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INDEX

1 INTRODUCTION

1.1 Background

Human manipulation of the environment and especially the non-sustainable exploitation of natural resources (Figure 1) have led to the disturbing equilibrium of different natural ecosystems, which affects the soil, water and atmosphere environments. Focusing on water resources, human activity has directly and indirectly altered the quality of fresh-water, and in some areas reduced the quantity of these resources.

Figure 1. Parc de la Jacques Cartier, Québec.

Wastewater can be defined as the flow of used water discharged from homes, businesses, industries, commercial activities and institutions, which is directed to treatment plants by a carefully designed and engineered network of pipes. The term “domestic wastewater” refers to flows discharged principally from residential sources generated by such activities as food preparation, laundry, cleaning and personal hygiene. Wastewater must be properly treated before discharging to the environment (i.e. rivers, lakes, seas). Pollution caused by untreated water can have a damaging ecological impact that can be harmful for water animals and aquatic plants. The overall water management objectives for wastewater treatment are associated with the removal of pollutants and the protection and preservation of our natural water resources, such as rivers, oceans or lakes.

The traditional way to treat domestic wastewater is by applying activated sludge processes. These are biological processes by which the activity of microorganisms, under controlled operating conditions, permits the biodegradation of organic matter and removal of nutrients (nitrogen and phosphorous) from wastewater. Wastewater treatment plants (WWTP) are designed and constructed to conduct these processes in an efficient way.

Primary treatment, known as well as mechanical treatment, is the first stage of wastewater treatment and is designed to remove gross, suspended and floating material by gravity in the grit chamber and primary settling tank (PST). The removal capacity of the primary clarifiers directly affects the performance of the following processing units. Thus, the primary clarifier can be regarded as a fundamental component of wastewater treatment plants.

In this sense, prim*EAU*, a project funded by John Meunier Inc. (JMI) and Natural Sciences and Engineering Research Council (NSERC), aims to improve primary sedimentation through better design and operation. The main project objectives are: (i) improve the knowledge on the dynamic behavior of the primary clarifiers ; (ii) improve the knowledge by the development of a new dynamic model for primary clarifiers; and finally (iii) study the behavior of primary treatment under the addition of chemicals (CEPT), used to maximize the amount of organic matter sent to the anaerobic digester. In this sense, different projects are currently in this line of research.

This thesis is framed within the ongoing research “Control of the alum addition to the primary treatment at the Quebec City WWTP” conducted by Sovanna Tik. Thanks to the PROMETEU program of the *Univesitat de Girona*, an internship of five months at model*EAU* was conducted during the first semester of the 2014/2015 academic year. The work at model*EAU* was directly supervised by Sovanna Tik (model*EAU* PhD student) and by Jordi Comas (professor at Univesitat de Girona), who are the supervisors of the thesis. Furthermore, there has been significant contribution of Prof. Peter Vanrolleghem (head of model*EAU*, PhD and superior of Sovanna Tik) and other members of the model*EAU* team.

1.2 Objectives

The main objective of this project is to contribute to a better understanding of particle sedimentation in the primary treatment in order to propose strategies to optimize the system in terms of pollution removal. First of all though, a model needs to be built and calibrated, to make sure that it fits with reality. To finish with, a validation of the model needs to be carried out before starting to evaluate strategies that optimize the particle settling.

The main objective will be pursued together with three sub-objectives:

A) To deepen the knowledge on the dynamic behavior of the primary clarifiers (key to the design and optimization of processes) and understand the operations in a WWTP.

B) To collect experimental samples and conduct their analysis in the laboratory in order to characterise the particles. The aim is to make sure the data extracted by sensors is in agreement with the laboratory results.

C) To develop, calibrate and validate a sedimentation model for chemically enhanced primary treatment (CEPT). Afterwards, a member of model*EAU* will use it to perform simulations and try to find the optimal conditions in terms of pollution removal.

1.3 Specifications and Scope

The focus of this project is the development, calibration and validation of a model with CEPT (Chemically Enhanced Primary Treatment). Once the model is validated, it will be used to find the optimal process conditions. The model development will be carried out together with other model*EAU* members. The tasks related to the three objectives defined in section 1.2. are:

A) Objective 1: To deepen the knowledge on the dynamic behavior of the primary clarifiers and understand the operations in a WWTP

- Acquire knowledge about wastewater treatment, WWTP configuration, primary treatment, and chemically enhanced primary treatment (CEPT).

B) Objective 2: To collect experimental samples and conduct their analysis in the laboratory.

- Visits to the WWTP of Beauport (Québec City, Canada) in order to collect experimental samples and perform sensors maintenance (cleaning, check their operation,...)

- Laboratory analysis of the samples in order to characterise particles (This work is carried out along other model*EAU* members).

C) Objective 3: To develop, calibrate and validate a sedimentation model for chemically enhanced primary treatment (CEPT).

- Get familiarized with the modelling software WEST (www.mikebydhi.com)

- Develop, calibrate and validate a primary clarifier model capable to predict the TSS concentration in the primary effluent when alum is added.

- Calculate statistical criteria to evaluate the model calibration and the subsequent validation.

2. MATERIALS AND METHODS

This section gives a general overview of the methodology used in this project for model calibration and subsequent validation, as well its background, explaining the future usefulness of the model once has been calibrated.

The next sections provide: i) a brief description of the previously acquired knowledge as a background of the project, ii) the explanation of the model implementation and the case of study and, iii) a description of the methodology used for model calibration, explaining the criteria used for its evaluation.

2.1 Previous Knowledge

2.1.1 Combined Sewer Overflows

In Quebec City (Canada), the wastewater treatment plants (WWTPs) are highly subject to weather conditions. For years, the Saint-Charles river (Quebec, Canada) has suffered from around fifty combined sewers overflows (CSO) annually. CSOs are the major cause of receiving water quality degradation. To reduce their occurrence, fourteen retention tanks (RT) were constructed to store storm water which exceeds the sewer network capacity, leading to retain a total capacity of 150,000 m³.

Figure 2. Retention Tank

These Retention Tank infrastructures (Figure 2) are quite expensive and are rarely managed to their full potential. Their emptying is usually controlled by water quantity-based rules: as a precaution, rules are set so the storage capacity is recovered as soon as possible to face another subsequent rain event. Therefore, at the end of a rain event, the RT are emptied in a way to reach the maximum acceptable flow rate at the inlet of the wastewater treatment plant (Tik *et al.*, 2014). However, when no rain is forecast, a more gradual emptying can be considered to reduce the wet weather impact on the WWTP and, consequently, on the receiving water quality.

Quebec City has two WWTP, named East and West, which collect wastewater of its 540.000 inhabitants. These plants have been designed to treat a mean flow rate of 9.625 m^3/h and 6.540 m^3/h, respectively . Their acceptable peaks flow rates are about 15.625 m^3/h and 13.125 m^3/h. With the current emptying management rules of the RT, the WWTPs have to operate at maximum capacity for extended periods of time after each major rain event. Such conditions can deteriorate the treatment process, especially primary clarification, and as a consequence, the next treatment stages.

In that sense, when the weather forecast prohibits an extended emptying period (i.e heavy rain, several subsequent rains in a short period of time,..) chemical addition in the primary treatment can be considered to increase the volume of water to be treated. This strategy based on alum dosing allows an improvement of primary treatment efficiency, leading to a further decrease in suspended solids discharge and permitting more water to be sent to the secondary stage of the WWTP (Tik *et al*., 2014)

2.1.2 Chemically Enhanced Primary Treatment (CEPT)

Chemically enhanced primary treatment (CEPT) by addition of coagulants/flocculants is, as mentioned above, often operated under wet weather conditions. Chemical products can be applied to achieve many different objectives in wastewater treatment facilities:

- To increase the TSS removal performance of a Primary Settling Tank (PST).
- To reduce organic loading rates, and in this way reduce demand on aerobic biological treatment facilities.
- To increase hydraulic loading rates to existing PST and therefore allow high wet weather flows to WWTP.

The first most significant application of CEPT was treated in the 1960s by Canadian and U.S. engineers to address the eutrophication of the Great Lakes through chemical precipitation of phosphorus. More recently, in the U.S., with increased emphasis on CSO control, agencies are searching for inexpensive and compact solutions, different from just increasing process capacity and secondary treatment hydraulics, to manage wet weather flows.

In this sense, CEPT has been extensively evaluated thanks to its minimal investment in new infrastructures. In fact, hydraulic capacities of existing primary settlers can be increased by a factor of up to 3 (Melcer *et al.*, 2012; Newman *et al.*, 2013), which is often sufficient to manage peak wet weather flows.

2.1.2.1 ***Control of the alum addition in the primary treatment***

A preliminary study of the Québec City treatment plant based on lab experiments recommended to use 70 mg/L of alum on a dry basis and 0.2 mg/L of polymer (*Lajoieand et al.*, 2008). However, other experiments have shown that in many cases such dosage is often excessive, resulting in operational problems and economical loss.

In that context, Tik *et al*. presented in 2013 a chemical addition control based on online turbidity data . The aim of the study was to set up control strategies to optimize chemical dosage in terms of reducing costs and resource use without degrading effluent quality.

A basic sedimentation model for chemically enhanced primary treatment (CEPT) was developed (Figure 5), showing that the effect of alum addition can be represented by varying two settling characteristics: the settling velocity and the fraction of non-settleable suspended solids (Figure 3).

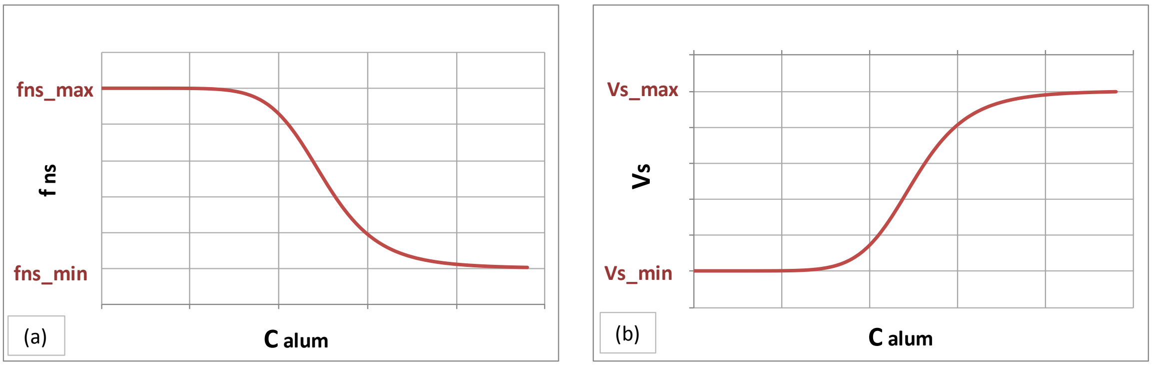

Figure 3. Proposed evolution of (a) the non-seattleable fraction of TSS (fns) and (b) the settling velocity (Vs), depending on the alum concentration (Calum). (Tik *et al.*, 2013)

Therefore, the model chosen to represent the CEPT was based on these two hypotheses:

- The increase of alum concentration (C_{alum}) causes a decrease of the TSS non-seattleable particles (f_{ns}) following a sigmoidal curve until a f_{ns_min} (saturation).
- The increase of alum concentration (C_{alum}) causes an increase of the particle settling velocity (V_s) following a sigmoidal curve until a $V_{s\ max}$ (saturation).

The proposed model allowed a fairly good simulation of the primary clarifier's outlet TSS concentration. The experiment was simulated during a full-scale alum addition test with step concentration changes (Figure 4). The results concluded that the model was sufficiently robust to satisfactorily describe dry weather conditions as well as wet weather conditions. However, further validation on other case studies are still required to confirm the usefulness of the model. In this sense, the model developed in this project goes in the same direction and tries to confirm the previous results.

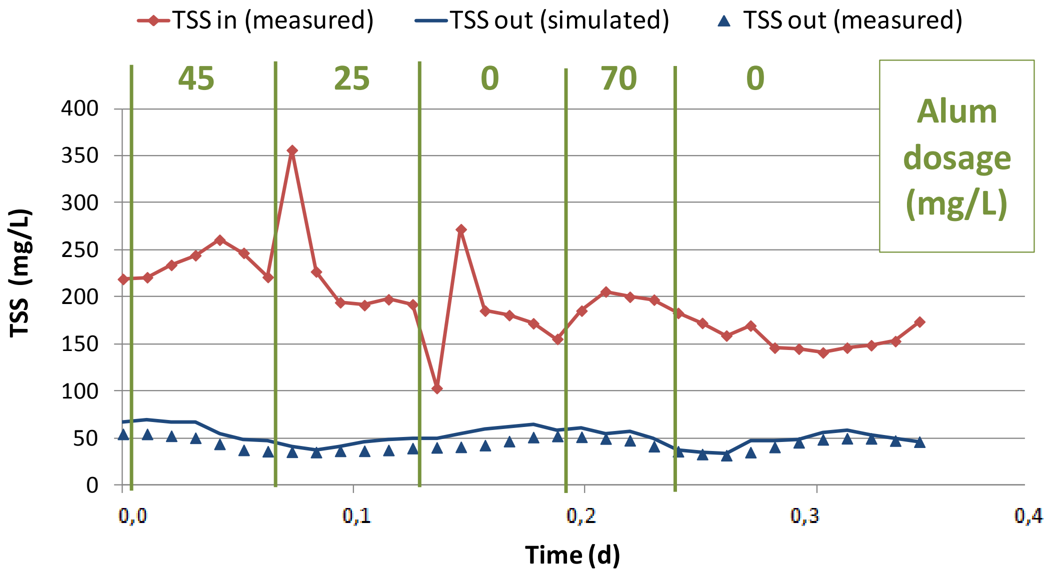

Figure 4. Experimental and simulated TSS results of a full-scale experiment on August 25th. (Tik *et al.*, 2013)

With that project Tik *et al.* (2013) could demonstrate it is possible to reduce alum addition by 30% compared to a constant alum dosage and provide the same performance in terms of maximum TSS concentration (in the primary effluent).

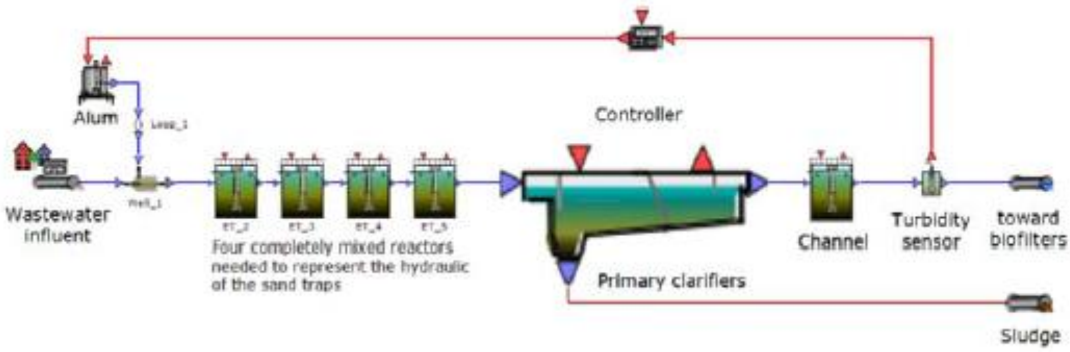

Figure 5. Model configuration of the East WWTP primary clarifier in WEST® (Tik *et al.*, 2013)

2.1.3 Particle Settling Velocity Distribution (PSVD)

Most of the existing settling models make a simple appoach and make use of a unique settling velocity for all particles even though the particles are heterogeneous and have different settling velocities.

Introducing the concept of particle settling velocity distribution (PSVD) in the model provides a better description of the behaviour of the particles in the PST. Moreover, even though little literature exists on the topic, a few studies have highlighted that a link exists between particle physical properties and particle biodegradation properties (Hvitved-Jacobsen *et al.*, 1998; Morgenroth *et al.*, 2002), emphasizing the need to focus more on how primary settler models and subsequent biological reaction models have to be complementary. Therefore, models of an adequate complexity need to be developed for a more accurate description of the primary settler tank (PST) behaviour and the chemical/biological phenomena that may affect particles, their settling velocity and, as a consequence, their removal (Maruéjouls *et al*., 2014).

As mentioned before, the efficiency of the PST directly influences the performance of the subsequent treatment units in WWTPs, since during settling, organic matter and suspended solids of the influent, as well as pollutants associated with them, are removed.

2.1.3.1 ***ViCAs experiment***

The ViCAs (*Vitesses de Chute en Assainissement*) experiment, is a batch settling protocol developed by Chebbo and Gromaire (2009). It is considered an excellent method to feed this type of PSVD-model, as it allows to experimentally determine the fraction of the different settling velocity classes, each characterised by a different settling velocity Vs.

The experiment consists in filling a settling column (H=60 cm, Ø=7cm) with a homogenized suspension. Solids settled during predefined time intervals are recovered at the bottom of the column and then weighed for TSS. From the time evolution of the cumulated mass of particles settled since the beginning of the experiment, it is possible to calculate the distribution of settling velocities. Therefore, each particle class is assigned a fraction of the influent TSS. However, given the dynamics of the wastewater composition, this assignment is not constant (Figure 6).

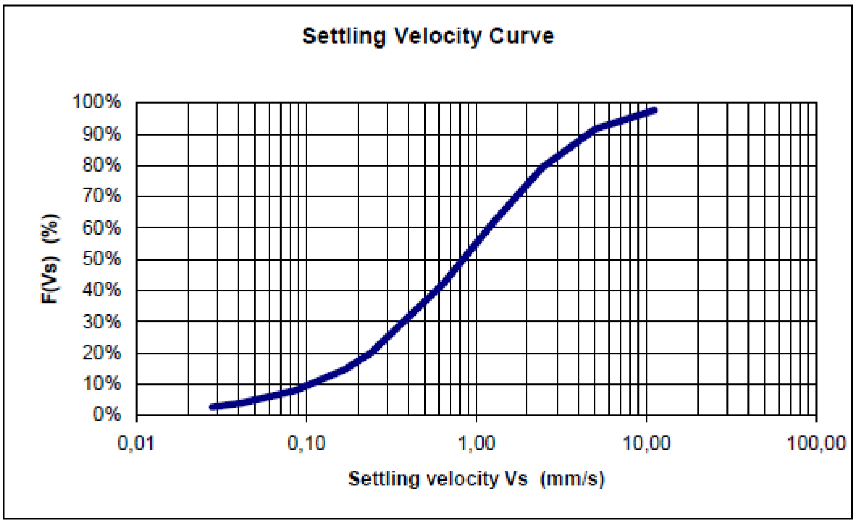

Figure 6. Example of TSS fractionation obtained from ViCAs experiment (Hasler *et al.,* 2007)

After several experiments it was observed that ViCAs curves were located between two boundaries: while higher limit is given for low TSS concentration, the lower is given for high TSS. This means that high TSS samples contains a larger fraction of rapidly settling particles (Bachis *et al.,* 2014).

Thus, given a sample with a certain TSS concentration, the assignment of the TSS fractions in the model is made by interpolating the PSVD curve between two boundary curves (Figure 7). More specifically, the assignment is performed as follows: for a certain settling velocity (on the x-axis), the two corresponding limiting TSS fractions are determined (y-axis) and a linear interpolation is made between them based on the influent TSS-value.

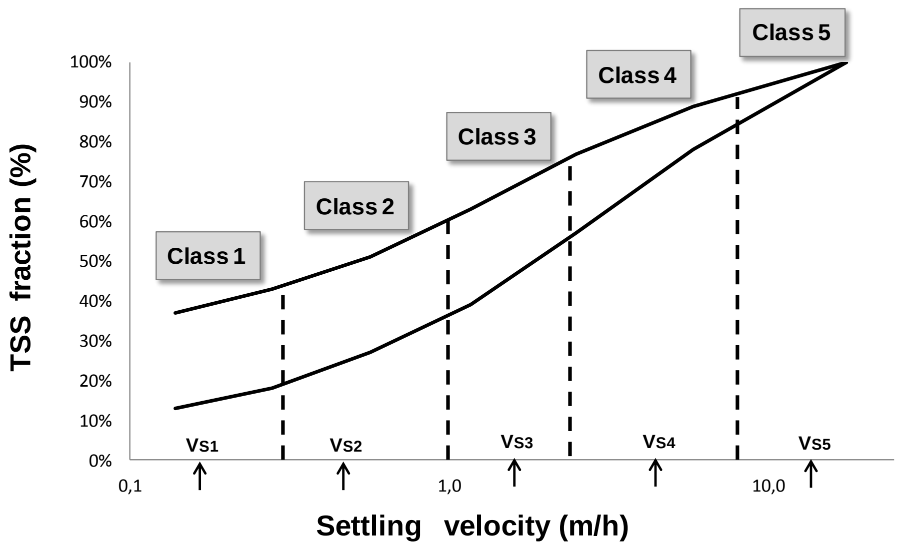

Figure 7. Primary settling velocity distribution (PSVD) boundary curves.

The observed relation between PSVD and TSS concentration is used to define the fraction of each class of the influent TSS. The settling velocities characterising each class are calculated as the geometrical mean of the settling velocity boundaries of the class (Eq.1).

$$V_{s_i} = \sqrt{V_{s\,max\,i} \cdot V_{s\,min_i}} \qquad \text{(Eq. 1)}$$

With this TSS-based relation, the influent PSVD-based TSS fractionation in five particles classes changes with time, depending on the actual TSS concentration.

Figure 8 is an example of the TSS fractionation in five particle classes. In grey we can see the typical PSVD zone observed in the sewer. Each particle class, characterized by a mean settling velocity (Vs_1 to Vs_5) is associated with its TSS mass fraction (f_1 to f_5) given by the curly brackets.

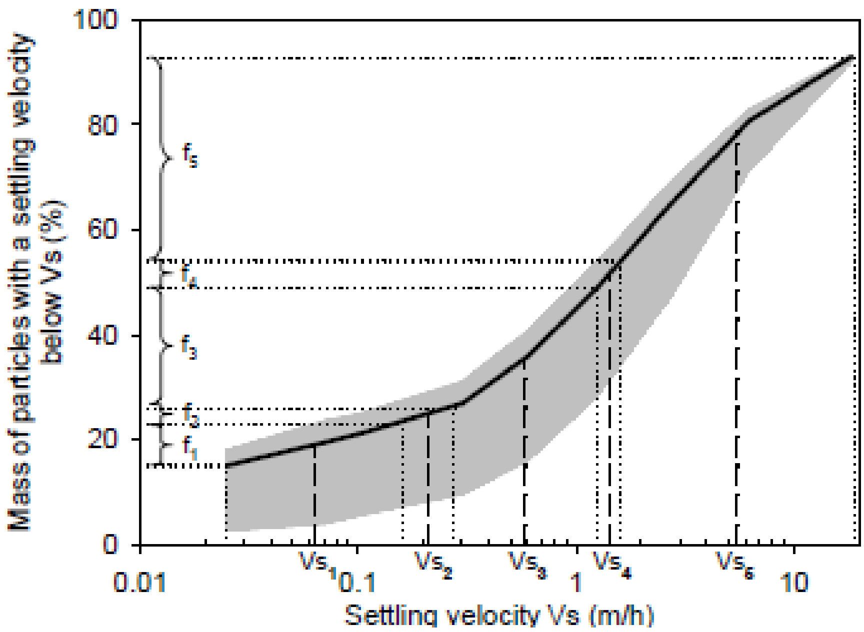

Figure 8. Example of TSS fractionation in five particle classes. (Tik *et al.,* 2014)

In this context, a new dynamic primary settler model based on the PSVD approach was presented by Bachis *et al.* (2014). The model allowed improved predictions in terms of effluent TSS compared to previous primary settling models. It could be shown that by creating a number of particle classes that cover the settling velocity distribution, a vertical gradient of the concentration of each of the particle classes and the pollutants associated to them can be calculated.

2.1.4 PSVD with CEPT

The effect of CEPT on the PSVD can also be characterised by means of ViCAs tests. To illustrate this, samples taken at the inlet of the pilot-scale PST after addition of chemicals were subjected to the ViCAs test. Results showed (Figure 9) that the inlet PSVD after chemical addition is shifted towards higher settling velocities, and outside the typical reference zone of the primary settler influent without CEPT (Bachis *et al.*, 2014). It could also be observed that the effect was more pronounced for slow settling particles. This is due to the aggregation of the particles produced by the addition of chemicals.

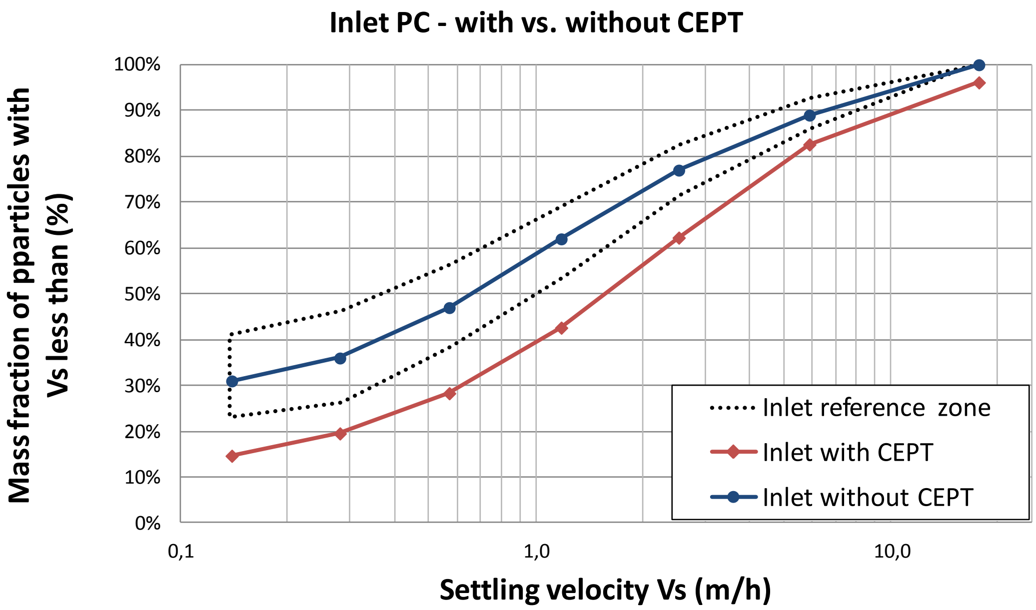

Figure 9. Comparison of PSVD observed at the PST inlet during operation without CEPT (Blue) and with CEPT (Red). (Bachis *et al.,* 2014)

This experimental approach may be very well suited to model the effect of the addition of chemicals on primary settling. Indeed, the curve with the appropriate PSVD (with or without chemical addition) may be used directly as input to the model, fractionating the TSS in the more appropriate settling fractions.

Applying the model using the PSVD with chemical addition resulted, as expected, in a significantly better TSS removal (Bachis *et al.,* 2014). Figure 10 illustrates the simulation of TSS of the primary clarifier effluent with and without CEPT. The simulations were obtained with the same influent.

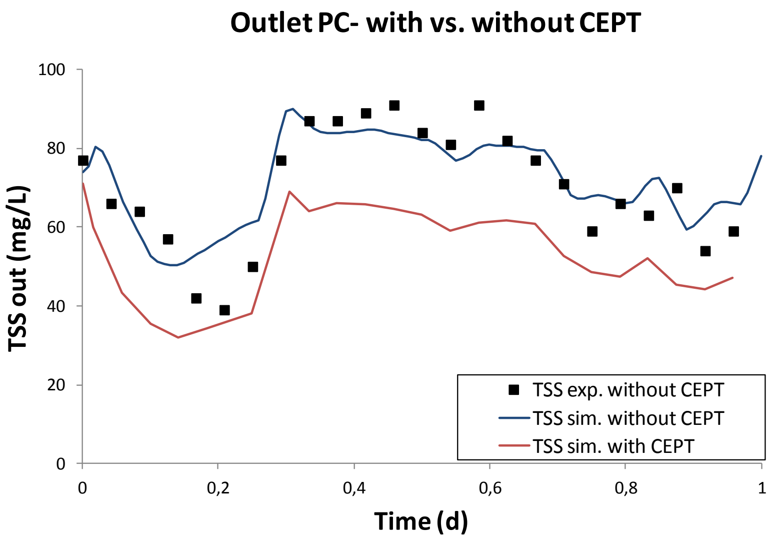

Figure 10. PSVD model fit for effluent TSS concentrations without CEPT (Blue) and simulation with CEPT (Red). (Bachis *et al.,* 2014)

With this, Bachis *et al.* (2014) could demonstrate that chemical addition in the primary treatment resulted in a significantly better TSS removal. In this same line of research further confirmations are under study. In this respect, the model developed in this project is also based on the PSVD approach, and attempts to be effective in predicting the TSS concentration in the primary effluent when alum dosage is applied.

2.2 Model Configuration

The aim of this section is to present the configuration of the developed WEST model and the data used for its calibration and validation.

2.2.1 Introduction

In environmental engineering it is frequently necessary to predict the behavior of complicated systems with highly variable boundary conditions . Often, important data and information are missing. With the help of models it is possible to transfer experience from one system to another, and partially compensate this lack of information (Gujer, 2008).

Modelling is thus an important aspect for engineering professions. Simulation makes use of these models and permits to make statements about the expected behavior of rather complicated systems. To simulate means to predict the behavior of a system of interest, typically with the help of numerical solutions of model equations. Simulation thus answer questions such as “*What would happen, if …?*”

Often, it is too expensive, illegal, or impossible, to run experiments with the plants or systems that we plan, design or operate because:

- Physical models (pilot plants) are expensive and difficult to operate.
- Experiments can endanger humans (drinking water) or the environment (wastewater), if we leave our field of expertise.
- Natural systems (running waters, lakes, groundwaters) cannot be endangered.
- Rain cannot be imitated in real systems.

Thanks to simulation, it is possible to explore the behavior of the real world and make predictions under certain conditions. These predictions can therefore help to design, optimize, and operate real-world systems.

In this sense, the performance of entire wastewater treatment plants under variable hydraulic and pollutant loads is currently simulated in the context of plant design. Moreover, simulation is used also to develop new control concepts for such plants.

2.2.2 Description of WWTP design general metodology

The widely-accepted methodology used for designing WWTPs is presented in Figure 11. First, the initial assumptions are defined, (i.e. influent, model parameters and design variables) which will be the inputs of the system. These assumptions are choices made by the different stakeholders involved in the design process (i.e. design engineer, operator, regulator, plant owner). Then, runing a simulation of the WWTP mathematical model, these initial assumptions are applied. The outcome of the model is a prediction of the WWTP effluent concentrations (i.e total suspended solids, ammonia, nitrate).

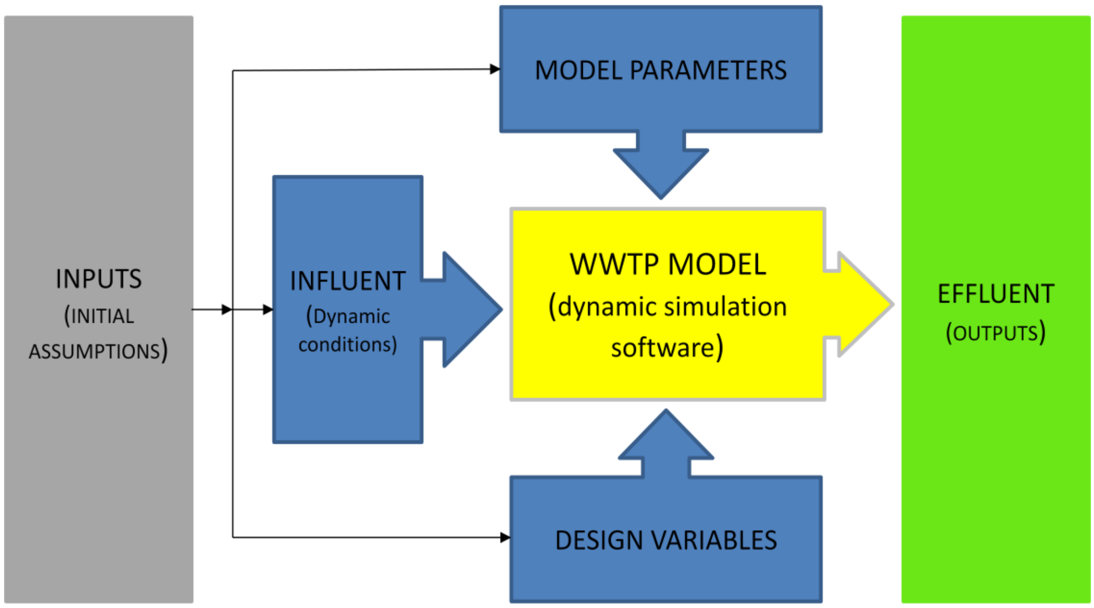

Figure 11. Typical design methodology for WWTP. (Altimir, 2012)

2.2.3 Simulation sofware utilized: WEST®

The software chosen for the modelling of our case study is WEST® (mikebydhi.com).

WEST® is a user-friendly software tool for dynamic modelling and simulation of wastewater treatment plants (WWTP) and other types of water quality related systems. It is designed for operators, engineers and researchers interested in studying physical, biological or chemical processes in WWTPs and sewer systems.

2.2.4 Case Study

This section presents the structure of the model utilized, showing their principal components and introducing the model parameters needed to calibrate it. First of all, a brief description of the Eastern Quebec WWTP is carried out, focusing on the primary treatment. A short explanation of the primary settler and its modelling follows. Finally, a brief description of the model configuration is presented.

2.2.4.1 *Eastern Quebec City WWTP*

As explained before, two WWTP (East and West) collect wastewater of 540.000 inhabitants in Quebec City. Figure 12 shows the Quebec City wastewater transport network. The West station (in red) , as its name suggest, collects the wastewater of the west side of the city; while the East station (in dark green), located at Beauport, collects the east side.

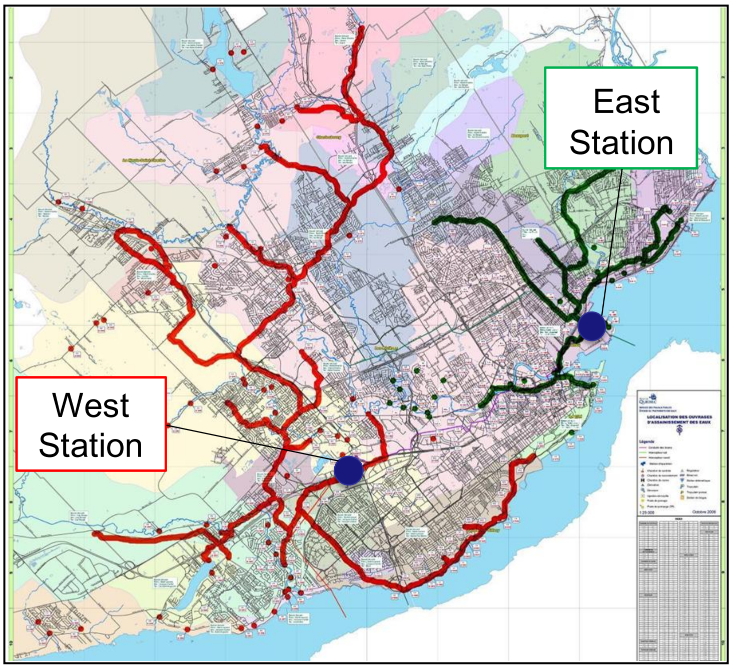

Figure 12. Quebec City WWTPs location

This project is based on the East WWTP (also known as the Beauport WWTP) which has been designed to treat a mean flow rate of 9.625 m^3/h with acceptable peak flow rates around 15.625 m^3/h. More specifically, the primary settler tanks (PST) of the Eastern WWTP are lamellar settlers, with a total surface of 27.000 m^2, treating a mean flow rate of 236.600 m^3/d during dry weather conditions.

2.2.4.2 ***Modelling the Eastern WWTP Primary Settler***

The role of primary settling in wastewater treatment has often been neglected and very few efforts have been made for its optimisation and modelling. It has been neglected either because primary settling is not considered very influential for modelling purposes, or because the simple models proposed earlier were considered sufficiently robust to describe primary settling tank (PST) behaviour (Otterpohl and Freund, 1992). In many modelling case studies, the boundaries of the wastewater treatment plant (WWTP) are defined from the primary effluent onwards, i.e. using the primary effluent as model input, keeping the primary settler out of the modelling scope. However, a better understanding and modelling of the processes taking place in PST result in a more accurate description of the primary effluent and waste sludge. As such, it results in improved operation of the subsequent treatment phases, i.e. the water and sludge treatment (Bachis *et al*., 2014).

In 2014, a new dynamic primary settler model of the Beauport WWTP, based on the PSVD approach, was presented by Bachis *et al.* The PSVD model was implemented in the modelling and simulation software WEST (mikebydhi.com). In order to describe the vertical gradient of particle class concentrations, the settler was divided into a number of layers (Figure 13) and a mass balance was calculated around each layer for each of the classes. Five particle classes with different (constant) settling velocities made up the final model. As a result of that, the model allowed better TSS effluent predictions compared to previous primary settling models.

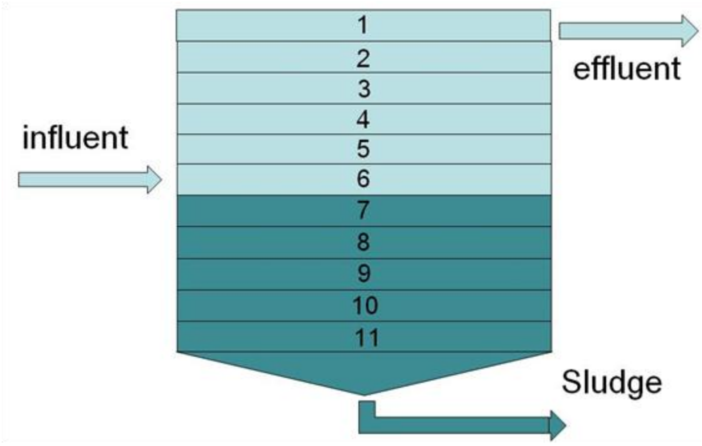

Figure 13. The Primary Settling Tank was divided in 11 layers (Bachis *et al*, 2014)

The primary settler model used in the current case study is the same as the one of Bachis *et al.* calibrated in 2014, as it tries to represent the same primary settler (Beauport WWTP, Québec City). Therefore, same parameter values could be taken from that work (i.e settling velocity for each of the five classes, PST dimensions, underflow rate,...)

2.2.4.3 ***Model Configuration in WEST***

The WWTP model in the case study (Figure 14) consists of a primary clarifier with chemical enhancement by alum addition. All modeled processes are described using the PSVD approach. Five particle classes enabled to adequately predict the TSS fluxes throughout the system. The integrated model presented in this project has been adapted from the model developed by Tik *et al.* (2013).

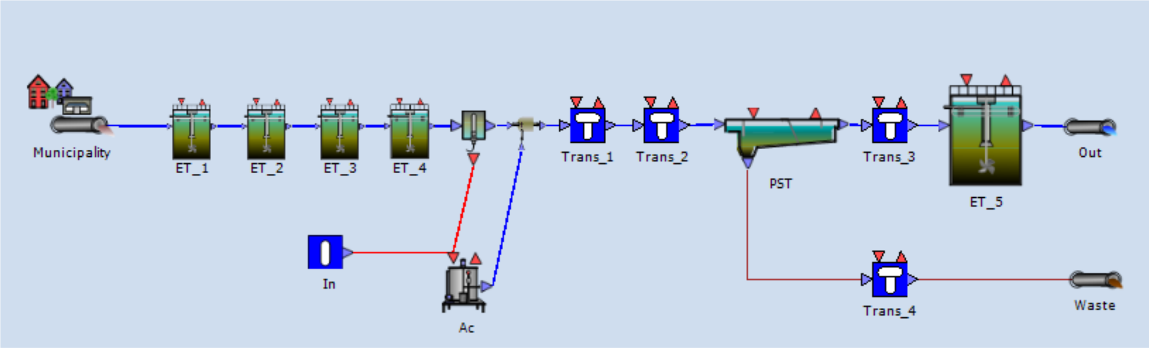

Figure 14. Layout of the model developed in WEST

A detailed explanation of the elements of the model is given below:

Municipality: Block responsible, together with the Input block *In*, to introduce the data inputs into the model. More specifically, its function is to add the inlet flow rate and the alum concentration (C_{alum}) into the system. Figure 15 shows the time series of the alum added during the simulation process.

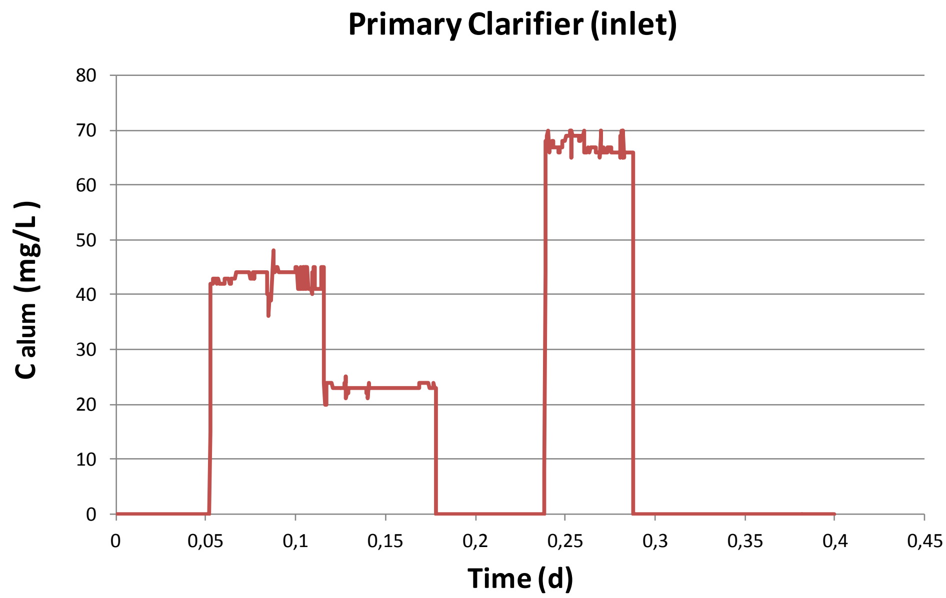

Figure 15. Alum concentation (Calum) during the simulation process.

Equalization Tanks (ET): Results from Tik *et al.* (2013) showed that the sand traps, at the inlet of which alum is injected, can be modelled by four completely mixed reactors. Thanks to them the delay between the alum addition changes with the flow rate and the related outlet TSS concentration variations can be represented.

_In:_ Block responsible to introduce the TSS data input. The data was collected in a sampling campaign in the Beauport WWTP (Québec City, Canada) on August 25th, 2011 (further information is given in section 2.2.5).

_Ac:_ Its function is basically mixing the TSS data input (coming from *In)* with the water flow rate input (coming from *Municipality)* and send them to the PST inlet.

Transformer 1: Is the responsible for the TSS fractionation in five particle classes. Therefore, it transforms the ASM1[1] configuration into a five class PSVD configuration. This block was already calibrated by Bachis *et* al. (2014).

Transformer 2: Is the responsible for transforming the PSVD configuration into a PSVD with alum configuration. It contains the model parameters that need to be calibrated (detailed explanation is provided in section 2.2.4.4).

Primary Settling Tank (PST): The primary clarifier can be fairly well represented by a reactor composed of homogeneous layers. In the present case, the process is modelled by discretizing the water column in eleven homogeneous layers. The reactor is fed in the sixth layer. Furthermore, a tracer test performed simultaneously on the seven parallel primary clarification units of the East WWTP showed excellent hydraulic distribution over the seven units, allowing them to be modelled together as one lane (Tik *et al.,* 2013). Further information in section 2.2.4.2.

Transformer 3/ Transformer 4: Blocks responsibles for transforming the PSVD with alum configuration configuration into ASM1. *Transformer 3* is used for the PST water effluent while *Transformer 4* for the sludge wastage.

Equalization Tank 5: Since the turbidimeter at the primary clarifiers outlet is located after a channel, the latter has also been modelled by inserting an additional reactor to ensure that the resulting delay is properly covered.

For a better understanding of the modelling approach, a general view showing the steps of theTSS fractionation during the simulation process, is presented (Figure 16):

[1] The Activated Sludge Model nº1 (ASM1) was developed in 1987 (Henze et al., 1987) in order to reach a consensus concerning the simplest mathematical model having the capability of realistically predicting the performance of single-sludge systems carrying out the decay of organic matter, nitrification and denitrification.

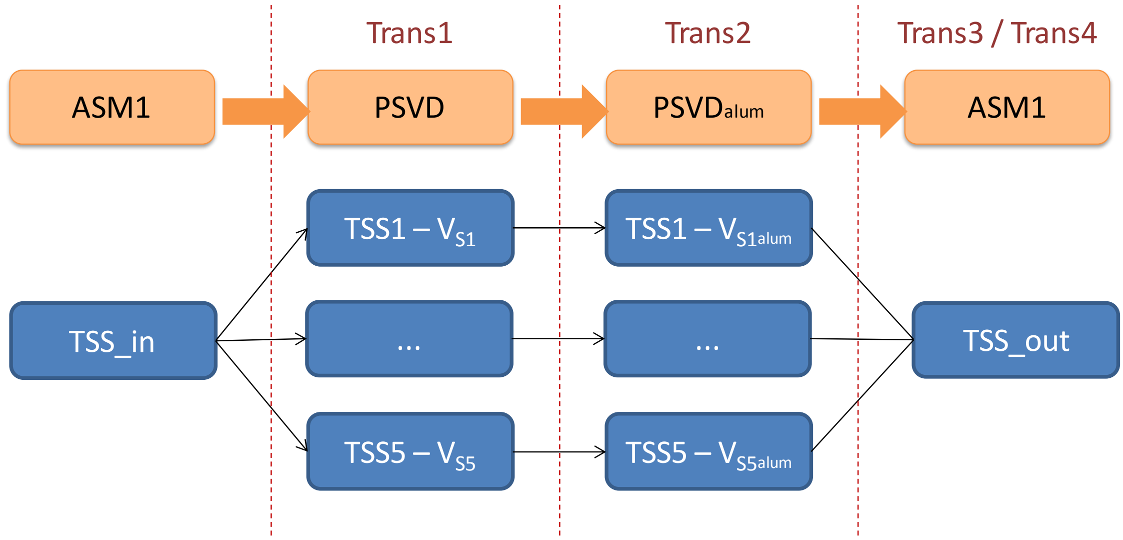

Figure 16. Modelling approach in the present case study

First, given a certain TSS concentration at the entrance, a fractionation of the TSS in five particle classes is made in *Transformer 1*. Each particle class is defined by a characteristic settling velocity (Eq. 1). The TSS assignment for each class is made by interpolating the PSVD curve between two TSS boundary curves at each characteristic settling velocity (see Figure 7 in section 2.1.3.1). Therefore, the influent composition and TSS fractions change with time, depending on the actual TSS concentration.

Then, in *Transformer 2*, a new PSVD curve with alum is calculated, changing the TSS fractions again for each particle class depending on the alum concentration (detailed explanation in section 2.2.4.4).

Finally, after the PST the TSS fractionation is converted into a single TSS concentration value in the outputs thanks to the *Transformers 3* and *4*.

2.2.4.4 ***Parameters to calibrate***

The TSS fractionation in five particle classes carried out in *Transformer 1* was already calibrated by Bachis *et al*. (2014). The PSVD model's settling velocity values (V_s) and the limit TSS fractions were found, resulting from a good fit in the calibration. Results are given in Table 1.

Table 1. Settling velocity (Vs) and boundary TSS fractions (F) associated to each of the 5 classes in the PSVD model and settling velocities used in *Transformer 1* (Bachis et al., 2014)

	Class 1	Class 2	Class 3	Class 4	Class 5
Class-characterizing Vs (m/h)	0,06	0,70	1,91	5,48	13,36
F (high TSS-low TSS) (%)	32-51	22-19	20-15	18-11	8-4

The effort of this project is focused on the calibration of the parameters contained in *Transformer 2,* where the curve is transformed into a curve with the aid of chemicals. Figure 17 shows a representation of the process. The PSVD curve (blue) is transformed into the PSDV curve with CEPT (red) for each class-characterizing V_s. Class 5 always reaches 100% of the TSS fractionation.

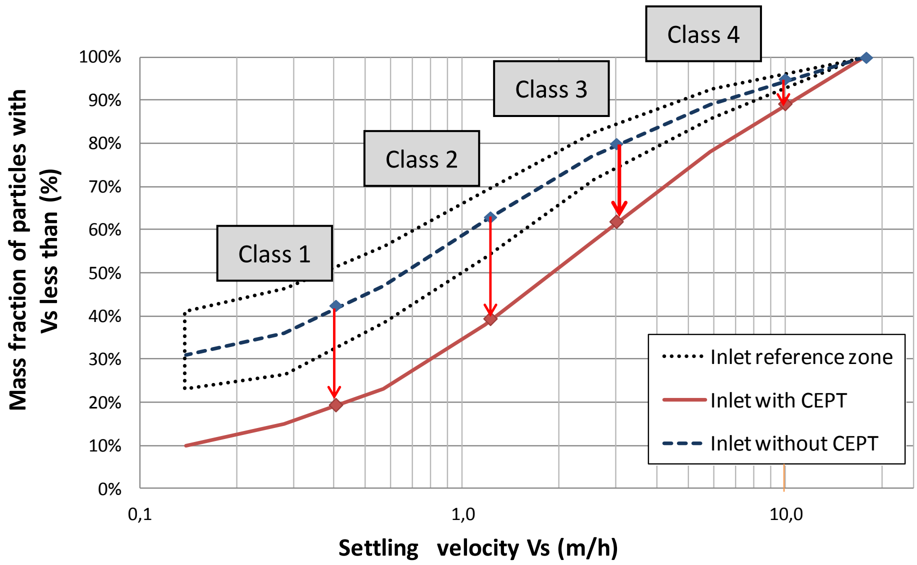

Figure 17. Representation of the process in *Transformer 2*

The approach to obtain the new curve with CEPT is based on the same hypothesis made by Tik *et al.,* in 2013 (Figure 3, section 2.1.2.1). Six parameters represent the process according to the next equation (Eq. 2).

$$PSVD_{alum\ i} = PSVD_i \cdot \left(1 - Delta_i \cdot \frac{C_{alum}{}^n}{K_{alum}{}^n + C_{alum}{}^n}\right) \qquad \text{(Eq. 2)}$$

A brief description of the parameters is presented below:

Delta Classes: Four delta classes (i in Eq. 2) represent the TSS fractionation difference between both curves in each class. Note that the fifth class doesn't need to be parameterized as it is considered to always reach the 100% of TSS fractionation. The new curve with CEPT is obtained by multiplying the curve without CEPT by a number between 0 and 1, so that the new obtained curve with CEPT is always below. Therefore, looking at Eq. 2, one can note that the *Delta Classes* must also be a number between 0 and 1. Figure 18 shows a representation of how the parameter *Delta* influences the model. It is possible to see that it defines the saturation point of alum addition.

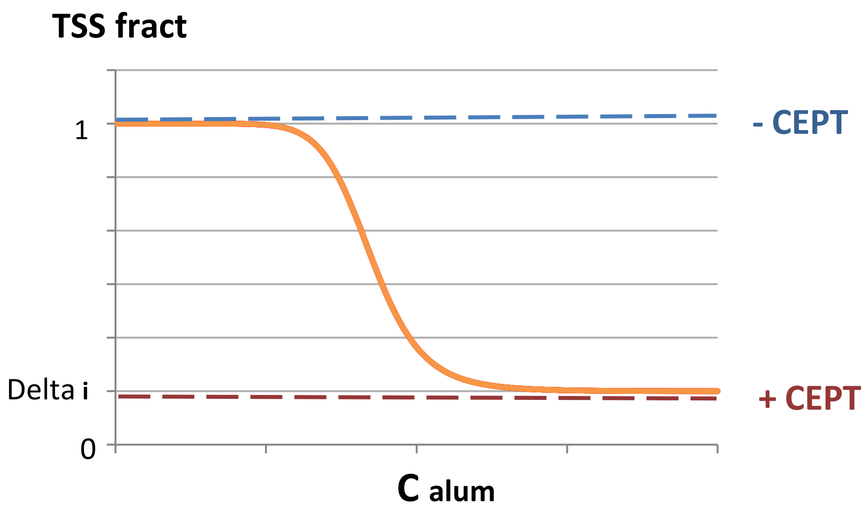

Figure 18. Evolution of the curve passing from PSVD to PSVDalum depending on the alum concentration (Calum)

Kalum and *n*: The parameters represent how the curve is moving from one curve to another when alum concentration is applied. The evolution of the curve with the alum concentration when different values of these parameters are applied is presented in Figure 19.

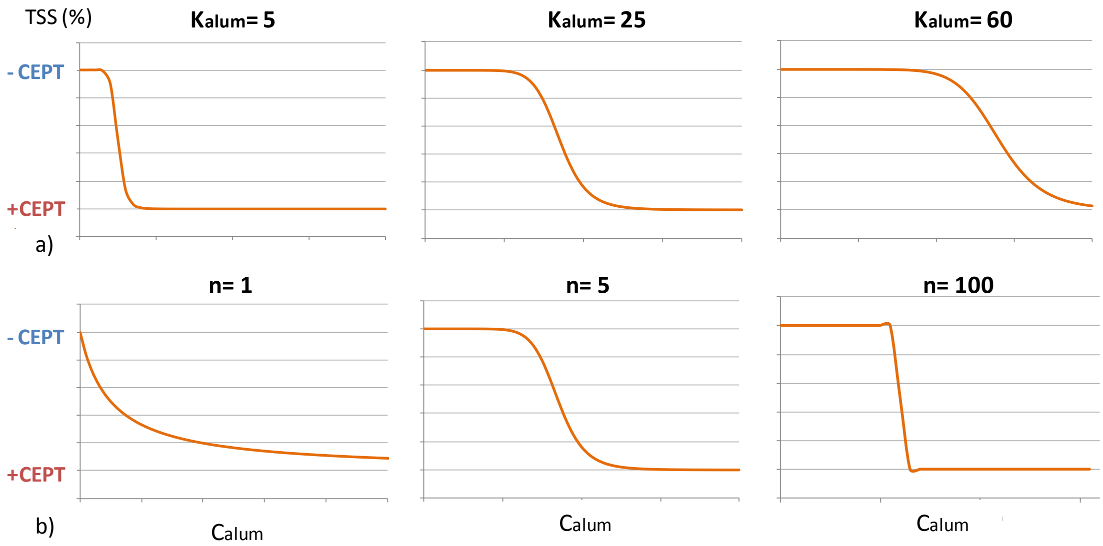

Figure 19. Evolution of the curve in front of alum concentration when different parameter values of *Transformer 2* are applied: (a) Kalum; (b) n

For a comprehensive view of the *Transformer 2* model, a three-dimensional representation is given in Figure 20. The PSVD curve with CEPT (in red) is obtained from the PSVD curve without CEPT (in blue). Note that the settling velocity axis is no longer logarithmic but linear, in contrast to other ViCAs curves. The new PSVD curve with CEPT depends on the alum contentration (C_{alum}). The transition between one curve to another is made in each class-characterizing Vs, and is defined by the following parameters:

- *Kalum* and *n* define the shape of curves from one curve to another in each class.

- *Delta 1*, *Delta 2*, *Delta 3* and *Delta 4* define the maxium range between both curves when alum contentration is applied (Figure 18).

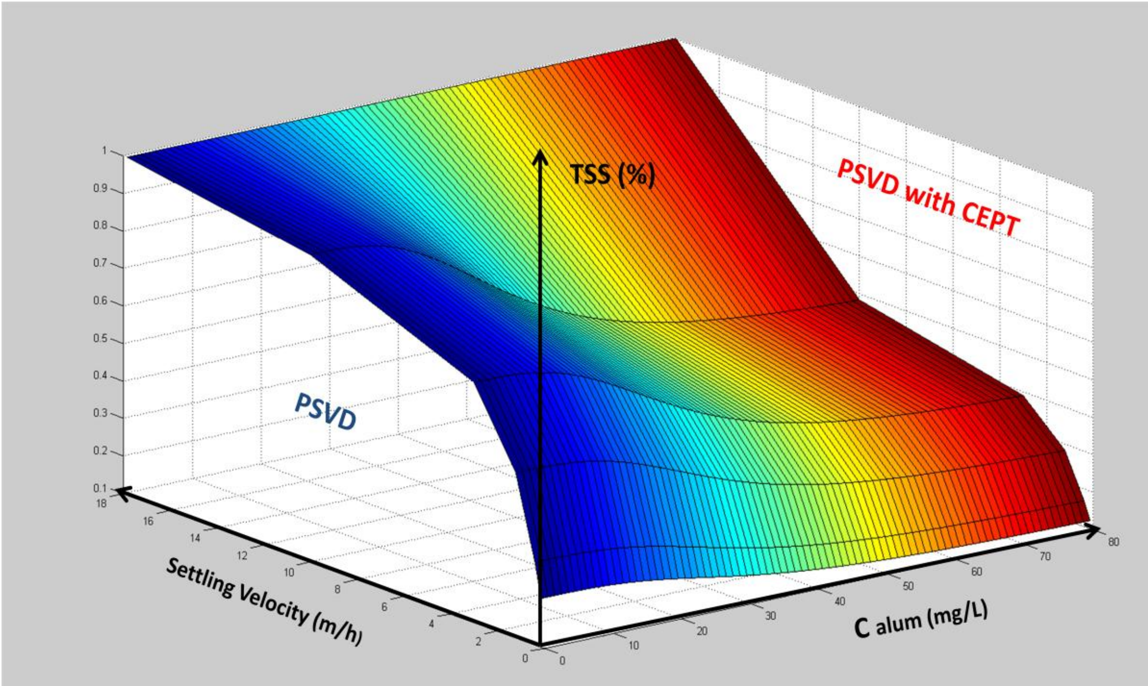

Figure 20. Representation of the process of obtaining the PSVD with CEPT from PSVD without CEPT depending on alum concentration (Calum)

2.2.5 Data Acquisition

The aim of this section is to present the model inputs used in the case study as well as the experimental outputs required for the calibration.

The relevant samples for this study are based on total suspended solids (TSS) concentration data. This type of analysis is time-consuming and expensive to produce due to the complexity of the ViCAs test (each sample needs to be analyzed in the laboratory).

The performance of the PSVD-based model for CEPT was evaluated through the simulation of the data from the Eastern wastewater treatment plant of Québec City (Canada). For this, two automatic samplers were installed at the treatment plant: the first one, at the inlet of the primary settlers and the other at the outlet (Figure 21). The data obtained for the calibration were collected during a sampling campaign in 2011 (under dry weather conditions). A 24h TSS evolution of the influent and the effluent at the full-scale primary settlers was obtained, taking samples of 250mL every 15min. Afterwards, this samples were analyzed in the laboratory to obtain the experimental values of TSS evolution in function of time.

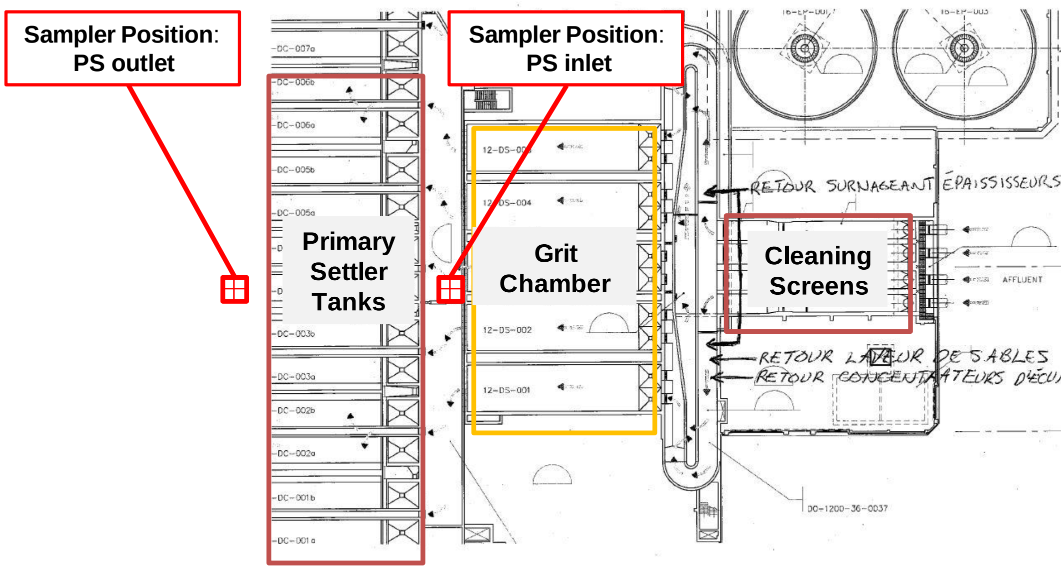

Figure 21. Layout of primary treatment of Beauport WWTP (Québec City, Canada)

The data for the validation was obtained in wet weather conditions, so as to test the robustness of the model when a different type of data is applied.

Another less time consuming and less expensive data acquisition method can be used when a high frequency TSS time series is needed. Turbidity data recorded by a sensor are very interesting as, unlike TSS, this data are immediately available, allowing a real-time controller development. However, turbidity sensors need maintenance and require a manual cleaning at least once per week.

2.3 Model Calibration

The objective of this section is to present the methodology used for the model calibration. A brief introduction of what calibration and validation are, is explained first. A detailed explanation of the methods used is finally given, focusing on the theoretical background.

2.3.1 About Model Calibration

Although no model can describe the whole reality, calibration and validation may give confidence that meaningful use of mathematical models can be made in a limited state and time space.

To calibrate a mathematical model means to achieve an optimum agreement between experimental observations and associated model prediction by adaptation of the model parameters. Validation on the other hand, is to test the quality of the model to answer the question posed. Therefore, calibration is based on a limited set of experiments and validation is done for a limited range of applications (a range of temperatures or concentrations, for a time period).

Figure 22 introduces a general procedure for the calibration of a mathematical model: Measured values from reality, which suffer from measuring errors, are compared with the predicted values from the model, which are computed based on disturbances (external influences) that likewise suffer from observation errors. With the help of a formal or informal (trial-and-error) procedure, the values of the model parameters are improved until sufficiently good agreement is reached between reality and the prediction of the model (Gujer, 2008).

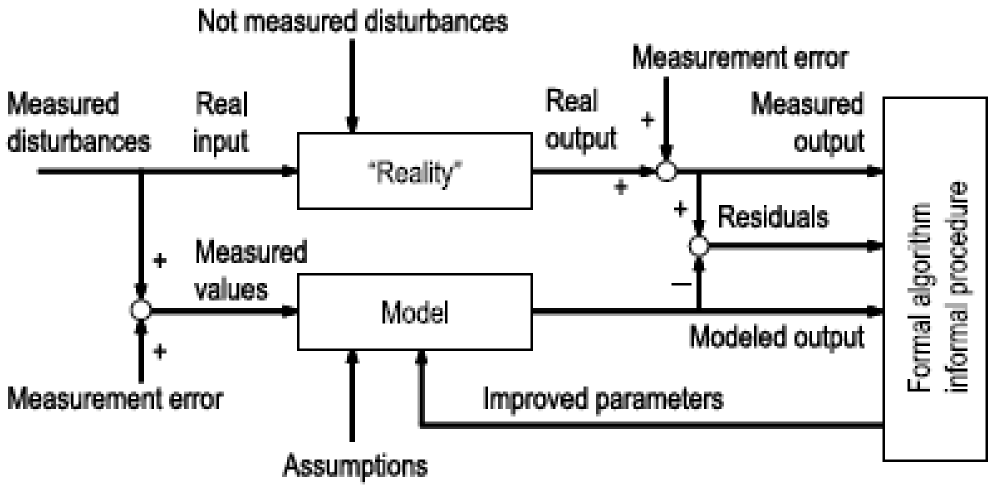

Figure 22. Calibration of a model. When validating, the improvement of the parameters is omitted (Gujer, 2008)

When a model is validated, observations of the real system that were not used for the parameter estimation of the calibration are used. If these observations cover the space in which the model is to be used, and the comparison between the prediction and observation is satisfactory, the model is regarded as validated for the application.

2.3.2 Parameter Uncertainty

In the compilation of a model assumptions are made about the behavior of the system to be modeled. Sometimes, thanks to knowledge or other related processes, it is possible to find a mathematical structure for the model.

However, in the natural sciences one often want to learn about new processes (i.e alum addition in our case study). Here, the mathematical structure for the description is a priori still unknown and part of the research question. Therefore one needs to fit the model prediction with the experimental observations to determine the associated model parameters.

2.3.3 Methodology for Parameter Identification

The process of searching the model parameters that fit the model predictions with the experimentally obtained data is called parameter identification. This process of experimenting is typically the most complex and time-consuming task. Therefore, one wants to gain as much reliable information as possible from each experiment (simulation).

In that sense, tools of sensitivity and identifiability analysis are used for more productive experiments in parameter identification. Statistical methods are used to determine the most likely values of model parameters from the observed data. In the case study, a *Chi-Squared Test* was the statistical method chosen to check the goodness-of-fit of the model (section 2.3.5).

The methodology used for parameter identification in the present study is shown in Figure 23. First, given the uncertainties associated with the model parameters, a local sensitivity analysis (LSA) is carried out together with a global sensitivity analysis (GSA) to determine influential and non-influential parameters. Then, a sensitivity analysis (screening method) is applied to understand how to the variation of one of the model parameters affects the fitting of the outputs. Finally, a trial-and-error procedure based on visual inspection is used to find the optimal parameter values. During this last process, a statistical criterion based on the *Chi-Squared Test* is applied to numerically check which are the optimal parameters.

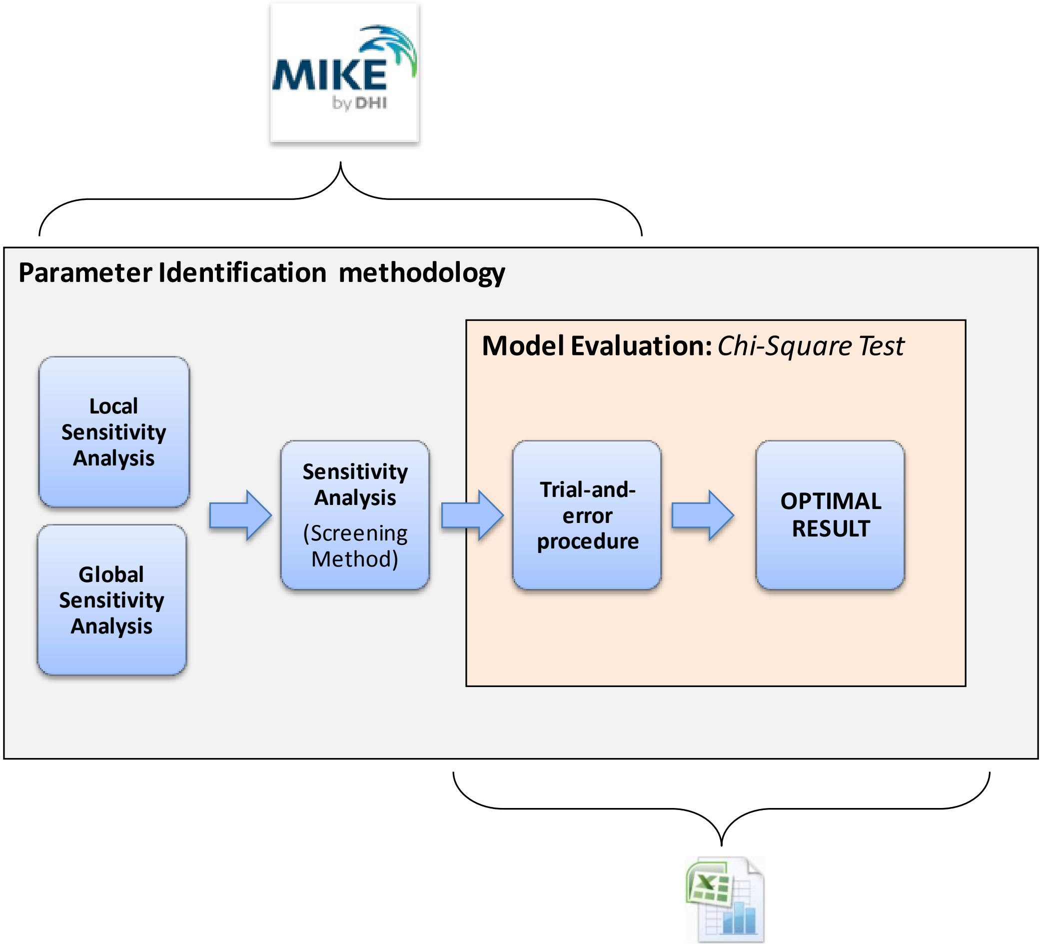

Figure 23. Methodology used for Parameter Identification

2.3.4 Sensitivity Analysis

Sensitivity analysis represents a powerful tool in the field of mathematical modelling as it provides information about how the variation in the outputs of the model can be apportioned to the variation of the model factors (parameters and inputs). There are three main classes of sensitivity analysis methods: screening methods, local methods and global methods.

- **Screening methods** provide visual intuition about how the change of a model parameter, keeping the other parameters fixed, affects the model output.

- **Local methods** provide a measure of how the model output is affected by infinitesimal model parameter changes at a specific location in factor space.

- **Global methods** provides information on how the model outputs are influenced by factor variation over the whole space of possible factor values.

In the wastewater modelling field the majority of sensitivity analysis applications are local. However, GSA may help the modeller to identify important input factors (factors prioritisation) as well as non-influential input factors. The main goal of factors prioritisation is to identify factors which determine model variance.

2.3.4.1 ***Local Sensitivity Analysis***

The method of local sensitivity analysis (LSA) investigates how small changes in a single parameter value affect the output. There are different types of LSA. The relative-relative function is chosen for the parameter estimation conducted here. Its calculation is based on the partial differentiation of the output with respect to the parameter (Eq. 3).

$$\delta_{y,p} = \frac{\delta y / y}{\delta p / p} \approx \frac{\Delta y / y}{\Delta p / p} \qquad \text{(Eq. 3)}$$

Where:

- y = state variable (output), whose sensitivity is determined [y]
- p = parameter which affects the state variable y [p]
- $\delta_{y,p}$ = local relative sensitivity function of the state variable y relative to the parameter p with the dimensions [y]/[p]

2.3.4.2 ***Global Sensitivity Analysis***

Global sensitivity analysis provides information about the respective contribution of structural parameters onto considered responses. One of its major tasks is the identification of relevant and non-relevant parameters for model reduction purposes. GSA may also improve the understanding of the model behavior and may clarify the interactions among parameters.

The main difference from LSA is that GSA investigates the sensitivity over the entire parameter space. In that sense, GSA methods require a higher number of simulations than local methods.

The GSA method adopted here makes use of a regression technique, which allows the sensitivity ranking to be determined based on the relative magnitude of the regression coefficients. The coefficients are indicative of the amount of influence the parameter has on the model as a whole.

The GSA has been carried out in the WEST simulation platform. 100 automatic random simulations have been run in order to obtain the standardized regression coefficients (SRC). Results are shown in section 3.1.2.

2.3.4.3 ***Sensitivity Analysis (Screening Method)***

Once the LSA and GSA are made and the influential and non-influential parameters are known, the screening method (sensitivity analysis) is applied. In principle, its application is a simple idea: change the model and observe its behaviour.

More specifically, the screening method shows how the model output is affected by the change of a model parameter (keeping the other parameters fixed). Thus, the approach is to numerically vary the parameter value through diferent levels and see what the result is.

The screening method has been applied to all *Transformer 2* parameters, which is the block responsible to transform the PSVD curve to the PSVD curve when the alum concentration is applied. Results are shown in section 3.1.3.

2.3.5 Evaluation of the Calibration

Finally, once all the sensitivity analyses are completed and the behaviour of the model in front of the model parameters is known, a trial-and-error procedure is applied to find the optimal parameter values. During this procedure a numerical evaluation criterion is needed to see how close the simulations are to the obtained experimental data.

Therefore, the goodness-of-fit of the model is statistically evaluated through the calculation of the *Chi-Squared* criterion (weighted least squares). The assumption of independent and normally distributed measurement errors is made.

2.3.5.1 ***Chi Square. Basic Principles***

The identification of model parameters requires that the differences of the model predictions and observed variables are evaluated. If a normal distribution of the measurement errors is accepted, the minimization of the χ^2 (Eq.4) leads to the most probable set of parameters, and thereby a good estimate of model behavior.

$$\chi^2 = \frac{1}{\sigma_i^2}\sum_{i=1}^{n}(X_{obs,i} - X_{sim,i})^2 \qquad \text{(Eq. 4)}$$

Where:

$\chi^2 =$ Chi square. Sum of the squares of the weighted difference between the measured and the computed state variables [−]

$X_{obs,i} =$ i^{th} measured value of a state variable in the real system, assumed to be a normally distributed random variable [X]

$X_{sim,i} =$ Result of model prediction with a set of a model parameters which corresponds to the measured $X_{obs,i}$ in kind, time, and space [X]

$\sigma_i =$ Standard error of the measurement of $X_{obs,i}$ [X]

$n =$ number of available data points [−]

During the evaluation, it is assumed that the individual measurement errors are normally distributed with $N(0,\sigma_m)$. Thus, the χ^2 obtained from Eq. (4) follows a χ2 distribution with v degrees of freedom (Eq.5)

$$\upsilon = n - 1 - n_p \qquad \text{(Eq.5)}$$

Where:

n_p= number of parameters which need to be determined from the set of n data points

For instance, as the number of points to which the model is fitted is 34 and the number of estimated parameters is 6, the χ2 obtained is compared to tabulated values of the *Chi-Squared* distribution for 27 degrees of freedom. With that it is possible to decide whether the model is justified by the data.

3. RESULTS

This section gives the specific information about the results provided by the environmental software WEST and how they are interpreted. The next section provides: i) the results obtained in the parameter identification steps, showing the different analyses carried out in the process, ii) a brief explanation of the issues encountered during the calibration, iii) the calibration of the model, and finally, iv) its validation, using a different set of experimental data.

3.1 Parameter identification

This section analyses the dynamic simulation results of the different sensitivity analysis experiments carried out during the parameter identification process. Given the uncertainties associated with the model parameters, a local sensitivity analysis (LSA) and a global sensitivity analysis (GSA) have been carried out first. Once the results have been available, it has been possible to determine the influential and non-influential parameters. Then, the screening method (sensitivity analysis) has been applied to understand how the variation of one of the model parameters affected the model output. Finally, though the results are not presented in detail, a trial-error-procedure was applied, where several simulations have been tried checking its goodness-of-fit (*Chi -Square Test*), until the best simulation in terms of fitting has been found (for a detailed explanation of the methodology used, see section 2.3.3).

In order to improve the understanding of this section, some clarifications are written below:

- The information provided with these analysis is basically visual. Therefore, the conclusions will be taken based on visual intuition and no numerical values will be shown.

- All analysis has been applied for the following parameters:

    1) Delta Clases (*Delta 1, Delta 2, Delta 3, Delta 4*)
    2) *Kalum*
    3) *n*

- For the whole results section, when reference is made to the output, it refers to the primary clarifier TSS effluent.

- All simulations have been run during 0,385 days (555min), which is the time interval in which the TSS experimental data were collected.

3.1.1 Local Sensitivity Analysis (LSA)

LSA investigates how small changes in a single parameter value affect the output. In our case, the LSA has been applied in order to see the impact of the estimated parameters with respect to the primary clarifier's TSS effluent (output).

Figure 24 represents the sensitivity of the *Delta Classes*, *Kalum*, *n* with respect to the output. At first sight, it is possible to observe that *Kalum* (dark blue), *Delta 1* (red) and *n* (green) are the most influential parameters. One can also note that the major part of its influence is produced during two periods: from 0,06 to 0,22 days and from 0,26 to 0,35 days. The main reason is that the alum concentration is applied during the same periods of time (see Figure 15; section 2.2.4.3).

The rest of the estimated parameters (*Delta 2, Delta 3, Delta 4*) appear to have little influence on the output.

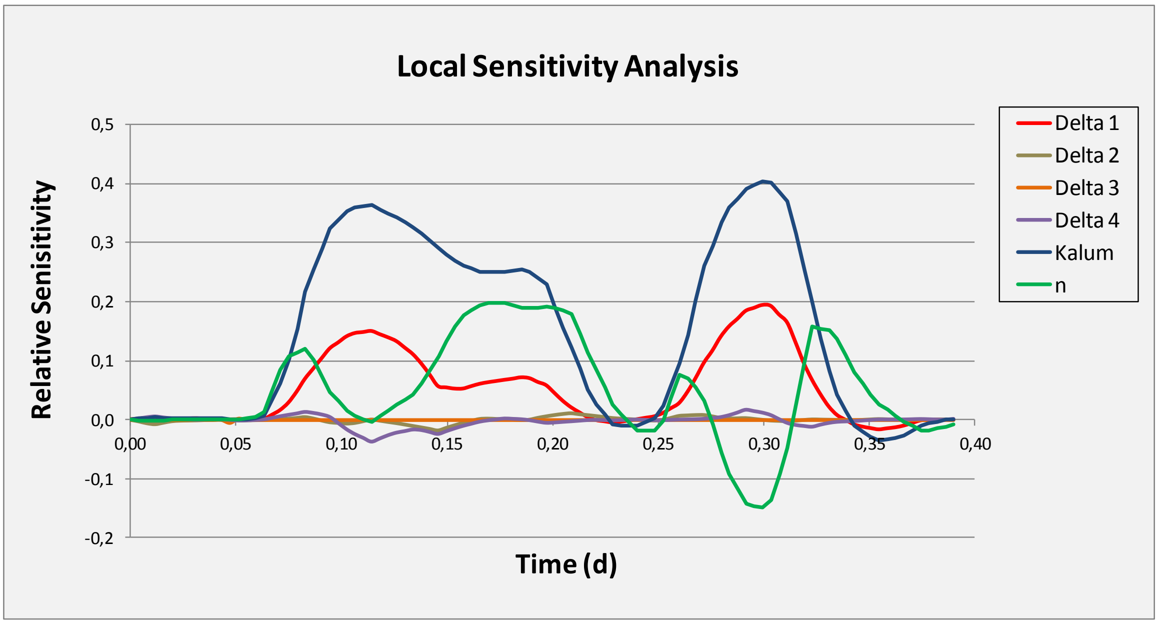

Figure 24. Local Sensitivity Analysis for the estimated parameters

3.1.2 Global Sensitivity Analysis (GSA)

GSA provides information on how the model outputs are influenced by parameter variation over the whole space of possible parameter values. Therefore the main difference with LSA is that GSA gives the sensitivity over the entire parameter space.

The histograms obtained from GSA are presented in Figure 25. At first sight, one can see that *Kalum*, *Delta1* and *n* have the greatest impact on the output. However, the parameter *n* has not the same impact as expected from the LSA. That might be mainly due to the fact that the boundaries for that parameter in this analysis were limited from 1 to 4; while in the LSA no boundaries are specified. One must remember that the parameter *n* is an exponent (see Eq.2, section 2.2.4.4)

In this analysis, the opposite sign indicates the contrary effect on the output: i.e the higher the n parameter value, the lower the output. The behavior of the model with respect this particular parameter will be studied by the SA method in the next section.

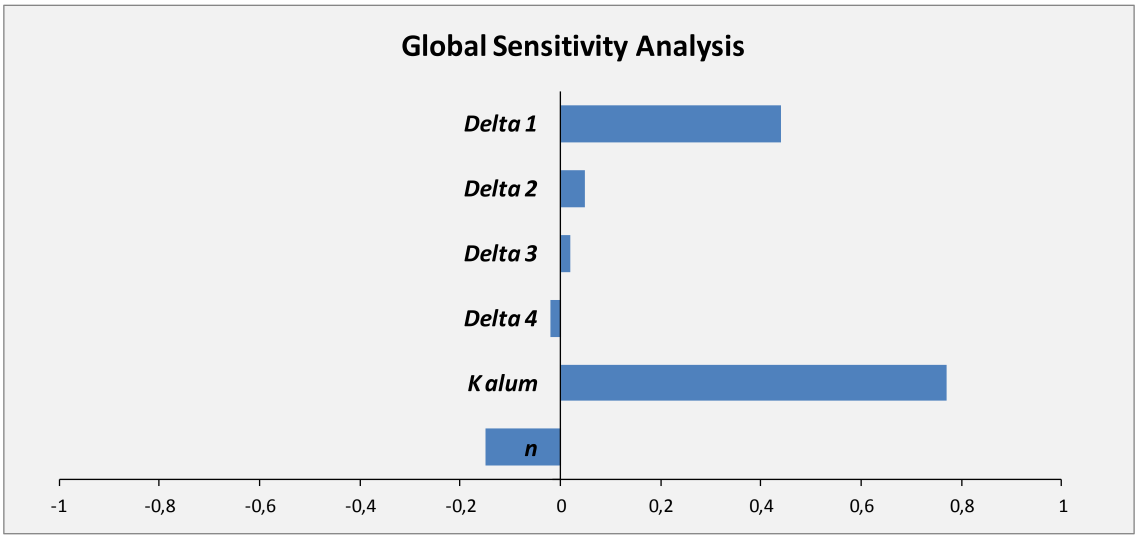

Figure 25. Global Sensitivity Analysis for the estimated parameters

3.1.3 Sensitivity Analysis (Screening Method)

Once the LSA and GSA results are known and the most influential parameters are identified, a Sensitive Analysis was made. In principle, its application is a simple idea: change the value of one model parameter, keeping the others fixed, and observe the behaviour in the output. Figure 26 presents the results obtained when the value of the most influential parameters (*Kalum* , *n*, *Delta 1*) was changed.

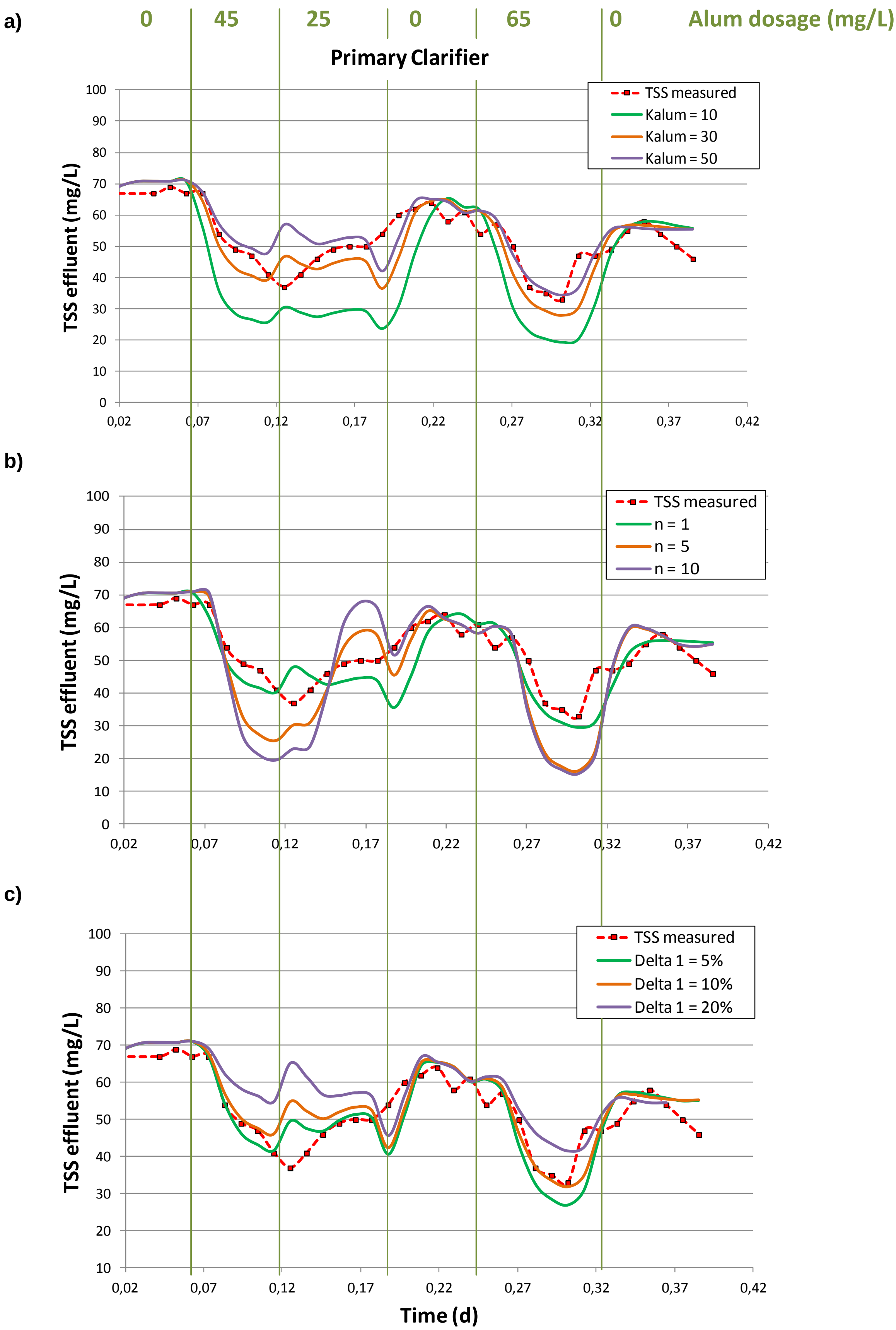

Figure 26. Sensitivity Analysis of the most influential parameters: (a) for Kalum; (b) for n; (c) for Delta 1

From Figure 26 it is possible to deduce what happens when we increase the value of the most influential parameters. For *Kalum* (Figure 26a) one can note that when its value increases the response in the output also increases. This can be concluded because for *Kalum*=50 (purple) the TSS in the PC effluent gets the highest values while for *Kalum*=10 (green) TSS is lowest. The same happens for the parameter *Delta 1* (Figure 26b): When the fraction of particles contained in the first class is high (20%; purple) the output is also high; while the output response gets lower when the fraction in this class is also low (5%; green). That means thus, that both parameters are correlated, and several well fitted results can be found if they are changed, i.e. approximately the same result is obtained if the parameter *Kalum* is increased and *Delta 1* is decreased, or the other way around.

However, the behavior in the output is different when the values of the parameter *n* are changed. For its highest value (n=10; purple) in Figure 26b, one can see that the response gets the higher or the lower values depending on the period. That is due to the effect of alum. At the top of Figure 26 the time-evolution of alum concentration is shown. From the results one can also highlight that there is no correlation between *n* and any other parameter. Therefore one can change that parameter independently in order to get close to the experimental values during the calibration.

Moreover, the output is not affected by the parameter values during the initial section (until 0,07 days). That is due the fact that there is no alum added into the system until this time (see the alum variation during the simulation on the top; Figure 26).

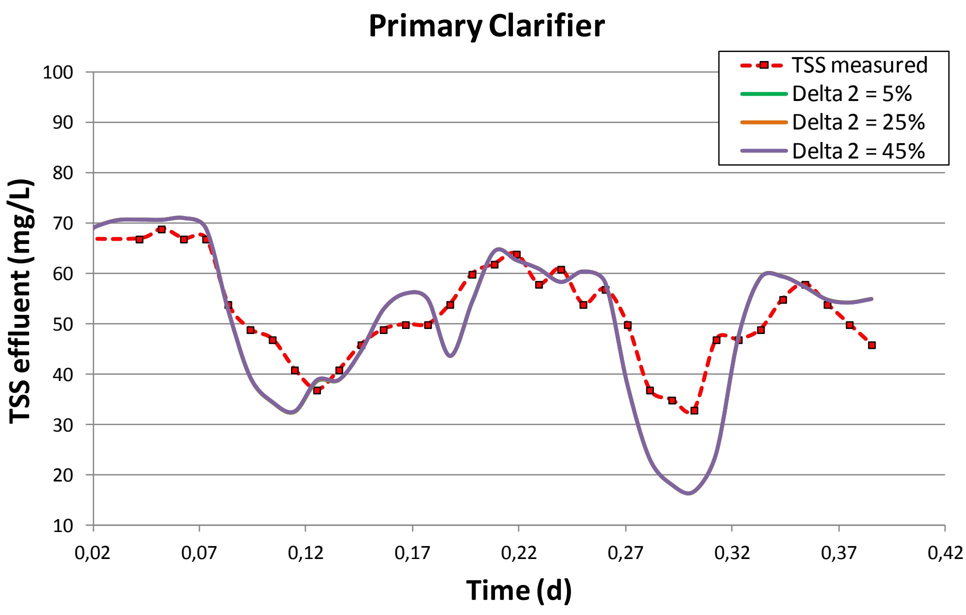

Figure 27. Sensitivity Analysis (SA) for the estimated parameter *Delta 2*

On the other hand, SA results for the parameter Delta 2 are shown in Figure 27. Although only this parameter is shown, it represents all the non-influential parameters (*Delta 2*, *Delta 3*, *Delta 4*), as the SA experiments made on them showed exactly the same behavior. The different simulations indicate the % of the particle mass contained in Class 2 (5, 25 and 45%). Surprisingly, the results show that the variation of these three parameters does not influence the final result. Consequently, although different values of these parameters are introduced (different % of particle mass in Class 2), the response in the output is practically the same. From the other analysis it was already known that these parameters did not have much influence on the output. However some variation in the response was expected.

Therefore, this result leads to the first conclusion: As the parameters *Delta 2*, *Delta 3* and *Delta 4* do not influence the model it is possible to conclude that the model structure has been overparameterized. However, this conclusion is obtained for a certain choice of class boundaries. Thus, one possible solution could be to move the velocity class boundaries to places where they make a difference on the output, it would mean to move them to lower settling velocities, since *Delta 1* is the lowest V_s class and has influence on the model.

3.2 Issues during the Calibration

During the process of parameter identification some problems occurred. Luckily they could be solved afterwards. After trying several simulations with several different parameter values, it was observed that a delay on the output occurred (Figure 28 shows the result in which the delay can be clearly observed). To deal with this, the structure of the model had to be changed. It was found that the volume of the Equalization Tanks, which respresent the flow delay in the grit chamber, was wrong leading to an excessive delay. Changing the volume of these four mixed reactors, the delay between the measured and experimental responses could be removed.

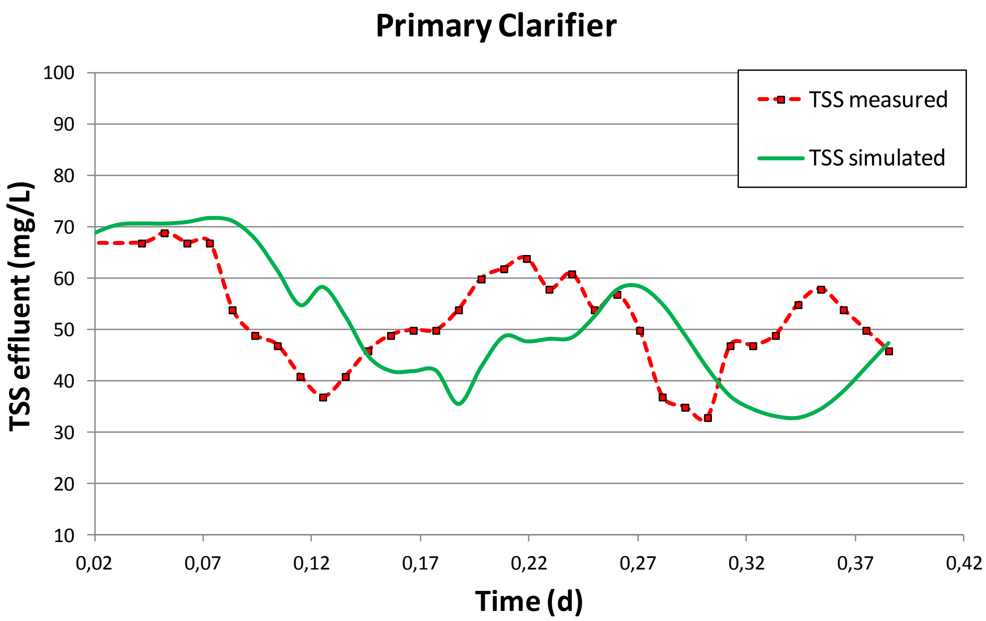

Figure 28. Result found with the wrong Equalization Tanks volume. A delay between the measured and simulated values is clearly observed

3.3 Calibration

Through a trial-and-error procedure and after several simulations with different parameter values, the model could be calibrated. The calibrated parameters are presented in Table 2.

Table 2. Parameter values obtained in the Calibration

Estimated Parameters					
Delta 1	***Delta 2***	***Delta 3***	***Delta 4***	***Kalum* (mg/L)**	***n***
0,1625	0,4167	0,5921	0,7447	45	1

The results from the *Chi-Squared Test* denoted a good goodness-of-fit of the model: The calculated χ^2 for the event was 10.3, while the critical value obtained from the tables for 27 degrees of freedom (n=34 and n_p=6) and a 99.5% of confidence is 11.8. Therefore, it can be concluded with 99.5% of confidence that the calibration is good, i.e. the model is justified by the data. Figure 29 presents the TSS in the primary clarifier effluent for the calibrated model.

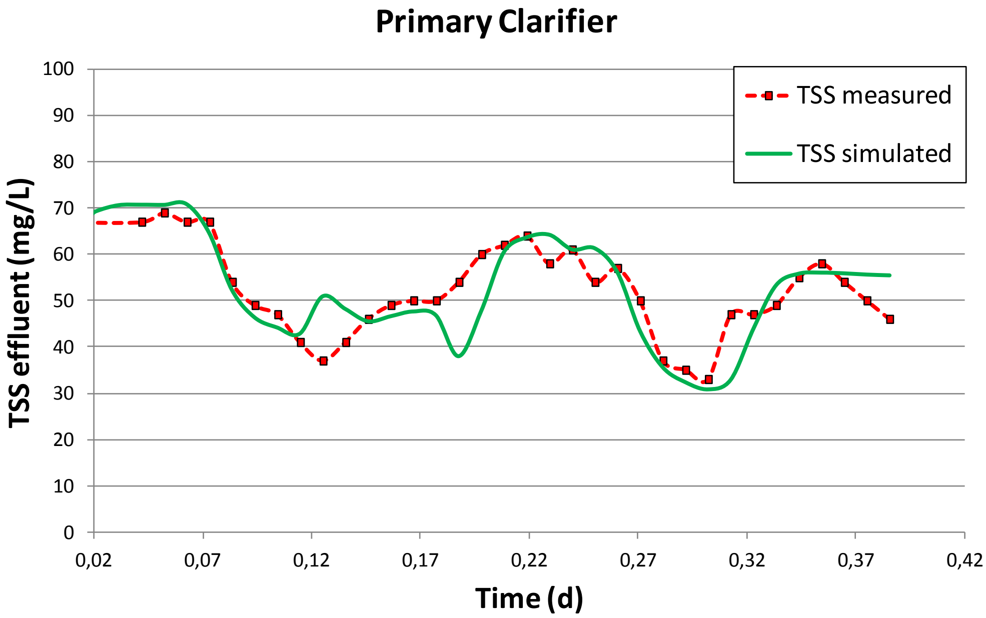

Figure 29. Calibration of the model, best fit obtained

As the parameters *Kalum* and *Delta 1* seem to be correlated, some other good calibrations with other parameter values could be found by playing with these two parameters. Table 3 shows other parameter values that resulted from another good calibration. In this case the confidence of the calibration (99%) was not as good as the first one, but highly acceptable.

Table 3. Parameter values obtained from another good calibration

Estimated Parameters					
Delta 1	***Delta 2***	***Delta 3***	***Delta 4***	***Kalum* (mg/L)**	***n***
0,5	0,6667	0,7895	0,9042	17	1,5

3.4 Validation

In order to validate the model, other data have to be used. Therefore other inputs have to be introduced into the model. The simulated values are compared with the data.

A challenging validation using wet weather data was tried. The *Chi-Squared Test* turned out negative, as the χ^2 obtained was 229 and too high for any χ^2 critical value.

Thus, it could not be accepted that the simulated values were fitting the experimental data.

The TSS results from the validation are presented in Figure 30. The TSS at the PC inlet (in blue) is also shown. It can be seen that the simulated values at the PC outlet (in green) follow the same pattern as the experimental ones (in red). However, there is too much difference between both responses. That's why the *Chi-Squared Test* denied the validation.

Furthermore, the effect of alum can be clearly observed: Coming from zero added chemicals, the simulated response (in green), which is the TSS in the PC effluent, decreases when alum is added (70 mg/L). Later on, TSS increases again in the middle section when there is no effect of chemicals. Finally, when a 40 mg/L of alum concentration is applied the TSS decreases again. Therefore, this graph reflects perfectly the improvement of TSS removal when chemical products are applied in primary treatment.

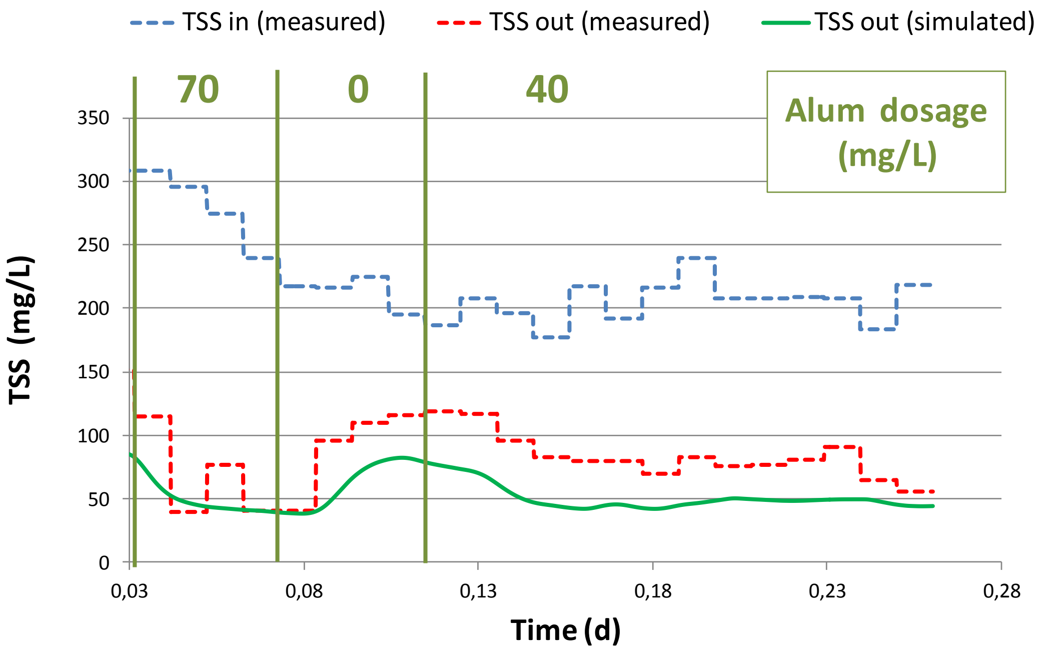

Figure 30. Validation of the model with wet weather data set

4. BUDGET SUMMARY

The total budget for the final project, which is broken down in the following Table 4, amounted to a total of **5.043,00 €**

Table 4. Budget Summary

Equipment	***Unit price (€/h)***	***Hours spent (h)***	***Total price (€)***
Computer depreciation	0,05	620	31,00
Software license depreciation	0,06	2.200	132,00
Printing / Photocopying			30,00
TOTAL COST EQUIPMENT			**193,00 €**
Labour	***Unit price (€/h)***	***Hours spent (h)***	***Total price (€)***
Researcher staff			
Meetings: Supervision of the work	25,00	25	625,00
Review of results and writing	25,00	15	375,00
Student			
Process of information gathering	10,00	75	750,00
Development of the model	12,00	150	1.800,00
Analysis and calibration of the selected case study	12,00	25	300,00
Writting of the project	10,00	100	1000,00
TOTAL COST OF LABOR			**4.850,00 €**
TOTAL COST			**5.043,00 €**

5. CONCLUSIONS

The work conducted in this project contributes to a better understanding of the wastewater primary treatment when chemicals are added. The methodology for parameter identification given the uncertanties of a model has been illustrated. The main conclusions are:

- A new primary clarifier model capable to predict the TSS concentration in the primary clarifier effluent when alum is added has been successfully developed and calibrated. The model will be used to develop control strategies for alum dosage in view of efficient TSS removal in the PC.

- The proposed modelling approach, based on Particle Settling Velocity Distributions (PSVD), has been shown to successfully predict TSS effluent concentrations under the addition of chemicals on the basis of influent TSS time series and a number of ViCAs characterisation experiments.

- Parameters *Delta 2*, *Delta 3*, *Delta 4* were found not to influence the model. New solutions will be developed to characterize the particle classes. One possible solution is to move the velocity class boundaries to lower settling velocities, where they can make a difference on the output.

- Validation results indicate that another calibration may be needed. From the sensitivity analysis it was found that there may be a correlation between *Kalum* and *Delta 1*. Therefore, different parameter values can be found that give an equally good calibration and can be tried in view of a better validation.

Québec City, 20th of January of 2015

Pau Llinàs de Cendra.

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7. GLOSSARY

ASM1	Activated Sludge Model No 1
C_{alum}	Alum Concentration [mg L^{-1}]
CEPT	Chemically Enhanced Primary Treatment
CSO	Combined Sewer Overflows
GSA	Global Sensitivity Analysis
LSA	Local Sensitivity Analysis
PC	Primary Clarifier
PST	Primary Settling Tank
PSVD	Particle Settling Velocity Distribution
RT	Retention Tank
SRC	Standardized Regression Coefficients
TSS	Total Suspended Solids [g TSS m^{-3}]
ViCAs	Vitesses de Chute en Assainissement (French)
V_s	Settling velocity [m h^{-1}]
WWTP	Wastewater Treatment Plant