

Article

Empirical Sewer Water Quality Model for Generating Influent Data for WWTP Modelling

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Abstract: Wastewater treatment plants (WWTP) typically have a service life of several decades. During this service life, external factors, such as changes in the effluent standards or the loading of the WWTP may change, requiring WWTP performance to be optimized. WWTP modelling is widely accepted as a means to assess and optimize WWTP performance. One of the challenges for WWTP modelling remains the prediction of water quality at the inlet of a WWTP. Recent applications of water quality sensors have resulted in long time series of WWTP influent quality, containing valuable information on the response of influent quality to e.g., storm events. This allows the development of empirical models to predict influent quality. This paper proposes a new approach for water quality modelling, which uses the measured hydraulic dynamics of the WWTP influent to derive the influent water quality. The model can also be based on simulated influent hydraulics as input. Possible applications of the model are filling gaps in time series used as input for WWTP models or to assess the impact of measures such as real time control (RTC) on the performance of wastewater systems.

Keywords: sewer system; empirical model; influent generator; influent modelling; gap filling

1. Introduction

Modelling of wastewater treatment plants (WWTPs) using activated sludge models (ASM) has become a standard in both industry and academia for a range of objectives, amongst others WWTP design [1,2], operation [3], and control [4,5]. Especially the latter objective, developing control strategies and assessing the performance of control strategies requires high frequency influent data [6]. In a comprehensive review, [7] discussed the available approaches for generating influent data. The approaches range from (1) data driven methods based on creating databases with monitoring and experimental data and derived models using the data; (2) very simple models based on harmonic functions; and (3) phenomenological models [8,9].

The data driven methods comprise two different approaches. The first method [10] uses pollutant release patterns derived from literature to generate dynamic influent data aggregating the punctual emissions from the database. The second method [11] interpolates available influent data at e.g., a daily timescale to e.g., hourly dynamics.

The simple models based on harmonic functions are very well suited for the analyses of dry weather flow (DWF) situations, but less so for wet weather flow (WWF) situations [7].

The phenomenological models are the most detailed influent models, that can give a phenomenological representation of dynamics of WWTP influent, including diurnal patterns, weekend, seasonal, and holiday variations as well as rain events [7,8]. Despite being labelled as ‘promising’ [7], today’s phenomenological models cannot adequately reproduce the dynamics in WWTP influent during wet weather due to a relatively poor representation of the build-up and wash off of urban pollutants. This is also true for the most recently published influent generator by [12], who use a mix of statistical and conceptual modelling techniques for synthetic generation of influent time series.

The limitations associated with the use of influent generators are not surprising given the state of the art knowledge on the physical-chemical, biological and transport processes occurring in sewer systems [13–17]. Sediment transport especially is not very well understood and not very successfully reproduced in deterministic sewer models. This is partly due to the fact that it is currently not possible to get enough data on the initial sewer sediment conditions throughout an entire sewer network. It is interesting to note that the developers of influent generators, showing many similarities with simplified or parsimonious sewer models [18,19], are facing the same issues as sewer modelers in the past, i.e., how to incorporate the contribution of in-sewer stocks during storm events to the outflow of sewers via either combined sewer overflow (CSO) or WWTP influent.

In order to overcome the limitations of deterministic sewer models, regression models have been proposed, which are validated against monitoring data. A recent successful example of this approach is given by [20], who developed an empirical model for storm water total suspended solids (TSS), event mean concentrations with rainfall depth, and antecedent dry weather period as input variables. These empirical relations, that are valid at a CSO or storm sewer outfall (SSO), however, are not suitable for the prediction of WWTP influent quality, as these models do not predict the influent quality during DWF. For WWTP influent modelling, the empirical model described by [21], relates the influent concentration to the daily flows. A weak point of this approach is the impossibility to account for the dynamics during storm events. This is a major drawback, as storm events typically do not last a full day.

Recent applications of water quality sensors have resulted in the availability of long time series of WWTP influent quantity and quality [22,23]. These time series contain a lot of information on the response of influent quality to storm events and the contribution of in-sewer stocks to WWTP influent [24].

In this study, time series analysis is used to understand the dynamics of WWF related variations in WWTP influent quality and to relate the variation in influent quality to influent hydraulics. This allowed the development of an empirical model based on understanding of the underlying physical processes.

The paper is organized as follows: first, the available data set of WWTP Eindhoven is described. Second, the model development and calibration method are presented. Next, the calibration results, model results and the transferability of the concept are presented, discussed, and finally, some foreseen applications of the model are introduced.

2. Materials and Methods

2.1. System Description: The Dommel River IUWS

The Dommel river is relatively small and sensitive to loadings from CSOs and WWTP effluent. The river flows through the city of Eindhoven (the Netherlands) from the Belgian border (south) into the River Meuse (north). The Dommel receives discharges from the 750,000 people equivalent (PE) WWTP of Eindhoven and from over 200 CSOs in 10 municipalities. In summer time, the base flow in the river just downstream of the WWTP comprises 50% of WWTP effluent, increasing to 90% during small storm events. The Dommel River does not yet meet the requirements of the European

only 38.5% of the data was considered to have an acceptable quality during the condition required. This percentage of data perceived ‘good enough’ after validation may seem relatively low. During earlier research projects (2007–2008) at WWTP Eindhoven on UV-VIS sensors, the percentage of ‘good enough’ data after data validation ranged between 50% and 75%, despite very intensive maintenance and surveillance [23] and without restrictions on the influent conditions. WWTP influent has shown to be a very difficult medium for water quality monitoring. The dataset after validation comprises approximately 30 storm events with good data for each calibration performed. In the model calibration, these events, including the antecedent dry day and several following dry days, were used. In Figure 2, and all other Figures, the data used for calibration is represented by the dark grey bullets, data not used for calibration with light grey bullets. An assessment of routine 24 h water quality samples of WWTP influent showed that the DWF does not show a noticeable seasonal pattern.

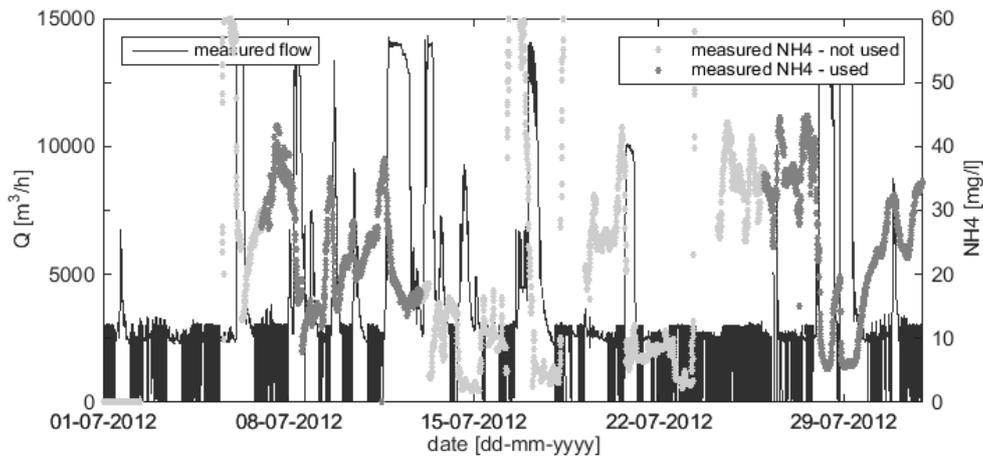


Figure 2. Example of quality evaluation of monitoring data.

2.3. Data Analysis

In earlier work [16], a part of this data set was used to study the dynamics of wastewater composition. This resulted in well described typical diurnal patterns during DWF and typical dynamics during WWF (Figure 3).

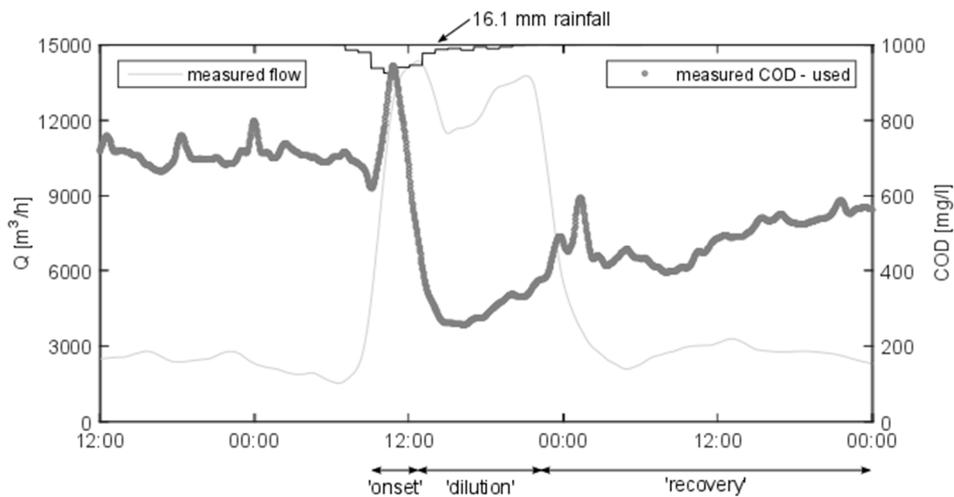


Figure 3. Wet weather flow (WWF) dynamics during the stages of a storm event on 12 June 2008 in Eindhoven Stad catchment.

For WWF, it has been observed that the concentration levels of the wastewater show a typical pattern during a storm event: a short period called ‘onset’ of the storm event, with an increased concentration level for particulate matter but not for dissolved matter, a longer period called ‘dilution’, where dilution of both dissolved and particulate matter takes place, and ‘recovery’, a period where dissolved and particulate matter slowly return to DWF levels.

2.4. Model Development

The general idea behind the model development is that the measured hydraulic influent data, i.e., flow and water level in the influent pumping station, can be used to make a distinction between the four patterns: DWF, onset of WWF, dilution during WWF and recovery after WWF. Each of these patterns is denoted as a system state, during which a certain relation between flow and concentration level applies. This allows the incorporation of the contribution of in-sewer stocks on top of the mixing process between wastewater and stormwater. The latter is a common feature of influent models applied to simulate both dry and wet periods, while explicitly accounting for the contribution of in-sewer stocks circumventing the relatively limited knowledge associated in sewer processes.

The water quality average dry weather diurnal pattern is the core of the model. As long as the system state is ‘DWF’, the average dry weather diurnal pattern based on monitoring data is used, together with the measured flow data. The average dry weather diurnal pattern has been derived from flow monitoring data by averaging the monitoring data of 10 dry days over 5 min intervals with the same timestamp.

During wet weather, the model superimposes a number of processes on the DWF pattern for water quality to mimic onset, dilution, and recovery. The type of parameter (NH_4 or COD) and the type of event (small, medium or large) determine which of these processes is to be applied. The type of event is used as characteristic of a storm event, as it was found that the relation between flow and concentration levels differs very much between small, medium, and large storm events. The measured hydraulics, in this case the flow and water level in the influent pumping station, are used to determine which of the described processes should be activated in the model, using the scheme of Figure 4.

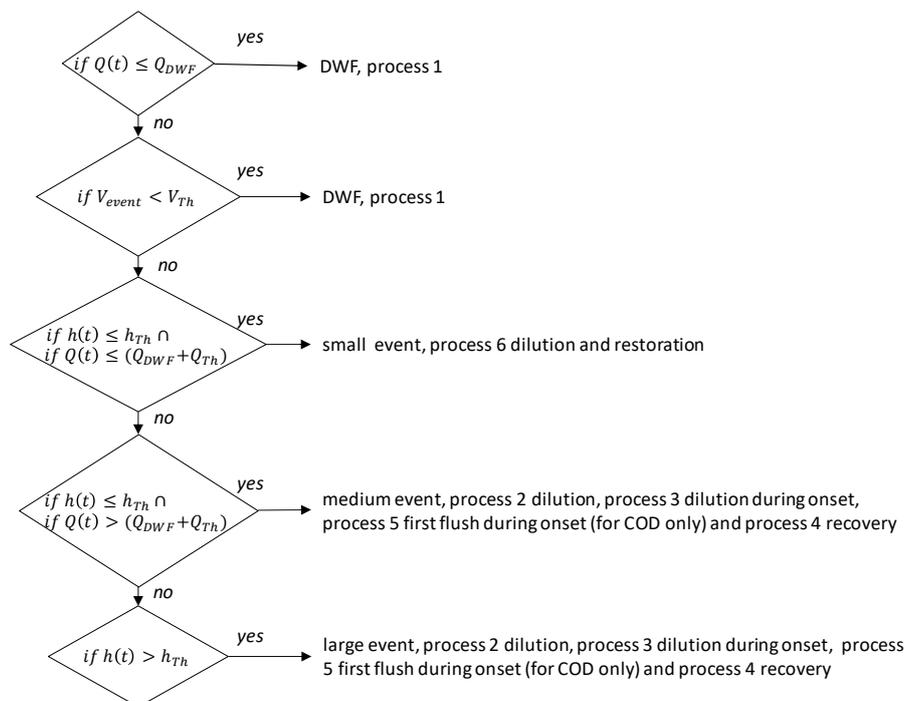


Figure 4. Selection of water quality processes to be superimposed on process 1 during dry weather (DWF), using information on hydraulics. The abbreviation Th in the figure is short for threshold.

As indicated in Figure 4, two conditions have to be met to change from DWF to WWF. The first is that the upper limit for dry weather conditions (Q_{DWF} , set at the 95th percentile of the flow values collected during dry weather at a specific timestamp) has to be exceeded, the second that the volume should exceed a certain threshold (set at 5000 m³). The second condition is added to exclude apparent events in the data caused by interference of the pump operation due to for example to maintenance. The value of 5000 m³, equivalent to the volume of 2 h of DWF, shown to be sufficient to filter flow values exceeding Q_{DWF} due to operational issues during DWF.

A small storm event is defined as an event for which the water level in the influent chamber does not rise above the DWF threshold value (set at 11.30 m AD) and the flow exceeds the 95 percentile DWF value with less than a threshold set at 4000 m³/h. These events are very small storm events, where the inflow is less than 0.2 mm/h or 2 m³/ha). Medium events are defined as events where the water level in the influent chamber does not exceed the DWF threshold value, but the flow exceeds the 95 percentile DWF value with more than the threshold. These events are typically relatively small, low intensity storm events, where the inflow is less than the available pumping capacity (which is equal to an interceptor capacity of 0.7 mm/h or 7 m³/ha). Large storm events are defined as events during which not only flow increases, but also the water level in the influent pumping station increases above the DWF threshold value. This occurs only if the sewer system starts filling during bigger storm events exceeding the pumping capacity of the WWTP.

The processes applied in the model are:

Process 1 the basic process for all parameters, is the DWF pattern for water quality. It is derived from high-frequency monitoring data collected during multiple dry weather days, by averaging over the same time stamps.

Process 2 mimics dilution and is based on the ratio between the actual flow (Q_{actual}) and the upper limit for the flow during DWF at that time of the day at the location of the WWTP inlet works (Q_{DWF}). The wastewater concentration is calculated using Formula (1):

$$C_{WWF}(t) = C_{DWF}(t) (a_1 Q_{DWF}(t)/Q_{actual}(t) - a_1 + 1) \quad (1)$$

With C_{WWF} = calculated concentration during wet weather, and C_{DWF} = the concentration during DWF conditions at that time of the day. The dilution factor a_1 (-) is introduced to allow adjustment to the dilution rate if necessary. A value of 1 for factor a_1 indicates that the dilution is exactly inverse to the increase in flow. A value of a_1 smaller than 1 would impose an increase in pollutant loads during the event, which could be necessary to account for pollutant contributions originating from in-sewer stocks. A value of a_1 larger than 1 would impose a decrease in pollutant loads during the event, which could be expected for a compound where in-sewer stocks are zero and a part of the pollutants would be discharged via a CSO. For low dilution ratios, i.e., $Q_{DWF}(t)/Q_{actual}(t)$ being close to 1, the factor a_1 has a limited influence, for higher dilution ratios, the factor a_1 contributes to a larger extent.

Process 3 accounts for dilution during the onset of storm events. Process 3 is described by a parabolic function, valid for the period between the start of the storm event and the moment of the maximum dilution. The length of this period, the duration of the onset a_3 , is determined during model calibration. This process is necessary to account for the delayed dilution observed in the monitoring data, see Figure 5. During the first part of the event on 28 July 2012, the influent flow increased rapidly to the maximum flow rate of 14,000 m³/h, while the NH₄ concentration gradually reduced to a minimum of 5 mg NH₄/l. Using Formula (1) during the onset of the storm event, would result in an overestimation of the dilution. Instead, Formula (3) applies during the onset of the storm event:

$$C_{WWF}(t) = C_{DWF}(t) \times (\text{dilution depth}/a_2^2) \times (t - t_{\text{end onset}})^2 - \text{dilution depth} + 1 \quad (2)$$

where a_2 = duration of onset and dilution depth = the minimal ratio $C_{DWF}(t)/C_{WWF}(t)$ during the onset of the storm event. Figure 5 shows how the parameters in the parabolic function of Formula (2) are defined.

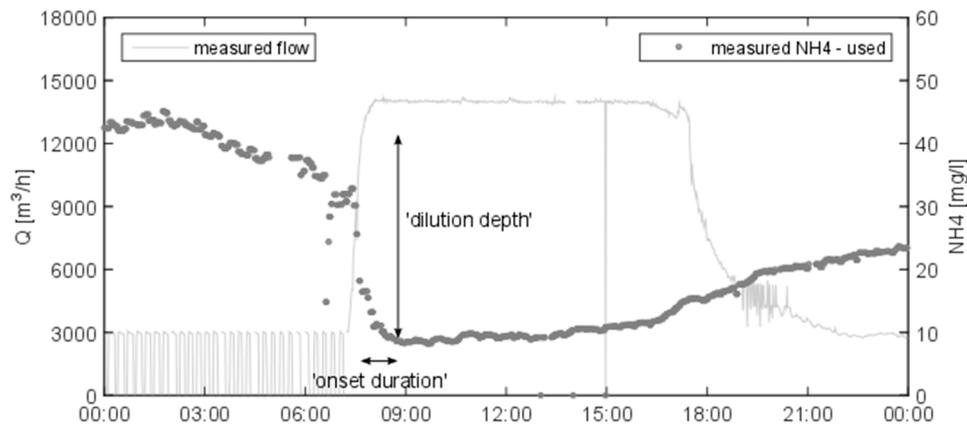


Figure 5. Parameters of parabolic function that describes the delayed dilution of the quality parameters compared to the flow.

Process 4 reproduces restoration, which describes the gradual return of concentration values to DWF values after the storm event. Based on the analysis of the available data set, restoration can be assumed to be a linear process at rate a_3 (mg/(L·s)) until the concentration returns to the DWF value. During the restoration phase, the concentration is calculated by:

$$C_{WWF}(t + 1) = C_{WWF}(t) (1 + a_3) dt. \quad (3)$$

Process 5 describes a first flush in concentration levels of particulate material (see Figure 3), it is thus not valid for soluble substances. This initial peak increases the concentrations during the first stage of storm events, before dilution becomes the dominant process. Process 5 is modeled as a triangle that causes an instant increase of the COD concentration of a_4 mg/l at the onset of the event, decreasing with a fixed rate a_5 (mg/(L·s)).

Process 6 regards dilution and restoration for small events. Process 6 describes the concentration profile as a fixed-shape triangle, where dilution takes place at a fixed rate a_6 (mg/(L·s)) during x h and recovery at the same rate a_6 (mg/L/s) during the next x h. In the case of Eindhoven Stad and Riool Zuid a duration of 13 h proved to be a good estimate of the duration of process 6.

2.5. Model Calibration

In this study the differential evolution adaptive metropolis (DREAM) algorithm is the method [30,31] applied to calibrate the parameters of the empirical model to find the minimal difference between the empirical model output and the monitoring data. The effectiveness of DREAM in water related model calibration has been demonstrated in many previous studies, e.g., [32–34].

Table 1 shows the model parameters, units and the searching range for the calibration procedure. The threshold values for selecting the type of event were derived during data analysis before the calibration of the model parameters and were consequently not included in the model calibration. Future users of the model on other catchments may include these parameters as part of the model calibration. For reasons of clarity, these parameters are listed here:

V_{Th} : threshold value for making distinction between real storm events and irregularities in the DWF due to operational issues. In this study set at equivalent of 2 h of DWF.

Q_{Th} : threshold value to distinguish medium from small storm events. Set in this study at an equivalent of 0.2 mm/h of runoff.

h_{Th} : threshold value to distinguish large from medium storm events. Set in this study at 0.30 m above the setpoint of the frequency controlled pumps.

x : duration of dilution and restoration for small events: Set in this study at 13 h.

Table 1. Model parameters, units, and search range. COD = chemical oxygen demand.

Model Parameter	Abbreviation	Unit	Search Range	Parameter
dilution factor	a_1	-	0–2	NH_4 , COD
dilution delay factor	a_2	minutes	0–600	NH_4 , COD
recovery factor	a_3	$\text{mg}/(\text{L}\cdot\text{s})$	0–0.01	NH_4 , COD
peak first flush concentration	a_4	mg/l	0–2000	COD
recovery factor first flush	a_5	$\text{mg}/(\text{L}\cdot\text{s})$	0–10	COD
recovery factor small events	a_6	$\text{mg}/(\text{L}\cdot\text{s})$	0–0.01	NH_4 , COD

The calibration is performed using 5000 iterations in DREAM for the COD model and 2500 for the NH_4 model, as it was found from test runs that the cumulative density functions of the parameters do not change (within the parameter stability) after a few thousand iterations. The last 50% of the iterations are used for further analysis: the optimal parameter set and model output are derived, and the model is run with all these parameter sets to determine the 95% confidence intervals for the NH_4 and COD concentrations.

3. Results and Discussion

This section presents an overview of the model results, a discussion of their quality and the transferability of the model concept. The model was first developed, tested and calibrated on data of Eindhoven Stad only and the data from the subcatchment Riool Zuid were used to be able to discuss the transferability of the concept.

3.1. Calibration Results

The DREAM algorithm was applied with a total of 5000 iterations for the COD model and 2500 for the NH_4 model. The algorithm uses $2 \times n$ Markov Chains, with n being the number of model parameters being evaluated. This resulted in 312 iterations for the COD model and 208 iterations for the NH_4 model. Figure 6 shows the variation in model parameter values during the calibration process for the model for NH_4 for catchment Eindhoven Stad for the first Markov Chain of each iteration. Parameters concerning medium and large storm events are denoted in Figure 6 as subscripts M and L respectively. The value of each of the model parameters is relatively stable during the calibration process, showing that the number of iterations was sufficient to converge.

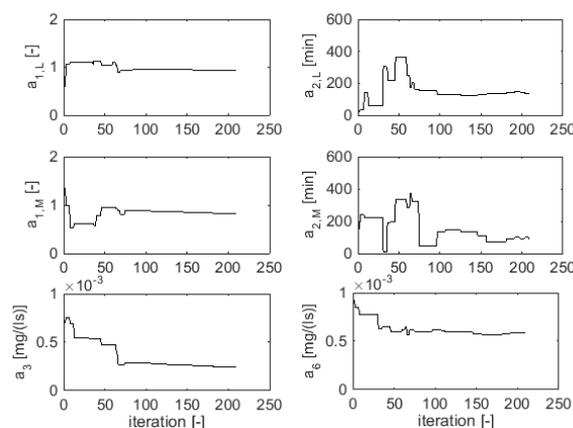


Figure 6. Parameter values during model calibration. For each iteration, only the first Markov Chain of the parameter set is shown.

The correlation between the model parameters was found to be limited from Figure 7, showing a high identifiability of the model parameters.

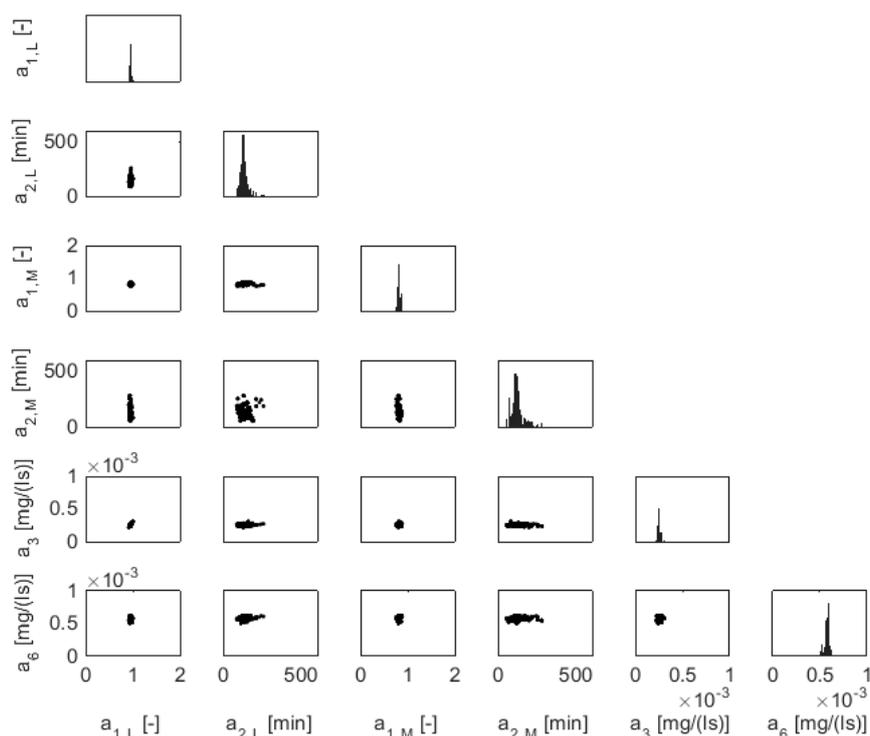


Figure 7. Posterior distribution of model parameters a_1 to a_6 for the NH_4 model for catchment Eindhoven Stad based on the second 50% of the iterations. The histograms represent the posterior distribution of individual model parameters and the scatter plots represent the relationships for various combinations of parameters.

The model parameter values are shown in Table 2 for the NH_4 and COD model. For the NH_4 model, there is no strong need to make a distinction between large and medium storms, as the model parameters are rather similar. For COD, however, the model parameters differ strongly for large and medium storm events. A value of 1 of the dilution factor would mean no contribution of in-sewer stocks and only perfect dilution, values below 1 would indicate a contribution of in-sewer stocks. The values for the dilution factor for NH_4 are just below 1, indicating that for NH_4 the contribution of in sewer stocks is relatively limited. For the COD, however, the values of a_1 are quite low. A value for a_1 of approximately 0.5 leads to $C_{\text{WWF}} = 0.57 \times C_{\text{DWF}}$ based on Formula (1) and the maximum ratio between Q_{actual} and Q_{DWF} ($15,000/2100 = 7.1$). This means that at a flow of $15,000 \text{ m}^3/\text{h}$, the concentration in the WWTP influent is still $0.57 \times C_{\text{DWF}}$. Consequently, the influent load at that moment will be approximately 4 (7.1×0.57) times the DWF load. This peak load factor was observed regularly in monitoring data for this catchment [23].

Table 2. Model parameters values for NH_4 and COD model for Eindhoven Stad Catchment. Subscript M and L in model parameters denote medium and large storm events.

Model Parameter	Abbreviation	NH_4 Model	COD Model
dilution factor, large storms	$a_{1,L}$	0.95 (-)	0.63 (-)
dilution delay factor, large storms	$a_{2,L}$	123 (min)	342 (min)
dilution factor, medium storms	$a_{1,M}$	0.82 (-)	0.47 (-)
dilution delay factor, medium storms	$a_{2,M}$	115 (min)	589 (min)
recovery factor	a_3	0.00025 (mg/(L·s))	0.00014 (mg/(L·s))
peak first flush concentration	a_4	Not applicable	48 (mg COD/(L·s))
recovery factor first flush	a_5	Not applicable	0.19 (mg COD/(L·s))
recovery factor small events	a_6	0.00059 (mg/(L·s))	0.00017 (mg/(L·s))

3.2. Model Results

Figure 8 shows the resulting predicted water quality and the measured water quality for NH_4 in the WWTP influent for Eindhoven Stad.

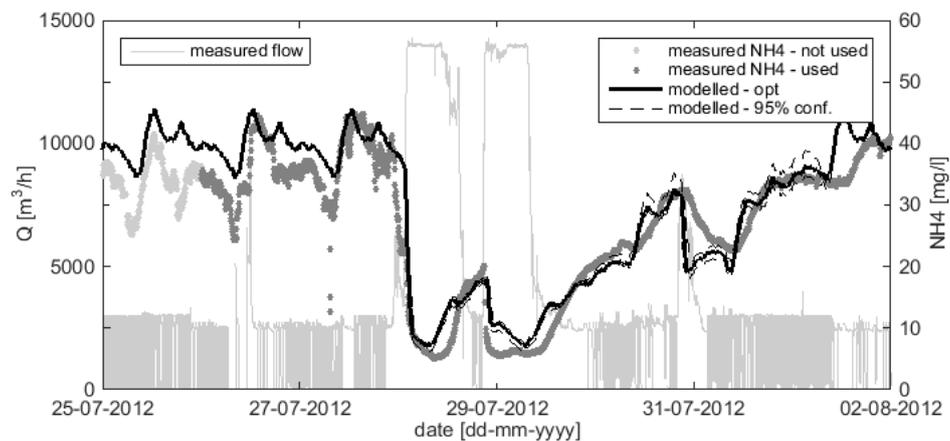


Figure 8. Model vs. monitoring data: NH_4 concentration in the wastewater treatment plant (WWTP) influent.

The results show that the dynamics in the model (solid black line) and the monitoring data (grey dots) show an overall good agreement in terms of dynamics and values during wet weather during the large events of 28 and 29 July. In the monitoring data, dilution starts a little bit earlier than in the model. During the medium event on 31 July, the model fit is less satisfying. During dry weather (25 July till 28 July), the daily variation in the measured concentration of NH_4 is represented well by the model. The remaining differences are due to the fact that the DWF dynamics in the model represent the average DWF concentration levels and the DWF varies per day. The root mean squared error (RMSE) for the NH_4 model based on the data used in the calibration is 6.3 mg NH_4 /l, or nearly 16% related to the mean DWF concentration. Figure 9 shows the normalized cumulative density function (CDF) of the model results and the monitoring data for NH_4 and COD. Both the RMSE and the CDF are based on the entire dataset used for modelling, which includes all storm events with sufficient data quality and the dry days preceding and following the storm event. As expected, the high concentrations, which occur during DWF, are not captured very well due to the daily variation in DWF concentrations. At lower concentration levels, the agreement between model and monitoring data is reasonable.

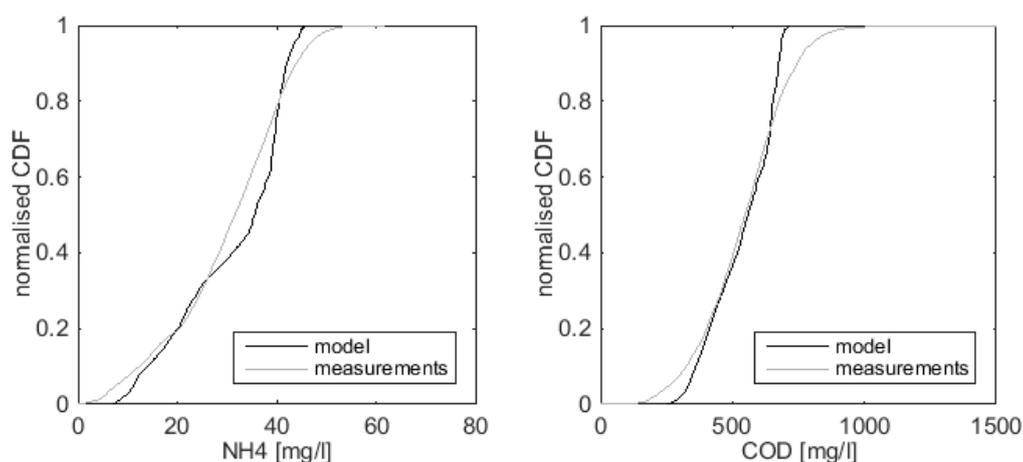


Figure 9. CDFs of model results and measurements for NH_4 and COD in WWTP influent for the Eindhoven Stad (ES) catchment.

The COD model also incorporates process 5 describing the peak first flush concentration that was observed in the monitoring data, see Figure 3. The model results for the COD model for the Eindhoven Stad catchment are shown in Figure 10. As expected, the model fit is not as good as the model fit for NH_4 , which is partly due to the difference in the quality of the monitoring data, illustrated by the outliers in the monitoring data shown in Figure 10 and partly due to the fact that modelling suspended solids is much more difficult than modelling of solutes. The RMSE for the COD model based on monitoring data used in the calibration is 109 mg COD/l, equivalent with 18% of the mean DWF concentration. This RMSE for COD is in relative terms comparable to the RMSE for NH_4 .

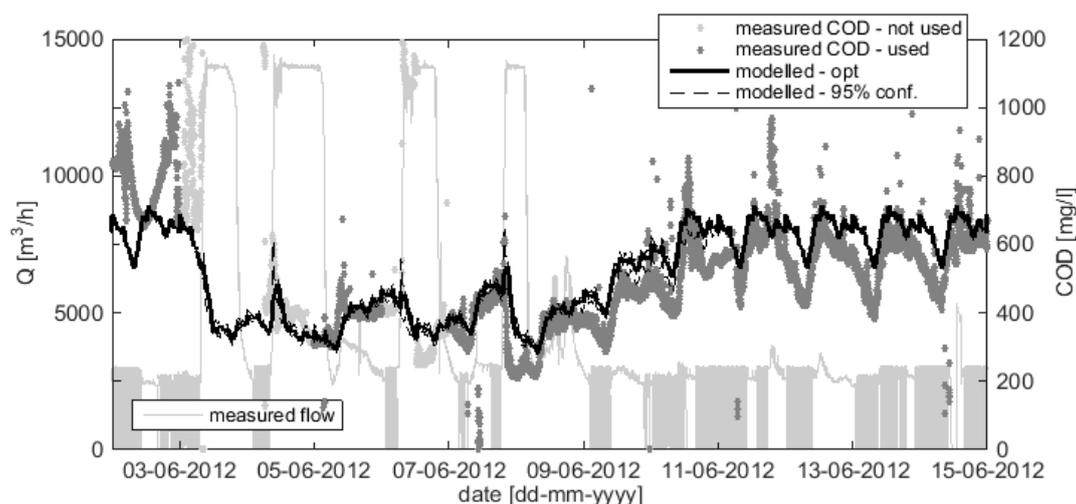


Figure 10. Model vs. monitoring data: $\text{COD}_{\text{total}}$ in the WWTP influent for Eindhoven Stad. The small peaks in influent concentration (typically referred to as ‘first flush’) at the beginning of storm events on 4 June, 6 June and 8 June are adequately represented by the model.

The influent model has been developed to be used to deliver input for WWTP models that is reliable enough to assess WWTP performance and to assess the impact of measures, such as real time control (RTC) in wastewater systems. An earlier version of this influent model presented has already been used for this purpose in the KALLISTO project at water board De Dommel [26,28]. The current version is applied in the assessment of the performance of the smart buffer concept at WWTP Eindhoven [29]. The values for the RMSE for NH_4 just meet the quality requirements for WWTP influent data derived by [35], while for COD they easily meet these requirements. This shows that the influent model is sufficiently good for the described modelling purposes.

3.3. Transferability of the Concept

The structure of the influent model was developed for the catchment Eindhoven Stad (ES) only. The data from the catchment Riool Zuid (RZ) were used to verify the concept, using the same routines for calibration. With respect to the transferability, it has to be noted that the subcatchments ES and RZ are independent catchments, allowing the transferability of the concept to be tested.

The model parameters are shown in Table 3. For catchment RZ, the model parameters for medium and large storms are very similar for both the NH_4 and COD model, showing that this distinction between large and medium events is not necessary for this catchment. The model parameter values for the dilution factor a_1 for the RZ catchment show a strong similarity with the model parameters for the ES catchment. For NH_4 , the dilution during the storm event, calculated by Formula (1), remains nearly reciprocal to the increase in influent flow during the storm event. This indicates that during the storm event, nearly all nitrogen in the WWTP influent stems from the wastewater, with only very limited contributions from the rainfall runoff and the in-sewer stocks.

Table 3. Model parameters values for NH₄ and COD model for Riool Zuid Catchment. Subscript _M and _L in model parameters denote medium and large storm events.

Model Parameter	Abbreviation	NH ₄ Model	COD Model
dilution factor, large storms	a _{1,L}	0.96 (-)	0.49 (-)
dilution delay factor, large storms	a _{2,L}	373 (min)	590 (min)
dilution factor, medium storms	a _{1,M}	0.98 (-)	0.49 (-)
dilution delay factor, medium storms	a _{2,M}	427 (min)	548 (min)
recovery factor	a ₃	0.00033 (mg/(L·s))	0.00034 (mg/(L·s))
peak first flush concentration	a ₄	Not applicable	60 (mg COD/(L·s))
recovery factor first flush	a ₅	Not applicable	0.06 (mg COD/(L·s))
recovery factor small events	a ₆	0.00027 (mg/(L·s))	0.00002 (mg/(L·s))

For the COD, the dilution factor of a₁ of 0.49 results in COD concentration levels during the high flow period of storm events of between 250 and 300 mg COD/L and, as a consequence, high influent peak loads. This additional load arriving via the influent at the WWTP during a storm event originates mainly from the in-sewer stocks [15], given the fairly low COD concentration in Dutch stormwater of 61 mg COD/L [36].

The overall model performance for the RZ catchment, expressed in terms of RMSE, is comparable with the performance for the ES catchment. The RMSE amounts to 8.9 mg NH₄/L, equivalent with 22% of the mean DWF value for the NH₄ model and to 126 mg COD/L, equivalent with 25% of the mean DWF value for the COD model. As for Eindhoven Stad, the cumulative density function for model results and monitoring data show reasonable agreement for both NH₄ and COD, see Figure 11, with once again the biggest differences being in the higher (DWF) concentration ranges.

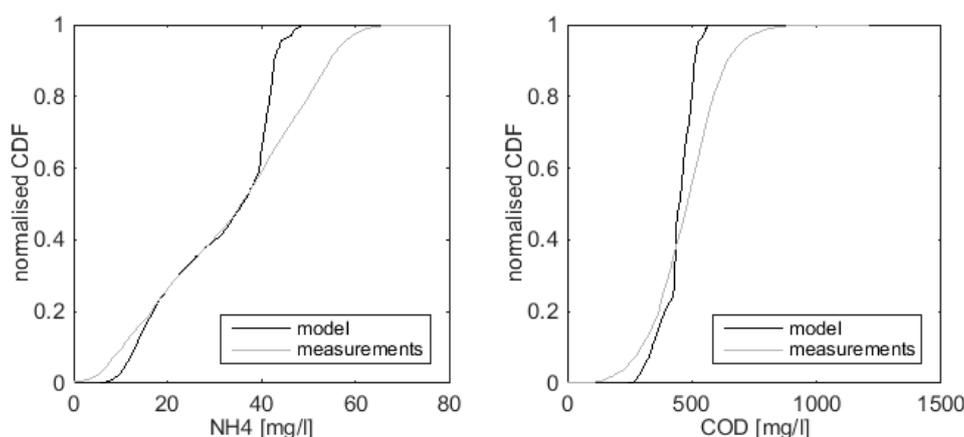


Figure 11. CDFs of model results and measurements for NH₄ and COD in WWTP influent for the Riool Zuid (RZ) catchment.

As there was no need to change the model structure, it was concluded that the model is in principle transferable to other catchments, provided that the dynamics during WWF show similar patterns as described in Figure 3. Literature confirms these patterns to be fairly general [37,38], A number of distinct phases in the influent pollutograph are defined during storm events:

Phase 1) increase of flow rate and subsequently an increase of the load arriving at the WWTP due to the ‘push’ of wastewater with DWF concentration levels. This phase is more distinct the more wastewater is stored downstream in either large interceptor sewers or rising mains.

Phase 2) increased concentration of suspended solids as eroded sewer sediments start to arrive at the WWTP. These sediments are usually transported with a velocity lower than the fluid velocity [14].

Phase 3) arrival of diluted wastewater at the WWTP.

Phase 4) return to DWF equilibrium. Equilibrium for dissolved compounds will be reached as soon as all remaining storm runoff has been transported (pumped) towards the WWTP. Reaching equilibrium for suspended solids may last longer since it takes time before all depressions within the sewer system are filled again with sediment.

Phases 1 and 2 are both part of the onset of the storm event, phase 3 is similar to the dilution stage, while phase 4 relates closely to the stage of recovery after the storm events. Despite the need of further research on the transferability, the similarities in system dynamics strongly indicate a wider applicability of the model than just for Eindhoven Stad and Riool Zuid.

The consistency in the dilution factors for NH_4 and COD for Eindhoven Stad and Riool Zuid (with dilution factors for NH_4 just a little smaller than 1, indicating a small contribution of in-sewer stocks and dilution factors for COD around 0.5, indicating a large contribution of in-sewer stocks) demonstrate that the empirical model is able to capture the contribution of in-sewer stocks during the dilution phase of the event adequately. This is an important benefit of the model compared with influent generators reviewed by [7]. The differences in model parameters related to the first flush and recovery after the event seem to be linked to the differences in lay out of the sewer system. Future research is necessary to further elaborate on the relation between parameter values and physical characteristics of the catchment. The amount of in-sewer storage relative to the pumping capacity of the WWTP will likely be related to the length of the recovery period, as these characteristics determine the emptying time of the sewer system, which will be related to the length of the recovery.

The differences in performance, although relatively small, can be attributed to the different characteristics of the RZ catchment and possibly also to the limited quality of the sensor data. This is illustrated by Figures 12 and 13. In Figure 12, the results for NH_4 are shown for the RZ catchment for the week after 16 July and in Figure 13 for the first two weeks of December 2012. During the events of 17 July and 21 July, the monitoring data show two distinct dilution phases during the events. One dilution phase occurs at the beginning of the storm event and one at the end. This phenomenon does not occur during the storm events of 2 and 4 December, but to a lesser extent on 10 December. The Riool Zuid catchment (the light grey catchments in Figure 1, left) has a very different structure compared with 'Eindhoven Stad' (the dark colored central catchment in Figure 1, left). While the ES catchment is a gravity system draining to one central point, the RZ catchment is 32 km long with a number of subcatchments of various sizes at different distances. It is assumed that the double dip is caused by a difference in transport times for two main areas in this catchment, which causes the concentrations to drop for a second time during a storm event. The double dilution dip is of course driven by rainfall and as a result, the spatial variation in the rainfall is the main explanatory factor for the differences per event.

In the model, this effect could be mimicked by dividing the Riool Zuid catchment into two catchment basins, with a cut at pumping station Aalst, see Figure 1 (left), and to add the transport time in the transport sewer to one of the basins. However, as the error made in the model results is relatively small due to the low influent flows, this adjustment was not considered necessary at this moment.

The base line of the model consists of the mean DWF concentration. Data analysis of available 24 h composite samples of the WWTP influent showed that there was no seasonal trend for NH_4 and COD. Despite the absence of a seasonal trend, the mean DWF concentration varied during the monitoring period. Due to a lack of sampling data, it could not be determined whether changes in this DWF concentration level were due to real changes or due to e.g., a temporary drift of the sensor. Differences in the main DWF concentration levels were observed for NH_4 , e.g., compare the concentration levels on 16 July in Figure 12 (around 40 mg/L) and 1 December in Figure 13 (around 55 mg/L). This difference is even bigger for COD, see Figure 14. The mean DWF, derived from monitoring data, is nearly 500 mg COD/L, while the monitoring data on 2 June are nearly 700 mg COD/L. In this study, the model has been calibrated using the mean DWF derived from all available monitoring data during DWF.

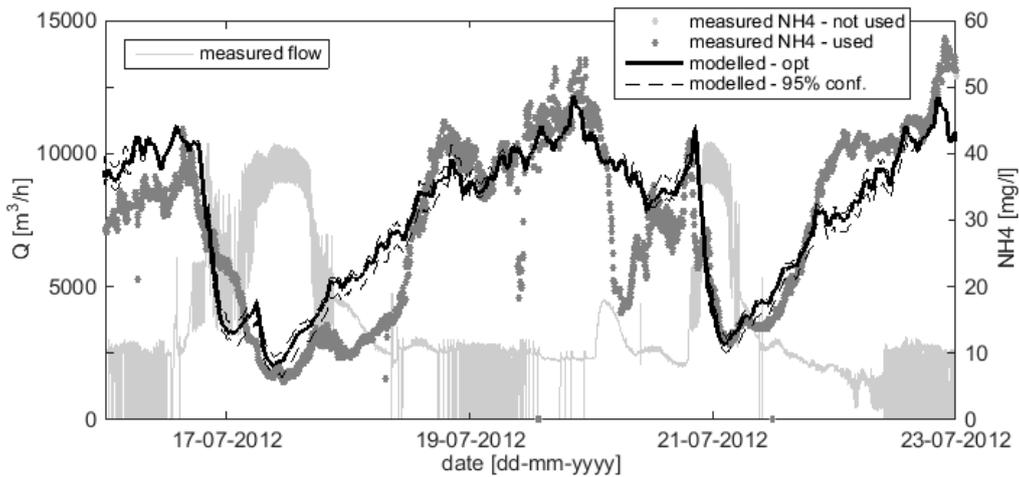


Figure 12. Model vs. monitoring data: NH₄ concentration in the WWTP influent catchment Riool-Zuid between 16 July and 23 July. ‘Double’ dilution dips occur at 17 July around noon and 18 July around midnight and on 21 July at 2:00 a.m. and 12:00 a.m.

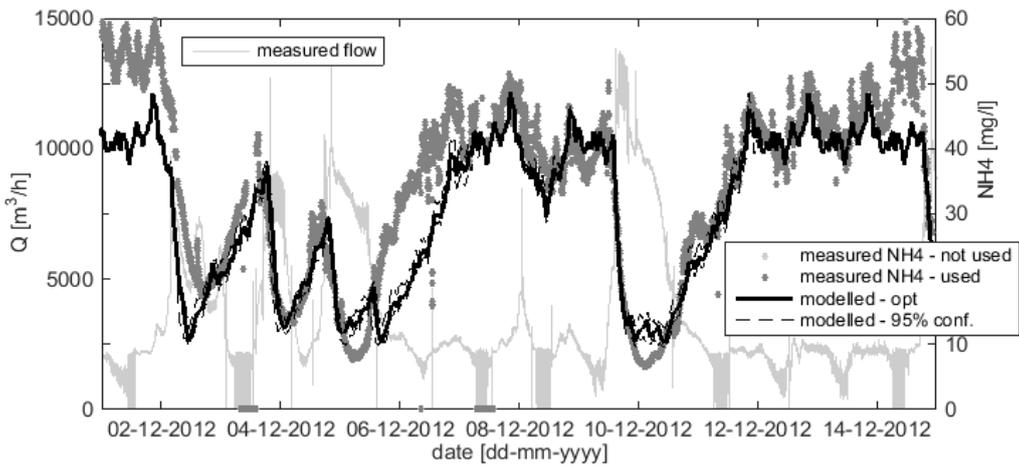


Figure 13. Model vs. monitoring data: NH₄ concentration in the WWTP influent catchment Riool-Zuid between 1 December and 15 December.

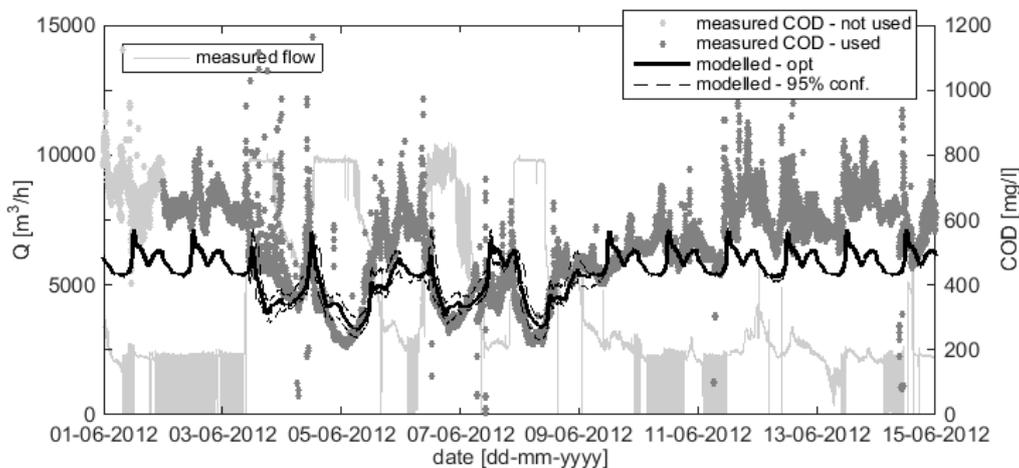


Figure 14. Model vs. monitoring data: COD concentration in WWTP influent catchment Riool-Zuid.

Finally, the results shown in this paper are based on NH_4 and COD only, where NH_4 is representative for solutes predominantly derived from wastewater and COD for parameters for which the in-sewer stocks, i.e., sediment and biofilm, contribute significantly to the pollutant load in the influent during storm events [24]. For WWTP modelling other parameters, such as phosphorous, also need to be taken into account. Total phosphorous is known to exert similar behavior as the COD and consequently, the COD model may be used to recalculate the total phosphorous concentration. Ortho-phosphate, on the other hand, is dissolved and behaves in the sewer like NH_4 [37] and consequently, the NH_4 model may be used.

3.4. Applications: Influent Generation, Surveillance of Monitoring Equipment and Gap Filling

The influent model as described in this paper generates influent water quality dynamics using measured influent hydraulics as input. This application was used in [29] to evaluate the performance of integrated RTC for urban wastewater system Eindhoven.

Another application of the influent model is described in [28], where (an earlier version of) the influent model was implemented in the WEST software [28] to generate influent water quality dynamics based on the simulated influent water quantity by the sewer sub model. In this application, a representative DWF curve based on monitoring data was used [28]. It would also have been possible to use harmonic functions for DWF and to use the influent model to complement the time series with WWF dynamics. In other words, the influent model can be applied on measured or simulated hydraulics and may also be applied in combination with the harmonic functions described in the introduction. Moreover, as the empirical influent model is developed to adequately mimic WWF dynamics, it might be included in the phenomenological influent pollutant disturbance scenario generator [9], which is the latest version of the phenomenological model developed by [8], replacing the relatively weak sewer model module of this model.

The influent model can also be used for surveillance of monitoring equipment at the inlet of the WWTP. e.g., earlier research has shown that the hydraulic monitoring data at WWTP Eindhoven is very reliable with over 99% good data [23]. Running the influent model continuously on measured hydraulic data and comparing raw monitoring data of the influent water quality with the simulated influent water quality data would allow easy detection of anomalies in the monitoring data. This could be used to alarm operators to check the monitoring equipment. Early detection of problems with sensors will possibly result in a higher yield of good quality data.

A final application of the influent model discussed in this paper is gap filling in time series [39]. Figure 15 shows an example of the application of gap filling. The dots show the measured NH_4 concentration in the influent of WWTP Eindhoven. The dark grey dots are data that could be used e.g., for assessing the performance of the influent model, the light grey dots show data that are rejected during the validation. The black line shows the simulated concentrations by the influent model. By applying gap filling a continuous time series is generated, the final time series is composed of the dark grey dots and where these are missing data are filled in using the influent model results.

For some of the potential applications of the model, such as gap filling or data validation, it is advisable to regularly check the absolute value of the sensor data during DWF to ascertain whether changes in the DWF concentration level are due to real changes or due to a sensor drift. In case these are due to e.g., seasonal variation in the influent concentration levels during DWF, this should be accounted for when applying the influent model. The routine 24-h samples typically available for WWTP influent may be used to check for a seasonal pattern.

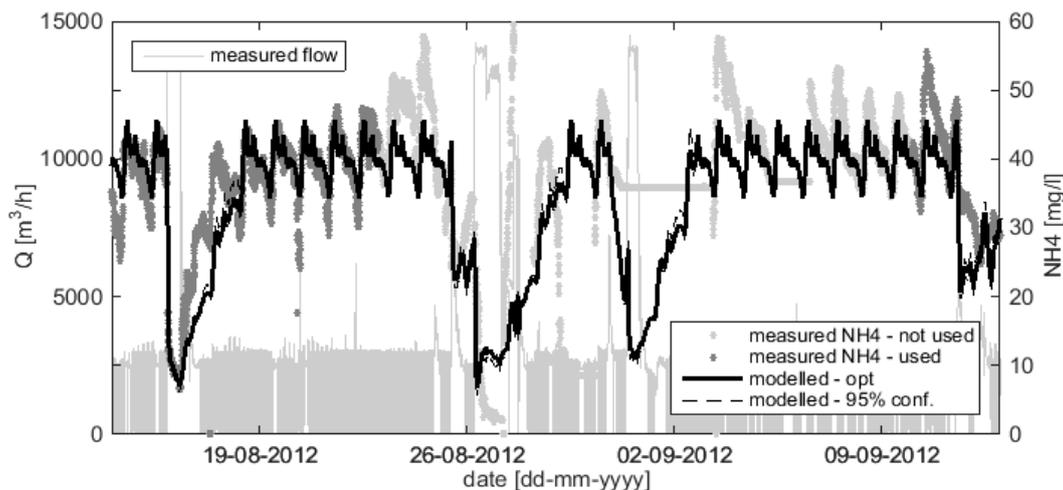


Figure 15. Gap filling with the influent model. Example for NH_4 in WWTP influent catchment Eindhoven.

4. Conclusions and Outlook

Modelling of influent quality is an increasingly important tool to enable WWTP models to optimize the performance of WWTPs during wet weather. The main issue in modelling wastewater quality during storm events is to account for in-sewer stocks, which have a varying contribution to the wastewater quality. Neither traditional sewer water quality models nor the available influent generators are capable of adequately addressing this issue. The proposed empirical model is based on a detailed study of the observed water quality and predicts it by combining a number of actual processes such as DWF, dilution, restoration, and first flush. Overall, the model shows that it is able to reasonably predict NH_4 concentration, which is a solute substance, as well as to reasonably predict COD concentration, which is to a large extent associated with particles.

The model structure was demonstrated to be transferable to a catchment with different characteristics. Eindhoven Stad is a large catchment with the WWTP located near the center, Riool Zuid comprises of a long interceptor sewer, which drains the wastewater from seven municipalities with a range of catchment sizes. Due to spatial variation of the rainfall and variation in travel times, ‘double dilution’ dips may occur in the influent coming from Riool Zuid. Despite these different dynamics and characteristics, there was no need to adjust the model structure of the empirical influent model. Future research in catchments in sewer systems with less in-sewer storage volume is needed to further explore the transferability of the model concept.

The model concept is used in ongoing research to test the performance of RTC of smart buffers at WWTP Eindhoven [28]. The model concept could also be used to fill gaps in time series for influent water quality and be used for advanced data validation to detect outliers and drift of water quality sensors, as these sensors are still very vulnerable and data quality control remains a difficult issue.

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