Metrology for Real-World
Domestic Water Metering

EMPIR

The EMPIR initiative is co-funded by the European Union's Horizon 2020 research and innovation programme and the EMPIR Participating States

**17IND13 Metrowamet**
**Metrology for real-world domestic water metering**

EURAMET

# Technical report describing the algorithms for the detection and evaluation of leakage

EMPIR Grant Agreement: **17IND13 Metrowamet**
Deliverable reference: **D5**
Lead Partner: TZW
Due date of the deliverable: **June 2021**
Actual Submission Date: **July 2021**

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# Introduction

This report summarizes the work done in Work Package 3 “Smart Monitoring of small flow rates” Task 3.4 “Algorithms for leak detection”. The aim of this task was to develop an algorithm for leakage detection for household water meters and implement them on a water meter device.

At first, a literature review was done on different algorithmic approaches for leakage detection. In a second step, an algorithm for leakage detection was developed and tested on simulated leakage data.

A hardware platform has been developed during the project for detecting small flow on domestic water meters using image-based correlation. The hardware platform is generic and is ready for implementing leak detection algorithms. However, the described algorithm still has to be implemented in the developed hardware platform.

# Investigation on leakage detection algorithms

The detection of leakage within a household or a distribution network can be done with various measures. Despite the actual search for leakage with instruments, the focus of this investigation was to review purely data driven approaches. That means, the identification of leakage was done by observing flow data derived from volume measurements with temporal and spatial distribution. The study area of the MetroWaMet Project is the household water meter. Therefore, the localisation of leakage was focused on a household level and a single water meter. But to get a complete overview, also leakage detection systems on a broader scope have been included.

Practically, the types of algorithms used to detect leakage in a system can be ordered by their complexity. A simple, fast and reliable method is the Minimum Night Flow (MNF). The basic assumption is that, during the night (usually between 2:00 am and 4:00 am) [1], the water consumption is reduced to a minimum and therefore water flow should be very low (on distribution network level) or zero (on household level). A more complex approach focuses on the possible consumption patterns on an end user level. The Flow Pattern Disaggregation (FPD) uses mostly statistical measures to identify recurring demand patterns (washing machine, toilet, bathtub etc.) and therefore also leakage patterns and events. The last class of measures tries to forecast future water demand with mainly data driven approaches, e.g. machine learning. The observed demand is then compared to the forecast. Deviations that occur will be labelled as water loss or leakage.

## Minimum Night Flow (MNF)

The Minimum Night Flow is a common approach to estimate leakage in a distribution system or on a household level. On a network level, this analysis is performed on district metering area (DMA) which is a discrete zone having permanent boundary defined by flow meters and closed valves [2]. A DMA has between 500 and 3000 service connections. Total water losses can be calculated by subtracting minimum night flow (MNF) from legitimate night flow (LNF). LNF is calculated based on an assumption that only 6 % of the population are active.

The water losses determined by the MNF are only representative for the night time and not for the daytime hours. Estimating the total volume of real losses for the whole day using these MNF losses would result in overestimation of the daily leakage, because of the lower average pressure during the daytime due to higher flow rates.

To overcome this problem, different studies have been undertaken to further improve the MNF concept on a network level [3–6].

In different studies, this approach has been extended to a household level by using automated water meter reading. Household leakage could be, among other things, identified via an alarm which is picked up during the meter reading process. This alarm is activated if no zeros (e.g. no closed valves in the household) in a number of consecutive time steps have been recorded [7, 8].

## Flow Pattern Disaggregation (FPD)

There are software and other approaches available on the market for the disaggregation of flow patterns. The main principle is to categorize water consumptions based on different measurements (flow, pressure, protocols, …). Unclassifiable consumptions are presumably consumptions that are not wanted, e.g. water loss or leakage. Trace Wizard [9] and Identiflow [10] use decision trees to distinguish water usage patterns from each other and categorize them. Other approaches like HydroSense [11] and SEQREUS [12] are based on machine learning techniques.

As already mentioned, Trace Wizard uses a decision tree algorithm on high resolution flow data. This data consists of information like minimum and maximum volume, peak flow rate and duration range. Additionally, a detailed overview of the efficiency rating of each household appliance/fixture is needed as well as a water use diary filled out by every resident over the duration of one week. The experts use these data to create flow templates to match water user patterns. Putting it all together concludes in a disaggregated water end use. The classification accuracy of a two-week data package is about 70 % [13]. In addition, the prediction accuracy of Trace Wizard is significantly reduced when more than two events occur concurrently [14].

In contrast to Trace Wizard, Identiflow uses fixed physical features of various water-use devices (e.g., volume, flow rate, duration, etc.) to classify the different end-use events. Its classification accuracy therefore depends on the physical features used to describe each fixture/appliance. Two different water events are likely classified into the same category if they exhibit similar physical characteristics.

HydroSense is a probabilistic-based classification approach which relies on data collected through pressure sensors. Water end-use events are classified with respect to the unique pressure waves that propagate to the sensors when valves are opened or closed. Its classification accuracy is about 90 % [11].

The SEQREUS approach proposes a combination of Hidden Markov Models (HMMs), Dynamic Time Warping (DTW), and time-of-day probability to automatically categorize the collected data at the household level into particular water end-use categories. To foster the accuracy of the model, disaggregation data obtained by Trace Wizard is used for training procedures. The tested classification accuracy is around 85 % [15].

Other than that, [16] proposed an algorithm, for discovering frequent activities from unlabelled sensor data. Their approach combines sequence mining and clustering algorithms to distinguish multiple activities interleaved in time, and activity sequences that occur in different order. Cardell-OIiver [17] introduced a new method for activity discovery through hourly water meter readings which addresses the following constraints: (i) observations are unlabelled and so unsupervised learning of activity types is required, (ii) only automatically collected readings are used, and (iii) coarse-grained hourly readings mask sub hourly concurrent and sequential activities. Automatic rule-based labelling is combined with hierarchical clustering. New criteria are introduced for evaluating the quality of discovered activity clusters.

## Data Driven Demand Forecast (DDDF)

Generally, the principles to detect leakage using a mathematical model are based on a variety of statistical and machine learning models. The basis for these models is the availability of water flow data on a consecutive time level in real time [18]. The basic principles of how leakage detection can be done relies on calculating the deviation from the average consumption and the comparison of steady water consumptions over a period of time. In the following, some of these models are discussed.

Artificial neural network (ANN) models can be used for demand forecasting [19–21] and for scanning large amounts of data like operational variable and historical records to identify a failure event [22–25] or to estimate failure patterns. Pattern sequences based forecasting (PSF) [28] are other efficient algorithms.

The Bayesian system identification methodology is a probabilistic leak awareness method which has been used by [30–32]. The main reason to use a Bayesian interface in leakage studies is to deal with different kinds of errors that cannot always be included in calculations. Therefore, to make more sense, the final discrete value is bounded with a certain probability that gives us more information about the result reliability. The drawback is that usually such procedures need a great deal of computer power for calculations.

Ye and Fenner [34] have used a Kalman filter for prediction of hydraulic parameters (flow and pressure) from past acquired data. Depending upon the difference between the predicted and measured field data, leakages are detected. This process is applied in water distribution systems (WDS) in the north of England. The proposed methodology is computationally less complex and requires less data when compared to other techniques such as ANN. This technique is useful for detecting small leakages and small abrupt changes.

Wu et al. [35] presented a model for leakage detection of WDS using genetic algorithms (GA). Leakages are assumed to be pressure dependent. Leakages in WDS are detected by calibrating the difference between simulated and measured hydraulic parameters. In this study, three objective functions have been used for simulation with GA, and the proposed algorithm is applied to a district water system in the UK. Twenty-two leaking pipes were detected in the given WDS.

Some works developed predictive models that mostly provide short-term forecast of the water demand at the individual (household) level. For instance, [36] implemented a stochastic simulation for predicting demand based on end use probabilities for pulse duration, intensity, and time of day of water usage.

Aksela [37] presented a probabilistic prediction based on mixtures of Gaussian Models. A linear regression model in conjunction with the k-means algorithm is used to predict the average weekly consumption. Then, a probabilistic model developed on the basis of Gaussian Mixture Model (GMM) for each of the four classes is obtained via the k-means algorithm. The latter, in conjunction with the prediction model, were utilized so that estimates for the demand pattern are obtained by sampling the probability distributions for individual single-family and semidetached houses.

GMM’s are also used by McKenna et al. [38] in a similar study to model the daily water demand of commercial and residential consumers of a district metered area. The parameters of the model are then clustered using the k-means algorithm into four demand patterns. The authors excluded weekends from this study.

Cahill et al. [39] simulate water use in a single-family residential neighbourhood using end-water-use parameter probability distributions generated from Monte Carlo sampling. This approach preserves the heterogeneity of the water users when it also samples the extreme values of the associated statistical distributions.

Kenney et al. [40] proposed a regression method that models household water demand as a function of two main categories. The first category comprises the factors which are within the control of water utilities (e.g., price, water restrictions, rebate programs), and the second one comprises the factors that are not (e.g., climate and weather, demographic characteristics). The results showed that some improvement has been achieved in comparison to the state-of-the-art methods in which these factors have not been considered.

Moreover, nonparametric statistical tests and advanced regression models [41–43] are used to identify key water consumption drivers and forecast urban water consumption. These studies have been demonstrated to successfully identify the main drivers of water consumption and to attain good forecast accuracy levels.

Lastly, multi-user models that examine social interactions and influences by mimicking mechanisms among the users can be applied to estimate water demand (e.g. [44]). The majority of these works relies on multi-agent systems, where each water user (agent) is defined as a computer system situated in some environment and capable of autonomous actions to meet its design objectives, but also able to exchange information with the neighbour agents and change its behaviour accordingly in this scene. Multi-agent systems are employed to study social network structures and mechanisms of mutual interaction and mimicking on the behaviours of water.

# Evaluation of the developed algorithm

## Methodology of the algorithm

The developed approach is a mixture of the Minimum Night Flow (MNF) and the Data Driven Demand Forecast (DDDF) as explained in the literature review. By using pattern recognition methods, the typical usage profile connected to the water meter is obtained. Principally, the consumption over time of each day shows similar characteristics. At night, consumption is very low due to inactivity of the household (absence, sleep). In the morning and early evening, a consumption peak event is taking place. The morning consumption is usually an overlap of hygiene (shower, bath, toilet, washing hands) and consumption (breakfast, drinking, meal preparation). In the middle of a day, water consumption is on a medium level. Although characteristics are similar, they are not identical. Small differences can be seen in regard to the event time and the level of the peak demands.

By using an affine non-negative matrix factorisation (aNMF), usual water consumption patterns can be identified. The aNMF is a method of dimension reduction and calculated as follows:

$$X = AH + a1^T + E$$

with Matrix $X \in \mathbb{R}^{m \times n}$, matrix $A \in \mathbb{R}^{m \times k}$, matrix $H \in \mathbb{R}^{k \times n}$, score vector $a \in \mathbb{R}^m$, single vector $1 \in \mathbb{R}^n$ and residual matrix $E \in \mathbb{R}^{m \times n}$. As a secondary condition, all values of A, a and H have to be positive. Further information on this topic can be found in [26]. This method is mainly used in analysis of spectroscopic data. Its major advantage is the ability of good chemical and physical interpretation because of the exclusively positive components.

In the present case, matrix X is a water consumption time series transformed into a two dimensional matrix. The first dimension is the intraday time step e.g. on a minute-by-minute basis this would be from 1 to 1440 (1 day = 1440 minutes). The second dimension are the recorded days.

In Figure 1 the aNMF identified exactly two water consumption patterns. Pattern 1 can be identified as a typical weekday consumption. Pattern 2 is a typical weekend-day pattern. Both are distinguishable (as already stated) by its occurrence and height of peak demand in the morning.

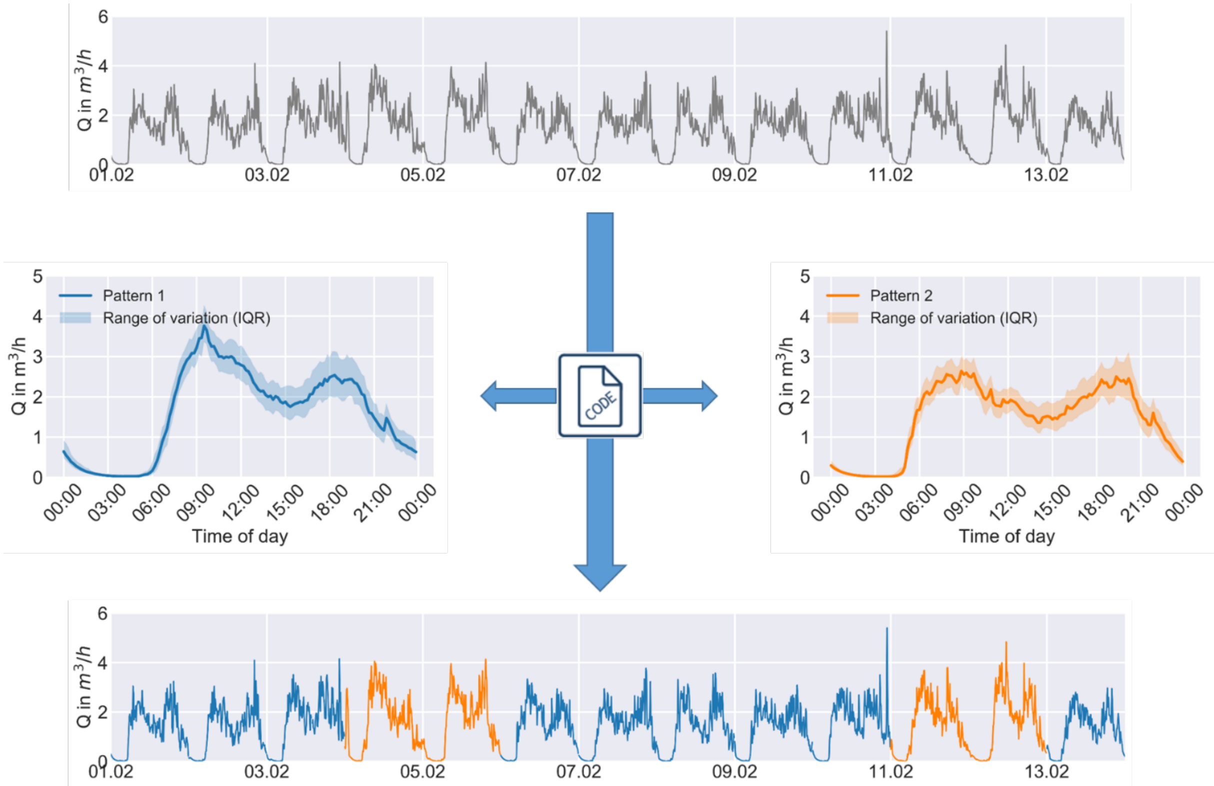


*Figure 1: Identification of typical water consumption patterns with NMF (Usage Pattern 1: typical workday, Usage Pattern 2: typical weekend day)*

Based on the normal behaviour, deviations are determined in a second analysis step, which are output as consumption anomalies and are based on simple statistical methods, such as Tukey's outlier detection [27]. The method differentiates between four different types of anomalies (Figure 2).

- Baseline Anomaly: an unusual consumption, constant over time (in other words leakage)
- Day Anomaly: an unusual consumption, occurring over a distinct period of time at day
- Night Anomaly: an unusual consumption, occurring over a distinct period of time at night
- Profile Anomaly: an unusual consumption profile, indicating errors in the meter

In addition to the determination of the anomaly types, the calculation of the daily water quantities caused by the respective anomaly type is performed simultaneously.

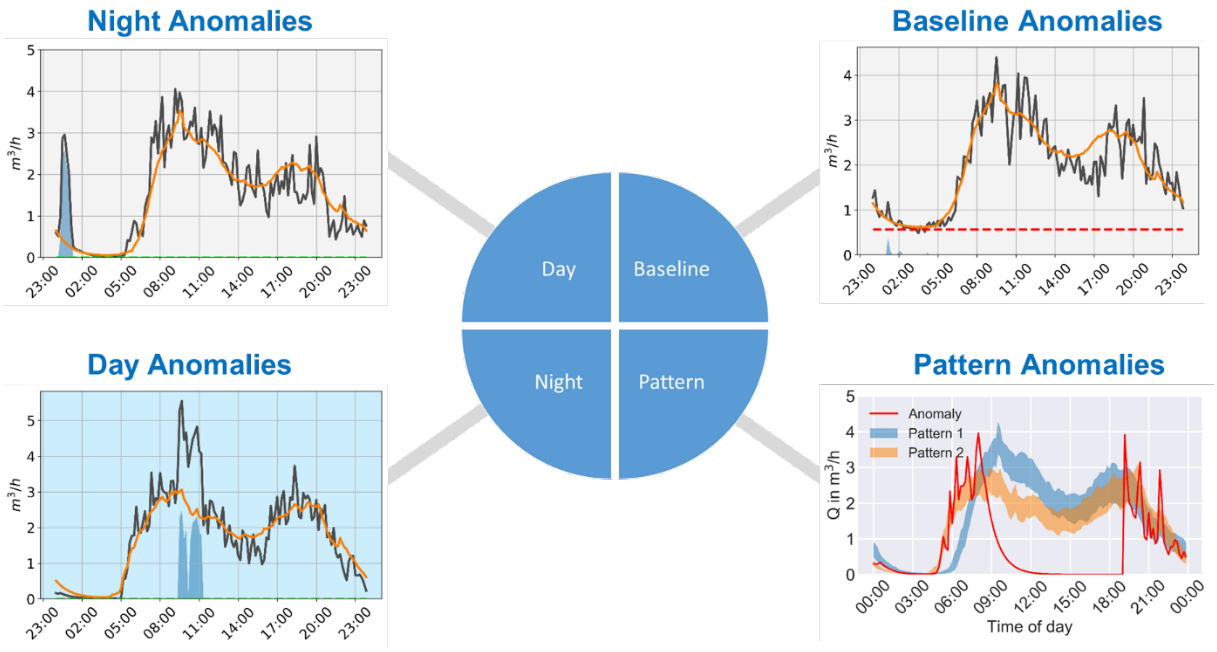


*Figure 2: Differentiation between four types of anomalies, whereas baseline-anomaly can be declared as leakage.*

## Data acquisition for the algorithm

To train and test the algorithm a database is needed. This database should consist of time series data of water usage with typical usage patterns. Typical patterns derived from water consumption such as bathing, showering, usage of toilet and washing hands etc.

Preferably, real measurements from end users should be used. The collection of such data is very time consuming and due to data security issues often a very bureaucratic process. This effort is out of scope in terms of time and resources in this project. Therefore it was decided to create artificial water consumption data that is based on real usage patterns derived from measurements from a regional project managed by DVGW-TZW [29].

The experimental setup at the TZW for this task is shown in Figure 3. A simplified arrangement of water meters in a residential building was to be simulated. The inflow to the system is at the bottom right as shown in the figure. The flow first passes the "house entrance meter", the water meter positioned at the house entrance, which in reality would be used by the water utility for billing. The meter positioned second is the "meter at dwelling", the meter at the entrance to an apartment of a residential building. In addition, it is used to control the motorized valves through which the withdrawals were performed automatically. Both water meters were electromagnetic flow meters made by company Bronkhorst with a nominal diameter of 8 mm and a pulse output of 4000 pulses/litre (type MVM-005-Q). The flow range of these two meters is from 15 l/h to 300 l/h (or with increased error between 6 l/h and 360 l/h).

Between "house entrance meter" and "meter at dwelling" exists a T-piece with a linear ball valve, through which small water leakages between the "house entrance" and the "dwelling" can be generated. The amount of leakage was set manually and confirmed by gravimetric measurements. The four profiles were each measured with leakage rates of 0 l/h (no leakage), 10 l/h, 20 l/h or 30 l/h.

In order to increase the difficulty for the algorithm, it was later on decided to not use the profiles with the manually set leakage, but to only use the profiles without leakage and to generate the leakage rates digitally on the PC.

The flow time series recorded at the "house entrance meter" form the data basis for the algorithm. The time series recorded at the "meter at dwelling" are only used as a reference for the actual consumptions.

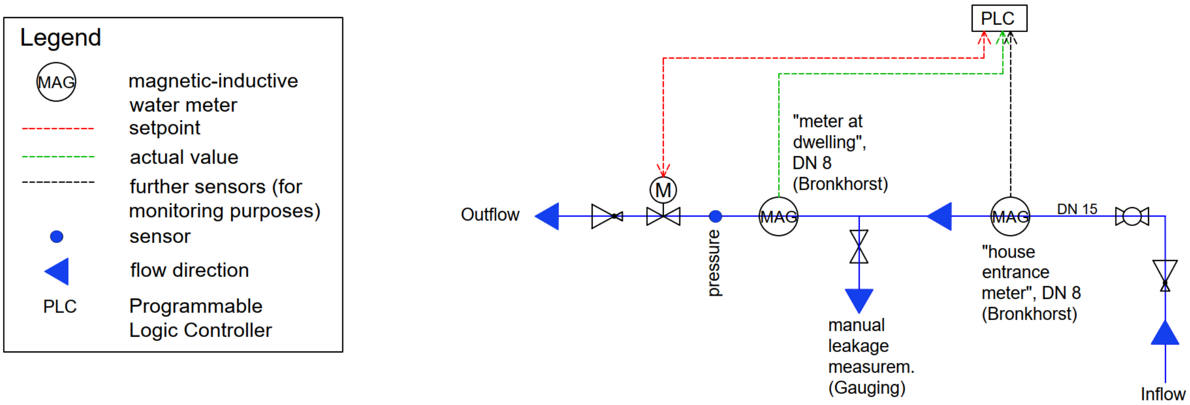


*Figure 3: Experimental setup to generate artificial flow patterns for leakage detection (source: DVGW-TZW)*

The four manually defined consumption profiles are based on findings from a national DVGW project, which was completed in 2017 [29]. As part of this project, high-resolution consumption measurements were carried out and typical flow rates of individual fittings or devices were determined. Since these real-world consumption flow rates cannot be realised by the existing measurement infrastructure at TZW, the flow rates were "compressed" and the observed consumption patterns were used for generating the profiles, e.g. a high flow rate over a longer period of time is typical for a showering procedure. The consumption patterns used for profiling are shown in Table 1. It should be noted that the time of a single consumption was also adapted to the control and regulation boundary conditions of the motor control valves, e.g. the refilling of a toilet tank does not take 3 to 5 minutes but usually about one minute in reality.

*Table 1: Single usage consumption patterns used to generate consumption profiles.*

| Consumption pattern | Typical consumption | Time [min] | Consumption [l/h] | Repetitions per consumption |
|---|---|---|---|---|
| A lot and short | toilet & valve | 3<br>4<br>5 | 170<br>190<br>210 | 1 |
| A lot and long | shower & bathtub | 15<br>20 | 150<br>170<br>200 | 1 |
| Little and recurring | dishwasher & washing machine | 3<br>4 | 80<br>90<br>100 | 3<br>4 |
| Little | e.g. semi opened valve | 5<br>10<br>20 | 70<br>90<br>100 | 1 |

Furthermore, it was not possible to operate the system over 24 h, so one day was "compressed" into a three-hour profile. These four, manually assembled base profiles are shown in Figure 4 to Figure 7.

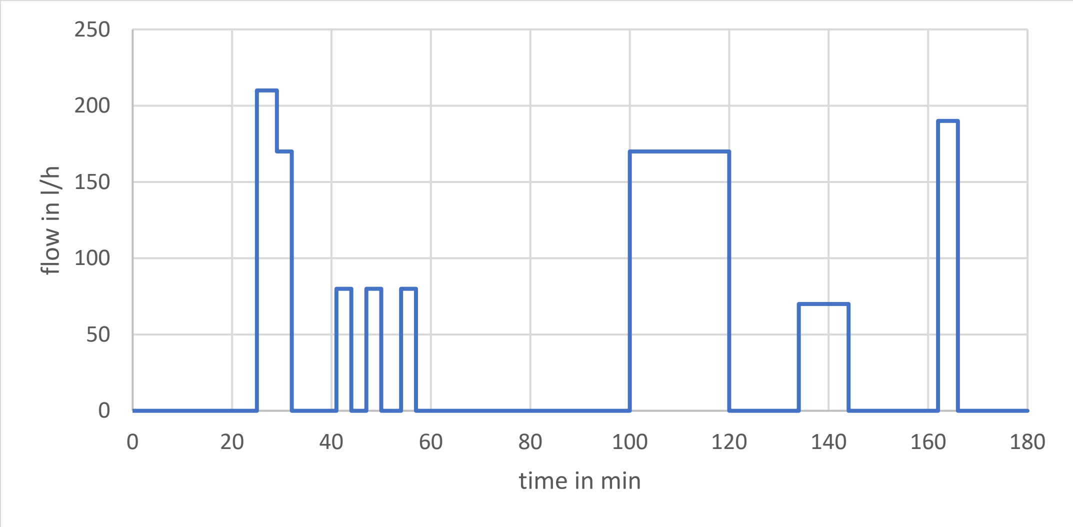


*Figure 4: Base profile 1*

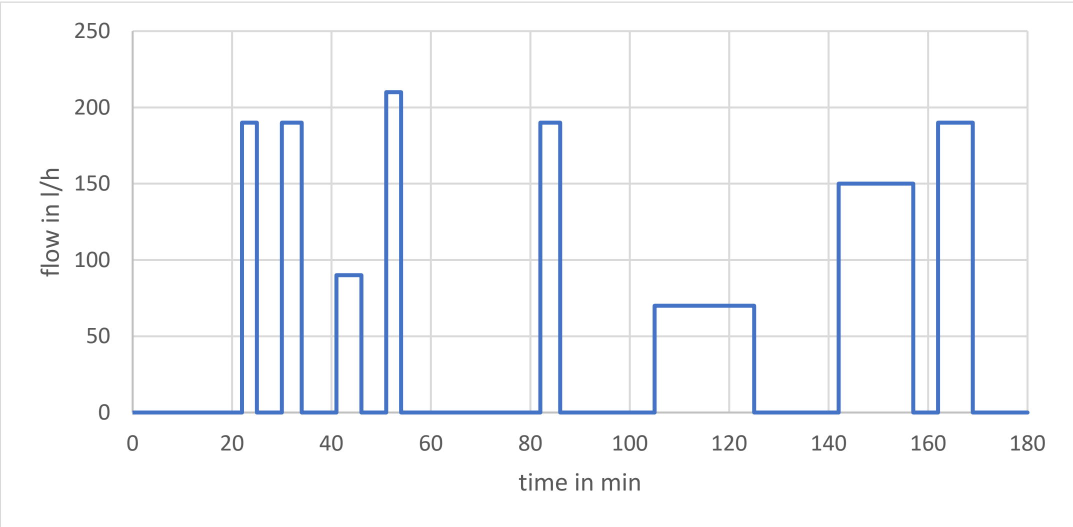


*Figure 5: Base profile 2*

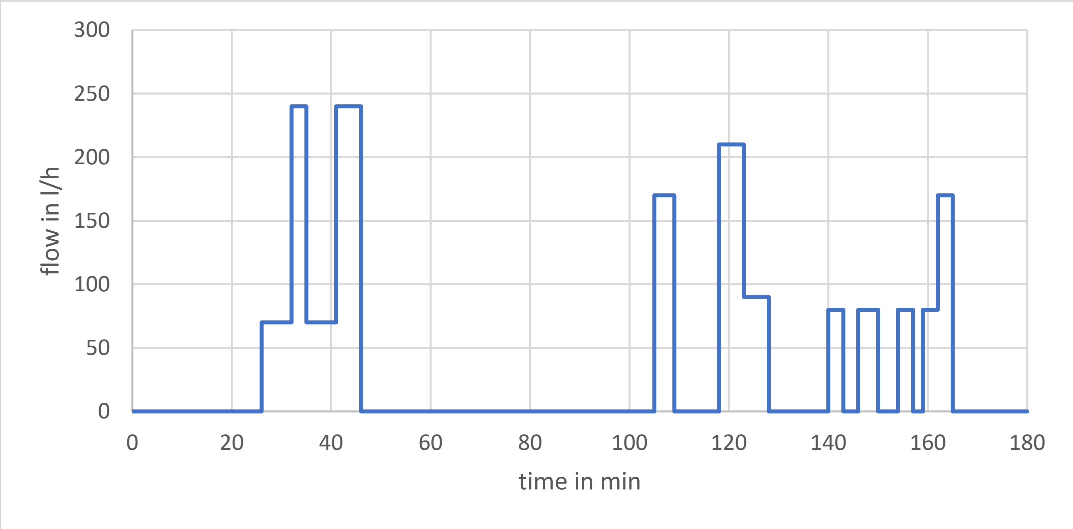


*Figure 6: Base profile 3*

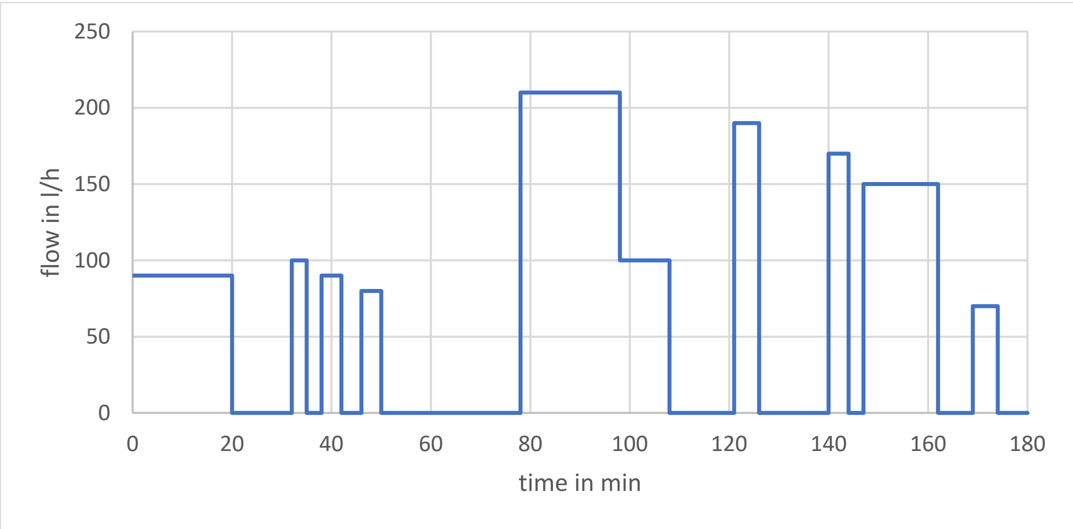


*Figure 7: Base profile 4*

The four base profiles could now be measured by the test facility of the TZW and the raw data recorded in the process were then used as raw data for the evaluation of the algorithm.

## Data pre-processing for the algorithm

In order to prepare the raw data for the algorithm, it had to be further processed to obtain a time series over 365 days including a leakage rate:

- Creation of 365 individual daily profiles. For this purpose, a randomized weighting of the four measured basic profiles was performed for each day to create a new daily profile, e.g. 30 % profile 1, 25 % P2, 10 % P3, 35 % P4.
- Generate artificial spikes, to replicate short-term extreme events.
- Create a baseline that increases gradually over the year with a maximum flow of 10 l/h at the end of the year to simulate the leakage flow (see Figure 8).

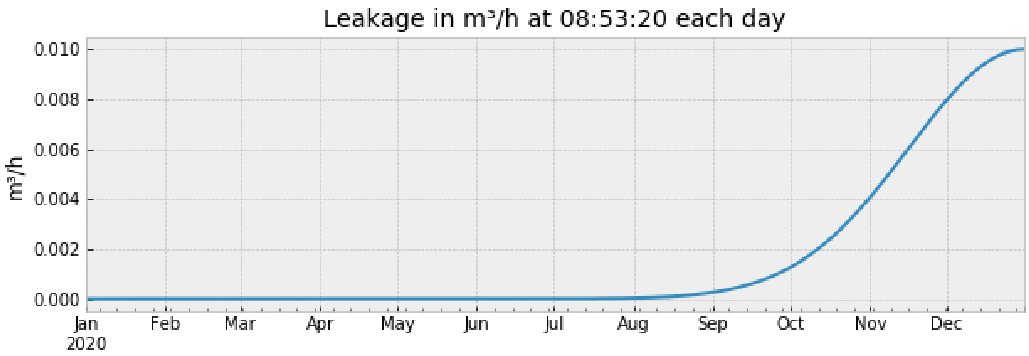


*Figure 8: Digital inserted leakage rate*

The final data set with all 365 generated profiles is shown in Figure 9. The increasing baseline (leakage) was not visible in the total daily flow, which means for this use case the daily total volumes are not sufficient for leakage detection. Subsequently a more advanced detection method is needed.

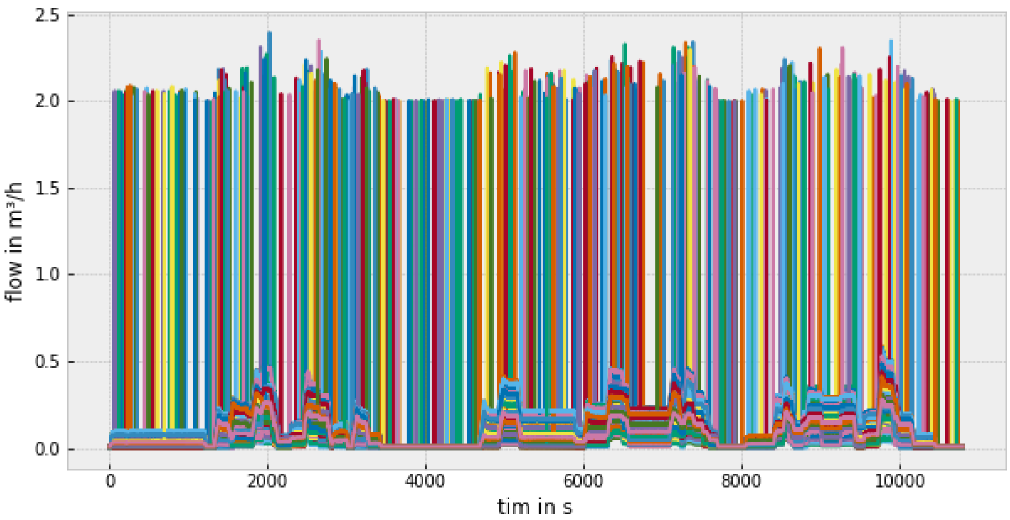


*Figure 9: All 365 randomly generated daily profiles based on the four profiles, the spikes and the increasing leak baseline*

## Results of the algorithm

When the algorithm is applied to the data set, it detects five components that make up all 365 daily profiles, see Figure 10. The weighting (left column) of each feature (right column) is shown for each individual day (sample). It illustrates what share each feature has in the daily profile.

The top four components match the four base profiles almost perfectly. For clarification, the detected profiles (upper line) are compared with the base profiles in Figure 11 (note: the order is not identical). The fifth component strongly resembles the baseline inserted as leakage.

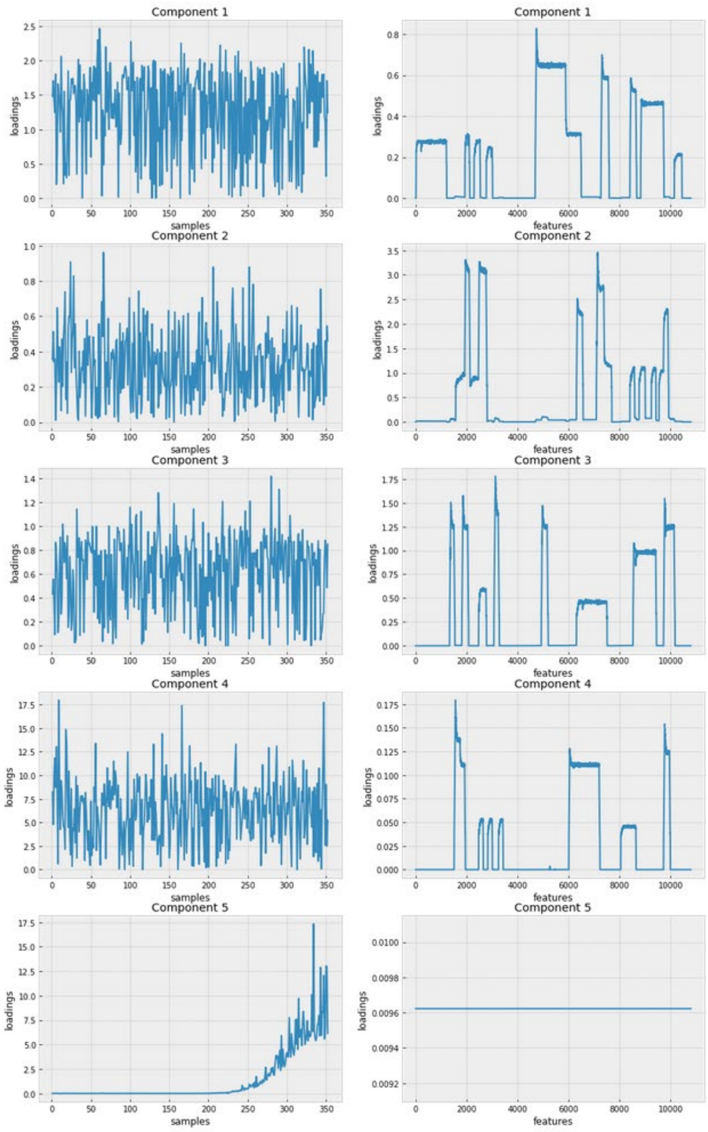


*Figure 10: Components (features and their loadings for each day) detected by the algorithm*

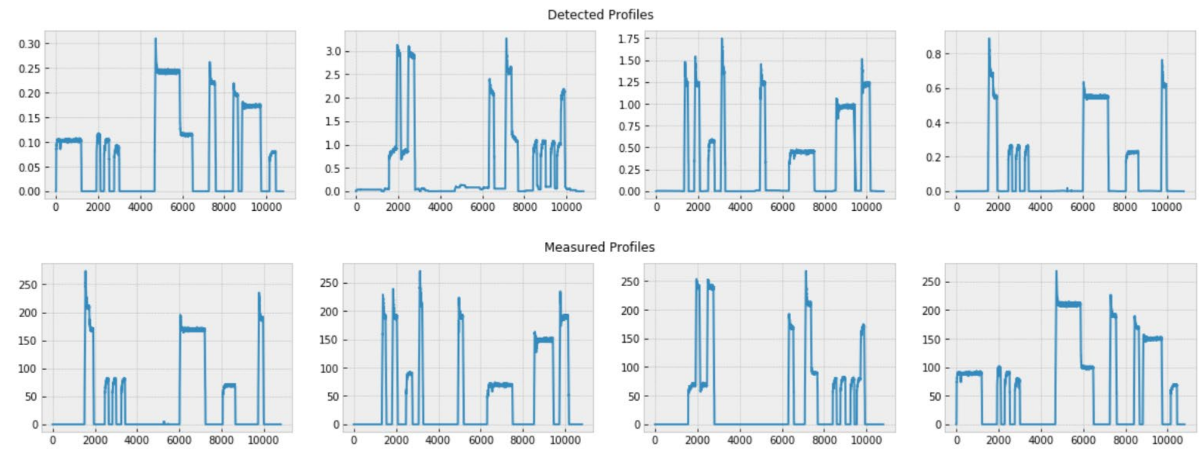


*Figure 11: Detected vs measured profiles*

Furthermore, the algorithm outputs three types of anomalies for this use case: baseline-, night time- and daytime-anomalies, see Figure 12. The baseline anomaly accurately represents the digitally inserted, slowly increasing leakage flow. The other two anomaly types are most likely caused by the inserted spikes, although the algorithm detected many of the spikes as outliers and did not consider them for the evaluation.

In addition, the algorithm quantifies the detected anomalies. The total leakage volume, of approximately 13.5 m³, was accurately recovered by the algorithm.

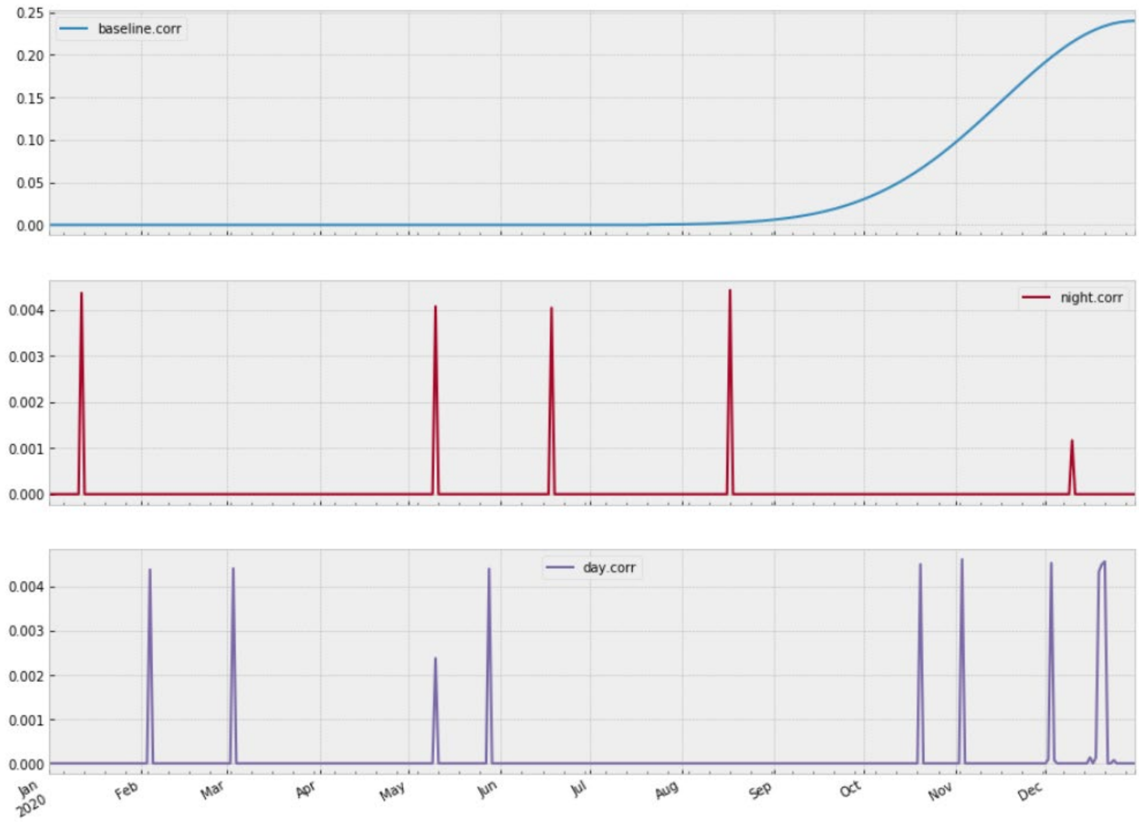


*Figure 12: Anomalies detected by the algorithm*

For the present use case, the algorithm performed very well, since both the leakage quantity was determined exactly and all the base profiles underlying the time series could be recovered.

Further tests of the algorithm with real-world, high-resolution consumption data are necessary to test its performance under more realistic conditions. Unfortunately, this data is hardly available, since correct labelling of leakage flows in real-world time series is difficult to obtain. A hardware platform is not available for the algorithm in its current state of development.

Anyhow, considering implementation efforts, the algorithm can be easily transferred to another platform. The code is written in Python. The Python programming language has a wide distribution among researchers and manufactures. Therefore, nearly all known hardware platforms have community-based or proprietary support for Python.

# Hardware platform for detecting small flow in domestic water meters

It was within the scope of the project also to develop a hardware platform, which could be used for implementing algorithms for leak detection on mechanical water meters. The developed platform is generic and versatile making it possible to implement different algorithms and allowing both wired and wireless communication.

The method developed and described in this section is based on image detection and subsequent analysis.

To develop and test an algorithm able to implement the water leak detection at the domestic level, a prototype consisting of a Raspberry Pi 4 [33] equipped with an 8-megapixel camera (3280x2464, 30fps) has been designed. The hardware was mounted in a plastic enclosure able to fit different types of existing mechanical water meters (Figure 13), and providing the possibility to regulate the camera position and the light scene illumination.

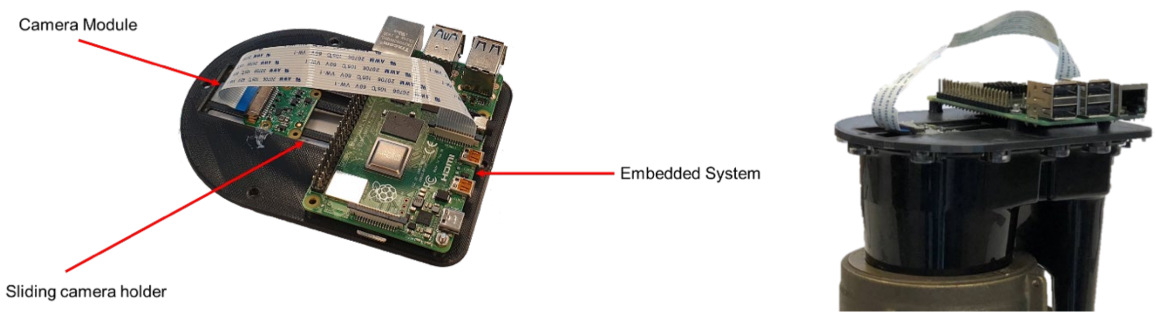


*Figure 13: Prototype for detecting small flow in domestic water meters*

The software on the device includes a genuine user interface (GUI) for choosing a region of interest (ROI) on the acquired image and to run the leak detection algorithm that can be loaded on the prototype (Figure 14). The software also stores the acquired images on the Raspberry Pi 4 SD CARD memory. The GUI allows the user to choose the duration of the acquisition, the frame rate, as well as the lighting level of the display.

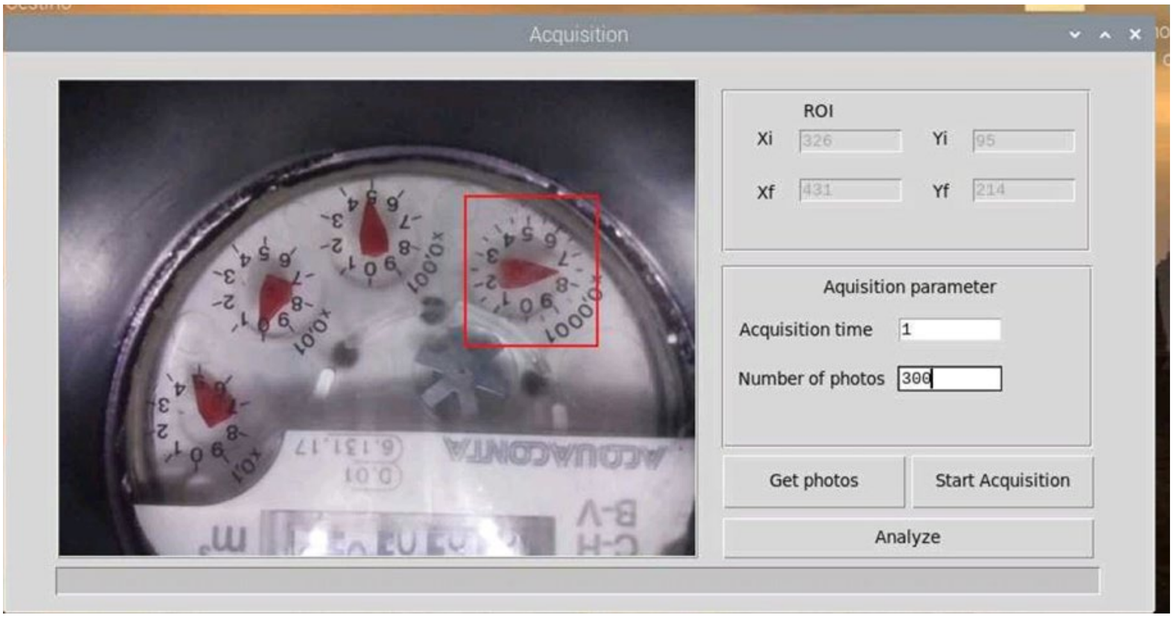


*Figure 14: The implemented user interface (GUI) of the prototype*

The following analysis reports the results of image and flow rate acquisition tests carried out at CETIAT (Lyon – France) during the period 30 and 31 Jan 2020. The test setup consisted of the previously described prototype used in combination with a flow test rig at CETIAT. The rig generates a calibrated constant flow and allows for several domestic water meters to be mounted in series. It includes a precise and compact Coriolis mass flow meter to measure and control the water mass flow (MINI CORI-FLOW™ M14 by Bronkhorst). Four meters were tested (Table 2) on three consumption profiles developed within the project (Figure 15, Figure 16, Figure 17); two of them were tested on a realistic profile.

*Table 2: Performance of tested water meters*

| Water Meter (WM) | Measuring principle | Starting Flow Rate [l/h] | $Q_1$ in l/h | $Q_3$ in l/h |
|---|---|---|---|---|
| WM1 | Multijet | 7 | 15.6 | 2500 |
| WM2 | Multijet | 8.5 | 20 | 1600 |
| WM3 | Piston | 4 | 16 | 1600 |
| WM4 | Piston | 1 | 16 | 1600 |

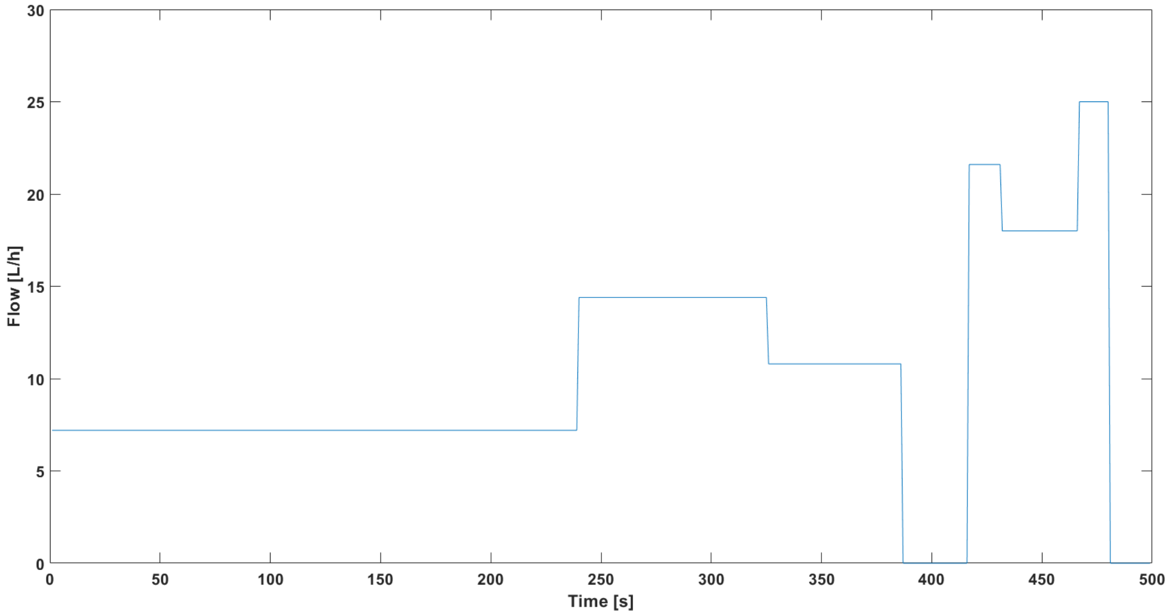


*Figure 15: Consumption Profile 1*

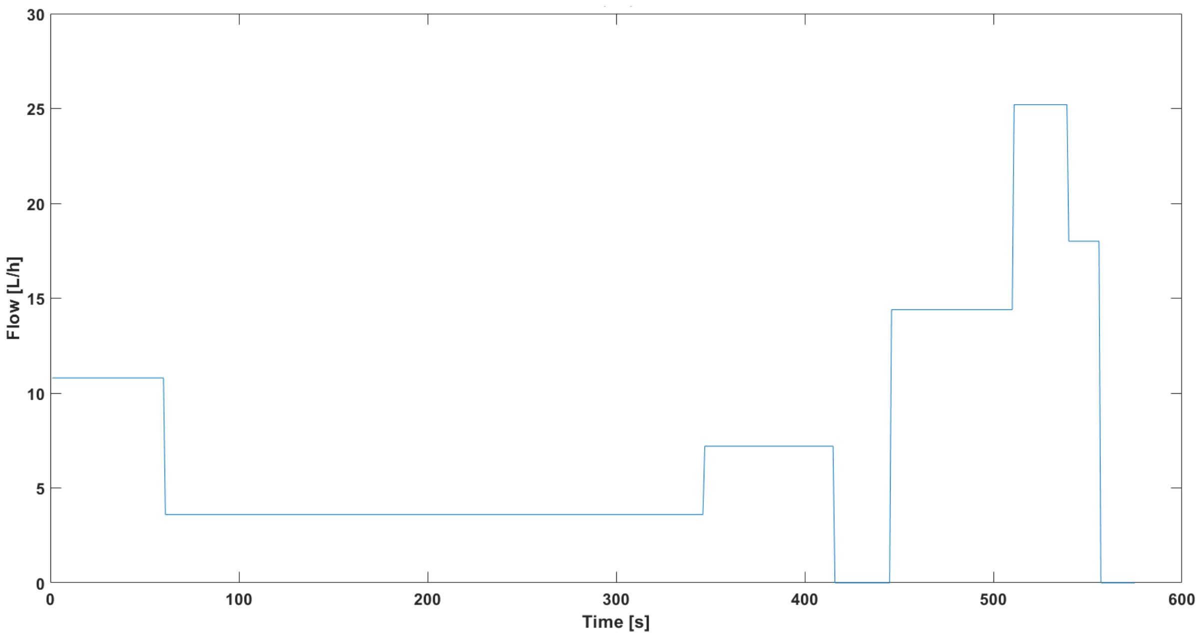


*Figure 16: Consumption Profile 2*

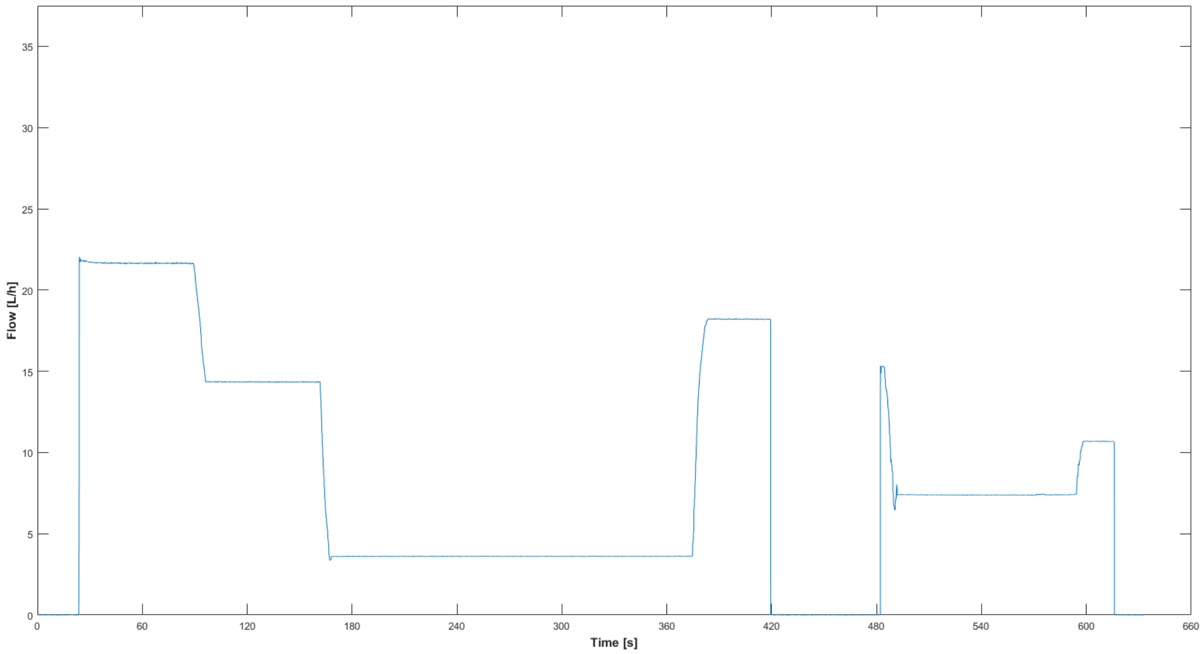


*Figure 17: Consumption Profile 3*

The camera's frame rate was set to one image every six seconds. The image processing depends on evaluating two correlations factors applied to a ROI, suitably selected for each meter (see Figure 18). The two correlation indices are calculated at each new frame. Subsequently the "zero flow detection" algorithm was run.

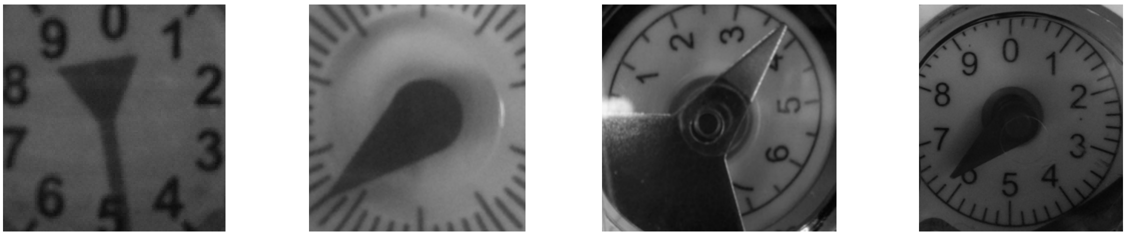

*Figure 18: The selected ROI for the four meters considered.*

The technique employed for the leak detection is independent of the type of mechanical meter used, assuming that the ROI has been defined and validated. The only limit set is the minimum average flow that can be calculated, which coincides with the sensitivity of the mechanical meter used. This considers that the analysed quantity, i.e., the correlation between two successive frames, is not necessarily linked to a precise value of flow that has crossed the meter but to the detection of an absence of total water consumption in a precise observation window. This condition would guarantee the absence of leaks. As previously introduced, two different types of correlation have been calculated:

a) Correlation A: starting from an instant t, the 2D correlation between the photo at instant k ($f_k$) and the subsequent k+1 ($f_{k+1}$) was evaluated (see equation 1)

$$Cx(k) = Cor(f_k, f_{k+1}) \text{ with k ranging from 1 to N}$$ *Equation 1*

b) Correlation B: Given an instant t, the 2D correlation between the photo at instant t ($f_t$) and the subsequent N photos was assessed (see equation 2)

$$Cr(k) = Cor(f_t, f_{t+k}) \text{ with k ranging from 1 to N}$$ *Equation 2*

The goal was to detect Period Without Null Consumption (PWNC) as the duration of zero flow to exclude small leaks during the day or the night. To this aim, the "zero flow" detection algorithm has as inputs a couple of correlation factors (A and B): when the slopes of both coefficients are less than a fixed threshold, and the Type B correlation exceeds a threshold, it means that no water is flowing through the meter (in short terms, the pictures i an i+1 are very similar and the differences among pictures 1 and i,i+1,.. are constant). This last condition seems to be strong enough to evidence the absence of water flow. In each graphic of the following analysis, it can be found: a) the measured flow rate, b) the correlation factor $I\text{-}I_0$ (correlation A), c) the points where a zero consumption was detected by the algorithm (in red), d) the correlation factor $I_i\text{-}I_{i-1}$ (correlation B).

The experimental results exhibit different behaviour of the four water meters on the three consumption profiles, primarily based on the working principle of the water meter. In particular, WM1 (Figure 19, Figure 20, Figure 21) is characterized by a "start and stop" operation due to its high starting flow. Indeed, both multi jet water meters WM1 and WM2 show wrong measurements for low flows.

This fact is also highlighted by both correlation graphs reported in the three different profiles (Figure 19, Figure 20, Figure 21), where a starting flow higher than 15 l/h is exhibited. This means that the zero-flow detection algorithm allowed only to isolate time intervals where the meter dial did not move, even if often water was still flowing.

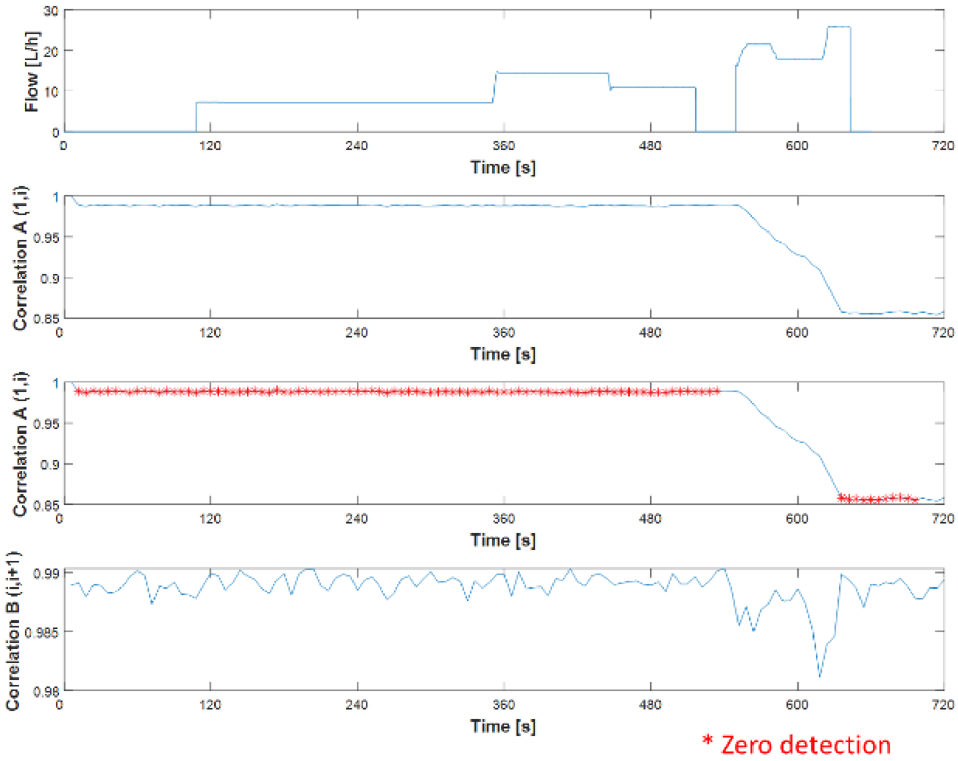


*Figure 19: Experimental results for water meter WM1 on profile 1 (from top to down: observed flow, correlation A (Equation 1), correlation A with zero detection and correlation B (Equation 2)*

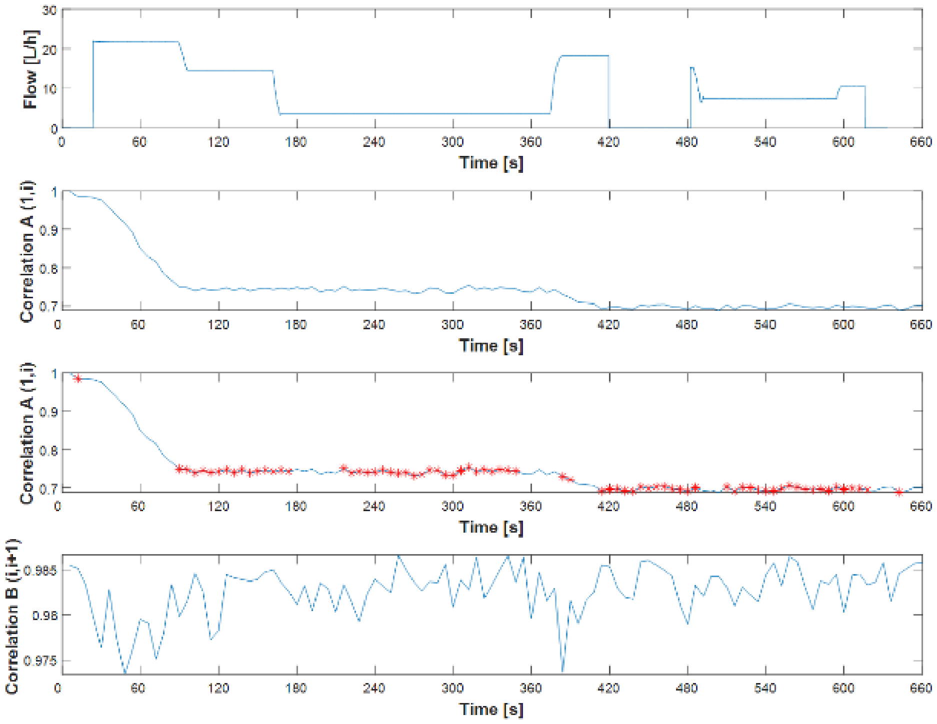


*Figure 20: Experimental results for water meter WM1 on profile 2 (from top to down: observed flow, correlation A (Equation 1), correlation A with zero detection and correlation B (Equation 2)*

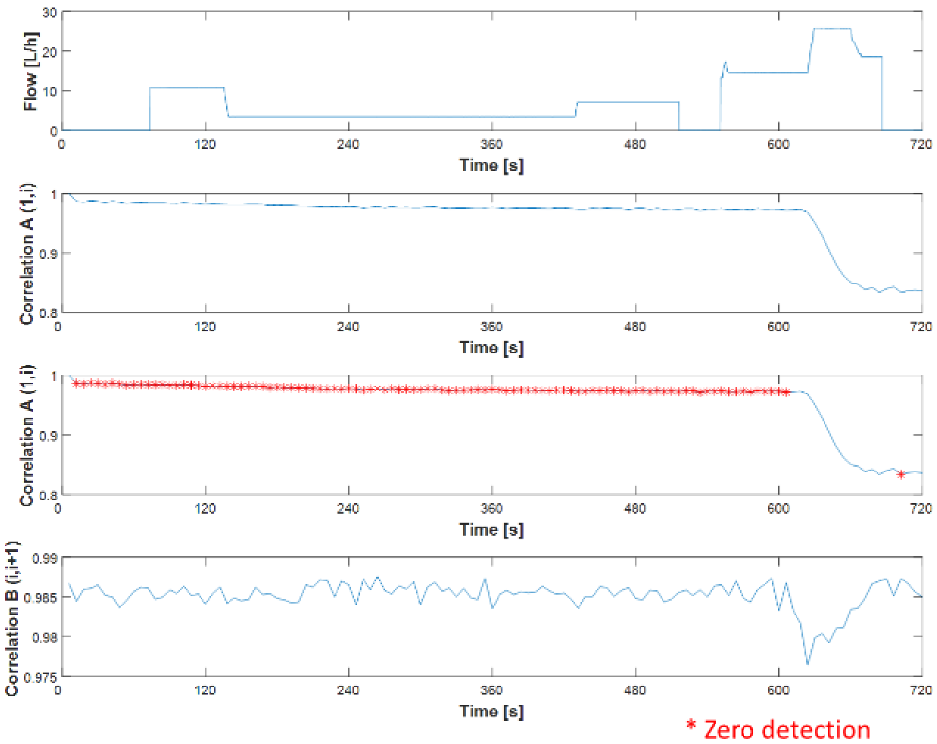


*Figure 21: Experimental results for water meter WM1 on profile 3 (from top to down: observed flow, correlation A (Equation 1), correlation A with zero detection and correlation B (Equation 2)*

For the second multi jet water meter WM2 (Figure 22, Figure 23, Figure 24) the same analysis could be performed, but with the exception that at this time, the starting flow is clearly shown (20 l/h), and there is not a "start and stop" operation condition (with an exception for profile 3). As it is possible to see in the figures, the water meter does not work under 20 l/h. Also, in these last two cases, the algorithm detected zero-flow points actually due to water meter stops (flow below 20 l/h). The zero-flow algorithm does not detect zero flow conditions on profile three since the profile begins with a high initial flow value and the rotational inertia probably avoids a full stop of the water meter in the short observation window.

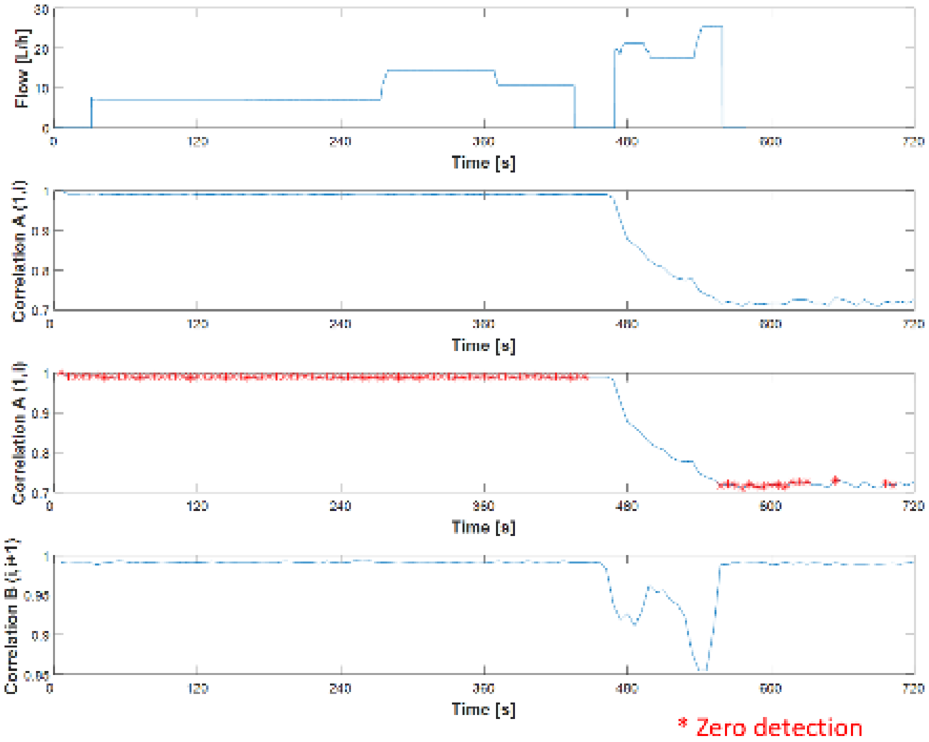


*Figure 22: Experimental results for water meter WM2 on profile 1 (from top to down: observed flow, correlation A (Equation 1), correlation A with zero detection and correlation B (Equation 2)*

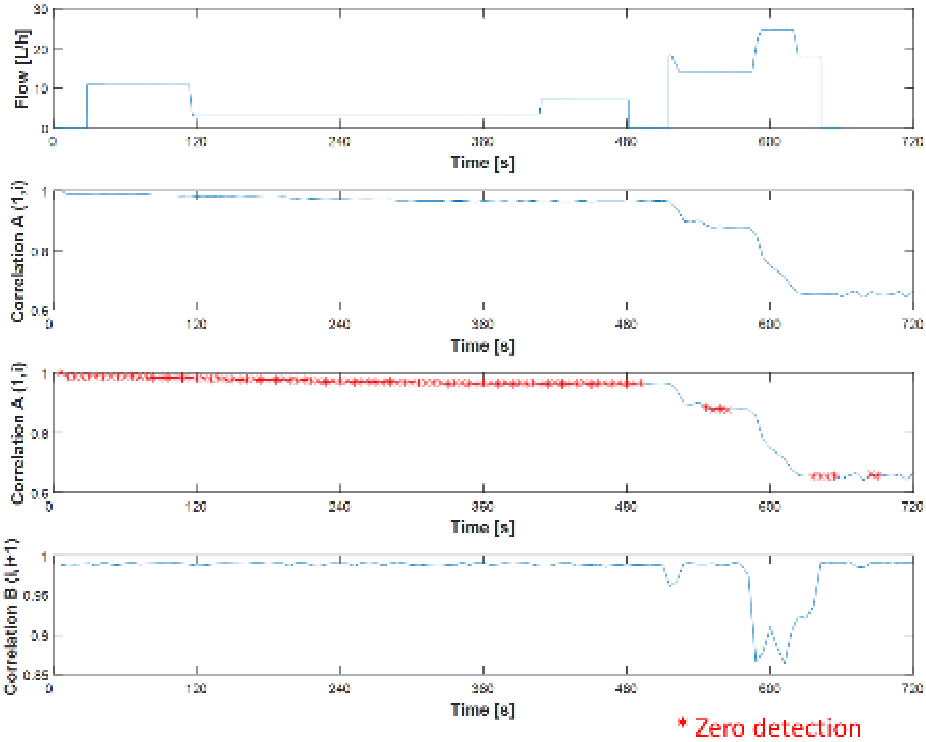


*Figure 23: Experimental results for water meter WM2 on profile 2 (from top to down: observed flow, correlation A (Equation 1), correlation A with zero detection and correlation B (Equation 2)*

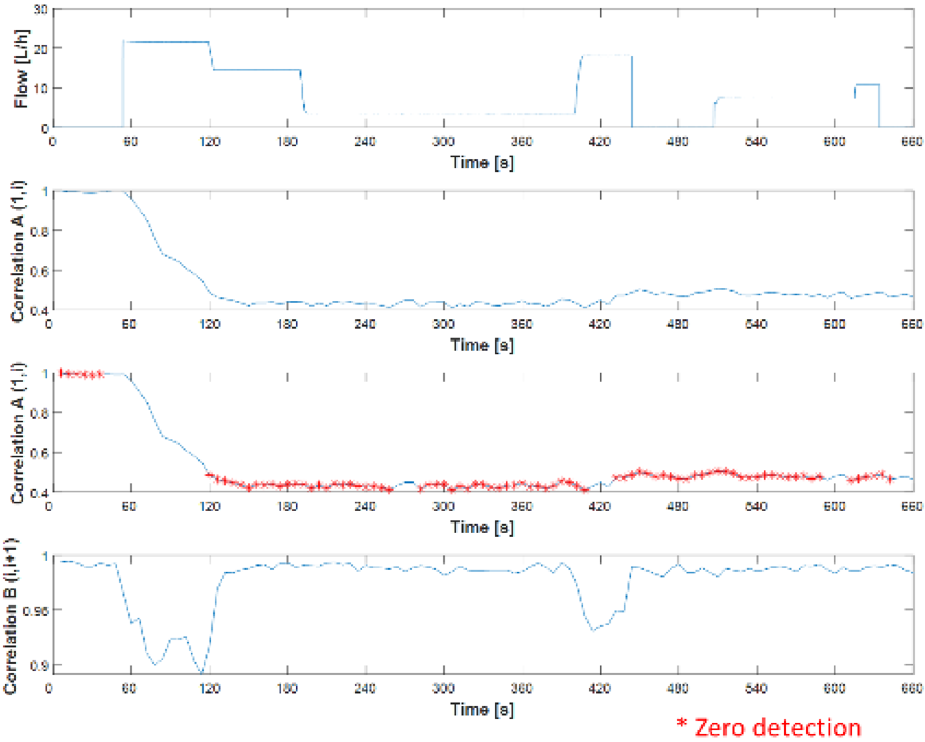


*Figure 24: Experimental results for water meter WM2 on profile 3 (from top to down: observed flow, correlation A (Equation 1), correlation A with zero detection and correlation B (Equation 2)*

In contrast to the multi jet meters (WM1, WM2), the algorithm tested on piston water meters WM3 and WM4 gave encouraging results since they did not present unexpected phenomena (start and stop conditions). However, both meters can operate with a minimum flow of 8 l/h; for this reason, the zero-flow detection algorithm reports the zero zones wherever the profiles are characterized by a flow rate lower than 8 l/h.

As for the realistic profile, only WM2 and WM4 water meters were tested. The results, as seen in Figure 25 and Figure 26, show the ability of both meters to allow the zero-flow detection (middle and final parts of the profiles).

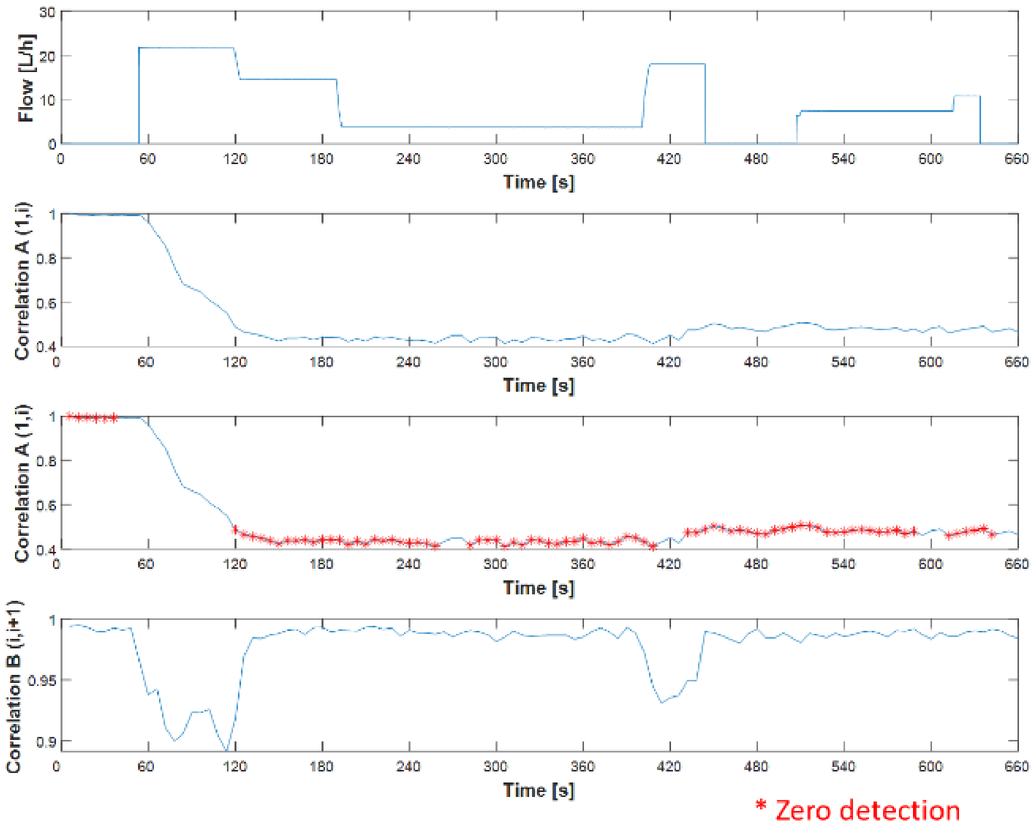


*Figure 25: Experimental results for the WM2 on realistic profiles (from top to down: observed flow, correlation A (Equation 1), correlation A with zero detection and correlation B (Equation 2)*

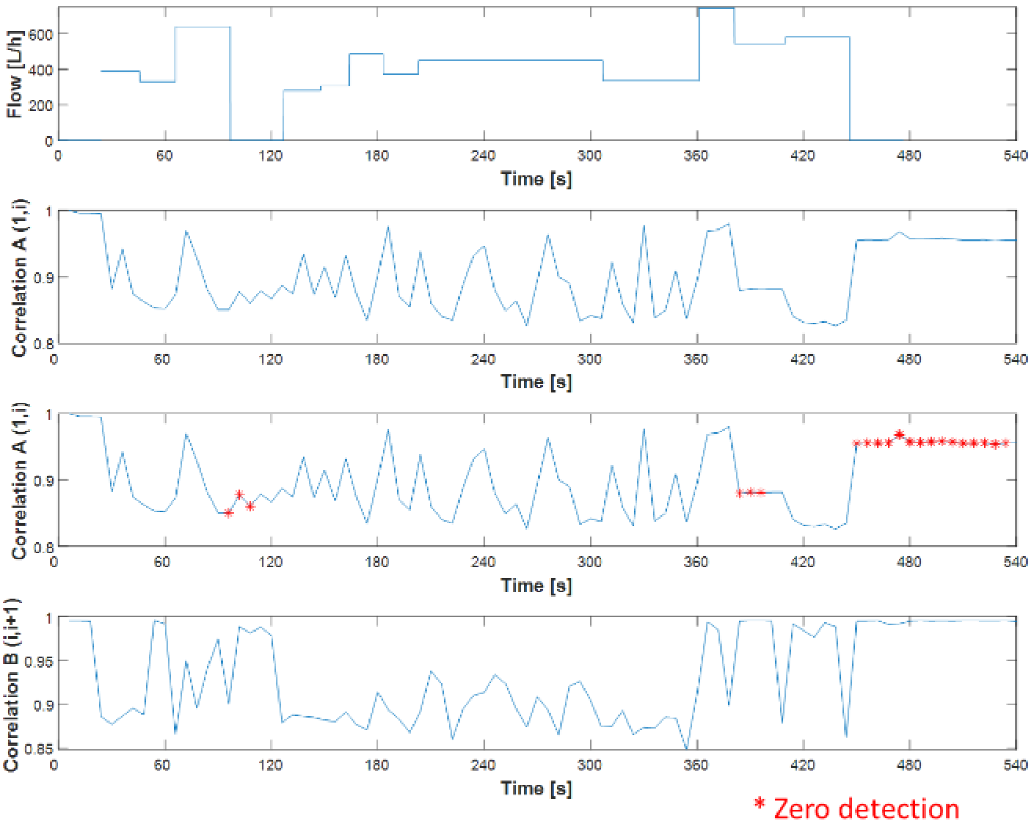


*Figure 26: Experimental results for the WM4 on realistic profiles (from top to down: observed flow, correlation A (Equation 1), correlation A with zero detection and correlation B (Equation 2)*

# Summary

This technical report describes the activities within the MetroWaMet project focusing on leak detection – both algorithms and hardware platform.

A promising leak detection algorithm has been developed and verified on a combined dataset of digitally simulated and recorded flow data. The latter was measured using a flow test setup developed and implemented in the project. The leak detection algorithm is capable to distinguish between recurring, “normal” consumption patterns, consisting of consumptions such as showering or flushing toilets, and anomalies, thereby distinguishing leakage from other, superimposed consumption activities.

An issue that needs to be investigated is how the sampling frequency of the flow pattern from the water meter influences the algorithms capability to extract the patterns. This is the constant compromise between data and temporal resolution and battery lifetime.

A generic hardware platform has been developed and an image-based approach for detecting low flow on mechanical domestic water meters has been implemented and tested. The platform allows for other algorithms to be implemented, such as the one described in the first section of this report. This has though not been possible within the timeframe of the project.

The image-based approach shows promising results for detecting small movements of the needle on the disc on the mechanical water meters used for the lowest flow activities. The approach is though limited by the low-flow cut-off of the water meter.

With the increase of installation of smart meters more temporal water consumption data is becoming available. This data will improve the training of algorithms, as the one developed and tested here, pushing the implementation of smart leak detection in smart meters.

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