Theoretical and Field Validation of Solutions Based on Simplified Hydraulic Models for the Real-Time Control of Sewer Networks

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Validations théoriques et expérimentales de solutions basées sur des modèles hydrauliques simplifiés pour la gestion en temps réel des réseaux d'assainissement

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ABSTRACT

Several of the Global Optimal Real Time Control (GO RTC) methods to manage sewer networks use a hydraulic model of the sewer system to compute the set points of each regulation structure in the network to minimize combined sewer overflows globally. Unfortunately, the hydraulic models that use the full St-Venant equation are difficult to integrate in a GO RTC control scheme. Thus, most of the model-based control schemes developed for the GO RTC of sewer networks use simplified hydraulic models. Good optimization models for GO RTC schemes are quick to execute, robust, easy to integrate in the control scheme and adaptable. The Moving Average (MA) model, successfully implemented in Csoft™, is presented in this paper. To guarantee that the hydraulic representation of the real behavior of the sewer network is represented well by the optimization model, the simplified models have to be calibrated on-line using measurements. The Csoft™ on-line calibration tool compares favorably to the Kalman Filter using data simulated by a SWMM 5 model. Finally, two examples of field validation using the Csoft™ on-line calibration tool are presented herein using data from the GO RTC systems applied to the sewers of Montreal and Quebec City.

RÉSUMÉ

Plusieurs des méthodes de contrôle en temps réel global et optimal (GO RTC) utilisent des modèles hydrauliques du réseau d'égouts afin de calculer les consignes de chaque régulateur minimisant globalement les déversements dans le milieu récepteur. Malencontreusement, les modèles hydrauliques utilisant les équations complètes de Saint-Venant sont difficiles à intégrer dans un schéma de GO RTC. Ainsi, la plupart des méthodes basées sur des modèles pour le contrôle des réseaux d'égouts utilisent des modèles d'optimisation simplifiés. Les caractéristiques d'un bon modèle d'optimisation incluent la rapidité d'exécution, la robustesse, et la facilité à s'intégrer dans le schéma de contrôle et l'adaptabilité. Le modèle de moyenne mobile (MA), implanté avec succès dans Csoft™, est présenté et utilisé dans cet article. Afin d'assurer une bonne représentativité hydraulique par le modèle d'optimisation, ce dernier doit être calé en ligne en utilisant des mesures. L'outil de calage en ligne de Csoft™ est favorablement comparé au filtre de Kalman en utilisant des données simulées à partir d'un modèle SWMM 5. Finalement, deux exemples de validation pratique de l'outil calage en ligne de Csoft™ sont présentés à partir de données des systèmes de GO CTR des villes de Québec et Montréal.

KEYWORDS

Model predictive control, real-time control, sewer networks, on-line calibration, hydraulic model

1 INTRODUCTION

Different technologies have been implemented to control urban pollution, and more specifically Combined Sewer Overflows (CSOs). Among them, we find approaches that use dynamic regulators such as gates and pump stations in real time to optimize the use of the existing storage, and the conveyance and treatment capacity of the entire network. Several of these Global Optimal Real Time Control (GO RTC) methods use a hydraulic model of the sewer system to compute the set points of each regulation structure in the network that will minimize CSOs globally.

Unfortunately, the hydraulic models that use the full St-Venant equation are difficult to integrate in a GO RTC control scheme due to the time needed by the numerical algorithms to compute flow rates and water levels, especially while the sewer network is in surcharge. Moreover, these algorithms can be unstable under certain hydraulic conditions. Although RTC simulations (Darsono and Labadie, Hajda *et al.*) and applications (Lindberg, *et al.*) have been tested with detailed hydraulic models, most of the model-based control schemes developed for the GO RTC of sewer networks use simplified hydraulic models, and more specifically linear models. The following characteristics are sought to implement an optimization model in a GO RTC scheme (Schutze *et al.*, 2004 and Assabbane and Bennis, 2000):

- **Speed of execution**: This is a necessary feature for GO RTC implementation because different control strategies must be simulated by the optimization model at each control step (usually in the 5 minute range) in order to find the one that will optimally meet the control objectives.
- **Robustness**: The optimization model must be stable under any hydraulic condition. In addition, mass conservation must be respected at all times.
- **Integration to the control scheme**: The optimization model must be easy to integrate to an optimization scheme such as a linear or non-linear programming algorithm. This is mandatory to find the flow management solutions that will reduce CSOs.
- **Adaptability**: The optimization model must be easy to calibrate on-line based on measured values. This is a key feature to efficiently implement on-line calibration and, therefore, to guarantee that the model will remain in phase with reality.

The most commonly-used hydraulic models for GO RTC applications are the pure delay model, the “Moving Average” (MA) model and the “Auto Regressive Moving Average” (ARMA) models. The pure delay model only allows a fixed input hydrograph to be transferred from place to place with a delay based on a given flow velocity. This hydraulic model has been mainly used in the early stages of GO RTC applications (e.g. Marinaki and Papageorgiou, 2005). The MA and ARMA models are also linear models that convey hydrographs in a sewer system. However, these models allow for flow attenuation. MA models have been successfully implemented in Csoft™, a GO RTC application currently in use in several cities, including Quebec City and Montreal, in Canada, as well as Louisville, Kentucky, in the United States of America (Pleau *et al.*, 1996 and Colas *et al.*, 2004). ARMA models have been used by Capodaglio *et al*, but have a clear disadvantage in terms of robustness compared to MA models. They can be unstable. For an ARMA model to be stable, poles must be within a unit circle in the complex plane. However, limiting the values of the poles within the unit circle requires highly non-linear constraints, which dramatically increase the computational time, so much that it becomes unthinkable to use such constraints in real-time applications.

Several advantages derive from using a simplified hydraulic optimization model for GO RTC instead of a detailed hydraulic model in a model-based approach. The most important ones are the short computation time and the stability of the optimization model. However, simplified models are by nature less accurate that detailed models. Therefore, to guarantee that the hydraulic representation of the real behavior of the sewer network will be well represented by the optimization model, the simplified models must be calibrated on-line using measurements. It is to be noted that the online calibration of the optimization model not only permits to the correction of flow prediction inaccuracies caused by model simplifications, but it also compensates for imperfections related to the estimation of inflows. These errors can come from hydrological model errors or from the inaccurate recording of the rainfall over the drained area.

In scientific literature, various approaches have been proposed to calibrate linear models, and more specifically MA and ARMA models. Several of these methods were tested in Fradet (2009), i.e. recursive least squares, four different expressions of the Kalman filter, four methods based on nonlinear programming and long range predictive identification (LRPI). Two of the most promising methods are presented herein.

The Csoft™ software developed by BPR CSO for the GO RTC of sewer networks has an imbedded on-line calibration tool for its MA optimization model. It is based on a non-linear programming method. This paper compares the Kalman filter to Csoft's on-line calibration tool using simulated events. It also presents two field validation examples of the Csoft™ on-line calibration tool with data from the GO RTC systems implemented in Montreal and Quebec City.

2 METHODOLOGY

2.1 Optimization Model

The kinematic wave equations are a simplification of the St. Venant equations, where the friction slope is considered equal to the bed slope. The Muskingum hydraulic model is an empirical form of the kinematic wave equations. One form of discretization of the Muskingum model leads to:

$$q_s(k) = C_0 q_e(k) + C_1 q_e(k-1) + C_2 q_s(k-1) \quad (1)$$

Where $q_s(k)$ is the outflow of the sewer section at time k; $q_e(k)$ is the inflow at time k, and $q_e(k\text{-}1)$ is the inflow at time k minus one time step of model discretization. C_0, C_1 and C_2 are model parameters that can be expressed as functions of the Muskingum Hydraulic model parameters. Using equation (1) recursively leads to:

$$q_s(k) = \sum_{i=0}^{N} \alpha(i) q_e(k-i) + C_2^N q_s(k-N) \quad (2)$$

Where $\alpha(0) = C_0$; $\alpha(i) = C_2^{i-1}(C_1 + C_0C_2)$ for $1 < i < N\text{-}1$ and $\alpha(N) = C_1C_2^{N-1}$. When N is sufficiently high, C_2^N tends towards 0 and the second part of equation (2) can be neglected. In this form, it is then equivalent to the MA model. The MA model reproduces the outflow as a weighted average of the past and present inflows. This discrete formulation is similar to a unit impulse response or a unit hydrograph in hydrology. In the case of multiple inflows to a conduit section, this model can represent the outflow as follows:

$$q_s(k) = \sum_{i=1}^{n_e} \sum_{j=0}^{n_{d_i}} \alpha_i(j) q_{e,i}(k-j) \quad (3)$$

Where $\alpha_i(j)$ are the model parameters for input i and time delay j; n_{di} is the number of time steps after which the input i is considered to have a negligible effect on the output and n_e is the number of input affecting the outflow. Typically, Csoft™ uses a 5-minute discretization time step for its MA model.

2.2 On-line Calibration

On-line calibration consist in knowing current and past measurements of the inflow(s) and of the outflow, and in adjusting the model parameters in order to reduce the difference between the modeled outflow and measured outflow. This is usually achieved using a set window (e.g. one hour) of past outflow and inflow measurements.

The on-line calibration of the optimization model involves two main difficulties. First, the inflows and outflows are linked to the weather conditions and to the physical structure of the network. The frequency spectrum of the data utilized is usually limited. In addition, the different inflows to a sewer section are often correlated. These two facts lead to difficulties in discerning cause and effect relations between inflows and outflows. Second, on-line calibration should be carried out on a limited time window of past data. Since hydraulic conditions can vary greatly in time and that the goal consists in correctly representing current and future conditions, data from a too distant past can come from different and changed hydraulic conditions.

These two difficulties lead to a high degree of freedom in the assessment of the model parameters. The model parameters must be chosen in accordance with process dynamics. If this physical realism is not met, the model quality, hence its predictive capacity, will be diminished (Natale and Todini, 1976 and Neuman and De Marsily, 1976).

2.2.1 Kalman Filter

The Kalman filter is an efficient recursive filter used in a wide range of engineering applications from Radar to process control. It estimates the state of a linear dynamic system from a series of noisy measurements and a state-transition model. Assabbane and Bennis (2000) used it for the on-line calibration of an MA model for sewer control and the same methodology is used herein. The recursive nature of the Kalman filter renders the calculation time very short, but the identified model parameters can be lacking in physical representativeness by not respecting hydraulic dynamics and inertia. Moreover, as it is recursive, past data always have an effect on current model parameters estimates. This could lead to a slower adaptation to quickly varying conditions.

2.2.2 Csoft™ On-line Calibration Tool

The Csoft™ on-line calibration tool uses non linear programming. It is based on the idea that constraints (Natale and Todini, 1976) and smoothing (Neuman and De Marsily, 1976) can lead to better identification results. The first term of the objective function seeks to reduce the difference between the measured outflow over a fixed calibration window and the outflow computed from the optimization model for the same calibration window, using the corresponding inflow measurements. A second term is also present in the objective function to ensure smoothing. In addition, constraints are applied to ensure the most realistic model parameters. For example, the MA model parameter estimates are constrained to a value equal to or greater than 0.

The optimization problem consists in minimizing the objective function, while respecting the constraints. It is solved at every time step by non-linear programming through the use of the MINOS™ optimization software. It uses a reduced-gradient method with quasi-Newton approximations to the reduced Hessian.

The size of the calibration window must be chosen wisely. The bigger it is, the bigger the risk of representing a past and revolute hydraulic condition. However, the smaller the size, the more freedom is given to the problem solution.

2.3 Performance Evaluation

To isolate the effects of on-line calibration and of the model type on outflow prediction performances, perfect inflow predictions were considered in this work. In a real-time application, inflow predictions based on short term weather forecasts and a detailed hydrological/hydraulic model would be used. Methot and Pleau (1997) have written on the effects of inflow estimation errors on the control performances of a model-based GO RTC scheme. Conversely, on-line calibration of the optimization model at time step k is executed only with data from time step k and previous time steps. Thus, it corresponds to the data that would be available in a real-time application.

The prediction performances of the models and calibration methods were evaluated using five indicators, i.e. the Nash-Sutcliffe coefficient (Nash and Sutcliffe, 1970), the correlation coefficient, the average prediction error, the prediction error variance and the prediction error root mean square (RMS). The Nash-Sutcliffe coefficient is widely used to evaluate the proper fit of hydrological models. A value near “1” means that the model is representative of the data. The correlation coefficient gives an evaluation of the strength and the direction of a linear relation between two variables. In this paper, the correlation is calculated between an outflow prediction and the synchronized outflow measurement. The average of the prediction error is an indicator of any bias in the predictions from the model. The prediction error variance allows the appreciation of the dispersion of model errors, while the RMS is an indicator of the model’s capacity to represent higher flows.

The indicators are calculated from all the predictions of the test and one value is computed for each time step of the prediction horizon. For example, all the predictions $k+i$, where k ranges from “1” to the end of the inflow and outflow time series, are used to compute the correlation coefficient for the prediction $k+i$.

3 RESULTS

The on-line calibration tests with simulation data presented in the following section compare the Kalman Filter to the Csoft™ on-line calibration tool. Precision of predictions from the models are compared over a given horizon. Then, field validation from the GO RTC systems implemented in Quebec City and Montreal are presented. However, only the estimation of the outflow prediction of one time step in the future is available.

3.1 Simulated Data

The inflow time series used in the tests were generated from filtered white noise. The outflows were calculated by feeding the inflows to two distinct SWMM 5 models: one with a single inflow and one with two inflows. The first model represents a 3 km sewer trunk with a diameter of 1.2 m and a slope of 0.1%. The inflow and outflow for the single input model are presented in Figure 1. The second SWMM 5 model is the same as the first, but a 400-meter pipe with a diameter of 0.5 meter and a slope of 0.5% is connected 600 m from the outfall. The inflows and outflow for the double input model are presented in Figure 2. On-line calibration was executed on these datasets and also on the datasets to which disturbance was added. The added disturbance emulates measurement noise and inflow estimation errors.

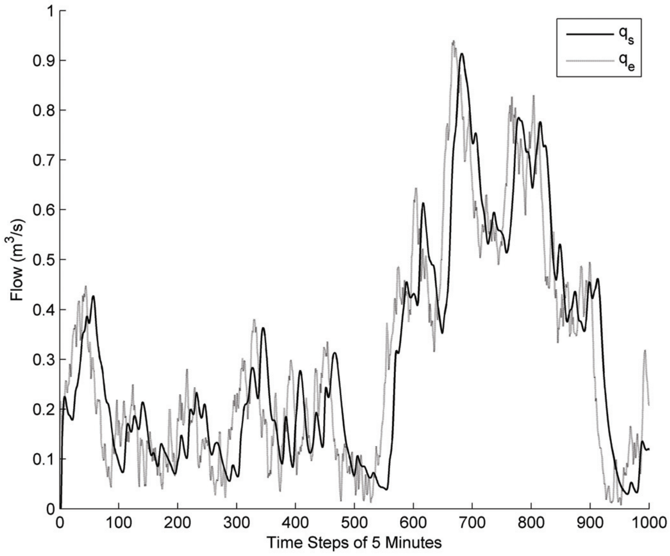

Figure 1: Inflow and Outflow for the Single Input Model

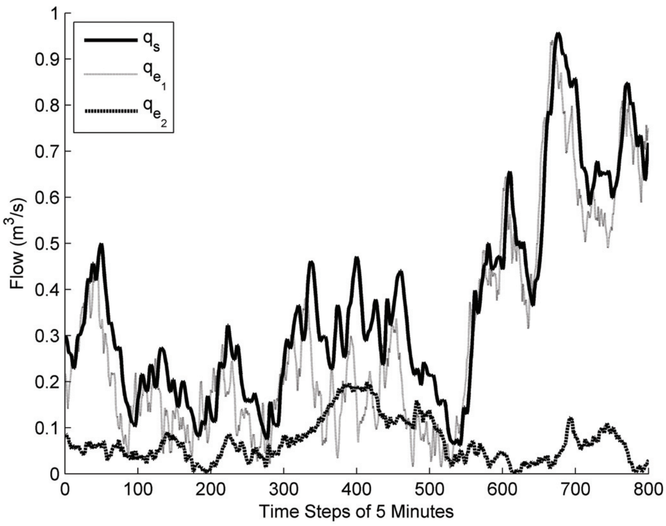

Figure 2 : Inflow and Outflow for the Double Input Model

Figure 3 and Figure 4 show the prediction performance indicators of the MA models calibrated on-line using the two techniques applied to the data. Although the prediction performances of the models adapted by the two on-line calibration techniques are similar, while no disturbance is applied, the inflow estimation error and measurement noise have a far greater impact on the Kalman filter technique. This might be due to the decreasing correction gain that characterizes this method and reduces its ability to follow rapidly changing parameters. In contrast, the Csoft™ on-line calibration tool’s limited window allows for a quicker response to changing dynamics. Also, an evaluation of the model's estimated parameter values shows that with the Kalman filter, negative parameters incompatible with the GO RTC control scheme are estimated. Negative model parameter values are not possible with the Csoft™ on-line calibration tool because constraints are taken into consideration. Figure 4 shows that the Csoft™ on-line calibration tool induces a slight bias in the model since the average prediction error is not null. However, this is greatly compensated by better results in all of the other performance indicators.

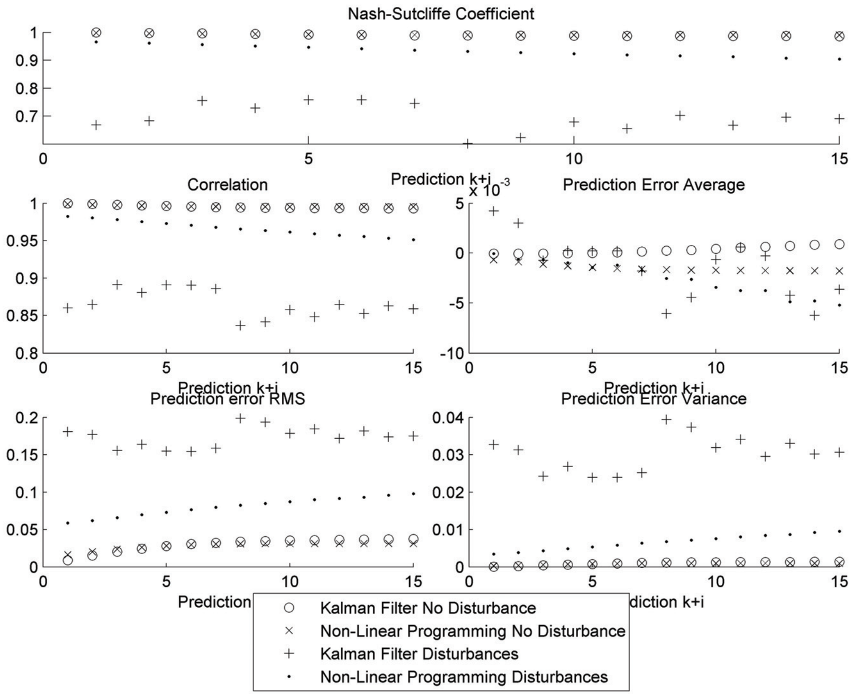

Figure 3:
Outflow Prediction Performance of the On-line Calibration
with and without Disturbances for the Single Input Model

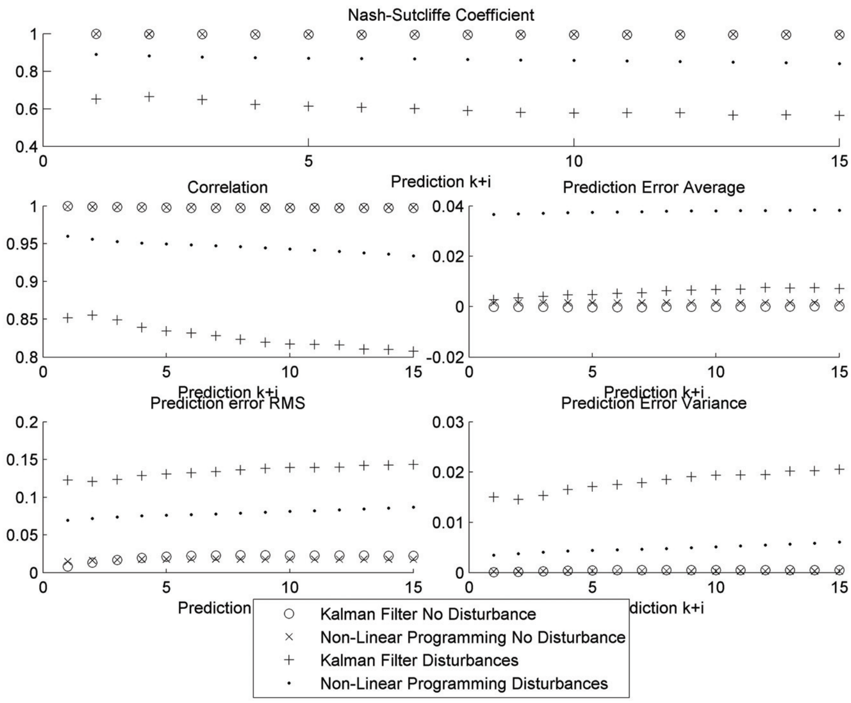

Figure 4:
Outflow Prediction Performance of the On-line Calibration
with Dataset 3 (No Disturbances) and Dataset 4 (with Disturbances)

3.2 Field Validation

3.2.1 Data from Quebec City's GO RTC System

Quebec City's Westerly sewer network includes 3 main combined sewer interceptors, i.e. *Versant Sud*, *Versant Nord* and *Métropolitain Nord*, as shown in Figure 5. The 3 interceptors meet in a junction chamber ("*Chambre de raccordement"* in Figure 5) to be conveyed to the Westerly Wastewater Treatment Plant (WWTP), which can treat up to 5.84 m³/s of water before release to the St. Lawrence River. A GO RTC system has been operating since 1999 to reduce CSO. Currently, 8 local stations are controlled by Csoft™. Up to 44,000 m³ of water can be retained in two tunnels and four retention tanks.

The *Metropolitain Nord* interceptor stretches for 12 km. It conveys the water from the northern part of the city to the "*Chambre de raccordement"*. Pipe diameters range from 1.37 m to 1.83 m. It can convey up to 4 m³/s of water in free flow conditions.

Figure 6 shows the flow as measured at each 5 minute time step by the flowmeter at the downstream end of the *Métropolitain Nord* interceptor during the rainfall event of October 23, 2009. The measurements are compared to the flows computed by the optimization model with and without on-line calibration. The Csoft™ on-line calibration tool allows for a much better flow estimation from the optimization model. The average flow delay has been shifted by 25 minutes or 5 time steps.

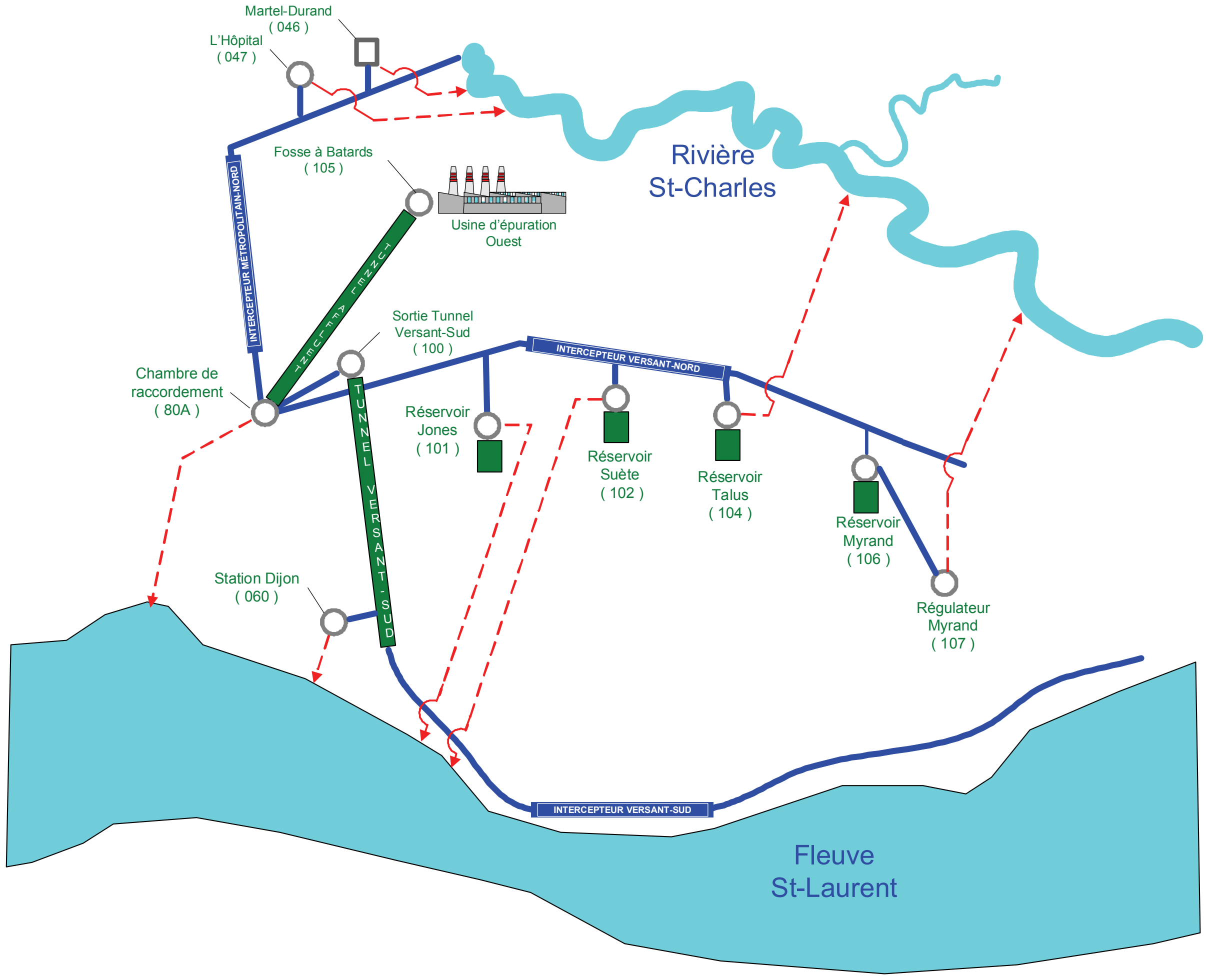

Figure 5: Quebec City's Westerly Sewer Network

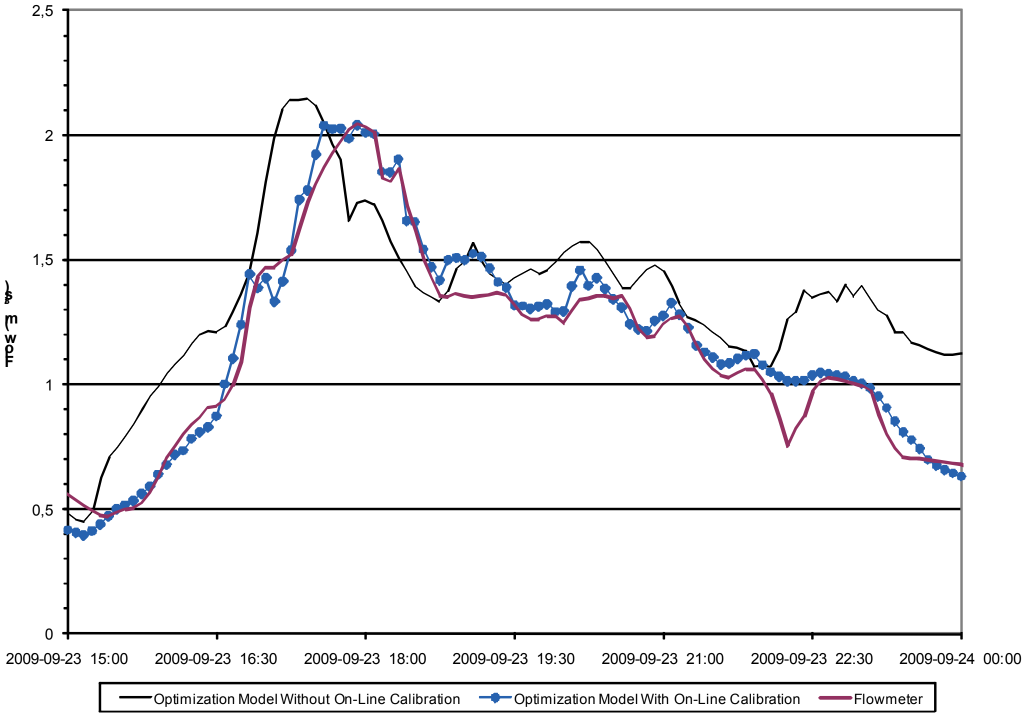

Figure 6 :
Métropolitan Nord Interceptor Flow from the Optimization Model With and Without On-Line Calibration Compared to Flowmeter Measurements

3.2.2 Data from Montreal GO RTC System

Montreal's sewer network includes three major interceptors: the South Interceptor, the North Interceptor and the Southwest Interceptor. These interceptors convey the flows to the Wastewater Treatment Plant (WWTP), which can treat up to 88 m³/s of wastewater. Out of 68 collectors connected to these interceptors, 36 are being controlled by Csoft™ since 2004 to maximize the use of the WWTP, thus minimizing CSOs. The South Interceptor is located on the south shore of the island of Montreal and stretches from LaSalle to the WWTP. Some 30 km in length, its diameters vary between 2.9 m and 5.5 m. It can convey up to 46 m³/s before surcharge. Figure 7 presents Montreal's sewer network.

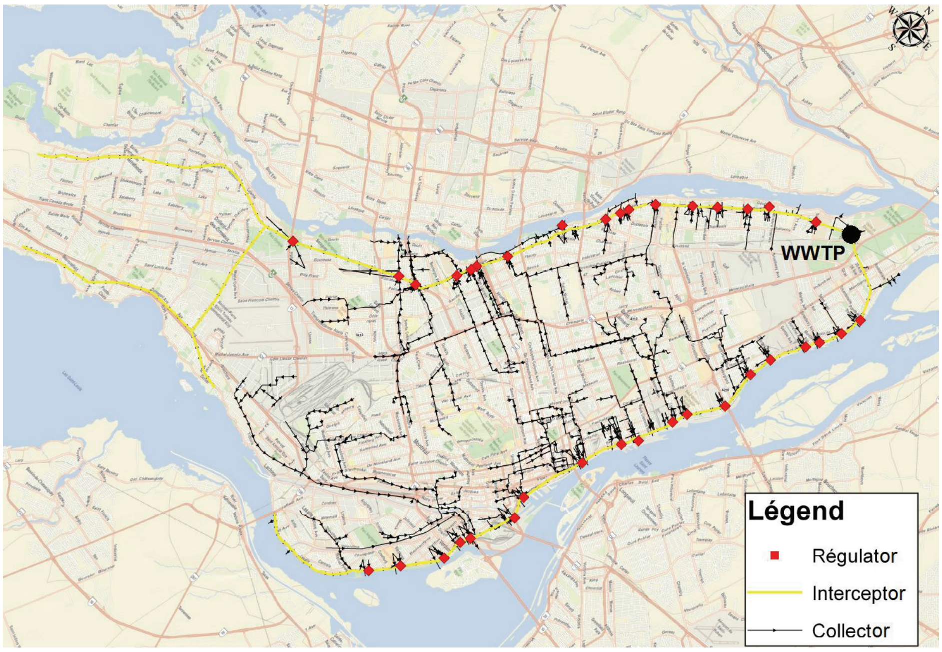

Figure 7: Montreal's Sewer Network

Figure 8 shows that the Csoft™ on-line calibration tool improved flow estimation at the downstream end of the South Interceptor for the rainfall event of October 29, 2009. The flowmeter measurements are compared to the flows computed by the optimization model with and without on-line calibration. Again, the Csoft™ on-line calibration tool allows for much more accurate flow estimation from the optimization model. During this particular event, the on-line calibration allowed for a better peak flow estimation, while the transport delay had already been correctly estimated by the optimization model without on-line calibration.

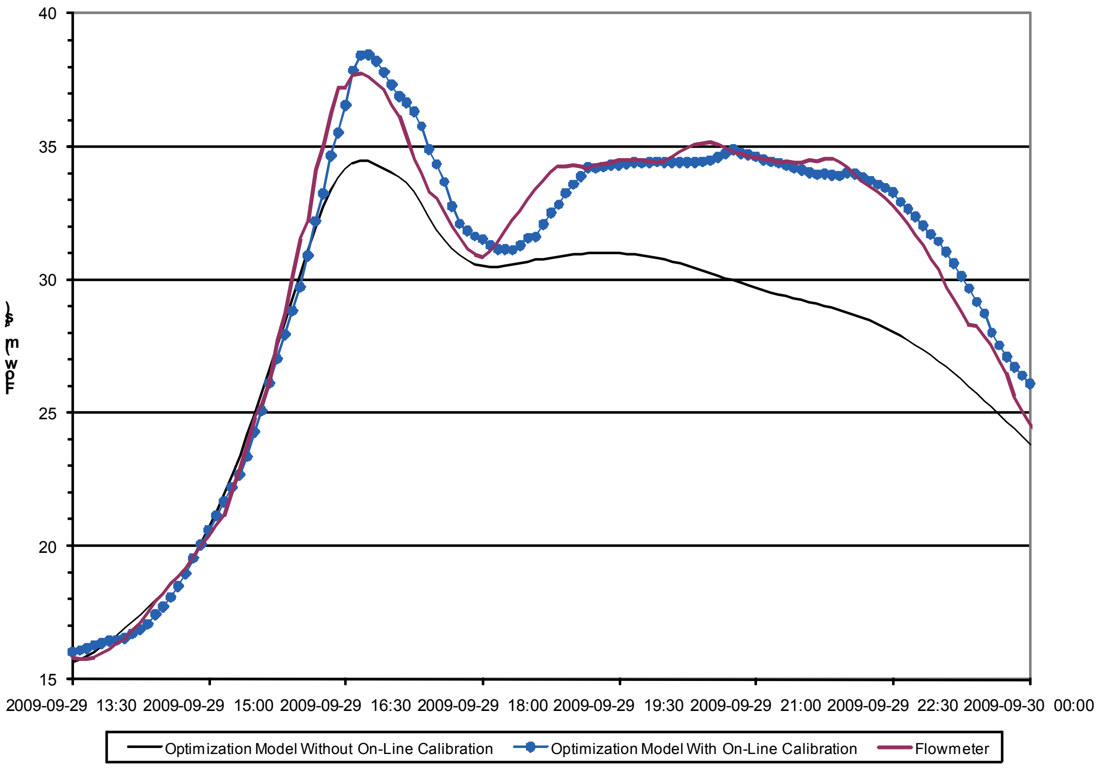

Figure 8:
South Interceptor Flow from the Optimization Model With and Without On-Line Calibration Compared to Flowmeter Measurements

4 CONCLUSION

Several of the GO RTC methods use a hydraulic model of the sewer system to compute the set points of each of the regulation structure that will minimize CSOs globally. Unfortunately, the hydraulic models using the full St-Venant equation are difficult to integrate in a GO RTC control scheme. Thus, most of the model-based control schemes developed for the GO RTC management of sewer networks use simplified hydraulic models. The characteristics of a good optimization model for implementation in a GO RTC scheme include speed of execution, robustness, easy integration in the control scheme, and adaptability.

The most commonly-used hydraulic models in GO RTC applications include the pure delay model, the MA model and the ARMA models. The MA model, successfully implemented in Csoft™, has been presented and used in this paper. This type of model features a short computation time and it is stable by definition. It was demonstrated that it can be derived from the full St. Venant equations.

The Csoft™ on-line calibration tool was compared favorably to the Kalman Filter using data simulated by a SWMM 5 model. Finally, two field validation examples of the Csoft™ on-line calibration tool were presented using data from the GO RTC systems implemented in Montreal and Quebec City.

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