**BABEŞ-BOLYAI UNIVERSITY**
*FACULTY OF CHEMISTRY AND CHEMICAL ENGENEERING*

*PhD Thesis Summary*

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# Model Based Control and Optimization of Biological Wastewater Treatment Plants

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# **Chapter 1 -** Introduction

Nitrogen and phosphorus are natural nutrients that are part of the aquatic ecosystems and they are necessary for plant growth and development. Nutrient pollution is one of the most widespread, costly and challenging environmental problems today. Excessive quantities of nitrogen and phosphorus in the receiving waters cause health problems in people, fish and animals, and damage forests, lakes, rivers, streams and oceans.

Wastewater treatment has two key objectives. The first one is the degradation of organic waste to a point where the dissolved oxygen demand exerted upon receiving waters is insignificant. The second objective is the removal of nutrients like nitrogen and phosphorus and therefore limiting the growth of organisms in receiving waters. The pollutant agents are removed from the wastewater by means of physical, biological, and chemical treatment.

The heart of the wastewater treatment is the activated sludge process which is an enhanced version of the natural treatment process of wastewater and since its discovery in 1914 it has been adopted as secondary biological treatment for domestic wastewaters. The process relies on different types of bacteria that, under diverse environmental conditions, use pollutants from the wastewater as substrate for growth.

Although the activated sludge process is considered to be the most economical, efficient and technological sustainable process for the wastewater treatment, due to improper operation, the activated sludge process can produce low quality effluents and even result in process failure with devastating consequences.

The intricate behavior of the microorganisms involved in the process coupled with large variations of the feed flows and feed concentrations, make the complexity of the activated sludge process to be unparalleled in the chemical industry. Nevertheless, the process has to operate continuously, at low operational costs and meet the perceptibly stricter discharge limits imposed by legislation (i.e. EU Water Framework Directive). As a result, mathematical models have become important tools in predicting the process behavior and in development of new control strategies, which are meant to bring a sense of balance between effluent pollutants and operational costs.

Taking into account above mentioned challenges, this thesis aims to meet the need for building new models of the activated sludge process, and to develop operation strategies based on advanced control coupled with optimization, meant to reduce the operational costs and improve the effluent quality. In consequence, four objectives have been defined in strong correlation with the needs in the field for controlling the WWTP:

I. The first objective is to perform a thorough analysis and concise review of the available international scientific literature with the aim of understanding and improving the existing activated sludge models by incorporating new components and new processes into the models.

II. The second objective is to implement the above mentioned models into computer simulators that have great potential in developing and assessing control strategies of the WWTP in terms of operational cost and pollutant removal.

III. The third objective is to analyze potential control strategies of the WWTP by using these computer simulators. The control structures will imply several hierarchical levels. At the regulatory level both PI and Model Predictive Control (MPC) will be used while at the higher level MPC and optimization based control will be applied.

IV. The fourth objective is to optimize the control strategies of the WWTP using a multi-criteria analysis to select the most suitable solution for different WWTP operation and weather condition scenarios, in terms of operational costs and effluent quality.

# Chapter 2 - The Activated Sludge Process

The Activated Sludge Process was pioneered in England in 1914 by Edward Arden and William T. Lockett from the River Committee of the Manchester Corporation (Arden and Lockett 1914). In our days the Activated Sludge Process has been adopted worldwide as a secondary biological treatment for domestic wastewaters.

## Biological Nitrogen Removal

Nitrogen is present in wastewater as ammonia, nitrite, nitrate and organic nitrogen. In activated sludge systems, nitrogen is primarily removed by means of nitrification and denitrification, which are chemical reactions that take place inside living cells or bacteria.

### Nitrification

The nitrification process represents the two step biological oxidation of ionized ammonia to nitrate nitrogen. The process is carried out by the autotrophic nitrifying bacterium which uses ammonia nitrogen and nitrite as substrate for growth in order to obtain energy for cellular activity and reproduction (Gerardi, 2002). The stoichiometry of the two steps and the total nitrification reaction are given below in Eq. 2.1, 2.2 and 2.3, respectively:

$$2NH_4^+ + 3O_2 \xrightarrow{\text{bacteria}} 2NO_2^- + 2H_2O + 4H^+ + \text{energy} \tag{2.1}$$

$$2NO_2^- + O_2 \xrightarrow{\text{bacteria}} NO_3^- + \text{energy} \tag{2.2}$$

$$NH_4^+ + 2O_2 \rightarrow NO_3^- + H_2O + 2H^+ + \text{energy} \tag{2.3}$$

The effectiveness of the nitrification process is highly dependent on the oxygen concentration, temperature, mean cell residence time, alkalinity and pH. The nitrifying bacteria are strict aerobes, they can nitrify only in the presence of dissolved oxygen (DO).

## Denitrification

The biological denitrification process represents the reduction of nitrate nitrogen to nitrogen gas under low oxygen condition. It is carried out by a part of heterotrophic bacteria called *denitrifying heterotrophic bacteria*, which have the ability to also use nitrate and nitrite as their terminal electron acceptors for the oxidation of organic material.

The biochemical pathways for denitrification are represented by the sequential steps of chemical reactions that take place inside the bacterial cells according to the following sequence:

$$NO_3^- \xrightarrow[\text{reductase}]{\text{Nitrate}} NO_2^- \xrightarrow[\text{reductase}]{\text{Nitrite}} NO \xrightarrow[\text{reductase}]{\text{Nitric oxide}} N_2O \xrightarrow[\text{reductase}]{\text{Nitrous oxide}} N_2 \quad (2.4)$$

The effectiveness of the denitrification process is affected by: absence of free molecular oxygen, the presence of an adequate and active population of denitrifying bacteria, pH, temperature, nutrients, and redox potential.

## Biological Phosphorus Removal

All bacteria incorporate a fraction of phosphorus in their biomass during growth which is used for DNA replication. In an activated sludge system, phosphorus removal is accomplished by a specific group of heterotrophic bacteria, called polyphosphate-accumulating organisms (PAO), which has the ability to store excessive quantities of polyphosphate. These types of bacteria are enriched in the bacterial community of an ASS in order to enhance phosphorus removal, hence the term Enhanced Biological Phosphorus Removal (EBPR). The biological mechanism for phosphorus removal by microorganisms in wastewater is presented in Figure 2.1.

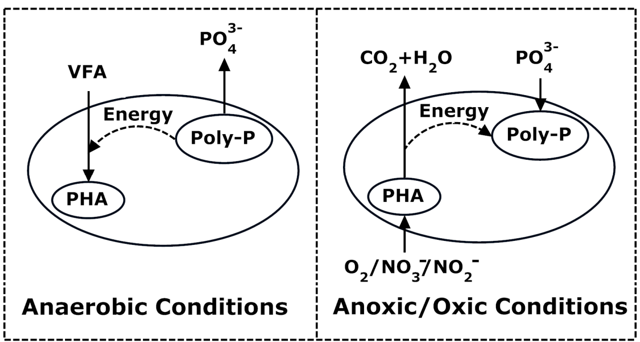


**Figure 2.1.** Biological mechanism for phosphorus removal by microorganisms in wastewater.

# **Chapter 3 -** Modeling and Simulation Aspects of the Activated Sludge Process

## Introduction

The Activated Sludge Model suite (Henze et al., 2000) proposed by the working group of the International Water Association (IWA) is considered to be the backbone for the biological wastewater treatment mathematical models. Four mathematical models were proposed by the IWA task group: Activated Sludge Model No. 1, 2, 2d and 3 (ASM1, ASM2, ASM2d, ASM3). The ASM1 and ASM3 describe the oxidation of organic carbon, nitrification and denitrification, while the ASM2 and ASM2d also include the removal of phosphorus.

The mathematical models used for this thesis are based on the ASM suite. Chapter 3 of the thesis presents a short description of the mathematical models proposed by the IWA task group.

## Enhanced Biological Nitrogen Removal Mathematical Models

### Activated Sludge Model No. 1 (ASM1)

The Activated Sludge Model No. 1 (ASM1) was presented by the International Association on Water Quality (IAWQ) in 1987 (Henze el al., 1987) and it is the most widely accepted biological wastewater treatment model. It is mainly used for urban activated sludge wastewater treatment plants and it incorporates organic carbon oxidation, nitrification and denitrification. The model considers two types of bacteria (heterotrophic and autotrophic) and is based on eight fundamental biological processes, described using the Monod kinetics: aerobic growth of heterotrophic biomass, anoxic growth of heterotrophic biomass, aerobic growth of autotrophic biomass, decay of heterotrophic biomass, decay of autotrophic biomass, ammonification of soluble organic nitrogen, hydrolysis of entrapped particulate organic matter, and hydrolysis of entrapped organic nitrogen. The model has 13 different components and the behavior of each component is described by a nonlinear differential equation. Figure 3.1 represents the transformations of the components of ASM1.

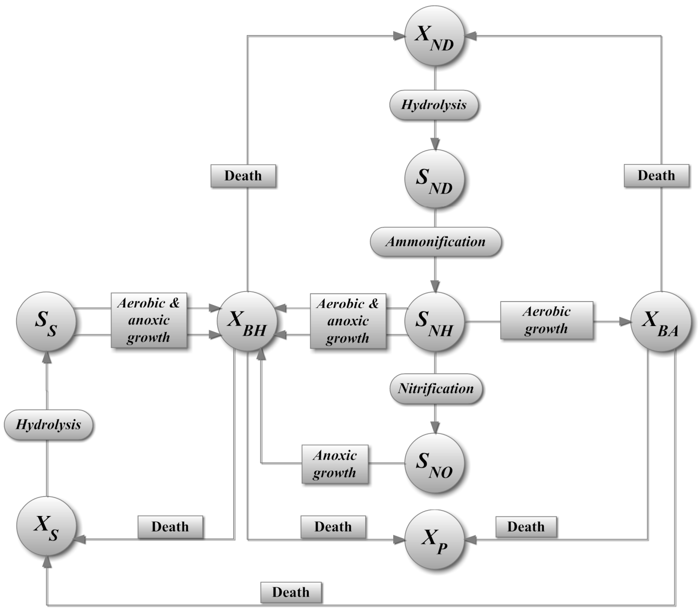


**Figure 3.1** General overview of ASM1.

## Activated Sludge Model No. 3 (ASM3)

The Activated Sludge Model no 3 (ASM3) was introduced by Gujer et al. (1999). The model was developed to describe the removal of organic carbon and nitrogen and it corrects a number of defects that have emerged from ASM1 applications (Henze et al., 2000).

The growth of the heterotrophic biomass for ASM3 is represented by a sequential two step process. The first step is represented by the storage of the readily biodegradable substrate in the form of cell internal storage products. For the second step, the internal storage products are used for biomass growth (Gujer et al., 1999). The storage process requires energy, which is obtained from aerobic or anoxic respiration.

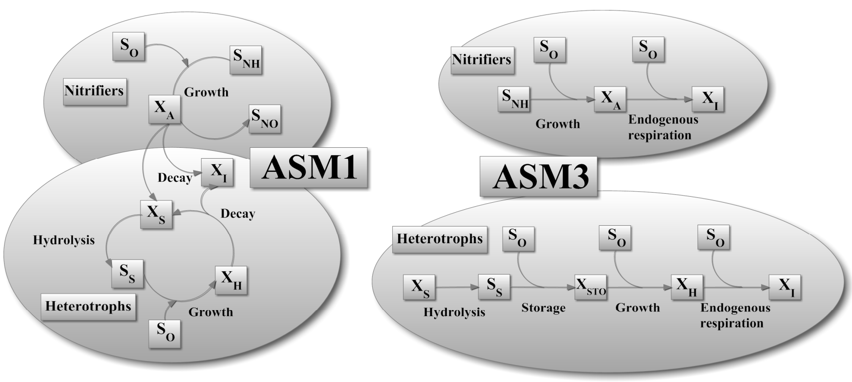


**Figure 3.2.** Flow of COD in ASM1 and ASM3 (Henze et al., 2000)

The COD flow in the ASM3 is not as complex as for the ASM1 (Figure 3.2). For the ASM1 the decay of the nitrifying biomass generates slowly biodegradable substrate which through hydrolysis is transformed into readily biodegradable substrate and then is used by the heterotrophic biomass a substrate for growth. As a result, the decay of nitrifiers enhances heterotrophic growth. For ASM3 nitrifiers and heterotrophs are clearly separated, no COD flows from one group to the other.

## Enhanced Biological Phosphorus Removal Mathematical Models

### Activated Sludge Model No. 2d (ASM2d)

The Activated Sludge Model No. 2 (ASM2) was first presented by Henze *et al.* in (1995). ASM2 incorporates carbon oxidation, nitrification, denitrification, and enhanced biological phosphorus removal (EBPR) for simultaneous C, N and P removal. The model also includes two processes that describe the chemical precipitation of phosphorus. ASM2 assumes that the phosphorus accumulating organisms uptake poly-phosphate only under aerobic conditions. This fact soon proved to be a shortcoming of the mathematical model, because it was proven that PAOs can use cell internal organic storage products for denitrification. As a result, in 1999 Henze *et al.* presents the Activated Sludge Model No. 2d (ASM2d). The ASM2d is an improved version of ASM2, and includes two additional processes that account for the storage of poly-phosphate under anoxic conditions.

The biological processes in the ASM2d are carried out by three groups of microorganisms: heterotrophic, autotrophic and phosphorus accumulating organisms. These three groups of bacteria are assumed to be representative for a vast variety of unknown species which are involved in the activated sludge process. The model incorporates 19 biological processes and 2 chemical precipitation processes.

## Modeling the settling process

The most important physical process in an activated sludge system is the separation of suspended solids from the water. This separation is done by gravity sedimentation, in secondary clarifiers which are also known as secondary settlers. The sedimentation process was simulated using the model described by Takács et. al 1991. The Takács secondary settler model is one-dimensional and predicts the solids concentration in the settler, by dividing it into 10 layers of constant thickness. In order to predict the suspended solids concentration in the settler a mass balance is calculated for each hypothetical layer. The continuity equation for the settler is:

$$\frac{\partial X}{\partial t} + \frac{\partial J}{\partial z} = 0 \tag{3.1}$$

where: X is the particulate component concentration [mg $L^{-1}$]; t – time [days]; J – solids flux [mg $day^{-1}m^{-2}$)]; z – layer height [m];

The settling velocities in the layers are calculated using the double-exponential settling velocity function by Takács *et al*. (1991), which is equally applicable for both hindered and flocculent settling conditions.

$$v_{sj} = v_0(e^{-rh(X - X\min)} - e^{-rp(X - X\min)}) \quad \text{and} \quad 0 \le v_{sj} \le v_0^{'} \tag{3.2}$$

where $v_0$ is the maximum Vesilind settling velocity; rh - hindered settling zone settling parameter; rp - low solids concentration settling parameter; TSS* - the difference between the total suspended solids in each layer (TSS) and minimum attainable suspended solids concentration ($TSS_{min}$); $TSS_{min}$ = fns×TSS with fns being the non-settable fraction of TSS; $v_0$' – maximum settling velocity.

## Benchmark Simulation Model No. 1 (BSM1)

The Benchmark Simulation Model No. 1 wastewater treatment plant was proposed by The International Association of Water Quality (IAWQ) and European Cooperation in the field of Scientific and Technical Research (COST) 624 group in 2002 (Coop et. al., 2002). The main purpose of the BSM1 is to investigate control strategies for biological wastewater treatment plants. The wastewater treatment plant considered in the BSM1 is a Modified Ludzak-Ettinger (MLE) process and is one of the most common architectures used for biological nitrogen removal in municipal wastewater treatment.

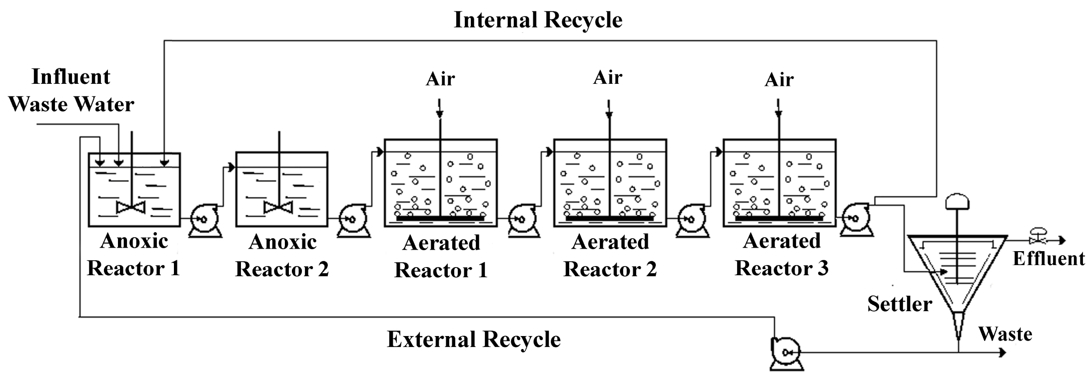


**Figure 3.3** Layout of the BSM1 benchmark simulation plant (Coop *et al.,* 2002)

General features of the BSM1 WWTP (Coop *et al.,* 2002):

- 2 fully mixed anoxic tanks and 3 fully mixed aerated tanks connected in series followed a secondary settler.
- The total volume of five bioreactors is 5999 $m^3$ (tank 1 and 2 is 1000 $m^3$ each while tank 3, 4 and 5 is 1333 $m^3$ each).
- Tank 3, 4 and 5 are aerated with a maximum limitation of $k_La = 240\ d^{-1}$.
- The dissolved oxygen saturated concentration in aerated tanks is 8 $gO_2\ m^{-3}$.
- The secondary settler is considered to be ideal, without reactions.
- Total volume of settler is 6000 $m^3$ (with a cross section of 1500 $m^2$ and depth of 4 m) which is divided into 10 layers of constant thickness.
- The feed flow enters the settler in the middle of the sixth layer (2.2 m from the bottom).
- The internal recycle flows at a default flow rate of 55338 $m^3$/d from the fifth tank back to the first tank.
- External recycle flows at a default flow rate of 18446 $m^3$/d from the bottom of settler to the first tank.
- Wastage flow rate equals 385 $m^3$/d.
- Operating temperature 15ºC.

The WWTP influent disturbance is an important factor when new control strategies are to be tested. The BSM1 provides three influent files that mimic three operating scenarios: dry-weather, storm-weather and rain-weather.

# **Chapter 4 -** Model Predictive Control Based on Modified ASM1 with Two-step Nitrification/Denitrification Model

The first part of this chapter focuses on the development of an enhanced Activated Sludge Model No.1 with two step nitrification/denitrification processes. The nitrification process is considered as a sequence of two steps carried out by two distinct genera of bacteria, ammonia oxidizing bacteria ($X_{AOB}$) and nitrite oxidizing bacteria ($X_{NOB}$), with nitrite as an intermediate product (Ostace *et al.,* 2011a) (Figure 4.1). The ammonia oxidizing bacteria accomplish the first step of the nitrification process and transform the ammonia nitrogen in to nitrite nitrogen. The second step of the nitrification is carried out by the nitrite oxidizing bacteria which oxidize the nitrite nitrogen to nitrate nitrogen.

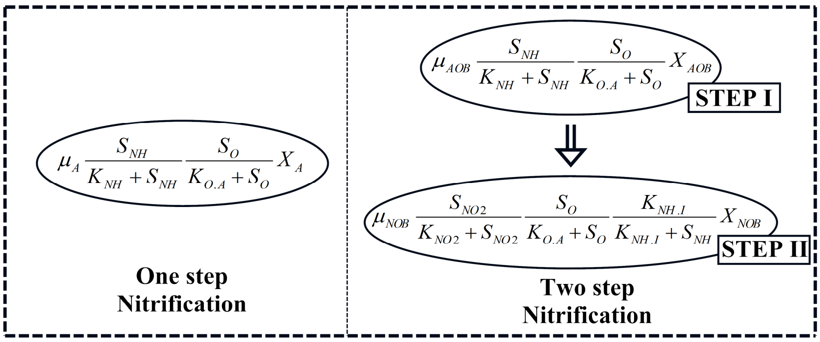


**Figure 4.1.** Schematic representation of the one and two step nitrification approach.

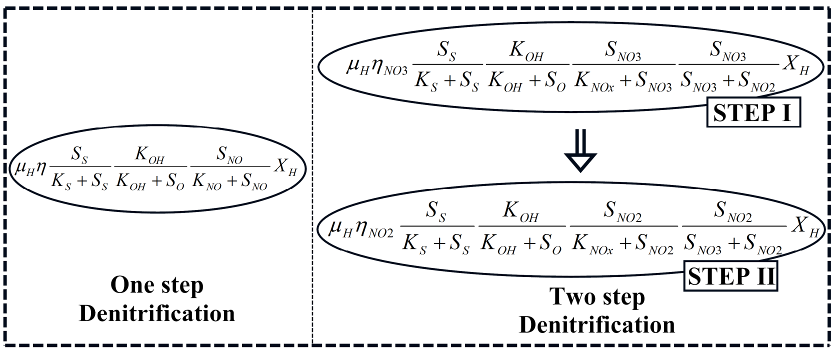


**Figure 4.2.** Schematic representation of the one and two step denitrification approach.

Denitrification is also modeled as a sequence of two steps but both steps are carried out by the same class of bacteria (Figure 4.2).

The new model was calibrated against the original Activated Sludge Model No. 1 using the Benchmark Simulation Model No. 1 by minimizing of the sum of absolute errors (SAE) between the two simulators. In order to avoid local minima three different search methods were tested: the Pattern Search (PS), the Nelder-Mead (NM) and the Genetic Algorithm (GA). Of these, Nelder-Mead proved to be the best suited.

The second part of the chapter presents the investigation of Model Predictive Control (MPC) approach for the advanced control of the wastewater treatment plant.

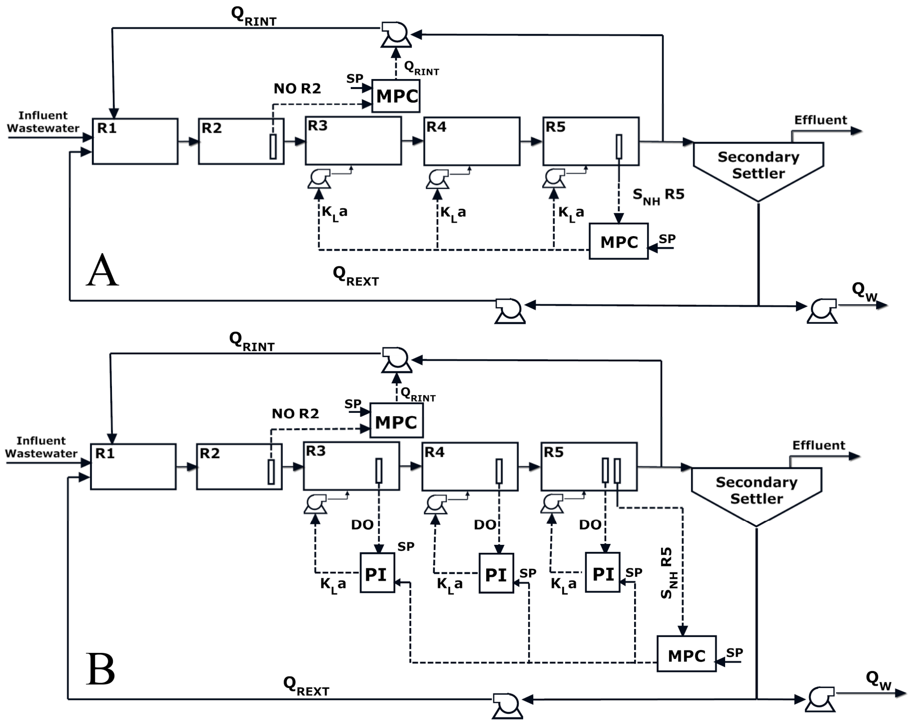


**Figure 4.3.** Schematic representation two control approaches: A) Control Strategy No. 1 ; B) Control Strategy No. 2

As its name suggests, MPC relies on an explicit representation of the process to be controlled, bringing the model of the process "inside" the control algorithm in a straightforward manner (Agachi et al 2006). MPC uses the model of the plant for explicit prediction of future process behavior and for the computation of appropriate corrective control action required to drive the predicted output as close as possible to the desired target values (Huang and Kadali 2008). All the MPC algorithms have three elements in common: prediction model, objective function, and the algorithms for obtaining the control law.

The model of the plant is a linear time-invariant system described by the equations:

$$\begin{aligned} x(k+1) &= A_m x(k) + B_{mu}\,\mathrm{u}(k) + B_{md}\omega(k) \\ y(k) &= C_m x(k) + D_{md}\omega\,(k) \end{aligned} \tag{4.1}$$

where: x(k) is the state variable vector of the plant with assumed dimension *nx*, u(k) is the vector of manipulated variables or input variables, y(k) is the process output; and $\omega(k)$ is the input disturbance unmeasured disturbance which is driven by the a random Gaussian noise nd(k), having zero mean and unit covariance matrix described by the equations (Bemporad et al. 2011):

$$
\begin{aligned}
x_d(k+1) &= A_d xd(k) + B_d nd(k) \\
\omega(k) &= C_d xd(k) + D_d nd(k)
\end{aligned}
\tag{4.2}
$$

Assuming that the disturbance model in Eq. 4.2 is a unit gain, for example $\omega(k)$ = nd(k) - a white Gaussian noise, the prediction model can be represented as (Bemporad et al. 2011):

$$
\begin{aligned}
x(k+1) &= \overbrace{\begin{bmatrix} A_m & B_{md}C_d \\ 0 & A_d \end{bmatrix}}^{A} x(k) + \overbrace{\begin{bmatrix} B_{mu} \\ 0 \end{bmatrix}}^{B} u(k) + \overbrace{\begin{bmatrix} B_{md}D_d \\ B_d \end{bmatrix}}^{Bd} n_d(k) \\
y(k) &= \overbrace{\begin{bmatrix} C_m & D_m C_d \end{bmatrix}}^{C} x(k)
\end{aligned}
\tag{4.3}
$$

Assuming $i$ prediction instants and that $n_d(i)=0$, the prediction of the future trajectories of the plant using the state vector known at time k=0 is given by Eq. (4.4):

$$
y(i\,|\,0) = C\left[ A^i x(0) + \sum_{h=0}^{i-1} A^{i-1}\left( B\left( u(-1) + \sum_{j=0}^{h} \Delta u(j) \right)\right)\right] \tag{4.4}
$$

The control action at each time step is computed by minimizing the objective function which is presented below:

$$
\min_{\Delta u(k|k),\ldots,\Delta u_m(m-1+k|k)} \left\{ \sum_{i=o}^{p-1} \left( \sum_{j=1}^{n_y} \left| w_{i+1,j}^{y} \left( y_j(k+1\,|\,k) - r_j(k+1\,|\,k) \right) \right|^2 + \sum_{j=1}^{n_u} \left| w_{i,j}^{\Delta u} \Delta u_j(k+1\,|\,k) \right|^2 \right) + \rho_\varepsilon \varepsilon^2 \right\} \tag{4.5}
$$

where: “( )j” denotes the j$^{th}$ component of a vector; (k+i|k) denotes the value predicted for time k+i based on the information available at time k, and r(k) is the current sample of the output reference.

The discontinuous plant model and disturbance model for the three MPCs used in this chapter are presented below:

Plant model for the NO controller:

$$x(k+1|k) = \begin{bmatrix} 0.9784 & 0.0355 & -0.0066 \\ -0.0355 & 0.9163 & 0.0391 \\ -0.0066 & -0.0391 & 0.7895 \end{bmatrix} x(k) + \begin{bmatrix} -4.19\text{E-}05 \\ -2.97\text{E-}05 \\ -6.53\text{E-}06 \end{bmatrix} u(k) \tag{4.6}$$

$$y(k) = \begin{bmatrix} -0.0603 & 0.0456 & -0.0119 \end{bmatrix} x(k)$$

Plant model for the SNH controller for CS1:

$$x(k+1|k) = \begin{bmatrix} 0.9606 & 0.0358 & 0.0485 \\ -0.0069 & 0.9664 & -0.0982 \\ -0.0487 & 0.0288 & 0.5897 \end{bmatrix} x(k) + \begin{bmatrix} 6.54\text{E-}5 & 1.35\text{E-}4 & 0.00062 \\ 2.24\text{E-}4 & 1.52\text{E-}4 & -6.66\text{E-}5 \\ -6.87\text{E-}5 & 1.19\text{E-}4 & 0.000367 \end{bmatrix} u(k) \tag{4.7}$$

$$y(k) = \begin{bmatrix} -0.9185 & 0.4035 & 0.7578 \end{bmatrix} x(k)$$

Plant model for the SNH controller for CS2:

$$x(k+1|k) = \begin{bmatrix} 0.9633 & -0.0480 & 0.0250 \\ 0.0009 & 0.9535 & 0.0532 \\ -0.0053 & -0.0202 & 0.9289 \end{bmatrix} x(k) + \begin{bmatrix} 0.0007 & 0.0013 & 0.0037 \\ -0.0017 & -0.0012 & 0.0016 \\ -0.0011 & 0.0010 & 0.0001 \end{bmatrix} u(k) \tag{4.8}$$

$$y(k) = \begin{bmatrix} -5.8507 & -3.8699 & 2.1483 \end{bmatrix} x(k)$$

The disturbance model for all MPC controllers is described by Eq.(4.9):

$$\begin{aligned} x(k+1|k) &= [1]x(k) + [6.9333\text{E-}4]u(k) \\ y(k) &= [3981.07]x(k) \end{aligned} \tag{4.9}$$

The state observer is designed using the state space presented in Eq. (4.3) and is defined by Eq. (4.10):

$$\hat{x}(k+1|k) = (A - AMC)\hat{x}(k|k) + AMy(k) + Bu(k) \tag{4.10}$$

where M is the observer gain.

The MPCs have been tuned by performing repeated simulations and taking into consideration the overall WWTP operation assessment measures. The best parameters for both controllers were found to be: sampling time of Δt = 1 minute, Hp = 200 and Hc = 3 (Ostace *et al.,* 2011b).

The performance of the WWTP is assessed on two levels. The main level of assessment addresses the overall effect of the control strategy on the WWTP (effluent quality index, (EQ), operational costs (Pumping Energy PE, Aeration Energy AE, Total

Energy $E_{tot}$ and Operational Costs Index OCI) and the second level is control performance (integral of the absolute error IAE and integral of the square error ISE).

The control strategies were simulated with different setpoints for each controller. As a result the ammonia nitrogen setpoint was varied between 0 and 4 mg/L with a step of 0.2 mg/L. The NO setpoint at the end of the anoxic part of the WWTP was varied form 0 to 2 mg/L with a step of 0.1 mg/L. The simulation results showed a minimum for the operational costs for both control approaches at ammonia setpoint equal to 1.8 mg/l and NO setpoint of 0.5 mg/L.

In order to asses the impact of the control strategies on the WWTP performance, the simulation result are compared to the open loop simulation. For the open loop control, constant $K_La$ values of 240 $day^{-1}$ were assumed for each aerated reactor and the internal recycle flow was set to 55,338 $m^3$/day. The results of the control strategies and the open loop simulation are presented in Table 4.2:

**Table 4.1.** Simulation results of both control strategies and the open loop simulation for all influent files.

| | | **EQ** [poll. unit/day] | **AE** [kWh/day] | **PE** [kWh/day] | **OCI** [€/year] | **$N_{Kj}$** [mg/L] | **$S_{NH}$** [mg/L] | **$S_{NO2}$** [mg/L] | **$S_{NO3}$** [mg/L] | **$N_{tot}$** [mg/L] |
|---|---|---|---|---|---|---|---|---|---|---|
| **DRY** | **OL** | 8109 | 8548 | 2966 | 693345 | 4.22 | 2.28 | 2.24 | 21.87 | 28.33 |
| | **CS1** | 5928 | 6329 | 1941 | 503214 | 5.01 | 3.03 | 4.51 | 5.15 | 14.67 |
| | **CS2** | 5837 | 5950 | 2249 | 496900 | 5.23 | 3.23 | 4.38 | 4.11 | 13.72 |
| **RAIN** | **OL** | 9533 | 8548 | 2966 | 764500 | 4.68 | 2.53 | 1.79 | 16.90 | 23.37 |
| | **CS1** | 7968 | 6644 | 2160 | 618500 | 5.43 | 3.24 | 4.01 | 4.41 | 13.85 |
| | **CS2** | 7996 | 5675 | 2580 | 606175 | 5.83 | 3.60 | 3.88 | 3.36 | 13.07 |
| **STORM** | **OL** | 8746 | 8548 | 2966 | 725192 | 4.60 | 2.52 | 2.04 | 18.37 | 25.01 |
| | **CS1** | 6940 | 6518 | 2135 | 563325 | 5.41 | 3.29 | 4.18 | 4.54 | 14.13 |
| | **CS2** | 6884 | 5922 | 2452 | 553550 | 5.66 | 3.51 | 4.06 | 3.36 | 13.35 |

The simulation results showed that:

I. The operational costs are greatly reduced when automatic control is implemented on the WWTP and the effluent quality is maintained.

II. The MPC proved to be good approach for controlling the WWTP form both economical and control performance point of view.

III. The setpoint value used for each control strategy has a major role in the performance of the WWTP.

IV. The performance of a controller implemented on a biological system is influenced by the biomass within the system, and the ability of the biomass to consume (produce) certain components (i.e. the control of the ammonia nitrogen is influenced by the nitrification capacity).

# **Chapter 5 -** Operational Cost Reduction by Means of Setpoint and Growth Substrate Correlation

This chapter presents the optimization of two control strategies of the wastewater treatment plant. The control architectures are assessed from an operational costs point of view, and improved by adding an upper, supervisory level of control. The upper control level dictates the optimal set-point for the two control structures by taking into consideration the quantity of ammonia nitrogen that enters the wastewater treatment plant (Ostace *et al.,* 2011c).

The study relies on the modified Activated Sludge Model No. 3 which was implemented in the Benchmark Simulation Model No. 1 (BSM1). The modification of the ASM3 is based on the studies of Krishna and van Loosdrecht (1999), Beun et al., 2000 a, b, Beccari et al., 2002, Carucci et al., 2001, Karahan-Gül et al., 2003, Pratt et al., 2004 who revealed that the storage and growth of the heterotrophic biomass occur simultaneously at the feast phase and the stored polymers are used as a carbon and energy source only after the depletion of the primary substrate. The ASM3 model was modified to introduce simultaneous storage and growth of the heterotrophic biomass by using three biological processes and considering two distinct but complementary phases: feast and famine (Sin, 2005). A schematic representation of the modified ASM3 is presented in Figure 5.1.

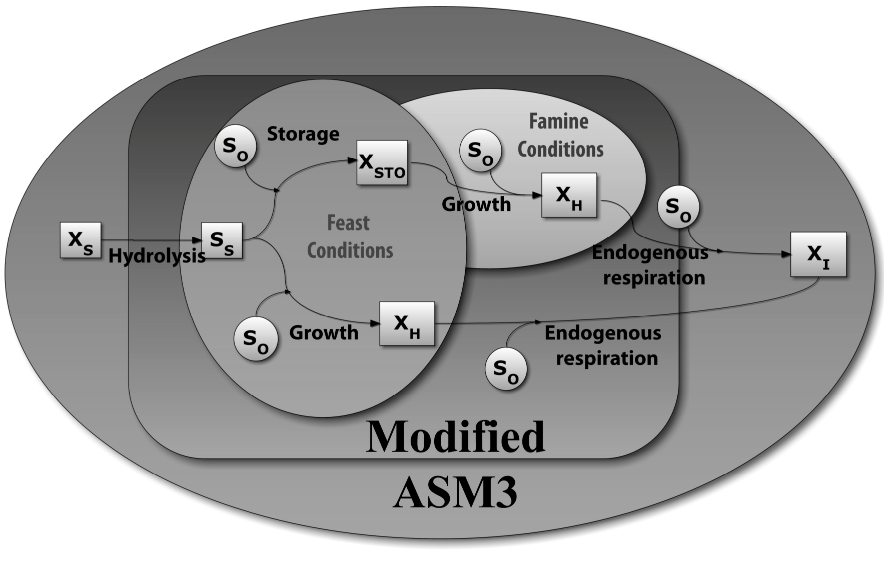


**Figure 5.1.** Schematic representation of the heterotrophic biomass processes under aerobic conditions for the modified ASM3 considering simultaneous growth.

The first control architecture evaluated in this work has three control loops. These control loops have to keep the Dissolved Oxygen (DO) concentration in the aerated reactors at the predefined setpoints by manipulating the air flow rate (indirectly, by the volumetric oxygen transfer coefficient $k_La$). The control scheme is built of three PI controllers, one for each control loop. The PI controllers are tuned as suggested in (Copp, 2002). This control architecture will be further referred to as 3DO and it is represented in Figure 5.2:

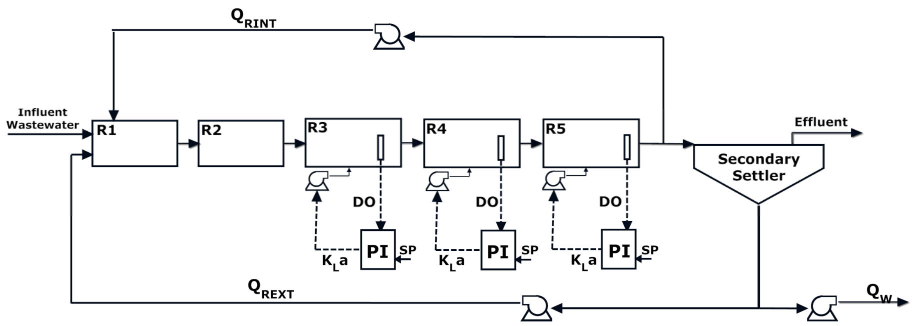


**Figure 5.2** 3DO control architecture schematic representation.

The second control architecture is a cascade control scheme. On the outer level of the cascade control architecture, a single input multi output MPC controls the nitrate ($S_{NO3}$) concentration in reactor 5 by manipulating the DO setpoint values for the aerated reactors. The inner control level consists of PI controllers that keep the DO concentration in the aerated reactors at the set-points imposed by the MPC. This control scheme will be further referred to as NO5.

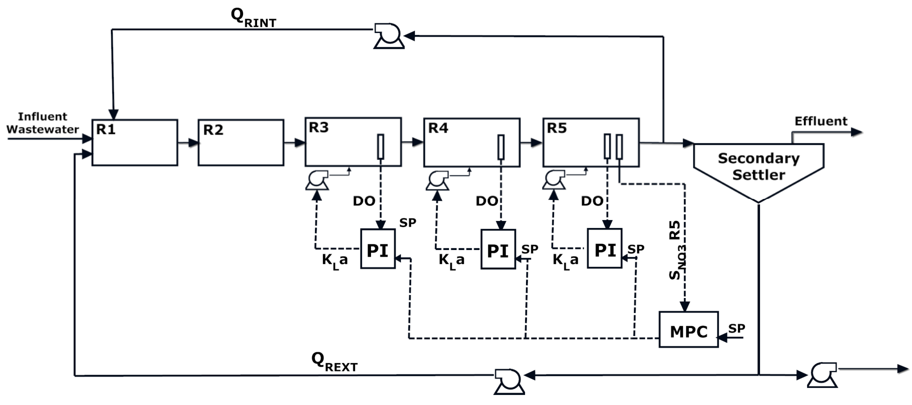


**Figure 5.3** NO5 control architecture schematic representation.

The control strategies were evaluated and optimized from an operational cost perspective. The operational costs were calculated using the following formula:

$$OC = EF + \gamma_E AE \tag{5.1}$$

where: $EF$ – represents effluent fines; $AE$ - aeration energy (kWh $d^{-1}$); $\gamma_E$ – electricity price 0.1 (€/kWh);

The effluent fines (Carstensen, 1994; Vanrolleghem et al., 1996; Vanrolleghem and Gillot, 2002; Stare et al., 2007) were calculated by comparing the total nitrogen, and ammonia concentrations in the effluent to their maximal allowable discharge limits. For each type of pollutant two hypothetical discharge costs are attributed. A lower cost when the pollutant is below the discharge limit and a higher cost when this limit is exceeded.

The average aeration energy costs were calculated using the equation proposed by Copp et al., 2002.

The control architectures were improved by adding an upper, supervisory level of control which dictates the optimal set-point for the two control structures by taking into consideration the quantity of ammonia nitrogen that enters the wastewater treatment plant. The relationship between the quantity of ammonia nitrogen that enters the WWTP and the optimal setpoint is established by means of linear and polynomial interpolations.

For the linear interpolation method (LIM) approach the relationship between the quantity of ammonia nitrogen that enters the WWTP and the optimal setpoint for any given control scheme was considered to be represent by a linear function and as a result the optimal setpoint could be determined with Eq. (5.2):

$$OSP = SP_{\min} + \frac{(SP_{\max} - SP_{\min})(S_{NH.in} - S_{NH.\min})}{(S_{NH.\max} - S_{NH.\min})} \tag{5.4}$$

where SPmin and SPmax are the minimum and maximum setpoints [mg/L]; SNH.min and SNH.max are the minimum and maximum values of the mass flow of ammonia nitrogen [kg/day] that enters the WWTP; SNH.in the mass flow of ammonia that enters the WWTP.

To ensure the best results by using the LIM, proper values for the minimum and maximum quantities of influent ammonia nitrogen must be defined. The best values were determined by model based optimization for each control strategy. The optimization algorithm returned the following functions:

$$SP\_DOR3 = -0.7008 + 0.0026 SNH_{in} \tag{5.3}$$

$$SP\_DOR4 = 0.0608 + 0.0022 SNH_{in} \tag{5.4}$$

$$SP\_DOR5 = -6.27 \cdot 10^{-4} + 0.0024 \cdot 10^{-3} SNH_{in} \tag{5.5}$$

In case of the NO5 after the optimization procedure, the function which varies the setpoint became:

$$SP\_NOR5 = 5.1429 + 0.0043 SNH_{in} \tag{5.6}$$

The second approach to linking the setpoints to the biodegradable substrate was the Polynomial Interpolation Method (PIM).

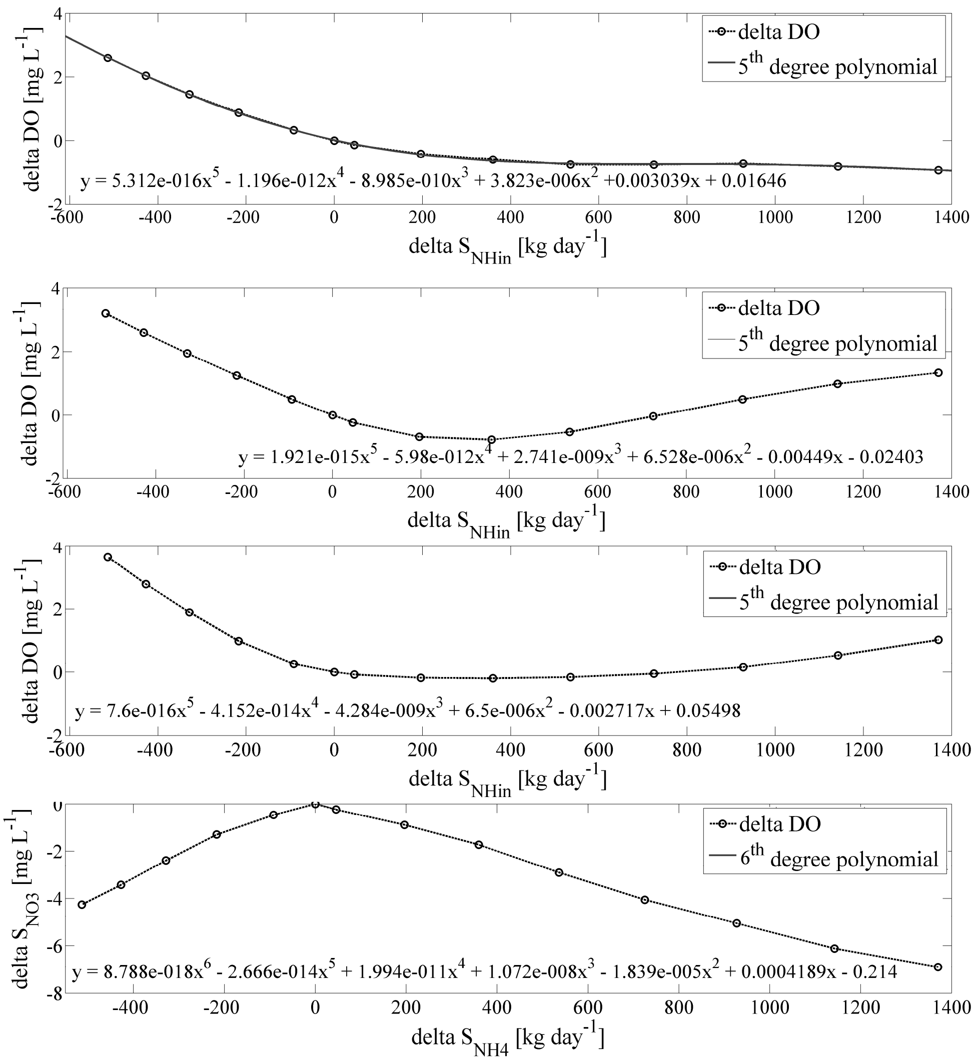

**Figure 5.4.** The fitted polynomial functions from domain of the ammonia gradient to DO co-domain gradient, respectively to SNO3 gradient in the aerated reactors: A) DO reactor 3; B) DO reactor 4; C) DO reactor 5;D) SNO3 reactor 5.

The polynomial relationship between the influent ammonia and the control variables was established using data generated by simulation of the plant with constant influent for 100 days. Fourteen simulations with different values for the influent ammonia, varying from 200 to 1600 kg/day, were made. The average ammonia nitrogen mass flow for the dry influent file is 755.36 kg/day. The steady state solution for the simulation with the inlet ammonia nitrogen mass flow of 755.36 kg/day was considered to be a threshold for the generated data. The threshold value for each variable was subtracted from the generated data and was plotted against the inlet ammonia variation (Figure 5.4). The final equation for the setpoint determination had the form:

$$SP = SP_{base} - SP_{poly} \tag{5.6}$$

where $SP_{base}$ is the root setpoint and $SP_{poly}$ is generated by the polynomial function.

The $SP_{base}$ was determined by model based optimization.

In order to asses the impact of the upper supervisory level of control on the simulated control strategies, both control approaches were first simulated with fixed setpoints. For the 3DO control strategy, the setpoint for all control loops was set to 2 mg/L while for the the NO5 control scheme the setpoint was set to 8 mg/L.

The control strategies were compared to each other and to the open loop simulation of the WWTP. The simulation result showed that by correlating the setpoint of the controllers to the ammonia influent mass flow the operational costs are reduced (Table 5.1).

**Table 5.1.** Results of the control approaches and open loop simulations for dry influent conditions.

| Influent | Control Strategy | AE €/Day | SNH €/Day | $NO_{tot}$ €/Day | EF €/Day | OC €/Day |
|---|---|---|---|---|---|---|
| Dry | OL | 855 | 284 | 687 | 971 | 1826 |
| | 3DO | 671 | 333 | 638 | 970 | 1641 |
| | 3DO LIM | 611 | 332 | 600 | 932 | 1543 |
| | 3DO PIM | 613 | 349 | 606 | 955 | 1568 |
| | NO5 | 642 | 454 | 617 | 1068 | 1713 |
| | NO5 LIM | 684 | 330 | 618 | 948 | 1632 |
| | NO5 PIM | 716 | 312 | 643 | 954 | 1670 |

The best results for the 3DO control was returned by the LIM approach with a mean value of the total operational costs of 1543 €/d, with a cost cutback of 15.5%

compared to the open loop results and almost 6% compared to the simple 3DO control scheme. The best results in case of the NO5 control strategy were obtained with the LIM optimization approach for the rain influent file.

# **Chapter 6 -** Assessment of Different Control Strategies of the WWTP Based on a Modified ASM3 with Three step Denitrification

The first part of this chapter presents the development and implementation in the Benchmark Simulation Model No 1 (BSM1) of a modified Activated Sludge Model No 3.

The enhanced ASM3 presented in this chapter has three modifications compared to the original ASM3:

1) The first modification is the modeling of the heterotrophic biomass growth, simultaneously, on the primary substrate and on the internal storage products as presented in chapter 5.
2) Second, nitrification is modeled as a two-step process carried out by two distinct classes of autotrophic biomass. This biomass is divided in Ammonium Oxidizing Bacteria (AOB) and Nitrite Oxidizing Bacteria (NOB). The first step of the nitrification process is carried out by AOB, which use free ammonia as substrate for growth and generate nitrite. The nitrite nitrogen is then used as substrate for growth by the NOB which oxidizes nitrite to nitrate nitrogen and complete the oxidation of ammonium nitrogen. Including nitrite as a component (an intermediate product of nitrification) brings an increased degree of complexity to the mathematical model (Ostace et al., 2012).
3) The denitrification process is modeled as a three step process with nitrite and nitric oxide as intermediates. The nitric oxide was introduced in the model to account for the inhibition effect of some enzymes that are responsible for the growth of the heterotrophic bacteria under aerobic conditions (Kappeler and Brodmann 1995). This modified ASM3 will be further referred to as ASM3N (Ostace et al., 2012)..

The second part of the chapter presents the development and implementation of a reactive secondary settler model in the BSM1. The built reactive settler model is the combination of the settler model described by Takács in 1991 and the enhanced ASM3 (Ostace et al. 2012).

The continuity equation of the reactive settler model has the form:

$$\frac{\partial X}{\partial t} + \frac{\partial J}{\partial z} + R_X = 0 \tag{6.1}$$

where: X is the particulate component concentration [mg $L^{-1}$]; t – time [days]; J – solids flux [mg $day^{-1}m^{-2}$)]; z – layer height [m]; $R_X$ – conversion rate of the particulate component.

The third part of this chapter consists of the investigation of five control strategies applied to the WWTP.

**Strategy #1 (S1)** - The first control scheme has two control loops. The first control loop has to keep the nitrogen concentration (the sum of nitrate, nitrite and nitric oxide) NO in the second anoxic reactor at a set point of 1 mg/L, by manipulating the nitrogen recycle flow rate. The second control loop involves the control of the Dissolved Oxygen (DO) in the third aerated reactor and its set point is of 2 $mgL^{-1}$, by manipulating the air flow rate (indirectly by the volumetric oxygen transfer coefficient $K_La$).

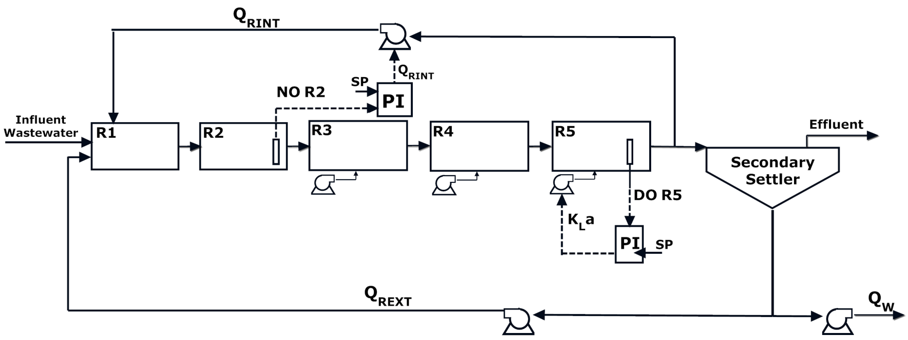


**Figure 6.1.** Control strategy no. 1 (S1) schematic representation.

**Strategy #2 (S2)** - The second investigated control architecture has three control loops. These control loops are designed to keep the DO concentration in the aerated reactors at a set point of 2 $mgL^{-1}$, by manipulating the $K_La$.

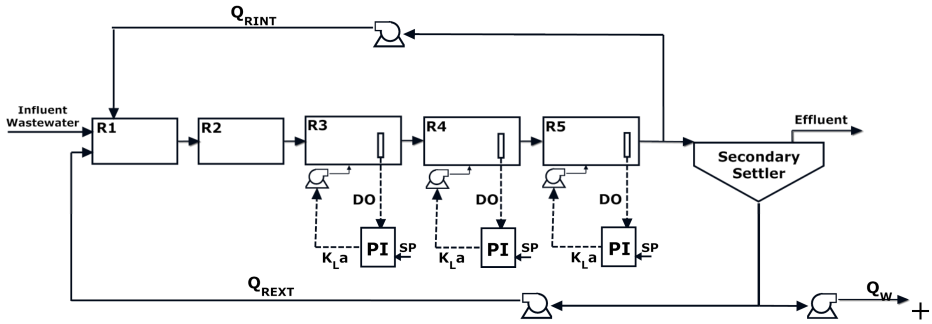


**Figure 6.2.** Control strategy no. 2 (S2) schematic representation.

**Strategy #3 (S3)** - Control strategy number three is a combination of S1 and S2. It has four control loops. The first three are controlling the DO in the aerated reactors and the forth control loop is keeping the NO in the second anoxic reactor at a set point of 1 $mgL^{-1}$. The manipulated variable for the NO control is the same as for S1, the internal recycle flow.

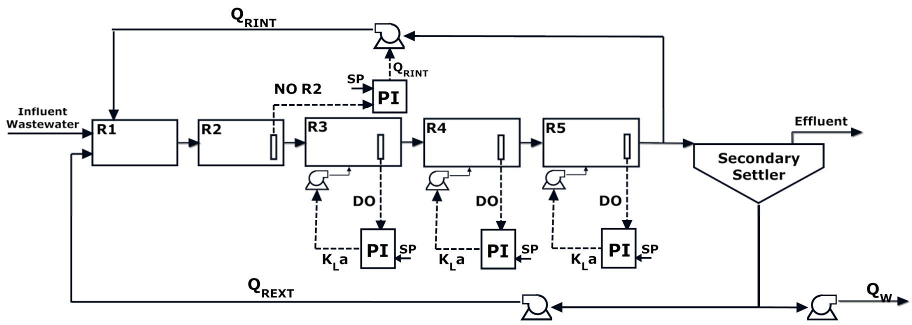


**Figure 6.3.** Control strategy no. 3 (S3) schematic representation.

**Strategy #4 (S4)** - The fourth control strategy investigated in this work has to keep the NO in the last aerated reactor at a set-point of 8 $mgL^{-1}$ and the NO levels in the second reactor at 1 $mgL^{-1}$. The NO in the last aerated reactor is controlled by manipulating the DO set-point values of the aerated reactors. For this control loop, there is an inner control level which consists of PI controllers that keep the DO concentration in the aerated reactors at the set-points imposed by the MPC. The set-points provided by the MPC are constrained to a maximum of 2 mg $L^{-1}$, to prevent excessive aeration. The second control loop manipulates the inner recycle flow rate in order to maintain the NO at the desired level.

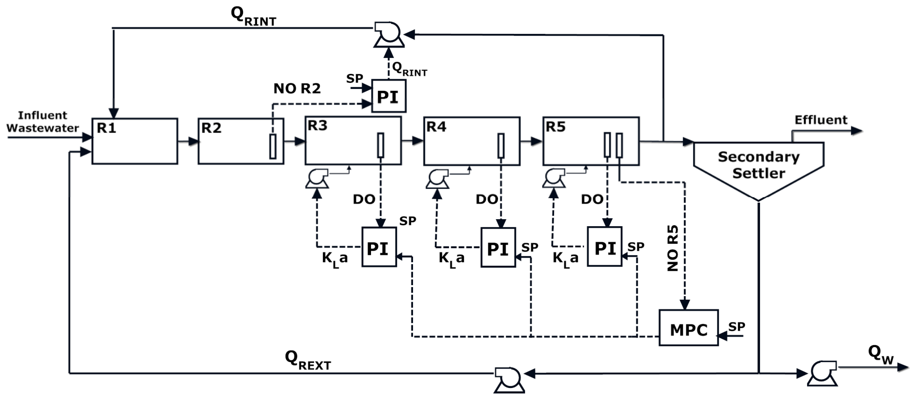


**Figure 6.4.** Control strategy no. 4 (S4) schematic representation.

**Strategy #5 (S5)** – The fifth strategy is identical in structure with the forth one, only that the controlled variables are the ammonia in the last aerated reactor and the NO in the second one. The set-points for both variables are set to 1 mgL$^{-1}$.

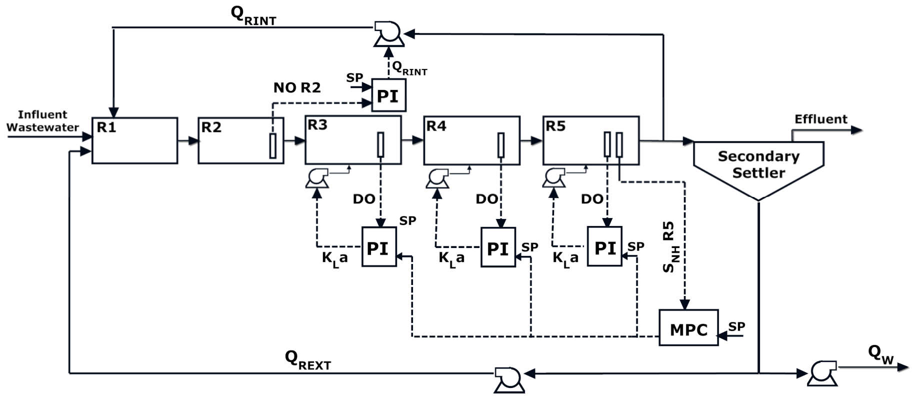


**Figure 6.5.** Control strategy no. 5 (S5) schematic representation.

The control architectures were analyzed from three points of view: operational costs, effluent violations, and controller performance.

The operational costs were calculated using the following formula:

$$OC = \gamma_E (AE + PE) + \gamma_{SP} SP + EF \tag{6.2}$$

where: $AE$ is the aeration energy [kWh day$^{-1}$]; $PE$ is the pumping energy [kWh day$^{-1}$]; SP – sludge production; $EF$ – effluent fines; $\gamma_E$ – electricity price 0.1 [€/kWh]; $\gamma_{SP}$ – cost standard for the treatment of 1 g of produced sludge [$5 \cdot 10^{-4}$ €·g$^{-1}$].

The sludge production (SP) was calculated with equation (6.3) (Guerrero et al., 2011, Machado et al. 2009):

$$SP = \frac{1}{T}\int_{t=22d}^{t=28d}(TSS_W(t)Q_w(t))dt \qquad (6.3)$$

where $TSS_W$ is the solids content in the purge.

The dry weather open loop simulation returned the highest operational costs: 3753.69 €/day, because of an excessive aeration. The aeration costs have a value of 854.84 €/day, and represent 22.8 % of the total operational costs. Although the effluent fines for the ammonia concentration have the lowest value for the open loop simulation, the total nitrogen fines reach a higher value compared to the control strategies. This high value for the effluent total nitrogen is the result of an insufficient internal recycle flow rate; this fact can be concluded from the pumping energy cost which has the smallest value for the open loop simulation.

**Table 6.1.** Operational costs for the control strategies (S#1-S#5) and open loop simulations (OL) for all influent files.

| Inf. | Control strategy | AE €/day | PE €/day | SP €/day | SNH €/day | SNO2 €/day | Ntot €/day | EF €/day | OC €/day |
|---|---|---|---|---|---|---|---|---|---|
| DRY | OL | 854.84 | 296.53 | 1252.01 | 194.96 | 533.13 | 622.20 | 1350.30 | 3753.69 |
| | S1 | 720.38 | 319.12 | 1270.02 | 220.08 | 528.25 | 547.52 | 1295.86 | 3605.39 |
| | S2 | 634.84 | 296.53 | 1277.75 | 239.79 | 617.11 | 562.97 | 1419.87 | 3629.00 |
| | S3 | 633.50 | 338.71 | 1274.28 | 239.74 | 540.40 | 534.13 | 1314.27 | 3560.77 |
| | S4 | 622.82 | 312.48 | 1286.10 | 281.45 | 618.90 | 543.83 | 1444.19 | 3665.61 |
| | S5 | 592.50 | 420.25 | 1331.12 | 253.64 | 634.25 | 460.03 | 1347.92 | 3691.81 |

**Table 6.2.** Mean effluent concentration and time above limit (TAL)

| Inf. | CS | SNH | | SNO2 | | Ntot | | COD | | BOD | | TSS | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Conc. m/L | TAL % | Conc. m/L | TAL % | Conc. m/L. | TAL % | Conc. m/L | TAL % | Conc. m/L | TAL % | Conc. m/L | TAL % |
| DRY | OL | 1.97 | 15.17 | 2.92 | 92.11 | 12.84 | 1.93 | 46.48 | 0.00 | 3.50 | 0.00 | 13.25 | 0.00 |
| | S1 | 2.18 | 16.36 | 2.91 | 95.68 | 11.34 | 0.00 | 46.40 | 0.00 | 3.47 | 0.00 | 13.35 | 0.00 |
| | S2 | 2.36 | 17.26 | 3.34 | 96.87 | 11.64 | 0.74 | 46.46 | 0.00 | 3.48 | 0.00 | 13.39 | 0.00 |
| | S3 | 2.35 | 17.11 | 2.98 | 97.02 | 11.06 | 0.00 | 46.43 | 0.00 | 3.48 | 0.00 | 13.38 | 0.00 |
| | S4 | 2.68 | 18.89 | 3.33 | 99.55 | 11.12 | 0.00 | 46.51 | 0.00 | 3.49 | 0.00 | 13.44 | 0.00 |
| | S5 | 2.50 | 17.11 | 3.41 | 98.06 | 9.50 | 0.00 | 46.72 | 0.00 | 3.52 | 0.00 | 13.67 | 0.00 |

The best results, for the dry influent file, are achieved by the simulation using the control strategy #3, with a mean total operational costs of 3560.77 €/day, i.e. a cutback of 192.92 €/day. This means a reduction of the operational costs in proportion of 5.14 %, which is equivalent to 70,500 €/year.

# Chapter 7 - Control Strategies for Optimal Simultaneous Removal of Carbon, Nitrogen and Phosphorus

This chapter presents the development of four innovative control strategies for the anaerobic-anoxic-oxic ($A^2/O$) wastewater treatment plant (WWTP) configuration that combines EBPR and nitrification/denitrification for simultaneous C, N and P removal. The WWTP and control strategies were implemented and simulated in Matlab/Simulink under different influent conditions (dry, rain and storm conditions). A systematic approach was conducted with all the strategies to assess their potential effectiveness, according to the following steps: theoretical design based on the current WWTP needs, setpoint optimization and, finally, a detailed comparison (based on plant pollutants removal efficiency and costs) of the control results against the open loop operation scenario and an optimized open loop scenario.

The WWTP configuration used for this chapter is the one proposed by Gernaey and Jørgensen (2004).

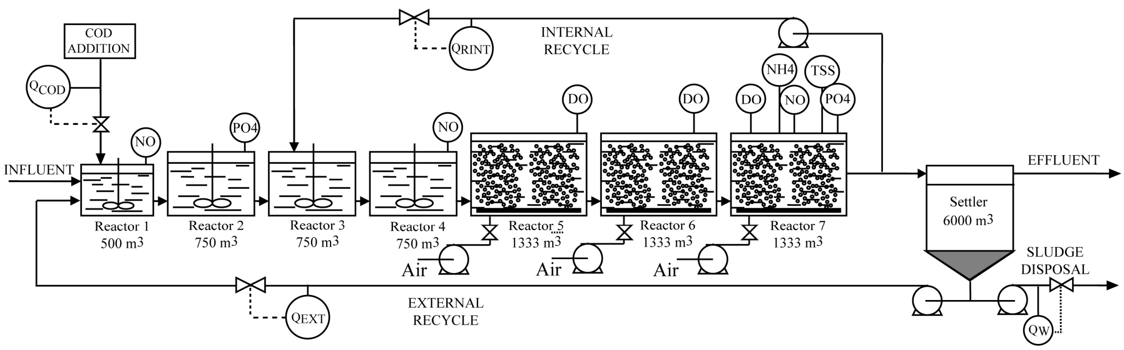


**Figure 7.1.** Scheme of the $A^2/O$ simulated plant for simultaneous C/N/P removal.

A schematic representation of the plant layout is presented in Figure 1 and it consists of:

- 7 continuous stirred tank rectors arranged in series followed by a secondary settler

- the total biological reactor volume is 6749 $m^3$ (two anaerobic tanks, the first one of 500 $m^3$, the second anaerobic tank of 750 $m^3$, two anoxic tanks each with a volume of 750 $m^3$, three aerobic tanks, each of 1333 $m^3$ )
- the anaerobic and anoxic tanks are fully mixed and operate at a temperature of 15 ºC
- the aerobic tanks are aerated using the $k_La$ which has a maximum of 240 $day^{-1}$
- Saturation concentration for the dissolved oxygen is 8 mg/L
- the secondary settler is considered non-reactive and has a volume of 6000 $m^3$ with a horizontal cross-section of 1500 $m^2$ and a depth of 4 m and is modeled using the 10-layer model proposed by Takács *et al*., (1991)
- the biomass from the bottom of the settler is returned to the first reactor by the external recycle flow ($Q_{REXT}$) which has a value equal to the influent flow rate ($Q_{INT}$) under dry weather conditions (average of 18,446 $m^3$/day)
- nitrate recycle ($Q_{RINT}$) from the 7th to the 3rd tank at a default flow rate of 300% of the influent flow rate (dry weather conditions: average of 55,338 $m^3$/day)

The bio-kinetic model used to describe the simultaneous C/N/P removal was ASM2d (Henze, *et al*., 1999). The ASM2d model equations for biomass decay were modified to make the decay process rates electron acceptor dependent accordingly with Gernaey and Jørgensen (2004).

**Table 7. 1**. Control loops and optimal setpoints of the implemented control strategies

| | Controlled parameter | Controller algorithm | Manipulated variable | Manipulated variable constrains | Optimal Setpoint (mg·L$^{-1}$) |
|---|---|---|---|---|---|
| **Control loops for S1** | $S_{O2}$ in R5, R6, R7 | PI | $k_La$ in R5, R6, R7 | 0 – 240 $d^{-1}$ | [1.50; 2.44; 1.00] |
| | $S_{NO3}$ in R4 | PI | $Q_{RINT}$ | 0 – 92230 $m^3 \cdot d^{-1}$ | 0.75 |
| | $S_{NO3}$ in R1 | PI | COD addition | 0 – 5 $m^3 \cdot d^{-1}$ | 0.2 |
| | $S_{PO4}$ in R7 | PI | $Q_{REXT}$ | 9223 – 27669 $m^3 \cdot d^{-1}$ | 1.00 |
| **Control loops for S2** | $S_{O2}$ in R5, R6, R7 | PI | $k_La$ in R5, R6, R7 | 0 – 240 $d^{-1}$ | [1.38, 1.88, 1.81] |
| | $S_{NO3}$ in R4 | PI | $Q_{RINT}$ | 0 – 92230 $m^3 \cdot d^{-1}$ | 0.38 |
| | $S_{PO4}$ in R2 | PI | COD addition | 0 – 5 $m^3 \cdot d^{-1}$ | 16.00 |
| **Control loops for S3** | $S_{NH4}$ in R7 | Supervisory MPC | $S_{O2}$ SP in R5, R6, R7 | 0 – 2 mg·L$^{-1}$ | 0.69 |
| | | Slave PI | $k_La$ in R5, R6, R7 | 0 – 240 $d^{-1}$ | Imposed by MPC |
| | $S_{NO3}$ in R4 | PI | $Q_{RINT}$ | 0 – 92230 $m^3 \cdot d^{-1}$ | 0.50 |
| | $S_{PO4}$ in R2 | PI | COD addition | 0 – 5 $m^3 \cdot d^{-1}$ | 16.00 |
| **Control loops for S4** | $S_{NO3}$ in R7 | Supervisory MPC | $S_{O2}$ SP in R5, R6, R7 | 0 – 2 mg·L$^{-1}$ | 11.25 |
| | | Slave PI | $k_La$ in R5, R6, R7 | 0 – 240 $d^{-1}$ | Imposed by MPC |
| | $S_{NO3}$ in R4 | PI | $Q_{RINT}$ | 0 – 92230 $m^3 \cdot d^{-1}$ | 0.38 |

| | | | | | |
|---|---|---|---|---|---|
| | $S_{PO4}$ in R2 | PI | COD addition | $0 – 5\ m^3 \cdot d^{-1}$ | 16.00 |
| **Common control loop** | TSS in R7 | PI | Qw | $300 – 500\ m^3 \cdot d^{-1}$ | 4400 |

The four different innovative control strategies proposed in this chapter are outlined in Table 7.1. The PI controllers were designed using the Internal Model Control (IMC) approach because it provides a reasonable tradeoff between performance and robustness (Rivera *et al.*, 1986). The MPC controllers for strategy S3 and S4 were tuned using the tuning rules presented in Maciejowski (2002) and by performing simulations.

The set-points of the control strategies were optimized using a pattern search (PS) algorithm so that the total operational costs of the WWTP were minimized as much as possible. For the performance assessment and set-points optimization only the last seven days of the simulation were taken into consideration.

The performance of the proposed control strategies was assessed from three points of view: total operational costs, quality of the effluent and pollutant removal. The operational costs were calculated using equation (7.1):

$$OC = \gamma_E (AE + PE) + \gamma_C EC + \gamma_{SP} SP + EF \tag{7.1}$$

where: AE represents the aeration energy ($kWh \cdot d^{-1}$); PE - the pumping energy ($kWh \cdot d^{-1}$); EC – external carbon addition; SP – sludge production; EF – effluent fines; $\gamma_E$ – electricity price ($0.1$ €$\cdot kWh^{-1}$); $\gamma_C$ – carbon addition price ($0.3$ €$\cdot kg^{-1}$); $\gamma_{SP}$ – cost for the treatment of 1 g of produced sludge ($0.5$ €$\cdot kg^{-1}$).

The external carbon addition (Eq. 7.2) was represented by the average external mass flow where CODs is the concentration of the carbon source and $Q_{COD}$ is the external carbon volumetric flow ($m^3 \cdot d^{-1}$).

$$EC = \frac{CODs}{T \times 1000} \int_{t=22d}^{t=28d} Q_{COD} dt \tag{7.2}$$

The results of the simulated control strategies were compared between each other and with the open loop (OL) simulation as well. In order to have a fair evaluation between the open loop simulation and the control strategies, the open loop configuration was optimized using the same pattern search algorithm that was used to optimize the set-points of the control strategies. The optimization algorithm returned the following values for the optimized open loop (OL+) simulation: $k_La$ in reactor five, six and seven were 196 $d^{-1}$, 220 $d^{-1}$ and 183 $d^{-1}$, while $Q_{RINT}$ was 18458 $m^3 \cdot d^{-1}$ and $Q_{REXT}$ 9230 $m^3 \cdot d^{-1}$. This configuration of the open loop simulation presented a reduction in the operational costs of 280 €$\cdot d^{-1}$(6 %) with a mean value for the last seven days of simulation of 4594 €$\cdot d^{-1}$ (for the simulation with the dry influent file).

The simulation results showed that all control strategies further reduced the total operational costs (Table 7.1) when compared to the open loop simulations (OL and OL+).

**Table 7.1.** Operational costs for the control strategies (S1)-(S4), open loop simulations (OL) and the optimized open loop simulation (OL+) for all influent files.

| inf | Control strategy | AE €/d | PE €/d | EC €/d | SP €/d | SNH €/d | Ptot €/d | Ntot €/d | EF €/d | OC €/d |
|---|---|---|---|---|---|---|---|---|---|---|
| **DRY** | **OL** | 623 | 297 | 0 | 1743 | 1076 | 352 | 783 | 2211 | 4874 |
| | **OL+** | 672 | 112 | 0 | 1711 | 489 | 583 | 1026 | 2099 | 4594 |
| | **S1** | 647 | 168 | 0 | 1445 | 640 | 287 | 892 | 1819 | 4078 |
| | **S2** | 666 | 186 | 153 | 1878 | 396 | 128 | 710 | 1233 | 4117 |
| | **S3** | 685 | 204 | 133 | 1874 | 382 | 135 | 680 | 1196 | 4092 |
| | **S4** | 685 | 186 | 15 | 1872 | 388 | 133 | 712 | 1233 | 4121 |
| **RAIN** | **OL** | 623 | 297 | 0 | 1599 | 1640 | 460 | 1025 | 3125 | 5644 |
| | **OL+** | 672 | 112 | 0 | 1578 | 966 | 644 | 1278 | 2887 | 5250 |
| | **S1** | 628 | 226 | 2 | 1475 | 1196 | 1088 | 1301 | 3584 | 5915 |
| | **S2** | 682 | 207 | 186 | 1835 | 790 | 262 | 894 | 1945 | 4855 |
| | **S3** | 705 | 223 | 171 | 1831 | 747 | 282 | 858 | 1887 | 4817 |
| | **S4** | 695 | 207 | 16 | 1830 | 789 | 263 | 898 | 1951 | 4857 |
| **STORM** | **OL** | 623 | 297 | 0 | 1730 | 1725 | 415 | 1063 | 3204 | 5853 |
| | **OL+** | 672 | 112 | 0 | 1709 | 964 | 639 | 1333 | 2936 | 5430 |
| | **S1** | 698 | 215 | 166 | 1863 | 896 | 388 | 1090 | 2374 | 5319 |
| | **S2** | 658 | 270 | 282 | 1739 | 968 | 207 | 872 | 2047 | 4997 |
| | **S3** | 686 | 283 | 278 | 1738 | 901 | 204 | 842 | 1946 | 4930 |
| | **S4** | 680 | 268 | 14 | 1737 | 934 | 206 | 868 | 2008 | 4972 |

The simulation results with each control structure using all weather influent files were compared with the performance of conventional open loop configuration and with the optimized open loop operation. These results proved that:

i) The optimization of the system variables under open loop can improve the operational costs of the WWTP, but does not assure a stable performance under disturbed operation. The optimized open loop managed to improve the operational costs by 6-7 % (about 102,000 €$\cdot$year$^{-1}$) for the dry weather, rain and storm weather conditions.

ii) Automatic control of the WWTP can significantly reduce the operational costs of the plant while maintaining low pollutant effluent concentrations for all the control strategies tested and achieving a more stable performance even under disturbed operation.

iii) Using the external carbon addition in the first anaerobic reactor as manipulated variable for phosphorus control was a successful strategy. The external carbon addition had the role of a "safety-mechanism" that prevented the competition between PAO and OHO for organic substrate and as a result, EBPR failure was avoided.

iv) Strategy S3 was the most efficient, leading to an operational cost reduction of 285,000 €$\cdot$year$^{-1}$ for dry weather conditions. Strategy S4 proved to be the second best due to its good performance during rain and storm events.

# Chapter 8 - Enhanced Biological Phosphorus Removal of a Modified Ludzack-Ettinger WWTP by Means of External Carbon Addition and Automatic Control

This chapter presents a theoretical approach to achieve EBPR and nitrification/denitrification for simultaneous C, N and P removal for a MLE configuration of the wastewater treatment plant. The Activated Sludge Model No. 2d was implemented in the Benchmark Simulation Model No. 1 and simulated in the Matlab/Simulink platform. EBPR was accomplished and maintained by using external carbon addition and automatic decentralized control. A systematic approach has been carried out to optimize the MLE process in order to achieve EBPR under open loop conditions. The control loops configuration was determined using the Relative Gain Array and the Partial Relative Gain. This approach resulted in two potential control strategies. In order to achieve low effluent pollutant concentrations and low operational costs the setpoints of the control strategies were optimized under different influent conditions (dry, rain and storm). The controllers were designed using the Internal Model Control (IMC) principle. The simulation results showed that EBPR can be accomplished and maintained using external COD addition. The simulation results using decentralized automatic control proved to maintain EBPR and reduce operational costs.

For this chapter the Benchmark Simulation Model No. 1 WWTP was modified to include an external carbon addition source. The external carbon is added in the first anoxic tank and is constrained to a maximum of 5 $m^3$ $d^{-1}$. The carbon source is considered to be acetate with a concentration of $4\times10^5$ mg $L^{-1}$. The mathematical model used to describe the simultaneous C/N/P removal was ASM2d (Henze et. al., 1999). The biomass decay rates were modified to make the process rates electron acceptor dependent as presented in Gernaey and Jørgensen (2004).

The optimization of MLE process for EBPR had two steps. The first step was the steady-state optimization of the plant. The optimization algorithm had to find the most favorable values for the $k_La$ in the aerated reactors, recycle flow rates, waste sludge disposal and COD addition flow rates in order to achieve simultaneous C, N and P removal with the minimum cost possible. Several optimization search methods were tested for the steady state optimization. The best result was provided by the *threshacceptbnd* function. This method finds the unconstrained or bound-constrained minimum of a function of several variables using threshold acceptance algorithm. The threshold accepting (TA) method, first introduced by Dueck and Scheuer (1990), is a variation of the classical simulated annealing algorithm.

The second step was the dynamic open loop optimization of the WWTP plant. The optimization was performed for all influent files. In this case the pattern search optimization method proved to be the most effective approach. The starting point of each dynamic simulation was the optimized steady state solution. For the performance assessment only the last 14 days of the simulation were taken into consideration.

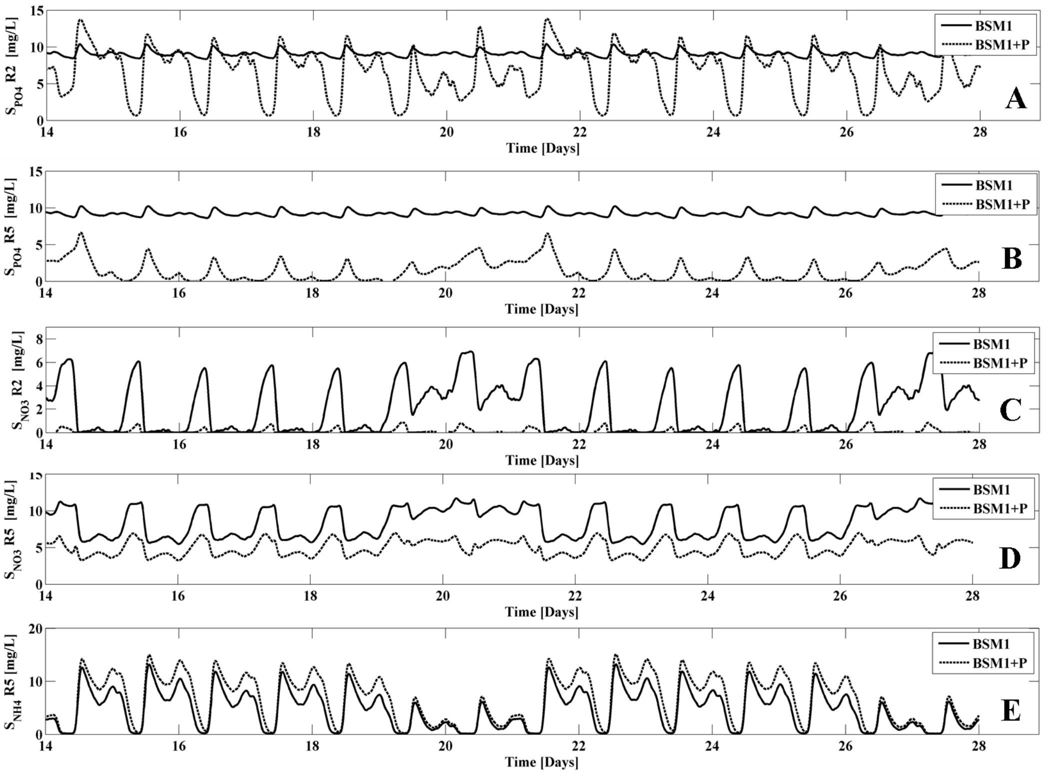


**Figure 8.1.** Dynamic variation of state variables in the system under dry weather conditions, for the last 14 days: A) $S_{PO4}$ in R2; B) $S_{PO4}$ in R5; C) $S_{NO3}$ in R2; D) $S_{NO3}$ in R5; E) $S_{NH4}$ in R5;

**Table 8.1.** 3×4 Transfer function model of the simulated WWTP.

| Outputs [g/m] | Inputs | | |
|---|---|---|---|
| | $Q_{COD}$ [m$^{-3}$/d] | $S_{O2}$ SP in R3 R4 R5 [gO$_2$/m] | $Q_{RINT}$ [m$^{-3}$/d] |
| $S_{PO4}$ R2 | $-0.8537\dfrac{(-0.0102s+1)e^{-0.3024s}}{0.5279s+1}$ | $1.0864\dfrac{(0.0164s+1)e^{-0.3125s}}{0.4452s+1}$ | $4.2947\cdot 10^{-6}\dfrac{(0.2199s+1)e^{-0.3032s}}{0.3425s+1}$ |
| $S_{PO4}$ R5 | $\dfrac{-2.0761e^{-0.2853s}}{0.6979s+1}$ | $2.9972\dfrac{(0.0525s+1)e^{-0.3076s}}{0.7161s+1}$ | $5.5178\cdot 10^{-5}\dfrac{(0.1177s+1)e^{-0.3125s}}{1.2683s+1}$ |
| $S_{NO3}$ R5 | $\dfrac{-0.2737e^{-0.2855s}}{1.0375s+1}$ | $1.3171\dfrac{(0.0019s+1)e^{-03081s}}{0.1685s+1}$ | $-6.2884\cdot 10^{-5}\dfrac{(0.0051s+1)e^{-0.3125s}}{0.2032s+1}$ |

| | | | |
|---|---|---|---|
| **$S_{NH4}$ R5** | $0.2479\dfrac{(3.5745s+1)e^{-0.3070s}}{14.1650s+1}$ | $\dfrac{-1.4475e^{-0.3125s}}{3.3594s+1}$ | $5.1887\cdot10^{-6}\,\dfrac{(0.0014s+1)e^{-0.3079s}}{0.2174s+1}$ |

Table 8.1 presents the 3×4 transfer function model of the WWTP. The plant model was obtained by system identification tests and each transfer function represents the relationship between a potential control input and a control output.

The first step in designing the structure of the decentralized control system was the pairing of the possible manipulated variables with the controlled variables, in 3×3 system configuration. Using the information provided by the transfer functions four possible combinations of the inputs and outputs were analyzed. The RGA matrix was calculated for each manipulated/controlled variable combination at two frequencies $\omega$ = 0 rad·d$^{-1}$ (static conditions) and $48\pi$ rad·d$^{-1}$ (hourly variation).

**Table 8.2.** RGA matrix for the 3×3 possible combinations between manipulated and controlled variable at frequency $\omega$ = 0 rad·d$^{-1}$ (static conditions) and $48\pi$ rad·d$^{-1}$ (hourly variation).

| **Combination** | **Controlled variables** | **Manipulated Variables** | | | | | |
|---|---|---|---|---|---|---|---|
| | | **$\omega$ = 0 rad·d$^{-1}$** | | | **$\omega$ = $48\pi$ rad·d$^{-1}$** | | |
| | | **$Q_{COD}$** | **$S_{O2}$R3-5SP** | **$Q_{RINT}$** | **$Q_{COD}$** | **$S_{O2}$R3-5SP** | **$Q_{RINT}$** |
| | **$S_{PO4}$ R2** | **3.9565** | -2.8105 | -0.1460 | **1.3507** | -0.2060 | -0.1447 |
| **1** | **$S_{NO3}$ R5** | -0.2287 | **0.8924** | 0.3363 | 0.0545 | 0.2070 | **0.7384** |
| | **$S_{PO4}$ R5** | -2.7278 | 2.9181 | **0.8098** | -0.4052 | **0.9989** | 0.4062 |
| | **$S_{PO4}$ R2** | **1.8037** | -0.5884 | -0.2154 | **1.4033** | -0.1918 | -0.2115 |
| **2** | **$S_{NH4}$ R5** | -0.2584 | **1.2237** | 0.0346 | 0.0017 | 0.1926 | **0.8057** |
| | **$S_{PO4}$ R5** | -0.5454 | 0.3646 | **1.1807** | -0.4050 | **0.9992** | 0.4058 |
| | **$S_{PO4}$ R2** | **1.2658** | -0.2711 | 0.0053 | **124.99** | -58.56 | -65.42 |
| **3** | **$S_{NH4}$ R5** | -0.3229 | **1.3985** | -0.0756 | 4.01 | -789.60 | **786.58** |
| | **$S_{NO3}$ R5** | 0.0571 | -0.1274 | **1.0703** | -128.01 | **849.17** | -720.15 |
| | **$S_{PO4}$ R5** | **1.2832** | -0.3115 | 0.0283 | -0.4096 | 1.0025 | **0.4071** |
| **4** | **$S_{NH4}$ R5** | -0.4748 | **1.5478** | -0.0729 | -0.0439 | **2.7870** | -1.7431 |
| | **$S_{NO3}$ R5** | 0.1916 | -0.2363 | **1.0447** | **1.4535** | -2.7894 | 2.3359 |

The simulation results showed that the 3×3 control schemes are unstable. The next step was the partial relative gain analysis. The first step was to close one control loop to obtain 2×2 systems configuration which are more reliable for RGA analysis. For the partial relative gain analysis it is indicated to pair the variables that present negative or zero relative gain values and also have a significant effect on the process.

The pairing that has this characteristic is the phosphorus in R2 with $Q_{RINT}$. The RGA element of this pairing has a negative value for both static and dynamic conditions. Additionally, the $Q_{RINT}$ manipulated variable has a significant effect on the $S_{PO4}$ controlled variable. As a result, the $S_{PO4}$R2 - $Q_{RINT}$ control loop was closed using a Proportional controller. For the tuning of the controller the inverse response was considered and the controller-steady state gain was assumed to be equal to the inverse of the model gain.

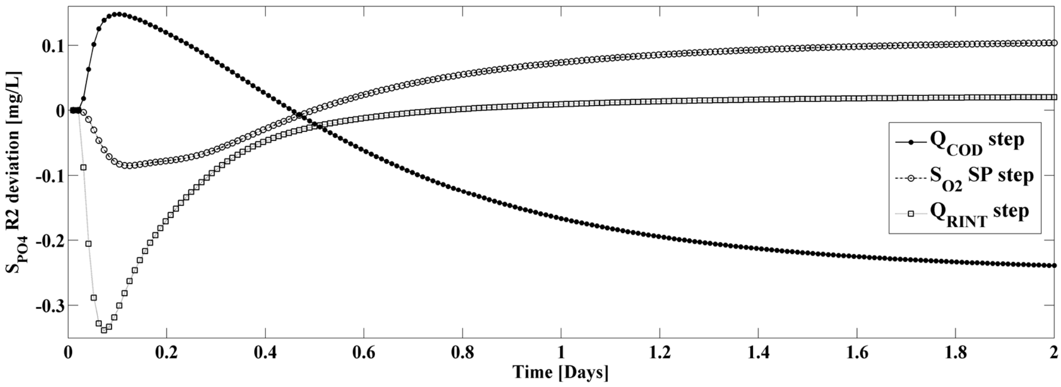


**Figure 8.2.** Step response of the $S_{PO4}$ R2 for the considered manipulated variables: $Q_{COD}$, $S_{O2}$ SP in R3-R5 and $Q_{RINT}$.

Subsequently the system identification tests were performed again. Table 8.3 presents the transfer function model for the 2×3 subsystem.

**Table 8.3**. 2×3 subsystem transfer matrix model of the simulated WWTP

| Outputs [g m$^{-3}$] | Inputs | |
|---|---|---|
| | **$Q_{COD}$ [m$^{-3}$/d]** | **$S_{O2}$ SP in R3 R4 R5 [g$O_2$/m]** |
| **$S_{PO4}$ R5** | $\frac{-0.1205e^{-0.3125s}}{2.8883s+1}$ | $\frac{0.0176e^{-0.3076s}}{(0.1551s+1)(20.6910s+1)(54.35s+1)}$ |
| **$S_{NO3}$ R5** | $\frac{-1.7567e^{-0.2853s}}{0.5323s+1}$ | $\frac{3.1937e^{-0.2852s}}{0.4622s+1}$ |
| **$S_{NH4}$ R5** | $2.0975\frac{(-0.9075s+1)e^{-0.3070s}}{(22.4480s+1)(0.2250s+1)}$ | $\frac{-2.2565e^{-0..3125s}}{5.5151s+1}$ |

**Table 8.4.** RGA matrix for the 2×2 possible combinations between manipulated and controlled variables at static conditions ω = 0 rad/d and at frequency of 48π rad/d (hourly variation).

| | Controlled variables | Manipulated Variables | | | |
|---|---|---|---|---|---|
| | | **ω = 0 rad·d$^{-1}$** | | **ω = 48π rad·d$^{-1}$** | |
| | | **$Q_{COD}$** | **$S_{O2}$R3-5SP** | **$Q_{COD}$** | **$S_{O2}$R3-5SP** |
| 1 | **$S_{PO4}$ R5** | **1.0875** | -0.0875 | **1.0000** | 0.0000 |
| | **$S_{NO3}$ R5** | -0.0875 | **1.0875** | 0.0000 | **1.0000** |
| 2 | **$S_{PO4}$ R5** | **1.1574** | -0.1574 | **1.0000** | 0.0000 |
| | **$S_{NH4}$ R5** | -0.1574 | **1.1574** | 0.0000 | **1.0000** |
| 3 | **$S_{NH4}$ R5** | **2.4494** | -1.4494 | **2.2492** | -1.2492 |
| | **$S_{NO3}$ R5** | -1.4494 | **2.4494** | -1.2492 | **2.2492** |

Table 8.4 presents the RGA results for the 2×2 combinations of the subsystem. Two potential control strategies emerge from the RGA matrixes.

The process controllers were designed using the Internal Model Control approach (Rivera et al., 1986) (Table 8.5). The setpoints of each control strategy was optimized for all weather files using a pattern search (PS) algorithm so that the total operational costs of the WWTP are minimized as much as possible. Additionally, the $Q_{REXT}$ and $Q_W$ were optimized for each control approach.

**Table 8.5.** Parameters of the process controllers used for the two control schemes

| Control loop | | Type of controller | Kc | Ti | λ |
|---|---|---|---|---|---|
| **Manipulated variable** | **Controlled variable** | | | | |
| $Q_{RINT}$ | $S_{PO4}$ R2 | P | -47141.04 | - | - |
| $Q_{COD}$ | $S_{PO4}$ R5 | PI | -2.5251 | 3.0446 | 10.0 |
| $S_{O2}$R3-5SP | $S_{NO3}$ R5 | PI | 1.2626 | 0.6048 | 0.15 |
| $S_{O2}$R3-5SP | $S_{NH4}$ R5 | P | -1.1762 | - | 2.00 |
| $K_La$ R3 | $S_{O2}$ R3 | PI | 500 | 0.001 | - |
| $K_La$ R4 | $S_{O2}$ R4 | PI | 500 | 0.001 | - |
| $K_La$ R5 | $S_{O2}$ R5 | PI | 500 | 0.001 | - |

**Table 8.6.** Optimal setpoints, $Q_{RINT}$ and $Q_W$ of the implemented control strategies for all weather files

| | Control Loop | Optimal Setpoint | | | Optimal External Recycle Flow | | | Optimal Waste Flow QW | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | **Dry** | **Rain** | **Storm** | **Dry** | **Rain** | **Storm** | **Dry** | **Rain** | **Storm** |
| **Control Strategy No. 1** | $S_{PO4}$ **R2** | 13.00 | 12.25 | 12.25 | 27615.24 | 27667.24 | 27429.24 | 375.81 | 455.31 | 487.81 |
| | $S_{PO4}$ **R5** | 0.62 | 0.69 | 0.81 | | | | | | |
| | $S_{NO3}$ **R5** | 10.5 | 10.13 | 10.63 | | | | | | |
| **Control Strategy No. 2** | $S_{PO4}$ **R2** | 12.25 | 11.75 | 12.00 | 27615.24 | 27668.24 | 27666.24 | 375.81 | 456.81 | 491.81 |
| | $S_{PO4}$ **R5** | 0.56 | 0.81 | 0.75 | | | | | | |
| | $S_{NH4}$ **R5** | 1.31 | 1.06 | 1.00 | | | | | | |

The simulation results showed that both control approaches managed to reduce the total operational costs compared to the open loop simulations, as it is presented in Table 8.7.

**Table 8.7.** Operational costs for the two selected control strategies and for optimized open loop simulation (OL+) in the case of all influent files.

| | Control strategy | AE €/d | PE €/d | EC €/d | SP €/d | SNH €/d | Ptot €/d | Ntot €/d | EF €/d | OC €/d |
|---|---|---|---|---|---|---|---|---|---|---|
| **DRY** | **OL** | 732 | 186 | 410 | 1868 | 433 | 275 | 688 | 1396 | 4595 |
| | **S1** | 624 | 133 | 221 | 1774 | 350 | 236 | 777 | 1363 | 4116 |
| | **S2** | 658 | 144 | 226 | 1777 | 322 | 242 | 736 | 1301 | 4105 |
| **RAIN** | **OL** | 725 | 186 | 402 | 2118 | 662 | 344 | 801 | 1807 | 5242 |
| | **S1** | 644 | 135 | 245 | 2050 | 531 | 272 | 889 | 1692 | 4765 |
| | **S2** | 673 | 141 | 248 | 2059 | 496 | 295 | 858 | 1649 | 4770 |
| **STORM** | **OL** | 751 | 182 | 418 | 2226 | 634 | 314 | 792 | 1740 | 5319 |
| | **S1** | 662 | 138 | 274 | 2144 | 505 | 257 | 868 | 1630 | 4848 |
| | **S2** | 688 | 144 | 275 | 2158 | 480 | 252 | 838 | 1570 | 4834 |

As a conclusion the simulations results showed that under dry weather conditions the upgraded MLE process can achieve the extent of 83% total P removal for the open loop operation using external carbon addition. Moreover, under rain and storm weather conditions the optimized MLE WWTP achieved the degree of 82.1% and 83.1% P removal, demonstrating that the upgraded WWTP is in agreement with the 91/271/EEC phosphorus removal performance. In addition, the high value of 89.7% ammonia removal is achieved under dry conditions and 87.5% for rain and storm scenarios. The mean effluent total nitrogen concentration has a value of 14.5 mg $L^{-1}$ which is below the value imposed by 91/271/EEC regulations.

The control approach proved to successfully maintain the EBPR and further improve the wastewater treatment process by reducing the operational costs while the pollutant removal performance was increased. The operational costs were reduced by 10% compared with the optimized open loop, and by 21% compared to the non-optimized open loop operation of the WWTP. The control schemes managed to attain a mean phosphorus effluent concentration of 1.9 mg $L^{-1}$ and a removal performance of 84% for all influent scenarios which is in good agreement with the 91/271/EEC Directive.

This thesis presents several control algorithms that proved to reduce the operational costs and improve the effluent quality. The control algorithms are based on Model Predictive Control and on conventional Proportional Controllers.

The most important conclusion of this thesis is that automatic control has the potential to significantly reduce the operational costs of the biological wastewater treatment process while insuring a good effluent quality.

Realistic dynamic computer simulations provide cost-effective means for the development and evaluation of different control strategies. Mathematical models are cheap but nevertheless very powerful tools for predicting the process behavior and to develop new control architectures.

## List of publications

This thesis contributed at the publication of the following pubications:

**ISI journals**

1. **George Simion Ostace**, Vasile Mircea Cristea, Paul Şerban Agachi - Evaluation of different control strategies of the wastewater treatment plant based on a modified activated sludge model no. 3. Environmental Engineering and Management Journal, 11 (1), 2012, 147-164. *Impact Factor 1.435*
2. **George Simion Ostace**, Vasile Mircea Cristea, Paul Şerban Agachi - Cost Reduction of the Wastewater Treatment Plant operation by MPC based on modified ASM1 with two-step nitrification/denitrification model. Computers and Chemical Engineering, 35 (11), 2011, 2469-2479. *Impact Factor 2.072*
3. **George Simion Ostace**, Vasile Mircea Cristea, Paul Şerban Agachi - Extension of activated sludge model no 1 with two-step nitrification and denitrification processes for operation improvement. Environmental Engineering and Management Journal, 10 (10), 2011, 1529-1544. *Impact Factor 1.435*

**Conference proceedings**

1. **George Simion Ostace**, Anca Gál, Vasile Mircea Cristea, Paul Şerban Agachi - Model based optimization of the operational costs and effluent quality of an

activated sludge process - 2nd Conference on „Applied Biocatalysis" and 7th Meeting of students and university professors from Maribor and Zagreb – November 2011, Abstract pp 52 (Full paper CD ISBN:978-961-248-299-2).

2. **George Simion Ostace**, Anca Gál, Vasile Mircea Cristea, and Paul Serban Agachi, Operational Costs Reduction for the WWTP by Means of Substrate to Dissolved Oxygen Correlation - A Simulation Study. Lecture Notes in Engineering and Computer Science: Proceedings of The World Congress on Engineering and Computer Science 2011, WCECS 2011, 19-21 October, 2011, San Francisco, USA, pp 945-950.
3. **George Simion Ostace**, Vasile Mircea Cristea, Paul Şerban Agachi - Investigation of Different Control Strategies for the BSM1 Wastewater Treatment Plant with Reactive Secondary Settler Model – (ESCAPE 20 – Ischia, Italy) Computer Aided Chemical Engineering, Vol. 28, 1841-1846, 2010.

**Chapters in books**

1. **George Simion Ostace**, Anca Gál, Vasile Mircea Cristea, and Paul Serban Agach (2012). Operational cost reduction of an activated sludge system - Correlation between setpoint and growth substrate. IAENG Transactions on Engineering Technologies, ISBN: 978-94-007-4785-2 (***in press***).

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