ISBN: 978-82-575-1382-5
ISSN: 1894-6402

Philosophiae Doctor (PhD), Thesis 2016:62

Wei Liu

Norwegian University of Life Sciences
Faculty of Environmental Science and Technology
Department of Mathematical Sciences
and Technology (IMT)

Philosophiae Doctor (PhD)
Thesis 2016:62

Enhancement of Coagulant Dosing Control in Water and Wastewater Treatment Processes

Forbedring av koagulant-doseringskontroll i renseprosesser for vann og avløp

Wei Liu

Norwegian University
of Life Sciences

Postboks 5003
NO-1432 Ås, Norway
+47 67 23 00 00
www.nmbu.no

Enhancement of Coagulant Dosing Control in Water and Wastewater Treatment Processes

Forbedring av koagulant-doseringskontroll i renseprosesser for vann og avløp

Philosophiae Doctor (PhD) Thesis

Wei Liu

Department of Mathematical Sciences and Technology
Faculty of Environmental Science and Technology
Norwegian University of Life Sciences

Ås (2016)

Thesis number 2016:62
ISSN 1894-6402
ISBN 978-82-575-1382-5

Supervisory team

Harsha Ratnaweera, Professor (main supervisor)
Department of Mathematical Sciences and Technology
Norwegian University of Life Sciences

Arve Heistad, Associate Professor (co-supervisor)
Department of Mathematical Sciences and Technology
Norwegian University of Life Sciences

Evaluation committee

Joachim Fettig, Professor (first opponent)
Department of Environmental Engineering and Applied Informatics
University of Applied Sciences Ostwestfalen-Lippe, Hoexter, Germany

Torleiv Bilstad, Professor (second opponent)
Department of Mathematics and Science
University of Stavanger, Norway

Volha Shapaval, Associate Professor (committee coordinator)
Department of Mathematical Sciences and Technology
Norwegian University of Life Sciences

Summary

Chemical coagulation is one of the most important treatment processes in wastewater treatment and drinking water treatment. Defining the optimal coagulant dosage is a vital operation that decides the treatment efficiency and economy of the coagulation process. Chemical coagulation is a well-defined process where the optimal coagulant dosage is dependent on the influent quality, expressed by particle concentration, pH, temperature, colour or phosphate, alkalinity, etc. However, no conceptual model has been developed due to the complexity of this process and the research on coagulant dosage control has continued for decades (Ratnaweera and Fettig, 2015). Among all the avenues of research, the model predictive control based on online measurements is the most promising concept for coagulant dosage control. It presents various methods of model calibration and well-defined testing procedures. A Feed-Forward (FF) model based concept of a multi-parameter dosing control system for wastewater was originally proposed by Ratnaweera et al. (1994) and then improved upon by Lu (2003) and Rathnaweera (2010). According to previous results of full-scale tests, the multi-parameter dosing control system has proven to provide acceptable effluent quality and improved economy on most occasions in several wastewater treatment plants.

The multi-parameter dosing control system relies on many online instruments and empirical models. Generally, there are four aspects challenging the performance and utilization of the system. Firstly, it is necessary for the empirical model to prove universality of utilization, which refers to the independence of diverse water sources and process dynamics. Secondly, the performance of such a system is challenged by abnormal inlet variation. Heavy rain particularly requires improvements of the model's capacity of dosage prediction. Thirdly, different requirements of treatment results should be met by the system, which needs to realise flexibility of utilization with other treatment processes in both full-scale wastewater and drinking water treatment. Fourthly, the model performance of real-time dosage control highly depends on data accuracy of online measurements and therefore demands efficient error detection of said online measurements. Hence, based on the existing multi-parameter dosing control system, this thesis approaches the aforementioned challenges and improves upon the existing system by pursuing full-scale tests and solutions.

Drinking water treatment is one of the major application fields for the coagulation process. This thesis extends the multi-parameter dosing control system originally developed for wastewater treatment to drinking water treatment. The testing results show that the system provides more even effluent results than flow-proportional dosing, and saves as much as 10 % coagulant consumption.

In view of control strategy, a feedback (FB) with outlet qualities is identified as a critical factor for system improvement. It is especially applicable to managing extreme inlet variations such as heavy rains, and also to achieve required outlet qualities presented by users. Thus, the inclusion of an outlet turbidity and a set point combined with the existing feed-forward (FF) model will improve the results. The testing results show that the model capacity improves by the dosage adjustment of the feedforward-feedback (FB-FF) model, ranging from 66 % to 197 % of the FF model. Consequently, related outlet quality can be more stable than the FF model, alongside coagulant consumption showing further reductions in the range of 3.7 %-15.5 %.

Utilization of the FF-FB model is limited because the outlet sensor is always several hours delayed in providing feedback information, due to the long hydraulic retention time of common sedimentation tanks. Hence, this thesis proposes the development of an outlet software sensor based on inlet sensors and the dosage. The software sensor can predict outlet turbidity before coagulated water goes through the sedimentation tank, which serves as a timely feedback for defining optimal dosage. The testing results show that the software sensor performs well within the main working range.

Reliability of the FF-FB model is highly dependent on the operative status of online instruments, which can fault and become out-of-order. In order to estimate and detect the potential measurement errors this thesis proposes a model-based measurement error detection. According to the testing results, the proposed detection method has a better efficiency to detect the measurement errors than a traditional method (the normal variation range checking). Consequently, the FB-FF model is enabled to work with accurate measurements of online instruments.

In conclusion, the applicability of an automated dosing control system for drinking water treatment and a concept to improve the system with the use of a FB-FF model is proposed. A software sensor for outlet turbidity is proposed to enable the FB model. Since all control systems based on online measurements are critically dependent on the measurement accuracies, a new concept to validate the measurement is proposed.

Sammendrag

Kjemisk felling er en av de viktigste enhetsprosessene i både avløps- og drikkevannsbehandling. Identifisering av optimal koagulantdose er sentralt i driften av koaguleringsprosessen, og avgjørende for både rensegraden og driftsøkonomien i prosessen. Kjemisk felling er en veldefinert prosess der den optimale koagulantdosen avhenger av kvaliteten på innkommende vann, gitt ved partikkelkonsentrasjon, pH, temperatur, farge eller fosfatinnhold, alkalinitet osv. Det finnes imidlertid ingen universielle konseptuell modell for å bestemme optimal dose ettersom prosessen er svært kompleks. Dette har ført til årtier med forskning på regulering av koagulantdosen (Ratnaweera og Fettig, 2015). Av de ulike forskningsretningene har prediktiv regulering basert på online målinger vist seg svært populært, og inkluderer forskjellige metoder for modellkalibrering og definerte testprosedyrer. Et konsept bestående av multi-parameter doseringsregulering for avløpsrensing ble opprinnelig foreslått av Ratnaweera et al. (1994) og forbedret av Lu (2003) og Rathnaweera (2010). Tidligere fullskala tester har vist at systemet for multi-parameter doseringsregulering gir akseptabel kvalitet på behandlet vann og forbedret driftsøkonomi i et antall avløpsbehandlingsanlegg.

Systemet for multi-parameter doseringsregulering avhenger av online målinger fra mange instrumenter, samt empiriske modeller. Generelt kan det identifiseres fire aspekter som utfordrer funksjonen og nytten til systemet. For det første må det demonstreres at den empiriske modellen er universelt nyttig, dvs. at den fungerer uavhengig av hvilken vanntype og prosessdynamikk man har. For det andre blir systemet utfordret av unormale variasjoner i innløpet, spesielt ved større nedbørshendelser, noe som krever utvidet modellkapasitet. For det tredje må systemet kunne oppfylle varierende lokale krav til rensegrad, noe som krever fleksibilitet når det gjelder bruk i ulike behandlingsprosesser i både avløps- og drikkevannsbehandling. For det fjerde avhenger funksjonen til sanntids doseringssystemer i stor grad av nøyaktigheten til online instrumenter, noe som krever et effektivt system for å avdekke feil i målingene. Med utgangspunkt i det eksisterende multi-parameter doseringssystemet vil avhandlingen ta tak i de ovenstående utfordringene og forbedre systemet basert på testing og verktøy i fullskala.

Drikkevannsbehandling er et av de viktige anvendelsesområdene for kjemisk felling. Denne avhandlingen utvider systemet for multi-parameter doseringsregulering, i utgangspunktet utviklet for avløpsrensing, til drikkevannsbehandling. Testresultatene viser at systemet ga mer

stabil utløpskvalitet enn mengdeproporsjonal dosering og ga opptil 10 % besparelse i koagulantforbruk.

Når det gjelder reguleringsstrategi, ble det benyttet en tilbakekobling (Feed Back, FB) som inkluderte utløpsturbiditet og en skal-verdi i kombinasjon med den eksisterende modellen basert på foroverkobling (Feed Forward, FF), som tar sikte på å håndtere unormal variasjon i innløpet, spesielt ved tung nedbør, og samtidig oppnå brukerens ønskede utløpskvalitet. Testresultatene viser at modellens kapasitet forbedres gjennom dosejusteringene til modellen basert på foroverkobling-tilbakekobling (FF-FB), fra 66 % til 197 % av modellen basert på kun foroverkobling. Det medfører at den tilhørende utløpskvaliteten kan holdes mer stabil. Samtidig påvises det at koagulantforbruket ytterligere reduseres med 3.7 %-15.5 %.

Utnyttelsen av modellen basert på foroverkobling-tilbakekobling (FF-FB) begrenses av det forhold at utløpssensoren alltid gir flere timers forsinket tilbakemelding på grunn av lange hydrauliske oppholdstider i typiske sedimenteringbassenger. I denne avhandlingen ble det derfor utviklet en soft-sensor basert på innløpssensorene og doseringsnivået. Soft-sensoren kan forutsi utløpsturbiditeten før koagulert vann passerer sedimenteringstanken og kan derfor gi rettidig tilbakemelding for å bestemme optimal dosering. Test-resultatene viser at soft-sensoren fungerte godt innenfor det primære arbeidsområdet.

Påliteligheten til modellen basert på foroverkobling-tilbakekobling er svært avhengig av driftsstatusen til online instrumenter. For å kunne detektere og estimere mulige feil i målingene, ble det i denne avhandlingen utviklet et modellbasert system for feildetektering. Ifølge testresultatene detekterer det foreslåtte systemet feil mer effektivt enn en tradisjonell metode (sjekk basert på variasjon innenfor normalområdet), noe som gjør det mulig for modellen basert på foroverkobling-tilbakekobling å arbeide med nøyaktige målinger fra online instrumenter.

Konkluderende foreslår tesen anvendelse av et automatisert doseringsstyresystem for drikkevannbehandling, samt et konsept for å forbedre systemet med bruk av en FB-FF-modell. En myksensor for utløp turbiditet foreslås for å muliggjøre anvendelse av en FB modell. Da alle styresystemer basert på elektroniske målinger er kritisk avhengige av målenøyaktigheter, er et nytt konsept for å validere målingen foreslått.

Acknowledgements

First of all, I would like to present my profound gratitude to my main supervisor prof. Harsha Ratnaweera, for making me the world of water treatment accessible, offering me scientific guidance and providing the opportunity to gain comprehensive knowledge. In addition, I deeply appreciate his trust, patience and inspiration during my whole PhD period.

Sincere thanks are extended to Mr. Song Heping for his communication with wastewater and drinking water treatment plants, which were highly supportive to my field work. I present my great thanks to Mr Jiang Yuejie from Haining No.2 DWTP and Mr Ma Xuefan from Haining Salcon DWTP, for their valuable support during my experiments.

I am glad to express my deep thanks to Mr Dejan Josik from INDAS Co Ltd., Serbia for his professional assistance to develop the CDCS software and signal communication, alongside his valuable online support.

I would like to show my deep gratitude to prof. Knut Kvaal for his guidance, knowledge and advices on statistics and modelling.

I highly appreciate DOSCON AS, Norway, for offering hardware support - the Coagulant Dosage Control System - and for funding my research. Without generous funding from DOSCON AS it would not have been possible to complete my PhD research.

I am honoured to express my deep gratitude to the supervisor of my Master's degree prof. Li Yawei, for his recommendation of my PhD application as well as his great encouragements.

I am happy to offer thanks to my fellow PhD candidates Lelum Manamperuma, Pavlo Kozminykh, Vegard Nilsen, Nataliia Sivchenko, Duo Zhang and Xiaodong Wang for every discussion and help shared during our PhD lives. I would like to offer my thanks to Vegard again for the translation of the summary of this thesis.

It is an honour for me to convey my appreciation to the Norwegian University of Life Science (NMBU) and Department of Mathematical Sciences and Technology (IMT) for providing me a rigorous course of study.

I offer my heartiest thanks to my parents and grandparents for their unlimited support, which provided me with great confidence in pursuing my PhD. I am deeply thankful to my loving wife Wenmin for her endless support, patience and understanding.

LIST OF ACRONYMS

AI	Artificial intelligence
ANFIS	Adaptive network-based fuzzy inference system
ANN	Artificial neural networks
CDCS	Coagulant dosing control system
CNI	Inlet conductivity
COD	Chemical oxygen demand
CVs	Controlled variables
DWTP	Drinking water treatment plants
DVs	Disturbing variables
FB	Feed-back
FF	Feed-forward
FNN	Fuzzy neural networks
HRT	Hydraulic retention time
MLR	Multiple linear regression
MPC	Model predictive control
MVs	Manipulated variables
N2DWTP	Haining Number 2 drinking water treatment plant, China
NIPALS	Non-linear Iterative Partial Least Squares
NOM	Natural organic matter
NRA WWTP	Nedre Romerike wastewater treatment plant, Norway
nonPF	Non-plug-flow
P	Phosphorus
PAC	Poly aluminium chloride
PCR	Principle component regression
PF	Plug flow
PLC	Programmable logical controller
PHI	Inlet pH
PLSR	Partial least squares
PHO	Coagulation pH
Qin	Water flow
R^2	Coefficient determination
RMSE	Root mean square error
SCD	Streaming current detector
SCADA	Supervisory control and data acquisition system
SDWTP	Haining Salcon drinking water treatment plant, China
STDEV	Standard deviation
TMP	Temperature
TN	Total nitrogen
TP	Total phosphorus
TUI	Inlet turbidity
TUO	Outlet turbidity
WWTP	Wastewater treatment plants

LIST OF FIGURES

LISTOF TABLES

Contents

1. INTRODUCTION

Chemical coagulation has been widely used in wastewater treatment plants (WWTP) for the removal of particulate matter and phosphates, and in drinking water treatment plants (DWTP) for the removal of particulate matter and Natural Organic matter (NOM) (AWWA, 2011). Considerable fractions of chemical oxygen demand (COD), total phosphorus (TP) and NOM are found in particulate or colloidal fractions, thus can be highly reduced by a coagulation process (Guida *et al*., 2007; Shutova *et al*., 2014). The removal process may occur according to all four coagulation mechanisms, i.e. neutralizing charge on particles, compressing double layers of charged particles, bridging particles together and by sweeping of flocs. These coagulated particulate matters are in a stage of destabilization and increased size after coagulation, and hence can be separated from liquid (Tchobanoglous *et al*., 1997). Furthermore, dissolved phosphates (P) as a pollutant can be removed after reacting with a metal coagulant and converting into particulate form, or by adsorption on to the other coagulated species.

A coagulation treatment process physically consists of coagulant dosing pumps, rapid mixing units, flocculation chambers, and flocs separation units such as sedimentation tanks, filtration and flotation systems. During the coagulation process, certain amount of coagulant is dosed into raw water primarily leading to the growth of flocs in flocculation chambers under the slow mixing. Finally particles with suitable size are separated.

Coagulation treatment plays an important role in water and wastewater treatment because of several reasons. Firstly, the coagulation treatment has high efficiency of particles, NOM and phosphate removal. Secondly, a full-scale coagulation process can be simply operated through few control parameters (e.g. coagulant dosage). Thirdly, coagulation has a short physical footprint of treatment process that in turn requires less land usage. Fourthly, in order to meet various treatment requirements, a coagulation process is flexible to work with other treatment processes, for example three combinations with biological treatment: pre-precipitation, simultaneous precipitation and post-precipitation (Tchobanoglous *et al*., 1997). Fifthly, less energy consumption and high tolerance of variations of treatment load are other notable advantages of a coagulation process (Ratnaweera *et al*., 2002). Therefore, coagulation is a competitive treatment process in both DWTP and WWTP.

1.1 Coagulant dosage control in practice

The optimal coagulant dosage is the least amount of coagulants required to achieve the anticipated treated water quality. Based on coagulation mechanisms, the optimal coagulant dosage depends on raw water quality such as particle concentration, pH, alkalinity, hardness, temperature, phosphate concentration (in wastewater treatment), NOM (in drinking water), ionic strength, etc. (Ratnaweera, 1991; Maier *et al*., 2004; Rathnaweera, 2010). Treated water quality is the result of these parameters, features of the separation stage and coagulant dosage. In laboratory, jar tests as the most common method are widely used for defining the optimal dosage for a given water quality. However, it becomes time-consuming and impractical to deal with rapid variation of the inlet water quality in full-scale treatment (Joo *et al*., 2000; Yu *et al*., 2000). Ratnaweera (2004) pointed out that water quality varies frequently in WWT, which could require a change in optimal dosages even within 15 minutes. Thus, it is necessary to define the optimal dosage for the incoming water in real-time and automatically.

It is difficult to control coagulant dosage in full-scale treatment plants. Ratnaweera and Fettig (2015) pointed out that universally accepted mathematical descriptions are still not available for the coagulation process because of the complexities presented within the coagulation process. Since influencing parameters are not changing proportionally, it is impossible to simplify the relationship by replacing one parameter with others (Guo *et al*., 2009) or by using one parameter for comprehensive coagulation control (Ratnaweera *et al.*, 2005), if one wants to run the process optimally and economically. Similar to most industrial processes, the water quality of treated water can be used as FB for dosage adjustment, without having much insight to the process dynamics. However, it is difficult to achieve in full-scale water and wastewater treatment because of hours long retention time of sedimentation tanks, combined with rapid change inlet qualities (Ratnaweera, 2004). Therefore, a number of researchers have been focusing on coagulant dosage control – both on conceptual and empirical models, based on inlet qualities (Dentel, 1991; Joo, *et al*., 2000; Baxter *et al*., 2001; Maier, 2004; Ratnaweera *et al.*, 2005; Rathnaweera, 2010).

Outlet particles and P concentration (if WWT), as the results of influence parameters and dosage, are key control targets of the full-scale coagulation process. As the main operating parameter, dosage should be controlled well to meet the effluent requirement.

In a coagulant dosing control system, it is important to involve user inputs to achieve different outlet requirements. Since the coagulation process often works before other treatment processes, the outlet quality should meet with requirements of the subsequent process. For instance, too low P concentration or/and too low pH in the coagulation outlet could cause poor performance in subsequent biological processes. This is because P is an essential element of organism growth. Furthermore, according to the latest Norwegian regulation for WWTP, overflow and bypass at the WWTP shall be included in the reporting of discharges. The WWTP must achieve overall 94 % of total-P removal, and that cannot be achieved without over 96 % of total-P removal of the portion which goes through the WWTP, so the annual average values will be within the acceptable levels. For DWTP, outlet particle concentration of the coagulation process can decide backwash frequency of downstream filtration treatment. Therefore, outlet requirements of the coagulation processes are variable with different treatment plants and dosage control should adapt to the different outlet requirements.

Dosage control also relates to operational cost, health and other issues. It is reported that chemical cost could be up to 20 % of total operational cost (Hangouet *et al*., 2007), and some reports show that the total operational cost is more or less equal to the cost of coagulant (VA Support, 2012). Furthermore, Siriprapha *et al*. (2011) pointed out that the coagulation-flocculation process usually generates large quantities of chemical sludge and Ødegaard (2009) presented calculations for the sludge production in coagulation plants in Norway. Thus, overdosage could yield unnecessarily high amounts of sludge, which leads to additional cost of sludge treatment. There is also a concern on using coagulated sludge as fertilizer, as the plant availability of phosphates. The overdosage results in stronger metal-P bond, which decreases plant availability of P and reduces the benefit of the coagulated sludge accordingly (Manamperuma *et al*., 2015). Furthermore, low pH in treated water resulted from overdosage creates increased potential for corrosion in water transport systems. Maier *et al*. (2004) pointed out that coagulation in drinking water treatment provides one of multiple barriers to protect public health. The optimal dosage can significantly contribute to remove microorganisms and hence reduce water borne illness among consumers.

1.2 Developments in coagulant dosage control

Researches on coagulant dosage control have been implemented for several decades. Along with the development of online instruments and understanding of coagulation process, methods of coagulant dosage control is being upgraded gradually (Jeppsson *et al*., 2002; Vanrolleghem and Lee, 2003; Ratnaweera and Fettig, 2015). According to Schlenger *et al*. (1996), process control can be classified into three stages: supervisory control, automatic control and advanced control.

Flow-proportional and time-proportional dosage are two simplified methods. Namely, coagulant feeding flow is proportional to incoming water flow and time. A survey among Norwegian treatment plants indicated that over 80 % of DWTPs and WWTPs use flow proportional, with or without over steering of pH, dosing control (Ratnaweera, 2004). According to both outlet quality and results of jar tests, operators have to adjust the proportional ratio regularly (Dentel, 1991). This scheme belongs to the supervisory control. Baxter *et al*. (2002) pointed out that operators need to consider the results of jar tests and implement corresponding operations. This scheme is suitable for raw water with relatively constant quality, such as lake and reservoir as water source of DWTP. However, Ratnaweera and Fettig (2015) points out that such a control scheme is not suited for real-time control of a continuous process, especially when the raw water quality varies over a short period of time with considerable amplitude.

In order to assist the flow-proportional dosage control, Stumm and O'Melia (1968) built up a control chart to illustrate how the destabilization of particulate matter is decided by both dosage and initial particle concentration. The control chart is helpful for operators to understand the definition of an optimal dosage. A diagram of coagulation domain, initially developed by Amirtharajah and Mills (1982), addresses that domination of each coagulation mechanism (charge neutralization, double layers compression, bringing and sweep flocs) depends on coagulation pH and dosage.

Based on *DLVO* theory (named after Derjaguin, Landau, Verwey and Overbeek), there is an attractive force and a repulsive force between two particles that generates an energy barrier when these two particles approach each other (Stumm and Morgan, 1995). Consequently, particles naturally stabilize and disperse in water (Hunter, 2001). Feeding metal-iron coagulant is the most common solution to destabilize particles, where charge neutralization is the predominant mechanism (Amirtharajah and Mills, 1982). In order to indicate the degree of charge neutralization, a streaming current detector (SCD) is able to provide an important reference (Dentel *et al*., 1989). SCD can work online to evaluate whether dosage is adequate to destabilize particles. SCD enables FB control through simple algorithms or linear models (Walker *et al*., 1996; Baxter *et al*., 2002; Adgar *et al*., 2005; Oh and Lee, 2005). Based on *Henry's Equation*, zeta potential analyzer is able to indirectly detect net charges of particles (Hunter, 1981; Sharp and Norris, 2015). It is often reported that SCD readings have a linear relationship with zeta potential measurements (Ratnaweera and Fettig, 2015). However, application of these electro-kinetic approaches are limited, because it proves to be useful mainly when charge neutralization mechanism predominates (Stanly *et al*., 2000). Dentel (1995) pointed out that the output of SCD sometimes exhibits a contradictory result for the coagulation activation, because both surface charge of particles and charged functional groups on NOM molecules are affected by pH. Consequently, although streaming current detectors are available from a number of suppliers, there has been no standard calibration procedure so far (Ratnaweera and Fettig, 2015).

Considering the complex physical dynamics and relationship between influence parameters and dosage, model predictive control (MPC) relying on multiple online measurements has been extensively studied and applied in full-scale coagulant dosage control (Baxter *et al*., 1999; Yu *et al*., 2000; Zeng *et al*., 2003; Hamed *et al*., 2004; Ratnaweera *et al*., 2005; Yu *et al*., 2011). As advanced control, MPC is more suitable for operating non-linear multivariate system than experienced operators (AlGhazzawi and Lennox, 2009). Since the conceptual model derived from chemical and physical features of coagulation process is still not available, MPC of coagulant dosage has been carried out by empirical models so far (Rietveld and Dudley, 2006; Maier *et al*., 2010; Ratnaweera and Fettig, 2015). Instead of including all relevant influence parameters and knowing the dynamics of the physical process, the empirical models are able to establish the relationship between a few online instruments and dosage (Zeng *et al*., 2003; Maier *et al*., 2004). The empirical model can be classified into two approaches: multivariate statistics and artificial intelligence (AI), both of which are driven by a large number of historical data (Bloch and Denoeux, 2003; Fortuna *et al*., 2007). There are many modelling methods belonging to these two approaches. Multivariate statistics approach includes principle component regression (PCR), multiple linear regression (MLR), partial least squares regression (PLSR), etc., whereas AI approach contains artificial neural networks (ANN), expert system, fuzzy logic and genetic algorithms (Dellana and West, 2009). MPC relies on the empirical model to become increasingly popular in coagulant dosage control.

Zhang and Stanley (1999) pointed out that it is difficult to realize coagulant dosage control by traditional methods because of complex physical and chemical phenomena included in the coagulation, flocculation and separation process. Whereas ANN as a proposed method can overcome the complexities and predict the optimal dosage. The authors calibrated an ANN model with 2 000 sets of operational data of a DWTP. The authors also suggest that the proposed approach can be used for other DWTP after minor modification. Later, Stanley *et al*. (2000) reported that the ANN model proved to be a useful method to predict coagulant dosage, concluded from test results at two DWTPs.

Because empirical models are derived from historical data, data quality is a key factor for the model performance. Joo *et al*. (2000) proved that data preprocessing is able to enhance the performance of ANN models. Hence, the paper specified a procedure of the data preprocessing. Input parameters of the model include temperature, pH, turbidity, and alkalinity. Root mean square error (RMSE) is suggested as an indicator of model performance. Notably, during rainy days especially in July and August, the authors point out that it is very difficult for process operators to cope with the rapid fluctuation of inlet quality.

During the rainy season, Yu *et al*. (2000) observe that rapid change of inlet water quality is a challenge for coagulant dosage control of DWT. The paper points out that daily data are not adequate for model calibration, which could miss information of inlet quality. Hence, water quality recorded every 15 minutes are used for the model calibration. Four online measurements including inlet turbidity, inlet pH, inlet conductivity and outlet turbidity of settling tank are used for inputs in the ANN model. Because an outlet parameter is involved into dosage prediction, the model contains both FB and FF parameters. The best result of coefficient determination (R^2=0.97, an indicator of model performance) indicates that the dataset fits the model well. Furthermore, the authors discover that a nonlinear model has better prediction results than a linear model.

Pilot-scale tests of coagulant dosage control were carried out by Baxter *et al*. (2002). Three-month operational data include temperature, particle counts, color, alkalinity, pH, hardness, water flow, outlet turbidity and dosage. These pilot-scale tests proved that the ANN model is able to achieve real-time dosage control based on online instruments. Because of the pilot-scale tests, the authors highlights that the ANN model is able to cope with different selected water flows. Moreover, the paper also illustrates that multiple models can be used for achieving different user identified effluent targets. Further full-scale tests are highly suggested by this paper.

Another notable pilot-scale test is carried out by Bloch and Denoeux (2003). The paper demonstrates that the ANN model is an efficient tool for coagulant dosage control of DWT, which leads to significant saving in coagulant usage. In addition, the paper points out that the model performance highly depends on the quality and completeness of training data. Thus, either pretreatment or longer period of the training data could improve the model performance.

Since high residual aluminium concentration in drinking water was reported to increase risk of Alzheimer's disease, Maier *et al*. (2004) uses the ANN models to achieve two objectives: predict treated water quality including the residual aluminium concentration and predict optimal aluminium dosage. According to R^2=0.90-0.98, prediction values are quite close to measurements and training data fit the model well. Furthermore, a user-friendly platform with a graphical user interface is developed with the aim of easy implementation of the ANN model to a full-scale process.

Wu and Lo (2008) uses adaptive network-based fuzzy inference system (ANFIS) to calibrate models. The ANFIS is the combination of both neural network and fuzzy logic principles in order to take both advantages of them. The authors compare ANN model with ANFIS model, which are calibrated from the same training dataset. From the results of R^2, ANN has a better performance than ANFIS in dealing with storms when inlet turbidity increases suddenly. The authors also prove that RMSE of the model without data normalization is lower than the one with normalization. This indicates that the data normalization is not necessary for improving the ability of the ANN model (Wu and Lo, 2010).

Huang *et al*. (2009) highlights that performing heuristic reasoning is a limitation of the ANN model while it is difficult for the fuzzy logic to design and adjust automatically. Thus, in order to avoid both shortages, authors combine ANN with fuzzy logic. This research focuses on coagulant dosage prediction of industry wastewater treatment (paper mill). The simulation results show that the combined model (FNN) is able to achieve the expected removal efficiency. Consequently, authors conclude that cost of coagulant consumption should be minimized by full-scale tests of the FNN model.

According to the above brief introduction of developments, MPC plays an important role in coagulant dosage control. AI approaches such as ANN, ANFIS and FNN are common tools of model calibration while multivariate statistical approach has not been observed during the literature review. Since there are several different indicators of particulate pollutants such as turbidity, particle counts, color, UV245 etc., these parameters are flexible to be selected as model inputs. Along with the development of online sensors, training data is obtained from laboratory at an early stage and later by online measurements in pilot-scale or full-scale treatment process. It is regularly reported that quality and competence of the training data are key factors for model performance. Namely, deleting measurement errors and longer operational data are important. R^2 and RMSE as two indication parameters that are often used for evaluating the model performance. Most researchers suggested that the model performance should be tested further with pilot-scale or full-scale treatment process. Overall, MPC of coagulation process is rapidly developing and able to achieve constant treated water quality and better economy than comparable traditional methods.

Ratnaweera (1994) proposed a concept of coagulant dosage control based on statistical approach, which was preliminary evaluated by Lu (2003) with a single model and later by Rathnaweera (2010) with multiple models. This coagulant dosing control system (CDCS) was based on monitoring of multiple parameters such as flow, inlet pH, inlet turbidity or suspended solids, inlet conductivity, inlet temperature, inlet phosphate and coagulation pH.

According to Rathnaweera's PhD thesis (2010), the testing results show that PLSR is able to provide better model performance than MLR and PCR. The model structure is shown in Equation 1. On the other hand, the author points out that recognizing and validating measurement errors of online sensors are necessary. Thus, a software-based floating error detection concept is proposed and hence multiple models excluding error parameters are used for dealing with various measurement errors. The CDCS is carried out by the hardware-Programmable Logical Controller (PLC), which can either work independently or work as partner of supervisory control and data acquisition system (SCADA). The CDCS is tested with one pilot-scale WWTP and three full-scale WWTPs. The testing results show that the system performs well in achieving acceptable outlet quality and a considerable coagulant saving. The highest saving of coagulant consumption has been over 31 % while maintaining the same effluent quality.

Dosage= f (WW flow, inlet TU, inlet pH, inlet conductivity, inlet phosphate, temperature, interaction among variables, variables squares) Equation (1)

Conclusions from the above is that despite the significant focus and contribution on development of CDCS, there are a number of unsolved challenges that need to be addressed. The research idea for this PhD thesis is initiated around these needs, which are highlighted in the next chapters.

1.3 Need for improvements in coagulation practice

According to the Chapter 1.2, there has been no conceptual model for coagulant dosage control, which is derived from chemical and physical features of the coagulation process leading to wide application (Ratnaweera and Fettig, 2015). The empirical models based on multi-parameter measurements, as a current solution of coagulant dosing control, are facing the following challenges.

1.3.1 Universality

Universality, as a feature of the control system, refers to the independence of various water source and process dynamics. Since an empirical model is developed under conditions such as a given water source, selected input parameters, limited sample amounts and a proposed model structure, each kind of empirical models should be tested extensively in full-scale treatment processes. Although previous research in Chapter 1.2 show that empirical models are able to provide qualified performance, real-time dosing of full-scale tests are still rare. Hence, it is necessary for each kind of empirical model to prove the universality in both WWTP and DWTP.

1.3.2 Model capacity of coagulant dosage control

High tolerance on treatment load is one of the competitive advantages of the coagulation process (Ratnaweera *et al*., 2002). Coagulant dosage, as the key manipulated variable of the treatment process, should be controlled well to deal with shock treatment load. However, it is frequently reported that model capacity of coagulant dosage control is not acceptable in DWT during heavy rain when there is abnormal variation in inlet quality (Kan and Huang, 1998; Wo and Lo, 2008; Liu *et al*., 2013). Such situations also happen to the municipal WWTP with combined sewer systems during heavy rain and ice melting (Li *et al*., 2003; Scherrenberg, 2006). Hence, the abnormal situations of treatment load challenge empirical models and the model capacity of coagulant dosage control should be enhanced accordingly.

1.3.3 Flexibility of utilization

In practice, coagulation processes have flexible application with other treatment processes in both WWTP and DWTP. In WWTP, when a coagulation process works prior to biological treatment, outlet quality of the coagulation process should meet with requirement of the biological treatment. For example, outlet P of the coagulation process is a nutrient for organism growth in the subsequent biological treatment. Hence, outlet P of the coagulation process is not as low as possible but should be suitably controlled. In DWT, the particle concentration of coagulation outlet is a key factor to decide backwash frequency of subsequent filtration. Baxter *et al*. (2002) pointed out that drinking water treatment must constantly balance the operational cost. Thus, the optimal dosage should be redefined considering the balance between coagulant consumption and the backwash frequency of filtration. However, a calibrated empirical model aims to generate targeted outlet water quality that is included in the training dataset (Maier *et al*., 2004). Consequently, empirical models cannot change the target of outlet water quality until it undergoes model recalibration with a different training dataset. Furthermore, it is difficult for plant operators to access the empirical model and modify the performance (Joo *et al*., 2000). Thus, it is necessary for empirical models to adjust dosage for different outlet targets, achieving the flexibility of coagulation process.

1.3.4 Data quality of online measurements

Model performance on real-time dosage control depends on the formation of the model itself determined during the model calibration, as well as data accuracy of online measurements. Data quality of online measurements are highly related to the reliability of the multi-parameter based MPC. Practically, online sensors cannot provide correct measurements all the time due to fouling, aging, operational mistakes, etc. Consequently, measurement errors can lead to large calculation deviations from the optimal dosage, which results in unacceptable outlet quality. Hence, the potential online measurement errors challenge the reliability of the model performance. Therefore, error detection of online measurements is critically important for the multi-parameter based MPC.

1.4 Research objectives

Chapter 1.3 presents a number of challenges with the existing CDCS. The research in this thesis presents analysis, causes and possible solutions for these challenges, using mathematical and statistical models and full scale experiments. Aiming to enhance the existing CDCS, Figure 1 shows the research framework of this thesis focusing on challenges of universality, model capacity, flexibility, and reliability. Thus, research objectives of this thesis is to solve these four challenges. Based on the possible solutions that papers present in the appendix chapter, the thesis is to achieve its research objectives in chapter 3 by the following procedure.

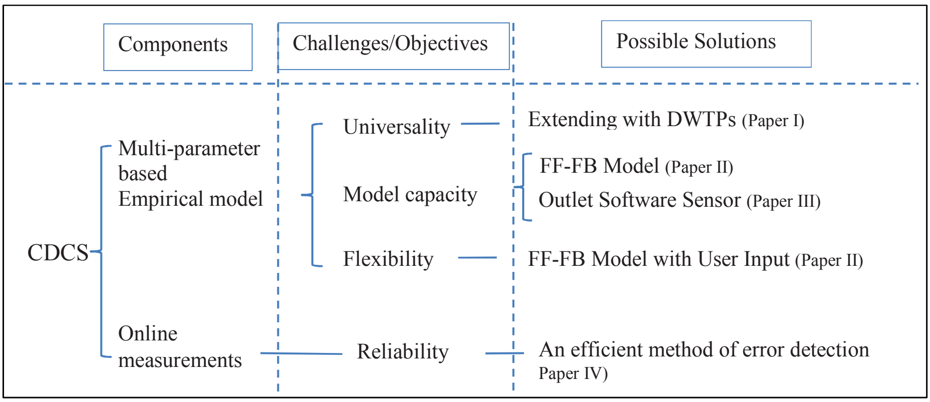

Figure 1, Research framework of this thesis. "FF-FB" indicates feedforward-feedback.

The existing CDCS has showed good performance of dosage control during wastewater treatment. The existing CDCS, based on empirical models, has to prove the universality with different water sources and treatment requirement. Previously, the existing CDCS has been tested in several WWTPs achieving acceptable results. Thus, one of the primary research objective of this thesis is to test the CDCS with a full-scale drinking water treatment processes.

When the existing feed-forward (FF) based CDCS concept with the empirical model are used in DWTPs, it sometimes experiences unexpected outlet quality during full-scale tests. This is because the empirical model with existing inlet parameters cannot deal with those inlet variations, which are quite different from what is included in the dataset of the model calibration. Those inlet variations, so-called abnormal inlet variations, are a potential risk to the performance of the existing CDCS. Thus, one of the research objectives here is to develop a FF-FB model aiming to use FB control to compensate the dosage prediction. Furthermore, taking advantage of feedback control, this thesis will use the set point of FB as a user input for achieving the user's desired outlet quality, which could strongly enhance the utilization flexibility of the CDCS.

The hydraulic retention time is a significant limitation factor for implementing the FF-FB model. This is because outlet measurements of common sedimentation tanks are always late to FB considering rapid inlet variations. Thus, this research aims to develop an outlet software sensor and to predict outlet measurement well in advance to the physical measurements, which can serve as timely FB for the FF-FB model. However, the non-plug-flow in sedimentation tanks could cause potential mixing effect and hence measurements of outlet turbidity could be mixed results of different ideal values that is generated under condition of plug-flow. Therefore, as a precondition of developing the software sensor, this thesis is to simulate plug-flow outlet turbidity and test the mixing effect by comparing the simulated plug-flow outlet turbidity with measured values.

In order to ensure the accurate dosage prediction, the error detection of online measurements is an essential part of the CDCS. Based on results of the software sensor, this research is to develop an efficient method of error detection of online measurements, aiming to enable the enhanced CDCS to work under the normal inlet measurements. In order to prove better efficiency of the newly developed method, this research is to compare the new method with the current method by a proposed approach.

2. EXPERIMENTAL METHODS AND PROCEDURES

2.1 Introduction of full-scale processes

2.1.1 Haining Number two DWTP

Haining Number 2 DWT plant (N2DWTP) lies in Haining, Zhejiang province, China. Overview of the plant is shown in the Figure 2. The plant capacity is 100 000 m^3/d and the treatment process consists of an aeration tank, coagulation process followed by sedimentation tanks, sand filtration and chlorination disinfection. Schematic of treatment process is shown in Figure 3. The treatment process is divided into two treatment lines in parallel. Each line of the coagulation process is equipped with a coagulant dosing pump and hence dosage of each line can be controlled individually. The water source is Changshan River, which passes by the plant. Normally, water quality is relatively constant, whereas considerable variations happen during storms.

Figure 2. Overview of Haining Number two DWT plant, Changshan River as water source, aeration tank, coagulation process and sand filtration are marked.

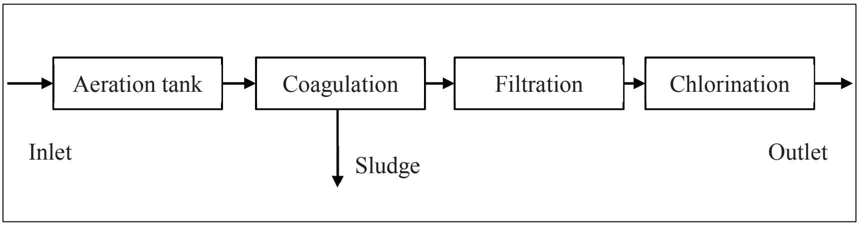

Figure 3. Schematic of treatment process in N2DWTP

Five online sensors are installed in the coagulation process. Three of them are located at the inlet including turbidity sensor, conductivity sensor and pH sensor, shown in the Figure 4. Another pH sensor lies in flocculation chamber after coagulant dosing point. Another turbidity sensor at outlet is responsible for measuring the treatment results. Inlet turbidity sensor has normal measurement range of 0.01-4000 NTU, while the turbidity sensor with low measurement range (0.001-9.999 NTU) is used for outlet measurement. All these online signals primarily transfer to SCADA from sensor controllers, which is used for process operators to monitor process status. Then these online signals transfer to the CDCS from SCADA. A department of N2DWTP was responsible for cleaning and calibration of these online sensors. Normally, maintenance frequency is once per week.

Figure 4. Inlet online instruments of N2DWTP. Including 3 inlet sensors: turbidity, conductivity, pH as well as sensor controllers

N2DWTP is using poly aluminium chloride (PAC) as coagulant. Before real-time dosage control by the CDCS, the plant used flow-proportional control. Referring to daily results of jar-tests and online measurement of outlet quality, in the control room operators adjusted the proportional ratio to reach the expected outlet quality. In this plant, outlet turbidity is used as indicator of treatment results and expected range of outlet turbidity of coagulation process is fixed to 2-3 NTU. Both outlets of two parallel treatment lines are equipped with turbidity sensors. In order to ensure good treatment performance for 24 hours per day, operators are divided into 5 groups where three groups work in daily monitoring and control. Because this plant lies on the east coast of China, storms and typhoons happen sometimes and outlet turbidity are observed to have sudden variation and large amplitude. Normally, operators cannot start to adjust dosage until poor outlet quality is measured at the end of the sedimentation tank. Thus, operators are always late for dealing with abnormal inlet variation. Consequently, the abnormal treatment results will not disappear until all coagulated water with incorrect dosage flow out of the sedimentation tank. During the full-scale tests, the CDCS controlled dosage for one of the lines while dosage in the other line was manually controlled by the operators as before. Thus, results of these two lines can be compared under the same water source and process conditions.

2.1.2 Haining Salcon DWTP

Haining Salcon DWTP (SDWTP) is located in the eastern part of Haining, 30km away from N2DWTP. The plant overview is shown in the Figure 5. Capacity of this plant is 300 000 m^3/d, treatment load during testing period was 150 000 m^3/d. The treatment process includes an aeration tank, coagulation process followed by sedimentation tank, sand filtration, carbon filtration and UV disinfection. Schematic of treatment process is shown in the Figure 6. In the coagulation process, there are four treatment lines in parallel and dosage of each line can be controlled separately. The water source of SDWTP lies in the downstream of Changshan River, compared to N2DWTP.

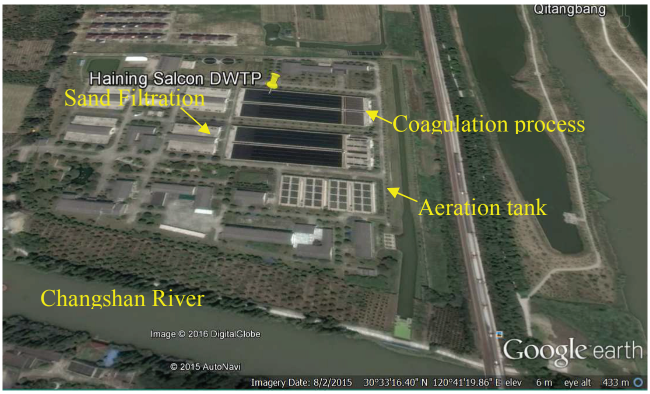

Figure 5. Overview of Haining Salcon DWT plant, Changshan River as water source, aeration tank, coagulation process ant sand filtration are marked

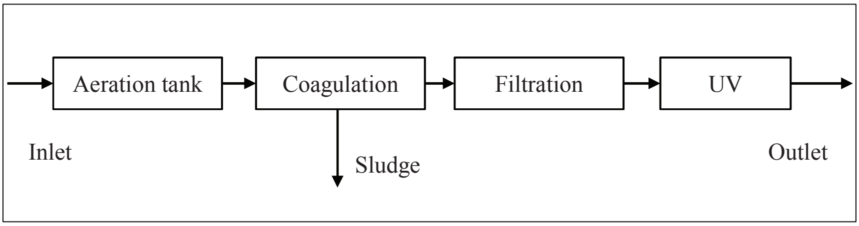

Figure 6. Schematic of treatment process in SDWTP

Same online instruments as N2DWTP are installed in the coagulation process of SDWTP. The Figure 7 shows inlet online sensors including turbidity, conductivity and pH. The other pH sensor and turbidity sensor with low measurement range lie in the flocculation chamber and the outlet respectively. Online measurement signals transfer in the same way as N2DWTP, which are available for both plant operators and the CDCS. The maintenance of online sensors is regularly carried out by plant workers.

Before testing the CDCS, coagulant dosage is manually controlled based on the daily results of jar tests and outlet turbidity. Generally, the expected range of outlet turbidity is less than 2 NTU. During full-scale tests, the expected range is often requested to change to meet the requirement of subsequent filtration. This is because the different expected ranges were related to backwash frequency of subsequent filtration. During the full-scale tests, dosage in one of the lines was controlled by the CDCS. It was also observed that outlet turbidity of this coagulation process remains difficult to control during storms.

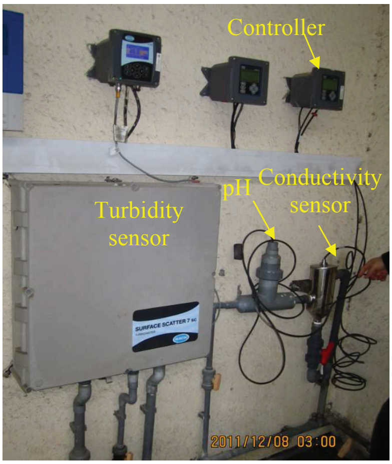

Figure 7. Inlet online instruments of SDWTP. Three sensors are used for measuring turbidity, conductivity and pH

2.1.3 Nedre Romerike WWTP

Nedre Romerike WWTP (NRA WWTP) is located in Lillestrøm Norway. This WWTP is built in a tunnel of rock. The treatment capacity is 50 000m^3/d, serving 110 000 PE. and covering four municipalities. The water source is a combined sewer system, which includes both municipal wastewater and rain water. Shown as the Figure 8, the treatment process consists of a grit chamber, primary settling tank, biological treatment process (sequencing batch reactor), coagulation process followed by sedimentation tank, and sludge treatment. The coagulation process is separated into two parallel lines.

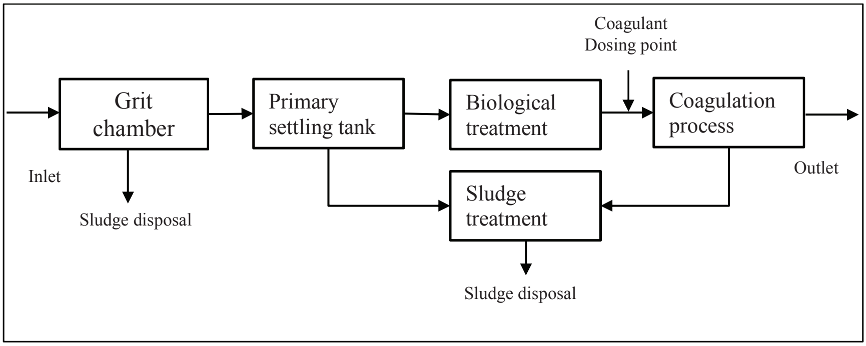

Figure 8. Schematic of treatment process in NRA WWTP

Online sensors are installed in the coagulation process for the dosage control. The Figure 9 illustrates a sampling tank, where inlet online sensors are installed. The other pH sensor is placed in the flocculation chamber. One of the two TUO sensors is installed at the end of one line and another is installed at the outlet of the coagulation process, where these two parallel lines join together. The sampling tank and all sensors are frequently cleaned and calibrated by plant workers. All these online signals first transfer to plant SCADA, then to the CDCS.

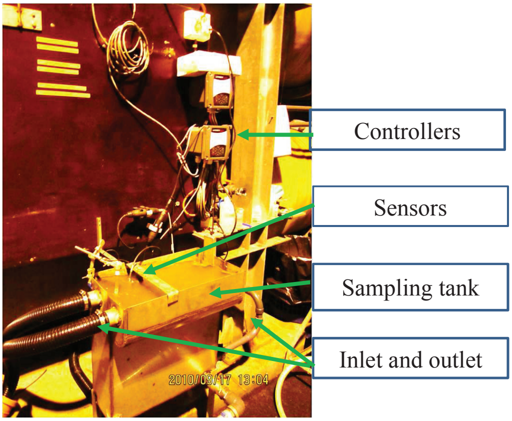

Figure 9. Inlet online instruments of NRA WWTP. Three sensors measure turbidity, conductivity and pH

The whole treatment process requires the removal of 96 % of phosphors, 80 % of nitrogen and 90 % of COD. The CDCS has been running since 2009, achieving constant outlet water quality and considerable coagulant saving. NRA WWTP spends 2.5 million NOK/year on coagulant consumption. There is a demand for this plant to save coagulant consumption. Another demand is to stabilize outlet quality during wet weather. It has been observed that outlet quality experiences big variation during heavy rain and ice melting. Therefore, it is necessary to improve the current model capacity to be able to deal with the above situation.

2.2 Introduction of hardware of the CDCS

The CDCS physically used for full-scale tests is shown in the Figure 10 (Provided by the DOSCON AS, Norway), which enables signal communication, dosage calculation, data recording and measurement error detection. The main part of the CDCS is a PLC (Programmable logical controller), which is a digital computer used for automation of industrial electromechanical processes. Depending on whether DWTP or WWTP have SCADA, the CDCS has two working modes. If without SCADA, the CDCS receives online measurement signals from sensor controllers by means of current analog signals (4-20 mA), and dosage signal is directly sent to dosing pump. If with SCADA, the CDCS works as a “slave” of SCADA. In this mode, online signals primarily transfer to SCADA and then SCADA sends them to the CDCS. In both working modes, there is no time delay during the signal transmission and dosage calculation. Data including online measurements and dosage were recorded at 15 minute’ interval and the CDCS enables to download the data via USB. The CDCS panel is able to show inlet measurements, dosage calculation and system settings, which are enabled to adjustments via the touch screen.

Figure 10. Profile of the Coagulant dosage control system

Based on software TwinCAT (The Windows Control and Automation Technology) (Beckhoff, 2015), various functions in the CDCS are programmed by the standard programming language-IEC61131-3. After models of dosage control are available, they can be uploaded by laptop.

2.3 Data preprocessing for model calibration

Since data quality is very important to the model performance, the original dataset downloaded from the CDCS cannot be directly used for model calibration until it undergoes data preprocessing in the following aspects. Windows Excel is used for data analysis and preprocessing. After preprocessing, the dataset is separated into two parts that are used for model calibration and validation.

2.3.1 Matching outlet data with inlet

Online measurement signals are continuously received by the CDCS and measurements recorded at same time are written in the same row of the dataset. Because there is a hydraulic retention time (HRT) of the sedimentation tank, the outlet measurement is not a real result of inlet measurements and dosage even though they are in the same row of dataset. Thus, such datasets cannot be used for model calibration until matching outlet measurement with inlet measurement. Theoretically, HRT can be calculated with wastewater flow and volume of the sedimentation tank. Since the real time HRT varies with the wastewater flow, each outlet turbidity is shifted and matched with inlet quality in the dataset considering real-time HRT.

2.3.2 Measurement error elimination

Although online sensors are cleaned and calibrated frequently, measurement errors are often observed because of the following reasons (Liu *et al.*, 2016c). Firstly, particles, grease and crystallized coating tend to stick on online sensors, which hinders the sensor to touch with wastewater. Secondly, aging causes unstable working status and drift from true value. Thirdly, due to communication interruption between online sensors and the CDCS, the measurement values are not updated. Fourthly, human mistakes such as wrong calibration and irregular operation also result in measurement errors. Hence, measurement errors in datasets appear in different styles such as peaks, straight line and drift. The current method of error detection is based on the normal variation range, which is fixed by referring to the *normal distribution*. The measurement values beyond the normal distribution are deleted manually. According to the dataset collected from N2DWTP, SDWTP and NRA WWTP, the data statistics show in Table 1. Qin, PHI, TUI, CNI, TMP and PHO respectively stand for water flow, inlet pH, inlet turbidity, inlet conductivity, temperature, and coagulation pH. The table specifies the low limitation and high limitation in the normal range.

Table 1, Normal measurement range of each parameter

		Qin, L/s	PHI	TUI, NTU	CNI, mS/m	TMP, °C	PHO
NRA WWTP	Mean	587	6.41	104	512	15.3	6.18
	Standard deviation	262	0.16	48	122	3.0	0.22
	Low limitation in the normal range	63	6.00	50	200	5.0	5.80
	High limitation in the normal range	1400	7.00	300	900	25.0	6.80
		Qin, m^3/h	PHI	TUI, NTU	CNI, µS/cm	TMP, °C	PHO
N2DWTP	Mean	1904	6.94	102	335	24	6.57
	Standard deviation	505	0.18	46	242	8	0.23
	Low limitation in the normal range	1000	6	30	100	4	5
	High limitation in the normal range	2600	7.0	250	600	30	6.8
		Qin, m^3/h	PHI	TUI, NTU	CNI, µS/cm	TMP, °C	PHO
SDWTP	Mean	1892	7.21	91	587	25	7.15
	Standard deviation	661	0.19	23	96	7	0.21
	Low limitation in the normal range	506	6.5	30	150	5	6.3
	High limitation in the normal range	3000	7.5	150	785	32	7.3

2.4 Model calibration

It is concluded from previous research that PLSR is the best statistical method compared to MLR and PCR (Rathnaweera, 2010). Based on the conclusion, this thesis uses PLSR as method of model calibration. Software Unscrambler® X version 10.3 (Camo, 2015) is responsible for PLSR. There are different types of algorithms such as Non-linear Iterative Partial Least Squares algorithm (NIPALS), Kernel PLSR, orthogonal scores PLSR. Since being best suited for the large number of samples (thousands of objects with few variables), Kernel PLSR is selected (Lindgren *et al*., 1993; De Jong and Ter Braak, 1994; Dayal and MacGregor, 1997; Svante *et al*., 2001). Cross validation with uncertainty test is implemented after the calibration (Amari *et al*., 1997).

This thesis uses R^2 and RMSE as indicators for evaluating the model quality and performance. R^2 illustrates how well the training data or testing data fits for the model. $R^2=1$ indicates that the data fit the model perfectly while $R^2=0$ indicates no fit. RMSE represents the deviations degree between prediction values and measurement values.

2.5 Current online detection of measurement errors

During full-scale tests, model performance depends on not only model accuracy but also measurement quality. Two approaches are used for online detection of measurement errors. Variation validation functions by checking whether sensors are actively working. If the variation range of a parameter is less than the setting within a certain time frame, then this parameter is defined as an erroneous parameter and the model without this parameter starts to work. If the variation range of this error parameter is larger than the setting, then the main model with this parameter restarts. The Figure 11 presents the setting interface for the variation validation, which is a screenshot of the CDCS.

The second approach of measurement error detection is based on the normal measurement range. Taking TUI as example, if TUI measurement is either lower or higher than the normal variation range, then it is defined as an error parameter until the measurement value returns to the normal range. When an error parameter appears, the model without this parameter is activated. The normal measurement range is fixed by referring to the *normal distribution*. The setting interface of this approach is shown in the Figure 12.

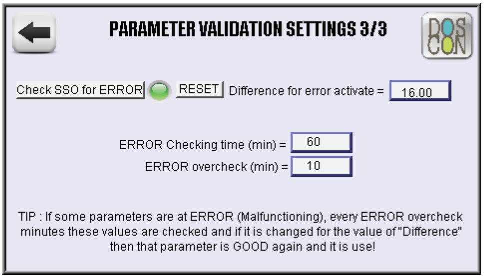

Figure 11. Setting interface of variation validation, the setting has three pages and this page is only for one parameter-outlet suspended solid (SSO)

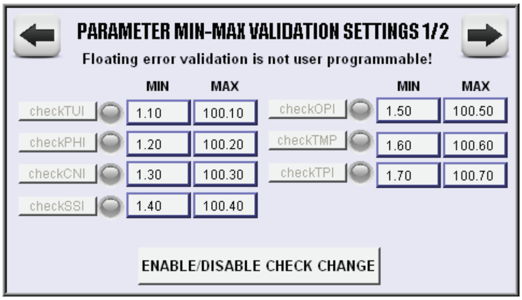

Figure 12. Setting interface of normal measurement range, this setting has two pages. MIN: low limitation of measurements and MAX: high limitation of measurements

3. RESULTS AND DISCUSSION

3.1 Testing the universality of the CDCS

The universality is one of challenges for empirical models, which refers to the independence of various water sources and process dynamics. In order to test the universality of the CDCS, this thesis focuses on implementing coagulant dosing control of the CDCS with two full-scale drinking water treatment processes, which have different water sources and treatment requirements from the previous tests with wastewater treatment. The full-scale tests were implemented in N2DWTP and SDWTP. Using the test results of these two DWTPs and previous results in NRA WWTP, the universality of the CDCS is analyzed in the 1st paper of this thesis (Liu *et al*., 2013).

3.1.1 Procedure of full-scale tests

The full-scale tests in two DWTPs are implemented according to the following procedure. After the control system and the online sensors are installed and commissioned, the full-scale tests start. The procedure of the full-scale tests include data collection, model calibration, validation of dosage predictions, model modification, and full-scale tests. The procedure is shown in the Figure 13. Validation of dosage prediction indicates that the model is tested with a new dataset, and dosage prediction is compared to the real control dosage. If the correlation between dosage predictions and real control dosage is acceptable then full-scale tests start. Otherwise, the model should be re-calibrated with an extended dataset, collected over a longer period of time. The full-scale tests are divided into two sub-stages; passive tests and active tests. In the passive tests, dosage prediction from the CDCS is used for comparison with real dosage instead of dosage control, a flow proportional dosage controlled by plant operators. When dosage prediction in passive tests prove to be acceptable, the CDCS takes over the dosage control and active tests start. The model is regularly recalibrated with newly extended datasets to confirm if it is necessary to the update model for the CDCS.

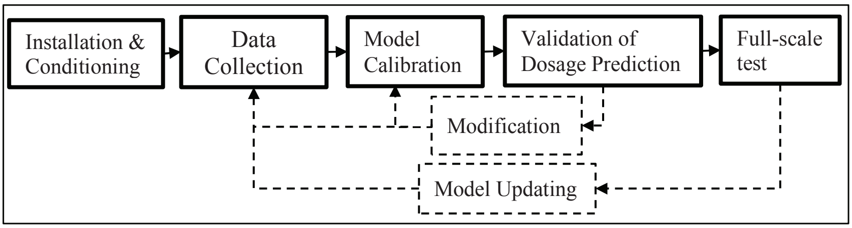

Figure 13. The procedure of full-scale tests. The solid line presents compulsory actions while the dotted line indicates non-compulsory actions

In N2DWTP, data collection started from 1st January 2012. The period of passive tests is from 8th March 2012 to 22nd April 2012 and then active tests starts. Since the CDCS receives pumping frequency (Hz) as the dosage signal, DCSCS provides the frequency as output to SCADA. In SDWTP, data collection started from 10th January 2012. The period of passive tests is from 8th March 2012 to 14th May 2012. Before the active tests in both DWTP, coagulant flow was proportional to water flow and the ratio was manually adjusted by plant operators considering TUO and a daily report of jar tests.

3.1.2 Results of passive tests

In N2DWTP, the model was calibrated with the dataset collected before passive tests, resulting in R^2=0.80 and RMSE=1.3. The Figure 14 shows the result of passive tests over one week with a sampling rate of 15 minutes. The blue line represents conventional dosage (signal of flow-proportional dosage) while the red line indicates experimental dosage (dosage prediction from the CDCS). The green line as well as the dotted yellow lines stand for TUO and expected ranges of TUO. Since it is in the stage of passive tests, conventional dosage is the real control signal and accordingly TUO is a result of the conventional dosage. According to the comparison between flow proportional dosage and dosage prediction from the CDCS, both dosages are similar. However, there are differences in some parts that are marked "A" and "B" in the Figure 14. In part A, TUO is lower than the expected range (2.0-3.0 NTU) and therefore the conventional dosage is over the optimal dosage, whereas the conventional dosage is under the optimal dosage in part B because TUO is higher than the expected range. When comparing the two dosages in part A and B, the experimental dosages are more close to optimal dosage than the conventional one. Thus, if experimental frequency is used as a control signal in this period, then TUO will become more stable and close to the expected range. Therefore, dosage control of the CDCS presents better performance than the conventional dosage control in the passive tests, which is a strong basis for the active tests.

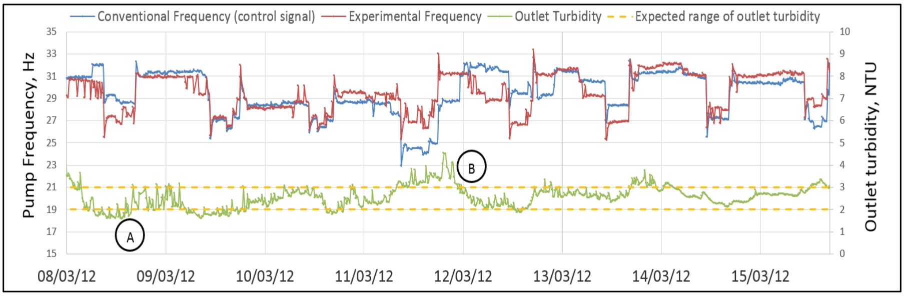

Figure 14. Comparison of conventional dosing and modelled experimental dosing at N2DWTP in stage of passive test. Conventional Frequency (blue line) is flow proportional dosing that control dosing pump while experimental frequency is prediction from the CDCS. The thin dashed line and left axis represent the outlet turbidity, while yellow dotted lines indicate the expected outlet turbidity range (2.0-3.0 NTU).

In SDWTP, the primary model for passive test was calibrated with R^2=0.74 and RMSE=53.5. The Figure 15 shows the result of passive tests over one week, comparing dosage prediction from the CDCS and the conventional dosage. The sampling rate is 15 minutes. SDWTP requested to obtain low TUO to reduce backwash frequency of the downstream filtration process, therefore the expected TUO range is fixed to 0.7-1.3 NTU. At most times, the experimental signal is able to follow the conventional signal. However, in part A the experimental signal is much lower than the conventional signal. Since TUO is lower than the expected range in part A, the conventional dosage as real control signal is higher than the optimal dosage and it should be close to the experimental signal. Therefore, within a narrow expected TUO range, the model performance is as good as the manual control by plant operators. Similar to N2DWTP, results of the passive tests have displayed a strong basis for the active tests.

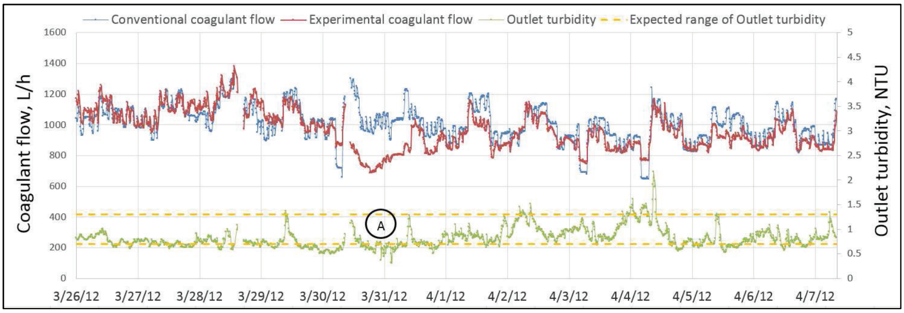

Figure 15. Comparison of conventional dosing and modelled experimental dosing at the Salcon DWTP. The thin dashed line and left axis represent the outlet turbidity, while the bold dashed lines indicate the desired outlet turbidity range (0.7-1.3 NTU). The thin and dotted lines refer to conventional dosage and estimated experimental dosages, respectively.

3.1.3 Results of active tests

Active tests were carried out in N2DWTP from May 2012. The CDCS was responsible for controlling dosage in one parallel line (experimental line). Another parallel line (conventional line) used flow-proportional dosage and the proportional ratio was decided by plant operators. Since two lines have same inlet water quality, TUO differences between two lines are related to dosage control. Average TUO (Avg. TUO) and standard deviation (STDEV) are used as factors to evaluate dosage control. Table 2 shows statistical results of these two lines (Liu *et al.*, 2013). Over a period of one year with active tests, the model was recalibrated for different expected TUO ranges. All monthly average TUO in the experimental line are within the expected TUO. Some monthly average TUO in the conventional line are under the expected TUO range, which are marked as red text. When comparing TUO stability of these two lines, STDEV of the conventional line shows more stability in the beginning. However, STDEV of the experimental line is lowering gradually and indicates stronger stability than the conventional line towards the end. This could be due to the model updating with extended data. The model with the longer training dataset leads to better performance. According to the data record in plant SCADA, the average dosage of the experimental line is 10 % less than conventional line during the active tests (Liu *et al.*, 2013).

During the full-scale tests, SDWTP tested the relationship between outlet quality and backwash frequency of subsequent filtration. Hence, expected TUO range was changed several times. In order to deal with different expected TUO ranges, several models were calibrated. Hence, full-scale tests in SDWTP mostly stayed in stage of passive tests under the testing procedure.

Table 2, Statistical results of experimental line and conventional line in N2DWTP

	Expected TUO range, NTU	Conventional line		Experimental line	
		Avg. TUO, NTU	STDEV	Avg. TUO, NTU	STDEV
2012 22/4-21/5, 1st Month	1.5-2.3	1.76	0.43	1.90	0.54
2012 22/5-21/6, 2nd Month	1.5-2.3	1.35	0.51	1.88	0.72
2012 22/6-21/7, 3rd Month	1.5-2.3	1.34	0.39	1.55	0.66
2012 22/7-21/8, 4th Month	1.5-2.3	2.05	0.42	1.72	0.46
2012 22/8-21/9, 5th Month	1.5-2.3	1.85	0.30	1.53	0.36
2012 22/9-21/10, 6th Month	1.5-2.3	2.06	0.35	2.26	0.35
2012 22/10-21/11, 7th Month	1.5-2.3	1.99	0.48	2.09	0.39
2012 22/11-14/12, 8th Month	1.5-2.3	2.49	0.37	2.30	0.27
2013 15/12-14/01, 9th Month	2.3-3.0	2.38	0.43	2.50	0.26
2013 15/01-5/02, 10th Month	2.3-3.0	2.22	0.67	2.48	0.33
2013 20/02-20/03, 11th Month	2.3-3.0	2.56	0.51	2.64	0.37
2013 20/03-22/04, 12th Month	2.3-3.0	2.61	0.41	2.62	0.26

Note: STDEV: standard deviation, Avg: average.

3.1.4 Dosage control during storms

It is often observed that the coagulation process experienced high TUO during storms (Liu *et al*., 2013). In the Figure 16, such issues always occur in summer and dosage prediction cannot respond to the high TUO, which are marked by "A". Although the model was updated with extended data that includes such a situation in 2012, the updated model still did not perform well when storms happened again in 2013. In such situations, plant operators need to switch control mode from the CDCS to manual control until TUO returns to the expected range. In NRA WWTP, TUO often exceeds the requirement (less than 3 NTU) during heavy rain, as shown in the Figure 17. In these two plants the model cannot identify such issues and adjust dosage accordingly.

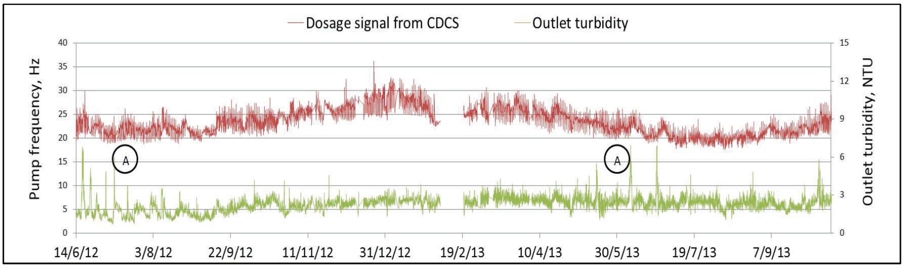

Figure 16. Large variation of outlet turbidity during storms in active tests of N2DWTP, The situations with high TUO during storm are marked as "A".

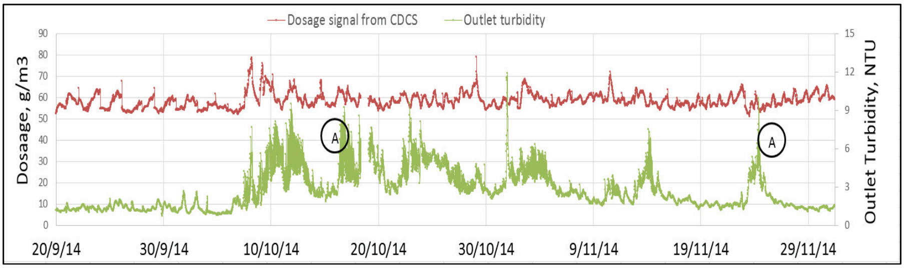

Figure 17. Large variation of outlet turbidity during wet weather in active tests of NRA WWTP, The situations with high TUO during storm are marked as "A".

3.1.5 Universality analysis of the CDCS

Based on the results of full-scale tests in two DWTPs, the CDCS is able to automatically control dosage to provide acceptable and even more constant outlet quality. Simultaneously, the CDCS displayed an ability of coagulant saving compared to manual control. Hence, the CDCS proved to be a good solution of coagulant dosage control in DWTP. Therefore, universality of the CDCS extended from WWTP to DWTP.

The full-scale tests showed that performance of the CDCS was unacceptable when storms happened, which are observed not only in two DWTPs but also NRA WWTP. Such issues indicates the limitation of model capacity of dosage control. Therefore, it is very necessary to improve model capacity for dosage control during storms. In addition, the full-scale tests in SDWTP displayed that the existing CDCS only focus on providing fixed outlet quality. The expected outlet quality of the CDCS cannot change until model recalibration, which is time-consuming. This is the reason why the full-scale tests in SDWTP mostly stayed in stage of passive tests. Therefore, it is very necessary for the CDCS to improve the utilization flexibility, which enables achieving different expected outlet turbidity without model recalibration.

3.2 Improvement of model capacity

In order to improve the model capacity of dosage control and flexibility of achieving different expected outlet turbidity, this section focuses on model improvement in view of control strategy. The proposed solution is to add an outlet parameter into the existing FF model to achieve feed-back control (Liu and Ratnaweera, 2016a), which is the 2nd paper of this thesis. Firstly, measurement parameters of the CDCS are identified in view of control strategy;

secondly, the concept of combining FF and FB control is proposed; thirdly, the FF-FB model is tested with operational data from N2DWTP and NRA WWTP.

3.2.1 Concept of combining feedforward and feedback model

In view of control strategy, the current model only uses the inlet quality but not outlet quality as input variables, known as feed-forward (FF) systems or open-loop systems. Theoretically, a FF model can react instantly to any measured disturbing variables (DVs, inlet quality measured by online sensors) through manipulated variables (MVs, coagulant dosage) and then controlled variables (CVs, outlet quality) will respond accordingly. In contrast, dosage variation from a pure feed-back (FB) model only depends on outlet variables instead of inlet variables, which means ignoring both measured and unmeasured disturbance from inlet. In many situations, especially when the raw water source is a lake or a calm river, a FF model can work efficiently in WWT or DWT even with a treatment process with high hydraulic delays (Ingildsen *et al*., 2002). Furthermore, because a FF model is able to react at the very beginning of a process, they lead to better economy by chemical and energy saving.

One disadvantage of the FF model is its low ability to handle situations with unmeasured disturbance, leading to unexpected outlet quality. This is essential because there is no compensation from outlet quality to dosage prediction. Earlier results in Chapter 3.1.4 show that the FF model cannot respond to unexpected outlet quality during heavy rain (Liu *et al.,* 2013). Conversely, the advantage of the FB control is the ability to adjust dosage based on measured error between set points and CVs. As a result, the unmeasured disturbance and related inaccurate dosage can be compensated. Therefore, it is very necessary to incorporate the advantages of these two control strategies with the purpose of improving model performance. The Figure 18 shows the concept of the dosing control system combining FF with FB.

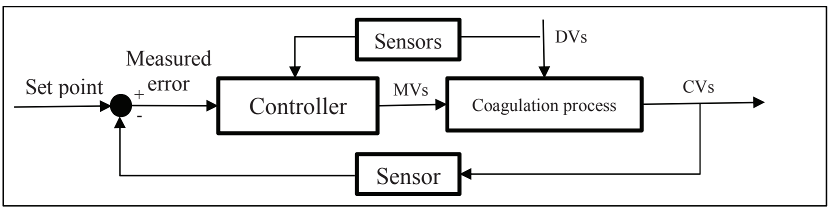

Figure 18. Control strategy of combining FF and FB

Equation 2 shows a FB as input parameter is added into the existing model, according to the concept in Fig 18. Equation 3 shows how the FB parameter is calculated with outlet quality (either turbidity or suspended solid) and the set point, hence why both outlet quality and the set point (presenting expected outlet turbidity) can influence dosage prediction.

$$Dosage = f\ (WW\ flow, inlet\ SS\ or\ TU, inlet\ pH, coagulation\ pH, inlet\ conductivity,$$
$$inlet\ phosphate, temperature, interaction\ variables, variables\ square\ , FB)$$

Equation (2)

$FB= f\ (outlet\ TU, set\ point)$ Equation (3)

3.2.2 Validation of the FF-FB model

In N2DWTP, the FF-FB model is calibrated by dataset collected from May 2012 to February 2013, achieving R^2=0.75. Whereas the FF model (R^2=0.71) is calibrated with the same dataset, but excludes TUO. Hence, the R^2 values indicate that the calibration data with TUO provide better a fit to the FF-FB model. The Figure 19 shows the results of passive tests with data collected from February 2013 to October 2013. The upper figure shows distributions of TUO measurement, which includes 20 108 samples. The statistics in the lower figure shows the dosage adjustment of the FF-FB model. The dosage adjustments are calculated with Equation 4. The results of dosage adjustments show that the FF-FB model is able to decrease the dosage predicted by the FF model when TUO < 2.3 NTU (set point), while the adjusted dosage becomes higher when TUO> the set point. Furthermore, the strength of this adjustment increases when TUO becomes further away from the set point. In case of TUO > 3.8 NTU, dosage of the FF model could not adjust adequately and the TUO starts to increase. This is because the plant operators switched to flow-proportional dosing control and increased the dosage manually. As a result of this, the difference between FF-FB model and real dosage is so small that dosage adjustments show the weak strength. Otherwise, in range of 3.8-5.8 NTU, the dosage adjustment of the FF-FB model should be approximately shown as dotted line bars. Therefore, the FF model after adding a FB variable is able to correctly compensate the dosage prediction, resulting in more stable TUO.

$$Dosage\ adjustment = \frac{(dosage\ from\ FF\_FB\ model - real\ dosage\ from\ FF\ model)}{real\ dosage\ from\ FF\ model} * 100\%$$

Equation (4)

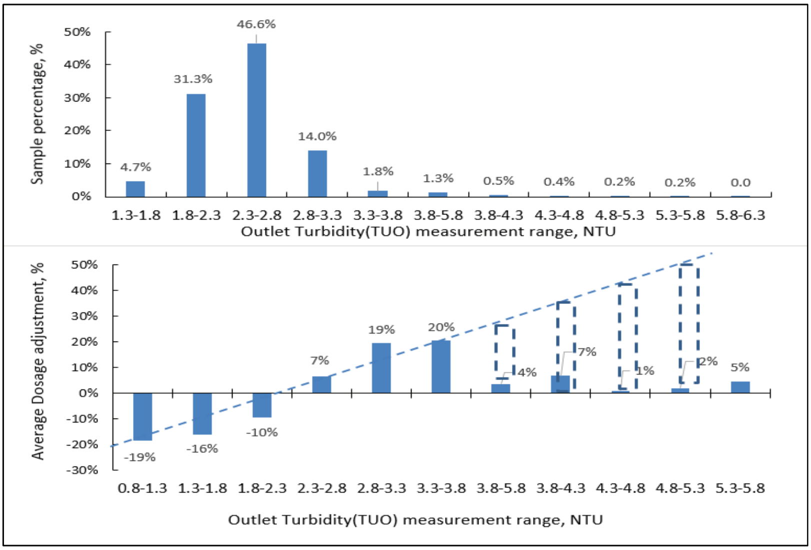

Figure 19. Statistics on passive test *of the FF-FB model in N2DWTP*

The data in the passive tests of the FF-FB model in NRA WWTP has shown a very good fit to the model after adding a FB variable, as R^2 improves to 0.87 from 0.61 of the FF model. Hence, this leads to a much better model performance than the FF model. The Figure 20 shows results of passive tests with the data (16 055 samples) collected from June 2014 to December 2014. Similarly, in this WWTP, the strength of dosage adjustment of the FF-FB model depends on the difference between TUO measurement and the set point. Therefore, the FF-FB model should have a stronger capacity to stabilize outlet quality for this WWTP during in the active tests.

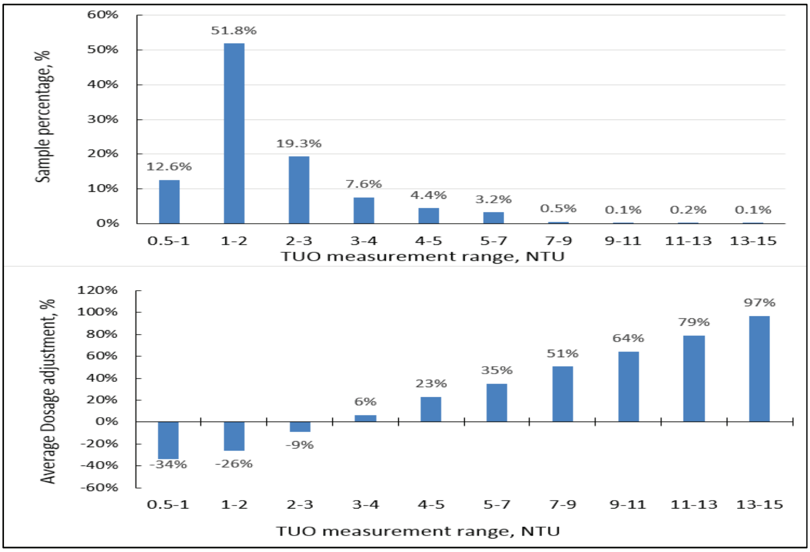

Figure 20. Statistics on passive test *of the FF-FB model in NRA WWTP*

3.2.3 Effect on coagulant consumption

Since the FF-FB model is able to adjust dosage to stabilize TUO, the coagulant consumption will be changed accordingly. Based on statistics data in Table 4 and 5, this section estimates potential changes of coagulant consumption under the FF-FB model control. In Table 3, the pump frequency as the system output is an indicator of coagulant flow, which is proportional to the coagulant dosing flow. For N2DWTP, during the period of the passive tests (9 months), the FF-FB model used 3.7 % less coagulant to prevent over-dosage. However, the overall coagulant consumption with the FF-FB model to secure more stable TUO was 2.6 % more than the FF model, because 12 809 data points originally had an under-dosage resulting in TUO>2.3. Whereas in NRA WWTP the total consumption of the FF-FB model became less, which could save 9.2 % coagulant during the passive tests (6 months). If the FB-FF model's task was only to reduce the over-dosage, the savings would be 15.5 %. Therefore, if inlet quality is similar to the passive tests and TUO can work as a non-delayed FB variable, the FF-FB model can provide approximately 9.2 % coagulant savings in future applications.

Table 3, Parameters of changes on coagulant consumption in Haining N2DWTP

TUO measurement range, NTU	0.8-1.3	1.3-1.8	1.8-2.3	2.3-2.8	2.8-3.3	3.3-3.8	3.8-5.8
Sample percentage, %	0.2%	4.7 %	31.3 %	46.6 %	14.0 %	1.8 %	1.3 %
Average Dosage adjustment, %	-19 %	-16 %	-10 %	7 %	19 %	20 %	4 %
Average pump frequency, Hz	26.81	25.19	24.46	24.91	25.21	26.83	36.88

Table 4, Parameters of changes on coagulant consumption in NRA WWTP

TUO measurement range, NTU	0.5-1	1-2	2-3	3-4	4-5	5-7	7-15
Sample percentage, %	12.6 %	51.8 %	19.3 %	7.6 %	4.4 %	3.2 %	1.0 %
Average Dosage adjustment, %	-34 %	-26 %	-9 %	6 %	23 %	35 %	73 %
Average real-time Dosage, ml/m^3	56.33	58.88	57.82	60.06	59.31	57.92	60.13
Average WW flow, m^3/h	428	493	644	984	1206	1271	1114

3.2.4 Improvement effect on the flexibility

According to the validation results, strong dosage adjustment of the FB significantly improved model capacity of dosage control. On other hand, flexibility of achieving different expected outlet turbidity is carried out. Since the dosage adjustment is implemented by the difference between outlet turbidity and the set point, the set point can be input as user expected outlet turbidity. Hence, according to different user inputs the FF-FB model can provide different strength of dosage adjustment to enforce outlet turbidity close to the expected value. Consequently, the CDCS has flexibility to achieve different expected outlet turbidity without model recalibration.

3.2.5 Limitation of the FF-FB model

Application of the FF-FB model is limited to the coagulation process that combine high efficient sedimentation tanks that have short hydraulic retention time. Outlet turbidity of common sedimentation tank (2-6 hour, hydraulic retention time) cannot provide timely FB to the CDCS. Considering rapid inlet variation, the late FB could result in wrong dosage adjustment. Thus, it is necessary to find out a solution for the late FB.

3.3 Preconditions of TUO software sensor development

The research in this thesis aims to develop a concept to estimate the outlet parameters as a possible solution to the issue of the late FB. However, there is an obstacle for the software sensor development. In practice, water goes through the sedimentation tank by means of non-plug flow (nonPF), which is not as ideal as plug-flow (PF). Hence, potential mixing effect could exist under the nonPF. Consequently, TUO measurements present the mixing results of different PF TUOs. Therefore, it is necessary to confirm if TUO measurements are accurate results of inlet quality and dosage. In order to test the mixing effect, this section simulates PF TUO and compares with TUO measurement (Liu and Ratnaweera, 2016b), as the 3rd paper of this thesis. This section is a precondition of the software sensor development, which is illustrated in the next chapter.

3.3.1 Definition of plug flow TUO

Definition of PF TUO in this thesis is based on tracer tests. Results of tracer tests were previously carried out in NRA WWTP (Rathnaweera, 2010). After a certain dosage of tracer (Rhodamin B) was added at inlet of sedimentation, results show that the tracer concentration at outlet of the sedimentation tank distributes with time. Thus, PF TUO can be defined by the distribution ratio and TUO measurement. This concentration distribution illustrates that each water segment at time t0 tends to distribute a certain amount of itself to other nearby water segments at times t±n, which is the process of converting PF TUO to nonPF TUO. Hence, PF TUO at time t0 equals many distributions that provide to TUO measurements at time t0 and t±n. Furthermore, the distribution of tracer concentration indicates the distribution range and ratio of PF TUO. According to the concept, Equation 5 illustrates the definition of PF TUO, where percentages present the distribution ratio and t±n indicates the distribution range.

In order to find out the significance of the distribution effect, PF TUO is simulated by Equation 5 under different distribution ratio of water segments, which is shown in Table 5. Considering the tracer test results, the longest mixing range in this paper is assumed as -90 minutes to +30 minutes. Since the water segments are measured every 15 minutes, the nine segments are considered to represent the distribution ratio as noted in Table 5

$$PF\ TUO_{t0} = f(TUO_{t-6}*a\,\% + TUO_{t-5}*b\,\% + TUO_{t-4}*c\,\% + TUO_{t-3}*d\,\% + TUO_{t-2}*e\,\% + TUO_{t-1}*c\,\% + TUO_{t0}*d\,\% + TUO_{t+1}*e\,\% + TUO_{t+2}*f\,\%) \qquad \text{Equation (5)}$$

Table 5, PF TUO simulation under the different distribution ratio

	-90mins	**-75mins**	**-60mins**	**-45mins**	**-30mins**	**-15mins**	**0 mins**	**+15 mins**	**+30 mins**
	TUOt-6	TUOt-5	TUOt-4	TUOt-3	TUOt-2	TUOt-1	TUOt0	TUOt+1	TUOt+2
	a %	b %	c %	d %	e %	f %	g %	h %	i %
set1	0	0	2.5 %	7.5 %	10 %	15 %	50 %	15 %	0
set2	0	2.5 %	5 %	7.5 %	10 %	15 %	40 %	15 %	5 %
set3	2.5 %	5 %	5 %	7.5 %	10 %	15 %	30 %	15 %	10 %

3.3.2 Simulation results of plug flow TUO

The Figure 21 shows the simulation results, in which each set of figures presents the correlation between PF TUO simulation and measured TUO value at various mixing degrees as noted in Table 5. In the right side of the figure, each point is plotted by PF TUO simulation and TUO measurement. Three equations illustrate a good correlation between them. In addition, R^2 shows very small deviation of data points from the correlation line (solid line). Regarding the right side of these figures, deviation from the correlation does not have a severely negative impact on R^2 because the majority of data points (67 867 samples in two years) concentrate at the correlation line. An important observation from these results is that despite the possible internal mixing conditions caused by non-plug-flow hydrodynamics in the sedimentation tank, the variable non-plug-flow conditions do not generate significant difference between PF TUO and TUO measurement. Thus, it is not necessary to use PF TUO for building up the soft-sensor in this plant and TUO measurement can be used instead.

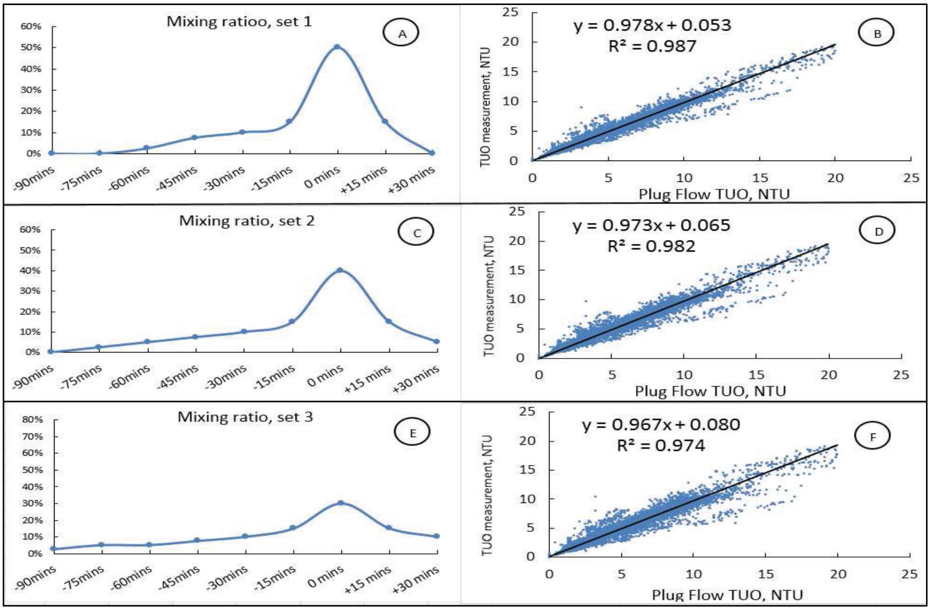

Figure 21. Significance of mixing effect under different mixing percentage

3.4 Development of TUO software Sensor

Based on the above conclusion that the non-plug-flow conditions have insignificantly impacted the composition of the outlet water portions, this section presents development of the TUO software-sensor using shifted TUO measurement (Liu and Ratnaweera, 2016b).

3.4.1 Concept of TUO software sensor

In Figure 22, the proposed TUO software-sensor, encircled by the dotted line, lies in front of the sedimentation tank, which can predict TUO measurement. According to simulation results of PF TUO in Chapter 3.3.2, PF TUO can be generally represented by TUO measurements (nonPF TUO) with small errors. Hence, the model of the TUO software-sensor can be built up with existing inlet water parameters, dosage and TUO measurements instead of PF TUO. Equation 6 shows the model structure of the software-senor. PLSR and Unscrambler® (version 10.3) are used for building up the relationship between inlet parameters, dosage and TUO measurement. Regarding dataset preparation, TUO measurements are shifted and matched to inlet parameters considering the theoretical HRT.

$$TUO = f\ (QIN, TUI, PHI, PHO, CNI, TMP, Dosage, interaction\ among\ variabes,\ variables\ square)$$

Equation (6)

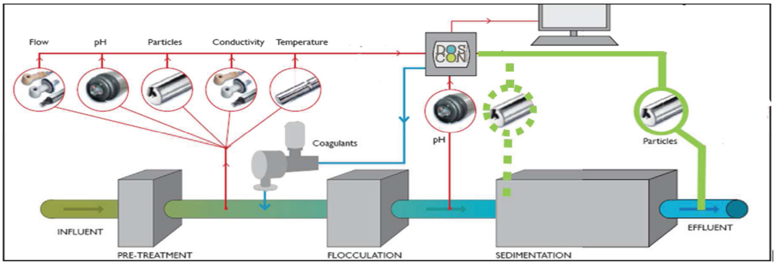

Figure 22. Concept of the TUO software-sensor (Instruments covered solid line present physical online sensors whereas the TUO software-sensor within the dotted line)

3.4.2 Testing of TUO software sensor

A model of the TUO software-sensor was calibrated with the dataset collected in 2013. R^2=0.86, as coefficient determination of calibration, indicates that the dataset fits the model. The Figure 23 shows the results of model validation with the dataset collected in 2014. X-axis stands for TUO prediction with inlet parameter, while Y-axis shows the corresponding TUO measurement (shifted TUO). Regarding the regression line, the slope (1.025) and intercept (0.186, crossing point with Y-axis) shows that the correlation line is very close to an ideal line Y=X, and R^2 indicates that most data points centralize to the correlation line.

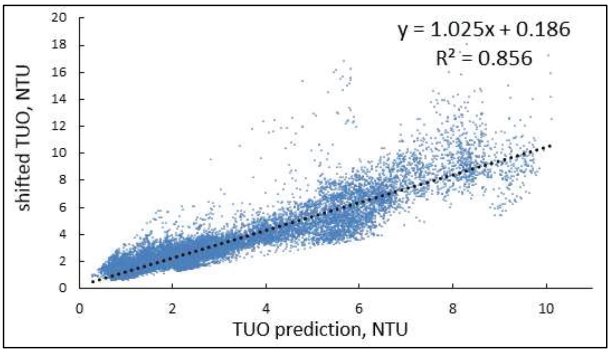

Figure 23. Correlation between shifted TUO and TUO prediction. The dotted line shows the ideal fit.

According to the results of accuracy analysis (Liu *et al.*, 2016b), accuracy of TUO prediction is 84 % in the majority range 1-5 NTU. Even with somewhat higher relative errors, the error in absolute values are less than 0.31 NTU for the working range (1-5 NTU), which is promising.

In full-scale treatment, it is often not an objective to obtain the lowest possible TUO, but an adequately good TUO. In most cases, TUO within 1-5 NTU is considered as an acceptable optimal. Sensitivity of model performance, which depends on the majority of the dataset, is not good enough when predicting TUO at low levels. Thus, the expected range of TUO measurement is mostly overlapped with the optimal working range of TUO software-sensor (1-5 NTU). When the TUO software-sensor is used as a FB for dosage control, the adjusted dosage will cause a narrower range of TUO measurement, where the software-sensor has a better performance.

3.5 Improvement on error detection of inlet measurements

Performance of the coagulant dosage control system highly depends on working status of online sensors. Although routine maintenances (cleaning and calibration) are carried out regularly by plant operators, measurement errors usually occur and challenge the reliability of the dosage control system. Thus, measurement error detection is an essential part of the dosage control system. Relying on the software sensor, this section is to build up a new method to detect inlet measurement errors (Liu *et al.*, 2016c), which is the 4th paper of this thesis.

3.5.1 Concept of the detection method

TUO measurements can be used as a reference in error detection of inlet measurements. As an indicator of treatment results, TUO measurements can respond to any change of related inlet parameters and dosage. Either under-dosage or over-dosage can cause TUO measurement outside of the expected range. Thus, TUO is a key parameter for the coagulation process. In practice, not only are turbidity sensors (or suspended solid sensors) sometimes double or triple installed at a process outlet, the TUO laboratory measurements are often used to compare with online TUO measurements to ensure its accuracy. Moreover, an improved working environment at the process outlet, where most particles settle down, reduces the error proneness of the TUO sensors. Therefore, TUO sensors are the most reliable instruments in the dosage control system and are able to function as the reference in the error detection.

The software sensor, presented in Chapter 3.4, enables the simulation of TUO at given inlet parameters and dosage. Hence, differences between TUO measurements and corresponding TUO simulations are generated. This thesis considers that these differences are caused by both model errors and inlet measurement errors. Model errors exist in all TUO simulations with unpredictable fluctuations around the mean value. This thesis assumes that model errors repeat within a certain range and the related differences are limited to the certain range accordingly. However, the differences caused by inlet measurement errors are similar to systematic errors, which happen occasionally with definite causes such as sensor faults, wrong calibration, communication pause, etc. Thus, the proposed concept of the error detection is that when the differences exceed the certain range that the model errors decide, the measurement errors of inlet sensors are considered to be the cause. The Figure 24 describes the above concept, where the red lines indicate that inlet measurement and model are sources of difference.

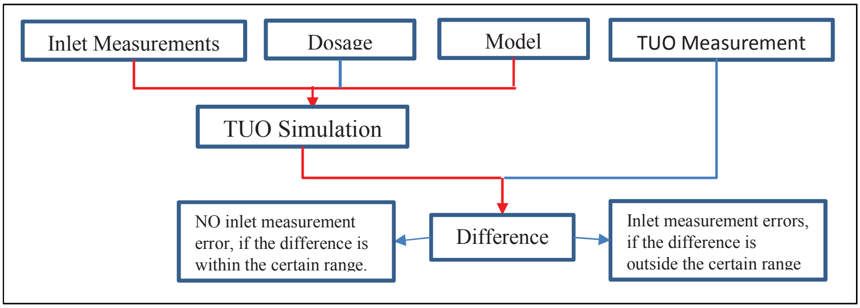

Figure 24. Concept of error detection of inlet measurements, the red lines indicate sources of difference

3.5.2 Detecting criterion of inlet measurement errors

Since there is an obvious boundary between model errors and inlet measurement errors, this section defines a criterion of error detection based on the boundary (Liu *et al.*, 2016c). The Figure 25 shows the correlation between TUO measurement (Y-axis) and TUO simulation (X-axis). Liu et al. (2016) proved that the model of TUO prediction is constant after several recalibrations with different random selection samples, so that the slope and offset are constant accordingly. Two lines (dotted lines) parallel with the correlation line are added to indicate the boundary between model errors and inlet measurement errors. These two lines are expressed by the Equation 7. Hence, these two lines can function as the detection criterion of inlet measurement errors. Namely, if a plotted point (a TUO measurement, a TUO simulation) lies between two lines described by Equation 8, there is an insignificant difference between TUO simulation and TUO measurement, hence inlet online sensors are working normally. Otherwise, plotted points lying outside these two lines indicate measurement errors of inlet online sensors.

$$TUOp = Slope * TUOm + Offset \pm K \qquad \text{Equation 7}$$

$$-K + Offset < TUOp - 0.82 * TUOm < K + offset \qquad \text{Equation 8}$$

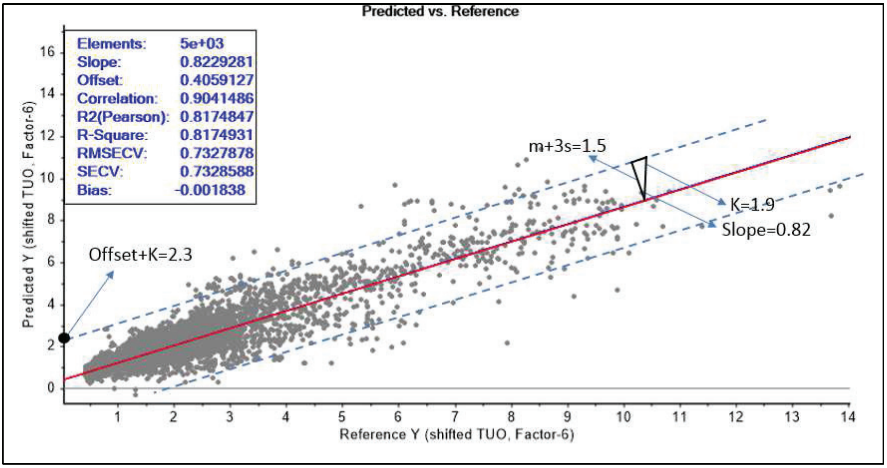

Figure 25. Detection criterion of inlet measurement errors, Solid line presents correlation line between simulations (X-Axis) and measurements (Y-Axis) of outlet turbidity. Based on the slope and the offset of the correlation line and defined range of model errors, two dotted lines parallel with the correlation line are defined as proposed detection criterion. Offset of additional lines=offset of correlation line ± K)

3.5.3 Comparison between the new method and the current method of error detection

In the previous section, the new detection method of inlet measurement errors was developed based on the software sensor. In order to prove the better efficiency of the newly developed method over the current method, the following section compares these two methods (Liu *et al.*, 2016c).

Two detection criterions (normal measurement range and variation validation) as the current method are responsible for detecting inlet measurement errors. The outliers detected by the normal variation range are assumed to influence TUO simulation and to generate significant differences between TUO simulation and TUO measurement. All points in the Figure 26 are checked with two current detection criterions and any point related to measurement errors are marked. The plotted points marked with various shapes represent different erroneous parameters. It can be seen that these marked points are not always outside of the detection lines. Taking square points (related to inlet turbidity outliers) as an example, some square points close to the correlation line indicate a small influence on TUO simulation while some square points far from the line generate a large influence. Other points with different shapes also have a similar tendency. Therefore, the results of the proposed detection criterion is not fully in agreement with the normal variation range as associated with a traditional method.

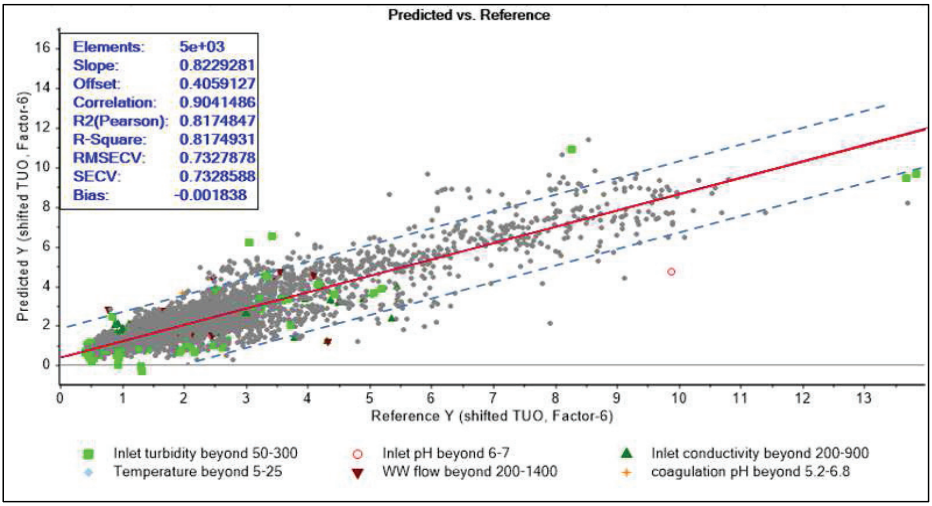

Figure 26. Comparison of proposed detection method and the traditional method (this figure bases on the correlation between simulation and measurements of outlet turbidity, solid line presents the correlation line and two dotted lines indicate proposed detection criterion of measurement errors, various points marked by different shapes are measurement errors defined by the traditional method).

The traditional method of normal variation range focuses on the sensor itself and could work universally but not as efficiently as the proposed method. The proposed detection method is only to identify the measurement error, which tends to deviate TUO simulation from TUO measurements. Hence, the proposed method has a higher efficiency of error detection than that of the current method. Consequently, the proposed method obviously enhances the reliability of the CDCS. Furthermore, the proposed method with its higher error detection efficiency can provide more accurate signals to call for maintenance of online sensors, which could reduce maintenance work compared with the current method.

3.6 Shorter period of data collection

According to the procedure of the CDCS implementation, data collection is the essential step after the installation of online sensors and the CDCS. Previously, it was very necessary to collect as much data as possible to obtain influent information, improve the empirical model's performance. Normally, this step needed a long time until the model performance proved to be acceptable. Hence, it is a time-consuming method to undertake prior to real dosage control. As an enhanced feature of the CDCS, this disadvantage can be compensated by the FF-FB model. The effect of the FB control shows a strong ability to adjust the inaccurate dosage that is calculated from the FF model. Thus, with the CDCS it is possible to shorten the data collection period (calibration period) and start the active dosing control earlier than before.

4. CONCLUSIONS

- The dosage control system was improved and verified in two DWTPs. Consistently improved treated water qualities and operational economies, also under extreme conditions, were documented in comparison to manual dosage control. The extended tests from WWTPs to DWTPs expanded the application universality of the dosing control system.

- The feedforward-feedback (FF-FB) model is built up by involving an outlet parameter as feedback. The feedforward-feedback (FF-FB) model proved more able to provide stronger capacities on dosage control than the previous feedforward (FF) model. Moreover, the feedforward-feedback (FF-FB) model is able to provide further coagulant savings compared to the previous feedforward model.

- The feedforward-feedback model with user input can achieve different outlet targets that considerably improves utilization flexibility of the coagulant dosage control system.

- Non-plug-flow condition of the sedimentation tank assumes to mix treated water batches, which is a potential obstacle for establishing a quantitative relationship between treated water quality and inlet parameters. This thesis proposes a method for simulating mixing effect and outlet turbidity under the plug-flow condition. It proved to be a useful solution to confirm whether the mixing condition has a significant effect on the outlet turbidity.

- The hydraulic retention time resulting from the conventional sedimentation tanks hinders the application of the feedforward-feedback model. This thesis proposes a soft-sensor for outlet turbidity. The software sensor can predict outlet turbidity before it is measured. Hence, it can highly contribute the feedforward-feedback model to have wide applications in the coagulation processes that involve conventional sedimentation tanks.

- Based on the outlet turbidity estimated by the software sensor, the novel method of inlet measurement error detection was developed to have a higher efficiency of error detection than previous methods. The novel method improved the reliability of the dosage control system.

- The dosage control system is enhanced by several solutions that underpin the thesis focus. An enhanced system with these solutions can enable a shorter period of data collection and improved operational economy.

5. RECOMMENDATIONS FOR FURTHER STUDIES

- Implementing further full-scale tests with the enhanced CDCS, especially in DWTP during storms.
- Involving more parameters as model inputs like phosphates, colour, hardness, etc.
- Developing other software sensors to predict different outlet parameters such as phosphate, colour, remaining aluminium, etc.
- With a broad operational data base, further attempts should be made to develop conceptual models.

6. REFERENCES

Adgar A., Cox C.S. & Jones C.A. 2005, 'Enhancement of coagulation control using the streaming current detector', *Bioprocess Biosyst*, vol. 27, pp. 349–357.

AlGhazzawi A. & Lennox B. 2009, 'Model predictive control monitoring using multivariate statistics', *Journal of Process Control*, vol.19, no.2, pp. 314-327.

Amari S., Murata N., Müller K.R., Finke M. & Yang H.H., 1997, 'Asymptotic statistical theory of overtraining and cross-validation', *IEEE Transactions on Neural Networks,* vol. 8, no. 5, pp. 985–996.

Amirtharajah A. & Mills K.M. 1982, 'Rapid Mix Design for Mechanisms of Alum Coagulation', *Jour. AWWA*, vol. 74, pp. 4-210.

American Water Works Association (AWWA). 'Operational Control of Coagulation and Filtration Processes, in Manual of Water Supply Practices', 3rd ed., AWWA: Denver, USA, 2011

Baxter C.W., Stanley S.J. & Zhang Q. 1999, 'Development of a full-scale artificial neural network model for the removal of natural organic matter by enhanced coagulation', *Journal of Water SRT-Aqua*, vol. 48, no. 4, pp. 129–136.

Baxter C.W., Zhang Q., Stanley S.J., Shariff R., Tupas R.T. & Stark H.L. 2001, 'Drinking water quality and treatment: the use of artificial neural networks', *Canadian Journal of Civil Engineering,* vol. 28, pp. 26–35.

Baxter C.W., Shariff R., Stanley S.J., Smith D.W., Zhang Q. & Saumer E.D. 2002, 'Model based advanced process control of coagulation', *Water Science and Technology*, vol. 45, no. 4-5, pp. 9-17.

Beckhoff, 2015, 'New Automation Technology', https://www.beckhoff.com/, (accessed 26 December 2015).

Bloch G. & Denoeux T. 2003, 'Neural networks for process control and optimization: Two industrial applications', *ISA Trans*, vol. 42, pp. 39–51.

Camo, 20015, 'Bring data to life', http://www.camo.com/, (accessed 22 December 2015).

Dayal B.S. & MacGregor J.F. 1997, 'Improved PLS algorithms', *J. Chemometrics*, vol. 11, no.1, pp. 73-85.

De Jong S. & Ter Braak C. J. F. 1994, 'Comments on the PLS kernel algorithm' *J. Chemometrics,* vol. 8, pp. 169-174.

Dellana S.A. & West D. 2009, 'Predictive modelling for wastewater application: Linear and nonlinear approaches', *Environmental Modelling & Software*, vol. 24, pp. 96-106

Dentel S.K. & Kingery K.M. 1898, 'Theoretical principal of streaming current detection', *Water Science and Technology*, vol. 21, pp.443-453.

Dentel S.K. 1991, 'Coagulant control in water treatment', *Critical reviews in environmental control,* vol. 21, no.1, pp. 71-75.

Dentel S.K. & Abu-Orf MM. 1995, 'Laboratory and full-scale studies of liquid stream viscosity and streaming current for characterization and monitoring of dewaterability', *Water Research,* vol. 29, no.12, pp. 2663-2672.

Fortuna L., Graziani S., Rizzo A. & Xibilia M. 'Soft Sensors for Monitoring and control of Industrial Process', Springer Science, London, 2007.

Guida M., Mattei M., Della Rocca C., Melluso G. & Meric S. 2007, 'Optimization of alum-coagulation/flocculation for COD and TSS removal from five municipal wastewater', *Desalination*, vol. 211, pp. 113–127.

Guo Y.F., Ma J., Zhai X.D. & Fan Y. 2009, 'Flocculent Dosage Optimizing in Water Treatment based on Nonlinear Mathematical Model', International Conference on Environmental Science and Information Application Technology

Hamed M.M., Khalafallah M.G. & Hassanien E.A. 2004, 'Prediction of wastewater treatment plant performance using artificial neural networks', *Environmental Modelling & Software*, vol. 19, no. 10, pp. 919-928.
Hangouet J.P., Pujol R., Bourgogne P., Ropert D. & Lansalot G. 2007, 'Optimizing chemical dosage in primary settling tanks', *Chemical Water and Wastewater Treatment IX,* Proceeding of the 12th Gothenburg Symposium 2007, Hermann H. Hahn Erhard Hoffmann Hallvard Ødegaard (eds), IWA Publishing, London, pp.59-67.
Huang M.Z., Ma Y.W., Wan J.Q. & Wang Y. 2009, 'Simulation of a paper mill wastewater treatment using a fuzzy neural network', *Expert Systems with Applications*, vol. 36, no. 3, pp. 5064-5070.
Hunter R.J. 'Zeta Potential in Colloids Science', Academic Press, New York, 1981.
Hunter R.J. 'Foundations of Colloid Science', Oxford University Press Inc., New York, 2001.
Ingildsen P., Jeppsson U. & Olsson G. 2002, 'Dissovled oxygen controller based on on-line measurements of ammonium combinning feed-forward and feedback', *Water Science and Technology*, vol. 45, no. 4-5, pp.453-460.
Jeppsson U., Alex J., Pons M.N., Spanjers H. & Vanrolleghem P.A. 2002, 'Status and future treads of ICA in wastewater treatment-A European perspective', *Wat. Sci. Tech*, vol. 45, no. 4-5, pp. 485-494.
Joo D.S., Choi D.J. & Park H.Y. 2000, 'The effects of data preprocessing in the determination of coagulation dosing rate', *Wat. Res.* vol. 34, no. 13, pp. 3295-3302.
Kan C.C. & Huang C. 1998, 'Coagulation monitoring in surface water treatment facilities', *Water Science and Technology*, vol. 38, no. 3, pp. 237–244.
Li J.G., Dhanvantari S., Averill D. & Biswas N. 2003, 'Windsor combined sewer overflow treatability study with chemical coagulation', *Water Qual. Res.* vol. 38, no. 2, pp. 317-334.
Lu L. 2003, 'Model based control and simulation of wastewater coagulation', PhD thesis, Agriculture University of Norway
Liu W., Ratnaweera H. & Song H.P. 2013, 'Better treatment efficiencies and process economies with real-time coagulant dosing control', 11th IWA conference on instrumentation control and automation, France
Liu W., & Ratnaweera H. 2016a, 'Improvement of multi-parameter based Feed-Forward coagulant dosing control systems with Feed-Back functionalities', Water Science and Technology (accepted)
Liu W., & Ratnaweera H. 2016b, 'Feed-forward based software sensor for outlet turbidity of coagulation process', *Journal Sensors* (submitted)
Liu W., Ratnaweera H. & Knut K, 2016, 'Model based measurement error estimation of coagulant dosage control system', *Journal Water* (submitted)
Lindgren F., Geladi P. & Wold S. 1993, 'the kernel algorithm for PLS', *J. Chemometrics,* vol. 7, no.1, pp. 45-59.
Maier H.R., Morgan N. & Chow W.K. 2004, 'Use of artificial neural networks for predicting optimal alum doses and treated water quality parameters', *Environmental Modelling & software,* vol. 19, no. 5, pp. 485-494.
Maier, H.R., Jain A., Dandy G.C. & Sudheer K.P. 2010, 'Methods used for the development of neural networks for the prediction of water resource variables in river system: Current status and future directions', *Environmental Modelling & Software*, vol. 25, pp. 891-909.
Manamperuma L., Ratnaweera H., Heistad A., Martsul A. & Vasenko L. 2015, 'Impact on plant availability of phosphorus in sludge after coagulation', Conference on Nutrient IWA, Removal and Recovery: moving innovation into practice 2015, Gdansk, Poland.
Oh J.I. & Lee S.H. 2005, 'Influence of streaming potential on flux decline of microfiltration with in-line rapid pre-coagulation process for drinking water production', *J. Membr. Sci.* vol. 254, pp. 39–47.

Rathnaweera S. 2010, ‘Modelling and Optimization of Wastewater Coagulation Process’, PhD thesis, Norwegian University of Life Sciences.
Ratnaweera H. 1991, ‘Influence of the degree of coagulant preploymerization on wastewater coagulation mechanisms’, Doctoral thesis, Norwegian Institute of Technology, Dissertation publishing, Michigan, USA.
Ratnaweera H., Blom H. & Aasgaard G., 1994, ‘Flexible coagulant dosing control system based on real-time wastewater quality monitoring’, Chemical water and wastewater treatment III, Hahn, H.H and Klute, R (eds), Springer-Verlag, Berlin, pp. 105-116.
Ratnaweera H., Lu L. & Lindholm O. 2002, ‘Simulation Program for Wastewater Coagulation, Chemical Water and Wastewater Treatment vii’, H.H.Hahn, E.Hoffmann and H. Oedegaard (eds), Gothenburg, Sweden, IWA publishing, London, pp. 253-260.
Ratnaweera H., Lei L., & Lindholm O. 2002, ‘Simulation program for wastewater coagulation’, *Water Science and Technology,* vol. 46, no. 5, pp. 27-33.
Ratnaweera H. 2004, ‘Coagulant dosing control-a review’, Chemical water and wastewater treatment VIII, HH Hahn, E Hoffmann, H Ødegaard (eds), IWA Publishing, London, pp. 3-13.
Ratnaweera H., Smoczyński L., Lewandowski A. & Bielecka M. 2005, ‘Efficient Coagulant Dosing Control in Wastewater Treatment’, *Pol. Acad. Sci*. vol. 505, pp. 347–352.
Ratnaweera H. & Fettig J. 2015, ‘State of the Art of Online Monitoring and Control of the Coagulation Process’, *Water*, vol. 7, pp. 6574-6597.
Rietveld L. & Dudley J. 2006, ‘Models for Drinking water treatment-review state of the art’, Report TECHNEAU, European Commission under the Sixth Framework Programme.
Sharp E. & Norris R. 2015, ‘Using online zeta potential measurements for coagulation control: A first for the UK water industry’. In Proceedings of the 6th IWA Specialist Conference on Natural Organic Matter in Drinking Water, Malmö, Sweden.
Shutova Y., Baker A., Bridgeman J. & Henderson R.K. 2014, ‘Spectroscopic characterization of dissolved organic matter changes in drinking water treatment: From PARAFAC analysis to online monitoring wavelengths’, *Water Res.* vol. 54, pp. 159–169.
Scherrenberg S.M. 2006, ‘Treatment Techniques for Combined Sewer Overflows: A literature study of the available techniques’, Master Thesis, Delft University of Technology.
Schlenger D.L., Riddle W.F., Luck B.K. & Winter, M.H. 1996, ‘Automation Management Strategies for Water Treatment Facilities’, Denver, CO.: AWWARF and AWWA.
Siripapha J., Sinchai K. & Suwapee T. 2011, ‘Evaluation of reusing alum sludge for the coagulation of industrial wastewater containing mixed anionic surfactants’, *Journal of Environmental Sciences*, vol. 23 no. 4, pp. 587-594.
Stumm W. & O’melia C.R. 1968, ‘Stoichiometry of Coagulation’ *Jour. AWWA,* vol. 60, no. 5, pp. 514-539.
Stumm W. & Morgan J. 1995, ‘Aquatic Chemistry: Chemical Equilibria and Rates in Natural Water’, John Wiley & Sons, Inc. New York.
Stanley SJ., Baxter CW. & Zhang Q. ‘Process Modelling and Control of Enhanced Coagulation’, AWWA research Foundation’, USA, 2000.
Svante W., Michael S. & Lennart E. 2001, ‘PLS-regression: a basic tool of Chemometrics’, *Chemometrics and Intelligent Laboratory Systems*, vol. 58, pp. 109–130.
Tchobanoglous G., Burton F. & Stensel D. 1997, ‘Water Engineering: Treatment and Reuse’, Edition 4, McGraw-Hill, Inc, New York.
Vanrolleghem P.A. & Lee D.S. 2003, ‘On-line monitoring equipment for wastewater treatment process, State of the art’, *Water Science and Technology*, IWA publishing, vol. 47 no.2, pp. 1.
Walker C.A., Kirby J.T. & Dentel S.T. 1996, ‘the Streaming Current Detector: A Quantitative Model’, *Journal of Colloid and Interface Science*, vol. 182, no. 1, pp. 71-81.

Wu G.D. & Lo S.L. 2008, 'Predicting real-time coagulant dosage in water treatment by artificial neural networks and adaptive network-based fuzzy inference system', *Engineering Applications of Artificial Intelligence*, vol. 21, no. 8, pp. 1189-1195.

Wu G.D. & Lo S.L. 2010, 'Effects of data normalization and inherent-factor on decision of optimal coagulant dosage in water treatment by artificial neural network', *Expert Systems with Applications*, vol. 37, no.7, pp. 4974-4983.

Yu R.F., Kang S.F., Liaw S.L. & Chen M. 2000, 'Application of artificial neural network to control the coagulant dosing in water treatment plant', *Water Science and Technology*, vol. 42, no. 3-4, pp. 403-408.

Yu W.Z., Gregory J., Campos L. & Li G. 2011, 'The role of mixing conditions on floc growth, breakage and regrowth', *Chemical Engineering Journal,* vol. 107, pp. 425-430.

Zeng G.M., Qin X.S., He L., Huang G.H., Liu H.L. & Lin Y.P. 2003, 'A neural network predictive control system for paper mill wastewater treatment', *Engineering Applications of Artificial Intelligence*, vol. 16, no. 2, pp. 288-291.

Zhang Q. & Stanley S. 1999, 'Real-Time Water Treatment Process Control with Artificial Neural Networks', *J. Environ. Eng.,* vol. 125, no. 153, pp. 153-160.

7. APENDIX-PUBLICATIONS

7.1 Better treatment efficiencies and process economics with real-time coagulant dosing control

Wei Liu, Harsha Ratnaweera, Heping Song

Paper presented at 11th IWA Conference on Instrumentation Control and Automation (ICA2013), Narbonne, France, 2013

7.2 Improvement of multi-parameter based Feed-Forward coagulant dosing control systems with Feed-Back functionalities

Wei Liu, Harsha Ratnaweera

Paper accepted by Journal Water Science and Technology

7.3 Feed-forward based software sensor for outlet turbidity of coagulation process

Wei Liu, Harsha Ratnaweera

Paper is submitted to International Journal of Research & Development Organization

7.4 Model based measurement error estimation of coagulant dosage control system

Wei Liu, Harsha Ratnaweera and Knut Kvaal

Paper is submitted to International Journal of Environmental Science and Technology

Paper I

Better treatment efficiencies and process economics with real-time coagulant dosing control

Wei Liu, Harsha Ratnaweera, Heping Song

Paper presented at 11th IWA Conference on Instrumentation Control and Automation, Narbonne, France, 2013

Better treatment efficiencies and process economics with real-time coagulant dosing control

L Wei*, H. Ratnaweera*, S. Heping**

*Norwegian University of Life Sciences, PO Box 5003-IMT, 1432 Aas, Norway. Email: wei.liu@umb.no

** Jiaxing ROSIM Co LtD, No1369 Chengnan Road, Jiaxing 314001, P.R. China.

ABSTRACT

Coagulation is the most widespread method for treatment of drinking water in the world. Accurate dosing of coagulants is vital both for health and process economics. Inability to estimate accurate dosages may result in poor treatment, high coagulant costs and negative subsequent in downstream processes. The optimal dosage depends on not only flow and pH but also particles, color and other impurities in raw water. By including these parameters in the estimation of optimal dosage, one can achieve significant process and economic improvements. A dosing control concept originally developed for wastewater treatment was modified and tested at full-scale with very good results. The treatment efficiencies were not only better but also proved possible to manage within desired outlet ranges, thus enabling a dosing control tailored for desired outlet turbidities. A comparison of performances between a flow proportional and multi-parameter based dosing control system is given with cost savings, while securing improved outlet qualities.

Keywords: coagulation; dosing control; drinking water treatment

1. INTRODUCTION

Coagulation is the world's most commonly used treatment method in drinking water treatment. Aluminum is the most common coagulant but it has two major disadvantages: Firstly, coagulation with aluminum functions within a narrow pH range, thus an optimal dosage is required to obtain the best performance as well as to achieve less coagulant cost (Gregory *et al.*, 1997). Secondly, an overdosing of aluminum or dosing under a wrong pH range might result in dissolved aluminum species in the treated water rather than the species that are favorable for coagulation (Rebhun and Lurie, 1993). Since the aluminum in drinking water is identified to be a potential risk factor for Alzheimer disease (Guidelines for drinking water quality, 2008), non-optimal dosage may create a health risk.

Since conditions of the plant operation and coagulant are more or less constant for a given plant, the optimal coagulant dosage is mainly dependent on parameters of water quality that include the content of particles, color produced by Natural Organic Matter (NOM) and coagulation pH (Edzwald J.K., 1993). However, most drinking water treatment plants (DWTP) in the world use a flow proportional dosage, sometimes combined with pH (Dentel, 1991). Some smaller DWTPs even use constant, time proportional dosage. Although it won't be a problem for DWTPs using raw water from lakes with rather stable water qualities, DWTPs using polluted and turbulent rivers as water source often experience rapid changes in raw water quality, which challenges the estimation of optimal dosage. Because the importance of these critical parameters is ignored, such practices often cause poor treatment results, high coagulant dosage and high operational costs. Moreover, the high coagulant dosage may also increase the filter load of downstream processes, which could results in process complications and higher operational costs.

The general understanding of the coagulation process indicates that the optimal dosage depends on water quality parameters like particles and colour, in addition to the commonly used flow and pH. However, it has been a challenge to achieve better dosing control systems due to the additional cost of online water quality instruments and the lack of suitable algorithms. Although the online instruments are now much more accessible and affordable than they were few years ago, suitable algorithms integrated with several parameters are still scarce (Ratnaweera, 2004).

DOSCON has developed a concept using multi-parameter surveillance of water quality for determination of the optimal coagulant dosage in real-time. Inputs used for dosage prediction in the DOSCON system include inlet flow, turbidity, conductivity, temperature, pH, and coagulation pH. The concept was initially developed for wastewater treatment (Ratnaweera *et al*, 2005) and further improved later (Rathnaweera, 2010). This paper presents its extension to drinking water treatment, which is verified by the full-scale tests.

The DWTPs, where the full-scale tests were conducted, had requirements of outlet turbidity within the limit (less than 3 NTU) in coagulation process considering the conditions for optimal performance of downstream treatment process. Until the experimental system was installed, operators daily adjusted the coagulant dosage manually by judging the outlet quality in the full-scale plant. Since the water quality varied regularly, it was a demanding task to keep turbidity within the requested range, especially during the rainy seasons. This paper presents the verification results of application of a multi-parameter based coagulant dosing control system for DWTPs.

2. MATERIALS AND METHODS

The full-scale tests were conducted at two DWTPs near Shanghai, Haining DWTP2 (capacity: 100 000m^3/day) and Salcon DWTP (capacity: 300 000 m^3/day). Both DWTPs receive water from the Changshan River where the water quality can vary significantly during a rainy period or a typhoon. The existing dosing strategy of both plants was flow proportional dosing.

Both DWTPs had some online instrumentation and were supplemented with others so the turbidity, pH, conductivity, temperature and flow in the inlet and pH and turbidity in the outlet were possible to monitor online. These signals were acquired in real-time by the Supervisory Control and Data Acquisition (SCADA) system of the DWTPs that were then processed by the DOSCON unit, consisting of an embedded PC and a range of algorithms.

Both plants have parallel treatment lines with the same water quality, hence it was possible to carry out the experiment with one treatment line using the conventional (flow proportional) dosing while a separate treatment line used the experimental (multi-parameter) dosing control system. The system started to collect operational data, which was used as calibration sets, as the generic algorithms of the DOSCON system need to be calibrated for each DWTP. After a special selection process of suitable datasets, the data were analyzed and relevant models constructed using software Unscrambler®.

3. RESULTS AND DISCUSSION

The ambition of the DWTPs was to keep the outlet turbidity just below 3 NTU. In practice, the outlet turbidity was well below the anticipated values, because the plants were unable to adjust dosage to result in exactly below 3 NTU with the conventional dosing control system. The result was to use a slightly higher dosage than the optimal dosage to secure effluent turbidities below required levels, which gave much lover effluent values at times.

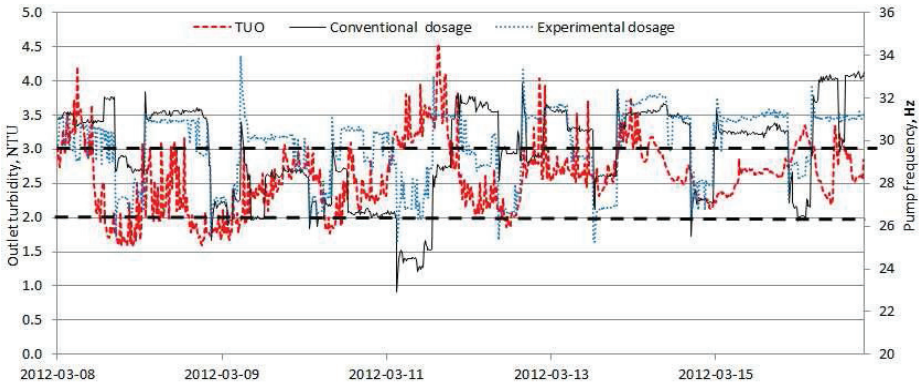

Figure 3.1. Comparison of conventional dosing and modelled experimental dosing at the Haining DWTP No 2. The thin dashed line and left axis represent the outlet turbidity, while the bold dahsed lines indicate the desired outlet turbidity range (2.0-3.0 NTU). The thin and dotted lines refer to conventional dosage and estimated experimental dosages, respectively.

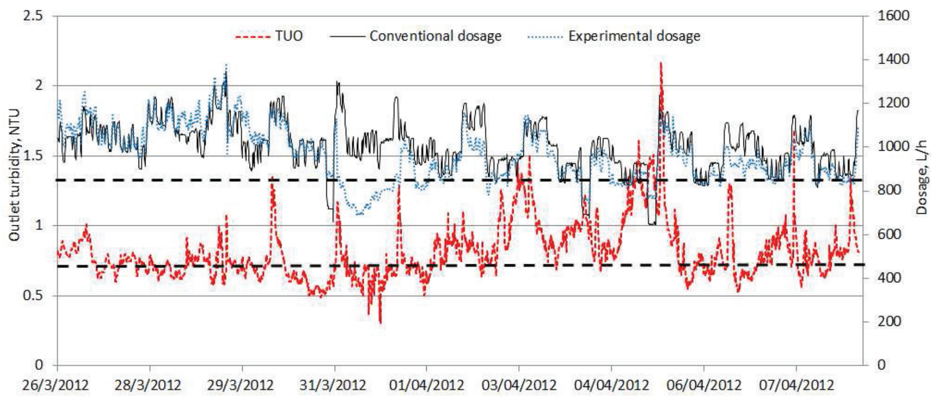

Figure 3.2. Comparison of conventional dosing and modelled experimental dosing at the Salcon DWTP. The thin dashed line and left axis represent the outlet turbidity, while the bold dashed lines indicate the desired outlet turbidity range (0.7-1.3 NTU). The thin and dotted lines refer to conventional dosage and estimated experimental dosages, respectively.

Fig 3.1 and Fig 3.2 present the results under the traditional flow proportional dosing control over a 10-day period in 2012, together with modelled dosing values using the experimental concept. As it is seen from the figures, the outlet turbidity (thin dashed line), on several occasions has gone beyond the desired range (bold dashed lines). A closer look at the data reveals that those periods when the outlet turbidity is beyond the maximum values the experimental dosage proposes a higher dosage than the conventional dosage. It also shows the opposite when the outlet turbidity is too low, which confirms the superiority of the experimental dosing concept.

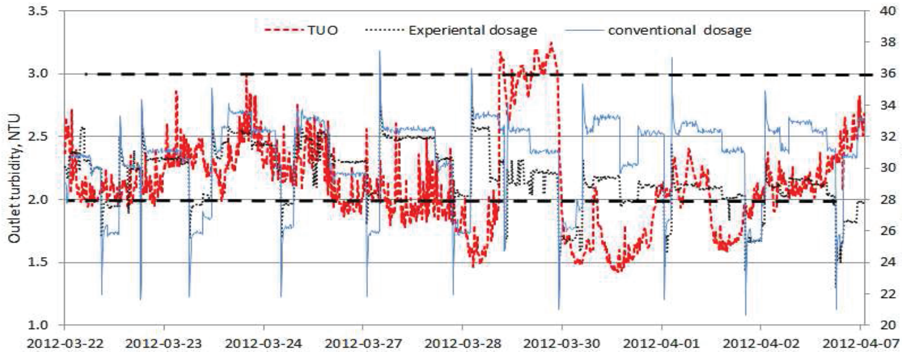

Figure 3.3. Comparative results from the experiments at the Haining DWTP No 2. The thin dashed line and left axis represent the outlet turbidity, while the bold dashed lines indicate the desired outlet turbidity range (2.0-3.0 NTU). The thin and dotted lines refer to conventional dosage and experimental dosages, respectively.

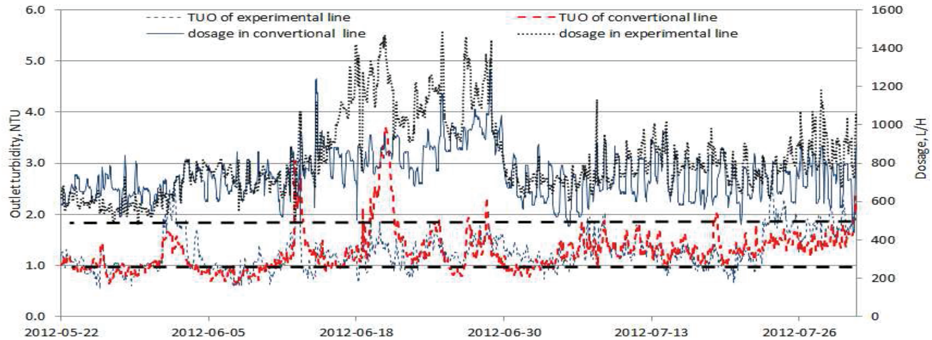

Figure 3.4. Comparative results from the experiments at the Salcon DWTP. The thin and dotted lines refer to conventional dosage and estimated experimental dosages, respectively, and dashed lines refer to outlet tubidities. The bold dashed lines indicate the desired revised outlet turbidity range (1.0-1.8 NTU)

Fig. 3.3 depicts the comparative full-scale operational results of the DWTP No.2 during a two week period in 2012. The outlet turbidity exceeds desired maximum levels only occasionally due to the initial stage of model calibration. The minimum and maximum peaks of conventional dosing (thin line) is a result of sudden changes in the flow, especially when the plant opens or closes one of the inlet water pumps to adjust water flow. Such variations are not observed with the experimental line as it includes several other parameters. Fig. 3.4 presents a comparison between the experimental and conventional dosing at Salcon DWTP over a 2 month period. The superiority of the experimental dosing concept is evident as the outlet turbidity stays mostly within the desired ranges than in the line with conventional dosing.

Table 1: Statistical data of experimental line and conventional line in last year

	Anticipated range, NTU	Conventional line		Experimental line	
		TUO, NTU	STDEV	TUO, NTU	STDEV
The 1st Month	1.5-2.3	1.76	0.43	1.90	0.54
The 2nd Month	1.5-2.3	1.35	0.51	1.88	0.72
The 3rd Month	1.5-2.3	1.34	0.39	1.55	0.66
The 4th Month	1.5-2.3	2.05	0.42	1.72	0.46
The 5th Month	1.5-2.3	1.85	0.30	1.53	0.36
The 6th Month	1.5-2.3	2.06	0.35	2.26	0.35
The 7th Month	1.5-2.3	1.99	0.48	2.09	0.39
The 8th Month	1.5-2.3	2.49	0.37	2.30	0.27
The 9th Month	2.3-3.0	2.38	0.43	2.50	0.26
The 10th Month	2.3-3.0	2.22	0.67	2.48	0.33
The 11th Month	2.3-3.0	2.56	0.51	2.64	0.37
The 12th Month	2.3-3.0	2.61	0.41	2.62	0.26

TUO: outlet turbidity, SEDEV: standard deviation

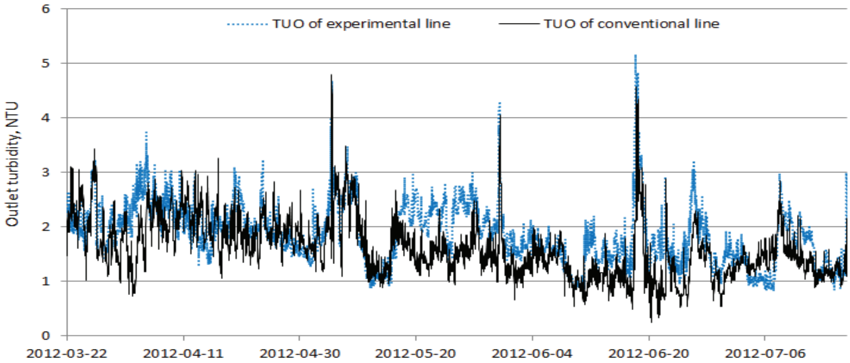

Figure 3.5. Turbidity comparison in DWTP2 with experimental (dotted) and conventional lines (thin).

Fig. 3.5 presents the outlet turbidity data from DWTP No.2 over a longer period, for 4 months in 2012. The plant management suggested to keep the outlet turbidity between 1.5-2.3 NTU of the anticipated range, thus the algorithms were calibrated accordingly. The results from the last 12 months together with their standard deviations are shown in Table 1. According to the data, outlet turbidity of the experimental line is getting more constant within the anticipated range. In addition, a comparison of coagulant consumption between the two lines indicates a 10% saving of coagulants.

CONCLUSIONS

- The experimental dosing system using a multi-parameter based dosing control provided more stable outlet results compared with conventional flow-proportional dosing.

- The algorithms for coagulant dosing could be calibrated to result in the anticipated outlet turbidity within a narrow range. The resulting outlet values were more accurately achieved through experimental dosing compared with conventional dosing.

- The overall coagulant consumption in the experimental line was 10% lower than in the conventional line, mainly due to more accurate dosing avoiding overdosing.

REFERENCES

Dentel S.K. 1991 Coagulant control in water treatment, *Critical Reviews in Environmental Control*, Volume 21, Issue 1, 41-135 pp.

Edzwald J.K. 1993 Coagulation in drinking water treatment: particles, organics and coagulants, *Water Science and Technology*. Volume 27, No.11, 21-35 pp.

Gregory J.E., Nokes, C. J., Fenton E. 1997 Optimising natural organic matter removal from low turbidity waters by controlled pH adjustment of aluminum coagulation, *Water Research*, Volume 31, Issue 12, 2949–2958 pp.

Guidelines for drinking water quality 2008. 3rd ed. Vol. 1, *World Health Organization*, Geneva, Switzerland.

Rathnaweera, S. 2010 Modelling and optimisation of wastewater coagulation process. PhD thesis, Dept. of Mathematical Sciences and Technology, Norwegian University of Life Sciences, Aas, Norway.

Ratnaweera H. 2004 Overview of coagulant dosing control . In: *Chemical water and wastewater treatment VII*, Hahn H.H., Hoffman E. and Ødegaard H. (Eds.), Volume VII, IWA publishing, London, 3-13pp.

Ratnaweera H., Smoczyński L., Lewandowski A. 2005 Efficient coagulant dosing in wastewater treatment, *Problems and Progress in Agricultural Sciences*, Polish Academy of Sciences, Volume 505, 347-352 pp.

Rebhun R. and Lurie M. 1993 Control of organic matter by coagulation and floc separation, *Water Science Technology*, Volume 27, No.11, 1-20 pp.

ACKNOWLDGEMENT

The authors gratefully acknowledge the assistance given by the personnel at the Haining DWTP No. 2 and Salcon DWTP during the experiments.

Paper II

Improvement of multi-parameter based Feed-Forward coagulant dosing control systems with Feed-Back functionalities

Wei Liu, Harsha Ratnaweera

Paper accepted by Journal of "Water Science and Technology"

Improvement of multi-parameter based Feed-Forward coagulant dosing control systems with Feed-Back functionalities

W. Liu*, H. Ratnaweera*

*Norwegian University of Life Sciences, PO Box 5003-IMT, 1432 Aas, Norway.
Email: wei.liu@nmbu.no

Abstract: Coagulant dosing control in drinking and wastewater treatment plants are often limited to flow proportional concepts. The advanced multi-parameter based dosing control systems have significantly reduced coagulant consumption and improved outlet qualities. Due to the long retention time in separation stages, these models are mostly based on Feed-Forward models. This paper demonstrates the improvement of such models with Feed-Back concepts with simplifications making it possible to use even in systems with long separation stages. Full-scale case studies from a drinking water treatment plant and a wastewater treatment plant were presented. The model qualities were improved by the dosage adjustment of the feedback model, ranging from 66% to 197% of the feedforward model. Hence, the outlet qualities became more stable and coagulant consumption were further reduced in the range of 3.7%-15.5%.

Keywords: feed-forward; feed-back; model; coagulation

1. Introduction

1.1 Background

Coagulation followed by separation is one of the most important treatment processes for drinking water treatment (DWT) and wastewater treatment (WWT). In WWT, after dosing a certain amount of coagulant, the destabilized particulate pollutants as well as precipitated phosphates will be converted into larger and heavier flocs and hence separated from liquid in subsequent separation processes. In DWT, colloids and particulate matter including Natural Organic Matter (NOM) are separated. Pathogenic and toxic matters can also be removed similarly during the coagulation process. Practically in full-scale treatment processes, defining optimal coagulant dosage is a vital operation for performance of the coagulation process (Baxter et al. 2002; Ratnaweera et al. 2005). Therefore, model predictive control (MPC) of coagulant dosing has been studied in recent years and a number of studies conclude that MPC is a more efficient way to gain stable treatment qualities than manual dosing control, which can lead to better economy (Yu et al. 2000; Zeng et al. 2003; Chu et al. 2004; Ashraf and Barry 2009; Maier et al. 2010).

However, the models commonly used in WWT are either flow proportional dosing or flow proportional dosing to achieve the optimal pH. Rathnaweera (2010) has shown that the efficiency of coagulation process can be improved with significant saving of coagulants when including additional water quality parameters, even over 30% of the saving in WWT. Later this control concept was adopted to full-scale DWT and achieved constant treatment performance alongside 10% coagulant savings comparing to a parallel treatment line with the same inlet water qualities, where has flow proportional dosing control (Liu et al. 2013). However, along with the stringent treatment requirements for lower and more stable outlet qualities and different desired range of outlet qualities, the limitation of the current control system emerges. Moreover, the practical issue on unexpected inlet disturbance and increasing variation of treatment efficiencies are challenging the reliability of the current control system and leads to improve the system.

1.2 Description of the coagulant dosing control model

Although coagulation process followed by settling tank belongs to a multivariate nonlinear system, it is well defined that outlet particle concentration highly depends on inlet particle concentration represented by turbidity (TU) and/or suspended solid (SS), pH, phosphate (for WWT), alkalinity, hardness, temperature as well as coagulant dosage. Because of non-proportional variation of these parameters and due to the complexity of coagulation process as well as the lack of universally accepted theoretical models, empirical models have been widely used for full-scale coagulant dosing control comparing with the theoretical model (Maier et al. 2010). Instead of converting the theory to mathematical formula and involving all related parameters, empirical models are able to establish the relationship between measured inlet variables and coagulant dosage by learning from large amount of data. Based on current availability of online sensors, the model what author used for previous research is shown in the following equation, which is empirical model and was validated in many full-scale WWT and DWT plants with the better results mentioned above. (Rathnaweera, 2010; Liu et al., 2013)

Dosage= ƒ (WW flow, inlet SS/TU, inlet pH, inlet conductivity, inlet phosphate, temperature, interaction among variables, variables squares) Equation (1)

In view of control strategy on coagulation process, this model only uses the inlet qualities but not outlet qualities as input variables, known as feed-forward (FF) systems or open-loop systems. Theoretically, a FF model can react instantly with any measured disturbing variables (DVs, inlet qualities measured by online sensors) through manipulated variables (MVs, coagulant dosage) and then controlled variables (CVs, outlet qualities) will be responding accordingly. In contrast, dosage variation from pure feed-back (FB) model only depends on outlet variables instead of inlet variables, which means ignoring both measured and unmeasured disturbance from inlet (Ogata 2010). In many situations, especially when the raw water source is a lake or a calm rive, a FF model can work efficiently in WWT or DWT even with a treatment process with high hydraulic delays (Ingildsen et al. 2002). Furthermore, because a FF model is able to react at the very beginning of a process, they lead to better economy by chemical and energy saving.

One disadvantage of a FF model is its low ability in handling situations with unmeasured disturbance, leading to unexpected outlet qualities. This is essentially because there is no compensation from outlet qualities to dosage prediction. Previous results of the author shows that a FF model cannot response to unexpected outlet qualities during heavy rain (Liu et al. 2013). Conversely, the advantage of FB control is the ability to adjust dosage based on measured error between set point and CVs (Ogata 2010). As a result, the unmeasured disturbance and related inaccurate dosage can be compensated (Vrecko et al. 2003). Therefore, it is very necessary to incorporate the advantages of these two control strategies with the purpose of improving model performance. Figure 1 shows the concept of the dosing control system combining FF with FB. FB signals like the streaming current and pH after coagulation are already used in some water works (Ratnaweera and Fettig, 2015). Both of these signals provide valuable information on the status of colloidal charge. Because these two signals do not consider the flow variations and mixing conditions, they do not always represent the outlet quality and their applications are limited. Stanly et al. (2000) pointed out that streaming current detectors (SCD) proves to be useful when the charge neutralization mechanism predominates. Dentel (1995) also pointed out that the output of the SCD sometimes exhibits a contradictory result for the coagulation activation, because surface charge of particles and the charge of the functional groups on NOM molecules are affected by pH. Although SCDs are available from a number of suppliers, there has been no standard calibration procedure so far (Ratnaweera and Fettig, 2015). Hence, this paper considers traditional outlet parameters such as outlet turbidity or suspended solid as feedback parameter of coagulant dosage control

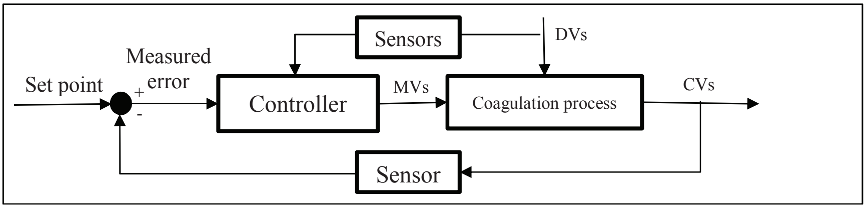

Figure 1, Control strategy of combining FF and FB.

1.3 Challenges

In coagulation processes, inlet wastewater qualities and WW flow can vary rapidly even in less than 1 hour and the normal hydraulic retention time of a commonly used sedimentation tank is over 2 hours. Thus, it is often too late for outlet quality to provide timely FB to the dosing control system, which can lead to inaccurate and even wrong dosage during rapid inlet variation. It is also a weakness that a black box system, what the empirical model in this paper refers to, cannot display any theory, or logic between input and output. Namely, the internal equations cannot be explained and changed purposefully. Therefore, two difficulties provide challenges to combining FB variables with the FF system.

1.4 Objective

Focusing on the second challenge primarily, the objective of this paper is to improve dosage accuracy and stabilize outlet qualities by combining FB with the current FF model without considering the hydraulic retention time. Hence, this paper assumes that outlet qualities are measured immediately after dosing coagulant and internal mixing during the separation process are negligible. The following equations show the concept of this objective.

Dosage= f (WW flow, inlet SS/TU, inlet pH, coagulation pH, inlet conductivity, inlet phosphate, temperature+ interaction among variables, variables squares + ***FB)***

Equation (2)

FB= f (outlet TU/SS, set point) Equation (3)

2. Material and Method

FF-FB model is calibrated respectively for a DWT plant and a WWT plant. The datasets include inlet flow (Qin), inlet turbidity (TUI), inlet conductivity (CNI), inlet pH (PHI), pH after coagulation (PHO), temperature (TMP), and outlet turbidity (TUO). These water qualities were measured by online sensors and recorded at 15 mins' interval.

A programmable logic controller (PLC), as hardware of the dosing control system, can receive real time signals of water qualities via supervisory control and data acquisition (SCADA, plant control system). After dosage is calculated by the PLC, the real time dosage signal is sent out to dosing pump via SCADA. In order to ensure the online sensors work as normal, plant workers clean and calibrate them once per week. Furthermore, several rules and criteria in the PLC apply to check measurement errors of online sensors, and various models with less input variables respond to different combinations of the measurement error (Rathnaweera 2010).

The model in this paper was calibrated by software Unscrambler® version 10.3, which is an efficient statistical tool to establish the relationship between many variables and response parameters. This software includes several regression methods including Principle Component Regression, Multiple Linear Regression and Partial Least Square Regression. Among these, the Partial Least Square Regression was tested to be the best method for coagulant dosage prediction by previous studies (Rathnaweera 2010). Furthermore, there are four methods for the Partial Least Square Regression, including classical PLSR, NIPALS (Non-linear Iterative Partial Least Squares), Kernel PLSR and Wide Kernel PLSR. Since the Kernel PLSR is best suited for a large number of samples (Dayal and MacGregor 1997) and the training data in this paper covers long-term samples, the Kernel PLSR is selected as the calibration method. During the model calibration, the training data is standardized for equalizing the weight of each variable to model. Cross validation is implemented after the calibration. The software enables to identify the outlier data that do not fit for model and to recalibrate model without the outliers to ensure better coefficient of determination (R^2). The model calibration is completed when the R^2 is acceptable and suitable factors are selected accordingly.

This paper presents results from two treatment plants in China and Norway. The first plant is called "Number two DWT plant" (N2DWTP), located in Haining China, has a treatment capacity of 100 000 m^3/day, and the raw water is taken from the Changshan River where the water quality is relatively constant. Sequentially, the main treatment process includes an aeration tank, a coagulation process and a filtration process. The second plant, Nedre Romerike WWTP (NRA), has a capacity of 110 000 PE., situated in Lillestrom

Norway, and has been using a FF based dosing control system since 2009. The treatment process contains a screen, a pre-sedimentation, a MBBR biological treatment and a coagulation treatment. WW comes from a combined sewer system, and the amplitude and the variation of WW flow becomes substantial after rain events.

A multi-parameter based FF system started dosing control from May 2012 at the N2DWTP, and the dataset used for calibrating and validating FF-FB model is from May 2012 to October 2013. Table 1 shows statistical data of water qualities.

Table 1, Statistical data of water qualities in Haining N2DWTP

Variables	Minimum	Maximum	Mean	Standard deviation
Inlet WW flow, m^3/h	1 004	2 723	2 036	2 60
Inlet turbidity, NTU	20	251	105	54
Inlet conductivity, μS/cm	163	882	359.9	120
Inlet pH	6.4	7.2	6.9	0.1
Inlet Temperature, °C	4.5	36.7	22.8	9.2
pH after dosing coagulant	6.3	7.1	6.7	0.1
Outlet turbidity, NTU	0.7	6.8	2.0	0.6

The distribution of TUO measurement under the FF control system is shown in Fig.2, which includes 40 271 samples in period of the data collection. Fig.2 shows TUO measurements usually varied within the expected variation (1.8-2.8 NTU) while undesirably high TUO (>3.8 NTU usually) was always observed during the heavy rain event. However, the inlet measured water qualities varied in normal range as before. Hence, the FF model showed no improvement after recalibration with these data. Although the sample percentage of high TUO is very low, the duration is not short enough to be accepted because of the large number of samples. For instance, total time of 0.1% sample is about 10 hours under the 15mins' interval of data recording. Since TUO is much higher than the expected range, the operators often had to switch the dosing control to the manual mode until TUO was back in the expected range. In addition, in order to evaluate the relationship between TUO and back-wash frequency of the filtration following coagulation, the FF model was requested to calibrate few times aiming at different expected TUO ranges. On the other hand, Fig. 2 also shows that >20% situations has TUO <1.8 NTU, indicating possible over dosages. Before calibrating FF-FB models for Haining N2DWTP, the set point in Equation (3) is fixed to TUO=2.3 NTU according to the plant's usual desired value.

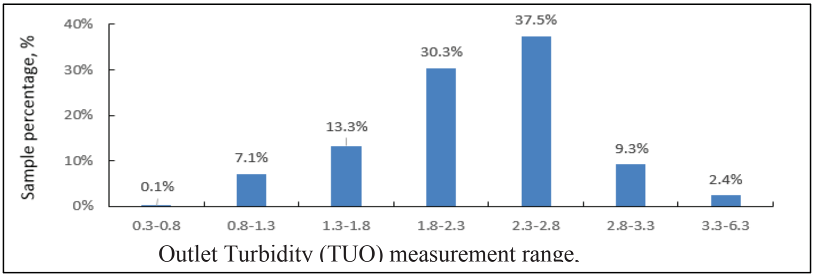

Figure 2, Distribution of outlet turbidity measurement under feedforward system control in Haining number two drinking water treatment plant.

The dataset from NRA during December 2013 to December 2014 was used for the analysis presented here. The set point is fixed to TUO=3.0 NTU as usual desired value. The statistical data is shown in Table 2.

Table 2, Statistical data of water qualities in NRA WWTP

Variables	Minimum,	Maximum	Mean	Standard deviation
Inlet WW flow, m3/h	109	*1 466*	*644*	*294*
Inlet turbidity, NTU	42	*411*	*102*	*33*
Inlet conductivity, µS/cm	*171*	*983*	*473*	*110*
Inlet pH	*5.9*	*6.8*	*6.4*	*0.1*
Inlet Temperature, °C	*7.6*	*22.0*	*15.6*	*3.6*
pH after dosing coagulant	*5.3*	*6.7*	*6.1*	*0.2*
Outlet turbidity, NTU	*0.5*	*14.9*	*2.8*	*2.1*

Fig.3 shows distribution of TUO measurement during the dosing control using the FF model at NRA and the figure is based on 32 124 data points. The expected TUO range is 1-4 NTU. It is also observed that 25% TUO measurements were beyond the expected range, in which 18.4% TUO measurement is higher than 4 NTU especially when inlet WW flow is varying in high level.

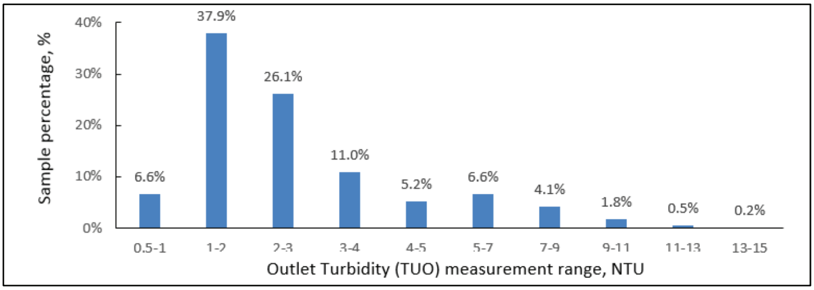

Figure 3, Distribution of outlet turbidity measurement under feedforward system control in Nedre Romerike wastewater treatment plant.

Data preparation is also necessary before feeding the dataset into the software Unscrambler® version 10.3. Firstly, the dataset was "cleaned" for potential measurement errors, identified with sudden high variation, not changing for long time, out of normal variation range and not complying with logical rule, etc. For example, data with PHO higher than PHI is considered as measurement error and were excluded. Secondly, the retention time during the separation process and the non-plug flow conditions in the settling tank complicates direct comparison of inlet-dosage-outlet datasets. The possible error arising from the latter is probably insignificant with high grade separation processes like Actiflo®. However, in this study we have assumed the error caused by non-plug flow conditions to be insignificant, thus only the average retention times served as pairing inlet and outlet data sets. At last, the datasets were divided into two equal parts, the first of which is used for model calibration while the latter part is used for model validation.

3. Results and Analysis

3.1 Case of drinking water treatment plant - N2DWTP

The FF-FB model is calibrated by first half of data with R^2=0.75. Comparing with R^2=0.71 when FF model was calibrated without TUO input, it indicates that the calibration data with TUO provide better fitness to model. Fig.4 shows the validation results, upper figure shows distribution of TUO measurement in the validation data from February 2013 to October 2013, which include 20 108 samples. The statistics in lower figure shows the performance of FF-FB model to adjust dosage in different TUO measurement range. The percentage of average dosage adjustment is calculated by equation 4. The FF-FB model seems to decrease the predicted dosage when TUO < 2.3 NTU (set point), while the dosage increases when TUO> the set point. Furthermore, degree of this adjustment is increasing when TUO becomes further away from the set point. In case of TUO > 3.8 NTU, dosage of the FF model could not adjust the adequately and the TUO starts to increase. Then the plant operators switched to original flow-proportional dosing control, which is manually -adjusted the dosage. Otherwise, the dosage adjustment of the FF-FB model should be approximately shown as dot line bars in range of 3.8-5.8 NTU.

$$Average\ dosage\ adjustment = \frac{(dosage\ from\ FF\_FB\ model - real\ dosage\ from\ FF\ model)}{real\ dosage\ from\ FF\ model} * 100\%$$

Equation (4)

Therefore, the FF model after adding a FB variable seems able to compensate for variations of the inlet qualities, resulting in more stable TUO.

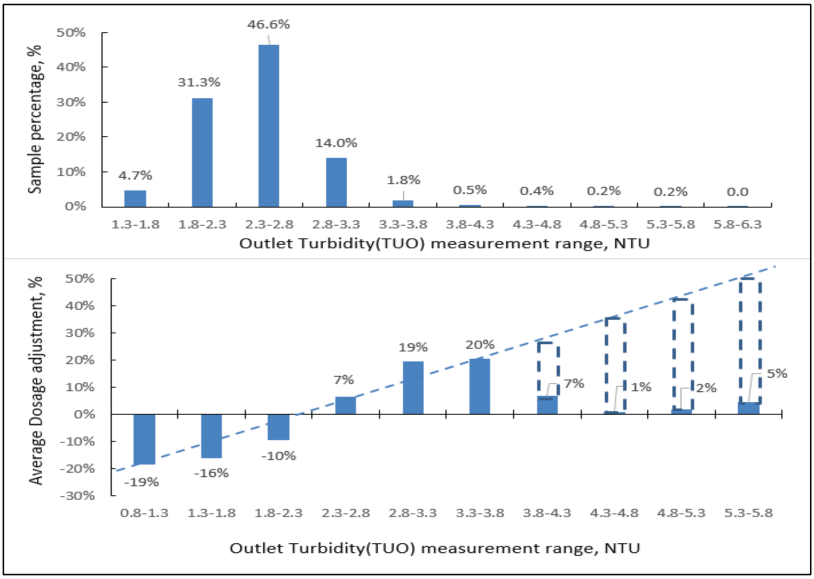

Figure 4, Statistics on validation result of feedforward-feedback model in Haining Number two drinking water treatment plant

3.2 Case of wastewater treatment plant - NRA

Regarding to the FF-FB model in NRA WWTP, the data has shown a very good fitness to the model after adding a FB variable, because R^2 is improved to 0.87 from 0.61 of the FF model. Therefore, the model performance is much better than the FF model in the validation stage. Fig.5 shows validation of the FF-FB model with 16055 samples from June 2014 to December 2014, and FB proved to be more active to adjust the predicted dosage comparing to the FF-FB model of N2DWTP. Therefore, the FF-FB model has a strong capacity to stabilize outlet qualities for this WWTP.

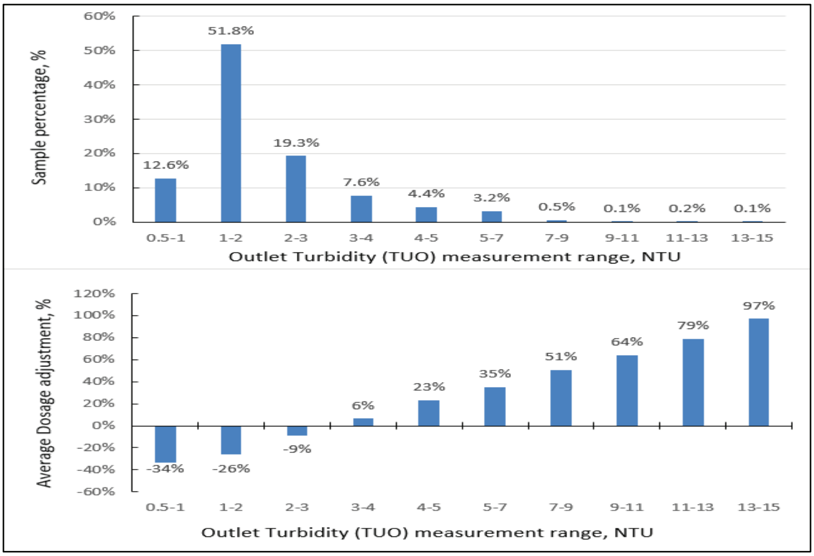

Figure 5, Statistics on validation result of the feedforward-feedback model in Nedre Romerike wastewater treatment plant.

3.3 FF and FB effects in the model

In practice, performance of FF-FB mdoel depends on both inlet water qualities (FF) and outlet qualities (FB). Hence, this section is to analyse the combinted effect of FF and FB. According to the above results, the FF-FB model of N2DWTP and NRA have the capability not only to predict dosage more accurately, but also to adjust it more efficiently when the outlet qualities are out of the expected range. Fig. 6 shows the relationship between TUO deviation from set-point (A-axis, presented by Equation 6) and dosage adjustment percentage (Y-axis, presented by Equation 5). If the pure FB control of dosage, the relationship between dosage adjustment percentage and TUO deviation from set-point should be a strict line like y=ax. In order to show the relationship with small amount of samples, Fig.6a and 6b contain 10% of total samples respectively, which are random-selected.

Y-axis: *Dosage adjustment percentage = (Dosage of FF-FB model - real Dosage)/ real Dosage*100%* Equation (5)

X-axis: *Outlet deviation=Outlet measurement - Set point* Equation (6)

Fig. 6a is from N2DWTP and Fig. 6b is from NRA WWTP. The relationship between outlet quality deviation and dosage adjustment is not as linear as the strict line (y=ax). This indicates that strengths of the dosage adjustment are not identical when the same TUO deviations from the set point happen. This is because inlet water qualities are different even under the same TUO deviations, which should generate vairous FF contributions to dosage prediction and differ the strengths of the dosage adjustment. Thus, the relationship in Fig. 6a and 6b pressent as the shape of a belt but not the strict line.

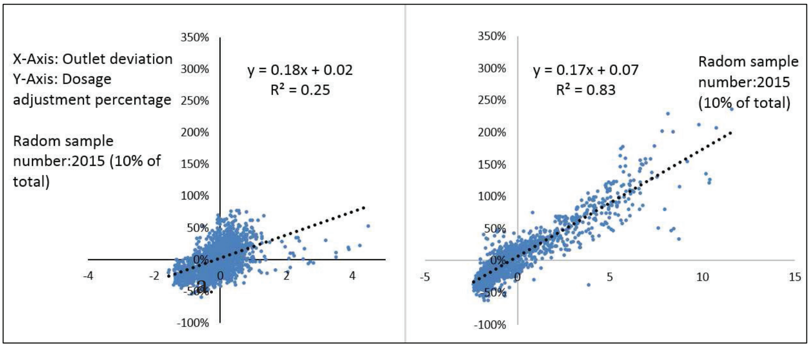

Figure 6, Relationship between outlet quality deviation from set-point and dosage adjustment percentage. (Dosage adjustment percentage = (dosage prediction-real dosage)/real dosage*100%, a. part is from Haining Number two drinking water treatment plant and b. part is from Nedre Romerike wastewater treatment plant.

3.4 Changes on coagulant consumption

Since the FF-FB model is able to adjust dosage to constant TUO, the coagulant consumption will be changed accordingly. Based on statistics data in Table 4 and 5, this section estimates potential changes on coagulant consumption under the FF-FB model control. In Table 4, the pump frequency as the system output is an indictor to coagulant flow, which is proportional to the coagulant dosing flow. For N2DWTP, during the period of validation (9 months), the FF-FB model used 3.7 % less coagulants to prevent over-dosage. However, the overall coagulant consumption with the FF-FB model to secure more stable TUO was 2.6% more than the FF model, because 12 809 data points originally had an under-dosage resulting in TUO>2.3. Whereas in NRA the total consumption of the FF-FB model became less, which could save 9.2% coagulant during the validation period (6 months). If the FB-FF model's task only was to reduce the over-dosage, the savings would be 15.5%. Therefore, if inlet qualities are similar to validation data and TUO can work as a non-delayed FB variable, the FF-FB model can provide approximately 9.2% coagulant savings in future applications.

Table 4, parameters of changes on coagulant consumption in Haining N2DWTP

TUO measurement range, NTU	0.8-1.3	1.3-1.8	1.8-2.3	2.3-2.8	2.8-3.3	3.3-3.8	3.8-5.8
Sample percentage, %	0.2%	4.7%	31.3%	46.6%	14.0%	1.8%	1.3%
Average Dosage adjustment, %	-19%	-16%	-10%	7%	19%	20%	4%
Average pump frequency, Hz	26.81	25.19	24.46	24.91	25.21	26.83	36.88

Table 5, parameters of changes on coagulant consumption in NRA WWTP

TUO measurement range, NTU	0.5-1	1-2	2-3	3-4	4-5	5-7	7-15
Sample percentage, %	12.6%	51.8%	19.3%	7.6%	4.4%	3.2%	1.0%
Average Dosage adjustment, %	-34%	-26%	-9%	6%	23%	35%	73%
Average real time Dosage, ml/m3	56.33	58.88	57.82	60.06	59.31	57.92	60.13
Average WW flow, m3/h	428	493	644	984	1206	1271	1114

4. Conclusions and Discussions

The options for the use of Feed-Forward (FF) and Feed-Forward combined with Feed-Back (FF-FB) were discussed.

A concept to integrate the FB values to the existing FF models was presented. The results of dosing control strategies based on the FB-FF models were superior to strategies based on the FF-models. The increased efficiency of the model were documented with data from full-scale tests both from drinking water and wastewater treatment plants.

The FF-FB models generated algorithms with better qualities compared with the FF only models. If the objective of the FF-FB model based control was only to avoid over dosage, it is possible to achieve savings in the range of 3.7-15.5%.

The possibility to generate more stable outlet qualities with the FF-FB model based controls were demonstrated. The outlet qualities became more stable but the overall coagulant consumption became only 9% less in WWTP while it increased by 3% in N2DWTP. The latter was a result of longer periods with under dosage leading to poor outlet qualities, and an increase in dosage was often required to produce better and consistent outlet qualities.

Since the empirical model has a strong ability to establish the relationship among variables from historical data, the model performance can be improved by the data with more accurate dosages. Considering the common retention time of sedimentation tanks and the associated internal mixing may be a challenge. However, a simplifications applied in this study shows a significant trend to improve the outlet quality. With reduced retention times in separation stages, the model accuracy will obviously be better as it can include measured outlet values in the models. Another solution could be the use of FF based soft sensors for outlet qualities, enabling the use of the FF-FB models in the separation stages with longer retention times (Liu and Ratnaweera 2015). However, the FF-FB model can still apply to DWT plants because inlet quality changes are often scaled by hours and days rather than minutes in most cases. The model could also apply to WWTP with high rate settling tanks such as lamella, Actiflo etc., which reduce the settling time from hours to minutes.

Acknowledgement: Authors appreciate the assistance provided by Haining N2DWTP, NRA WWTP, and DOSCON Co Ltd. (www.doscon.no) for providing access to the multi-parameter based dosing control system.

Reference

Ashraf A. & Barry L. 2009, 'Model predictive control monitoring using multivariate statistics', *Journal of Process*, vol. 19, no.2, pp. 314-327

Baxter CW., Shariff R., Stanley SJ., Smith DW., Zhang Q. & Saumer ED. 2002, 'Model-based advanced process control of coagulation', *Water Science and Technology*, vol. 45, no. 4-5, pp. 9-17

Chu JZ., Jang SS., & Chen YN. 2004, 'A Comparative Study of Combined Feedforward/Feedback Model Predictive Control for Nonlinear Systems', *Canadian Journal of chemical Engineering*, vol. 82, pp. 1-10

Dayal, BS. & MacGregor, JF. 1997, 'Improved PLS algorithms', *J. Chemometrics*, vol.11, no.1, pp: 73-85

Dentel SK. and Abu-Orf MM. 1995, 'Laboratory and full-scale studies of liquid stream viscosity and streaming current for characterization and monitoring of dewaterability', *Water Research,* vol.29, no.12, pp: 2663-2672

Liu W., Ratnaweera H. & Song HP. 2013, 'Better treatment efficiencies and process economies with real-time coagulant dosing control', 11th *IWA conference on instrumentation control and automation*, France

Liu W. & Ratnaweera H. 2015, 'Feed-forward based software-sensor for outlet turbidity of coagulation process' (in preparation)

Ingildsen P., Jeppsson U. & Olsson G. 2002, 'Dissolved oxygen controller based on on-line measurements of ammonium combining feed-forward and feed-back', *Water Science and Technology*, vol. 45, no.4-5, pp. 453-460

Maier HR., Jain A., Dandy GC. & Sudheer KP. 2010, 'Methods used for the development of neural networks for the prediction of water resource variables in river systems: Current status and future directions', *Environmental Modelling & Software* vol. 25, no. 8, pp. 891-909

Ogata K. 2010 'Modern control engineering', Fifth Edition, Pearson Education, New Jersey

Rathnaweera S. 2010 'Modelling and optimization of wastewater coagulation process', PhD thesis, Dept. of Mathematical Sciences and Technology, Norwegian University of Life Sciences, Aas, Norway

Ratnaweera H., Smoczyński L. & Lewandowski A. 2005, 'Efficient coagulant dosing in wastewater treatment', *Problems and Progress in Agricultural Sciences, Polish Academy of Sciences*, vol. 505, pp. 347-352

Ratnaweera H., and Fettig J. 2015, 'State of the art of online monitoring and control of the coagulation process', *Water,* vol.7, pp:6574-6597

Stanley, SJ., Baxter C.W. and Zhang, Q., 2000, Process Modelling and Control of Enhanced Coagulation, AWWA Research Foundation, Washington DC, USA

Vrecko D., Havla N. & Carlson B. 2003, 'Feedforward-feedback control of an activated sludge process: a simulation study', *Water Science and Technology*, vol. 47, no. 12, pp: 19-26

Yu FR., Kang SF., Liaw SL. & Chen MC. 2000, 'Application of artificial neural network to control the coagulant dosing in water treatment plant', *Water Science and Technology*, vol. 42, no. 3-4, pp. 403-408

Zeng GM., Qin XS., He L., Huang GH., Liu LH. & Lin YP. 2003, 'A neural network predictive control system for paper mill wastewater treatment', Engineering Application of Artificial Intelligence, vol. 16, no.2, pp. 121-129

Paper III

Feed-forward based software sensor for outlet turbidity of coagulation process

Liu Wei, Ratnaweera Harsha

The paper is submitted to International Journal of Research & Development Organization

Feed-forward based software-sensor for outlet turbidity of coagulation process

Wei Liu [1*] and Harsha Ratnaweera [12]

[1] Norwegian University of Life Sciences,

* Author to whom correspondence should be addressed; E-Mail: wei.liu@nmbu.no; Tel.: +47-9396-4044, PO Box 5003-IMT, 1432 Aas, Norway.

[2] E-Mail: harsha.ratnaweera@nmbu.no

Academic Editor: name

Received: date; Accepted: date; Published: date

Abstract: Physical online sensors are widely used in wastewater treatment plants. The high costs of acquisition and maintenance as well as the delayed response due to long hydraulic retention times, applications of some physical online sensors are limited. Consequently, studies on developing software sensors have been drawn attentions these years. Aiming to predict treatment results after water is coagulated, this paper focuses on developing a software sensor of outlet turbidity for coagulation process. Solution to address the potential non-plug-flow conditions in sedimentation tanks are discussed. Model validation results shows that the proposed software sensor has good performance within the main working range. Since the software sensor enables to know the treatment results without waiting for long hydraulic retention time of sedimentation tank, it not only shortens the response time of manual dosing control but also serves as a feedback parameter to define optimal dosage for coagulant dosing control systems.

Key words: software-sensor, turbidity, coagulation process, plug flow

---

1.Introduction

Online sensors are becoming more and more common in modern waste water treatment plants (WWTP), and measurement signals from these online sensors provide a basis for process monitoring, modelling and control [1]. Although cleaning and calibration of online sensors are part of the routine works at WWTP, they are still unable to provide accurate measurements continuously throughout the day because of fouling, drifting, aging problems, operational errors etc. Moreover, time lag, resulting from long hydraulic retention time (HRT) of treatment processes, hinders some online sensors at outlet to feed timely information back to monitoring and control. In addition to the above two disadvantages, high costs and harsh working conditions are sometimes also challenges for the application of online sensors in WWTP.

A software-sensor is a proposed solution to substitute the traditional physical online sensor. It has many advantages compared with physical online sensors, as it does not require any additional investments or maintenance, but utilises exiting online sensors measuring other parameters. Based on the process knowledge and other online sensors, software-sensors as conceptual devices are already reported used for estimating some of the key measurements of a treatment process [2]. Software-sensors can be classified into two groups according to their building concept: as model-driven and data-driven. The model-driven group is based on a first principle model, which is derived from chemical and physical feature of processes such as mass and energy balance; whereas data-driven software-sensors are obtained from information found in large amount of process data [3]. In addition to substituting important online sensors or work as reserve sensors, the software-sensor can also be responsible for monitoring process status (e.g. sludge bulking in active sludge reactor) and detecting physical sensor faults. Therefore, an increasing number of researches and applications of this field have been seen in wastewater treatment (WWT). Significant efforts are made towards developing procedures (data acquisition, data pre-processing, model design and model maintenance) and selection of modelling methods such as artificial neural network (ANN), partial least square (PLS) as well as principle component analysis (PCA) (Kadlec et al., 2011).

1.1. Software-sensor development in WWT

Fortuna et al. [4] pointed out some attractive properties of software-sensors: it remains a low cost alternative to expensive hardware devices, has the ability to work in parallel with hardware sensors for faults detection, is easily implementable with existing hardware devices, and performs real-time estimation of parameters that are time-consuming to measure online. Harsh working environments in WWT and slow hardware sensors have induced the increased development of software-sensors in WWT.

Kadlec et al. [5] and Luttmann et al. [1] and Haimi et al. [3] reviewed current researches on software-sensor development in WWT. Results show that almost all software-sensors were established from a data-driven building concept and that only two cases are a type of gray model to combine model-driven and data-driven concepts. Furthermore, ANN and PLS are two of the most common tools in the data-driven group. 56% articles are related to key parameter predictions, 37% are about monitoring process status and 7% focus on sensor faults detection. Among the articles on parameter prediction, chemical oxygen demand (COD), suspended solid (SS), NH4-N and BOD are top 4 out of 15 key parameters, taking up 27%, 15%, 12% and 10% respectively. However, within the scope of these article reviews, we found no article focusing on software-sensor development for the specific challenges in coagulation process control.

1.2. *Necessity of outlet software-sensor in the coagulation process*

The coagulation process is mainly used for removal of particles and phosphates in WWT. Common coagulation systems physically consist of a coagulant dosing pump, rapid mixing unit and flocculation chamber followed by separation processes such as a sedimentation tank, flotation tank or filter. The coagulation process is gaining popularity in WWT because it requires comparatively less area and is easier to operate, has a higher tolerance for treatment load variation, smaller operating costs, etc. The coagulation systems must have a dynamic dosing control to cope with the variable raw water qualities. Thus, in view of automation and control, various coagulant dosing control systems are widely studied. The WWTP as a data source of this paper has been using a model-based multiple parameter dosing control system, which proved to satisfy the treatment requirements and save chemical costs by defining real time coagulant dosage [6].

Outlet qualities such as turbidity or suspended solids and phosphates are key parameters to evaluate treatment performance and chemical costs, which are usually used as feedback for manual dosing control. The sludge treatment costs are also an important factor, which is directly proportional to the coagulant costs. Conventional sedimentation tanks have HRT of few hours while the inlet quality in a WWTP changes within few minutes. Thus, the outlet measurements after conventional sedimentation tank cannot function as a timely online feedback for real time dosing control [7]. This paper focuses on developing a software-sensor, which could be instrumental in establishing a feed-back based coagulant dosing control system.

1.3. *Challenges*

Outlet qualities are difficult to predict because of the complexities of coagulation dynamics [8]. First principle models for full-scale application are yet to be developed as a result of these complexities, leading to no comprehensively conceptual relationship between outlet qualities and inlet variables such as wastewater (WW) flow, coagulant dosage and inlet qualities. Parameters of inlet qualities, including particle concentration, temperature, pH, hardness, alkalinity and phosphate are not changing proportionally to each other, thus none of the parameters can be substituted with another [9]. Furthermore, physical online sensors for some of these parameters yet to be developed.

Sedimentation tank as a conventional separation unit plays an important role in removing coagulated particles. In practice, sedimentation tanks do not have ideal operational conditions of plug flow (PF), and potential mixing could often exist [10]. On the other hand, dead zones in sedimentation tanks and short-circuiting contribute to the non-plug-flow conditions, where WW does not move evenly with flow [11]. Therefore, to some extent, each outlet measurement could be a mixing result from different PF batch so that the outlet measurements do not solely represent the specific batch of inlet water qualities and dosage.

Coagulation treatment in WWT is a continuous process, in contrast to batch processes such as sequential batch reactors (SBR) in biological WWT, chemical and food industry [2]. Time lag due to HRT of continuous process presents a significant challenge to build up outlet software-sensor with inlet parameters. Sedimentation tank as a conventional floc settler of the coagulation process could show outlet qualities only after 1-3 hours after water is coagulated, as noted above. However, real time calculation of HRT is difficult and results in potential mismatches between inlet and outlet measurements. Therefore, overcoming the time lag of the coagulation process is an important aspect in building up the outlet software-sensor.

1.4 Objectives and Research procedures

Based on operation data of a full-scale coagulation process, this case study aims to develop a data-driven software-sensor of outlet turbidity (TUO). The concept is shown in Figure 1, where the TUO software-sensor (within green dotted line) lies in front of the sedimentation tank, assuming that the software-sensor is able to predict TUO at this position before it is measured at the end of the tank, namely TUO measurement (within the green solid line). We assume that the dead zones could be very small in a well-designed sedimentation tank, which causes negligible difference between actual HRT and theoretical HRT. Thus, this paper uses the theoretical HRT for matching TUO with inlet qualities in the dataset, and noted as "HRT" in the subsequent text.

Therefore, the research procedure of this paper are i) preprocess data to exclude potential instrument errors, and match TUO with inlet qualities according to HRT as well as separating the dataset into two for model calibration and validation; ii) simulate PF TUO under the different mixing conditions and compare PF TUO with TUO measurement; iii) calibrate and validate model for TUO software-sensor; iv) evaluate performance of TUO software-sensor.

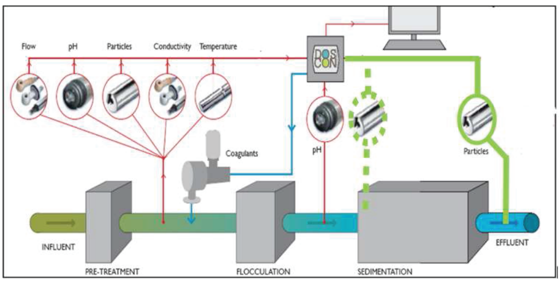

Figure 1. Concept of the TUO software-sensor. The sensor covered by dotted line indicates the proposed software-sensor

2. Materials and methods

The dataset used for calibrating the software-sensor model is from Nedre Romerike (NRA) WWTP, located in Lillestrom Norway. The plant capacity is 110 000 PE. and the main treatment process consists of screen, pre-sedimentation, MBBR biological treatment and coagulation treatment. Four rectangular sedimentation tanks in parallel apply for settling coagulated particles and treated water from these four tanks are combined to one outlet. The total volume of the sedimentation tank is 1500 m^3. The WW is from a combined sewer system, the WW qualities and flow have normal variation while WW flow may increase several folds during rains and snow melting periods.

A dosing control system (DOSCON Co Ltd, Norway) has been operating in NRA WWTP since 2009, which receives input signals from online sensors and provides real time dosage as output signal to the plant control system. Communication between online sensors and the dosing control system is carried out either by means of Modbus or analog signal. There is no time delay during the communication. All online signals as inputs are inlet turbidity (TUI), WW flow (QIN), inlet pH (PHI), pH after coagulation (PHO), temperature (TMP), inlet conductivity (CNI) and outlet turbidity (TUO), which are shown in Figure 1. During the real time dosing control, all online signals were recorded into the system at 15 minutes' interval. Online sensors were calibrated and cleaned once per week. The duration of the dataset used for model calibration and validation lasts two years from January 2013 to December 2014. Table 1 shows statistics of water parameters. The first and second half of the dataset are used for calibration and validation, respectively.

Table 1. Statistics of water parameters

Variables	Minimum	Maximum	Mean	Standard deviation
Inlet WW flow, m3/h	108.5	1466.3	643.7	294.4
TUI, NTU	41.7	411.1	101.7	32.9
CNI, μS/cm	170.9	983.2	473.1	110.0
PHI	5.9	6.8	6.4	0.1
TMP, °C	7.6	22.0	15.6	3.6
PHO	5.3	6.7	6.1	0.2
TUO, NTU	0.5	14.9	2.8	2.1

Partial Least Squares (PLS), one of the most common methods for calibrating data-driven models, is selected to develop the TUO software-sensor. Since the kernel-PLS is suitable for dealing with a large number of samples, it is used in this research [12]. Software Unscrambler® (version 10.3) applied to carry out kernel-PLS regression. The coagulation process is a nonlinear multivariate system and previous researches on coagulant dosing control proved that it can be modelled by a multivariate quadratic equation [6]. Thus, we have assumed that a model for TUO prediction could be designed as noted in Equation 1, where the interaction among variables indicates product of two single variables (e.g. Qin*PHO) and variable squares indicates square of each single variables (e.g. Qin^2)

TUO= f(QIN, TUI, PHI, PHO, CNI, TMP, dosage, interaction among variables, variable squares (1)

During the preprocessing of data, erroneous measurements due to instrumental errors were removed. To construct the model, it is necessary to consider the non-PF conditions described previously and the HRT associated with inlet batch and dosage. The dataset includes measurements for both inlet and outlet recorded at every 15 minutes over a long sampling period. If the sedimentation tank had plug flow condition, it would be straight forward to match the corresponding outlet qualities to each inlet and dosages, knowing the HRT at variable flow rates. A simplified procedure to match the data sets was used, as described below. First, each outlet data (TUO) in the dataset was shifted and matched to the closest row in the data set according to HRT. Secondly, in order to test the mixing effect, Equation 2 was suggested for the estimation of outlet turbidity under plug flow conditions (PF TUO). Numerous tracer studies conducted by the authors and others have indicated that the outlet is a mixture of various inlet water segments, where the majority of water segments matches with the ±30minutes of the HRT [6]. Equation 2 includes a number of water segments before and after the segment corresponding to the HRT, and the simulation of PF TUO is based on a mixture of segments in various proportions. The tn stands for the water segments measured or simulated at time n. The percentages in the Equation 2 (e.g. a %) stand for the contribution degree of each water segment.

PF TUOt0 = f(TUOt-n*a % +…+ TUOt-2*b % + TUOt-1*c % + TUOt0*d % + TUOt+1*e % + TUOt+2*f % +…+TUOt+n*g %) (2)

3. Results and Analysis

3.1 PF TUO simulation and TUO measurement

In order to find out the significance of the mixing effect, PF TUO is simulated by Equation 2 under different mixing percentages of water segments, which is shown in Table 2. Since the HRT of the sedimentation tank is 2 to 3 hours considering the tracer test results, the longest mixing range in this paper is assumed as -90 minutes to +30 minutes [6]. Since the water segments are measured every 15 minutes, the nine segments are considered to represent the required mixing as noted in Table 2.

Table 2. PF TUO simulation under the different mixing percentage.

	-90mins	-75mins	-60mins	-45mins	-30mins	-15mins	0 mins	+15 mins	+30 mins
set1	0	0	2.5%	7.5%	10%	15%	50%	15%	0
set2	0	2.5%	5%	7.5%	10%	15%	40%	15%	5%
set3	.5%	5%	5%	7.5%	10%	15%	30%	15%	10%

Figure 2 shows the simulation results, in which each set of figures presents the correlation between PF TUO simulation and measured TUO value at various mixing degrees as noted in Table 2. In the right side of the figure, each point is plotted by PF TUO simulation and TUO measurement. Three equations illustrate a good correlation between them. In addition, R2 shows very small deviation of data points from the correlation line (solid line). Regarding figures on right side, deviation from the correlation line increases with a widening data group when the TUO measurement goes up, but it does not have a severely negative impact on R2 because the majority of data points (67 867 samples in two years) concentrate at the theoretical HRT and the correlation line. An important observation from these results is that despite the possible internal mixing conditions caused by non-plug-flow hydrodynamics in the sedimentation tank, the variable non-plug-flow conditions do not generate significant difference between PF TUO and TUO measurement. Thus, it is not necessary to use PF TUO for building up the soft-sensor in this plant and TUO measurement can be used instead.

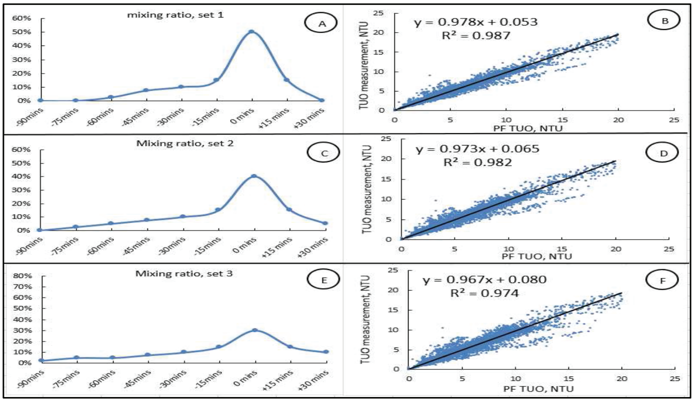

Figure 2. Significance of mixing effect under different mixing percentage. Each row stands for the correlation between plug-flow outlet turbidity (X-Axis) simulated by Equation 2 and measurement of outlet turbidity.

The conclusion from the above analysis is that the non-plug-flow conditions have insignificantly impacted the composition of the outlet water portions. Thus, TUO measurements can be used for model calibration in next step instead of PT TUO. If the TUO can be estimated in real-time with a software-sensor it can be an important tool in coagulation process control. The models used in this analysis can therefore be used as a software-sensor for TUO in a feedback control system.

3.2 Model calibration and validation

A model of the TUO software-sensor was calibrated with the dataset collected in 2013. R2=0.86, as coefficient determination of calibration, indicates that the dataset fits the model. Figure 3 shows the results of model validation with the dataset collected in 2014. X-axis stands for TUO prediction with inlet parameter, while Y-axis shows the corresponding TUO measurement (shifted TUO) matched with inlet parameters. Regarding the regression line, the slope (1.025) and intercept (0.186, crossing point with Y-axis) shows that the correlation line is very close to ideal line Y=X, and R2 indicates that most data points centralize to the correlation line.

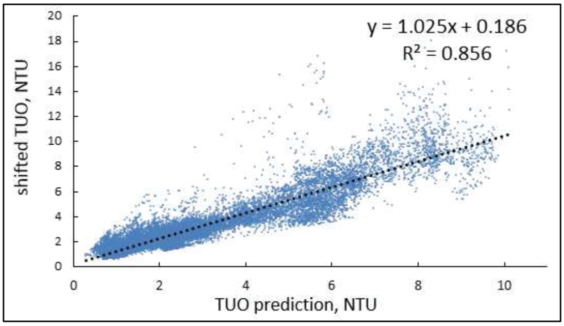

Figure 3. Correlation between shifted TUO and TUO prediction. The dotted line shows the ideal fit.

Errors of TUO prediction are analyzed by means of average relative error, and results shows in Table 3. The average relative error is shown by Equation 3, which represents accuracy of the prediction performance. In the Table 3, analysis is carried out in different TUO prediction ranges at 1-10 NTU. The majority of TUO predictions lies in the range of 1-5 NTU, taking up 65% of total samples, and it has 16% of average relative error. Average relative error is increasing when TUO prediction lies in either low or high level (rightmost and leftmost columns in Table 3), especially spiking to 30% in range of 0-1 NTU. Accuracy of TUO prediction is 84% in the majority range 1-5 NTU. Even with somewhat higher relative errors, the error in absolute values are less than 0.31 NTU for the working range (1-5 NTU), which is promising.

$$\text{Average relative error} = \left(\sum \frac{|TUO\ prediction - shifted\ TUO|}{shifted\ TUO} * 100\%\right) / sample\ number \quad (3)$$

Table 3. Statistics of TUO prediction by the software-sensor

	0-1	**1-2**	**2-3**	**3-4**	**4-5**	**1-5**	**5-10**	**0-10**
Sample percentage	20%	33%	22%	6%	4%	65%	15%	100%
[1]Average Relative Error	30%	18%	16%	12%	14%	16%	18%	19%
Standard deviation of relative error	0.18	0.13	0.15	0.11	0.12	0.14	0.14	0.16

[1]Equation 3 presents average Relative Error.

In full-scale treatment, it is often not an objective to obtain the lowest possible TUO, but an adequately good TUO. In most cases, TUO within 1-5 NTU will be considered as an acceptable optimum. Thus, the expected range of TUO measurement is mostly overlapped with the optimal working range of TUO software-sensor (1-5 NTU). Sensitivity of model performance, which depends on the majority of the dataset, is not good enough when predicting TUO at low levels. This could be the reason that range of 0-1 NTU results in high average relative error. Furthermore, when the TUO software-sensor is used as a feedback for dosage control, the adjusted dosage will cause a narrower range of TUO measurement, where the software-sensor has a better performance.

4. Conclusions and discussions

Based on the results and analysis, the TUO software-sensor of coagulation is built up for this WWTP under the research procedure. Following conclusions can be drawn in this case study.

- The simulation on mixing effect of sedimentation tank shows that there is a small difference between measured TUO and anticipated plug flow TUO under normal variation of outlet qualities.
- Selected kernel-PLS, variables and model structure proved to be suitable to develop the TUO software-sensor.
- The TUO software-sensor, based on the measurements prior to sedimentation is anticipated to estimate the TUO well before a physical measurement can be made.
- Accuracy of the software-sensor depends on working range, while unexpected TUO range caused by either under dosage or over dosage may lead to high prediction error.

Because the TUO software-sensor can provide instant estimates without waiting for long HRT, application of the TUO software-sensor not only shortens the response time of manual dosing control but also serves as a feedback parameter to define optimal dosage for dosing control systems.

Accuracy of the TUO software-sensor varies with different working ranges. Further work should target achieving good TUO prediction at high level as well, possibly by collecting more data including high TUO such that an individual model can be calibrated and tested with these datasets.

Acknowledgement: The authors appreciate the assistance provided by NRA WWTP and DOSCON CO Ltd. (www.doscon.no) for providing access to the multi-parameter based dosing control system.

Author Contributions: Wei Liu and Harsha Ratnaweera conceived and designed the experiments; Wei Liu performed the experiments; Wei analyzed the data; Wei Liu wrote the paper.

Reference

1. Luttmann, R.; Bracewell, DG.; Cornelissen, G.; Gernaey, KV.; Glassey, J.; Hass, VC.; Kaiser, C.; Preusse, C.; Striedner, G. & Mandenius, C. 2012, Soft sensors in bioprocessing: A status report and recommendations, Biotechnol. 2012, 7. 1040-1048.

2.Kadlec, P., Gabrys, & Strandt, S. Data-driven Soft Sensors in the process industry. Compt. Chem. Eng. 2009, 33. 795-814.
3.Haimi, H.; Mulas, M.; Corona, F. & Vahala, R. Data-derived soft-sensors for biological wastewater treatment plants: An overview. Environ. Modell. Softw. 2013, 47, 88-107.
4.Fortuna, L.; Graziani, S.; Rizzo, A. & Xibilia M. Soft sensors for monitoring and control of industrial process-Advances in industrial control. Springer, London, 2007, 30-35.
5.Kadlec, P.; Grbic, P & Gabrys, B. Review of adaptation mechanisms for data-driven soft sensors. Compt. Chem. Eng. 2011, 35, 1-24.
6.Rathnaweera, S. Modelling and optimization of wastewater coagulation process. PhD thesis, Dept. of Mathematical Sciences and Technology, Norwegian University of Life Sciences, Aas, Norway, 2010.
7.Liu, W., and Ratnaweera, H. Improvement of multi-parameter based Feed-Forward coagulant dosing control systems with Feed-Back functionalities. Wat. Sci. & Tech. 2015, (Submitted).
8.Ratnaweera, H.; Ødegaard, H. & Fettig, J. Coagulation with prepolymerized aluminium salts and their influence on particle and phosphate removal. War. Sci. Tech. 1992, 26(5-6), 1229-1237.
9.Ratnaweera, H.; Smoczyński L; Lewandowski, A.; Bielecka, M. An Efficient coagulant dosing in wastewater treatment', Problems and Progress in Agricultural Sciences. Pol. Acad. Sci. 2005, 505, 347-352.
10. Adams, E. and Rodi, W. Modeling Flow and Mixing in Sedimentation Tanks. J. Hydraul. Eng. 1990, 7, 895-913.
11. Zhou, S. & McCorquodale, J. Modeling of Rectangular Settling Tanks. J. Hydraul. Eng. 1992, 118(10), 1391–1405.
12. Dayal, BS. & MacGregor, JF. Improved PLS algorithms', Journal of Chemometrics, 1997, 11, 73-85.

Paper IV

Model-based measurement error detection of coagulant dosage control system

Liu Wei, Ratnaweera Harsha, Knut Kvaal

The paper is submitted to International Journal of Environmental Science and Technology

Model-based measurement error detection of a coagulant dosage control system

Wei Liu[1]*, Harsha Ratnaweera[12] and Knut Kvaal[13]

[1] Norwegian University of Life Sciences, PO Box 5003-IMT, 1432 Aas, Norway.

*Author to whom correspondence should be addressed; E-Mail: wei.liu@nmbu.no; Tel.: +47-9396-4044.

[2] E-Mail: harsha.ratnaweera@nmbu.no

[3] E-Mail: knut.kvaal@nmbu.no

Abstract: Online instruments are widely used in wastewater treatment plants and drinking water treatment plants for process monitor and control. Although maintenances of online sensors are important routine works, potential measurement errors of online sensors are challenging not only monitoring of coagulation process but also coagulant dosage control system, what this paper is focusing on. In order to estimate and detect the potential measurement error, this paper proposes a concept of model-based measurement error detection. Based on the concept, this paper enables to quantify the measurement errors and build up a novel detection method. In addition, the paper compares the proposed detection method with a traditional method-the normal variation range. The results show that the proposed method has a better efficiency to detect the measurement error.

Keywords: Error detection; model; coagulation, online sensors, normal distribution

---

1. Introduction

In order to monitor, simulate and control wastewater treatment and drinking water treatment, online sensors are widely used. Relying on the online sensors, performance of each treatment section can be monitored and corresponding operations can be carried out in time. Hence, measurement accuracy of online sensors is very important to process monitor and control. Although online sensors are regularly maintained, the measurement errors occur frequently (Thomann et al., 2002). Consequently, the measurement errors lead to inaccurate or even wrong operation, which could result in poor treatment efficiency and high operation costs. Accuracy of online measurements is still a weak point in the control chain (Winkler et al., 2004; Rieger et al., 2005; Rieger and Vanrolleghem, 2008). Therefore, the detection method of online measurement errors is necessary to study.

1.1 Background

In wastewater treatment plants (WWTPs) and drinking water treatment plants (DWTPs), measurement errors of online sensors generate by several reasons. Firstly, particles, grease and crystallized coating tend to stick on sensor surface, which hinders the sensors to touch with wastewater. Secondly, aging issue causes unstable working status and measurement deviation from true value. Thirdly, due to the communication interruption between online sensors and the plant control system, the measurement values cannot be updated. Fourthly, human mistakes such as inaccurate calibration and wrong settings also result in the measurement errors. In practice, since inlet water quality continually changes with time, the measurement errors in the variation curve show as different styles such as peak, constant, and drift.

Detection methods of the measurement errors are comprehensively studied, which are divided into two categories in general. Model-free approach focuses on single parameter measurement instead of considering the correlation among multiple parameters. Because of simple implementation, the model free approach such as normal distribution, discordant test and Rosner test are widely used (Rosner, 1983; Edward and Charles, 2014). Model based approach is to detect whether the correlation among many parameters are either statistically correct or in agreement with chemical or physical properties of the system (Robinson et al, 2005; Lo et al., 2016). Regarding the model-based approach, the empirical model are becoming popular for measurement error detection and several methods prove to be useful such as Artificial Neural Network (ANN), Partial Least Square Regression (PLSR) and Principal Component Analysis (PCA) (MacGregor et al., 1994; Luo et al., 1999; Misra et al., 2000; Venkat et al., 2003).

The coagulation process, what this paper is focusing on, is a multivariate non-linear system (Rathnaweera, 2010; Maier et al., 2010). The outlet quality of coagulation process, taking wastewater treatment as example, highly depends on coagulant dosage and inlet parameters including pH, turbidity, phosphate, temperature and so on. In order to achieve expected outlet quality (controlled variable), coagulant dosage as a key manipulated variable should be close to optimum value to deal with rapidly changeable inlet quality (disturbing variables) (Liu and Ratnaweera, 2016a). In other side, erroneous online measurements of inlet quality leading to inaccurate the dosage prediction cause unexpected outlet quality. Hence, outlet quality highly is dependent on working status of these inlet sensors when the coagulant dosage control system is running. In practice, although routine maintenances (clean and calibration) are regularly carried out by plant workers, measurement errors of online sensors usually occur and are challenging the reliability of the dosage control system. Thus, the error detection of inlet measurements is very necessary for a multi-parameter dosage control system.

Modelling of coagulant dosage control has been widely studied (Maier et al., 2004; Ratnaweera and Fettig, 2015). Since there has been no a conceptual model so far due to the complexity of coagulation process, relationships between inlet parameters, dosage and outlet parameters are generally expressed by empirical models (Ratnaweera and Fettig, 2015). Since the empirical models are derived from large number of historical data instead of chemical and physical properties of coagulation process, the equation embedded in empirical model is difficult to be explained by chemical and physical knowledge (Maier et al., 2000). A multi-parameter dosage control system, using PLSR as the method of model calibration, was tested and applied in many WWTPs and DWTPs achieving acceptable results (Rathnaweera, 2010; Liu et al., 2013). Equation 1 presents model structure of the multi-parameter dosage control system. By receiving online signals including wastewater flow (QIN), inlet pH (PHI), inlet turbidity (TUI), pH after coagulation (PHO), inlet conductivity (CNI), temperature (TMP) and outlet turbidity (TUO), the control system calculates real-time coagulant dosage. Hence, basing on the modelling method and the model structure, this paper is to develop a model-based measurement error detection for the coagulant dosage control system.

Dosage prediction = *f* (*QIN, TUI, PHI, PHO, CNI, TMP, TUO, interaction among variables, variables squares*) Equation (1)

Lo et al. (2016) pointed out that the process of sensor fault diagnosis can be classified into four steps: (1) detection (detecting whether there are any faulty sensors in the system), (2) isolation (determining which sensor(s) is (are) faulty), (3) identification (determining the type of faults that occurred) and (4) recovery (estimating the correct output of the faulty sensors). The model-based measurement error detection, what this paper proposes, belongs to the first step of the sensor fault diagnosis.

1.2 Concept of the proposed error detection

Reference is a key factor of the proposed error detection in this paper. Since outlet quality measured by outlet sensors indicates the treatment performance, outlet sensors has importance role in coagulation process. Hence, this paper uses outlet sensor as the reference sensor of the proposed error detection. In practice, in order to ensure working status of outlet online measurements, online sensors are sometimes double or triple installed at process outlet so that difference between them can reveal the potential measurement error. Furthermore, in order to check the accuracy of outlet online measurements, laboratory measurements of grasping samples are often compared with online measurements. Moreover, much better working environment at the process outlet, where most particles settled down, reduces error possibilities of outlet sensors. Therefore, outlet sensors are some of the most reliable instruments in the dosage control system, which is able to function as the reference sensor of the error detection of inlet measurement. Since the coagulation process as testing field of this paper is using turbidity to indicate outlet quality, the outlet turbidity sensor (TUO) is consider as the reference sensor.

Based on the TUO software sensor as the result of authors' previous research (Liu and Ratnaweera, 2016b), it enables to simulate TUO at given inlet parameters and dosage. Hence, there are differences between TUO measurements and corresponding TUO simulations. This paper considers that these differences are caused by both model errors and inlet measurement errors. Model errors are related to model accuracy, which causes unpredictable fluctuations of TUO simulation. This paper is to prove model errors repeat within a certain range and the related differences caused by the fluctuations are limited to the certain range. Thus, the proposed concept of the error detection is that when the differences exceed the certain range what model errors decided, the measurement errors of inlet sensors are considered to happen. Figure 1 describes the above concept, where dotted lines indicate sources of differences.

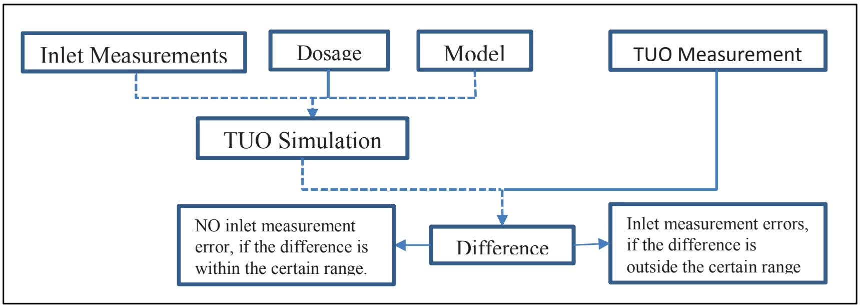

Figure 1. Concept of error detection of inlet measurements, dotted lines indicate sources of difference

1.3 Objectives and research procedure

Based on the TUO simulation model, this paper aims to i) define the difference range what is caused by model error, ii) build up a detection criterion for inlet measurement errors, iii) compare the proposed method with a traditional method-normal variation range what the current dosage control system is using. The research is carried out by following procedure. Firstly, operation data was collected from a full-scale coagulation process, measurement errors of each parameter are defined by traditional method referring to the normal distribution and these errors of each parameter are marked in dataset. Secondly, based on previous research on the TUO simulation model (Liu and Ratnaweera, 2016), TUO simulation model is calibrated with the dataset including the marked errors. Thirdly, analyze the deviation of TUO simulations and define the range of model errors. At last, build up a criterion of the error detection and compare it with the traditional method.

2. **Materials and methods**

The operation data was collected in Nedre Romerike (NRA) WWTP, located in Lillestrom Norway. The capacity is 110 000 PE. and treatment process consists of a screen, a pre-sedimentation, a MBBR biological treatment and a coagulation treatment. Figure 2 shows schematic of the treatment process. The coagulation process includes two treatment lines in parallel. Inlet sensors mentioned above are installed in one of lines before the coagulant dosing pump, the PHO sensor lies in the flocculation chamber as a section of coagulation process, and one of two TUO sensors is installed at the end of one line and another is installed at the outlet of the process where these two parallel lines join. Online measurement signals are sent to supervisory control and data acquisition (SCADA, WWTP control system) at first and then transfer to the dosing control system by means of Modbus communication. These measurement signals are recorded at 15 minutes' interval and there is no time delay during the signal transferring. Normally, these online sensors are maintained once per week. The operation data was collected from January 2013 to December 2014.

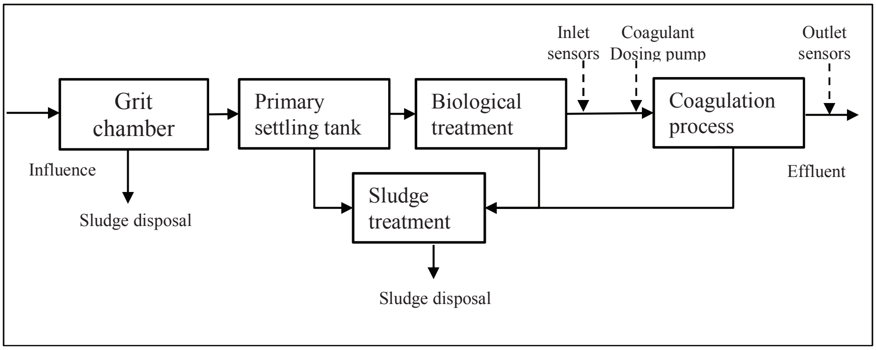

Figure 2, Schematic of treatment process in NRA WWTP, dash lines indicate the location of device and online sensors

The current dosage control system contains two criteria as the error detection of inlet measurements. The first criterion is to define whether inlet measurement values are within the normal range. Variation checking, as the second criterion, is to detect whether each sensor is active to work or signal communication pauses. Both two criteria belong to the univariate approach, which is used to compared with the proposed error detection method.

The normal variation range is determined by referring to standard deviation of measurements, mean value and historical observations. Based on the operation data, Figure 3 shows measurement distribution of each parameter. Total amount of samples is 67 872. Height of each bar indicates occurrence frequency within the total amount. Table 1 shows the normal range of each parameter. Some measurements with short bar, lying outside of the normal variation range, are identified as inlet measurement errors. Those errors defined by the normal variation range are marked in the dataset. The research in this paper is carried out with the operation data.

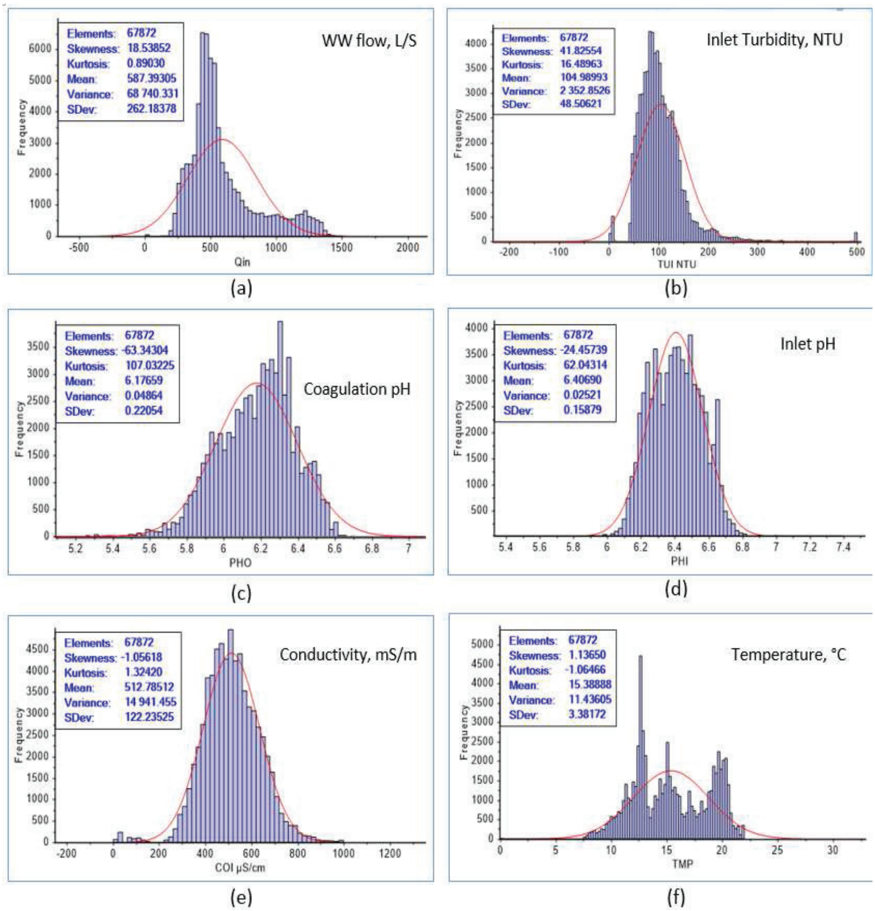

Figure 3. Online measurement distribution of each parameter during data collection. (a) distribution of WW flow, (b) distribution of inlet turbidity, (c) distribution of coagulation pH, (d) distribution of inlet pH, (e) distribution of conductivity, (f) distribution of temperature (features of the each distribution show in upper left of each figure, sample number=elements and SDev=standard deviation)

Table 1. Normal variation range of each parameter

PARAMETER	QIN, L/S	PHI	TUI, NTU	CNI, MS/M	TMP, °C	PHO
MEAN	587	6.41	104	512	15.3	6.18
STANDARD DEVIATION	262	0.16	48	122	3.0	0.22
LOW LIMITATION IN THE VARIATION	50	6.00	50	200	5.0	5.80
HIGH LIMITATION IN THE VARIATION	1400	7.00	300	900	25.0	6.80

Partial Least square Regression (PLSR), as method of model calibration, applies to build up the relationship among TUO, inlet parameters and dosages. The model structure is shown as Equation 2, where interactions among variables mean to product of two inlet parameters (e.g. Qin*PHO) and squares are responsible for the non-linear relationship. PLSR is carried out by Software Unscrambler® (version 10.3). Considering retention time of sedimentation tank, TUO measurements are not results of inlet parameters and dosages, which are recorded at the same time and written in the same row of dataset. Thus, before inputting the collected dataset in the software, TUO measurements are shifted and matched to inlet parameters considering the hydraulic retention time.

TUO prediction = f(*QIN, TUI, PHI, PHO, CNI, TMP, dosage, interaction among variables, variables squares*) Equation (2)

3. Results and discussions

The TUO simulation model was calibrated by the above concept and method, which enables to simulate TUO with given inlet parameters and dosage. Since random sample indicates that each individual sample has same possibility to be selected, it has advantage of avoiding classification interruption such as sampling time and data duration (Yates et al., 2008). Hence, in order to check stability of model errors, certain amount of random samples are selected from total samples (67 872) for the model calibration. Table 2 shows statistics results of five models. Four of them are calibrated with different 5000 samples that are randomly selected from total samples, whereas one of them is calibrated with total samples. The results show that there are small variations among these five models. This not only indicates that the relationship among inlet parameters, dosage and TUO is quite constant when models are calibrated with different small amount of data, but also results of root mean square error (RMSE) reveal that model errors are so stable that the proposed method of error detection can rely on. Due to small variations among these five models, model 4 is selected to display the performance of TUO simulation, which is shown in figure 4 and plotted with TUO simulations and TUO measurements. Equation 3 represents the correlation line (black line) between TUO simulations (TUOs, shown as predicted Y on Y-axis in figure 4) and TUO measurements (TUOm, shown as reference Y on X-axis figure 4), which is used for detection criterion in chapter 3.2.

Table 2. Statistics of outlet turbidity simulation models with different sample selections

parameter	Model 1 with 5000 random-selected sample	Model 2 with 5000 random-selected sample	Model 3 with 5000 random-selected sample	Model 4 with 5000 random-selected sample	Model 5 with whole samples
R^2	0.817	0.823	0.823	0.817	0.814
slope	0.817	0.825	0.817	0.823	0.814
Offset	0.426	0.404	0.406	0.406	0.431
RMSE[1]	0.727	0.716	0.732	0.733	0.732

[1] RMSE is abbreviation for Root Mean Square Error. Model with 5000 random-selected samples is able to show constant results, comparing with 50 or 500 random-selected samples.

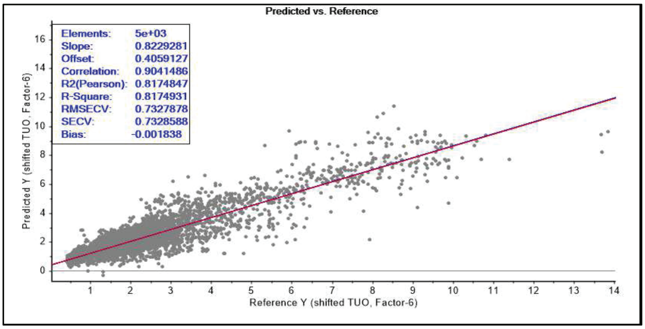

Figure 4. Correlation between simulations and measurements of outlet turbidity, black line presents the correlation line.(Sample number=elements, Slope, Offset, R^2= coefficient of determination and RMSE=root mean square error as main parameters of the correlation line list in the upper left of the figure)

$$TUOs=Slope*TUOm + Offset \quad (3)$$

3.1 Defining the range of model errors

Since model errors and the measurement errors cause difference between TUO simulation and TUO measurement, the plotted points deviate from the correlation line. Hence, a distance from a plotted point to the correlation line indicates model error and measurement error. The feature of model errors is similar to random errors, which repeats constantly and is caused by unknown and unpredictable changes (Taylor, 1999). This section is to define the range of model errors by the distance. Hence, the distances from every point to the correlation line in Figure 4 are calculated. The distance distribution is shown in Figure 5, where length of each bar presents sample percentage. In probability theory, the normal distribution presents there are 68% of possibility for a sample lying in the range of m±s (m: mean value and s: standard deviation), 95% of possibility for a sample lying in the range of m±2s and 99.7% of possibility for a sample lying in the range of m±3s. According to the mean distance=-0.007 and standard deviation of distance=0.508 of distribution results, this paper chooses m±3s (±1.5) as the distribution range. The Figure 5 displays that there are 98.4% of possibility for a sample lying the range of ±1.5, which is close to the ideal value 99.7%. This distribution range (±1.5) is considered as maximum range what model error causes. If the sample lies outside of the distribution range, this sample has big possibility to relate to inlet measurement error. Thus, the distribution range serve as a boundary between model errors and inlet measurement errors. Based on this boundary, the differences caused by model errors and inlet measurement errors can be separated.

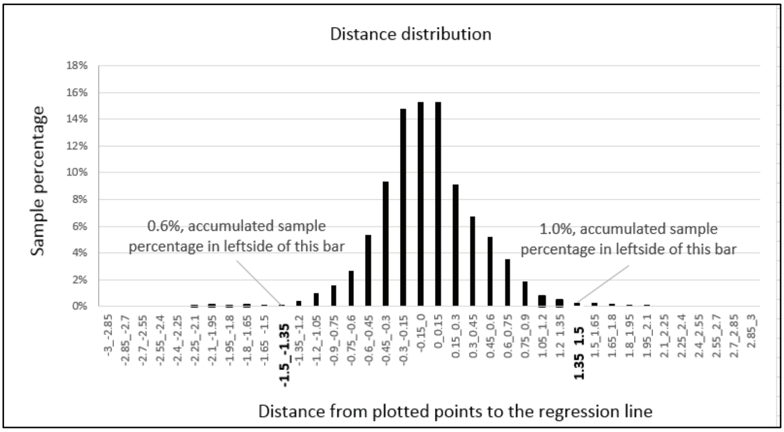

Figure 5. Defining the range of model errors based on the distance distribution. The total random sample number is 5000. Mean distance=-0.007 and standard deviation of distance=0.508. The range of model error is defined as mean± 3*standard deviation (±1.5).

3.2. Detection criterion for inlet measurement errors

According to the boundary between model errors and inlet measurement errors, this section is to definite detection criterion for inlet measurement errors, which aims to display the boundary in the Figure 4. Two lines with the same slope as the correlation line are added and the distances to the correlation line equal to 1.5 (m+3s), which is shown in the Figure 6. These two lines expressed by the Equation 4. According to the slope=0.82 and distance=1.5, K in Equation 4 equals to 1.9 as a side of the right triangle (solid line in the Figure 5). Offset ± K are intercepts of the two additional lines. These two lines can function as detection criterion of inlet measurement errors. Namely, if a plotted point lies between two lines that described the Equation 5, then there is an insignificant difference between TUOs and TUOm and hence inlet online sensors are working normally. Otherwise, the plotted points beyond this range indicates measurement errors of inlet online sensors. When implementing the proposed method of error detection, TUO simulation is generated continuously and compared with TUO measurement by Equation 5. If the comparison result displays the significant difference, measurement errors are considered to happen to inlet sensors and message of claiming sensors maintenance will generate.

$$\text{TUOs}=\text{Slope}*\text{TUOm} + \text{Offset} \pm \text{K} \tag{4}$$

$$\text{Detection criterion: } -\text{K}+ \text{Offset}< \text{TUOs}-\text{Slope}*\text{TUOm}<\text{K}+ \text{Offset} \tag{5}$$

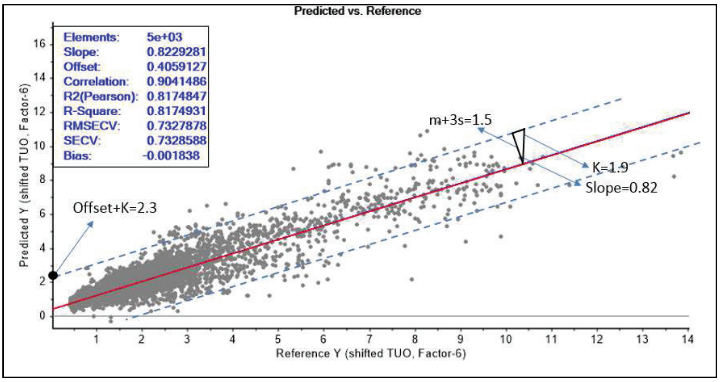

Figure 6. Detection criterion of inlet measurement errors, Solid line presents correlation line between simulations (X-Axis) and measurements (Y-Axis) of outlet turbidity. Based on the slope and the offset of the correlation line and defined range of model errors, two dotted lines parallel with the correlation line are defined as proposed detection criterion. Offset of additional lines=offset of correlation line ± K)

3.3. Testing the detecting criterion

As a new method of error detection, it is necessary to comparing with the traditional method in order to validate working efficiency. The outliers of inlet measurements have been defined previously by a traditional method-the normal variation range, which is already shown in Table 1. These outliers are assumed to influence TUOs and to generate significant differences between TUOs and TUOm. This section is to test the proposed method with these outliers. Since previously marked in the whole dataset, these marked outliers are also randomly selected during the model calibration. In Figure 7, the plotted points related to random-selected outliers are marked. The plotted points with various shapes represent different inlet parameters. It can be seen that these random-selected outliers do not always result in the obvious difference. Taking square points (related to inlet turbidity outliers) as an example, some square points close to the correlation line indicate small influence to TUOs while some square points far from the line generate the large influence. Other points with different shapes also have such situation. Therefore, the results of proposed detection criterion is not fully in accordance with the traditional method-the normal variation range.

This inconsistency is analyzed below. According to the TUO simulation model shown as Equation 2, any single parameter has two ways to contribute TUOs. Firstly, the direct contribution is carried out by the single parameter. Secondly, interactions among variables are combined contributions with two parameters (e.g. PHO *dosage in equation 2). This combined contribution could become insignificant when one of two parameters is varying in low level, whereas the combined contribution could be significant when both parameters are varying in high level. Hence, a difference between a TUOs and a TUOm depends on whether a parameter with the measurement error has a significant influence. If an insignificant influence leads to the unobvious difference between TUOs and TUOm, then it is unnecessary to identify the inlet measurement errors under such situation. Therefore, the traditional method of normal variation range focuses on sensor itself and could work universally but not as efficiently as the proposed method. The proposed detection method is only to identify the measurement error, which tends to deviate TUOs from TUOm.

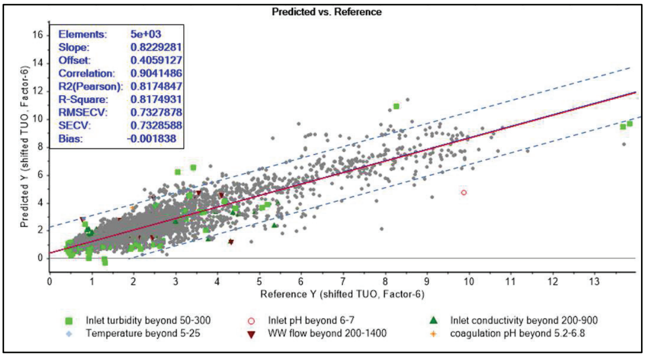

Figure 7. Comparison of proposed detection method and the traditional method (this figure bases on the correlation between simulation and measurements of outlet turbidity, solid line presents the correlation line and two dotted lines indicate proposed detection criterion of measurement errors, various points marked by difference shapes are measurement errors defined by the traditional method)

4. Conclusions

In order to detect potential inlet measurement errors for the coagulant dosage control system, a concept of model-based measurement error detection is proposed in this paper. This concept is implemented by the differences between measurements and simulations of outlet turbidity. This paper considers that the differences are caused by model errors and inlet measurement errors. If the differences are outside of the range what model errors decided, then inlet measurement errors are considered to happen. The concept proved to be effective based on results. And following conclusions can be drawn.

- The model error of the multi-parameter dosage control system can be quantified by the difference between simulation and measurement of outlet turbidity. Moreover, model errors proved to repeat constantly within the certain range.
- The range of model errors can be defined by means of probability theory and is able to functions as detection criterion of inlet measurement errors.
- Proposed detection method of inlet measurement errors has a better efficiency than the traditional method-the normal variation range.

This paper suggested that the sensitivity of the proposed error detection method should be improved with shorter range of model errors, which can be achieved by improving model accuracy. Since treatment results cannot be measured until coagulated water go through subsequent sedimentation tank, there is a time delay for the proposed error detection. However, in practical, the proposed detection method could be more efficient to claim maintenance of online sensors than the weekly maintenance.

Acknowledgement: The authors appreciate the assistance provided by NRA WWTP, and DOSCON Co Ltd. (www.doscon.no) for providing access to the multi-parameter based dosing control system.

Author Contributions: Wei Liu and Harsha Ratnaweera conceived and designed the experiments; Wei Liu performed the experiments; Wei Liu analyzed the data; Knut Kvaal provided analysis tools and knowledge on statistics; Wei Liu wrote the paper.

Reference

Edward, N.; Charles, F.; *Essentials of Testing and Assessment: A Practical Guide to Counselors, Social Workers and Psychologists*. 3rd ed.; Brooks Cole: California, USA, **2014;** 34-39.

Liu, W.; Ratnaweera, H.; Song, HP. Better treatment efficiencies and process economies with real-time coagulant dosing control, 11th IWA conference on instrumentation control and automation, Narbonne, France, Sep. 2013.

Liu, W.; Ratnaweera, H. Improvement of multi-parameter based Feed-Forward coagulant dosing control systems with Feed-back functionalities, Water Science and Technology, 2016a, (in press)

Liu, W.; Ratnaweera H. Feed-forward based software sensor for outlet turbidity of coagulation process, Sensors. 2016b (Unpublished results).

Lo, C; Lynch, P.; Liu, M. Distributed model-based nonlinear sensor fault diagnosis in wireless sensor networks. Mechanical Systems and Signal Processing. 2016, 66-67, 470-484

Luo, R.; Misra, M.; Himmelblau, DM. Sensor fault detection via multiscale analysis and dynamic PCA. Ind. Eng. Chem. Res. 1999, 38, 1489–1495.

MacGregor, JF.; Jaeckle, C.; Kiparissides, C.; Koutoudi, M. Process monitoring and diagnosis by multi block PLS methods. AIChE J. 1994, 40, 826–838.

Maier, HR.; Jain A.; Dandy G.C. & Sudheer KP. Methods used for the development of neural networks for the prediction of water resource variables in river system: Current status and future directions', Environ. Modell. Softw. 2000, 25, 891-909.

Maier, HR.; Morgan, B.; Chow, C. Use of Use of artificial neural networks for predicting optimal alum doses and treated water quality parameters. Environ. Modell. Softw. 2004, 19, 485-494.

Maier, HR.; Jain, A.; Dandy, G.C; Sudheer K. Mothod used for the development of neural networks for the prediction of water resource variables in river system: Current status and future direction. Environmental Modelling & Software, 2010, 25, 891-909.

Misra, M.; Kumar, S.; Qin, SJ. Seemann, D. Recursive on-line data compression and error analysis using wavelet technology. AIChE J. 2000, 46, 119–132.

Rathnaweera S. Modelling and optimization of wastewater coagulation process', PhD thesis, Norwegian University of Life Sciences, Aas, Norway, 2010.

Ratnaweera, H.; Fettig, J. State of the Art of Online Monitoring and Control of the Coagulation Process. Water. 2015, 7, 6574-6597.

Rieger, L.; Thomann, M.; Gujer, W.; Siegrist, H. Quantifying the uncertainty of on-line sensors at WWTPs during field operation, Water Res. 2005, 39, 5162-5174.

Rieger, L.; Vanrolleghem, PA. MonEAU: a platform for water quality monitoring, Water Sci. Technol. 2008, 57, 1079-1086.

Robinson, RB.: Chris, D.; Odom, K. Identifying Outliers in Correlated Water Quality Data,. Environ. Eng. Sci. 2005, 131, 651-657.

Rosner, B. Percentage Points for a Generalized ESD Many-Outlier Procedure. Technometrics. 1983, 25, 165-172.

Thomann, M.; Rieger, L.; Frommhold, S.; Siegrist, H.; Gujer, W. An efficient monitoring concept with control charts for on-line sensors, Water Sci. Technol. 2002, 46 (4-5), 107-116.

Taylor JR. An Introduction to Error Analysis: The Study of Uncertainties in Physical Measurements. University Science Books. California, USA, 1999, 94-96.

Venkat, V.; Raghunathan, R; Kewen, Y.; Surya, NK. A review of process fault detection and diagnosis Part I: Quantitative model-based methods. Comput. Chem. Eng. 2003, 27, 293-311.

Winkler, S.; Rieger, L.; Saracevic, E.; Pressl, A.; Gruber, G. Application of ion-sensitive sensors in water quality monitoring, Water Sci. Technol. 2004, 50(11), 105-114.

Yates, DS.; David, SM.; Daren, SS. The Practice of Statistics, 3rd ed.; Freeman, New York, USA, 2008, 178-188