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Predictive maintenance of pipe networks - Smart technology for optimised flushing of sewer lines

Master's thesis in Infrastructure and environmental engineering

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CHALMERS UNIVERSITY OF TECHNOLOGY

Gothenburg, Sweden 2026

www.chalmers.se

MASTER'S THESIS 2026

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Master's Thesis 2026

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Cover: Flushing vehicle during an operation. Photo by Jonas Lunding Andersson,
Sustainable Waste and Water, City of Gothenburg.

Typeset in L^AT_EX

Printed by Chalmers Reproservice

Gothenburg, Sweden 2026

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Abstract

Reoccurring blockages in sewer systems may reduce flow capacity and increase the risk of sewer overflows, resulting in environmental and societal consequences. To minimise the occurrence of such events, regular maintenance flushing of sewer lines with known blockage-related issues can be performed. Converting from a strategy based on pre-scheduled time-intervals to a predictive maintenance strategy could optimise these operations. This study investigates how a predictive maintenance strategy based on water level measurements from sensors mounted in manholes can be designed and implemented. The data analysed in the project was collected from two sensors installed by Sustainable Waste and Water (SWW), in Gothenburg, along with twenty datasets from sensors in Malmö, provided by VA SYD. The proposed method consists of three main steps: data collection, data analysis and warning system design. The results indicate that the proposed method is applicable for various conditions and sewer systems, including Gothenburg. For the studied datasets, the warning system successfully identified increased water levels associated with build-up and blockage events without generating any false alarms. However, longer monitoring periods and data from additional sites are required to fully evaluate the reliability and long-term potential of the method. Especially, regarding pipes which are subjected to blockages consisting of fats, oils and grease. A predictive maintenance strategy could however reduce unnecessary maintenance flushing operations, resulting in lower green house gas emissions and more efficient utilisation of operational personnel and resources.

Keywords: Predictive maintenance, Sewer blockages, Blockage detection, Level sensors, Anomaly detection, Maintenance flushing, Backwater effects, Sewer overflow, Real-time monitoring

Acknowledgements

This Master's thesis was conducted during the spring of 2026, as the concluding component of the Master's Programme in Infrastructure and Environmental Engineering, at Chalmers University of Technology. The thesis was done in collaboration with Sustainable Waste and Water, City of Gothenburg.

We would like to thank the professionals at Sustainable Waste and Water, for their involvement in the project and for their valuable insights. We also extend our thanks to the professionals at VA SYD for providing data and for their assistance in the data analysis, as well as professionals at Knightec for carrying out the hydraulic simulation.

We would also like to thank our supervisors, Glen Nivert and Professor Frank Persson, for their guidance and support throughout the project. Finally, we express our gratitude to our examiner Oskar Modin.

Mirja Backlund

Kim Lennartsson

Gothenburg, June 2026

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1

Introduction

1.1 Background

A functioning sewer system is a crucial part of urban infrastructure. In the city of Gothenburg there are currently 1,605 km of combined and sanitary sewers that everyday conveys wastewater from households, industries and commercial areas to the wastewater treatment plant (Göteborgs Stad, n.d.). Effective maintenance strategies are essential for optimised sewer network functionality. Sewer pipes are subjected to stresses which may cause decreased flow capacity, malfunctions, or pipe failure. One crucial aspect is to keep sewer lines free from blockages caused by accumulation of materials such as sedimented soil and natural waste, fats, oils and grease (FOG) and consumer products including sanitary products and wipes (Ribalta et al., 2021).

When a blockage appears the wastewater can not flow as intended through the pipe, causing hydraulic and environmental problems (Campisano et al., 2004). If left unresolved it might cause sanitary sewer overflows or combined sewer overflows. In order to decrease the amount of blockages and consequential overflows, regular flushing of the pipes is a useful strategy. The sewers are cleaned by flushing devices which discharge large water volumes during a short time period (Campisano et al., 2004). This enables flushing waves with high enough flow velocities and shear stresses to break off and mobilise the build-up in the pipes.

In the city of Gothenburg, the department Sustainable Waste and Water (SWW) work daily with providing the city's inhabitants with clean drinking water and sufficient waste and wastewater management. At SWW, regular maintenance flushing is common practice in locations of the wastewater network which are known to be at high risk of blockage. The flushing operations are performed by two technicians, using flushing trucks equipped with water tanks, suction hoses and hoses which can produce strong jets of water. The hose is positioned in the pipe through a manhole so that the water jet is aimed at the blockage to sever it from the pipe. The water jets are aimed backwards which makes the material flow back to the manhole where it is collected by the truck through the suction hose.

When build-up in a sewer line is obstructing the water flow enough to cause noticeable consequences, for example overflows, this is usually reported to SWW by civil society. Technicians then go out with a flushing vehicle to resolve the blockage.

If a certain sewer line have reoccurring issues, maintenance flushing of the site might begin. The sewer line will then be flushed with a set time interval. There are 197 such locations with scheduled maintenance flushing in the city of Gothenburg. The flushing frequency varies from 1 to 25 times a year, with a median occurrence of 3 times/year. These intervals are set depending on how often blockages are estimated to happen and the dimension of the sewer pipe. Intervals are shortened if the problems persist and blockages or overflows are reported between flushing operations. The intervals are likewise extended if the flushing is deemed excessive, as it is repeatedly discovered on site that there is no or an insignificant amount of build-up since the last flushing operation.

While this strategy has decreased the risk of blockages occurring in the sewer system, it is unclear how well the need for flushing is estimated. To optimise maintenance flushing it is therefore of interest to create a methodology for detecting and predicting blockages according to the state of the sewer line. Moving towards a predictive strategy has the potential to eliminate unnecessary maintenance and in turn leave room for resources to be put towards other improvements of the sewer network. Less maintenance flushing would also lead to a decrease in greenhouse gas (GHG) emissions which would benefit SWW's work towards having close-to-zero GHG emissions by 2030 (Kretslopp och vatten, 2024).

One approach for implementing a more predictive strategy is to introduce smart technology in the form of sensors for data collection and monitoring of the condition of the pipe network. The immense development of Internet of Things has enabled the use of efficient and affordable sensing equipment for urban water management (Tatiparthi et al., 2025).

In the south of Sweden, the organisation VA SYD have deployed water level sensors and utilised the correlation between blockages and an increased water level upstream, to detect blockages. This is done through real-time monitoring and visual analysis of the time series of level measurements.

This data-driven approach has been proved useful by VA SYD, as it was found that maintenance flushing could be significantly decreased, leading to more effective use of resources. To improve the strategy further, a system which automatically notifies the operators about relevant level deviations could be implemented. This could aid the operator in determining when a pipe needs flushing without increasing the workload, since continuous monitoring and interpretation of the level curves

would not be required.

1.2 Aim and objectives

The aim of this thesis project is to develop a method which utilises level sensors to predict blockages in sewer pipes and to investigate the potential to optimise maintenance flushing with a data-driven strategy. The results of the investigation and the proposed strategy should be applicable in the City of Gothenburg and contribute to SWW's work towards implementation of smart technology and predictive maintenance of the sewer network. In order to achieve this aim, the objectives of this project are specifically to:

- Assess the cause of reoccurring blockages and the maintenance flushing strategies in Gothenburg and Malmö prior to the implementation of level sensors.
- Model and compare the relationship between water level and blockage size for FOG and sediment blockages.
- Measure water levels in sewer lines where maintenance flushing is done in Gothenburg.
- Analyse water level data from Malmö to determine the characteristics of a blockage event.
- Develop a method for data pre-processing and a system that warns operators of an ongoing blockage based on the water level data.
- Apply the proposed method to the collected data in Gothenburg.
- Evaluate the benefits of decreasing the number of yearly maintenance flushing operations.

1.3 Limitations

Due to the limited scope of the project, the study is limited to and by the following:

- The research focuses on the Malmö and Gothenburg area. Maintenance strategies and data from other municipalities are not examined.
- Only water level sensor measurements are used for blockage detection. Other flow parameters are not measured or considered in the proposed method.
- The method is developed to detect blockages in pipes. Other reasons for maintenance flushing such as gas formation and problems with odour are not considered.
- An extensive review and comparative analysis of different methods for blockage prediction suggested in current research is not included.

- Data is only collected in two of the locations with maintenance flushing in Gothenburg for a limited time. The performance of the proposed method is therefore not evaluated for other conditions and scenarios.
- The simulation of the effect of FOG and sediment blockages is limited to two flow scenarios and two blockage shapes, one for each blockage type, using the pipe parameters and hydraulic data for one location in Gothenburg.

2

Theory

2.1 Maintenance flushing in Gothenburg and Malmö

In both Malmö and Gothenburg the problems with reoccurring blockages mainly stem from pipe sections with dips and FOG accumulation. Maintenance flushing is common practice at SWW and VA SYD, as a way to avoid sewer overflows caused by these blockages and the consequences they bring. Although both organisations use maintenance flushing to address similar problems in their sewer networks, their specific maintenance flushing strategies differ notably.

In Gothenburg there are currently 197 sites where maintenance flushing is occurring. The frequency of how often the flushing occurs is specific for each sewer line and adjusted if the personnel notices that it happens too often or too seldom. 176 sites have a maintenance flushing frequency less than 6 times a year and 21 of them are maintained 6 times a year or more. In total 647.5 maintenance flushing procedures occur every year. One site is flushed every other year, which results in half a flushing per year when the average is calculated. The total length of the sewer lines in Gothenburg (sanitary and combined sewer) is 1,605 km and 22 km of these are included in the maintenance flushing schedule. This results in 0.014% of the sewer lines being regularly flushed. In 2025, around 3,000 hours were spent maintenance flushing and the flushing vehicles emit approximately 30 tonnes of CO₂/year. Moving towards a more optimised strategy could possibly decrease the number of sites which would result in working hours spent on other parts of the network as well as a decrease in the environmental impact from SWW.

In Table 2.1, some comparable parameters regarding maintenance flushing in Gothenburg and Malmö are presented. Even though VA SYD have fewer sites that needs maintenance flushing compared to SWW, the number of times the flushing occurs each year per unit of sewer network length, is higher. On the other hand, SWW spend more hours each time they flush, with an average of 4:40 hours:mins/flushing, while VA SYD only spends 2:00 hours:mins/flushing. A reason for this difference could be the frequency distribution of maintenance flushing for the sites. Figure 2.1

and 2.2 shows how common a certain frequency of maintenance flushing at a site is in Gothenburg and Malmö, respectively. The median in Gothenburg is 3 times/year while the median in Malmö is 12 times/year.

Table 2.1: Parameters for maintenance flushing (MF) comparison between Gothenburg and Malmö.

Parameter	Malmö	Gothenburg
Length of sewer network	1,200 km	1,605 km
Number of blockages per km sewer line	0.032 blockage/km	0.074 blockage/km
Number of sites that need MF	40	197
Total number of MFs	584 times/year	648 times/year
Average time spent on each MF	2:00 h	4:40 h

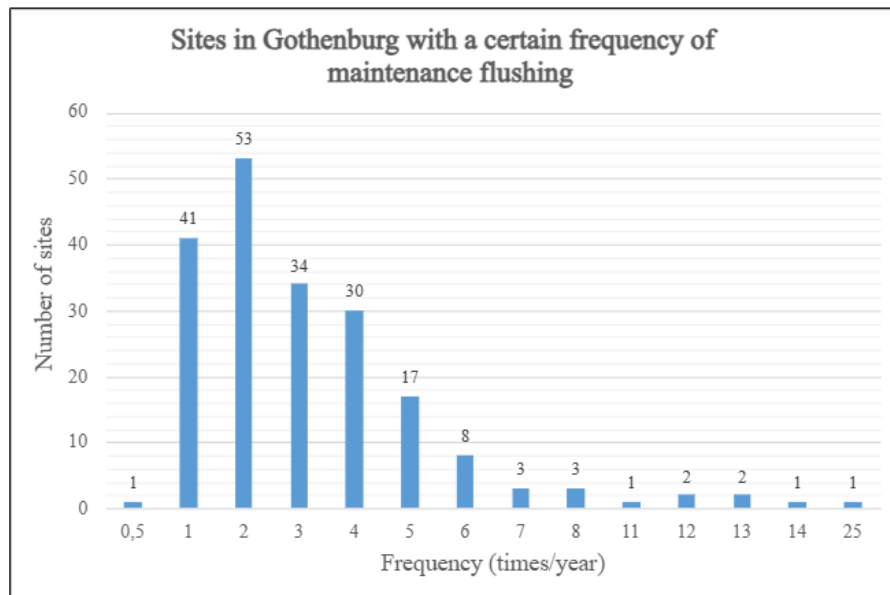


Figure 2.1: Frequency distribution for the maintenance flushing sites in Gothenburg.

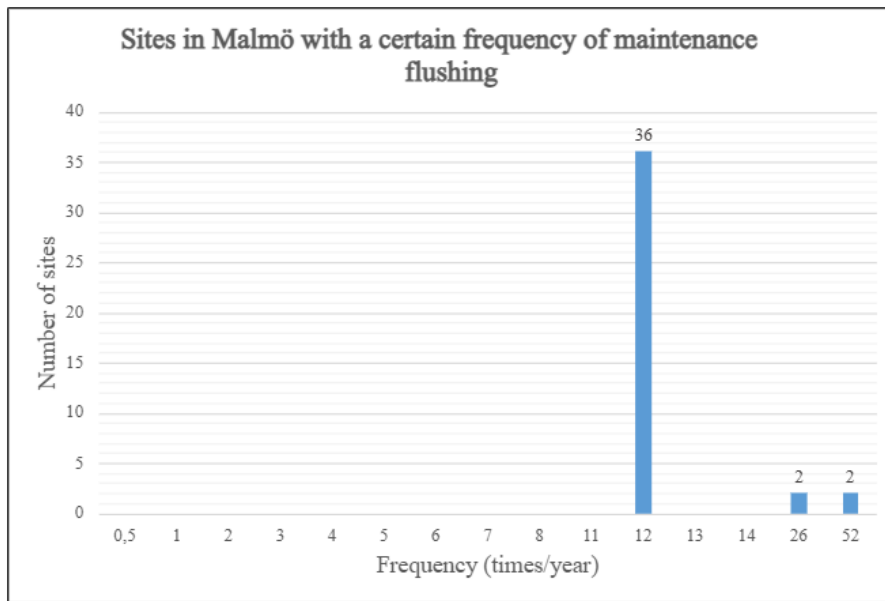


Figure 2.2: Frequency distribution for the maintenance flushing sites in Malmö.

After the installation of level sensors and the implementation of data-driven decision-making for maintenance flushing, VA SYD was able to significantly reduce the number of maintenance flushing operations. The 20 sites where the sensors are now installed were flushed a total of 270 time/year prior to the implementation of the sensors. That number has now been reduced to 10 times/year, which corresponds to a decrease with 96.2%.

The results achieved in Malmö indicate that there is large potential to optimise maintenance flushing with real-time level measurements. The stark differences in the existing maintenance flushing strategies in Gothenburg and Malmö, however, implies a lack of a common, cohesive and structured way of estimating the need for flushing between organisations. Consequently, implementation of level sensors has the potential to reveal ineffective flushing schedules in other sewer networks but the expected decrease in flushing operations would largely vary depending on how well the required flushing frequency was estimated in the previous strategy.

2.2 Water level sensor based blockage monitoring methods

The potential for optimising maintenance with blockage prediction and identification through data collection has inspired an abundance of research on the topic.

Faris et al. (2024) studied the state-of-the-art data-driven blockage prediction and real-time blockage monitoring methods. Data-driven blockage prediction methods focus on forecasting blockage events based on historical pipe performance data in combination with meta data which correlates with the probability of a blockage forming (Faris et al., 2024). For instance, pipe parameters, physical and environmental factors as well as operational aspects have been used to model the likelihood of blockage formation in sewer networks. The data-driven prediction methods are significantly limited by the need of a large reliable data base for accurate blockage prediction. Historical data might not be available and the data collection process could be extensive. Furthermore, blockage formation is highly unpredictable which limits the prediction methods to informing the planning of inspections and scheduled cleaning.

Real-time monitoring methods, on the other hand, provide information about the current state of the pipe networks, enabling a predictive maintenance strategy (Faris et al., 2024). Continuous monitoring of parameters affected by blockages notifies the operator of anomalies indicating blockages as they start to form.

The real-time detection of blockages therefore amount to analysis of time series data of these parameters. Time series analysis is widely used to understand the nature of phenomena occurring in a system over time (Kadri et al., 2016). The time series consists of a sequence of observations indexed over time. Anomaly detection and diagnosis within these datasets is essential for operational reliability of various complex systems (Kadri et al., 2016). Anomaly detection includes the identification of any event which deviates from the nominal behaviour of the system. It is a binary description of the studied system where it is either operating under normal or abnormal conditions. The anomalies can be divided into two distinguished types, abrupt or gradual development.

Anomalies within water level data is one parameter that has been used frequently as an indicator for blockages. Cuong Do et al. (2022) investigated the utilisation of Internet of things-enabled level sensors to identify sewer blockages in an area of Adelaide, Australia. The measurements from the sensors revealed two characteristics of blockages within water level data, namely irregular peaks and durations of abnormally high levels. These anomalies were identified through comparison to historical water level data within the monitored manholes, which were considered to represent the nominal state. The researchers' analysis concluded that most blockages happened abruptly but that continuous collection and analysis of water level data still enabled detection of potential blockages before overflows occurred.

Additionally, Cuong Do et al. (2022) developed a method for alarm activation.

The proposed method included a simple high-level threshold as well as low priority alarm. The low priority alarm was only activated according to a set of rules relating to a few parameters. These were adjustable and unique to each sewer system. The parameters included level deviations, water level in relation to the pipe diameter and the duration of the abnormally high water level. In comparison with three evaluated statistical methods, the proposed method identified small water level deviations accurately with lower false alarm rates, for the studied sewer network.

Li et al. (2023) found that the local water level changes both upstream and downstream the blockage point within a few minutes after a blockage event. Based on analysis of the range and rate of water level change, threshold values for these parameters could be calculated. These were used to identify and position blockages in a full-scale experiment conducted in an area of Weihai City in China.

Faris et al. (2024) introduced a data pre-processing algorithm, Shewart control rules and an alarm suppression system to optimise blockage detection with level sensors in the Hong Kong sanitary sewers. The resulting method achieved high efficiency in preventing sanitary sewer overflows in Hong Kong. The study highlighted the efficiency of real-time monitoring for predictive maintenance. It was also established, however, that comprehensive methods for interpretation of level data and isolation of faulty data are required to enable utilisation of the large amounts of data generated by online monitoring systems.

Tatiparthi et al. (2025) constructed an Ultra high frequency radio frequency identification (UHF-RFID) water depth ruler, which uses electromagnetic fields to identify and track the ruler tags to measure both water level and surface velocity. The UHF-RFID system could identify both the presence and severity of artificially created vertical blockages positioned at the bottom of the open channel flume. The study found that the blockages caused upstream water level rise and velocity reduction. Downstream velocity increased as well as sensor trapping in hydraulic jumps. These features acted as diagnostic characteristics and enabled locating of the blockage between two monitoring points.

2.3 Backwater effect of different blockage types

The fundamental principle behind using water level measurements for blockage prediction is that a blockage causes upstream hydraulic responses leading to an increase in the water level. Blockages alter multiple factors such as flow patterns and velocities, the hydraulic grade line, pipe roughness, effective cross-sectional area and water level (Kargar & Joksimovic, 2025).

Sanitary system blockages mainly occur as a result of accumulation of either FOG, sediment, consumer products such as wipes or a combination of these materials. The formation mechanisms, physical structure and shape as well as resulting hydraulic responses differ depending on the blockage type (Kargar & Joksimovic, 2025). Sediment deposits form gradually at the bottom of the pipe when flow velocities are too low to keep particles suspended. FOG, on the other hand does not sediment and instead form hardened obstructions adhered to the pipe walls due to chemical reactions, namely saponification, crystallization, and calcium aggregation (Hu et al., 2025). Wipe blockages are usually formed dynamically at pipe defects where wipes get snagged and entangled into obstructions of various shapes which change and move over time (Kargar & Joksimovic, 2025).

Blockages formed by wipes and other consumer products cause significant backwater effects with increased water depth upstream the blockage point across different flow rates and blockage sizes (Kargar & Joksimovic, 2025). Similarly, blockages at the bottom of pipes such as sediment blockages also cause a measurable increase in water level. Water level measurements can therefore be used to identify blockages for different flow scenarios (Tatiparthi et al., 2025). However, the effect on the back water profile depends not only on the size and position of a blockage but also the geometry of the blockage itself (Zayed, 2023). Specifically, the local hydraulic characteristics caused by a blockage with a slope differs from the effects of a strictly vertical blockage. A smaller slope angle reduces the backwater rise.

3

Methods

A framework for implementation of data-driven monitoring of sewer line blockage incidents was developed and followed in the current project. It consists of three main steps: data collection, data analysis and warning system development. This framework aims to systematically implement a strategy for blockage detection and maintenance flushing in Gothenburg using real-time data from level sensors. What the steps entail is as follows:

1. **Data collection:** Install radar sensors for continuous level measurement in manholes upstream the blocking point of sewer lines which are flushed regularly due to reoccurring blockage issues. Collect enough data to determine the nominal behaviour of the system.
2. **Data analysis:** Visualise the collected water level measurements as time-series curves and interpret the data. Determine what level fluctuations constitute the nominal behaviour and anomalies for each dataset. Differentiate between faulty records and actual anomalies in the water level. Isolate and remove faulty data. Apply a moving average filter to the pre-processed data and visually analyse the curve to identify indications of blockage events.
3. **Warning system design:** Establish a system for blockage detection by defining threshold values for the water level and water level change which correlates with overflow and blockage events. Design a warning system which notifies the decision-makers when the water level is high enough to impose a risk of overflows for an extended time period and when the average water level deviates enough from the nominal behaviour for an extended amount of time to indicate partial blockage.

3.1 Data collection

The collected data consisted of water level measurements from 20 sensors in Malmö and two sensors in Gothenburg. One sensor in Malmö monitored a combined sewer while the other 21 were installed in sanitary sewers. The monitored sewer lines were

of different sizes and included pipes with diameters of 152 to 1600 mm.

SWW installed two water level sensors, of the type VEGAPLUS Air 41, at two different locations in Gothenburg. The sensors were mounted in manhole covers, see Figure 3.1, of manholes along sewer lines which are currently flushed five and six times a year respectively. The selected manholes were those upstream and closest to the usual blockage point. After the sensor was mounted, a signal suppression was performed by measuring the distance between the sensor and the current water level. The aim with this procedure is to enable the sensor to detect which echoes represent the water surface and which are irrelevant. This can be particularly important in manholes where there are other stationary surfaces, such as step irons or concrete benching. A thorough installation of the sensors is an important part of the process since it impacts the likelihood of outliers in the dataset.

The two sensors measured the water level approximately every 15 minutes from the middle of February to the middle of May. LoRaWAN (Long Range Wide Area Network) was used to transmit the data from the sensors to SWW. The sensors are connected through LoRa to a VEGA gateway. This gateway then transmitted the data via mobile radio to a central server.



(a) Sensor from above.



(b) Sensor from the side.

Figure 3.1: Sensor installed by SWW.

This project also utilised data collected from the sewer network in Malmö, where VA SYD have installed water level sensors with a similar set up, see Figure 3.2. However, VA SYD did not perform the signal suppression on these sensors since their real-time data is manually monitored. Two of the sensors are manufactured by Milesight and the other 18 sensors are of the type VEGAPLUS Air 41. Water

level measurements from 2025 and pipe properties were collected through VA SYD.



Figure 3.2: Sensor installed by VA SYD.

3.2 Data analysis

The time series of level measurements recorded by each sensor were graphed to enable visual analysis of patterns within each dataset. Fluctuations in the water level are expected within the bounds of the nominal behaviour. Blockages are characterised by an increase in water level which deviates from the nominal fluctuations.

Peaks in water levels could, however, also be caused by precipitation. Precipitation data was therefore also collected through VA SYD and graphed with the level measurement to evaluate if increased water levels coincided with higher precipitation. No anomalies in the datasets could be explained by rain events and further analysis of the influence of precipitation in blockage detection was thus excluded. Furthermore, the data from the level sensors also included random errors which had to be distinguished from actual water level deviations. The data therefore required pre-processing.

3.2.1 Data Pre-processing

The faulty data mainly consisted of negative values, unreasonably large values, singular readings with large deviations from neighbouring data points and reoccurring readings at a certain level outside the range of nominal fluctuations. The presence of faulty readings could be due to sensor faults or faulty sensor instalment, difficult measurement conditions and false echoes.

The false echoes occur when signals are received from surfaces in the manhole other than the water surface. Random peaks could be caused by foams or foreign objects floating through the pipe, while reoccurring incorrect measurements at approximately the same level could be signals received from stationary objects in the manhole such as the concrete benching or step irons.

Different types of faulty data were present in the datasets from all sensors in Malmö. Therefore, the data was pre-processed and the faulty data points removed, resulting in a dataset which was more representative of the real water level variations. This increased the reliability of the system.

The data pre-processing encompassed a chain of three steps which correspond to three methods for isolation of faulty data. Each method was developed to isolate the types of faulty data identified in the data sets. An application created by SWW was used for this process. One, two or three of the methods were applied to each data set based on the type of errors present. The pre-processing algorithms were developed using Python and integrated in a web application for data processing at SWW. Each method included adjustable parameters which were tweaked to optimise outlier isolation in the data set of each respective sensor. These parameters were defined and faulty data was removed in the web application.

3.2.1.1 Range filter

The first method addressed data points outside the range of reasonable values for the water level. The minimum and maximum water levels were defined and the data points which fall outside of that range were removed.

3.2.1.2 Band filter

The second method was used to isolate bands of reoccurring faulty readings at approximately the same level. These are commonly due to permanent objects in the manhole, such as step irons or concrete benching. The procedure was done by defining a narrow range in which the faulty data points are located. All data points within this range were then removed. The range that the band covers can

differ between the datasets. The number of isolated outliers had to be evaluated in relation to the number of true data points captured within the same range. If the number of included valid measurements were deemed excessive, the range was adjusted or excluded from further use.

3.2.1.3 Spike detection

The third method detected spikes to isolate random peaks and drops. A sliding window was defined by assigning its 'Look around', meaning a certain number of readings on each side of the data point. Different 'Look arounds' were tested for each dataset and the window size which best isolated the outliers was determined and applied. The median value of the readings within the window was calculated and each data point was compared to the median of the neighbouring values. If the deviation from the median was larger than a specific threshold, the data point was identified as an outlier and removed from the data set. The threshold for each dataset was determined through comparison of the spike levels and the base level. The optimal sliding window size could vary depending on the proximity of the outliers. If multiple spikes are close to each other, the window size must be bigger to include a majority of real readings to compare the data points to.

3.2.2 Moving average

After removing inaccurate data points, the new datasets better represented the actual water level in the manhole. For the purpose of blockage detection, the pattern and the trend for the water level is considered more relevant than the actual specific values. Therefore, a 12-hour moving average was applied to each dataset. The cleaned datasets were exported from the pre-processing application and a python code, see Appendix A, was written to apply the moving average filter.

The moving average is a tool that simplifies visual analysis of a graph by evening out quick changes in the water level and reducing noise. A moving time window creates an average of the containing data points. When the time window moves a new data point will be included in the calculation and the oldest one will be discarded. A moving time window of 6, 12 and 24 hours was tested. While the moving average reduces noise and the impact of remaining outliers, it also causes a delay between the time that the sensor registers a new reading until the data is displayed in the moving average curve. The delay increases with an increased window size, which means that sensitive sites where delays are unwanted might benefit from a shorter time window. The 12-hour option was deemed well suited and was therefore used

for all the studied datasets.

The moving average of a time widow consisting of k data points is described by Equation 3.1. MA_k is the resulting moving average of k values, k is the number of data points in the time window, n is the place the data point has in the time series and P_i is a data point in the time window (Faris et al., 2024).

$$MA_k = \frac{P_{n-k+1} + P_{n-k+2} + \dots + P_n}{k} = \frac{1}{k} \sum_{i=n-k+1}^n P_i \quad (3.1)$$

The moving average further reduced the influence of the faulty data and smoothed out the graphs, which made them easier to interpret. The short-term fluctuations were reduced and the overall water level pattern was highlighted. The normal fluctuations were identified as well as anomalies which provided the basis for the implementation of the warning system.

3.3 Warning system design

The proposed warning system was designed to notify the operator when water levels in a sewer line was elevated to an abnormally high level. Three of the collected datasets from Malmö featured confirmed blockages and flushing operations and the warning system was designed based on these datasets.

The warnings indicated changes in the condition of the sewer line and signalled that further investigation may be required. After reviewing the visualised water level data, the decision maker could assess whether flushing of the sewer line is necessary. Two types of warnings were proposed: a yellow warning and a red warning.

The yellow warning indicated that the water level had remained abnormally high over an extended time period. The change in water level could suggest build-up in the pipe, even if the water level remains low enough to not indicate a significant overflow risk. A threshold level for abnormal behaviour was defined based on the nominal water level in the manhole and the diameter of the sewer pipe. Since previous studies have showed that blockages are characterised by durations of elevated water level, see 2.2, a duration requirement was also added. The duration requirement was determined through analysis of the character of the partial blockage events in the studied data. The acceptable time between build-up forming and the operators being made aware of it was also taken into consideration. It was estimated through discussion with the engineers at SWW. If the water level exceeded the threshold continuously for the full duration, according to the requirements, the yellow warning was triggered and stayed active until the level dropped below the

threshold. See 4.4 for the proposed requirements.

The red warning indicated that the water level was unacceptably high. A threshold level which could infer a risk of overflow was defined based on the characteristics of the more severe blockages in the datasets from Malmö. The alarm was triggered when the water level exceeded the threshold for several hours. The threshold for the red warning was higher compared to the yellow warning but the required duration above the threshold was considerably shorter, to account for the risk of overflows and the consequential urgency for taking action to remove the potential blockage.

The duration requirement and calculations of warning thresholds for the two types of warnings are further described in 4.4. The code for the warning system is a continuation of the python code for applying moving average and is shown in Appendix A.

4

Results of the blockage detection method

4.1 Characteristics of the collected data

The collected datasets featured large variability in hydraulic conditions under normal operation. Some pipes conveyed low flows in relation to their dimensions resulting in a shallow base water level while other pipes were almost full. At these sites, the base water level was close to the pipe crown due to either damming in the system caused by pipe dips, or higher flows. The flow patterns featured in the data were often tied to daily variations.

The data from one of the 20 sites in Malmö did show a lower base water level during December compared to the rest of the year. This could be explained by seasonality, however, it can not be confirmed until enough data is collected to compare yearly variations. Another dataset from Malmö showed peaks in the water level which coincided with precipitation data from Malmö, also provided by VA SYD. Surprisingly, this was not the case for the combined sewer.

Apart from these two datasets, the water levels did generally not show any visually distinguishable correlation with precipitation data nor any seasonal variations. The seasonal patterns could not be evaluated for the data from Gothenburg since they had only been operational for three months.

Three datasets featured confirmed blockages or partial blockage events with subsequent flushing operations. There were both gradual and abrupt developments. There was no indication of build-up in 11 of the datasets. The data from the remaining sensors contained anomalies which could be indications of small build-ups in the pipes. The pipes were however never flushed and the state of the pipes was never confirmed. It is possible that build-up did occur but was washed away as pressure upstream increased. Even if that is the case, the water level did not increase significantly enough to cause any risk to the system and did not indicate any need for flushing.

4.2 Data pre-processing performance

The faulty data points were identified through visual analysis of the curves in consultation with the engineers at VA SYD who are responsible for their sensor instalment and data analysis. After this, the relevant data pre-processing methods were applied in accordance to the types of faulty data present within the datasets. Different configurations of values for the adjustable parameters were tested for each data set in order to isolate as many of the intended data points as possible, without removing accurate data.

The data from sensor 1 included faulty readings of all the three main kinds explained in Chapter 3.2.1, namely spikes, negative values and reoccurring false echoes. The raw data is illustrated in Figure 4.1. Therefore, all three methods for faulty data isolation were applied to the data in order to obtain an undisturbed dataset and sensor 1 is used to demonstrate the pre-processing result.

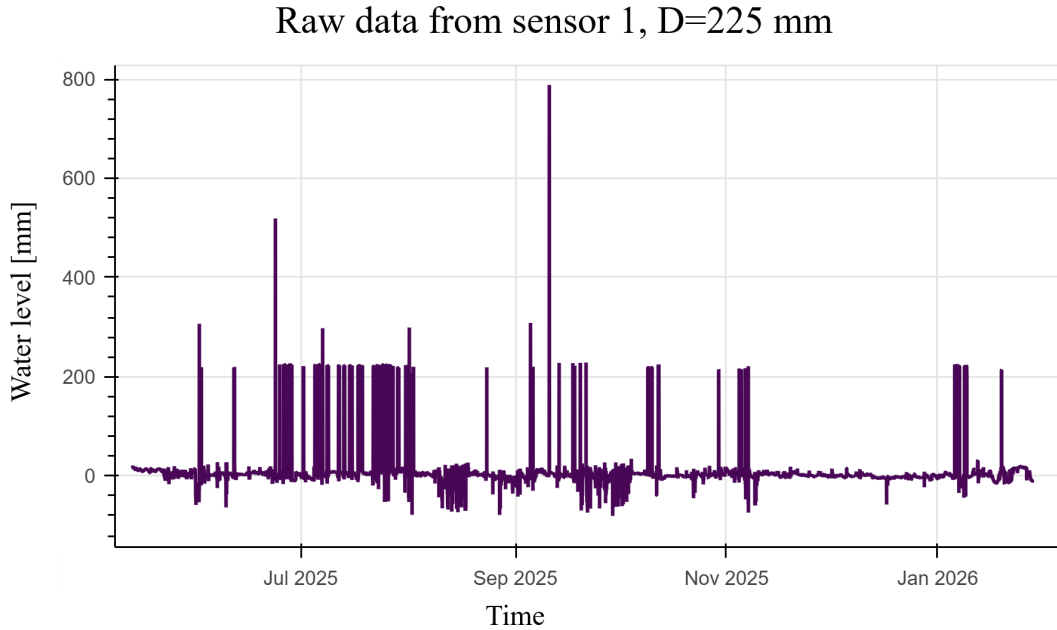


Figure 4.1: Raw water level data from sensor 1.

The range of reasonable values for level readings from sensor 1 was defined as -10 mm to 1000 mm. All accurate level readings are expected to fall within this range. Negative water levels are impossible and are generally faulty readings, but down to -10 mm was included because of potential errors regarding the distance measured from the bottom of the pipe to the sensor. This could shift the actual water level readings slightly, meaning that some negative data points close to zero

might not be outliers and still reflect real water level fluctuations. The upper limit corresponds to a level that is higher than the pipe inlet and reflects a situation where the water has started to rise up in the maintenance hole. The data points which were isolated with the range filter are marked with squares in Figure 4.2. The isolated data points were then removed from the dataset prior to the next filtering step, see Figure 4.3.

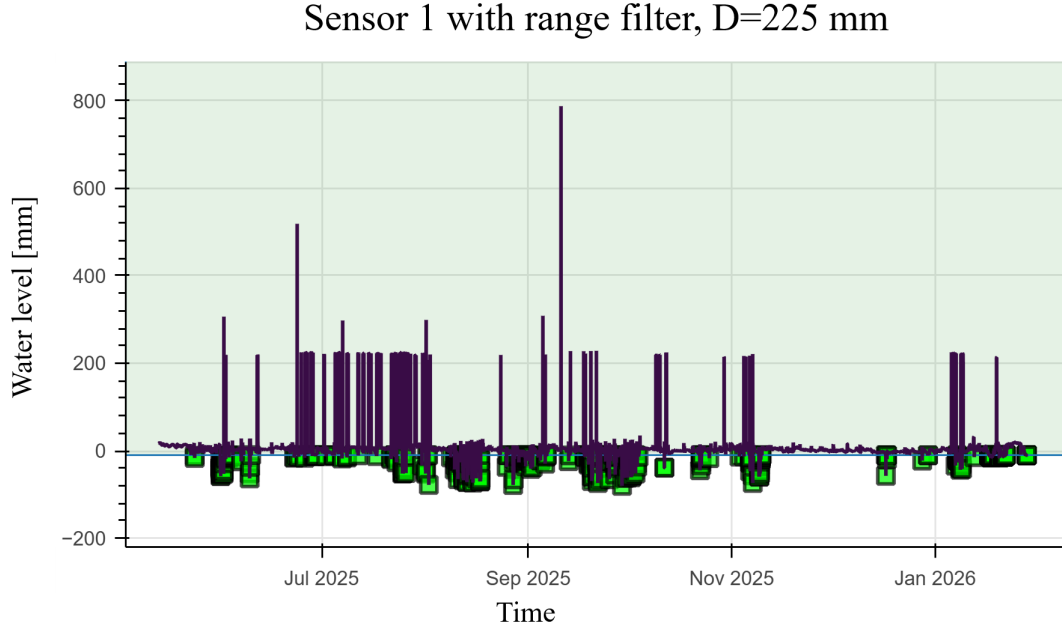


Figure 4.2: Raw water level data from sensor 1 with range filter activated. Each green square marks a data point that is outside of the determined range.

After the removal of the negative values the band filter was applied at level 223 ± 5 mm to remove reoccurring false echoes, see Figure 4.3. The isolated data points from sensor 1 are circled in this graph.

Since the band filter removes all data points within a chosen range, it inherently risks removing accurate measurements which fall inside the same range if the water level reaches it. To minimize unnecessary data loss, the band must therefore be defined as narrowly as possible. As a result, the function is only useful in cases where reoccurring false echoes are at a consistent enough level to be fully contained within a narrow band. Under these conditions, the water level should fluctuate enough outside the band to ensure enough valid data points remain for accurate water level estimation.

As can be seen in Figure 4.3 all reoccurring faults could be captured within a

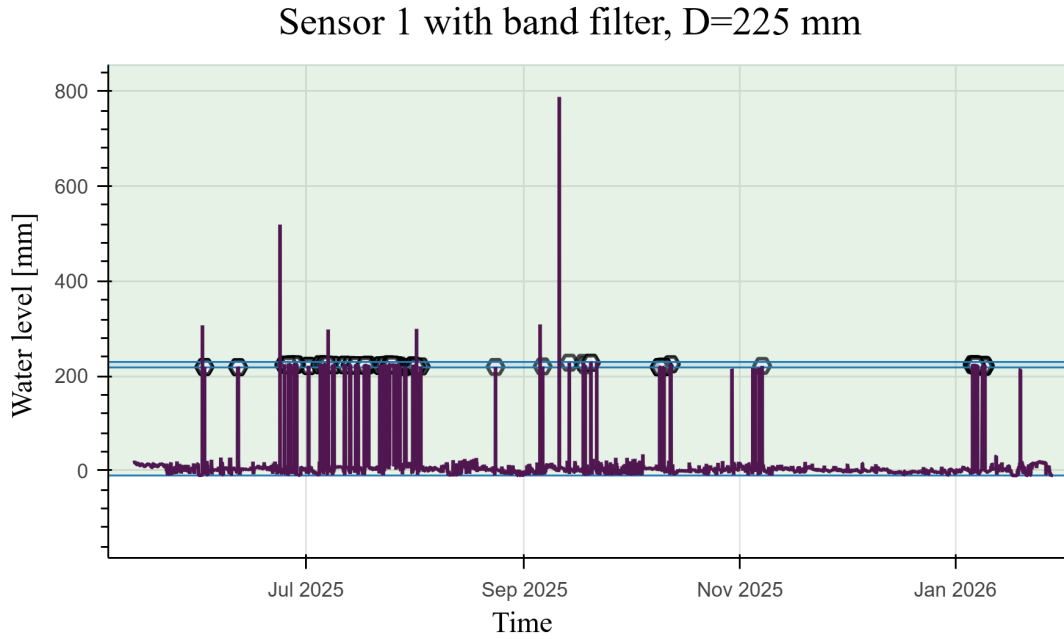


Figure 4.3: Raw water level data from sensor 1 with band filter activated. Each hexagon marks an outlier within the determined band.

10 mm range, at a significantly higher level compared to the nominal level. Additionally, the nominal fluctuations are larger than 10 mm. Therefore the filter was deemed acceptable considering a level rise would be detected before data points are removed and the higher level would likely still be visible in the clean dataset even if a number of points within the band would be removed.

However, the data from sensor 1 was the only dataset, out of the 20 from sensors in Malmö, which was processed with the band filter. In the other instances where reoccurring false echoes were identified, they tended to span a larger range. This is likely due to the stationary objects in the manhole not having completely flat surfaces. Consequently, the returned signal amplitudes differed slightly depending on the exact point from which the transmitted wave was reflected. In many cases the reoccurring false readings were also sparser than in the case of sensor 1, which meant that they could be isolated with the spike detector filter instead.

The spike detector filter was applied last to remove the remaining faulty data. This data is characterised by singular data points which deviate significantly from their neighbours. See Figure 4.4 where these data points from sensor 1 are marked with triangles. The function's threshold was adjusted to remove data points which deviated more than 160 mm from the median of the sliding window. The Look around was set to 10, which made the sliding window contain 10 readings on each side of the evaluated data point. After removal of faulty data points with spike

detector, all outliers had been removed from the dataset, see Figure 4.5.

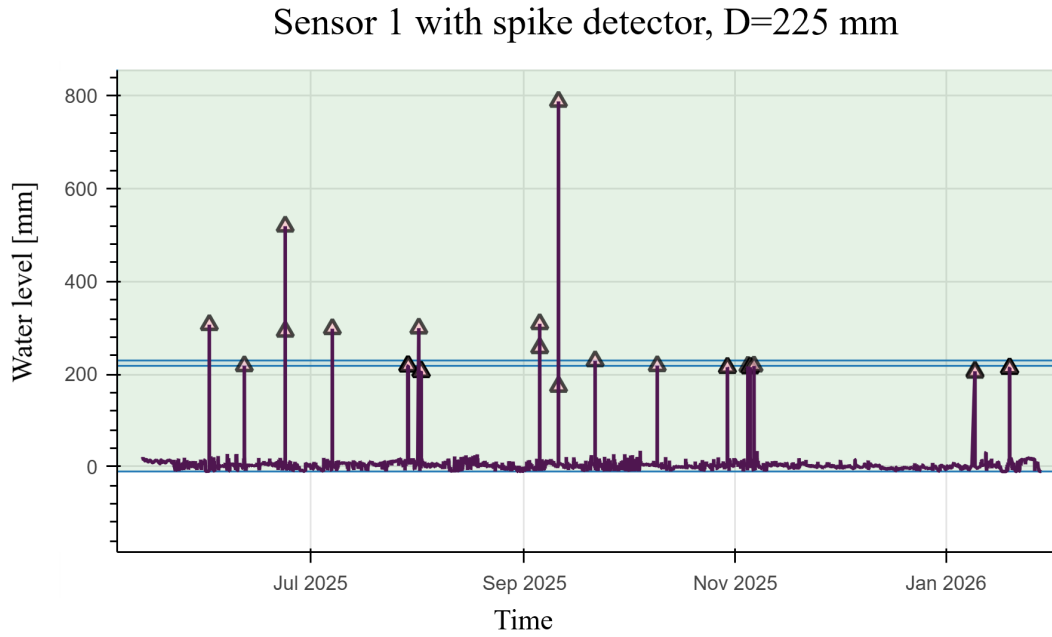


Figure 4.4: Raw water level data from sensor 1 with spike detector activated. Each triangle marks an outlier isolated by the spike detector.

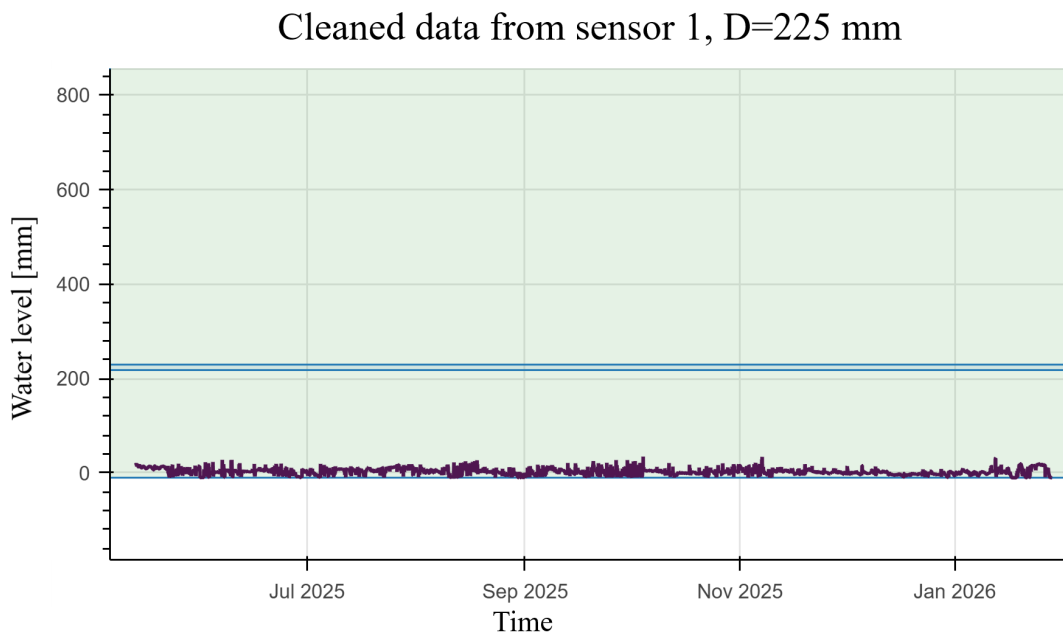


Figure 4.5: Cleaned water level data from sensor 1 as a result of outlier isolation and removal.

Since the ranges, thresholds and look around were adjustable the three methods for data pre-processing could sufficiently be used to isolate the intended data points in the datasets from all sensors, as long as the faulty data could be visually discerned in the time series curves. In three of the 20 datasets faulty or noisy data dominated enough to make it impossible to distinguish accurate water level readings from outliers with adequate certainty. At one of these locations the measuring conditions were difficult because of the significant depth of the man hole. At the other two locations the flow was low and floating objects were frequently transported through the manhole. This lead to the sensor signal frequently being reflected from the concrete and other objects instead of the actual water surface. For example, the data from sensor 2 was difficult to interpret, see Figure 4.6. Since the nominal level fluctuations could not be distinguished and defined, neither could faulty data and actual water level deviations potentially indicating blockages. Consequently, the subsequent moving average filter was affected by the outliers and did not effectively display an accurate representation of the trend in water level fluctuations. Similarly, the proposed warning system could not be applied and evaluated in these cases.

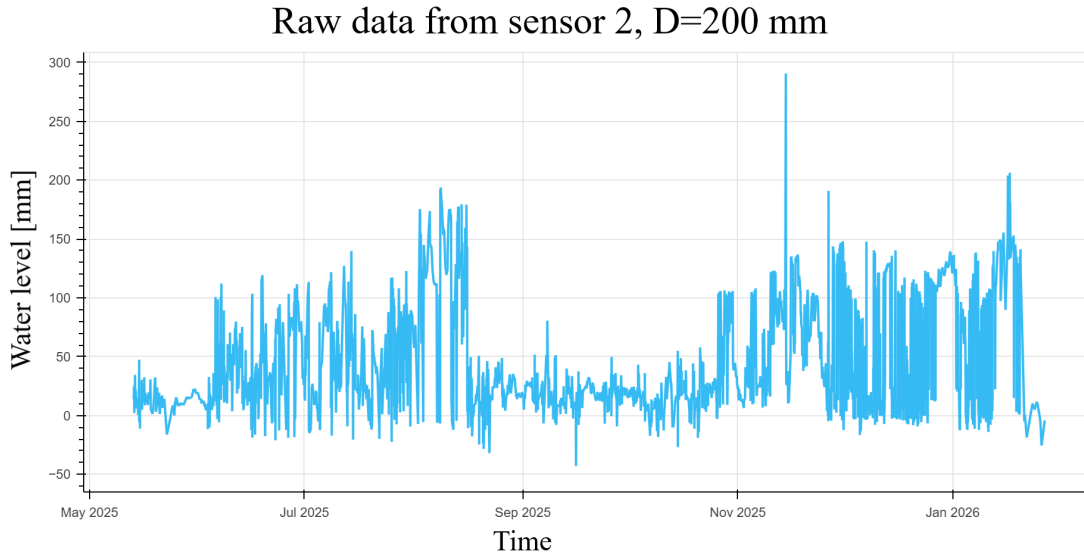


Figure 4.6: Raw water level data from sensor 2, which is an example of a dataset dominated by outliers.

At the other 17 locations the data quality was high enough to enable successful pre-processing with the proposed method. In most cases, the vast majority of data points which were considered faulty could be isolated and removed. The outliers which remained in the datasets were few and featured small deviations from the assumed actual water level. After being smoothed out with the moving average

filter, they did not generate false positives in the alarm system.

4.3 The effect of Moving average

The moving Average was calculated for a 12 hour time window and applied to all pre-processed datasets. In this project a trailing moving average was used. This means that the average for the moving time window represent the previous 12 hours, which causes a delay in the data, see Figure 4.7. A centred moving average could have been used, where the average is created based on six hours before and after the specific data point. However this would result in the moving average for a specific data point not being registered until six hours after the data point has been registered.

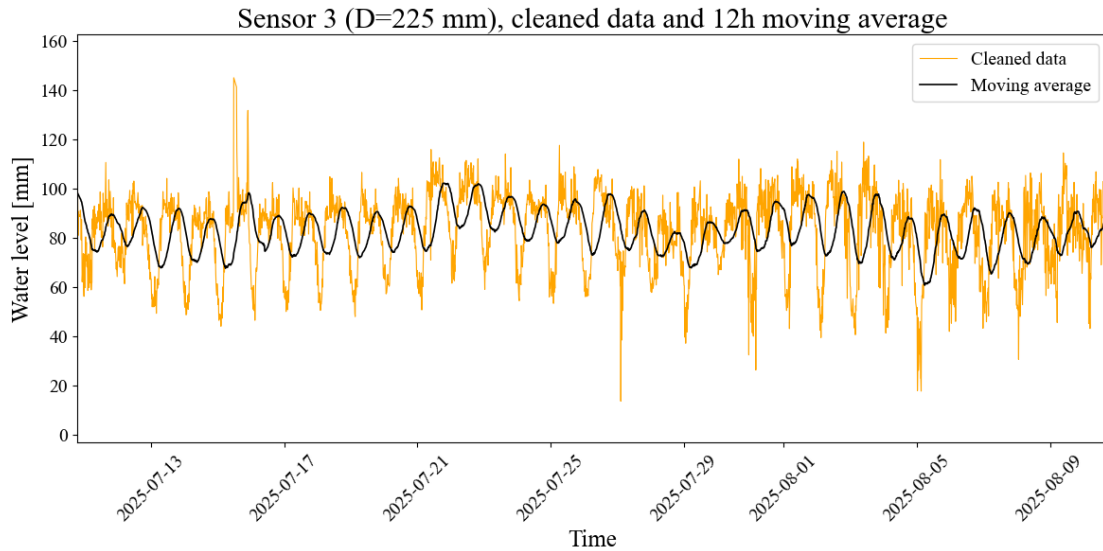


Figure 4.7: The effect of moving average of water level readings from sensor 3.

The moving average reduced the fluctuation in level readings and limited the influence of the remaining outliers. Furthermore, it reduced noise and highlighted the trends, which are more relevant to monitor for the purpose of identifying build-up and predicting blockages. Figure 4.7 shows the effect of the moving average on data from sensor 3. The figure illustrates how the moving average follows the daily variation of the water level with a 12 hour delay. The time window was adjustable to enable optimisation of the trade off between the delayed blockage detection and reduced noise and outliers. The 12 hour window yielded sufficient results for all sensors, meaning that blockages could be identified in the resulting curves and the induced delays in the generated alarms from the warning system were considered acceptable.

4.4 Blockage detection performance

In the water level data blockages were characterised by an increase in water level that remained for an extended period of time. Three of the 20 datasets from Malmö contained data from sites where maintenance flushing had occurred and confirmed a blockage or distinct build-up. In the data from sensor 5 there were multiple blockage events which caused abrupt anomalies. The other two datasets contained one blockage event each, where blockages were characterised by a more gradual development after the initial abrupt water level elevation. The data from sensor 4 reflected build-up and the data from sensor 6 showed a full blockage event. After flushing was performed, it was visible in the graphs as an abrupt drop back to the base water level, at all three sites. The warning system was designed based on these three datasets and evaluated using the remaining datasets.

A specific base level, reflective of the nominal behaviour for each site, was determined through analysis of the moving average graphs. Through discussion with personnel at SWW and analysis of the graphs, two types of warnings were suggested. The purpose of the warnings is to notify the operator that the water level in the sewer line has increased. The personnel could then review the data and decide if the sewer line needs maintenance and how urgent it is. Taking the base flow and the pipe diameter into consideration, specific water level thresholds were defined for each site and warning level.

The first warning, a yellow warning, would be activated when the base level increased but did not yet pose an overflow risk. The purpose of this warning is to make the operating personnel aware that there might be a build-up or another type of obstruction in the sewer line. The warning would remain activated until the level drops below the threshold.

The second warning, a red warning, aims to notify the personnel that the water level in the sewer line indicates a blockage and could pose a risk for overflow. This would be a more urgent warning and would replace a yellow warning even if the requirements for the yellow warning were fulfilled. The red warning would remain as long as the water level is above the threshold. If the water level drops to a level between the yellow and red thresholds the warning would downgrade to a yellow warning.

To avoid false alarms caused by momentarily increased water levels, residual outliers, or temporary blockages that clear on their own, exceeding a water level threshold alone was not considered sufficient to activate an alarm. A duration criterion was therefore also implemented in the system. The required time above

the threshold differed between the yellow and red warnings. The yellow warning used a lower threshold and represented a less urgent indication of build-up. It therefore required a longer duration than the red warning, which signalled a more critical condition.

The requirements for each warning to be activated were as follows:

- Yellow warning: The water level has exceeded the base level + 20% of the pipe diameter for 4 days.
- Red warning: The water level has exceeded 80% of the pipe diameter for 12 hours.

The proposed warning system worked sufficiently with the requirements above for all datasets available in this project. The chosen thresholds and durations resulted in warnings being activated during the identified blockage events and no false warnings were generated. Due to the highly variable circumstances of different sewer lines, adjustments might however need to be made to these warning requirements if applied to new data sets. For instance, a rise with 20% of the pipe diameter corresponds to a larger deviation if the base level is low. This implies that smaller anomalies are less likely to be detected in pipes with low flow. Anomalies with smaller deviations could be captured by the warning system by modification of the yellow warning requirement, if it is of interest to keep the pipe at full capacity at all times. Furthermore, a red warning might be appropriate when the water level reaches a threshold smaller than 80% of the diameter. A lower level might constitute a risk in a large pipe or a sensitive system. Similarly, a sensitive system might require immediate action. This means that the warning should notify the operators after a shorter duration.

Table 4.1 shows the thresholds for the three datasets with confirmed blockages or build-up. The graphs of the moving average for these datasets with the warning system activated are shown in Figure 4.8, 4.9 and 4.10. The horizontal lines show the threshold for the water level for both types of warnings. The vertical coloured areas illustrate the periods during which a warning was activated.

Table 4.1: Thresholds implemented in the warning system for sensor 4, 5 and 6. The duration requirement for build-up is 4 days and risky water level is 12 hours.

Sensor	Pipe diameter [mm]	Base level [mm]	Build-up threshold [mm]	Risky threshold [mm]
4	300	100	160	240
5	225	90	135	180
6	225	10	55	180

Figure 4.8 shows the data from sensor 4. During the measurement period the water level in this manhole would only have triggered the yellow warning. The water level started to increase in the middle of July and after approximately 2 weeks the first warning would have been activated. This increase continued and despite fluctuations, the warning criteria would have been met multiple times before the sewer line was flushed in the end of October. The water level fluctuations would sometimes have deactivated the yellow warning while the water level could still be considered abnormally high. This could have been avoided if the duration requirement was lowered. However, reducing the duration requirement below four days would likely have caused the warnings to be triggered during the spikes in November and December. These spikes should not activate the warning since they likely derive from residual outliers and have a short enough duration to not indicate any need for flushing.

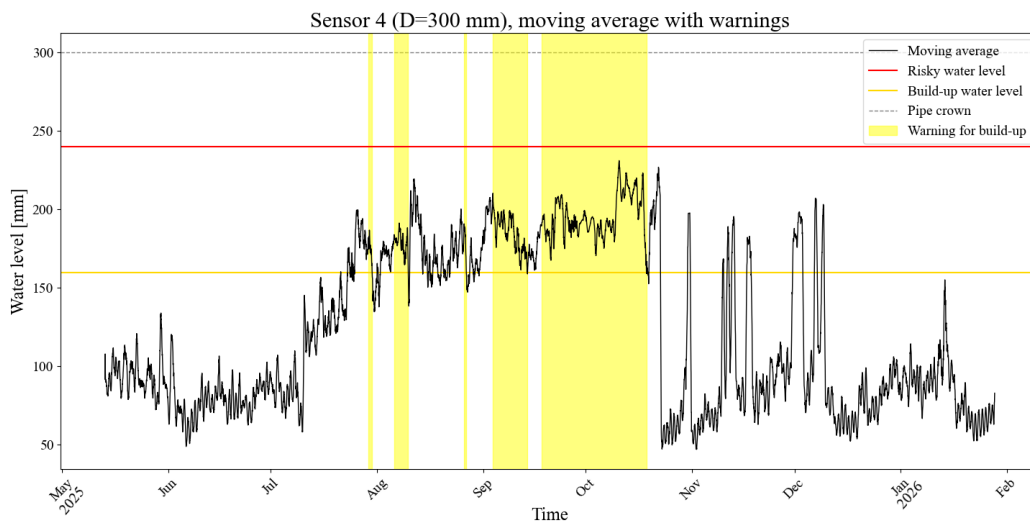


Figure 4.8: Moving average for dataset from sensor 4 with warning system activated.

In Figure 4.9 the data from sensor 5 is shown. This dataset had many distinct and rapid blockages. During each blockage event, the water level increased to approximately the same height and remained there until maintenance flushing was performed. This was because sensor 5 monitored a manhole that was designed to overflow at a certain height. Therefore, when the blockage occurred and the water level increased rapidly it started to overflow. This resulted in the stable high water levels visible in the graph. During these rapid increases, the red warning would have been activated. In the end of June the base level remained elevated for a sufficient duration for the yellow warning to have been activated. Even though the yellow warning would only have been activated for less than a month, the base level remains increased. The base level did not return to normal levels until the last flushing of the sewer line. The last blockage event lasted longer than previous ones. This was due to VA SYD performing maintenance flushing of all other sewer lines in the area in order to investigate if the source of the problem came from elsewhere. It was found that build-up in another pipe caused increased water levels in the monitored pipe which is why the level returned to its nominal behaviour only after this.

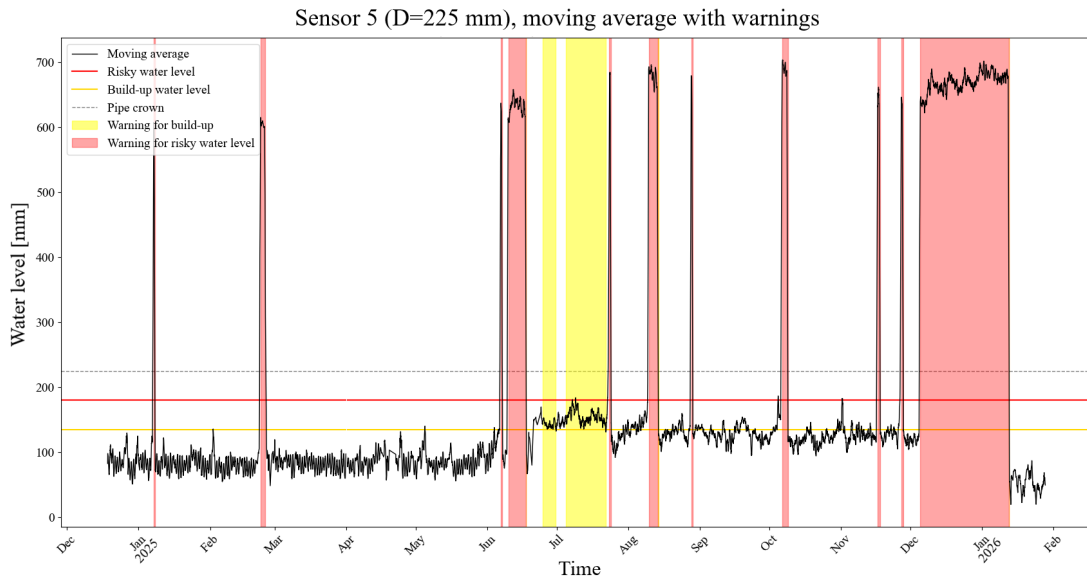


Figure 4.9: Moving average for dataset from sensor 5 with warning system activated.

Figure 4.10 shows the data from sensor 6 with a blockage clearly visible. The blockage caused an initial rapid increase in water level followed by a more gradual

development. During the blockage event both the red and the yellow warnings would have been activated. The water level rose quickly and would have activated the red warning, but then the blockage partially cleared without intervention and the water level decreased again. However, the base level was still elevated and the yellow warning would have continued to be activated. This illustrates the importance of including a yellow warning as well as the red warning.

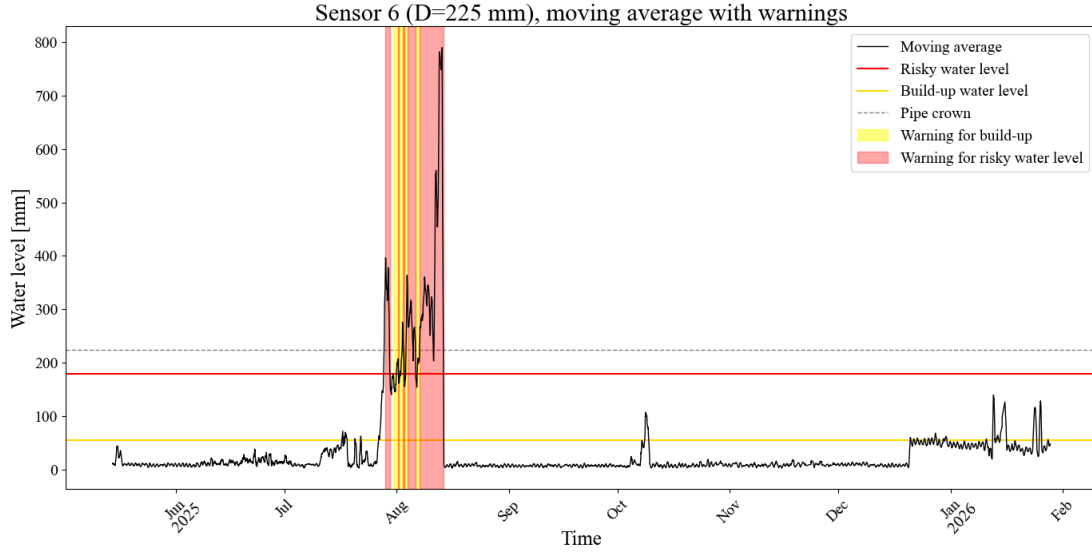


Figure 4.10: Moving average for dataset from sensor 6 with warning system activated.

4.5 Application of method in Gothenburg

Sensors 7 and 8 measured the water level in two manholes in two different places in Gothenburg. Sensor 7 monitored a sewer line with a diameter of 500 mm and where maintenance flushing occurs 5 times per year. The sewer line along which sensor 8 was mounted is 225 mm in diameter and is maintenance flushed 6 times per year. Water level data from these two sites were collected during 3 months, from 2026-02-17 to 2026-05-17, and then analysed.

4.5.1 Data pre-processing

Figure 4.11 shows the raw water level data from sensor 7, before the data pre-processing. The majority of the outliers can be found in the beginning of the mea-

surement period. During the first two weeks, the sensor predominantly registered one of two different levels. Either a high value, close to the height where the sensor itself is mounted, or a value around 450 mm which corresponds with the level of the concrete benching in the manhole.

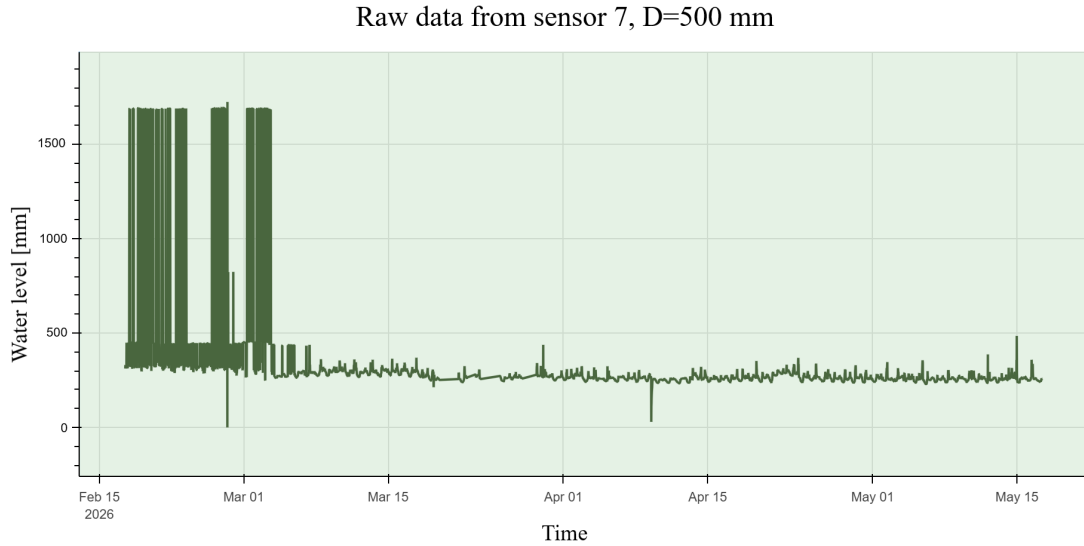


Figure 4.11: Raw water level data from sensor 7.

A site visit was planned, where the suppression of false signals would be redone as an attempt to improve the sensor calibration. However, this was not necessary since the sensor started measuring correctly in the beginning of March. The cause of this change in the behaviour of the sensor remains unknown. The sewer line which sensor 7 monitored was maintenance flushed in early April, which caused the distinct dip visible in Figure 4.12. However, the water level rapidly returned to and remained at approximately the same height after the flushing as before.

Figure 4.13 shows the raw water level data from the second sensor installed in Gothenburg, namely sensor 8. The sewer line where sensor 8 is mounted was scheduled for maintenance flushing during this time period as well, but it was postponed due to other flushing operations taking priority. In the dataset from sensor 8, the main outliers consist of spikes, see Figure 4.13.

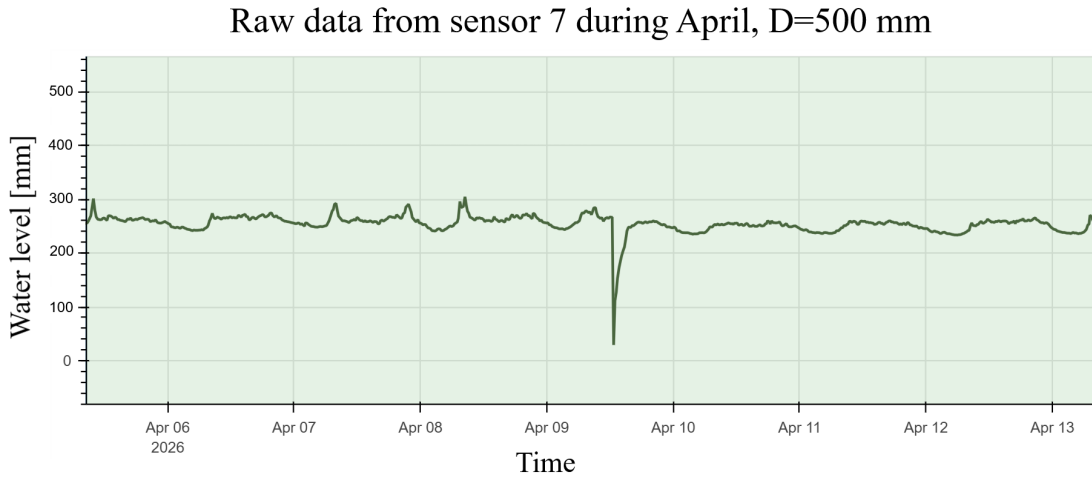


Figure 4.12: Raw water level data from sensor 7 during April, when the sewer line was flushed.

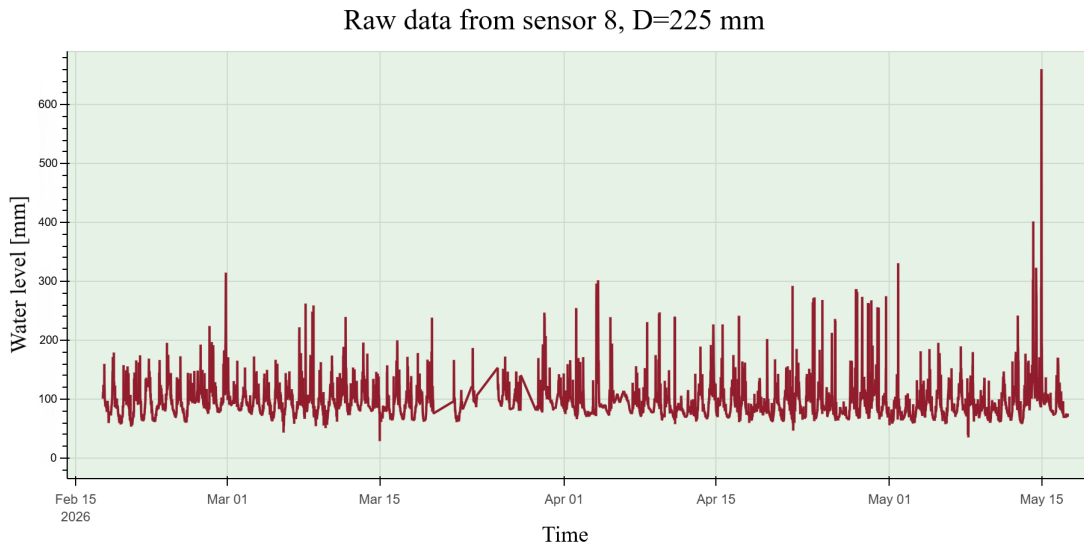


Figure 4.13: Raw water level data from sensor 8.

Between the 20th and the 26th of March, the system for sensor connection at SWW was updated. As a result, no measurements were registered during this time. This caused the straight lines that are visible in the graphs at this time.

The outlier isolation applied to the two datasets is described in Table 4.2. The data from sensor 7 included faulty data of all three main types and was consequently processed with all faulty data isolation methods. Sensor 8, on the other hand, only featured spike outliers and all identified outliers could be removed with only the spike detector. The graphs of the cleaned data are shown in Figure 4.14 and Figure

4.15. There are still a few potential outliers present in the beginning of the data from sensor 7, but compared to the raw data, most of the faulty data points were removed. Increasing the sensitivity of the outlier isolation process would likely remove remaining data points. However, it would also increase the risk of removing valid measurements in future data.

Table 4.2: Outlier filters used on the datasets from sensor 7 and 8, in Gothenburg. *T* stands for *Threshold* and *La* stands for *Look around*.

Sensor	Range filter	Band filter	Spike detector
7	Max=1000, Min=-10	450 ± 0.5 mm	T=100 mm, La=20
8	—	—	T=100 mm, La=10

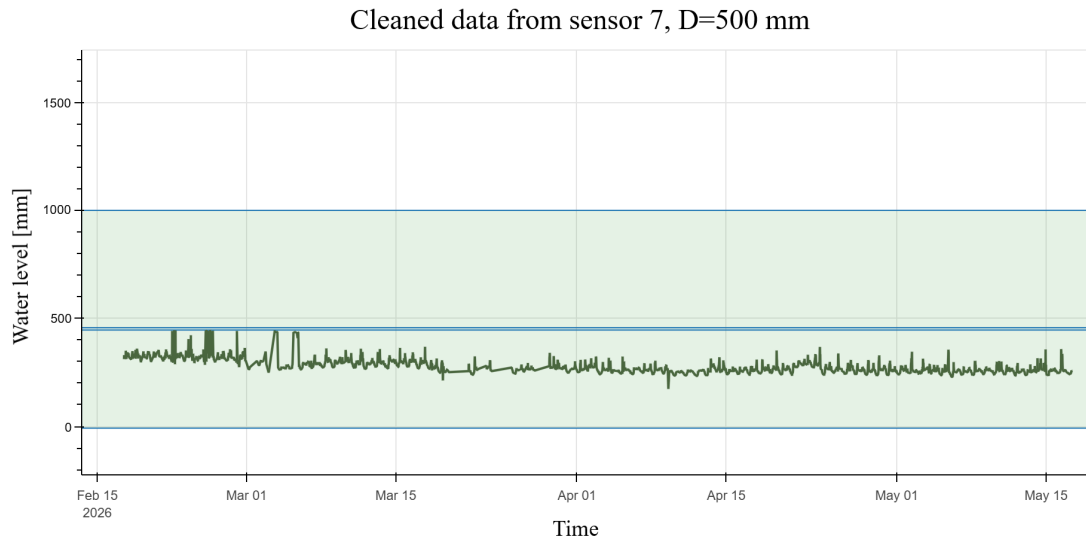


Figure 4.14: Cleaned water level data from sensor 7 as a result of outlier isolation and removal. The blue lines at -10 mm and 1000 mm symbolises the applied range filter. The blue lines around 450 mm symbolises the applied band filter.

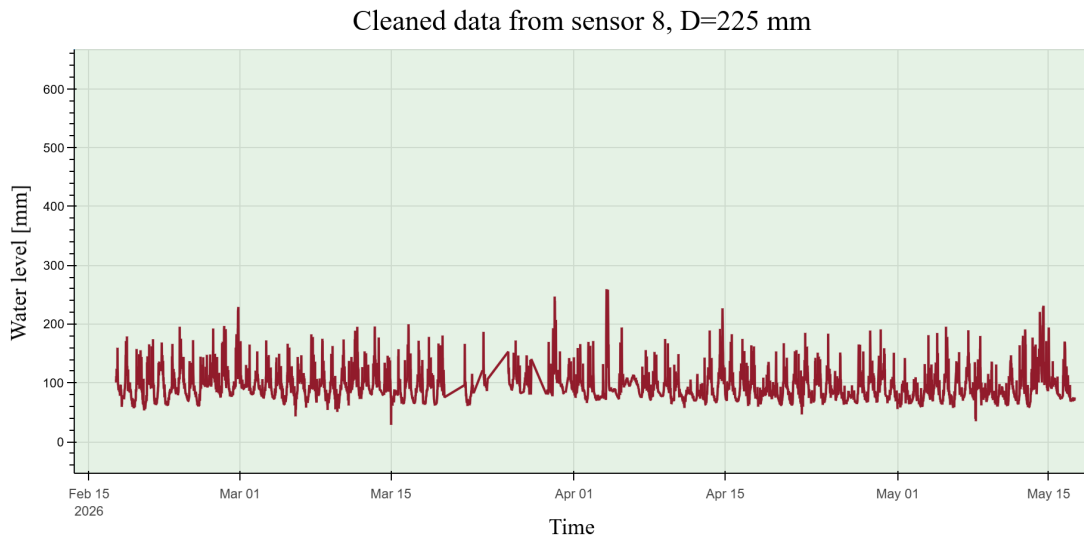


Figure 4.15: Cleaned water level data from sensor 8 as a result of outlier isolation and removal.

When the data had been pre-processed the moving average was applied. Figure 4.16 and Figure 4.17 shows how the moving average relates to their respective cleaned datasets. Sensor 7 registered a higher base flow and some peaks during the first month of monitoring compared to the last two months. This can be due to changes in water flow or a consequence of remaining outliers. The base level from sensor 8 stays consistent throughout the whole measurement period.

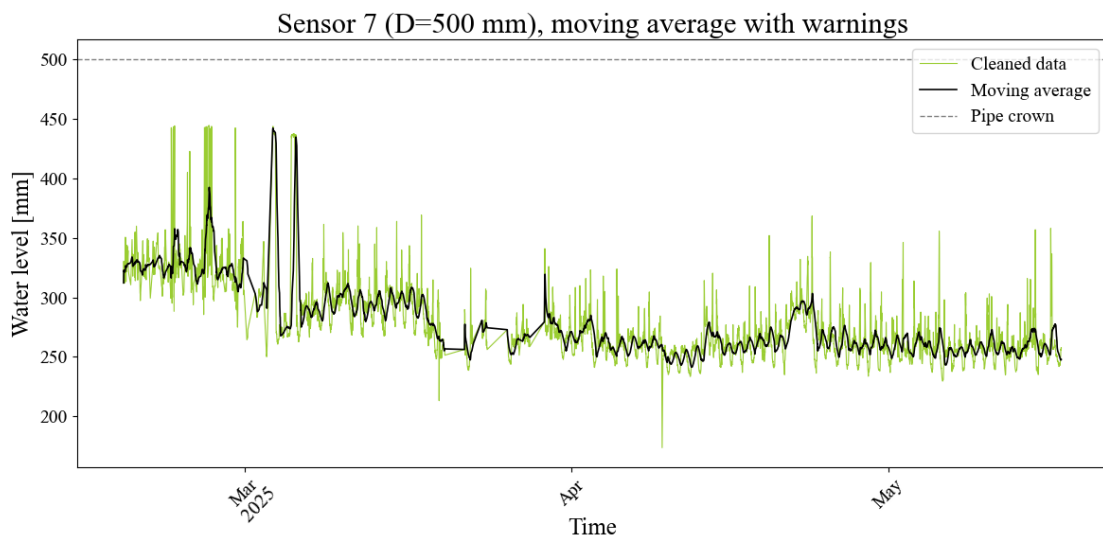


Figure 4.16: Cleaned data from sensor 7 with moving average.

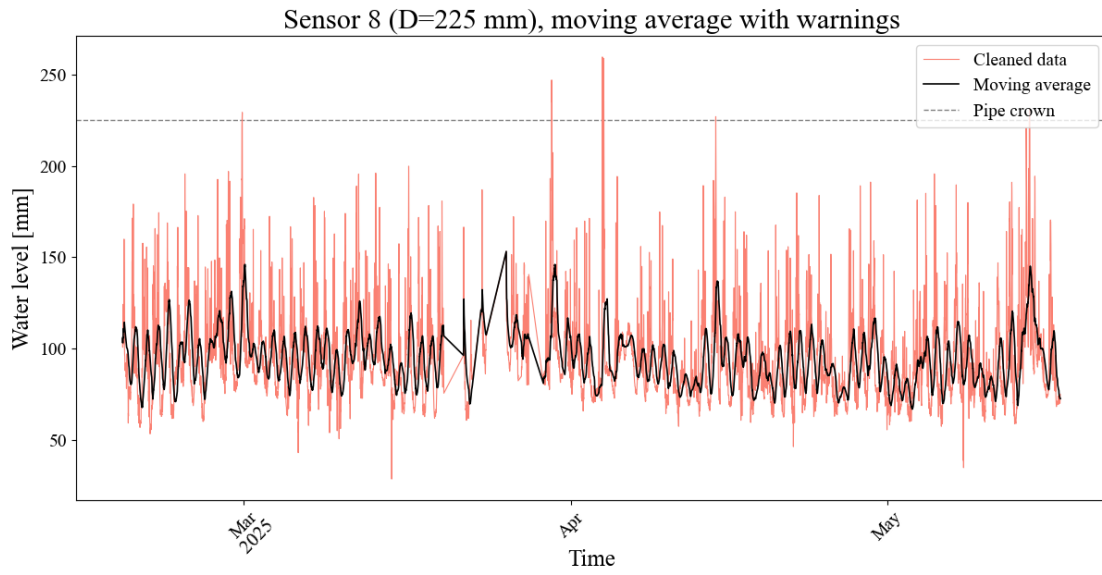


Figure 4.17: Cleaned data from sensor 8 with moving average.

4.5.2 Warning system

With the moving average generated, the warning system could be applied. The thresholds for the two different warnings were calculated in the same way as for the other 20 datasets. The resulting thresholds are presented in Table 4.3. The duration for which the water level needs to exceed the threshold in order to activate a warning were the same as those used for previous datasets, with 12 hours for the red warning and 4 days for the yellow warning.

Table 4.3: Thresholds implemented in the warning system for sensor 7 and 8. The duration requirement for build-up is 4 days and risky water level is 12 hours.

Sensor	Pipe diameter [mm]	Base level [mm]	Build-up threshold [mm]	Risky threshold [mm]
7	500	260	360	400
8	225	90	135	180

Figure 4.18 and Figure 4.19 shows the moving average for these two datasets with the warning system activated. During the three months of data collection, the water level at neither of the sites exceeded any of the thresholds long enough to trigger a warning.

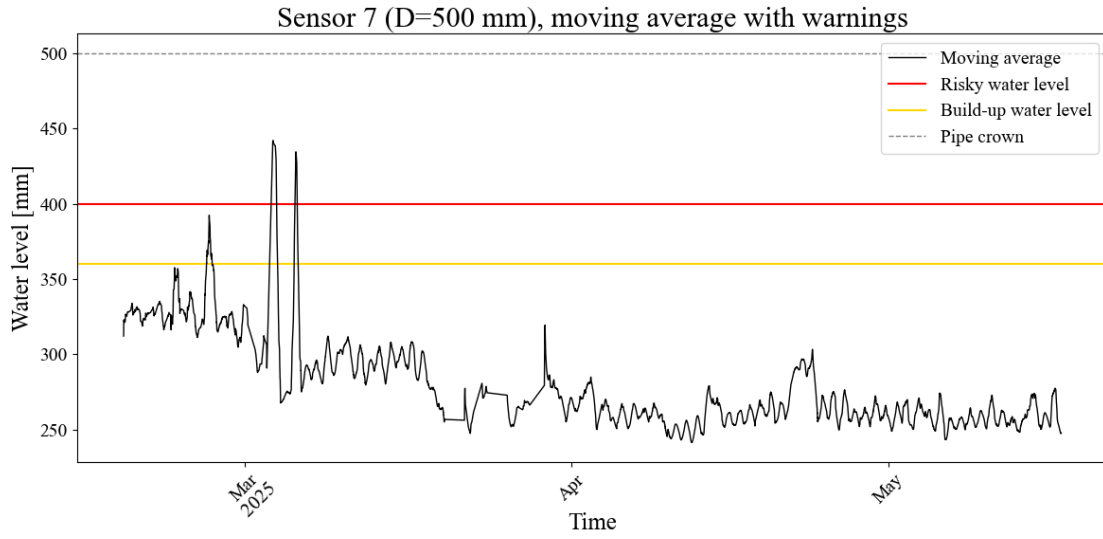


Figure 4.18: Moving average and warnings for sensor 7.

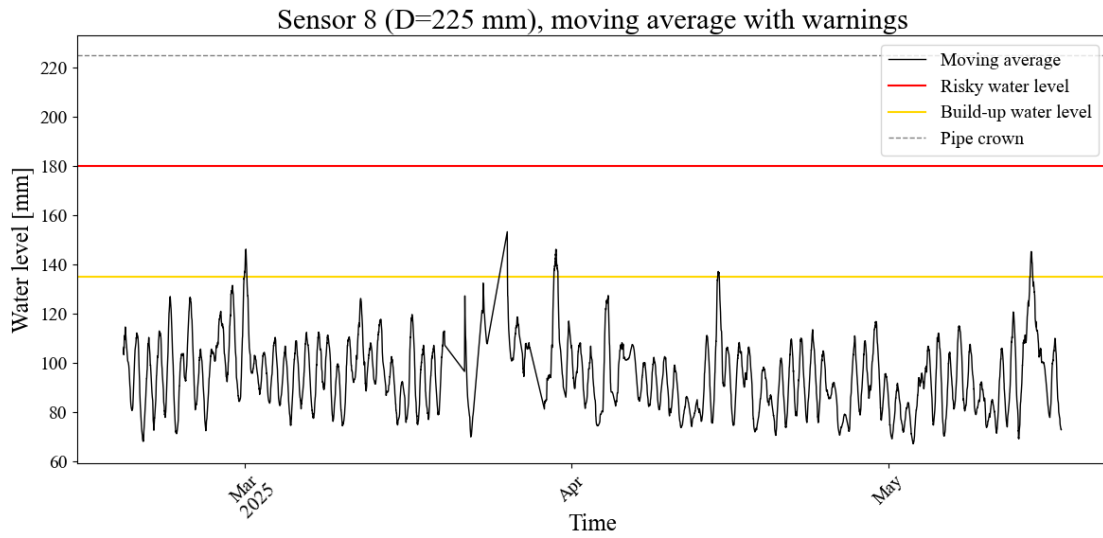


Figure 4.19: Moving average and warnings for sensor 8.

4.5.3 Implementation in Gothenburg

The three methods for outlier isolation and filtering were adequate to pre-process the data from the two sensors in Gothenburg. Just like with the data from the first 20 sensors, the band filter was only used on one of the datasets. However, this isolation method is very useful when needed. This was demonstrated by the pre-processing

of sensor 7, since it, especially in the beginning, struggled with recognising what was the water level and what was the concrete benching. Sensor 7 also exemplifies how important a proper sensor instalment is. If the the sensor would have continued with the same issues as in the beginning of the measurement period, the data would be useless. The purpose is to utilise the water level data and if the water level is not measured but something else in the manhole is, then the purpose can not be fulfilled.

The proposed method is adjustable. The sewer line monitored by sensor 7 is an example of where the thresholds for the warnings might need to be lower than the standardised system for the other sensors. The pipes leading to neighbouring houses are connected to this sewer line lower than usual practice. This means that if the water level in the sewer line is high, the water will go in to the connecting sewer pipes. This might cause build-up and blockage issues in these pipes, which are not maintenance flushed. Therefore the risky water level for this site might need to be lower than 80% of the pipe diameter.

The water level at this site remained at a similar height before and after the maintenance flushing. This indicates that the water level was reflective of nominal conditions in the system and that it was not abnormally high due to any build-up in the pipe at the time of the flushing operation. This was confirmed on site by the technicians, who did not find any significant build up. This confirmed that the lack of warnings generated by the proposed system was suitable for the site. Furthermore it suggests that the flushing interval could be extended. However, at this site it is not only the risk for blockage that is the reason behind the maintenance flushing. The site also has an odour problem which can be avoided by regular flushing.

Sensor 8 seems to have been working well. The data shows a daily variation of water level which was expected. The base level is around the same height throughout the entire measurement period. Even though the maintenance flushing that was scheduled during this time period was postponed, the water level did not increase. Moreover, there were no reports of overflow at the site. This could be an indicator to the sewer line not needing maintenance as often as previously estimated and scheduled.

5

Hydraulic modelling

Since most methods for real-time monitoring for blockage detection presented in the literature, see 2.2 and 2.3, do not consider the differences in water level increase depending on the blockage type and geometry, this relationship was further studied through a simulation. The water surface in a pipe with properties which can be found in the sewer network in Gothenburg was simulated across two flow scenarios for two blockage types. The simulated pipe had a diameter of 500 mm, no slope and a standard value for pipe roughness in a concrete pipe. The simulation was carried out by Knightec with a model based on computational fluid dynamics, where the water column was calculated as a function of reduced cross-sectional area.

5.1 Model design

According to personnel at SWW, the majority of blockages mitigated by maintenance flushing in Gothenburg are caused by FOG in pipes with dips and insufficient slopes. Therefore, the focus of the simulation was to model how obstructions attached to the pipe wall compared to vertical blockages for a system both with and without damming.

In the first flow scenario a flow of 1.4 l/s was used for the flow entering and exiting the studied pipe section with a free outlet flow boundary condition. The flow corresponded to the average dry-weather flow in the pipe which was used as a basis for the other pipe parameters. The second flow scenario included damming in the pipe where the nominal, stabilised water level was constrained to 0,26 m. This corresponds to a half full pipe at 0% blocked cross sectional area. In the second scenario the flow was slightly higher, at 2.3 l/s which reflected the maximum dry-weather flow in the simulated pipe.

It was assumed that the sediment blockage would form vertically and that the FOG blockage would form radially along the entire circumference of the pipe. The simulation was run for multiple blockage severities, which corresponded to different percentages of blocked cross-sectional area. The geometry of each of the two blockage

types is illustrated by two examples in Figure 5.1 and Figure 5.2. The figures shows what the vertical blockage looked like when the cross-sectional area was decreased by 80% and what the radial blockage looked like when the cross-sectional area was decreased by 94%. The columns in the figures represent the continuation of the pipe and the modelled canal is longer upstream, to allow for an increased water column and corresponding pressure.

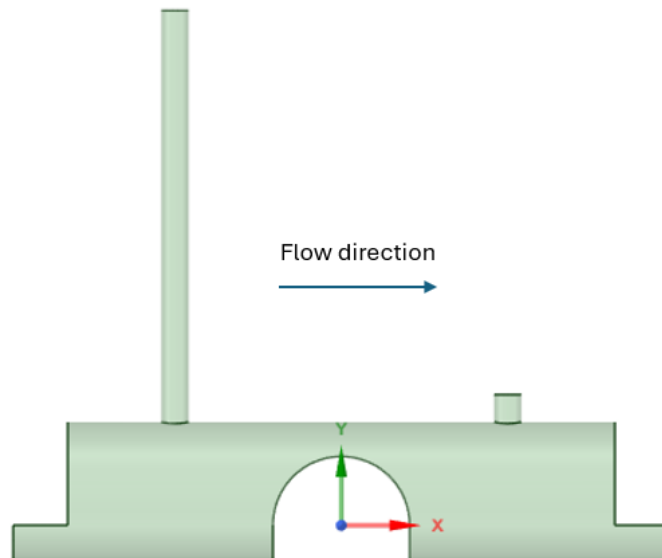


Figure 5.1: Geometry of the simulated sediment blockage at the 80% blockage point. The blockage is modelled as a vertical obstruction from the bottom of the pipe.

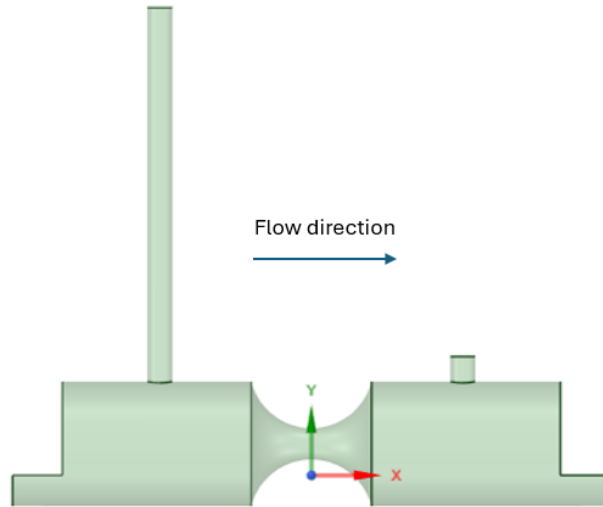


Figure 5.2: Geometry of the simulated FOG blockage at the 94% blockage point. The blockage is modelled as a radially decreased cross-sectional area.

5.2 Simulation results

With the chosen parameters, the water level in the pipe was assumed to be stabilised at 124 mm for scenario 1 and this was used as the water level in the system under normal conditions. The water level upstream the blockage point was simulated for a vertical blockage covering 0, 50, 80, 93, 97 and 99% of the cross-sectional area and for a radial blockage covering 0, 30, 50, 75, 94 and 99% of the cross-sectional area. The resulting water levels for both blockage types are shown in Figure 5.3.

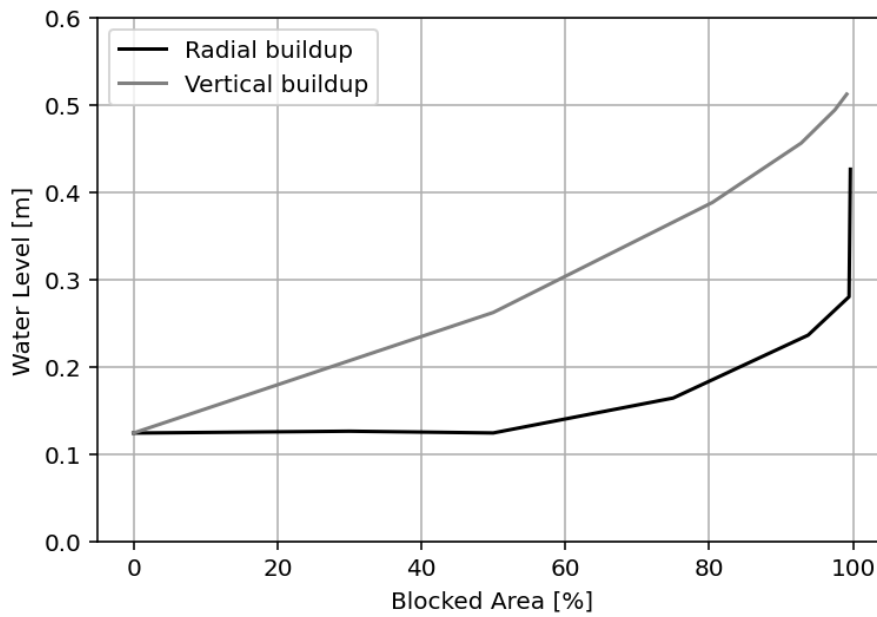


Figure 5.3: Graph showing the water level upstream the blockage point as a function of percentage of cross-sectional area blocked by a radial obstruction (representing FOG) and a vertical obstruction (representing sediments), according to Knightec's simulation for flow scenario 1.

The result of the simulation indicates that a radial blockage does not cause a significant, measurable increase of the water level until the blockage has become very severe, covering over approximately 80% of the cross-sectional area. The same water level rise occurs around the 20% blockage point for a vertical build-up from the bottom of the pipe.

For scenario 2 the nominal water level at the 0% blockage point was increased to show how the result in a dammed system. With this change, this effect was further pronounced, see Figure 5.4. The water level was simulated for a vertical blockage covering 0, 50, 80, 90 and 99% of the cross-sectional area and a radial blockage covering 0, 95, 99 and 99.5% of the cross-sectional area. In the dammed system there is no distinguishable backwater effect unless the pipe is over 50% blocked vertically. The water level stays stable even at sizeable radial blockages and no significant water level increase happens unless the cross-sectional area of the pipe is blocked by more than 90%.

5.3 Implications of the simulation results

The simulation indicates that the crucial factor determining the water level increase is the height of the blockage from the bottom of the pipe. An obstacle higher than

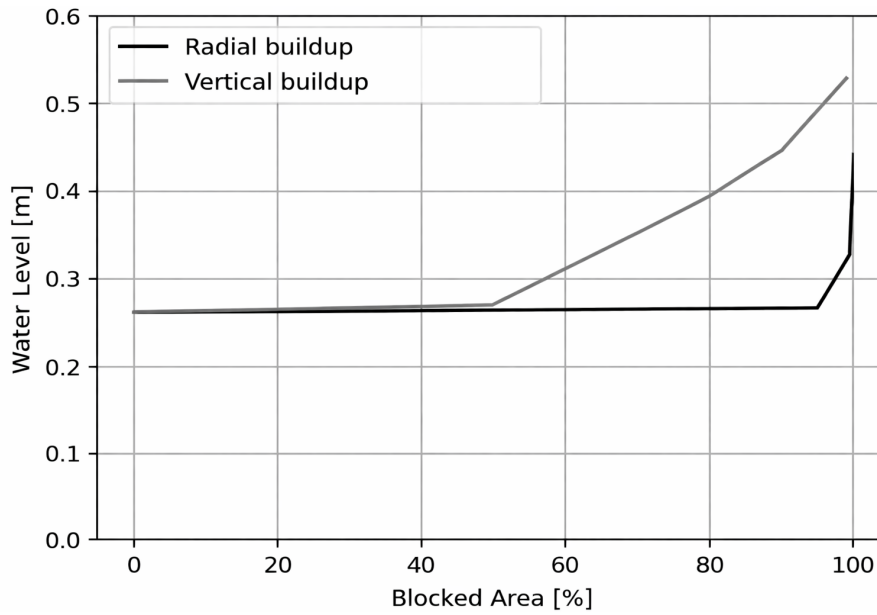
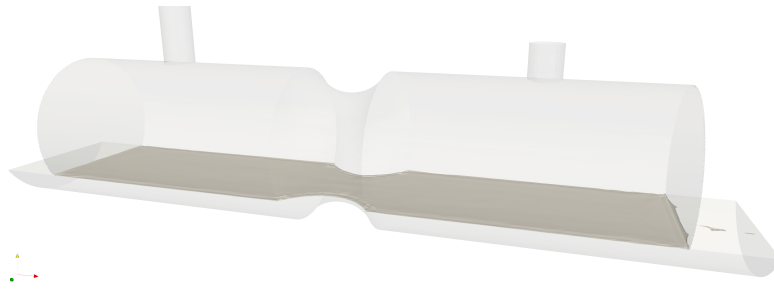
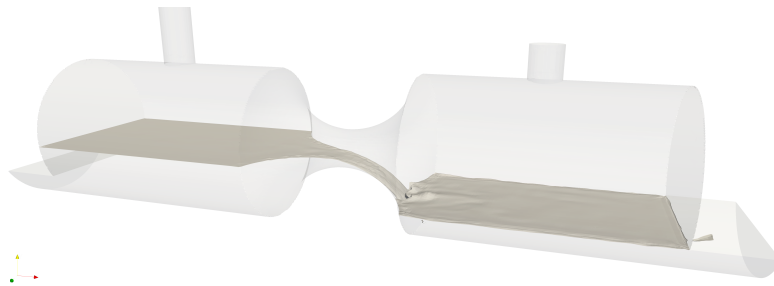


Figure 5.4: Graph showing the water level upstream the blockage point as a function of percentage of cross-sectional area blocked by a radial obstruction (representing FOG) and vertical obstruction (representing sediments), according to Knightec’s simulation for flow scenario 2.

the nominal water level prevents the flow from progressing through the pipe line, resulting in a raised backwater profile. For a radial blockage, the blockage height is small in relation to the blocked area. In contrast, the sediment blockage in the simulation builds vertically, meaning that the blockage height increases more significantly with reduced effective cross-sectional area. This results in a more significant water level rise for a less severe sediment blockage. This indicates that FOG blockages might be more difficult to identify in water level data compared to sediment blockages, since they do not necessarily accumulate at the bottom of the pipe which leaves a flow path for the water to exit the pipe through, without an increased hydraulic head. This phenomena is illustrated in Figure 5.5 and Figure 5.6 where the water surface in the pipe during a less severe blockage event and an almost fully blocked pipe is demonstrated for the two blockage types.

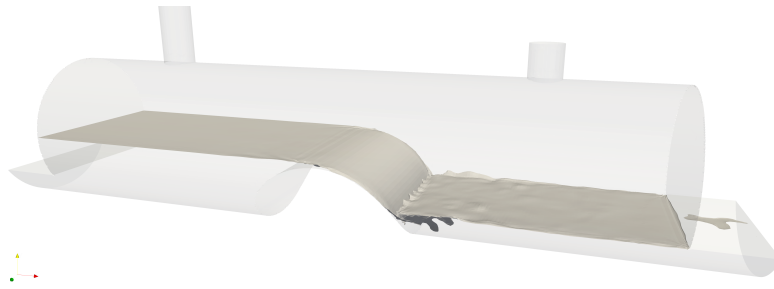


(a) Water level corresponding to a radial blockage of 50% of the cross-sectional area.



(b) Water level corresponding to a radial blockage of 93,75% of the cross-sectional area.

Figure 5.5: The water level in the pipe section for a radial blockage at two different severities.



(a) Water level corresponding to a vertical blockage of 50% of the cross-sectional area



(b) Water level corresponding to a vertical blockage of 92,79% of the cross-sectional area.

Figure 5.6: The water level in the pipe section for a vertical blockage at two different severities.

The simulation highlights how damming and blockage geometry influences the backwater rise in sewer lines. In a dammed system with a relatively low flow compared to the pipe diameter the effective cross-sectional area would in theory need to be severely decreased before the water level increases. Consequently only severe blockages could be identified by analysis of water level measurements. This is especially critical in the case of a radial blockage. Flushing might be needed before the blockages are that severe, to avoid a more time consuming and difficult flushing operation. Furthermore, the risk of sudden overflows are high in the case of a severely blocked pipe since only a small amount of debris such as wipes would be needed to fully restrict the flow.

The model is however simplified and does not fully reflect the complex conditions in a real sewer network. For instance, the flow was kept static whereas the flow generally fluctuates in sewer lines. Similarly, pipe roughness was kept constant, even though blockages do affect this parameter as well as the effective area. The blockage shapes in the simulation were moreover highly idealised as localised points of strictly vertical or radial build-up. In reality blockages may have a more irregular shape and build-up could occur throughout a longer pipe segment. A sediment blockage with a less severe slope angle would likely be harder to identify in the water level data. A

FOG blockage is unlikely to build in the upper part of the simulated pipe since the water which the FOG is transported with is never in contact with the upper parts of the pipe wall, owing to the fact that the water level is never that high. A blockage located in strictly the lower part of the pipe would lead to a bigger backwater rise relative to the blocked area. In contrast, the worst case scenario for a FOG blockage would be if it formed strictly on the sides or upper part of the pipe.

The simulation does nonetheless give an indication of how the relationship between blockage size and backwater rise is highly variable which makes a monitoring system based on water level data sensitive to missing blockages depending on their geometry. Although water level measurements have been used successfully for prediction and identification of blockages in previous studies, it is not certain that it would work for all pipe conditions and blockage shapes.

6

Benefit analysis of potential decrease of maintenance flushing operations

The aim of implementing predictive maintenance strategies is to decrease unnecessary use of resources which in its turn has economical benefits and improves sustainability. The main benefit of an optimised maintenance flushing strategy is the reduction of working hours required to keep the sewer network functional. A decreased amount of flushing operations also comes with the benefit of decreased GHG emissions from the flushing vehicles.

The project results show that a predictive strategy has the potential to optimise maintenance flushing in Gothenburg. How significant of a decrease of flushing operations could be expected with the proposed method was, however, not determined. While the noteworthy decrease of 96,2% achieved in Malmö highlights the value of data informed maintenance in a similar system with similar blockage challenges, the notable differences in prior strategies regarding flushing operations make their result far from directly transferable. The decrease in working time, GHG emissions and in relation to different decrease percentages in flushing operations in Gothenburg was examined for evaluation of the method's potential.

6.1 Environmental impact

The City of Gothenburg has adopted an environmental and climate program for the time 2021-2030. This program aims to provide guidance for the city as a whole when it comes to environmental work and is the foundation for the transition towards a sustainable city by 2030. The city's climate goal is to reduce the impact annually and to achieve net-zero emissions as quickly as possible (Göteborgs Stad, 2021).

SWW has developed a long-term strategy to decrease the GHG emissions from their work with wastewater management based on the city's overall climate plan.

The report states that the work is aligned with the climate plan for the municipality and the main goal is to emit near-zero GHG emissions by 2030 (Kretslopp och vatten, 2024).

The City of Gothenburg has also established goals to foster a high-quality physical living environment for its residents (Göteborgs Stad, 2021). One of the goals concerns traffic by motorised vehicles. The city aims to decrease the number of driven kilometres by 2030.

Maintenance flushing constitutes a small fraction of the practical work done by SWW. However, with the ambitious environmental goals, the department has established all emission-generating activities need to be optimised. Through optimisation of the maintenance flushing strategy the emissions from this operational area can decrease, which would contribute towards the close-to-zero emissions goal by 2030.

6.1.1 Environmental impact calculations

By implementing an optimised strategy for maintenance flushing, unnecessary GHG emissions will be avoided. The total, annual CO₂-emissions from SWW's two flushing vehicles were calculated and are shown in Table 6.1. The data regarding emission rate and average payload is obtained from the Swedish transport commission.

The flushing vehicles are not only used for maintenance flushing. They are also used to remove acute blockages or to clean sewer lines to prepare for filming operations. Therefore, the total annual driving distance is not representative of the distance driven specifically for maintenance flushing. To calculate a more accurate number, the percentage of working hours spent on maintenance flushing was used. Through the human resources system at SWW, it was found that 59% of all working hours related to flushing operations during 2025 were devoted to maintenance flushing. Therefore it was assumed that 59% of the total amount of kilometres driven with these vehicles in a year had the same purpose. This resulted in an estimated annual driving distance of 28,808 km with the purpose of maintenance flushing.

Table 6.1: CO₂ emissions from SWW's two flushing vehicles.

Emissions [gCO ₂ /tkm]	Average payload [tons]	Distance [km/year]	Total emissions of CO ₂ [tons/year]
102	9.81	29,000	30

6.2 Potential savings

The direct operational emissions at SWW were calculated for the year 2020 and amounted to 1,905 ton CO₂-equivalents (Kretslopp och vatten, 2024). Assuming that the emissions from the flushing vehicles were similar in 2020 and 2025, the maintenance flushing was estimated to account for 1.51% of the total direct emissions from SWW. This share could potentially be reduced through an optimisation of the maintenance flushing strategy.

Fewer unnecessary flushing operations would decrease GHG emissions as well as motorised traffic in Gothenburg. Furthermore, it would increase the available working time for operational personnel. This time could go towards taking over jobs that are currently performed by hired companies which adds financial benefits. Resources could also become available for improving other parts of the sewer system.

Table 6.2 presents examples of the potential reductions in CO₂ emissions and working hours as a result of decreased maintenance flushing. A decrease with 10% would make 300 additional working hours available. That is equivalent to 3.8 weeks of working time for two technicians. The emissions from maintenance flushing are a small part of the total emissions from the organisation but to reach the climate goals established by the department, every part of the organisation needs to be improved.

Table 6.2: Savings from potential decrease in maintenance flushing.

Decrease in flushings	Emissions of CO ₂ -eq [tons]	Percentage of direct emissions from SWW [%]	Driven distance [km]	Working time [hours]
10%	3	0.15	2,900	300
30%	9	0.45	8,700	900
50%	15	0.76	14,500	1,500
100%	30	1.51	29,000	3,000

7

Discussion

7.1 Method validation and limitations

An important condition for implementing the presented method is to expand the data collection. Only three of the twenty datasets provided by VA SYD contained data showing build-up or blockage. Since the warning system was designed based on these datasets the method has not been validated against other blockages. In Gothenburg, data was only collected from two sites during three months. This makes it difficult to validate the method only based on these two datasets.

Installing more sensors would be the first necessary action towards a more predictive maintenance strategy. Data from more sites and during longer time will give further insight to how the sewer lines are different in operational behaviour. Data collection during a longer period would also give more insight to whether and how the sewer line is affected by rain or seasonal changes.

The results of the data analysis of the studied datasets did, however, align with the conclusions of previous research on the topic. As Cuong Do et al. (2022) established, blockages could be detected through identification of anomalies, more specifically prolonged, often abrupt, increased water levels. These characteristics were found in the data from Malmö as well.

Cuong Do et al. (2022) also suggested identification of these events through one high-level threshold and one low-level threshold based on a comparison of the upcoming measurement to a subgroup of reference values. This enabled blockage detection before overflows in a majority of cases in the study. Faris et al. (2024) also utilised anomaly detection in time series data and included a framework for their methodology consisting of data collection, data pre-processing and system development. This yielded good results with no missed blockages and low false alarm rates, when applied to the Hong Kong sewer network.

The line of previous research, together with the results of this thesis, implies that the general framework for blockage detection using level sensors should be applicable and useful in various sewer networks. This conclusion is supported by

the fact that the framework is similar across all proposed methodologies and that level data exhibits similar behaviour during blockage events in all studied networks.

It is advised, though, that the maintenance flushing continues during the transition between strategies. First of all, it enables evaluation of the difference in water level before and after the flushing. If the water level remains at the same height and no apparent build-up is noticed during the flushing operation, as was the case for sensor 7, this would indicate that the site does not need flushing as frequently. Secondly, it eliminates the risk of decreased operational reliability during the period where the applicability of proposed strategy at each maintenance flushing location is evaluated.

Furthermore, each adjustable step of the proposed method including the pre-processing parameters, moving average time window and alarm thresholds have not been validated. The parameters were defined based on the available data. Whether the faulty data isolation, moving average and warning system continue to generate the desired results with the settings adapted to each pipe as new data is continuously added, comes with some degree of uncertainty.

The lack of knowledge regarding how FOG build-up impacts the water level is also a limitation for the project. Based on the simulation presented in Chapter 5, it is evident that blockages which do not build vertically from the bottom of the pipe have a different effect on the backwater rise. The simulation results indicated that FOG blockages might cause a less significant upstream level rise and consequently not be detectable by water level time series analysis unless the blockage is very severe, especially in a dammed system.

Over half of the maintenance flushing sites in Gothenburg are flushed due to issues with FOG and pipe dips. Since it is unclear how well the water level can indicate FOG build-up, it might be difficult to fully rely on the sensor to indicate when the risk for this type of blockage has increased. Further studies should investigate the geometry of FOG blockages and how blockage geometry influences the hydraulic response. Additionally, more studies are needed to determine the geometry of blockages which are made up of combinations of FOG, consumer products and sediments. Some maintenance flushing locations are subjected to both FOG and other materials and how well these can be predicted by level data remains uncertain. However, there are still 85 sites where the main reason for maintenance flushing is not FOG. Here the proposed method could be extra useful.

7.2 Sensor installation

The results of this project also highlighted the importance of high-quality data and with this, the need for proper sensor instalment. The installation of the sensors can largely impact the occurrence of outliers in the dataset. Consequently, it can reduce the need for outlier filtering and decrease the risk of removing true data points. For deep manholes, the personnel at VA SYD found that the sensor VEGAPLUS Air 42 is more suitable. This sensor has a lower angle of diversion which increases the likelihood of transmitted signals being reflected by the water surface rather than other objects in the manhole. At one site, where VEGAPLUS Air 41 was mounted in a deep manhole, the data quality was lacking due to the measurements being disturbed enough by noise, to hinder the data analysis. Since the proposed method is based on identifying the nominal and abnormal behaviour in each pipe, it could not be applied. According to VA SYD, the level curve was interpretable after the sensor had been switched to the 42 model.

As previously showed, the sensors are mounted differently by SWW and VA SYD. The mounts used by VA SYD are attached to the manhole wall and these can adjust the angle of the sensor which enables a more precise water level detection. SWW mounted the sensors in the stationary manhole cover where no adjustments could be made to the angle. Using the same mounts that VA SYD uses could ease the installation of the sensor and achieve more accurate sensor readings.

There are also other options for level monitoring. The UHF-RFID sensors developed by Tatiparthi et al. (2025) had good accuracy in both level and surface flow velocity measurements. The inclusion of velocity measurements enabled point-source event detection which could be hugely useful for monitoring all types of blockages within the larger network. But for the purpose of this project, locating the blockage is irrelevant as the method is meant to be used for predictive maintenance flushing, monitoring locations where it is already known that blockages form.

7.3 Site adaptation

The quality and characteristics of the data can vary between the sensors. Subsequently the outlier filtering needs to be individual for each dataset. The three methods used in this project should be adequate to cover all outlier isolation needs. However, which of them that are required and the specific ranges and thresholds will need to be adjusted for each dataset. During outlier filtering, the removal of true data points must be balanced against retaining too many outliers in the dataset. Re-

moving valid measurements may result in actual build-up or blockage events being missed in future data. Conversely, retaining excessive outliers can distort the moving average and trigger false warnings. Determining this balance would ultimately be the responsibility of the operating personnel.

Similarly, the range of the time window for the moving average filter set to 12-hours worked for all the studied data but can be adjusted to balance the consequential alarm delay with data smoothing and a lower false alarm rate. The durations and water level thresholds included in the warning system can also be altered. This might be necessary at sites where neighbouring properties will suffer large consequences due to an overflow. Decreasing the duration or the threshold would increase the possibility of false warnings. However, in some circumstances this might be preferable over missing a slight build-up.

The risk for overflow is not the only reason for maintenance flushing. Some sites are flushed due to problems with odour. These issues would remain if a predictive maintenance strategy would be implemented. These sites might need to be flushed with the same interval that is currently established, in order to avoid these issues.

Decreasing the maintenance flushing operations in sewer lines known for always containing build-up can also create issues. Even if the build-up does not pose a risk for overflow, clearing a pipe can be straining for the technicians performing the flushing operation. Therefore, letting the build-up increase more can cause additional labour for the personnel.

The adjustable nature of the proposed method addresses the complex of problems stemming from the highly variable conditions in the sewer network. However, it consequentially requires a lot of time spent analysing multiple data sets in the implementation stage. It also requires the operating personnel to determine the risks associated with certain level elevations for each location. Further research should evaluate the relationship between a local water level rise and the risk of overflows and the factors influencing this relationship. Additionally, it should be established what severity of blockage is acceptable before flushing, considering both the risk of sudden overflows and difficulty of flushing operations.

Faris et al. (2024) developed a method which had a similar general framework to the proposed method in this report but used fewer adjustable parameters which still achieved an adequate blockage detection for all their datasets. For instance, outliers were defined as readings larger than three standard deviations away from the mean of a 80 minute time window. This was sufficient for their data sets which mainly contained spikes, with extreme deviations from the neighbouring data points. In contrast, the data from Malmö and Gothenburg was noisy and included faulty

data types which needed to be isolated with different methods. This could be due to differences in sensor accuracy or the sewer networks.

It is also worth mentioning that combining machine learning with real-time level measurements also has potential for further automation the data analysis process. The state-of-the-art and possible methods for utilising machine learning for sewer blockage detection was however outside the scope of this project.

7.4 System implementation in Gothenburg

This report describes a method for transitioning to a predictive maintenance flushing strategy based on water level measurements. The method is applicable in Gothenburg. However, how to practically implement it is not studied. The application for outlier filtering that was used is created and provided by SWW. Here all three methods, range filter, band filter and spike detector, are included. If a moving average filter function would be created as well, then all the data pre-processing could be made using this tool.

SWW also have an application for visualising and monitoring real-time data from sensors. This application could serve as a platform for implementation of the proposed warning system. The moving average data series for each sensor could be visualised within the application, while activated warnings could be displayed in the already existing alarm tab. Such an implementation would provide operating personnel with a fast and intuitive indication of which sensors and sewer lines exhibit changes in water level pattern.

In addition to the moving average, both raw and cleaned datasets should remain accessible. During the initial implementation phase, continuous evaluation of the method would be important. Changes in water level before and after flushing operations should be analysed as maintenance flushing initially continues according to the existing schedule. The condition of the sewer line during these operations should also be documented, including the presence and extent of any build-up. This would ease the transition to a predictive maintenance strategy. If repeated build-up is observed in sewer lines without corresponding changes in water level, the suitability of the method for those specific sites may need to be reconsidered.

As discussed in Chapter 6, converting to a predictive maintenance strategy could provide several operational and environmental benefits. Reduced GHG emissions from maintenance flushing operations would contribute towards SWW's goal of achieving near-zero emissions by 2030. In addition, a predictive strategy would likely reduce the number of maintenance flushing operations performed annually,

which would enable more efficient utilisation of personnel and operational resources.

Furthermore, implementing the predictive strategy provides insight to the operators about the conditions and behaviours of the monitored pipes. Data-driven management of the sewer network increases the maintenance strategy's robustness as decisions can be made by the operator based on real-time data rather than estimations. For instance, if a blockage unexpectedly occurs between scheduled maintenance flushing operations, the proposed method could detect it. As a result, the risk of overflow and the economical, societal and environmental costs could be avoided.

Even in the case of an unexpected FOG blockage, with a shape that might make it hard to predict as it builds, a data-driven strategy could be useful. This owes to the fact that the water level rise would still occur and be detectable as the sewer line starts to overflow. Consequently, it might still be possible to remove the blockage before the water damages property or the environment, as long as the warning system is adapted to have less delay for sites where such blockage events could happen.

Additionally, blockages which are sudden and not gradually formed are not only harder to predict with water level measurements, but also harder to take proactive action against with a scheduled flushing operation. If the aim of the flushing operation is not only to avoid overflows but to remove build-up before it has become severe, it serves no purpose if no build-up happens before the pipe is abruptly blocked enough to start to overflow. In these scenarios the preferable option might be a reactive strategy where flushing is done after the risky water level threshold has already been exceeded. With level monitoring there is potential to detect such a blockage event before overflows affects properties or the environment. Further studies should assess whether abrupt blockages without prior build-up occurs to a significant extent. This can not be determined simply by studying the characteristics of blockages through water level data, because of the uncertainty regarding the water level increase for different build-up shapes.

8

Conclusion

In conclusion the results of the project indicate that a predictive maintenance strategy utilising radar sensor water level measurements is both feasible and beneficial and that the proposed method is applicable in Gothenburg. The studied datasets along with previous research strongly suggests that blockages are characterised by a prolonged increased water level in time series data. Therefore, analysis of such anomalies can be used to detect build-up and blockage events.

However, the data from the level sensors may contain various types of faulty data. Therefore the proposed method includes a methodology for faulty data isolation and removal, which sufficiently reduces the influence of outliers in the studied datasets. Furthermore, the suggested warning system, applied to the moving average of the pre-processed data, successfully indicated build-up and blockage events within the datasets, without continuous, manual monitoring of the water level data.

The proposed method for blockage detection is adjustable to account for the highly variable pipe conditions in sewer networks. Through continuation and implementation of the proposed method, it can be validated and its usefulness can be evaluated for different site conditions. Uncertainty particularly remains regarding measurable water level deviations as a result of FOG blockages.

However, real-time monitoring provides the operator with valuable intel about the condition of the sewer network which enables well-informed, data-driven decision making. Additionally, the significant potential benefits of reduced GHG emissions and optimisation of operational resources at, makes the implementation of a predictive maintenance flushing strategy worth pursuing.

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A

Python code

Appendix A show the python code that was created for application of the moving average filter, see Chapter 3.2.2 and to implement the warning system, see Chapter 3.3. The resulting graphs for different datasets generated by the code are described and shown in Chapter 4.3, 4.4 and 4.5.

```
%matplotlib qt
import pandas as pd
import matplotlib.pyplot as plt
import matplotlib.dates as mdates

# =====
# Load the data
# =====
df_cleaned = pd.read_excel("data_clean_ny.xlsx")

matare = 22 # Choose sensor

kolumn_namn = df_cleaned.columns[matare]
delar = kolumn_namn.split(",") # Divide the column name

adress = delar[0].strip() # Adress, specified in the column name
D = float(delar[1].strip()) # Dimension, specified in the column name
B = float(delar[2].strip()) # Base level, specified in the column name

c_df = df_cleaned.iloc[:, [0,matare]].copy()
c_df.columns = ["Time", "Cleaned"]

# =====
# Define variables
# =====
R = 0.8*D # Risky level
U = B+0.2*D # Build-up level

print(D) # Print dimension
print(B) # Print base level
```

```
print(U) # Print build-up level
print(R) # Print risky level

# =====
# Convert time
# =====
c_df = c_df.dropna(subset=["Time", "Cleaned"])

c_df["Time"] = pd.to_datetime(c_df["Time"], utc=True, errors="coerce")
c_df["Time"] = c_df["Time"].dt.tz_localize(None)

# Put time as index
c_df = c_df.set_index("Time").sort_index()

# =====
# Create moving average
# =====
c_df["MA_12h"] = c_df["Cleaned"].rolling("12h").mean()

# =====
# Warning system
# =====

def hitta_varningsintervall(df, kolumn, grans, period):
    over_grans = df[kolumn] > grans
    grupper = (over_grans != over_grans.shift()).cumsum()
    intervall = []
    for _, grupp in df.groupby(grupper):
        if grupp[kolumn].iloc[0] > grans:
            tid_langd = grupp.index[-1] - grupp.index[0]
            if tid_langd >= pd.Timedelta(period):
                start_tid = grupp.index[0] + pd.Timedelta(period)
                kandidat = grupp.loc[start_tid:]
                if not kandidat.empty:
                    start = kandidat.index[0]
                    slut = grupp.index[-1]
                    intervall.append((start, slut))

    return intervall

## Create function for removing the yellow warning if the red one is activated
def ta_bort_overlap(gula, roda):
    resultat = []
    for g_start, g_slut in gula:
```

```
delar = [(g_start, g_slut)]
for r_start, r_slut in roda:
    nya_delar = []
    for d_start, d_slut in delar:
        # No overlap
        if r_slut <= d_start or r_start >= d_slut:
            nya_delar.append((d_start, d_slut))
        else:
            # Cut the left part
            if d_start < r_start:
                nya_delar.append((d_start, r_start))
            # Cut the right part
            if d_slut > r_slut:
                nya_delar.append((r_slut, d_slut))
    delar = nya_delar
    resultat.extend(delar)
return resultat

## Yellow warnings
gula_intervall = hitta_varningsintervall(
    c_df, "MA_12h", grans=U, period="4D"
)

## Red warnings
roda_intervall = hitta_varningsintervall(
    c_df, "MA_12h", grans=R, period="12h"
)

## Remove overlap
gula_intervall = ta_bort_overlapp(gula_intervall, roda_intervall)

# =====
# Plot
# =====
fig, ax1 = plt.subplots(figsize=(12,6))

## Show months with name instead of numbers
ax1.xaxis.set_major_formatter(mdates.DateFormatter('%b'))
ax1.xaxis.set_major_locator(mdates.MonthLocator())
plt.xticks(rotation=45)

## Adjust font and text size
scale = fig.get_size_inches()[0] / 12

plt.rcParams.update({
```

```
"font.family": "Times_New_Roman",
"font.size": 14 * scale,
"figure.titlesize": 30 * scale,
"axes.titlesize": 22 * scale,
"axes.labelsize": 18 * scale,
"legend.fontsize": 14 * scale,
"xtick.labelsize": 14 * scale,
"ytick.labelsize": 14 * scale
})

## Plot data from sensor
ax1.plot(c_df.index, c_df["Cleaned"], linewidth=0.8, color="salmon", label="Cleaned")
ax1.plot(c_df.index, c_df["MA_12h"], linewidth=1, color="black", zorder=4, label="MA_12h")

ax1.set_xlabel("Time")
ax1.set_ylabel("Water_level [mm]")
#ax1.set_title(f"{address}, {D:.0f}") # If address instead of number
ax1.set_title(f"Sensor_5 (D={D:.0f} mm), moving average with warnings")

## Threshold lines
ax1.axhline(y=R, color='red', linestyle='--', label="Risky_water_level")
ax1.axhline(y=U, color='gold', linestyle='--', label="Build-up_water_level")

## Pipe crown line
ax1.axhline(y=D, color='grey', linestyle='--', linewidth=1, zorder=1, label="Pipe_crown")

## Warnings
for i, (start, slut) in enumerate(gula_intervall):
    ax1.axvspan(
        start, slut,
        color="yellow",
        alpha=0.5,
        zorder=1,
        label="Warning_for_build-up" if i == 0 else None
    )

for i, (start, slut) in enumerate(roda_intervall):
    ax1.axvspan(
        start, slut,
        color="red",
        alpha=0.35,
        zorder=2,
```

```
        label="Warning_for_risky_water_level" if i == 0 else None
    )

## Legend
lines1, labels1 = ax1.get_legend_handles_labels()
ax1.legend(lines1, labels1, loc="upper_right")

plt.tight_layout()
plt.show()
```

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