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Optimizing the Coagulation Process at Solumstrand Wastewater Treatment Plant

Optimalisering av den Kjemiske Renseprosessen ved Solumstrand Renseanlegg

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Forord

Denne masteroppgaven betegner avslutningen på mitt studie innenfor Industriell Økonomi - Vann-og Miljøteknikk, på Fakultetet for realfag og teknologi ved Norges Miljø- og Biovitenskapelige Universitet (NMBU). Oppgaven utgjør 30 studiepoeng.

Hensikten med oppgaven har vært å optimalisere den automatiske doseringen i den kjemiske fellingsprosessen ved Solumstrand renseanlegg. Fokuset har vært å undersøke forskjellen i vannkvaliteten i de to utløpene ved Actiflo-prosessen, og å finne årsaken til avvikene. Temaet ble fremmet av Professor Harsha C. Ratnaweera ved NMBU.

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Snorre Katrud Karlsen

2. Juli 2020, Ås

Sammendrag

Renseanlegg i Norge har lenge benyttet seg av jartesting og mengdeproporsjonal dosering for å bestemme doseringen ved den kjemiske fellingsprosessen. Disse metodene har blitt benyttet ettersom hovedmålet til renseanleggene har vært å maksimere fjerning av fosfor og partikler, uten å ta hensyn til overdosering av kjemikalier. Nylig har det derimot blitt lagt mer vekt på å minimere kjemikaliebruk ved renseanlegg. Målet med å minimere kjemikaliebruken er å minke kostnader relatert til den kjemiske fellingen, samt å redusere slamproduksjon. Dette har ført til at automatiske doseringssystemer har blitt installert på mange norske renseanlegg. Solumstrand renseanlegg benytter seg av et av disse avanserte doseringssystemene. Anlegget bestemmer doseringen basert på relevante innløpsparametere, samt noen utløpsparametere som benyttes for doseringskorrigering. Dette systemet har blitt tatt i bruk og har forbedret renseprosessen ved Solumstrand renseanlegg og har i tillegg redusert kostnader relatert til dosering, men det er fortsatt rom for forbedring.

Denne oppgaven forsøker å visualisere korrelasjonen mellom de relevante vannkvalitetsparameterne på Solumstrand renseanlegg, samt å kvantifisere parameterne som ikke blir målt av sensorer på renseanlegget med hensyn på renseanleggets optimaliseringsmuligheter. Dette ble gjort ved hjelp av labanalyser, fullskalatester av koagulant- og polymerdosering, og statistiske analyser. Hensikten med denne oppgaven er å se på hvilke deler av den kjemiske fellingsprosessen som kan optimaliseres med hensyn på økonomiske og miljømessige besparelser. På grunn av Corona-virus pandemien i verden ble fullskalatestene kansellert, og metodikken rundt oppgaven ble deretter omstrukturert. Et større fokus ble satt på teori, på grunnlag av diskusjoner med fageksperter som er tilknyttet renseanlegget, og på de statistiske analysene som var tilgjengelige med sanntidsbasert data tilgjengelig på nett.

Denne studien viser til at implementering av sensorer som måler spesifikke parametere er nødvendig. Ved bruk av sensorer vil overvåkning og prosesskontroll på anlegget gjøre systemet lettere å regulere, samt optimalisere doseringen ved den kjemiske fellingen. I tillegg anbefales videre undersøkelse av renseanlegget, blant annet gjennomføring av fullskalatester av forskjellige koagulant- og polymerdoseringer.

Abstract

Wastewater treatment plants in Norway have long used jar testing and flow-proportional dosing when deciding the coagulant dosage at the chemical coagulation process. Treatment plants utilize these methods because the primary goal has been to maximize the removal of phosphorus and particles, without taking overdosing of chemical coagulants into consideration. However, in more recent times, the emphasis has been on minimizing chemical usage at treatment plants. The goal is to reduce costs related to chemical coagulation and to reduce the production of sludge. This change in priority has led to the use of automatic dosing systems at many treatment plants in Norway. Solumstrand treatment plant uses one of these advanced dosing systems. The treatment plant decides the dosage based on relevant inlet parameters while using some outlet parameters for feed-back correction. Implementing this system has improved the treatment process at Solumstrand and has reduced costs related to dosing, but there is still room for improvement.

This thesis attempts to visualize the correlation between the water quality parameters at Solumstrand treatment plant and quantify the water quality parameters to look at optimization possibilities. Lab analyses, full-scale tests of coagulant and polymer doses, and statistical analyses were the baseline of the thesis work when working towards the set goal. The aim is to optimize the chemical coagulation process for economic and environmental purposes. After the coronavirus pandemic hit Norway, full-scale tests could no longer be completed, and the methods had to be restructured. Because of this, discussions with subject matter experts and the statistical analyses available through real-time data accessible online were given a larger emphasis.

Results from the thesis work suggest the implementation of sensors that measure specific parameters. Increasing surveillance and process control will make the system more flexible, and it will be easier to optimize the dosing at the chemical coagulation process. Further research is also recommended, especially in the form of full-scale tests of both coagulant and polymer dosages.

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Abbreviations

BOD	Biological Oxygen Demand
COD	Chemical Oxygen Demand
FNU	Formazin Nephelometric Units
LDA	Linear Discriminant Analysis
MLR	Multiple Linear Regression
MVA	Multivariate Analysis
NIPALS	Nonlinear Iterative Partial Least Squares
NMBU	Norwegian University of Life Sciences
NOM	Natural Organic Matter
NTU	Nephelometric Turbidity Units
PCA	Principal Component Analysis
PCR	Principal Component Regression
PLSR	Partial Least Square Regression
RPM	Revolutions Per Minute
SCADA	Supervisory Control And Data Acquisition
SME	Subject Matter Expert
SS	Suspended Solids
Tot-N	Total Nitrogen
Tot-P	Total Phosphorus

1. Introduction

Coagulation is an essential process in wastewater treatment. It has been practiced since ancient times, and a variety of substances have been used. As early as 2000 BC, the Egyptians cleaned river waters by smearing almonds around vessels. (Bratby, 2016). A protein in the almonds would cause the particles to clump together in the water, creating an early coagulation concept. As the development of water treatment progressed, the requirements for the water quality increased. One example of this is in the United States, where the regulatory limit for treated water turbidity has been steadily reduced from 1.0 Nephelometric Turbidity Units (NTU) in 1989, to 0.3 NTU in 2016 (Bratby, 2016).

Jar tests and flow-proportional dosing systems controlled by water flow and pH have long been used to determine coagulant dosages at wastewater treatment plants and are still heavily used today. The primary goal at treatment plants has long been to maximize phosphorus and particle removal. However, the current and future treatment plants' goals are no longer to remove as much phosphorus and particles as possible but to optimize the treatment process. By reducing chemical use by automating the process, the goal is to reduce costs related to coagulant usage, reduce sludge volume, and enhance plant availability of phosphates (Ratnaweera & Fettig, 2015). Jar tests and flow-proportional dosing systems do not provide the required flexibility to optimize dosages that occur due to sudden changes in the water quality going into the treatment plant. Therefore, a greater focus has been to create automatic dosing systems that optimize the coagulant dosage used during the coagulation process.

The implementation of automatic dosing control systems has proven to reduce coagulant dosing at treatment plants (Nataliia Sivchenko et al., 2018). The automated dosing system can survey and control the dosage 24 hours per day, which increases flexibility, especially when including feed-back correction for dosage control.

Although dosing control systems have improved the coagulation process, there is still room for improvement, as operators manually curate polymer dosing at most treatment plants. The implementation of polymer dosing in the automatic dosing control systems is a natural step in optimizing the coagulation process. Treatment plants also struggle with individual issues

during chemical coagulation. Several different variables can cause this, such as mechanical differences and differences in the treatment plant's design.

Solumstrand treatment plant, located in Drammen, Norway, implemented an automatic dosing system in 2016. The treatment plant has since seen a reduced usage of coagulants in the chemical treatment process, but there is further room for optimization at the treatment plant. The next chapter introduces the treatment plant in Drammen and the issues present at the coagulation stage. Chapter Three will discuss the theory relevant to the treatment plant's coagulation process and other knowledge related to the thesis work. Chapter Four explains the methods used throughout the thesis work, including data collection and analysis, evaluation procedures, and changes caused by unforeseen circumstances. Chapter Five presents the final results and discusses solutions and suggestions for further research. Finally, Chapter Six concludes with some recommendations based on the results and discussion in Chapter Five.

2. Background

This chapter presents the issue at Solumstrand treatment plant, its basic functionalities, and the goal of the thesis.

Solumstrand treatment plant uses an advanced dosing system during chemical treatment that automates and optimizes the coagulant dosage used. This process is described in Chapter 3.5.4. The dosing system is based on an algorithm that accounts for inlet parameters in the chemical coagulation process and some outlet parameters for feed-back correction. During chemical coagulation, the water flow is divided into two treatment lines that run parallel. Initially, only one of the treatment lines used the dosing system. However, at the beginning of 2020, the dosing system was implemented in the second treatment line. The dosing system now controls the dosing of both treatment lines during chemical treatment. These two treatment lines are referred to as line one and line two throughout the thesis.

After the dosing system began running on the second treatment line, discrepancies were found in the outlets of the chemical coagulation process. Since the two treatment lines received the same amount of water from the same source and used similar coagulant doses, the quality of the treated water should have been the same in both outlets. However, the outlet of line two consistently had lower pH and higher turbidity than in the outlet of line one.

The lower pH results from a larger dosage of coagulants in line two compared to line one. The higher turbidity in the outlet of line two is one of the unknown factors at the treatment plant. Even when supplying a larger dose of coagulants, the line still underperformed compared to the parallel process in line one. This difference might result from a lower treatment efficiency in line two, caused by inadequate dosing, poor settling conditions, or some mechanical discrepancies between the separation of the two lines and the chemical coagulation. However, the operators may see the discrepancy of the turbidity in the two lines and change the dosing system coefficients accordingly.

The goal of this thesis is to explore potential strategies to optimize the treatment plant in Solumstrand. The first subgoal is to determine the reason for the quality discrepancies in the

two treatment lines, and what can help reduce the difference between them. The second subgoal is to look at the polymer dosage at the treatment plant and decide whether automating polymer dosing will be helpful to the optimization process or not.

3. Theory

This chapter will focus on the underlying theory related to optimizing a wastewater treatment plant and specifics related to the Solumstrand treatment plant. The basics of coagulation and the algorithm used by DosCon will be explained, as well as the relevant process parameters for analyzing water samples.

3.1 Solumstrand Wastewater Treatment Plant

Solumstrand is a wastewater treatment plant in Drammen, Norway, with Drammensfjorden as its recipient. The plant treats the wastewater of approximately 65,000 people, including the water from surrounding industries.

The treatment plant uses a chemical-biological treatment process. The first step of the process is a biofilm facility that breaks down and removes organic matter using microorganisms attached to a medium in the biofilm. Following the biological process is the chemical coagulation process. This process uses ferric chloride as its coagulant to remove particles in the water, with micro-sand and polymer as help flocculants. The coagulation stage runs two simultaneous lines, both of which use the DosCon® automatic dosing system. Solumstrand uses the Actiflo method, a physical-chemical treatment process, to remove solid matter and phosphorus. First, the coagulant is added to the water, followed by micro-sand. This process causes the particles and the micro-sand to form bigger aggregated solid matter, called flocs. The next step is the addition of an anionic polymer strengthening the bond between the micro-sand and the flocs generated from the coagulation (Seip, 2017). The process is described in more detail in Chapter 3.5.4.

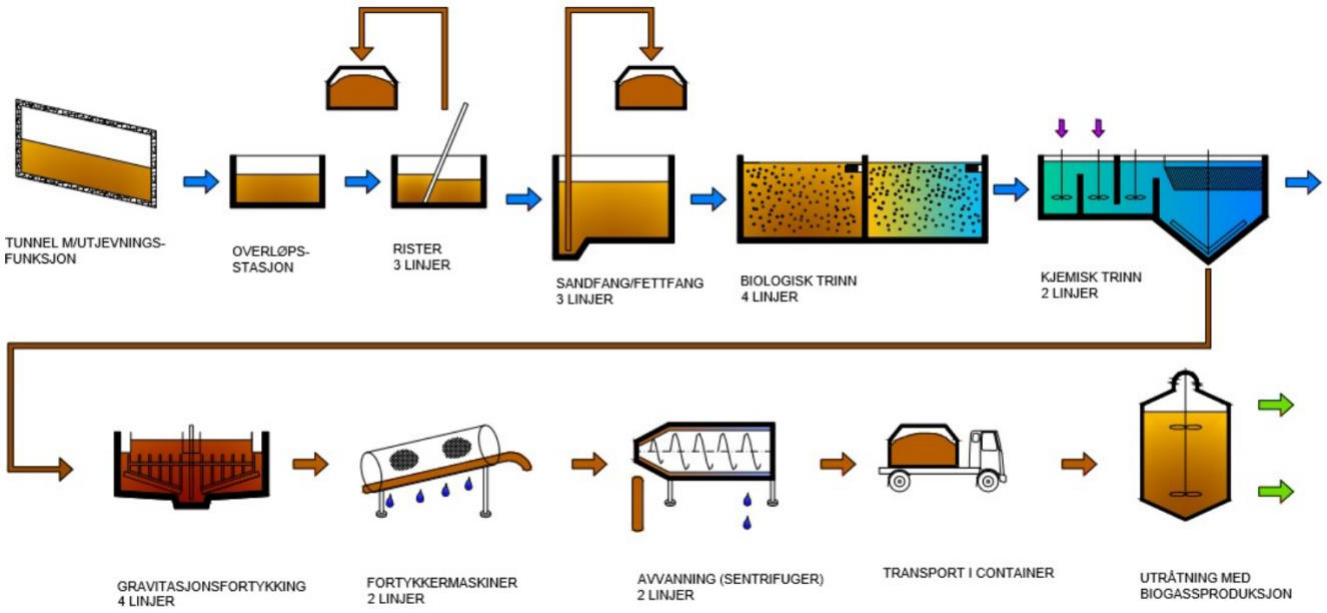

Figure 3-1: *Flowsheet of the treatment process at Solumstrand (Seip, 2017)*

3.2 Dosing Systems

3.2.1 Optimizing Dosage Control

With the advancement of coagulation technology, maximum removal of particles and phosphates is no longer the primary goal of treatment plants. Instead, optimizing dosage through controlled removal of phosphates and minimizing the usage of coagulants has become a more significant objective, to reduce sludge volume and enhance plant availability of phosphates (Ratnaweera & Fettig, 2015).

Despite jar testing being almost 100 years old, it is still used to optimize coagulant dosages. However, because it is unsuited for real-time control of a continuous process, online sensors have become a popular way to monitor raw water quality and outlet qualities. These sensors are described further in Chapter 3.6. This form of real-time control is especially necessary when the water quality changes rapidly in time and amplitude (Ratnaweera & Fettig, 2015). By giving real-time feed-back to the operators, the online sensors are more flexible than traditional methods like jar tests and can provide more accurate predictions for coagulant dosages.

3.2.2 DosCon

DosCon® produces the DosCon® controller (Fig. 3-2), which automates and optimizes the coagulation process at both water and wastewater treatment facilities. While typical dosage methods use jar tests or the flow-proportional model, DosCon uses specific parameters to create an accurate and reliable prediction of the optimal coagulant dose (Ratnaweera & Fettig, 2015). The goal of the process is to calculate the coagulant dosage through a regression analysis that accounts for inlet wastewater quality parameters such as flow rate, turbidity, conductivity, temperature, and pH (N. Sivchenko et al., 2017).

Figure 3-2: *The DosCon® controller and the parameters measured by DosCon*

Solumstrand installed the DosCon® controller to monitor the Actiflo-process in the summer of 2016. After installation, DosCon operated on one of the two Actiflo-lines in the coagulation stage at Solumstrand. At the beginning of 2020, the controller was connected to the second treatment line, giving DosCon full access to the Actiflo-process.

3.3 Laws and Regulations for Wastewater Treatment in Norway

Solumstrand Wastewater Treatment plant follows the laws and regulations given by the wastewater directive (2004). Part four of Chapter Twelve of the wastewater directive presents the treatment demands for total phosphorus, total nitrogen, biochemical oxygen demand (BOD), chemical oxygen demand (COD) and suspended solids (SS) (Lovdata, 2020). These treatment demands are based on the yearly mean value of the water added to the wastewater plant.

The treatment plant's recipient, Drammensfjorden, is a coastal body of water. Solumstrand must follow the outlet demands for this specific body of water, and workers are required to take monthly samples at the emission point of the treatment plant to test the amounts of total phosphorus. These samples are analyzed to see if they fulfill the outlet demands given by the wastewater directive. In Drammen, the county governor in Oslo and Viken is the wastewater authority and gives outlet permission at the treatment plant (Miljødirektoratet, 2019).

Table 3-1: *Treatment demands given by the county governor of Buskerud* (Anderson & Moum, 2013)

Parameter	*Limit of Quantification (µg/l)*
Chlorophyll a	0,5
Tot-P	3,0
Tot-N	10,0
Nitrate (NO_3-N)	10,0

3.4 Parameters

This section will define the parameters that are relevant to the automatic dosing control during chemical coagulation. The subchapters will also explain each parameters' relevance and effect on the treatment plant's chemical process.

3.4.1 pH

pH is a measure of the acidity or alkalinity of a solution. The definition of pH is the logarithmic amount of hydrogen ions in a substance:

$$pH = -Log10[H^+]$$

The pH of untreated sewage water can vary. pH is an important parameter during the coagulation process, and optimal conditions are dependent on optimal pH. Incorrect pH measurements can lead to insufficient removal of turbidity, natural organic matter (NOM), pathogens, taste, and an increase in sludge production.

At a treatment plant, the pH might need to be adjusted during treatment. Different processes will require different pH levels; even different coagulants require different pH levels. To achieve this, the plant adds a base or an acid to change the pH to the desired level. It can also add excessive amounts of coagulants to reach the same effect. Several of the treatment processes will change the pH and must be accounted for when treating the wastewater.

3.4.2 Turbidity

Turbidity is the measurement of how many particles are in the water and how sludgy the water is. It is measured by testing the water's light dispersion. The measurement is done by sending a light source through the water and having a sensor capture the dispersed light. An increased light dispersion intensity means that there are more particles in the water and that the water has higher turbidity than a sample with less light dispersion. The units used for turbidity are Formazin Nephelometric Units [FNU] and Nephelometric Turbidity Unit [NTU]. The two units have the same conversion, meaning one NTU equals one FNU, but the measurement methods are different. NTU is best used to read turbidity measurements performed with a white light at a 90-degree detection angle, while FNU is used when the analysis is performed at a 90-degree detection angle through a near-infrared light (YSI Inc, 2020). NTU is the most common unit and is used when standard methods of measuring turbidity are used.

Turbidity is an important parameter because it indicates how dirty the water is. By reading the turbidity, one can also estimate the suspended solids and the dissolved colored material in the water. However, it should not be used as an exact measurement. The turbidity will not include settled solids or sediments that roll along the container's bottom with the water. In general, turbidity is used as a primary indicator of water quality.

3.4.3 Total Suspended Solids

Total Suspended Solids (SS) is a measurement of the concentration of particles in the water. SS will consist of both settleable matters and freely floating material. The unit for SS is [SS/m^3] and is found by filtrating a certain amount of water and weighing the deposited particles after drying. As with turbidity, SS is a highly visible water parameter and is essential in wastewater treatment. SS is used for dimensioning, operation control, and emission control. Excessive amounts of SS can lead to lower water quality, lower navigation for the water due to blockage, and increased flood risks (Fondriest Environmental Inc, 2014)

3.4.4 Total Phosphorus and Orthophosphates

Total phosphorus (Tot-P) is the total amount of phosphorus, both organic and inorganic, found in water. Inorganic phosphorus can be divided further into orthophosphates (PO_4^{3-}) and polyphosphates ($P_2O_7^{4-}$ and $P_3O_{10}{}^{5-}$) (Ødegaard, 2014).

Orthophosphates and total phosphorus are vital parameters in the wastewater treatment process. Plants use the orthophosphates in phosphorus as nutrition, and the two parameters are therefore analyzed separately. Orthophosphates and total phosphorus are commonly found using a laboratory analyzer and are both measured in [mg/L].

Phosphorus is commonly removed through chemical coagulation in Norway. Biological treatment can also be used to remove phosphorus, but it is uncommon in Norway due to the lack of easily degradable organic material (Ødegaard, 2014). Phosphorus is a natural nutrient in water, but controlling its emission is vital for the environment. A large concentration of phosphorus can lead to structural changes in the ecosystem at the recipient of the wastewater plant.

3.4.5 Conductivity

Conductivity is a measurement of the amount of salt in the water and is measured in [µS/cm]. A high concentration leads to an increased ability to conduct electricity. This measurement is often used to look for leakage from seawater, as well as to look for signs of corrosion in the pipelines.

3.5 Coagulation

3.5.1 Coagulation in Wastewater Treatment

The primary purpose of coagulation in wastewater plants is to remove dissolved phosphorus and particles in colloidal form. Coagulation in wastewater mainly creates three chemical reactions: Precipitation of metal hydroxides (1), precipitation of metal phosphates (2), and an inert reaction. The reactions happen in parallel, and the first two can be simplified as (Ødegaard, 2014):

(1) $Me^{3+} + 3H_2O \rightleftarrows Me(OH)_3 + 3H^+$

(2) $Me^{3+} + H_3PO_4 \rightleftarrows MePO_4 + 3H^+$

[Me] is used as the common denominator for metals used in coagulation, such as iron and aluminum. The metal reacts with both the phosphates in the water, as well as with the water itself, giving precipitation of both metal phosphates and metal hydroxides simultaneously. Even though these equations are simplified, they explain how there is no pure precipitation of phosphates, and how the coagulation affects the water's alkalinity and pH. The acidic nature of the two reactions causes the water's pH to drop when metals are used as coagulants.

3.5.2 Ferric Chloride

Solumstrand treatment plant uses ferric chloride ($FeCl_3$), a dark-brown solution that is highly acidic and corrosive, as its coagulant (Ødegaard, 2014). The iron cations are subjected to hydration reactions in the water and form insoluble metal hydroxides (Gabelich et al., 2002). It is used to remove impurities as well as to sequester odors. Below pH values of 8, Fe^{3+}, $Fe(OH)_2$, and $FeOH2^+$ are the main soluble species in the coagulant, but the concentrations are still magnitudes lower than that of $Fe(OH)_{3(s)}$ (Gabelich et al., 2002).

The general equation for ferric chloride ($FeCl_3$) added to waters with natural bicarbonate alkalinity is:

$2\ FeCl_3 + 3\ Ca(HCO_3)_2 \rightarrow 2\ Fe(OH)_3 + 3\ CaCl_2 + 6\ CO_2$

(Mallevialle et al., 1996)

3.5.3 Micro-sand and Polymers

In addition to ferric chloride, polymers and micro-sand are often added to the chemical treatment process in modern wastewater treatment plants. The addition of these materials creates a ballasted coagulation process, where the goal is to develop larger flocs that can settle and be filtered out faster and more efficiently. This ballasted sand flocculation process is called the Actiflo method and was introduced in 1990 (Kumar et al., 2016).

Micro-sand as a ballast material has become a common and efficient method of treating wastewater in recent years. It increases both the velocity and the overflow rate of the process, reducing the system's footprint compared to conventional coagulation processes (Kumar et al., 2016). The size and dosage of micro-sand depend on the treatment plant, but it is usually sized between 40-150µm and is dosed in a range of two to twelve grams per liter (Kumar et al., 2016).

The dosing of micro-sand is determined by using an Imhoff cone (Nadya et al., 2015). This method determines the concentration of micro-sand balance at any given time. The Actiflo system will pursue a micro-sand concentration between 1.6 and 3.0 kilogram per cubic meter. The loss of micro-sand can then be determined theoretically by performing a micro-sand test and calculating the current balance and the required amount to be added back to the Actiflo system (Nadya et al., 2015). The micro-sand balance is given by the equation (Nadya et al., 2015):

$$m = \frac{n \times 1.5 \times 144\frac{m^3}{hr} \times 2}{4416.67\frac{m^3}{hr}}$$

Table 3-2: *Description of the variables and constants applied in the micro-sand balance equation.*

Description	*Variable/Constant*	*Unit*
Reading of micro-sand balance test	*n*	$[kg/m^3]$
Specific gravity of micro-sand	1.5	Not Applicable
Recirculation pump volumetric flow rate	144	$[m^3/hr]$
Number of recirculation pumps	2	Not Applicable
Actiflo tank volumetric flow rate	4416.67	$[m^3/hr]$

Without proper control of the dosing of micro-sand, overdosing will be a common issue. Overdosing micro-sand leads to poor recirculation, wastage, and increased maintenance costs due to the equipment breaking down from the excessive use of micro-sand.

Polymers can be added to the treatment process along with micro-sand. Polymers are large organic molecules that are added to the treatment process to improve coagulation and flocculation. They are often called “help coagulants” because they help the main coagulant with the flocculation process. Polymers are usually synthetically made and are either cationic, anionic, or non-ionic, depending on their electrical charge (Ødegaard, 2014). Even though polymers of all charges can be used as flocculants, anionic polymers are most commonly used in combination with a cationic coagulant like iron or aluminum (Ødegaard, 2014). When using anionic polymers, a coagulation mechanism called floc bridging takes place. The polymers stick to a particle’s surface, and when several particles gather along with the polymers, a chain of bridge flocs are created.

Although coagulants are commonly added through a dosing system, polymers are usually added manually, with either a constant or a flow-proportional dose. The use of manual dosing is due to the complexity of the flocculation and the polymer’s costs. Costs related to wasting polymers through control-dosing inaccuracies are significantly higher than costs caused by wastage of coagulants. Due to these restrictions, dosing control needs to be very flexible and precise before it can be considered a reliable polymer dosing process.

3.5.4 Actiflo

Solumstrand treatment plant uses the physical-chemical treatment process Actiflo when treating wastewater. The Actiflo method is utilized because of its efficient removal of suspended solids and phosphorus. Actiflo combines chemical precipitation and lamella settling with micro-sand incorporation into the flocs, resulting in a weighted settling (Fig. 3-3). Doing this increases the settling speed, optimizing the coagulation process of the plant.

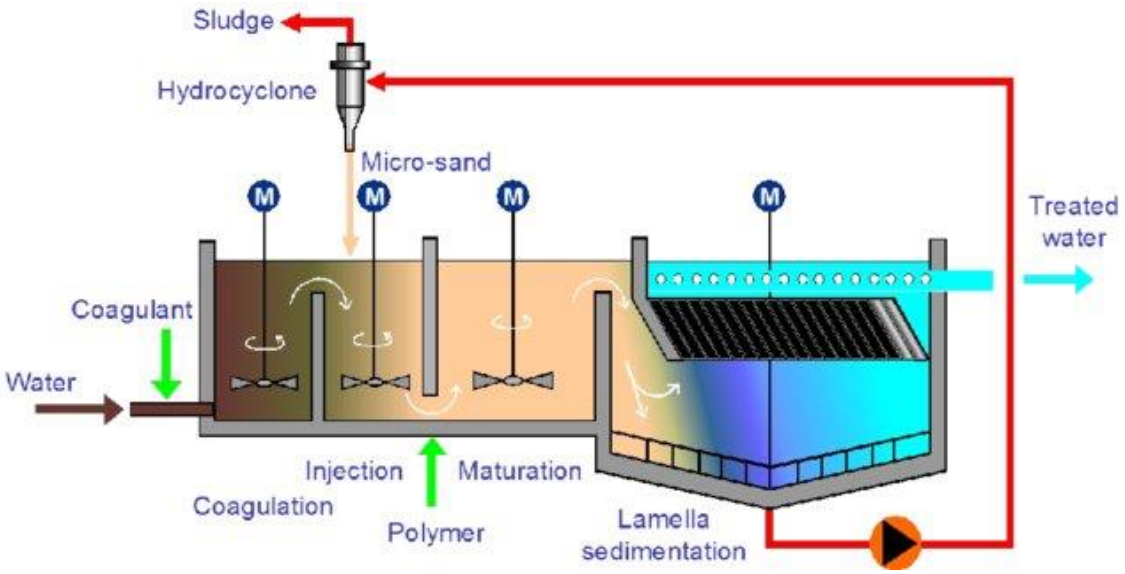

Figure 3-3: *Outline of an Actiflo plant* (Margareta et al., 2017)

The first step of the Actiflo-process at Solumstrand is the ferric chloride's addition before it reaches the injection tank. Then, when the water reaches the injection tank, micro-sand is added. The materials are mixed at a high number of revolutions per minute (RPM) to enhance floc formation and increase settling speed (Kumar et al., 2016). When the water reaches the maturation tank, the Superfloc A130HMW polymer is added, and the mixing process continues at a lower RPM (Kumar et al., 2016; Plum et al., 1998). The addition of the polymer leads to larger flocs forming in the maturation tank. Once the water reaches the lamella separator, the flocs settle quickly, due to the weight added from the micro-sand (Plum et al., 1998).

3.6 Real-Time Sensors

Real-time sensors are used at treatment plants to supervise and control the treatment process at treatment plants. Using these sensors makes the process more flexible to changes in the dosage system. Direct dosage control is based on these real-time parameters. It can be divided into three main models: Feed-forward control based on the inlet qualities, feed-back control based on outlet qualities, and feed-back control based on dosed water quality (Ratnaweera & Fettig, 2015).

3.6.1 The DosCon® Controller

The DosCon® controller uses a regression analysis based on flow rate, turbidity, conductivity, temperature, and pH at the plant's inlet and outlet, to calculate an optimized dosage of coagulants. The algorithm is based on the feed-forward model, with feed-back correction. This algorithm focuses on the inlet qualities with some outlet qualities, like outlet turbidity, used as feed-back for dosage control(Liu & Ratnaweera, 2016, 2017). The main disadvantage with a simple feed-forward system is the low flexibility when handling unmeasured disturbances. Situations such as heavy rainfall will lead to unexpected outlet qualities, and since these qualities will not impact the dosage prediction, the system will not update the dosage (Liu & Ratnaweera, 2016). With the implementation of feed-back corrections, these unmeasured disturbances and inaccurate dosages can be corrected (Liu & Ratnaweera, 2016). The water going through Solumstrand has a residual time of approximately fifteen minutes. With a low residual time, the system can correct the dosage through feed-back corrections more accurately than at a treatment plant with higher residual time.

3.6.2 SCADA

Supervisory Control And Data Acquisition (SCADA) is a computer-based system that optimizes control processes by controlling them remotely (Spellman, 2013). Using a central computer, an operator can control and monitor multiple networked computers at remote locations, enabling them to control mechanical processes such as pumps and valves.

SCADA in wastewater treatment has its strengths and weaknesses. On the one hand, automation can help optimize processes and reduce human flaws by controlling the dosage itself (Seip, 2017). On the other hand, there are some significant security concerns related to the system because they are often part of critical infrastructure. Due to the possibilities of cyberattacks, network security is crucial when automating and monitoring processes with SCADA.

3.7 Statistical Analysis

Statistical tools are used to model, predict, and optimize wastewater treatment processes. Multivariate analysis (MVA) is commonly used to analyze several variables at the same time. MVA is based on the principles of multivariate statistics, and this technique is often used to find a relationship between the measurements and the structure of experimental data (Olkin & Sampson, 2001).

This thesis will use MVA mainly in the form of Principal Component Analysis (PCA), Partial Least Square Regression (PLSR) and Linear Discriminant Analysis (LDA), with some use of Principal Component Regressions (PCR) and Multiple Linear Regressions (MLR), to find a relation between the variables measured at the wastewater treatment plant.

Variance, covariance, and correlation are terms commonly used to describe the output when using statistical analysis. Understanding these terms is vital to make proper use of multivariate analysis. When explained mathematically, *x* and *y* are used as variables, while $\overline{x}$ and $\overline{y}$ are used as their respective averages. The amount of measurements is described by *n*, and *i* is the number of the observation. For smaller quantities of measures, *n – 1* is typically used as a divisor instead of *n* (Johnson & Wichern, 2007).

Variance is a measure of the spread between a selection of data. This variance is an estimate of the actual theoretical variance and is given by Johnson and Wichern (2007) as:

$$Var(x) = \frac{1}{n-1}\sum_{i=1}^{n}(xi - \bar{x})^2$$

Covariance is a measure of the linear context between the included variables. When the variables correlate with each other when they are of similar value, the covariance is positive. Similarly, a covariance will be negative if the greater value of one variable corresponds to the other variable's lesser value. Mathematically this is explained by Johnson and Wichern (2007) as:

$$Cov(x,y) = \frac{1}{n-1}\sum_{i=1}^{n}(xi - \bar{x})(yi - \bar{y})$$

Correlation is a statistical technique used to show the relationship between variables and see if they are related to one another. Correlation is used to predict the relationship between causal variables. When variables are causal, the correlation between the variables exists because one or more of the variables are affected by another. Not all variables that correlate are causal. Correlation is explained theoretically by Johnson and Wichern (2007) as:

$$r = \frac{Cov(x,y)}{\sqrt{Var(x) * Var(y)}}$$

3.7.1 PCA

PCA is a projection method used to visualize data provided in a data table. The goal of the projection method is to compress the size of a dataset by extracting the relevant data, to simplify the description of the data set. This extraction makes it easier to analyze the structure of the observations and the variables (Abdi & Williams, 2010). By using a collection of points, new variables can be created based on the variables in the original data. The new variables will be linear combinations of the original variables. Linear combinations are often called principal components, and there are as many principal components as new variables. After creating principal components based on the correlation in the data, a new coordinate system can be created with a smaller amount of data. With unnecessary data reduced to a minimum, the dataset is easier to interpret. This type of modeling is used to differentiate samples and determine which variables contribute the most to the difference and how much each variable contributes (Camo Analytics AS, 2020).

The principal component, $i = 1, 2, \ldots, p$, is given as:

$$Yi = ei'X = ei_1X_1 + ei_2X_2 + \ldots + ei_pX_p$$

Where $X_1, X_2 \ldots X_p$ are variables of p, and ei_p is the p_{th} eigenvector component in eigenvector i (Johnson & Wichern, 2007).

3.7.2 PCR and PLSR

PCR is a regression analysis technique often performed after a PCA. The regression coefficients can be estimated by using a standard linear regression model. After completing a PCA, a select set of principal components obtained are used. The observed vector is then

regressed on the selected principal components through linear regression, resulting in a vector of the estimated regression coefficients. By transforming the vector back to scale through the PCA eigenvectors, regression coefficients characterizing the original model are created. PCR is often used to solve multicollinearity problems, when two or more variables are almost collinear, excluding some of the low-variance principal components.

PLSR is a statistical method closely related to PCR. Its main goal is to predict or analyze a set of dependent variables from a broader set of independent variables or predictors (Abdi, 2003). Imagine the vector as *Y* and the full rank as *X*. When the number of predictors is large compared to the number of observations, *X* is likely to be singular. In these situations, measures beyond a standard multiple regression are necessary due to multicollinearity (Abdi, 2003). Whereas PCR uses the principal components of the *X* matrix as regressors on *Y*, PLSR finds components from *X* that are also relevant for *Y*. The PLSR searches for a set of components that performs a decomposition of *X* and *Y* with the constraint that these components explain as much as possible of covariance between *X* and *Y* (Abdi, 2003).

3.7.3 MLR

When a linear regression model gets additional explanatory variables, they are called MLR models (Tranmer, M., Murphy, J., Elliot, M., Pampaka, 2020). As Tranmer and Elliot (2008) explained, the equation for multiple linear regressions looks the same as for simple linear regressions, but with more terms:

$$y_i = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_p x_{pi} + e_i$$

Here β_0 is the constant, as well as a predicted value of *y* when all explanatory variables are zero, and e_i is the difference between the expected value and the actual value. With *p* amounts of explanatory variables, each variable has its own β coefficient. This analysis aims to investigate how a set of explanatory variables is related to a response variable.

3.7.4 LDA

LDA is often used for classification and dimensionality reduction, similarly to PCA (Balakrishnama & Ganapathiraju, 1998). The prime difference between PCA and LDA is that PCA does feature classification, while LDA does data classification. While PCA changes the

shape and location of the original data when transformed into a different space, LDA attempts to provide more class separability, drawing a decision region between the given classes. It is often used to handle cases where within-class frequencies are unequal, and their performances have been examined on randomly-generated data sets (Balakrishnama & Ganapathiraju, 1998).

There are three classifiers available when using LDA through Unscrambler, the Linear, the Quadratic, and the Mahalanobis method. The Linear method is most effective when the difference between two groups can be explained by a linear function, while the Quadratic method is used when it is best explained by a curved line. The Mahalanobis method is a way to measure the distance between two groups of observation in k-dimensional space while considering that the k-variables may have different scales and can be intercorrelated (Garrido-Varo et al., 2019).

4. Method

An analytical approach was taken to optimize the wastewater treatment plant. Initially, water tests and lab analyses were used to help explain the discrepancies in the treatment lines. Water samples were collected manually and by using the Teledyne Isco – 6712C and were analyzed at the labs accessible at the treatment plant and at NMBU. MVAs were done on online data at Solumstrand with the statistical program Unscrambler X version 10.4.

Due to the Coronavirus pandemic (COVID-19), the data collection methods for this thesis had to be changed. The manner of collecting data changed from a lab analysis to a more theoretical research. Hypothetical solutions were sought, instead of concrete solutions to the problem. In addition, Subject Matter Experts (SMEs) were interviewed to help reach a feasible conclusion.

4.1 Equipment

4.1.1 Sensors

Solumstrand treatment plant uses industrial online sensors to measure most of the parameters in the Actiflo-process, sending data in real-time to operators. Optical sensors are used to measure turbidity and suspended solids, while the Create pH-1110A plug-in sensor is used to measure pH (Lindhjelm, 2017). Conductivity is measured by the CRD-2000 Digital Conductivity Sensor (Lindhjelm, 2017).

The turbidity and pH sensors are placed close to the lamella settlers. The turbidity sensors were tested to see if the difference in the outlet's turbidity could be due to calibration differences in the two sensors. This was a simple test performed to search for a possible reason for the discrepancies and should not be considered conclusive. The test was performed by taking the sensors out of their respective lines, drying and cleaning them off to remove residue of wastewater, and then putting them in a bucket filled with tap water (Fig. 4-1). The results were read off from a Standard Controller 100 (SC 100) (Fig.4-1). Other parameters,

such as total phosphorus and COD, are not read from real-time sensors but are tested through lab analysis twice a month at Solumstrand.

Figure 4-1: *Turbidity sensors tested in tap water and read from the SC 100*

In the short test that was performed, the results show a difference in outlet turbidity of approximately eight NTU between the two sensors. This could be caused by calibration errors or by the residue of wastewater on the sensors.

4.1.2 Programming and Statistical Algorithms

The statistical program Unscrambler X version 10.4 was used to model and predict the data available. Data gathered from online measurements was analyzed to find relationships between the relevant parameters at the inlet and outlet of the treatment plant. PCA, PLSR, LDA, MLR, and PCR analyses were run through the statistical program. Analyses were done separately for the two treatment lines.

The analyses were run on two different data sets. Data set one contained polymer data and polymer amounts used at Solumstrand. The main purpose of analyzing this data set was to interpret and predict the necessary polymer dosages through regression analyses. Data set two was taken online from SCADA and was used to interpret and predict coagulant dosages through similar regression analyses. The general purpose of these analyses was to find

relationships between polymer dosages, coagulant dosages, and other inlet and outlet wastewater parameters.

PCA

PCA analyses were run on the data sets to see correlations between variables. For the polymer data, the PCA was run with five parameters for each line; polymer amount [mg polymer per liter water], coagulant dosage [ml/m^3], inlet flow [m^3/h], outlet pH, and outlet turbidity [NTU]. PCA analyses on the SCADA data divided the parameters between those measured in each line separately, and those measured before the split into two treatment lines. Eight parameters were used in total for each analysis. Outlet turbidity [NTU], inlet flow [m^3/h], outlet pH, coagulant dosage [ml/m^3], and temperature [C] were measured separately for each of the two lines. Inlet turbidity [NTU], inlet pH and conductivity [µS/cm] were measured before the water splits into the two lines. The analyses were run with random cross-validations containing 20 segments. The algorithm used was Nonlinear Iterative Partial Least Squares (NIPALS), commonly used for finding eigenvectors (Risvik, 2007).

PLSR and PCR

PLSRs and PCRs were done on both the polymer data and on the SCADA data. The analyses were run with the same characteristics as the PCA analyses, except for the X and Y weight. These weights were set to:

$$\frac{1}{Standard\ Deviation}$$

Doing this allowed all variables to contribute to the model, regardless of whether they had a small or large standard deviation from the outset (Camo Process AS, 2006). Analyses were run separately for both of the lines in both data sets.

With the polymer data, the goal was to predict the polymer amount and the coagulant dosing with separate regression analyses. When predicting the polymer amount, a PLS regression was run with coagulant dosage, inlet flow, outlet pH, and outlet turbidity as the predictors (X) and polymer amount as the response variable (Y). The four parameters (X) built a model to predict the polymer amount (Y).

For the SCADA data, PLS regressions were run for each of the lines to create a model that predicted the coagulant dosage in the two lines. The inlet flow, outlet pH, outlet turbidity, and the temperature for each line were used as predictors (X). The conductivity, inlet pH, and

inlet turbidity were measured before the lines split into two. Coagulant dosage was used as the response variable (Y).

PCRs were also run for both data sets and compared with the PLSR results. After examining the two regression analyses, the model that best predicted the response variable (Y) was selected for each of the data sets.

MLR

MLR analyses were run for both data sets, predicting coagulant dosage, and creating a linear equation using all the coefficients from the model. The same predictors used in PCR and PLSR analyses were utilized for MLR, but validation was done through leverage correction.

A Kennard-Stone sample selection was made on an existing PCA to create a good model for the MLR on the polymer data and the SCADA data. One thousand samples were selected through uniform distribution and were used to create a new data set.

LDA

LDAs were done on the SCADA data set. Turbidity outlet values were separated into two categories in the raw data, categorizing them into values below nine and above nine [NTU]. Inlet turbidity, inlet pH, and conductivity before the line splits, as well as outlet pH, temperature, and coagulant dosage for each respective line were set as predictors, and the outlet turbidity categories were set as the classifier. The LDA models were created using the same Kennard-Stone samples that were used on the MLRs. The LDA then created a model that predicted whether the outlet turbidity would be above nine NTU or not. A good model would be able to predict the classification of the outlet turbidity with high accuracy. The analyses were run with the Linear, the Quadratic, and the Mahalanobis method.

4.2 Water Samples

Water samples were taken at Solumstrand throughout the six months. Samples were taken during both dry and wet weather and by using the Teledyne Isco – 6712C Compact Portable Sampler. Samples were taken with the portable sampler during dry weekdays, wet weekdays, and a dry weekend.

4.2.1 Manual Water Samples

The manual water samples were taken throughout February. Wet samples were collected on February 10th, while dry water samples were collected on February 24th. The water samples were collected from three areas at the treatment plant shortly before the Actiflo process. One sample was taken before the water split into two separate lines, while the other two samples were collected right before the entrance to the two Actiflo chambers. The samples were collected in 250-milliliter bottles in intervals of approximately one hour over a seven-hour period. A total of 21 bottled samples were taken.

The purpose of gathering the samples at these three specific areas was to see if the relevant parameters differed significantly from each other. A difference in values between specific parameters could be used to deduce why the treatment efficiency differed between the lines.

4.2.2 The Teledyne Isco – 6712C Compact Portable Sampler

A Teledyne Isco – 6712C Compact Portable Sampler (Fig. 4-2) was programmed to take samples over a longer period of time. It was scheduled to run over 48-hour periods. It was set to run three times, once during the weekend, once during a dry two-workday period, and once during a wet two-workday period. The sampler was set to collect eight samples per bottle. The bottles had a 500-milliliter volume, and with a total of 24 bottles, the interval between each sample was 15 minutes, each sample collecting 60 milliliters of water. It was run during the weekend of March 7th through March 9th and was exposed to both wet and dry weather.

Figure 4-2: *The Teledyne ISCO – 6712C Compact Portable Sampler* (Teledyne Isco, 2020)

The purpose of these samples was to see if there was a significant difference between the lab analysis of the parameters and the online measurements that were done in real-time. If large differences were found, some of the treatment plant's problems might lie with the sensors.

4.3 Lab Analysis

Analysis of the relevant parameters was done both on-site and at the NMBU lab, depending on the availability of the lab and its equipment. Some measurements, such as pH and turbidity, were taken on-site to prevent drifting, which would cause inaccurate results. The purpose of these analyses was to look for a quantifiable difference between the parameters in the Actiflo-process.

4.3.1 pH

pH was measured using the 'pH 3110' from WTW® (Fig. 4-3). The result was read by putting the electrode into the water sample. The pH meter was first calibrated by testing it in pH 7 and pH 4 solutions to get accurate results. The electrode was dried with a paper towel between measurements to prevent the water samples from affecting each other.

Figure 4-3: *pH 3110*

Figure 4-4: *pH-meter used for analysis at NMBU*

4.3.2 Turbidity

Turbidity was measured in the lab at NMBU, as well as on-site at Solumstrand. The wet weather samples were analyzed at NMBU using the 2100N IS Turbidimeter (Fig. 4-5). The water samples were gently shaken before being added to the turbidimeter so that the sample was homogenous. The test glass was dried before it was added to the turbidimeter to prevent light radiation from disturbing the analysis. As the samples sedimented, the value displayed on the turbidimeter decreased. Therefore, the maximum measured value was used [NTU]. After measuring a sample, the test glass was rinsed by filling it with a bit of the new sample, pouring that solution out, and then filling it up again with the new sample. This process was done to remove any residue from the previous sample that could affect the results.

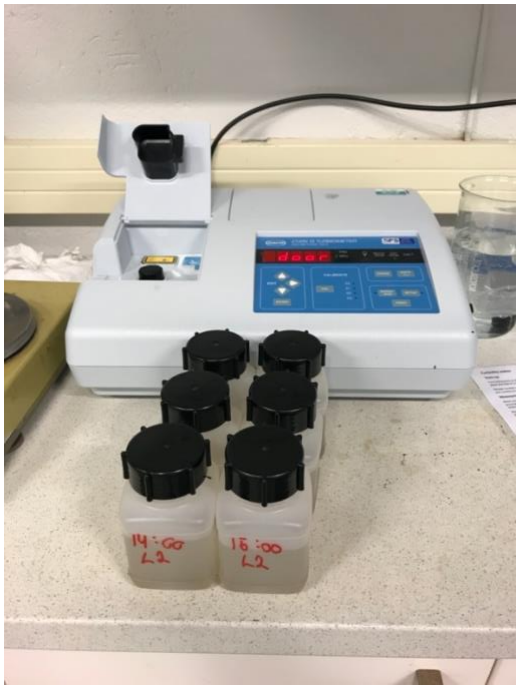

Figure 4-5: *2100N IS Turbidimeter*

The dry weather samples were measured on-site using the 2100Qis Portable Turbidimeter (Fig. 4-6). The procedure for the test glass was the same as for the 2100N IS Turbidimeter, and the results were read directly from the turbidimeter. The turbidity was measured by reading the results five times, making sure to take the test glass out, and gently flip it each time to prevent sedimentation. The calculated average of the five readings was used as the turbidity value [FNU].

Figure 4-6: *2100Qis Portable Turbidimeter*

4.3.3 Total Suspended Solids

Suspended Solids (SS) were analyzed by weighing the residue from filtrated water samples. First, the filters were prepared and weighed individually. Then, the samples were filtrated in 100-milliliter water samples, and the filters with particles on them were put into an incubator, set at 100°Celsius for approximately one hour. After drying, the filters' weights were measured again (Fig. 4-7). The weight of the filter was subtracted from the total measured mass to calculate the suspended solids' weight. The mass was then divided by the filtrated volume to get the concentration of the suspended solids in the water in milligrams per liter.

Figure 4-7: *Weighing the filter and suspended solids after drying*

4.3.4 Orthophosphates

Filtered samples were used to measure the amounts of orthophosphates in the water samples. These filtered samples were the result of filtrating the untreated water samples when measuring the suspended solids. Approximately one milliliter of each filtered water sample was run through the EasyChem Plus^{TM} from Systea (Fig. 4-8). The reactants used in the EasyChem are displayed in Table 4-1 and Table 4-2.

Figure 4-8: *The EasyChem Plus™ from Systea*

EasyChem Plus™ uses two reactants when measuring orthophosphates and total phosphorus. The water sample is first mixed with the ammonium molybdate in the first reactant (Table 4-1) to create an antimony-phospho-molybdate complex. This complex is then reduced by adding the ascorbic acid from reactant two (Table 4-2), creating an intensely blue-colored complex. The intensity of the blue color is directly proportional to the total amount of phosphorus in the water (Environmental Protection Agency, 2012). Before using the EasyChem Plus™, it was run with two test tubes, one containing deionized water and another with 1000ppm phosphate-phosphorus (PO_4-P). The PO_4-P solution is created by drying potassium dihydrogen phosphate (KH_2PO_4) in an incubator and measuring the correct amount for a 1000ppm PO_4-P solution.

Table 4-1: *Reactant one – color reactant*

Ingredient name	*Chemical formula*	*Amount*
Ammonium Molybdate 4%	$NaMoO_4 * 2\ H_2O$	15 ml
Sulfuric Acid (5M)	H_2SO_4	50 ml
Antimony Potassium Tartrate 0.3%	$K(SbO)C_4H_4O_6 * 0.5\ H_2O$	5 ml

Table 4-2: *Reactant two – reduction reactant*

Ingredient name	*Chemical formula*	*Amount*
Ascorbic Acid	$C_6H_8O_6$	4.5 g
Deionized Water	H_2O	250 ml

4.3.5 Total Phosphorus

Total phosphorus was measured using the water samples collected at Solumstrand. These samples had to be prepared before analysis. First, five milliliters of each water sample was mixed with two drops of sulfuric acid and approximately 0.1 grams of potassium peroxydisulfate (Table 4-3). This solution was then heated in a CertoClav Classic (Fig. 4-9). After the heating process, the solution was run through the EasyChem Plus™. The reactants used were the same as for orthophosphates (Table 4-1 and Table 4-2).

Table 4-3: *Ingredients used to prepare Tot-P for analysis*

Ingredient name	*Chemical formula*	*Amount*
Sulfuric Acid	H_2SO_4	0.1 ml (2 drops)
Potassium Peroxydisulfate	$K_2S_2O_8$	0.1 g

Figure 4-9: *The CertoClav Classic*

4.3.6 Conductivity

Conductivity was measured using the Cond 3210 (Fig. 4-10). When measuring conductivity, the electrode was placed into the water sample and stirred to make it more homogenous. The

conductivity was read directly from the Cond 3210 [µS/cm], and the electrode was dried between each sample.

Figure 4-10: *Cond 3210*

4.4 Evaluation Procedures

4.4.1 Structuring the Process

The thesis was initially structured with two needs in mind, the need to properly quantify the difference in the quality between the two treatment lines and the need to implement automatic dosing to the polymers. The plan was to conduct lab analyses and statistical analyses to see if there was a clear difference between the two lines and plan for the implementation of full-scale dosing of polymers. The goal was to optimize the dosage of the two parameters by performing full-scale tests of polymer and coagulation dosages.

Due to the Coronavirus pandemic, the methods had to be restructured, and some of the objectives were changed. Health precautions were implemented, and visiting the treatment plant was no longer considered safe. It was no longer an option to test the different coagulant dosages and polymer dosages, and planning the implementation of full-scale dosing of polymers became very difficult. Labs were also closed, causing the lab analyses to stop midway through and rendering the results inconclusive. Therefore, a new goal general optimization of the Actiflo-process at Solumstrand was set. This demand would be based on the lab analyses that were completed before the Coronavirus pandemic, statistical analyses of

online data, and SME's opinions. These results can provide recommendations for future work at Solumstrand after the Coronavirus pandemic has settled.

4.4.2 Discussion with Subject Matter Experts

Discussions with SMEs were vital to the thesis work to determine why the discrepancies between the lines existed. Harsha C. Ratnaweera, the founder of DosCon, and Nataliia Sivchenko, a process engineer at DosCon, were consulted throughout the thesis. The head of Solumstrand treatment plant, Alexander Vedeler, was also an important contributor to early theories, particularly concerning possibilities related to mechanical and reasons for the discrepancies. These theories included the design of the inlet duct by the Actiflo-process, a difference in individual water flow in the two lines, and opinions on whether the constant polymer dosage resulted in poor and inflexible mixing conditions.

5. Results and Discussion

The results of the thesis work will be presented in two sections. The first section focuses on the central issue stated in the thesis, the discrepancy between the two Actiflo-processes. The second section focuses on a more general problem related to polymer dosing. The first section contains visual presentations of the laboratory results and the statistical analyses to find some context and correlation for the parameters measured by the DosCon® controller. It also discusses various coagulant dosages and whether changing these dosages can optimize the treatment plant. The second section reviews the statistical results from a data set containing current polymer dosing at Solumstrand and discusses if replacing or automating the dosage could optimize the treatment process.

5.1 Two Treatment Lines – Different Treatment Results

In theory, the two Actiflo treatment lines should exhibit identical treatment results. In reality, however, treatment line two has exhibited poorer water quality. Line two has a lower pH, higher turbidity, and generally a higher use of coagulants than line one. Possible reasons and solutions to these discrepancies will be discussed in the following subchapters.

5.1.1 Consulting Subject Matter Experts

One of the main theories from the SMEs was that the treatment lines' discrepancies were due to design differences in the inlet duct. Based on blueprints and 3D-plans from when the plant was redesigned, there are two possibilities for the design of the inlet duct:

1. The water comes through a compartment that divides further into two separate compartments, where the chamber that leads to line one is smaller than the one that leads to line two.
2. Water goes through to the chamber in line one and then flows through a channel to the compartment that leads to line two.

In the first situation, the water would be divided between the two compartments, possibly through hatches. The fact that line two has a larger compartment could lead to a longer residual time because the water flow would be lower. The lower flow could cause the particles to settle for longer, resulting in poorer mixing when the coagulant is added to the injection tank.

In the second situation, some of the water in line one would flow directly to line two. The settled particles could move along the bottom of the compartment of line one and into the compartment of line two, instead of going into the injection chamber of the first Actiflo line. Line two would gain a larger number of settled particles, resulting in poorer mixing in the injection tank. The flow into compartment two would be lower than in compartment one due to compartment one's water dividing itself between the injection chamber and the compartment of line two. This division would cause longer residual time, causing the particles to settle in the water for longer and giving it higher turbidity.

Even though the DosCon® dosing system was implemented for both of the treatment lines at the beginning of 2020, the dosing is still based on a single signal from line two. This is because a second signal was not installed in treatment line one when the dosing system was implemented. Because of this, the dosing system is set to use the same coagulant dosage for both of the treatment lines despite the different outlet qualities. Theoretically, this should not be a problem, because the water flow and water qualities that enter the two lines should be the same. However, if the water flow is different in the two lines, this would mean that line two is dosed based on incorrect parameters. Because discrepancies have been found, operators compensate by slightly altering the coefficient in the algorithm of the dosing system for each specific line.

Figure 5-1: *pH and coagulant dosage at Solumstrand treatment plant throughout January 2020*

The difference in water flow can also be visualized by some of the parameters in the treatment process. Fig (5-1) shows the coagulant dosage and outlet pH at Solumstrand in January 2020. The red line portrays treatment line two, while the blue line shows treatment line one. The pH for the two treatment lines is almost the same throughout the entire month. However, the coagulant dosage is almost always higher in line two than in line one, usually around 50 l/h. This difference can especially be seen at around 11:10 on January 29th, where

the pH in the outlet of the two lines are almost identical, even though the coagulant dosage is larger in treatment line two. When the coagulant is added to the water, the pH of the water is reduced. A more significant amount of water will lead to a reduced effect on the pH from similar coagulant doses. Since the pH is seemingly less affected by the increased coagulant dosage in line two, there is a possibility that the amount of water that flows through line two is larger than in treatment line one. This observation would contradict the theory related to the design of the inlet duct previously mentioned.

Contradicting theories like this is an excellent example of why it is necessary to quantify the differences in the treatment lines accurately. Currently, the flow through each line is found by simply dividing the total flow in the inlet by two. If the design makes the water flow in different amounts in the two lines, this could lead to substantial errors in the calculated water flow of each line. Implementing sensors for individual flow in the Actiflo-lines may be beneficial in the long run for this reason. The calculations done by the DosCon® controller would be more precise by measuring the water flows individually, resulting in more optimized coagulant dosing.

5.1.2 Lab Results

Manual samples were taken on the 10th and 24th of February and were analyzed in the hydro lab at NMBU. The Teledyne Isco – 6712C was set up for a weekend sample between the 7th and 9th of March, but not all of the parameters were analyzed before the labs were closed due to COVID-19. Due to lab analysis being cut short during the thesis work, it cannot be considered conclusive. However, the results from the analyses can still be used as a starting point and visual aid. The data for figures 5-2 through 5-7 can be found in attachment A.

Manual water samples

Figures 5-2 through 5-5 represent lab results from samples collected manually. Samples were collected in varying intervals and analyzed both on-site at Solumstrand and the NMBU lab, depending on the available equipment. The figures are based on single samples and might not always be representative of the actual values at the treatment lines.

Figures 5-2 and 5-3 represent lab results from samples taken on February 10th. Due to heavy rain on February 9th, these samples were collected and analyzed as wet weather samples. These samples have a smaller concentration of particles than samples collected during dry weather. Samples were gathered from 11:00 until 16:00 in intervals of approximately one hour.

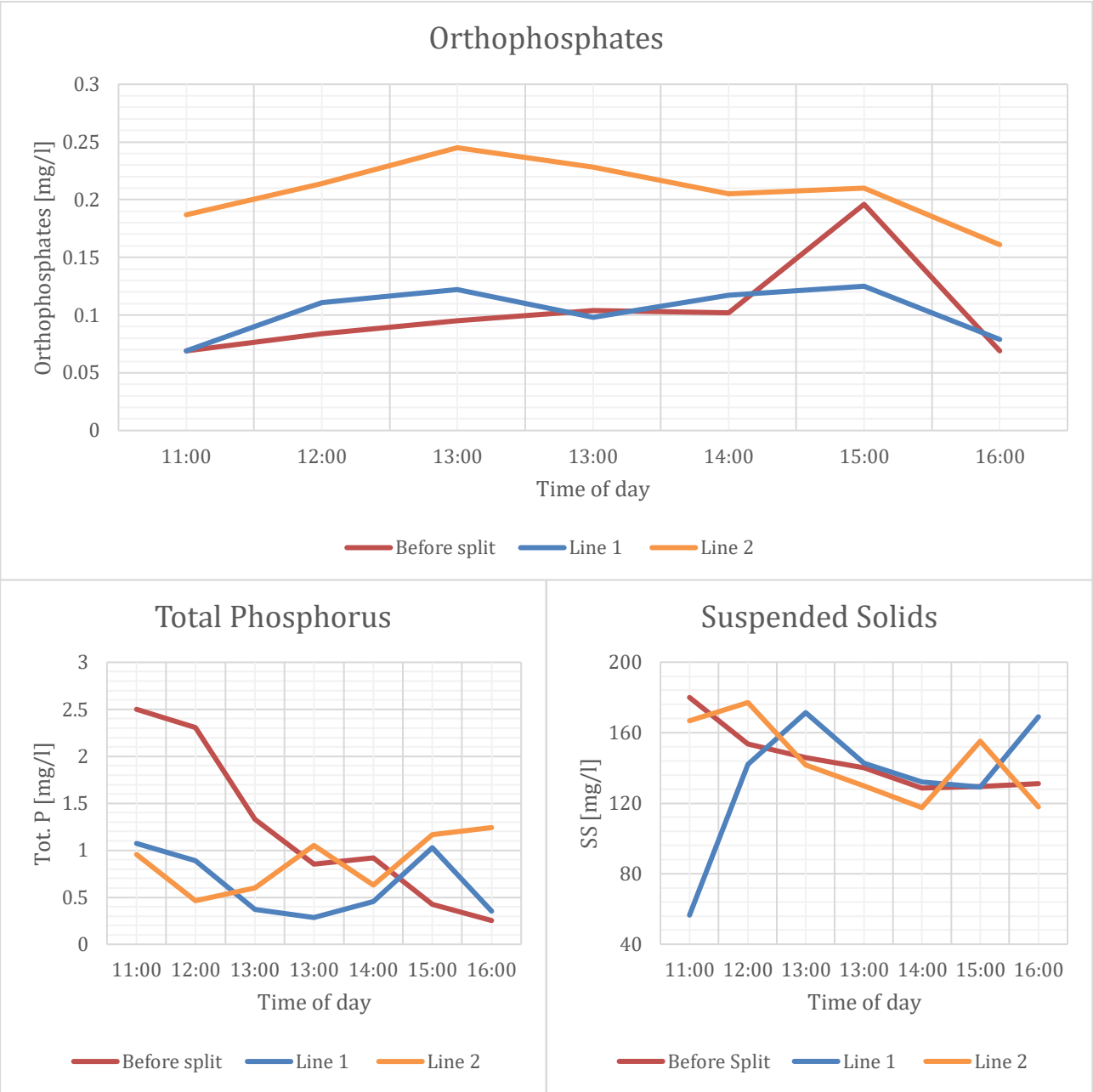

Figure 5-2: *Lab results of orthophosphates, suspended solids and total phosphorus from samples collected on February 10th*

The most consistent pattern in Figure 5-2 can be found in the orthophosphates graph. Line two contains more orthophosphates than the other two sample points at all sampling times. The outliers in the first measurements of total phosphorus and suspended solids can be considered incorrect measurements and should be ignored. Line two shows a slightly higher level of total phosphorus than line one, while the suspended solids are a bit higher in line one at most times, but they are overall reasonably similar for all sampling points.

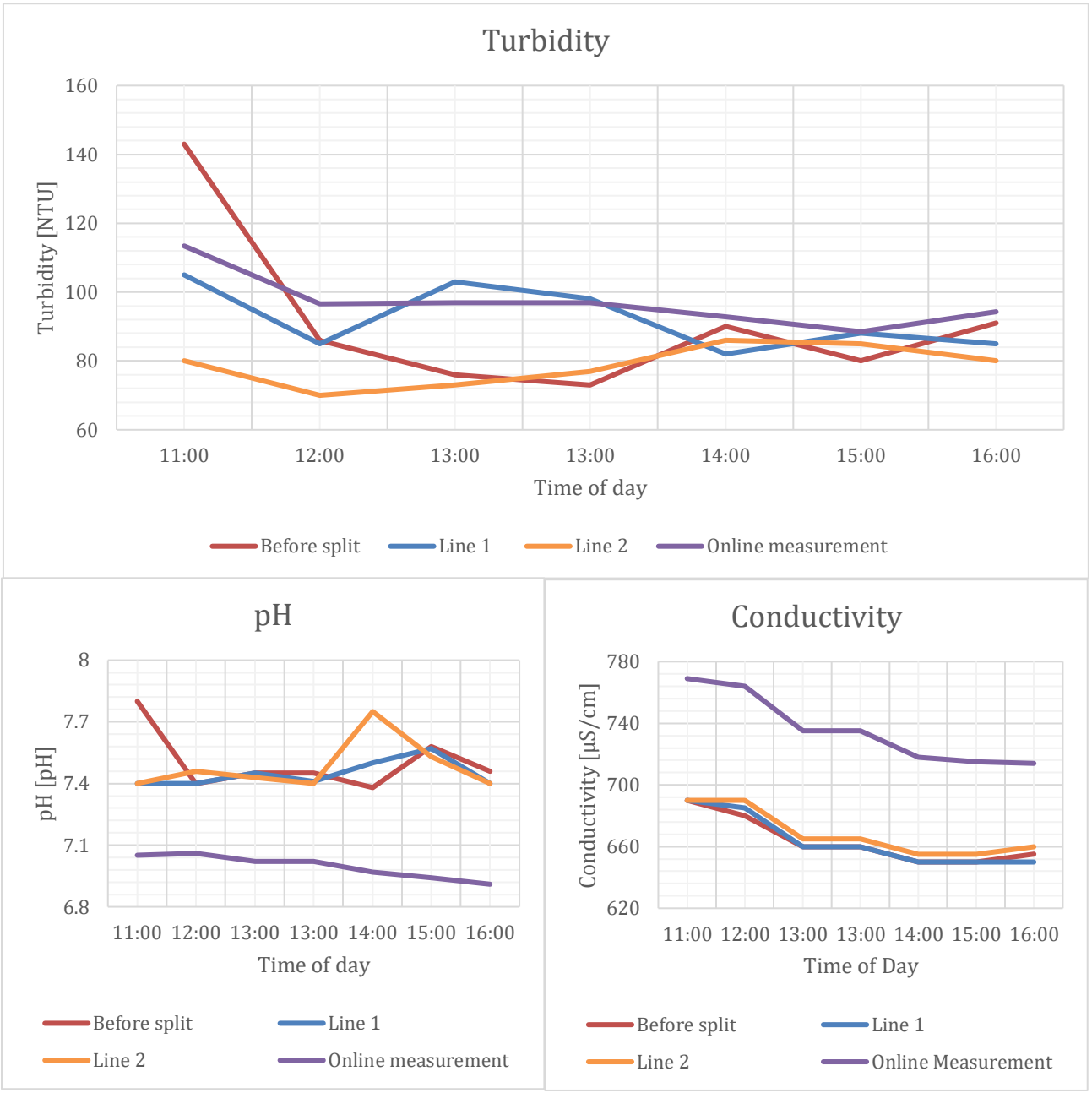

Figure 5-3: *Lab results of turbidity, pH and conductivity of samples collected on February 10th compared with online measurements*

The online measurements are included in these figures. They should be compared with the sample point before the split because the sample point is roughly in the same area that the sensors measure the parameters. These figures show that the lab results for turbidity are pretty similar to the online measurements made by the sensors. Meanwhile, lab results of both pH and conductivity show different values than the online measurements done at Solumstrand, but they have very similar patterns. These patterns mean that either the equipment used at the lab or the sensors at Solumstrand are poorly calibrated.

Figures 5-4 and 5-5 represent lab results from dry weather samples collected on February 24th. Samples were collected from 10:15 until 14:30 in intervals ranging from approximately 30 minutes to 75 minutes.

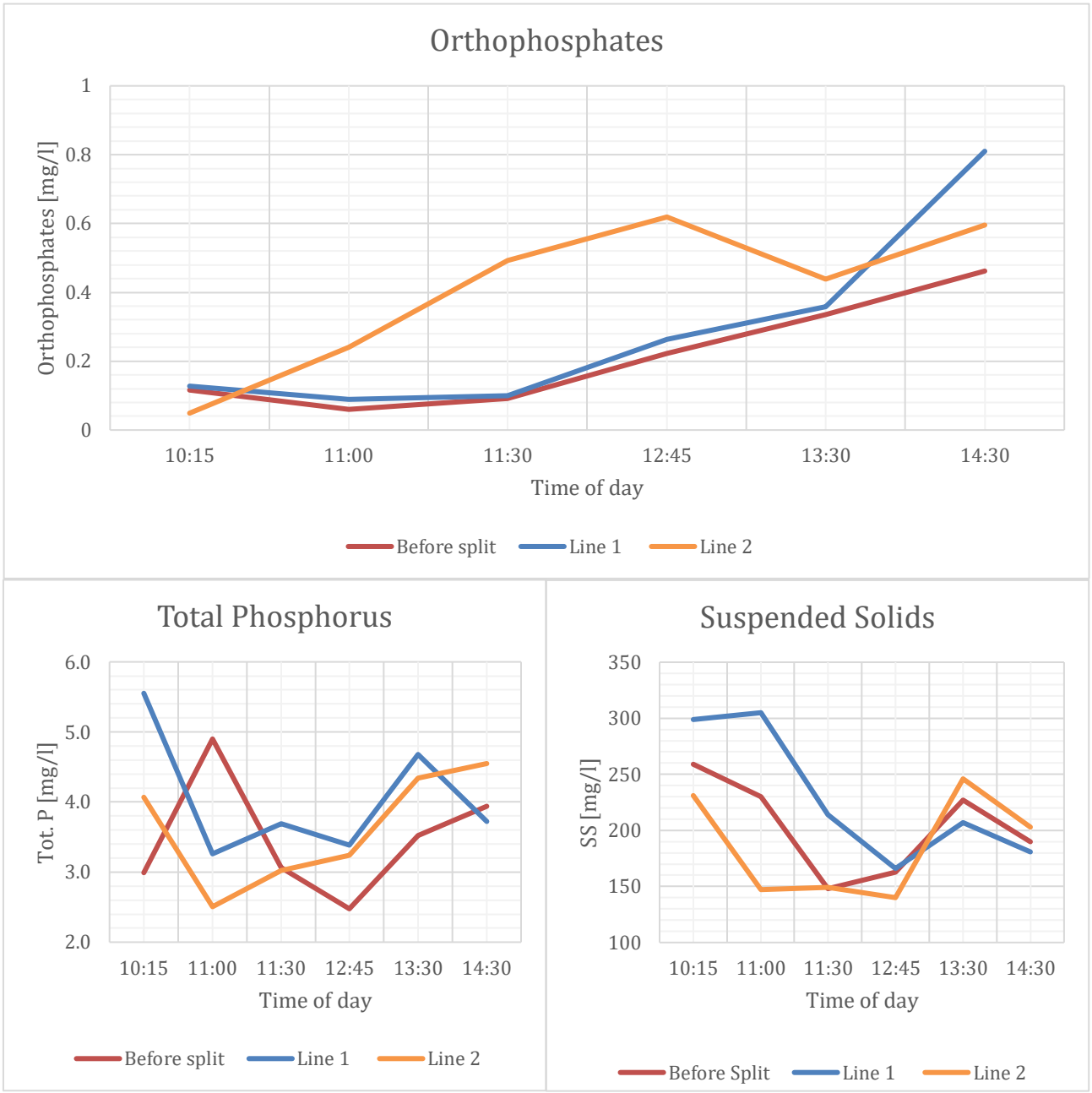

Figure 5-4: *Lab results of orthophosphates, suspended solids and total phosphorus from samples collected February 24th*

Similarly to in figure 5-2, orthophosphate levels are consistently higher in line two than in the other sample points, with a few exceptions. Suspended solids and total phosphorus are generally a bit higher in line one than in the other sample points.

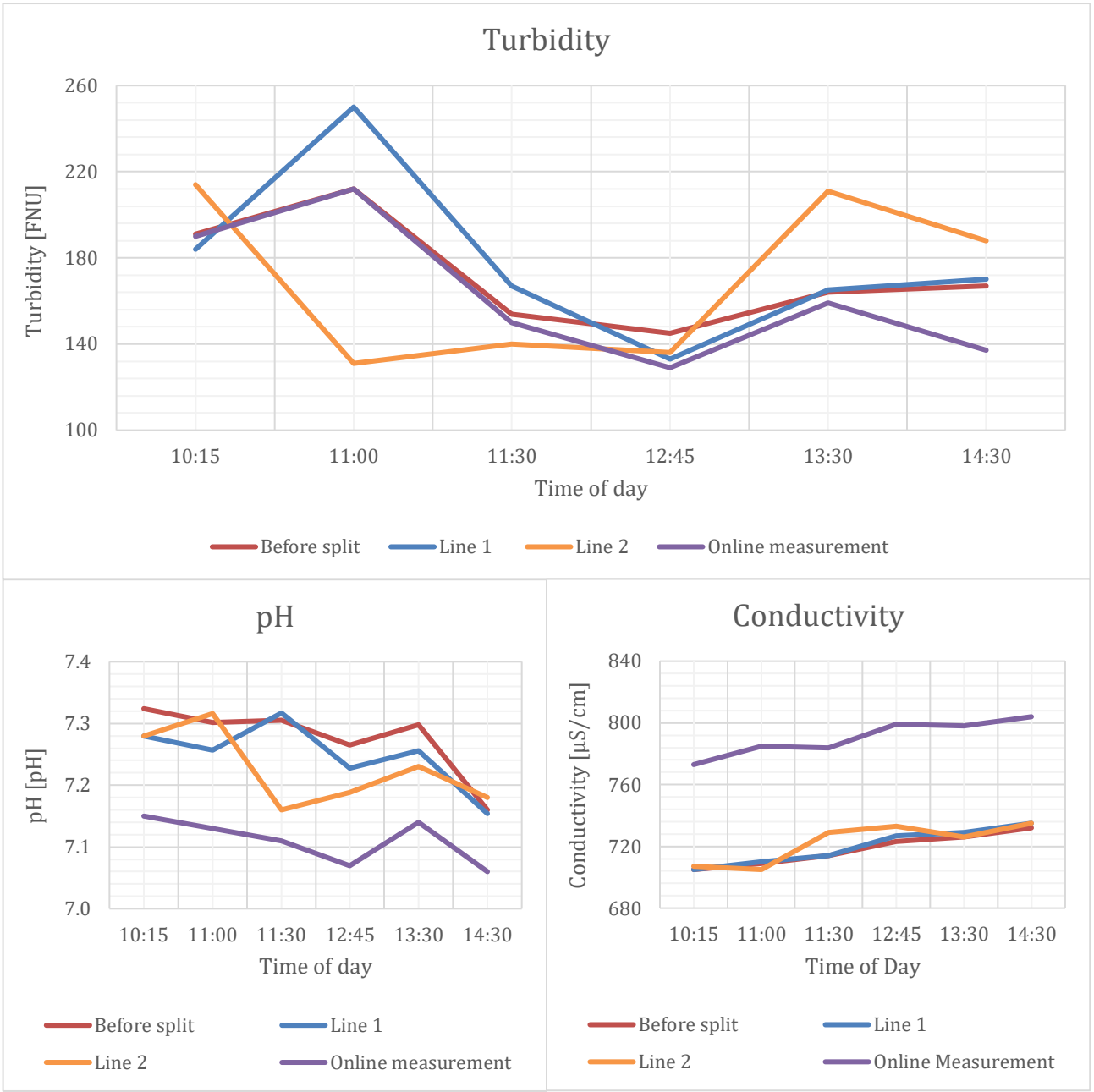

Figure 5-5: *Lab results of turbidity, pH and conductivity of samples collected on February 24th compared with online measurements*

In figure 5-5, the online measurements' patterns match the lab results for all the parameters involved. Turbidity values show no clear trend, while the pH and conductivity differ with a fairly high amount. This pattern suggests poor calibration either at Solumstrand or with the labs at NMBU, similar to figure 5-3.

Samples collected with the Teledyne Isco – 6712C

Figures 5-6 and 5-7 represent lab results from samples taken with the Teledyne Isco. These samples were collected over a 48-hour period, starting at 00:00 on March 7th and ending at 00:00 on March 9th. A bottle represents each interval, and every bottle collected eight samples over a two-hour period, resulting in 24 bottled samples.

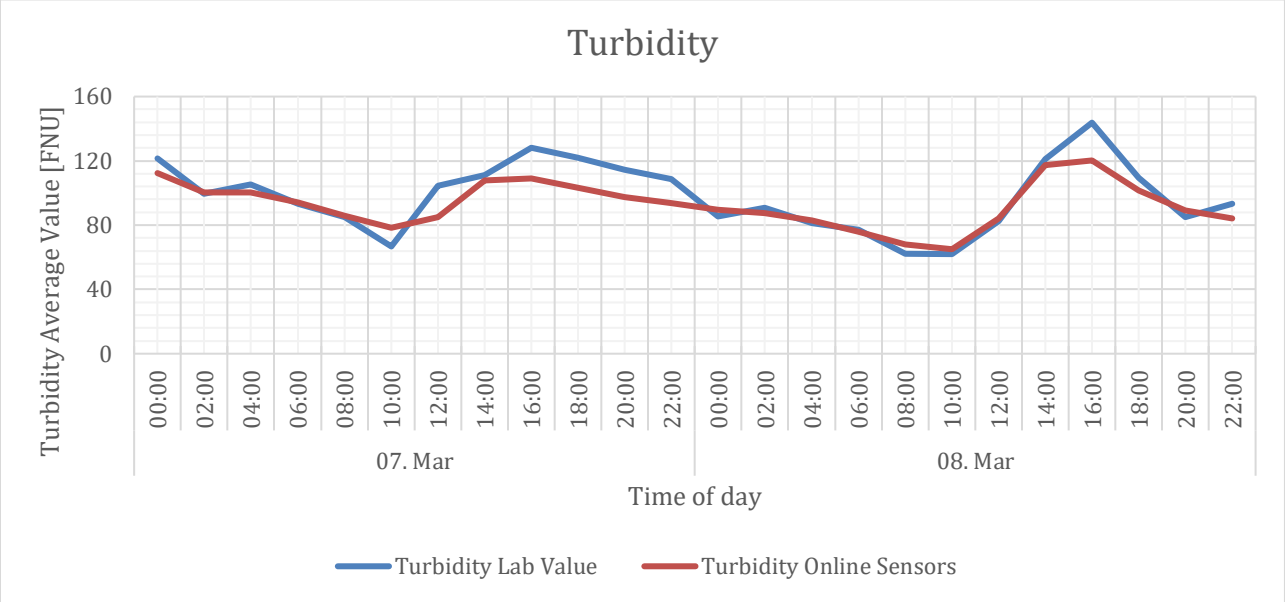

Figure 5-6: *Turbidity lab results from Teledyne sampler compared with online measurements*

Figure 5-6 shows that the values from online measurements correspond very well with values from the lab results. Because this is recurring, as seen in Figure 5-2 and 5-4, it is highly likely that the turbidity sensors were well-calibrated upon testing.

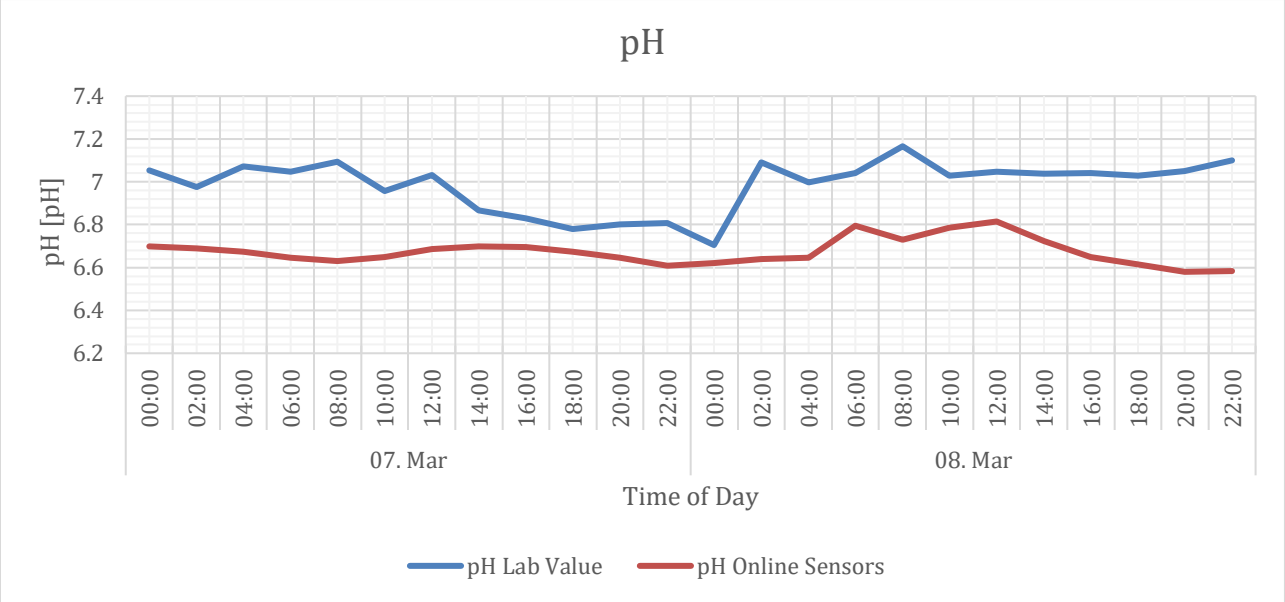

Figure 5-7: *pH lab results from Teledyne sampler compared with online measurements*

Figure 5-7 shows a discrepancy of approximately 0,31 pH on average between the online sensors and the lab results. This discrepancy could be the result of poor equipment calibrations, similar to in Figures 5-3 and 5-5. However, samples were collected and analyzed on March 11th, two days after sampling ended. The period between sample collection and analysis could have resulted in drifting of the lab's pH values, skewing the results.

These results are mostly used for visual aid to see if there is an apparent discrepancy between the parameters at the treatment plant and cannot be considered conclusive. The pH and conductivity results were quite different for each sample between the online measurements and the lab results. These differences indicate that there is a calibration problem with either the sensors at Solumstrand or with the measuring equipment at the NMBU lab. The most consistent result in the laboratory analyses is the higher number of orthophosphates in line two than in the two other sampling spots.

5.1.3 Results from Statistical Analysis

This subchapter will present and discuss the results found when analyzing the data obtained from SCADA.

PCA

In treatment line one, the PCA described 96.3% of the variance, and the cross-validation explained 95.1% of the model after outliers were removed (Table 5-1). The correlation loadings for two PCs show that inlet water flow is negatively correlated with conductivity and coagulant dosage (Fig. 5-8).

Table 5-1: *Explained variance for different PCs in treatment line one, for the calibrated and validated model*

Explained X		PC-0	PC-1	PC-2	PC-3	PC-4	PC-5	PC-6	PC-7
		1	2	3	4	5	6	7	8
Calibration	1	0,0000	84,4776	96,3297	98,8112	99,9959	99,9987	100,0000	100,0000
Validation	2	0,0000	82,2598	95,1057	98,0975	99,9919	99,9966	99,9998	99,9999

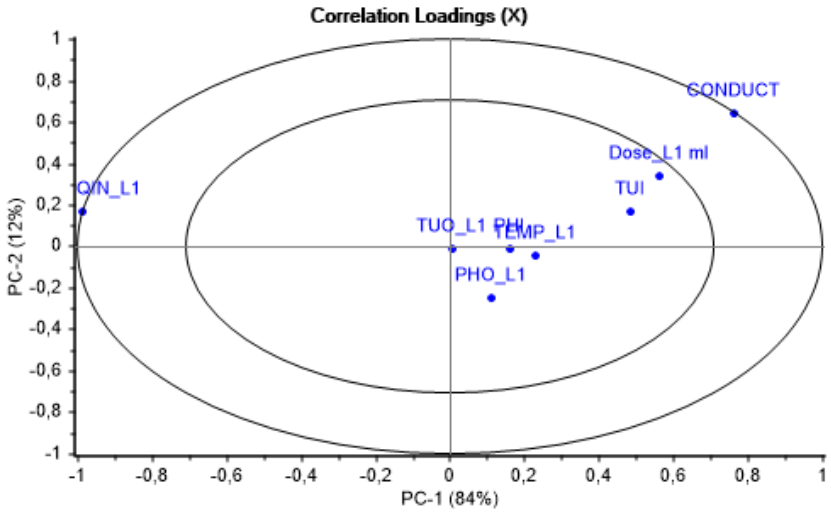

Figure 5-8: *Correlation loadings for treatment line one using two PCs*

The PCA for treatment line two showed nearly identical results for both the explained variance and the correlation loadings. Two PCs described 96.3% of the variance, while the cross-validation described 95% after outliers were removed (Table 5-2). The analysis also showed a negative correlation between inlet water flow and conductivity and coagulant dosing (Fig. 5-9). The negative correlation between inlet flow and coagulant dosing is slightly stronger in the PCA of treatment line two.

Table 5-2: *Explained variance for different PCs in treatment line two, for the calibrated and validated model*

Explained X		PC-0	PC-1	PC-2	PC-3	PC-4	PC-5	PC-6	PC-7
		1	2	3	4	5	6	7	8
Calibration	1	0,0000	84,9914	96,3175	98,7629	99,9934	99,9978	100,0000	100,0000
Validation	2	0,0000	82,8470	95,0895	98,0199	99,9869	99,9941	99,9999	99,9999

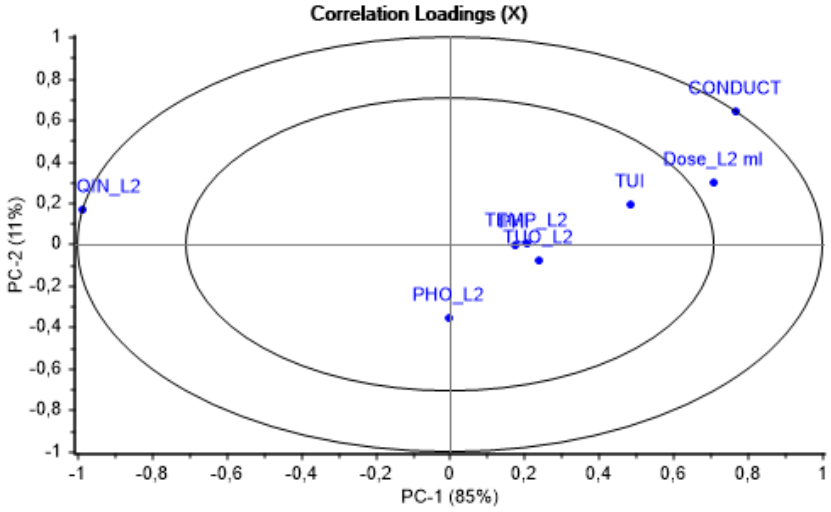

Figure 5-9: *Correlation loadings for treatment line two using two PCs*

MLR

The parameters used in treatment line one to create an MLR were the inlet turbidity, outlet turbidity, inlet flow, inlet pH, outlet pH, conductivity, and temperature. These parameters create a linear equation for the coagulant dosage:

$$Coagulant\ \left[\frac{ml}{m^3}\right] = 233{,}25 + 0{,}04\ Turbidity_{in}\ [NTU] - 7{,}50\ Turbidity_{out}\ [NTU] - 0{,}03\ Q_{in}\left[\frac{m^3}{h}\right] + 48{,}05\ pH_{in} - 81{,}13\ pH_{out} + 0{,}10\ Conductivity\ \left[\frac{\mu s}{cm}\right] + 14{,}30\ Temperature\ [C]$$

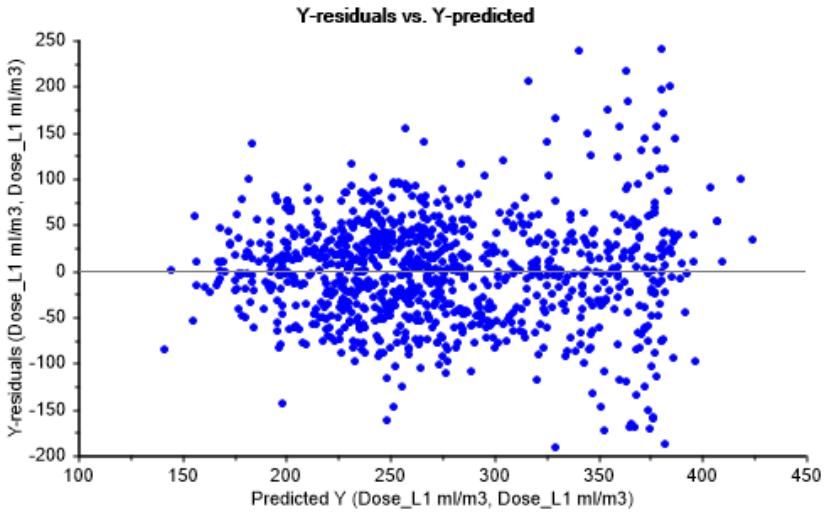

Figure 5-10: *Y-residuals versus Y-predicted from MLR analysis of treatment line one*

The MLR uses the same parameters to create a linear equation that predicts the coagulation dosage in treatment line two:

$$Coagulant\ \left[\frac{ml}{m^3}\right] = -69{,}02 + 0{,}08\ Turbidity_{in}\ [NTU] - 4{,}83\ Turbidity_{out}\ [NTU] - 0{,}07\ Q_{in}\left[\frac{m^3}{h}\right] + 56{,}95\ pH_{in} - 34{,}81\ pH_{out} + 0{,}12\ Conductivity\ \left[\frac{\mu s}{cm}\right] + 15{,}30\ Temperature\ [C]$$

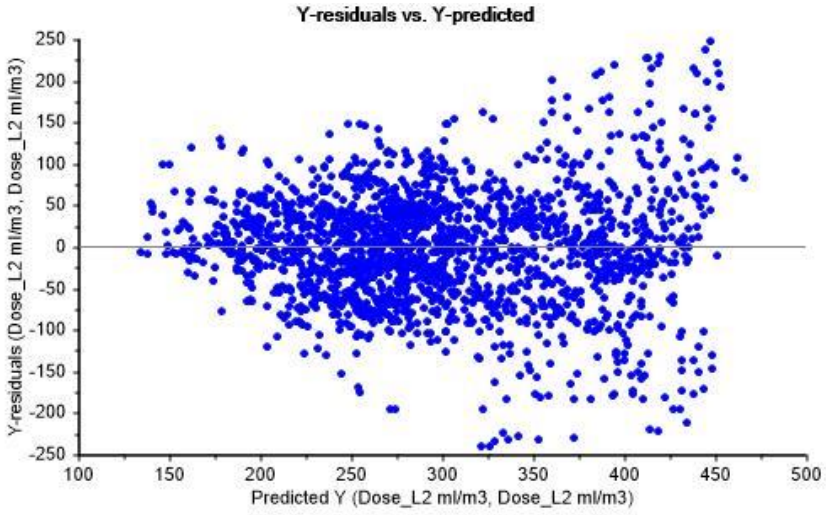

Figure 5-11: *Y-residuals versus Y-predicted from MLR analysis of treatment line two*

Figure 5-8 and Figure 5-9 show similar tendencies where a higher residual value gives a higher coagulant dosage. These conditions are most likely due to one of the treatment lines closing down, leaving the other one to dose for the entire water flow.

PLSR and PCR

For the PLSR and PCR analyses, the predictors were inlet flow, outlet pH, outlet turbidity, temperature, conductivity, inlet pH, and inlet turbidity. Coagulant dosage was set as the response variable. The PCR results were used for treatment line one because the R^2 values were higher than for the PLSR analysis, meaning more of the variation in the model is explained.

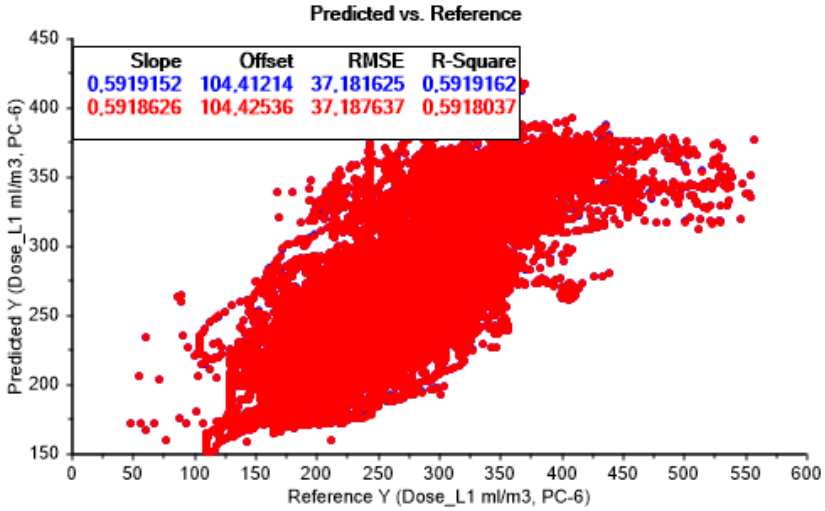

Figure 5-12: *Predicted versus reference values from PCR analysis of treatment line one*

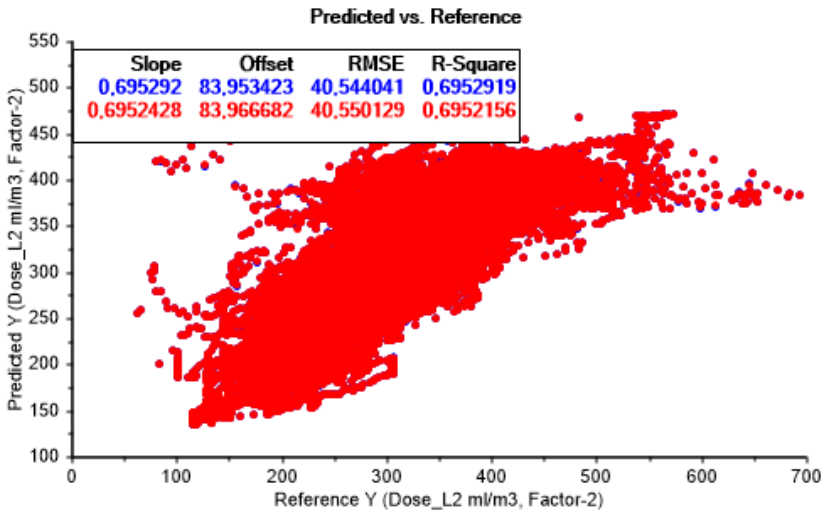

Figure 5-13: *Predicted versus reference values from PLSR analysis of treatment line two*

The explained variance for the analyses is represented by the R^2 values. The PCR of treatment line one has an R^2 value of 0.59, while the PLSR of treatment line two has an R^2

value of 0.69 (Fig. 5-12 and Fig. 5-13). These values mean that 59% and 69% of the variances respectively are explained by the model. These are poor estimations of the coagulant dosage.

LDA

The LDA analyses show high accuracy for predictions of classifications of the outlet turbidity, especially for treatment line one. The Unscrambler X settings differed a bit between the treatment lines to give the most accurate predictions for both treatment lines. For treatment line one, Unscrambler's "Prior Probabilities" setting was set to "Assume equal prior probabilities". For treatment line two, the "Prior Probabilities" setting was set to "Calculate prior probabilities from training set".

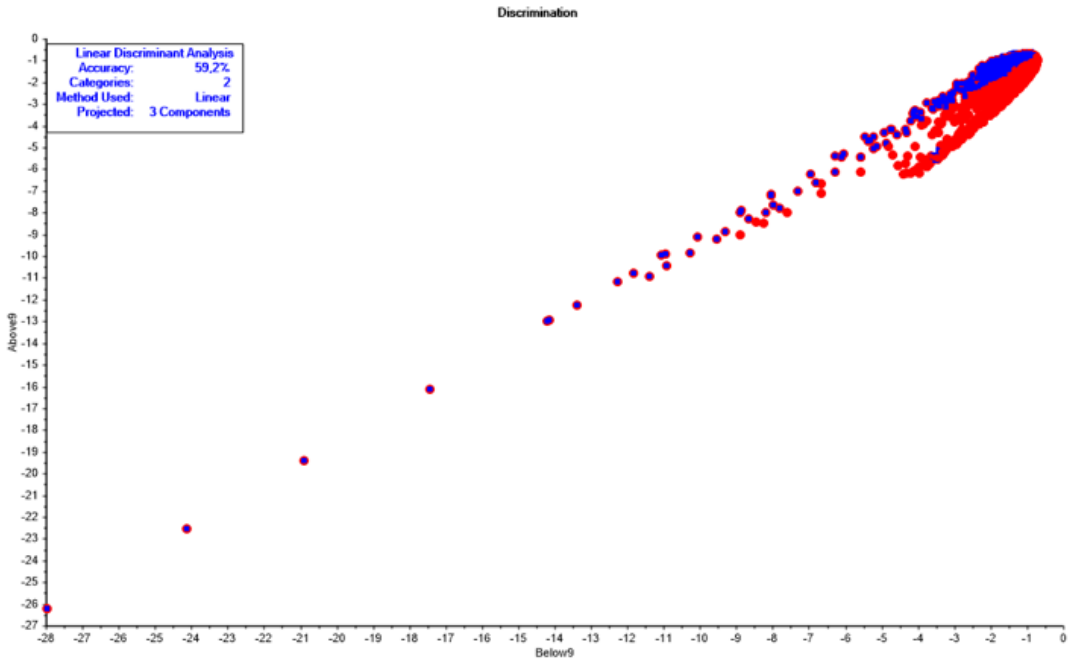

Figure 5-14: *Using the Linear method to classify the outlet turbidity in treatment line one*

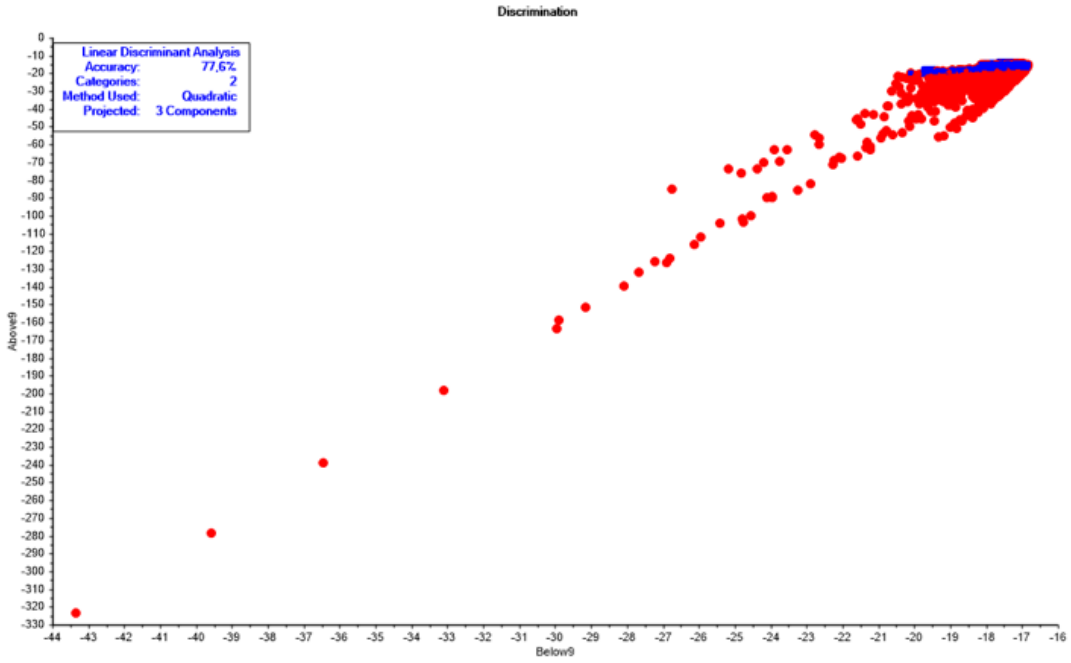

Figure 5-15: *Using the Quadratic method to classify the outlet turbidity in treatment line one*

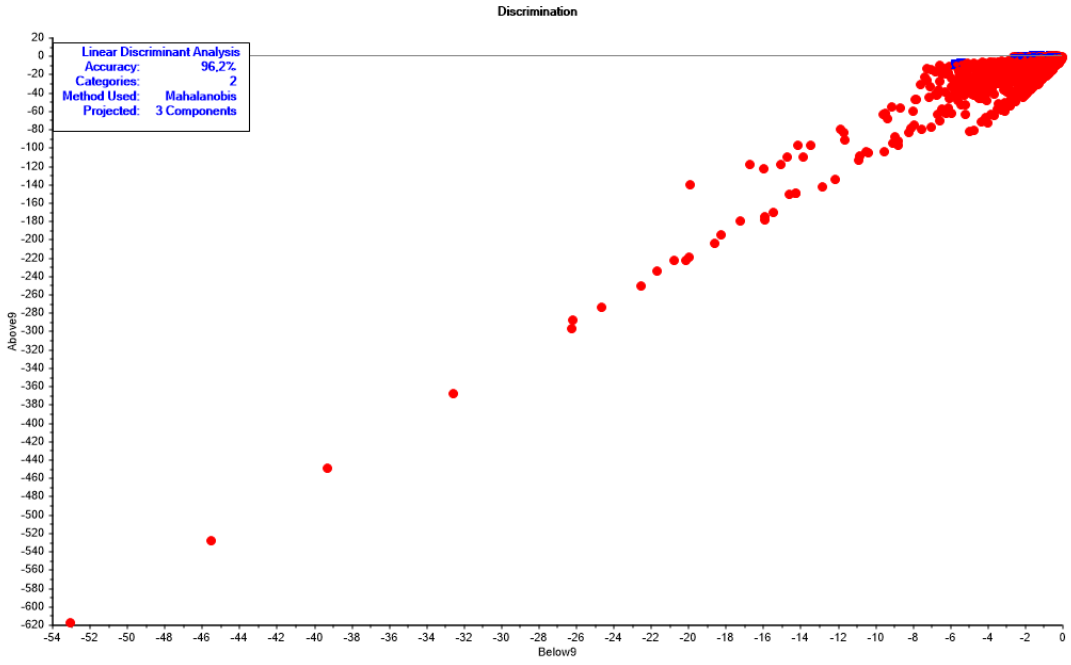

Figure 5-16: *Using the Mahalanobis method to classify the outlet turbidity in treatment line one*

Treatment line one shows an increase in accuracy from 59.2% (Fig. 5-14) with the Linear method to 77.6% (Fig. 5-15) with the Quadratic method, and 96.2% (Fig. 5-16) using the Mahalanobis method.

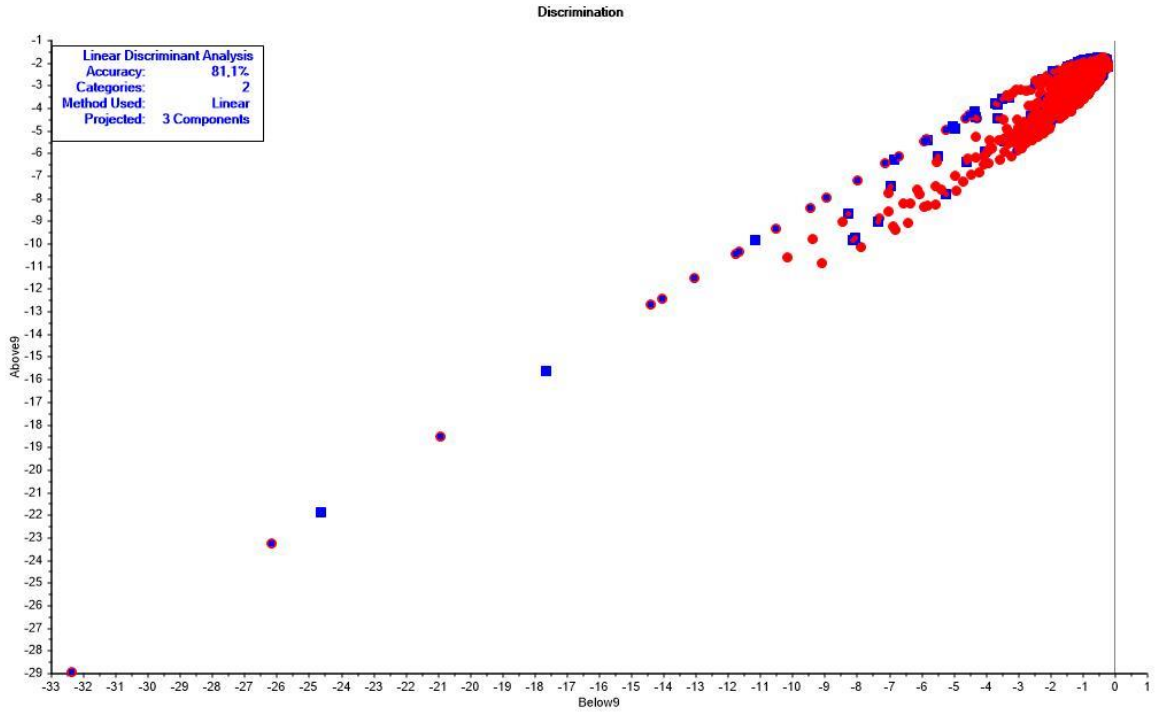

Figure 5-17: *Using the Linear method to classify the outlet turbidity in treatment line two*

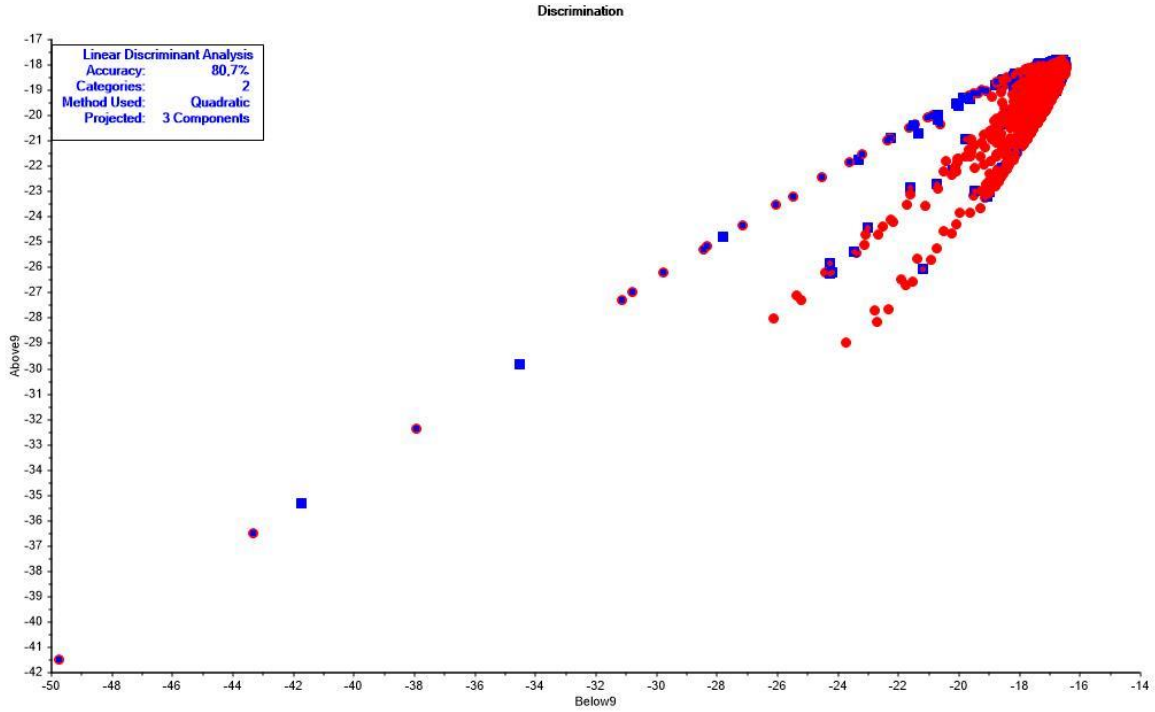

Figure 5-18: *Using the Quadratic method to classify the outlet turbidity in treatment line two*

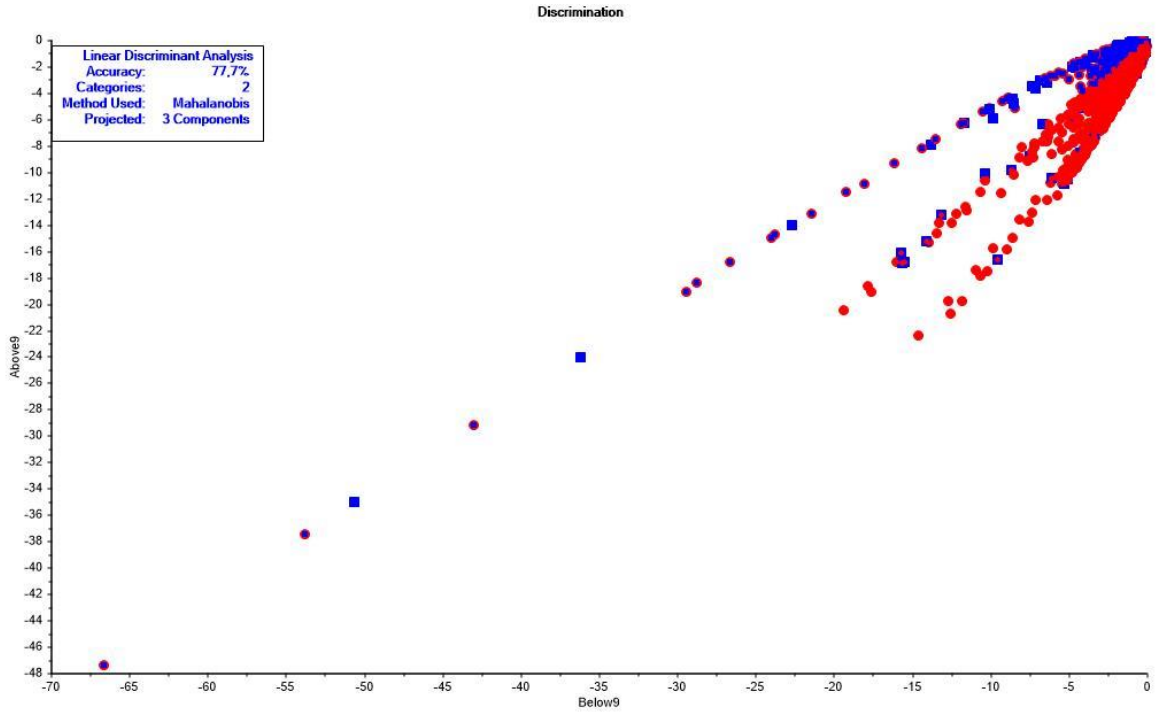

Figure 5-19: *Using the Mahalanobis method to classify the outlet turbidity in treatment line two*

Treatment line two has slightly different results in the LDA. The Mahalanobis method is the least accurate at 77.7% (Fig. 5-19), while the Linear and the Quadratic method are very similar at 81.1% and 80.7%, respectively (Fig. 5-17 and Fig. 5-18).

Table 5-3 and Table 5-4 present the confusion matrix results from the LDA with the best results performed on treatment line one and treatment line two, respectively. The confusion matrix shows the LDA predictions and quantifies how many of its predictions were correct for the two categories.

Table 5-3: *The confusion matrix of the LDA performed on treatment line one using the Mahalanobis method*

	Actual	Below 9	Above 9
Predicted			
Below 9		945	17
Above 9		21	17

The errors made in treatment line one consist of 21 incorrect guesses of outlet turbidity above nine, and 17 incorrect guesses of outlet turbidity below nine (Table 5-1). Because the outlet

turbidity is rarely above nine in the data set, 21 incorrect guesses is fairly high. These errors might be caused by the closure of one of the treatment lines. When one of the treatment lines opens up again, the outlet turbidity can increase for a short time because the new water brings the settled particles that were still in the treatment line with it. This closure and opening of the treatment lines could be influencing the parameters in the LDA, making it expect more cases of turbidity above nine.

Table 5-4: *The confusion matrix of the LDA performed on treatment line two using the Linear method*

	Actual	Below 9	Above 9
Predicted			
Below 9		803	167
Above 9		22	8

In treatment line two, 22 incorrect guesses were made for outlet turbidity above nine, and 167 incorrect guesses were made for outlet turbidity below nine (Table 5-2). In treatment line two, there are significantly more measurements of outlet turbidity above nine. Most of these measurements were predicted to be below nine by the LDA, causing the accuracy of the model to decrease.

5.1.4 Testing Different Dosages of Coagulants

The lab results presented in 5.1.2 show that turbidity values are slightly higher in line one than in the two other sampling points. However, there is not a clear enough pattern or enough sample points to consider these tests conclusive. The intention was to implement full-scale tests where different dosages of coagulants were tested in the two lines. Because line one outperforms line two, the intent was to try a smaller dosage of coagulants in line one and a larger dosage in treatment line two. By measuring the two lines and the outlet qualities, it could be determined whether using different constants in the dosing algorithms of the two lines would cause an overall water quality improvement. Due to the Coronavirus pandemic, this part of the thesis work was canceled. It is recommended to test different dosages for further optimization work at the treatment plant.

5.1.5 The Way Forward

More water samples should be analyzed in different weather conditions, both manually and by using the Teledyne Isco – 6712C to determine the cause of the discrepancies in the treatment lines. Operators on the treatment plant should be consulted, and different coagulant and polymer doses should be tested to determine whether the variances are linearly correlated.

For long-term solutions, an increased focus on sensors is necessary. Adding sensors to measure flow individually in the two lines can make calculations more precise and make it easier to adjust the coagulant's dosage in the two lines (Harsha, 2020). The current solution of calculating the flow in the two lines by merely dividing the total flow in half can create larger discrepancies than expected, assuming that the water does not flow equally into the two treatment lines. Implementing more sensors is a simple solution that can save a lot of money in the long run. Additional SS sensors can also be added to one or both lines to improve process control (Harsha, 2020). The more correct the relevant parameters sent to the DosCon® controller, the easier it will be to calculate the proper coagulant dosages.

A tracer test should be conducted to test the division of the water flow. By injecting a chemical tracing into the inlet and monitoring the levels right before the Actiflo-process, the division of the water-flow can be quantified (Axelsson et al., 2005). The water containing the tracer should run through the Actiflo-lines after approximately one hour. Performing this test several times will help the treatment plant determine the flow-paths of the treatment lines. The treatment plant can then make an informed decision about whether installing sensors that measure water flow individually is necessary or not.

Another option is emphasizing some of the outlet qualities more in the algorithm. Increasing the impact of the outlet pH when correcting the dosage can help, as the parameter's value often correlates with the water flow. If the outlet pH is lower in one treatment line, while the coagulant dosage is similar in the two treatment lines, it suggests that there is less water flowing through the treatment line with the lower outlet pH.

Installing a signal that can be read from line one is also vital to optimizing the treatment process, especially if there is a difference in water flow in the two lines. This added signal could serve as an alternative solution to installing individual water flow sensors. With the

added signal, the two treatment lines will be dosed individually, without the need of operators changing the algorithm's coefficient in the two lines. If the algorithm focuses more on the outlet pH and turbidity in the separate treatment lines, quantifying water flow might not be necessary. Dosing can then be optimized with more focus on feed-back correction from outlet qualities.

5.2 Improving General Treatment Efficiency with Polymer Dosages

The goal of this section is to at ways to optimize polymer dosing at Solumstrand. Results from statistical analyses performed with accessible polymer data will be discussed, as well as the possibilities of performing full-scale tests with different polymer dosages to see if they affect the water quality in the coagulation process.

5.2.1 Results from Statistical Analysis

This subchapter will present and discuss the statistical results found from analyzing the polymer data at Solumstrand treatment plant.

PCA

The PCA of treatment line one described 98.4% of the variance for two PCs, while the cross-validation explained 97.3% (Table 5-5). The inlet flow and the coagulant dosage for the treatment line are almost on the edge of the outer circle, meaning that they are close to the 100% explained variable ellipse (Fig. 5-20).

Table 5-5: *Explained variance for different PCs in treatment line one, for the calibrated and validated model*

Explained X		PC-0	PC-1	PC-2	PC-3
		1	2	3	4
Calibration	1	0,0000	91,2591	98,3670	99,9908
Validation	2	0,0000	89,0644	97,2753	99,9769

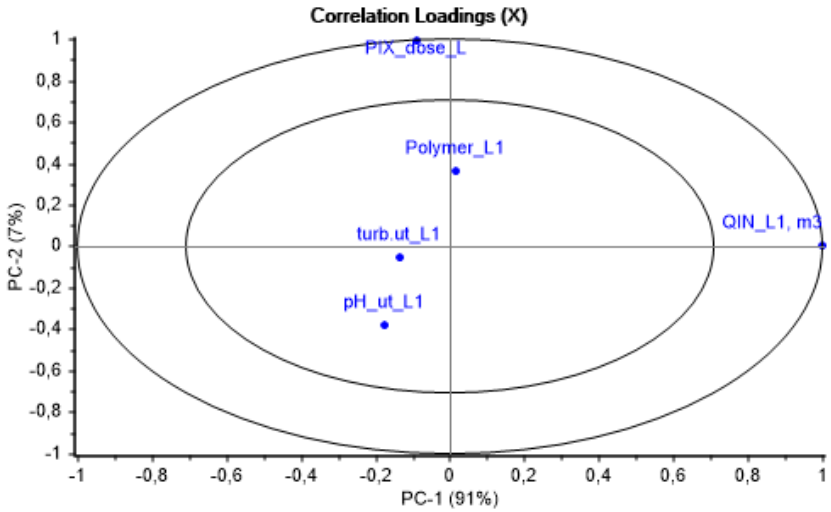

Figure 5-20: *Correlation loadings for treatment line one using two PCs*

In treatment line two, the PCA explained 98.1% of the variance for two PCs, and the cross-validation explained 96.8%. (Table 5-6). The polymer dosage has a larger effect on the explained variance than in treatment line one, and the polymer dosage and coagulant dosage are negatively correlated with inlet flow (Fig. 5-21).

Table 5-6: *Explained variance for different PCs in treatment line two, for the calibrated and validated model*

Explained X		PC-0	PC-1	PC-2	PC-3
		1	2	3	4
Calibration	1	0,0000	93,7246	98,0729	99,9882
Validation	2	0,0000	92,1529	96,7810	99,9704

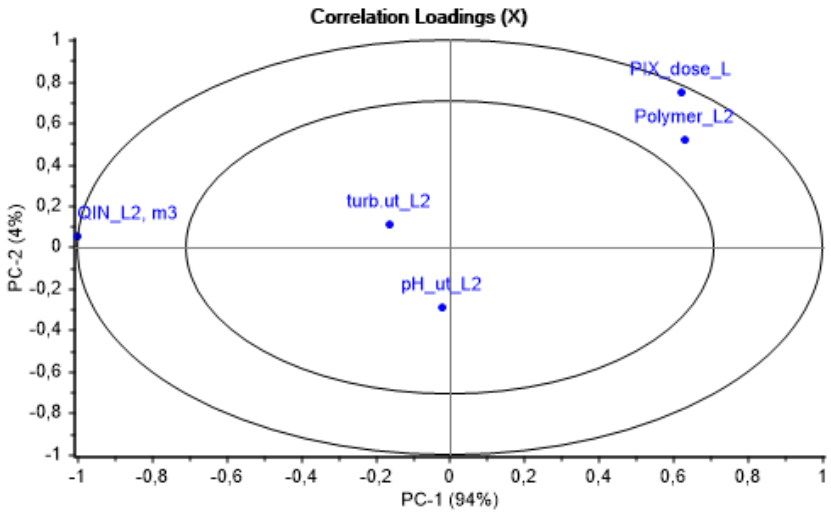

Figure 5-21: *Correlation loadings for treatment line one using two PCs*

PLSR and PCR

The PLSR analyses used coagulant dosage, inlet flow, outlet pH, and outlet turbidity as the predictors (X) and polymer amount as the response variable (Y).

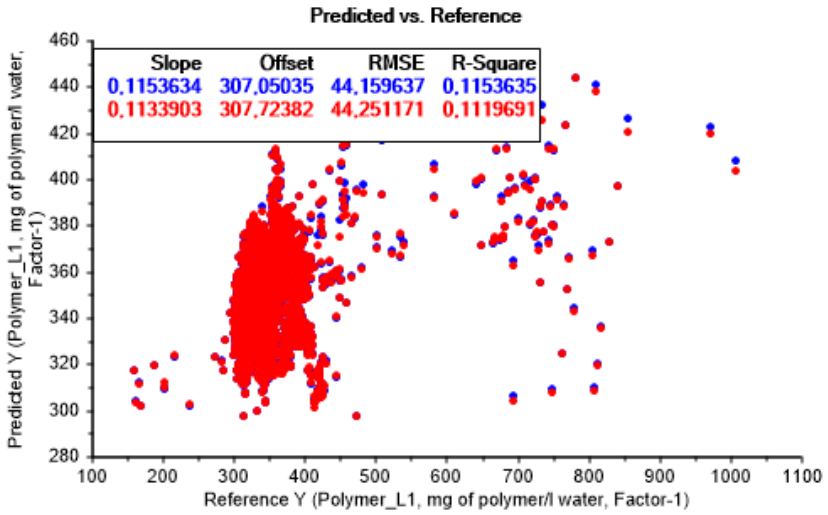

Figure 5-22: *Predicted versus reference values from PLSR analysis of treatment line one*

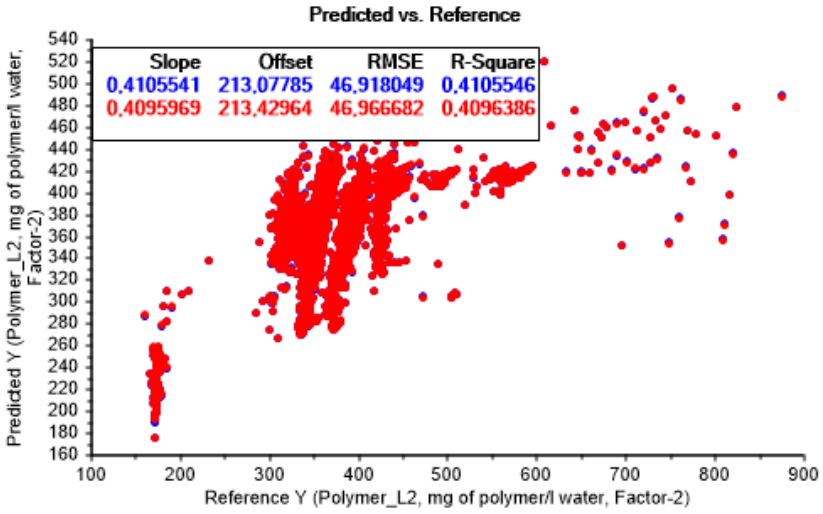

Figure 5-23: *Predicted versus reference values from PLSR analysis of treatment line two*

The explained variance for both treatment lines was extremely low, especially for treatment line one (Fig. 5-22 and Fig. 5-23). For line one, the explained variance was 0.11, and 0.41 for line two, resulting in 11% and 41% of the variances being explained by the model. These low results are mostly because the polymer dosing is done manually. Since there is no logic to the dosing, it is hard to create a good prediction model for the polymers. The R^2 is higher in treatment line two because the dosage is changed slightly more often than in treatment line

one. The increased frequency of changes in polymer dosing is more visible in Figure 5-24. The figure shows empty space between the plots along the reference Y axis. Each of these group samplings most likely represent one of the constants of polymer dosing used by the operators.

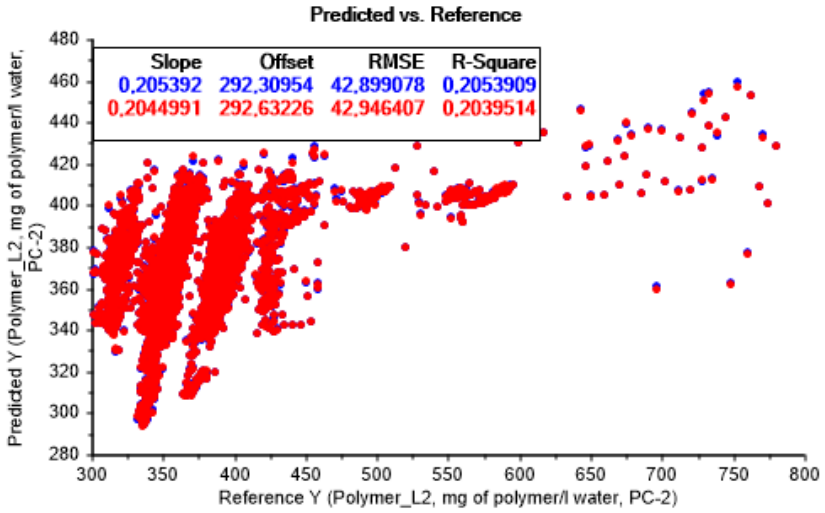

Figure 5-24: *PCR analysis showing Predicted versus Reference values for treatment line two*

MLR

The MLR of the polymer data used the parameters coagulant dosage, inlet flow, outlet pH, and outlet turbidity to create a linear equation for the polymer dosage:

$$Polymer\left[\frac{mg}{l}\right] = 527{,}2548 + 0{,}1516\ Coagulant\ \left[\frac{ml}{m^3}\right] - 0{,}0698\ Q_{in}\ \left[\frac{m^3}{h}\right] - 30{,}0975\ pH_{out} + 1{,}6194\ Turbidity_{out}[NTU]$$

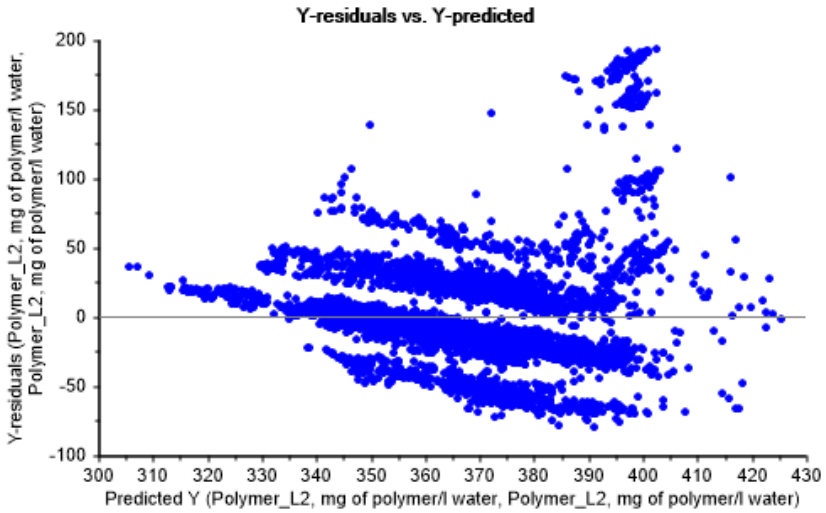

Figure 5-25: *Y-Residuals versus Y-predicted from MLR analysis in treatment line two*

Figure 5-25 shows distinct differences between levels of residuals, creating a pattern. This pattern is caused by the different constant polymer dosages set by the operators.

5.2.2 Testing Different Polymer Dosages

Currently, the polymer dosing is set at different constant levels every week, usually ranging between 1.00 mg/L and 1.40 mg/L. These dosages are set manually by the operators. The adjustments are a result of an increase in the turbidity in the outlet when micro-sand and coagulants are confirmed not to be the issue. There is a possibility that unstable mixing conditions occur due to the constant dosage of polymers. In instances like heavy rainfall, where water flow is increased, the unchanging dosage of polymers could create mixing conditions that are not optimal. By testing different polymer dosages, the treatment plant can determine whether the polymer dosage substantially affects the outlet qualities.

The goal of the thesis work was to include full-scale testing of different polymer dosages. Similarly to the examination of varying coagulant dosages, plans were changed due to the Coronavirus pandemic. Access to the treatment plant became restricted, and the workload increased for the workers at the treatment plant. Thus, the full-scale tests were abandoned for the thesis work.

Operators note that there is a minimal difference in the water quality when they manually change the polymer dosage. However, full-scale tests of different polymer dosages are still recommended for further research at Solumstrand, especially due to the increased interest in automizing polymer dosages at treatment plants. By testing different polymer dosages at the treatment plant more meticulously, it will be easier to quantify the polymer dosing's impact on the treatment process.

6. Conclusion

This thesis presents the challenges observed in the automatic dosing system due to the possible differences in parallel process lines at the Solumstrand treatment plant and some possible solutions to optimize the coagulation process. The solutions offered seek to minimize the effect of any unknown variables in the treatment process, as well as to create a basis for further research and testing.

Due to the Coronavirus pandemic, most of the planned and in-progress tests were canceled, both at the laboratory and at the treatment plant. Thus, the thesis presents an inconclusive analysis that serves as a visual aid to help determine possible reasons for the discrepancies in the treatment lines. It also presents recommendations for further work and testing at Solumstrand treatment plant.

Recommendations include installing dedicated dosing control signals for each of the Actiflo-processes so that the two treatment lines will be dosed based on the water quality parameters of two different algorithms. Installing more sensors in the two treatment lines might also help optimize the treatment process by enhancing process control. Adding individual sensors to measure water flow in the two treatment lines can help quantify the observed water quality differences. Alternatively, the focus on outlet pH and coagulant dosage in the algorithm can be increased to quantify the water flow, as the outlet pH and coagulant dosage are directly correlated with water flow.

Polymer dosing is a vital step in the optimization process of the coagulation process at treatment plants. Caution is advised upon implementation, as it is a more complicated process, and it will depend on both the coagulant and micro-sand dosing, as well as the traits of the polymer used. It is also essential that the dosing system is installed separately from the coagulant dosing system so that the two can be controlled and shut down individually.

The recommendations above will serve to increase surveillance and control of the coagulation process. Enhanced process control will lead to reduced usage of coagulants and polymers, reduced sludge production, and lower costs for the treatment plant.

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Attachment A: Results from Lab Analysis

Table 0-1: *Water samples taken February 10th*

Sample number	Time of day	SS, mg/l			Turbiditet Middelverdi [NTU]				pH [pH]				Conductivity [µS/cm]				Total fosfor concentration [mg/l]			Ortofosfate concentraction [mg/l]		
		Before split	Line 1	Line 2	Before split	Line 1	Line 2	Online sensor	Before split	Line 1	Line 2	Online sensor	Before split	Line 1	Line 2	Online sensor	Before split	Line 1	Line 2	Before split	Line 1	Line 2
1	10:15	259,00	299,00	231,00	191	184	214	190	7,32	7,28	7,28	7,15	705,00	705,00	707,00	773	2,99	5,552	4,068	0,116	0,127	0,049
2	11:00	230,00	305,00	147,00	212	250	131	212	7,30	7,26	7,32	7,13	709,00	710,00	705,00	785	4,9	3,261	2,506	0,06	0,089	0,24
3	11:30	148,00	214,00	149,00	154	167	140	150	7,31	7,32	7,16	7,11	714,00	714,00	729,00	784	3,067	3,693	3,025	0,091	0,1	0,493
4	12:45	163,00	166,00	140,00	145	133	136	129	7,27	7,23	7,19	7,07	723,00	727,00	733,00	799	2,476	3,389	3,242	0,223	0,264	0,619
5	13:30	227,00	207,00	246,00	164	165	211	159	7,30	7,26	7,23	7,14	726,00	729,00	726,00	798	3,525	4,676	4,344	0,336	0,359	0,439
6	14:30	190,00	181,00	203,00	167	170	188	137	7,16	7,15	7,18	7,06	732,00	735,00	735,00	804	3,937	3,721	4,549	0,462	0,81	0,595

Table 0-2: *Water samples taken February 24th*

Sample number	Time of day	SS [mg/l]			Turbidity Average Value [FNU]				pH [pH]				Conductivity [µS/cm]				Total Phosphorus Concentration [mg/l]			Orthophosphates Concentraction [mg/l]		
		Before split	Line 1	Line 2	Before split	Line 1	Line 2	Online sensor	Before split	Line 1	Line 2	Online sensor	Before split	Line 1	Line 2	Online sensor	Before split	Line 1	Line 2	Before split	Line 1	Line 2
1	10:15	259,00	299,00	231,00	191	184	214	190	7,32	7,28	7,28	7,15	705,00	705,00	707,00	773	2,99	5,552	4,068	0,116	0,127	0,049
2	11:00	230,00	305,00	147,00	212	250	131	212	7,30	7,26	7,32	7,13	709,00	710,00	705,00	785	4,9	3,261	2,506	0,06	0,089	0,24
3	11:30	148,00	214,00	149,00	154	167	140	150	7,31	7,32	7,16	7,11	714,00	714,00	729,00	784	3,067	3,693	3,025	0,091	0,1	0,493
4	12:45	163,00	166,00	140,00	145	133	136	129	7,27	7,23	7,19	7,07	723,00	727,00	733,00	799	2,476	3,389	3,242	0,223	0,264	0,619
5	13:30	227,00	207,00	246,00	164	165	211	159	7,30	7,26	7,23	7,14	726,00	729,00	726,00	798	3,525	4,676	4,344	0,336	0,359	0,439
6	14:30	190,00	181,00	203,00	167	170	188	137	7,16	7,15	7,18	7,06	732,00	735,00	735,00	804	3,937	3,721	4,549	0,462	0,81	0,595

Table 0-3: *Water samples taken with the Teledyne Isco on the weekend March 7th-9th*

Date	Sampling started	Sampling ended	Sample number	Turbidity Average Value [FNU]	Turbidity Online Sensors	pH [pH]	pH Online Sensors
07. Mar	00:00	02:00	1	121,5	112,25	7,052	6,7
	02:00	04:00	2	99,6	100,5	6,977	6,69
	04:00	06:00	3	105,3	100,5	7,071	6,675
	06:00	08:00	4	93,2	94,25	7,046	6,645
	08:00	10:00	5	85,1	85,75	7,094	6,63
	10:00	12:00	6	66,8	78,5	6,956	6,65
	12:00	14:00	7	104,5	85	7,031	6,685
	14:00	16:00	8	111,3	107,75	6,866	6,698
	16:00	18:00	9	128,3	109,25	6,83	6,695
	18:00	20:00	10	121,8	103,25	6,78	6,675
	20:00	22:00	11	114,5	97,25	6,801	6,645
	22:00	00:00	12	108,5	93,5	6,808	6,61
08. Mar	00:00	02:00	13	85,4	89,75	6,705	6,62
	02:00	04:00	14	90,8	87,5	7,092	6,64
	04:00	06:00	15	81,3	82,75	6,996	6,645
	06:00	08:00	16	77,3	75,75	7,042	6,795
	08:00	10:00	17	62,2	68	7,166	6,73
	10:00	12:00	18	62,0	65	7,028	6,785
	12:00	14:00	19	82,4	84,25	7,048	6,815
	14:00	16:00	20	121,0	117,25	7,038	6,725
	16:00	18:00	21	143,8	120,25	7,042	6,65
	18:00	20:00	22	109,5	101,75	7,03	6,615
	20:00	22:00	23	84,8	89,25	7,05	6,58
	22:00	00:00	24	93,4	84,25	7,1	6,585

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