UNIVERSITY OF BATH

University of Bath

A Bottom-up Approach to Estimate Dry Weather Flow in Minor Sewer Networks

J. A. Elías-Maxil [*], Jan Peter van der Hoek [**], Jan Hofman[***] Luuk Rietveld [*]
[*] Department of Water Management. Delft University of Technology. Stevinweg 1. 2628 CN Delft; The Netherlands
(E-mail: J.A.EliasMaxil@tudelft.nl; J.P.vanderHoek@tudelft.nl; *L.C.Rietveld@tudelft.nl)*
[**] Waternet, Korte Ouderkerkerdijk 7, 1096 AC Amsterdam, The Netherlands
(E-mail: jan.peter.van.der.hoek@waternet.nl)
[***]KWR Watercycle Research Institute, PO Box 1072, 3430BB Nieuwegein, The Netherlands
(E-mail: *Jan.Hofman@kwrwater.nl*)

Abstract. In order to evaluate the feasibility to install decentralised installations for wastewater reuse in cities, information about flows at specific spots of a sewer is needed. However, measuring intermittent flows in partially filled conduits is a technical task which is sometimes difficult to accomplish.

This paper describes a method to model intermittent discharges in small sewers by linking a stochastic model for wastewater discharge to a hydraulic model to predict the attenuation of the discharges and its impact on the arrival time to a defined spot. The method was validated in a case study. The model estimated adequately the wastewater discharges on working days.

Keywords Stochastic water discharge modelling, wastewater prediction, free surface flow, minor sewer network, Dry weather flow modelling.

INTRODUCTION

The emerging necessity for water and energy reuse will require more site-specific methods for design, monitoring and control of decentralized systems. However, flow in free surface sewer networks is one of the most difficult parameters to quantify with accuracy due to the inherent characteristics of wastewater and drainage infrastructure (Lynggaard-Jensen 1999; Larrarte *et al.* 2010). In small scale sewer systems (which constitute the major part of a sewer system inside cities), it is more difficult to measure wastewater flow since the flow can be lower than the resolution of the equipment and the flow tends to be more intermittent. In dry weather flow, the dynamics of discharges is mainly dominated by behavioural factors of water use by the consumers and type of water demanding appliances.

A bottom-up approach to calculate wastewater discharge inside households, takes into account the behaviour of water users and type of water-demanding appliances together with the hydrodynamics of the sewer system. Alcocer-Yamanaka *et al.* (2012); used a stochastic model that simulates water demand with variable time intervals in the total simulation time (Neyman-Scott Rectangular Pulse) the expected flow was emended to the software EPANET to simulate the flow and pressure in a drinking water network. The authors found that the experimental flow was more variable than the expected results obtained by the model. Based on a probabilistic approach, Wong and Mui (2007) simulated the expected flow as wastewater discharge of toilets in a residential building in Hong Kong. The purpose of the research was

the better understanding of peak flows of toilets in order to better design drains in buildings with high density population. A standardized probabilistic method takes into account discharge units inside a building and frequency factors (CEN 2000) which asses the probability of the use of a water discharging appliance in a period of time. Another approach, presented by Butler and Graham (1995), used a binomial distribution to simulate the expected flow, which was used as input of a second model to describe the hydraulics of the discharges along the sewer. The authors stated that the water demand of a water-requiring activity (equivalent appliance) in the expected flow is intermittent, and after its use the discharge to the sewer is transformed to a continuous pattern. The second model consisted of a simplified version of the Saint Venant equations for continuous surface water flow in shallow depths. For comparison with observed data, the authors averaged the measured flow recorded during 25 days into one single day which resulted in a continuous flow. In order to describe the discharge flow more accurately, the initial model can be improved by modifying and integrating stochastic models for water demand and the hydraulic models to calculate varying flow.

Stochastic modelling

The stochastic modelling of drinking water demand on a household level has been conceptualised by the addition of intermittent water pulses characterised by three factors: Intensity, duration and frequency of water use. Buchberger and Lin (1995) developed a first concept to predict (drinking) water demand at the dead-end branch as a non-homogeneous Poisson-rectangular-pulse. After one year of monitoring in four households, the researchers concluded that although the variance of water use (as a pulse) was quite high to be described by a Poisson rectangular pulse, it was still a good approximation to describe indoor water use (Buchberger & Wells 1996).

A Monte Carlo technique to generate rectangular pulses has been used to model drinking water demand from households and other type of buildings (Blokker 2010), which demonstrated that the prediction is adequate using a comparison of mean error, root mean square error and coefficient of determination. This technique used statistical information which is often available in common census data. The model is based on the model presented by Buchberger and Wells (1996).

The fundaments of the model is stated in equation (1) which indicates that the total water discharge (Q) in every household is the summation of rectangular pulses (B) characterized by a particular intensity (I), duration (D) and time of occurrence along the day (τ) from $k=1$ to M equivalent appliances of $j=1$ to N users as well as $i=1$ to F frequency of user j and end user k ($j*k$). The block function B (continuous line in Figure 1) is a flow value where i, j and k represent busy times, users and equivalent appliances of a residence characterised by an intensity I at the time interval $[\tau, \tau+D]$ and 0 in the remaining time period T (24 hours).

$$Q = \sum_{k=1}^{M} \sum_{j=1}^{N} \sum_{i=1}^{F_{jk}} B\left(I_{ijk} D_{ijk} \tau_{ijk}\right) \quad \textbf{(1)}$$
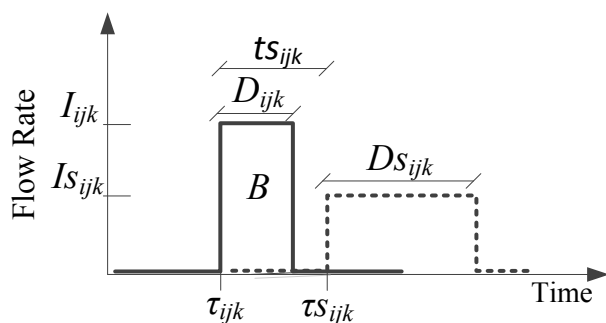
Figure 1. Block function of a rectangular water pulse

The input for the Monte Carlo method can be found from surveys. It uses some relations between the variables. For the equivalent appliances (i), the penetration rate (percentage households that own an appliance) of eight appliances is needed and related to the house size. Some appliances are subdivided in type (such as water saving or old fashioned water closets). The users (j) of a household are divided in age, gender, occupation. The number of users is also related to the household size. The frequency of use for each equivalent appliance (k) is taken from probabilistic relations of the users and the type of appliances that they use (Poisson, Negative binomial and binomial, depending on the appliance). The intensity (I) and duration (D) of the pulse is related to the type of appliance in use (The I and D of a water saving are different from an old-fashioned water closet) while the time of occurrence (τ) is related to the age, occupation and inhabitants in the household. These data can also be found in surveys. The Monte Carlo method generates water pulses from the combination of the mentioned data. A more detailed methodology to generate the water demand patterns is described in further readings (Blokker et al. 2010).

This paper describes a method where data, found in demographic surveys, was used to predict the dry weather flow in a sewer network by linking two types of models; the first one is a probabilistic-based model to assess water consumption patterns inside households, and the second is a hydraulic model for free surface flow. The drinking water demand patterns were transformed to water discharge patterns by taking into account the residence time of drinking water in households and the attenuation when the liquid flows downstream from the house to the sewer and from the sewer to a point of interest. This method is aimed to more accurately estimate the expected flow at a given location of the sewer system, in small time frames, and when the flow pattern tends to be intermittent (as in small sewer systems). The model results were compared with flow measurements (and measurement errors) in a case study.

MATERIALS AND METHODS

Case study

The study was performed in a drainage area located in the north of Amsterdam. Taking as reference point the pumping station, which is downstream, it was divided into two sections (Southwest and Northeast) with 59 and 84 residences respectively. The southwestern sewer section (SW) is 159 m long; while the length of the northeastern (NE) part is 203 m.

The SW section has 12 buildings with four apartments in every building (each apartment has an area of approximately 90 m^2) and 1 building with 11 single-room households (approximately 40 m^2) and one large room. In this section there are 29 wastewater connections distributed along the sewer pipe. There is one connection for every apartment located on the ground floor in every building, and one connection serving the remaining three apartments that constitute one building. The building with the single-room apartments has two connections for the two single-room apartments on the ground floor and three connections serving three residences per connection.

The NE section has 68 connections distributed along the sewer pipe. In this section there are eight buildings with four apartments each like the previously described for the SW section with the difference that one of these buildings does not have the apartment on the ground floor; this segment of the sewer has 15 wastewater connections. The remaining 53 connections discharge the wastewater of 25 semidetached houses and 28 single-room apartments. The houses have an area of approximately 140 m^2 (excluding garden) while the single-room apartments have a size of approximately 55 m^2 each. All the buildings were constructed at the same time by the same company and their configuration is similar; because the edifications were constructed in blocks, it is expected that the interior of the households is the same according to the type of residence.

The buildings and the sewer system were finished in 1987. The sewer is a separate system; both sections are made of round PVC pipes of 235 mm of internal diameter. The wastewater of both streams is delivered to a 400 mm concrete pipe. The wastewater is collected into a pit and when once a certain level is reached, it is pumped to another sewer system. The pumping station (Figure 2) consists of two pumps that work intermittently and alternatingly to transport the water from the chamber to the external drainage system.

Flow measurement and hydraulic calibration of the case study
The quantification of the wastewater discharge for the whole sewer system was performed at the pumping chamber according to equation (2) proposed by Scherer and Jia (2010) the method was chosen because the amount of fat inside the pit made its shape irregular; moreover, the equation is adequate for calculating the mean discharge in a duty interval when there are little variations in the initial and final level.
The flow depends on the pumping time (t_{On}-t_{Off}), the time when the pump is in stand-by (t_{Off}-t_{Off}) and the pump capacity (Cap). The on and off pumping times were obtained when there was a sudden change (second derivative of the filling rate) of water inside the pit. The water level inside the pit (Figure 2) was measured with hydrostatic pressure sensors (Schlumberger Diver™) which were protected with a PVC hose to avoid noise of hydraulic pressure due to turbulences of the incoming flow rate and the operation of the pump.
To estimate the uncertainty of the time resolution in the water level measurements, the pressure sensors were installed simultaneously for a cross-checking test. An error analysis of the measurements of the pump capacity was also made.

$$\dot{V}_{[t_{off(n-1)}, t_{off(n)}]} = \frac{Cap \cdot t_{[t_{off(n+1)}, t_{on(n)}]}}{[t_{off(n-1)} - t_{off(n)}]} \qquad \textbf{(2)}$$

The roughness and pump capacity of the sewer system were calibrated with controlled discharges of water. Because the households discharged water at the time of the hydraulic calibration, a flow rate of 6 lit/sec was chosen to avoid interference with anthropogenic discharges from them. It was expected to have a mean wastewater discharge from the households of approximately 0.2 lit/sec at the time of calibration which represents less than 3.5% of added flow rate to the pumping pit. The calibration parameters for the roughness were the arrival time of the flow from the farthest manhole to the downstream manholes, and the difference in water depth along the sewer at steady state. The Colebrook-White equation was chosen to measure water depth since it is more appropriate for pipes smaller than 1 m (Swaffield & Galowin 1991). The infiltration was neglected in the hydraulic model. The geometry of the sewer system was measured one year before these experiments took place (in 2011). The working capacity of the pumping station was also measured. The monitoring campaign took 15 days in total.
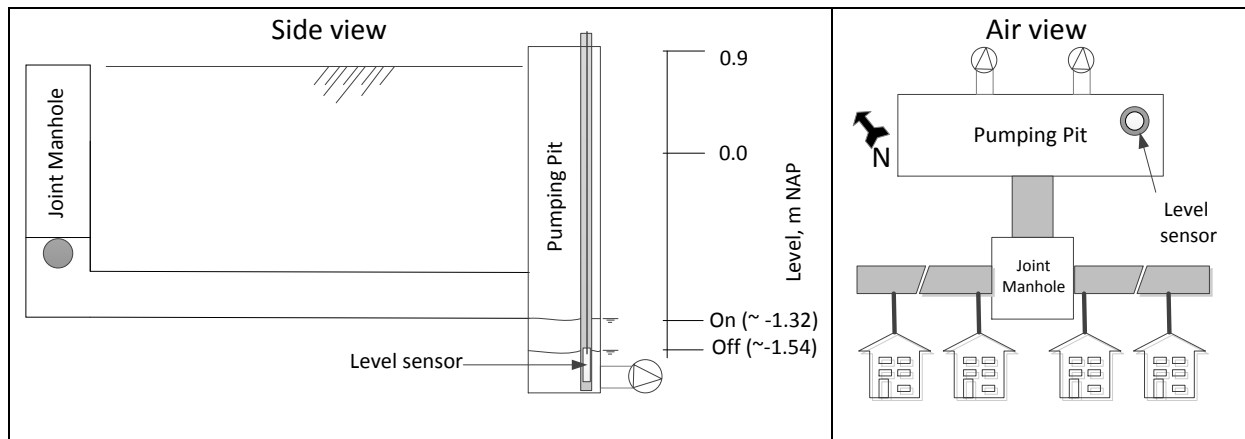

Figure 2. Schematic representation of the pumping pit.

Modelling approach

The modelling approach started with the generation of drinking water demand patterns. Data needed for the simulation was obtained from statistical data commonly found in demographic surveys (BOS 2011) for Amsterdam and for the Netherlands. This type of information includes the number of residents per house, age, gender, type of residences in a given area of the city, number of hours that people work outside and inside their households. Information of water-demanding activities, appliances, and number of appliances was also needed. The Monte Carlo method was used to propagate rectangular pulses of water per appliance (shower, kitchen tap, bathtub, bathroom tap, washing machine, dish washer, toilet, and outside use) with a duration (D), Intensity (I) and time of the day when the demand occurred (τ).

The dotted line in Figure 1 represents the conversion of a drinking water pulse to wastewater generation inside houses. Once water is used, it is discharged in every appliance after a residence time (t_s). Therefore, the expected time of discharge (τ_s) is equal to $\tau+ts$. Different durations D_s and residence times for discharges (t_s) were incorporated, depending on the type of equivalent appliance (Table 1). The intensity of discharge depended on the volume to

discharge and the duration of every discharge ($D*I/D_s$). The t_s for the shower and the kitchen tap was assumed to be 45 and 30 seconds, respectively, because there is no or a small water storage during the activity. The t_s for the bathtub, the dishwasher and the washing machine were changed, as well as their discharge duration. The toilet flush was considered to last approximately nine seconds. While water used outside the tap was not considered as a source of wastewater. The summary of parameters needed to transform water demand patterns to discharge is shown in Table 1.

Table 1 Discharge patterns. Source: (De Paepe _et al._ 2003; Persson 2007; Blokker _et al._ 2010)

Equivalent Appliance	D (sec)	I (lit/sec)	t_s (sec)	D_s (sec)
Shower	600	0.123	45	Same as D
Kitchen tap	16|48|15|37	0.083|0.125	30	Same as D
Toilet	45-106	0.042|0.884	0	9
Bathroom tap	40 | 15	0.042 | 0.042	2700	Same as D
Washing machine	120*	0.167|0.083	3840|1260	300*
Dish Water	21*	0.19*	1800*	120*

\|: Separation of sub-activities or cycles
*: The same parameter was included in the remaining 3 cycles

After simulating the time and volume of wastewater discharge into the sewer system, the flow dynamics were calculated using the St. Venant equations for a one dimensional flow. The simulation consisted of two types of situations: the connecting pipe of each building to the sewer and the sewer itself which is filled with the lateral discharges from the connecting pipe of each building. For this purpose, the software Sobek® was used. To avoid numerical errors when there was no water, a flow of 1 ml/sec was added in every connection and later subtracted from the final results. The discharge patterns were generated for working days (Monday to Friday) and weekends, considering that the daily water consumption also depends on the occupancy of the residence.

Model validation
In order to assess the performance of the model, the simulation was compared to the wastewater flow measurements according to parameters that were previously used to test stochastic models for water demand simulation (García _et al._ 2004; Blokker _et al._ 2010) . The chosen parameters were maximum flow (Q_{max}) and average flow (Q_{mean}) in several temporal scales (6, 10, 60, 300, 600, 1800 and 3600 seconds). The parameters were presented as cumulative frequency distributions (CFD). The goodness of fit was evaluated with the computation of the mean average error (_ME_), the root mean square error (_RMSE_) and the similarity of the patterns was evaluated with coefficient of determination (R^2). The evaluation was done for the one-day average values of the observed and estimated data. The day was divided into sets of values according to the different time scales. Q_{max} and Q_{mean} of the observed and estimated data were obtained for each set of values. The integer percentiles from 1 to 100 of the parameters were evaluated with the equations for _ME_, _RMSE_ and R^2 (equations 3 to 5). More parameters were not considered due to the lack of wastewater flow data for separated houses since the wastewater flow was measured only at one location.

$$ME = \frac{1}{N}\sum_{i=1}^{N}(y_i - x_i)^2 \qquad\qquad \textbf{3}$$

$$RMSE = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(y_i - x_i)^2} \qquad\qquad \textbf{4}$$

$$R^2 = 1 - \sum_{i=1}^{N}(y_i - x_i)^2 / \sum_{i=1}^{N}(x_i - \bar{x})^2 \qquad\qquad \textbf{5}$$

RESULTS AND DISCUSSION

Stochastic discharge generation

Figure 3 shows the stages of the model in a household in a time frame of two hours. The generation of the drinking water pulse with the Monte Carlo method (dotted line) followed a rectangular water pulse as well as the conversion to water entering to the drainage (Dark continuous line). The intensity and duration of the drinking water pulse was modified in four pulses, since the appliance (Washing machine) has a different discharge than filling pattern. Other pulses were delayed and their intensity and duration were not modified. The delay of the discharge caused that the rectangular discharge pulse appeared after the drinking water pulse. The attenuation of the rectangular pulse after 15 m of travel along the sewer system was caused by the hydrodynamics discharges in free surface flow.
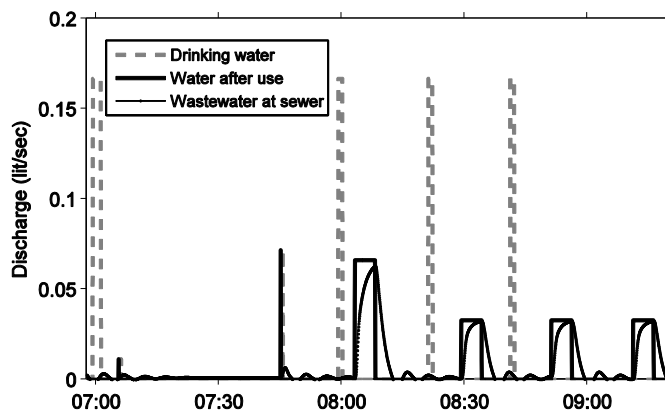

Figure 3. Conversion from water demand to water discharge into the sewer

The stochastic model was restricted to houses with no more than four inhabitants, and therefore, the total number of inhabitants was set on 295 for a working day and 281 inhabitants for a non-working day (average population density of 2.0 inhabitants/household). The summation of all the wastewater flows in time gave the total discharge into the sewer. Table 2 shows the average observed and estimated results of the simulation according to the type of simulated day (working and weekend day).

The average day of the simulation showed that the wastewater production per capita was approximately 109.5 lit/day; the observed discharge to the sewer was 108 lit/day. According to statistical data for the country, the expected wastewater production at the system was 36 m³/day, considering water use per capita of 127 lit/day, and 10% of losses. In our simulation,

the wastewater discharge was 31.1 m^3/day (with a population density of 2 inhabitants/household).

Table 2. Observed and estimated results of simulation in average working and weekend day.

Parameter	Working day	Weekend
Days of simulation	~ 9	~ 6
Population density	295	281
Observed wastewater flow (lit/cap/day)	101.3	117.4
Estimated drinking water flow (lit/cap/day)	93.2	117.9
Estimated water after use (lit/cap/day)	92.8	111.7
Estimated wastewater flow (lit/cap/day)	105.6	113.9

Flow measurements and hydraulic model calibration
The sensors recorded the water level in the pit every three seconds. All the sensors detected the same number of pumping intervals. The cross-checking test showed that the confidence intervals for the pumping episodes (t_{On}-t_{Off}) and (t_{Off}-t_{Off}) were 3.2 and 3.1 seconds respectively. Since the average pumping and stand-by duration were 27 and 617 seconds, it can be considered that 10% of accuracy in our measurements was lost due to the resolution of the three seconds measurements. The geometry of the system was drawn in the hydraulic model with a clustered Colebrook-White roughness of 15 mm which could be considered as high. However, this was not surprising since the sewer is the beginning of the network and we had installed a cable of 0.8 cm diameter at the bottom of the sewer for other experiments. The calibration of the pump station showed a pump capacity of 8.4 ± 0.47 lit/sec at 95% confidence level.

Flow simulation
The confidence limits of the sudden change in water level, and the pumping capacity were used to obtain a maximum and minimum observed flow interval during the monitoring campaign (91 - 126 lit/cap/day). The average observed flow of 109. lit/cap/day, was approximately 20% lower than the country's average. The result could be explained because there were more one-room households than the average and the expected number of inhabitants is also lower. In the city of Amsterdam, the average household occupation is 2.2 inhabitants/household and 3 rooms/residence (BOS 2011) but for this case, it was assumed that the population density was lower since there were no detached houses at the study case and because of the higher abundance of single-room apartments.
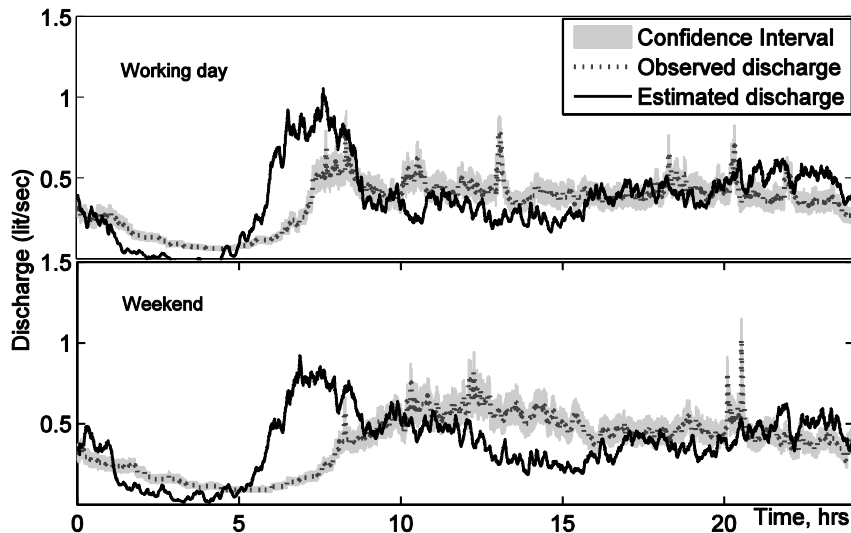
Figure 4. Experimental Discharge and upper and lower limits at 95% confidence interval

Figure 4 represents the flow pattern of the monitoring period for working days and weekend days. It can be seen that the observed average discharge pattern of a weekend day has more frequent discharges in the afternoon than at a working day, suggesting that the occupancy of the households played a role in the modelling of water demand. Moreover, the variation in discharge patterns during weekends and holidays was higher than during working days. The mean error between the estimated and observed flow was 0.6 lit/sec.

The estimated peak of wastewater discharge appeared earlier than the observed discharge in both average days. Added to the demographic density of the case study, a factor that could have influenced the experimental discharge pattern is the size of the area. From a top-down approach (Drinking water measurements in main water pipes), Bakker *et al.* (2013) reported that the errors in water demand prediction are inversely proportional to the size of drinking water networks. Furthermore, the authors mentioned that in comparison to normal working days, the peak of drinking water consumption in holidays and normal Sundays is found after more than one hour later. Also, the variability of drinking water demand is higher between the types of holiday (New Year, summer holiday, normal Sunday) than the variation found in normal working days. In our case, the measurements included the Easter season which might have affected the behavioural consumption of drinking water and hence, the wastewater discharged to the sewer. In addition, the drainage area is located near the city centre and the central train station; it can be possible that if the people living in the drainage area spend less time traveling than the average people (average higher than 70 min/day (van Wee *et al.* 2006)) they tend to wake up later than the average. Occupation, and age of the people is a key factor that influences the stochastic modelling of drinking water demand (Blokker *et al.* 2010) because it determines the start time of water consumption and the diurnal pattern. In our case, when we increased the concentration of senior people and people that stay at home (groups that tend to sleep later and wake up early) to be around 70% of the population, the highest peaks of wastewater discharge are found approximately one hour later than the flow shown in Figure 4, suggesting that the simulated results could be improved with site-specific information from surveys.

The cumulative frequency distribution helps to visualize the data which fits inside of a specific interval of values; in our case, flow rate at different time frames. Figure 5 represents

the observed and estimated data from two different time scales. It can be noticed that at Q_{max} of ten seconds and five minutes, the behaviour of the estimated data is similar to the observed data. In small time scales, the higher values of estimated maximum water flow rate were not well matched with the higher values of the observed data. A different pattern was found at a time scale of one hour where the lower and middle estimated values were slightly different from the observed values. But still, the trend of the estimated data followed the trend of the observed data. A very similar situation was found with the Q_{mean} computed at the same time scales.
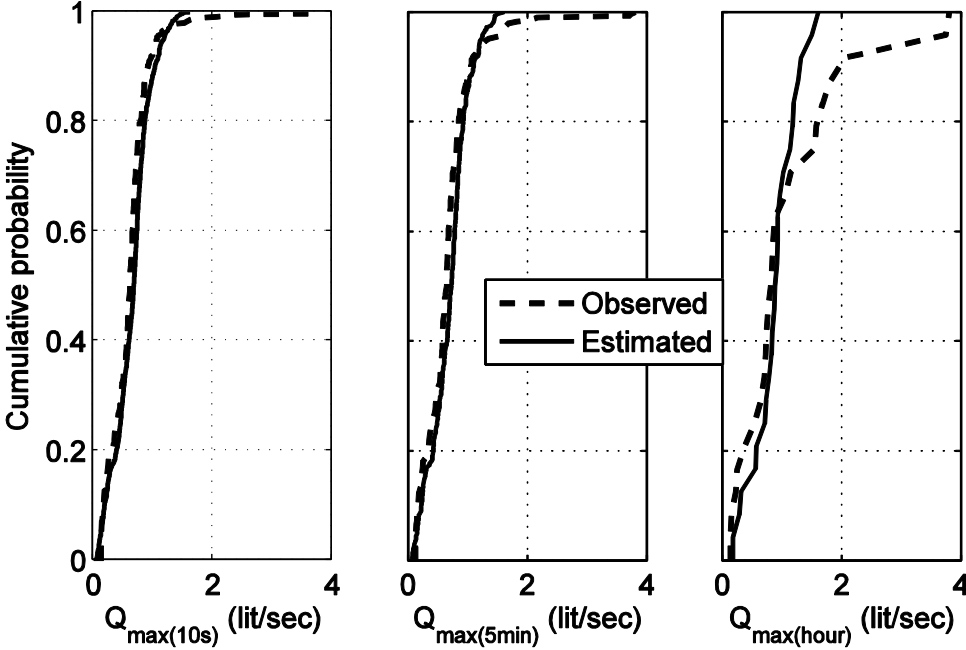

Figure 5. Comparison of observed and estimated Qmax at different timescales for an average working day and weekend. Re result is presented as cumulative frequency distribution
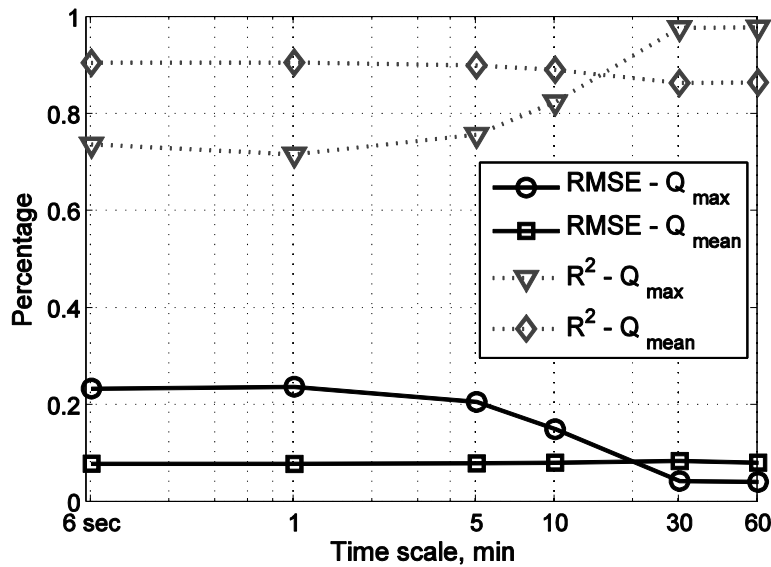
Figure 6. Goodness of fit and similarity analysis (RMSE and R²) of Q_max and Q_CFD between observed and estimated flow values at different time scales.

The goodness of fit and similarity of shape estimated with the help of *ME*, *RMSE* and R^2 at different timescales (Figure 6 and Table 3) showed an agreement between the estimated and observed values (*ME* < 1 lit/sec, *RMSE* ~ 9% and R^2 > 85%). Both estimators were almost constant from a time scale of three seconds to five minutes for Q_{max} and Q_{CFD} and changed in time scales from five to ten minutes. This analysis suggests that if a good time resolution is needed without the handling of large amounts of data, the accuracy of results between one second and five minutes would be similar. For larger time scales, the accuracy of the model increased.

Table 3. Goodness of fit parameters at different time scales.

Time frame	Q_{mean}			Q_{max}		
	ME (lit/sec)	*RMSE* (%)	R^2 (%)	*ME* (lit/sec)	*RMSE* (%)	R^2 (%)
10 sec	0.75	8.0	90.6	0.75	8.0	90.6
1 min	0.77	7.9	90.7	0.77	7.9	90.7
5 min	0.78	8.1	90.1	0.78	8.1	90.1
10 min	0.78	8.2	89.2	0.78	8.2	89.2
30 min	0.75	8.6	86.5	0.75	8.6	86.5
1 hour	0.75	8.2	86.6	0.75	8.2	86.6

CONCLUSIONS

A stochastic model for water demand was modified to predict the wastewater flow in small sewers. The modification included the transformation of a rectangular pulse to a another rectangular pulse considering the retention time of the drinking water pulse and the attenuation of the discharge during the travel time from the household to the sewer and from

the point of lateral discharge to a downstream point where water is collected in a small sewer system. The adequacy of the model (*ME*<1 lit/sec, *RMSE* ~9% and R^2>85%) can be enhanced with detailed information from surveys for the site where the bottom-up approach is going to be used. The accuracy of the model in relation to the time resolution was stable from time scales of seconds to five minutes and increased for larger time scales.

REFERENCES

Alcocer-Yamanaka V. H., Tzatchkov V. G. and Arreguin-Cortes F. I. (2012). Modeling of drinking water distribution networks using stochastic demand. *Water Resources Management* **26**(7), 1779-92.

Bakker M., Vreeburg J. H. G., van Schagen K. M. and Rietveld L. C. (2013). A fully adaptive forecasting model for short-term drinking water demand. *Environmental Modelling and Software* **48**, 141-51.

Blokker E. J. M. (2010). *Stochastic water demand modelling for a better understanding of hydraulics in water distribution networks*. PhD, Water Management, Delft University of Technology, Netherlands.

Blokker E. J. M., Vreeburg J. H. G. and van Dijk J. C. (2010). Simulating residential water demand with a stochastic end-use model. *Journal of Water Resources Planning and Management* **136**(1), 19-26.

BOS (2011). Amsterdam in Cijfers, in Milieu en water. In: Amsterdam BOeS (ed.), Geemente Amsterdam.

Buchberger S. G. and Lin W. (1995). Model for instantaneous residential water demands. *Journal of Hydraulic Engineering - ASCE* **121**(3), 232-46.

Buchberger S. G. and Wells G. J. (1996). Intensity, duration, and frequency of residential water demands. *Journal of Water Resources Planning and Management - ASCE* **122**(1), 11-9.

Butler D. and Graham N. J. D. (1995). Modeling dry weather wastewater flow in sewer networks. *Journal of Environmental Engineering* **121**(2), 161-73.

CEN (2000). Gravity drainage systems inside buildings - Part 2: Sanitary pipework, layout and calculation. In, European Comitee for Standarization, Brussels, Belgum, p. 41.

De Paepe M., Theuns E., Lenaers S. and Van Loon J. (2003). Heat recovery system for dishwashers. *Applied Thermal Engineering* **23**(6), 743-56.

García V., García-Bartual R., Cabrera E., Arregui F. and García-Serra J. (2004). Stochastic Model to Evaluate Residential Water Demands. *Journal of Water Resources Planning and Management* **130**(5), 386-94.

Larrarte F., Joannis C. and Bonakdari H. (2010). Qualification and design of flow meter measurement sites within sewer networks. *Qualification et conception de sites de mesures débitmé triques en réseaux d'assainissement*(277), 31-41.

Lynggaard-Jensen A. (1999). Trends in monitoring of waste water systems. *Talanta* **50**(4), 707-16.

Persson T. (2007). Dishwasher and washing machine heated by a hot water circulation loop. *Applied Thermal Engineering* **27**(1), 120-8.

Scherer T. F. and Jia X. (2010). A simple method to measure the flow rate and volume from tile drainage pump stations. *Applied Engineering in Agriculture* **26**(1), 79-83.

Swaffield J. A. and Galowin L. S. (1991). *The engineered Design of Building Drainage Systems*. Ashgate, Great Britain.

van Wee B., Rietveld P. and Meurs H. (2006). Is average daily travel time expenditure constant? In search of explanations for an increase in average travel time. *Journal of Transport Geography* **14**(2), 109-22.

Wong L. T. and Mui K. W. (2007). Modeling water consumption and flow rates for flushing water systems in high-rise residential buildings in Hong Kong. *Building and Environment* **42**(5), 2024-34.