourrait répondre aux normes effluentes exigées, cependant, en ne capturant pas les solides en suspension en juste proportion,

a pu causer un échec possible dans l'opération du service. Pour cette raison, six modèles secondaires unidimensionnels de colon ont été présentés et comparés basé sur un 'Simulation Benchmark'. Les résultats des simulations dynamiques ont prouvé que sensiblement des concentrations suspendues par différences en solides peuvent être estimées avec les différents modèles en utilisant les paramètres modèles édités.

En conclusion, l'applicabilité de modeler mathématique est prouvée par cas-étude. Le phénomène d'une augmentation énergique de concentration en phosphore de l'effluent a été étudié et résolu en utilisant la technique assistée par ordinateur de simulation. Les résultats pratiques ont justifié que modeler de traitement des eaux résiduaires peut efficacement être aussi bien employé dans le cas des équipements de fonctionnement.

PhD theses

Within the framework of my PhD research, a biological wastewater treatment simulator program has been developed in Matlab/Simulink program. This allowed the modelling of the activated sludge wastewater treatment process based on the Activated Sludge Model No. 1 and the modelling of the secondary settling tank based on different one-dimensional settling tank models. By using this simulator program, the following scientific results were achieved:

1. **It was found that the effluent nitrogen pollution load of intermittently aerated wastewater treatment plants can be reduced by more than 10% using optimal aeration periods in certain cases based on the results of computer simulation.**
   Since the operation of the intermittently aerated wastewater treatment process is challenging both for economical and technical reasons, an operational optimization method has been introduced for the efficient operation of these facilities. The goal of the introduced procedure is to reduce the effluent pollution load in the receiving body by determining the adequate aeration cycle lengths. It was found that applying this stochastic optimization method on an alternating activated sludge process using simulated case study approach, the effluent pollution load can be reduced by more than 10%. It can be also concluded, that the TKN and NO_3-N can be reduced with more than 10% (0.2–0.5 g/m^3), while the COD/BOD_5 reduction is not so significant.

2. **It has been shown that model predictive control algorithm can be efficiently applied for the dissolved oxygen level control of aerated basins, furthermore, gives better tunability than traditional control methods.**

   Activated sludge wastewater treatment processes are difficult to be controlled because of their complex and nonlinear behaviour, however, the control of the dissolved oxygen level in the reactors plays an important role in the operation of the facility. For this reason a new approach has been studied: model predictive control has been applied to control the dissolved oxygen concentration in an aerobic reactor of a wastewater treatment plant. The proposed control approach has been tested on a pre-denitrification plant and on an alternating activated sludge process using simulated case-study approach. The results show that this method can be efficiently used for dissolved oxygen control: the maximum deviation of the concentration from the pre-defined setpoint remained under 0.2 g O_2/m^3 in spite of the significantly changing quality and quantity of incoming wastewater.

3. **Different published one-dimensional settling tank models give significantly different estimation of the over- and underflow suspended solids concentration, however, the solids distributions around the inlet point are similar at all models.**

   The biological reactor might be meeting the required effluent standards, however, by not capturing the suspended solids adequately, could cause a possible failure in compliance with the COD (BOD_5), total N and P standards. The applied mathematical models allow the influences of inlet arrangement, sludge collection systems and sludge density currents to be modelled accurately. For this reason, six one-dimensional secondary settler models have been introduced and compared (the model of Takács, Härtel, Otterpohl, Dupont, Hamilton and a reactive model) based on a Simulation Benchmark. The results of the dynamic simulations – under dry and wet weather conditions with daily and weekly change in the influent wastewater composition and quantity – showed that significantly differences suspended solids concentrations can be estimated with the different models using the published

model parameters. The highest effluent solids concentration is estimated by the Dupont model (30-35 g/m3), the lowest concentration is predicted by the Otterpohl model (10 g/m3) while the Takács model defined in the Simulation Benchmark approximated 12.5 g/m^3 effluent concentration.

Contents

List of symbols

Abbreviation	Name	Unit
AE	Aeration energy	kWh/d
B_i	Weight factor for effluent quality index	-
b_H	Decay rate coefficient for heterotrophic organisms	d^{-1}
b_A	Decay rate coefficient for autotroph organisms	d^{-1}
BOD_5	Biochemical oxygen demand – 5 days	mg O/L
COD	Chemical oxygen demand	mg O/L
$E.Q.$	Effluent quality index	-
f_{ns}	Fraction of biomass yielding (inert) particulate products	-
f_p	Fraction of total influent which is unsettleable	-
i_{XB}	Mass N/mass COD in biomass	-
i_{XP}	Mass N/mass COD in products from biomass decay	-
J_{clar}	Special flux function for the clarification zone of the settler	$g/(m^2\ d)$
J_{diff}	Flux due to an effective diffusion process	$g/(m^2\ d)$
J_{dn}	Downward flux of SS due to downward bulk flow	$g/(m^2\ d)$
K_{NO}	Nitrate half-saturation coefficient for denitrifying organisms	mg N/L
K_{NH}	Ammonia half-saturation coefficient for autotrophs	mg N/L
$K_{O,A}$	Oxygen half-saturation coefficient for autotrophs	mg O/L
$K_{O,H}$	Oxygen half-saturation coefficient for heterotrophs	mg O/L
K_S	Half saturation coefficient for heterotrophs	mg COD/L
K_X	Half-saturation coefficient for for hydrolysis of slowly biodegradable substrate	mg COD/L
k_a	Ammonification rate	mg N/mg N
k_La	Oxygen mass transfer coefficient	d^{-1}

Abbreviation	Name	Unit
N_{tot}	Total nitrogen concentration	mg N/L
Q_0	Influent flow rate	m^3/d
Q_a	Internal recycle flow rate	m^3/d
Q_e	Effluent flow rate	m^3/d
Q_r	Sludge recycle flow rate	m^3/d
Q_w	Wastage flow rate	m^3/d
Q_u	Underflow rate	m^3/d
r_h	Settler model parameter for hindered settling	$m^3(g\ SS)^{-1}$
r_p	Settler model parameter for low solids concentrations	$m^3(g\ SS)^{-1}$
PE	Pumping energy	Wh d^{-1}
S_{ALK}	Alkalinity	molar unit
S_{I}	Inert soluble organic matter	mg COD/L
S_{S}	Readily biodegradable substrate	mg COD/L
S_{NH}	Ammonia and ammonium nitrogen	mg N/L
S_{NO}	Nitrate and nitrite nitrogen	mg N/L
S_{ND}	Soluble biodegradable organic nitrogen	mg N/L
S_{O}	oxygen	mg O/L
SS	Suspended solids concentration	mg/L
v_0	Maximum (theoretical) settling velocity	m/d
v_0'	Maximum (practical) settling velocity	m/d
$X_{\text{B,A}}$	Active autotrophic biomass	mg COD/L
$X_{\text{B,H}}$	Active heterotrophic biomass	mg COD/L
X_{I}	Particulate inert organic matter	mg COD/L
X_{ND}	Particulate biodegradable organic nitrogen	mg N/L
X_{S}	Slowly biodegradable substrate	mg COD/L
X_{P}	Particulate products arising from biomass decay	mg COD/L
Y_A	Autotroph yield coefficient	mg COD/mg N
Y_H	Heterotroph yield coefficient	mg COD/mg COD
η_g	Correction factor for anoxic growth of heterotrophs	-
η_h	Correction factor for anoxic growth of autotrophs	-
μ_A	Maximum specific growth rate for autotrophic organisms	d^{-1}
μ_H	Maximum growth rate for heterotrophs	d^{-1}

Chapter 1

Motivation

Wastewater treatment processes can be considered as the largest industry in terms of treated mass of raw materials. In the European Community, for instance, a daily wastewater volume of approximately $40{\cdot}10^6$ m^3 has to be processed . However, studies have shown that even well attended WWT plants fail to meet the required effluent quality standards up to 9% of the operation time, not including the short upsets lasting less than one day. The U.S. Environmental Protection Agency estimated that one out of three treatment works were not in compliance with discharge limitations and in Germany and the Netherlands clarification problems were found to occur in almost half of the evaluated treatment. Besides poor design, overloading and inadequately trained operators, a lack of process control leading to excessive effluent quality variations, was reported as the main cause.

Over the last decade, the increased public awareness, as reflected in more stringent effluent regulations, has considerably increased the requirements imposed on treatment plants. Not only the organic carbon pollution of a wastewater must today be eliminated but also nutrients (i.e., nitrogen and phosphorus). With biological nutrient removal being the most economic way of treatment (in most cases), rather complex process configurations have resulted.

A closer look at the current operation of wastewater treatment plants shows that automation and control, while introduced in the late sixties, can still be considered minimal. Few plants are equipped with more than a few elementary sensing elements and control loops, mostly concerning flow metering and control, and for monitoring the basic plant performance over longer periods of time. For this reason, automation and control techniques are also addressed in this work.

1.1 Goals

The activated sludge wastewater treatment process consists of two main parts: the biological part and the clarification-thickening part. In the biological part the most frequently used control variable is aeration intensity which is important also from the aspect of energy consumption. For the simulation of the secondary settler, still traditional distributed parameter models are applied based on empirical settling velocity functions. These two sub-processes will be addressed in this thesis from a certain aspect.

The aeration control is of great importance due to the generally large energy consumption of the aeration system. In spite of their widespread use, many small-size wastewater treatment plants are still operated on the basis of pre-determined air-on/air-off sequences, where the duration of each stage is identical from one day to another. More flexibility of the aeration strategy can be obtained by specifying switching conditions from the measurements of the dissolved oxygen concentration or the redox potential.

Although these strategies result in considerable performance improvements, it is not rare however that the concentration of either the organic or nitrogen compounds largely exceeds the standards defined by the European Union. An alternative method to improve the activated sludge process performances is to apply dynamic optimization techniques based on detailed mathematical models. These methods aim at rigorously determining the best

transient control profile that minimizes a given objective function, on a given time horizon, and satisfies a (possibly empty) set of constraints.

A similar approach is going to be studied in this work based on a certain stochastic optimization technique. Genetic algorithms have proved to be a robust and fast solution for global minimum (maximum) problems. Therefore, it is going to be investigated how it could enhance the optimal aeration of intermittently aerated wastewater treatment plant where the length of the aerated periods determines both the effluent quality and the energy consumption of the plant.

Besides intermittently aerated wastewater treatment plants, the control of the dissolved oxygen concentration plays a significant role in the aerated basin of the activated sludge process. It has to be high enough to maintain efficient nutrient removal, however, unnecessarily high rate of aeration wastes significant amount of energy. Nowadays, basic control methods are applied in the real-life applications, therefore, the applicability of a more advanced control technology, model predictive control, is going to be studied in this thesis.

While the presence or absence of dissolved oxygen has a determining part in the process rate of the bio-chemical reactions in the biological part of the activated sludge process, the biological mechanisms are often neglected in the mathematical model of the secondary settling tank where the separation of the clarified water and the activated sludge takes place. Several empirical models have been suggested in literature for describing the settling of the suspended solids since the beginning of the 1990s, however, no comparative study of these models can be found in literature. It is going to examined in this thesis how these models operate under the same conditions. The suspended solids concentration profile under steady-state conditions and the daily change of the effluent sludge sludge concentration are also addressed in this study.

1.2 Methods

Using mathematical modelling, the validation and verification of the applied model is inherent part of the simulation method. Furthermore, parameter estimation can also be a time consuming part of modelling. However, in the area of activated sludge wastewater treatment internationally accepted standard mathematical models enhance the work of the modelling engineer. The first activated sludge wastewater treatment models were published in the 1980s and the model development has been continuously going since that time as it will be introduced in Chapter 2. Furthermore, besides standardized models, the appearance of a simulation benchmark has improved the acceptance of innovating control strategies. This simulation benchmark – introduced in Section 4.5 – also creates a solid basis for the proposed control strategies in this thesis and provides a good environment for the comparison of different secondary settler models.

This simulation benchmark defines a platform independent model of a wastewater treatment plant, however, issues arising at different modelling tools (e.g. GPS-X, Matlab, Fortran) are also discussed in that manual. For the results presented in this thesis, the simulator package of Matlab/Simulink has been selected and all results are based on this simulation environment. Matlab/Simulink is a widely accepted simulator program in academic research and provides a visual interface for the better understanding of the simulated processes. However, since the simulation of a complete model of a wastewater treatment plant requires the solution of more then 100 differential equations, large part of the model has been implemented in C++ program code using the Matlab standard functions. Hence, the advantage of the graphical interface and efficient computation could be exploited using this approach.

Chapter 2

Introduction to the mathematical modelling of biological wastewater treatment

Over the last decades, increasing awareness of the adverse impact that wastewater discharges have on the aquatic environment (e.g. eutrophication) has led to the introduction of more stringent legislation controlling the quality of the effluents discharged from wastewater treatment plants. To comply with the more stringent effluent quality standards, new wastewater treatment systems have been developed and older ones have been improved. Activated sludge systems have been extended from carbonaceous energy (COD, BOD_5) removal only to include nitrogen removal by nitrification and denitrification, furthermore, the biological removal of excess phosphorus. Additionally, the system is required to produce a good clarifying and settling sludge by flocculating well and controlling the proliferation of filamentous organisms.

As a result, the activated sludge system configuration and its operation have increased in complexity and concomitantly, the number of physical, chemical and biological processes and compounds influencing the effluent quality has increased to decrease chemical or biological oxygen demand

(COD, BOD_5), free and saline ammonia, nitrate (NO_3-N), nitrite (NO_2-N), total and orthophosphorus (TP and PO_4^{3-}) and suspended solids (SS) concentrations.

The modelling of biological wastewater treatment systems has also passed through the above sequences: first, the removal of organic matter only; second, for nitrification; and third, for nitrogen removal by biological denitrification. Wastewater treatment practice has now progressed to the point where all of these can be accomplished in a single-sludge system. Because of the interactions within such systems, the mathematical models depicting them are quite complex, which has detracted from their use. This is unfortunate because it is with such complex systems that the engineer has the most to gain from the use of mathematical models.

Modelling is an inherent part of the design of a wastewater treatment system, regardless of the approach used. At the fundamental level, a design model may be merely conceptual; that is the engineer reduces the complex system with which he is dealing with a conceptual image of how it functions. That image then determines the design approach employed. Often, however, the engineer recognizes that the conceptual model alone does not provide sufficient information for design and thus he constructs a physical model, such as a lab-scale reactor or a pilot plant, upon which various design ideas can be tested. Given sufficient time for testing, such an approach is entirely satisfactory. However, the engineer may find that time and money limitations prevent exploration of all potentially feasible solutions. Consequently, the designer often turns to the use of mathematical models to define further design alternatives. Empirical models may be devised which incorporate a statistical approach to mimic the end results obtained by studies on the physical model, or if the conceptual understanding expands sufficiently, he may attempt to formulate mechanistically based models which seek to account for the major events occurring within the system itself.

These mechanistic models are more powerful since they allow extrapola-

tion of the design space to conditions beyond that experienced on the physical model. In this way, many potentially feasible solutions may be evaluated quickly and inexpensively, thereby allowing only the more promising ones to be selected for actual testing in the physical model.

Realizing the benefits to be derived from mathematical modelling, while recognizing the reluctance of many engineers to use it, the International Association on Water Pollution Research and Control (IAWPREC) formed a task group in 1983 to promote the development, and facilitate the application of, practical models to the design and operation of biological wastewater treatment systems. The first goal was to review existing models and second one was to reach a consensus concerning the simplest one having the capability of realistic predictions of the performance of single sludge systems carrying out carbon oxidation, nitrification and denitrification. The model was to be presented in a way that made clear the processes incorporated into it and the procedures for its use.

2.1 Model applications

The purpose for wastewater treatment plant (WWTP) model studies can be [46, 73] : (1) learning, i.e. use of simulations to increase process understanding, and to develop people's conception of the system; (2) design, i.e. to evaluate several design alternatives for new WWTP installations via simulation; (3) process optimisation and control, i.e. to evaluate several scenarios that might lead to improved operation of existing WWTPs. The two latter ones are applications of the model in a service role. An application of the model in an analysis role can for example be a study where the suitability to describe a particular process is evaluated for several modelling concepts enclosed in different activated sludge models.

WWTP model simulations for learning

Simulations with WWTP models can be applied in different ways to increase the process understanding of the user. For the WWTP operator, simulations might for example be useful to indicate the consequences of process operation modifications on the activated sludge composition and the WWTP effluent quality. Similarly, simulations with e.g. the benchmark plant [17] for different weather disturbance scenarios are very informative to get an idea of the behaviour of a WWTP under variable weather conditions.

WWTP model simulations for design

During the design phase, process alternatives can be evaluated via simulation. Such a model study was presented e.g. by Salem et al. [80], where different alternatives for the upgrade of a biological N removal plant were evaluated with a focus on appropriate treatment of sludge reject water. The WWTP model simulations provided the knowledge basis that was needed to decide on full-scale implementation of one of the proposed alternatives. In this context, modelling can substantially reduce the scale-up time, because different options can be evaluated before a pilot plant is built.

WWTP model simulations for process optimisation

Process optimisation can be used in different contexts. Off-line process optimisation refers to applications where off-line simulations with the calibrated model are used to determine how to optimally run the process, whereas the result is later on implemented and tested on the full-scale plant. In on-line process optimisation simulations with the calibrated model are applied in an on-line optimisation scheme, for example in the frame of a plant-wide supervisory control system. Off-line process optimisation is often needed because new stricter demands are imposed to existing WWTPs, or considerable changes in the plant load have occurred, or deficiencies have appeared dur-

ing WWTP operation such that the initially required effluent quality cannot any longer be obtained. In this context, simulations are often used to evaluate whether the pollutant removal efficiencies can be improved within the existing plant lay-out, e.g. via improved process control.

2.2 Mathematical models of the activated sludge process

In this section the most frequently used activated sludge models will be introduced. Particular attention will be devoted to the ASM1 model, since it is still used as a state-of-the-art model nowadays, furthermore, significant part of the latter chapters will be based on the application of this model. Furthermore, the ASM3, the ASM2 and ASM2d, and the TUDP models will be considered in this chapter. Introduction of these models is based on the Scientific and Technical Report of the International Water Association [41] and other papers [17, 30].

2.2.1 ASM1

The Activated Sludge Model No. 1 [38] can be considered as the reference model, since this model triggered the general acceptance of WWTP modelling, first in the research community, later in the industry. This evolution was undoubtedly enhanced by the availability of more and more powerful computers.

Even today, the ASM1 model is in many cases still the state-of-the-art for modelling activated sludge systems [79]. ASM1 has become a major reference for many scientific and practical projects, and has been implemented in almost every commercially available WWTP simulation software. Copp [17] reports on experiences with ASM1 implementations on different software platforms.

The development of activated sludge theory was inhibited for a long time by the lack of a consistent measure of the concentration of organic material in wastewater. Three measures have gained acceptance and are widely used: biochemical oxygen demand (BOD), total organic carbon (TOC), and chemical oxygen demand (COD). Of these, COD is the superior measure because it alone provides a link between electron equivalents in the organic substrate, the biomass and the oxygen utilized. Furthermore, mass balances can be made in terms of COD. Consequently, the concentrations of all organic materials, including biomass, are in COD units in the following model. The organic matter in a wastewater may be subdivided into a number of categories [21]. The first important subdivision is based on biodegradability. Non-biodegradable organic matter is biologically inert and passes through an activated sludge system unchanged in form. Two fractions, depending on their physical state, can be identified: soluble and particulate. Inert soluble organic matter, S_{I}, leaves the system at the same concentration that it enters. Inert suspended organic matter, X_{I}, becomes enmeshed in the activated sludge and is removed from the system through sludge wastage. Because the waste sludge flow rate is smaller than the system inflow rate, a mass balance requires the concentration of X_{I} in the system to be higher than in the influent.

Biodegradable organic matter may be divided into two fractions: readily biodegradable and slowly biodegradable. For purposes of modelling, the readily biodegradable material, S_{S}, is treated as if it were soluble, whereas the slowly biodegradable material, X_{S}, is treated as if it were particulate. It should be recognized, however, that some slowly biodegradable material may actually be soluble. The readily biodegradable material consists of relatively simple molecules that may be taken in directly by heterotrophic bacteria and used for growth of new biomass. A portion of the energy (COD) associated with the molecules is incorporated into the biomass, whereas the balance is expended to provide the energy needed for the synthesis. The electrons asso-

ciated with that portion are transferred to the exogenous electron acceptors (oxygen or nitrate). In contrast, the slowly biodegradable material, consisting of relatively complex molecules, must be acted upon extracellularly and converted into readily biodegradable substrate before it can be used. It is assumed that conversion of slowly biodegradable substrate into the readily biodegradable form (hydrolysis) involves no energy utilization and thus there is no utilization of electron acceptor associated with it.

The specific rate of hydrolysis of slowly biodegradable substrate is usually considerably lower than the specific rate of utilization of readily biodegradable substrate, so that it becomes the rate-limiting factor in the growth of biomass when X_{S} alone is present as substrate. Furthermore, the rate of hydrolysis is lower under anoxic conditions (only nitrate available as the terminal electron acceptor) than under aerobic conditions [89]. The division of substrate into two forms provides a built-in lag in uptake of electron acceptor which allows space-time dependent variations in oxygen and nitrate utilization to be modelled. Heterotrophic biomass is generated by growth on readily biodegradable substrate under either aerobic or anoxic conditions, but is assumed to stop under anaerobic conditions. Biomass is lost by decay, which incorporates a large number of mechanisms including endogenous metabolism, death, predation and lysis. For reasons to be explained later, decay is assumed to result in the conversion of biomass into slowly biodegradable substrate and particulate products, X_{P}, which are inert to further biological attack [21]. The loss of biomass by decay is assumed to occur at a rate which is independent of the nature or concentration of the electron acceptor present, but the conversion of the resultant slowly biodegradable substrate to a form that can be used for regrowth of new cells is influenced by the nature of the electron acceptor as discussed in the preceding paragraph. Nitrogenous matter in a wastewater, like carbonaceous matter, can be divided into two categories: non-biodegradable and biodegradable, each with further subdivisions. With respect to the non-biodegradable fraction, the particulate

portion is that associated with the non-biodegradable particulate COD; the soluble portion is usually negligibly small and is not incorporated into the model. The biodegradable nitrogenous matter may be subdivided into: 'ammonia' (both the free compound and its salts), S_{NH} ; soluble organic nitrogen, S_{ND}; and particulate organic nitrogen, X_{ND}. Particulate organic nitrogen is hydrolysed to soluble organic nitrogen in parallel with hydrolysis of slowly biodegradable organic matter. The soluble organic nitrogen is acted on by heterotrophic bacteria and Ionverted to ammonia nitrogen. The ammonia nitrogen serves as the nitrogen supply for synthesis of heterotrophic biomass and as the energy supply for growth of autotrophic nitrifying bacteria. For simplicity, the autotrophic conversion of ammonia nitrogen to nitrate nitrogen 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 conditions, yielding nitrogen gas. Cell decay of either autotrophic or heterotrophic biomass leads to release of particulate organic nitrogen which can re-enter the cycle. Both heterotrophic and autotrophic biomass may be present in the wastewater itself, thereby having a strong effect upon system performance. However, the prevalence and intensity of this occurrence is still unknown and thus it was not considered by the task group in developing the model. It should be noted, however, that the only change required for its inclusion would be the addition of input terms to the appropriate mass balance equations.

Processes in the model

The fundamental processes incorporated into the model are listed in the leftmost column of Table 2.1, while their rate expressions are listed in the rightmost column. Basically, four processes are considered: growth of biomass, decay of biomass, ammonification of organic nitrogen, and 'hydrolysis' of particulate organics which are entrapped in the biofloc. To facilitate modelling, readily biodegradable material is considered to be the only substrate

Table 2 Process kinetics and stoichiometry for carbon oxidation, nitrification, and dentrification

Component → / j	Process ↓	1 S_I	2 S_S	3 X_I	4 X_S	5 $X_{B,H}$	6 $X_{B,A}$	7 X_P	8 S_O	9 S_{NO}	10 S_{NH}	11 S_{ND}	12 X_{ND}	13 S_{ALK}	Process Rate, ρ_j $[ML^{-3}T^{-1}]$
	Soluble inert organic matter $[M(COD)L^{-3}]$														
	Readily biodegradable substrate $[M(COD)L^{-3}]$														
	Particulate inert organic matter $[M(COD)L^{-3}]$														
	Slowly biodegradable substrate $[M(COD)L^{-3}]$														
	Active heterotrophic biomass $[M(COD)L^{-3}]$														
	Active autotrophic biomass $[M(COD)L^{-3}]$														
	Particulate products arising from biomass decay $[M(COD)L^{-3}]$														
	Oxygen (negative COD) $[M(-COD)L^{-3}]$														
	Nitrate and nitrite nitrogen $[M(N)L^{-3}]$														
	$NH_4^+ + NH_3$ nitrogen $[M(N)L^{-3}]$														
	Soluble biodegradable organic nitrogen $[M(N)L^{-3}]$														
	Particulate biodegradable organic nitrogen $[M(N)L^{-3}]$														
	Alkalinity – Molar units														
1	Aerobic growth of heterotrophs		$-\frac{1}{Y_H}$			1			$-\frac{1-Y_H}{Y_H}$		$-i_{XB}$			$-\frac{i_{XB}}{14}$	$\hat{\mu}_H\left(\frac{S_S}{K_S+S_S}\right)\left(\frac{S_O}{K_{O,H}+S_O}\right)X_{B,H}$
2	Anoxic growth of heterotrophs		$-\frac{1}{Y_H}$			1				$-\frac{1-Y_H}{2.86\,Y_H}$	$-i_{XB}$			$\frac{1-Y_H}{14\cdot 2.86\,Y_H}-\frac{i_{XB}}{14}$	$\hat{\mu}_H\left(\frac{S_S}{K_S+S_S}\right)\left(\frac{K_{O,H}}{K_{O,H}+S_O}\right)\times\left(\frac{S_{NO}}{K_{NO}+S_{NO}}\right)\eta_g X_{B,H}$
3	Aerobic growth of autotrophs						1		$-\frac{4.57-Y_A}{Y_A}$	$\frac{1}{Y_A}$	$-i_{XB}-\frac{1}{Y_A}$			$-\frac{i_{XB}}{14}-\frac{1}{7Y_A}$	$\hat{\mu}_A\left(\frac{S_{NH}}{K_{NH}+S_{NH}}\right)\left(\frac{S_O}{K_{O,A}+S_O}\right)X_{B,A}$
4	'Decay' of heterotrophs			$1-f_P$	-1			f_P					$i_{XB}-f_P i_{XP}$		$b_H X_{B,H}$
5	'Decay' of autotrophs			$1-f_P$			-1	f_P					$i_{XB}-f_P i_{XP}$		$b_A X_{B,A}$
6	Ammonification of soluble organic nitrogen										1	-1		$\frac{1}{14}$	$k_a S_{ND} X_{B,H}$
7	'Hydrolysis' of entrapped organics		1		-1										$k_h\frac{X_S/X_{B,H}}{K_X+(X_S/X_{B,H})}\left[\left(\frac{S_O}{K_{O,H}+S_O}\right)+\eta_h\left(\frac{K_{O,H}}{K_{O,H}+S_O}\right)\left(\frac{S_{NO}}{K_{NO}+S_{NO}}\right)\right]X_{B,H}$
8	'Hydrolysis' of entrapped organic nitrogen											1	-1		$\rho_7(X_{ND}/X_S)$
	Observed Conversion Rates $[ML^{-3}T^{-1}]$	$r_i=\sum_j \nu_{ij}\rho_j$													
	Stoichiometric Parameters: Heterotrophic yield: Y_H Autotrophic yield: Y_A Fraction of biomass yielding particulate products: f_P Mass N/Mass COD in biomass: i_{XB} Mass N/Mass COD in products from biomass: i_{XP}														Kinetic Parameters: Heterotrophic growth and decay: $\hat{\mu}_H$, K_S, $K_{O,H}$, K_{NO}, b_H Autotrophic growth and decay: $\hat{\mu}_A$, K_{NH}, $K_{O,A}$, b_A Correction factor for anoxic growth of heterotrophs: η_g Ammonification: k_a Hydrolysis: k_h, K_X Correction factor for anoxic hydrolysis: η_h

Table 2.1: The Petersen-matrix of the ASM1 model from [38]

for growth of the heterotrophic biomass. Slowly biodegradable material is considered to be removed from suspension instantaneously by entrapment in the biofloc. Once there, it is acted upon by reactions which convert it into readily biodegradable substrate. These reactions are simply called 'hydrolysis' in the model, although in reality they are likely to be much more complex. The net result of their inclusion is to introduce a time delay into the utilization of oxygen since it is only associated with the growth of the organisms at the expense of readily biodegradable substrate. Decay is assumed to result in the transformation of active biomass into inert particulate products and into slowly biodegradable substrate which re-enters the cycle of hydrolysis, growth, etc. This allows more straightforward expression of decay under the various environmental conditions encountered in a single sludge system. It also has several important ramifications with respect to the values of the parameters, as will be discussed later.

First consider process 1, *aerobic growth of heterotrophic biomass.*

$$\rho_1 = \hat{\mu}_{\mathrm{H}} \left(\frac{S_{\mathrm{S}}}{K_{\mathrm{S}} + S_{\mathrm{S}}} \right) \left(\frac{S_{\mathrm{O}}}{K_{\mathrm{O,H}} + S_{\mathrm{O}}} \right) X_{\mathrm{B,H}} \tag{2.1}$$

On studying the equation defined in row 1 of Table 2.1, it can be concluded that of row 1 shows that growth occurs at the expense of soluble substrate and results in the production of heterotrophic biomass. This is associated with the utilization of oxygen. (See left side of Fig. 2.1.) Since COD units are used for both substrate and biomass, and since oxygen may be considered to be negative COD, continuity requires that the oxygen requirement equal the net COD removal (soluble substrate removed minus cells formed). Ammonia nitrogen will be removed from solution and incorporated into cell mass. The kinetics of aerobic growth of the heterotrophic biomass are assumed to be subject to double nutrient limitation, with the concentrations of both readily biodegradable substrate and DO being rate determining. The primary purpose of the oxygen term is as a switching function which stops

aerobic growth at low DO concentrations and thus the value of the saturation coefficient, $K_{\mathrm{O,H}}$, is small. Removal of readily biodegradable substrate is considered to be proportional to growth. No provision is made for the storage of soluble substrate because that phenomenon is limited to only a few substrates such as soluble monosaccharides and acetate. However, it is widely recognized that substrates can be removed without associated biomass growth. This event is handled in the model through the immediate entrapment of slowly biodegradable substrate.

Row 2 of Table 2.1 represents *anoxic growth of the heterotrophic biomass* with nitrate nitrogen as the terminal electron acceptor.

$$\rho_2 = \hat{\mu}_{\mathrm{H}} \left(\frac{S_{\mathrm{S}}}{K_{\mathrm{S}} + S_{\mathrm{S}}} \right) \left(\frac{K_{\mathrm{O,H}}}{K_{\mathrm{O,H}} + S_{\mathrm{O}}} \right) \left(\frac{S_{\mathrm{NO}}}{K_{\mathrm{NO}} + S_{\mathrm{NO}}} \right) X_{\mathrm{B,H}} \qquad (2.2)$$

Like aerobic growth it occurs at the expense of readily biodegradable substrate and results in heterotrophic biomass. Nitrate nitrogen serves as the terminal electron acceptor and its removal is in proportion to the amount of readily biodegradable substrate removed minus the quantity of cells formed. As in aerobic growth, ammonia nitrogen is converted into organic nitrogen in the biomass. The rate expression for anoxic growth is analogous to the one for aerobic growth. In fact, the effect of readily biodegradable substrate on the rate is identical, including the value of the saturation coefficient, K_{S}. However, that the maximum rate of substrate removal under anoxic conditions is often less than it is under aerobic conditions. This could either be because $\hat{\mu}_{\mathrm{H}}$ is lower under anoxic conditions or because only a fraction of the heterotrophic biomass is able to function with nitrate as the terminal electron acceptor. It is currently impossible to differentiate between these possibilities. Thus, from a modelling standpoint, the easiest way to incorporate the effect is to add an empirical coefficient, η_{g}, to the rate expression, where $\eta_{\mathrm{g}} < 1.0$. Anoxic growth depends upon the concentration of nitrate nitrogen in a manner analogous to the way in which aerobic growth depends upon

the dissolved oxygen concentration. Furthermore, anoxic growth is inhibited when oxygen is present and the term $K_{\mathrm{O,H}}/(K_{\mathrm{O,H}} + S_{\mathrm{O}})$ is incorporated to reflect that fact. The coefficient $K_{\mathrm{O,H}}$ has the same value as in the expression for aerobic growth so that as aerobic growth declines, anoxic growth increases. Like the other similar terms, its primary use is as a switching function.

Aerobic growth of autotrophic biomass is depicted in row 3 of Table 2.1.

$$\rho_3 = \hat{\mu}_{\mathrm{A}} \left(\frac{S_{\mathrm{NH}}}{K_{\mathrm{NH}} + S_{\mathrm{NH}}} \right) \left(\frac{S_{\mathrm{O}}}{K_{\mathrm{O,H}} + S_{\mathrm{O}}} \right) X_{\mathrm{B,A}} \tag{2.3}$$

Soluble ammonia nitrogen serves as the energy source for growth of the nitrifiers resulting in autotrophic cell mass and nitrate nitrogen as end products. (See left side of Fig. 2.1.) In addition, a small amount of ammonia is incorporated into the biomass. Oxygen is used in proportion to the amount of ammonia nitrogen oxidized. A double saturation function is used to express the dependency of the autotrophic specific growth rate upon the soluble concentrations of both ammonia nitrogen and oxygen, with the latter serving as a switching function. Both the saturation coefficients, K_{NH} and $K_{\mathrm{O,A}}$, are small. Although aerobic growth of autotrophic biomass is known to be influenced by the pH of the wastewater in which the organisms are growing, this dependency was not included in the rate equation because of the difficulty of actually predicting the pH in a bioreactor. Rather, any potential problems with pH should be checked through use of the alkalinity term, as discussed earlier.

The approach adopted for modelling *decay of the heterotrophic biomass* is basically the death-regeneration concept and is depicted in row 4 of Table 2.1.

$$\rho_4 = b_{\mathrm{H}} X_{\mathrm{B,H}} \tag{2.4}$$

There it can be seen that the adopted rate expression is quite simple, i.e. first order with respect to the heterotrophic biomass concentration. The

rate coefficient, however, is different in both concept and magnitude from the usual decay coefficient. In this case, decay acts to convert biomass to a combination of particulate products and slowly biodegradable substrate. (See left side of Fig. 2.1.) No loss of COD is involved in this split and no electron acceptor is utilized. Furthermore, decay continues at a constant rate regardless of the environmental conditions (i.e. b_{H} is not a function of the type of electron acceptor or its concentration). The slowly biodegradable substrate formed is then hydrolysed, as depicted in row 7 of Table 2.1, releasing an equivalent amount of readily biodegradable COD. If conditions are aerobic, that substrate will be used to form new cells with concomitant oxygen uptake. If conditions are anoxic, cell growth will occur at the expense of nitrate nitrogen. If neither oxygen nor nitrate nitrogen are availabie, no conversion occurs and slowly biodegradabie substrate will accumulate. Only when aerobic or anoxic conditions are resumed will it be converted and used.

The magnitude of the decay coefficient used herein will be different from that of the more usually encountered rate constant because of the recycling of substrate which occurs. In the usual technique, the loss of one unit of cell mass COD leads to the utilization of one unit of oxygen minus the COD of the inert particulate products formed. In this model, the loss of one unit of cell mass COD results in the ultimate formation of one unit of COD due to readily biodegradable substrate minus the COD of the inert particulate products formed. When the readily biodegradable COD is used for cell synthesis, only a fraction of a unit of oxygen will be required because of the energy incorporated into the cell mass. That cell mass must in turn undergo decay etc. before the unit of oxygen is finally removed. Consequently, to give the same amount of oxygen utilization per time due to decay, the decay coefficient must be larger. This has the result of increasing the turnover rate of cell mass, thereby making the actual microbial growth rate higher far a given solids retention time.

The *decay of autotrophs*, given in row 5 of Table 2.1, is handled in exactly

the same manner as the decay of heterotrophs.

$$\rho_5 = b_{\mathrm{A}} X_{\mathrm{B,A}} \tag{2.5}$$

The justification for this is the likelihood that the decay observed in enrichment cultures of autotrophic bacteria is actually due to predation and lysis, with subsequent growth of adventitious heterotrophic bacteria upon the lysis products. While it is likely that the magnitude of the decay coefficient for autotrophic bacteria will be less than that for heterotrophic bacteria, even more questions can be raised about this process.

Another impact of biomass decay is to recycle nitrogen through the system. The conversion of biomass to slowly biodegradable substrate and then to readily biodegradable substrate has associated with it a parallel conversion of organic nitrogen to ammonia: *soluble organic nitrogen is converted to ammonia nitrogen* through the reaction depicted in row 6 of Table 2.1.

$$\rho_6 = k_{\mathrm{a}} S_{\mathrm{ND}} X_{\mathrm{B,H}} \tag{2.6}$$

This simple first order equation is empirical in nature but has been found to be adequate for modelling the conversion when coupled with the process rate equation for hydrolysis of entrapped organic nitrogen [22].

Rows 7 and 8 in Table 2.1 show the models that have been adopted for *hydrolysis of slowly biodegradable organic matter and biodegradable organic nitrogen.*

$$\rho_7 = k_{\mathrm{h}} \frac{X_{\mathrm{S}} X_{\mathrm{B,H}}^{-1}}{K_{\mathrm{X}} + X_{\mathrm{S}} X_{\mathrm{B,H}}^{-1}} \left[\left(\frac{S_{\mathrm{O}}}{K_{\mathrm{O,H}} + S_{\mathrm{O}}} \right) + \eta_{\mathrm{h}} \left(\frac{K_{\mathrm{O,H}}}{K_{\mathrm{O,H}} + S_{\mathrm{O}}} \right) \left(\frac{S_{\mathrm{NO}}}{K_{\mathrm{NO}} + S_{\mathrm{NO}}} \right) \right] X_{\mathrm{B,H}} \tag{2.7}$$

$$\rho_8 = \rho_7 X_{\mathrm{ND}} X_{\mathrm{S}}^{-1} \tag{2.8}$$

The degradation of slowly biodegradable organic matter is very important to realistic modelling of activated sludge systems because it is primarily re-

sponsible for the attainment of realistic space-time and real time dependent electron acceptor profiles. Consequently, a great deal of effort was devoted to this topic by the task group. Within the past few years, the major changes and innovations in activated sludge modelling have been directed toward the development of equations depicting the fate of entrapped particulate or stored soluble substrates. Careful examination of all of the available literature revealed that very little experimental work has been conducted specifically on the kinetics and mechanisms of degradation of particulate organic material. Most studies in the wastewater treatment field have been done as part of complex model systems, thereby making it difficult to verify independently the portions dealing with hydrolysis and degradation of particulates. Nevertheless, it was evident that certain features were required in order for the overall system models to give realistic electron acceptor profiles. One aspect was that the rate was first order with respect to the active heterotrophic biomass present. Another aspect was that the rate appeared to saturate as the amount of entrapped substrate became large in proportion to the biomass. Finally, because of the need for enzyme synthesis it was supposed that the rate would be dependent upon the concentration of electron acceptor present. It is assumed that the rate decreases to zero in the absence of both oxygen and nitrate. Examination of row 7 in Table 2.1 shows that all of these features were incorporated. The organic nitrogen was assumed to be uniformly distributed throughout the slowly biodegradable substrate so that the rate of hydrolysis of entrapped organic nitrogen would simply be proportional to the rate of hydrolysis of slowly biodegradable substrate.

Model assumptions and limitations

- *Temperature*: Kinetic model parameters are temperature dependent, and consequently one has either to estimate the model parameters when calibrating the model for a specific temperature, or to develop appropriate temperature correction factors to include the temperature

dependency of the reaction kinetics in the simulations. Henze et al. [38] provided two sets of typical parameters for 10 and 20 °C, respectively. Later models, such as ASM2 [39] and the TUDP model [91], use an Arrhenius type temperature dependence. Different reactions have different temperature dependencies, where nitrification is generally most sensitive.

- *pH*: In ASM1, it is assumed that the pH is constant and near neutrality. Including alkalinity as one of the state variables in the model allows detection of possible pH problems. For some reactions, specific functions can be added to the model to describe inhibitory pH effects.

- *Toxic components*: Nitrification is especially sensitive to inhibition by toxic components. In ASM1, the nitrification parameters are assumed to be constant. This means that any inhibitory effect of the wastewater on the nitrification kinetics is assumed to be included in the calibrated nitrification parameters. It is thus only possible to represent an "average inhibitory effect" of the wastewater. Alternatively, the nitrification rate equation can be extended to represent sudden acute inhibition by specific chemicals. It is then up to the modeller to select the best inhibition kinetics model for the actual inhibition problem.

- *Wastewater composition*: The activated sludge models were developed for simulation of municipal WWTPs. Model modifications are typically needed for WWTP systems where industrial contributions dominate the wastewater characteristics. Acute nitrification inhibition by toxic components related to industrial activity is one of the model modifications that are often necessary.

- The net growth rate or SRT of the biomass must be within the range that allows a flocculent biomass to develop. For example if the SRT falls below 3 days, there are likely to be severe problems with sludge

settleability in an activated sludge system. Since the model does not consider sludge settling, the suer must ensure that all conditions employed will result in a sludge which settles properly.

- Proper sludge settling is also dependent upon the concentration of solids entering the finall settler. Thus, while it is possible mathematically to make the reactor hydraulic retention time small by making the activated sludge concentration very large, such a trade-off may not work in practice because it may be difficult to get the highly concentrated sludge to settle sufficiently to obtain a clear effluent.

2.2.2 ASM3

During the years of application of ASM1 several defects had become obvious and the IAWPRC Task Group decided on correcting these defects by publishing ASM3. These disadvantages were the followings:

- ASM1 does not include kinetic expressions that can deal with nitrogen and alkalinity limitations of heterotrophic organisms.

- ASM1 includes biodegradable soluble and particulate organic nitrogen as model compounds. These cannot easily be measured and made the use of ASM1 complicated.

- The kintecs of ammonification in ASM1 cannot be easily quantified, moreover the process is fast and therefore hardly affects model predictions.

- ASM1 differentiates inert particulate organic material depending on its origin, influent or biomass decay, but it is impossible to differentiate between this two fractions in reality.

- Lysis combined with hydrolysis and growth is used to describe the lumped effects of endogenous respiration of, for example, storage com-

pounds, death, predation and lysis of the biomass. This may lead to further difficulties in the evaluation of kinetic parameters.

The ASM3 model [33] was also developed for WWTPs biological N removal, with basically the same goals as ASM1. The ASM3 model was intended to become the new standard model, correcting for a number of defects that have appeared during the usage of the ASM1 model. The reason was that in 1985, when ASM1 was first published, computing power was still scarce. The simplest description possible saved computation time. Today, as computation is not limiting in simulation, a more realistic description of decay processes is introduced in ASM3: the major difference between the ASM1 and ASM3 models is that the latter recognises the importance of storage polymers in the heterotrophic activated sludge conversions. In the ASM3 model, it is assumed that all readily biodegradable substrate (S_S) is first taken up and stored into an internal cell component (X_{STO}) prior to growth (see Fig. 2.1). The heterotrophic biomass is thus modelled with an internal cell structure, similar to the phosphorus accumulating organisms (PAOs) in the biological phosphorus removal models. The internal component X_{STO} is subsequently used for biomass growth in the ASM3 model. Biomass growth directly on external substrate as described in ASM1 is not considered in ASM3.

A second difference between ASM1 and ASM3 is that the ASM3 model should be easier to calibrate than the ASM1 model. This is mainly achieved by converting the circular growth-decay-growth model, often called death-regeneration concept, into a growth-endogenous respiration model (Fig. 2.1).

The complexity of ASM3 is comparable to ASM1. There is a shift of emphasis from hydrolysis to storage of organic substrates, a process, which has been postulated and observed by many researchers. Characterization of the wastewater must consider this change. Readily available organic substrates (S_S) should be estimated based on the storage rather than the growth process.

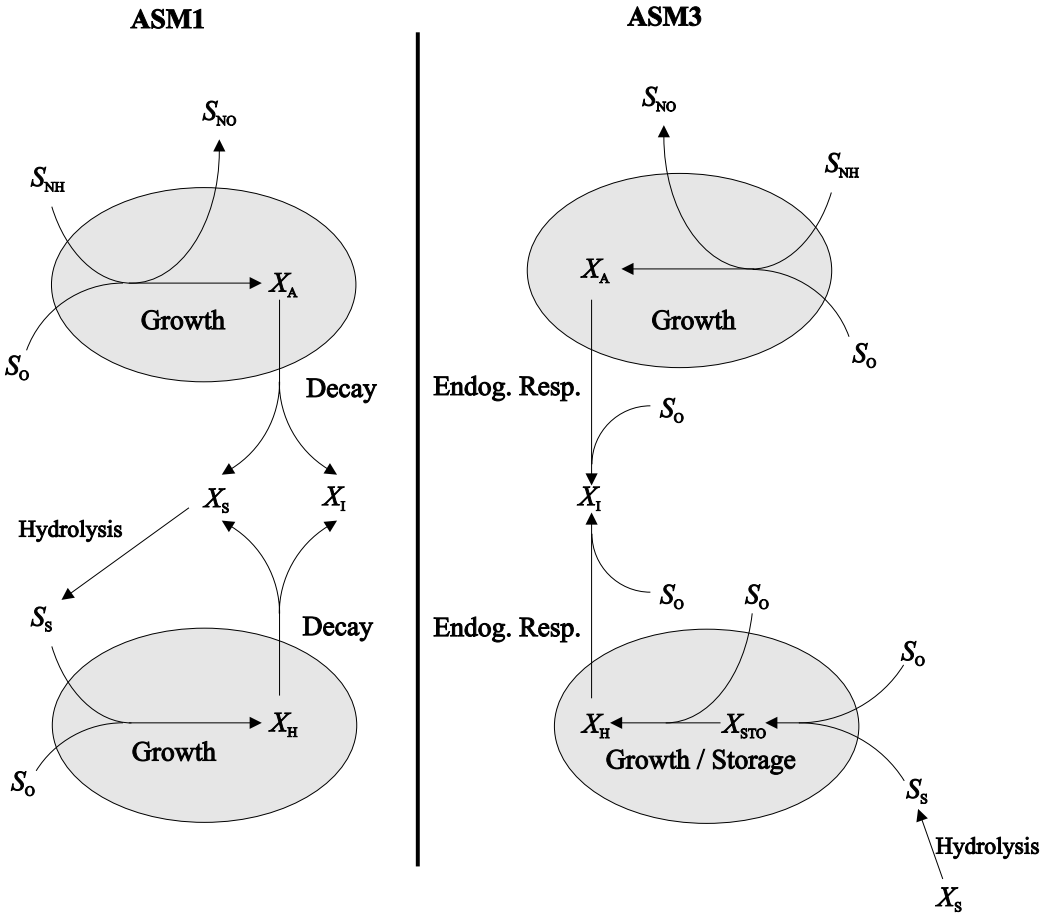

Figure 2.1: Substrate flows for autotrophic and heterotrophic biomass in the ASM1 and ASM3 models

ASM3 includes cell internal storage compounds what requires the biomass to be modelled with cell internal structure. Decay processes (which include predation) must include both fractions of the biomass, hence four decay processes are required (aerobic and anoxic loss of X_{H} as well as X_{STO}) and the kinetics of the growth processes (aerobic and anoxic) must relate to the ratio of $X_{\mathrm{STO}}/X_{\mathrm{H}}$.

Whereas in ASM1 effectively all state variables are directly influenced by a change in a parameter value, in ASM3 the direct influence is considerably lower thus ensuring a better parameter identifiability. Koch et al. [55] concluded that ASM1 and ASM3 are both capable of describing the dynamic behaviour in common municipal WWTPs, whereas ASM3 performs better in situations where the storage of readily biodegradable substrate is significant (industrial wastewater) or for WWTPs with substantial non-aerated zones. The ASM3 model can be extended with a bio-P removal module.

2.2.3 Models including biological phosphorus removal

The overview of models including bio-P will start with the ASM2 model [39], which extends the capabilities of ASM1 to the description of biological phosphorus removal. In addition, chemical P removal via precipitation was also included. The ASM2 publication mentions explicitly that this model allows description of bio-P processes, but does not yet include all observed phenomena. For example, the ASM2d model [40] builds on the ASM2 model, adding the denitrifying activity of PAOs which should allow a better description of the dynamics of phosphate and nitrate. Bio-P modelling in ASM2 is illustrated in Fig. 2.2: the PAOs are modelled with cell internal structure, where all organic storage products are lumped into one model component (X_{PHA}). PAOs can only grow on cell internal organic storage material; storage is not depending on the electron acceptor conditions, but is only possible when fermentation products such as acetate are available. In practice, it means that storage will usually only be observed in the anaerobic activated sludge tanks.

Processes of phosphorus-accumulating organisms

It is assumed that PAO may release phosphate ($S_{\mathrm{PO_4}}$) from poly-phosphate (X_{PP}) and utilize the energy which becomes available from the hydrolysis in order to store cell external fermentation products (S_{A}) in the form of

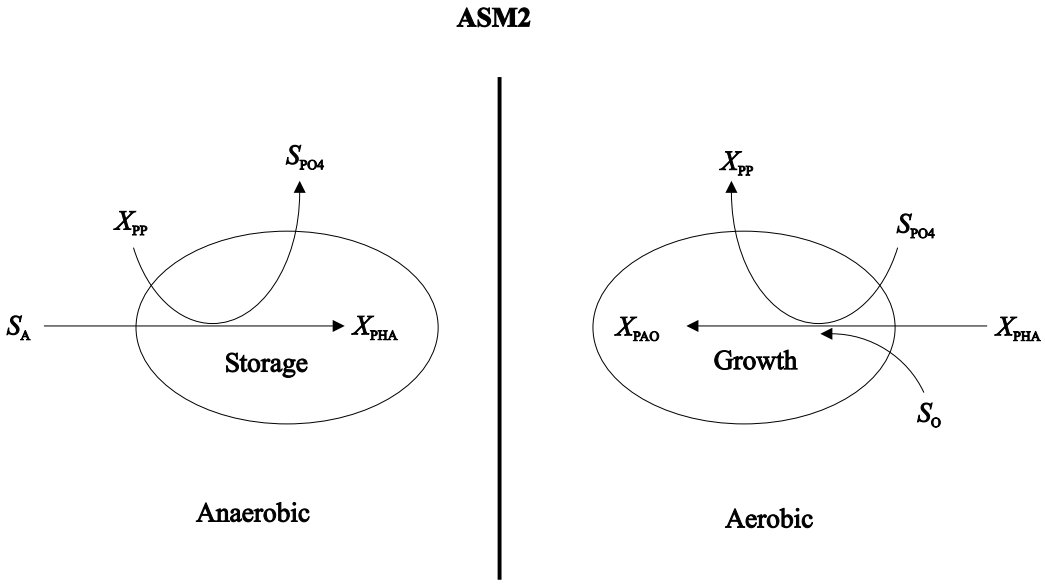

Figure 2.2: Substrate flows for storage and growth of PAOs in the ASM2 model

cell internal organic storage material (X_{PHA}). (See left side of Fig. 2.2.) The process is primarily observed under anaerobic conditions. However, the process has also been observed under aerobic and anoxic conditions.

Storage of ortho-phosphate (S_{PO4}) in the form of cell internal poly-phosphates (X_{PP}) requires the PAO to obtain energy which may be gained from the respiration of X_{PHA}. The regeneration of poly-phosphates is a requirement for the growth of PAO, because the organic substrates are stored only upon the release of poly-phosphate.

These organisms are assumed to grow only at the expense of cell internal organic storage products (X_{PHA}). As phosphorus is continuously released by the lysis of X_{PP}, it is possible to assume that the organisms consume ortho-phosphate as a nutrient for the production of biomass. Growth of PAO is modelled as an obligate aerobic process. (See right side of Fig. 2.2.)

Whereas ASM1 was based entirely on COD for all particulate material, as

well as the total concentration of the activated sludge, ASM2 includes polyphosphates, a fraction of the activated sludge which is of prime importance for the performance of the activated sludge process, but which does not exert any COD. For this reason, total suspended solids (TSS) is introduced in the model.

The TUDP model [7, 91] combines the metabolic model for denitrifying and non-denitrifying bio-P with the ASM1 model (autotrophic and heterotrophic reactions). Contrary to ASM2/ASM2d, the TUDP model fully considers the metabolism of PAOs, modelling all organic storage components explicitly (X_{PHA} and X_{GLY}). The TUDP model was validated in enriched bio-P sequencing batch reactor laboratory systems over a range of sludge retention time values, for different anaerobic and aerobic phase lengths, and for oxygen and nitrate as electron acceptor [64].

Chapter 3

Aeration optimization of a wastewater treatment plant using genetic algorithm

The results introduced in this chapter are party based on the article *Aeration optimization of a wastewater treatment plant using genetic algorithm* published in the journal *Optimal Control Applications and Methods* [42].

This chapter discusses the aeration optimization problem of an intermittently aerated wastewater treatment plant by the application of a stochastic optimization approach, genetic algorithm (GA). In the alternating activated sludge process the alternating aerobic and anoxic conditions needed for nitrogen removal is realized in a single basin by switching the aeration sequentially on and off. Since the operation of these plants may be challenging both for economical and technical reasons, several previous work have investigated the possibility of reduction of the operating cost, however, it turned out that for long-term application these methods can save only limited percent of the cost. Furthermore, these investigations also had to make problem simplifications in order to use optimization methods which usually need significant computational effort to give – only a local optimum – of the problem. The

objective of this chapter is to demonstrate an optimization procedure to minimize the pollution load in the receiving water body using a complete model of the treatment process. The results were evaluated based on rigorous evaluation criteria and showed that using GA-based optimization strategy an optimal solution can be efficiently found where both pollution load and energy consumption savings can reach up to 10% compared to traditional control strategies.

3.1 Introduction

The activated sludge wastewater treatment process is the most widely used biological wastewater treatment process. While in the beginning it served to remove mainly organics and ammonium from the wastewater, the need for total nitrogen removal has risen partly due to the increasing attention to eutrophication in the aquatic environment, party due to the stepwise introduction of the European Directive 91/271/EEC in the European Union. Total nitrogen removal is often realized in small-size wastewater treatment plants (<20,000 p.e.) by a modification of the activated sludge process, the so-called intermittent aeration or – often referred as the – alternating activated sludge (AAS) process, where both nitrification and denitrification take place in a single basin resulting in low investment cost.

The typical setup of an AAS treatment plant consists of a unique aeration tank where the incoming wastewater is mixed with the recycled activated sludge and the biological reactions take place; and a settler where the settleable fraction is separated from the treated water by sedimentation. A certain amount of sludge is removed from the system with the wasted activated sludge to maintain a constant biomass concentration in the system. Despite the spatial separation in traditional activated sludge processes, the aerobic and anoxic conditions needed for the total nitrogen removal are separated in an AAS in time by running the turbines sequentially. During

aerobic conditions the ammonium is oxidised into nitrate by the autotrophic organisms (nitrification step), while during anoxic conditions the produced nitrate is transformed into nitrogen gas by heterotrophic organisms (denitrification step). Organic compounds are eliminated under both conditions by the heterotrophic biomass.

Investigating the efficiency of a wastewater treatment plant (WWTP), two operational parameters have to be investigated. On one hand, the operation of the process has to satisfy the effluent requirements defined by state or other regulations (e.g. the aforementioned EU directive). For example, the maximum concentration for the most restrictive component, the total nitrogen, is generally 10 mg/l. Furthermore, the pollution load should be kept at low level because of the environmental fee. On the other hand, operational costs have to be kept as low as possible. This generally includes the cost for the disposal of the wasted sludge, the cost for the energy consumed for the aeration and the pumping the recycled sludge. However, aeration energy makes up to 50–60% of the global operational cost, therefore, control of the aeration is essentially important [49, 103]. In practice, several feed-back control strategies exist based on the following assumptions: fixed and equal cycle length are used and the aeration is running until a specified condition is met (e.g. maximal concentration of the dissolved oxygen or a threshold concentration of ammonium is reached). Wastage flow rate can also be used to influence the organic and nitrogen removal process, however, Vaccari et al. have shown [88] this is unsuitable for active control.

Several previous works have been focusing on the energy consumption minimization while satisfying effluent quality standards [3, 34, 37, 45, 52], however, in this contribution, the effluent quality optimization is addressed to the keep environmental fee low. The case study used for illustration in this work has been investigated by several papers, therefore, the results are particularly appropriate for comparison. In the first paper investigating this optimization problem, Chachuat et al. have found an aeration profile that

lead to a reduction in the energy consumption of 30% [14]. In their work, the hybrid dynamic optimization problem was converted into a non-linear programming (NLP) problem then solved by gradient method. However, in a later work of Chachuat et al. [12] it was discussed that this operating mode eventually leads to a biomass washout for longer application time and long time horizon optimization guaranteeing durable functionality results in lower (10–15%) savings. The minimization of the nitrogen discharge was also investigated in another work of Chachuat et al. [13] where the solution was found with SQP (gradient-based method). Finally, for the optimization of the aforementioned case-study two feedback rules were proposed [27]. Based on their optimal stationary state profiles, the feedback policy has been related the start and stop of the aeration to nitrate and dissolved oxygen level, respectively.

The problem of effluent quality optimization of an AAS-WWTP is addressed in this paper. Previous works had to make model simplifications in order to use their optimization methods which usually need significant computational effort to give a local optimum of the problem. However, in this work simulations are carried out considering long-term horizons and full model of the wastewater treatment plant is used (including biological reactions and one-dimensional settler model). Since both require substantial computational effort, a efficient and robust optimization method (genetic algorithm) has been applied to solve this problem.

Genetic algorithms (GAs) originated from the studies of cellular automata, conducted by John Holland and his colleagues. Until the early 1980s, the research in genetic algorithms was mainly theoretical with few real applications. This period is marked by ample work with fixed length binary representation in the domain of function optimisation. From the early 1980s the community of GAs has experienced an abundance of applications which spread across a large range of disciplines [31]. Applications in the field environmental engineering were also spreading: groundwater monitoring [78],

surface water flow forecasting [61] and real-time control of wastewater treatment plants [77]. Specifically, in the field of biological wastewater treatment, GAs have been applied for the calibration of the stoichiometric and kinetic parameters of the ASM1 model by Kim et al. [53]. In their work steady-state and dynamic data of the simulation benchmark [17] and measured data sets from the Haeundae wastewater treatment plant were used for calibration. Furthermore, Doby *et al.* developed a framework for design and optimization of biological nutrient removal WWTPs [20]. A multiobjective optimization was introduced in their work by generating a tradeoff curve between cost and total nitrogen in the effluent. According to their results, the GA-based approach is practical in WWTP design and it outperforms classical programming routine both with respect to solution quality and robustness [62]. In our contribution we are going to show that GA-based optimization can be efficiently used for AAS-WWTP design as well.

3.2 Genetic algorithms in the optimization of WWTPs

Classical optimization approaches with nonlinearities can be categorized into those where derivates can and cannot be calculated easily. If they can be calculated easily, they can be solved easily with classical nonlinear programming methods. If not, derivatives can be estimated through parametric evaluations, although these evaluations can be computationally very intensive. If the problem has a discrete aspect as well, computational need may be even larger. It is into this last category, where WWTP optimization problems fall, therefore other, more effective optimization algorithms should be considered. In this dissertation, a relatively novel optimization method, genetic algorithm is used for the solution of the problem.

Genetic algorithms are stochastic search techniques based on the mechanics of natural selection and natural genetics. The GA is a stochastic global

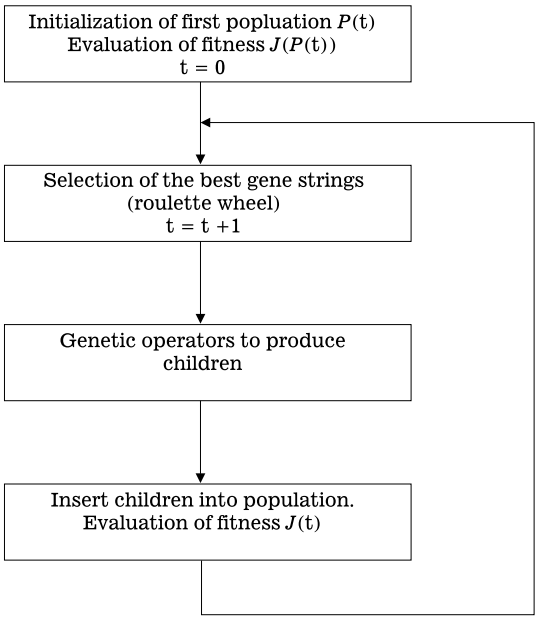

Figure 3.1: Simple genetic algorithm structure

search method that mimics the metaphor of natural biological evolution. GAs operate on a population of potential solutions applying the principle of survival of the fittest to produce (hopefully) 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. This process leads to the evolution of populations of individuals that are better suited to their environment than the individuals that they were created from, just as in natural adaptation.

Individuals, or current approximations, are encoded as strings, chromosomes, composed over some alphabet(s), so that the genotypes (chromosome values) are uniquely mapped onto the decision variable (phenotypic) domain. The most commonly used representation in GAs is the binary alphabet {0, 1} although other representations can be used, e.g. ternary, integer, real-

valued etc. In our example, the two variables (the length of the air-on and air-off period, x_1 and x_2), may be mapped onto the chromosome structure (Fig. 3.2) where x_1 and x_2 are both represented on 10 bits. The chromosome representation itself is independent from the problem to be solved, it is only with the decoding of the chromosome into its phenotypic values that any meaning can be applied to the chromosome structure.

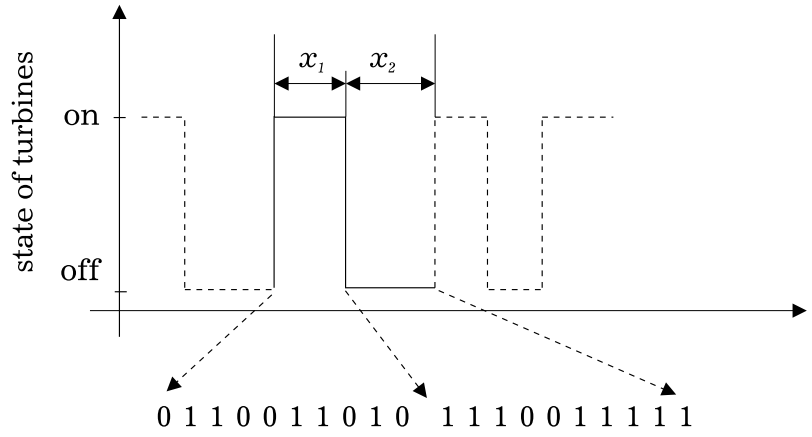

Figure 3.2: Coding the aeration profile into chromosomes

The algorithm of a classic GA can be seen in Fig. 3.1. After having decided on the representation, the first step in the GA is to create an initial population. This is usually achieved by generating the required number of individuals using a random number generator that uniformly distributes numbers in the desired range.

The selection algorithm selects individuals for reproduction on the basis of their relative fitness. The applied selection technique employs a "roulette wheel" mechanism to probabilistically select individuals based on some measure of their performance. The basic roulette wheel selection method is stochastic sampling with replacement. Here, the segment size and selection probability remain the same throughout the selection phase and individuals are selected according to the procedure outlined above.

Having decoded the chromosome representation into the decision variable domain, it is possible to assess the performance of individual members of a population. This is done through an objective function that characterizes an individual's performance in the problem domain. In our example, the fitness of an individual is measured by the effluent quality index defined in Section 3. Thus, less pollution load belongs to higher fitness value. Once the individuals have been assigned a fitness value, they can be chosen from the population, with a probability according to their relative fitness, and recombined to produce the next generation. Genetic operators manipulate the characters (genes) of the chromosomes directly, using the assumption that certain individual's gene codes, on average, produce fitter individuals. The recombination operator is used to exchange genetic information between pairs, or larger groups, of individuals.

Mutation is generally considered to be a background operator that ensures that the probability of searching a particular subspace of the problem space is never zero. After recombination and mutation, the individual strings are then, if necessary, decoded, the objective function evaluated, a fitness value assigned to each individual and individuals selected for mating according to their fitness, and so the process continues through subsequent generations. In this way, 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.

3.3 Illustrative case study

In this work a complete industrial-scale AAS wastewater treatment plant is considered as a case-study described by [12]. This setup consists of an aeration basin ($V = 2050$ m^3) equipped with three surface aerators ($P = 3 \times 30$ kW, $k_La = 4.5$ h^{-1}) which provide oxygen for the organisms and mix the incoming wastewater with the recycled activated sludge (Fig. 3.3). The

settler is a flat bottom cylindrical tank with the surface of 855 m^2 and the depth of 2.8 m. The sludge from the bottom of the settler is either recycled to the aeration tank ($Q_{\mathrm{rec}} = 7600\ m^3/d$) or extracted from the system with the flow rate of $Q_{\mathrm{w}} = 75\ m^3/d$.

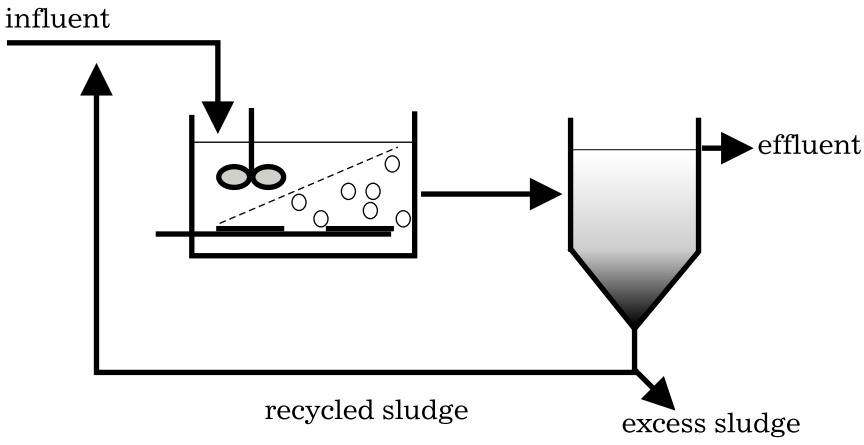

Figure 3.3: The wastewater treatment plant setup

The influent average flow rate ($\overline{Q_{in}}$) is about 3050 m^3/d and the average organic ($\overline{COD}$) and nitrogen ($\overline{TN}$) concentrations are 343 g/m^3 and 33 g/m^3, respectively. The daily variations are approximated by their Fourier rows using the following weighting functions:

$$Q_{\mathrm{in}}(t) = \tau_{\mathrm{Q}}(t)\overline{Q_{\mathrm{in}}} \tag{3.1}$$

where

$$\tau_{\mathrm{Q}}(t) = \sum_{k=1}^{3}[a_k \cos(2k\pi t) + b_k \sin(2k\pi t)] \begin{cases} a_1 = -0.32; & b_1 = -0.18 \\ a_2 = 0.23; & b_2 = -0.01 \\ a_3 = -0.06; & b_3 = -0.01 \end{cases}$$

and

$$COD_{\mathrm{in}}(t) = \tau_{\mathrm{COD}}(t)\overline{COD_{\mathrm{in}}} \tag{3.2}$$

where

$$\tau_{\mathrm{COD}}(t) = \sum_{k=1}^{3} [c_k \cos(2k\pi t) + d_k \sin(2k\pi t)] \begin{cases} c_1 = -0.32; & d_1 = -0.18 \\ c_2 = 0.23; & d_2 = -0.01 \\ c_3 = -0.06; & d_3 = -0.01 \end{cases}$$

Since the concentration of total nitrogen in the influence shows little variations, it is assumed that TN_{in} is constant:

$$TN_{\mathrm{in}} = \overline{TN_{\mathrm{in}}}. \tag{3.3}$$

The influent flow rate and organic reach their maximum and minimum at the same time at 11:00 a.m. (Fig. 3.4). This unusual behavior is due to the significant industrial activity between 9:00 and 5:00. The average wastewater composition is presented in Table 3.1 where the mass fractions are related to the state variables of ASM1 (see Table 1 in Appendix).

Table 3.1: Fractions of the incoming wastewater

COD	**Mass-fraction**(%)	**TN**	**Mass-fraction**(%)
$f_{\mathrm{S,I}}$	5	$f_{\mathrm{S,NH}}$	66
$f_{\mathrm{S,S}}$	35	$f_{\mathrm{S,NO}}$	0
$f_{\mathrm{X,I}}$	10	$f_{\mathrm{S,ND}}$	3
$f_{\mathrm{X,S}}$	35	$f_{\mathrm{X,ND}}$	32
$f_{\mathrm{X,BH}}$	15		
$f_{\mathrm{X,BA}}$	0		

3.3.1 Model of the aeration tank

The aeration tank is modelled as a continuously stirred tank reactor (CSTR) where the mixing of the incoming wastewater and the recycled activated sludge and the biological reactions take place according to the following mass

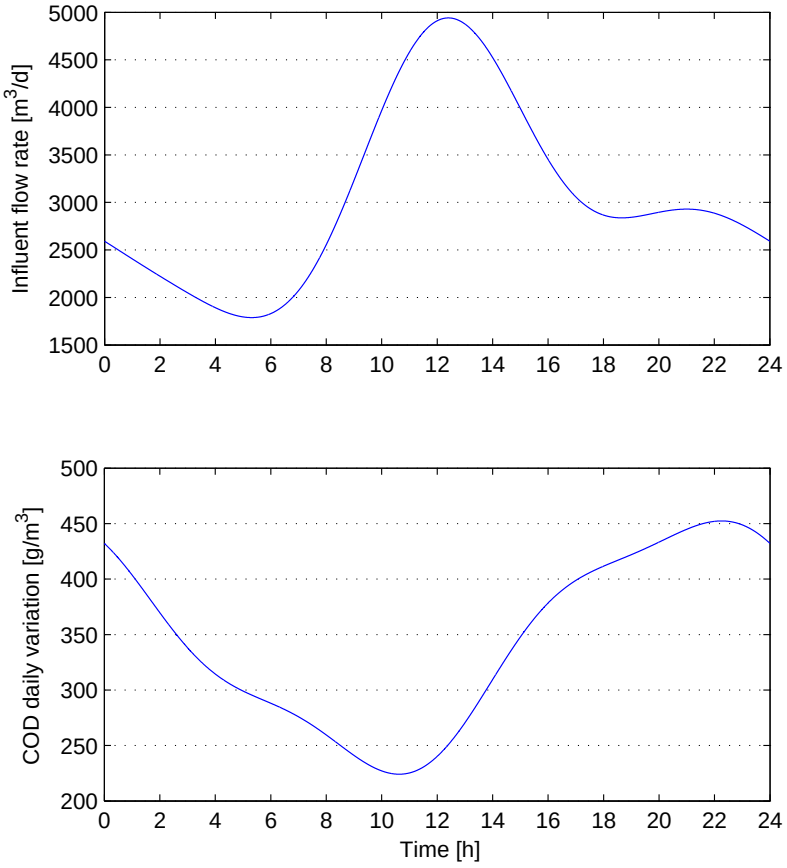

Figure 3.4: Influent daily variations

balance:

$$\frac{\mathrm{d}x_i}{\mathrm{d}t} = \frac{Q^{in}x_i^{in} + Q^{rec}x_i^{rec} - (Q^{in} + Q^{rec})x_i}{V} + r_i(x_i) \tag{3.4}$$

where: r_i is the reaction rate of component x_i [102]. To model the complete wastewater treatment process two internationally accepted models were chosen: the Activated Sludge Model No. 1 [38] was chosen to simulate the biological reactions under aerobic and anoxic conditions and the double-exponential settling velocity function of Takács et al. [84] has been applied

to model the clarification and thickening processes in the secondary settler of the wastewater treatment plant.

Since the first introduction of the Activated Sludge Model No. 1 (ASM1) several modifications have been suggested (ASM2, ASM2d, ASM3) and there are several limitations with ASM1, however, its universal appeal and practical verification overshadow these limitations (see Section 2.2.1). Basically, the removal of organic substances and nitrogen compounds are modelled in ASM1. ASM1 has 13 components (state variables) and 8 processes; they are related by stoichiometric and kinetic parameters. The values used for simulation can be found in the Appendix. The values approximate those that are expected at 15 °C.

3.3.2 Model of the secondary settler

The model of the secondary clarifier is based on a traditional one-dimensional model applying flux-theory. It is assumed that the horizontal velocities profiles are uniform and that horizontal gradients in concentrations are negligible. Consequently, only processes in vertical dimensions are modelled. Biological reactions are also neglected. The transport of solids takes place via the bulk movement of the water and the settling of the sludge relative to the water. The differential conservation equation describing this process is:

$$-\frac{\partial X}{\partial t} = v\frac{\partial X}{\partial y} + \frac{\partial v_s X}{\partial y} \tag{3.5}$$

with t as time, y as vertical coordinate with origin to the surface, X as solids concentration and V as the vertical bulk velocity. The two terms of the right-hand side refer to the bulk flux and the settling flux. Assuming constant horizontal cross section A over the entire depth, the bulk velocity V depends only on whether the observed cross section is in the underflow

region or in the overflow region above the inlet position y_{in}:

$$V = \begin{cases} v_{un} = \frac{Q_R}{A} & \text{if } y \leq y_{in} \\ v_{ov} = -\frac{Q_E}{A} & \text{if } y > y_{in} \end{cases} \tag{3.6}$$

where Q_R and Q_E are the underflow and effluent flow rates, respectively. The settling velocity v_s is determined according to the actual settling approach, which relates v_s to the sludge concentration, the sludge volume index and in some cases also to the position y. The settling velocity function is related only to the suspended solids concentration according to the double-exponential settling velocity function of [84]:

$$v_s(X) = \max[0, \min\{v_0', v_0(\exp^{-r_h(X-X_{\min})} - \exp^{r_p(X-X_{\min})})\}] \tag{3.7}$$

where v_0' is the maximum settling velocity, $X_{\min}$ is the minimum attainable suspended solids concentration and r_h and r_p are the hindered and flocculant zone settling parameters. The exact parameters used for the simulation can be found in the Appendix.

3.4 Optimization problem statement

In this section we will define the goal of the optimization, introduce two cost functions (effluent quality, aeration energy) for the evaluation of different solutions and at last, we will impose certain constraints on our problem to satisfy assumptions concerning our model.

The removal of nitrogen and organic compounds from the wastewater is realized by switching the aeration on and off what results in an alternating aerobic and anoxic environment. During the aerobic conditions the growth heterotrophic biomass occurs at the expense of soluble substrate and dissolved oxygen; and the autotrophic biomass growths where soluble ammonia serves as energy source. During the switched-off periods, anoxic growth of the

heterotrophic biomass takes place with nitrate nitrogen as terminal electron acceptor.

Therefore, the aeration profile can be seen as a sequence of cycles where each cycle consists of one aerated and one non-aerated period. The goal of the optimization process is to find an aeration profile (the number of cycles and the length of the aerated and non-aerated periods) which minimizes the pollution load in the receiving body. Since in previous works it was found that aeration energy consumption can be reduced with less than 10–15%, effluent quality improvement is addressed in this work, rather than minimization of the energy consumption. In order to compare the results of different simulations, quantitative evaluation of the results have been selected: the pollution load is measured by an effluent quality index [87] and the energy consumption is measured by the cost functions defined in the Simulation Benchmark [17].

3.4.1 Effluent quality index

The effluent quality index (EQ) is used to quantify into a single term the effluent pollution load into the receiving water body.

$$\begin{aligned} EQ &= \frac{1}{1000}\int_{t=0}^{t=1\text{day}} B_{\text{SS}} \times SS_{\text{e}}(t) + B_{\text{COD}} \times COD_e(t) + B_{\text{NKj}} \times S_{\text{NKj,e}}(t) \\ &+ B_{\text{NO}} \times S_{\text{NO,e}}(t) + B_{\text{BOD}_5} \times BOD_{5,\text{e}}(t)\text{d}t \end{aligned} \tag{3.8}$$

where EQ is the effluent quality index (kg poll. unit/d), B_{i} are weighting factors, SS is the suspended solids concentration, COD and BOD are the chemical and biological oxygen demands, S_{NO} is the nitrite- and nitrate concentration and S_{TKN} is the total Kjeldahl nitrogen (all concentrations are in g/m^3).

Table 3.2: Weighting factors for the different types of pollution

Factor	Value
B_{SS}	2
B_{COD}	1
$B_{\mathrm{NK_j}}$	20
B_{NO}	20
$B_{\mathrm{BOD_5}}$	2

3.4.2 Aeration energy

The aeration energy is the amount of energy used by the turbines for the aeration of the activated sludge basin per day.

$$AE = 24 \int_{t=0}^{t=1\mathrm{day}} \sum_{i=1}^{n} [0.62(K_L a_i(t))^2 + 12.06 K_L a_i(t)] \mathrm{d}t \tag{3.9}$$

where: $K_L a$ is the mass transfer coefficient in h^{-1} of the compartment. It is important to remember that extra-power consumption during the actuation the turbines is not accounted in this model, therefore, the final energy consumption is proportional to the daily operating time.

3.4.3 Constraints

Further constraints have to be imposed in order to prevent the turbines from early deterioration, satisfy the assumptions made for the modelling process and define the search space for the optimization algorithm. Lower limits are defined for the air-on and air-off periods in order to avoid too frequent switching of the turbines. Moreover, lower limit of the air-on period ensures the assumption of the completely mixed reactor, since short aeration time may lead to the settling of the sludge to the bottom of the basin during the non-aerated period. Though, it was shown [90] in pilot-scale experiments that the assumption of complete mixing without aeration is valid for 33% of the hydraulic retention time. Hence, low limits of 15 min for the air-on and

air-off periods are sufficient.

Maximal air-on time prevents the early deterioration the turbines, while maximal air-off time helps maintain the homogeneous particle distribution in the basin. Therefore, the maximal time has been set to 120 min in both cases.

During the optimization approaches used in AAS optimization, one crucial question is the investigation of the long-term effect of an aeration profile. Using short-term optimization, the optimal aeration profile is determined from given initial concentrations. However, these aeration profiles may fail to work for longer periods (several weeks) because of the wash-out phenomenon. In this case, the certain part of the biomass would gradually decrease due to the dominance of aerobic and anoxic periods. In Fig. 3.5 the dominance of anoxic periods (30% air-on and 70% air-off with 2 hours cycles) leads to the washout of the nitrifying biomass from the system, what leads to the significant dominance of TKN in the effluent over nitrate and nitrite. Therefore, the simulation time has to be chosen long enough to take into account the slow biological processes also.

3.4.4 Chromosome representation of the 24-hour aeration profile

As a general approach the lengths of the aerated and non-aerated periods are all independent variables to be optimized. In this work the number of cycles is kept constant during an optimization, which is in agreement with the approach of Chachuat *et al.* [12]. Determining the length of all aerated and non-aerated periods requires significant computational effort, however, one optimization is finished within one hour on an ordinary PC (2.6 GHz). In this case the number of variables is 2Nc (Nc is the number of cycles) since each cycle consists of air-on and air-off period. One of the challenges inherent applying GAs to any problem is determining an appropriate manner of representing design genes. During our first approach to solve the AAS opti-

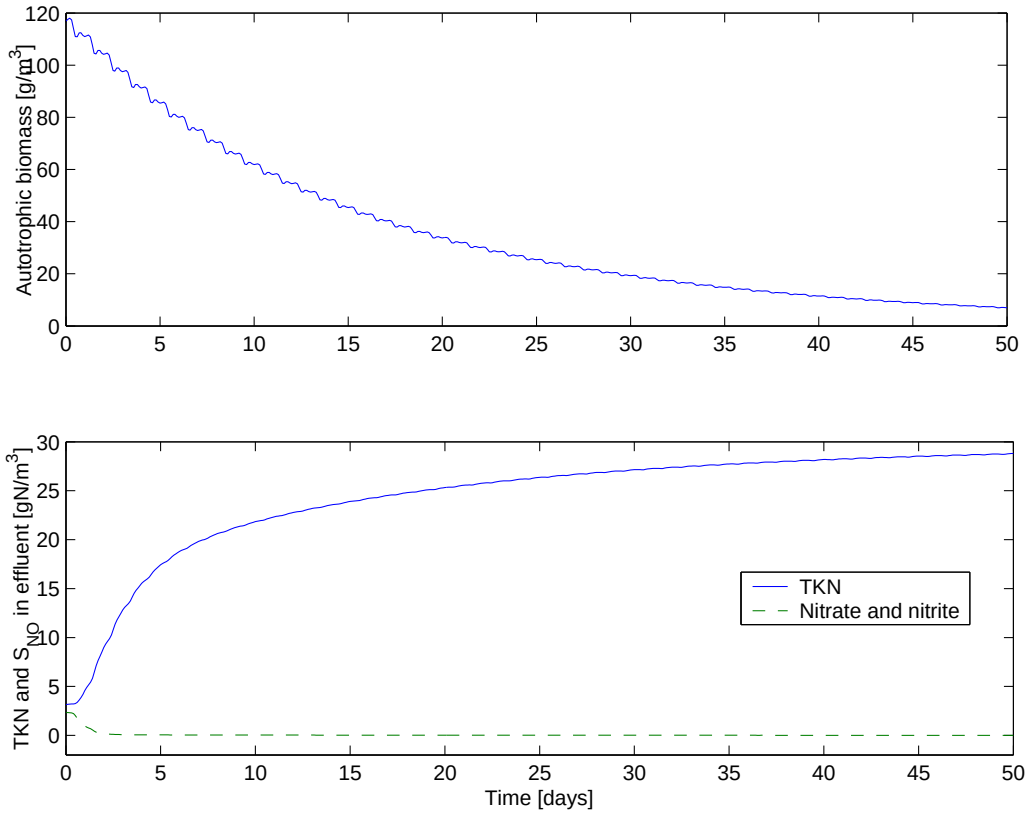

Figure 3.5: Washout phenomenon of the autotrophic biomass

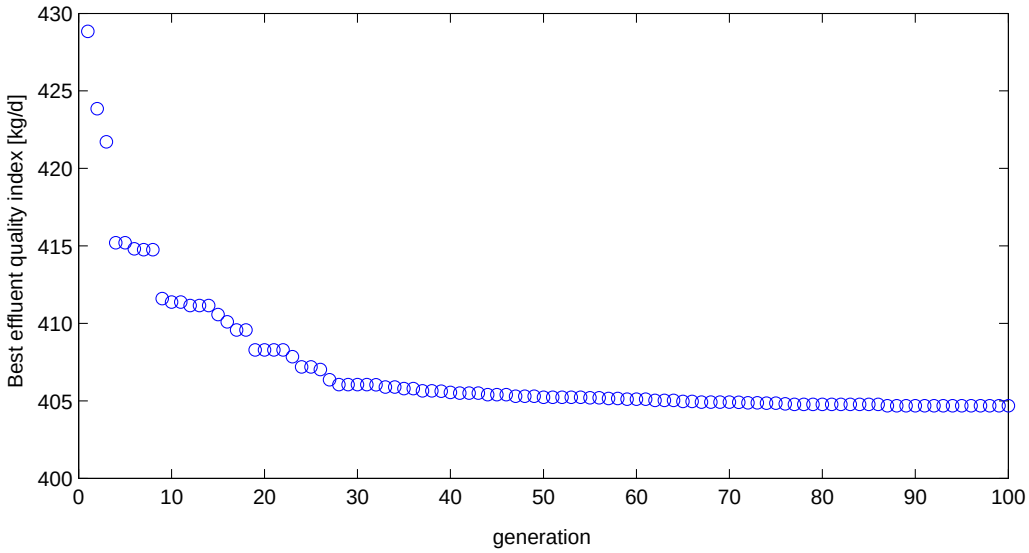

Figure 3.6: Best effluent quality index vs generation number

mization problem with 2Nc variables, a commonly used representation of the vector consisting the 2Nc variables was used: single level binary string. To encode the variables, Gray-code was applied to overcome the hidden representational bias in conventional binary representation as the Hamming distance between adjacent values is constant.

A crucial point in the problem was to maintain the 24-hour profile during chromosome mutation. Since mutation randomly changes the value of a few variables, the length of the complete profile may be longer or shorter than 24 hours. To avoid this problem, the following procedure was used: the chromosomes are decoded into their phenotypic values before and after the mutation to determine which values have been modified. The modifications are summed, then proportionally extracted from (added to) the phenotypic values not influenced by the mutation. Finally, the values are encoded to chromosomes again. Using this algorithm, it can be assured that the length of the aeration profile can be kept at 24 hours.

In order to reduce the computational effort needed to compute optimal aeration profiles, a simplification of the problem can be used which reduces the number of variables to be optimized. Instead of varying length of cycles, equal cycle length can be considered which reduces the number of parameters from 2Nc to Nc. To maintain the 24-hour aeration profile is relatively simple in this case, the effect of genetic mutation is extracted from (added to) the next air-off period. It will be shown in the next section that this approach gave similar results to the previous one in spite of the reduction of variable number.

3.5 Optimization results

In this section we will introduce the results based of the GA-based optimization, compare the optimized performance with a traditional oxygen-based feedback control and finally we give a summary on the advantages and disadvantages of GA-based wastewater aeration optimization.

Chacuat *et al.* has applied successive quadratic programming (SQP) to solve the presented optimization problem. While this problem have been addressed in their several papers [12, 13], unfortunately, little information can be found either on the run of the solver, or on the computational time needed to solve the problem. However, it is mentioned in [12] that they had to face usually large computational time which contained several hundreds of SQP iterations where each SQP iteration takes 10–20 seconds for one-day long simulation (PIII-500MHz). Since, getting more realistic realistic results requires several weeks of dynamic simulation, they made simplifications to the optimization problem, however, the computational complexity after this is not addressed in their article.

Table 3.3: GA parameters

GA parameter	Parameter value
Population size	20
Initialization	Random feasible
Selection	Random wheel
Crossover operator	Single point
Mutation rate	0.01
Generation gap	0.5
Termination criterion	100 generations

3.5.1 Optimal aeration strategies

Optimal aeration profiles have been computed using the previously described optimization approach for $2Nc$ variables applying simple enumeration. The corresponding optimized values (effluent quality index and aeration energy) can been found in Fig. 3.7. It can be seen that the effluent quality index is decreasing as the number of cycles increases. Using 10 cycles a day (i.e. 10 air-on and 10 air-off periods) an effluent load of 467 kg/d and an aeration energy consumption of 744 kWh/d can be reached. Increasing the number of cycles up to 26 per day, the effluent load reduced to 405 kg/d while the energy consumption of the aeration also decreased somewhat, down to 718 kWh/d. After 26 cycles per day, the effluent quality cannot be improved due to the constraint imposed on the minimal length of the air-on period. The different aeration strategies had insignificant effect on the amount of excess sludge produced for disposal, it remained at a constant value of 298 kg/d.

The influence of the length of the air-on period has also been investigated. The simulation results with 25 cycles and different air-on minimal time are shown in Table 3.4. Increasing the minimal time of air-on period over 20 minutes significantly worsened the effluent quality, however, the air-on time under 20 minutes had little effect on the effluent quality index. It is due to the fact that optimal air-on time is between 15 and 25 minutes for this cycle

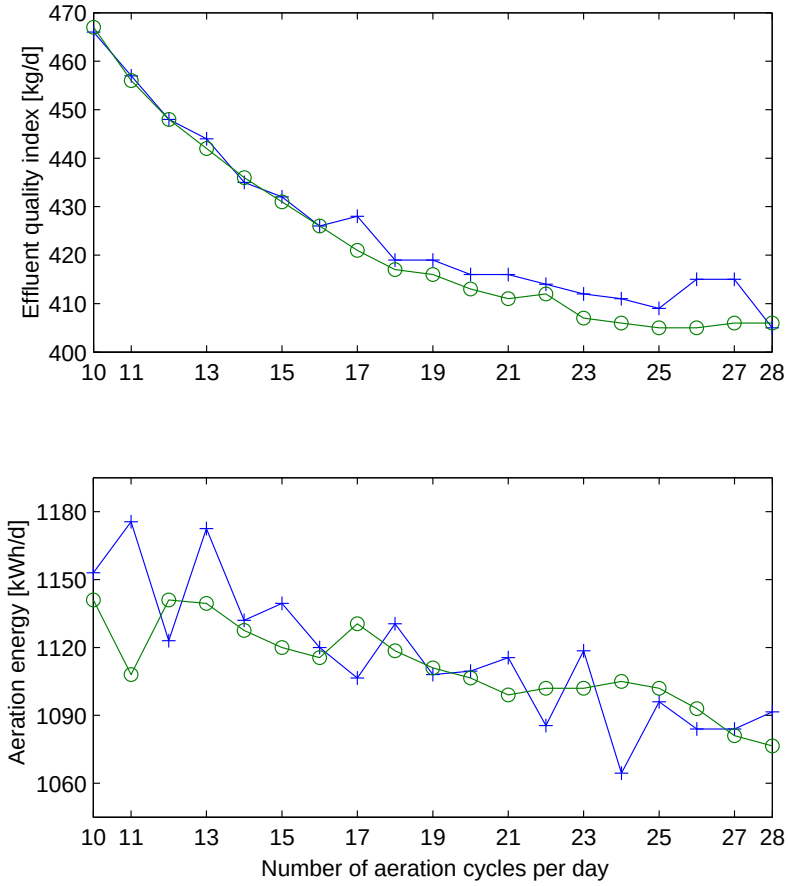

Figure 3.7: Optimization results vs cycle number

number.

Table 3.4: The effect of minimal air-on time on the effluent quality

Minimal air-on time	5	10	15	20	30
Best effluent quality index	403	405	405	405	483
Aeration energy	716	718	715	718	723

During the experiments the computation of one iteration (one simula-

tion for a 10-day optimization period) requires 15 seconds. Assuming 15 individuals and 50 generations during the GA, computational time may hit 1 hour (Personal Computer, 2.6GHz CPU). This is due to the small time steps during the numeric integration and the high dimension of state variables. Therefore, optimization horizon must be sufficiently long to consider the slowest dynamics in the system (e. g. growth of autotrophic biomass) and as short as possible to save computational time. To overcome these difficulties two techniques will be introduced here.

- To examine the long-term effect of the aeration profile, however, to avoid large computational time, initial concentrations have to be selected carefully. It was found that using the final steady-state concentrations of a simulation with the same number of cycles as to be optimized - but with 50% aerobic and 50% anoxic time – as initial concentration will result in steady-state conditions in a few days (7–10 days) compared to the 60 days simulation recommended by [12]. Consequently, for an optimization with a certain cycle number, the initial concentrations are determined first and used afterwards during the optimization.

- Another simplification of the optimization problem was investigated. The number of variables can be reduced by using fixed length cycles, that is to say 1440/Nc minutes a cycle. Using this approach, only the lengths of the air-on periods have to be optimized, the lengths of the air-off periods are determined by the difference between the air-on periods and the full lengths of the cycles. With this simplification the number of variables to be optimized is reduced to half which results in faster convergence to the optimal result.

3.5.2 Comparison between a traditional oxygen based aeration strategy and the optimized operating mode

In order to evaluate the potential benefits of the optimal aeration profile it should be compared to traditional aeration techniques. In practice, rule-based operating modes are applied with fixed and equal cycle length where the aeration is running until a specified condition is met (e.g. maximal concentration of dissolved oxygen or minimal concentration of ammonium is reached) [54, 69]. In this subsection we compare our results to a rule-based operation mode which switches on the aeration every second hour and switches off if the dissolved oxygen reaches up to 2 mg/l concentration (Fig. 3.8).

It has to be emphasized that the studied traditional aeration strategy is a feedback control, therefore, a measurement has to be carried out before any action is taken [100, 101, 47, 48]. This method provides more flexibility to the control strategy to adapt to new conditions, however, it will be shown that significantly better results can be achieved with optimization. Summing up the results of the comparison it can be seen, that using the oxygen based feedback control, the energy consumption of the aeration is high, and still grows with the number of cycles (grows from 755 kWh/d to 770 kWh/d). On the contrary, using the pre-optimized aeration strategy the energy consumption is to some extent lower at 10 cycles a day, and is expected to be even lower at higher number of cycles. On the other hand, the effluent quality behaves in a similar manner in both cases, monotonically decreasing until 25 cycles per day. Though, the effluent quality is somewhat better (5–10% in the effluent quality index) in the pre-optimized case at all cycle numbers. Both the biological oxygen demand (BOD) and the chemical oxygen demand (COD) improved, however, the most significant improvement can be found at the nitrogen compounds. Nitrate- and nitrite-nitrogen concentration in

the effluent decreased with 40%, the total Kejldahl nitrogen decreased with 15% (Fig. 3.9).

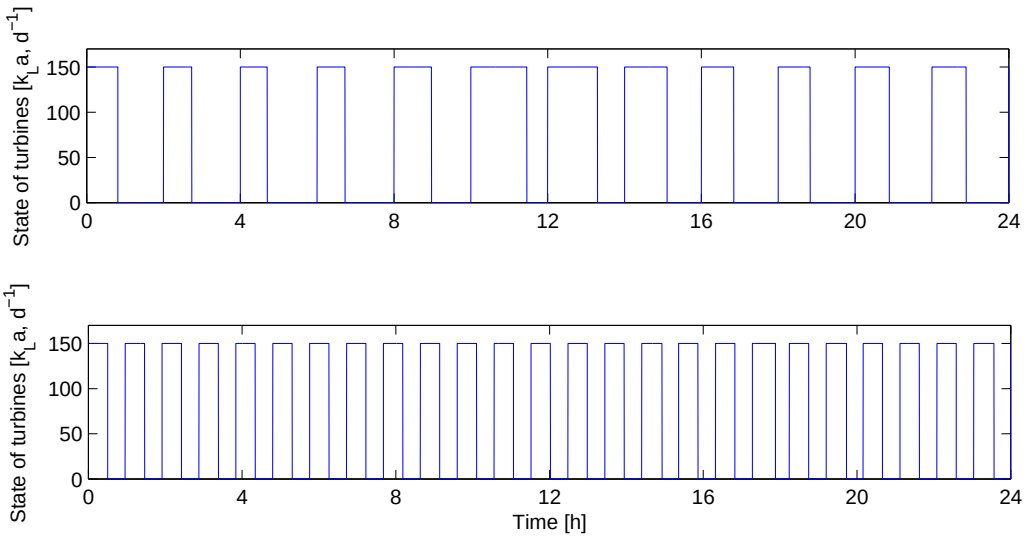

Figure 3.8: Aeration profile using traditional control and in an optimized case

3.5.3 Advantages and disadvantages of GA-based optimization methods

The major advantage of GA-based optimization is its global nature, its ability to outperform a nonlinear programming procedure in certain cases. Another advantage of GA-based optimization is flexibility, since GAs alleviate the representation of objectives and constraints in the strict mathematical manner required by classical optimization procedures. This can be outstandingly useful in WWTP optimization where complex chemical and biological processes are incorporated. Computational intensity was found to be one the drawbacks which results from the fact that each individual is tested during the algorithm in every generation [20] which can sum up to thousands of

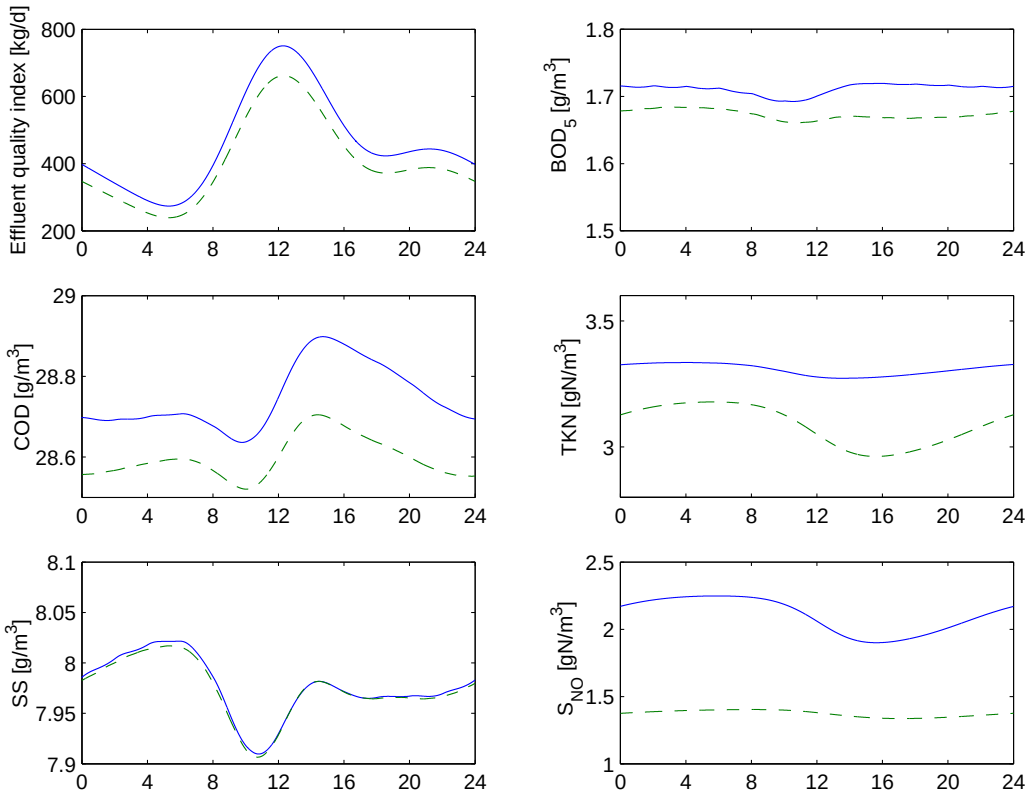

Figure 3.9: Effluent quality parameters using traditional control (solid line) and in an optimized case (dashed line)

simulations. Notwithstanding, classical programming techniques may require even higher computational time if the gradients are computed parametrically. On the other hand, our experiments showed that the adequately chosen initial concentrations and other techniques can keep the computational time – therefore, generation and individual number – low.

Since the dynamic model of the WWTP is nonlinear, the problem may exhibit several local optima, therefore, the global optimality of the aeration profile cannot be guaranteed with traditional techniques (e. g. gradient method). GAs also have the limitations of converging to suboptimal solu-

tions, though, the mutation operator ensures that the probability of searching a particular subspace of the problem is never zero, therefore, inhibits the convergence to a local optimum, rather than the global optimum. Eventually, proper GA parametrization (e. g. population and generation size, mutation rate, initial population, etc.) can help avoid local optimal solutions and make efficient algorithm usage.

3.6 Conclusions

In this contribution, an optimization problem of the so-called AAS process was investigated. Since this problem possesses several characteristics which make it difficult to solve with traditional optimization methods, a stochastic optimization method (genetic algorithm) was used to solve this problem. The goal was to find the most efficient aeration method (length of the air-on and air-off periods) which minimizes the pollution load of the effluent in the receiving body. Other operational parameters (energy consumption of the aeration, the disposal of excess sludge) were also taken into account.

During the optimization only solutions with long time horizon were used in order eliminate solutions which do not take into consideration the slow dynamics in the wastewater process. However, to efficiently handle the large computational intensity of the long time horizon simulations, different techniques have been presented. It was found that adequate determination of the initial concentration for the simulation and proper selection of the GA parameters can keep the computational time reasonably low. Summarizing our results, it was found that using GA approach optimal solutions can be efficiently found, furthermore, the optimized result can reduce the pollution load with 10%. The energy consumption for the aeration also decreased, nevertheless, the effect of frequent switching of turbines at short aeration periods are not taken into consideration.

In order to validate the results achieved with this optimization method

further investigations should be carried out both for pilot-scale and full-scale treatment plants. These should include the aeration optimization together with the stoichiometric and kinetic parameter estimation from experimental data, even though, the results may still fail to give the expected results under large flow rate and load variations. Optimization should always be used as a powerful planning, analysis and design tool for human-based modifications. Speeding the GA computations by parallelizing and applying hybrid GAs can be subject of further research. The latter approach can the advantage of GA's robust search at the beginning of the optimization procedure, then switches to local search when the algorithm has converged sufficiently.

Chapter 4

Dissolved oxygen control using model predictive control

In this chapter, a dissolved oxygen control problem will be addressed like it is in the previous chapter, however, here not the length of the aerated period will be controlled but the aeration intensity will be tuned in order to reach better effluent quality. The results presented in this chapter are party based on the article *Dissolved oxygen control using model predictive control* accepted for publication in 2007 to the journal *Computers & Chemical Engineering*.

Activated sludge wastewater treatment processes are difficult to be controlled because of their complex and nonlinear behavior, however, the control of the dissolved oxygen level in the reactors plays an important role in the operation of the facility. For this reason a new approach is studied in this paper using simulated case-study approach: model predictive control (MPC) has been applied to control the dissolved oxygen concentration in an aerobic reactor of a wastewater treatment plant. The control strategy is investigated and evaluated on two examples using systematic evaluation criteria: in a simulation benchmark – developed for the evaluation of different control strategies – the oxygen concentration has to be maintained at a given level

in an aerobic basin; and a changing oxygen concentration in an alternating activated sludge process is controlled using MPC technique. The effect of some MPC tuning parameters (prediction horizon, input weight, sampling time) are also investigated. The results show that MPC can be effectively used for dissolved oxygen control in wastewater treatment plants.

4.1 Introduction

Wastewater treatment plants are large non-linear systems subject to significant perturbations in flow and load, together with variation in the composition of the incoming wastewater. Nevertheless, these plants have to be operated continuously, meeting stricter and stricter regulations. The tight effluent requirements defined by the European Union a decade ago (European Directive 91/271 "Urban wastewater") become effective in 2005 and are likely to increase both operational costs and economic penalties to upgrade existing wastewater treatment plants in order to comply with the future effluent standards. Many control strategies have been proposed in the literature but their evaluation and comparison, either practical or based on simulation is difficult. This is partly due to the variability of the influent, to the complexity of the biological and biochemical phenomena and to the large range of time constants (from a few minutes to several days) but also to the lack of standard evaluation criteria (among other things, due to region specific effluent requirements and cost levels). A benchmark has been proposed by the European program COST 624 for the evaluation of control strategies in the wastewater treatment plants [17, 93]. This study is in agreement with the benchmark methodology especially from the viewpoint of control performances.

In the literature several extensive surveys based on simulation can be found on activated sludge process control [16, 18]. Dissolved oxygen concentration, internal recycle flowrate, sludge recycle flowrate and external carbon

dosing rate are the frequently investigated manipulated variables in these systems [8, 15, 63, 98, 99]. Nevertheless, the dissolved oxygen (DO) control is the most widely-spread in real-life, since the DO level in the aerobic reactors has significant influence on the behavior and activity of the heterotrophic and autotrophic microorganisms living in the activated sludge. The dissolved oxygen concentration in the aerobic part of an activated sludge process should be sufficiently high to supply enough oxygen to the microorganisms in the sludge, so organic matter is degraded and ammonium is converted to nitrate. On the other hand, an excessively high DO, which requires a high airflow rate, leads to a high energy consumption and may also deteriorate the sludge quality. A high DO in the internally recirculated water also makes the denitrification less efficient. Hence, both for economical and process reasons, it is of interest to control the DO. Several control strategies have been suggested in the literature. As a basic strategy, a linear PI controller with feedforward from the respiration rate and the flow rate was presented [28, 10, 11]. [4] based their design on a recursively estimated model with a linear oxygen mass transfer coefficient, but the excitation of the process was improved by invoking a relay which increases the excitation. [11] have applied autotuning controller based on the on-line estimation of the oxygen transfer rate. A strategy for designing a nonlinear DO controller was developed by [60]. [9] have developed a multicriteria control strategy with Takagi–Sugeno fuzzy-supervisor system to decrease the total cost although keeping good performances. In this paper, a model predictive control is depicted to maintain the dissolved oxygen concentration at a certain setpoint based on a linear state-space model of the aeration process.

Model predictive control (MPC) refers to a class of computer control algorithms that utilize an explicit process model to predict the future response of a plant. Originally developed to meet the specialized control needs of power plants and petroleum refineries, MPC technology can now be found in a wide variety of application fields including chemicals, food processing, automotive,

and aerospace applications [5, 29]. In recent years the MPC utilization has changed drastically, with a large increase in the number of reported applications, significant improvements in technical capability, and mergers between several of the vendor companies. Qin and Badgwell gives a good overview of both linear and nonlinear commercially available model predictive control technologies [74]. Model predictive control has also been implemented on several complex nonlinear systems [24, 82, 97, 104], furthermore, Ramaswamy et al. [75] have recently applied MPC to control a non-linear continuous stirred tank bioreactor. Steffens et al. [83] already applied model predictive control on an activated sludge system, however, their work has been based on the assumption of a multivariable control problem rather than focusing on the dissolved oxygen control. Consequently, this control method seems to be a good candidate for the oxygen control of wastewater treatment plants, too.

4.2 Modelling aspects

4.2.1 Modelling the biological reactions

In the simulation studies two internationally accepted models were chosen to simulate the processes in the wastewater treatment plant: the Activated Sludge Model No. 1 [38] was chosen to simulate the the biological reactions in the aerobic and anoxic reactors and double-exponential settling velocity function of [84] has been applied to model the clarification and thickening processes in the secondary settler of the wastewater treatment plant.

4.2.2 Modelling the aeration process

Aeration is a crucial part of the whole activated sludge process, because microorganisms have to be supplied with enough oxygen so that they have enough electron acceptor capacity for their metabolism process. The equipment used to deliver oxygen to the aeration system is typically provided by

surface mechanical type aerators or diffused aeration systems. Some common types of mechanical surface aeration equipment include low speed mechanical aerators, direct drive surface aerators, and brush type surface aerators. Diffused aeration systems include a low pressure, high volume air compressor (blower), air piping system, and diffusers that break the air into bubbles as they are dispersed through the aeration tank. The most commonly used blowers are positive displacement type blowers, and centrifugal blowers (single and multi-stage).

The whole process while oxygen transports from the air bubbles to the cells of the microorganisms is complex, which can be divided into several subprocesses: convective mass transfer within the air bubble to the gas–liquid border surface; getting through the phase border; mass transfer within the liquid phase to the microbial flocs. Within the flocs, after getting to the cell wall the oxygen has to diffuse through the cell wall. Nevertheless, the slowest of these processes is the second one (transfer through the phase border), so it soon becomes the determining factor for the whole transfer process. This complex process can be described with the oxygen mass transfer coefficient (K_La) which is used as a manipulated variable during the simulations.

The aeration details of the model are introduced as a dissolved oxygen mass balance on a completely stirred tank reactor. This is shown by the following equation:

$$\frac{\mathrm{d}S_O}{\mathrm{d}t} = \frac{Q \times S_{O,in} - Q \times S_O + K_La(S_{sat} - S_O)}{V} + r_{SO} \tag{4.1}$$

where: V is the rector volume; S_O is the concentration of dissolved oxygen in the reactor; Q is the flow rate; $S_{O,in}$ is the DO concentration entering the reactor; K_La is the overall mass transfer coefficient; S_{sat} is the DO saturation concentration and r_{SO} is the rate of use of DO by biomass. The flows, concentrations and reaction rates are known from the activated sludge model, therefore, saturated oxygen concentration and oxygen mass transfer coefficient have to be calculated.

The saturated oxygen concentration can be calculated by using Henry's law:

$$S_{sat} = \frac{k \times \beta \times \rho \times P_{O_2}}{H_{O_2}} \tag{4.2}$$

where: k is a unit conversion factor; β is a salts and ions correction factor; ρ is water density; P_{O_2} is the corrected partial pressure of the oxygen and H_{O_2} is the Henry's law constant for DO. During the simulation K_La is used for the description of the aeration process, which should be corrected to the temperature according to the following equation:

$$K_La(T) = \alpha K_La(20°C)\theta^{(T-20)} \tag{4.3}$$

where: $K_La(20°\text{C})$ is the mass transfer coefficient at temperature 20° C, θ is the temperature correction factor and α is a coefficient.

Control of the dissolved oxygen concentration

In order to maintain the dissolved oxygen concentration at a given level, the following process model is used. The dissolved oxygen concentration is measured by an ideal sensor (assuming no measurement error) in the reactor; the concentration value is processed by the control method to calculate K_La; the K_La is corrected according to the temperature if needed; finally K_La is applied to change the oxygen concentration level in the biological reactor. Using this value, the cost for the aeration and the volume of air blown by the diffusors can also be calculated.

4.3 Model predictive control

Model predictive control refers to a class of algorithms that compute a sequence of manipulated variable adjustments in order to optimize the future behavior of a plant. At each control interval the MPC algorithm attempts to optimize future plant behavior by computing a sequence of future ma-

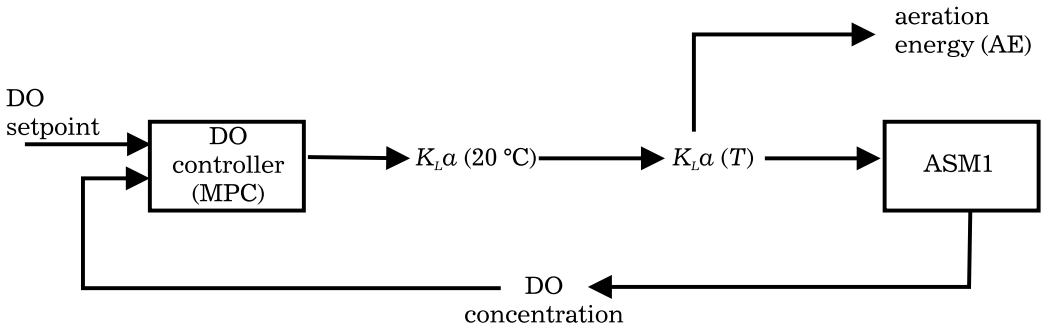

Figure 4.1: Schematic view of the dissolved oxygen control process

nipulated variable adjustments. The first input in the optimal sequence is then sent into the plant, and the entire calculation is repeated at subsequent control intervals.

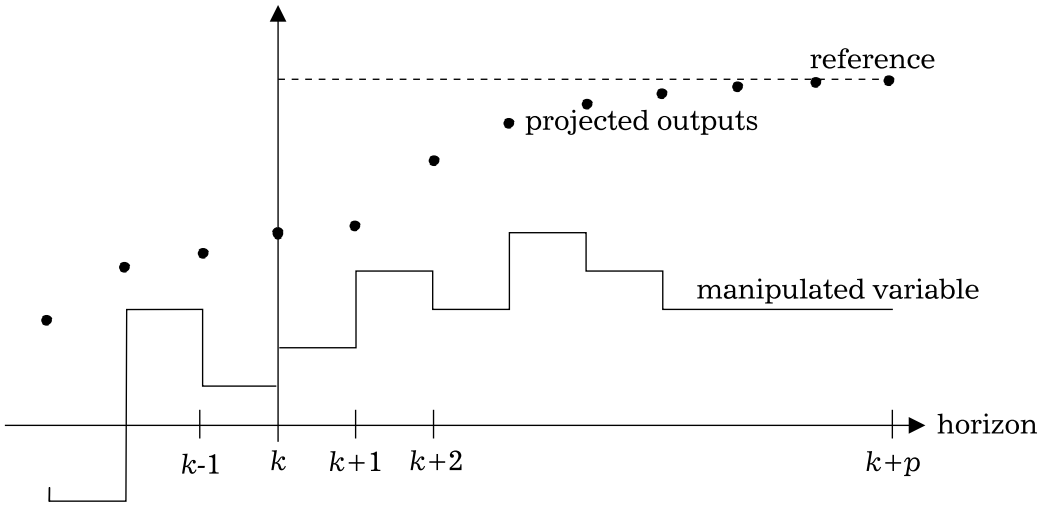

Figure 4.2: Model predictive control

For any assumed set of present and future control moves $\Delta u(k), \Delta u(k+1), \ldots, \Delta u(k+m-1)$ the future behavior of the process outputs $y(k+1|k), y(k+2|k), \ldots, y(k+p|k)$ can be predicted over a horizon p. The m

present and future control moves ($m < p$) are computed to minimize a quadratic objective of the form:

$$\min_{\Delta u(k),\Delta u(k+1),\ldots,\Delta u(k+m-1)} \begin{array}{ll} \sum_{l=1}^{p} & \|\Gamma_l^y[y(k+l|k) - r(k+l)]\|^2 + \\ \sum_{l=1}^{m} & \|\Gamma_l^u[\Delta u(k+l-1)]\|^2 \end{array} \quad (4.4)$$

subject to inequality constraints:

$$\begin{array}{rrll} \underline{y} \leq & y(k+j) & \leq \overline{y} & j = 1,\ldots,p \\ \underline{u} \leq & u(k+j) & \leq \overline{u} & j = 0,\ldots,m-1 \\ \Delta\underline{u} \leq & \Delta u(k+j) & \leq \Delta\overline{u} & j = 0,\ldots,m-1 \end{array}$$

Here Γ_l^y and Γ_l^u are weighting matrices to penalize particular components of y or u at certain future time intervals. $r(k+l)$ is the (possibly time-varying) vector of future reference values (setpoints). Though m control moves $\Delta u(k), \Delta u(k+1), \ldots, \Delta u(k+m-1)$ are calculated, however, only the first one ($\Delta u(k)$) is implemented. At the next sampling interval, new values of the measured output are obtained, the control horizon is shifted forward by one step, and the same computations are repeated. The predicted process outputs $y(k+1|k), \ldots, y(k+p|k)$ depend on the current measurement ($y(k)$) and assumptions we make about the unmeasured disturbances and measurement noise affecting the outputs.

4.3.1 Controller design

The state-space model for the controller design model is generated by the linearization of the aeration process in the ASM1 model at a steady-state operating point of the wastewater treatment plant. The steady-state is reached by applying constant concentration parameters for the influent for 100 days, which can be also used as a starting point for later simulations. The exact parameters can be found in the simulator manual [17], however, they are

beyond the scope of this paper.

From the point of view of process modeling for model predictive control, the following input variables can be separated: manipulated variables, unmeasured disturbances and measured disturbances. Moreover, measurement noise can also be added to the plant output. In the investigated example, the concentration of the dissolved oxygen is considered as the plant output, the manipulated variable is the oxygen mass transfer coefficient ($K_L a, [d^{-1}]$), all the other inputs to the reactor are considered as unmeasured disturbances. No noise on the value of the measured dissolved oxygen concentration is supposed which is also falls in with the recommendations of the benchmark: the oxygen sensor is ideal, neither sampling, nor delay time, the low detection limit is zero and no measurement noise is taken into consideration.

Using sampling time low enough to capture the dynamic properties of the system, the dissolved oxygen concentration has been determined around the steady-state at different aeration intensity. This resulted in the following continuous-time state-space model:

$$\begin{aligned} \frac{\mathrm{d}x}{\mathrm{d}t} &= \mathrm{A}x + \mathrm{B}u \\ y &= \mathrm{C}x + \mathrm{B}u \end{aligned} \tag{4.5}$$

where: x is the state vector, u and y are the input and output vectors and A,B,C and D are the state-space matrices. A second-order model proved to be a good representation of the aeration process.

State-space models of the aeration process have been set up around different steady states of the wastewater treatment plant using prediction error method based on iterative minimization. State-space models can be characterized by their step response: step response at high dissolved oxygen level is depicted by the dashed line (Step response 2) in Fig. 4.3. Responses at lower dissolved oxygen level gave results of lower amplitude (Step response 1 at 1.5 mg/l, response 2 at $<$ 1mg/l). Since in the dissolved oxygen concentra-

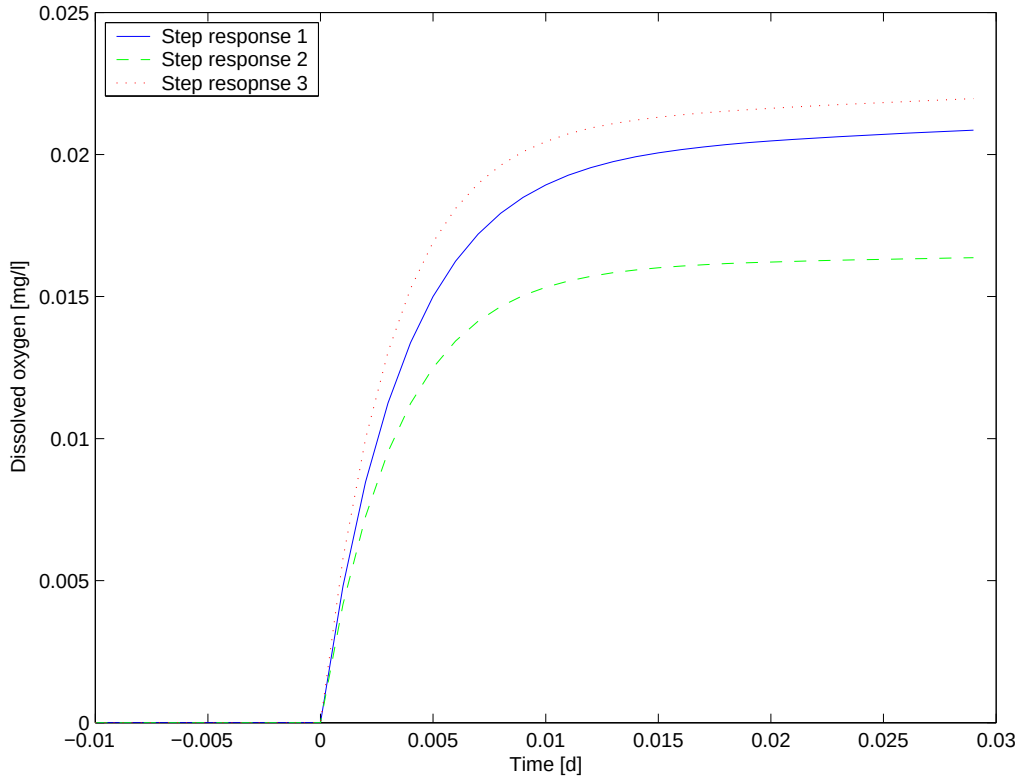

Figure 4.3: Step response of the identified model at different steady-states of the system

tion generally has to be maintained about 2 mg/l, the following continuous spate-space matrices were selected for the simulation:

$$A = \begin{bmatrix} -100.03 & 115 \\ 167.77 & -211.47 \end{bmatrix} B = \begin{bmatrix} 0.87 \\ -1.55 \end{bmatrix} \tag{4.6}$$

$$C = \begin{bmatrix} 7.55 & 0.32 \end{bmatrix} D = 0$$

A number of tuning parameters such as control and prediction horizons, weight matrices, influence the performance of the controller. Trial-and-error

method was used for the identification of these parameters.

For the tuning process a setpoint-change at $t = 0.03$ d and an input disturbance (reducing the input dissolved oxygen concentration with 1 mg/l) at $t = 0.07$ d were used. In Fig. 4.4 the responses of the contolled and manipulated variables to the setpoint change and the input disturbance can be seen at different tuning parameters. The setpoint can be seen in the upper figure marked with dashed line. The continuous line represents the response of a controller with sampling time $\Delta t = 2.5 \cdot 10^{-4}$ day and controller tuning parameters: $\Gamma^y = 1, \Gamma^u = 0.01, m = 1$ and $p = 10$. Reducing the prediction horizon gave the response marked with dotted line in Fig. 4.4 and increasing the input weight resulted in the line marked with dashed-dotted line. The simulation studies show the lower prediction horizon gave faster responses but significantly increasing the overshot amplitude, while larger input weight increased both response time and overshoot.

4.4 Performance assessment

The process assessment is performed at two different levels: IAE (integral of absolute error) and ISE (integral of square error), maximal deviation from setpoint and error variance serve as a proof that the proposed control strategy has been applied properly. In this paper emphasis is put on the first level of assessment, however, assessment of a activated sludge treatment process (effluent quality, costfactor for operation) in the benchmark example is also carried out for the sake of comparison. Length of the observation period is 7 days in the first example as defined in the benchmark and 12 hours in the second example.

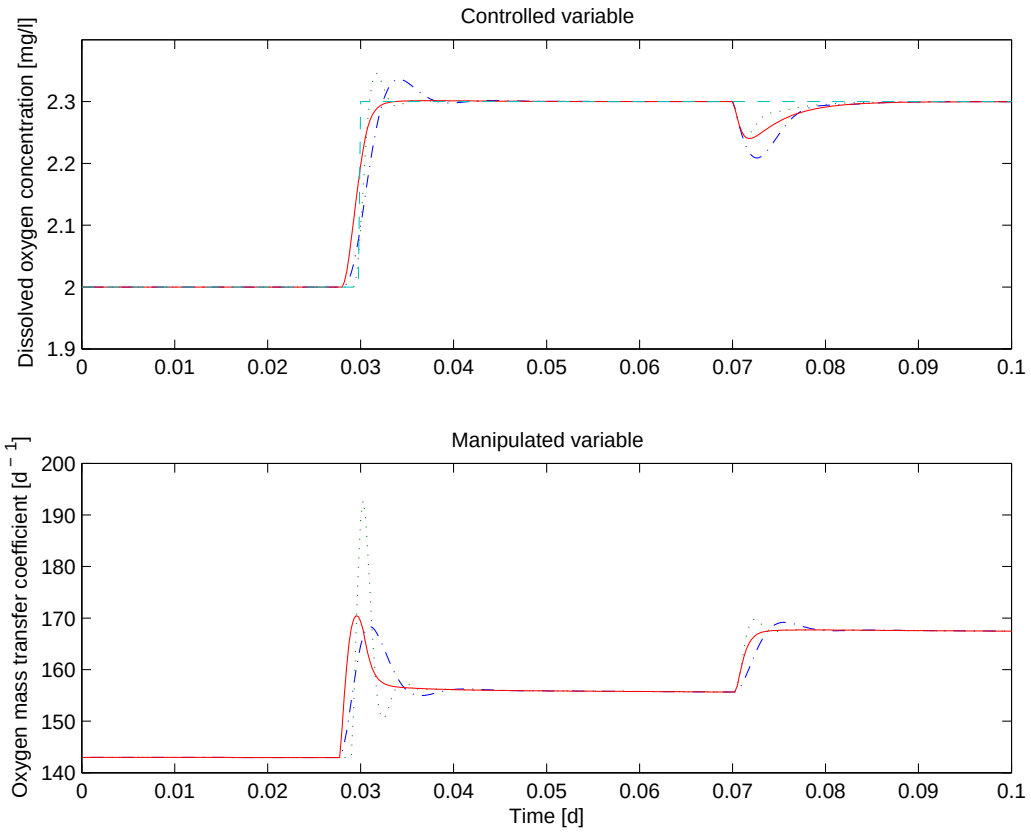

Figure 4.4: Controller response to input disturbance and setpoint change at different parameters (dotted line shows fast response and semi dotted line shows slow response

4.4.1 Controller performance

Integral of absolute error is defined as:

$$IAE = \int_{t_1}^{t_2} |e| \mathrm{d}t \tag{4.7}$$

where: e is the error ($e = y^{\text{setpoint}} - y^{\text{measured}}$) and t_1 and t_2 is the beginning and the end of the observation period, respectively.

The integral of square error can be computed using the following formula:

$$ISE = \int_{t_1}^{t_2} e^2 \mathrm{d}t \tag{4.8}$$

Moreover, maximal deviation from the setpoint is given as follows:

$$Dev^{\max} = \max\{|e|\} \tag{4.9}$$

and variance of error:

$$Var(e) = \overline{(e^2)} - (\overline{e})^2 \quad \text{with} \quad \overline{e} = \frac{\int_{t_1}^{t_2} e \, \mathrm{d}t}{T} \qquad \overline{(e)^2} = \frac{\int_{t_1}^{t_2} e^2 \, \mathrm{d}t}{T} \tag{4.10}$$

Maximum deviation in the manipulated variable

$$\max(Dev^{MV}) = u_{max} - u_{min} \tag{4.11}$$

where: u is the manipulated variable and the maximum and minimum are determined over the observation period.

Maximum deviation in the change of the manipulated variable

$$\max(\Delta u) = \max(|u(t + \Delta t) - u(t)|) \tag{4.12}$$

where: Δt is the sampling period.

4.4.2 Effluent quality index and operating cost

At the second level of the controller assessment, effluent quality operating cost is defined in the simulation benchmark. Effluent quality index represents the levies or fines to be paid due to the discharge of pollution in the receiving bodies. The effluent quality is averaged in the first example over a 7-day observation period based on a weighting of the effluent loads of compounds.

$$EQ = \frac{1}{1000T}\int_{t_1}^{t_2} B_{SS} \times SS_e(t) + B_{COD} \times COD_e(t) + B_{NKj} \times S_{NKj,e}(t) + B_{NO} \times S_{NO,e}(t) + B_{BOD_5} \times BOD_{5,e}(t)\mathrm{d}t \quad (4.13)$$

where: EQ is the effluent quality index (kg poll. unit/d), B_i are weighting factors, SS is the suspended solids concentration, COD and BOD are the chemical and biological oxygen demands, S_{NO} is the nitrite- and nitrate concentration and S_{TKN} is the total N (all concentrations are in g/m^3). The energy needed for the aeration is of special interest in this study, which is determined by the following formula:

$$AE = \frac{24}{T}\int_{t_1}^{t_2} \sum_{i=1}^{n} [0.4032(K_L a(t))_i^2 + 7.8408 K_L a_i]\mathrm{d}t \quad (4.14)$$

where: $K_L a$ is the mass transfer coefficient in h^{-1} of the i-th compartment. The sludge production to be disposed (P_{sludge}) is calculated from the total solid flow from wastage and the solids accumulated in the system over the 7-day period. The pumping energy is calculated as:

$$PE = \frac{0.04}{T}\int_{t_1}^{t_2} (Q_a(t) + Q_r(t) + Q_w(t))\mathrm{d}t \quad (4.15)$$

where: Q_a is the internal recirculation flow rate, Q_r is the sludge recirculation and Q_w wasteage flow rate, all expressed in m^3/d.

4.5 Application example I: Control of the Simulation Benchmark

To enhance the acceptance of innovating control strategies the evaluation should be based on a rigorous methodology including a simulation model, plant layout, controllers, performance criteria and test procedures. The

COST 682 Working Group No.2 has developed a benchmark for evaluating by simulation, control strategies for activated sludge plants [17]. The benchmark is a simulation environment defining a plant layout, a simulation model, influent loads, test procedures and evaluation criteria. For each of these items, compromises were pursued to combine plainness with realism and accepted standards. Once the user has validated the simulation code, any control strategy can be applied and the performance can be evaluated according to certain criteria.

The layout is relatively simple: it combines nitrification with pre-denitrification, which is most commonly used for nitrogen removal. The benchmark plant is composed of a five-compartment reactor with an anoxic zone and a secondary settler. A basic control strategy is proposed to test the benchmark: its aim is to control the dissolved oxygen level in the final compartment of the reactor by manipulation of the oxygen transfer coefficient and to control the nitrate level in the last anoxic compartment by manipulation of the internal recycle flow rate. In this paper, only the control of the dissolved oxygen level is selected for the demonstration of the efficiency of the MPC controller.

The plant layout can be seen in Fig. 4.5. The first two compartments makes up the anoxic zone with individual volume of 1000 m^3, and 3 compartments create the aerobic zone with individual volume of 1333 m^3. The oxygen mass transfer coefficient rate is set to 240 d^{-1}, while the K_La at the last compartment is controlled in order to maintain the dissolved oxygen concentration at 2 mg/l. The flowrate of the internal recirculation is kept at 55338 m^3/d. The secondary settler has a conical shape with the surface of 1500 m^2 and the depth of 4 m. The flowrate of the sludge recirculation is 18446 m^3/d and the excess sludge is removed from the settler at 385 m^3/d.

Since disturbances play an important role in the evaluation of controller performances, influent disturbances are defined for different weather conditions. In this paper, dry-weather data are considered containing 2 weeks of influent data at 15 minutes sampling interval. Parameters for the second

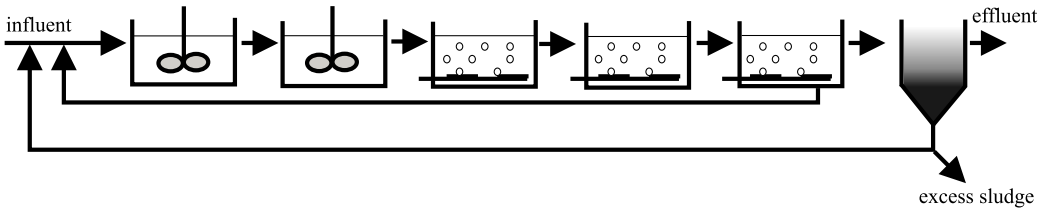

Figure 4.5: Simulation benchmark plant layout

week influent are depicted in Fig. 4.6. Diurnal variations and weekly trends (lower peaks in weekend data) are also depicted by these data. The primary goal of the control is to maintain the dissolved oxygen concentration at the 2 mg/l level in the last compartment.

The controller tuning process in described in Section 4.4, but it is emphasized that sampling time has a significant effect on the effectiveness of the controller. Sampling time was selected at $\Delta t = 10^{-3}$ day $\approx$ 1 min 25 sec, later simulations were carried out at $\Delta t = 2.5 \cdot 10^{-4}$ day $\approx$ 20 sec what resulted in considerable effect on the performance of the controller. Parameters of the controller were tuned by trial-and-error method. On one hand, the main goal was to maintain the dissolved oxygen concentration at the desired level, on the other hand, high energy consumption and rapid changes in the air flow rate should be avoided.

Data of the second week of a 2-week dry weather dynamic simulation are of interest, preceding days are used for stabilization of the system. The assessment – as described in Section 4.4 – can be seen in Figs. 4.7 and 8.1 and in Tables 4.1 and 4.2 compared to the PI controller described originally in the benchmark for process control. It has to be noted, that internal recycle flow control was also applied in the benchmark besides the DO control, however, for the sake of direct evaluation only DO control has been applied in this simulation, recycle flow rate is kept at constant flowrate. Using this setting, better effluent quality index was achieved, nevertheless, pumping energy is almost double of that achieved with control. The energy consumptions for

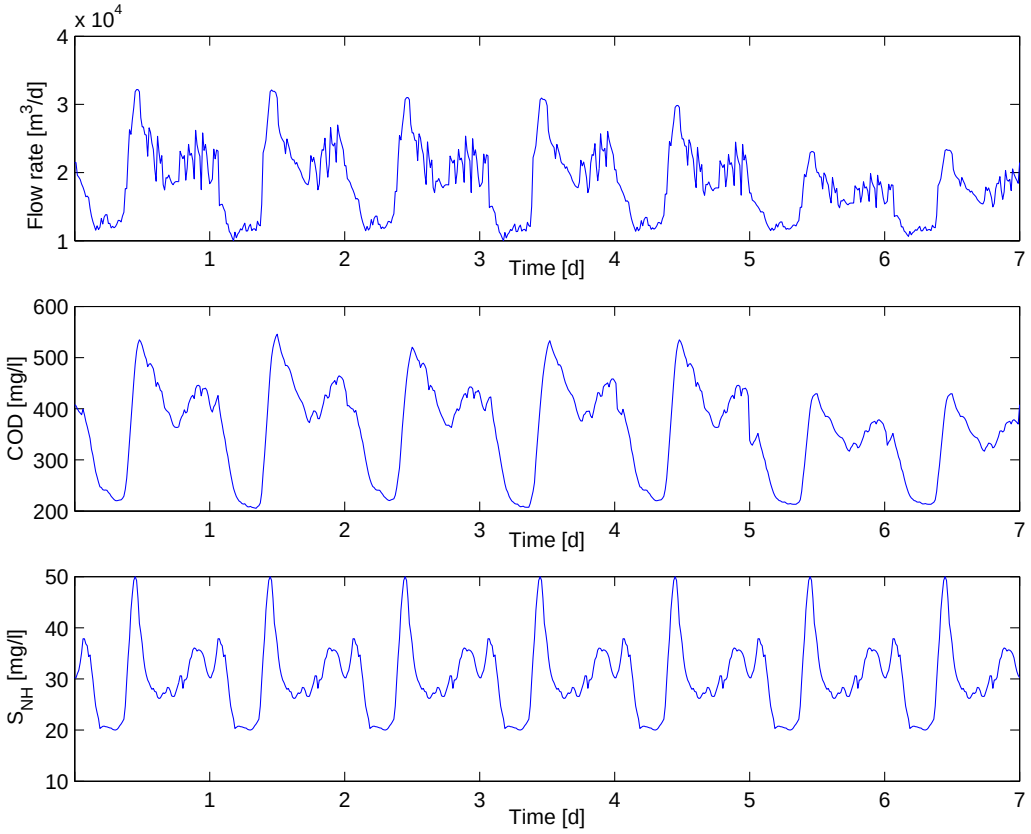

Figure 4.6: Influent characteristics

the aeration are approximately the same using either control strategy.

The performance of the model predictive controller – largely determined by the parameters of the controller, like sampling time, prediction horizon and input weight – is compared to the benchmark results. PI controller performance is also influenced by the parameters, the values presented here are the average results taken from the simulator manual. In this simulation, two sampling times were used for evaluation. It can be seen from Table 4.2 that that reducing the sampling time to its one-fourth, (from 10^{-3} to $2.5{\cdot}10^{-4}$ day) reduced the integral of absolute error with more than 50% and reduced

Table 4.1: Performance of the activated sludge process

	PI control benchmark	DO **MPC** $\Delta t = 10^{-3}$d	DO **MPC** $\Delta t = 2.5 \cdot 10^{-4}$d
Influent quality (kg poll. unit/d)	42042	42042	42042
Effluent quality (kg poll. unit/d)	7605	7560	7560
Sludge production (kg SS)	17100	17117	17116
Aeration energy (kWh/d)	7248	7277	7277
Pumping energy (kWh/d)	1458	2966	2966

the integral of square error with more than 80%. Maximum deviation from setpoint and variance also descreased as the absolute error is significantly less during the whole observation period.

Table 4.2: Performance of the oxygen controller

	PI control benchmark	DO **MPC** $\Delta t = 10^{-3}$d	DO **MPC** $\Delta t = 2.5 \cdot 10^{-4}$d
Controlled variables ($S_{O,5}$)			
Setpoint (gCOD/m^3)	2	2	2
Integral of absolute error (gCOD/(m^{3}d))	0.15	0.1950	0.0892
Integral of square error ((gCOD/(m^{3}d))^2)	0.02	0.0128	0.0026
Max deviation from setpoint (gCOD/m^3)	0.21	0.1648	0.0781
Variance of error (gCOD/m^3)	0.04	0.0427	0.0196
Manipulated variable ($K_L a_5$)			
Max deviation of MV (d^{-1})	204.5	187.39	187.19
Max deviation of ΔMV (d^{-1})	28.71	33.12	18.89
Variance of MV	59.85	59.79	59.76

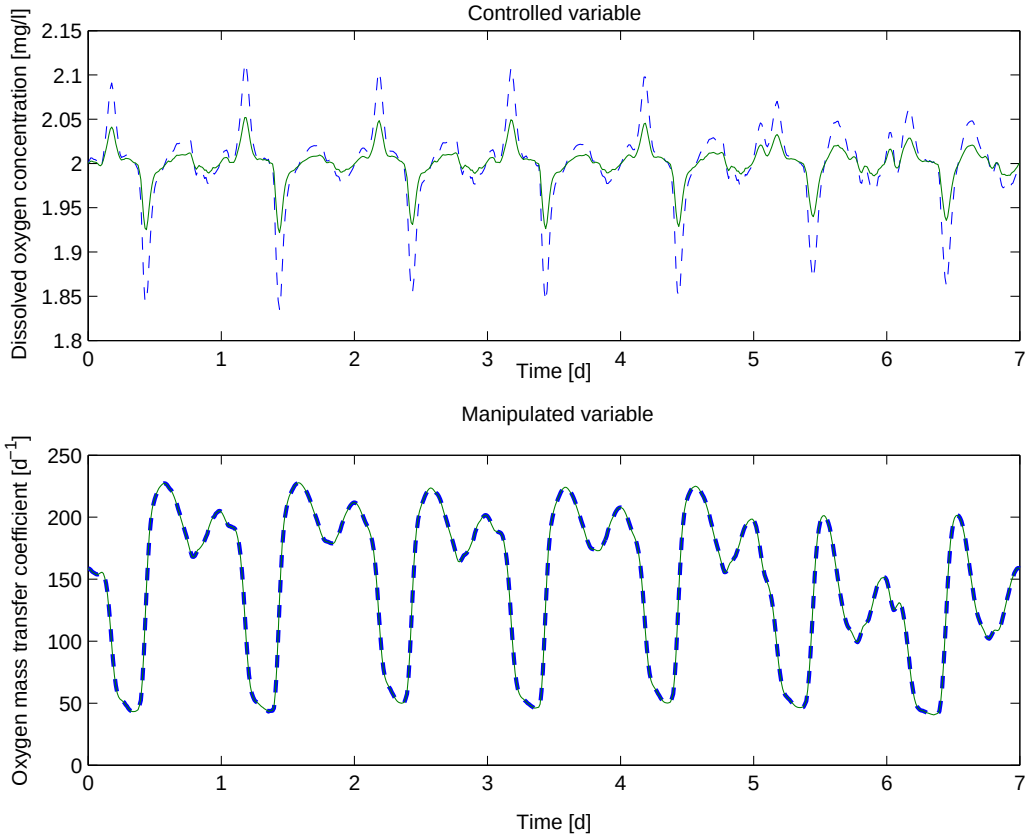

Figure 4.7: The dissolved oxygen concentration and the oxygen mass transfer coefficient in the third aerobic basin (solid line $\Delta t = 2.5 \cdot 10^{-4}$; dashed line $\Delta t = 10^{-3}$)

4.6 Application example II: control of an alternating sludge process

Most municipal wastewater treatment plants use an activated sludge process. More specifically, for small-size treatment facilities the process generally consists of a single aeration basin configuration in which oxygen is either supplied by surface turbines or diffusers, and is known as the alternating activated sludge (AAS) process. Nitrogen removal is realized simply switching the aeration system on and off to create continuous alternating aerobic and anoxic conditions, respectively. During switched-on periods, ammonium is converted into nitrate which is subsequently used to remove organic carbon in switched-off periods. An important feature of the AAS process is its flexible control ability which makes it suitable for optimization of operating costs. Since the process consists of alternating aerated and nonaerated periods and the aeration induces 60–80% of the global energy consumption (and subsequently operating costs) of a treatment plant, oxygen control is therefore of great importance.

In this study, an industrial-scale AAS treatment plant is considered described in literature [14]. The process consists of a unique aeration tank ($V = 2050\text{m}^3$) equipped with three mechanical surface aerators (turbines) which provide oxygen ($P = 3 \times 30\text{kW}, K_L a = 4.5\text{h}^{-1}$) and mix the incoming wastewater with biomass (Fig. 4.8). The settler is a cylindrical tank where the solids are either recycled to the aeration tank ($Q_{rec} = 7600\text{m}^3/\text{d}$) or extracted from the system ($Q_w = 75\text{m}^3/\text{d}$). During the simulation constant influent flow rate and composition were supposed in order to evaluate the efficiency of the controller subject to rapid setpoint changes.

In this simulation the alternating sludge process is realized by changing the dissolved oxygen setpoint between 0 and 2 mg/l in the bioreactor at 72 minutes (0.05 day). The manipulated variable (oxygen mass transfer coefficient) is varied between 0 and 240 d^{-1} to reach the desired DO-level

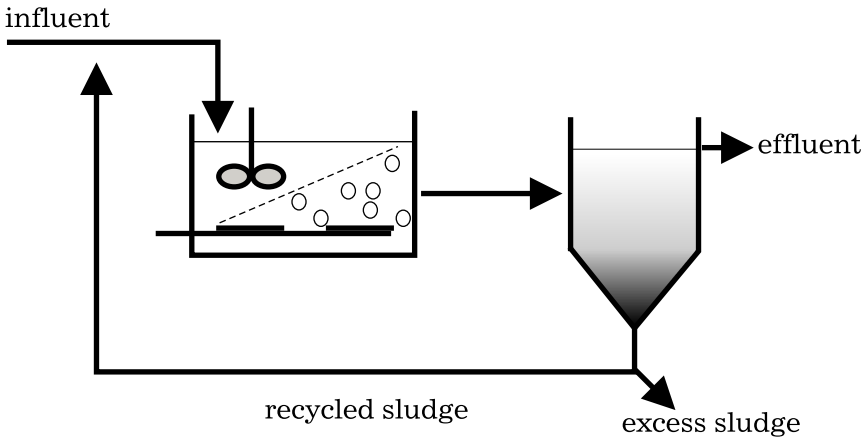

Figure 4.8: The alternating activated sludge process

using model predictive control. The controller is based on a linear state-space model of the aeration process assuming ideal controller and measurement described in Section 4.4. The changing dissolved oxygen concentration can be seen in Fig. 4.9 and in Table 4.3 with different prediction horizons of the controller.

Simulations were carried out at several parameter settings to evaluate the performance of the controller during the 0.5 day observation period. Sampling time was $2.5 \cdot 10^{-4}$ day ($\approx$ 20 sec). The output weight was fixed to 1, while the input weight was varied between 0.001 and 0.01. The control horizon was also fixed to 1, the prediction horizon was changed between 3 and 100. The results showed that lower prediction horizon reduced significantly the integral of absolute and square error, however, input weight had insignificant effect on the error according the prediction horizon (Fig. 4.11). Reducing the prediction horizon from 10 to 3 moves ($\Gamma_u = 0.005$), decreased the integral of absolute error with more than 40%, nevertheless, maximal change in the manipulated variable between two sampling times increased from 45 to 157 d^{-1}. It can be observed in Fig. 4.10 that both lower prediction horizon and lower input weight can significantly increase the maximum

Table 4.3: Performance of the oxygen controller in the alternating activated sludge process

Prediction horizon	$p = 3$	$p = 5$	$p = 10$
Controlled variables (S_O)			
Setpoint (gCOD/m^3)	0/2	0/2	0/2
Integral of absolute error(gCOD/(m^{3}d))	$2.08{\cdot}10^{-2}$	$2.18{\cdot}10^{-2}$	$3.48{\cdot}10^{-2}$
Integral of square error ((gCOD/(m^{3}d))^2)	$9.46{\cdot}10^{-3}$	$5.99{\cdot}10^{-2}$	$1.33{\cdot}10^{-2}$
Max deviation from setpoint (gCOD/m^3)	$2.32{\cdot}10^{-2}$	$2.73{\cdot}10^{-2}$	$4.55{\cdot}10^{-2}$
Manipulated variable (K_La)			
Max deviation of MV (d^{-1})	240	240	240
Max deviation of ΔMV (d^{-1})	157.28	126.05	45.38

deviation in the change of K_La, at $\Gamma_u = 0.001$ and $p = 3$ the change in the value of the K_La reaches 240 d^{-1}, which is near to its maximal value (270 d^{-1}).

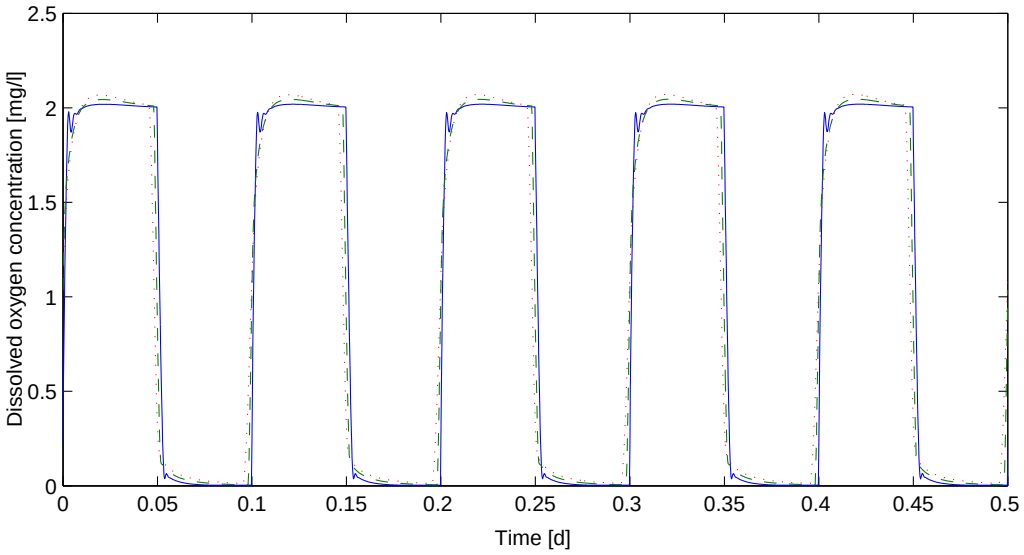

Figure 4.9: Dissolved oxygen control in the alternating activated sludge process (solid line: $p = 3$; dashed line: $p = 10$; dotted line: $p = 20$)

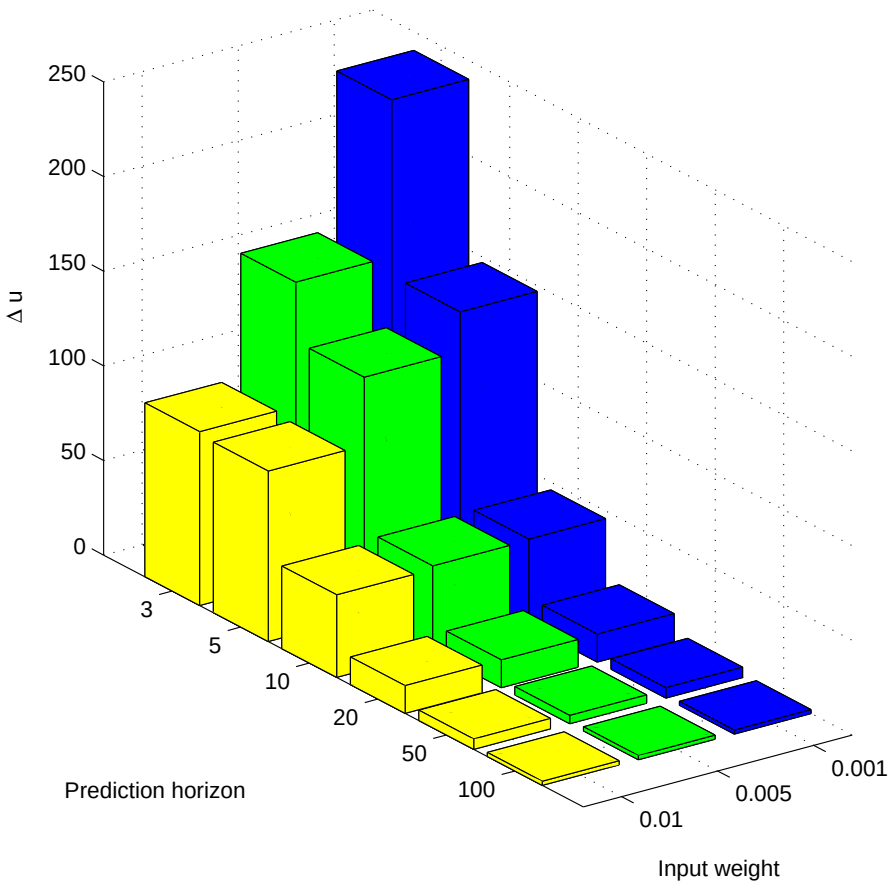

Figure 4.10: Maximum deviation in the change in the oxygen mass transfer coefficient over the 12 h simulation period

4.7 Conclusions

Model predictive control strategy of the dissolved oxygen concentration has been quantitatively investigated on two simulated case-studies: the dissolved oxygen concentration has to be maintained at 2 mg/l in the an aerobic basin of a pre-denitrification process with influent disturbances and an alternating

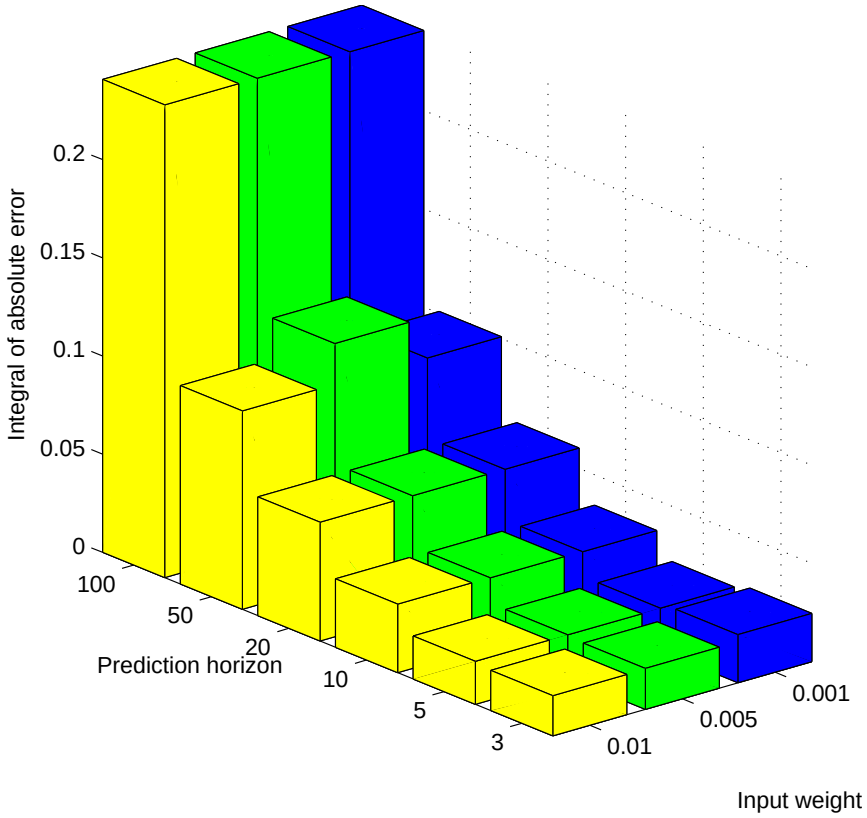

Figure 4.11: Integral of absolute error over the 12 h simulation period

dissolved oxygen level has to be kept up in an alternating activated sludge process. To evaluate the results systematic performance criteria were set up and calculated during the simulations concerning the performance of the controller. Several tuning parameters of the controller (input weight, prediction horizon, sampling time) were also investigated. Based on the simulation results presented in this chapter, model predictive control can be effectively applied in the control of dissolved oxygen concentration of wastewater treat-

ment plants.

Results from the first case-study show that the performance of the controller can be considerably enhanced by decreasing the sampling time, however, this improvement has no significant impact either on the the whole activated sludge process, or the energy consumption used for the aeration process. The integral of absolute error decreased with 40% by reducing the sampling time from 1 min 25 sec to 20 sec, however, the effluent quality index remained at 7560 kg (pollution unit)/day and the energy for the aeration remained at 7277 kWh/d.

The goal of the alternating sludge process simulation was to investigate how efficiently model predictive control can follow the rapidly changing dissolved oxygen setpoint. From the results it can be concluded that lower prediction horizon and input weight can decrease the error between the setpoint and the dissolved oxygen concentration, however, this will increase overshot and cause rapid moves of the manipulated variable what can be avoided imposing constraints on the manipulated variable.

Chapter 5

Mathematical modellig of secondary settling tanks

The results presented in this chapter are party based on the article *Comparison of one-dimensional secondary settling tank models* published in 2006 to the *Journal of the European Water Association* [43].

Whereas the major developments over the past decades have focused on the biological reactor, e.g. biological N and P removal, the secondary settling tank (SST) has a major role in achieving the increasing stringent effluent quality standards. The biological reactor might be meeting the required effluent standards, however, by not capturing the suspended solids adequately, could cause a possible failure in compliance with the COD (BOD_5), total N and P standards. Indeed, at many wastewater treatment plants significant improvements in effluent COD, TN and TP concentrations can be achieved by reducing effluent SS concentrations. In many cases this can be done without the increased cost of effluent filtration, but with improved SST design and operation in general and improved flocculation features in particular.

Earlier SSTs were designed only by empirical hydraulic criteria such as overflow rate that do not take into consideration sludge concentration and settleability. Today there are available not only much improved design pro-

cedures but also hydrodynamic models for simulating the distribution and flows of water and solids in full-scale SSTs. These models allow the influences of inlet arrangement, sludge collection systems and sludge density currents, all of which can affect the effluent SS concentration, to be modelled with remarkable accuracy.

Malfunction of the secondary settling tanks may also be the bottleneck of the whole activated sludge wastewater treatment process. Therefore, when using computer simulation for the design and optimal operation of wastewater treatment plants, the SST model has to be selected adequately besides the model describing the activated sludge process. For this reason, six SST models are introduced and compared in this chapter using the framework of the Simulation Benchmark developed by the COST 'Integrated Wastewater Management' 682 group [17]. The Takács-model is described in the Benchmark in detail, combination of it with the Härtel–Pöpel correction function is investigated is this study. The models of Otterpohl and Dupont having three component fractions, the model of Hamilton which adds a diffusion term to the convective process description and a reactive SST model are also simulated and analysed in this contribution.

5.1 Introduction to secondary settling tanks

In the activated sludge process, the biological sludge mass has to be separated from the treated water to produce clear final effluent. This solid-liquid separation process is usually achieved by gravity sedimentation in traditional secondary settling tanks (SSTs, often referred as secondary settlers, final clarifiers or secondary thickeners).

From the biological reactor the mixed liquor enters the secondary clarifier where it should be sufficiently clarified in order to produce an effluent of acceptable quality. The sludge should also be adequately thickened so that the desired solids level in the bioreactors can be maintained through sludge re-

circulation. Furthermore, secondary settlers should function as storage tanks to store sludge under high solids loading rate and high surface overflow rate typically under peak wet weather conditions. Should any of these functions fail, suspended solids (SS) will be carried over the effluent weirs and escape with effluent. Besides the resulting poor effluent quality, excessive loss of SS may result in the decrease of mixed-liquor suspended solids and hence the sludge age, what affects the whole biological process (e.g. nitrogen removal efficiency can significantly decrease).

The behaviour of the secondary settler in its clarification, thickening and storage function is influenced both by the settling tank design features (e.g. flow rate, inlet arrangement) and the conditions in the biological reactor. For example, under-aeration can decrease the settleability and thickenability of the sludge owing to the proliferation of filamentous bacteria, which leads to bulking. However, over-aeration can lead to poor flocculation and pinpoint floc formation, which result in poor clarification even though the sludge might otherwise have good settling characteristics. Therefore, the functions of the SST and biological reactor are closely related to each other, so the design and operation of one cannot be undertaken independently of the other. Mathematical modelling used for plant design and operation also has to take into account the physical and biological processes in the SST since practical experience showed that that the SST is often the main bottleneck of the entire activated sludge process.

5.2 One-dimensional secondary clarifier models

Common one-dimensional models are based on the sedimentation flux theory of Kynch [59]. It is assumed that in clarifiers the profiles of horizontal velocities are uniform and that horizontal gradients in concentration are negligible. Consequently, only the processes in the vertical dimension are modelled. The

resulting idealized settling cylinder is treated as a continuous flow reactor. Fig. 5.1 shows the flow scheme. At the inlet section, the inflow and the introduced suspensions are homogeneously spread over the horizontal cross section and the suspension is diluted by convection as well as other transport processes. The flow is divided into a downward flow towards the underflow exit at the bottom, and an upward flow towards the effluent exit at the top. [56] Both liquid and suspended solids enter the cylinder through the inlet cross section and are withdrawn at the bottom and at the top. Further assumptions are also taken into consideration:

- The concentration of SS is completely uniform within any horizontal plane within the settler;
- The bottom of the solids-liquid separator represents a physical boundary to separation and the solids flux due to gravitational settling is zero at the bottom;
- There is no significant biological reaction affecting the solids mass concentration within the separator.

Under steady-state conditions the flow and mass balances are:

$$\begin{aligned} Q_{\mathrm{F}} &= Q_{\mathrm{E}} + Q_{\mathrm{R}} \\ Q_{\mathrm{F}} X_{\mathrm{F}} &= Q_{\mathrm{E}} X_{\mathrm{E}} + Q_{\mathrm{R}} X_{\mathrm{R}} \end{aligned}$$

with Q and X as flow rate and SS concentration, respectively, and the subscripts F, E and R for feed, effluent and recycle, respectively.

The transport of solids take place via the bulk movement of the water relative to the side wall and the settling of the sludge relative to the water. The total flux J_{T} consists of the bulk flux $J_{\mathrm{B}} = vX$ and the settling flux $J_{\mathrm{s}} = v_{\mathrm{s}}X$ and becomes

$$J_{\mathrm{T}} = vX + v_{\mathrm{s}}X \tag{5.1}$$

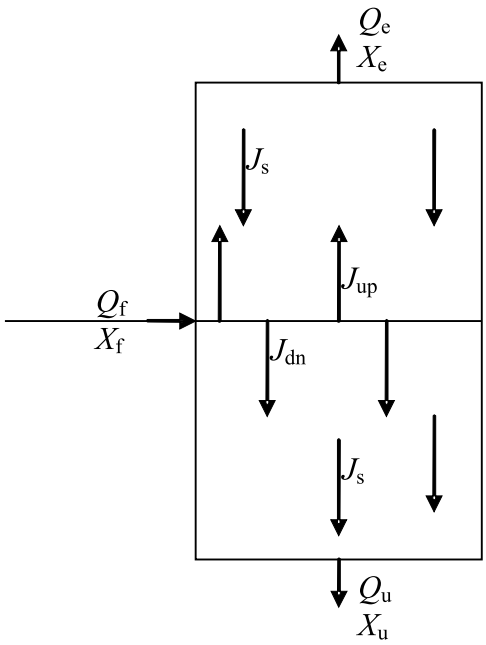

Figure 5.1: Flux directions of the one-dimensional SST model approach

where v denotes the vertical bulk velocity, v_s the settling velocity of the sludge and X the sludge concentration. The form of differential conservation equation describing this process is:

$$-\frac{\partial X}{\partial t} = v\frac{\partial X}{\partial y} + \frac{\partial v_s X}{\partial y} \tag{5.2}$$

with t as time and y as vertical coordinate with the origin at the surface. The two terms on the right-hand side refer to the bulk flux and the settling flux. This equation does not include any inlet source or outlet sinks. Assuming constant horizontal cross section A over the entire depth, the bulk velocity v is dependent only on whether the observed cross section is in the overflow region over the inlet position or in the underflow region.

The flux theory is made operational in computer programs by splitting up the tank into a number of horizontal layers and by discretizing the differential

conservation equation on these layers. The bulk and settling fluxes out of any layer i and j are always related to the concentration X_i or X_j in the respective layer. For continuity reasons the fluxes must be identical with those of the neighboring layers through the common boundary. The full set of mass balance equations will be presented below. First, let us consider the top layer (see top layer in Fig. 5.2). Suspended solids are removed from this layer with the effluent and by gravity sedimentation, however, SS is arriving from the layer below. Therefore, the mass balance for the top layer can be formulated as:

$$\frac{\partial X_1}{\partial t} = \frac{J_{\mathrm{up},2} - J_{\mathrm{up},1} - J_{\mathrm{s},1}}{z_1} \tag{5.3}$$

where

$$\begin{aligned} J_{\mathrm{up,i}} &= v_{\mathrm{up}} X_\mathrm{i} \\ v_{\mathrm{up}} &= \frac{Q_\mathrm{e}}{A} \\ J_{\mathrm{s,i}} &= \begin{cases} J_{\mathrm{s,i}} & \text{if} X_{\mathrm{i+1}} < X_\mathrm{t} \\ \min(J_{\mathrm{s,i}}, J_{\mathrm{s,i+1}}) & \text{if} X_{\mathrm{i+1}} > X_\mathrm{t} \end{cases} \end{aligned}$$

An empirical threshold concentration X_t was defined in order to describe the behaviour in the upper section of the settler. Whenever the solids concentration is greater than X_t is was assumed that the settling flux in that layer will affect the rate of settling within adjacent layers. It was presumed that the threshold concentration corresponded to the onset of hindered settling behaviour. The top of the sludge blanket was determined by the highest layer with solids concentration equal to or greater than X_t.

In the clarification zone (between the top layer and the inlet layer, from layer 2 to $m-1$) the following equation can be used:

$$\frac{\partial X_\mathrm{i}}{\partial t} = \frac{J_{\mathrm{up,i+1}} - J_{\mathrm{up,i}} + J_{\mathrm{s,i-1}} - J_{\mathrm{s,i}}}{z_\mathrm{i}} \tag{5.4}$$

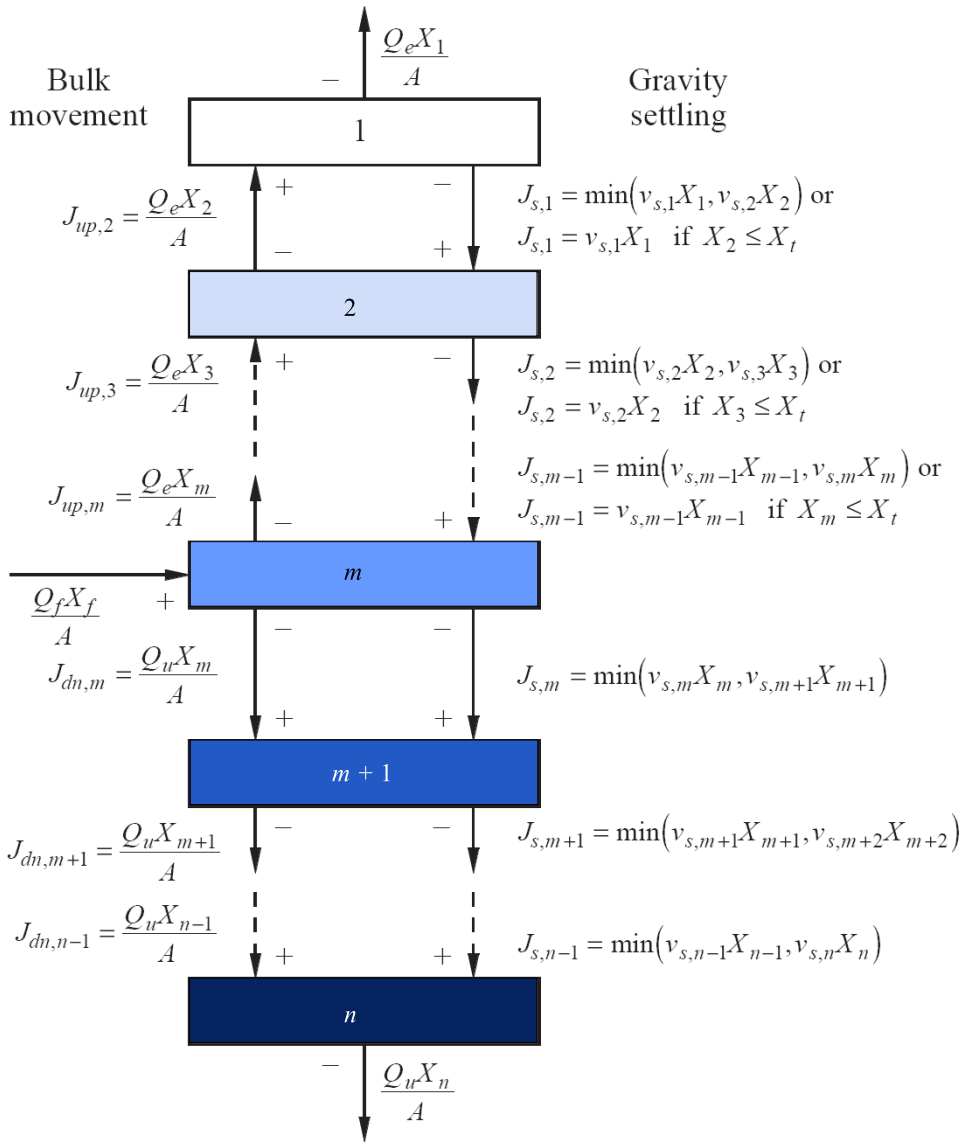

Figure 5.2: General description of the traditional one-dimensional secondary settler layer models

since SS arrive with the upwards flux from the layer below and the settling flux the layer above and SS are removed by settling and with the upward flux from the examined layer.

In the feed layer (m) there is a bulk fluid movement upward with velocity v_{up} and downward with velocity v_{dn}, additionally, the incoming SS have to considered with the assumption of instant homogenous distribution. Therefore, the mass balance equation is in the form below:

$$\frac{\partial X_{\mathrm{m}}}{\partial t} = \frac{\frac{Q_{\mathrm{f}} X_{\mathrm{f}}}{A} - J_{\mathrm{up,m}} - J_{\mathrm{dn,m}} + J_{\mathrm{s,m-1}} - J_{\mathrm{s,m}}}{z_{\mathrm{m}}} \tag{5.5}$$

where

$$\begin{aligned} J_{\mathrm{dn,i}} &= v_{\mathrm{dn}} X_{\mathrm{i}} \\ v_{\mathrm{dn}} &= \frac{Q_{\mathrm{u}}}{A} \end{aligned}$$

For the thickening zone layers (below the feed layer, from layer $m+1$ to $n-1$) a downward flux has to be considered due to the sludge removal at the bottom of the settling tank instead of the upward flux of the clarification zone.

$$\frac{\partial X_{\mathrm{i}}}{\partial t} = \frac{J_{\mathrm{dn,i-1}} - J_{\mathrm{dn,i}} + J_{\mathrm{s,i-1}} - J_{\mathrm{s,i}}}{z_{\mathrm{i}}} \tag{5.6}$$

For the bottom layer

$$\frac{\partial X_{\mathrm{n}}}{\partial t} = \frac{J_{\mathrm{dn,n-1}} - J_{\mathrm{dn,n}} + J_{\mathrm{s,n-1}}}{z_{\mathrm{n}}} \tag{5.7}$$

where the recycled and wasted sludge concentration is defined to be X_{n}. Since X_1 represents the effluent SS concentration, top and bottom layers are treated likewise. The settling flux of the calculated domain is zero at the effluent or at the underflow. Only the bulk flux is considered as a boundary flux. Therefore, the concentrations in the boundary layers are equal to the respective effluent or recycle concentrations which practically mean that the

sludge concentration at the bottom after the thickening process is the same as in the recycle flow to the aeration tank.

A load increase simulated accordingly to the equations above will cause shock wave propagation from the inlet layer towards the bottom of the tank. These waves remain sharp and mathematically discontinuous and are not dampened with time. [19] Moreover, the boundary conditions at the bottom and the top do not include any expression of the settling and thus do not absorb the shock waves. The full reflection of the shock waves at the top and bottom boundaries induce a complex wave pattern that finally leads to numerical instability. This difficulty is the main reason that the existing layer models introduce some kind of restriction of the settling flux relative to that of the layer below. In widely applied rigid approaches, the settling flux of a certain layer is bound to that of the layer below. Thus, the settling flux $J_{\mathrm{s,i}}$ out of layer i is defined as:

$$J_{\mathrm{s,i}} = \min(v_{\mathrm{s,i}} X_{\mathrm{i}}, v_{\mathrm{s,i+1}} X_{\mathrm{i+1}}) \tag{5.8}$$

This equation ensures that a shock wave cannot be created downward and that the concentration profile will never show an inverse gradient within the underflow and overflow region.

The model described above functions as a framework for practically all layer models today. However, in its original form it deals mainly with underflow concentration, leaving realistic effluent suspended solids concentration prediction to empirical or statistical models. This was partly because the settling velocity function used in the original model was of a type that predicted unreasonably high settling velocities for low solids concentration. A number of empirical settling velocity functions have been proposed in literature, majority of the functions are based either on the exponential ($v_{\mathrm{s}} = k\mathrm{e}^{-nX}$) or the power function ($v_{\mathrm{s}} = kX^{-n}$).

5.2.1 The Takács-model

The most wildly used model is that of Takács et al. who based his work on the Vesilind model [92] but suggested a new, so-called double-exponential settling velocity which is capable of predicting the effluent SS concentration more realistically than the exponential function of Vesilind. He based his results on the measurements of the Pflanz full scale data [71]. The double-exponential settling velocity function proposed by Takács:

$$v_s = \max[0, \min\{v_0', v_0(\exp^{-r_h(X-X_{\min})} - \exp^{r_p(X-X_{\min})})\}] \tag{5.9}$$

where v_0 and v_0' are the maximum theoretical and practical settling velocity, respectively, r_h and r_p are the hindered and flocculant zone settling parameters. $X_{\min}$ is the minimum attainable suspended solids concentration in the effluent and is a function of the influent SS concentration to the settler:

$$X_{\min} = f_{\mathrm{ns}} X_\mathrm{f} \tag{5.10}$$

where f_{ns} is the non-settleable fraction of X_f. The inclusion of X_f will directly influence the behaviour of the settler, especially within the clarification zone. While Abusam and Keesem showed that parameters have little effect on SS in the underflow [1], at higher load the hindered settling parameter will determine the compactibility of the sludge, the return concentration that can be achieved and the loading when the clarifier will fail.

The function divides the settling velocity into four regions in order to describe the behaviour of the different sludge fractions (unsettleable fraction, slowly settling fraction, rapidly settling fraction). For $X < X_{\min}$ the settling velocity is zero since in this case the concentration is under minimum achievable effluent SS concentration. When $X_{\min} < X < X_{\mathrm{low}}$ the settling velocity is dominated by the slowly settling particles. For low concentrations of SS, Patry and Takács showed that the mean particle diameter increases as the solids concentration in the free settling zone of the clarifier

gets higher [70]. An increasing particle diameter implies a higher settling velocity and this effect is reflected in the behaviour of the settling velocity within the region $X_{\min} < X < X_{\text{low}}$. When $X_{\text{low}} < X < X_{\text{high}}$ (usually from 200 to 2000 g/m3) the settling velocity is considered to be independent of the concentration as the flocs reach their maximum size. Finally, when the SS concentration grows above X_{t} the model uses the traditional exponential velocity function describing the effects of hindered settling.

The original model proposed by Takács et al. does not take into account the effect of sludge volume index (SVI) explicitly, however, incorporation of SVI is possible through the modification of the settling velocity parameters. E.g. r_{h} can be estimated with a correlation between SVI and r_{h} ($r_{\text{h}} = a + bSVI + cSVI^2$ where a, b, c are the SVI correlation coefficients).

5.2.2 The Härtel correction function

In the proposal of Härtel and Pöpel [36] a correction of the settling function was suggested besides the boundedness of the settling flux to that of the lower layer. The correction function is based on empiricism and is dependent on the sludge volume index (SVI), the vertical position (y), the position of the inlet layer (h_0) and the feed solids concentration (X_{f}). The settling flux is smoothly reduced through the Ω function from a height somewhat below the inlet layer downward and reaches zero at the bottom. The inconsistency at the bottom layer is overcome by having a settling flux tending towards zero near the bottom. Therefore, the settling flux equation can be reformulated as:

$$J_{\text{s,i}} = \Omega(y, SVI, h_0, X_{\text{f}}) \min(v_{\text{s,i}} X_{\text{i}}, v_{\text{s,i+1}} X_{\text{i+1}}) \tag{5.11}$$

In Fig. 5.3 the value of the Ω function can be observed at different SVIs in the function of the settler height.

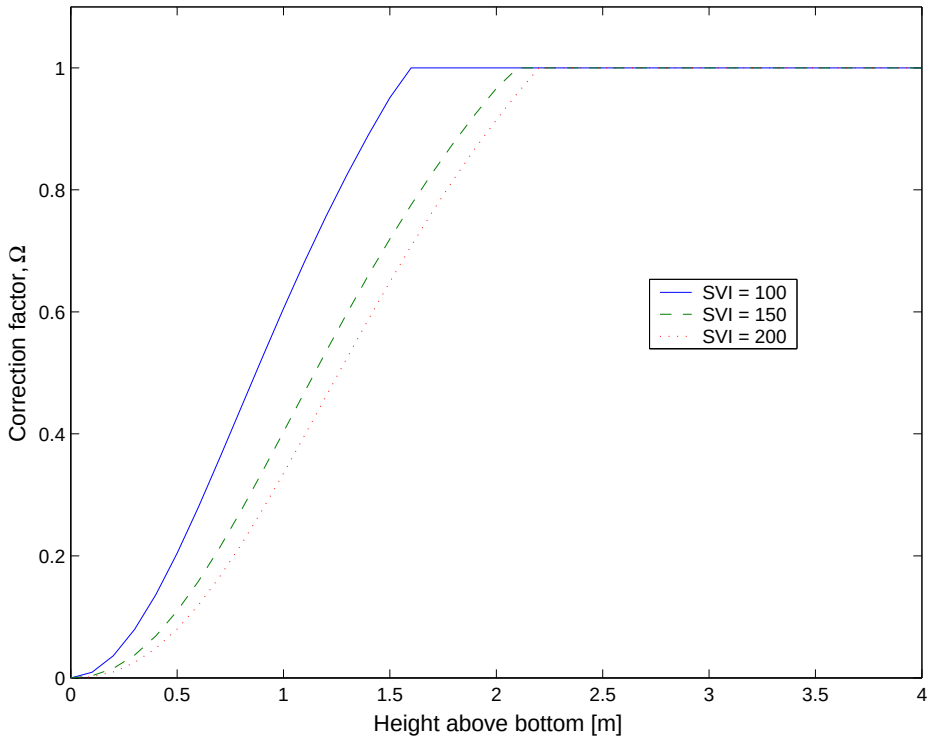

Figure 5.3: The Härtel-Pöpel correction function for an inlet position at 2.2 m above the bottom at different sludge volume indexes

5.2.3 Model of Dupont and Dahl

The mixed liquor is a flocculent suspension in which larger particles can be formed by the coalescening of particles which have collided. These larger particles generally enhance settling characteristics. The particle distribution is bimodal with primary particles (miroflocs) in the 0.5 to 5 μm and flocs (macroflocs) in the 10 to 5000 μm range. The settling properties of a sludge depends both on the distribution of primary and floc particles and on how easily the primary particles are entrapped into larger flocs.

Therefore, the components of the influent to the settling tank are divided

into three fractions according to the model of Dupont and Dahl [25]: soluble components, non-settleable particulate components (referred as primary particles) and settleable components (macroflocs). Soluble components and primary particles are considered to follow the hydraulic flow in the settling. The transport of macroflocs in the settling tank is modelled according to the traditional flux theory. The model selected for estimating the amount primary particles is describing the concentration of primary particles in the influent to the settling tank as a function of the effluent flow rate:

$$X_{\mathrm{PP}} = SS_{\mathrm{Init}} + K_1 \left(\frac{Q_{\mathrm{efl}}}{A} \right)^{K_2} \tag{5.12}$$

The parameter values in the work of Dupont and Dahl are 3 mg/l, 1.6 and 3 for SS_{Init}, K_1 and K_2, respectively. Consequently, the concentration of macroflocs in the influent to the settling tank is given by:

$$X_{\mathrm{SS}} = X_{\mathrm{SS,I}} - X_{\mathrm{PP}} \tag{5.13}$$

Settling velocities of the macroflocs for both free and hindered sedimentation were measured and a new model for the settling velocity was proposed. The model was validated with data measured at the wastewater treatment plant Lynetten, Copenhagen, Denmark. The settling velocity has an increasing value for increasing concentrations at low suspended solids concentrations (free settling zone where the mean particle diameter increases with increasing SS concentration) and a decreasing value for increasing concentrations at high suspended solids concentration (hindered settling). The mathematical formulation selected by Dupont and Dahl for the description of the settling velocity is the log normal function of the total concentration of particles ($X_{\mathrm{SS}} + X_{\mathrm{PP}}$) in the suspension. It is emphasised that the calculation of the settling velocity depends on the total concentration, while the settling

velocity refers only to the macroflocs (X_{PP}) of the suspension.

$$v_{\mathrm{s}} = v_0 \exp\left(-0.5\left(\frac{\ln\left(\frac{X_{\mathrm{SS}}+X_{\mathrm{PP}}}{n_1}\right)}{n_2}\right)^2\right) \tag{5.14}$$

The suggested model parameters are 8.9024 m/h, 630 m^3/g and 1.065 for v_0, n_1 and n_2, respectively.

A model for the phenomenon of short-circuiting is also proposed in the work of Dupont and Dahl. Differences in the density of the influent and the density of the suspension in the settling tank will induce density currents in the tank. In the inlet zone the density current will cause a vertical transport of the influent through the settling tank. Together with the vertical flow caused by the return sludge removal, a substantial part of the influent is transported to the return sludge pit without taking part in the actual settling process. Hereby the suspension withdrawn from the bottom of the settling tanks is diluted to give the actual suspended solids concentration in the return sludge. The proposed model divides the whole influent into two parts: one part makes up the actual influent to the settling part of the settling tank model; the other part of the influent makes up the short-circuiting flow which bypasses the settling part of the settling tank model.

5.2.4 The Otterpohl and Freund model

Otterpohl and Freund also proposed a three components model in their work [67] which can describe the behaviour of the secondary settler under dry and wet weather flows. In their work, experiments were made at three municipal wastewater treatment plant operating with different sludge ages. Activated sludge drawn from the effluent of the aeration tank was settled in 1 litre cylinders. The supernatant was analysed for its solids content both by turbidity measurement and filtration at different dilution rates. The results of measurements for small solids components (microflocs) relative to the solids

concentration in the aeration tank is given in the following function:

$$f_l = f_0 \mathrm{e}^{-aX} \tag{5.15}$$

where f_l is the fraction of small solids in the aeration tank, f_0 and a are parameters (0.04 and 0.78, respectively). According to their observations, the settling speed of small sludge flocs is constant and

$$v_{\mathrm{s,microflocs}} = 0.01\mathrm{m/h} \tag{5.16}$$

This proved not to be a sensitive parameter until the effluent flow becomes very small. For the estimation of the settling velocity of the macroflocs, the results of Härtel were used. The settling velocity function for macroflocs:

$$v_{\mathrm{s,macroflocs}} = (17.4\mathrm{e}^{-0.00581SVI} + 3.931)\left(\mathrm{e}^{-(-0.9834\mathrm{e}^{-0.00581SVI}+1.043)X}\right) \tag{5.17}$$

Furthermore, the settling flux is multiplied with the Ω correction function of Härtel. Therefore, the resulting settling flux can be formulated as:

$$J_{\mathrm{s,i}} = \Omega(y, SVI, h_0, X_{\mathrm{f}}) \min(v_{\mathrm{s,i}} X_{\mathrm{i}}, v_{\mathrm{s,i+1}} X_{\mathrm{i+1}}) \tag{5.18}$$

in the thickening zone.

5.2.5 Model of Hamilton

To treat the phenomenon of propagating shock wave a conceptual hydrodynamic approach was used by Hamilton et al. [35] and other authors [2, 68]. An additional eddy diffusion term was added, therefore, the conservation equation can be rewritten as:

$$-\frac{\partial X}{\partial t} = v\frac{\partial X}{\partial y} + \frac{\partial v_{\mathrm{s}} X}{\partial y} - D\frac{\partial^2 X}{\partial y^2} \tag{5.19}$$

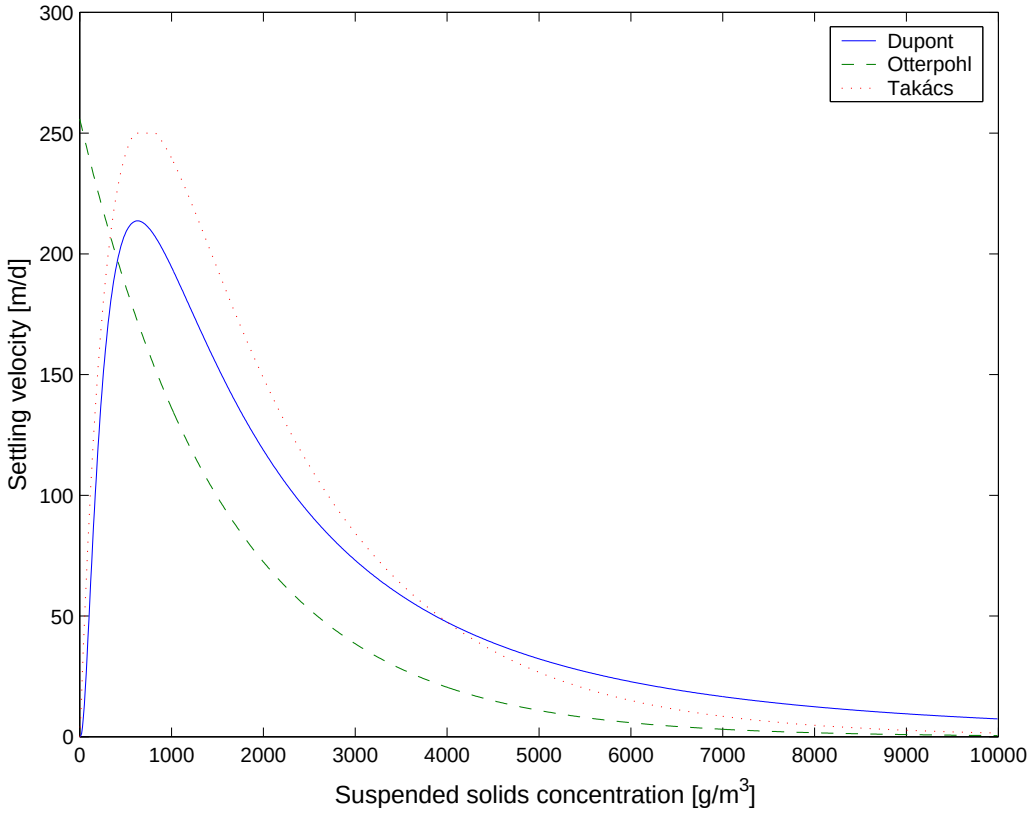

Figure 5.4: Settling velocity vs SS concentration in the SST model of Dupont, Takács and Otterpohl

where D is the pseudo-diffusivity coefficient. Owing to the diffusion term, the gradient of a shock wave front is decreased while the propagation and the numerical procedure become stable. Nevertheless, it has to be emphasized that D is pseudo-diffusivity coefficient which not only describes the real physical diffusion process, but incorporates turbulent diffusivity, 2-D and 3-D dispersion, errors introduced by numerical methods and the sludge removal process. The introduction of a diffusion term also changes the partial differential equation from convective to convective-diffusive, which makes the final solution become independent of the initial conditions. The model is

constructed in the same way as the other models: the mass balance equation is discretized by dividing the settler into a number of layers. In this case, the mass balance for layer i in the thickening zone ($m < i < n$):

$$\frac{\partial X_{\mathrm{i}}}{\partial t} = \frac{J_{\mathrm{dn,i-1}} - J_{\mathrm{dn,i}} + J_{\mathrm{s,i-1}} - J_{\mathrm{s,i}} + D(X_{\mathrm{i+1}} - X_{\mathrm{i}})/z_{\mathrm{i}} - D(X_{\mathrm{i}} - X_{\mathrm{i-1}})/z_{\mathrm{i}}}{z_{\mathrm{i}}} \tag{5.20}$$

The suggested model parameter for D is 0.54 m^2/h by Hamilton. [35]

5.2.6 Reactive one-dimensional models

All the aforementioned models used the assumption that biological reactions are negligible within the secondary settling tank, only the physical reactions were considered. However, in some cases investigation of the biological reactions can be necessary because high denitrification rate can lead to the appearance of nitrogen bubbles and therefore, to the rising of the sludge [81]. Modelling the biological reactions as well as the physical processes in the SST, each layer has to be considered as a continuously stirred tank reactor where biological reactions take place, soluble components are carried by the hydraulic movement and SS are carried by sedimentation and bulk movement. Propagation of the soluble components can be described by the following equation in the thickening zone:

$$\frac{\mathrm{d}S_{\mathrm{i}}}{\mathrm{d}t} = \frac{v_{\mathrm{dn}}(S_{\mathrm{i-1}} - S_{\mathrm{i}})}{z_{\mathrm{i}}} \quad \text{where} \quad v_{\mathrm{dn}} = \frac{Q_{\mathrm{e}}}{A} \tag{5.21}$$

For the description of the biological processes traditional activated sludge models can be used like ASM1, ASM2, ASM2d, ASM3. In our contribution the ASM1 model [38] is applied for modelling the biological processes while the physical settling process is still described by the Takács model.

5.2.7 Further model developments

Certainly, several new one- (or even two or three) dimensional models can be found in literature. Jeppsson and Diehl [19, 50, 51] proposed the application of the analytical Godunov approach for the treatment of the propagating shock wave phenomenon. Their calculation is numerically stable, however, it is possible to observe a very sharp front in the upwards direction. Since their procedure is combined with zero-volume boundary layers, the resulting concentration profile is not bounded by the effluent and recycle values. It was also shown in their work, that the model of Takács et al. is dependent on the number layers, while the model of Jeppsson is not.

Ossenbrugen and McIntire [66] assigned a maximum total flux at the level referring to a certain, high sludge concentration, which again results in the settling flux curve reaching zero at some high concentrations. A numerical method was applied where an initial sludge profile had to be prescribed and in which a second-order term was introduced causing numerical diffusion for stability reasons.

Randall et al. [76] introduced a model with a dispersion term dependent on concentration and feed velocity. Motivation for their model derived from the analysis of a model employing a constraion on the gravity flux which has been shown to give excellent fits to a previously published data set. It was also observed that the gravity flux constraint disappears as the level of discretization increasing, a difficulty that this model can overcome.

5.3 Simulation benchmark

For the purpose of comparison of the different secondary settling tank models, the Simulation Benchmark has been used. The COST 682 Working Group No. 2 has developed a benchmark for evaluating by simulation, control strategies for activated sludge plants [17]. The benchmark is a simulation environment defining a plant layout, a simulation model, influent loads, test

procedures and evaluation criteria. Detailed description of this simulation environment can be found in Section 4.5.

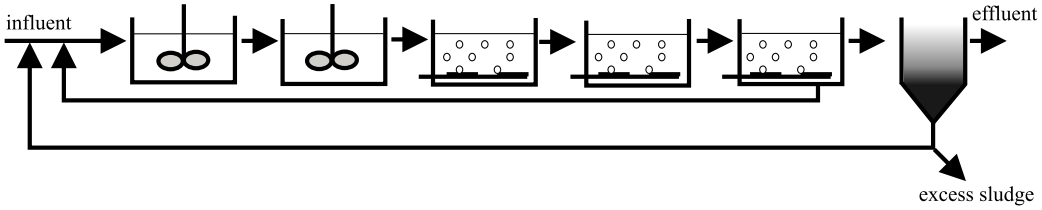

Figure 5.5: Wastewater treatment plant setup

The plant layout can be seen in Fig. 5.5. The first two compartments makes up the anoxic zone with individual volume of 1000 m^3, and 3 compartments create the aerobic zone with individual volume of 1333 m^3. The oxygen mass transfer coefficient rate (K_La) is set to 240 d^{-1}, while the K_La in the last compartment is 80 d^{-1}. The flowrate of the internal recirculation is kept at 55338 m^3/d. The secondary settler has a conical shape with the surface of 1500 m^2 and the depth of 4 m. The flowrate of the sludge recirculation is 18446 m^3/d and the excess sludge is removed from the settler at 385 m^3/d.

Since influent quality and flow rate disturbances play an important role in the operation of wastewater treatment plant, influent disturbances are defined for different weather conditions. In this paper, both dry weather data and wet weather conditions are considered containing 2 weeks of influent data at 15 minutes sampling interval. Parameters for the second week influent are depicted in Fig. 5.6. Diurnal variations and weekly trends (lower peaks in weekend data) are also depicted by these data.

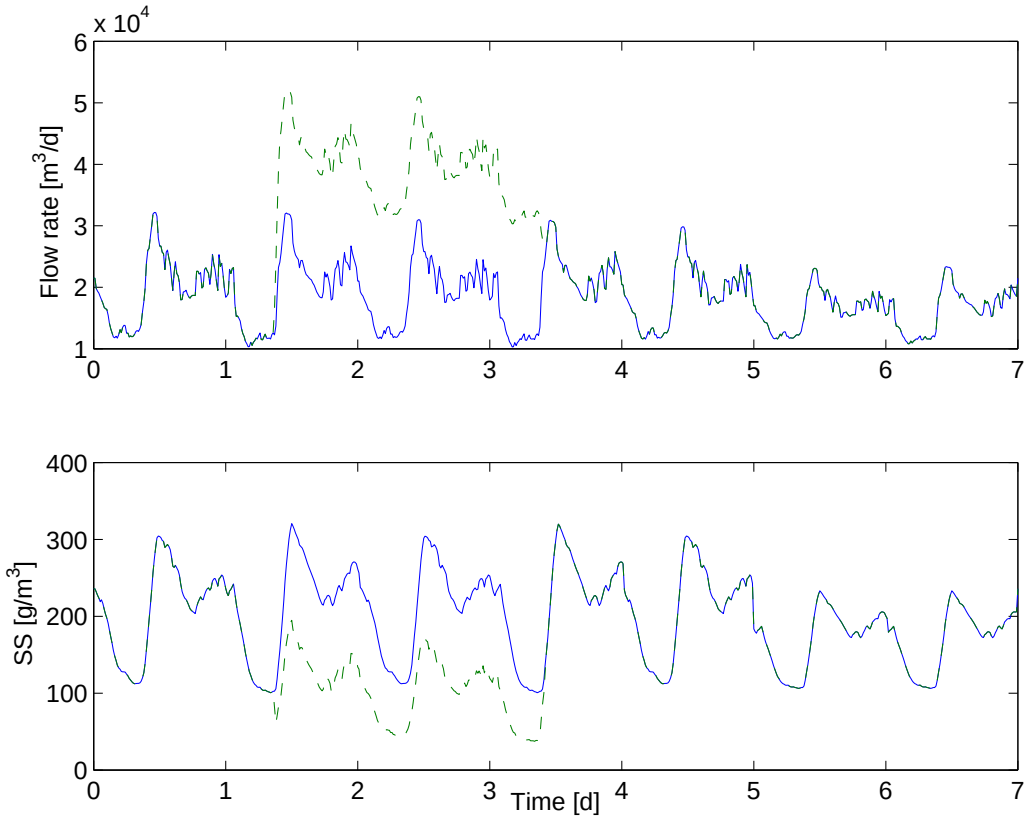

Figure 5.6: Influent flow characteristics under dry and wet weather

5.4 Simulation results

Simulations were carried out using the framework of the Simulation Benchmark but substituting the secondary settler model with the currently investigated model. Both dry and wet weather dynamic simulations were examined. The SST was divided into 10 vertical layers in all cases as described in the Benchmark. Finally six models were compared: the originally described Takács-model; combination of the Takács-model with the Härtel–Pöpel correction function (applied earlier also by [32]); the three fraction models of Otterpohl and Dupont, however, the short-circuiting model was omitted from

the Dupont model for better evaluation; the Hamilton-model and a reactive model.

5.4.1 Steady-state results

Investigating a secondary settler model, the initial step is to examine the steady-state SS profile in the secondary settler which can be the starting point for other dynamic simulations. Since, steady-state solvers often fail to find a steady-state solutions, the steady-state is achieved by using a constant influent until the system reaches the steady-state. It was found that 100–200 days simulation is enough and the final values can be accepted as steady-state values.

The resulting steady-state profiles can be seen Fig. 5.7. The effluent SS concentrations are usually between 10 and 30 g/m^3 according to the 12.5 g/m^3 of the Simulation Benchmark which applies the Takács-model. The lowest concentration is predicted by the Otterpohl & Freund model (9.77 g/m^3) which is unambiguously due to the settling velocity model estimating very high settling velocity at low SS concentrations (see Fig. 5.4). The highest effluent SS concentration (31.0 g/m^3) is predicted by the Dupont & Dahl model because of the low settling velocity at very low SS concentration. It can be concluded from Fig. 5.7 that that the inlet layer (1.6–2.0 m depth) is dominated by the influent concentration, its concentration moves between 340–360 g/m^3 for all models except the Otterpohl model which predicts lower concentration due to very high settling velocity in the 0–500 g/m^3 SS concentration range. The underflow SS concentrations ranges between 5700 and 6400 g/m^3 according to settling velocity in the thickening zone, however, the distribution of the sludge in the thickening zone shows significant difference: the Härtel, Hamilton and Otterpohl model gives a smooth distribution, the sludge concentration gradually increases with depth. On the other hand, the Takács settling function, the Dupont and the reactive model results in a considerably uniform sludge distribution (350–360 g/m^3) in the thickening

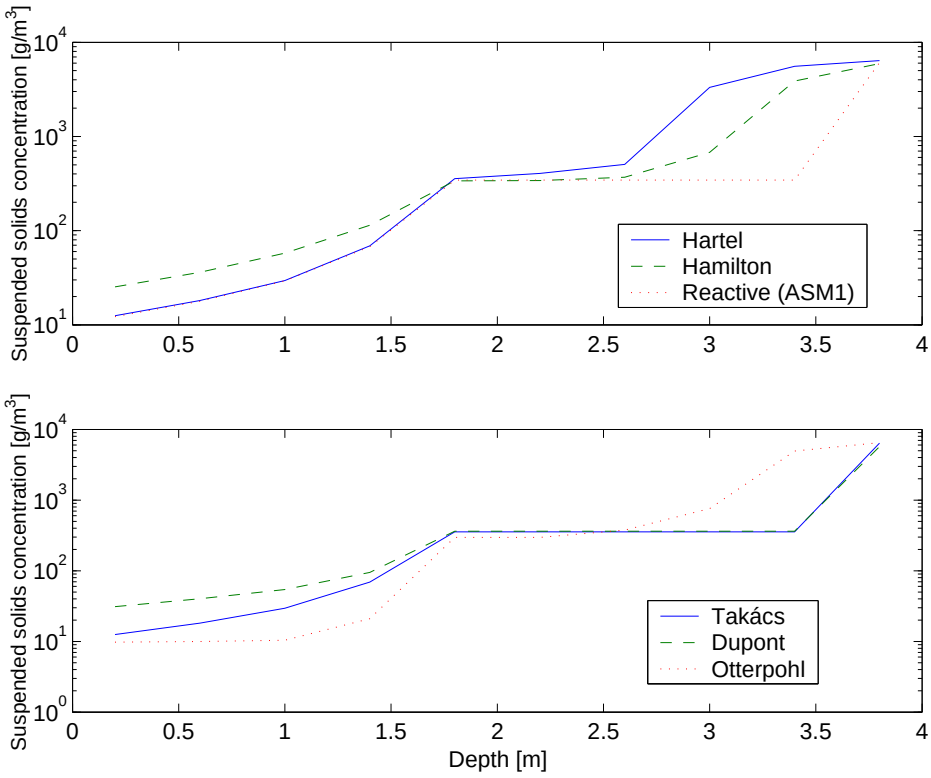

Figure 5.7: Sludge distribution in the secondary settling tank under steady-state conditions (note the logarithmic scale)

zone.

5.4.2 Dynamic simulations

After having found the steady-state solution, dynamic simulations can be carried out using the influent data depicting the variations in the influent flow and load. Starting from the steady-state the dry weather influent data are used for a 14-day simulation. From the states achieved, further 14 days are simulated using the dry weather and rain event influent data. That is, for any system at steady-state a 28-day dynamic simulation is performed,

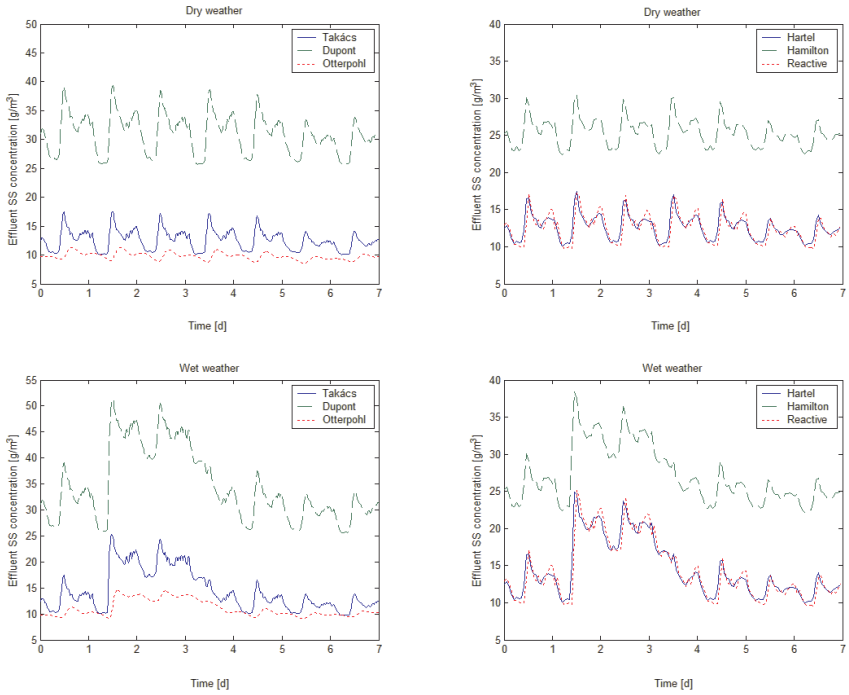

Figure 5.8: Effluent SS concentration under dry and wet weather conditions

from which the data of the last seven days are used for process evaluation.

The predicted effluent SS concentrations can be seen in Fig. 5.8. The daily and weekly load variation can be well observed from the results: the diurnal daily deviation and the low weekend flow determine the effluent quality. As expected from the steady-state results, the Dupont and the Hamilton models estimate the highest effluent SS concentrations and the highest daily variation. The second two plots depict the effect of a rain event on the effluent. According to the Dupont model, the SS in the effluent may reach up to 50 g/m^3 during the rain, while the lowest predicted concentration (Otterpohl model) remains below 15 g/m^3.

The underflow SS concentrations were also investigated during the simulation, since these are also important parameters as the recycled sludge is

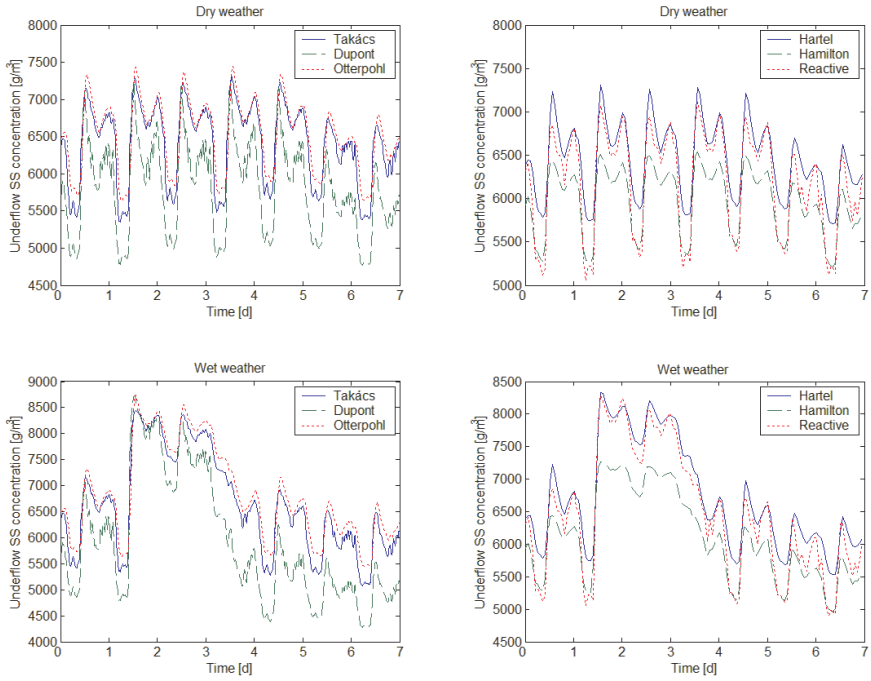

Figure 5.9: Underflow SS concentration under dry and wet weather conditions

used to maintain the SS in the biological reactors, furthermore, the cost for the sludge disposal can be estimated knowing the wasted sludge quantity. The resulting underflow sludge concentration is mainly influenced by the settling velocity value at high sludge concentration in the thickening zone. The highest concentration is predicted by the Otterpohl model which estimated the lowest effluent SS concentration. This is due to the characteristic of the exponential settling velocity model: very high settling velocity in the clarification zone and very low settling velocity in the compression zone. The lowest concentrations are predicted by the Dupont and the Hamilton models.

The change in the sludge concentration profile during a 7-day dynamic simulation can be seen in Fig. 8.2. The first figure depicts the profile change

during a dry weather scenario and on the second figure a significant rainfall results in the SS concentration increase in the thickening zone of the SST.

5.5 Conclusion

The application of one-dimensional models coupled with the activated sludge models gives a good approximation of the sludge balance and of the sludge shift from the aeration tank to the SST where it is partly stored during wet weather loading. Furthermore, application of these models does not require less computation capacity then 3-D models. However, in real plants there exists several phenomena that cannot be reflected in 1-D models like the geometry of the SST (e.g. inlet and outlet arrangement), flow (e.g. short-circuits from the inlet to the outlet; re-suspension of the settled sludge blanket) and the sludge removal process (the sludge at the bottom of the tank is diluted). Nevertheless, one-dimensional models are widely used and accepted in computer simulation of wastewater treatment plants nowadays.

Chapter 6

Case study of a computer-aided wastewater treatment plant reconstruction

The results presented in this chapter are party based on the article *Effect of long retention time in the settler on phosphorus removal from communal wastewater* published in 2005 to the journal *Environmental Science & Pollution Research* [23].

The objective of the chapter is to illustrate the solution of a chronic problem occurring in a wastewater treatment facility with a capacity of 120 000 inhabitant equivalent. Drastic phosphorus concentration increase (two or three times higher than the Hungarian limit of 1 mg/l) was observed in the wastewater treatment facility for a long time (12–24 h) with changing time periods indicating malfunctioning in the operation of the facility. Computer aided simulation technique was used to develop a solution for the treatment of the problem using a software developed by the Department of Environmental and Chemical Engineering, University of Veszprém, Hungary.

The simulation studies show that if the nightly inflow is less than 200 m^3/h at least for two hours, then the system doesn't receive enough fresh

nutrients which can cause a deficiency in the nutrient uptake of the PAOs in the anaerobic zones. This can result in the fact that the PAOs accumulate less phosphorus in the aerobic zones. Long retention time (10h) is the reason of the problem, namely – under special conditions – the phosphorus in the sludge of the settling tank of the wastewater treatment plant. The problem was caused by phosphorus dissolution from the sludge of the settling tank during the undesirably long retention time.

6.1 Introduction

Controlling phosphorus discharged from municipal and industrial wastewater treatment plants is a key factor in preventing eutrophication of the surface waters. The theory of luxury uptake of phosphorus by organisms is now well developed. It has been shown that exposing the mixed liquor to an anaerobic/aerobic sequence in the biological reactor selects microorganisms that accumulate higher levels of intracellular phosphorus than other microorganisms.

At a Hungarian wastewater treatment facility drastic periodic phosphorus concentration increase (two or three times higher than the Hungarian limit of 1 mg/l) was observed for a long time (10 h) with changing time periods. At first, the source of the problem had to be identified. The analytical monitoring of the inlet wastewater did not support the notion that the illegal wastewater discharges into the sewage caused the sudden phosphorous concentration change. As another possibility, hidden toxicity was hypothesized, however, the available data and information failed to prove it. The real source of the problem was identified by using computer aided simulation and the appropriate treatment process has been devised for eliminating the problem.

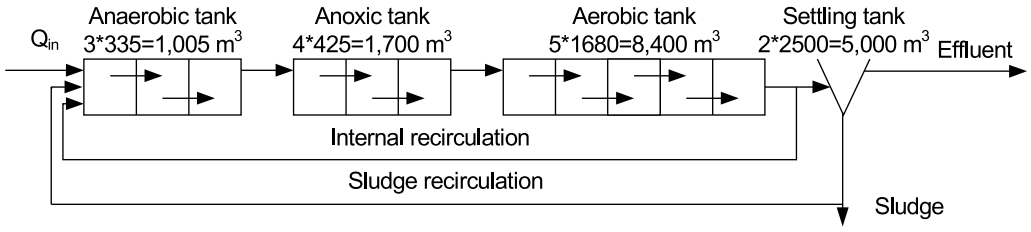

Figure 6.1: Scheme of the wastewater treatment plant

6.2 Description of the wastewater treatment facility

The inflow of the wastewater treatment plant is about 12,000–13,000 m^3/d. 95% of the wastewater is municipal wastewater and remaining 5% comes from stock-farm sources. The whole tank-capacity of the plant is 11,100 m^3. 10% of the capacity (1,000 m^3) is anaerobic, 15% (1,700 m^3) is anoxic, and the remaining 75% (8,400 m^3) is aerobic tank capacity. The capacity of the settler is 5,000 m^3. Figure 6.1 shows the scheme of the wastewater treatment plant. Considering the model of the plant, it can be realized that the operation of the plant is very doubtful since the internal and sludge recirculation are also connected into the anaerobic tank. In such a design, the nitrate present in the mixed liquor will to a large extent consume carbon source which otherwise could have been used to form storage materials in the PAOs (Petersen et al., 1998) and theoretically the anoxic zone has no functionality, since no nitrate-rich stream is directed to the tank. In spite of these facts, the wastewater treatment plant is capable of removing efficiently the pollution from the wastewater.

Effluent quality of the plant is much better than Hungarian limit of load as shown in Table 6.1. It can be due to oversizing of the facility, because a wastewater treatment facility with the capacity of 8,000 m^3d^{-1} would be sufficient for this amount of influent.

Table 6.1: Limit value of the Hungarian 1st category, special limit of this plant and similar EU category of water quality and the inflow concentration parameters

Parameter	Unit	Hungarian limit	Special limit of this plant	EU limit	Measured inflow
COD	mg/l	150	150	125	900
BOD_5	mg/l	75	100	25	560
NH_4–N	mg/l	10	10	Σ15	Σ62
NO_X–N	mg/l	5	5		
Σ P	mg/l	1	1,2	2	11

Table 6.2: Main operating parameters of the wastewater treatment plant

Parameter	Unit	Value
Quantity of inflow wastewater (in a day)	m^3/h	300–900
Sludge recirculation	% (of influent)	100
Internal recirculation	m^3/h	2,000
	% (of influent)	666–222
Sludge concentration	mg/l	5,500

As shown in Table 6.2, the quantity of the inflow has been extremely alternating. It is caused by the city that is a "dormitory" type. During the low load period, anaerobic zones are formed in bottom sludge zones of aerobic tanks. It may cause major fermentation.

The quality of the inflow is very stable. Table 6.1 includes the main inflow parameters. This can be due to the separated rainwater collecting system, the extended wastewater-system using temporary reservoirs and the entire absence of industrial facilities. These values changed only by 10% during the test run.

6.3 Problem identification

Data from the laboratory measurements had been examined by the operating staff, and it was concluded that the biological phosphorus removal efficiency decrease unaccountably frequently, about once a month. It lasted from a few hours till several days. This effect manifested as an increased phosphorus concentration in the effluent, occasionally it reached up to 2 mg/l. After a long term examination it turned out that neither chemical materials (e. g. toxicity), nor psychical effects (e. g. detergents) could cause this problem. After this resolution a computer aided simulation analysis was requested for the purpose of solving this operating anomaly.

During the study, a wastewater treatment expert system was used developed by the Department of Environmental Engineering and Chemical Technology, University of Veszprém and with the involvement of one of the largest Hungarian computer programming firm. This software is able to model – and optimize – every communal wastewater treatment plant using any of the IAWQ models. The IAWQ Task Group for Mathematical Modelling for Design and Operation of Biological Wastewater Treatment introduced the Activated Sludge Model No. 1 in 1987 which allows the simulation of the behaviour of nitrifying and denitrifying activated sludge systems which treat primarily domestic wastewater. Model No. 1. [38] has become a major reference for further research work and is the basis for many packages applied for design and operation of treatment plants.

For the modelling of the secondary settler the double-exponential model of Takács [84] and another model based on the settling velocity functions of the particulate components have been applied within the frame of simulation software. Using the latter model, the settler is divided into two parts according to the speed of the upwards flow and the distribution of the particulate and soluble components is computed in the upper ("clear") and the lower ("sludge") phase. The main advantage of this method is the fact that the biological processes can be modelled more easily.

6.4 Problem solution

In order to fasten and simplify the modelling process, the scheme of the wastewater treatment plant has been simplified during the first step of the simulation. Serially connected reactors with the same functionality are considered as one, what resulted in 1 anaerobic reactor having a volume of 1005 m^3, 1 anoxic reactor of 1700m^3, and aerobic reactor of 8400m^3 and one settler with the volume of 5000m^3.

Using typical values of the daily inflow rate (Figure 6.2), the result of the simulation shows the fact that the analyzed wastewater treatment plant should work perfectly. As Figure 6.3 shows, the effluent parameters of the plant are predominantly below the limit.

During the analysis of the reactors it was noticed that the wastewater had a very long retention time – occasionally 12 hours – in the settlers because of the oversizing of the wastewater treatment plant according to the internationally accepted standards. It may cause significant phosphorus dissolution from the sludge into the cleaned water. Phosphorus transports to the beginning of the wastewater treatment process by the recycle stream raised the inflow concentration. Usually this increase doesn't cause a problem whereas phosphorus accumulating organisms (PAOs) can accumulate phosphorus under favourable conditions.

It is currently not well understood how the DO setpoint andthe level of oxygen supply affects the overall phosphorus removal performance. However, the evidence available in the literature seems to suggest that a low DO concentration and/or aerobic volume is more favorable. It is obvious that the presence of oxygen in the anaerobic reactors negatively affects phosphorus release thus deteriorating overall phosphorus removal performance. It is known that the presence of oxygen and nitrate/nitrite inhibits the phosphorus release. However, it is also possible that the negative effect over a longer period may result from the competition between the ordinary heterotrophic organisms with phosphorus accumulating organisms for the limited volatile

fatty acids available. This is suggested because significant phosphorus release is observed to occur even under aerobic/anoxic conditions so long as acetate is present. Regardless what the mechanism is, the recirculation of oxygen from the aerobic zone to the anaerobic phase should be minimized.

During the external factor analysis it was realized that the quantity of nutrients in the inflow at night is just enough to support the continuous phosphorus cycle. Since the measurements showed steady wastewater quality therefore, it was examined what happened to the wastewater treatment plant if the nightly inflow was decreased below the measured minimum. The simulation studies show that if the nightly inflow is less than 200 m^3/h at least for two hours, the system doesn't get enough fresh nutrients. This causes a deficiency in the nutrient uptake of the PAOs in the anaerobic zones. Therefore, PAOs accumulate less phosphorus in the aerobic zones, so the effluent phosphorus concentration rises. If the inflow is low for a longer period of time - at least for 3 hours - then the normal effluent phosphorus concentration of the wastewater treatment plant will be restored only 12–48 hours later. Figures 6.2 and 6.3 give an example for this "critical time" case.

Figure 6.3 shows a phosphorus concentration increase by the morning of the third day as there was a major influent decrease, occasionally decreased down to $200m^3/h$ (over three hours during the second night (Figure 6.2)). This concentration increase terminates by the end of the third day.

After the measurements and the simulation, a difficulty had to be eliminated similar to the one that Krühne and Temmink had described [58, 86]: after of a long time period of low load the system has to restore its normal behaviour, in addition, high phosphorus concentration can be observed in the influent. Generally PAO releases phosphorus to gain maintenance energy under anaerobic conditions and to take up any volatile fatty acid produced by anaerobic fermentation of the organic carbon substrates by ordinary heterotrophs [65]. Considering the recommendation of Brdjanovic [6] concerning the problems connected to the P removal problems after weekends, the re-

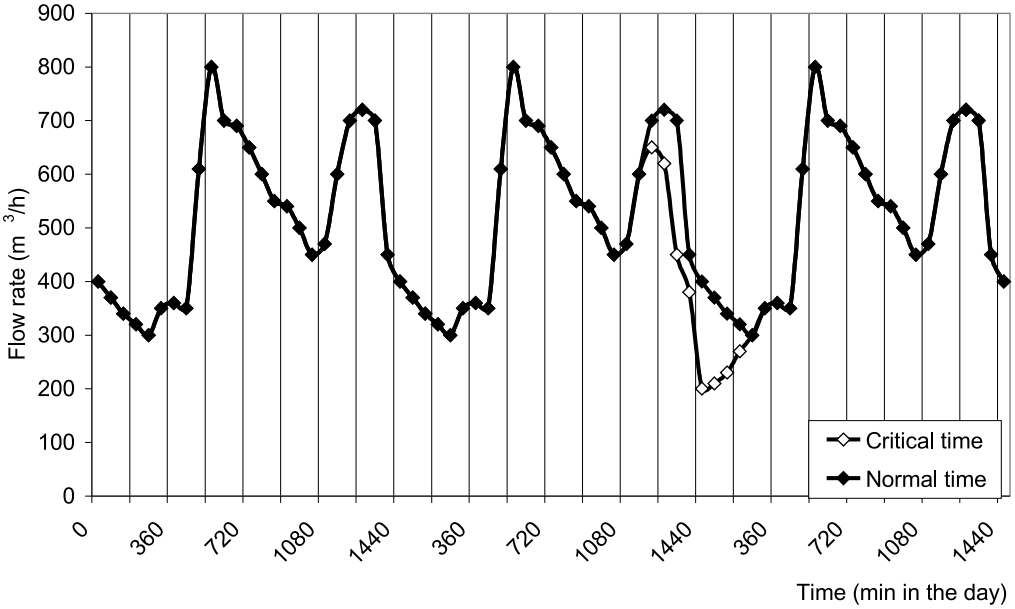

Figure 6.2: Change of the volumetric load of the plant (2nd day 1000–1400 min)

moval one of the settlers seemed to be the best solution. This mechanism, often referred as the "*Monday Phenomenon*", – that phosphorus removal performance deteriorates after weekend, during which a low carbon supply from the influent wastewater is coupled with a high DO concentration – is due to the fact that extensive aeration in the aerobic reactor results in over consumption of the PAO intracellular carbon storage (polyhydroxyalkanoates or PHA). Obviously, an aerobic reactor should not run devoid of oxygen and nitrate to avoid secondary phosphorus release.

According to the simulation results, reducing the settler capacity to half of the original capacity reduced the hydraulic residence time, which proved to be short enough to prevent from the phosphorus re-dissolution and to prevent from the abnormally high phosphorus concentration in the effluent after the return to the normal state of plant.

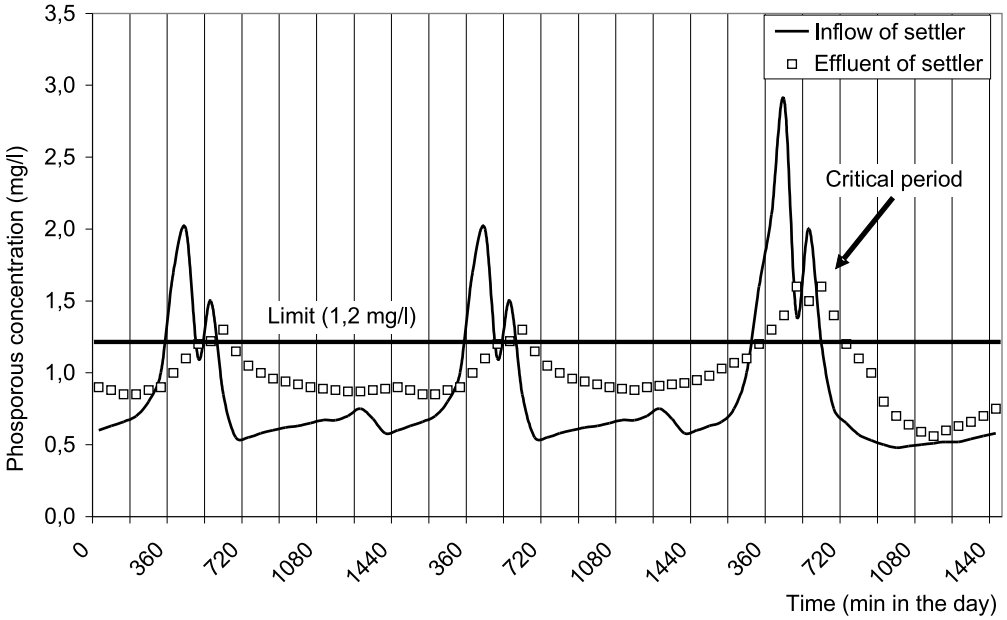

Figure 6.3: Changes in the P removal efficiency

After the promising simulation results, it had to examined whether the reduced settler capacity was sufficient. According to the Hungarian law on wastewater treatment the minimum settler capacity can be computed by the following formula. The parameters of the settler are determined using the average flow rate per hour according to the Hungarian standard. Therefore, the hydraulic load is computed using the following formula:

$$V = \frac{Q_{\mathrm{day}}/24}{F} \tag{6.1}$$

while the hydraulic residence time:

$$t_{\mathrm{t}} = \frac{V}{Q_{\mathrm{day}}/24} \tag{6.2}$$

The minimal hydraulic residence time is determined in Table 6.3.

Table 6.3: Highest permitted hydraulic load and lowest permitted residence time of a secondary settler in activated sludge systems

Parameter	Vertical flow	Dorr-type	Dortmund-type
	secondary settler	secondary settler	secondary settler
V_F [m/h]	1,2	0,8	1,2
t_t [h]	2,0	2,7	3,0

Dorr type secondary settlers are used in the examined wastewater treatment plant with the surface of 710m^2. Leaving out one of the settlers, the Hungarian regulations (1462,5m^3) are still amply satisfied even considering the highest daily load in the influent (13000m^3).

For the sake of comparison, the methodology described in the US10 States Standard [85] was used to compute the load of the settler. The peak surface load is recommended to be between 24–32 [m^3/m^2*d]. According to the measurements, the highest load of the settler is 900m^3/h, so the surface load

$$V_F = \frac{Q_{\text{top}} \times 24}{F_{\text{V}}} = \frac{900m^3/h \times 24}{710m^2} = 30.42 \tag{6.3}$$

also satisfies the standard.

Due to financial reasons, the reconstruction of the plant was not considered as a possible solution. The simulation was repeated with a modified plant and the original inflow stream. As Figure 4 shows the phosphorus concentration of the effluent of the new system was better than that of the original set up.

The new system scheme was tested in a hypothetical crucial event. As Figure 6.4 shows the results substantiate our hypothesis. It is noticeable, the effect cannot be completely eliminated, but the maximum of phosphorus concentration of the system effluent decreased to the official limit. (Table 6.1, Figure 6.4)

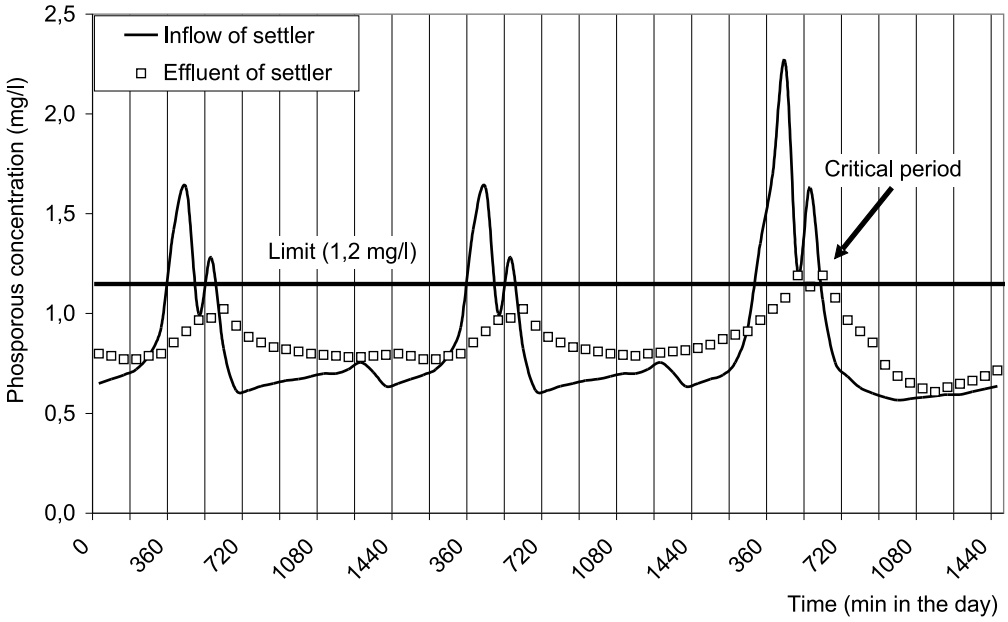

Figure 6.4: concentration change in the modified plant during a critical period

6.5 Conclusions

The phenomenon of drastic phosphorus concentration increase in the effluent is examined in this study. Long retention time is the reason of the problem outlined in this paper, namely – under special conditions – the long retention of phosphorus in the sludge of the settling tank. The problem was caused by phosphorus dissolution from the sludge of the settling tank into the effluent during the undesirably long retention time. Under certain circumstances it could reach up to 60–80% of the phosphorus contained in the sludge of the settling tank. This scope shows a possible problem of oversized wastewater treatment plants. This problem appeared as a random and short time phosphorus-removal efficiency decrease. With classical methods (monitoring, laboratory experiments, etc.), it might be rather difficult to identify the real cause of the anomalous operation. The real source of the problem was determined rapidly at a minimum cost using computer aided modelling.

Chapter 7

Summary

The biological behaviour of biotechnological processes occurring in bioreactor has a complexity unparalleled in the chemical industry. As consequence, to predict its behaviour from information about the environmental conditions is extremely difficult. The number of reactions and species that are involved in the system may be very large. An accurate description of such complex systems can therefore result in very involved models, which may not be useful from a control engineering viewpoint.

Modern control systems rely heavily on adequate process models. Design of advanced controllers is based on a mathematical description of the process. Since the involved biological processes are highly non-linear, time varying and subject to significant disturbances, the models require adjustment on-line, based on available data from various sensors. Partly due to the lack of available sensors and the complexity of the processes, a compromise must be made between the complexity and the accuracy of the used models.

Taking into consideration the aforementioned aspects, control and optimization problems of the wastewater treatment were investigated. Specially, control and optimization of the dissolved oxygen concentration in activated sludge processes were examined and novel methods have been suggested: a stochastic optimization algorithm using genetic algorithms have been devel-

oped for better aeration of alternating activated sludge processes and model predictive control has been applied for dissolved oxygen level control using computer simulation approach.

However, promising results have been achieved using mathematical modelling, in order to validate the results further investigations should be carried out both for pilot-scale and full-scale treatment plants. These should include application of the proposed method together with the stoichiometric and kinetic parameter estimation from experimental data, even though, the results may still fail to give the expected results under large flow rate and load variations.

Chapter 8

Appendix

Table 8.1: Components in the ASM1 model

Component	**Name**	**Unit**
S_{I}	inert soluble organic matter	M(COD)L^{-3}
S_{S}	readily biodegradable substrate	M(COD)L^{-3}
X_{I}	particulate inert organic matter	M(COD)L^{-3}
X_{S}	slowly biodegradable substrate	M(COD)L^{-3}
$X_{\mathrm{B,H}}$	active heterotrophic biomass	M(COD)L^{-3}
$X_{\mathrm{B,A}}$	active autotrophic biomass	M(COD)L^{-3}
X_{P}	particulate products arising from biomass decay	M(COD)L^{-3}
S_{O}	oxygen	M(-COD)L^{-3}
S_{NO}	nitrate and nitrite nitrogen	M(N)L^{-3}
S_{NH}	ammonia and ammonium nitrogen	M(N)L^{-3}
S_{ND}	soluble biodegradable organic nitrogen	M(N)L^{-3}
X_{ND}	particulate biodegradable organic nitrogen	M(N)L^{-3}
S_{ALK}	alkalinity	Molar unit

Table 8.2: Stoichiometric and kinetic parameters of the activated sludge model

parameter	unit	value
Y_A	g cell COD formed (g N oxidized)$^{-1}$	0.24
Y_H	g cell COD formed (g COD oxidized)$^{-1}$	0.67
f_p	dimensionless	0.08
i_{XB}	g N (g COD)$^{-1}$ in biomass	0.08
i_XP	g N (g COD)$^{-1}$ in endogenous mass	0.06
μ_H	day^{-1}	4
K_S	g COD m^{-3}	10.0
$K_{O,H}$	g O_2 m^{-3}	0.2
K_{NO}	g NO_3-N m^{-3}	0.5
b_H	day^{-1}	0.3
η_g	dimensionless	0.8
η_h	dimensionless	0.8
K_X	(g cell COD)$^{-1}$	0.1
μ_A	day^{-1}	0.5
K_{NH}	g NH_3-N m^{-3}	1.0
b_A	g day^{-1}	0.05
$K_{O,A}$	g O_2 m^{-3}	0.4
k_a	m^3 COD(g·day)$^{-1}$	0.05

Table 8.3: Double-exponential settling velocity parameters

parameter	unit	value
v_0'	md^{-1}	250
v_0	md^{-1}	474
r_h	m^3(g SS)$^{-1}$	$5.76{\cdot}10^{-4}$
r_p	m^3(g SS)$^{-1}$	$2.86{\cdot}10^{-3}$
f_{ns}	–	$2.28{\cdot}10^{-3}$

Table 8.4: Weighting factors for the different types of pollution

factor	value
B_{SS}	2
B_{COD}	1
B_{NK_j}	20
B_{NO}	20
B_{BOD_5}	2

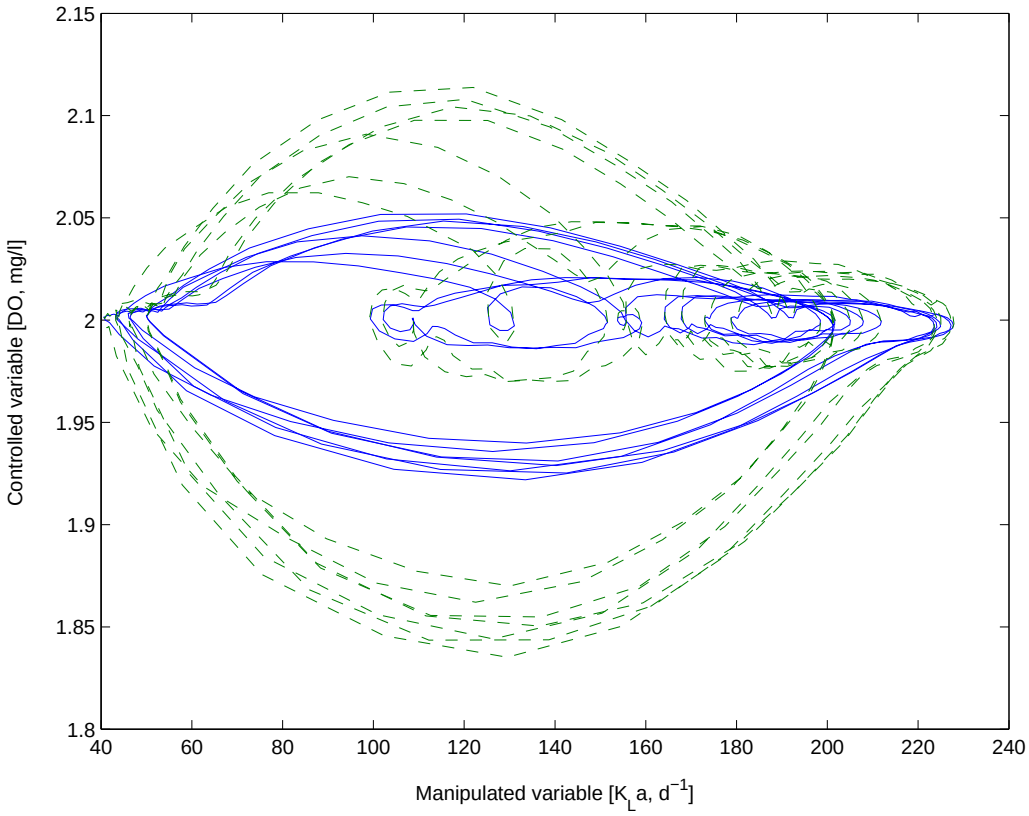

Figure 8.1: Controlled variable vs manipulated variable (solid line $\Delta t = 2.5 \cdot 10^{-4}$ d; dashed line $\Delta t = 10^{-3}$ d)

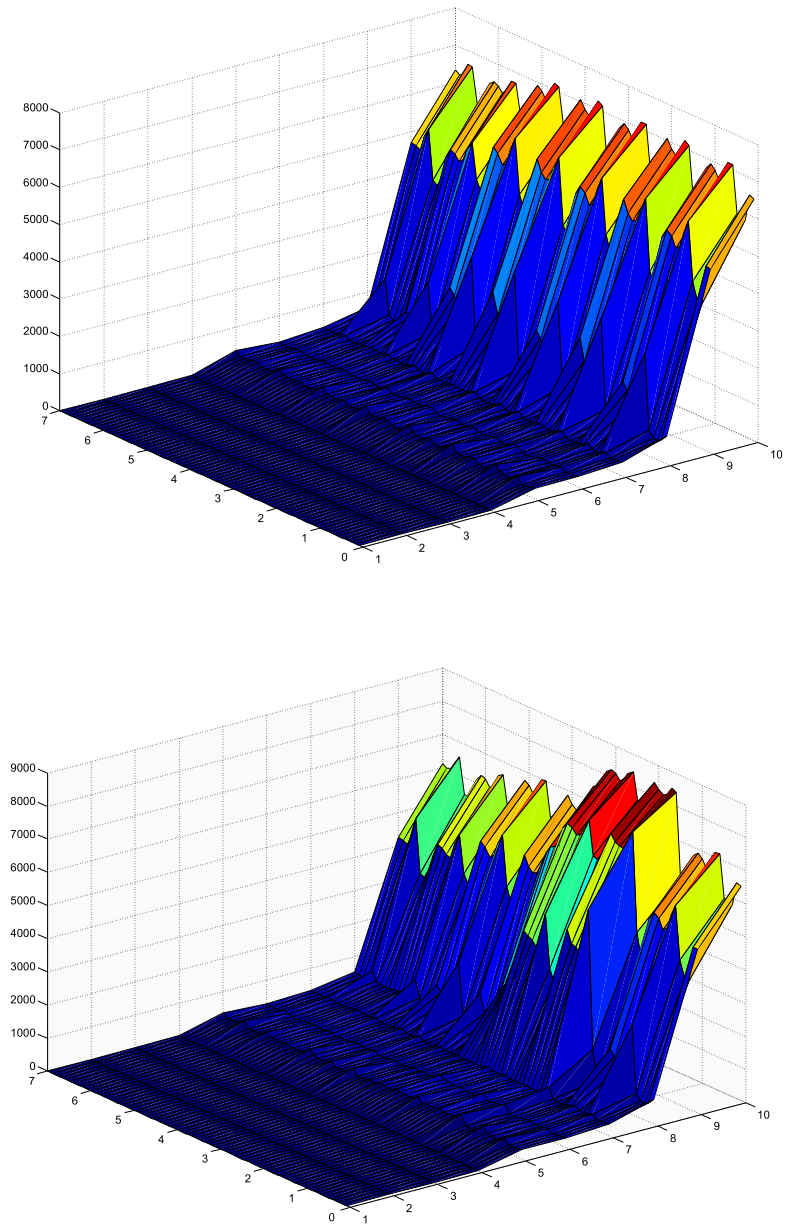

Figure 8.2: SS concentration (mg/l) during dry and wet weather simulations as a function of time (0–7 days) and depth (layer 0–10)

Chapter 9

Publications

1. Holenda B, Domokos E, Rédey Á and Fazakas J (2007) Dissolved oxygen control of the activated sludge wastewater treatment process using model predictive control. Accepted for publication in *Computers and Chemical Engingeering*

2. Holenda B, Domokos E, Rédey Á and Fazakas J (2007) Aeration optimization of a wastewater treatment plant using genetic algorithm. *Optimal Control Applications and Methods*, 28(3), 191–208.

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11. Holenda B, Domokos E, Rédey Á and Fazakas J (2005) Dissolved oxygen control of small-size wastewater treatment plants using model predictive control. Presented at 10th EuCheMS-DCE International Conference, Rimini, Italy, 4-7 Sept 2005.

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14. Holenda B, Domokos E, Rédey Á and Fazakas J (2005) Dissolved oxygen control of a wastewater treatment plant using MPC technology. Presented at microCAD 2005, Miskolc, Hungary, 10–11 March, 2005.

15. Holenda B, Domokos E, Rédey Á and Fazakas J (2004) Modelling the suspended solids concentration in the secondary clarifier of a wastewater treatment plant using different settling velocity functions, presented at 9th EuCheMS-DCE International Conference, Bordeaux, France, Sept 4–7, 2004.

Chapter 10

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