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Extremum Seeking Control Applied to a Deammonification Process

Extrempunktsökande reglering av en deammonifikationsprocess

Olle Trollberg

ABSTRACT

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Eutrophication of lakes and coastal areas is considered as one of the big environmental issues in Sweden. To reduce this problem research is ongoing to find novel ways to remove plant nutrients, such as nitrogen, from wastewater. These novel treatment methods often depend on good process control. The goal of this master thesis was to develop and implement a controller for one such process, a deammonification process used to convert ammonium into dinitrogen gas at Hammarby Sjöstadsverk.

The project was initiated by a literature study and identification of the system to be controlled. No mathematical representation of the system could be developed due to the lack of suitable data. However, an estimator of the dinitrogen-gas production was developed in order to allow feedback in the controller. The literature study indicated that the process could be controlled by the DO-level inside the reactor.

The developed controller was based on an extremum seeking algorithm. The algorithm searched for the optimum DO-level by taking steps and analysing the change in dinitrogen gas production. Before the controller was implemented on the real process, simulations of the behaviour of the controller during different scenarios were made. The simulation results were used to analyse the performance of the controller during testing.

Implementing the controller took longer than expected which reduced the time available for testing. The three tests that were performed indicated that the controller had the potential to find the optimum but further testing would be needed in order to confirm this.

Keywords: Extremum seeking, control, deammonification, anammox, partial nitrification, wastewater treatment, nitrogen removal

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REFERAT

Extrempunktsökande reglering av en deammonifikationsprocess

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Övergödning av sjöar och kustområden är ett av Sveriges stora miljöproblem. För att minska problemet pågår forskning inriktad mot att hitta nya sätt att avlägsna växtnäringsämnen såsom kväve från avloppsvatten. De nya metoderna är ofta beroende av en effektiv processreglering. Målet med detta examensarbete var att utveckla och implementera en regulator för en sådan ny process, en deammonifikations process som används för att omvandla ammonium till kvävgas vid Hammarby Sjöstadsverk.

Projektet inleddes med en litteraturstudie och identifikation av systemet som skulle regleras. Ingen matematisk modell av systemet kunde utvecklas på grund av brist på lämplig data. En estimerare för kvävgasproduktionen togs dock fram för att tillåta återkoppling i regulatorn. Litteraturstudien antydde att syrenivån i rektorn kunde användas för att styra processen.

Regulatorn som skapades var baserad på en extrempunktssökande algoritm. Algoritmen ändrade syrenivån i steg och analyserade förändringen i kvävgasproduktionen. Innan regulatorn implementerades på den riktiga processen utfördes ett antal simuleringar av olika scenarier. Resultaten användes för att analysera regulatorns beteende under de efterföljande testen.

Att implementera regulatorn tog längre tid än väntat vilket minskade möjligheterna att utförligt testa regulatorn. De tre test som utfördes indikerade att regulatorn hade potential att finna processens optimum men fler tester skulle behövas för att konfirmera detta.

Nyckelord: Extrempunktssökning, reglering, deammonifikation, anammox, partiell nitrifikation, avloppsrening, kväveavlägsning

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PREFACE

This report documents the efforts made by me in order to finish my degree project for a Master of science in Aquatic and Environmental engineering. The project has been associated with a project called *Control and optimization of the deammonification process* which is run in collaboration between IVL, KTH, Syvab and Cerlic.

Thanks go to Anders Björk from IVL, and Jozef Trela from the Division of Water Resource Engineering at KTH, who have been my supervisors during this project. Many thanks also go to Bengt Carlsson at the Department of Information Technology, Uppsala University, who has been my academic supervisor. Without these three, this project would never have been possible.

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POPULÄRVETENSKAPLIG SAMMANFATTNING

I dagens Sverige är övergödning av sjöar och kustområden ett stort problem. Utsläpp av växtnäringsämnen såsom kväve och fosfor orsakar algblomning, syrefria bottnar och förändringar i känsliga ekosystem. För att komma till rätta med dessa problem har Sverige lagstiftat om hur mycket kväve och fosfor reningsverken får släppa ut i sjöar och hav. På senare år har lagstiftningen skärpts, något som har lett till en ökad forskning inom området. Bland annat utreds nya processer för kväverening.

Hammarby Sjöstadsverk är en forskningsanläggning I Stockholm som är inriktad mot forskning inom området vattenrening. Ett projekt som drivs där heter *Teknik för att styra och optimera deammnifikation*. Inom projektet studeras deammnifikations-processen, en ny process för kväverening. Processen är speciellt lämpad för att rena vatten med höga halter av ammonium, en kväveform som är vanligt förekommande.

Processen är biologisk och bygger på att olika typer av mikroorganismer omvandlar ammoniumet till kvävgas. Kvävgas är en lämplig slutprodukt då den till skillnad mot ammonium är svår för växter att använda och alltså inte fungerar som ett näringsämne. Kvävgasen släpps direkt ut i atmosfären där den är harmlös. Atmosfären består ju redan till större delen av just kvävgas.

De olika mikroorganismer som deltar i processen är dels bakterier som omvandlar ammonium till nitrit (en annan form av kväve), t.ex. Nitrosomonas, och dels bakterier som använder nitrit och ammonium för att bilda kvävgas. Den senare gruppen bakterier kallas för anammox bakterier. Anammox bakterierna upptäcktes för c:a 20 år sedan till många forskares förvåning. Man hade nämligen trott att det krävdes syre för att bakterier skulle kunna rå på ammonium men dessa bakterier använder nitrit i stället.

Att bakterierna använder nitrit istället för syre är en stor fördel om man vill rena bort ammonium. Det kostar nämligen mycket pengar att tillföra syre till processen. Genom att bakterierna använder nitrit kan man sänka kostnaderna rejält. Så genom att kombinera bakterier som omvandlar ammonium till nitrit och anammox bakterierna så kan man få bort ammoniumet ur vattnet till en låg kostnad.

Problemet är att processen är känslig. Den kräver väldigt specifika förhållanden för att fungera optimalt. För att uppnå dessa förhållanden i processen kan man använda reglerteknik som styr vissa egenskaper hos processen. Tidigare forskning har visat att man kan maximera avlägsnandet av ammonium genom att variera olika processparametrar. Målet med det här projektet var att skapa en regulator som reglerar dessa parametrar på ett sådant sätt att så mycket ammonium som möjligt omvandlades till kvävgas.

För att göra detta undersöktes tidigare forskning om processen för att kartlägga hur olika parametrar påverkade kvävgasproduktionen. Det visade sig att syrehalten i processen var lämpad för att styra processen. Utav den anledningen skapades en regulator som varierade just syrehalten. Regulatorn var en så kallad extrempunktssökande regulator. Genom att variera syrehalten i processen i steg och observera kvävgasproduktionen fick regulatorn information om hur syrehalten påverkade processen. Den informationen användes sedan av regulatorn för att närma sig den optimala syrehalten.

Innan regulatorn implementerades på den riktiga processen gjordes ett antal

simuleringar. Dessa gjordes för att kunna utvärdera hur bra regulatorn fungerade under olika omständigheter. På detta sätt kunde olika beteenden identifieras och användas för att diagnostisera den riktiga regulatorn när den väl var igång. Några av regulatorns begränsningar blev också uppenbara.

Innan regulatorn kunde testas på den riktiga processen var den tvungen att implementeras. Implementationen bestod av två delar, dels en hårdvarudel där en del ny utrustning behövde installeras, och dels en mjukvarudel som bestod av en del programmering. Implementationen tog mycket längre tid än beräknat och det gjorde att det tyvärr inte var möjligt att testa regulatorn så utförligt som det var planerat från början.

Tre test av regulatorn utfördes. Under det första testet gick tyvärr en del av mätutrustningen sönder varvid försöket var tvunget att upprepas i det andra testet. De två sista testen visade att regulatorn hade potential att fungera som tänkt men tyvärr var tiden för kort för att kunna hitta rätt inställningar av regulatorn.

Slutsaterna av projektet var att en extrempunktssökande regulator har potential att fungera väl för att reglera deammonifikationprocessen men detta kunde inte bevisas, mest på grund av tidsbrist.

Contents

1 INTRODUCTION

Eutrophication of lakes and coastal areas is commonly recognized as one of the largest environmental issues in Sweden. In fact, it is explicitly listed among the national environmental goals (Naturvårdsverket 2011). Eutrophication is mainly caused by the release of excessive amounts of nutrients, such as nitrogen, into sensitive aquatic ecosystems. One way to lessen this problem is to remove nitrogen from wastewater.

In Sweden, it is common to remove nitrogen from municipal wastewater by the use of bacteria in an process referred to as nitrification/denitrification. It is an effective way to remove nitrogen from wastewater by converting the nitrogen into dinitrogen gas. The dinitrogen gas is then allowed to dissipate into the atmosphere where it is harmless. The atmosphere already consists of 78% dinitrogen gas, which is inert and largely bio-unavailable. However, recent changes in the Swedish legislation have lowered the allowed limits of nitrogen in treated wastewater and this, among other things, have made it interesting to look at novel ways to remove nitrogen.

Many novel nitrogen removal techniques are based on a relatively recently discovered type of bacteria, called anammox, used in combination with partial nitrification. These processes tend to be very effective at low cost and therefore financially viable. However, these processes tend to be quite sensitive and therefore require good control of the process parameters to function properly.

Hammarby Sjöstadsverk, or Sjöstadsverket, is a research and development facility that is run cooperatively by IVL (Swedish Environmental Research Institute) and KTH (Royal Institute of Technology). It is located within the premises of Henriksdal's WWTP (wastewater treatment plant) in Stockholm. Originally the plant was built by Stockholm Vatten AB in connection with the development of the eco-oriented housing area Hammarby Sjöstad, but it was later sold to a consortium lead by IVL and KTH in 2008.

The facility is mainly devoted to research in the field of wastewater treatment and related environmental technologies. The facility is used to test new technology as well as developing new methods. One of the methods tested is a deammonification process used to remove nitrogen from wastewater. For more information please visit www.sjostadsverket.se.

1.1 OBJECTIVE

The objective of this master thesis project was to develop and implement a controller for a deammonification process. The control-objective of the controller should be to convert as much ammonium as possible into dinitrogen gas. The resulting controller should be robust, simple enough to explain to non-control oriented people, and cheap enough to implement with a limited budget. The controller should primarily make use of available instrumentation.

1.2 OUTLINE OF THE PROJECT

To object of the project was clearly specified from the beginning of the project, however, the way to achieve the object was not. The specific control strategy to be used was not known at the beginning of the project and no suitable description of the system to be controlled was available. For this reason the work was divided into a number of stages. The project was initiated by a literature study and identification of the system to be controlled. The results from the first stage was used to create the controller which was then simulated and implemented.

Due to the "sequential" fashion of the project the final result was hard to predict in the beginning of the project. At certain stages in the project a number of attempts had to be made before the final result was found. This was especially true regarding the system identification. Some of the attempts that were unsuccessful have been included below in order to motivate the final solutions.

2 BACKGROUND

In order to create a controller for the deammonification pilot plant it was necessary to first conduct a study of the process to be controlled. The composition and operation of pilot plant itself was studied as well as the biological processes involved. The partial nitrification and the anammox process were studied both separately and combined as the deammonification process. A few basic control theory concepts were also reviewed.

2.1 PILOT PLANT

One of the projects at Hammarby Sjöstadsverk is called *Control and optimization of the deammonification process*. The aim of the project is to evaluate the deammonification process and related technologies which is used to remove nitrogen from wastewater streams. The deammonification process is designed for streams with high concentration of ammonium and relatively low concentrations of biodegradable organic material (Trela et al. 2009). Such streams are often produced by sludge-digesters or sludge dewatering processes. These streams can contain up to 25% of the total nitrogen load in a conventional WWTP (Wastewater Treatment Plant) while only representing about 1 % of the volumetric load (Janus and van der Roest H.F. 1997) Thus it makes sense to treat these streams separately.

The deammonification-process is of interest since it may significantly lower the cost of nitrogen removal compared to other commonly used methods. This is due to the fact that the process has no need for any external carbon sources and it uses less oxygen than conventional nitrogen-removal methods. These are often major costs for a WWTP and reducing them would be desirable.

2.1.1 Layout and Process

The deammonification pilot plant consists of two reactors that are operated as two separate one-step reactors. These reactors can easily be converted into a single two-step system. The reactors are made in the shape of cuboids with an open top. The base of the reactor has the shape of a square with a side measuring 50 cm. The height is 80 cm which yields a total volume of approximately 200 l per reactor. Each reactor is fitted with an aeration system, a heater, a mixer, and a set of on-line measurement probes. Table 1 lists the equipment fitted to each reactor.

Table 1 List of the instrumentation fitted to the reactors.

Instrument	Reactor 1	Reactor 2
Conductivity	X	X
PH	X	X
Redox-potential	X	X
Dissolved Oxygen	X	X
Conductivity (Inflow)	X	
Redox-potential (Inflow)	X	
Temperature		X

The reactors are fed with a stream of reject water from a sludge dewatering process at Bromma

WWTP. The reject water is supplied to the facility by truck and is stored in a large tank before it is pumped into the reactors. This makes sure that the process is supplied by a real-world substrate.

Since the reject water is stored in a large tank which is only refilled occasionally, the composition of the substrate tends to be nearly constant between refills. Table 2 shows typical values of the components of the reject water used as substrate in the pilot plant. One important thing to take note of is the high level of organic matter, measured as COD (chemical oxygen demand), compared to substrates used in other projects. The presence of organic matter allows growth of heterotrophic bacteria within the reactor. This is the main difference of the deammonification process at Sjöstadsverket compared to the CANON-process (completely autotrophic nitrogen-removal over nitrite) which normally do not involve any heterotrophic bacteria (K A Third et al. 2001).

Table 2 The typical composition of the reject water used by the pilot plant.

Reject Water Components	Concentrations
Ammonium [$mg\, NH_4^+\text{-}\, N\, l^{-1}$]	1000
Alkalinity [$mmol\, l^{-1}$]	80
COD [$mg\, O_2\, l^{-1}$]	1000

The effluent from the process is withdrawn from the reactors by a overflow outlet. It is then passed through a sedimentation tank in order to remove excess biomass before it is released from the system. In a full scale implementation this excess biomass could be used to improve the efficiency of other processes (Parker and Wanner 2007).

Since the growth-rate of the biomass used in the deammonification process is very low it is necessary to retain as much as possible of the biomass in the reactor. This is done by letting the biomass form biofilm on carriers. The carriers used in the reactors are called Kaldnes-carriers: small rings made out of plastic with an outer diameter of approximately 9 mm. The amount of biofilm in the reactor is close to 40 m² with an average thickness of 1.2 mm.

The aeration system is used to control the level of DO (dissolved oxygen) in the reactor. The aeration system consists of a PID (proportional integral derivative) controller which controls an air-valve. The air-valve in turn controls the amount of compressed air which is blown through the reactor adding oxygen to the bulk liquid.

Figure 1 shows a schematic drawing of the system components and how they are connected. The figure only shows one reactor but the pilot plant consists of two practically identical systems. The drawing is somewhat simplified and does not contain the heater or any of the electrical equipment connected to the system.

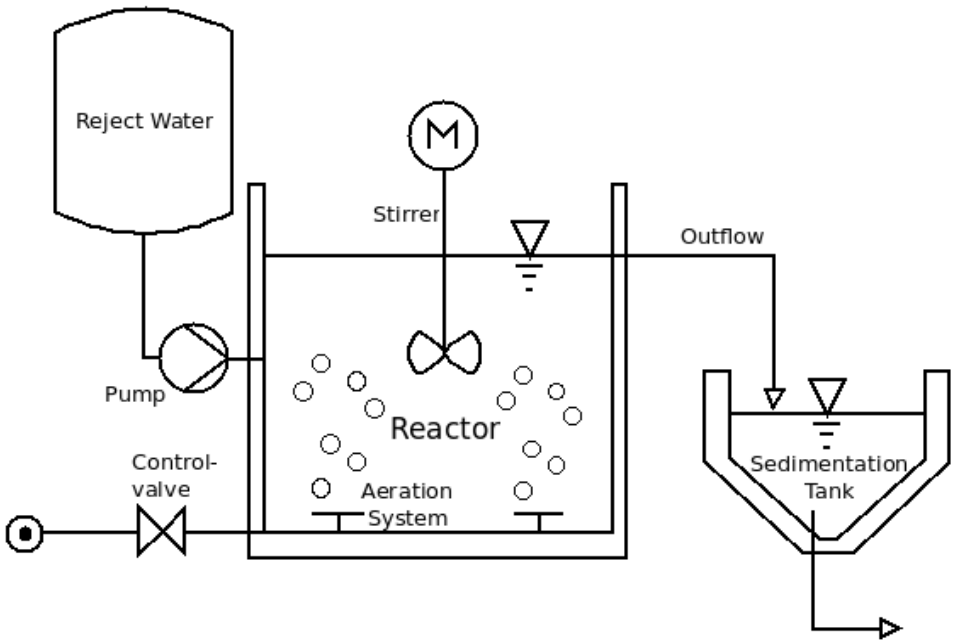

Figure 1 Schematic overview of the deammonification pilot plant's different parts.

2.1.2 Data Collection

Data from the pilot plant's on-line measurement equipment is stored on a computer. The computer is running a LabVIEW program that uses a DAQ (Data acquisition)-unit to collect data from the instruments at an interval of one second. The one-second data is averaged and stored in files as one-minute average values. Data in the form of these one-minute average values is available from most of the time the pilot-plant has been in operation.

In order to assess the process efficiency, samples of the influent and the effluent are analysed in a laboratory at regular intervals. The outflow is typically sampled twice a week and the inflow is sampled once a week. The following parameters are analysed for: NH_4^+-N (-N means the nitrogen part of the compound), NO_2^--N, NO_3^--N, alkalinity and COD. This data is also available from most of the time the plant has been operable.

2.2 THE PARTIAL NITRIFICATION PROCESS

The partial nitrification process is an important part of the deammonification process. Since the process is well known compared to the anammox process, the bacteria involved is not described further here. Instead, the process is contrasted with ordinary nitrification and the environment necessary for the process to function is described.

2.2.1 Nitrification and Partial Nitrification

Nitrification is a naturally occurring two-step reaction where ammonium is converted first to nitrite and then to nitrate by oxidation with oxygen. The reaction is catalysed by different bacteria (Eriksson et al. 2005, 235) commonly referred to as nitrifiers. These could be divided into two groups, the ammonium-oxidisers and the nitrite-oxidisers. Among the former of those two are the Nitrosomonas, Nitrospira and the Nitrosococcus, all of which are able to perform the first step of the reaction, that is, to oxidise ammonium with oxygen into nitrite. The fundamental reaction catalysed by these bacteria is described by equation 1 (Schmidt et al. 2003).

$$NH_4^+ + 1.5\,O_2 \rightarrow NO_2^- + 2\,H^+ + H_2O \qquad (1)$$

Nitrobacter, Nitrospina, and Nitrococcus belong to the second group, those who oxidise nitrite with oxygen to nitrate. The reaction catalysed by these bacteria could be described by equation 2 (Seviour 2010, 45).

$$NO_2^- + 0.5\,O_2 \rightarrow NO_3^- \quad (2).$$

The term partial nitrification refers to a process where only the first of the two steps in normal nitrification is performed. That is, the ammonium is oxidised to nitrite but the nitrite is never oxidised further into nitrate. During natural circumstances, in soils for example, this rarely happens (Eriksson et al. 2005, 236), but it has turned out to be possible to achieve this reaction by carefully controlling the process environment.

2.2.2 Environmental Factors

Certain parameters have been shown to affect the ammonium-oxidisers differently then they affect the nitrite-oxidisers. By carefully adjusting these parameters it is possible to create an environment where ammonium-oxidisers are favoured at the expense of nitrite-oxidisers, which is necessary for a partial nitrification process.

One such parameter is temperature. It has been shown that the maximum growth-rate for the bacteria is dependent on the temperature, and this dependency differs between ammonium-oxidising bacteria and nitrite-oxidising bacteria. By operating the process at a temperature close to 35 °C the growth-rate of the ammonium-oxidisers are approximately twice that of the nitrite-oxidisers (Dongen, M. S. M. Jetten, and Loosdrecht 2001, 8). This could be used to wash out the nitrite-oxidisers while retaining the ammonium-oxidisers by adjusting the retention time in the system.

Another parameter affecting the two types of bacteria differently is pH. It has been shown that the actual substrates used by the bacteria are not actually the ions, but rather their uncharged counterparts, NH_3 and HNO_2. Since the pH will affect the equilibrium between the ions and their uncharged form, the pH will also affect the amount of substrate available for the bacteria. A higher pH will benefit the ammonium-oxidisers while it will put the nitrite-oxidisers at disadvantage (Van Hulle et al. 2010).

The dissolved oxygen level will also affect the process. At low levels of DO, both the ammonium-oxidisers and the nitrite-oxidisers will suffer from oxygen deficiency, but the nitrite-oxidisers will be affected more strongly. This is believed to be due to the fact that ammonium-oxidisers get more energy for the same amount of consumed oxygen (Van Hulle et al. 2010).

By combining these factors it is possible to create an environment within the reactor where the nitrite-oxidisers are out-competed. This will allow partial nitrification to occur within the reactor which is necessary for the deammonification process.

2.3 THE ANAMMOX PROCESS

A lot of research have been devoted to the anammox process in recent years, not least since the process seems promising for treatment of wastewater. In this section the unique properties of the bacteria involved in the process are described, followed by the catalysed reactions and the environment necessary for a well functioning process.

2.3.1 Anammox Bacteria

The anammox group of bacteria was first discovered in the early 1990s (J. Gijs Kuenen 2008), much to the surprise of the scientific community. They have an unique ability to oxidise ammonium with nitrite to form dinitrogen gas. Their name, anammox, is an abbreviation of this ability,

anaerobic ammonium oxidation. The bacteria had been predicted to exist from a thermodynamical perspective (Broda 1977) but were subsequently thought not to exist for various reasons.

The anammox bacteria have a number of very special properties worth mentioning. The bacteria's metabolism create an intermediate product called hydrazine (J. Gijs Kuenen 2008). Hydrazine, which is a very toxic substance used as rocket fuel, has a hydrophobic structure. This enables it diffuse through most known biological membranes. However, the anammox bacteria contains a special type of membranes made out of ladderane lipids, so far unique in nature. Membranes formed from these lipids are unusually impermeable(Nouri and Tantillo 2007).

The membranes form a compartment within the bacteria called the anammoxozome where the catabolism takes place, thus isolating the hydrazine's toxic properties from the rest of the organism. This allows the bacteria to use hydrazine as an intermediate product in its catabolism: a necessary step in order to oxidise ammonia with nitrite.

Another striking property of the anammox bacteria is their exceptionally slow growth-rate. The doubling time is approximately two weeks (J. Gijs Kuenen 2008). This should be compared to a doubling time of less than 20 minutes for many fast growing bacteria (Mason 1935). The slow growth-rate of the anammox bacteria make them easy to out-compete for other bacteria if given the chance. It is therefore necessary to carefully control the conditions within the reactor in such a way that the anammox bacteria is favoured.

2.3.2 The Anammox Reaction

The main reaction catalysed by the bacteria can be expressed as in equation 3 (J. Gijs Kuenen 2008).

$$NH_4^+ + NO_2^- \rightarrow N_2 + 2\,H_2O \tag{3}$$

Ammonium is oxidised by nitrite into dinitrogen gas and water. In reality this reaction is not taking place directly. Instead a number of intermediate products, e.g., hydrazine, are formed within the bacteria before the final products are produced. The energy released from equation 3 is used by the bacteria for cell synthesis and other internal processes. If these are included the overall reaction can better be described by equation 4 below (M. Strous et al. 1998).

$$NH_4^+ + 1.32\,NO_2^- + 0.066\,HCO_3^- + 0.13\,H^+ \rightarrow \\ 1.02\,N_2 + 2.03\,H_2O + 0.26\,NO_3^- + 0.066\,CH_2O_{0.5}N_{0.15} \tag{4}$$

One of the most noteworthy differences between equation 3 and 4 is that nitrate is formed in the latter. This is due to the fact that nitrite is not only used as an electron donor for the ammonium, but it is also used as an electron acceptor for the assimilated carbon dioxide (J. Gijs Kuenen 2008). The reaction described by equation 4 is often simplified (K A Third et al. 2001) as:

$$NH_4^+ + 1.32\,NO_2^- \rightarrow 1.02\,N_2 + 0.26\,NO_3^- + 2\,H_2O \tag{5}$$

This is not an entirely stoichometrically correct equation, but it is still useful from a process perspective as it describes the ratios between the different formed and consumed substances of interest.

2.3.3 Environmental Factors

As can be seen in equation 5 above, the anammox bacteria use nitrite as a substrate. However, nitrite also have inhibitory effects on the anammox process. The exact nitrite-level were this effect occurs depends on the specific type of bacteria, temperature, and a number of other parameters, but in one experiment a nitrite-level of 100 $mg\,NO_2^- \text{-} N\,l^{-1}$ inhibited the process completely (M.

Strous, J. Gijs Kuenen, and Mike S.M. Jetten 1999).

Other substances, such as phosphate, acetate, glucose, and pyruvate have also been shown to have negative effects on the process (van de Graaf et al. 1996). Most notable of the inhibitory substances is oxygen. Even concentrations as low as 0.01 $mg\,l^{-1}$ can inhibit the process completely (van de Graaf et al. 1996). However, the inhibiting effect of oxygen has been shown to be reversible by experiments with intermittent aeration (M. Strous et al. 1997).

pH and temperature have effects on the efficiency of the process as well. A range of suitable pH-values have been found to be 6.3 – 8.3 with an optimum close to 8.0 (Van Hulle 2005). The optimum temperature depends on the specific type of anammox bacteria and optimum has been found to be 12 ^{o}C, 15 ^{o}C and 37 ^{o}C in different studies (Rysgaard et al. 2004; M. Strous et al. 1997; Egli et al. 2001; Dalsgaard and Thamdrup 2002).

Another factor of importance is the concentration of biomass. The anammox process have been shown to be active only in biomass concentrations of more than 10^{10} – 10^{11} cells per ml (M. Strous et al. 1999) A number of hypotheses of the reason for this has been put forward, but they still remain unproven.

2.4 DEAMMONIFICATION

By combining partial nitrification with the anammox process it is possible to convert most of the ammonium in a wastewater stream into dinitrogen gas, and this is the basis of the deammonification process. As a first step, partial nitrification is used to oxidise part of the incoming ammonium into nitrite. This provides the anammox bacteria with the nitrite they need in order to oxidise the remaining ammonium into dinitrogen gas.

For an optimal performance of the deammonification process, only slightly more than half of the incoming ammonium should be oxidised into nitrite by the partial nitrification sub-process. It is clear from the stoichiometry of equation 5 that the anammox process needs a ratio of 1.32:1 of nitrite to ammonium. This means that the partial nitrification should ideally convert 57% of the incoming ammonium into nitrite.

The overall reaction for the deammonification system is given by the combination of equation 5 and equation 1. This yields the following equation which can be used to describe the entire deammonification process (Khin and Annachhatre 2004).

$$1\,NH_4^+ + 0.85\,O_2 \rightarrow 0.435\,N_2 + 0.13\,NO_3^- + 1.3\,H_2O + 1.4\,H^+ \qquad (6)$$

The deammonification process can convert most of the incoming ammonium into dinitrogen gas, but some of the ammonium will be converted into nitrate (equation 6). This formation of nitrate sets a theoretical cap of 87% as the maximum total nitrogen removal possible to achieve with the deammonification process with the described mechanisms(K. A. Third et al. 2005). However, in some systems denitrification will also occur. This could potentially increase the maximum possible total nitrogen removal above 87% (Trela et al. 2009).

2.4.1 Deammonification Process Configurations

The two sub-processes partial nitrification and anammox can be combined into a deammonification process in more than one way (Fig. 2). The first possibility is to have two reactors, one for each sub-process. In this configuration the first reactor is housing the partial nitrification sub-process. The Sharon process (Hellinga et al. 1998) is well suited for this task. The outflow from this reactor is fed into the next reactor, which contains the anammox process (van Dongen, M. S. M. Jetten, and Van Loosdrecht 2001).

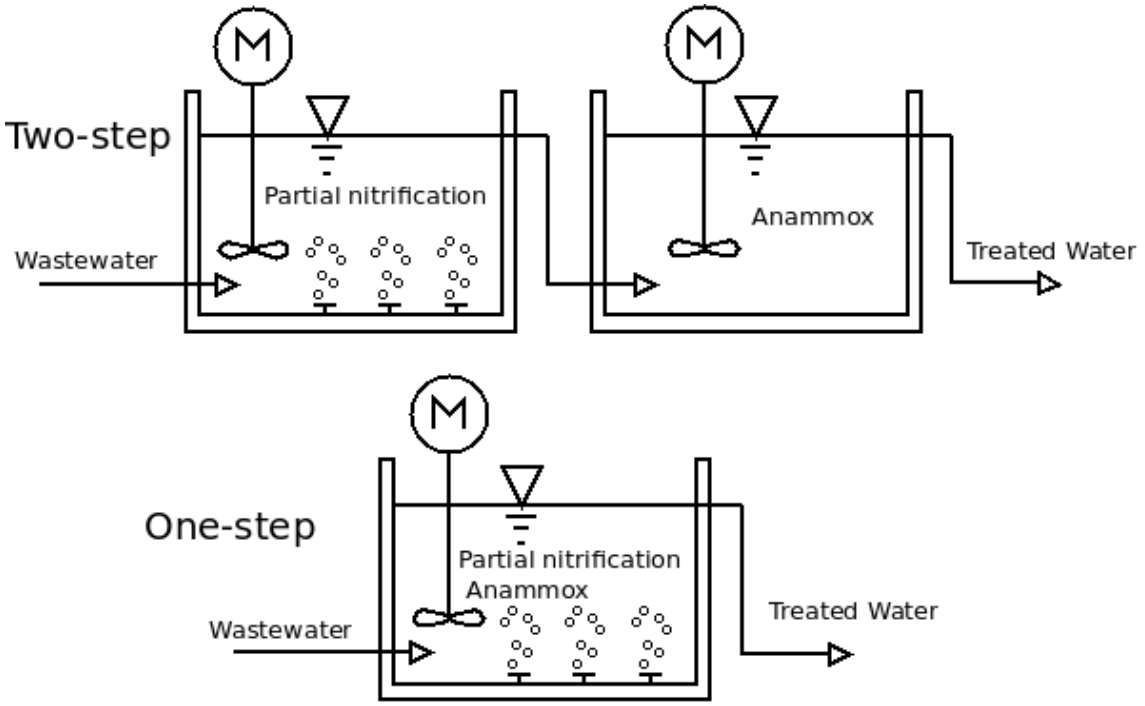

Figure 2 The deammonification process implemented as a one or a two-step process.

The second possibility is to combine both processes in a single reactor. This configuration is often referred to as the CANON system (K A Third et al. 2001). The biomass then forms a biofilm with multiple layers. The outer part of the biofilm will be dominated by the nitrifying bacteria. These will use the available oxygen in order to oxidise ammonium. This will create an anoxic inner layer in the biofilm dominated by the anammox bacteria.

There is a number of advantages and disadvantages for each of these configurations. The two-step implementation will have a larger footprint and have higher initial cost than the one-step implementation (Van Hulle et al. 2010). However, in the two-reactor model each sub-process can be controlled individually which allows for better/easier control of the process. In the rest of this text, it will be assumed that the one-reactor system is considered if not explicitly stated otherwise.

2.4.2 Biofilm

The biofilm in the deammonification process is of crucial importance and has multiple functions. As mentioned earlier, the biofilm provides the different conditions required by the different bacteria involved in the process. It also retains the biomass within the reactor. Since the anammox bacteria has such an exceptionally low growth-rate this is necessary to avoid washout (I. Fernández et al. 2008).

Figure 3 shows a conceptual model of the biofilm used in the deammonification process. The anammox bacteria is closest to the carrier material forming an inner layer of the biofilm. The nitrifying bacteria form an outer layer which effectively shield the anammox-bacteria from the oxygen. Between the biofilm and the bulk liquid there is a laminar boundary layer. Experiments with the FISH (fluorescence in situ hybridization) technique have confirmed the layout of the biofilm (Michael Nielsen et al. 2005).

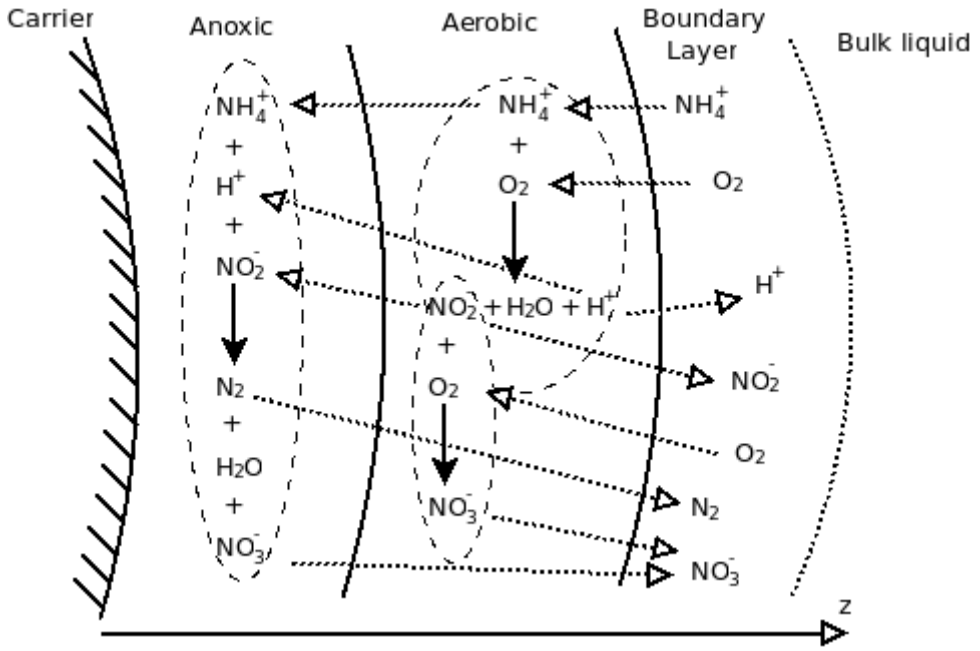

Figure 3 Conceptual model of the biofilm in the reactor. Dotted arrows indicate transport of different substances. Reactions are marked with ellipses. The figure is redrawn from Hao et al. (2002).

Oxygen and ammonium will diffuse from the boundary layer into the outer layer of biofilm where it will be used by the nitrifying bacteria to oxidise ammonium into nitrite. Not all of the ammonium will be used up by this process due to oxygen limitations. Some of the remaining ammonium will diffuse further into the anoxic layer of the biofilm together with some of the nitrite formed in the outer layer. These will act as substrates for the anammox bacteria which will oxidise the ammonium with the nitrite into dinitrogen gas. Some nitrate will be formed in the inner layer and this will diffuse out into the bulk-liquid. There will also be a net transport (not shown in the figure above) into the biofilm of alkalinity which is consumed for growth of the biomass (Hao, J. J Heijnen, and van Loosdrecht 2002).

The transport rate of the different substances in and out of the biofilm depend on a number of factors. Some of the most important factors include concentrations in the bulk liquid, thickness, density and porosity of the different layers in the biofilm and temperature (Hao, J. J Heijnen, and van Loosdrecht 2002).

2.4.3 Process Parameters

The ASL (ammonium surface load), which is defined as the mass of ammonium-nitrogen each square meter of biofilm have to treat per day $[g\,NH_4^+\text{-}N\,m^{-2}\,d^{-1}]$, can be used to express the current ammonium-load on the process. When the ASL increases the process' oxygen demand will also increase. This is clear from the stoichiometry of equation 6.

The DO level in the bulk liquid will be of crucial importance to the process efficiency since it affects the transport rate of oxygen to the biofilm. A too low level of DO will result in a too slow oxygen transferral rate into the nitrifying layer of the biofilm. This could create a deficit of nitrite within the anoxic layer of the biofilm. If this happens, some of the ammonium will remain unoxidised, which will lead to elevated levels of ammonium in the effluent (Hao, J. J Heijnen, and van Loosdrecht 2002). Figure 4 show the results of a simulation of how the ammonium in effluent varies with the DO (Van Hulle 2005). It is clear from the simulation made by Van Hulle that the system behaves as expected with high levels of ammonium in the effluent for low DO-levels. This

particular simulation was done assuming an influent concentration of $NH_4^+ - N$ of 100 $mg\,l^{-1}$.

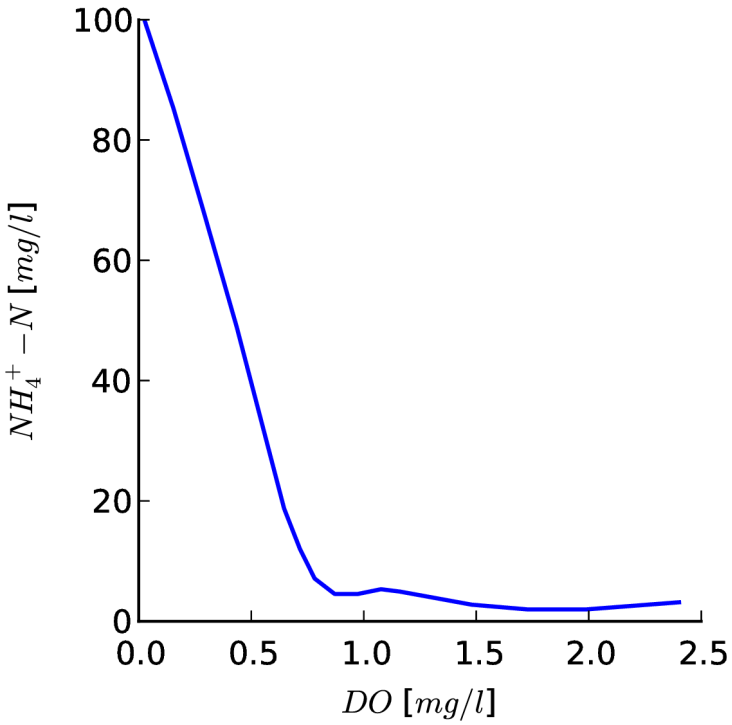

Figure 4 The steady state ammonium content in the effluent as a function of dissolved oxygen according to simulations made by Van Hulle (2005). The simulation was done under the assumption that the process was fed by a substrate containing 100 $mg\,NH_4^+$- $N\,l^{-1}$.

A too high DO level can trigger a number of possible mechanisms that affect the process efficiency. Oxygen could breach through the aerobic nitrifying layer into the normally anoxic inner layer of the biofilm. This oxygen would inhibit the anammox bacteria causing a negative impact on the process efficiency. The aerobic layer could also start producing to much nitrite. Some of this nitrite would be excessive and thus not used for ammonium oxidation. This would lead to elevated levels of nitrite in the reactor and the effluent. Figure 5 show a simulation of how the nitrite levels in the effluent varies with the DO (Van Hulle 2005). It is clear that a high level of dissolved oxygen leads to a build up of nitrite in the reactor.

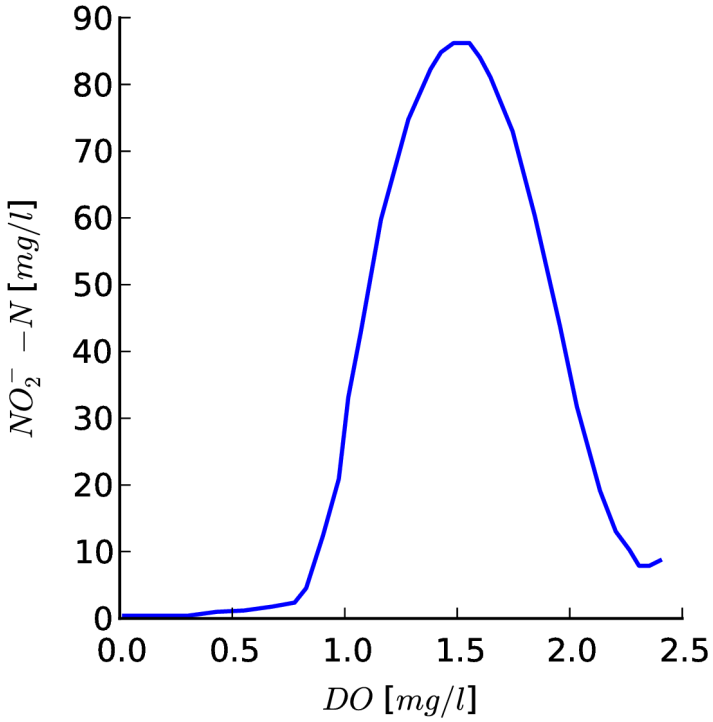

Figure 5 The simulated steady-state amount of nitrite in the effluent as a function of dissolved oxygen according to simulations made by Van Hulle (2005). The simulation was done under the assumption that the process was fed by a substrate containing 100 $mg\ NH_4^+\text{-}N\ l^{-1}$.

Elevated levels of nitrite could also have inhibitory effects on the anammox bacteria, further reducing the efficiency of the process. A too high DO level could also allow growth of nitrite oxidisng bacteria (e.g. Nitrobacter) which could disturb the process.

A combination of the factors mentioned above will limit the maximum allowed DO level in the reactor for which the process is still effective, i.e., produces dinitrogen gas. This maximum will vary with the conditions in the reactor and the biofilm. Figure 6 show a simulation of how the steady-state production of dinitrogen gas of the process depend on the DO for a certain ammonium load. It is clear that a DO level, during the conditions in the left plot, should not exceed 1.5 mg/l and that the optimal DO level are close to 0.8 mg/l. In the right plot the optimal DO level are close to 1.3 mg/l.

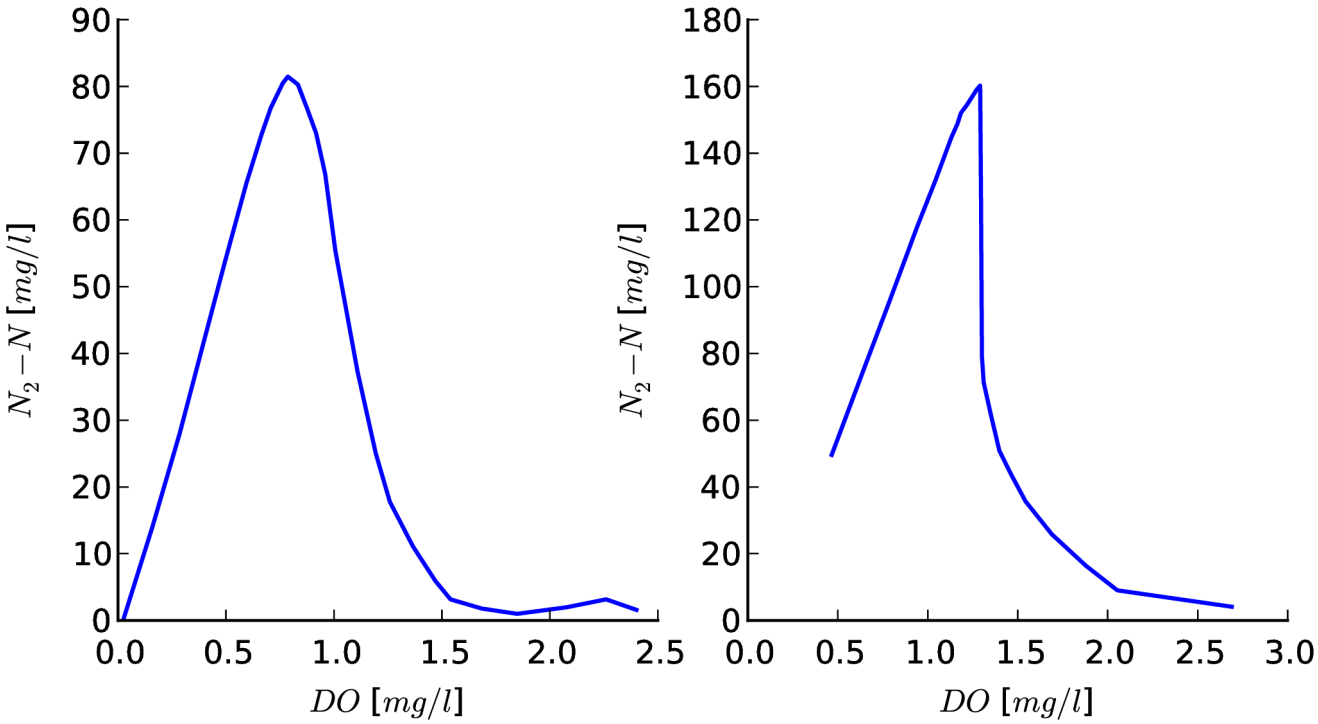

Figure 6 The simulated steady-state amount of dinitrogen gas dissolved in the effluent as functions of dissolved oxygen according to simulations made by Van Hulle (2005). The simulation to the left was done under the assumption that the process was fed by a substrate containing 100 $mg\ NH_4^+\text{-}\ N\ l^{-1}$ while the right simulation assumed a substrate containing 200 $mg\ NH_4^+\text{-}\ N\ l^{-1}$.

The optimal DO level is dependent on all the factors that affects the transport rate of oxygen into the nitrifying layer, such as the thickness of the biofilm's boundary layer and temperature in the reactor (Hao, J. J Heijnen, and van Loosdrecht 2002). It is also affected by the ammonium load on the process. Figure 7A-C illustrates how the optimal DO level varies as a functions of different process parameters.

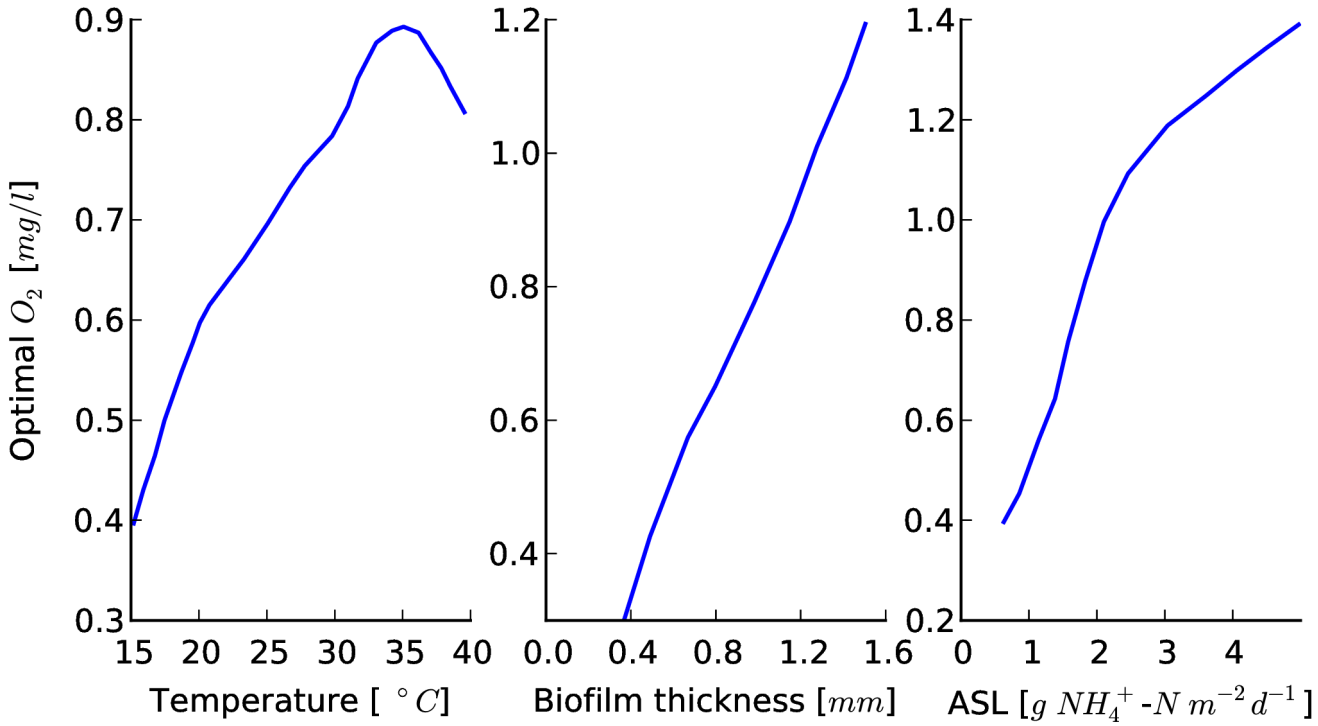

Figure 7 Simulations of how the optimal dissolved oxygen concentration varies with different process parameters. The data is extracted from the work of Hao et al. (2001).

2.5 BASIC CONTROL THEORY CONCEPTS

This section is primarily based on the books *Reglerteknik* (Glad and Ljung 1981) and *Reglerteori* (Glad and Ljung 2003) and it aims to explain some basic control theory concepts used in the remaining part of this report. However, most of the content should be considered common knowledge within the field of control theory and thus few references are included. For the interested, the concepts presented here should be covered in depth by most books on the subject of basic control theory. The topics are divided into those related to general systems, control of systems, and extremum seeking control.

2.5.1 Systems

In order to make a controller for a process, it is good practice to first represent the process as a system. There are many definitions of what a system is but in this text, a system will be assumed to be something of interest which have a boundary, inputs and outputs. The outputs will generally depend on the inputs and the state of the system in some way. Figure 8 presents a simple system graphically.

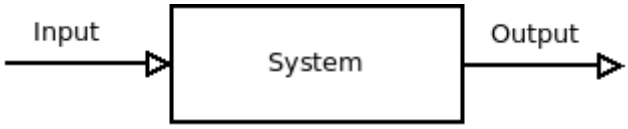

Figure 8 A simple system with an input and an output.

The systems boundary is often, but not necessarily, physical. However, it is possible to define systems with no clear physical boundary. The inputs are anything that affects the system's inner

state and/or output, while the outputs are something of interest that comes out of the system, often depending on the system's state and/or on the inputs. A simple example of a system could be a buffer-tank with an inflow and an outflow. The tank wall is the boundary, the inflow is the input, the outflow is the output, and the level in the tank could be its inner state (Fig. 9).

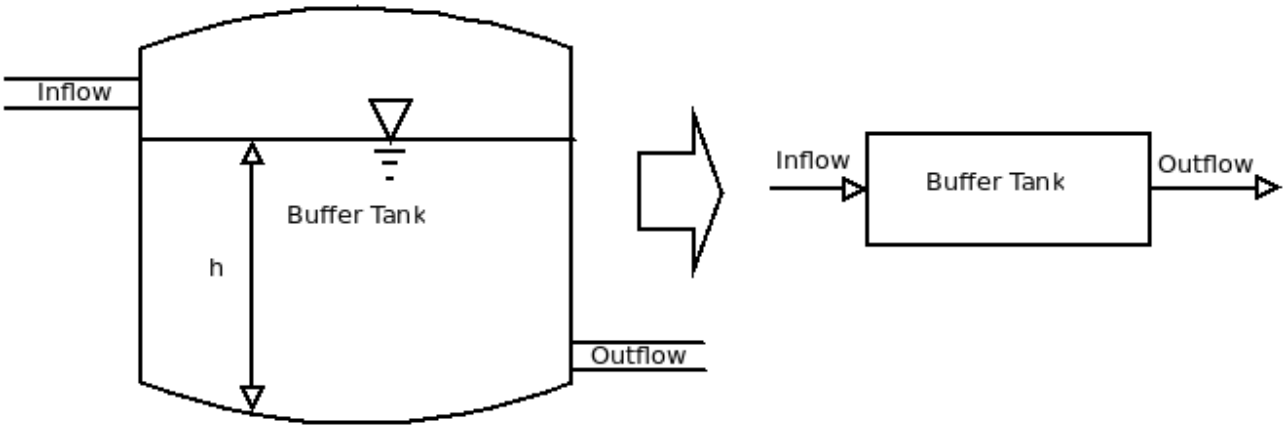

Figure 9 A buffer tank could be regarded as a system with the inflow as input, the outflow as output, and the tank-level as an internal state of the system.

A system can in itself contain other sub-systems. The buffer-tank in the example above could be a sub-system of a larger system, a food-processing plant for example.

Representing a process as a system is useful in many ways. First of all it forces one to think about how to classify various process parameters. Which parameters are considered important for the process? Which parameter is to be controlled? Secondly it sets up a good framework for developing a mathematical model of the process, which is a crucial part of control theory.

Most systems can be said to map a certain set of inputs $u(t)$, to a certain set of outputs $y(t)$, by applying an operator H to the inputs, that is, $y(t)=H\{u(t)\}$. This operator is often modelled mathematically by use of differential equations or difference equations. If the system is static, the current outputs only depend on the current input to the system. That is, in a static system the outputs are not dependent on anything that have happened previously in the system.

A dynamic system is a system in which the outputs depend on the current inputs as well as the previous inputs. The state of the system could be described as the amount of information needed to remember what happened to the system previously.

A system can have a number of properties which could be related to the mathematical model. One such property is linearity. A linear system is scalable and obeys the superposition principle. Assume that

$y_1(t)=H\{u_1(t)\}$ and $y_2(t)=H\{u_2(t)\}$ is true. If the system is linear then the following must also be true: $\alpha y_1(t)+\beta y_2(t)=H\{\alpha u_1(t)+\beta u_2(t)\}$.

Another important property of systems is time-invariance. A time-invariant system does not explicitly depend on time; if the output $y(t)$ is produced by input $u(t)$, and the system is time-invariant, then a time shift in the in-signal $u(t+\delta)$ should result in an equal time shift in the out-signal $y(t+\delta)$.

A system that is both linear and time-invariant is called a LTI-system (Linear Time-Invariant). The mathematical properties of these systems are useful when developing controllers and a number of theorems regarding popular control-strategies are only valid for LTI-systems.

2.5.2 Controller, Feedback, Feed-forward

In control theory the input to a system is usually divided into two categories. The control signals and the disturbances. The control signals are the inputs that we have control over and can use to influence the system's outputs. The disturbances are all other inputs. Being inputs, the disturbances also affect the system's state and outputs but we cannot exert control over them.

A controller is a system which tries to control the outputs from another system in accordance to some reference signal (Fig. 10). The outputs from the controller are connected to the inputs of the controlled system as control signals. This allows the controller to influence the controlled system so that control error becomes as small as possible. The control error is defined as the difference between the reference signal and the controlled system's output.

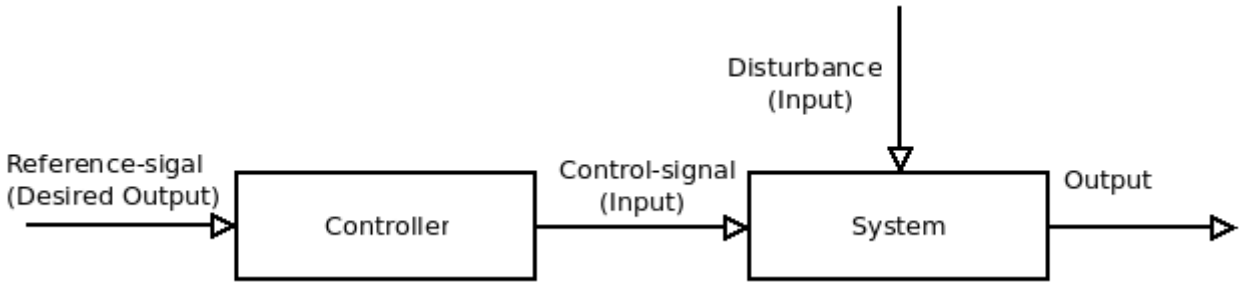

Figure 10 A controller generates a control-signal in order to change a systems outputs to some desired value specified by the reference-signal.

In order to achieve good control (i.e., to have a small control error) of the controlled system it is often necessary to provide the controller with some extra information in excess of the reference signal. This is typically done by the concept of feedback (Fig. 11). The outputs from the controlled system is connected back to the controller as inputs. This gives the controller information about the size of the control error, that is how close the outputs are to the desired value, the reference signal. If feedback is not used, the control error can grow without the controller ever "knowing" about it.

Another common way to provide the controller with more information is feed-forward (Fig. 11). It is sometimes possible to measure disturbances even if they cannot be controlled. This information could be used to counteract the effects of the disturbances on the controlled system before they are visible in the output. Feedback can only be used to restore the output to the reference signal after it has been disturbed while feed-forward can prevent the output from deviating from the reference signal in the first place.

Cascade control is another concept that is sometimes used to improve performance of certain systems. One outer controller is used to control the main process output. The control-signal from this controller is used as a reference signal for a secondary controller which control some sub-system affecting the main process. However, it is mostly useful only when the inner sub-system is considerably faster than the main process. In the system illustrated in Figure 11 the concepts of cascade control, feed-back and feed-forward are implemented.

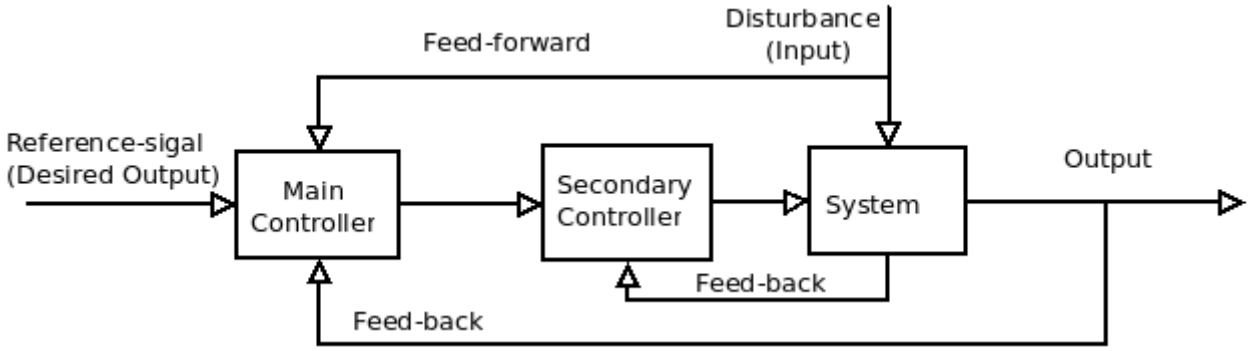

Figure 11 A control system with cascade-control, feed-back and feed-forward. The main controller generates a reference-signal for the secondary controller which it uses to generate some control-signal to the system being controlled.

A very common controller today is the PID controller which is based on the feed-back concept described above. PID stands for proportional, integral and derivative which refers to how the control-signal depends on the control error. By making the control-signal proportional to the control error, the controller responds to an increasing control error by increasing the magnitude of the control-signal. The integral part means that the control error is integrated over time and added to the control-signal. This is useful since it gets rid of static control errors. The derivative part of the controller looks at the derivative of the control error. This makes it possible to "predict" the future behaviour of the system and act in accordance in order to prevent the control error from growing.

Many of today's control-strategies, such as PID, LQ (linear quadric) and LQG (linear quadric gaussian) are assuming that the system to be controlled is a linear system. This is not actually true for many systems but often it does not matter since the system can be assumed to be linear close to some working-point of interest, or sometimes it is possible to linearise the system by applying an inverted version of the non-linearity. Other control strategies might not be inherently dependent on a systems linearity but instead they might be heavily dependent on accurate models. An example of such a control strategy is MPC (model predictive control).

2.5.3 Extremum Seeking Control

For many processes the control objective is to maximize or minimize an output. The problem becomes to find for which reference value of some input the output is optimised. When the system is non-linear, it can be difficult to find the optimal value, especially if no model of the system is available. If the optimum remains constant over time, it is usually sufficient to make an experiment to find the optimal value, which then can be set as a fixed reference value for the process. However, the optimum is not always constant and then a single experiment will not suffice since the optimum will change over time.

There is a number of controllers dealing with this problem that commonly is referred to as extremum seeking controllers. Some are based on known trajectories of the optimum, others require less knowledge of the system. The latter typically perturb the control signal in some way while analysing the output in order to find information about the extremum point. One strong point of those controllers is that they usually make relatively few assumptions about the system to be controlled (Ariyur and Krstić 2003, 3).

3 CONTROLLER SYNTHESIS

A number of steps needs to be performed when creating a controller. This section aim to describe the steps performed in this project. First the deammonification process is described as a system. This is followed by modelling of the system, selection of control strategy, description of the chosen control-algorithm, and finally simulation of the chosen control-algorithm.

3.1 IDENTIFYING THE SYSTEM & SUITABLE CONTROL-SIGNALS

In order to create a controller for the deammonification process it was necessary to represent it as a system. Since the deammonification reactor seemed to be the point of interest in the pilot plant, the system's boundary was assumed to coincide with the reactor walls. With reference to the theory about the deammonification process a number of process parameters of interest was identified:

- Inflow of ammonium (i.e., the ASL), COD, air and heat
- Outflow of different nitrogen forms such as NH_4^+, NO_3^-, NO_2^-, and N_2
- pH, DO level and temperature inside the reactor

Optimisation of the production of N_2 within the reactor was considered the main control-goal of the process, and thus chosen as the desired output from the system. The inflow of ammonium, alkalinity, COD, air, and heat into the reactor was considered important for control of the process, and thus desired as control-signals. All other inputs were considered as disturbances. In order for the process to work well, the pH, DO level and temperature inside the reactor was considered most important and these were regarded as possible system states.

However, measurements were only available for two of the process parameters mentioned above, namely the pH and DO level inside the reactor. Measurements of other parameters not considered as vital for control of the process were also available. These were conductivity and redox-potential measurements of both the inflowing reject water and the bulk liquid in the reactor. Either new sensors had to be bought or the parameters would have had to be estimated from those already measured.

The control-signals possible to use in a real implementation at the pilot plant was identified as:

- The pumping rate of reject water into the reactor
- The reference for the DO level within the reactor

These differed some from the desired control-signals mentioned earlier.

The pumps pumping reject water into the reactor were possible to control remotely, so the inflow of reject water into the reactor could be controlled. This would allow control over the mass inflow of either alkalinity, ammonium, or COD, assuming the concentrations of these substances in the reject water could be estimated. Controlling the mass inflow of ammonium would essentially be the same as controlling the ASL since the two would be proportional to each other. The ASL was considered to be the most important process parameter of the three, and therefore selected for use as a control-signal if possible. This would, however, be dependent on an estimation of the ammonium concentration in the incoming reject water.

The DO level inside the reactor was controlled by a PID-controller. The PID-controller exerted control over the DO level by varying the airflow through the aeration system in the reactor. The PID-controller's reference signal was set manually to a constant, but it could be controlled remotely.

Remote controlling the PID's reference signal would allow control of the DO level inside the reactor in a cascade-control fashion.

The inflow of air had been selected as a desired control-signal, but to control the DO-reference directly would be even better. The reason for this was that the DO affected the process directly while the airflow would only affect the process through affecting the DO. Thus, the reference signal for the DO level in the reactor was chosen as another suitable control-signal for the system.

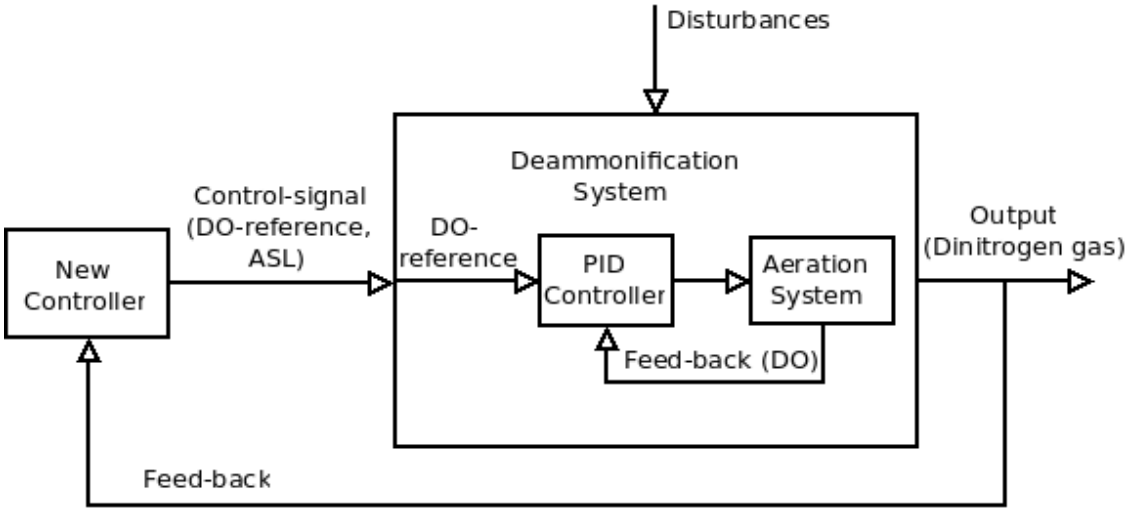

Figure 12 The initial system used to represent the deammonification process including the new controller. The DO-reference signal and ASL had been identified as suitable control-signals. The dinitrogen gas was selected as the variable to be controlled.

The initial system that was used for the controller synthesis is illustrated in Figure 12. The reactor was used as a base for the system. The ASL and the DO reference value was specified as suitable control-signals. All other inputs was considered as disturbances. The N_2 production in the reactor was regarded as the output of the system.

3.2 MODELLING THE SYSTEM

To create a mathematical model of the system, it was necessary to first obtain data on the control-signals and the output. As mentioned in the previous section, the production of N_2 in the reactor was not measured and had to be estimated from other measurements. This was true for the ASL on the process as well, so the next step was to try and find good estimators for these process parameters based on the measurements that was available. A black-box approach, in this case creating estimators based on linear least squares fits, was used since physical modelling of the relations between the parameters was assumed to take too much time to be feasible in this context.

3.2.1 ASL Estimator

The first attempt to create an estimator for the ASL was based on the hypothesis that the conductivity would be linearly correlated to the concentration of NH_4^+ in the incoming reject water. This was motivated by the fact that the conductivity depends on the amount of ions and other charge-carrying particles dissolved in the water (Atkins 2005). Normally this relation is not strictly linear, but previous studies (Trela et al. 2009) had shown linear correlations between these parameters for the range of interest. If the hypothesis was correct, it would allow a linear least squares fit to be calculated for the NH_4^+-concentration and the conductivity. This least squares fit could then be used to predict the NH_4^+-concentration from the conductivity. The predicted NH_4^+-

concentration together with the known biofilm area and inflow rate of reject water could then be used to estimate the ASL.

In order to verify this hypothesis the available data was reviewed. The one-minute average conductivity data (see section 2.1.2, page 4) was purged from a number of outliers. These most probably originated from measurements recorded during calibrations of the instruments. The remaining conductivity data turned out to be nearly constant for long periods of time. This was unfortunate since the lack of variation meant that the data contained less useful information for modelling. Data on the reject water's NH_4^+-concentration was only available from lab analyses. The reject water had been sampled approximately once a week so only a relatively small amount of data was available for modelling.

In order to calculate the correlation between the NH_4^+-concentration and the conductivity, it was necessary to find the conductivity values that matched those of the NH_4^+-concentration in time. Only the date of the laboratory analyses had been recorded and the exact time of the day when the samples had been collected had varied. This made it impossible to pick out only the correct one-minute average conductivity values that exactly matched the NH_4^+-concentration data in time. Instead the available conductivity data was averaged over the office-hours for the dates the NH_4^+-concentration had been analysed. Reviewing the conductivity data showed that the conductivity had been nearly constant during these periods so the averaging should not have removed too much significant variation from the conductivity data.

The correlation between the two datasets was calculated, but found to be very low. The Pearson correlation-coefficient was only approximately 0.3. This was surprising since Trela et al. (2009) had shown a correlation coefficient of 0.74 for reject water of a similar origin. The reason for the low correlation was assumed to be the lack of variation of the operating conditions. Since the process had been operated with a nearly constant ASL, other factors, such as temperature fluctuations, could dominate the variation in the conductivity. Thus, the hypothesis was not considered to be either proved nor refuted. However, since the correlation was so low for the available data, the linear least squares fit was not considered well suited for use as a predictor. Instead, it was decided that a constant value for the NH_4^+-concentration had to be used. Due to the constant nature of the NH_4^+-concentration in the reject water such a value could be motivated.

By assuming a constant NH_4^+-concentration, the ASL-estimate would be directly proportional to the inflow of reject water since the third parameter, the biofilm area, also was constant. The inflow was to be controlled by a remote controlled pump, thus the estimation of the ASL was considered good enough.

3.2.2 N_2 Estimator

An attempt to get an estimator of the N_2-production was made using linear least squares. However, no direct measurements of the system's N_2-production was available. This made it impossible to make an estimator explicitly for the N_2-production directly from the measured parameters. To work around this problem a number of assumptions were made. It was assumed that all nitrogen entering the system entered as NH_4^+ and that it exited the system in four different forms, namely, N_2, NO_2^-, NO_3^- and NH_4^+. A mass balance would then reveal the production of N_2 if the outflow rates of the other nitrogen-forms were known together with the assumption that no build-up of nitrogen occurred in the reactor.

Data on the concentrations of the different nitrogen-forms in the influent and effluent was available from the laboratory-analyses. Since the inflow was only rarely sampled on the same date as the

outflow, the inflow data was discarded. Instead, the NH_4^+ concentration in the inflow was assumed to be constant. The N_2-production was finally estimated as the difference between the NH_4^+ inflow and the total outflow of NO_2^-, NO_3^-, and NH_4^+ out of the reactor.

To be able to check if the estimates of the N_2-production were correlated with any of the measured on-line parameters, the on-line data had to be prepared. In the same manner as the conductivity had been prepared earlier, the outliers due to calibrations of the instruments were removed from the data and the data was averaged over the office-hours for the dates of interest. While reviewing the on-line data it was noted that many parameters were nearly constant over time.

A number of linear least squares fits were made between the N_2-production estimates and different sets of the on-line parameters in order to get an estimator of the N_2-production based on the on-line parameters instead laboratory measurements. The correlation coefficient did not get much better than 0.6 which was considered too low to be of use. A few tries with squares and logarithms of the different on-line parameters did not improve the result considerably. Two factors explaining the low correlation was identified, the first was the lack of variation in the data. This lack of variation would allow noise and disturbances to dominate the variations, thus leading to low correlations. The second was that the theory indicated that the relation between some of the on-line parameters and the N_2-production was non-linear.

Since the method based on using a linear least squares fit did not produce a good enough estimator, another approach had to be taken. At this point an ammonium-meter became available which made it possible to measure the NH_4^+-concentration in the reactor on-line. If these measurements could be combined with estimates of the concentration of NO_2^- and NO_3^- it would be possible to estimate the N_2-production much in the same way as from the laboratory measurements.

The on-line parameters were used to calculate linear least squares fits for both the NO_2^-- and the NO_3^--concentrations in the same manner as before. The correlation achieved for the NO_2^--concentration was low but a useful correlation was found between the pH and the NO_3^--concentration (the correlation-coefficient was 0.7).

By reviewing the available laboratory data, it was found that the NO_2^--concentration had been very low and almost constant in comparison to the NH_4^+- and NO_3^--concentrations during the entire time the reactor had been active. It was assumed that while the process was working, the NO_x^--concentration would remain low and could thus be neglected from the mass balance used to calculate the N_2-production.

Thus, the final predictor of the N_2-production was based on the on-line ammonium measurements and the pH value of the outflow.

$$2[N_2] = C - [NH_4^+ - N] + k \cdot pH \qquad (7)$$

The predictor had a large number of assumptions tied to it but during the circumstances it was considered the only available option. The perhaps largest weakness of the estimator was that it would not detect a build-up of nitrite in the reactor due to the assumptions. Another problem was that the on-line ammonium meter introduced a time-delay of several hours due to the way the meter was built and placed in the facility.

3.2.3 System model

A part of the reason for developing the estimators was to use them to create a mathematical model of the system. This turned out to be impossible in the context of the project, mainly for two reasons.

First of all, the estimator for the N_2-production was dependent on data from the ammonium-meter. Since this had yet to be installed there was no data to use for model calibration and validation. It could have been possible to use the N_2-production estimates calculated from the laboratory measurements, but these were so few that it would be doubtful if they would yield a good model. Secondly, the model devised had to be rather simple due to the constraints in time and resources available. Biological systems tend to be both non-linear and able to adapt to changes in the environment so any good model would necessarily be rather advanced. The models used by other authors (Michael Nielsen et al. 2005; Hao, J. J Heijnen, and van Loosdrecht 2002; Van Hulle 2005) to simulate the deammonification process was by far too advanced to be possible to adapt and implement in this project.

3.3 CHOOSING CONTROL STRATEGY

The lack of a mathematical model made selection of possible controllers rather narrow. All relatively advanced controllers based on models, such as MPC, LQ, LQG, etc., was not considered further. The theory about the deammonification process suggest that the system will be highly non-linear and thus the PID controller would not be well suited either since it is mainly designed for LTI-systems. Instead, focus was turned to the field of extremum-seeking control.

From simulations (Van Hulle 2005; Hao, J. J Heijnen, and van Loosdrecht 2002) of the process it was assumed that an optimum in N_2-production existed with respect to the DO (see Figure 6, page 12) and also that the ASL (see Figure 7, page 13) could be used to change this optimum. It was decided to start by creating a controller using only the DO-reference signal as a control-signal, while connecting the ASL in a feed-forward manner if possible. One reason for this was the available time left to complete this work and another reason was that many simpler extremum-seeking control algorithms investigated was based on a single control-signal.

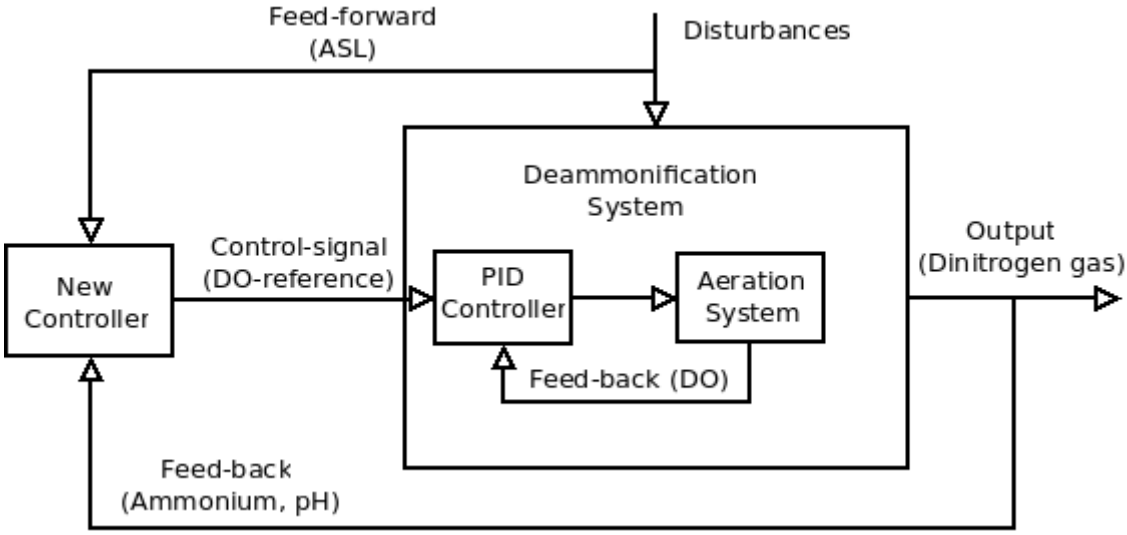

Figure 13 Modified system used to design the controller.

Focus was first directed at different control schemes based on sinusoidal perturbations of the control-signal. These schemes typically find the optimum within a time frame similar to the system dynamics (Ariyur and Krstić 2003). This type of controller would most probably have been very well suited for the task but it had to be turned down for a number of reasons. The first being that the scheme was rather complex. Fully understanding and implementing the theory would exceed the available time left for this project. Another problem with complex controllers is that they are hard to explain to people without a background in control: one of the specifications the controller should meet. Also, the ammonium-meter had a time-delay of several hours which seemed to greatly exceed

the rest of the system dynamics. It was uncertain if the suggested control-scheme would be stable during these conditions. Instead a very simple extremum seeking control scheme was devised based on changing the control-signal in steps and observing the system response after the transients had settled.

3.4 CONTROL ALGORITHM

The control algorithm had to fulfil a list of basic demands.

- It had to be able to find the optimum and follow it
- It had to not overshoot the optimum too much
- It had to be easy to explain to people with no background in control
- It had to be simple to implement

A number of extremum-seeking algorithms was considered. However, since the shape of the relation between the control-signal and the output could vary (see Figure 6, page 12) methods like Newthon-Rapsons and similar methods risked overshooting the the optimum too much. Instead a fixed-step based method was used. This method is called the stepping method (Ma 1997, 10).

The algorithm (Fig. 14) was based on two parameters, the step size of the control-signal Δu and the time delay between steps Δt. Initially the control-signal u was set to a starting guess based on a priori information. After the time period Δt the controlled variable y was stored and the control-signal was changed to $u_1 = u_0 + \Delta u$. After each following time period of the length Δt, the following happened. First the difference in the controlled variable $\Delta y = y_n - y_{n-1}$ was computed. Then the sign of Δu was reversed if Δy was negative, $\Delta u = sign(\Delta y) \cdot \Delta u$. The control signal was updated by $u_{n+1} = u_n + \Delta u$ and the value of the controlled variable was stored until the next iteration.

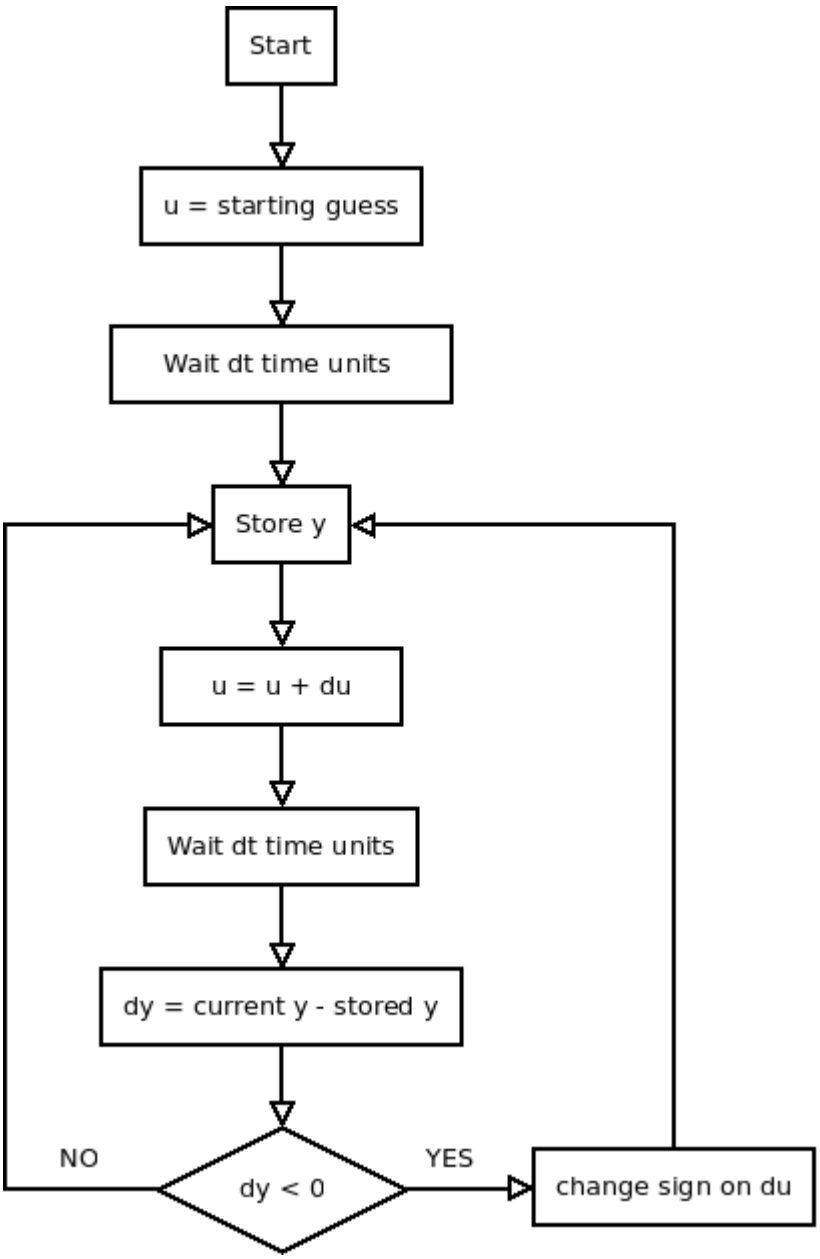

Figure 14 Flowchart of the controller algorithm. u is the control-signal and y is the controlled variable. Δu and Δt are represented by du respectively dy in the figure.

The chosen algorithm had some interesting properties worth noticing. First of all, it made a minimum of assumptions about the process. Basically, the only assumption made was that the controlled variable had a maximum for some control-signal and that no local extremum points existed. Secondly, the algorithm did not depend on any absolute value of the controlled variable, it only depended on the variation.

3.5 SIMULATIONS

In order to evaluate the control algorithm's possible performance, a number of scenarios testing different aspects were simulated. An implementation of the algorithm was written in Python (a programming language, see www.python.org for more information) and the results was presented as plotted figures. Before the simulations could be performed it was necessary to create a model of the system to test the controller on.

3.5.1 Simulator Model

No model of the system had been developed so a very simple, general model had to be devised. The qualitative shape of the system's mapping from control-signal to controlled variable was assumed to be bell-like (see Figure 6, page 12).

More specifically, the simulations were made assuming that the mapping between the control-signal u and the controlled variable y was static and that it could be represented by a function, f, i.e., $y(t)=f(u(t))$. Furthermore, $f(u)$ was assumed to be strictly increasing for $u<0$ and strictly decreasing for $u>0$, in other words, f was assumed to have only one extremum-point, a maximum for $u=0$.

The optimum control-signal, α, was introduced as a disturbance which could change independently of u. A change in α only affected the mapping by shifting it, $y=f(u-\alpha)$. Thus, the mapping's shape was conserved. A suitable function fulfilling the assumptions above was found to be $f(u)=C-u^2$. Including α, the mapping became $y=C-(u-\alpha)^2$, where α represented the optimum control-signal and C the optimal value of controlled variable (Fig. 15). In all simulations below, C was given the value of one, meaning that the value one was the best value the controlled variable could possibly achieve.

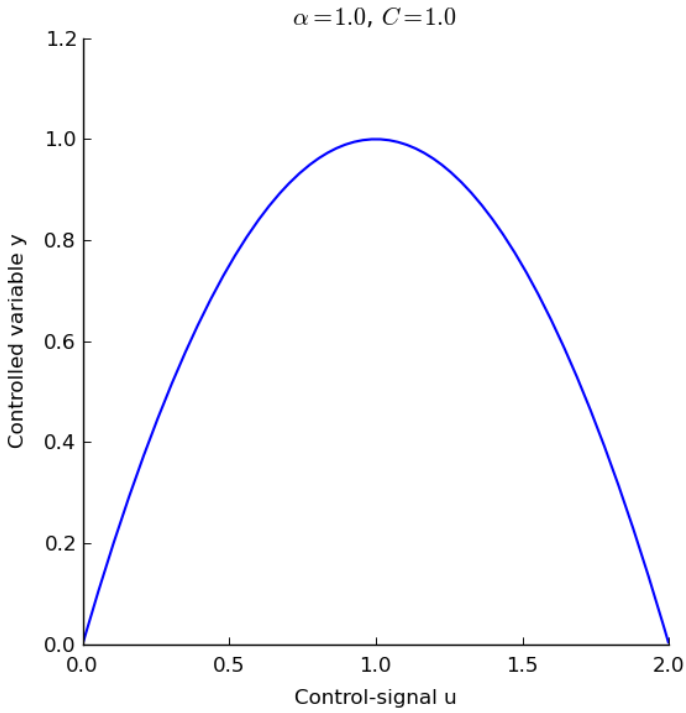

Figure 15 The relation between the control-signal and the controlled variable used for simulations of the control-algorithm.

3.5.2 Scenarios

The simulated scenarios were designed to test various aspects of the control-algorithm. How would the controller react to a time delay or to a varying optimum? How does it behave during constant conditions? Table 3 summarises the settings used for each simulation.

Table 3 Summary of the settings used in the simulations.

No	Optimum α	Step size Δu	Time delay between steps Δt	Description
1	1.0	0.05	120	Constant optimum
2	1.0	0.01	60	Constant optimum
3	1.0+0.3sin(ωt), $\omega = 2\pi 10^{-4}$	0.05	120	Slow variation of optimum
4	1.0+0.3sin(ωt), $\omega = 12\pi 10^{-4}$	0.05	120	Fast variation of optimum
5	1.0+0.3sin(ωt), $\omega = 12\pi 10^{-4}$	0.08	60	Fast variation of optimum
6	$5t\ 10^{-4}$	0.03	120	Optimum ramp
7	$5t\ 10^{-4}$	0.08	60	Optimum ramp
8	1.0	0.03	50	Time delay: 100
9	1.0	0.03	50	Time delay: 500

3.5.3 Simulation Results

For a constant α, i.e., the control-signal had a constant optimum, the simulations indicated that the algorithm would find the optimum and stay close. Different values on Δt and Δu affected the time it took to find optimum initially and how much the control-signal would vary around the optimum (Fig. 16). The simulation also showed that the controller had a tendency to overshoot before changing direction. Even if optimum had been surpassed, the next step could sometimes be in the same direction as the previous. This was due to the fact that even if the optimum had been passed, the value of the controlled variable, y, could have been better than the previous value. This would prevent the controller from changing the sign of Δu and thus the controller would have to overshoot before detecting a decrease in y, causing it to change direction.

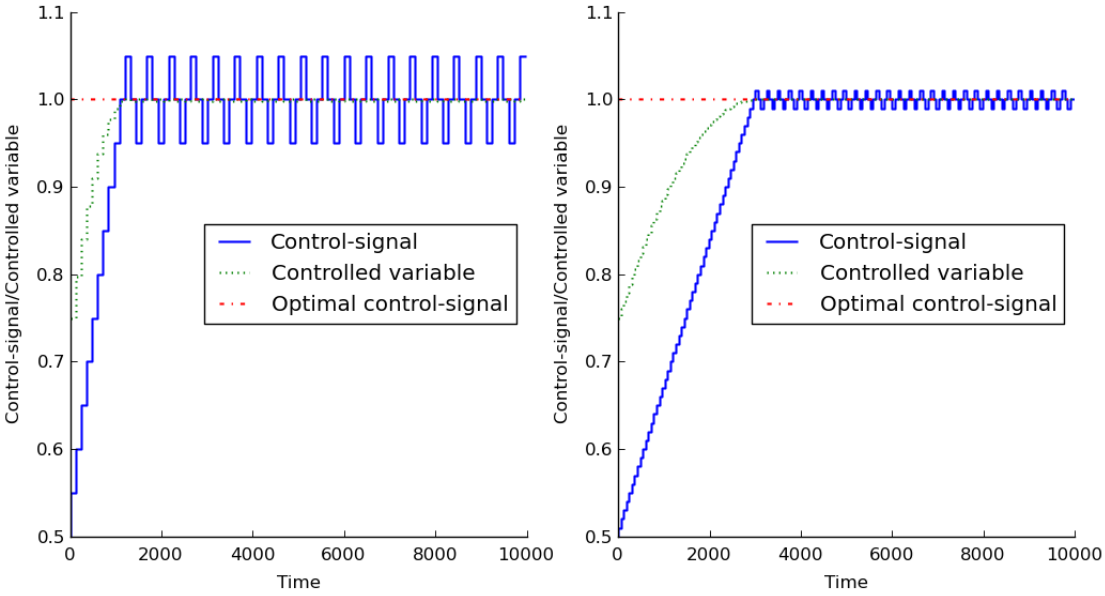

Figure 16 Simulations of the control algorithm's behaviour with a constant optimum value for the control-signal. Two different sets of Δu and Δt was used.

The scenario shown in Figure 16 could also be regarded as a system without any disturbances. Since the algorithm only responds to variations, it could be regarded as a high-pass filter, and thus the effect of a constant α would simply be filtered away (except for the fact that it changed the optimum of the control-signal). Regarded from this point of view, the control algorithm could be said to work well when there were no disturbances on the system.

when α was varied slowly, as in the simulation shown in Figure 17 where α was assumed to the sum of a constant and a low-frequency sine-signal, the control-signal followed the optimum well. This scenario could also be regarded as a disturbance around a constant optimum. From this point of view the simulation showed that the controller was sensitive to large disturbances.

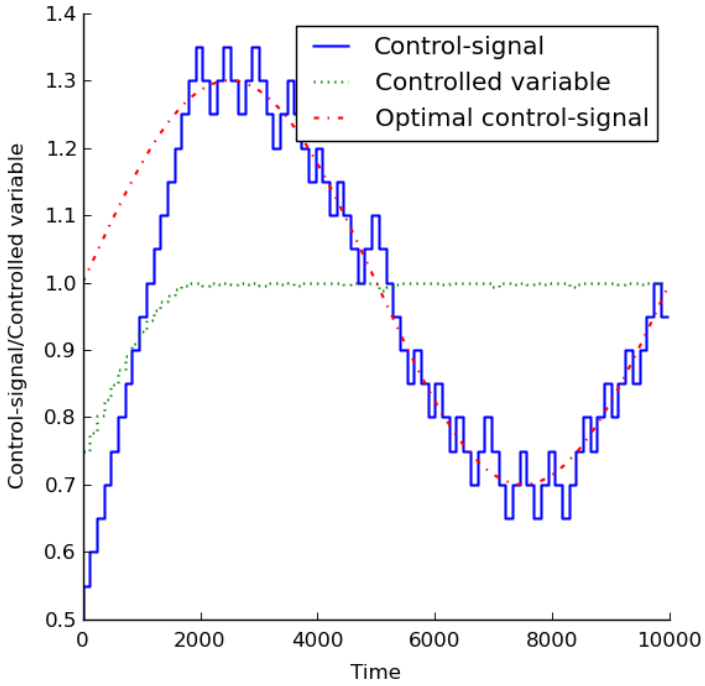

Figure 17 Simulated behaviour for a slow variation of the optimum.

When α was varied faster, but still as a sine added to a constant level, the control-signal was not able to follow the optimum (Fig. 18, left figure), but reducing Δt and increasing Δu could remedy the situation. If the variations in α was regarded as a disturbance around a constant optimum value instead, the simulations again showed that the control algorithm was sensitive to disturbances with large variance. However, the control algorithm behaved differently for different frequencies of the disturbance.

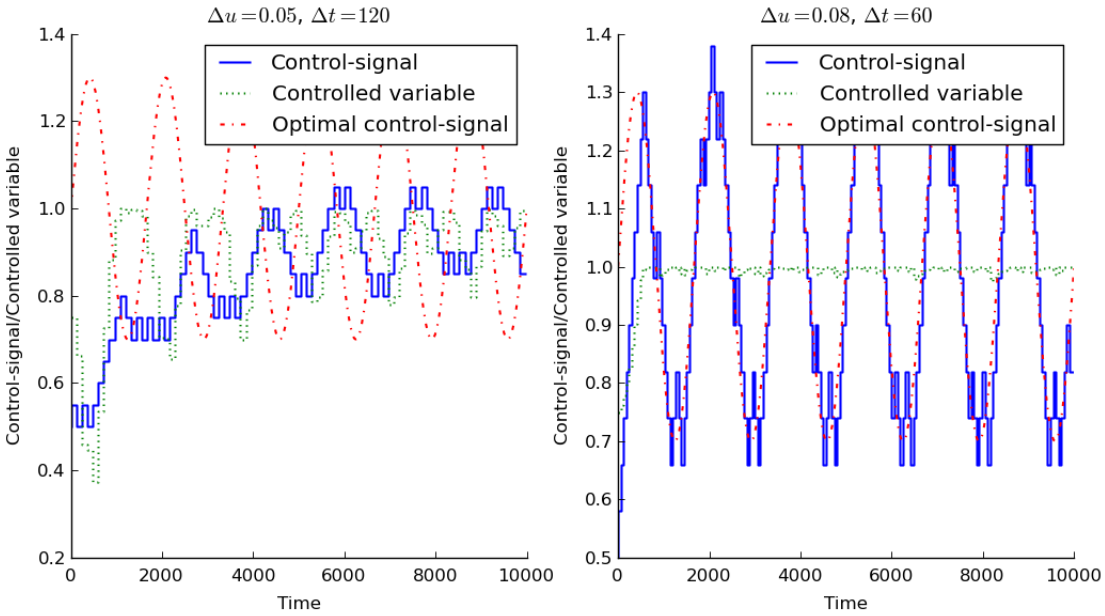

Figure 18 The simulation show how the control-signal fail to follow the optimum if the optimum varies fast. Two different sets of Δu and Δt was used.

The control-algorithm was based on the assumption that the change Δu of the control-variable u was the only change affecting the controlled variable y. Thus the controller neglected any influence of disturbances. This meant that any effects on y due to disturbances (in this case a changing α) was treated as if the change was caused by the change in u. If the disturbances caused a larger change in y than the change Δu did, then the behaviour of the controller could become somewhat unintuitive.

The simulations shown in Figure 19 illustrates this. If α was changed faster than u could grow (as in the left plot in Figure 19), the change in y depended more on α then on u. At first, u was constantly changed in same direction since y was increasing. u was actually changed in the wrong direction but since α affected y more than u, y increased regardless. The controller acted as if the change in y was due to the change in u and thus kept on changing u in the same faulty direction (Note that the control algorithm could just as well have changed u in the correct direction if it would have started with a negative Δu.). When the rapidly changing optimum α overtook u the behaviour changed. y started to decrease no matter which direction u was changed. This caused the controller to switch sign of Δu every iteration, effectively "locking" u since it would only alternate between two values. In the other simulation (the right plot in Figure 19) the change in α was slower than the maximum growth-rate of u and thus the problems with u growing in the wrong direction or becoming locked did not occur.

Another way to look at the scenario analysed above was that y changed independent of u. If y was independent of u and increased, u would constantly be changed in one direction. On the other hand, if y was independently decreased, u would get locked between two values.

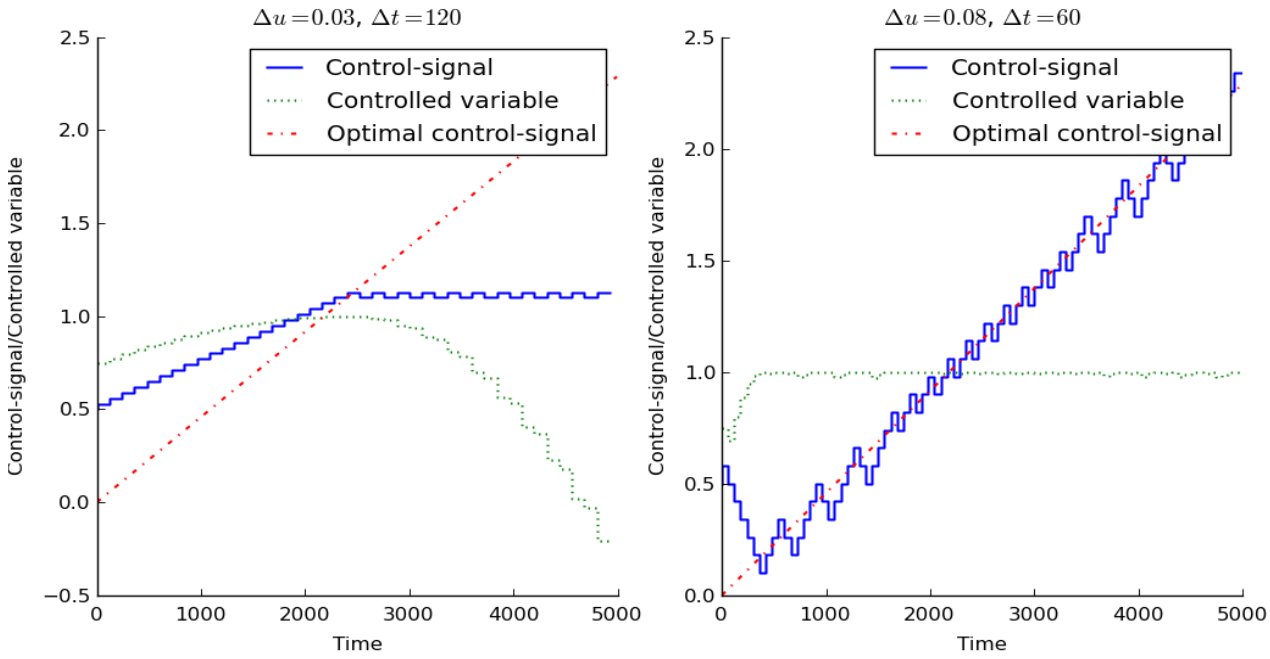

Figure 19 Simulations of a fast change in optimum. Two different sets of Δu and Δt was used.

When a time delay was introduced to the system, the simulations showed that the controller started to behave erratic (Fig. 20). The exact behaviour of the control algorithm was hard to predict since it depended both on the time delay and the mapping between the control-signal and the controlled variable. If the time delay was less than Δt (not shown here) it did not have any serious effects on the system since the simulated system was static. It could in some cases cause the controller to overshoot the optimum with one extra-step as a worst-case scenario. The effects of small time delays would be dependent on the mapping between control-signal and controlled variable and for other mappings the effects could possibly have been more severe.

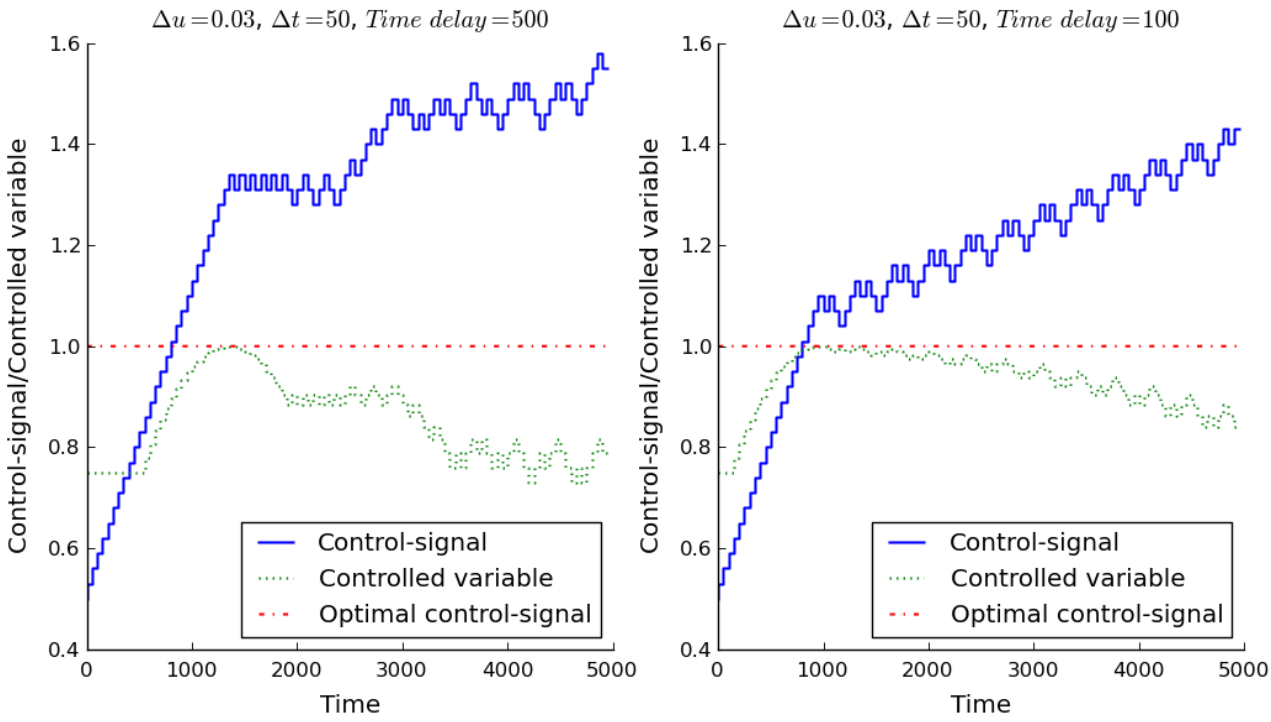

Figure 20 Simulations of the behaviour when the system is affected by time-delays.

The different behaviour patterns simulated above could be used to diagnose a system controlled by this control algorithm. The controlled parameter seemed to vary in certain distinct patterns depending on the state of the system. If these patterns could be identified in a controlled system, they could possibly give hints of how to change the controller settings, i.e., Δu and Δt, in order to improve the controller performance.

For example, if the control-signal u got locked and only changed between two values, it was very possible that one of the following causes was to blame: The mapping between the control-signal and the controlled variable changed fast and the control-signal could not follow the optimum. The controlled variable y was not dependent on the control-signal u. A time delay caused u to overshoot the optimum which in turn caused y to decrease a bit later while locking u at its current level.

4 IMPLEMENTATION

One of the main goals of the master thesis was to actually test the controller on the process. This included a number of steps. New hardware had to be installed, old hardware had to be modified and software controlling the hardware had to be written.

4.1 HARDWARE

The hardware that was most vital for the implementation of this project mostly consisted of equipment related electrical signals. The instruments used to measure various process parameters generated electrical signals proportional to the measurements, the remote controlled pumps was controlled by a varying voltage, the PID-controllers accepted a varying voltage as an external reference signal, the DAQ-units converted analogue electrical signals to digital electrical signals, and the PC logged the digital signals generated by the DAQ-units.

The instrumentation was wired to the PC via two DAQ-units made by Advantech. The measurements was sent to the DAQ-unit as 4-20 mA analogue current-signals. The DAQ-unit then converted the currents into digital values which were read by the computer.

Before the controller was implemented the process had only been run with manual configurations of the pumping-rates and the DO-reference signals. The PID-controllers could be set up to accept an external reference-value in the form of a voltage between 0V and 10V. The same was true for the pumps responsible for pumping reject water into the reactor. However, there were no cables installed for this purpose and no equipment was able to convert the digital signals generated by the computer into voltage outputs. This equipment had to be bought.

The hardware bought to generate the electrical control-signals was a DA-unit (digital to analogue) from National Instruments called NI-9263-USB. It had four channels with a resolution of 16 bits and it was connected to the computer via the USB-bus. The unit was selected mostly because of the good support offered by NI and because of its compatibility with LabVIEW, which was used to create the software implementation of the controller. Some signal-cables was also bought and used to wire the DA-unit to the pumps and PID-controllers.

The function of the new DA-unit was tested by wiring it to one of the pumps. It turned out to be surprisingly easy to control the pumps with the new hardware. Since the function-test had been satisfactory the new unit was wired into the system, connecting both the pumps and the PID controllers to the same unit. However, when this was done the PC stopped being able to read data from the Advantech DAQ-units, much to the author’s surprise since they were seemingly two different systems.

An investigation showed that the process instrumentation was connected to a number of separated electrical systems within the facility. Between these systems there existed a DC potential difference of about 40V. There was also an AC voltage of about 17 VRMS between the different electrical systems. By connecting both the pumps and the PID-controllers to the same DA-unit, these systems were connected, causing the Advantech DAQ-units to malfunction.

It turned out to be hard to work around this problem without investing in more hardware and thus it was decided to only control one of the PID-reference values. This kept the different electrical systems separate and thus the Advantech DAQ-units functioned as intended. However, it made it impossible to control the pumps from the computer. It also made it impossible to estimate the ASL since the inflow to the reactor couldn't be specified from the computer as originally intended. This meant that using the ASL in a feed-forward manner was made impossible as well.

It would have been useful to be able to run experiments with a varying ASL and feed-forward, but

the time would not allow such experiments since it took such a long time to find and fix the hardware-problem. Instead the pumps were allowed to continue to run with a constant pumping-rate which caused the ASL to be constant.

4.2 SOFTWARE

The controller was to be implemented in software on a PC located in the vicinity of the process. The PC was already used to read and store process data (the on-line data previously mentioned) via a DAQ-unit. Since there was a program that already had the ability to collect data from the process, it was decided that the controller should be implemented as an extension to that program. The program was made with LabVIEW.

4.2.1 LabVIEW

This section is based on information from National Instruments website (National Instruments 2011).

LabVIEW (Laboratory Virtual Instrumentation Engineering Workbench) is software package developed by National Instruments used to create programs in a programming language called G. LabVIEW is often used for data acquisition, industrial control and for controlling instruments.

LabVIEW-programs usually consist of two parts, a front panel and a block diagram. The front panel simulates a user interface similar to those seen on real instruments. It can contain different controls, like knobs and switches, used input data to the program. It can also contain indicators like displays, or charts, used to show different results. The block diagram consist of a canvas where different blocks are wired together allowing data to flow in certain patterns. Blocks can have two different connections, sinks and sources. Data from a source on one block can be wired into sinks on other blocks. By connecting a number of blocks together, the data flows through a network of interconnected blocks.

A block can be many different things, for example, it could represent a knob on the front panel. Data input by the user via the knob on the front panel would then become available from the block as a data source. This data could then be wired into a data sink on another block, possibly a block representing a display on the front panel. Any data wired into the display-block in the block diagram will then be visible on the display on the front panel when the program is executed. Thus, if the user would turn the knob on the front panel, the new value would be displayed on the display.

The block diagram can also contain blocks which are not visible on the front panel. These blocks typically use or modify the data wired into them before the data is propagated into other blocks. The connection diagram can also contain various structures like the for- and while-loop used to direct program-execution. By combining different blocks, wires, and structures, different programs can be implemented.

4.2.2 Drivers

In order to make LabVIEW able to utilise the hardware (DAQ- and DA-units), a number of drivers had to be installed. These drivers supplied an interface between the hardware and LabVIEW which LabVIEW could use to manipulate the hardware. However, it turned out that the version of the LabVIEW runtime environment that was installed didn't work well with the drivers supplied by the hardware vendors. This was not immediately apparent and the entire computer had to be replaced before the fault was found. This caused a further delay in the project.

4.2.3 The Existing Program

The existing program, used to read and store on-line data, consisted of an initialization code, a producer loop and a few consumer loops. The initialization code was mainly used to initialize hardware, read settings from disk, and check for a few prerequisites needed for the program to function properly. This code was only run once when the program was started.

The producer loop was responsible for collecting the process measurements from the hardware and putting it into a data queue. The hardware was queried for data at an interval of one second. The raw queried data was in the form of mA readings from the DAQ-units. This raw data was rescaled into proper units, representing the measured quantities, and grouped together with a time stamp before it was pushed onto the queue. The queued data was available for a number of consumer loops. These loops were responsible for calculating average values and storing them to disk, as well as displaying the data on the programs front panel.

The front panel consisted of a single pane with a number of tabs. The different tabs switched between showing the measurements and a chart containing the data from the last few days, the raw mA readings, and an error interface showing if any errors had occurred.

4.2.4 Controller Extension

The controller extension of the existing program basically consisted of the controller-algorithm, described by the flow-chart in Figure 14, implemented as another consumer loop, the control-loop.

Each iteration of the control-loop first began by unbundling the measurements from the data on the producer-queue. The unbundled data was then filtered by a smoothing filter to remove measurement noise. The ammonium-readings and the pH-readings were fed to a block responsible for estimating the efficiency (dinitrogen gas production) of the process. This estimate was used as the controlled variable y. The efficiency estimate was then propagated to the control-algorithm which was implemented as another block. If a certain interval, Δt, had passed, the control-block generated a new control-signal u, i.e., a new reference value for the DO in the reactor. This control-signal was then fed to a DA-unit generating the necessary electrical signals used to control the system.

In order to avoid serious mishaps the control-algorithm was extended with user specified maximum- and minimum-limits for the DO reference value. These were specified by the user on a new tab on the programs front panel. The two control-parameters Δu and Δt, as well as a manual DO-reference value could also be set on the new control-tab. Furthermore the control-tab contained a button used to turn the automatic control on or off plus a display for the scaled and the raw mA value of the control-signal currently sent to the process.

5 IMPLEMENTATION RESULTS & DISCUSSION

5.1 TREATMENT OF DATA

Some of the data presented below have been pre-treated to make the results more visible. Two types data operations have been performed, smoothing and variance normalisation.

5.1.1 Smoothing

The on-line DO measurements tended to vary a lot about the specified DO reference. In order to better be able to see the changes of the DO level, an ageing filter was applied to the data. The filter could be described by the following equation.

$$y_n = \alpha y_{n-1} + (1-\alpha) u_n \qquad (8)$$

The filter was a basic low-pass filter, i.e., it removed fast variations from the data. However, it also introduced a time-lag/distortion which depended on α. Instead of going into detailed analysis about the filter's effect, the effect of the filter on the DO on-line data was demonstrated in Figure 21 for different values of α. As can be seen in the figure, a higher α removed more of the variations but introduced more distortion as well.

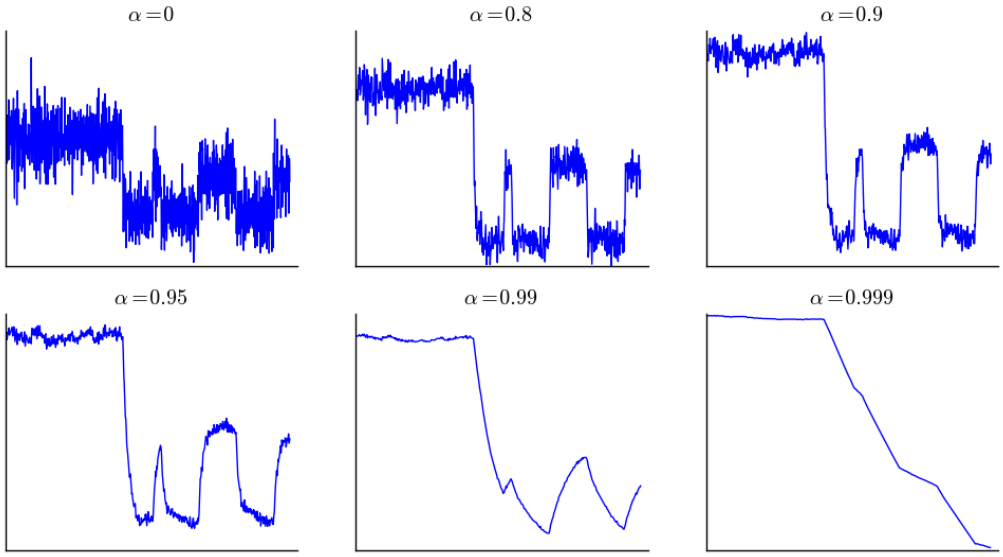

Figure 21 Illustration of how an ageing filter can affect the data for various choices of α. On-line DO data from January 10, 2011 was used.

All DO-data presented below has been filtered with by $\alpha = 0.93$. This value of α seemed like a reasonable compromise between clarity and distortions. The discrete changes of the DO level induced by the controller became clearly visible without introducing serious distortions.

5.1.2 Normalisation of data variation

In order to compare how the different parameters were affecting each other, the variation in the data was "extracted". This was done in two steps, the first was to subtract the mean value from each data point, thus leaving the variation around the mean. The variation was then normalized by its standard

deviation. The second step allowed comparison between variables with different units. Figure 22 illustrate the effects on the data.

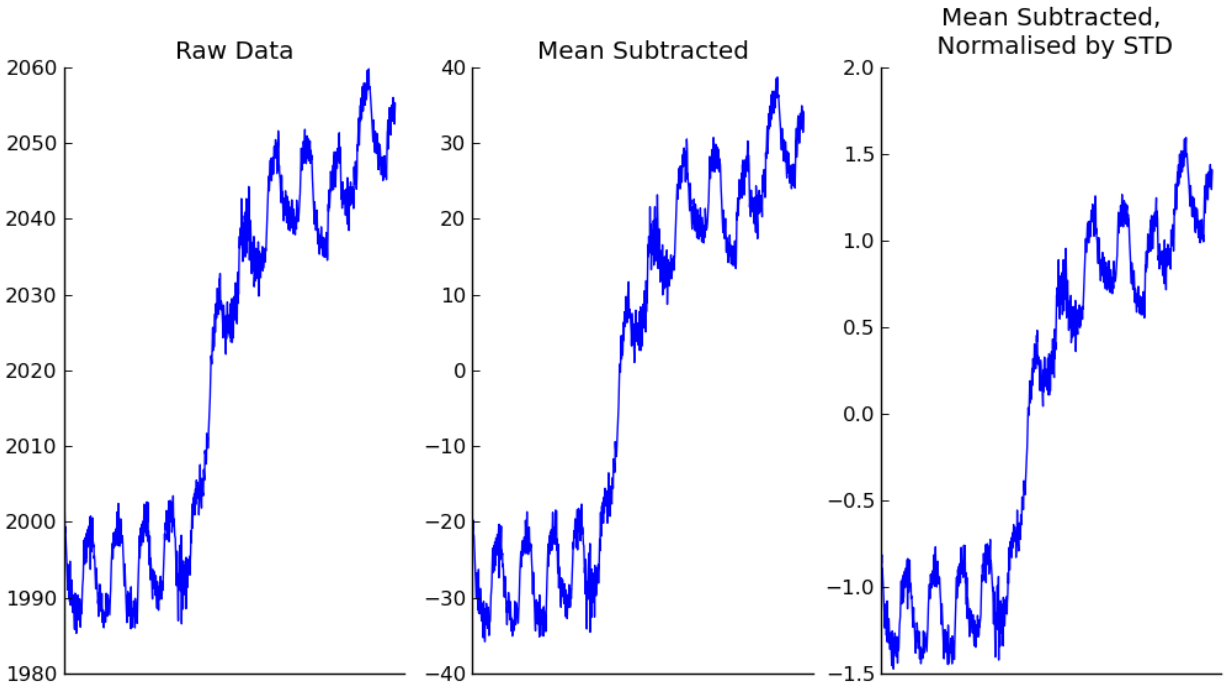

Figure 22 The data is normalised by subtraction of the mean value and by scaling with the standard deviation.

Treating the data like this allowed plotting of variables with very different units in the same figure while retaining the qualitative characteristics of the variation in the data. A consequence of this data treatment was that two variables that were directly proportional to one another would get the exact same shape if both were normalised.

5.2 TESTS OF CONTROLLER

Originally, a series of several tests had been planned. These would include a number of initial experiments used to decide suitable values of Δt, Δu and a suitable DO-range as well as tests with both a constant and a varying ASL. However, due to problems with the implementation the initial experiments had to be skipped and only three tests could be performed. A summary of the settings used during these tests is presented in table 4 below.

Table 4 Summary of the settings used for the tests of the controller.

Test No	**Min DO** $[mg\,l^{-1}]$	**Max DO** $[mg\,l^{-1}]$	Δu $[mg\,l^{-1}]$	Δt $[h]$
1	0.8	1.6	0.1	2
2	0.8	1.6	0.1	3
3	0.8	2.0	0.2	3

5.2.1 Test 1

The first test with automatic control of the process was executed in late December 2010. The controller settings used during the test can be seen in table 4.

The ammonium-meter broke after one day of testing. This is visible in Figure 23 which shows how the ammonium-meter suddenly started to record a constant NH_4^+- N-level of 300 $mg\ l^{-1}$. This was the maximum-level the ammonium-meter was configured to measure. After an investigation the fault turned out to be a broken membrane within the meter.

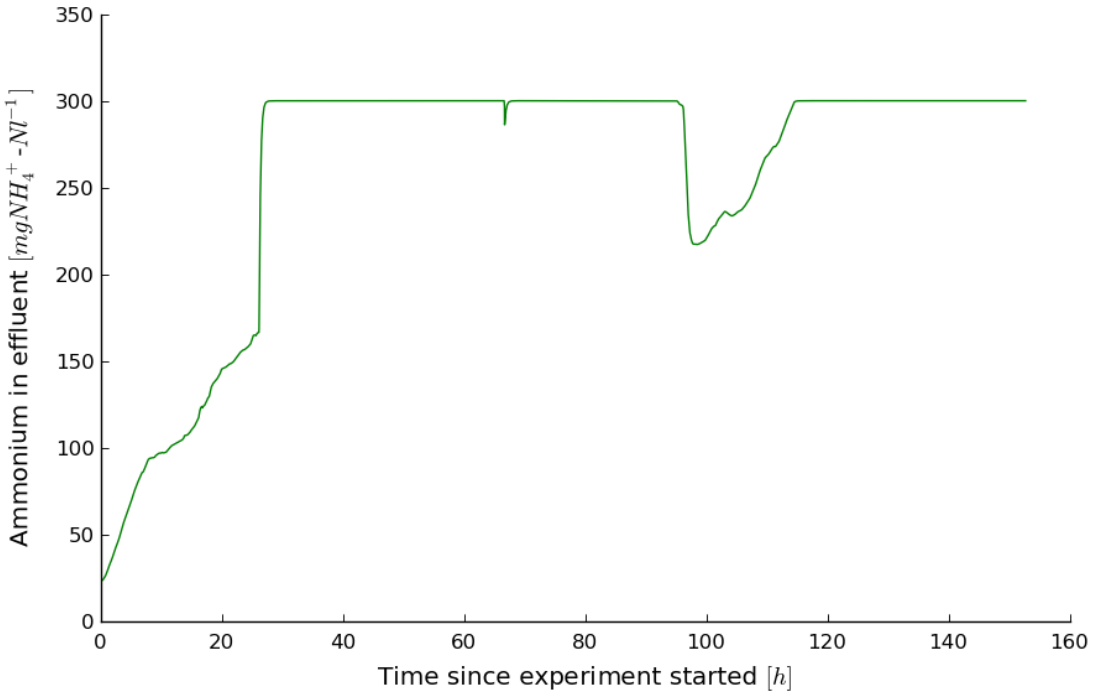

Figure 23 The ammonium-level according to the ammonium-meter. An ion selective membrane on the measuring-probe was penetrated after about one day of testing, causing the meter to report faulty values.

Since the ammonium-meter malfunctioned during most of the test, the automatic controller did not work as intended. However, the results from the test were still considered interesting and thus included here. The pH-meter was still functioning and causing variation in the estimate of the N_2 production. In fact, the pH (Fig. 24 A) varied abnormally much compared to data gathered during previous operation of the process.

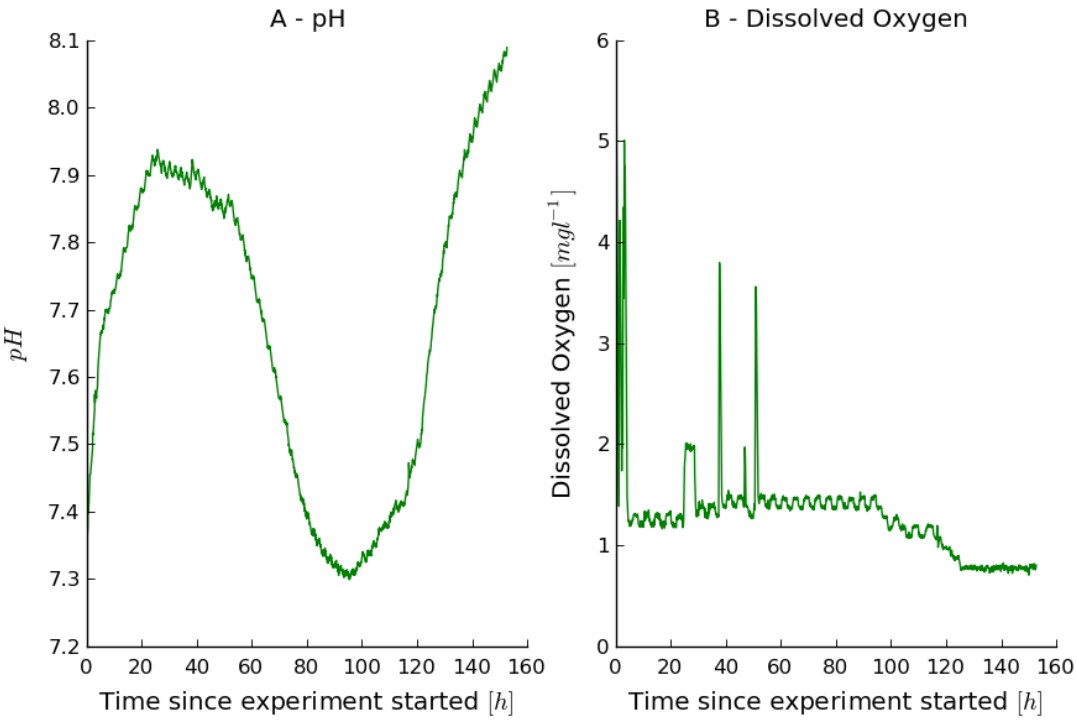

Figure 24 A: The variation in pH-level during the first test. **B**: The variation in DO during the first test. At some points the DO measurements increased to very high levels. This was due to the oxygen-meeter being removed from the reactor for cleaning. About 30 h into the test the DO-reference value was manually set to 2.0 mgl^{-1} for some time.

The DO level (Fig. 24 B) varied mainly about the discrete steps set by the controller. The DO-reference value used as control-signal was not recorded so the time delay and risetime for a step in the reference signal had to be measured manually. This was done through observation of the DO level as the reference-value was changed by the controller. No time-delay was observed and the risetime was less than 2 minutes for a DO reference step of 0.1 $mg\ l^{-1}$.

During the first five days of the experiment, the controller behaved very similar to one of the simulations made earlier. The value mostly switched between two different reference-values. The simulations showed that this behaviour typically occurred when the controlled parameter responded more to disturbances than to the control signal. Since the ammonium-meter was broken and showed a constant level, the only parameter affecting the controlled variable (that is the N_2-estimate) was the pH. Apparently, with the used settings, the controller did not have sufficient control over the pH, that is, the N_2-estimate varied mostly independent of the DO level. This scenario was interesting to analyse further since the N_2-estimate would normally be dependent on the DO level. An analysis could give good insight into how the controller behaved when affected by large disturbances.

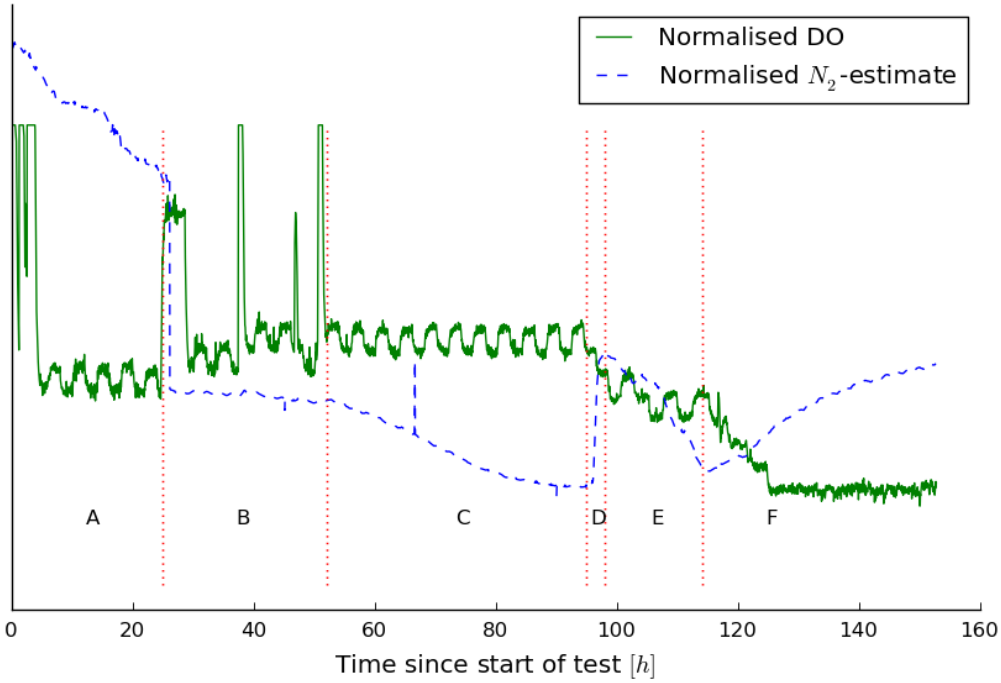

Figure 25 The controller-output varied depending on the estimate of the dinitrogen gas production. The figure is divided into sections A-F in which the controller behaved differently.

To properly analyse the behaviour of the controllers the N_2-estimate was needed. The controllers N_2-estimate had not been recorded, instead this estimate was calculated in the same way the controller calculated it, from the stored on-line data. The estimate was normalised and plotted together with a normalised version of the DO level (Fig. 25) in order to compare the controllers behaviour to the N_2-estimate. The plot was divided into sections A-F by dotted red lines. The controller behaviour in each section could be predicted from the variation in the N_2-estimate (Note that only the variation of the estimate was of interest since the controller was independent of the absolute values. This allowed the analysis to be done with the normalised data.).

In section A, C, and E the the N_2-estimate was falling independently of the changes in DO. This caused the controller to "lock" and only change between two different values. This behaviour had previously been predicted by the simulations for this exact situation. For section A and E the ammonium-meter was giving a varying signal, however, it was likely that the data was erroneous. Still, the variation in the N_2-estimate in these two sections was dominated by the NH_4^+- N-variation. Since the ammonium was going up (see Figure 23) - seemingly unaffected by the changes in DO level - the N_2-estimate was going down. In section C the falling N_2-estimate was caused by a falling pH value (see Figure 24).

Section B was characterised by an almost constant N_2-estimate. This made the behaviour of the controller somewhat unpredictable since small variations in either direction could have effects on the DO level.

In the short section marked, D, the ammonium-meter seemingly started to work again (see Figure 23). The hole in the perforated membrane might have been temporarily covered. The quick drop in the measurements of NH_4^+- N made the N_2-estimate go up. This caused the controller to start decreasing the DO level. The reason it was decreasing (as opposed to increasing) was that the last change the controller had done before the ammonium-meter came to life was in that direction.

In Section F the ammonium-meter was once again showing a constant value. As a consequence, the only variation in the N_2-estimate was due to a changing pH. The pH was going up, causing the N_2-estimate to increase. The controller "assumed" this was due to the most recent decrease in DO and thus continued to decrease the DO. The lowest DO level allowed was 0.8 $mg\ l^{-1}$ and since the controller could not decrease it further it stayed constant for the remainder of the test. If the limit had not been in place the controller would eventually have turned the DO off completely.

Summary Test 1

The first test was dominated by a malfunctioning ammonium-meter which caused the N_2-estimate to be seemingly independent of the DO-level in the reactor. This was unfortunate but it allowed a real-world analysis of the controller behaviour with independent variations in the N_2-estimate. This analysis confirmed that some of the behaviours identified in the simulations also occurred in a real implementation.

5.2.2 Test 2

Since the ammonium-meter malfunctioned during the first test, another test with almost the same controller settings as Test 1 was performed. The only difference was that Δt was set to 3 hours instead of 2 (Table 4).This time, the ammonium-meter worked as intended.

The first process-parameter examined was the DO(Figure 26). It did not vary in the way expected around an optimum (see simulations in figures 16 & 17) so the optimum was assumed to not have been found.

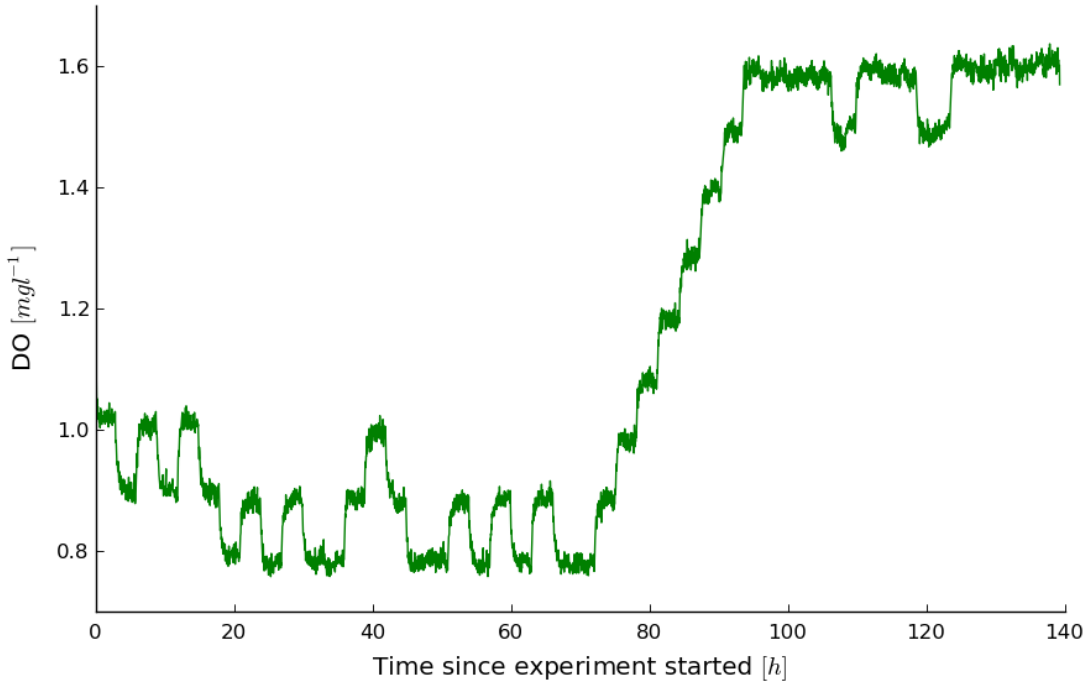

Figure 26 The DO level during the second test.

In order to analyse the controller's behaviour the pH and NH_4^+ measurements were reviewed (Fig. 27). Both the NH_4^+ and the pH seemed to vary in a very similar way, indicating that both these parameters might have been influenced by the variation in DO.

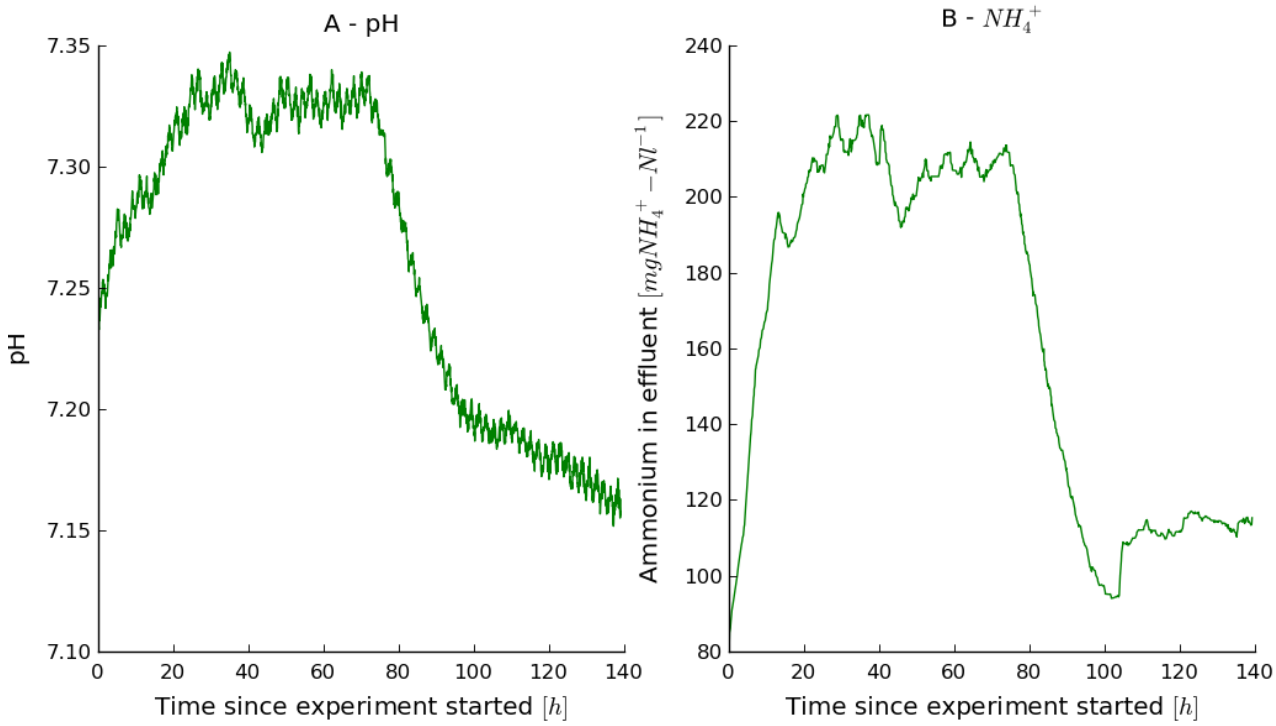

Figure 27 The pH and Ammonium level during the second test.

A comparison between Figure 26 and 27 indicated that the variation in NH_4^+ and pH might have been proportional (with a negative proportionality constant) to the variation in DO. This was investigated by normalising the data and plotting them together (Fig. 28). The variation in the signals was strongly correlated during the entire test, except for a short initial period. This was an expected behaviour for the NH_4^+ but somewhat unexpected for the pH since it had seemed independent of the DO during the first test. However, the variation in pH was much smaller during the second test than during the first test. The pH's standard deviation during the second test was only 0.0632 compared to 0.237 of the first test. That might indicate that the pH was affected by the DO during the first test but the variation was hidden due to some other factor with a stronger influence over the pH variation.

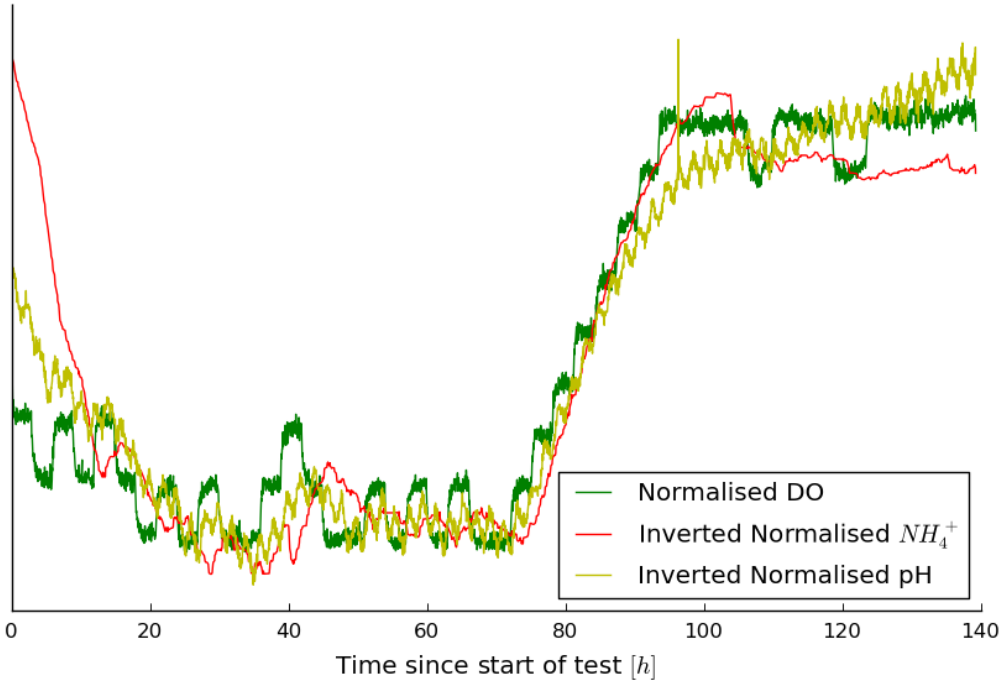

Figure 28 The normalised variation of DO, pH and NH_4^+ plotted together to illustrate the correlation between the variables.

A closer inspection shows that there is a time delay of a few hours between a change in DO level and a change in NH_4^+. The pH also seemed to be delayed but by a shorter amount of time.

It was obvious from Figure 28 that both pH and NH_4^+ were affected by the DO. However, the pH and NH_4^+ have opposing effects on the efficiency so the one affecting the efficiency the most would in effect be the controlled parameter. The NO_3^--estimate was calculated from the pH-values and compared to the NH_4^+ values and the efficiency in Figure 29.

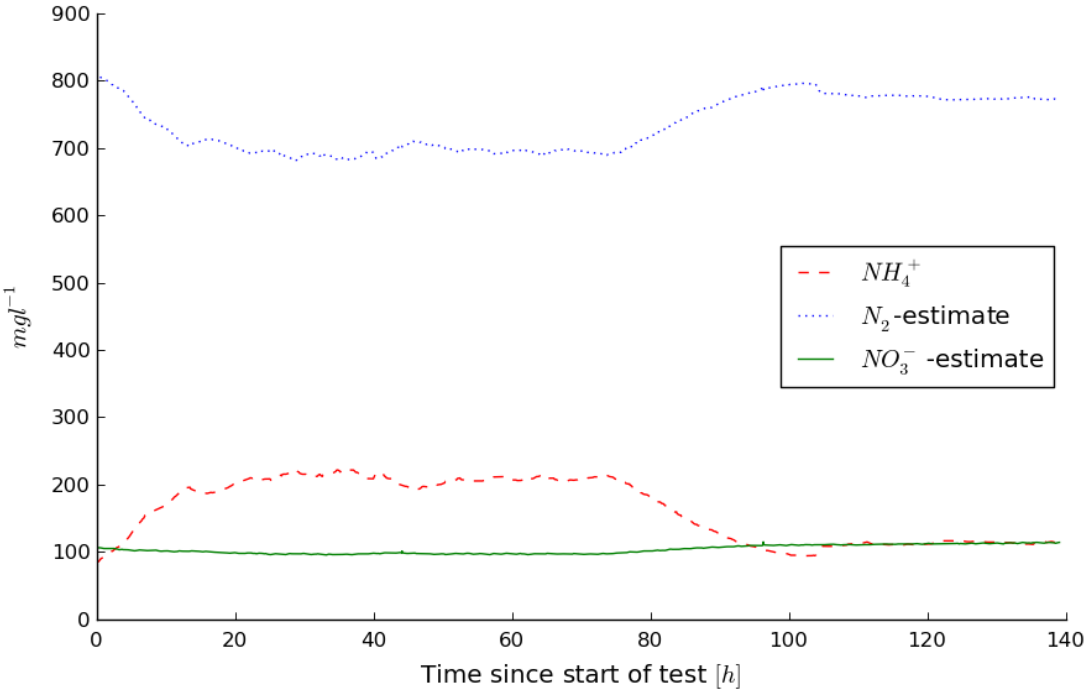

Figure 29 The variation in N_2-estimate, NO_3^+-estimate and the measured NH_4^+-level.

It was obvious that the variation in the N_2-estimate were primarily induced by the variations in the NH_4^+ measurements. This had the effect that the controller primarily controlled the NH_4^+-level.

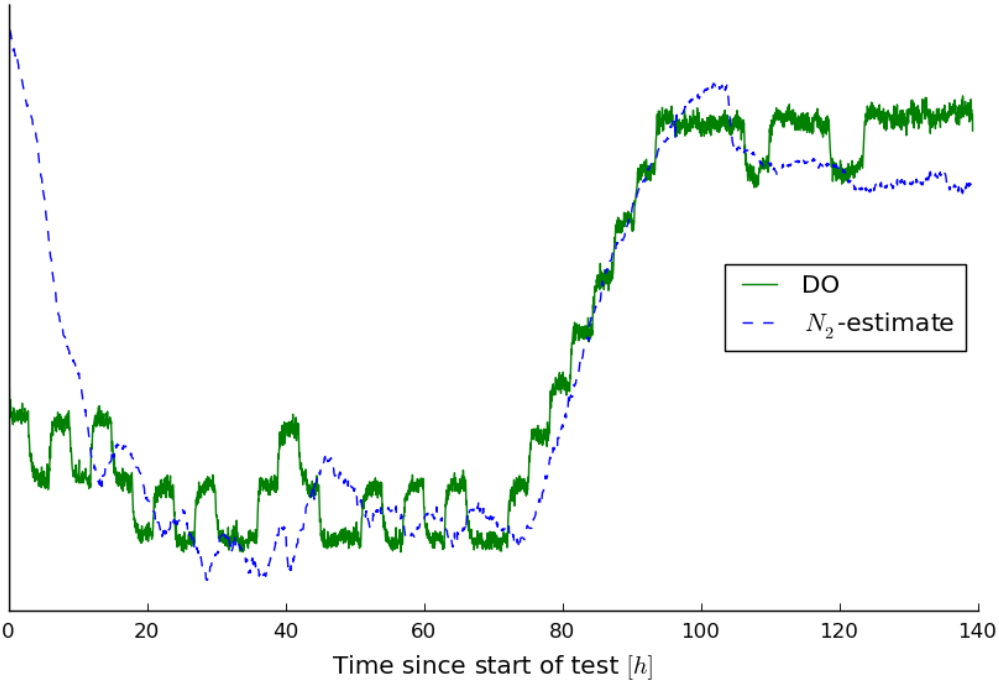

Figure 30 The normalised variation of the dissolved oxygen and the dinitrogen gas estimate.

In order to analyse the behaviour of the controller, the variations in the N_2-estimate was normalised and plotted together with a normalised version of the DO level (Fig. 30). During the first 10 hours of the test the N_2-estimate dropped and showed little correlation with the variation in DO. The ammonium-meter had been serviced only hours before the test and that was believed to be the cause of the sudden change in the ammonium-measurements. Since the N_2-estimate dropped independently of the DO, the controller got "locked" and only varied between two values.

About 10 hours into the test the uncontrolled drop in the N_2-estimate stopped and the estimate started to vary with the DO level. However, there seemed to be a time delay involved which caused the controller to behave somewhat erratic. However, after about 75 hours the controller increased the DO-reference-level twice. This allowed the controller to detect the positive effect on the N_2-estimate even though it was delayed. This caused the controller to keep increasing the DO-reference level to the maximum-level where it stayed for most of the remainder of the test.

Summary of Test 2

The second test showed that the N_2-estimate was dependent on the DO level. The variations in both ammonium and pH seemed to vary proportionally with the variations in DO level, at least for DO-levels between 0.8 and 1.6 $mg\,l^{-1}$. The result for the pH was somewhat surprising since the pH didn't seem to be affected by the DO-level in the first test. However, it was the variation in the ammonium level that mainly caused the variations in the N_2-estimate.

The test also indicated that the time delay between a change in the DO level and a change in the N_2-estimate was long enough to cause the controller to behave faulty. A longer Δt should probably have solved the problem but this was never confirmed with a test.

5.2.3 Test 3

A third test was conducted directly after the second test. During this test, the maximum allowed DO level was increased to 2.0 mgl^{-1} and the control-signal step size, Δu, was increased to 0.2 mgl^{-1} (see table 4). If the second test had been analysed before the third test was set up, the time step, Δt, would probably have been increased in order to tackle the longer than expected time delay that showed up in the second test.

About half way through the third test the ammonium-meter was serviced. This caused faulty values to be recorded for a few hours (Fig. 31B). The pH also showed (Fig. 32) a sudden change approximately 46 h into the test due to to a calibration of the pH-meter. The controller was turned off during this period and restarted after about 3 hours. This was reflected as a constant DO level for six hours about 50 h into the test (Fig. 31A).

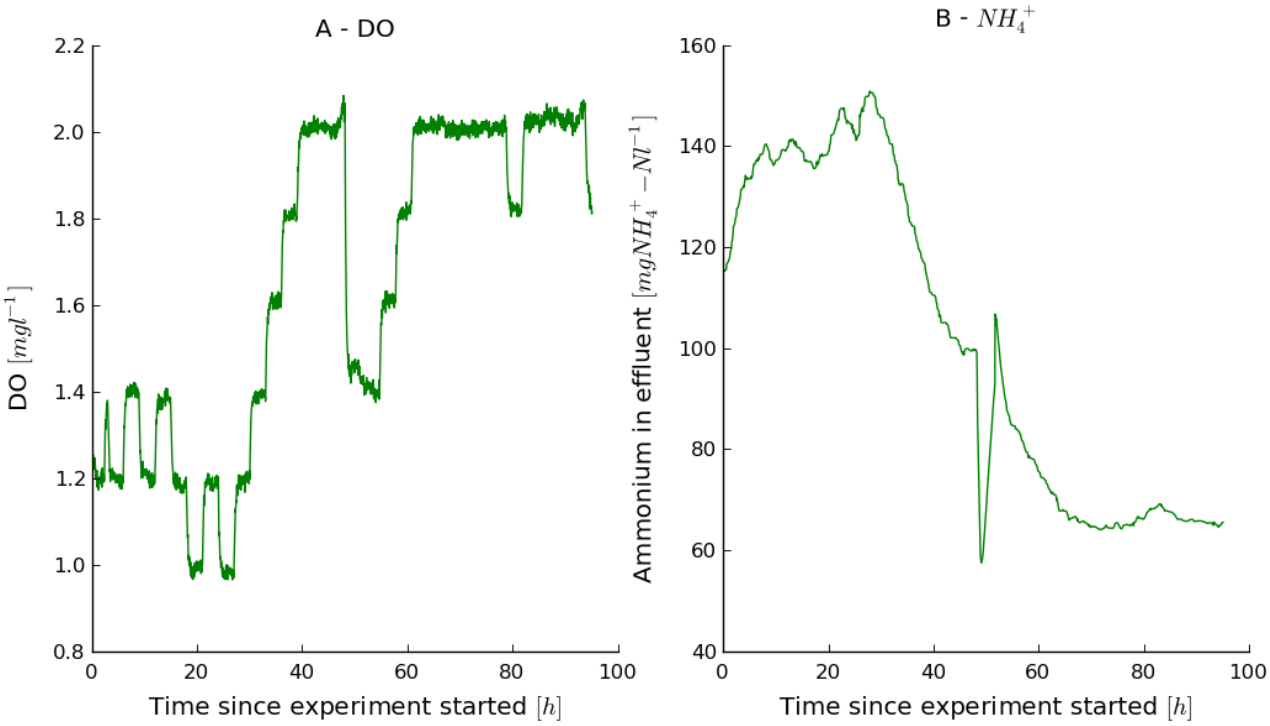

Figure 31 A: The DO level during the third test. The controller was turned off and restarted about halfway through the test. **B:** The ammonium-meter was serviced about halfway through the test. This is reflected in the plot as a sudden drop in the ammonium-level.

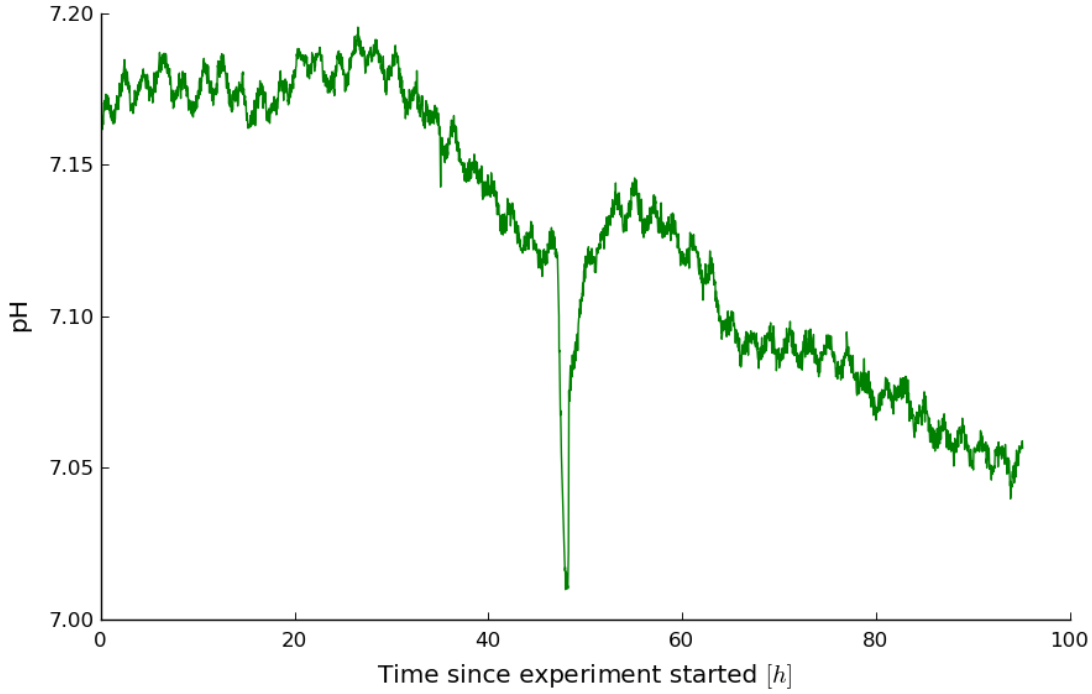

Figure 32 The pH level during the third test. The pH-meter was calibrated 46 h into the test.

The third test generally behaved similar to the second test (Fig. 33). This was expected since the time delay still had not been properly addressed by a longer Δt. The test was initiated by a slightly erratic behaviour believed to be caused by the time delay. After about 27 h the DO-reference-value started to increase and continued until the maximum allowed DO level was reached. When the controller was reset it immediately started to increase the DO-reference value until it settled at the maximum-value again. In the later part of the test, the DO dropped temporarily. This was most likely due to a disturbance affecting the N_2-estimate.

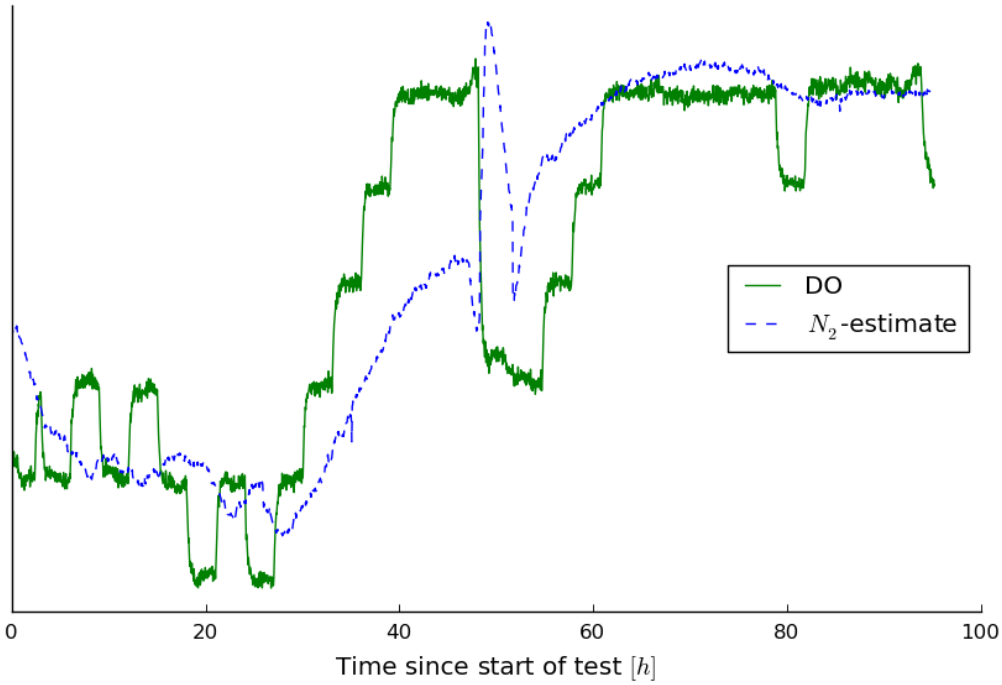

Figure 33 Normalised DO-level and N_2-estimate during the third test.

5.3 FURTHER DISCUSSION

5.3.1 General

None of the tests performed showed signs of an optimum. The main reason for this was believed to be that the optimum actually was outside the range of allowed DO-values.

Most of the variation of the N_2-estimate was indicated to be caused by the variation in the ammonium level (see Figure 29) due to a changing DO, at least for the second test. An interpretation of this could be that the DO was varied in a too small interval of an to find the optimum.

One consequence of the way the N_2-estimate was calculated (the difference between a constant and the sum of ammonium plus nitrate), was that the N_2-estimate would mostly vary due to variations in ammonium level for low levels of DO, and due to variations in nitrate level for high levels of DO. This was clear from studies (Van Hulle 2005) of the relationship between DO and ammonium or nitrate. Figure 4 clearly showed that the relationship between DO and ammonium was almost proportional for low DO levels. For higher DO levels, most of the ammonium would have been oxidised and the ammonium would vary very little. The opposite would probably be close to the truth regarding the nitrate.

By inspecting the plot in Figure 28, it became clear that the ammonium tended to vary in a proportional fashion with the DO. This indicated that the DO-interval did not include the critical limit where the ammonium stopped varying with the DO (the "knee" in Figure 4). A reasonable assumption could be that the optimum DO value would lie after that knee, that is, in the region where most of the ammonium had been oxidised. Since the interval did not seem to encompass this area at all, the optimum was assumed to lie outside the range that was searched.

Another factor that supported the hypothesis that the optimum lied outside the examined range was the fact that in both the third and second test, the DO eventually tended to hit the upper limit and stay there. The N_2-estimate was also highest during these periods.

5.3.2 N_2-Estimate

The estimate of the N_2-production used during the tests was based on rather strong assumptions. The perhaps biggest issue with those assumptions was probably the disregard of nitrite. Since the estimate was independent of the nitrite-level, which was assumed to be very low, a build up of nitrite within the reactor could occur without affecting the N_2-estimate. In fact, all nitrite that was formed would look like an increase in the N_2-estimate. This meant that the control-algorithm, when combined with this particular N_2-estimate, could actually be regarded as an algorithm used to maximize nitrite production in the reactor as well as production of N_2.

During the experiments, the nitrite production was limited by specifying a range for the DO where the production of nitrite was known to be limited from earlier experiments, thus avoiding this scenario. However, since the the DO range had to be limited, it was also be possible that the optimum fell outside the specified range. According to the discussions above, this seemed to be the case.

Another possible flaw in the estimation of the N_2-production was that it was based on the pH. A correlation had been found between pH and nitrate but it should be noted that correlation is not equal to causation. In other words, there might have been another factor influencing both pH and nitrate levels causing the correlation. It was, however, likely that the nitrate level affected the pH. If nitrite was oxidised directly to nitrate by nitrifying bacteria, e.g., Nitrobacter, the hydrogen ions normally consumed by the anammox process (see equation 4, page 6) would remain in the reactor, thus affecting the pH.

A last flaw related to the N_2-estimate worth noting was the fact that the deammonification process actually produced nitrate when it was working as intended. The nitrate was formed as a by-product due to the growth of anammox bacteria. The control-algorithm combined with the current N_2-estimate would try to make the nitrate level as low as possible, thus, inhibiting the anammox-reaction would be preferable to the controller. This could lead to a controller that would work towards a system where all ammonium were converted to nitrite and none actually converted to dinitrogen gas.

It should be noted that all the flaws affecting the process mentioned in this section could be removed by improving the estimate of the N_2-production.

On a related note, if the anammox reaction could be assumed to be the only process producing nitrate in the reactor, the nitrate level would be proportional to the N_2-production. That would mean that it would be perfect as an estimator of the N_2-production. This was actually considered for some time, but later abandoned since the assumption was not believed to hold true.

The low quality of the N_2-estimate had its origin in the lack of suitable data. The data collected from the process, before this project was initiated, was of good quality, but it lacked the necessary

variations crucial to the development of the estimator. The reason for this was that the data had not been collected with modelling in mind. The most important data, i.e., data considering the different forms of nitrogen in the process, was not available as on-line data. This also made it hard to use this data to estimate short-term variations since the fastest variations visible in the data was on a weekly time scale.

5.3.3 Control-algorithm, controller settings.

The control-algorithm devised in this project was considered well suited for the task. The system to be controlled was operated with a continuous inflow of reject water where the variations could be assumed to be slow. For such a system it would not matter greatly that the initial time to find the optimum could be quite long since it would be a one-time cost. The control-signal would then vary about the optimum with a variance depending on the step size, Δu. By initially increasing the step size, Δu, the time to find the optimum could be reduced. When the optimum had been found, the step size could easily have been decreased by an operator to lessen the variance about the optimum.

To get the controller to work as intended, a number of requirements would have needed to be fulfilled. First off all, the controller was based on a feedback scheme, and so it was dependent on reliable information about the process efficiency. If the quality of this information was questionable, the quality of the controller's performance would also become questionable. During the tests of the controller, the information available through feedback was probably of low quality since the estimator of the N_2-production was based on some doubtful assumptions. This could have caused the controller to behave erroneous, even if the basic control-algorithm was sound.

Secondly, the controller settings, Δu and Δt, would need to be set to reasonable values. Since the system was affected by time delays, a too small value of Δt would cause the controller to behave erratic. The controller was actually designed with the criterion that Δt would be long enough to allow for both a time delay and for the system dynamics to settle. On the other hand, if Δt was too long, the controller would become unable to follow faster variations and also become more sensitive to disturbances. During the tests of the controller, the time step, Δt, was slightly too short to accommodate the time delay induced by the slow ammonium-meter. This made it impossible to actually get good controller performance during these tests since the controller had not been tuned properly.

A third requirement was that the controlled variable had to be dependent on the control-signal. From the three tests above, it was obvious that the N_2-estimate was affected by the chosen control-signal in a manner similar to that which was expected and hoped for. This was not at all guaranteed to be true before the tests had actually been performed.

There was good reason to believe that DO would affect the ammonium in a way similar to the one observed in the tests, for example, Figure 4 suggested that the ammonium would vary with the DO-level. However, the simulation results presented by Van Hulle (2005) was concerning steady-state values. That is, they did not really specify the behaviour for short-term variations in the DO-level. It was reasonable, but not guaranteed, that the behaviour would be similar as hoped.

The reasoning considering the ammonium above was equally true for the nitrate concentration. It was assumed that the short-term dependency between nitrate and DO would resemble the long-term dependency, just as it was assumed for the ammonium. This was probably less likely to be true since the steady-state values would allow for bacterial growth of nitrite-oxidising bacteria. Normally, the Nitrosomonas and the anammox bacteria affecting the ammonium would already be present during short-time variations in the DO level, but the Nitrobacter bacteria would, normally, not be present to the same degree. Thus the steady-state values of the nitrate should carry less weight than the steady-state values of ammonium considering short-term variations.

During the preparation of an estimator for the nitrate level, a correlation was found between the pH and the nitrate concentration. This was taken as another indicator that the DO would actually have short-term effects on the nitrate concentration. However, the correlation that was found was only valid for mid-to-long term variations since it was based on data sampled at a rate of two times per week. Naturally, this correlation could not really “guarantee” anything about the variations on a time scale of hours. Also, the correlated variation between nitrate and pH could not be proved to be dependent on the DO-level, this was just assumed.

The tests above did primarily confirm that the assumptions about the ammonium levels dependency on the DO was correct, at least for the DO interval used in the tests. This could be stated because the variation in the ammonium level was shown to be well correlated to the variations in DO level. Actually, they seemed to vary in a proportional fashion. The tests did not confirm the nitrates DO-dependency to the same degree. The pH was indeed shown to be well correlated to the DO, but since the pH could vary for other reasons than a changing nitrate level – correlation is not causation – the variations in nitrate could not be confirmed to be dependent on the DO.

6 CONCLUSIONS

The extremum seeking controller developed in this master thesis was simple but well suited for control of the deammonification process. This was confirmed by simulations and the tests on the real system showed promise even though they failed to find the optimum DO-level. Other, more advanced extremum seeking control algorithms could possibly improve the results by reducing the time needed to find the optimum as well as being more robust. The DO-level was a suitable parameter for controlling the process. It had been indicated by the literature study and it was confirmed by the tests.

The control strategy used feedback from an estimation of the dinitrogen-gas production. This method was preferable to a control system based only on the ASL on the system since there was no suitable and accurate model available and an open-loop control scheme could lead to large control errors. Feed-forward of the ASL would be beneficial but not crucial for the controller. However, the dinitrogen gas estimate could not be made very accurate due to lack of suitable data for modelling. To get good results from the implemented control algorithm it would be necessary to improve the estimator of the dinitrogen gas production or replace the estimator by a real measurement of the dinitrogen gas production.

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