Preliminary analysis of turbidity measurements during a flushing operation in combined sewer channel

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Gashin Shahsavari[1], Gilles Arnaud-Fassetta[1], Roberto Bertilotti[2], Hossein Bonakdari[3], Isa Ebtehaj[3], Hamid Moeeni[3], Carlo Modica[4], Alberto Campisano[4]

[1]Department of Geography, University of Paris Diderot, Rue Albert Einstein - 75013 Paris, France (Email: *gashin.shahsavari@univ-paris-diderot.fr*, *gilles.arnaud-fassetta@univ-paris-diderot.fr*)

[2]PROLOG Ingénierie, 3-5 Rue de Metz -75010 Paris, France, (E-mail: *bertilotti@prolog-ingenierie.fr*)

[3]Department of Civil Engineering, Razi University, Kermanshah, Iran (Email: *bonakdari@yahoo.com*, *isa.ebtehaj@gmail.com*, *h.moeeni68@gmail.com*)

[4]Department of Civil Engineering and Architecture, University of Catania, Viale A. doria, 6, 95125 Catania, Italy, (E-mail: *cmodica@dica.unict.it*, *acampisa@dica.unict.it*)

Abstract

Flow turbidity at different elevations was continuously monitored in five cross-sections of a real combined-sewer channel stretch during a flush experiment. The preliminary analysis of the collected turbidity data in terms of quality and spatial variability of the time series is presented in this paper. Also, an Autoregressive Moving Average (ARMA) model was setup to evaluate potential prediction of turbidity values showing a good estimation performance with relatively small errors.

Keywords

ARMA model, combined sewer, flush, turbidity monitoring.

INTRODUCTION

Sewer flushing is recognized as an economically and operationally efficient technique to limit the sediment accumulation in combined sewers and then to restore the full flow capacity of channels (Ashley et al., 2005). Since more than two decades, the use of this technique has been studied to evaluate the sediment-removal efficiency associated to different types of flushing devices. However, sediment transport during the flush in sewer channels is not yet well understood due to the complexity of sewer conditions as well as the lack of observations. Researches mainly conducted under laboratory controlled conditions have allowed characterizing the flow and sediment parameters playing a major role during the flush (Dettmar et al., 2002; Campisano et al., 2004; Creaco and Bertrand-Krajewski, 2009). Field experiments pointed out the occurrence of both bedload and suspended load transport depending on established flow conditions (Shahsavari et al., 2016).

Turbidity has been recognized to be an indicator of suspended (total) sediment transported by the flow in natural and artificial channels (Christensen et al., 2001; Hannouche et al., 2011). Recently, the use of turbidity sensors is considered to be effective for the continuous monitoring of in-sewer turbidity dynamics during dry weather as well as wet weather conditions (Bertrand-Krajewski, 2004; Métadier and Bertrand-Krajewski, 2011). Many challenges are rising from this technology, basically concerning methods to convert turbidity readings into sediment transport measurements or relationships between turbidity and flow (Bertrand-Krajewski et al., 2007; Lepot et al., 2013).

The Paris Municipality (Ville de Paris) has elaborated a plan for investigating the scouring performance of flushing operation in a large-size channel of the combined sewer network of the city. In this regard, a field flush experiment in a pilot channel was carried out for a full monitoring flow and turbidity during the flush.

This paper presents the preliminary results of the analysis of the turbidity time series collected during the experiment. First the analysis addressed to the data consistency. Secondly, the potentiality of using an Autoregressive Moving Average (ARMA) model to predict turbidity was analysed for one of the available turbidity time series.

METHODOLOGY

Field experimental setup and data storage

Field experiments were conducted in a large size trunk characterized by a compound cross-section with lateral banks in the sewer subnetwork of combined sewer network of Paris 11th arrondissement. The pilot channel is 1.1 km long (signed hereafter by S_{-50} and S_{+1050} with reference to the gate location at S_0) and it is prone to sedimentation. The average slope of the trunk is 0.8‰ and some longitudinal irregularities are present along the channel. The channel cross-section and longitudinal profile are illustrated in Figure 1a. The channel was equipped with a flushing gate that allows in-line storage of dry-weather flow in the upstream portion. For the experiment, the flush is produced followed by a sudden opening of the gate and release of the stored water through the channel.

The channel stretch was equipped by flow devices and automated turbidity sensors in five cross-sections (called hereafter, S_{-50}, S_{-5}, S_{+5}, S_{+50} and S_{+100} ; see Figure 1b). Figure 1c shows the position of these devices in the cross-section. At each measuring section a flow meter, an ultrasound sensor and three turbidity sensors were installed. Turbidity was measured in nephelometric turbidity unit (NTU) in 10s time intervals. Technical properties of the monitoring devices such as sampling range, accuracy, and measuring interval are outlined in table 1.

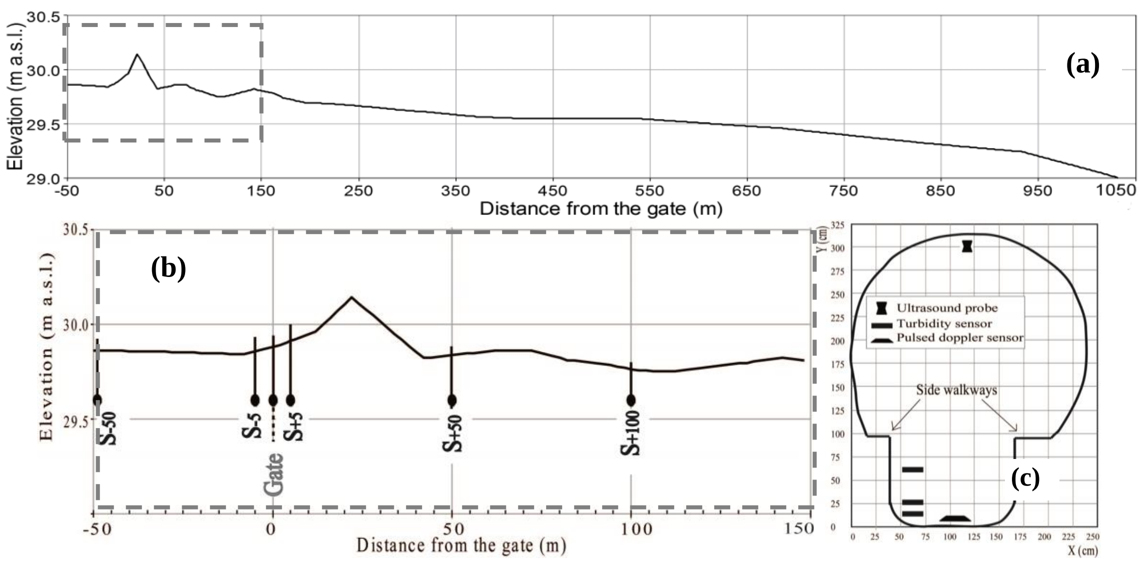

Figure 1. a) Longitudinal profile of the sewer channel; b) five monitoring cross-sections; c) scheme of measuring devices and their position in the transversal cross-section.

Table 1. Summary of flow and turbidity instruments used for the flush experiment.

Devices	Sampling range	Accuracy at full scale	Measuring technique	Acquisition frequency (Hz)
Pulsed doppler sensor	±5 m/s	±1% of readings	beam-pulsed doppler	0.1
Turbidity sensor	0-4000 NTU	±5% of readings	Nephelometric (θ=90°)	0.1
Ultrasound sensor	0-3 m	4 mm	acoustic imaging	0.067

Three elevations were chosen for turbidity sensors installation (15, 25 and 65 cm from the bed, called hereafter T15, T25 and T65) at each of the five monitoring sections (15 turbidity sensors in total) in order to observe the turbidity vertical pattern during the flush. Turbidity sensors were calibrated off-line before the flush experiment using Formazin solution between 0-2000 NTU. During the flush test, real-time data acquisition was obtained using a portable PC. Flow data time series were provided by all the flow sensors with the exception of sections S_{+100} as well as of S_{+50} during the peak period. Turbidity time series were obtained from all the sensors except for two (T15-S_{+5} and T25-S_{+50}).

Turbidity data analyzing

The dataset was firstly "cleaned" by eliminating records showing values out of the detection range of sensor. The noisiest time series correspond to the sensors close to the bed (T15) where the sediment fouling and bed load transport during the flush were mainly were more developed.
The analysis of turbidity values from all sensors was carried out to assess the quality of the measurements. To this purpose, the distribution of data obtained from each sensor was separately checked using Normal, Lognormal, Exponential and Weibull functions to verify the best fitting distribution. Then, the best fitting distribution was identified to compare distribution parameters among all the turbidity sensors installed at the same elevations to evaluate the consistency of recorded data.
Furthermore, in order to show the application of the validated turbidity values (in NTU) the analyses developed by plotting these turbidity values against the corresponding flow discharge (in m^3/s) in 10s time scale. This method could help to describe the overall impact of the flush on the turbidity during the fast rising and falling limbs of the flow showing by hysteresis loop of the both time series (discharge vs turbidity) which could support the investigation of flow turbidity variations.

Autoregressive model

Turbidity time series were used to test application of Autoregressive Moving Average model (ARMA) in order to obtain the relationship between turbidity values at different times. The used ARMA model is based on following equation:

$$(1-\varphi_1 B-\varphi_2 B^2-...-\varphi_p B^p)x_t=(1-\theta_1 B-\theta_2 B^2-...-\theta_q B^q)\varepsilon_t \qquad (1)$$

where x_t is the observed value of turbidity, ε_t is the stochastic or noise term, B is a differential operator as $B(x_t)=x_{t-1}$, p and q are order of autoregressive and moving average (respectively) and φ and θ are the parameters of autoregressive parameters and moving average orders (respectively).
Among the 469 turbidity records, 329 values are used to model calibration and the rest of data (140 data) were considered for the validation. The number of autoregressive order was taken between zero and ten and allowed combining 121 different models.
To evaluate the performance of the proposed model Mean Absolute Percentage Error (*MAPE*), Root Mean Square Error (*RMSE*) and Scatter Index (*SI*) were used as indicated in Eq. 2 to 4.

$$RMSE=\sqrt{\left(\frac{1}{n}\right)\sum_{i=1}^{n}(x_i-y_i)^2} \qquad \text{(NTU)} \qquad (2)$$

$$MAPE=\left(\frac{100}{n}\right)\sum_{i=1}^{n}\left(\frac{|x_i-y_i|}{x_i}\right) \qquad (\%) \qquad (3)$$

$$SI = \frac{RMSE}{\bar{x}} \qquad (-) \qquad (4)$$

where y_i and x_i are the modelled and observed values, respectively, and $\bar{x}$ is the mean of observed values.

RESULTS

Turbidity data analyzing

Preliminary fitting distribution check was applied for all T15 sensors and revealed that time series were Weibull distributed (Eq. 5), which was then confirmed by an analytical Chi-square test (with significant level of ≤ 0.05). The two maximum likelihood parameters of fitted Weibull distribution (a and b as scale and shape, respectively) are presented in Table 2.

$$f(x|a,b) = \frac{b}{a}\left(\frac{x}{a}\right)^{b-1} e^{-(x/a)^b} \qquad (5)$$

Table 2. The Weibull distribution parameters obtained for all T15 time series.

parameters	S_{-50}	S_{-5}	S_{+50}	S_{+100}
a (scale)	1683.8	4247.1	4806.0	2959.0
b (shape)	3.21	1.54	1.94	1.01

The probability distribution of turbidity time series for all T15 is illustrated in Figure 2 for the sections S_{-50}, S_{-5}, S_{+50}, S_{+100}. The figures clearly show good fitness of turbidity time series distribution to records for all the T15 sensors, which is indicating the data consistency among the sensors positioned at the same elevation. In other words, the sensors from the same position behaved in the same way to observe the turbidity variation during the flush and this is indicating the consistency of the recorded data.

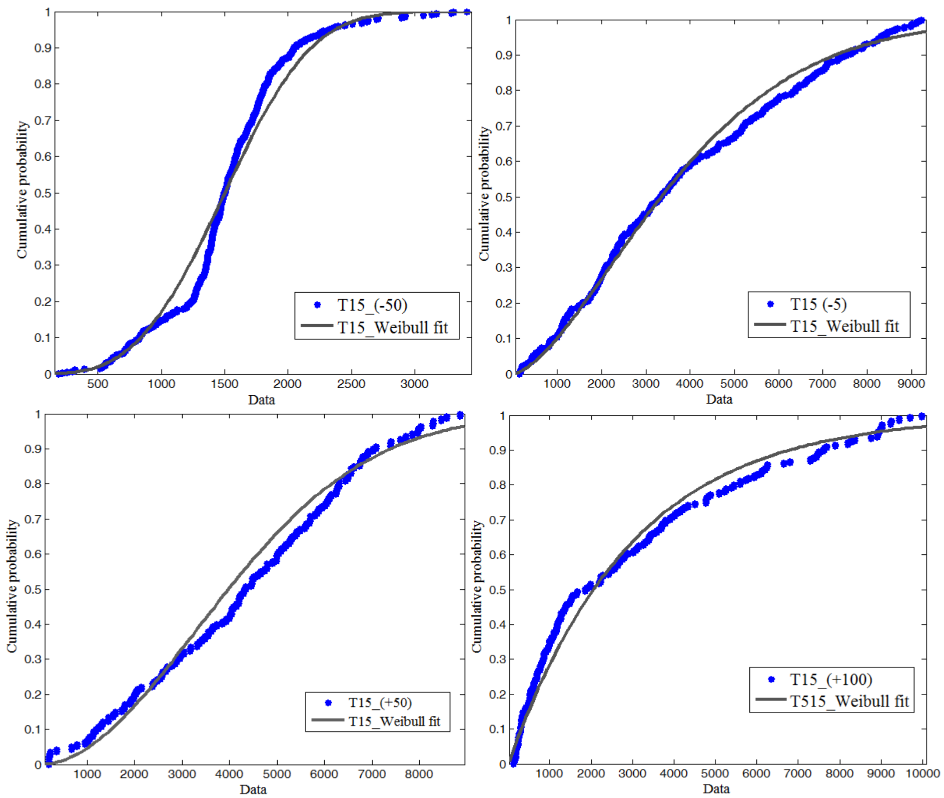

Figure 2. Cumulative probability plot and fitted Weibull distribution for the sections S_{-50}, S_{-5}, S_{+50}, S_{+100}.

The spatial variation of the turbidity records during the flush for all sensors was evaluated. Table 3 presents the main statistics of turbidity data.
On one hand, the vertical comparison of mean values confirms that the higher values of turbidity in the water column were observed close to the bed with values decreasing going from the bed to the water surface. Also, the more the sensor is far from the bed (T15), the more it provided dispersed values. On the other hand, a decrease of the average turbidity throughout the channel reveals the effect of the flush. Sensors located close to the gate exhibit high values of the turbidity with a general decreasing trend toward downstream. The same decreasing trend was observed for all three vertical positions except for T65. In fact, the T65 sensor in the last measuring cross-section has strangely recorded a very high peak after about 45 minutes after the flush releasing which was lasting for a few minutes. This was perhaps due to a temporary covering of the sensor by sanitary paper.

Table 3. Statistical description of all turbidity time series in NTU included mean and standard deviation (Values exceeding the detection range are excluded).

Sensors		Mean (NTU)	SD (NTU)	CV (-)
T65	S_{-50}	35.4	26.9	0.8
	S_{-5}	335.5	355.2	1.1
	S_{+5}	132.8	16.4	0.1
	S_{+50}	40.1	66.8	1.7
	S_{+100}	428.1	989.7	2.3
T25	S_{-50}	219.6	75.1	0.3
	S_{-5}	460.3	283.6	0.6
	S_{+5}	2666.6	1469.5	0.6
	S_{+50}	---	---	---
	S_{+100}	1819.4	1890.3	1.0
T15	S_{-50}	1515.3	497.0	0.3
	S_{-5}	3836.0	2447.0	0.6
	S_{+5}	---	---	---
	S_{+50}	4301.4	2210.8	0.5
	S_{+100}	3105.3	2775.4	0.9

In addition, as an example, the flow and turbidity data from S-5 were chosen to investigate the relationship of the two time series. Linear regression between discharge and NTUs showed a weak relationship with a coefficient of determination R2 of 0.01. The fluctuations of turbidity time series were reduced by applying the linear filtering over 1-min time scale. The figure 3 shows the NTU values and corresponded flow discharge in m3/s. Interestingly, the figure shows a hysteretic behaviour with the rising and falling limbs of the flush hydrograph for flow discharge-turbidity relations similarly to what has been observed in river streams (Lawler et al., 2006; Lloyd et al., 2015; Mukundan et al., 2013). This anticlockwise hysteresis indicates the last-flush process with time-lagged arrival of turbidity peak after the flow peak characterizing the chronological contribution of turbidity sources to the flow. Also, the form of the hysteresis is indicating the rate of the transport of turbidity sources. The result would be a material for future work to analyse the response of the turbidity to the flush flow by evaluating the pattern of the hysteresis for other sensors.

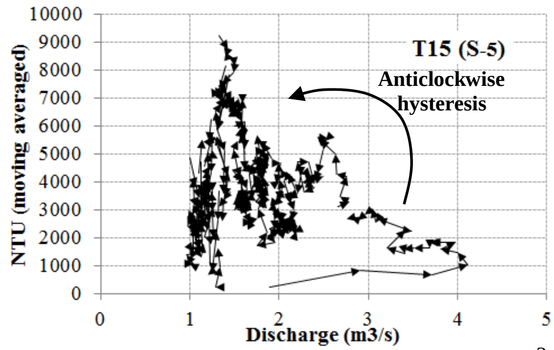

Figure 3. Example of temporal dynamic between flow discharge (m^3/s) and associated turbidity (NTU) in S_{-5}.

Model results

The results of ARMA model provided the following equation:

$$x_t = 0.9994x_{t\text{-}1} - 0.5184\varepsilon_{t-1} - 0.2635\varepsilon_{t-2} \qquad (6)$$

Figure 4a shows the results of the calibration of the model. Globally, the observed values show the peaks larger than the modelled values. The model validation graph (figure 4b) shows also the same trend reducing the amount of maximum and minimum values in fluctuations. Overall, the ARMA model shows good performance in estimating turbidity so that the difference between predicted and observe value are relatively small. The *RMSE*, *MAPE* and *SI* for proposed model are equal to 174.3 NTU, 8.33 % and 0.107 (-) for validation. Therefore, the use of ARMA model (Eq. 6) in prediction of turbidity leads to reliable results.

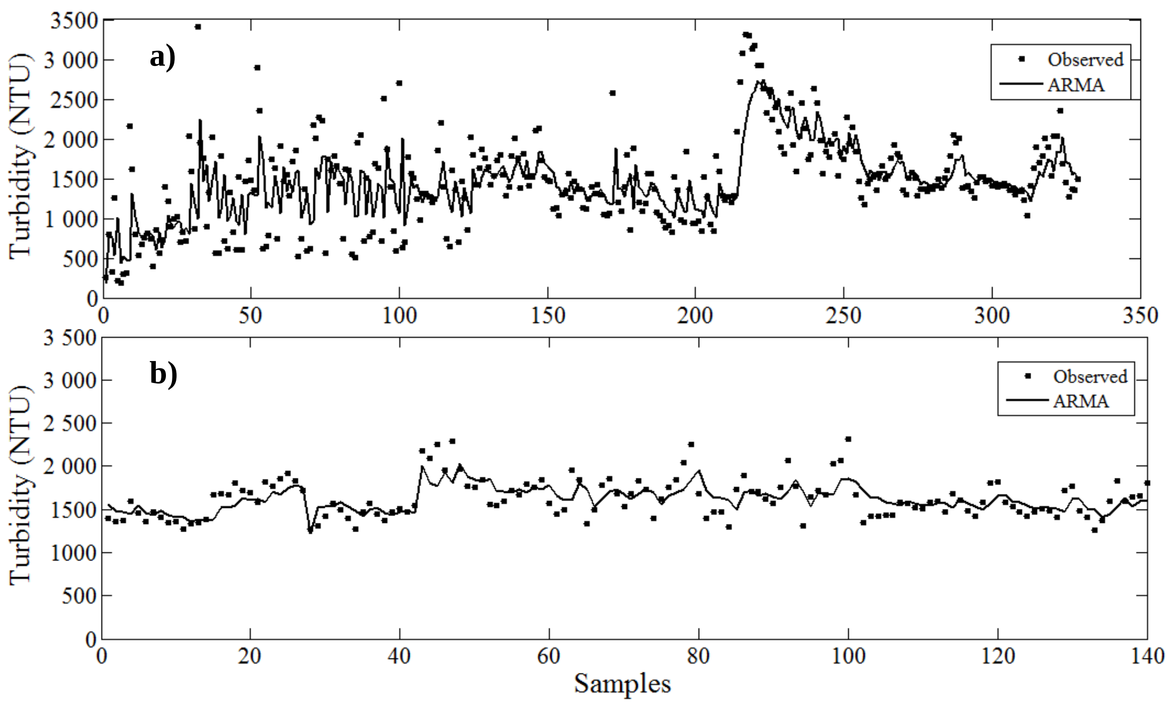

Figure 4. Performance of ARMA model in prediction of turbidity in NTU for T15 sensor in S_{-50}, a) for the calibration, and b) for the validation.

CONCLUSION

The turbidity fluctuations during a flush event were preliminary continuously monitored in three different elevations in five cross-sections of a real combined-sewer channel stretch. The preliminary results of the analysis of the collected turbidity time series were investigated in terms of data quality and spatial variability was presented. The relationship between these data and corresponding flow discharge was evaluated and was showing a characteristic hysteretic behaviour. Also, an Autoregressive Moving Average (ARMA) model was setup to evaluate potential prediction of turbidity values showing a good estimation performance with RMSE, MAPE and SI equal to 174.3 NTU, 8.33 % and 0.107 (-), respectively.

Further work is needed to investigate the quality of the time series recorded from other sensors in different elevations of each section and their relationship with the flow discharge in order to confirm the results.

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