PROJECT DELIVERABLE REPORT

Greening the economy in line with the sustainable development goals

D4.1 Urban Water models – Mid-term

Project Title:

A holistic water ecosystem for digitisation of urban water sector

SC5-11-2018

Digital solutions for water: linking the physical and digital world for water solutions

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0.2	25/11/2020	IHE	Incorporation of review comments
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2	11/5/2021	IHE	Incorporation of PO comments

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Abbreviations

ANN	Artificial Neural Networks
DDA	Demand Driven Analysis
DSS	Decision Support System
FTP	File Transfer Protocol
GUI	Graphical User Interface

ICT	Information and Communications Technology
IoT	Internet of Things
JSON	JavaScript Object Notation
KPI	Key Performance Indicator
PDA	Pressure Driven Analysis
UCAx	Use Case Alicante. x = 1,2,3
UCBx	Use Case Braila. x = 1,2
UCCx	Use Case Carouge. x = 1,2
UClsWTP	Use Case lab scale Water Treatment Plant
WDN	Water Distribution Network

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1 Introduction

1.1 Context and scope

The urban water module in NAIADES is one of the elements for data integration and has the main objective of producing probabilistic-based big data related to critical events, including estimates of uncertainty in the models outputs due to uncertainty in the model inputs (e.g., demand in water supply systems), and in their parameters (e.g., roughness coefficients). In this task, large amounts of data related to critical events, will be generated. The critical events will be based on the stakeholder requirements (T2.4), and will include the selection of critical scenarios caused by both internal and external incidents to the water systems, for which historic data does not exist or is very limited. In brief, the idea is to simulate enough data so that the AI/ML models can use this data to train.

This report is the first of two parts, which elaborates on the use of urban water models in the NAIADES use cases. This deliverable describes the needs for water modelling from the NAIADES perspective according to discussions among partners and stakeholders during the first half of the project. The methodology and results for the definition of the urban water modelling activities, needed to develop services in each pilot, are presented. As explained in D2.5, the cases of Alicante and Braila are suitable for this task, whereas, due to the nature of the use cases of the Carouge pilot, no urban modelling exercise could be defined. Please refer to D2.5 for more details.

1.2 Chapters organization

The deliverable is organized as follows: first, a background to the task in the framework of NAIADES is presented, followed by the methodology to achieve the objectives, which includes the pilots needs for urban water modelling, the data collection procedure, the description of the preliminary modelling exercises and the mid-term results achieved. The deliverable finishes with conclusions and future steps.

2 Background

A model is a simplified description of reality. Computer-based models are computer programs that are designed to get input data, perform calculations and produce results in terms of output files, graphs, maps, tables, animations and other visualisation techniques. In the water context physically-based and data-driven models (such as those based on AI) are the most popular (Price and Solomatine 2009). The former are based on laws of physics that describe the mechanisms of water flow, whereas the later rely on observed data to establish cause-effect relationships among variables. Modelling can be used to improve knowledge and to make predictions (Alfonso et al. 2016). For example, Mandel et al. (2015) uses models to understand water quality evolution in water distribution systems and Marquez Calvo et al. (2019) and (Quintiliani et al. 2019) analyse the operational effect of valves in water distribution networks, based on (Alfonso et al. 2010).

Whereas the NAIADES project aims to develop an AI framework, the physically based models in task 4.1 brings the opportunity include the knowledge of the water flow physics that is encapsulated in water modelling systems. In this context, the urban water task in NAIADES has the main objective of producing large amounts of data related to critical events using models. The critical events will be based on the stakeholder requirements (T2.4), and will include the selection of critical scenarios caused by both internal and external incidents to the water systems, for which historic data does not exist or is very limited. Data will be produced to feed the selected Artificial Intelligence components in WP5, making the AI framework aware of potential events that have not been recorded.

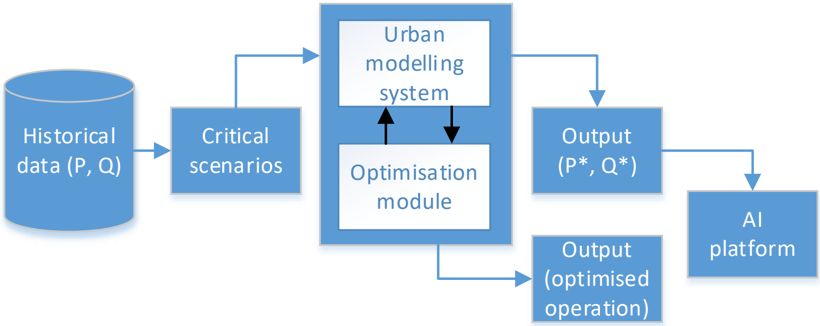


Figure 1. Initial flowchart of the role of urban water models in NAIADES

3 Methodology

The methodology to achieve the objectives of the task in this mid-term report consists of three steps, namely a review of the need for modelling in the pilots, a data collection activity according to the previous review, and a preliminary modelling exercise in the selected pilots.

3.1 Pilot's needs for urban water modelling

In the framework of T2.1 to T2.2 reported in D2.1 and D2.2, interviews were carried out with all pilot owners, as well as telco discussions regarding all the use cases partners. The main idea was to match the activities of the task with the requirements and possibilities of the use cases. Visits have been executed and planned under WP2.

3.1.1 Alicante

A visit to Aguas de Alicante was held from 9 to 11 Sep 2019. Data requirements and critical events that can be considered were discussed. The water utility has a hydraulic model that is used to plan their expansions and to analyse operational issues when needed. In order to start the modelling task, area of Benalúa was selected.

3.1.2 Braila

The water utility of Braila was visited on 19 Nov 2019 to discuss about modelling and the critical events they find important to consider. The water distribution model of the city was, at that time, being developed by a university in Bucharest and it became available in April 2020. As the utility does not have any drainage model, and they suffer from floods during heavy rainfall events and during high levels on the Danube River, initial discussions pointed to the possibility to build a model, provided all data is available. They communicated that some data is in their GIS, but that they do not have data about flows in the pipes. However, data of pump operation schedules is available, so in principle flows could be estimated from these schedules. In the meeting in Athens on 3 Dec 2019 the possibility to connect the data-driven water quality model that AIMEN is developing with the hydraulic model of the distribution network was considered. Discussions were held in this regard, but discarded because of the lack of specific treatment data.

3.1.3 Carouge

Communication with Carouge was achieved with the same aim of understanding the needs for modelling. However, it became quickly apparent that no clear role for 4.1 was foreseen in this pilot, due to the fact that the partner involved is the municipality and not the water utility. The water challenges they face are, therefore, more on watering garden boxes and checking water quality at fountains, and not anything related to water distribution or drainage networks, and explicitly expressed in an email conversation of 18 Oct 2019 not to see value on urban flood models. For this reason, this report, as well as the final report, will not include Carouge as a pilot for task 4.1.

3.2 Data collection

3.2.1 Alicante

Alicante provided data consisting of GIS files with characteristics of the network, locations of hydrants, valves, pipes, nodes and historic demands and pressures from the 17^{th} of July 2017 to the 4^{th} of February 2018.

Although Alicante has their own models, they extracted this information for us to build an independent, open source model for the area of Benalúa.

3.2.2 Braila

On April 14 2020 the EPANET model of the water distribution system of Braila, with corresponding reports (in Romanian) became available. We are treating this information with confidentiality. Since then IHE has been analysing the documents and made run tests of the model, as well as analysing in detail the system, as it is mentioned in the subsequent sections of this report. A confirmation that IHE has not received the information to advance with the urban drainage model was discussed in the visit of Nov 2019, and in the plenary meeting in Jan 2020. As explained in D2.5, the final use cases for Braila did not include the drainage model and therefore the idea of developing it was abandoned.

3.3 Preliminary modelling exercises

A series of modelling exercises were executed in both Alicante and Braila, and although these are still ongoing, the current progress is reported here. It must be noted that the modelling framework is based on optimization methods that have been developed in the context of multi-objective optimization at the Hydroinformatics core (see e.g., Alfonso et al 2010, Marquez-Calvo et al 2019) and that tools have been adapted here for our particular goals within the project. The modelling exercise and execution have been done in collaboration with MSc students as reported below for each pilot.

3.3.1 Alicante

The developed codes for T4.1 have been tested and improved in a complex optimisation problems in the pilot of Alicante are part of the MSc thesis of Mr. Alessandro Farina, after a methodological adaptation and development of the available tools. The code concentrates on the critical event of fire occurrence within the supply area of the Benalúa neighbourhood, located in the East of the Spain, whereas the study itself concentrates on the optimisation of pipe rehabilitation to improve network performance during fire events.

3.3.2 Braila

Similarly, the developed codes for T4.1 have been tested and improved for the pilot of Braila and preliminary results for the Braila case are part of the intern Danilo Rodriguez and two master students who are currently developing their master theses. The codes are being used in complex multiobjective optimisation problems regarding robust optimisation for placing sensors to detect leaks in water distribution systems and the optimisation of pump operation for the same aim.

4 Mid-term results

The results of the first part of the project are briefly reported in this section for the cases of Alicante and Braila. Table 1 summarises these efforts, including the critical events considered, methodological considerations and the potential use cases where the methods can be applied.

4.1.1 Summary of preliminary modelling exercises

Table 1. Summary of preliminary modelling exercises

Critical event considered	Applied to	Methodological considerations	Ready to be applied to use case
Fire event	Area of Benalúa	Inclusion of Pressure Driven Approach Optimisation of operational interventions	UCA1 – demand prediction
Pipe burst	Area of Radu Negru	Inclusion of Pressure Driven Approach Modelling to assist sensor location Robust optimisation of operational interventions of pump stations	UCB1 – demand prediction UCB2 – leakage reduction

4.1.2 Alicante

BACKGROUND ON FIRE AS CRITICAL EVENTS

A fire occurs when an unchecked chemical reaction called "combustion" is triggered by basically putting three elements together: a fuel source, an oxygen source and an initial energy source. Fuel is then rapidly oxidized resulting in heat, light and sub-products. In an urban environment and especially in buildings, fires may occur for different reasons, including faulty appliances and leads, faulty fuel supply, misuse of equipment or appliances and placing articles too close to heat.

Negative effects of fires include hazard to human life, properties, jobs, atmospheric pollution, and water contamination (AWWA 2008), Lentile et al (2006), so it is easy to understand the importance for a community of being able to prevent, manage and extinguish a fire. Fire prevention in buildings is usually addressed with the use of fire detection alarms. Fire can be effectively controlled in buildings through the installation of automatic fire suppression systems such as sprinklers or chemical systems.

Although there are many ways to effectively extinguish a fire, we concentrate here on the use of water (AWWA 2008), which needs to be sufficient (Milke 1980). In this context, in addition to the general purpose of a water distribution network of providing potable water to users under normal conditions, it must also provide enough pressure, volume and quality under abnormal conditions, including fires (Mays 2000, Wu and Walski 2006).

When dealing with fires, supplying water to suppress a fire is normally assigned to private or public firefighting water supply systems. However, when such a system does not exist or the fire extends this task is assigned to potable water supply systems. If the water supply system is able to provide a sufficient fire flow to effectively manage urban fires, then the water distribution system can be adequate for fire protection (Xiao et al 2014). It is important to remember, however, that drawing large amounts of water from the public water supply system is not the preferred method of fire suppression, but in order to make this possible and to improve the firefighting capability of the city, plenty of hydrants are installed in WDNs.

Hydrants

Fire hydrants are connection points installed throughout WDNs, with the primary purpose of enabling firefighters to have access to the water supply (Wu and Song 2014). A hydrant can be located underground or above the ground and it can have different colours depending on use destination or regulations. They can be very numerous (hundreds and even thousands), depending on the size of the city. In case of need, firefighters get on the place and attach a hose to the hydrant on one side and to the fire truck engine on the other side with the aim of suppling the truck's tank with water. Then, they operate a valve on the hydrant to open it and let the water flow into the storage. From here, a powerful pump is used to boost the water pressure and possibly split it into multiple streams to reach the necessary height to successfully manage the fire. For this reason, it is important to know the actual capability of hydrants in delivering an adequate flow at an adequate pressure as well.

Hydrant flow tests may be conducted to estimate available fire flow; in addition, they also can be used for hydraulic model calibration (Walski 1983), leakage hotspot detection Sage et al (2010) and flushing the pipelines to ensure adequate water quality (Wu and Song 1983, Shah et al 2001, Walski 2014). However, these tests are disruptive, time consuming, prohibitively costly and only approximate (Boulos et al 2006).

DATA AVAILABLE

All information was made available by AMAEM via GIS files, which include physical connections between the WDN elements, the elevation of all nodes (Figure 2) as well as their geographical locations (Figure 4).

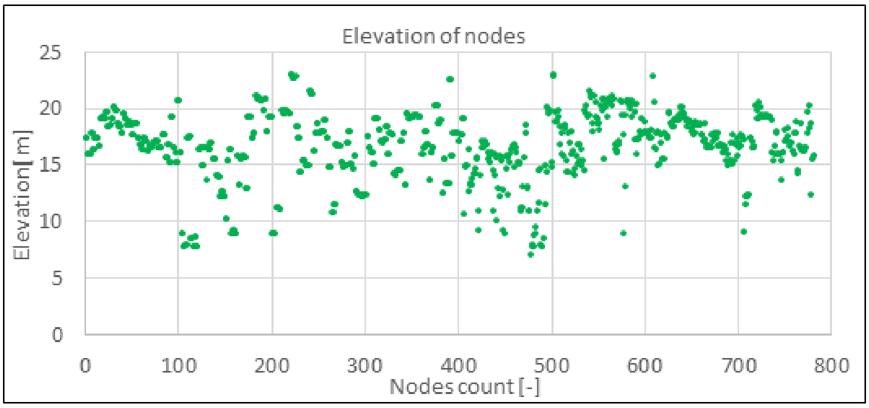


Figure 2: Elevation of nodes in Benalúa, Alicante.

The network is composed by 783 nodes, of which 236 actually deliver demand; each of them supplies 30 people on average. Figure 3 shows water demand in blue in a heat map.

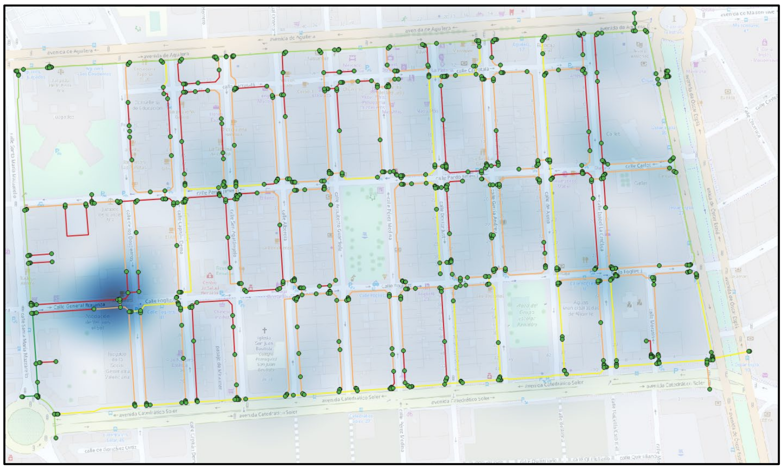
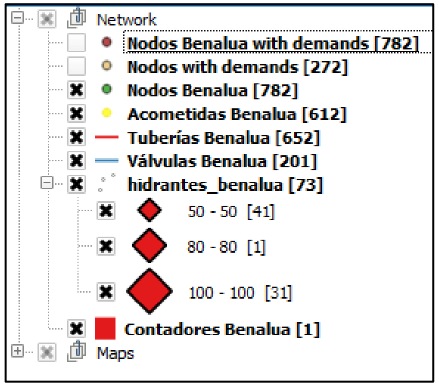


Figure 3: Water demand heat map, with the data provided from July 2017 to February 2018.

There are 654 pipes, with known location, length and diameter with known material.



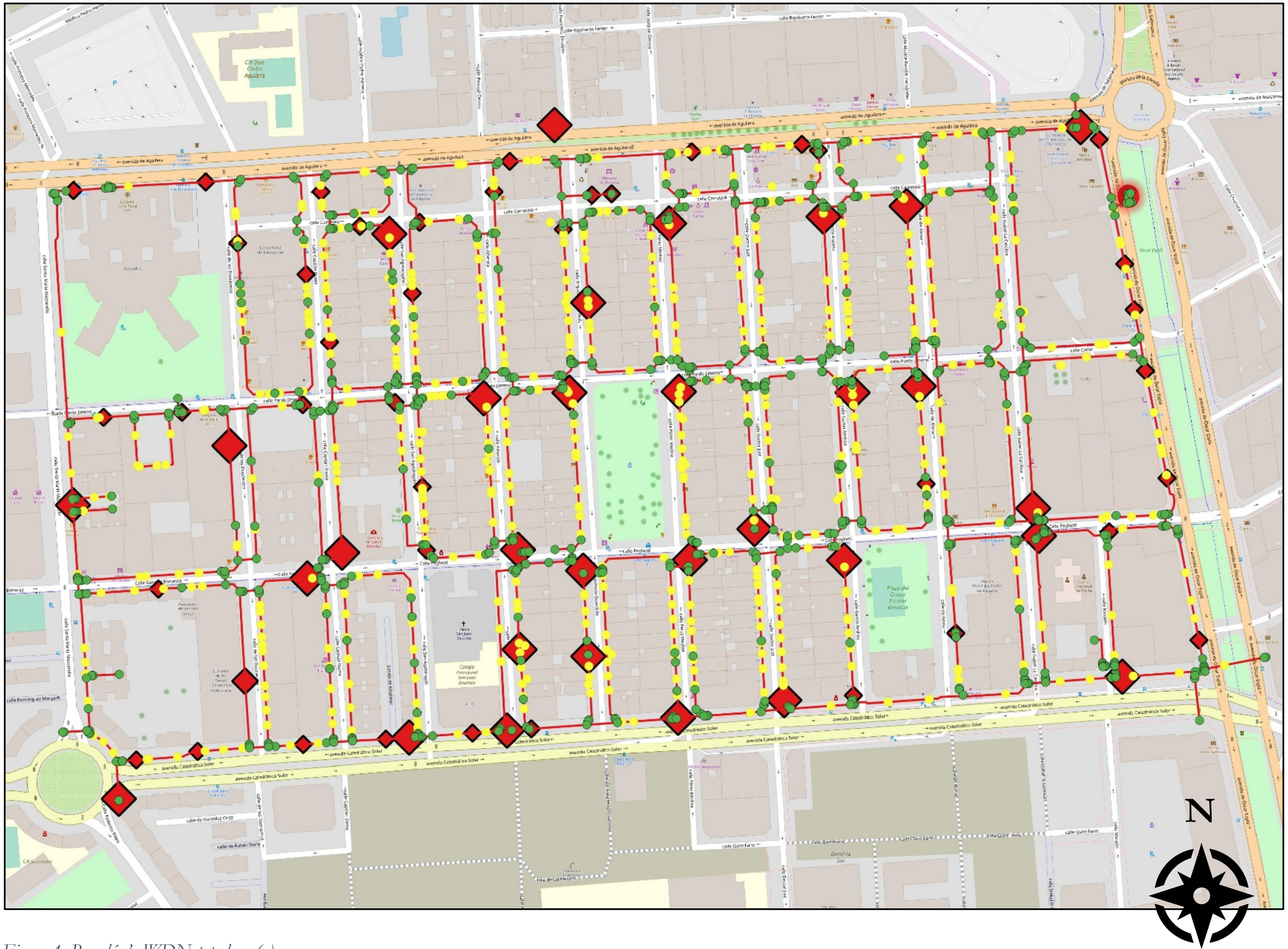


Figure 4: Benalúa's WDN topology (a).

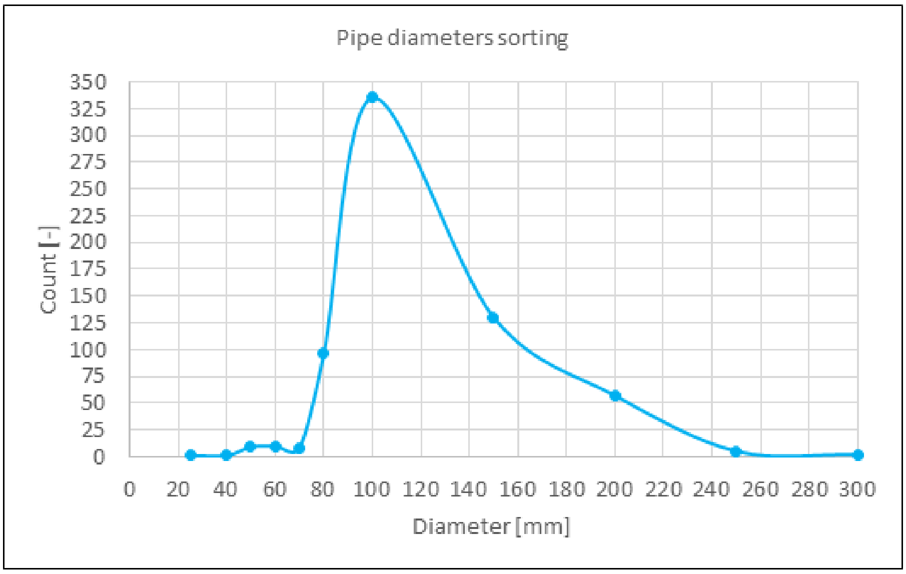


Figure 5: Pipe diameters sorting.

The area has 202 valves, which are supposed to be either fully open or fully closed. Another valve has been artificially included in the model, between the upstream part of the network and downstream Tank1, with the aim of calibrating the model using pressure measurements of node 253. There are 74 loops, 73 underground hydrants (marked as red diamonds in Figure 4), of which 31 are DN100, one is DN80 and 41 hydrants are DN50.

WATER DEMAND

Water demand data is available through data collecting with a Flow Meter "Contador" placed upstream the WDN and by water accounting at delivery points. Seven days of hourly measurements at Contador were conducted in July 2017. The average day trend is reported in Figure 6.

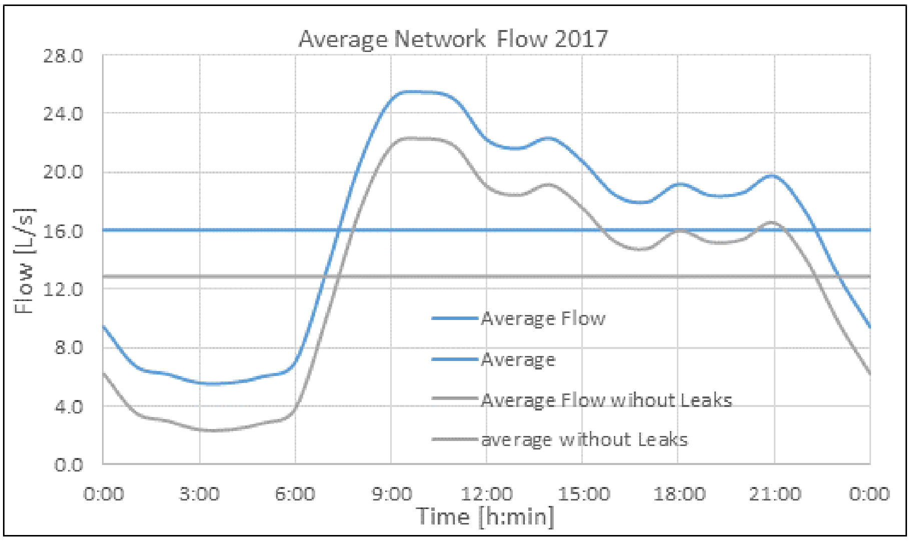


Figure 6: Average day in July 2017.

As explained above, due to Leakages, an additional 22% of demand has been taken into account (accordingly with water accounted at delivery points) to consider the leakages in the network.. The average flow in the network, considering +22% leakages, is $Q_m = 16\ L/s$, whereas the maximum observed flow is

$Q_{observed} = 25.5\ L/s$. The average consumption per connection in the month of July 2017 is presented in Figure 7.

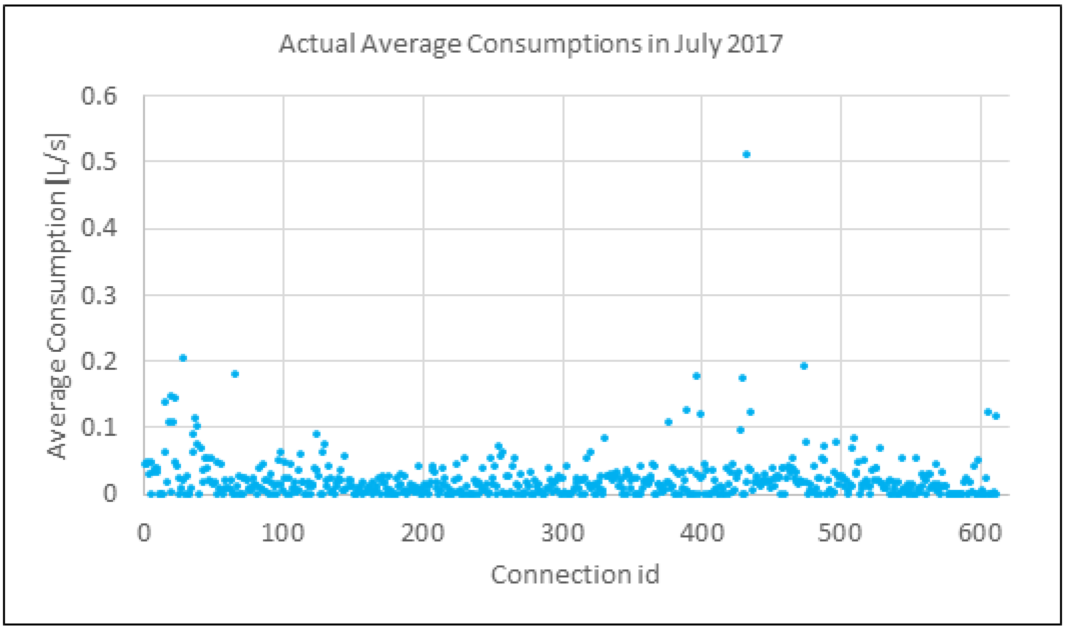


Figure 7: accounted water demand in July 2017.

The water peak demand modelling is analysed using the Peak Coefficient Gumbel CDF as reported in Figure 8.

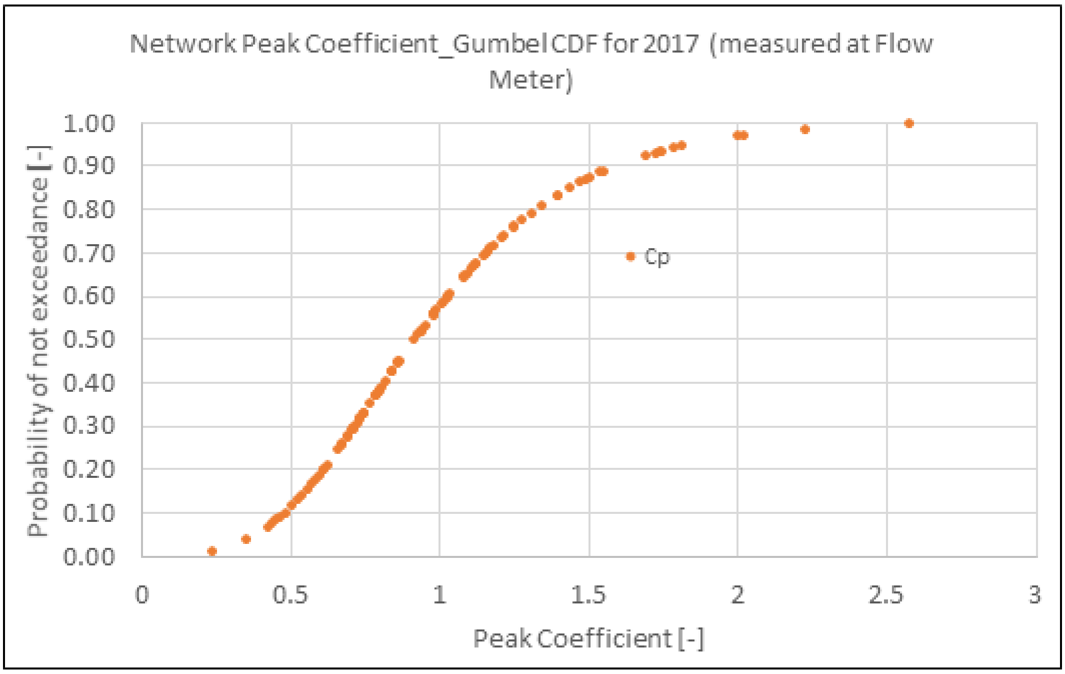


Figure 8: Network Peak Coefficient Gumbel CDF.

In addition, since a critical Peak Demand with a probability of not exceedance $P[S] = 99\%$ was chosen, corresponding Peak Coefficient is $C_P = 2.5$ and Peak Demand in the network is, consequently, $Q_P = 40\ L/s$.

PRESSURE MEASUREMENTS

Pressure measurements are also available for Benalúa's WDN (Figure 9). They were taken at Node 253 at the same time that network flow was recorded at Contador. Since measurements were taken for 7 days in July 2017, an average day is shown, similarly to what has been done for network flow.

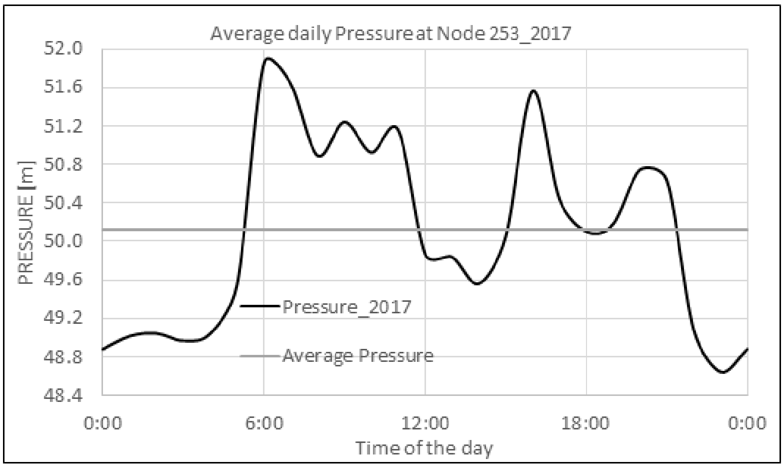


Figure 9: Average daily Pressure at Node 253 in July 2017.

Note: it is reasonable to think that this Case Study's WDN is a District Metered Area (DMA). Usually DMAs allow improving pressure management, water budget and leaks detection, compared to classical redundantly looped networks (Di Nardo et al 2016).

CALIBRATION

Calibrating the network was needed for two reasons. First, no information about the kind of water source is available for Benalúa's WDN. Although it is known where water enters the Benalúa's DMA (Contador, Figure 4), it is not known how water is stored or supplied to DMA. In consequence, pressure results from network analysis (Rossman, 2000) did not match with pressure measurements on field at Node 253. These issues were tackled by including a tank element into the model, so that the maximum pressure variability observed in average day (almost $\Delta P = 3.2m$) matches with maximum water level variability Δw in Tank1, in an average conditions simulation. Tank1 is placed upstream the WDN and it is supplied with $Q_m = 16\ L/s$. For roughly calibrating the network towards network analysis pressure results at Node 253 that initially differed from pressure measurement at the same node, it was necessary to rule a dummy Valve1 Figure 10 so that modelled and observed pressures matched. Practically, hourly head losses were imposed manually, until pressure measurements and pressure results from analysis matched.

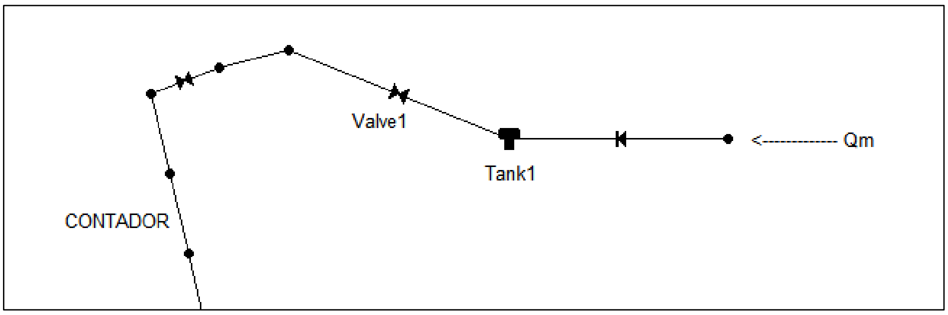


Figure 10: Adapted Tank1 and Valve1 for WDN calibration.

EPANET 2.2 (PDA)

The resulting model for the Benalúa case was made with the EPANET modelling system. The .inp Epanet input file has been manually set up, taking care of the fact that, since EPANET 2.2 with PDA is being used, some additional parameters have to be carried out. A screenshot of the model is presented in Figure 11.

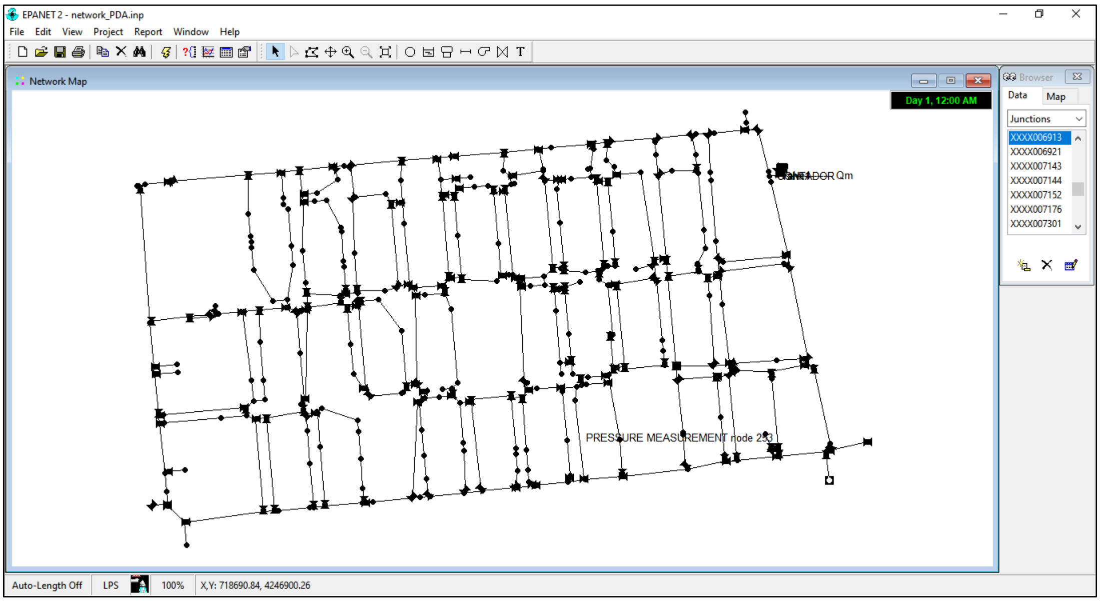


Figure 11: Benalúa's WDN in EPANET 2.2.01.

PYTHON 3 SCRIPTING AND IMPLEMENTATION

Even though the graphical EPANET UI is very useful for some aims, it only allows to run one manual EPS at a time. Since the analysis requires many runs to analyse different network configurations, automation is required. To this aim the Epanet 2.0 Programmer Toolkit (Rossman, 1999) and the Epanet Toolkit Python Wrapper (OpenWaterAnalytics 2019) have been both used and combined into Python 3 scripting. Specifically, an implementation of Python 3.7.4 has been used with Spyder 4 code editor within a 32 bit Anaconda environment. A 32bit version has been used because the Epanet 2.2 Toolkit library ("epanet2.dll") has not been coded in 64bit architecture at the moment of edition of this document.

GENERATION OF CRITICAL EVENTS IN ALICANTE

As mentioned above, the critical event to be considered in Alicante is fire events, which can generate abnormal flows and pressure patterns that must be accounted for within an AI framework. Firstly, average normal conditions (no critical fire event) are shown. Average condition means that the average network demand is set as $Q_m = 16\ L/s$, with an average user demand (as in Figure 7). The average water level in Tank1 is set to 1.4m. The results obtained from Steady State network analysis yield and average pressure in normal conditions of 41.78m, see Figure 12.

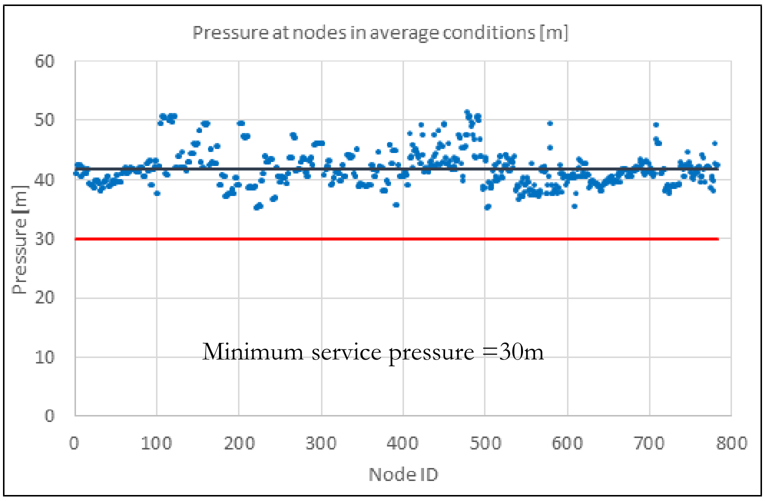


Figure 12: Pressure at nodes in average conditions.

In the fire event scenario conditions, hydrants are (one at a time) operated, in 73 different simulations and pressures in the network and at hydrants' nodes are checked with a peak network demand $Q_m = 40\frac{L}{s}$.

Tank1 operates with a minimum water level of 0.1m, and a 2-hours fire event is set to occur with varying location, increasing the demand at one node at a time to $Flow = 32L/s$, required at hydrants, with a requirement of $14m$ of minimum pressure available for all the city. Results are shown in Figure 13.

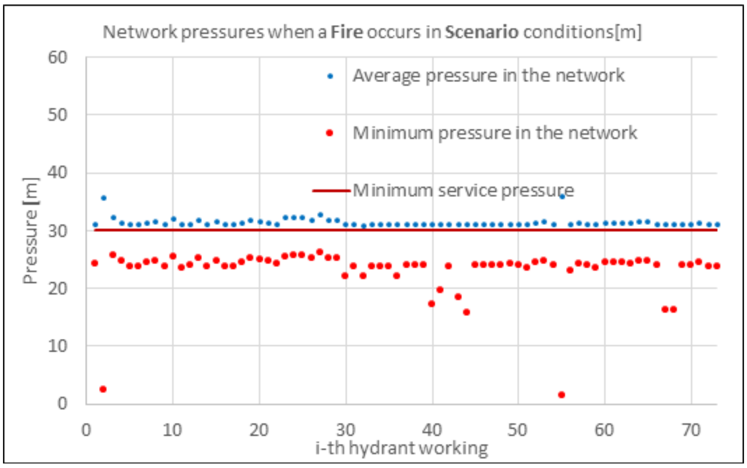


Figure 13: Network pressures when a Fire occurs in Scenario conditions[m].

It is found that when fire occurs at any point of the network, the average network pressures still stay above the minimum service pressure, but the minimum network pressure does not. The residual pressures and available fire flow at each hydrant are shown in Figure 14 and Figure 15.

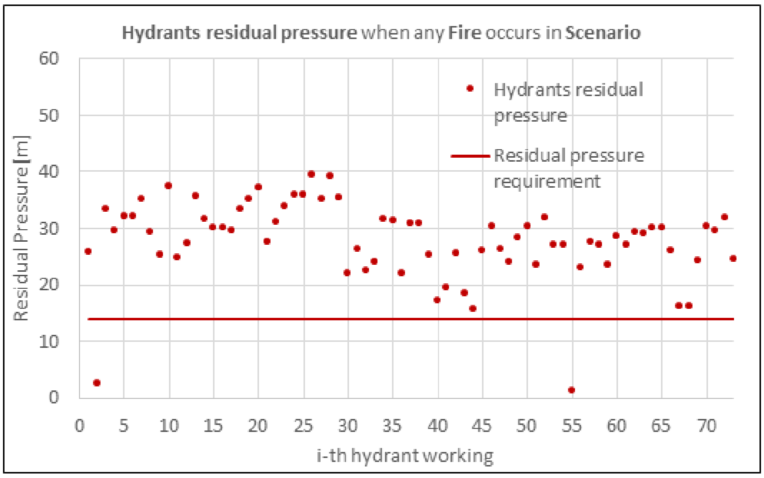


Figure 14: Hydrants residual pressure when Fire occurs in Scenario [m].

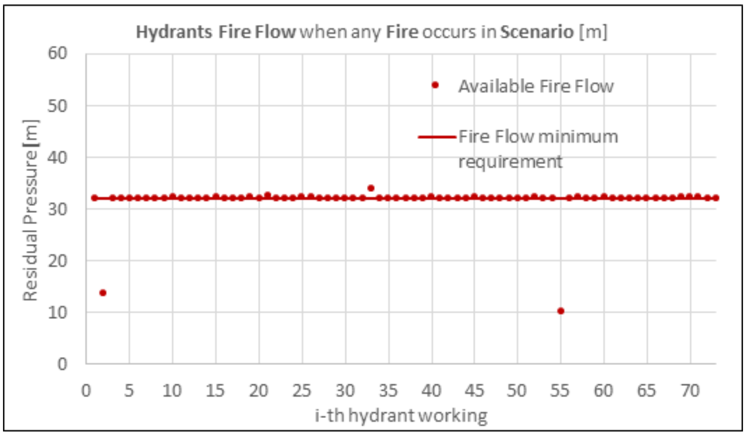


Figure 15: Hydrants Fire Flow when any Fire occurs in Scenario [m].

It can be seen that Hydrant 2 and Hydrant 55 don't meet minimum requirements and other hydrants barely do that, like 40, 41, 43, 44, 67, 68. It can be also seen that analysing the results in terms of available fire flow is limiting because it is imposed as a fixed nodal demand. Instead, it is preferable to make the analysis in terms of residual pressure, as differences among hydrants is more pronounced.

The developed Python script was tested within a multi-objective optimisation procedure for pipe rehabilitation in order to increase the network performance in fire events. A fire flow is set as a fixed node demand. The objective functions are 1) maximizing the residual pressure in the network; 2) minimize total rehabilitation costs. The decision variables are the pipes to be replaced. Although detail methods and descriptions are not provided here, the reader can find them in Farina (2019). Valuable to mention is that the most frequent pipes to be consistently replaced by the optimisation algorithm are Pipe 199, Pipe 61, Pipe 303, Pipe 127, Pipe 248, Pipe 63, Pipe 292. Replacing this set of pipes could lead a 5 ~ 10m gain in residual pressure to all hydrants.

The developed codes are ready to be used to feed the AI framework for NAIADES. This will be done during the second part of the project, in close collaboration with T5.1.

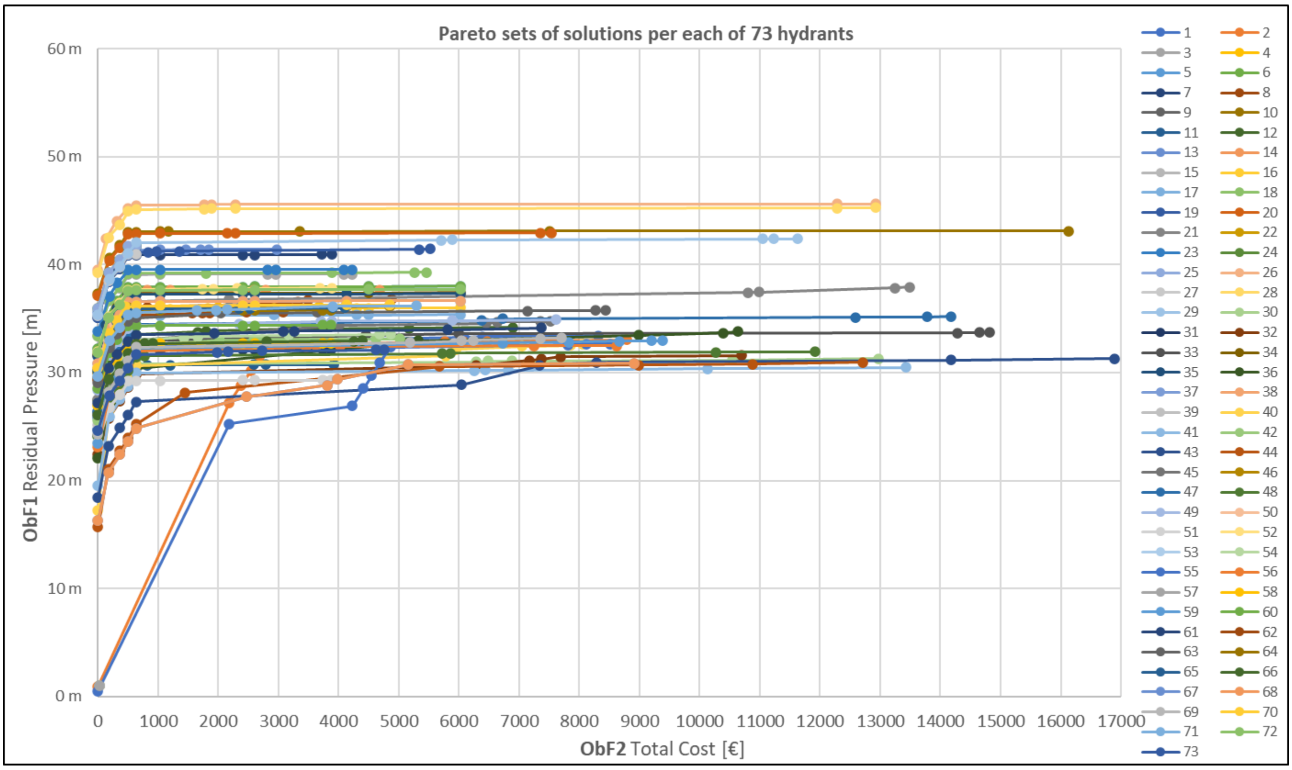


Figure 16. Pareto fronts obtained for the optimisation problem where the Python code was tested, considering individual fire events that activate separately each hydrant in the system. The pareto fronts of hydrants 2 and 55

4.1.3 Braila

In parallel, IHE has been working on the design of the critical events generator for the case of Braila, in particular for the use case of leak detection. The idea is to generate data of leakages events –given the confirmation that leakages is a study case using the available model provided by CUP Braila. The model has to be converted from a demand-driven analysis to a pressure-driven analysis using Epanet 2.2.

The utility company of the city has been using the Supervisory Control and Data Acquisition (SCADA) system to manage the operation of the water distribution network, although operation is not assisted by a Real Time Control System, and the management practice was not sufficiently supported by modelling tools. However, the company recently acquired a WDN model which can be used to assist the operational management of the system.

The water distribution model of the city is developed using a demand-driven analysis by EPANET modelling software. The system consists of 4172 junctions, 6 reservoirs, 3184 Pipes, 14 pumps and 1505 valves. The Network is subdivided into District Metering Areas (DMAs). There are 8 existing and 12 projected DMAs. Leakage was not separately considered in the modelling process. Therefore, now, leakage will be incorporated to the model using pressure driven analysis.

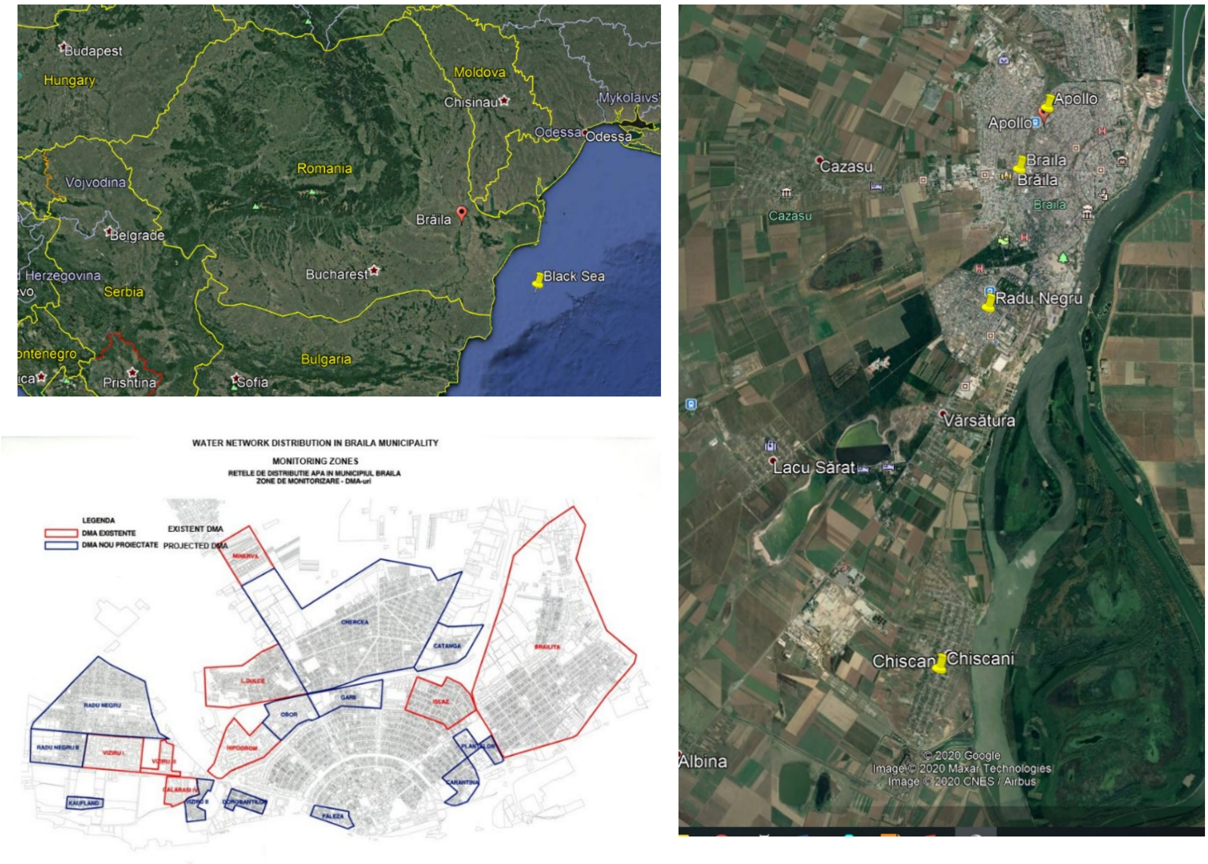


Figure 17 Map of Braila, Romania and DMAs of the water Distribution Network

The study area is Radu Negru, located in the south part of Braila-Romania, which has an area of 2.6 km2 and is projected to implement a monitored district area (DMA).

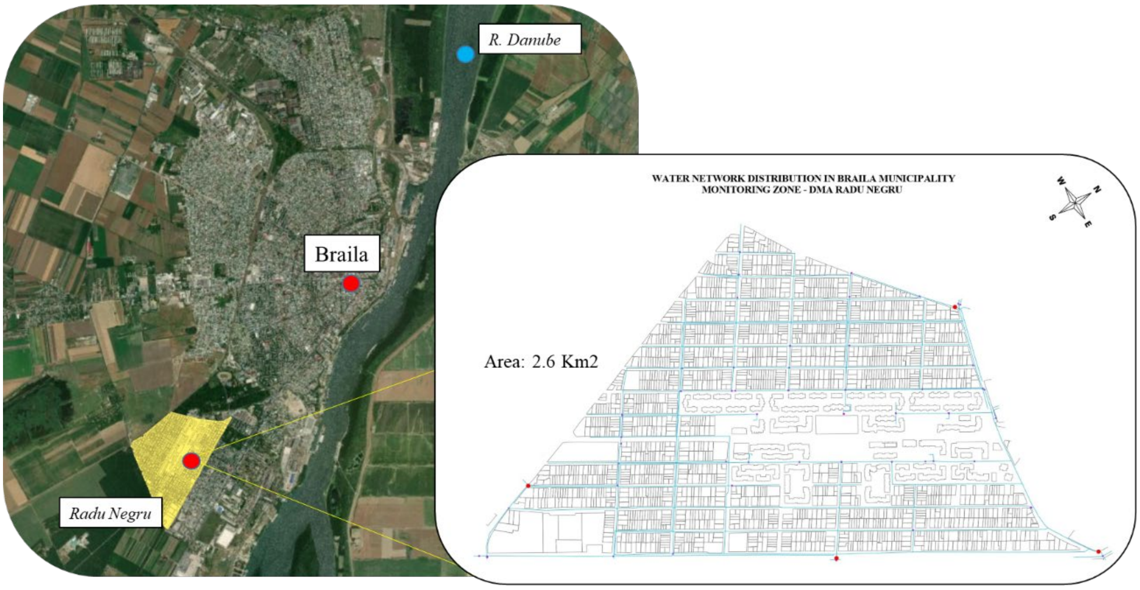


Figure 18 Location of the project Radu Negru area.

AVAILABLE DATA

Braila's municipality provided us the calibrated hydraulic model of its water distribution system (WDS); this is a model in *.inp* format and can be read by the modelling tool EPANET (Rossman, 2000). The model is composed by 4172 junctions, 6 reservoirs, 3184 pipes and 14 pumps. The simulation time is 24.00 hrs. The model represents the entire city of Braila; for our task, only the part corresponding to the Radu Negru sector will be used, therefore, it is necessary to reduce the model to the area shown in Figure 19.

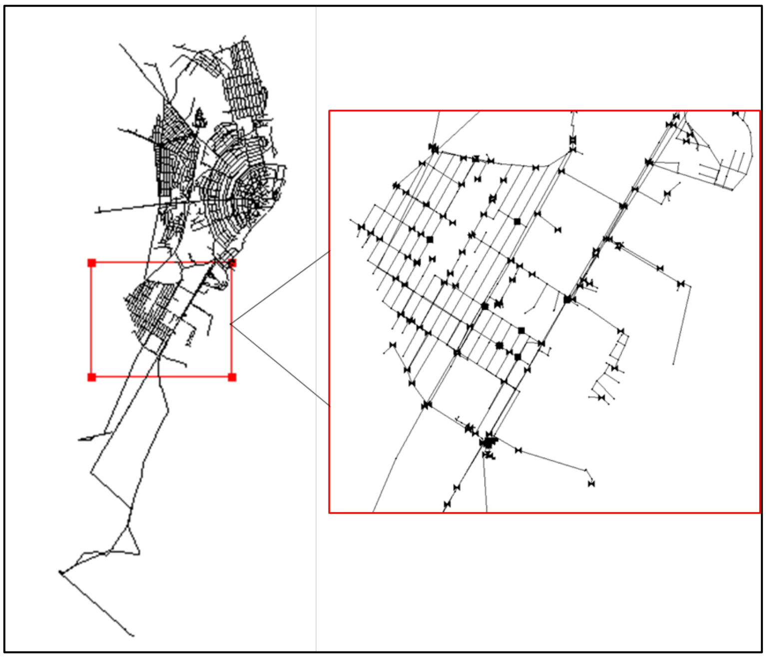


Figure 19Model of the WDS of Radu Negru - Braila.

In addition to the hydraulic model, shapefiles with cadastral information, pipes' characteristics, service nodes, hydrants, roads, and primary connections are available. This information was filtered to obtain only the information required in the sector of Radu Negru.

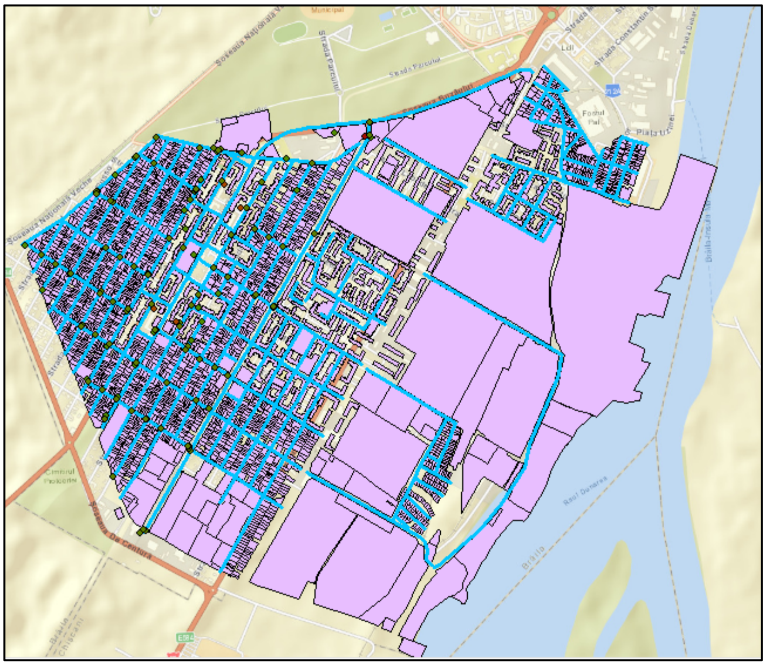


Figure 20 Shapes files of the WDS-Braila.

LEAKS IN WATER DISTRIBUTION SYSTEMS

The presence of leaks in a water distribution system (WDS) causes a variety of problems, including the loss of drinking water (Capponi et al., 2017), the deterioration of the quality of supply water due to the intrusion of substances into the system (B. Farley et al., 2009), the structural damage caused by infiltrations (Ponce et al., 2014) and the uneven distribution of pressures and flows in the network. These problems may trigger others, such as the loss of trust by users towards water entities due to the malfunctioning of the system (Quintiliani & Vertommen, 2020).

For this reason, water utilities regularly work on developing methods that help locate leakages in the least possible time and take the corresponding decision-making actions to reduce water loss and other related problems. These methods can be active and/or passive, depending on the strategy used. On the one hand, the active methods include a physical inspection of the pipes, the use of acoustic sensors or gas tracers, ground penetration radar, infra-red imaging, among others (M. Farley & Trow, 2015). However, although the leak can be pinpointed directly, these approaches are not appropriate for large systems because of economic limitations (Sanz et al., 2016).

On the other hand, the passive methods depend on secondary evidence of leakage, such as checking unexpected changes in the network's pressure values (Raei et al., 2019). Generally, the presence of leaks increases the flow in the network and causes a decrease in pressure. Therefore, if the pressure values detected at a node are outside the normal range, we could infer leaks in the network.

A common way to estimate the expected pressure values in a network is by using computer models, which are mathematical representations of the entire network that simulate –after proper calibration, their behavior for a range of functioning scenarios. Furthermore, real pressure values are obtained from measurements in the field, for example, with the help of pressure sensors. The difference between an expected pressure value and a measured pressure value can warn about leaks' potential existence (Raei et al., 2018). Although installing many sensors in a network could be ideal for leak detection, this is not always possible due to limited resources. Indeed, it is common to have only a few sensors available, and is fundamental to optimally decide where the available sensors should be located to maximize their usefulness.

Optimal distribution of sensors will help identify the presence of leaks with more extensive network coverage and, combined with methods for finding their specific location, can reduce the time in which leaks are detected, the loss of water, and associated damages (Bohorquez et al., 2020). Most leak detection studies use passive methods because their operational costs are lower than the active methods. Multiple investigations have been developed to build a computational framework for the optimal location of sensors.

However, these optimization methodologies are affected by the high computational load. Many simulations are required for networks with many nodes. The researchers were forced to simplify the problem, decrease the decision space (skeletonization), and use faster but less accurate optimization algorithms (Mohammad S Khorshidi et al., 2018). The problem of skeletonizing the network is eliminating nodes that could provide valuable information and is not a reliable representation of its functionality. Even in models for detecting contaminants, it was estimated that this practice could not guarantee an early detection or a minimal health impact (Diao & Rauch, 2013).

Although progress has been made in developing methodologies, there are still gaps that can be addressed by future research. Firstly, according to the literature review, most of the researchers applied methods based on a demand-driven approach (B. Farley, Boxall, and Mounce 2009; Pérez et al. 2009; Sanz et al. 2016; Raei et al. 2018; Quintiliani and Vertommen 2020). Consequently, they assumed that all nodes' demand could be supplied regardless of the network's pressure values. The use of pressure-driven models offers more realistic results than demand-driven models (Braun et al., 2017). When leaks occur, there may be interruptions in water service, i.e., nodes where the pressure is too low that demands are reduced or not supplied. Consequently, the demands should be a function of the pressure (Raei et al., 2019); in this task, the use of a pressure-driven model to generate critical events of leaks (see below) is proposed.

METHODOLOGY FOR BRAILA

According to the task objectives, the methodology can be subdivided into two different workflows. The first part consists of the hydraulic model's simulation using a pressure-driven approach and its calibration. The second part includes manipulating the information obtained from the model (pressure values of the nodes) and creating a workflow to obtain data of critical leak events and also to robustly optimize WDS sensors' placement. The model of the WDS of Braila was developed using EPANET 2.0, this version executes the hydraulic analyses using a demand-driven approach (DDA), assuming that all nodes' demand could be supplied regardless of the network's pressure values. The considered critical scenarios mostly imply a fall in the distribution network pressure, and the capacity to cover the demand of this network is reduced. For this reason, it is important to model the water distribution systems using a Pressure Driven Approach (PDA) model, where demands are a function of the system´s pressures.

In order to realize this analysis, the use of the tool EPANETTOOLS was explored. It is a tool developed by Dr. Assela Pathirana from IHE-Delft. It uses the Python programming language to extract information (pressures, demands, physical characteristics, etc.) from the .inp files generated by the EPANET software[1]. In addition to extracting information, this application has the Epanet-emitter engine enabling a pressure-driven approach, so its functionality will be revised, further research is required. The information about the pressures and demands of the network will be obtained, following the methodology presented in Figure 21.

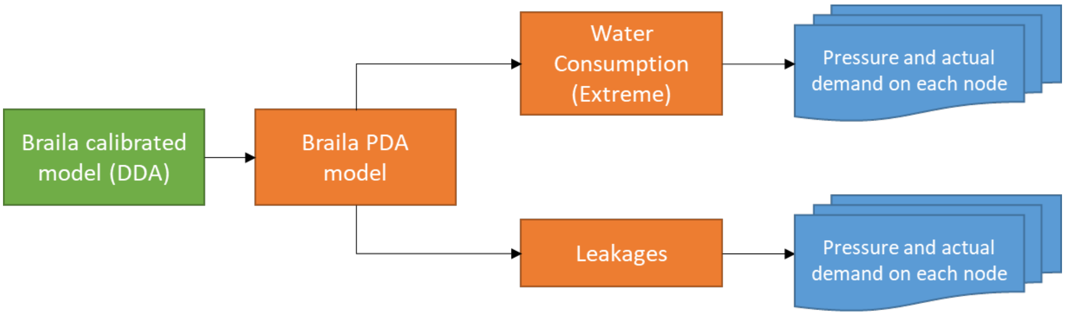


Figure 21. Work Flow for PDA

MODEL CALIBRATION

In this part, the output (pressures and discharges) of the Braila WDS initial model (original calibrated) are compared with the results of the simulation of the same model on Python using the EPANETTOOLS library, for both approaches, DDA and PDA. This will allow identifying if any further calibration is required for the WDS simulation in the PDA; the process is explained in Figure 22.

[1] For more information: https://pypi.org/project/EPANETTOOLS/

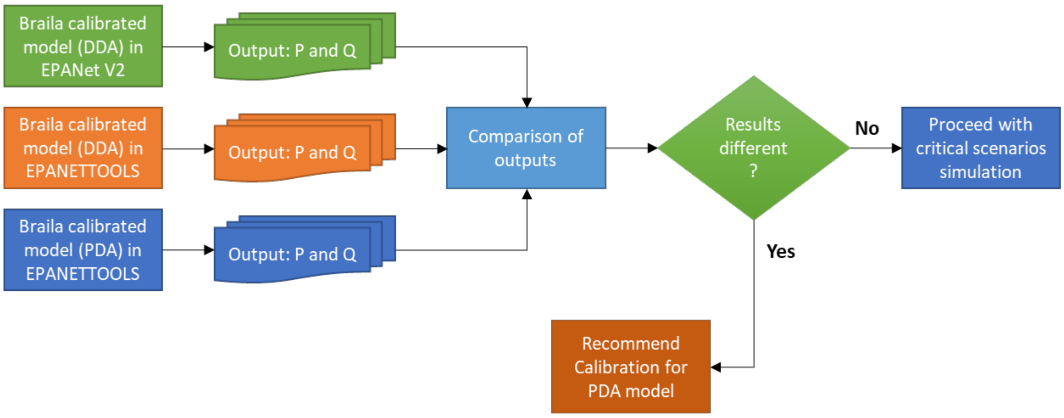


Figure 22. Workflow for calibration.

To consider the effects of the demand pattern, leaks will have different sources. We assumed that the leaks start at the zero hours of the simulation, to develop the initial framework. Later, the variation of the starting point will be studied. The approach consist of add extra demand to one node at a time, increasing it at each time step; the model is run and the pressure of the remaining nodes is read and stored and a (1 x N) array, where N is the number of nodes. The process continues until the end of the simulation time. A matrix of pressure variation for each node is obtained, the size of each matrix is (T x N), where T is the number of times.

Preliminary results show pressure results in Braila obtained with the mathematical model (see Figure 23).

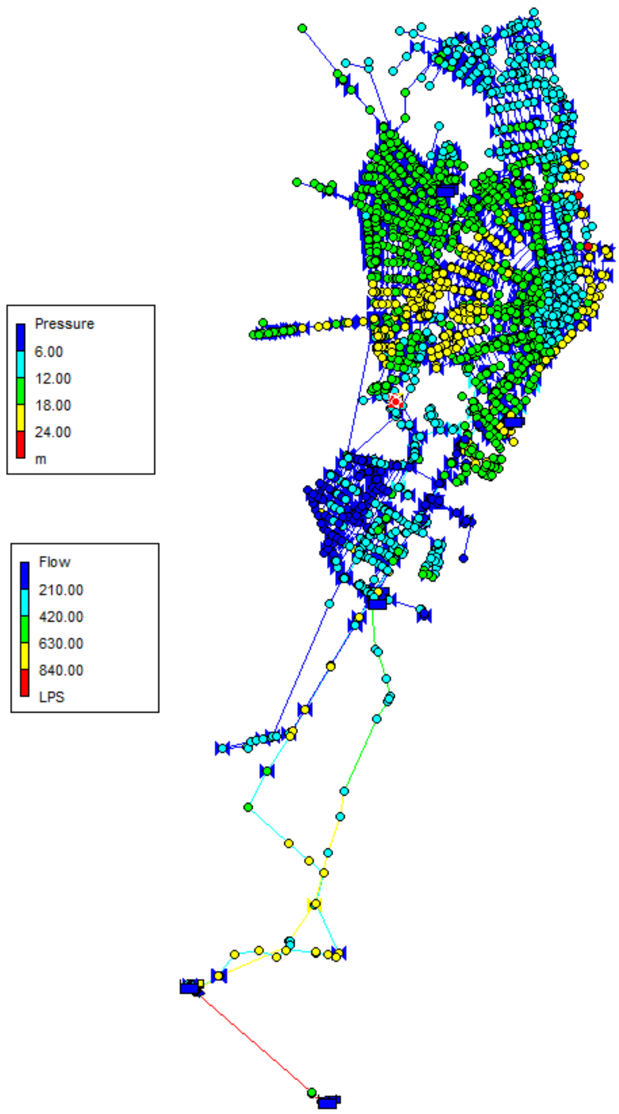


Figure 23. Distribution of pressures and flows according to the available hydraulic model.

GENERATION OF CRITICAL EVENTS IN BRAILA

The considered critical event, which is in line with UCB2, is pipe burst, in which the fall in the pressure of the WSN of a specific location is detected, due to the increased discharge of water lost. A direct consequence of this situation is the decay of the WSN capacity to deliver the base demand. This scenario is modeled in Epanet by adding an emitter on the nodes on the ends of the pipe assumed as burst with an orifice diameter equals to the Equivalent Burst Diameter. Only critical nodes are selected for this scenario simulation. The critical nodes would be selected based in the age of the connected pipes, pressures and external stresses.

To this end, a Python script was developed to produce input files of pressure decay at different time frames, due to the sudden increase of water demand in all the nodes of the network. The script produced more than 6.2 million records for the area of Radu Negru, for which the first seven are shown in Table 2. Note that time step refers to the elapsed time in seconds, from the 0:00h of simulation until 23:55. In the table, leak node ID refers to the node in which an artificial increment in demand was assigned, by multiplying its current base flow demand by the leak factor (column 3), considered to be 1.5, 2 and 5. The reported node refers to the node in which the pressure obtained after running the simulation with a change of demand in the leak node ID, by a leak factor. For example, 3600s after the simulation starts (i.e., at 1:00am), an increment of the demand of node wNode_355 by a factor of 1.5, produces a pressure of 7.13m in node wNode_355 (the same node in this case; however, this value is reported for all nodes in the area).

Table 2. Sample of the seven first records out of 6.2 million for the Radu Negru area

Time step (s)	Leak node ID	Leak factor	Reported node	Pressure (mcw)
0	wNode_355	1.5	wNode_355	7.09
3600	wNode_355	1.5	wNode_355	7.13
7200	wNode_355	1.5	wNode_355	7.29
10800	wNode_355	1.5	wNode_355	7.26
14400	wNode_355	1.5	wNode_355	6.94
18000	wNode_355	1.5	wNode_355	6.82
21600	wNode_355	1.5	wNode_355	6.67

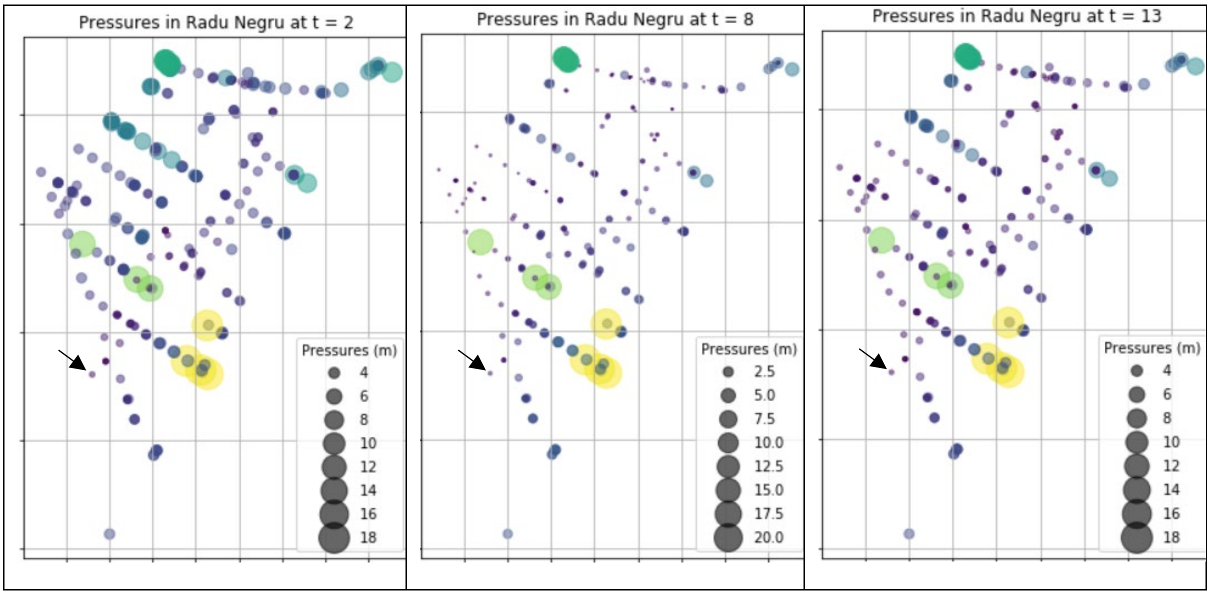


Figure 24. Model outputs for different times of the day, showing instant pressures in Radu Negru for a critical leak event at node wNode_355 (arrow).

The provided model has served the initial purpose of developing the Python code to generate the data for critical events in terms of leaks. Figure 24 shows the model outputs in terms of pressure at 2:00 am, 8:00am and 1:00pm, for an increment of the demand due to leak in node wNode_355 (black arrow) by a factor of 1.5, for different times of the day. It can be appreciated that, as expected, pressures drop during the day as water is consumed.

However, it must be noted that an improved version of the model is under construction, as it was detected that the modelled pressures under normal operation conditions (i.e., no leaks) are deviated from those pressures currently monitored. Once the model is ready, a bigger set of critical events will be generated and connected with the AI platform, in close collaboration with T5.1.

5 Conclusions and Future steps

This deliverable D4.1 has described the activities and results of the first part of the project related to Task 4.1. The needs for modelling have been identified, as well as the type of critical events we can consider in each case. The preliminary results of the modelling exercises for selected critical scenarios have been drawn, being fire events in the case of Alicante and leak events in the case of Braila. The Python codes are available to be used to explore more critical events if needed, than can be more related to the current use cases in these two pilots. A closer collaboration with WP5 will start, in order to define how the modelling inputs can complement the data sensors. In principle, it has been agreed that the modelling task is a one-time exercise to produce data, so no presence of modelling as a service is needed in the NAIADES platform. However, the data of critical events generated using the developed codes will complement the sensor data. This is the priority for the second part of the project, in collaboration with task 5.1. Also, as mentioned before, the urban water model task is not going to be applied for the pilot of Carouge due to the fact that the considered use cases do not contemplate the water distribution or the sewage networks.

The deliverable has been concentrated mainly on developing the modelling framework to generate data to feed the AI platform. This modelling framework has been built for the preliminary pilots of Alicante and Braila and will be used to simulate a range of other critical events in the second part of the project, including mechanical failure and substance intrusion. For example, mechanical failure scenario consists of possible, partial or full, failure of the pumping systems (e.g., for Braila) which can also affect the normal trends of pressure, demands and discharges in the system. This is introduced in the modelling software as a time pattern for the pumps operation via Python scripts. These critical events, as well as others, will be considered given the progress with the selected use cases. The specifics of using this data to feed the AI platform is also a main objective in second part of the project for this task.

An issue we are facing for Braila at the moment is that the pressures that the model is reporting for Radu Negru are too low, compared to the real ones. This is something that has been commented to CUP Braila and that must lead to a model improvement in the coming months. The resulting data is useful for experiments with AI while the sensors, recently installed, start to gather many more data records.

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