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CRITICALITY ASSESSMENT IN DOMESTIC WASTEWATER DRAINAGE NETWORKS USING MACHINE LEARNING

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Abstract

When it comes to the management of a city, wastewater drainage, treatment and disposal assume an essential role in providing the population with adequate sanitary conditions. Domestic wastewater drainage networks are designed to collect wastewater from the private networks of buildings and establishments and transport it to wastewater treatment plants. Operation and maintenance of a domestic wastewater drainage network must be properly managed, or it will otherwise result in preventable economic, environmental and social impacts.

In order to guarantee that the decision making regarding the management of a network is adequately performed, two aspects must be evaluated for each network section or structure: its performance and the impact should it malfunction. These two indicators can be combined into one indicator expressing the criticality of a certain network section or structure, which is a measure of how much resources should be assigned to it, in the global scale of the network. The main hypothesis for the development of this work was that intervening proactively in a certain section is beneficial when compared to intervening reactively, after a malfunction has occurred. It was determined, based on the case study's data, that resorting to proactive intervention implies an average 56% increase in the malfunction free time of the pipe network installed in a street, when compared to reactive intervention. A street's adequate proactive intervention frequency can be discerned from its estimated criticality. This work analysed several performance and impact indicators, using collected information supplied by Águas do Porto E.M., regarding Porto's domestic wastewater drainage network. The performance on pipe and street scale was evaluated through an indicator of interventions per pipe length per year and several pipe characteristics such as age, diameter, and pipe length per restaurant. Impact was mainly evaluated through the development of an indicator of equivalent inhabitants per pipe length, which allowed for both the influence of residential and commercial areas to be quantified without disregarding either.

The network's pipes and streets were classified regarding their criticality, resorting to indicators specifically adjusted to each scale, based on the conclusions drawn from the aforementioned analysis. Geographical representations of street criticality showed how proximity to the city's historical centre, where commercial activity and restaurant presence are both high, implied considerably higher street criticality. This was also correlated to the fact that the areas within the historical centre and in its vicinity are the oldest areas of the city, developed before the construction of Porto's domestic wastewater drainage network had started. Consequently, the network in these areas was originally dimensioned for a much smaller population compared to that of current days, resulting in a considerable extension of the network likely being currently under dimensioned. Criticality scores were ranged continuously from 0 (very low) to 10 (extremely high) and were used in the development of a proactive intervention plan, that is complementary to the one already being used by the company Águas do Porto, E.M. Its main premise is assigning a multiplier to each street, which depends on its criticality, and then multiplying it with each street's real intervention frequency to obtain the adequate proactive intervention frequency.

Machine Learning models were developed in order to implement the aforementioned classification methodology semi automatically, with the help of a spreadsheet where all relevant pipe and street information was stored. Three supervised learning algorithms were used, including two classification algorithms (Random Forest and Gradient Boosted Decision Trees) and one regression algorithm using Artificial Neural Networks (Multi-Layer Perceptron Regressor). Classification models achieved k-fold cross validation scores of approximately 89%, using 10 folds, while the regression model developed achieved a score of over 98%. As such, it was suggested that regression is the most suitable learning method for use in the context of this work.

Resumo

A drenagem e o tratamento de águas residuais são componentes essenciais da gestão de uma cidade, sem as quais não é possível fornecer à população as condições sanitárias adequadas. As redes de drenagem de águas residuais domésticas têm como objetivo recolher a água vinda de redes privadas, instaladas em edifícios e estabelecimentos, e transportá-las até uma estação de tratamento de águas residuais (ETAR). A boa gestão da operação e manutenção de uma rede de drenagem de águas residuais domésticas permite evitar que a rede seja associada a impactos ambientais, económicos e sociais.

De forma a garantir que as decisões relacionadas com a gestão da rede são adequadamente fundamentadas, é necessária a avaliação de dois principais aspetos relacionados com as suas secções ou estruturas: o seu desempenho e os impactos associados à ocorrência de uma falha no seu funcionamento. A partir destes indicadores é possível criar um indicador que expresse a criticidade de uma dada secção ou estrutura inserida na rede, que está relacionada com a quantidade de recursos que devem ser alocados à sua manutenção. O pressuposto inicialmente utilizado para o desenvolvimento desta tese foi que a intervenção preventiva numa dada secção da rede é benéfica para o seu desempenho, face à intervenção reativa, após a ocorrência de alguma falha. Foi determinado, com base na informação disponível, que intervir preventivamente leva a um aumento em média de 56% do tempo de funcionamento sem falhas da extensão, em comparação com a intervenção reactiva. A frequência de intervenção preventiva ideal pode ser discernida da criticidade estimada para uma dada rua. Nesta tese foram analisados diversos indicadores de desempenho e de impacto, recorrendo à informação disponibilizada pela empresa Águas do Porto, E.M., referente à rede de drenagem de águas residuais domésticas do Porto. O desempenho da rede foi avaliado à escala de ruas e de coletores, através de um indicador de intervenções por extensão de coletor por ano, e de diversas características dos coletores, como a idade, o diâmetro e a extensão total por restaurante. O impacto foi avaliado através da criação de um indicador de habitantes equivalentes pela extensão de coletores instalada em cada rua, possibilitando a consideração da influência de tanto zonas residenciais como de zonas comerciais.

As ruas e os coletores inseridos na rede foram classificados de acordo com a sua criticidade, recorrendo a indicadores ajustados especificamente a cada escala, com base nas conclusões retiradas da análise anterior. As representações geográficas da criticidade da rede demonstram como a proximidade ao centro histórico da cidade, onde a presença de restaurantes e a restante atividade comercial são elevadas, implica uma criticidade consideravelmente maior. As áreas descritas são as mais antigas da cidade, tendo sido maioritariamente desenvolvidas antes da construção da rede de drenagem de águas residuais começar. Consequentemente, a rede inserida nestas áreas foi dimensionada considerando consumos de água consideravelmente inferiores aos atuais, levando a que, atualmente, diversas secções da rede possam ser consideradas como sub dimensionadas. Foram atribuídos às ruas valores de criticidade compreendidos entre 0 (muito baixa) e 10 (muito alta), que foram posteriormente utilizados no desenvolvimento de um plano de intervenção preventiva, complementar ao que é atualmente utilizado na Águas do Porto, E.M. A frequência de intervenção ideal para cada rua foi obtida através da multiplicação de um valor (dependente da criticidade) pela frequência de intervenção real da rua.

Foram desenvolvidos modelos de Machine Learning com o objetivo de serem utilizados para implementar a classificação descrita, com o auxílio de uma folha de cálculo com a informação necessária. Foram usados os algoritmos de classificação Random Forest e Gradient Boosted Decision Trees, obtendo valores de validação cruzada K-Fold (10 folds) de aproximadamente 89%, e foi usado o algoritmo de regressão Multi-Layer Perceptron Regresso, obtendo um valor de 98%. Foi concluído que a regressão é a forma de aprendizagem supervisionada mais adequada ao contexto desta tese.

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Nomenclature

AdP	Águas do Porto, E.M.
AdDP	Águas do Douro e Paiva, E.M.
AI	Artificial Intelligence
ANN	Artificial Neural Networks Algorithm
CCTV	Closed-Circuit Television
COF	Consequence of Failure
DTAR	Wastewater Drainage and Treatment Department
DT	Decision Tree algorithm
DHE	Data Handling Errors
GIS	Geographic Information System
HDPE	High Density Polyethylene
LOF	Likelihood of Failure
ML	Machine Learning
MLPR	Multi-Layer Perceptron Regressor
NaN	Not a Number
PIP	Proactive Intervention Plan
PMA	Porto Metropolitan Area
PP	Polypropylene
PVC	Polyvinyl Chloride
ReLU	Rectified Linear Unit
RF	Random Forest Classification Algorithm
ROF	Risk of Failure
SeLU	Scaled Exponential Linear Unit
SMAS	Serviços Municipalizados de Águas e Saneamento do Porto
WLS	Water Lift Station
WTP	Water Treatment Plant
WWTP	Wastewater Treatment Plant
XGB	Gradient Boosted Decision Trees Algorithm

1. Introduction

1.1. Relevance and Motivation

Wastewater drainage and treatment are essential components of a city's management. Malfunctions in a domestic wastewater drainage network, such as obstructions or collapses, present a multitude of economic, environmental and social impacts. Poor network management eventually leads to higher malfunction occurrence, which in turn implies additional costs regarding the clearance of obstructions and the repair, renovation or replacement of damaged structures. In separative wastewater networks, the existence of by-pass structures between the domestic and pluvial wastewater drainage networks can be responsible for the infiltration of domestic wastewater into the pluvial network, whenever the domestic network is obstructed near such structures. This results in domestic wastewater being disposed of without having undergone treatment and, therefore, polluting the body of water in which it is transported to. Further environmental impacts can be associated to drainage pipe fissures or collapses, as wastewater can infiltrate the surrounding soil and contaminate groundwater. Social impacts of network malfunctions are typically associated with population discontent, leading to lower reputation of the managing entity. It is, therefore, important for the impacts of domestic wastewater drainage networks to be minimized, and this can be achieved through an increase in the efficiency of the network's management (Butler 2000).

The overall performance of a network can be evaluated through indicators such as the number of drainage pipe collapses, the number of pollution incidents occurring due to overflows and the number of properties at risk of flooding due to insufficient pipe capacity (Butler 2000). While the evaluation of network-wide indicators is important to determine by which kind of malfunctions a network is currently being most affected by, it is equally important to analyse the characteristics of the network and of the city where it is installed, and determine which characteristics are influencing the network's performance, and where. Previous works have been published regarding the development of a methodology to estimate these influencing factors on drainage pipe scale. One such work described the influence of pipe characteristics, including pipe age, depth, diameter, length, material and distance from above ground water sources and restaurants (Rossi 2015).

This work was developed with the intent of analysing the characteristics of Porto's domestic wastewater drainage network's pipes and streets and determining which characteristics display the highest influence both on pipe and street performance. All information was provided by Águas do Porto, E.M. (AdP). The potential impact of obstruction occurrences was estimated on street scale, and a classification methodology was developed, combining both performance and impact indicators to create an overall indicator descriptive of the criticality of a certain pipe or street. Machine Learning models were then trained in order to correctly estimate pipe or street criticality, thus effectively implementing the methodology, using an information spreadsheet and support.

1.2. Objectives

The main objective of the work developed is to improve the performance of domestic wastewater drainage networks and minimize the economic, environmental and social impacts associated with network malfunctions. This can be achieved by promoting planned intervention in key structures, with an adequate frequency, therefore lowering the need to intervene reactively to the occurrence of network obstructions. The stages that lead to the accomplishment of this objective are summarised below:

1. Validation of the hypothesis that proactive intervention positively impacts network performance. Analysis of the network's operation procedures and of the parameters and network characteristics that can influence a pipe or a street's sensibility to the occurrence of obstructions;
2. Development of a classification methodology that can estimate the criticality associated with a certain pipe or street, based on criteria supported by the conclusions drawn from the prior analysis, and of a proactive intervention plan complementary to the one currently used by Águas do Porto, E.M.;
3. Development and use of Machine Learning models capable of implementing the formerly developed methodology.

1.3. Structure

This thesis is divided into the following chapters:

- Chapter 1, the present chapter, describes the relevance and motivation behind this work, its main objectives and how it is structured;
- Chapter 2 contains the literature review that was considered relevant to this work, focusing on aspects regarding the operation and maintenance of wastewater drainage networks, methodologies that can be used to evaluate network performance and the main principles of Machine Learning;
- Chapter 3 presents the specific objectives of this work;
- Chapter 4 provides an introduction to Águas do Porto, E.M., addressing its historical background, management processes, its current services and the operating conditions of the city and of its domestic wastewater drainage network;
- Chapter 5 provides an overview of the case study, the validation of its main hypothesis, the data selection and treatment procedures, the statistical analysis performed, the geographical representations produced, the classification methodology developed and the specifics regarding the Machine Learning models used;
- Chapter 6 presents the results obtained and their discussion;
- Chapter 7 contains a summary of the main conclusions derived from the results and recommends future analysis that can further complement this work.

2. Literature Review

2.1. Urban Water Cycle

Water is an essential resource for both human sustenance and for a vast amount of processes and activities that are characteristic of the human lifestyle. Water supply and retrieval processes are, consequently, integral to the management of any human settlement. As of 2018, 55% of the world's population lived in urban areas, with projections suggesting that this percentage will have increased to 68% by 2050 (United Nations 2019). The increase in urbanization in or around a city adds additional pressure over its implemented water management processes. This implies an increased need to optimize the processes involved in what is defined as the urban water cycle. Unlike the hydrological cycle, in which water goes through natural condensation, evaporation and precipitation processes, the urban water cycle is man-made and consists of engineered processes encompassing capturing water, providing it to a certain settlement and collecting the resulting wastewater for safe disposal, along with every intermediate process (Sowby 2014). This cycle consists of the processes depicted in Figure 1.

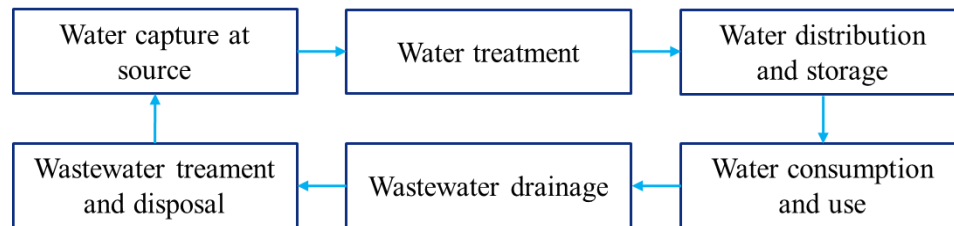


Figure 1: Urban water cycle, adapted (Jensen 2020)

Freshwater is mainly collected from surface water sources, such as lakes, reservoirs and rivers, while it is also possible to extract groundwater through the use of wells. It is important to consider water quality, availability, proximity of the source to the settlement and economic and legal aspects when choosing the most appropriate water source for a settlement (Sowby 2014).

Captured water must undergo a treatment process, aimed at removing contaminants and pathogens, before it can be distributed. The specific processes may vary, depending on water quality. Typically, water is subjected to pre-treatment processes involving pressurized filtration. Treatment can then consist of a multitude of oxidation, coagulation, flocking, sedimentation and disinfection processes, aimed at removing algae, microorganisms and suspended particles (Cheng 2016).

Water is typically subjected to quality control at several stages during the treatment process. Once the process is finished and the water displays adequate characteristics, it is then lifted to one of several reservoirs (Águas do Douro e Paiva 2020). The distribution of water is performed through a network of pipes operating under pressurized flow and aided by strategically placed pumps, valves and reservoirs. Once water reaches customers, it can be used for a wide variety of purposes.

Whether water is used for consumption, personal hygiene or for daily activities of businesses and industries, its use is always associated with a certain amount of contamination (Sowby 2014). Consequently, it is important for contaminated water, i.e. wastewater, to be collected and forwarded to treatment before it is disposed of, so it does not negatively impact the receiving ecosystem.

2.2. Wastewater Drainage and Treatment Systems

Urban wastewater drainage and treatment systems are designed for the collection, transportation and treatment of wastewater, and are generally composed of drainage pipe networks, which collect wastewater and transport it to emissary pipes, which in turn forward it to a Wastewater Treatment Plant (WWTP). These systems work with two types of wastewater, domestic and pluvial. Domestic wastewater originates from human and, to a lesser extent, industrial activities. While in certain cases it can be treated in private treatment systems, such as septic tanks, the majority of a city's domestically produced wastewater enters the wastewater drainage network through the buildings' plumbing systems. Industrial wastewater can only enter the drainage network if it is not corrosive to the materials the drainage pipes are built of, nor does it disrupt the treatment processes in practise at the water treatment plants. Otherwise, it is subjected to treatment prior to entering the network. Pluvial wastewater is generated by precipitation, entering the wastewater drainage network through drainage systems installed in buildings or through gutters, carrying any materials it may have dragged along with it. (Butler 2000)

Wastewater drainage networks begin at connecting branch chambers, which connect the private and public sections of the network, and end in wastewater lift stations (WLS), meant to insert the water into emissary pipes (Águas do Porto E.M. 2015). They can be separative or combined. In separative networks, the pipes used for transportation of domestic and pluvial wastewater don't intercept, with domestic wastewater being transported to WWTPs through emissary pipes, and pluvial wastewater being directly disposed of safely at convenient natural bodies of water. In combined networks, the pipes transporting domestic and pluvial wastewater eventually intercept, with pluvial wastewater being joined with domestic water at the emissary pipes, and all wastewater being transported to WWTPs. These networks require the existence of a storm unloader upstream of the WWTPs, in order to bypass high pluvial wastewater volumes during heavy rain periods (Valente 2007). The constituent parts of a wastewater drainage network and the trajectories of the wastewater types within it are represented in Figure 2.

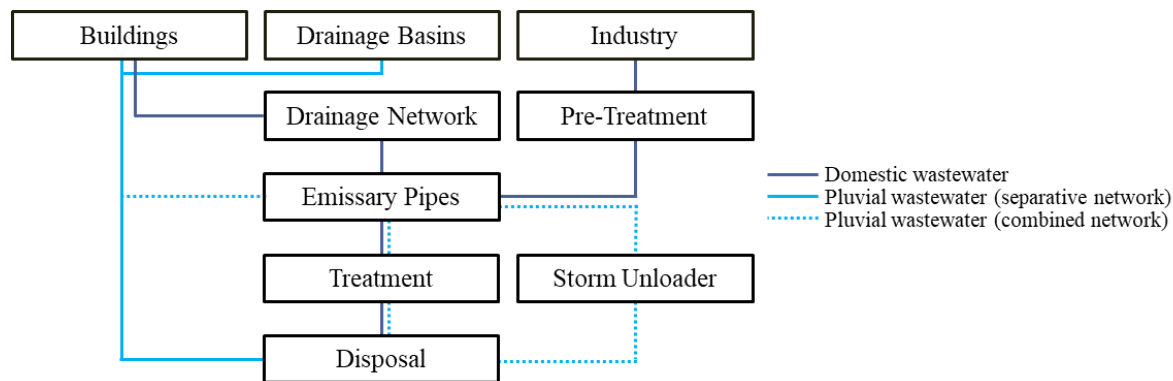


Figure 2: Constituent parts of wastewater drainage and treatment systems, adapted (Valente 2007)

Older wastewater drainage and treatment systems are usually combined, while recent systems are separative. Changing from combined to separative systems presented advantages in the form of reduced pollution, network capacity and treatment cost. During heavy rain periods, the network's storm unloader may need to be used. Given that domestic and pluvial wastewater are combined, discharging a certain volume of wastewater implies that a fraction of that volume is untreated domestic wastewater, which presents negative environmental impacts for the receiving ecosystem. By separating pluvial wastewater, which does not need a specific treatment to be properly disposed of, from domestic wastewater, a considerably lower volume of water is treated, which involves lower treatment costs. This separation also allowed for pluvial wastewater drainage networks to be sectioned, distributing wastewater to different bodies of water, allowing for drainage pipes to be dimensioned with lower diameters.

Domestic wastewater drainage networks are generally constituted by circular section pipes, which operate mainly under free surface flow. The installation of domestic wastewater drainage pipes must, therefore, adapt to the city's topography, unlike water distribution networks, which operate under pressured flow. Drainage pipes are dimensioned according to their expected maximum and minimum flow, with flow velocities above regulated values deemed unsafe and very low flow velocities allowing for the sedimentation and build-up of particles suspended in the wastewater. Due to their conditioning, these pipes typically display linear trajectories, and visit chambers are installed in every direction change.

Emissary pipes are large diameter pipes that receive wastewater from the drainage network and forward it to water lift stations or wastewater treatment plants. Due to the high wastewater volume flowing through them, emissary pipes operate under pressured flow and it is, therefore, uncommon for these pipes to receive wastewater directly from domiciliary drainage systems. Emissary pipes are, similarly to WLSs and WWTPs, typically installed in topographic depression areas downstream of the drainage network, in order to minimize the necessity of lifting the water into the treatment plant. In cities located near big water courses, it is common for the topography of the region to allow several drainage basins to flow towards the water course. Emissary pipes located along its margins are named interceptor pipes (Valente 2007).

The treatment of domestic wastewater typically involves the following stages:

- Preliminary treatment: designed to remove non soluble solid waste, such as grease, oils, paper, plastic items, sand and vegetation. It is important to initially remove the aforementioned waste, as it can severely disrupt the following treatment processes and obstruct and damage equipment. Paper, plastic and vegetation are removed through a variety of screening and sifting procedures, while sand is removed through gravitational decantation and grease and oils are removed through flotation (Cheng 2016);
- Primary treatment: uses sedimentation techniques to significantly reduce the suspended solids present in the wastewater;
- Secondary treatment: aimed at removing organic compounds, typically performed in a biological reactor;
- Tertiary treatment: usually involves the disinfection of the wastewater or the removal of a specific pollutant (L. Metcalf 1991).

Lastly, wastewater is deodorized before being disposed of, while sludge resulting from the treatment processes is stabilized using anaerobic digestion processes (Cheng 2016).

The disposal of treated wastewater, providing it displays adequate quality parameters, is performed through pipes with characteristics similar to those of emissary pipes.

2.3. Domestic Wastewater Drainage Network Management

2.3.1. General Considerations

When a domestic wastewater drainage network is displaying adequate performance levels, there can be a tendency to disregard some of its maintenance and intervene reactively to the network's few malfunctions. However, despite networks seemingly working well, the materials of which drainage pipes and the remaining structures are built of may corrode, erode and generally deteriorate over time. This can lead to obstructions in the network, or more severe malfunctions such as collapses. Several arguments can be made for how an adequate wastewater drainage network maintenance is of high importance. Primarily, it is paramount that public health is maintained. As has been previously addressed, wastewater is water that has been contaminated by human use, whether domestic or industrial, and as such, it is important that it is directly transported through the drainage network from its emission location to a WTP. Poor network maintenance can lead to situations in which wastewater is allowed to infiltrate either the ground or properties that are connected to the network, resulting in possible contaminations that likely could have been preventable (Butler 2000). Should separate wastewater drainage networks have occasional connections between the domestic and pluvial drainage pipes (referred to as by-passes), an obstruction in a domestic drainage pipe can lead to domestic wastewater infiltrating the pluvial wastewater drainage network, where it would be emitted without treatment (Valente 2007). Adequate drainage network maintenance is further supported by its economic benefits, as there should be a lower need to replace the network's components, and the minimization of the disruption to the general public, which should translate to a higher reputation of the entity responsible for the network's management (Butler 2000).

2.3.2. Obstruction Causes

A pipe obstruction is defined as a partial or full blockage of the pipe's section area. It is typically associated with either a system defect, such as a displaced joint or excessive change of direction, or pipe characteristics that make it more susceptible to problems that lead to obstructions (Butler 2000). Such characteristics can include small diameters, low inclinations and the material of which the pipe is built of (Rocha 2017). Pipe obstruction effects involve the partial or full loss of pipe capacity (Butler 2000). Obstructions commonly have the following causes:

- Debris sedimentation: debris (highlighted in Figure 3) can enter a wastewater drainage network mainly through sanitary use (primarily consisting of faecal and organic matter, paper and other flushed materials), with materials also originating from commercial and industrial sources. Debris sedimentation is usually associated with partial pipe obstruction;



Figure 3: Debris build-up in the visitation chamber of a wastewater drainage network (Águas do Porto E.M. 2020)

- Grease accumulation: the presence of significant amounts of grease inside domestic wastewater drainage networks is typically associated with commercial establishments, such as restaurants, in which grease enters the network through high temperature dishwashers. It then cools further downstream in the network and solidifies (as depicted in Figure 4). This is more frequent in pipes that either experience low wastewater flows or have low inclinations (Butler 2000).

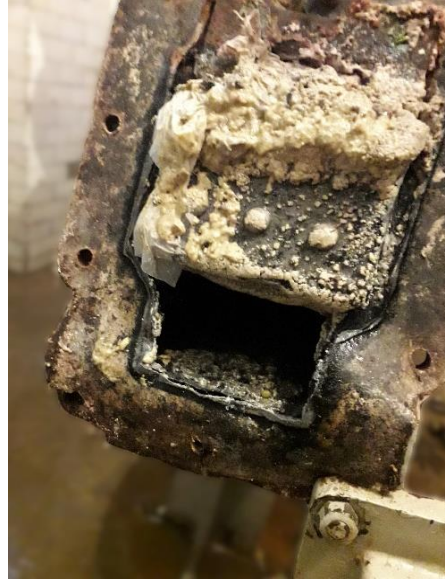


Figure 4: Grease accumulation in one of Porto's wastewater drainage network's Shone ejectors (Águas do Porto E.M. 2020)

- Tree root infiltration: the joints between pipes are particularly vulnerable to the infiltration of tree roots, which can be observed in Figure 5 (left), through the use of Closed-Circuit Television (CCTV). Significant tree root infiltrations can lower flow velocity and facilitate the build-up of materials (Rocha 2017).



Figure 5: Tree roots observed inside a drainage pipe, through CCTV inspection (left) and the roots after removal (right) (Águas do Porto E.M. 2020)

- Other causes: the insertion of abnormal materials in the network, whether through sanitary use or through manholes, considerably increases the likelihood of obstruction. Poor construction practises can lead to the intrusion of other pipes or structures in the drainage pipes, causing capacity reduction (Rocha 2017).

2.3.3. Maintenance

The maintenance of a drainage network can be performed reactively and/or proactively. Reactive intervention is performed after a certain obstruction or failure has occurred. This is, to a certain extent, a necessary type of intervention, as it is natural that some problems do occur, regardless of the kind of maintenance that is performed in the network. It is, however, not possible to improve a network's performance through reactive intervention, as the cause of the failure typically is not addressed. In order to improve a drainage network's performance, it is essential to plan interventions and, therefore, intervene proactively so that a significant amount of malfunctions can be avoided (Butler 2000).

In order to adequately perform proactive interventions, it is necessary to study the intervention history and the characteristics of a specific section of the network, so that the elements contributing to its poor performance can be identified and conclusions can be drawn regarding the adequate solution for that specific network section. The following types of proactive interventions can be performed:

- Inspection: most commonly performed manually or resorting to CCTV. It can be used to both determine whether an extension of pipes needs to be intervened, allowing for pipe cleaning resources to be applied in other network areas in the case of no intervention being needed, or to monitor if an intervention has had the desired effect. Manual inspection is performed in few circumstances, whenever conditions prevent other methods from being used. CCTV inspection involves the insertion of a camera equipped with a light source inside the pipe, with the image being transmitted to the surface, where it is viewed and recorded. Two types of CCTV equipments are presented in Figure 6. Equipment A is manually pushed, once it has been inserted in the pipe, and can cover extents of up to 60 m. Equipment B is automated, and can cover pipe extensions of up to 150 m. Images B1 to B4 show the working conditions of this equipment, which requires a vehicle in which it can be stored and charged, and where images can be analysed.

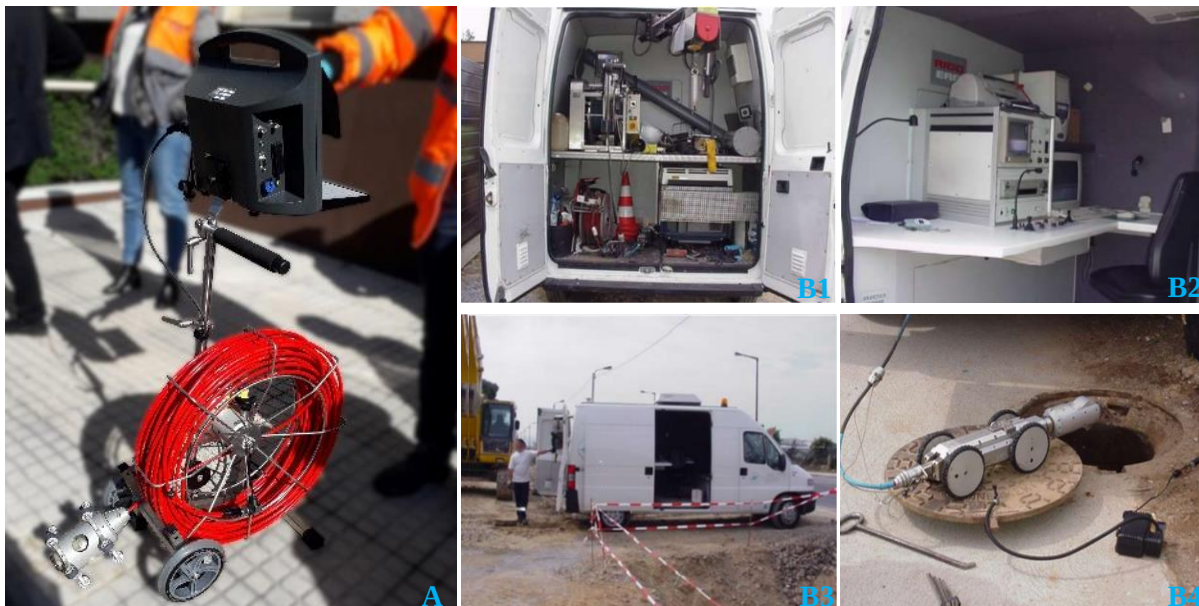


Figure 6: CCTV equipments used in AdP, with manual operation (A) and automated (B) (Águas do Porto E.M. 2020)

- Cleaning techniques: primarily used with the purposes of proactively removing waste accumulations in order to maintain the pipe's performance, reactively clearing pipe obstructions and aiding pipe repair or renovation (Butler 2000). The most commonly used techniques throughout history are the following:
 - Manual rodding: consists of manually inserting short flexible rods that are screwed together into obstructed pipes. This procedure is limited to pipes of relatively low diameter and to obstructions located near visitation chambers (Lester 1979);
 - Mechanical rodding: consists of mechanically pushing a rodding device attached to a tank truck through a certain pipe extension. Through its rotation, the device will remove the waste accumulations, or infiltrated roots (with the extension presented in Figure 7). This technique is typically performed proactively (Rocha 2017);



Figure 7: Mechanical rodding tank truck (left) and equipment for removing tree roots (right) used in AdP (Águas do Porto E.M. 2020)

- Jetting: consists of using a high pressure water stream, downstream of the pipe, in order to dislodge material accumulations from the walls of the pipes, transporting them further downstream, where they can be removed (Butler 2000).
- Pipe rehabilitation, involving repair, renovation or replacement: typically performed when pipes have collapsed or have otherwise consistently underperformed.

Overall, an intervention plan should attempt to minimize the operation and maintenance costs associated with a certain network section, by considering which type of intervention would be better for the long term. As such, it is helpful to analyse the maintenance hierarchy presented in Table 1.

Table 1: Sewer maintenance hierarchy (Butler 2000)

Level	Task	Type	Consequence of Omission
1	Periodic cleaning	Planned	Level 2 task needed
2	Blockage removal	Reactive	Failure
3	Repair	Planned	Level 4 task needed
4	Renovation	Reactive	Level 5 task needed
5	Replacement	Reactive	Failure

It is implied that the lowest level (1) represents what is typically the best approach to maintaining a domestic wastewater drainage network, which is periodically cleaning its most sensible sections. Failing to do so can eventually result in pipe obstructions, for which reactive intervention is necessary. Periodic cleaning

typically involves intervening in larger distances when compared to obstruction clearance, with its cost being mostly dependent on worker salary, equipment operation and, in certain cases, the displacement between the locations of the equipment and the section of the network. Obstruction clearance involves the aforementioned costs and the potential cost of its negative consequences, should it disrupt the network's performance.

2.3.4. Performance

The importance of good performance in a domestic wastewater drainage network has previously been highlighted. The evaluation of a network's performance is increasingly being performed resorting to performance indicators. These allow for the representation of the network's processes and provide foundations for its monitoring and regulation. Indicators that are commonly used to evaluate a network's performance are the number of drainage pipe collapses, the number of pollution incidents occurring due to overflows and the number of properties at risk of flooding due to insufficient pipe capacity (Butler 2000).

The focus of this study was, however, on indicators regarding characteristics of the network that may influence its performance on pipe and street scale, and not indicators that evaluate the performance as a whole. Prior works have described methodologies developed specifically for determining the likelihood of failure within network components, which was, in some cases, combined with the consequences of failure. One of such methodologies can be summarised by the following equation:

$$ROF = LOF \times COF \quad 2-1$$

in which *ROF* is the risk of failure, *LOF* is the likelihood of failure and *COF* is the consequence of failure (Moss 2013).

The risk of failure within a network's pipes can be determined through the classification of both likelihood and consequence of failure, which must be determined themselves based on properly evaluated parameters. (Rossi 2015) tested and created a scoring system for each of the following parameters:

- Pipe material and age/installation date;
- Distance from restaurants;
- Distance from any above ground water source;
- Pipe depth below the ground surface;
- Pipe length;
- Amount of vehicular traffic.

The scoring is presented on Table 2.

Table 2: Parameter scoring system, adapted (Rossi 2015)

Score	Condition
0	Best
1	Very good
2	Good
3	Average
4	Bad
5	Very bad

Each pipe was then scored based on the 6 aforementioned parameters. It was concluded that pipe material, age and distance from above-ground water sources had the greatest impact in pipe performance. Consequence of failure was estimated through the perceived economic, environmental and social impact associated to the parameters (Rossi 2015).

2.4. Machine Learning

2.4.1. Definition and Historical Background

Artificial Intelligence (AI) is defined as the study of computer algorithms that are capable of performing tasks involving automatic performance improvement through experience (Mitchell 1997). Such tasks usually involve learning from data or surrounding environments, decision making, or the recognition of images or speech. Having been first developed during the 1950's decade, AI has seen a sharp increase in its use in recent years, which has been apparent in science fields and technologies involving automated responses.

The term Machine Learning (ML) was coined in 1959 by Arthur Samuel, and it refers to a subset of AI that studies the use of computer algorithms to enable the machine to analyse data autonomously, find meaningful patterns between parameters and improve with experience and with the addition of new data. It is best used as a tool to extract information from large datasets and to make predictions for future events based on the data of past events (Koza 1996). Currently, ML is a significant part of technologies used in the following fields:

- **Accident prevention:** equipping vehicles with learning algorithms capable of analysing the vehicle's surroundings and identifying and preventing accidents;
- **Digital cameras:** performing facial recognition and camera autofocus;
- **Fraud detection:** determining abnormal behaviour in credit card usage;
- **Navigation:** traffic mapping and congestion estimation in order to help minimize the duration of a route, used mainly on GPS dependent apps;
- **Online customer support:** enabling chatbots, which are used to interact with clients instead of human employees, to improve their responses to clients based on past interactions;
- **Scientific developments:** ranging from applications in medicine, such as diagnosing illnesses using image classification, to applications in meteorology;
- **Search engines:** determining the most relevant search results;
- **Social media features:** personalizing the ads shown to users based on their past searches and in suggesting new social connections to users based on data related to their connections;
- **Spam and malware filtering:** determining what is spam or malware and learning from newly created malware in order to update the response to it;
- **Video surveillance:** tracking unusual and abnormal human behaviour in attempts to stop crimes before they happen;
- **Virtual personal assistants:** voice and character recognition and personalization of responses and results shown by the apps according to past interactions with the user.

Traditional computer software is developed in a way that both the input data and the algorithm are provided to the computer, which will then produce the output. In ML techniques, it is often the output data that is provided along with the input data, with the computer producing an algorithm that attempts to accurately transform the input into the output. It is expected, therefore, that should the output data change, the algorithm will be changed as well (Alpaydin 2004). There are, however, other ML approaches which do not require previous knowledge of what the input or output data is.

2.4.2. Learning Methods

Several approaches to ML can be taken, depending on the task that is expected to be performed and on the intended input and output data. Different types of learning algorithms must be used in order to perform different approaches to a task. As such, existing algorithms can be divided into categories, which are most commonly defined as supervised learning, unsupervised learning and reinforcement learning (Bishop 2006). Semi-supervised learning algorithms, which combine characteristics of both supervised and unsupervised learning (namely, labelled and unlabelled data, respectively) can also be used in certain situations.

2.4.2.1. Definition of Supervised Learning

Supervised learning algorithms are used with the purpose of discovering connections or patterns between two sets of data, the input (containing one or more variables that can influence the output) and the output (the desired outcome of the input data). Therefore, it is necessary for the user to initially provide both sets of data, which can be labelled as training data (Russell 2010). The algorithm will then create a mathematical function that can approximately represent the relations between the input and output data, allowing the ML model to be able to predict the outcomes of unavailable or future data when provided only the input set. As more data is provided to the model, it will attempt to change in a way to better represent the expanded data set, managing to learn from experience over the course of its use. There are a few subtypes of supervised learning algorithms, with the context of the problem determining the most adequate algorithm (Bishop 2006). The main subtypes are the following:

- Classification algorithms: used with the purpose of categorizing data. The models are trained to associate the input data with two or more classes as the output. This can be useful in problems involving image classification (such as diagnosing illnesses) or prediction of market values. In all the aforementioned cases, it is expected that the model is able to determine whether a certain characteristic is verified or not in the data: whether there is an illness in the input image or not, or whether the market value of something will increase or decrease. These are examples of binary classification, in which the output consists of only two classes that can usually be interpreted as “Yes” or “No”. Classification involving more than two output classes is defined as multiclass classification (Alpaydin 2004). An example of this would be if the model was expected to determine several types of an illness based on an image.
- Regression algorithms: used when the output is a continuous variable and, therefore, a real value. Most commonly, problems for which regression algorithms are recommended involve predicting quantities, such as determining the future value of an asset based on its past values or determining the amount of days until the occurrence of a certain event based on its former periodicity.
- Anomaly detection: used with the purpose of identifying groups of data that are not consistent with the overall pattern of the input data. The determination of abnormal groups of data can prove useful in problems such as fraud detection, through the identification of behaviour that strays from the patterns of the overall data and can be interpreted as abnormal, signalling a potential fraud.

2.4.2.2. Supervised Learning Algorithms

There are many supervised learning algorithms, each with different characteristics and tailored to solve problems with differing contexts and outcomes.

In the development of this work, supervised ML models were developed using the classification and regression algorithms that are described below.

Random Forest

Random Forest (RF) algorithms essentially consist of a combination of Decision Tree (DT) algorithms and, as such, it is necessary for these to be defined first. DT algorithms are used with the purpose of aiding decision making, and can be used in the context of classification problems (DT classifiers) or regression problems (DT regressors). The models are named after the presentation of their resulting function, which is the graphical form of a decision tree. It consists of nodes and branches, which facilitates the interpretation of the rules established by the model. Each node can either be classified as a division (or decision) node or leaf (or terminal) node. Division nodes contain a conditional test (commonly structured as “if... then”) evaluating one attribute of the data sample based on its value. The division node at the root of the tree is referred to as root node. Leaf nodes represent the classes in which the algorithm categorises the data and have no further divisions (Ho 2016). Figure 8 shows an example of a simple structure of a DT algorithm.

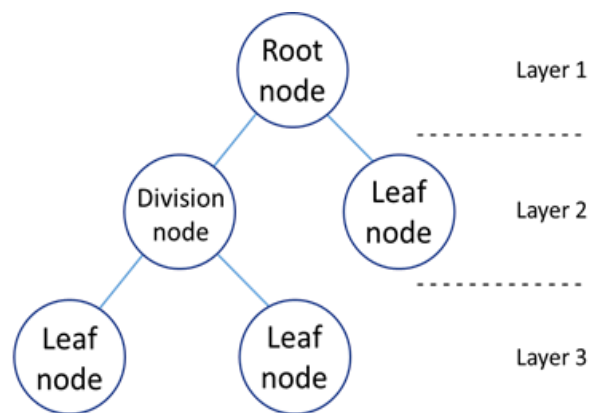


Figure 8: Basic decision tree algorithm structure (Braga 2017)

In DT classifiers, classification rules are determined through heuristic processes in which the algorithm chooses the local optimal decision in order to establish a rule in a certain division node. Every decision made in a node is evaluated through the purity metric. This metric dictates that a node is 100% pure when all of its data is within the same class, while a node is 100% impure when its data is evenly split between two classes. Purity can be evaluated through several methods, of which the Gini index and entropy are the most relevant in the context of RT models. In order to obtain a better model, purity should be maximised and impurity should be avoided. The implementation of such metric could result in overly complex trees that can be sensible to overfitting. To combat this, the user can implement a maximum depth for the decision tree (a maximum number node layers it can have, e.g. 3 for the DT shown in Figure 8) or a minimum amount of data points needed for a node to be split. Should the model remain sensible to overfitting or should the original data set contain a considerable amount of noise data, it may prove necessary to reduce the complexity of the decision tree by removing branches that provide little help in classifying the data. This technique is referred to as pruning, and it can be done either after the model is built or during its construction (Princeton University 2017).

RF models consist of ensembles of unpruned DT models, with its results determined by a combination of the results of the several decision trees. Commonly, the combined results are better than the results obtained by each DT model individually, as RF models don't tend to overfit and are not sensible to the presence of outliers in the data. They are, however, not the best suited models for regression, as they tend to overestimate the minimum values and sub estimate the maximum values of the input set (Braga 2017).

Gradient Boosted Decision Trees

ML algorithms don't always achieve what can be defined as acceptable results in the context of the problem approached. An algorithm's weak correlation to the true classification of the input data can be attributed to a wide variety of causes, ranging from insufficient or poorly presented data to approaching the problem with an inadequate algorithm, considering its context. Hypothesis boosting techniques, commonly referred as simply boosting techniques, attempt to solve the aforementioned weak correlation issues through the creation of an ensemble model, capable of minimizing bias and variance. A boosting algorithm that is well correlated to a data set (i.e. a strong classifier) is built by combining algorithms that are poorly correlated to the data (i.e. weak classifiers) in an iterative form. The prediction errors made by a weak classifier are calculated and the next model is built with improved sensibility to such errors in an attempt to correct them. Gradient boosting is applicable to problems involving classification, regression and ranking of data (L. Cheng 2019).

Artificial Neural Networks

Artificial Neural Networks (ANN) are algorithms that, structure wise, attempt to resemble that of the human brain. They are designed to recognise numerical patterns within data sets, and consist of circuits of units referred as neurons or nodes. These neurons are organised in layers, and the overall network structure is represented in Figure 9. The input and output layers are unique, while there can be one or more intermediate layers, referred to as hidden layers. The connections between layers are performed between the neurons and are associated to weights that represent the model's process of adaptation to the data set. Higher and lower weights act as encouragement and discouragement stimuli, respectively. Since the amount of hyperparameters such as neurons and hidden layers can vary, the optimal number for each parameter must be found, which implies a certain trial and error approach (Samarasinghe 2016).

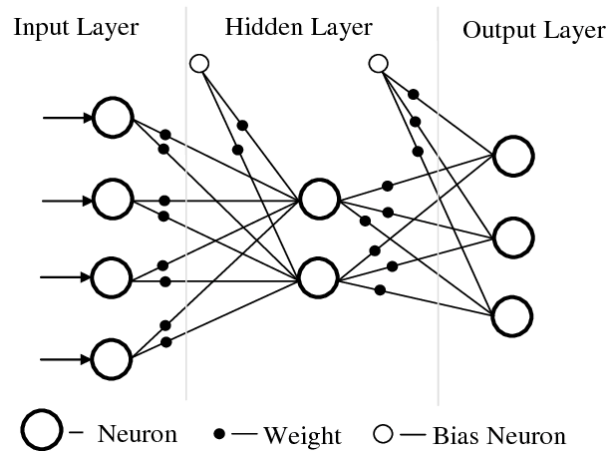


Figure 9: Basic structure of an artificial neural network (Kulkarni 2017)

For every neuron, the input value that reaches it can be expressed by Equation 2-2. This input is combined with the connection weights by a mathematical function referred to as activation function, which can be of one of many types (e.g. sigmoid, Rectified Linear Unit, ReLU, and Scaled Exponential Linear Unit, SeLU):

$$u = \sum_{j=1}^n x_j w_j \quad 2-2$$

Where:

- u is the overall input received by the neuron;
- n is the number of input connections in the neuron;
- x_j is the value present in connection j ;
- w_j is the weight present in connection j ;

The biggest advantages of using ANNs are the ability to learn non-linear models and of producing outputs that are not limited to the ranges of the input (Samarasinghe 2016). ANNs commonly have applications in fields involving the following purposes:

- Data processing, such as filtering or clustering;
- Pattern and sequence recognition, relevant in medical fields;
- Regression based analysis, such as time series regression, which is common in financial fields.

2.4.2.3. Unsupervised Learning

Unsupervised learning algorithms are used when there are no expected outcomes, meaning the data set consists solely of input data. The algorithm creates a model able to determine patterns within the data and sort it into groups, allowing the user to extract meaningful insights about the structure and variety of the information they provide to the model (Bishop 2006). The most commonly used unsupervised learning algorithms rely on one of the following techniques:

- Clustering: through the determination of patterns within the data set, the algorithm is able to sort the data into two or more groups (i.e. clusters) based on either similarities or differences between a particular data object and the rest. This is performed without the model having prior knowledge of data labels;
- Association rules: these algorithms are used to find connections between variables, such as a combination of two variables leading to a certain value for a third variable.

Both techniques are regularly used in fields such as digital marketing. Through the collection of personal data, software specifics or behavioural patterns, it is possible to personalise ads to specific target audiences, such as different age groups or nationalities.

2.4.2.4. Reinforcement Learning

Reinforcement learning algorithms are used to create systems that are capable of improving themselves through trial and error interactions with their surrounding environments, and they are commonly used in the field of robotics (Bishop 2006). Labelled data is combined with data provided by the aforementioned interactions. For every action taken by the system, the consequences are observed and registered. For the algorithm to be aware of the consequences of the actions it elects, reward signals are used. In a situation in which consequences are interpreted as positive or negative, two reward signals are used: one to reward positive actions and encourage the algorithm to persist with a similar performance, and one to penalise negative actions and encourage the algorithm to alter some of its characteristics in order to avoid being penalised. The algorithm is expected to maximise positive and minimise negative rewards. Situations with over two categories of consequences work under the same principle, only with higher complexity.

2.4.3. Data Processing

As stated in previous sections, ML algorithms are used to extract meaningful information from data, with some even being used to reduce the amount of unnecessary data within a data set. However, the results the models obtain are highly influenced by the way data is presented and its overall quality. Different representations of the same data set may yield considerably different results, while data sets with too much meaningless or flawed data (containing inconsistent or inaccurate values, or duplicated or missing data) are bound to obtain worse results (Alpaydin 2004). Furthermore, the data needs to be presented in a way that is understandable to the algorithm, meaning that it is important to have knowledge of the characteristics of the data and pre-process it before any algorithm is used.

2.4.3.1. Data Characterisation

Several types of data can be dealt with when approaching a problem recurring to ML. Most commonly, two major data types are recognised, encompassing two types of data scales each:

- Quantitative data: it is data that consists of numbers that have meaning as measurement of a certain variable, hence it also being referred to as numerical data. Quantitative data can be categorised into the following scale types:
 - Ratio Scale (i.e. continuous quantitative data): it can assume an infinite number of values within a certain range, as is the case with physical properties such as lengths, weight or velocities. It is not ordered in time. Mathematical operations such as addition, subtraction, multiplication and division between attributes are possible and may provide additional information.
 - Interval Scale (i.e. as discrete quantitative data): it assumes a finite number of values within a certain range that are meaningful when expressed in the form of a count. Typically expressed in whole numbers, it is used to convey counts of a multitude of variables that may exist in the problem's context, such as the number of people, days, or occurrences of a certain event. Differences in values may be meaningful, but this kind of data cannot be divided in a way that enhances its meaning. Another example of discrete quantitative data would be time series data, which consists of ordered sequences of numbers obtained in either consistent or inconsistent intervals over the course of a certain period of time, granting this type of data temporal value (Braga 2017).
- Qualitative data: also referred to as categorical data, is used to describe variables based on their properties, and it provides no quantitative value. It can be used either in numerical or text form. Two data scales are defined within it:
 - Nominal Scale (i.e. nominal qualitative data): represents characteristics of a variable that is associated with a certain problem, such as if an event occurred or not, or if a certain object has a red, green or blue colour. This data can be expressed in the form of numbers (e.g. 1 for red, 2 for green and 3 for blue), but there is no mathematical meaning attached to them, and therefore they cannot be ordered meaningfully.
 - Ordinal Scale (i.e. ordinal qualitative data): combines features of both qualitative nominal data and numerical data, as in that the attributes are divided into classes but these classes can be ranked following certain criteria. If the data describes situations such as whether an event had a mild, moderate or severe impact, these classes (i.e. 1 for mild, 2 for moderate and 3 for severe) can be ordered in ascending or descending order in a meaningful way regarding the seriousness of the impact, while the classes regarding the aforementioned nominal qualitative data aren't ordered in similar fashion.

2.4.3.2. Data Pre-Processing Techniques

Data pre-processing techniques are used with the purpose of improving the overall quality of data sets and enable ML algorithms to create models that express the patterns within the data set more accurately, therefore obtaining better results. Such improvement is achieved by minimising the aforementioned problems that can affect data sets (Braga 2017). When starting an approach to a problem recurring to ML, it is recommended that at least some of the following techniques are used to treat the collected data before ML algorithms are developed.

Data Quality Assessment

Depending on its source, factors such as measuring device limitations, flawed data storage or human error contribute to the existence of flaws in, realistically, any collected data set. A ML model should only be trained after the quality of the input data is assessed (Alpaydin 2004). Therefore, it is important to address potential issues such as the following:

- **Missing values:** ML algorithms will not work properly when the input data set has missing or non-numerical values, labelling such values as “NaN” (i.e. “Not a Number”). One method of addressing this issue is by eliminating the rows of data containing NaNs, which can be applied to attributes as well, should they have a considerable amount of missing values. This method loses its efficiency when there is a high number of data rows with missing values. Another method to be considered is estimating the missing data. Commonly, this is performed by filling an attribute’s missing values with the attribute’s mean or median value, although values can also be interpolated if there are conditions to do so.
- **Inconsistent values:** it is possible that a collected data set has some inconsistencies within it, such as mislabelled attributes or implausible values, which is why a thorough analysis of the data is advised.
- **Duplicate values:** the removal of such values is performed with the purpose of preventing a certain bias to be attributed to them when running the algorithm.
- **Redundant or unnecessary attributes:** removing from the data set any attributes that are duplicated, redundant (e.g. attributes with very similar data, or data that can be easily obtained by combining other attributes) or otherwise not relevant in the context of the problem (e.g. removing the attributes containing the personal names of people involved in a certain medical study) will allow the algorithm to focus only on relevant data, leading to better results.

Data aggregation

It consists of integrating two or more sets of data collected from different sources into the same file and ensuring there is consistency among all collected data. Further aggregations can be applied in order to reduce the amount of data (e.g. transforming daily data into monthly or yearly data), which can increase an algorithm’s performance.

Data Sampling

It is a method that is used when the data set is deemed too large to be worked with due to memory or time limitations. To solve this issue, it is possible to use a sampling algorithm to obtain a representative sample from the original data (i.e. a sample that approximately retains the characteristics of the original set). This method proves useful when the original data set is balanced, i.e. when there isn’t a great variation in ratio between classes. Such a variation can cause a data set to become unbalanced, which may lead to a wrongful

adjustment of the model towards the data, referred to as overfitting. Data sampling can be applied in two ways:

- Sampling without replacement: selected data is removed from the original set;
- Sampling with replacement: selected data is not removed from the original set, meaning it may be selected more than once.

Dimensionality Reduction

It is a method that is more common in image recognition, and it is used when there is a considerably big number of attributes, that can also be referred to as dimensions, in the data set. A higher number of dimensions means a more complex problem and, consequently, it is harder to represent it visually. The method consists of lowering the number of dimensions by combining previous attributes to create new ones (van der Maaten 2009). This can facilitate visualization of the data, as well as improve the performance of ML algorithms.

Data Encoding

It consists of transforming the data in a way that makes it understandable for ML algorithms without losing meaning. The purpose of this method is to prevent poor algorithm performance caused by the existence of data in a form it cannot work with or by unscaled data, which can lead to unreasonably high performance times when using the algorithms that are most sensitive to it (Braga 2017). Different transformation methods may be applied, depending on the algorithm that is intended to be used:

- Qualitative to quantitative conversion: this type of conversion can involve processes such as one-hot encoding (Harris 2012);
- Quantitative to qualitative conversion: involves processes meant to transform numerical data into categorical data;
- Quantitative attribute transformation: it is a method used to scale quantitative variables without losing meaning by simply multiplying or dividing them by a constant (e.g. every new value can be the former value dividing by the maximum value found in the attribute, resulting in having the variables scaled from 0 to 1).

2.4.4. Cross Validation

ML algorithms are trained to fit models into the data that is provided to them. However, it cannot be concluded that a model that accurately fits its training data is capable of adapting properly to data it has not been trained with, unless it is validated. Cross validation techniques exist as a way to statistically evaluate how the model can respond to unseen data compared to how it responded to training data (Alpaydin 2004). This is achieved by dividing the original data set into a training set and a test set, with the training set being used by the algorithm to create a model and the test set being used to validate said model, using evaluation metrics. These techniques are important not only to evaluate a certain model, but to assist in model selection as well. The most commonly used cross validation techniques are addressed below.

2.4.4.1. Holdout Method

One simple method of cross validation is the Holdout Method. It consists in removing a fraction of the data of the original data set before training the model, and later using the model to predict the outcomes present in the removed data. The method can often lead to high variance, since by removing only one group of data, said group may not be representative or contain all patterns present in the original data set. Therefore, it is possible that considerably different results are obtained when running the code on two separate occasions (Kohavi 1995).

2.4.4.2. K-Fold Cross Validation

When using the k-fold cross validation technique, the original data set is shuffled randomly and is then divided into k equal or approximately equal groups, referring to the amount of samples. From that point, the process consists of one unique group being randomly selected to be used as the test set, with the remaining groups constituting the training data set. The model is then trained, evaluated and discarded. This process repeats itself for k times, each time with a new data group, meaning that by its end all unique groups will have been used as the test set (Braga 2017).

With k being the only parameter that needs to be specified when using this technique, the selection of this parameter becomes important. It can be selected based on several criteria:

- Representativeness: involves selecting a number for k that will allow the data groups generated to be big enough to be representative of the original data set;
- Selecting k between 5 and 10: having a fixed k parameter of 5 to 10 has proven to be generally effective by providing low algorithm bias and moderate variance. This is most commonly verified with the k parameter set to 10;
- Selecting $k = n$, with n being the number of data points in the set. This method is referred to as Leave One Out cross validation.

2.4.5. Evaluation Metrics

The aforementioned evaluation metrics chosen depend on the context of the problem and on the algorithm used. The use of several metrics is recommended, since ML models can perform well according to a certain metric, while performing poorly according to others. The most commonly used evaluation metrics are addressed below.

2.4.5.1. Logarithmic Loss

This metric is commonly used in problems involving data classification. In such problems, the output predicted by the model is presented in the form of the probability of the sample belonging to each class, scaled from 0 to 1. For a model that works with 2 classes, A and B, the results can be printed in the form of [probability of A, probability of B] (Shen 2005). Should the results of a certain sample be [0.09, 0.91], it would indicate that the model had predicted that the sample belongs to class B. The logarithmic loss metric is based on the aforementioned probabilities and the information of whether or not the samples belong to the predicted classes, and it is calculated as is presented on Equation 2-3:

$$\text{Logarithmic Loss} = \frac{-1}{N} \sum_{i=1}^N \sum_{j=1}^M y_{ij} \times \log p_{ij} \quad 2-3$$

in which:

- N is the number of samples;
- M is the number of classes;
- y_{ij} refers to whether sample i belongs to class j ;
- p_{ij} refers to the predicted probability of sample i belonging to class j .

The logarithmic loss metric can assume values in the $[0, \infty[$ range. The closer the values are to 0, the higher the model's accuracy, meaning it is important to minimise this function.

2.4.5.2. Confusion Matrix and Associated Metrics

This metric provides a matrix that describes the performance of a model by comparing its predictions with the actual outcomes of the data samples. For a binary classification problem consisting of classes “Yes” and “No”, the matrix is built as described in Table 3.

Table 3: ML prediction outcomes

Real Outcomes	Predicted Outcomes	
	Yes	No
Yes	True Positive (TP)	False Negative (FN)
No	False Positive (FP)	True Negative (TN)

It can be observed that the true positive and negative values represent the model’s accurate predictions, while the false positive and negative values represent its incorrect predictions. Having knowledge of Table 3’s values enables the evaluation of the model through the calculation of the following parameters (Braga 2017).

- **Accuracy:** represents the amount of correct predictions in relation with the amount of predictions made. The meaning of its value depends heavily on the context of the problem (i.e. an 80% accuracy can be interpreted as good for some problems and average or poor for other problems). This metric is better suited to data sets in which each class has a similar number of data samples. If one class has considerably more samples than the remaining classes (e.g. class A amounting to 90% of the total samples in the data set and classes B and C amounting to 5% of the samples each), it is possible that a model’s high classification accuracy (e.g. 92%) is achieved by it predicting correctly the data correspondent to class A and mostly failing to predict accurately the data related to classes B and C. Accuracy is calculated according to Equation 2-4:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad 2-4$$

- **Precision:** expresses how often the model is correct when it predicts a positive outcome. It is defined as the ratio between the correctly predicted positive outcomes and the total number of positive predictions, as shown in Equation 2-6:

$$Precision = \frac{TP}{TP + FP} \quad 2-5$$

- **Recall:** expresses how often the model predicts a positive outcome when the real outcome is indeed positive. It is defined as the ratio between the correctly predicted positive outcomes and the total number of positive outcomes, as show in Equation 2-7:

$$Recall = \frac{TP}{TP + FN} \quad 2-6$$

- **F-measure:** expresses the harmonic mean between the Recall and Precision values, in order to create a value that is representative of both. The harmonic mean will be closer to the lowest of the two values mentioned. It is calculated according to Equation 2-5:

$$F - measure = \frac{2 \times Recall \times Precision}{Recall + Precision} \quad 2-7$$

3. Introduction to Águas do Porto, E.M.

3.1. Company Description

3.1.1. Historical Background

The oldest historical record referring to water distribution and drainage concepts in the city of Porto, Portugal is dated back to 1392, referring to the public use of fountains. Over the course of the next five centuries, further reports refer to the construction of water adduction and distribution structures such as the plumbing of the water in order to transport it into the city, which was concluded by 1607 (Águas do Porto E.M. 2015).

The city was the first in the country to develop and install a wastewater drainage system. The process was started in 1896, in response to numerous plagues and increasingly precarious hygienic conditions, arising from practices such as the disposal of wastewater on the streets. An international public procurement was won by English firm Hughes & Lancaster, and the installation of the main sewerage pipes and supporting equipment occurred from 1903 to 1909. Several years of system verification work and pipe production and installation followed. On the 1st of April of 1927 the Serviços Municipalizados de Águas e Saneamento do Porto (SMAS, Municipal Water and Sanitation Services of Porto) was created. The entity's first areas of intervention were the construction of the Nova Sintra reservoirs and water treatment plants. It was established in 1934 that SMAS would also be responsible for the water distribution in the cities of Gondomar, Matosinhos and Vila Nova de Gaia. The following decades were marked by the construction of new capture wells, reservoirs and lifting plants, while the remaining expansion of the water drainage network was carried out mostly between 1950 and 1970.

By the 1990 decade, the need for investment in water capture and treatment processes led to the creation of a public stock corporation, Águas do Douro e Paiva, S.A (AdDP). On the 5th of January of 1998, AdDP began supplying high level water to the region of Porto Metropolitan Area (PMA), comprising 17 municipalities. Consequently, SMAS became responsible for just the low level water distribution in the region. In October of 2006, SMAS was transformed into a municipal company and consequently renamed Águas do Porto, E.M (AdP). The company currently operates the integrated management of the urban water cycle in the municipality of Porto. The current company structure is depicted in Figure 10.

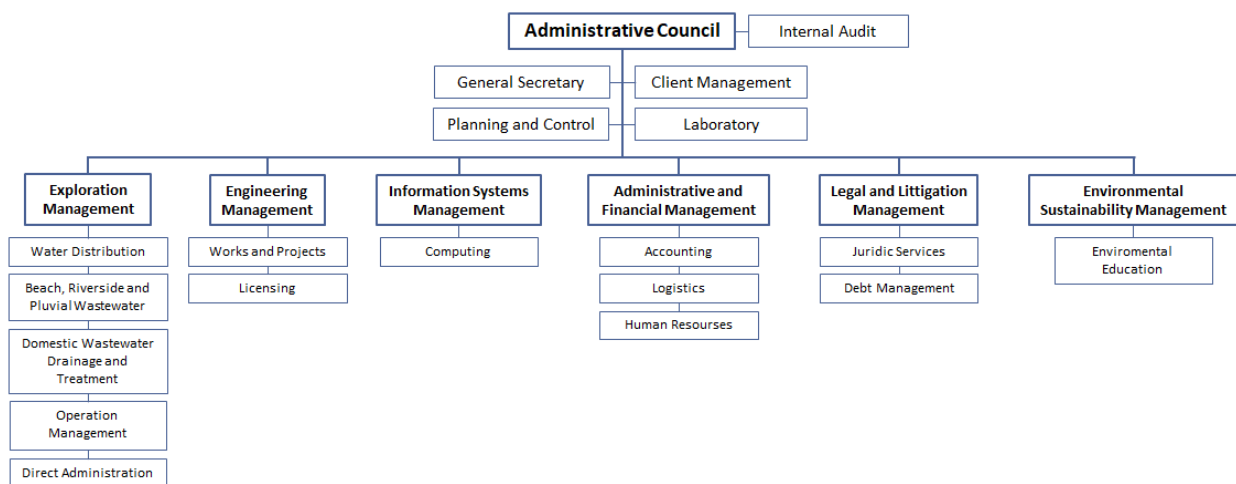


Figure 10: AdP's current structure. Adapted from (Águas do Porto E.M. 2020)

3.1.2. Services and Infrastructure

As of September 2020, Águas do Porto, E.M. operates in the entirety of the city of Porto, providing services such as water distribution and wastewater drainage to approximately 150,000 clients. The distributed water originates from the Lever I (Gaia) and Lever II (Porto) captures and from the Lever WTP, with the adductor system connecting the treatment plant to two multi municipal reservoirs, Jovim and Ramalde. The water is then conducted from these reservoirs through two adductor systems (North and South) to 12 entry points to AdP's water distribution network. The entity responsible for the described high level water supply processes that lead up to it entering AdP's network is AdDP.

AdP's water distribution network has an extension of 812 km, with 59 being adductor pipes and the remaining being distribution pipes. Upon entering the network, the water can be stored in six reservoirs, which amount to a total storing capacity of 125.430 m³. An average of 57.000 m³ of water enter the water distribution network daily, meaning the storing capacity of the network allows over two days of ordinary water distribution (Águas do Porto E.M. 2020). Porto's wastewater drainage network is separative, meaning that domestic and pluvial wastewater are collected and transported in independent systems. The domestic wastewater drainage network (see Figure 11) has an extension of approximately 560 km, and operates mainly in free surface flow (i.e. gravitational flow). The wastewater is collected and transported to the WWTPs of Freixo and Sobreiras, which treat a combined daily capacity of 90.000 m³. The water is then disposed in the Douro river, complying with the national and European standards for the discharge of domestic wastewater into bodies of water. The pluvial wastewater drainage network has an extension of approximately 600 km and serves the purpose of collecting and transporting wastewater into bodies of water where it can be safely disposed of (Águas do Porto E.M. 2015).



Figure 11: Drainage pipes of Porto's domestic wastewater drainage network (Águas do Porto E.M. 2015)

Apart from its services regarding water distribution and wastewater drainage, AdP is also involved in the management of Porto's beaches and riversides. Services include the creation of guidelines for the safe use of the beaches and the development of the Structure Plan for the Seafront, which aims to promote a sustainable use of the bathing waters and areas and their surrounding environments. The main objectives of the plan include the development of a monitoring plan with verifiable indicators and the enhancement and requalification of bathing areas in an attempt to preserve them while adding social and economic value. The main directives of the management involving riversides involve their cleansing, de-intubation and rehabilitation (Águas do Porto E.M. 2020).

3.1.3. Management Platform

The majority of the data used in this work was collected from AdP's management platform, which uses (Navia Agile Operations Software 2020). This software is designed for the management of systems that encompass several operations, and it is widely used by companies and entities responsible for the operation of water distribution and sanitation systems in Portugal. Its main feature is the possibility of encompassing the entire operation and maintenance procedures of a system in a single platform, allowing for easier access to information and for a more efficient management of the system. The platform is accessible through an internet browser, for every worker with assigned login credentials.

Using this software, information of newly planned, ongoing or finished interventions is updated in real time. In the case of Porto's domestic wastewater drainage network, every intervention in the network (such as the aforementioned CCTV inspection and proactive and reactive interventions) is registered by the field workers immediately after completion, resorting to a Tablet device, and readily becomes available for consultation. The information used in the development of this work was extracted from the platform's Geographic Information System (GIS), in which information regarding every structure of Porto's domestic wastewater drainage network is stored. It is presented in Figure 12.

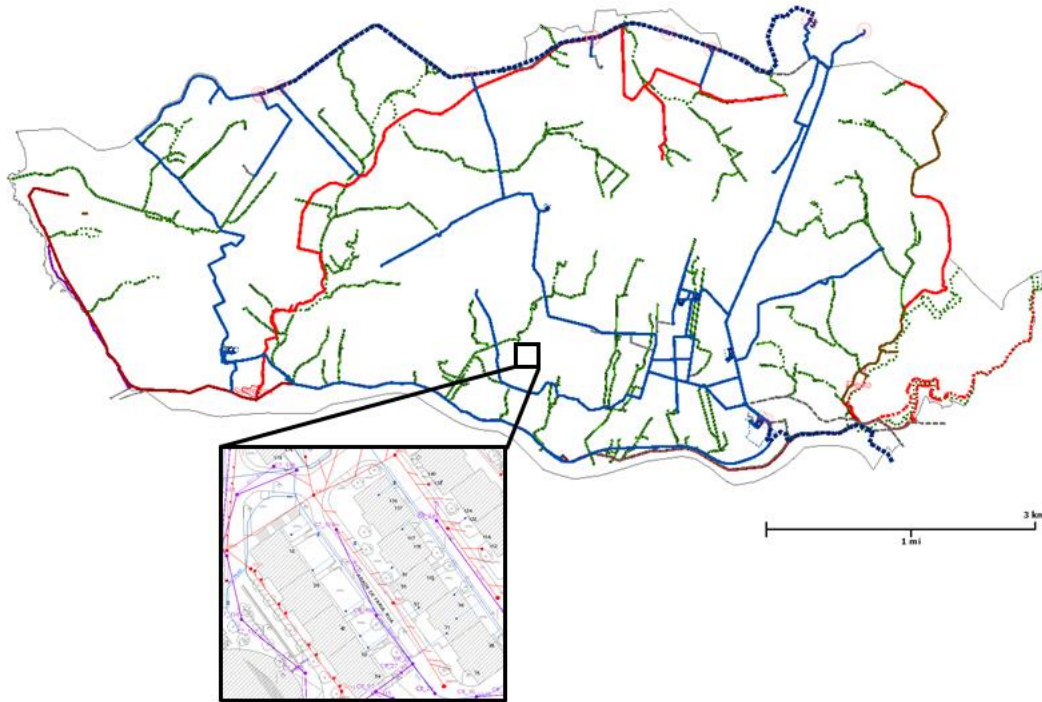


Figure 12: Porto's wastewater drainage networks represented in AdP's Navia platform's GIS (Águas do Porto E.M. 2020)

3.2. City and Network Circumstances

3.2.1. City Overview

Porto is located on the Northern Portuguese coast. The city has an area of 41.42 km², with altitude varying between sea level and 160 m due to its corrugated topography. As of the 2011 censuses, the Porto's population was 237,591 (Porto City Hall 2014). Porto's Metropolitan Area (PMA) is considerably larger, with an area of 2,395 km² and an estimated population of 1,323,000 residents (Demographia 2020).

It is currently administratively organised in 7 civil parishes, of which three are, in fact, unions. The city had been organised in 15 parishes (see Figure 13) until 2013 (Porto City Hall 2020).

AdP's information records refer to these original parishes when identifying structures or interventions and, as such, statistical analyses and geographical representations on parish scale presented in the case study refer to the aforementioned 15 parishes, with results considering parish unions being easily discerned.



Figure 13: Porto's original parishes. Adapted from (Porto City Hall 2020)

The city is currently administratively organised into the following parishes:

- Aldoar, Foz do Douro and Nevogilde union;
- Bonfim;
- Campanhã;
- Cedofeita, Miragaia, Santo Ildefonso, São Nicolau, Sé and Vitória union;
- Lordelo do Ouro and Massarelos union;
- Paranhos;
- Ramalde.

Population density was, as of 2011, distributed as is presented in Figure 14.

It assumed, for the purpose of some conclusions drawn during this work, that population density changes from 2011 to 2020 were reasonably similar for all parishes.

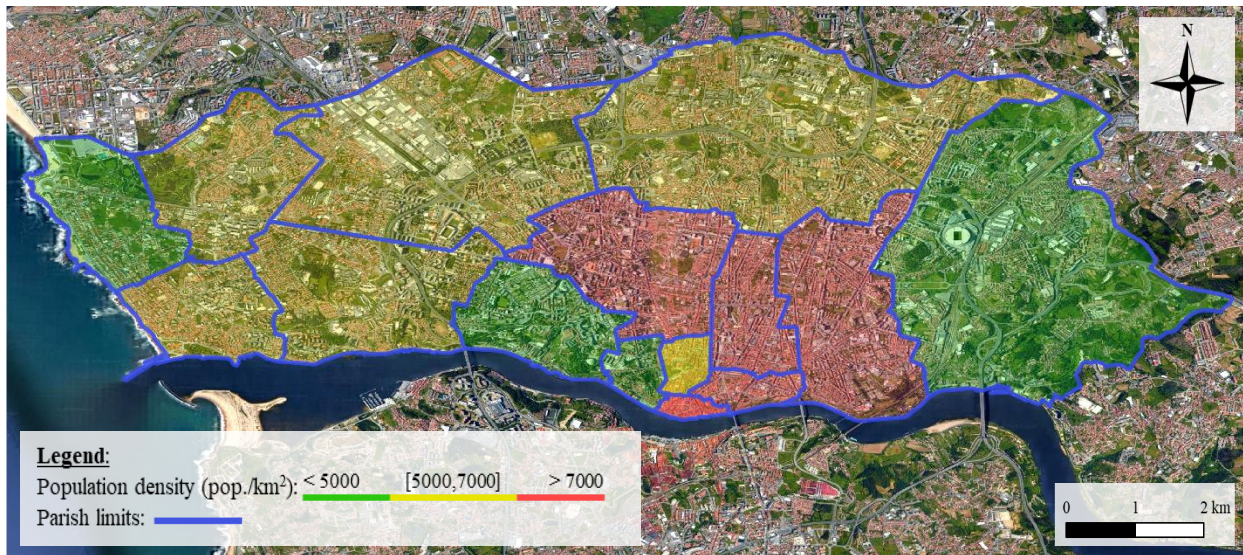


Figure 14: Population density on parish scale. Results based on Table D-1

3.2.2. DTAR and Porto's Domestic Wastewater Drainage Network

This work was developed in the working environment of the Wastewater Drainage and Treatment Department (DTAR), which is part of the Exploration Management department. DTAR is responsible for the management of Porto's wastewater drainage network, which collects domestic wastewater from the buildings where it is produced and transports it to the WWTP's of Freixo and Sobreiras, where it is treated and forwarded to its receiving medium.

3.2.2.1. Network Description

Porto's low level domestic wastewater drainage network has an extension of approximately, 515.4 kilometres, of which 505.4 km are composed by 14,353 drainage pipes that are currently in service and operating under gravitational flow. As previously mentioned, the construction of this network was started in 1903. Figure 15 presents Porto's blueprint at this time (Cortês 1903).

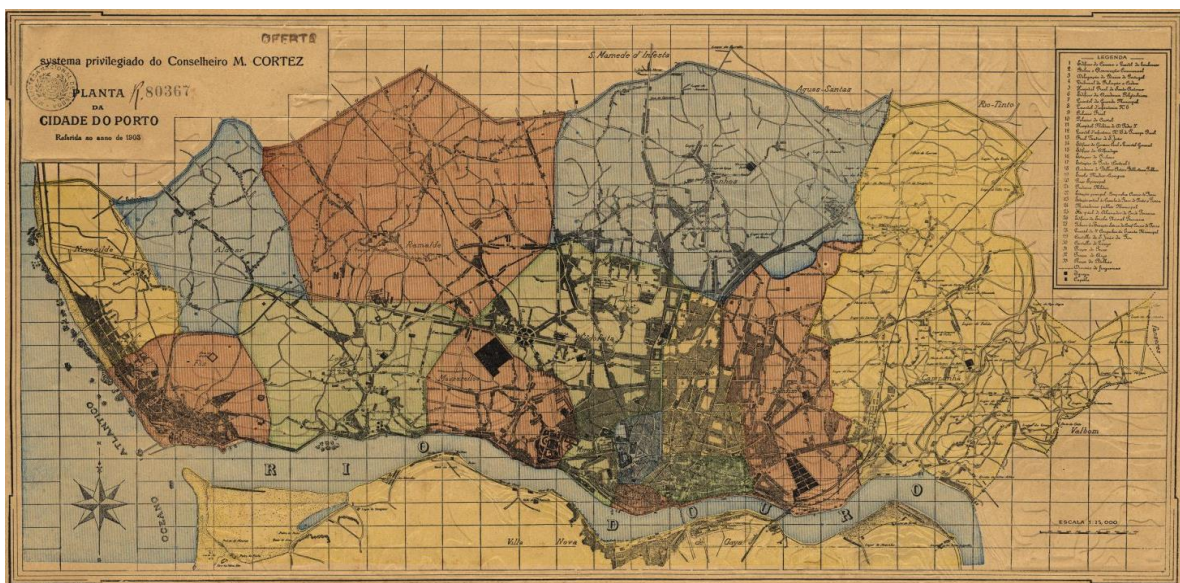


Figure 15: Blueprint of Porto (Cortês 1903)

It can be observed how the parishes that, as of 2011, presented the highest population density (Figure 14) values mostly correspond to the parishes that were already considerably developed in 1903 (Figure 15). It is reasonable to assume that the oldest portions of the network are contained within these parishes. Prior works had analysed the network of streets of the city, which largely corresponds to the city's low level domestic wastewater drainage network, as drainage pipes are typically installed along streets.

The aforementioned 505.4 km active pipe extension of the low level domestic wastewater drainage network is composed of pipes with diameters ranging from 125 to 500 mm. The most common diameters are presented on Figure 16. It was decided at an early stage of this work that most analysis would not consider the full extension of the network, and would be solely focused on the most critical streets. The selected portion of the network encompassed a pipe extension of 257.9 km, the composition of which is presented on Figure 17.

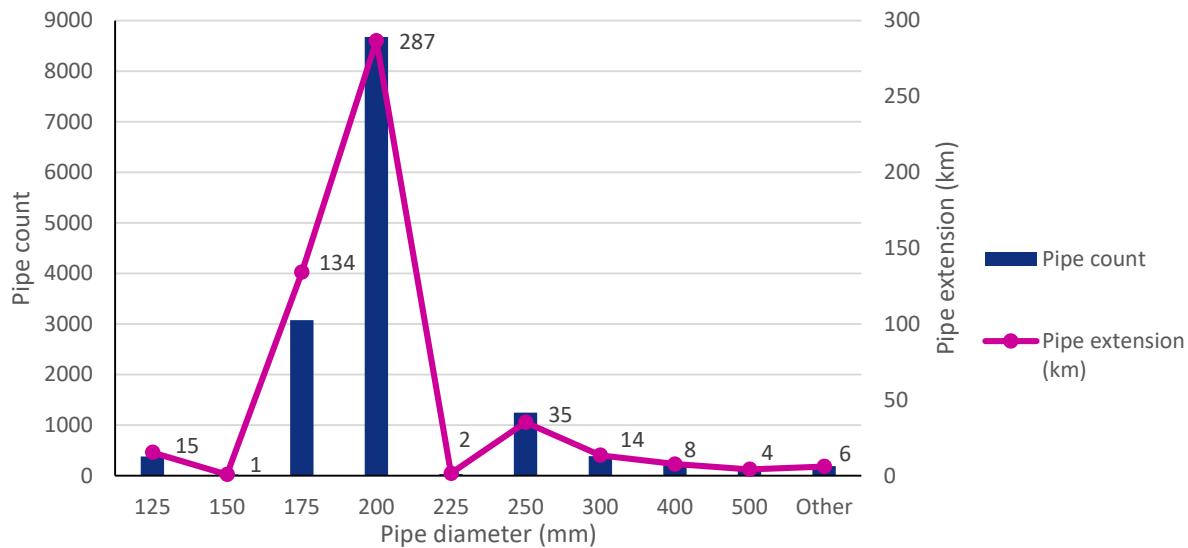


Figure 16: Pipe count and extension per diameter for the whole network

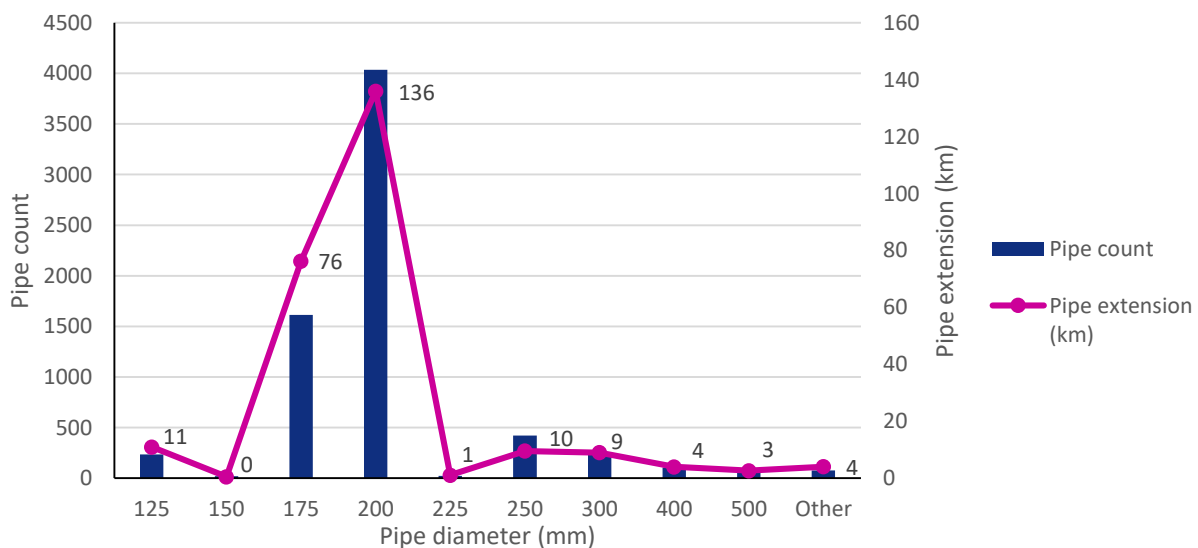


Figure 17: Pipe count and extension per diameter for the selected portion of the network

A smaller portion of the network was selected in an attempt to eliminate from analysis information that might have led to inaccurate results being obtained. It can be observed how the selected portion is seemingly representative of the whole network regarding pipe diameter. The category of pipe diameters designated as “Others” had an average pipe diameter of approximately 345 mm in both the selected portion and the whole network.

The analysis presented on Figure 18, produced using Space Syntax software, shows the different levels of network integration displayed by each street (Morais 2017). In the context of a domestic wastewater drainage network, highly integrated streets are likely to be central both in the network and in the city itself, displaying high population or employment densities and operating with considerably high wastewater volumes, meaning that obstruction impact might be at its most severe in these streets.



Figure 18: Porto's axial map, obtained through Space Syntax analysis (Morais 2017)

3.2.2.2. Network Operation and Maintenance

As previously mentioned, Porto's domestic wastewater drainage network operates mainly under gravitational flow. However, towards the latter parts of the network, it is often necessary to elevate wastewater into entering the network's emissary pipes, which will transport it to the wastewater treatment plants. This process can be performed resorting to water lift stations. In Porto's domestic wastewater drainage network, it is mostly performed by pneumatic sewage ejectors, also referred to as Shone ejectors (Figure 19) in reference to their designer, Isaac Shone.

Shone ejectors operate mechanically, in cyclical manner. Compressed air is used to lift the wastewater, and is typically at an average pressure of 2.5 bar. Their operation is dictated by a pilot valve that controls the flow of atmospheric and compressed air, and by inlet and discharge check valves that control the wastewater flow. The compressed air is fed to the shone ejectors through a dedicated compressed air network that originates in the Freixo and Sobreiras WWTPs and connects to every ejector.

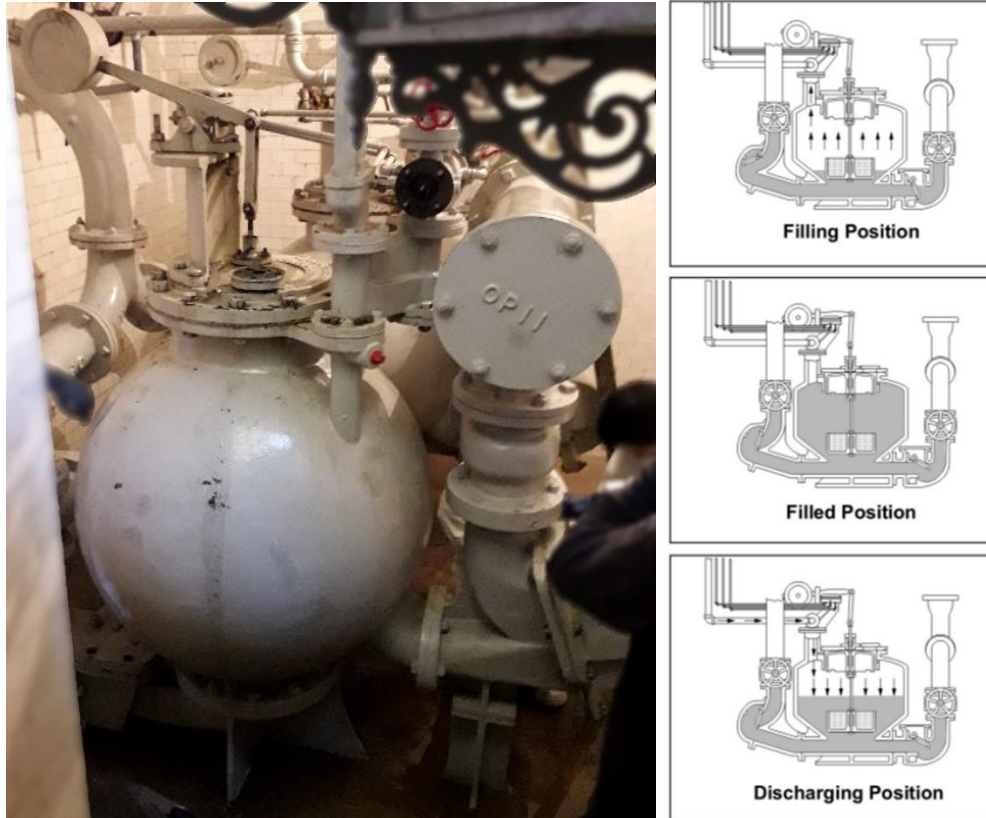


Figure 19: Pair of Shone ejectors in Foz, Porto (left) (Águas do Porto E.M. 2020) and operation sequence (right) (Yeomans Chicago Corporation 2001)

The operation of Shone ejectors can be summarised in 3 steps:

- **Filling:** when the reservoir is empty, the weights (upper and lower) are in their lower positions, exerting all their weight on the rod, and the slide valve is open, allowing compressed air to hold the piston valve closed to compressed air and open to atmospheric air. This prevents the entry of compressed air in the reservoir while ensuring it is ventilated while it is filled. With the reservoir at atmospheric pressure, the weight of the wastewater enables it to enter it by holding the inlet valve open.
- **Filled:** as the wastewater fills the reservoir, it progressively lifts the weights, which begin to exert less pull on the rod. After enough decrease in pull (achieved when the ejector is full), the counterweight on the pilot valve is lowered, switching its position so that it is now closed to atmospheric air and open to compressed air.
- **Discharging:** once full, compressed air enters the reservoir, causing the inlet check valve to close and the discharge check valve to open. Under the increased pressure, the wastewater is forced to exit the reservoir. As the water leaves, the weights become exposed again and start exerting their usual force on the rod, overcoming the counterweight. This reverts the position of the pilot valve to the one it had while in the Filling step: closed to compressed air and open to atmospheric air, which ensures the continuity of the cycle.

It is common to have two Shone ejectors installed beside one another. In such situations, the ejectors will operate with a certain lag between their cycles. Typically, the second ejector will start its Filling step when the first ejector is already about half way full.

The locations of the 30 active ejectors of Porto's domestic wastewater drainage network, as of 2015, are represented in Figure 20, along with the high level portions of the network and the compressed air network.

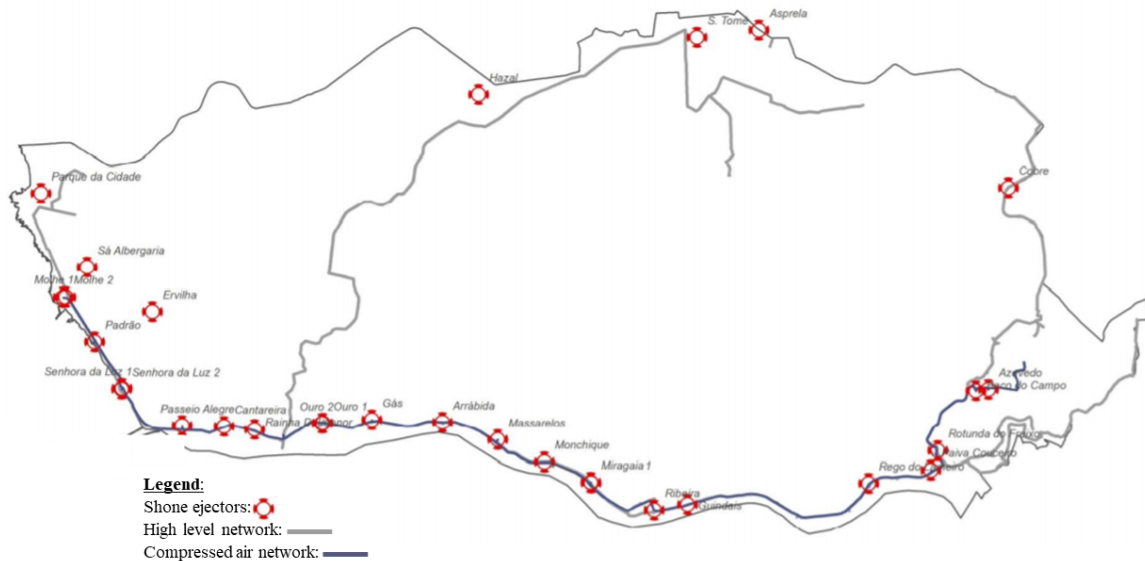


Figure 20: Location of Porto's domestic wastewater drainage network's Shone ejectors, high level network and compressed air network (Águas do Porto E.M. 2015)

The operation of a wastewater drainage network requires permanent maintenance in all its integrated parts. It is therefore necessary to monitor and intervene in key areas of the network such as drainage pipes and lift stations.

Porto's domestic wastewater network is mostly affected by malfunctions such as obstructions in drainage pipes and in Shone ejectors. This work focused solely on determining the parameters that influence drainage pipe malfunction occurrence and on how these can be minimized. AdP's current strategy towards reducing obstruction occurrence and impact involves frequent CCTV inspection of critical areas and a proactive intervention plan, which is addressed in the following subchapter.

3.2.3. Current Proactive Intervention Plan

AdP's current proactive intervention plan was established in late 2017 and is expected to be in effect from 2018 to 2021. A network extension of 148 km (Figure 21) is planned to be intervened two to four times each year, quarterly or biannually, with the rest of the network being divided in sectors and intervened with a four-year periodicity (Figure 22). Operation involves planned cleaning of pipes resorting to the tank truck formerly presented in Figure 7. There are two operation teams, each working on a different shift (morning and afternoon) and consisting of two workers specialized in the exploration of wastewater networks and one specialized driver. All intervention details and additional information are registered by the operators in a Tablet device and are subsequently uploaded to the Navia management platform formerly described in section 3.1.3. Each intervention team has the capacity of cleaning approximately 400 m per shift, with two daily shifts therefore amounting to 800 m. Over the course of a year, considering 15 days for the maintenance of the tank truck, it is possible to intervene in approximately 280 pipe km (Rocha 2017).



Figure 21: Variable proactive intervention plan (quadrennial intervention). Adapted from (Rocha 2017)



Figure 22: Fixed proactive intervention plan (intervening quarterly or biannually). Adapted from (Rocha 2017)

4. Case Study

This case study was developed with the aim of analysing the performance of Porto's wastewater drainage network and developing a classification methodology describing the criticality of the network's pipes and streets. This criticality can then be used in the development of a Proactive Intervention Plan (PIP) for the Porto's domestic wastewater drainage network. The methodology was first developed in a MS Excel spreadsheet, where the statistical analyses were also produced. Geographical representations were produced in a QGIS platform. The methodology was then taught to a variety of ML models, which, receiving the data from the information spreadsheet, can be used to implement the methodology in a way that the classification of pipe and street criticality is updated whenever information is added or altered. Analysis focused on intervention records and physical pipe characteristics and impact indicators deemed to theoretically influence the criticality of network sections. Street scale analysis and classification were developed in order to suggest an ideal planned intervention frequency for each street, while pipe classification was performed with the intent of providing insight regarding the possible creation of sections within streets.

The work was conducted on the hypothesis that by intervening proactively in pre-determined key structures within the network (namely pipes, but potentially also other structures, such as pipe branches or connection chambers), it is possible to not only avoid the consequences involved in obstruction occurrence and the consequent reactive interventions associated, but also extend the period in which pipes work with adequate performance.

4.1. Data Extraction and Treatment

In order to both validate the study's initial hypothesis and to develop further analysis, it was necessary to gather information regarding the operating conditions of the network and its history of interventions. As previously stated, it was important to conduct the analysis both on pipe and street level. As such, the gathered information reflects this, with some portions of it referring to specific pipe characteristics and others referring to broader scales such as the streets in which the network is installed, or city wide geographical distribution of pipe characteristics and interest points.

4.1.1. Intervention and Street Information

Gathering information regarding the history of interventions performed by AdP associated with the geographical location of the intervened structure was essential to the development of this study. Information fitting this description was extracted from AdP's Navia management platform, H2Porto, where interventions can be planned and are also registered when executed.

The data extracted spanned the decade of 2010-2019, and included, for every intervention, the type (clearance, flood or planned cleaning), the execution date and the street where it occurred. Clearances referred to the reactive cleaning of a pipe obstruction, whereas floods referred to the clearance of obstructions that lead to floods. Planned interventions referred to proactive cleaning of pipes, usually resorting to jetting or mechanical rodding. The term "street" was used as a broad term that can englobe alleys, residential districts and squares.

Information was collected for a total of 9,491 interventions (5,908 clearances, 1,920 floods and 1,663 planned interventions) during the aforementioned period. Interventions lacking associated information such as location or execution date were not considered. As mentioned before in section 3.2.3, AdP's current management of planned intervention in Porto's wastewater drainage network involves a general directive of intervening in every street of the network at least once every 4 years. In an effort to narrow the analysis down to the most critical streets, only streets with 3 or more interventions over the 10-year period were considered, as streets with a maximum of 2 interventions every 10 years (e.g. once every 5 years) seemingly

fit the already implemented directive of intervening in a street once every 4 years. A total of 7,757 interventions spanning 468 streets was, therefore, considered for analysis.

In an effort to estimate the impact an obstruction might have in a certain street, additional information was gathered. This information included the water consumption volume for each street of the city, during the year of 2019, which should be similar in value to the volume of domestic wastewater drained in each street during the year. Only streets with over one consuming establishment were considered, with 1,776 accounting for a 17,974,172 m³ consumption. For the 468 considered streets, this consumption amounted to 11,043,981 m³. Information regarding a street's average value for a pipe characteristic (e.g. diameter) was calculated based on the values associated to the pipes located in said street, which is described below.

4.1.2. Pipe Information

Prior research showed that a pipe's sensibility to the occurrence of obstructions can be influenced by several physical characteristics. Information regarding drainage pipe characteristics was extracted from the GIS of AdP's Navia management platform. It was possible to extract information regarding the relevant physical characteristics of each pipe in the network, such as diameter, material, inclination, installation date and length, along with geographical information detailing the location of the pipes (latitude, longitude, associated street and associated parish). The obstruction history associated with the pipes was also extracted, referring to the five-year period of 01/01/2013 to 01/01/2018, with information extraction for the ten-year period selected for the street level analysis not being feasible, due to missing data regarding the location of pipe obstructions. It is important to note that, while the 10-year intervention history extracted for the street level analysis included all intervention types (clearance, floods and planned cleaning), the intervention history extracted for pipe scale analysis included only obstructions, meaning only clearances and floods are represented.

Information was gathered for a total of 16,149 pipes, of which 530 were registered as either being inactive or having been removed, leaving 15,619 active pipes. High level network pipes and pipes operating under pressured flow were not considered, the later as they do not share the sensibility to obstruction of pipes operating under gravitational flow. Pipes missing values for essential characteristics such as diameter or location were not considered as well, while missing values for the remaining characteristics were either filled with a properly justified value or left void. As a result of these criteria, a further 1,266 pipes were removed from consideration, leaving 14,353 considered pipes, with an extension of 505.4 km spanning 1,938 streets and accounting for 2,110 obstructions over the five-year period. Having established that only streets with 3 or more interventions over the 2010-2019 period would be considered for analysis, which amounted to 468 streets, only pipes installed in said streets were considered. This amounted to 6,857 pipes, spanning 257.89 km.

4.1.3. Information Summary

The connection between both information sets was made through the street code (typically the street's name), which was common to both. Through a simple comparative analysis, it was possible to note how the intervention percent in considered streets is considerably higher when compared to pipe and pipe extension. Related information is presented on Table 4.

Table 4: General information extracted on pipe and street scale

Parameter	Considered	Excluded	Total	Considered (%)	Excluded (%)
Interventions (pipe scale)	2,110	636	2,746	76.8	23.2
Interventions (street scale)	7,817	1,411	9,228	84.7	15.3
Pipes	6,857	7,496	14,353	47.8	52.2
Pipe Extension (km)	257.89	247.51	505.40	51.0	49.0

It is evident from the previous table how approximately half of the network's pipe extension (51%) is responsible for the vast majority of the interventions performed in the network (76.8% for interventions associated with specific pipes over the 2013-2017 period and 84.7% for interventions associated with streets over the 2010-2019 period). The discrepancy between the street and pipe scale percentages can be explained by the consideration of planned cleaning in streets, which is not available for pipe data. Table 5 presents a different perspective over the contrast between selected and excluded pipes and streets, comparing the interventions per pipe kilometre per year for each scale, while Table 6 presents the selected and the total pipe extension per parish and parish union, from which excluded values can be deduced.

Table 5: Interventions per pipe km per year on pipe and street scale

Scale	Sample Size (years)	Sample	Interventions per pipe km per year
Pipe	5 (2013-2017)	Selected	1.64
		Excluded	0.51
		Total	1.09
Street	10 (2010-2019)	Selected	3.03
		Excluded	0.57
		Total	1.83

Table 6: Selected and total pipe extension per parish and parish union

Parish	Pipe extension (km)		Pipe extension (%)		
	Total	Selected	Total	Selected	Selected/Total
Aldoar	30.0	14.8	6.1	5.9	49.3
Bonfim	42.2	28.4	8.6	11.3	67.2
Campanhã	75.2	28.3	15.3	11.3	37.6
Cedofeita	38.1	25.2	7.8	10.0	66.1
Foz do Douro	28.5	12.5	5.8	5.0	43.9
Lordelo do Ouro	42.8	20.0	8.7	8.0	46.8
Massarelos	22.2	12.6	4.5	5.0	56.5
Nevogilde	15.8	8.9	3.2	3.6	56.5
Miragaia	6.5	2.7	1.3	1.1	41.8
Paranhos	80.4	45.3	16.3	18.1	56.4
Ramalde	66.1	28.1	13.5	11.2	42.5
Santo Ildefonso	22.3	15.8	4.5	6.3	71.1
São Nicolau	4.5	2.1	0.9	0.4	48.8
Sé	9.8	4.7	2.0	1.9	48.3
Vitória	7.4	2.6	1.5	1.0	35.2
Parish Union	Pipe extension (km)		Pipe extension (%)		
	Total	Selected	Total	Selected	Selected/total
Aldoar, Foz do Douro, Nevogilde	74.3	36.2	15.1	14.4	48.8
Bonfim	42.2	28.4	8.6	11.3	67.2
Campanhã	75.2	28.3	15.3	11.3	37.6
Cedofeita, Miragaia, São Nicolau, Sé, Santo Ildefonso, Vitória	88.5	52.0	18.0	20.7	58.8
Lordelo do Ouro, Massarelos	65.0	32.6	13.2	13.0	50.1
Paranhos	80.4	45.3	16.3	18.1	56.4
Ramalde	66.1	28.1	13.5	11.2	42.5
Totals	491.7	250.9	-	-	51.0

Selected streets exhibit 5.3 times more interventions per pipe kilometre per year than excluded streets (Table 5), further establishing the difference in criticality between both groups. With the 4-year minimum intervention frequency directive having only recently been applied, it is reasonable to hypothesize that this measure alone can further minimize the obstructions in excluded streets. However, this hypothesis can only

be properly evaluated over the next half decade at least, and preferably excluding the year of 2020 from analysis due to abnormal circumstances.

The comparison between the selected and total pipe extension for each parish (Table 6) suggests the parishes that may need more interventions and, therefore, also provides a general idea of city areas most in need for planned intervention. The results were compared to the more specific analysis performed further into this work. It was considered that the formerly presented tables provide enough information to conclude that focus should be shifted to the selected streets alone for the remainder of the study. Including in the analysis information regarding nearly half of the network's extension that is responsible for a very minor percentage of interventions could produce misleading results.

4.2. Initial Validation of the Study's Hypothesis

In order to rightfully establish the aforementioned hypothesis of planned intervention being beneficial when compared to pipe clearances as a foundation for this work, it was of the highest importance to validate it with real data. This was achieved through comparing, for every street, the average number of days between intervention x and intervention $x+1$ in the same street, should intervention x be reactive or proactive. It is important to note that, for the sake of this analysis, all intervention types were considered equal in the sense that, should a proactive intervention not have been performed in a certain pipe, that pipe would have obstructed around the same date.

This approach, although not fully accurate, was considered to be more accurate than the exclusion of proactive intervention from being considered as the intervention $x+1$ in any occasion, resulting in analysing only the amount of days from intervention x until the next obstruction. The reasoning was that if this had been done, the exclusion of proactive intervention would have falsely presented obstructions as being farther separated in time than they realistically would have been had no proactive intervention been performed. Only in rare situations were two planned interventions performed consecutively.

Floods were not considered as intervention x , nor displayed in comparison to either clearances or proactive intervention because, even though they are technically an obstruction, the typical response to a flood resembles the proceedings of a proactive intervention more than it does of a clearance, meaning floods do not fit well into either class in this analysis.

Figure 23 shows the average number of intervention free days after clearances and proactive interventions are performed in a certain street.

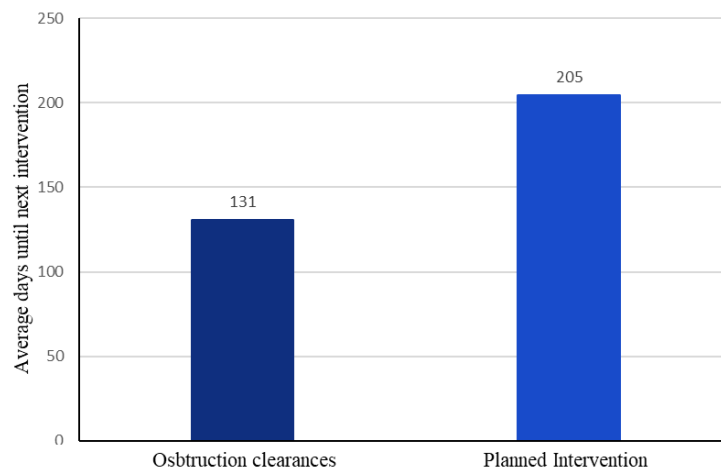


Figure 23: Average days until next intervention per intervention type

With a sample size of 7,349 interventions (differing from the formerly presented 7,817 since the latest intervention in each of the streets was not considered in the analysis), planned intervention was shown to have kept streets intervention free for an average additional 74 days when compared to clearances. This represents an average 56% increase in the amount of time that a street is obstruction free. It is logical to assume that, considering the aforementioned limitations of this analysis, in reality, the increase in obstruction free time is likely not as high as 56%. It is, however, reasonable to conclude that not only is there a real increase, but it is also highly relevant.

The hypothesis could also be validated by analysing the amount of each type of intervention over the selected ten-year period, as is presented on the graph in Figure 24.

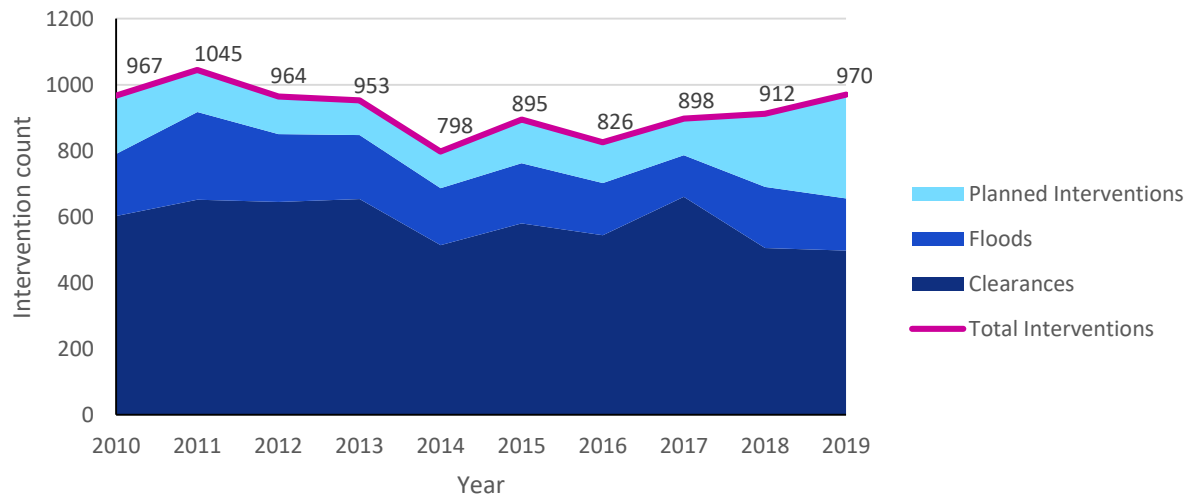


Figure 24: Intervention amount per type and year. Results based on Table C-1

With the amount of planned interventions remaining approximately constant during the first 8 years of the decade, the yearly total amount of interventions depended largely on the amount of clearances. It is difficult to identify the causes for clearance number to vary from as low as 514 to as high as 661 in the space of three years (2014 to 2017), although a wide variety of factors are certainly involved. These factors may include the effectiveness with which intervention procedures were performed, fluctuations of the wastewater volume drained and the general unpredictability associated with obstruction occurrence, meaning that some periods of time are simply bound to be worse than others. The increase in proactive intervention is highly noticeable in the last two years of the decade, and it is accompanied by a decrease in the amount of clearances, which is most evident from 2017 to 2018, when the company started the current PIP. It is worth noting that, while a 99.1% increase in proactive intervention from 2017 to 2018 saw a considerable decrease in clearances (23.6%), from 2018 to 2019 further increasing proactive intervention (by 42.1%) no longer registered a meaningful clearance decrease (1.4%). The same tendencies are observed if considering the sum of clearances and floods instead of clearances alone.

Although the clearance decrease from 2017 to 2018, as proactive intervention increased, points to the positive influence proactive intervention can have on the network and cannot be dismissed as coincidental, analysis does suggest that purely increasing proactive intervention further may not be an effective way of lowering the amount of obstructions. Instead, focus should lie on determining which structures do need an increased intervention frequency, as well as which structures may not need to be intervened as much as they have been. It is due to this that a rigorous classification of each street and each pipe is needed, in order to derive a more effective PIP that can further reduce reactive interventions.

4.3. Performance Analysis

Having established a valid premise for the remainder of the study, it was then possible to analyse the gathered information in order to determine the influence each indicator has on obstruction occurrence on street and pipe scale. This analysis enabled the determination of an adequate way to classify each indicator and, therefore, provide meaningful feedback with the intent of changing the currently implemented network management directives. Analysis of pipe characteristics was first conducted on pipe scale, with it being expected to achieve more accurate results regarding the influence of a specific characteristic in performance, while the street scale analysis mostly took into consideration the average value of the characteristic present in the pipes of a certain street in order to evaluate the overall influence characteristics. In both cases, characteristics were organized into categories that were descriptive of their formerly perceived criticality obtained through literature review, and the interventions per pipe km per year of each category were compared.

It is worth referring back to Table 5, in section 4.1.3, which presents indicators of the selected portion of the network's actual performance throughout the last decade. Information regarding pipe performance referring to the period of 2013 to 2017 considered only obstruction occurrence (including floods), disregarding the influence of planned interventions, as these are registered on street scale and to assume all the pipes installed in a street were intervened would be inaccurate, as usually only the critical extension of the street is intervened. For the selected network portion, the value for obstructions per pipe km per year during the aforementioned period was 1.64. Information regarding street performance referring to the period of 2010 to 2019 considered both obstruction occurrence and planned intervention, with a network average of 3.03 interventions per pipe km per year. The conditioning on both information sets suggest that, while each set can adequately provide a foundation to classify both pipes and streets, it isn't accurate to compare results in a quantitative way between pipe and street scale.

The network wide values of 1.64 and 3.03 (obstructions and interventions per pipe km per year, respectively) are representative of what an average pipe or street should display, and prove useful for comparison to the values obtained for the categories created along this chapter. The relevant values used to produce each graph that is presented are given in the tables in the Appendix section, with a certain graph's corresponding table being identified in its legend. While the results obtained are specifically representative of Porto's domestic wastewater drainage network, it is expected that most of the analysis can be applied to any network with reasonably similar characteristics.

4.3.1. Interventions per Pipe Extension per Year

This indicator was analysed first as it accurately represents the actual performance of both pipes and streets during the respective selected time periods, as opposed to the remaining indicators, which provide information regarding the performance that can be expected of a certain pipe or street.

4.3.1.1. Statistical Analysis and Geographical Representation

As mentioned previously, pipe scale analysis involved information regarding only pipe clearances, enabling the creation of an obstructions per pipe extension per year indicator, while an interventions per pipe extension per year indicator was used for street scale. Pipe extensions were represented in km. Both indicators provide quantitative information regarding the functioning of the network during each respective period, such as which pipes or streets display the best and worst performances. For the period of 2013 to 2017, the 6,857 pipes that constitute the selected portion of the network displayed an average of 1.64 obstructions per pipe km per year, with a maximum of 201.8, for a pipe associated with 31 obstructions, the most in the network, and a minimum of 0, for 5,921 pipes that did not register a single obstruction during the five-year period. A total of 2,110 obstructions were registered.

Only 936 pipes registered obstructions, representing 13.7% of the selected pipes, corresponding to 17.6% of the selected network portion's pipe extension. Pipes with at least one obstruction registered an average of 0.45 obstructions per pipe per year and an average of 9.3 obstructions per pipe km per year.

From 2010 to 2019, 7,817 interventions were registered in the 468 streets selected for having been intervened more than 2 times over the ten-year period, of which 63.4% were regular obstruction clearances, 19.9% were clearances of obstructions that had led to floods and 16.7% were planned interventions. The streets registered an average of 1.67 interventions per street per year and an average 3.03 interventions per pipe km per year. Figure 25 provides a geographical representation of the areas with obstruction occurrence during the 2013-2017 period and of the performance of the selected streets during the 2010-2019 period. It was assumed, for several maps produced, that the areas of higher obstruction occurrence were approximately the same during both periods. Figure 26 represents average street performance on parish scale.

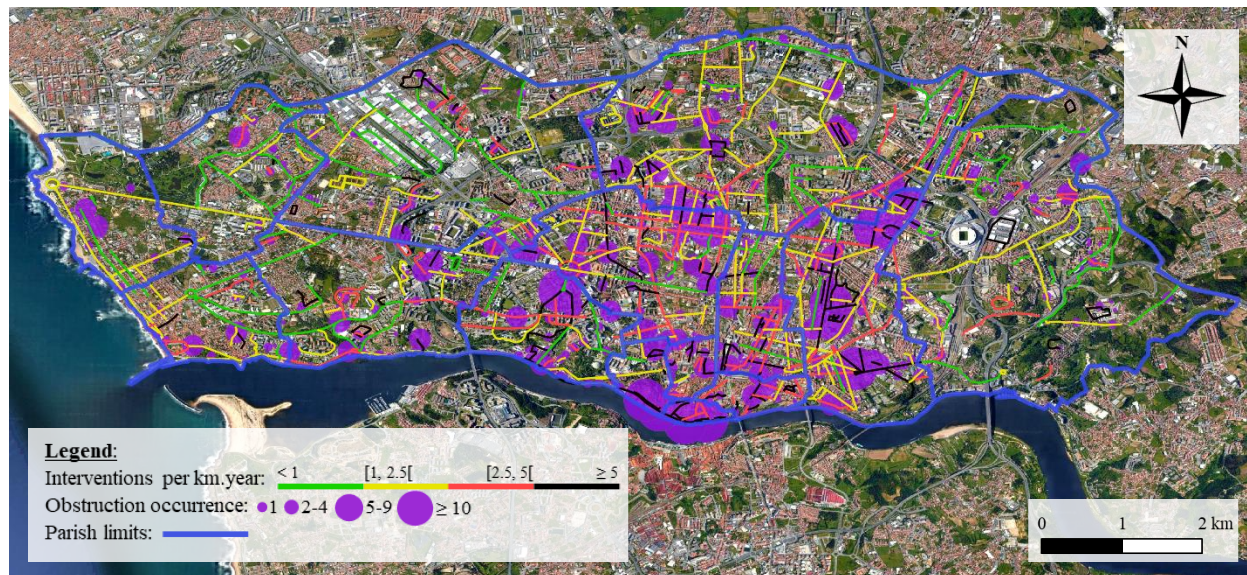


Figure 25: Street interventions per pipe km per year vs obstruction location

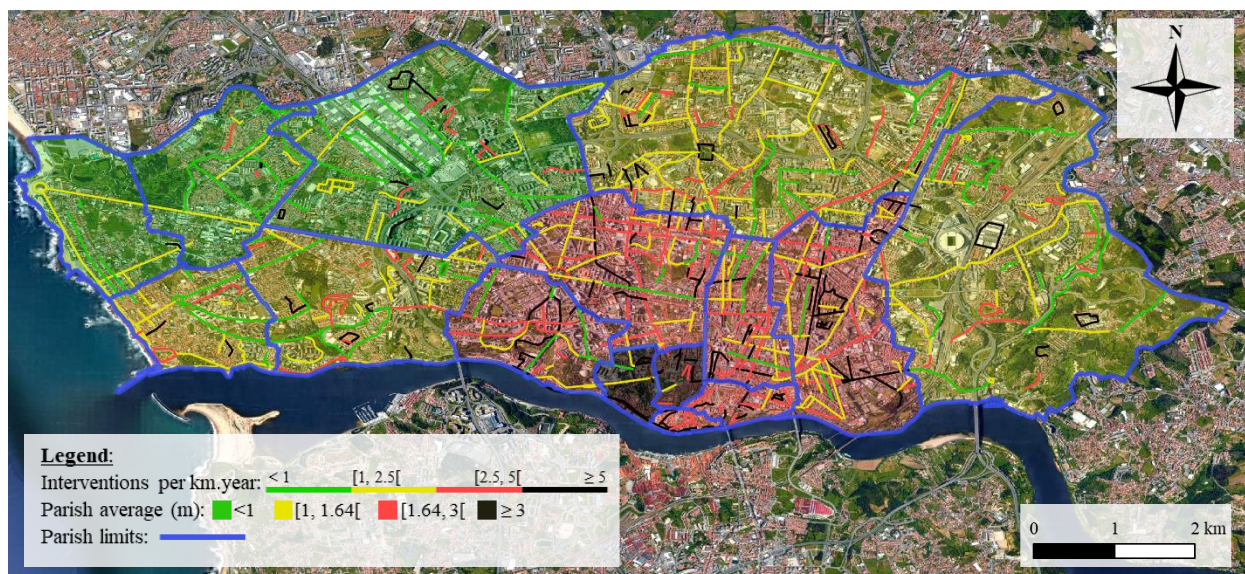


Figure 26: Street interventions per pipe km per year on parish scale

It can be observed on Figure 25 how areas of high obstruction occurrence coincide with streets with poor performance, which indicates the information sets used are consistent with each other. Most pipe interventions and obstructions occur in central areas of the city, as is best represented on Figure 26, where the disparity between the average street performance in parishes located near the city's historical centre and parishes located in the city's periphery is evident.

4.3.2. Pipe Age

It had been noted in literature review that prior works had highlighted excessive pipe age as an indicator of poor performance. When discussing which indicators were of such importance that a pipe lacking information regarding them would not be considered for analysis, pipe installation date was not included as one, despite a considerable amount of pipes lacking values for it. An analysis of AdP's record keeping over the past 60 years showed that, for this period of time, it can be assumed that all pipe installations are accounted for. As such, pipes lacking installation date information were considered to be over 60 years old. Since the construction of the network started early in the 1900's, and was mostly carried out between 1950 and 1970, 1950 was considered an adequate intermediate date and was established as the installation date for every pipe missing an accurate value.

4.3.2.1. Statistical Analysis

The considered extension of the network had, as of 2020, an average age of 56.9 years. The 6,857 selected pipes were initially grouped in 3 categories regarding their age: under 30 years, between 30 and 60 years, and over 60 years. It was intended to represent pipes with over 60 years of age in one of the categories, as 60 years is the approximate lifespan of stoneware pipes, which constitute the vast majority of the network's extension. Pipes with unknown exact installation year were also grouped in this category.

The remaining two categories were established in order to represent the newest pipes (under 30 years of age) and pipes approaching their theoretical lifespan (between 30 and 60 years of age). Figure 27 presents the comparison between each category's pipe age range and obstructions per pipe km per year parameter. This is complemented by a representation of the percentage of total obstructions and total pipe extension associated with each category. The influence of pipe age is clearly presented, with pipes installed less than 30 years prior to analysis displaying an obstructions per pipe km per year value that is less than half of the average presented on Table 5, in section 4.1.3. Pipes installed over 60 years prior to analysis displayed above average values, as was expected.

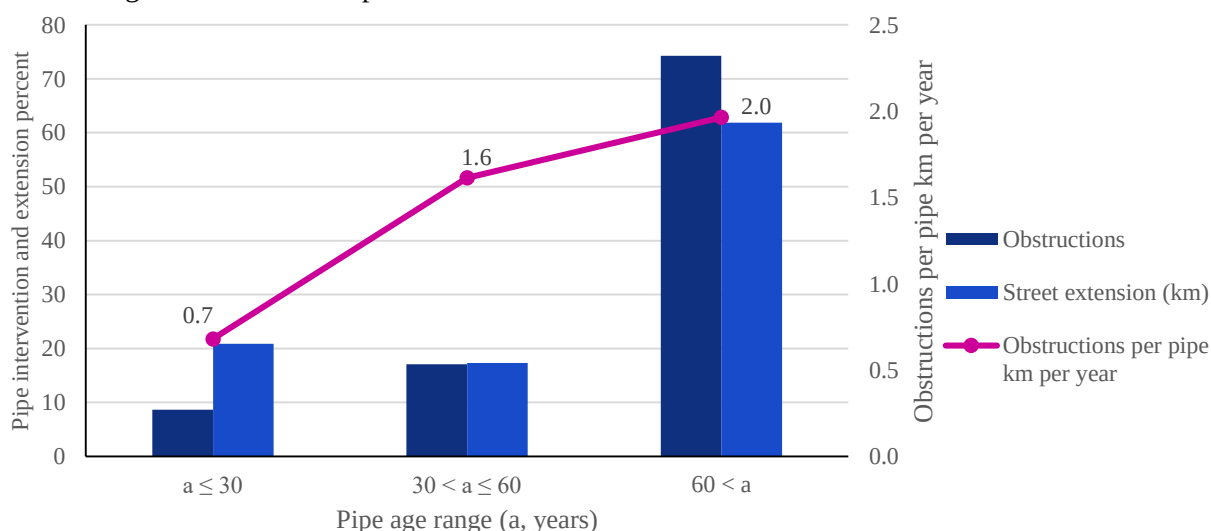


Figure 27: Pipe age influence on obstruction occurrence. Results based on Table B-1

A similar analysis was produced on street scale using the same categories (see Figure 28). This was performed in order to evaluate whether the influence of the average age of street's pipes leads to similar results as the analysis that was carried out considering each individual pipe. Further into this study, this would allow for pipes and streets to be classified according to pipe age using criteria specific to each of them.

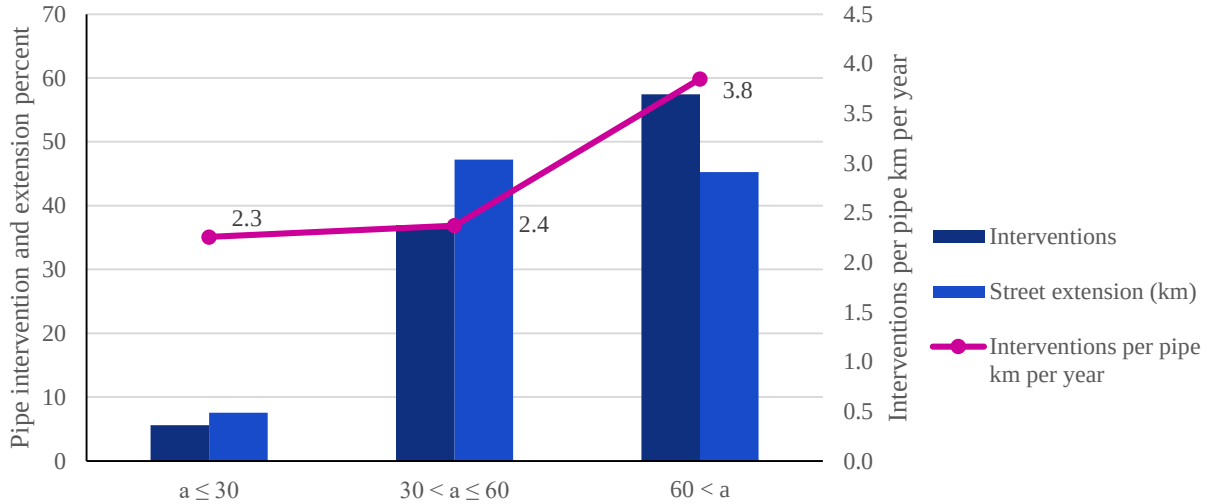


Figure 28: Average pipe age of streets influence on intervention occurrence. Results based on Table C-2

It can be observed that, unlike what had been verified on pipe scale, the relation between pipe age and sensibility to interventions may not be as linear as previously thought, when considering whole streets. It can, however, be noted that the category of pipes under 30 years of age amounts for just 5.6% of total interventions and 7.5% of total pipe extension, which could suggest that this category may contain a sample size that is not significant enough for comparison with the other two categories. By joining the two lowest age categories, focus can be shifted to the disparity between pipes that were installed under and over 60 years prior to this analysis.

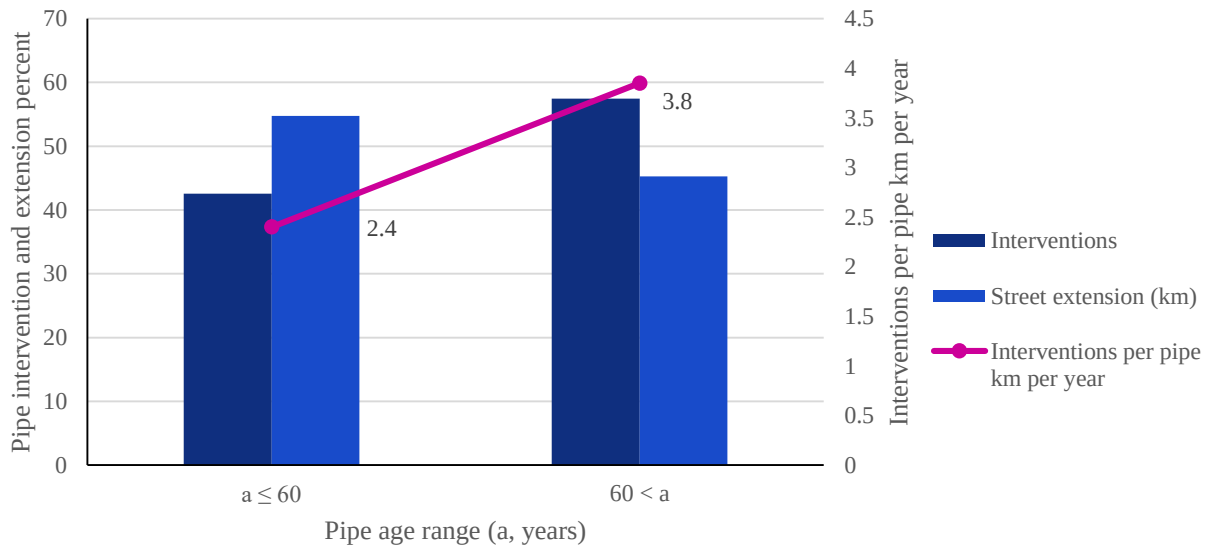


Figure 29: Average pipe age of streets influence on intervention occurrence, featuring less categories

The pipe extensions of the two categories are reasonably close (54.8 to 45.2%), whereas streets with pipes under of 60 years of age amounted for just 42.5% of interventions, compared to 57.5% for streets with an average pipe age of over 60 years. Both graphs (Figures 28 and 29) suggest that the average age of a street's pipes only becomes of considerable relevance when approaching or exceeding 60 years. With the network consisting almost entirely of stoneware pipes, which have a 60-year lifespan, it can be hypothesised that the pipes approaching or exceeding 60 years of age will start to display irregularities in their walls or be more easily infiltrated by tree roots, which promote obstructions and, therefore, lower the pipe's performance. While an argument can be made that certain pipes can remain functional several years past their theoretical lifespan, supported by network old network portions that are rarely intervened, analysis shows that, on average, pipe performance does worsen as pipe age increases.

4.3.2.2. Geographical Representation

Having analysed how a pipe's age influences its performance, the results were then represented geographically. Both maps (Figures 30 and 31) represent the average pipe age of the 468 selected streets, with the first comparing it to the locations of pipe obstructions from 2013 to 2017 and the second comparing the average pipe age of each parish.

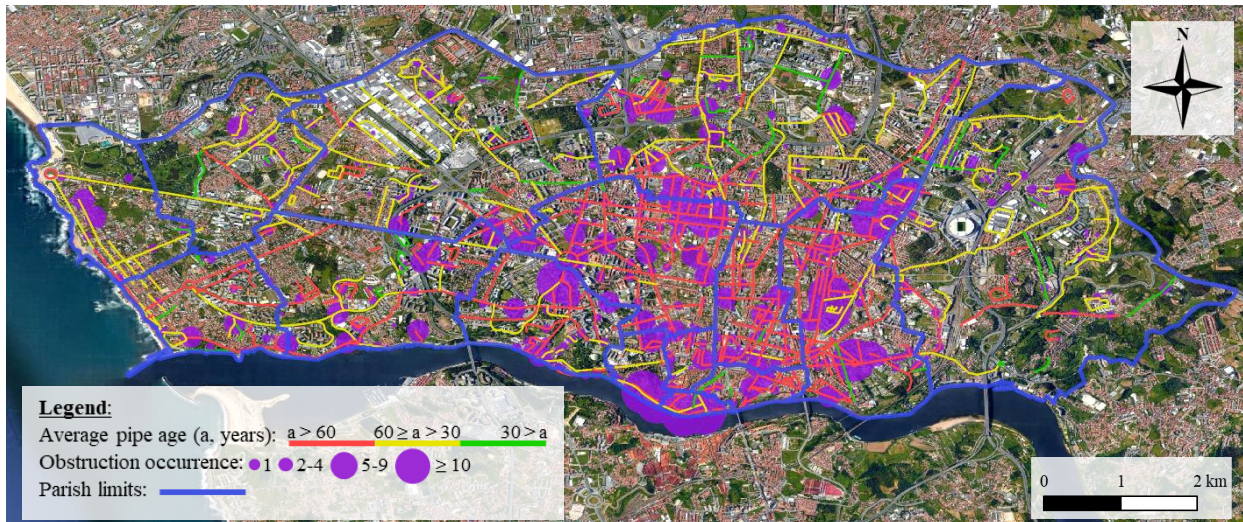


Figure 30: Average street age vs obstruction location

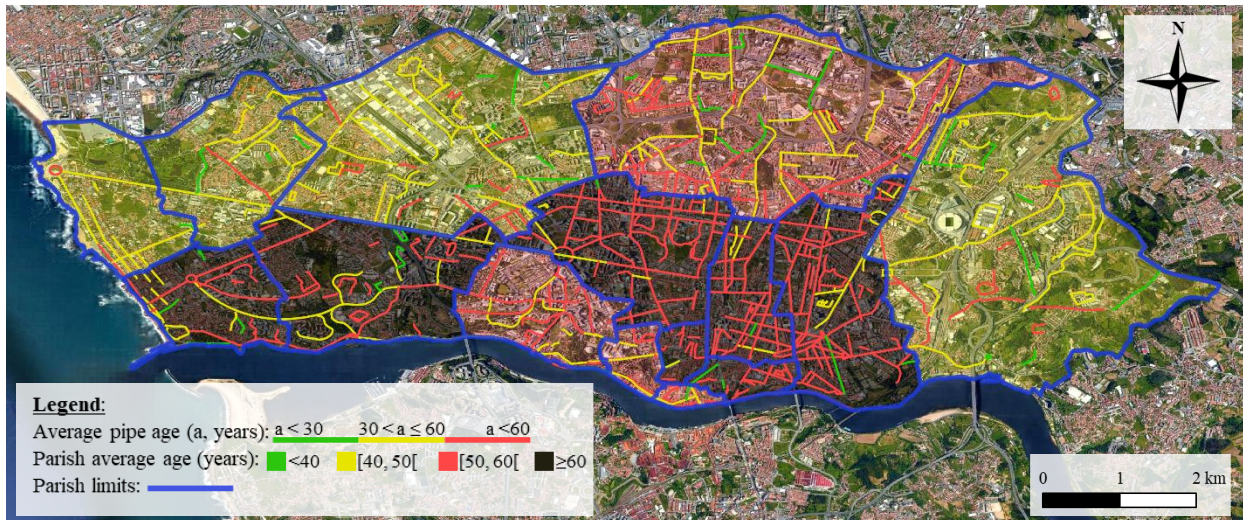


Figure 31: Average pipe age on parish scale. Results based on Table D-1

The highest average pipe ages are mostly seen in central parishes of the city, coinciding with its most developed areas as of 1903 (Figure 15, Chapter 3.2.2). Despite not having statistically concluded a very strong connection between a pipe's age and its performance, it can be observed how the majority of pipe obstructions occurred in areas with generally older pipes. This could be explained by a tendency for older pipes to possess other characteristics that harm their performance, such as lower diameters, while it is also worth noting that the reality of the city (in terms of water consumption and, consequently, of drained wastewater) when these pipes were dimensioned was substantially different from what it is at the time of this analysis, resulting in the pipes being currently considered under dimensioned. It can be hypothesised that, while pipe age certainly does influence performance, that influence is likely predominantly associated with the contrast between the network's operating conditions present upon their installation and current conditions than it is to physical degradation of the pipes as a product of their age itself.

4.3.3. Pipe Diameter and Material

AdP's internal regulations currently define 200 mm as the minimum diameter for newly installed pipes. Consequently, already installed pipes with lower diameters are considered to be under dimensioned. Given that these pipes amount for 29.7% of the network's extension (Figure 17), network wide replacement is not viable. Firstly, it is important to analyse the connection between pipe diameter and obstruction occurrence, so that conclusions can be drawn regarding which diameters can generally be considered adequate. The analysis of pipe diameter can then be combined that with other pipe and street characteristics, such as the previously analysed pipe age, to determine which pipes display the best and worst working conditions. For the latter, decisions should be taken regarding whether to intervene proactively or proceed to the repair, renovation or replacement of the pipe. The majority of the pipes that constitute Porto's domestic wastewater network are built of stoneware, while alternate materials include cast iron, HDPE (high density polyethylene), PP (polypropylene) and PVC (polyvinyl chloride). Information extracted from AdP's management platform described the external diameter of HDPE, PP and PVC pipes, as opposed to the internal diameter, considered to be more adequate for analysis. External diameters were consequently converted using the conversion rates presented in Table 7.

Table 7: Diameter conversions of HDPE, PP and PVC pipes, adapted (Scope Metals Group 2020). (*) – interpolated values

Material	Diameter (mm)	
	External	Internal
HDPE	125	117.4
	150	140.6*
	160	150.2
	200	187.8
	250	234.8
	315	295.8
	355	333.4
PP	400	375.6
	160	134.0
	200	167.0
	250	209.0
	300	250.5*
	315	263.0
PVC	400	335.0
	125	118.8
	160	152.0
	200	190.2
	250	237.6
	300	285.2*

4.3.3.1. Statistical Analysis

Analysis on pipe scale was conducted first. Five diameter categories were created, describing five theoretically differentiated ranges. One category was created for diameters lower than 175 mm, which was mostly comprised of pipes with 125 mm, few with 150 mm and values obtained through the conversions presented on Table 7. It was expected that this would prove to be the most critical category, as pipe diameter was much lower than the regulated acceptable value of 200 mm. Two categories were created to reflect the network's two most common pipe diameters, 175 and 200 mm, with the small amount of pipes with diameters ranging between these values being included in the same category as the 200 mm pipes. Lastly, two categories were created for pipes with over 200 mm diameters, one ranging from 200 to 350 mm, and one above 350 mm.

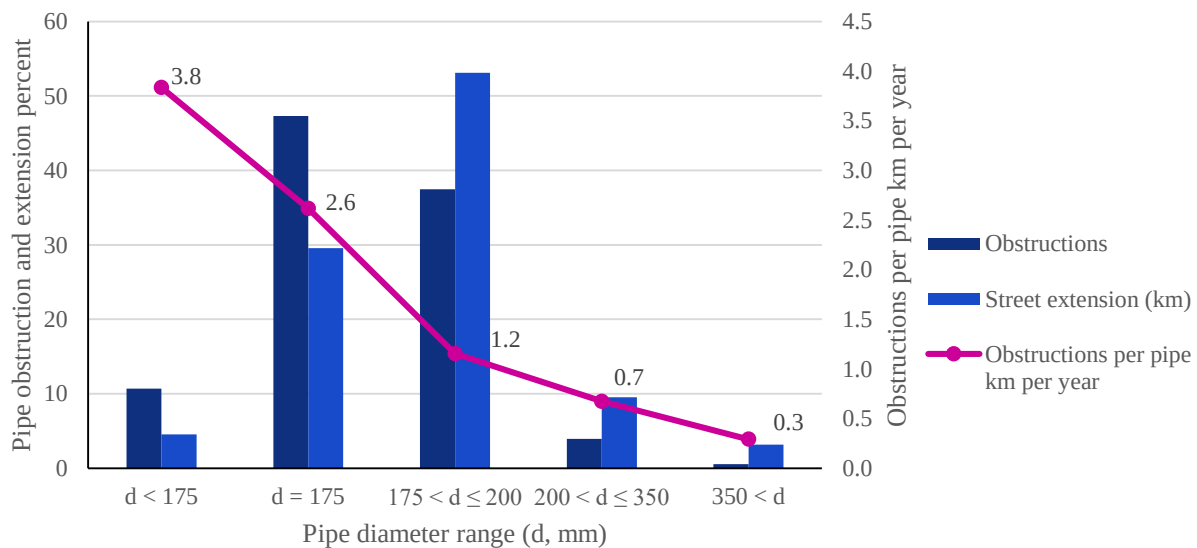


Figure 32: Pipe diameter influence on obstruction occurrence. Results based on Table B-2

Results showed that pipes with lower diameters do perform worse, with each successive category with higher pipe diameters displaying less obstructions per pipe km per year, on average. The discrepancy observed between the most critical class ($d < 175$) and the 3 least critical classes (for which the most critical class displayed 3.2, 5.4 and 12.7 more obstructions per pipe km per year) suggests that a pipe's diameter influences its performance considerably more than pipe age, for which the most critical category (pipe age over 60 years) had displayed just 2.9 more interventions than one for the newest pipes. Pipes with a 175 mm also displayed a considerably worse performance when compared to higher diameters. It can be observed how pipes with diameters of 175 mm or lower have interventions per pipe km per year values well above the average of 1.64, and are associated to a higher percent of interventions when compared to the percent of the network's extension that they represent, as opposed to the remaining categories. The difference in performance between 175 and 200 mm pipes suggests that, when viewing the selected portion of the network as a whole, 200 mm can be considered an adequate minimum diameter, and pipes with diameters ranging from 125 to 175 mm are where the majority of proactive intervention should focus.

The influence of a street's average pipe diameter in its performance was also studied, with the intention of determining whether the pipe diameter's influence is also relevant on street scale. The analysis procedure was similar to the one adopted for pipe scale analysis, with five categories being created, now regarding the average pipe diameter of the selected streets. Working with pipe diameter averages instead of individual pipe diameter values implied the need to slightly adjust the formerly created categories in order to maintain their representativeness.

A category was created for streets with average diameters under 175 mm, expected to be the most critical, as had been the case with the pipe scale analysis, while another was created for averages ranging from 175 to 200 mm. A third category was created to evaluate the performance of streets with an average diameter of 200 to 205 mm, while the remaining two categories were established as being from 205 to 225 mm and over 225 mm. It can be observed that the categories with average pipe diameter lower than 200 mm were once again the most critical, as can be seen in Figure 33.

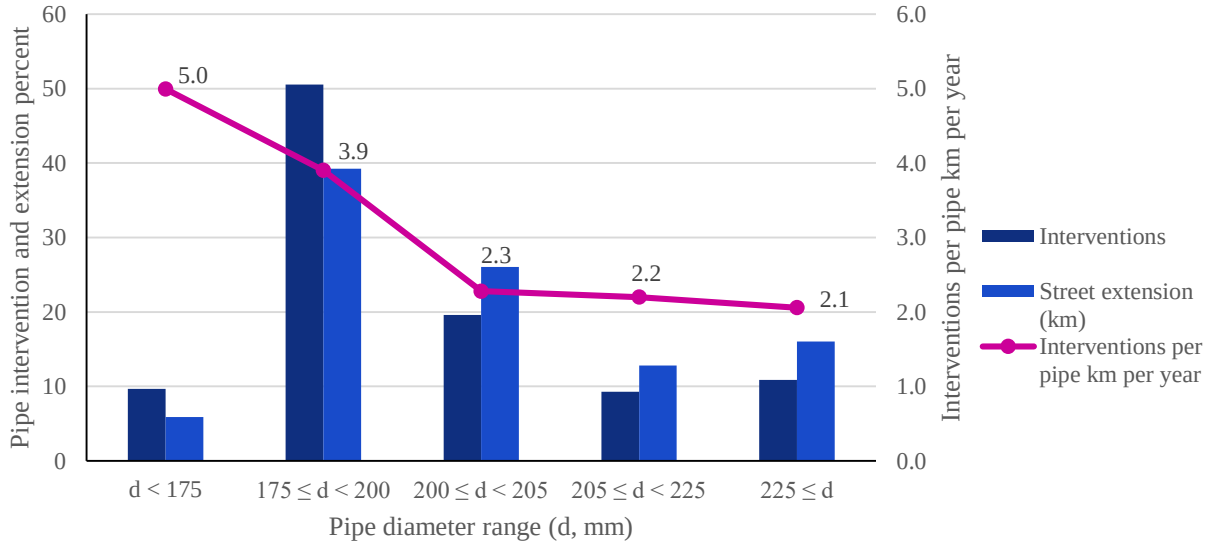


Figure 33: Average street diameter influence on interventions occurrence. Results based on Table C-3

The tendency of higher pipe diameters being associated with less interventions per km per year that was clearly observed in the pipe analysis is also evident regarding streets, although the discrepancy between categories above 200 mm is minimal, with the three comprised between 2.1 and 2.3 interventions per km per year. The performance-wise closeness of the 200 to 205 mm category to the two categories with higher diameter further suggests there is a substantial difference between network sections operating with 175 and 200 mm pipes, underlining the conclusions drawn from the prior analysis and further showing the 200 mm minimum diameter is adequate.

A potential connection between pipe age and pipe diameter was explored, with the intention of determining whether critical pipes regarding one indicator of the analysed indicators tend to be critical as well regarding the other, as had previously been hypothesised. Table 8 presents the total extension and average pipe age for each of the most common pipe diameters, considering all pipes of the selected portion of the network, while Table 9 presents a comparison between the aforementioned pipe diameters, for which only pipes over 60 years of age as of 2020 were considered.

Table 8: Average pipe age for most common pipe diameters

Pipe diameter (mm)	Extension (km)	Average pipe age (years)
125	10.55	69.02
175	76.28	68.97
200	133.40	50.79
All diameters	257.89	56.91

Table 9: Percentage of over 60 years old pipes per diameter

Pipe diameter (mm)	Extension (km)	Percentage of all pipes over 60 years of age	Percentage of pipes that are over 60 years of age
125	9.94	6.23	94.22
175	71.88	45.06	94.23
200	61.75	38.71	46.29
Other	15.96	10.00	-
Total	159.52	100.00	-

The results presented demonstrate how the vast majority of pipes with diameters considered critical (namely 125 and 175 mm) were installed 60 or over years prior to this analysis, when the city was less developed and the drained volume of domestic wastewater was certainly considerably lower. It is clearly exposed how a critical pipe is likely to be poorly classified regarding both its age and diameter and, as such, the classification methodology should either consider the two indicators together or highly favour the indicator that displays a more concrete connection between its categories and pipe performance, which in this case would be pipe diameter.

The influence of pipe material in obstruction occurrence was also hypothesised, based on the hypothesis that certain materials may be more prone to developing irregularities, cracks or being infiltrated by roots, which increase the likelihood of becoming obstructed. The exact representation of each material within the selected network portion is displayed in Figure 34.

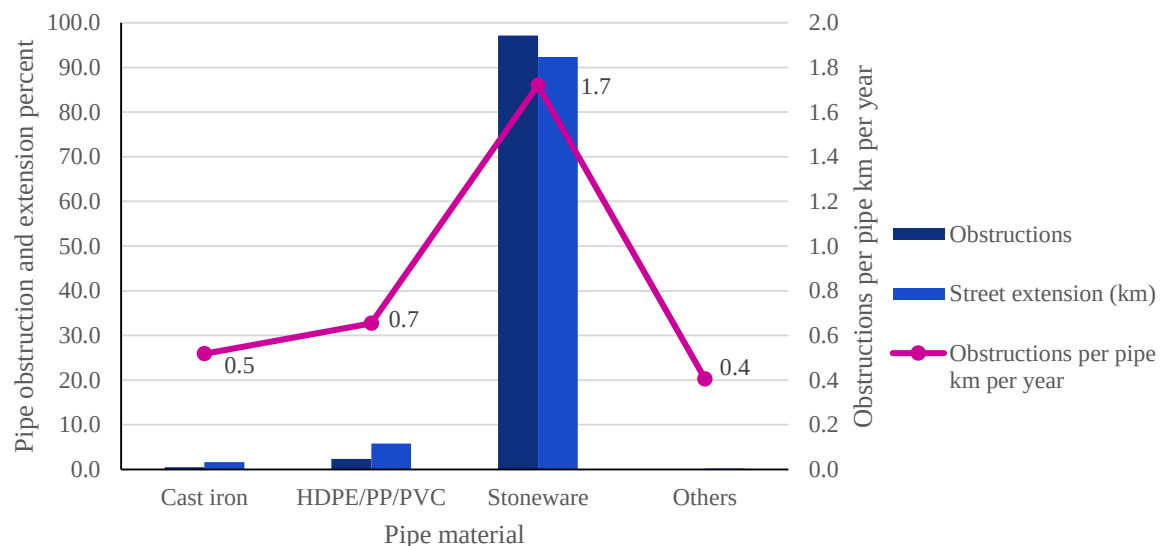


Figure 34: Pipe material influence on obstruction occurrence. Results based on Table B-3

Stoneware constitutes over 90% of the considered portion of the network, both when considering pipe count and pipe extension. HDPE, PP and PVC pipes are the second most common, amounting for 5.8% of the extension. Interventions per pipe km per year are also displayed. The average for this indicator was 1.64 (Table 5, section 4.1.3). Stoneware pipes had a slightly above average value for obstructions per pipe km per year, while the remaining pipes displayed values considerably below the average. It can be hypothesised that, due to the high percentage of stoneware pipes, the remaining pipe materials are not represented enough. In order to further clarify whether conclusions can be drawn from these results, the average diameter of pipes made of each material was determined and analysed. Results are presented in Figure 35.

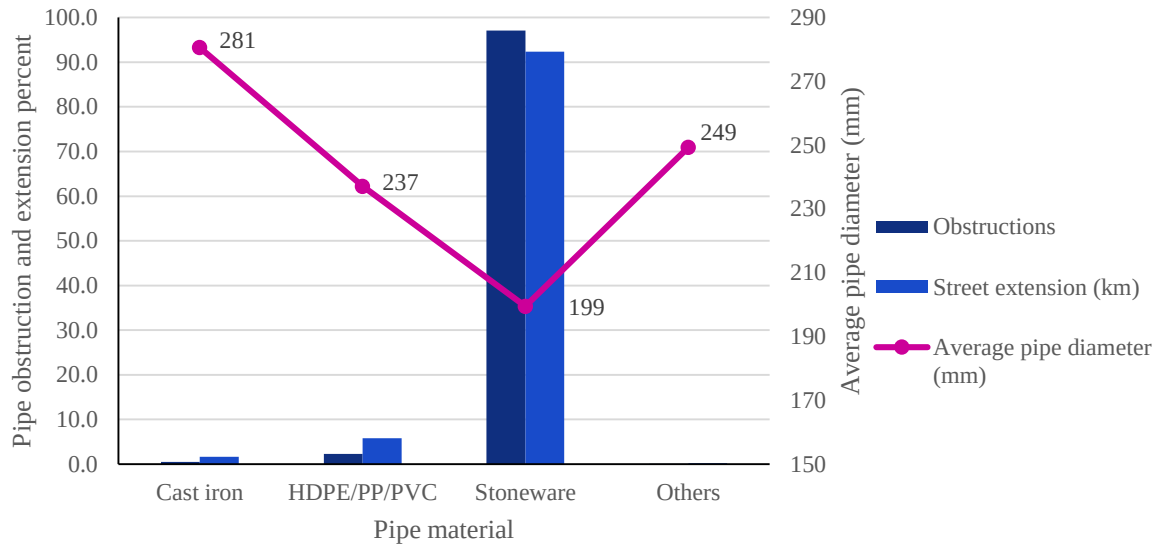


Figure 35: Average diameter per pipe material

Stoneware pipes have an average diameter of 199.5 mm, slightly below the network's average of 201.4 mm, whereas pipes made of the remaining materials each displayed average diameter values highly above average, which have previously been associated with lower intervention per pipe km per year values during the diameter analysis (Figure 33). It can also be considered that, with pipes made of any material except stoneware having either low or very low representation within the network, they are not likely to be exposed to many critical network areas and there is not enough information to properly evaluate their performance. Taking into account these considerations, an argument that stoneware pipes perform worse when compared to other materials would be unfounded.

4.3.3.2. Geographical Representation

The geographical analysis of pipe diameter was conducted similarly to the one produced for pipe age, with the average pipe diameter of all selected streets being compared to the location of obstructions over the 2013 to 2017 period (Figure 36) and between the city's parishes (Figure 37). Given stoneware's prevalence within the network, no geographical representations of pipe material were produced.

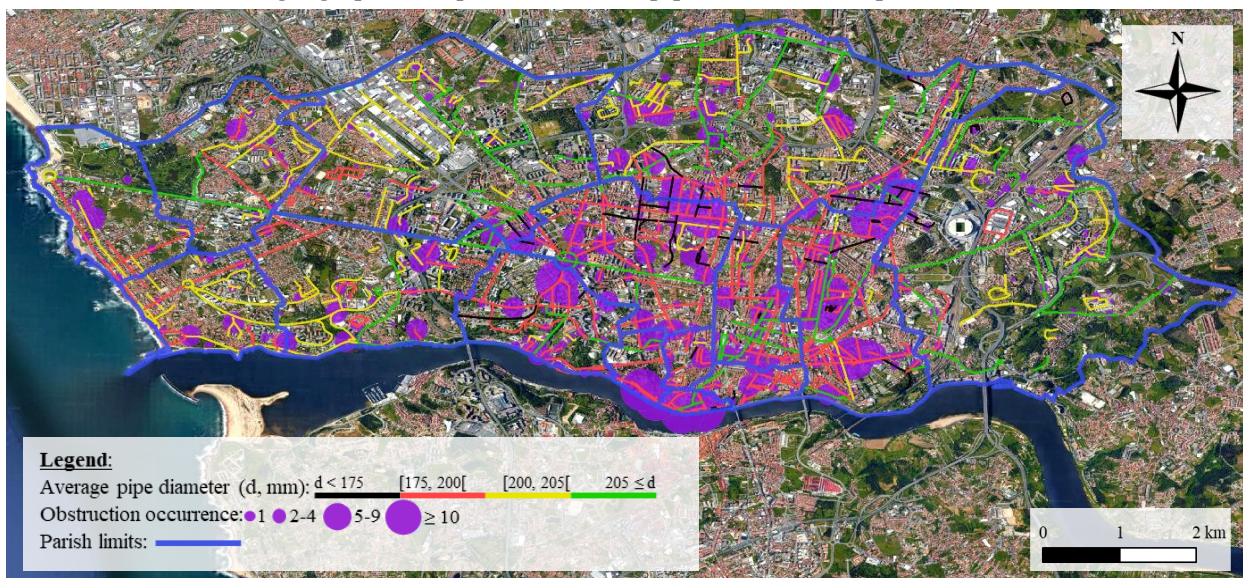


Figure 36: Average street diameter vs obstruction locations

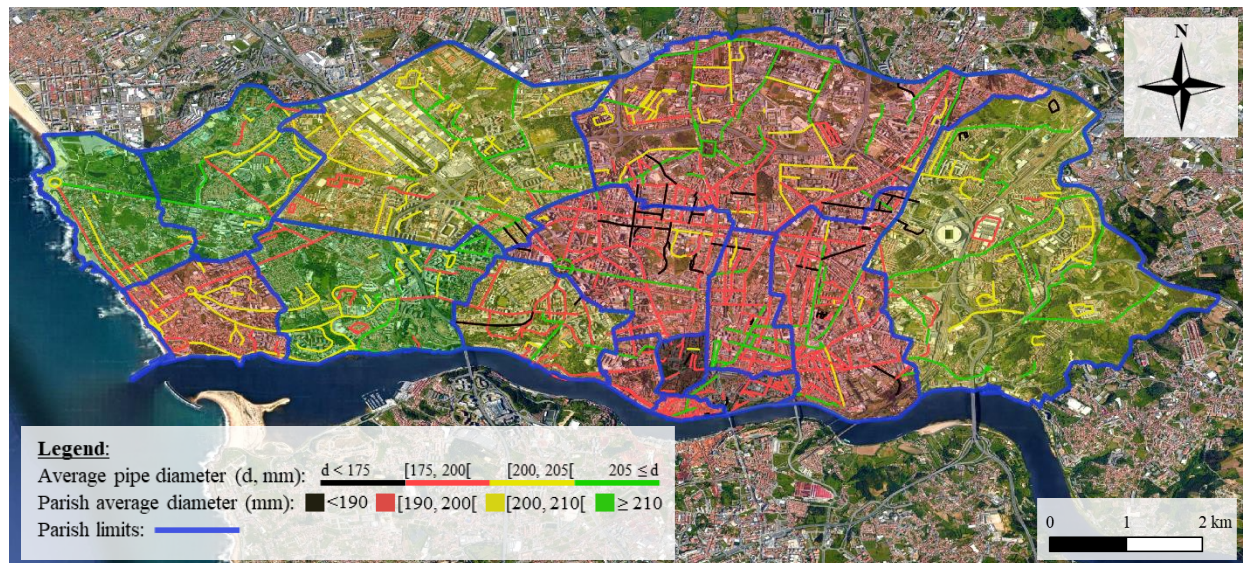


Figure 37: Average street diameter on parish scale. Results based on Table D-2

Similarly to what had been observed regarding pipe age, streets with the most critical average diameters generally coincide with the geographical representation of obstruction occurrence (Figure 36). The majority of the most critical parishes regarding the average street diameter indicator (Figure 37) coincide with the city's most developed parishes in 1903 (Figure 15), which can explain the low average diameter displayed by the Foz do Douro parish. Most of the parishes displaying the lowest average diameters either overlap with or are in close vicinity to Porto's historical centre, which is one of the most frequented parts of the city due to its leisure activities and high tourist appeal and are likely to be considered high impact areas. This originally prompted the need to statistically confirm whether it can be stated that older pipes indeed display lower diameters, with the results of the analysis having been previously presented in Tables 8 and 9 of the previous section.

It can be observed how a considerable amount of the streets included in the most critical category coincide with the most central streets within the network, as displayed in the Space Syntax analysis presented in Figure 18 of section 3.2.2, namely the streets connecting to *Rua da Constituição* on the north of the Cedofeita parish. Being in a central position of the network with low average diameter suggests that, should the diameters be currently under dimensioned, the impact of pipe obstructions in these streets could manifest in several of the adjacent streets higher in the network.

4.3.4. Pipe Extension per Restaurant

Wastewater drained from different sources can vary in composition regarding the main activities performed in the source. When streets have a significant restaurant presence, it results in the drained wastewater having higher amounts of grease when compared to streets located in residential or industrial areas. Grease tends to solidify and cause build-ups in the walls of the pipes, theoretically increasing their likelihood of obstruction. As of 2020, the city of Porto is a popular destination for tourism, with the local cuisine being one of its main attractions. Consequently, there is a large amount of restaurants and similar establishments throughout the city's most visited areas. Influence of restaurant presence on Porto's domestic wastewater drainage network was, therefore, analysed.

4.3.4.1. Statistical Analysis

Information regarding restaurant presence was collected from Google Maps and, therefore, it could only be used on street scale. Restaurants were not differentiated by criteria such as yearly water consumption or surface area. The pipe extension of each street was divided by the number of restaurants associated with it, creating an indicator of pipe extension (m) per restaurant, which displays the average distance between restaurants for a certain street. Despite the distance itself not having significant meaning, as restaurants were considered from both sides of the streets, it was considered to provide a considerably accurate depiction of restaurant density in a street. It was determined that, for streets with at least one restaurant, restaurants are on average 250 m apart along the network's pipe extension.

Five categories were created to reflect the restaurant presence on the selected streets. Three categories with below average values were created: under 75 m, representing streets with very heavy restaurant presence, from 75 to 150 m and from 150 to 250 m. Streets with above average pipe extension per restaurant values were all included in a fourth category. The fifth category included streets without a known restaurant or similar establishment. For later classification purposes, the pipe extension per restaurant for these streets was assumed to be equal to the highest value verified for streets with at least one restaurant. Results are presented in Figure 38.

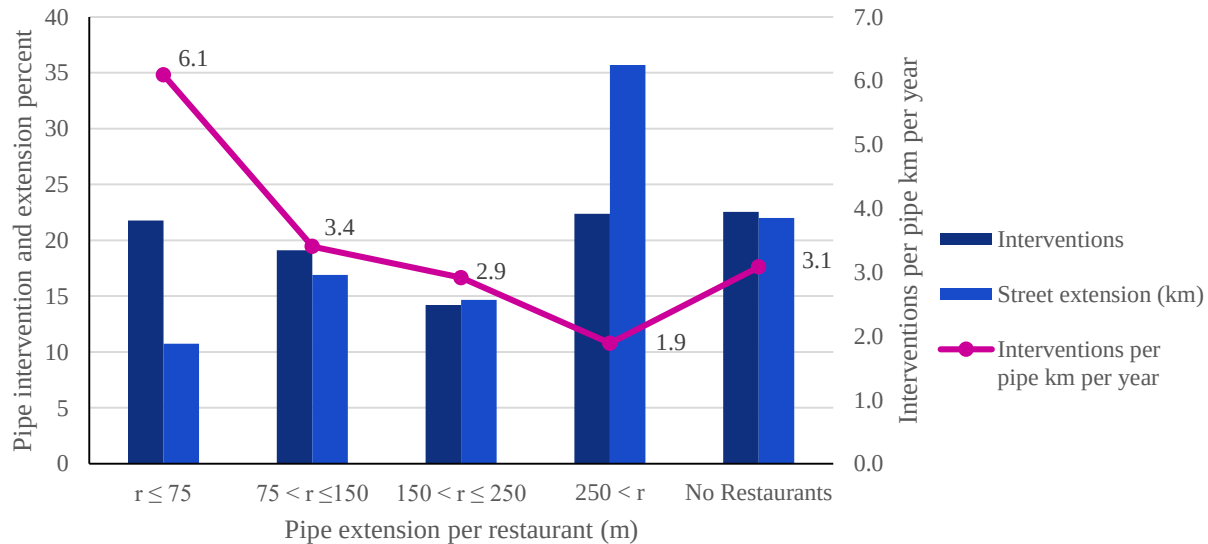


Figure 38: Pipe extension per restaurant influence on intervention occurrence. Results based on Table C-5

Analysis revealed how streets with very heavy restaurant presence, despite amounting to only around 10% of the selected network portion's extension, are responsible for more than 20% of interventions, while displaying 6.1 interventions per pipe km per year. This values, especially in comparison to the ones obtained for the remaining categories, suggests that heavy restaurant presence negatively influences the performance of a street's pipes substantially. A trend can be observed in the first four categories, which include all streets with restaurants, for which the higher the average distance between restaurants, the lower the amount of interventions per pipe km per year, further suggesting that the influence of restaurant presence can be observed even between streets with lower presence, albeit less dramatically. Streets without restaurants displayed a slightly above average interventions per pipe km per year value (3.1), which does not fit the aforementioned trend. This suggested that results regarding restaurant presence might be influenced by other pipe characteristics.

Having analysed pipe age and diameter and observed that, statistically, pipe diameter is more influential in a street's performance, the average diameter of the five categories presented in Figure 38 was determined and analysed. Results are presented in Figure 39.

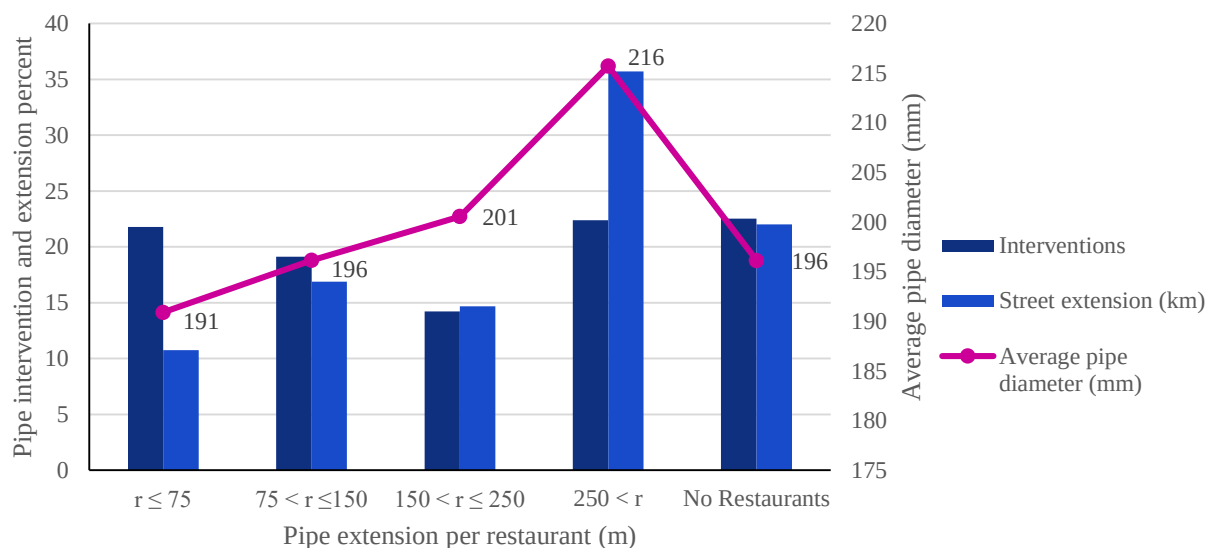


Figure 39: Pipe extension per restaurant vs average pipe diameter. Results based on Table C-5

It can be observed that the average pipe diameter and interventions per pipe km per year indicators display similar trends across the five categories, regarding their criticality. That is, the category that displayed the highest interventions per pipe km per year also displayed the lowest and therefore most critical diameter. As categories described lower restaurant presence, both indicators assumed less critical values, with interventions per pipe km per year lowering and average pipe diameter increasing. This trend was observed in all categories with the exception of the one including only streets without restaurants. Analysis of this category showed that interventions per pipe km per year had increased when compared to the category directly beside it, and average pipe diameter had considerably lowered to a less than acceptable value (196 mm). The lowering of the average pipe diameter between the two categories, from a seemingly adequate 216 mm to 196 mm, can now be used to justify the poor performance that streets without restaurants had unexpectedly displayed.

The graphs displayed in Figures 38 and 39, despite presenting consistent results between them, raised doubts over whether restaurant presence had indeed a substantial impact in pipe and street performance or if the results were mainly due to the influence of the average pipe diameter. Arguments could be made for the influence of restaurant presence being noticeable, as the category for streets with a considerable amount of restaurants (75 to 150 pipe m per restaurant) had more interventions per pipe km per year than the category for streets without restaurants (3.4 to 3.1 interventions per year) with similar average diameter (196 mm), or as streets with heavy restaurant presence, with an average diameter of 191 mm, performed worse than streets with an average diameter of under 175 mm (Figure 33, section 4.3.3), with 6.1 and 5.0 interventions per pipe km per year, respectively.

These were, however, considered to not be conclusive enough, and as such, an analysis was performed in which the performance of the same five categories regarding restaurant influence were evaluated separately for four different diameter ranges. These diameter ranges used had already been concluded to display reasonably different influences on street performance, whether through pipe or street scale analysis. The results of this analysis are presented on Figure 40.

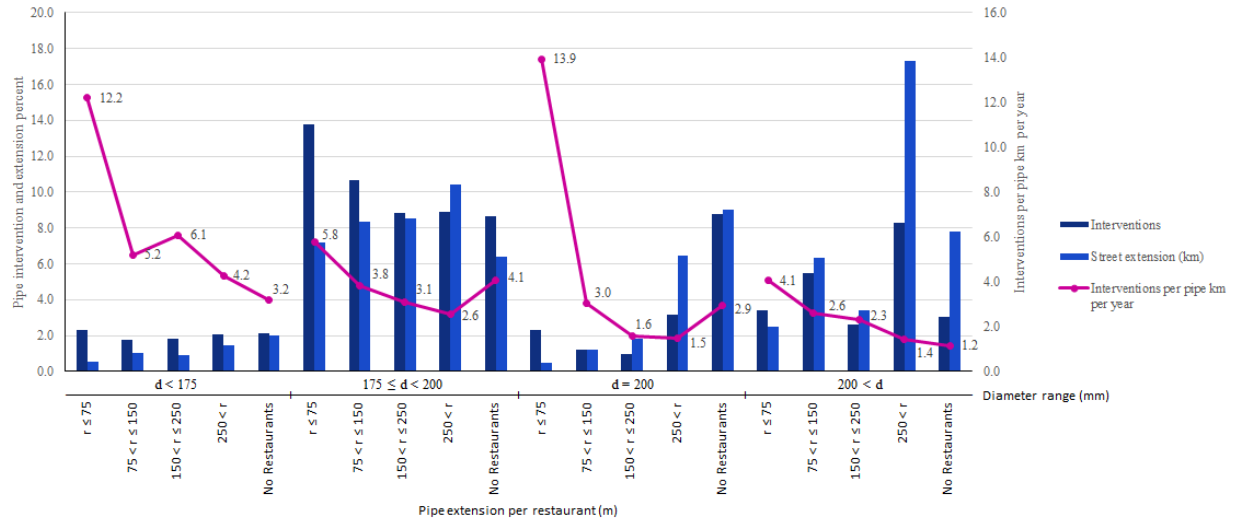


Figure 40: Restaurant presence influence on street performance, evaluated for different average diameter ranges. Results based on Table C-6

Results showed that when considering only streets with certain ranges of average pipe diameter, streets with heavy restaurant presence always displayed the worst performance of all categories, with above average interventions per pipe km per year for all diameter ranges. The formerly analysed trend between restaurant presence and interventions per pipe km per year was present in three of the four diameter ranges, with just one value inconsistent with the trend verified in the remaining range. Streets combining very low (under 175 mm) or 200 mm diameters with heavy restaurant presence displayed very high interventions per pipe km per year values (12.2 and 13.9), not observed in any prior analysis. This suggests that not only is restaurant presence influential in a street's performance, but also its combined effect with low diameters is characteristic of a considerable amount of the network's most critical streets.

4.3.4.2. Geographical Representation

Having established restaurant presence as a valid and important indicator, a preliminary geographical representation was produced, showing the location of the city's restaurants (Figure 41).

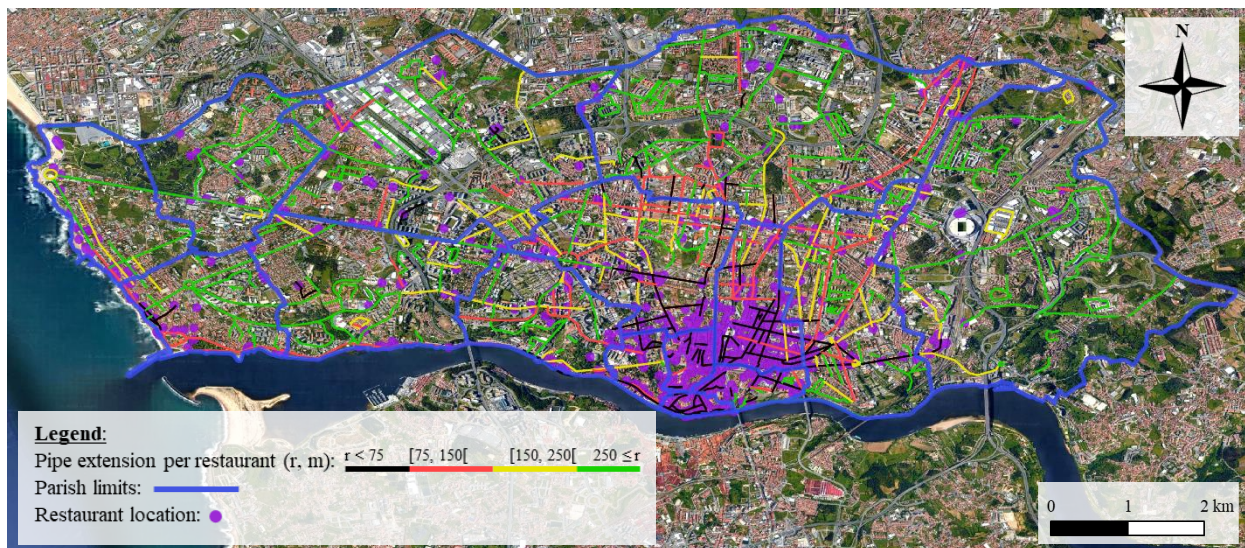


Figure 41: Restaurant presence in streets vs restaurant locations

Only restaurants in the 468 selected streets were represented, amounting to a total of 1,523.

Further geographical representation was produced. Figure 42 compares obstruction locations to the streets classified according to the formerly created categories, while Figure 43 presents restaurant presence on parish scale.

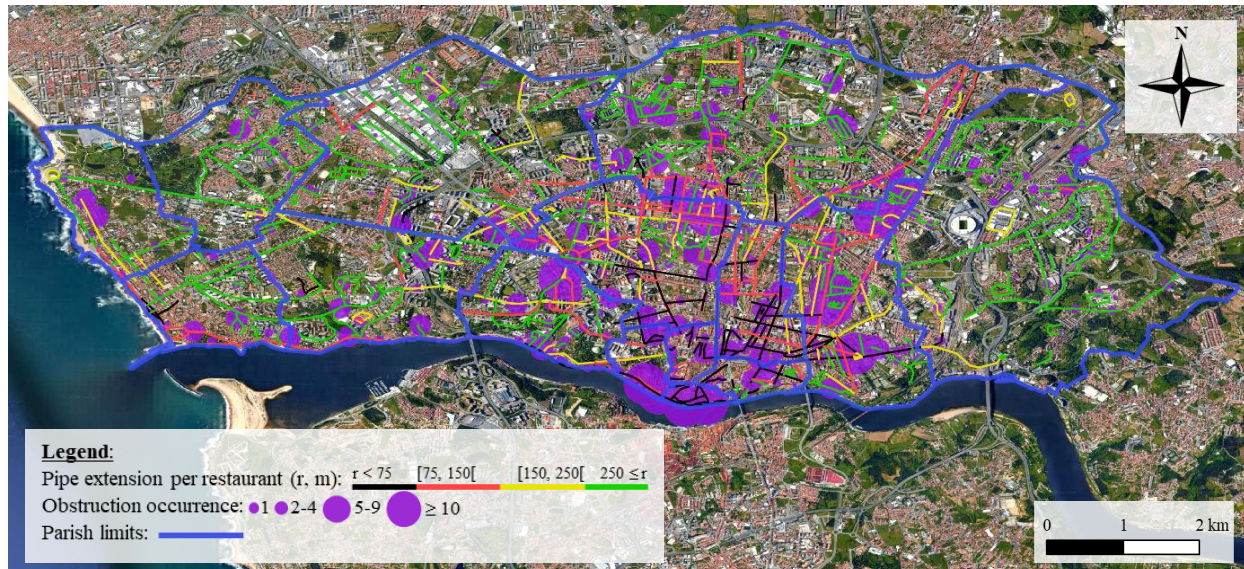


Figure 42: Restaurant presence in streets vs obstruction occurrence

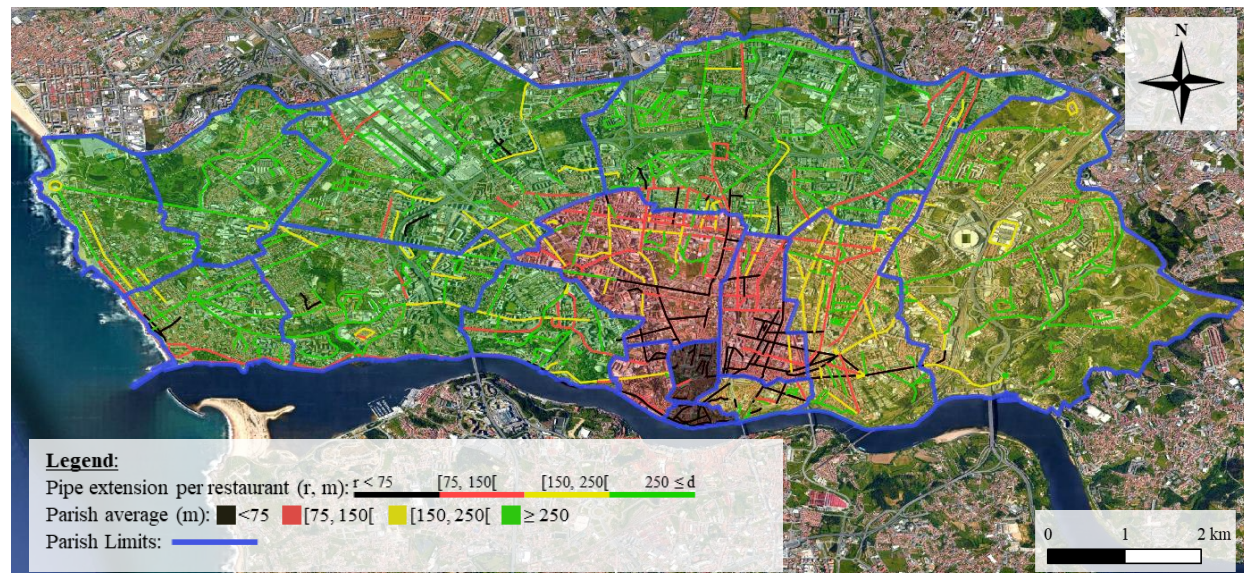


Figure 43: Restaurant presence on parish scale. Results based on Table D-2

Restaurants are heavily located in the central part of the city, which is the area of the city that gathers the most interest from residents and tourists alike. The parishes with the worst conditions regarding restaurant presence are mostly the same that had previously displayed the most critical average pipe age and diameter values, with the exception of Foz do Douro and Paranhos, which are the most peripheral of the mentioned parishes.

It is worth noting how the Vitória parish combines an average pipe extension per restaurant of under 75 m and an average pipe diameter under 175 mm, being the only parish to display both indicators in their most critical classes. Cedofeita, Miragaia and Santo Ildefonso also display considerably poor performance from both aforementioned indicators. All of these parishes overlap with or are located in the periphery of Porto's historical centre, which indicates that most of their wastewater drainage pipes are also very old, as can be observed in Figure 15 of section 3.2.2. It is, therefore, logical that, by displaying worse than average values in every indicator analysed, these parishes are the ones displaying higher interventions per pipe km per year values, as observed in Figure 26 of section 4.3.1.

4.3.5. Pipe Inclination

Pipe inclination was previously described as theoretically being capable of considerably influencing a pipe's performance. This was due to pipes with very low inclinations being associated with more frequent interventions, as water flows slower and therefore the likelihood of build-ups capable of obstructing a pipe forming increases. AdP's current internal regulations indicate an inclination of 0.3% as the minimum adequate inclination and a maximum of 15%, in order to limit the wastewater's flow velocity.

4.3.5.1. Statistical Analysis

When analysing pipe performance indicators regarding whether their value should be essential for considering a pipe (meaning pipes without it would be excluded from analysis), pipe inclination was not established as essential. As such, approximately 10% of the 6,857 considered pipes lacked information regarding inclination. Considering this was a rather high percentage and without having an acceptable criterion for attributing a certain inclination value to pipes lacking it, the statistical analysis on both pipe and street scale was then performed without considering these pipes.

The first category created included pipes with inclinations below 0.5%, considered to be too low. The following three categories each represented similar pipe extension percentages, with inclinations ranging from 0.5 to 1, 1 to 2, and 2 to 5%. The remaining category included pipes with inclinations above 5%. Considering the low representation of pipes with over 15% inclination within the network, no category was created to specifically include pipes with that characteristic. Results are presented in Figure 44.

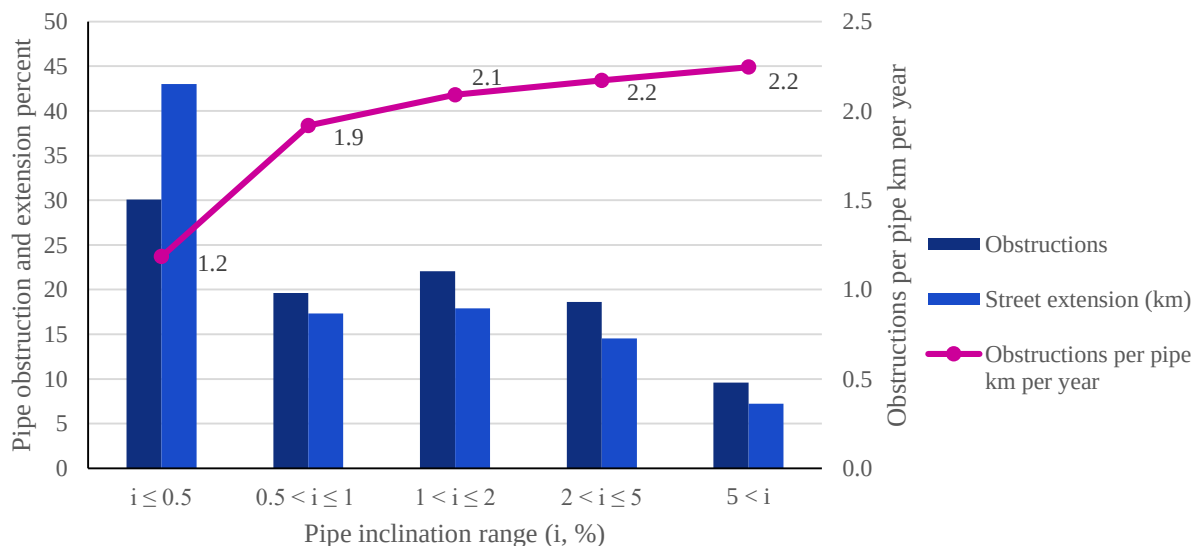


Figure 44: Pipe inclination influence on obstruction occurrence. Results based on Table B-4

Analysis on pipe scale showed that pipes with lower inclinations displayed less obstructions per pipe km per year, with the category of pipes with less than 0.5% inclination displaying not only the best performance but also being the only category performing below the average of 1.64 obstructions per pipe km per year. Such results were considered highly questionable, as they contradicted the theoretical knowledge regarding pipe inclination. Nonetheless, a similar analysis was performed on street scale in order to verify whether results remained consistent regardless of scale, as had been the case for the three indicators that had previously been analysed. This analysis is presented on Figure 45.

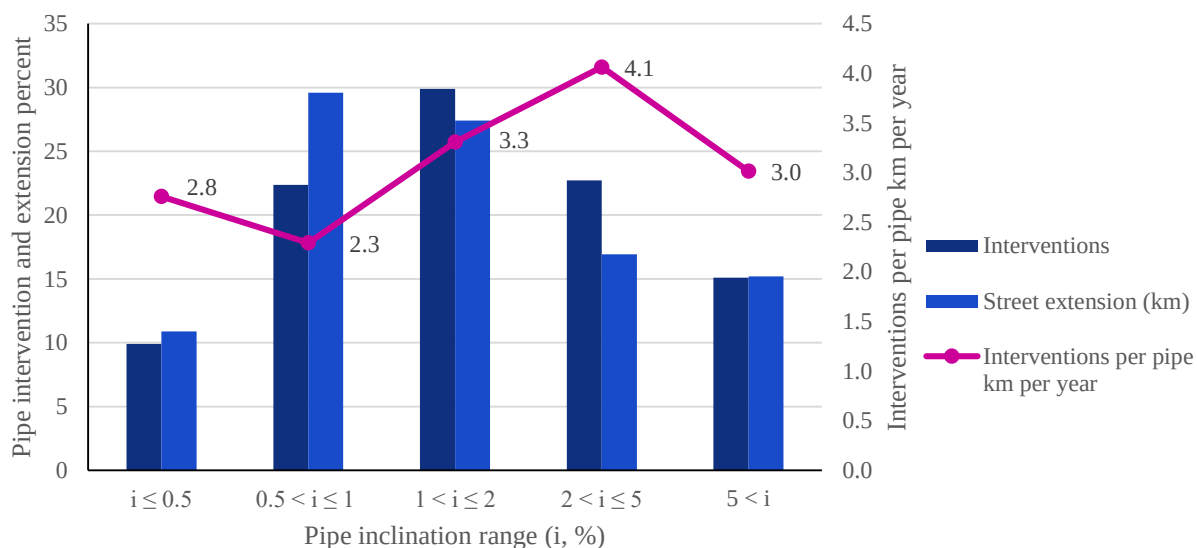


Figure 45: Average street pipe inclination influence on intervention occurrence. Results based on Table C-4

As can be observed, there is no discernible connection between the average street pipe inclination and the performance of streets. This could be attributed to the influence of pipe inclination being reduced when compared to other indicators such as pipe diameter or restaurant presence, meaning these indicators could be disrupting the results of pipe inclination analysis. Another hypothesis for having obtained inconsistent results regarding this indicator is that either the initial sample was not representative enough, as 10% of the pipes were excluded, or a certain amount of pipes had not been associated with their real inclination value. The latter seemed reasonable to assume, since it would be uncharacteristic of a wastewater drainage network operating on gravitational flow to have over 40% of its pipe extension with an inclination below 0.5%.

It was decided not to consider the influence of pipe inclination in the pipe and street classification process, as results raised doubts regarding the information sample extracted and suggested pipe inclination influence on pipe and street performance might be negligible when compared to the influence displayed by other indicators.

4.4. Impact Analysis

Having analysed the indicators of actual and expected pipe and street performance, it was then important to quantify the impact of an intervention for each street. The impacts an intervention can have on a street depend on the type of intervention and can manifest as both consequences of the cause of the intervention and consequences of the intervention itself. For reactive interventions, performed after the occurrence of an obstruction, impacts are mainly associated with disturbances on the client's end of the network, sightings of water reaching street level and potential damages in the buildings connected to the network (mostly associated with floods). Planned interventions are mostly associated with longer partial or total conditioning of street lanes, as these are lengthier since they are usually performed in high percentages of the street's pipe extension. It's reasonable to state that pipe obstructions can negatively impact a company both monetarily and in reputation, which must be considered a bigger impact than the discomfort caused by any street conditioning associated to planned intervention.

The following analysis of potential impact indicators was performed with the intent of developing a classification methodology for the impact associated with a street, which can then be used to prioritize streets in order to avoid negative impacts for all parties.

4.4.1. Equivalent Consumers per Street Extension

The use of water consumption per pipe extension associated to a certain street as an indicator of the street's performance was considered during the development of this work. This indicator was created by first collecting information regarding the total water consumption associated with each street during the year of 2019. The values of yearly consumption were converted to daily values and divided by each street's pipe extension (km) and by the city's daily average consumption of one inhabitant (140 L per day) (Águas do Porto E.M. 2020), producing an indicator of equivalent consumers per street extension, which could be used to express the amount of wastewater passing through each street's pipes, on average, or to express the amount of people that could be affected by or exposed to the consequences of a pipe obstruction. This indicator allows for areas with few residents but with high commercial activity and restaurant presence to be accurately represented, as the average consumption of the area is assumed to be more accurate than indicators such as population or employment density. Statistical and geographical analyses were performed. They are presented on Figures 46 and 47.

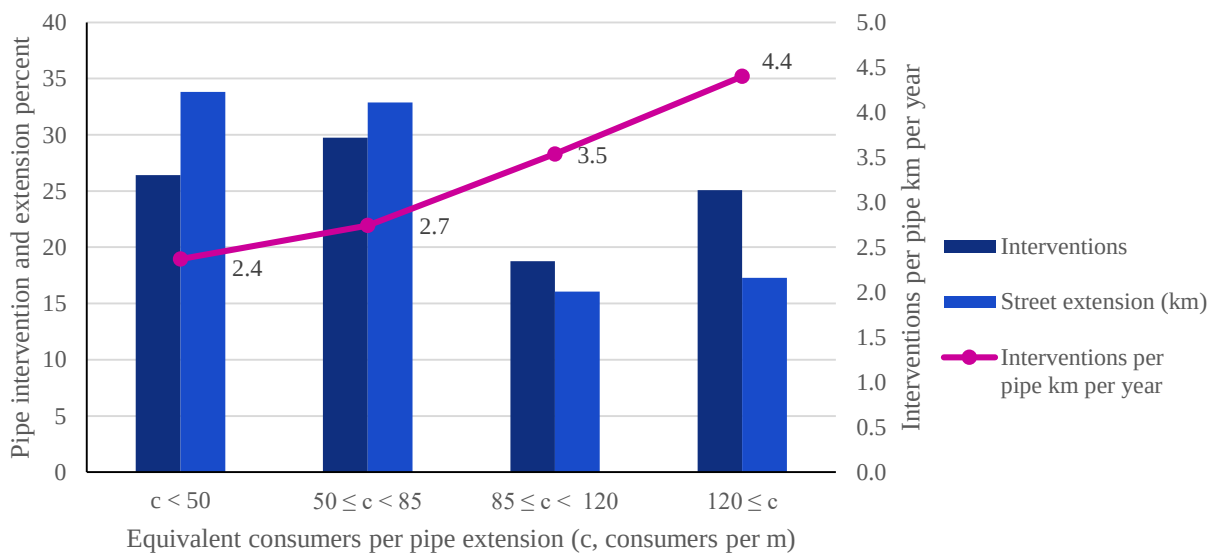


Figure 46: Equivalent consumers influence on intervention occurrence. Results based on Table C-7

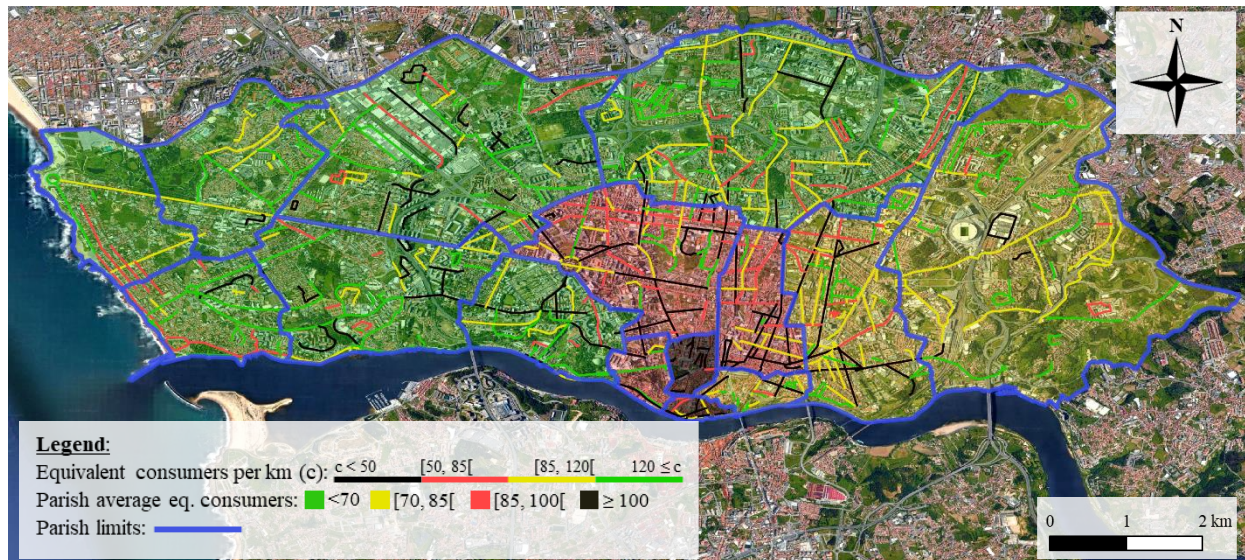


Figure 47: Equivalent consumers per street extension, on parish scale. Results based on Table D-2

Results show that streets with more equivalent consumers per pipe km do display a higher amount of interventions per km per year, but whether it can be stated that water consumption alone is responsible for such results is unclear. The primary argument supporting this is that there is considerable geographical overlap between streets with high water consumption and streets with high restaurant density, barring a few exceptions (namely streets near university campuses). This does not necessarily imply that the higher amounts of water consumption are due to the presence of restaurants, although it would be fair to assume they are indeed impacted by such presence. What it does imply is that restaurant presence might be responsible for the apparent criticality of streets with high water consumption. While both indicators describe the contents inside the pipes, restaurant presence provides insight to the amount of grease that may pass through the pipes, while the total wastewater volume does not. Considering a high grease percent is more critical than high volume of water, restaurant presence was selected as the indicator used to represent a street's wastewater content. Furthermore, a similar argument could have been made for the overlap of high consumption streets with low diameters and older pipes, which were previously described as being most prominent in central areas of the city. Another argument could be made for the statistical analysis of restaurant presence providing a higher discrepancy between the values of its classes, leading to more meaningful classification. It is worth noting that none of the considered indicators provides information regarding the actual wastewater flow for any given street, as this depends not only on the consumption associated to it but also on the flow that enters the street from streets upstream in the network.

The equivalent consumers per pipe extension parameter was instead used as an indicator of the impact associated with each street. Streets with more equivalent consumers per pipe extension are either densely populated or have commercial or industrial activities with high water consumption. Obstruction occurrence can impact streets in either situation. Densely populated streets have high impact likelihood if the effects of an obstruction are felt in the houses of the clients. While this is also true for streets in commercial and industrial areas, these streets also present a higher likelihood of more people being exposed to pipe obstructions, should water reach street level.

4.4.2. Street Level Impact

As stated before, intervening in a wastewater drainage network can produce two main types of impact on street level. Intervening after an obstruction has occurred involves the risk of water reaching the street or causing floods somewhere in the network. While the potential impact of floods can be estimated with the previously presented equivalent consumers per street extension indicator, an alternative method of estimating street level exposure to pipe obstructions was developed. Planned intervention's most relevant form of impact was considered to be traffic conditioning and, as such, analysis was performed in order to determine which streets should be intervened obeying to specific measures, and which measures should be taken.

4.4.2.1. Street Conditioning

With the city of Porto having a population of 237.591, as of the 2011 censuses, and with there being a high amount of employment related displacements of inhabitants between Porto and its surrounding cities, naturally a considerable amount of the city's streets suffers from traffic congestion. AdP currently operates according to time restrictions established by the Municipal Department of Mobility and Public Road Management of the Porto City Hall. These restrictions are applied for a certain amount of referenced streets and serve the purpose of preventing street level interventions that would require partial (see Figure 48) or total lane cuts, in an effort to prevent further traffic congestion. As such, they are enforced during pre-determined peak hours regarding the traffic patterns of the city.



Figure 48: Proactive intervention with partial lane cut

The unrestricted intervention times for referenced streets are presented on Table 10. Figure 49 provides a geographical representation of the referenced streets that coincide with the previously selected critical streets associated with Porto's domestic wastewater drainage network.

Table 10: Table of hourly restrictions for traffic conditioning (Porto City Hall 2020)

Traffic Conditioning Type	Unrestricted Intervention Time	
	Referenced streets	Non referenced streets
Partial lane cut	Every day, from 00h to 07h, 10h to 16h and 21h to 24h	Without time restrictions
Total lane cut	Every day, from 00h to 07h and 21h to 24h	Without time restrictions

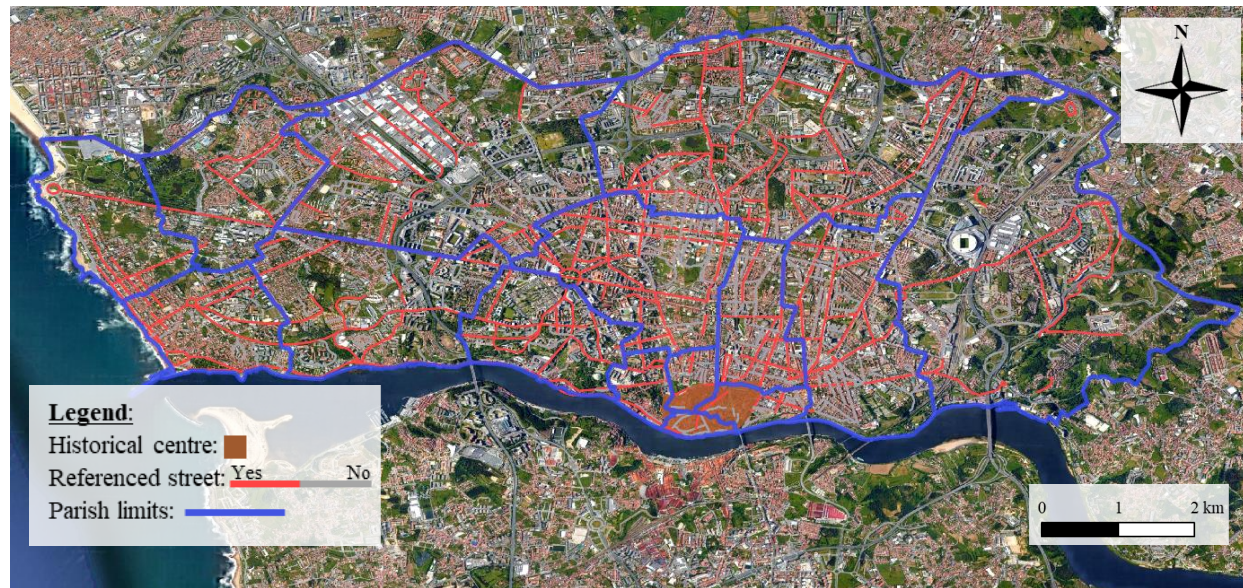


Figure 49: Selected streets referenced for having time restrictions for interventions

Regardless of whether an intervention on a referenced street requires a partial or total lane cut, it can be observed that, for these streets, interventions cannot be performed from 00h to 07h and from 21h to 24h. The additional unrestricted time for interventions requiring partial lane cuts implies that the periods from 07h to 10h and 16h to 21h are the peak traffic congestion periods.

The geographical representation of the referenced streets that had been previously selected for analysis shows how these are characterised by being the most central and longest of the city. It had been expected that a higher amount of streets located in the historical centre of the city would have been referenced, as this area is characterised by poorly accessible streets. It can be assumed that most of the streets belonging to the historical centre were not referenced as traffic in the area is itself limited, allowing for interventions to be performed with lesser impact. However, interventions are typically performed resorting to a tank truck, meaning that intervening in the streets of the historical centre still implies a certain difficulty in access some streets and a consequent impact on street level. It was therefore established that, for this work, streets located in the historical centre of the city should be analysed similarly to referenced streets.

Firstly, as has been previously performed regarding other indicators, the interventions per pipe km per year between categories that, in this instance, described whether a street was located in the historical centre, or whether it had been referenced, were compared. The results are presented on Figure 50.

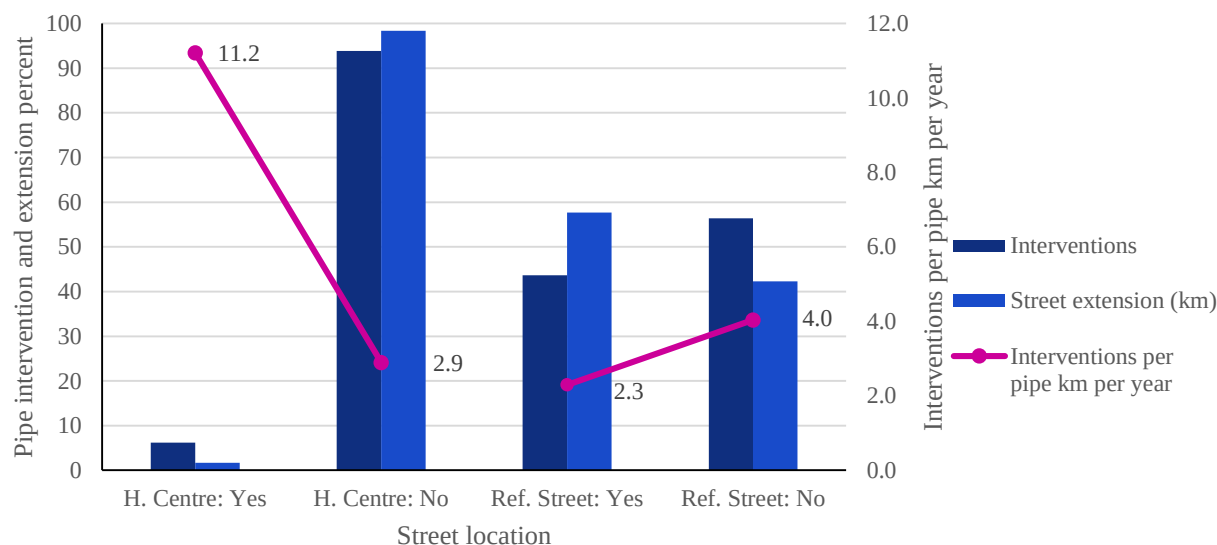


Figure 50: Street characteristics' influence on pipe performance

Streets located in Porto's historical centre, albeit constituting a small sample of the selected critical streets, displayed a very high value of interventions per pipe km per year, which cannot be dismissed. The value itself can be explained by the geographical analysis performed on several expected pipe performance indicators, such as pipe age, pipe diameter and restaurant presence per pipe extension, based on which it was concluded that areas within and in the periphery of the historical centre featured pipes that combined some of the worst operating conditions in the entire network. Additionally, though, the value suggests that, for an updated PIP, interventions in the historical centre are likely to be fairly regular. Therefore, considering the time restrictions in place and the difficulty of access to certain streets, the location of a street within the historical centre should be prioritized, as pipe performance is poor and obstruction occurrence is associated to a wide variety of impacts.

Analysis on referenced streets concluded that, despite involving a much more considerable street level impact, performance-wise these streets display better values than non-referenced streets. This could possibly be explained by these streets possessing better pipe characteristics as a consequence of the central places they occupy within the network, such higher diameters. Analysis of expected performance indicators was, therefore, performed in order to confirm this hypothesis. It is presented on Table 11.

Table 11: Relevant performance indicator analysis for streets with different characteristics

Parameter	Description	Average diameter (mm)	Restaurants per km
Historical Centre	No	203.4	5.3
	Yes	194.3	38.6
Referenced Street	No	194.2	6.1
	Yes	209.9	5.7

Referenced streets do have a considerably higher average diameter, which can be associated to their better performance. The difference in restaurant presence between referenced and non-referenced streets appears to be negligible. Regarding the historical centre of the city, the analysis presented in Table 11 suggested that both pipe diameter and restaurant presence can undeniably be pointed out as responsible for the poor performance of the streets in that area of the city.

4.4.2.2. Public Exposure to Obstructions

The alternative way of estimating the amount of people exposed to obstructions on street level that was developed consisted of associating streets with points of interest around which crowds can form, such as public transport stations, health care institutions, small businesses and big commercial surfaces. Each point of interest type was assigned a reasonable weight based on how its presence contributes to an increase in the amount of people walking in the street. Street characteristics such as being located within Porto's historical centre or having previously been referenced as particularly congested regarding traffic were also considered. The attributed weights are presented on Table 12:

Table 12: Parameters considering in estimating public exposure to obstructions and respective associated weights

Category	Parameter	Weight
Location	Historical centre and/or referenced	10
Public transportation stations	Bus	2
	Subway	5
	Train	5
Services	Commerce (large scale)	10
	Commerce (small scale)	2
	Health care	5
	Restaurants	1

The total amount of weights attributed to each street was divided by the street's pipe extension in order to create an indicator that quantitatively represents the expected street level exposure to obstructions for each street. An average value of 54 points per pipe km was obtained for selected streets, and it was established that 200 points per pipe km would represent the maximum impact, with streets associated to higher values being considered as having achieved this score. The geographical representation of the developed street level exposure indicator, as well as the aforementioned street characteristics and points of interest is presented below, in Figure 51. Restaurant location was not included, as it had already been presented in Figure 41 of Chapter 4.3.4.

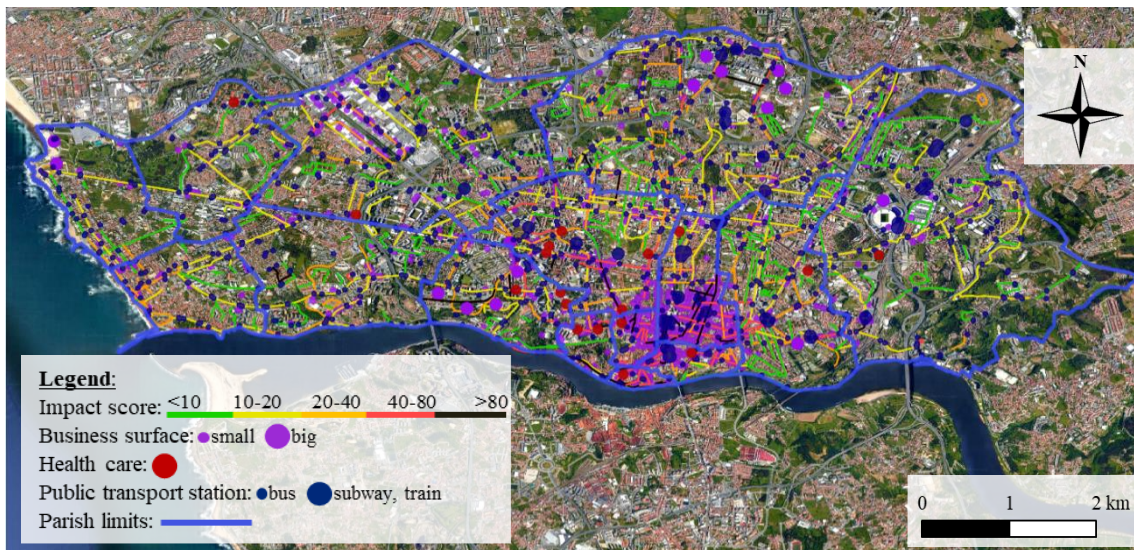


Figure 51: Street level exposure to obstruction occurrence estimation

It can be observed that, similarly to restaurants, small scale services are predominantly located near the city's centre, in the Cedofeita, Santo Ildefonso, Sé and Vitória parishes, indicating that these areas display both higher sensibility to obstruction occurrence and higher expected impact on establishment and street level.

4.5. Classification Methodology

The previously presented analysis was performed with the intent of providing the foundations for the development of classification methodologies adapted to Porto's domestic wastewater drainage network on both pipe and street scale. Analysed indicators provide information regarding the network's expected performance, based on pipe and street characteristics, its actual performance, measured by both obstruction and intervention count per pipe km per year, and regarding the potential impact associated with network obstructions or proactive interventions.

The categories of each indicator that was considered to be relevant were first classified by being assigned weights between 0 and 10, determined according to the analysis of the network's reality. For a certain street or pipe, being assigned a weight of 0 regarding an indicator means that the indicator had negligible influence over the street or pipe's performance or impact, whereas a weight of 10 means a very strong influence. Indicators were then attributed weights within each category, determined by the amount of influence displayed in the prior analysis. Indicators of Actual Performance, Expected Performance and Impact were created for both pipes and streets. A global Performance indicator was created by considering both actual and expected performance, and the criticality of streets and pipes was then evaluated through the results of multiplying the global Performance and Impact indicators.

The previously described classification procedure was used similarly for pipes and streets. However, as can be discerned from the analysis of some performance and impact indicators, pipe classification could not be developed completely independently from street classification, due to the inability of quantifying indicators such as restaurant presence and obstruction and street level impact at pipe scale. Nevertheless, an assumption was made, when classifying a certain pipe, that the aforementioned indicators varied little along the pipe's associated street and, therefore, pipes were classified with the indicators of the streets in which they were installed. This was considered to be accurate for the vast majority of the selected streets, of which 318 of the 468 streets had pipe extensions below the sample average of 551.0 m, allowing for little indicator variation. Streets with very high pipe extension, however, might have justified being divided into sections, allowing for a more precise analysis.

Considering, along with the aforementioned limitations regarding pipe indicators, that planned intervention is most commonly performed in a considerable amount of a street's pipe extension, if not the whole extension, street classification was established as the central point of this work, with pipe classification providing complementary information regarding street criticality and insight into critical street sections.

4.5.1. Street Scale Classification

4.5.1.1. Actual Performance

The actual performance of streets was evaluated solely through the interventions per pipe km per year indicator. The selected streets had averaged 3.03 interventions per pipe km per year, with 218 out of 468 performing above this average. The value of 10 interventions per pipe km per year was attributed the maximum weight of 10, meaning approximately 10% of the network's streets were classified as having performances deemed the worst, within reasonable limits. Having only selected streets with at least 3 interventions over the considered ten-year period, streets with the lowest interventions per pipe km per year value (in the case of this analysis, 0.3, meaning the streets had been intervened 3 times in 10 years) were classified with a null value for this indicator. The remaining streets were classified with linearly proportional weights, between 0 and 10. The distribution of assigned weights compared to indicator values can be observed below, in Figure 52.

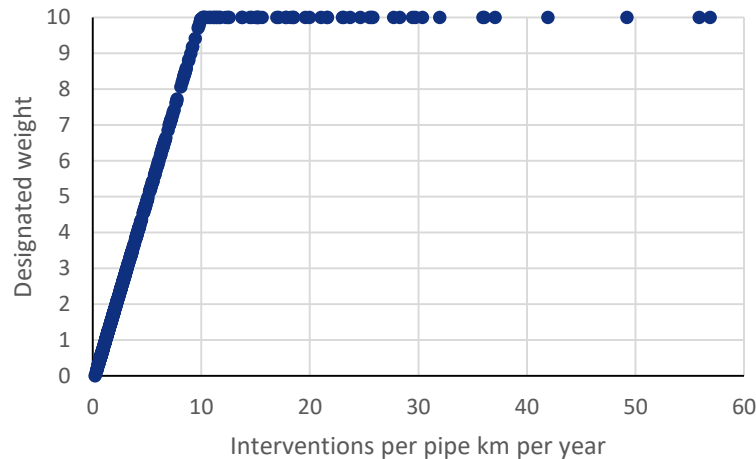


Figure 52: Interventions per street extension per year classification

4.5.1.2. Expected Performance

Expected performance indicators analysed included average pipe age, diameter, inclination and restaurant presence. Pipe material was also analysed, although not to the extent of the remaining indicators. This indicator was disregarded at street scale, given the low representation of every pipe material aside from stoneware. Results regarding average pipe inclination were deemed inconclusive, leaving the three remaining indicators to be considered, along with pipe material.

The average pipe age of the selected streets ranged from 6 to 92, with an aforementioned average of 56.9 years. When analysing the influence of a street's average pipe age in intervention occurrence, the categorization of pipes had been done considering the lifespan of stoneware and cast iron, which is approximately 60 years (Scope Metals Group 2020).

It had been hypothesised that, even assuming pipes can perform near the full extent of their capacity, performance would surely start to deteriorate sometime after the lifespan was reached. An average age of 70 years was defined as the age from which age related issues should start being considered. As such, a weight of 10 was assigned to streets with average pipe ages equal to or above 70 years. A weight of 5 was assigned to streets with an average pipe age of 60 years, marking the theoretical point in time from which they may start underperforming. Lastly, the weight of 2 was assigned to streets with average pipe age of 30, with the intention of slightly distinguishing the criticality of average ages under 30 years and between 30 and 60 years. The weights attributed between the 0 to 2, 2 to 5 and 5 to 10 intervals were linearly proportional within each range.

The visual representation of the weights and values can be observed on Figure 53.

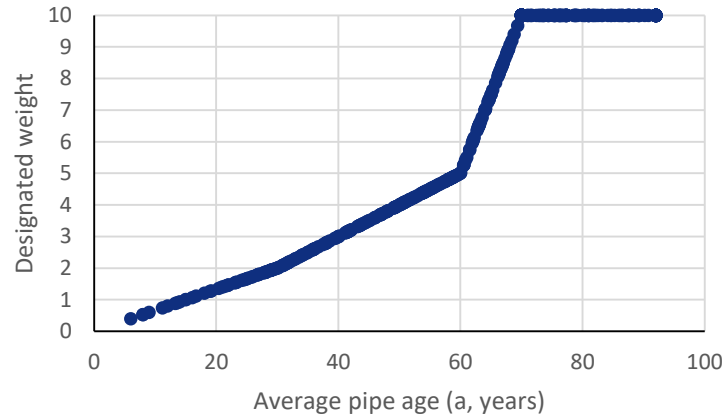


Figure 53: Average street age classification

Average pipe diameter below 200 mm had been observed to negatively influence street performance considerably more than higher diameters, with average pipe diameters under 175 mm proving particularly critical. This indicator was therefore classified in order to reflect this. The minimum average pipe diameter of 125 mm (verified in streets in which all installed pipes have this diameter) was assigned a weight of 10, signifying the worst possible conditions in the network regarding pipe diameter. Weights of 8 and 4 were assigned to 175 and 200 mm pipes, in an attempt to represent the high discrepancy observed in the intervention occurrence associated with streets with these two pipe diameter averages. The highest average diameter verified in a selected street was attributed a null weight, with all remaining indicator values being attributed linearly proportional weights within aforementioned ranges. Figure 54 provides a visual representation of the weight to indicator value comparison.

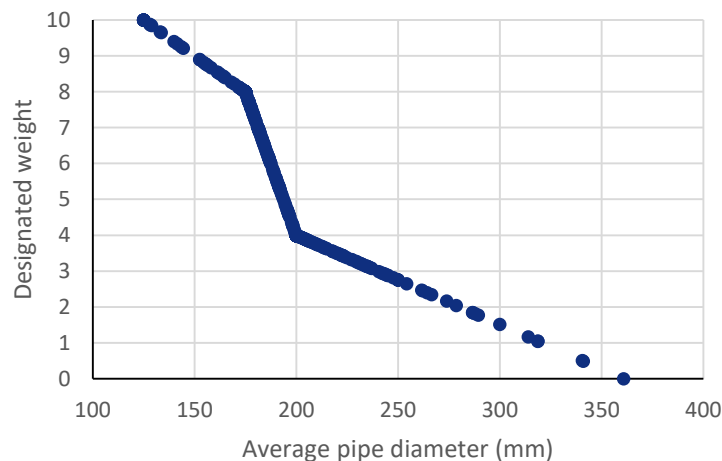
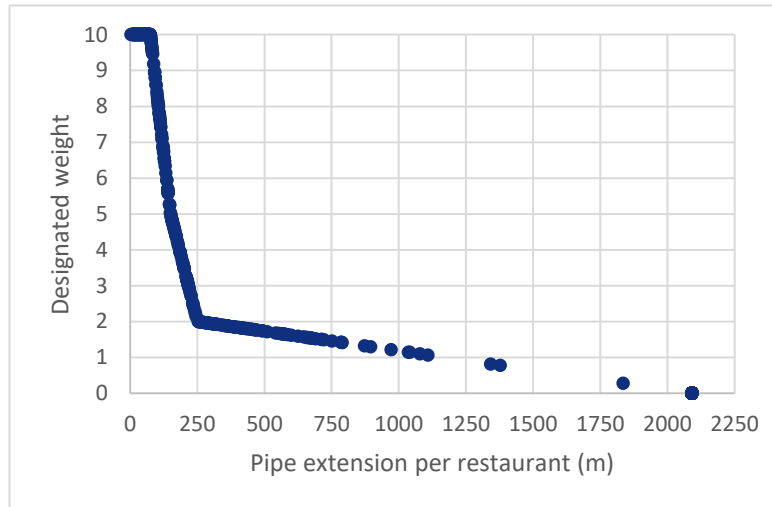


Figure 54: Average street diameter classification

Restaurant presence had been evaluated through the pipe extension per restaurant indicator, which represented a theoretical average distance between each of the street's restaurants, in an attempt to represent their significance to the network's performance. Analysis showed how very high restaurant presence often leads to very poor street performance. The indicator was concluded to be partially influenced by average pipe diameter, but its influence on network performance was also clearly observed within several diameter ranges. As such, this indicator was classified independently from pipe diameter.

Analysis had suggested that restaurant influence negatively influenced street performance when there were less than 150 pipe m per restaurant in streets, with very critical intervention per pipe km per year values being displayed when considering streets with under 75 pipe m per restaurant. The latter were classified with a weight of 10, representing the maximum influence of restaurant presence in street performance. A value of 5 was assigned to streets with 150 pipe m per restaurant, as these streets displayed only slightly above average interventions per pipe km per year. Streets with over 150 pipe m per restaurant were shown to perform better than the average street and, as such, were attributed lower weights, while streets without restaurants were grouped with the street with the highest amount of pipe m per restaurant and attributed a null weight. The representation of the described classification can be observed on Figure 55.



Streets either located within the city's historical centre or previously referenced in the work performed by the Municipal Department of Mobility and Public Road Management were automatically assigned a weight of 10 for the Intervention Conditioning indicator, with the remaining streets being assigned a null weight.

4.5.1.4. Criticality

The classification methodology used attempted to accurately combine the previously classified indicators. It is presented on Equations 4-1 to 4-5. Actual performance was evaluated solely through the interventions per pipe km per year indicator. A street's expected performance was evaluated by average pipe diameter (65%), restaurant presence (25%) and average pipe age (10%). The weights of each indicator attempted to differentiate them according to their influence in street performance. The influence of average pipe diameter had been very clearly identified, while analysis of restaurant presence had also suggested considerable influence, although usually verified in low diameter pipes. Average pipe age was considered a less determining factor regarding street performance, but its influence was nonetheless verified and it was logical to consider this indicator, despite its lower associated weight. When classifying performance as whole, a higher weight was assigned to actual performance, as it indicates the real performance that streets display, while the expected performance indicator provides information regarding the theoretical criticality of the street's conditions. The impact of the consequences of obstructions was considered to be considerably higher than the impact of performing interventions and, the impact indicator was created accordingly. Criticality was obtained by multiplying the Performance and Impact indicators. It was divided by 10 so its values range from 0 to 10, similar to all other indicators.

$$\text{Actual Performance} = \text{Interventions per pipe km per year} \quad 4-1$$

$$\text{Expected Performance} = 0.10 \times \text{Avg. Pipe Age} + 0.65 \times \text{Avg. Pipe Diameter} + 0.25 \times \text{Restaurant Presence} \quad 4-2$$

$$\text{Performance} = 0.65 \times \text{Actual Performance} + 0.35 \times \text{Expected Performance} \quad 4-3$$

$$\text{Impact} = 0.8 \times \text{Equivalent Consumers per pipe km} + 0.2 \times \text{Intervention Conditioning} \quad 4-4$$

$$\text{Criticality} = \frac{\text{Performance} \times \text{Impact}}{10} \quad 4-5$$

4.5.2. Pipe Scale Classification

4.5.2.1. Actual Performance

Similarly to the criteria used for street classification, actual pipe performance was solely evaluated through an interventions per pipe km per year indicator, which effectively was an obstructions per pipe km per year indicator as only information regarding obstruction occurrence had been collected. The value of 25 obstructions per pipe km per year was assigned the maximum weight of 10. Approximately 10% of the 936 pipes with at least one obstruction over the selected five-year period displayed indicator values over the established maximum value of obstructions per pipe km per year, and were therefore deemed to be severely underperforming. The average of the previously mentioned indicator for pipes with at least one obstruction registered (9.3 obstructions per pipe km per year) was considered, rounded to 10 and assigned a weight of 5. The remaining indicator values were assigned linearly proportional weights within the 0 to 5 and 5 to 10 intervals, with pipes without registered obstructions being assigned a null weight.

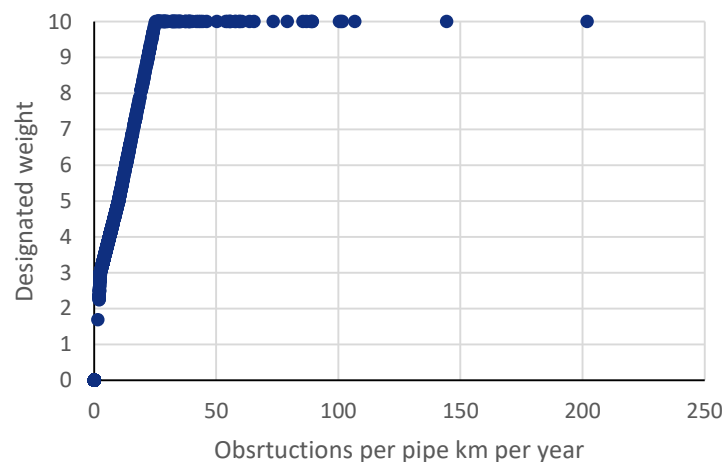


Figure 57: Obstructions per pipe extension per year

4.5.2.2. Expected Performance

When classifying the average pipe age on street scale, the influence of pipe material had been disregarded, as most materials are considerably under represented within the network as a whole and, consequently, within the selected streets as well. On pipe scale, however, pipe material is relevant, as it can greatly influence the pipe's lifespan. As such, pipes made from plastic based materials were assigned weights of 10 due to their relatively short lifespan of 30 years, while the remaining pipes, mainly made of stoneware and cast iron, were classified with weights consistent with those that had been used during street scale average pipe age classification (Figure 53).

Pipe diameter classification followed the same overall logic used for street scale average diameter classification (Figure 54). Small weight adjustments were made in order to better represent analysis performed for this indicator, which had shown that street scale pipe diameter averages of 175 and 200 mm (weights of 8 and 4, respectively) were associated with worse performance than the same values on a pipe scale. Weights of 7 and 3 were assigned to these pipe diameters. The highest pipe diameter (500 mm) was assigned a null weight. The classification of this indicator can be seen on Figure 58.

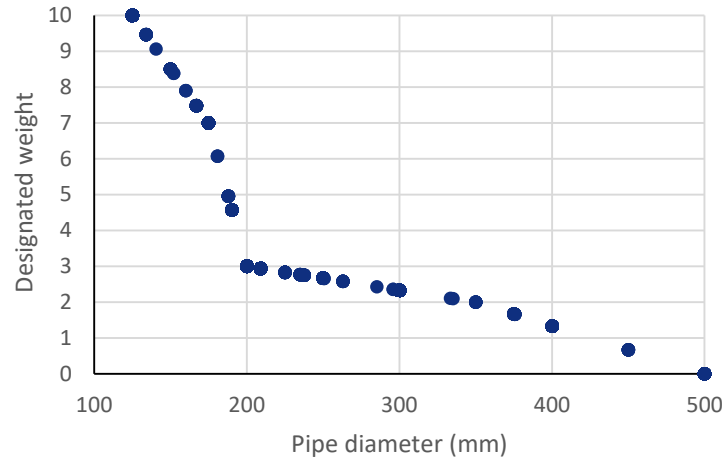


Figure 58: Pipe diameter classification

As previously stated, the classification process regarding restaurant influence was not performed on pipe scale. As such, each pipe was classified with the weight attributed to the indicator's value associated to the street in which the pipe was installed.

4.5.2.3. Impact

Similarly to the restaurant presence indicator, impact was not classified on pipe scale, with each pipe assuming the weights attributed to the street in which it was installed.

4.5.2.4. Criticality

The classification methodology of the network's criticality on pipe scale (Equations 4-6 to 4-10) was developed similarly to the one on street scale (Equations 4-6 to 4-10). Small adjustments were made in order to represent the Actual and Expected Performance indicators on pipe scale. Pipe age and material were classified together and assigned a weight of 20% within the Expected Performance indicator. Consequently, the weights assigned to pipe diameter and restaurant presence were reduced by 5% each.

$$\text{Actual Performance} = \text{Obstructions per pipe km per year} \quad 4-6$$

$$\text{Expected Performance} = 0.20 \times \text{Pipe Age and Material} + 0.60 \times \text{Pipe Diameter} + 0.20 \times \text{Restaurant Presence} \quad 4-7$$

$$\text{Performance} = 0.65 \times \text{Actual Performance} + 0.35 \times \text{Expected Performance} \quad 4-8$$

$$\text{Impact} = 0.8 \times \text{Equivalent Consumers per pipe km} + 0.2 \times \text{Intervention Conditioning} \quad 4-9$$

$$\text{Criticality} = \frac{\text{Performance} \times \text{Impact}}{10} \quad 4-10$$

4.5.3. Proactive Intervention Plan Foundations

The criticality of pipes and streets was determined through the formerly presented methodology in order to provide the foundations for the development of a Proactive Intervention Plan for Porto's domestic wastewater drainage network. It was established that this plan would be defined based on the street scale Criticality scores, considering the aforementioned characteristics of planned intervention.

It was determined, during the validation of the case study's main hypothesis, that planned intervention in a certain street (as opposed to intervening reactively) leads to an average 56% increase in the time until the next intervention in the same street. Despite certainly being a reasonably accurate value, the assumptions made for the analysis raised concerns over considering such a high value. A more conservative approach was taken, and it was assumed that, in the overall context of the network, a 40% increase in time until the next intervention was an adequate value for the development of the plan.

During the development of this work, the intervention frequency of selected streets was determined and can be observed in Table F-1. The main concept for the development of the PIP was that, if a street with an average Criticality score has displayed an intervention frequency of x , then the street's proactive intervention frequency should be 40% higher (i.e. $1.4 \times x$), theoretically allowing for a reduction in obstruction occurrence. The aforementioned value refers to a conservative approach to the 56% increase in intervention free number of day, formerly presented in Figure 23, section 4.2. It is worth noting that, while no reasonable proactive intervention frequency will ever fully eliminate the likelihood of obstruction occurrence, it is logical to assume that the closest proactive intervention frequency is to the actual intervention frequency displayed so far, the lower the likelihood of obstruction occurrence is. Considering the streets included in the selected portion of the network are associated with a wide range of Criticality scores, the relation between proactive and actual intervention frequency should not be the same for all streets, and should instead be adjusted to each street's own Criticality scores. That is, the more critical streets should have higher proactive intervention frequencies, in order to further reduce the likelihood of obstruction occurrence, with less critical streets being assigned lower proactive intervention frequencies. This was implemented by creating a multiplier ranging from 1 (for a Criticality score of 10) to 2 (for a Criticality score of 0), by which the actual intervention frequency of a street is multiplied, in order to determine its adequate proactive intervention frequency. The value distribution of this multiplier is presented below, in Figure 59.

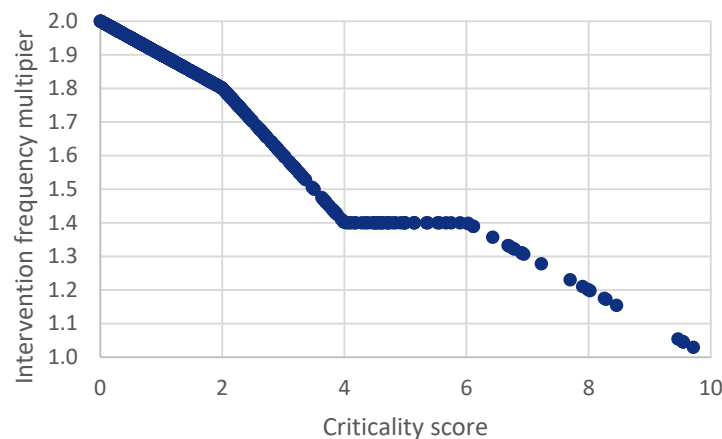


Figure 59: Intervention frequency multiplier vs Criticality score

4.6. Machine Learning Model Development

The main focus of the classification methodology was to associate each selected street with a value representing its criticality, regarding the need for adequately timed planned intervention. Therefore, all ML models developed aimed to estimate the criticality of streets by using as input the performance and impact indicators analysed in subchapters 5.3 (Performance Analysis) and 5.4 (Impact Analysis). The previously presented PIP should be interpreted as merely an example of what can actually be implemented, as more insight is needed into specific characteristics of streets (such as known operation difficulties and other influencing factors) to properly establish a plan for the city's entire network. For these reasons, ML models used Criticality as output, and not the intervention frequency multiplier.

4.6.1. Information Spreadsheet

The information regarding every indicator was stored in a MS Excel spreadsheet (seen in Figure 60), with integrated Visual Basic code allowing for a quick way to update the spreadsheet and the indicator values whenever an obstruction occurred (through the "Update Variables" button). The training sets for ML were created in this spreadsheet, and it is also where ML results at any certain point in time can be exported to, being immediately multiplied by the formerly introduced proactive intervention multiplier and consequently updating the adequate intervention frequency for each street. The dates of the last intervention in each street were registered, along with the type of said intervention. This allows for the possibility of determining how many days are left until each street should be proactively intervened once again. Since every street is associated to one or more parishes, it is, therefore, possible to determine the parish that should be intervened next. Similarly, priorities regarding the PIP can be established.

Update Variables	Latest Date: 27/12/2019		Pipe Characteristics						Street Characteristics				
	Latest Street: 1		Lengths (m)		Pipe Age (years)		Pipe Diameter (mm)		Restaurant Presence		Equivalent Consumers		
	Intervention Type: P		Pipes	Street	Avg. Inst. Year	Avg. Age	Minimum	Average	Count	Pipe M/Restaurant	Total Consumption (m3)	Daily Consumption (l)	Eq. Consumers
Street Code	ID												
24 DE AGOSTO, CAMPO	1		936.7	500	1957	51	175	314	4	234	24843	68063	486
ABADE DE FARIA, RUA	2		73.9	220	1987	33	200	200	0	No Restaurant	3493	9570	68
ABRACOS, RUA	3		122.1	200	1962	58	175	175	0	No Restaurant	3397	9307	66
ACACIO LINO, RUA	4		100.4	140	1950	70	175	181	0	No Restaurant	125	342	2
ACADEMICO FUTEBOL CLUBE, RUA	5		548.2	500	2005	15	200	200	0	No Restaurant	25464	69764	498
ACTOR FERREIRA SILVA, RUA	6		541.5	850	1957	63	175	199	1	542	1502	4115	29
ADELAIDE ESTRADA, RUA	7		275.1	170	1989	31	200	200	0	No Restaurant	21576	59112	422
ADOLFO CASAIS MONTEIRO, RUA	8		307.8	350	1942	76	175	191	4	77	10779	29532	211
AGRA DO AMIAL, BAIRRO	9		193.8	265	1959	61	175	175	4	48	14490	39699	284
AGUAS, TRAVESSA	10		199.4	220	1950	70	175	196	0	No Restaurant	3169	8682	62
ALCACER CEGUEIR, RUA	11		132.9	180	1998	30	200	231	1	133	1470	4027	29
ALCANTARA, RUA	12		531.1	600	1962	60	200	203	0	No Restaurant	10975	30068	215
ALDOAR, BAIRRO	13		1172.3	300	1972	45	125	193	2	586	36676	100483	718
ALEGRIA, PRACA	14		783.6	350	1945	70	175	200	1	784	11187	30649	219
ALEGRIA, RUA	15		2090.7	2100	1937	82	175	175	13	161	181427	497060	3550
ALEIXO DA MOTA, RUA	16		412.8	400	1988	31	200	200	0	No Restaurant	48294	132312	945
ALEIXO, BAIRRO	17		425.2	580	1957	61	175	179	2	213	20642	56553	404
ALEXANDRE BRAGA, RUA	18		198.8	200	2001	19	200	361	5	40	6490	17781	127
ALEXANDRE HERCULANO, RUA	19		442.1	430	1931	89	175	175	10	44	34945	95740	684
ALFREDO KEIL, RUA	20		718.1	550	1950	70	200	200	0	No Restaurant	51925	142260	1016

Figure 60: Excerpt of the MS Excel spreadsheet used as ML support, showing the performance and impact indicators used

The values used during the classification process can easily be updated as more knowledge about the network is acquired and as AdP's records are improved (as can be the case with pipe inclination).

4.6.2. General Considerations

The specific street indicators used for the training of the ML models were the following:

- Performance indicators:
 - Interventions per pipe km per year;
 - Average pipe age;
 - Average pipe diameter;
 - Restaurant presence;
- Impact indicators:
 - Equivalent consumers per pipe extension;
 - Intervention conditioning score.

All indicator values were rescaled to a range of [0, 1] by dividing each value by the indicator's maximum value. Regarding the restaurant presence indicator, it was established that the value representing streets without restaurants would be 0.

The data set was composed of indicator information regarding each selected street at the time they were intervened, amounting to 7.817 independent examples. Several assumptions were made when creating this data set. Firstly, a street's average pipe diameter, restaurant presence, equivalent consumers per pipe extension and intervention conditioning score were assumed to have been constant throughout the considered 10-year period. These conditions were considered as few streets had pipes replaced over the considered time period and the change of the remaining indicators over the last decades was deemed to have been slow. Nonetheless, further work might benefit from updated indicator values. The interventions per pipe km per year and average pipe age indicators were adjusted to the time of each intervention, for every street. All models developed used a holdout of 80% and 20% for training and testing, respectively.

The ML models were developed using the Python programming language, resorting to libraries such as NumPy, matplotlib, pandas, scikit-learn and Seaborn (Pires 2020). The library hierarchy within the Python working environment is represented on Figure 61, while the computational environment details are on Table 13.



Figure 61: Python libraries used (Pires 2020)

Table 13: Computational environment details

Computational Environment Details	
CPU	Intel i5-8250U 1.60 GHz
Graphics card	NVIDIA GeForce MX130
RAM	8 GB
ML Model Development	
Integrated Development Environment	Pycharm 3.7
Language	Python

4.6.3. Classification Models

As addressed in Literature Review (section 2), supervised classification algorithms are used with the purpose of associating each set of input variables with an output class, with the possibility of working with two classes (binary classification) or more (multiclass classification). None of these scenarios involves having an output value that is continuous, as is the intended output of street criticality. As such, it was necessary to group the formerly obtained street criticality values in classes, prior to the development of the model. A similar procedure had already been made in section 4.4.3, where a multiplier range had been assigned to several criticality classes. One solution would have been to consider the average criticality within each class, and therefore later attributing it its associated multiplier, also the average within its own range. However, this presented a complication, in that classes containing the highest criticalities would have been severely unrepresented. As such, more representative criticality classes created in an attempt to both mitigate the aforementioned problem and remain true to the meaning associated to each class. Results are presented on Table 14.

Table 14: Street classes regarding Criticality score

Class	Criticality range (C)	Streets	Average criticality	Associated multiplier
1	$0 \leq C < 1$	195	0.51	1.95
2	$1 \leq C < 3$	174	1.79	1.82
3	$3 \leq C < 5$	63	3.92	1.42
4	$5 \leq C < 7$	23	6.08	1.39
5	$7 \leq C \leq 10$	13	8.59	1.14

While adjusting the criticality range within each class to the average class criticality did help prevent underrepresentation of streets within classes, the five created classes were still considered to be significantly unbalanced. Correcting this proved challenging, as further readjusting or lowering the number of classes would have resulted in loss of class representativeness regarding the Criticality scores.

The RF and XGB algorithms were used, due to the characteristics referred in Literature Review (section 2), such as not overfitting easily. Both classification models developed were evaluated with accuracy, f-measure, precision and recall scores. K-fold cross validation was also performed, with ten folds (i.e. $k = 10$).

The optimisation of the RF algorithm was largely dependent on one hyperparameter, which described the number of estimators (i.e. individual decision trees) to be used. The model was first tested using a minimum of 10 estimators, with further testing increasing estimator number by 10 up to a maximum of 200. Evaluated by both the aforementioned metrics and k-fold cross validation, it was observed that the model's performance improved until 100 estimators were being used, from which point it essentially stabilized. As such, the model was developed using 100 estimators. The Gini index was used as the model's criterion towards minimizing misclassification probability.

Similarly, the optimisation of the Gradient Boosted Decision Trees algorithm was also dependent on estimator number. The model was first tested with 10 estimators and estimator number was increased by 10 with each subsequent test, up to a maximum of 500, in an approach similar to that of a grid search. The evaluation of the model's performance showed significant improvements until 250 estimators were being used, with an increase of up to 250 further estimators resulting in very little improvement. Consequently, 250 estimators were used in the development of the model.

4.6.4. Regression Model

Regression models are used for the prediction of real values, meaning that, for these models, it was not necessary to adjust the formerly obtained criticality scores in any way. The model was developed using the Multi-Layer Perceptron Regressor algorithm (MLPRegressor), which is supervised learning ANN algorithm designed to learn functions through dataset training and specifically adapted for regression problems (Pedregosa 2011).

As previously mentioned, a proper definition of the hidden layer hyperparameter (whether in number of hidden layers or the neurons each layer has) is essential to obtain a good performance from the model. Based on Literature Review (section 2), the model was tested with one to three hidden layers, from which it was concluded that it performed the best with two. Using two hidden layers, the optimal neuron number was then tested following three base combinations: [10, 5], [5,10] and [5,5]. Each base combination was then doubled and tested until the combinations of [200, 100], [100, 200] and [200, 200] were reached. The model was then developed using two hidden layers with 100 neurons each.

Evaluation of the model's performance was done via the coefficient of determination (i.e. r^2 score).

5. Results and Discussion

5.1. Street Scale Classification

An overview of the results derived from the methodology presented in section 5.5 for the selected streets regarding the Performance and Impact indicators, is presented on Table 15, while results regarding the street Criticality indicator are on Table 16.

Table 15: Street performance and impact classification results by street count and percent

Indicator	Performance										Impact									
Score	1	2	3	4	5	6	7	8	9	10	1	2	3	4	5	6	7	8	9	10
Count	19	96	100	74	46	32	26	28	31	16	83	62	77	65	56	34	24	35	11	21
%	4.1	20.5	21.4	15.8	9.8	6.8	5.6	6.0	6.6	3.4	17.7	13.2	16.5	13.9	12.0	7.3	5.1	7.5	2.4	4.5

Table 16: Street criticality classification results by street count (A) and street percent (B)

Streets (A)		Impact										Streets (B)		Impact									
		1	2	3	4	5	6	7	8	9	10			1	2	3	4	5	6	7	8	9	10
Performance	10	2	1	1	2	4	1	0	0	0	5	Performance	10	0.4	0.2	0.2	0.4	0.9	0.2	0.0	0.0	0.0	1.1
	9	5	4	5	3	3	1	2	6	2	0		9	1.1	0.9	1.1	0.6	0.6	0.2	0.4	1.3	0.4	0.0
	8	5	2	2	5	3	3	0	4	0	4		8	1.1	0.4	0.4	1.1	0.6	0.6	0.0	0.9	0.0	0.9
	7	3	2	6	3	4	4	1	3	0	0		7	0.6	0.4	1.3	0.6	0.9	0.9	0.2	0.6	0.0	0.0
	6	7	5	1	3	2	2	2	5	1	4		6	1.5	1.1	0.2	0.6	0.4	0.4	0.4	1.1	0.2	0.9
	5	7	4	6	10	2	5	3	6	3	0		5	1.5	0.9	1.3	2.1	0.4	1.1	0.6	1.3	0.6	0.0
	4	9	11	12	7	13	5	9	4	1	3		4	1.9	2.4	2.6	1.5	2.8	1.1	1.9	0.9	0.2	0.6
	3	23	15	15	17	8	9	5	5	2	1		3	4.9	3.2	3.2	3.6	1.7	1.9	1.1	1.1	0.4	0.2
	2	17	12	23	13	17	4	2	2	2	4		2	3.6	2.6	4.9	2.8	3.6	0.9	0.4	0.4	0.4	0.9
	1	5	6	6	2	0	0	0	0	0	0		1	1.1	1.3	1.3	0.4	0.0	0.0	0.0	0.0	0.0	0.0

It can be observed how the majority of the selected streets were assigned a Performance indicator ranging from 2 to 5 (Table 15). The small percentage of streets scoring the best Performance indicator (1) suggests that a certain likelihood of obstruction occurrence can be verified all over the network, with very few streets performing at a near optimal standard. 16% of the selected streets score a value of 8 or above regarding their performance, effectively being highlighted as the streets where pipe conditions may not be up to the standard required.

The vast majority (73.3%) of the selected streets displayed Impact indicator scores of 5 or below. The most critical streets regarding this indicator can be assumed to either be located in the city's historical centre or having been referenced as particularly congested regarding traffic, as these characteristics amounted for 20% of the Impact indicator score. The most critical streets displayed, additionally to the aforementioned characteristics, a very high correlation between the amount of equivalent consumers represented and their installed pipe extension. The longer a street is, the more unlikely it is for it to display high equivalent consumer density along all its extension. Consequently, it isn't expected that the city's longest streets were classified as being critical, although they may experience the most movement on street level overall. Critical streets were certainly ones where pipe extension was relatively low, which, combined with high equivalent consumer density, practically ensures that if an obstruction occurs and produces visible effects, those effects will be felt by the local population and the impact will be considerable.

Street criticality was observed to be low on average, as a relatively low percentage of the streets combined poor performance with high impact. This can, however, be a helpful consequence of the classification methodology used, as it truly highlights critical streets, which must be prioritized when developing a PIP.

The geographical representation of Performance, Impact and Criticality scores on street and parish scale are presented on Figures 62, 63 and 64.

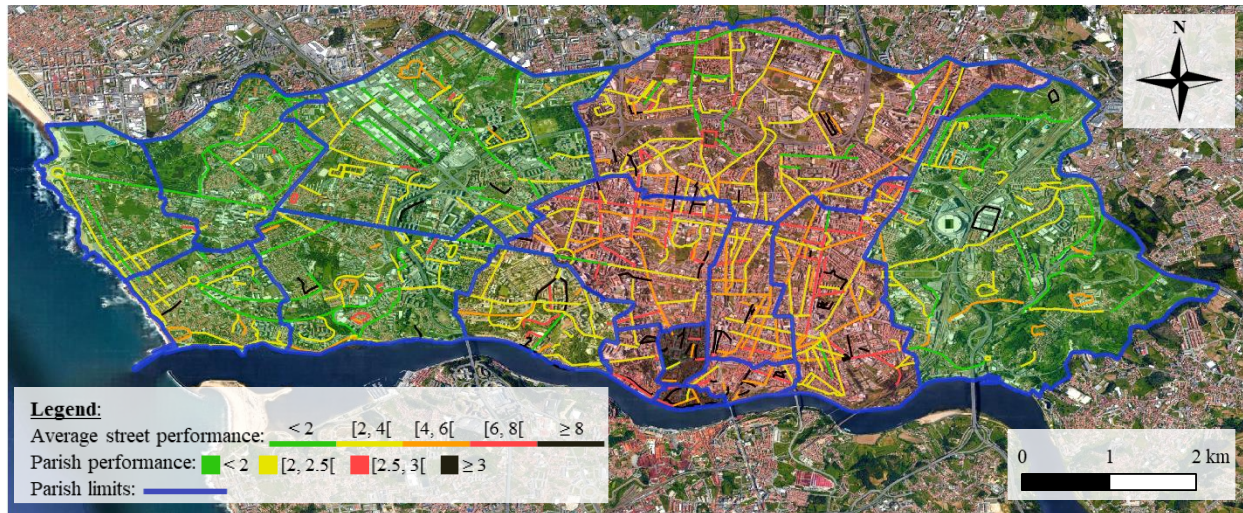


Figure 62: Performance classification on street and parish scale. Results based on Table D-2

Street performance can be observed to be worse in the central parishes of the city. The average age of the network in these parishes (which, with the exception of Paranhos, coincide with the most developed parishes in 1903, as seen in Figure 15) play a substantial role in this, as not only are older pipes more susceptible to structural decay, but they also tend to have lower diameters. These are, in turn, especially critical when combined with heavy restaurant presence, which is verified in all the aforementioned parishes, once again with the exception of Paranhos.



Figure 63: Impact classification on street and parish scale. Results based on Table D-2

The parishes where the impact of obstruction occurrence is highest are, logically, the same where the indicator of equivalent inhabitants per pipe extension had been determined to be higher.

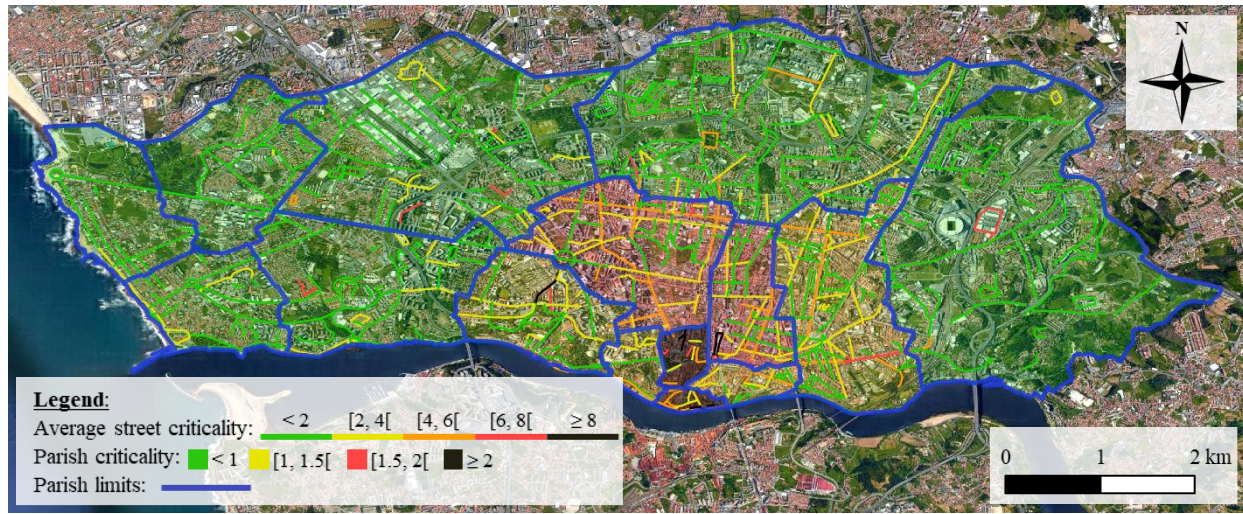


Figure 64: Criticality classification on street and parish scale. Results based on Table D-2

The parishes of the city that display worse performance also display a highest impact, on average. Consequently, it is logical that these parishes are the most critical. São Nicolau (5.6) and Vitória (2.4) displayed the highest average Criticality indicator scores, out of all parishes. These truly combine all the worst possible conditions verified in Porto's domestic wastewater network, ranging from pipe characteristics (old pipes, low diameters) to street characteristics (historical centre location or proximity, heavy restaurant presence), while also displaying high Impact indicators due to the high relation between equivalent consumers and pipe extension.

The peripheral parishes of the city are, expectedly, less critical, as these areas were developed a considerable time after the areas represented on the city's 1903 blueprint. Consequently, not only are these areas still not as developed commercially, which greatly influences the equivalent inhabitant indicator, but it can also be hypothesised that the network in these areas was dimensioned at a time when the city had a considerably higher population, when compared to 1903, and is, therefore, more compatible with the current reality of the city.

5.2. Pipe Scale Classification

Pipe classification was developed with the intent of providing further insight into the manner in which streets should be sectioned, regarding proactive intervention, and to highlight the pipes displaying the worst performances. Only 936 pipes out of 6,857 had registered at least one obstruction over the considered five-year period. Consequently, it was expected that the majority of pipes would be classified as having very low Performance score and, therefore, low Criticality score as well. This was indeed verified, as 4,006 pipes displayed performance scores that were rounded to one. This further clarifies how the criticality observed on street and even parish scales can actually be traced to a relatively low number of pipes. Pipe performance, impact and criticality indicators are described in Tables 18 and 19.

Table 18: Pipe performance and impact classification results by pipe count and percent

Indicator	Performance										Impact									
Score	1	2	3	4	5	6	7	8	9	10	1	2	3	4	5	6	7	8	9	10
Count	4006	1327	865	216	149	105	67	67	50	5	966	742	1205	1082	1381	467	343	346	135	190
%	58.4	19.4	12.6	3.2	2.2	1.5	1.0	1.0	0.7	0.1	14.1	10.8	17.6	15.8	20.1	6.8	5.0	5.0	2.0	2.8

Table 17: Pipe criticality classification results by pipe count (A) and pipe percent (B)

Pipes (A)		Impact										Pipes (B)		Impact									
		1	2	3	4	5	6	7	8	9	10			1	2	3	4	5	6	7	8	9	10
Performance	10	2	1	0	0	0	0	2	0	0	0	Performance	10	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	9	7	5	6	4	10	4	4	4	2	4		9	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.0	0.1
	8	16	9	12	6	9	5	1	6	0	3		8	0.2	0.1	0.2	0.1	0.1	0.1	0.0	0.1	0.0	0.0
	7	9	9	12	7	10	4	6	5	2	3		7	0.1	0.1	0.2	0.1	0.1	0.1	0.1	0.1	0.0	0.0
	6	16	11	14	18	11	12	8	7	3	5		6	0.2	0.2	0.2	0.3	0.2	0.2	0.1	0.1	0.0	0.1
	5	16	23	24	24	11	16	14	15	4	2		5	0.2	0.3	0.4	0.4	0.2	0.2	0.2	0.2	0.1	0.0
	4	32	23	30	24	32	21	20	25	7	2		4	0.5	0.3	0.4	0.4	0.5	0.3	0.3	0.4	0.1	0.0
	3	78	61	100	122	149	85	91	83	44	52		3	1.1	0.9	1.5	1.8	2.2	1.2	1.3	1.2	0.6	0.8
	2	205	117	231	188	210	127	58	96	60	35		2	3.0	1.7	3.4	2.7	3.1	1.9	0.8	1.4	0.9	0.5
	1	585	483	776	689	939	193	139	105	13	84		1	8.5	7.0	11.3	10.0	13.7	2.8	2.0	1.5	0.2	1.2

According to the developed methodology classification, very few pipes can be referred to as being extremely critical. While this may suggest that some criteria might have been under evaluated, it can also be noted that, due to the relatively low number of pipes which actually registered obstructions, any classification methodology would have presented results showing that the vast majority of pipes perform at a high standard. Furthermore, the classification results obtained allow for the few critical pipes to be identified and further evaluated, in order to determine if it is necessary or convenient to renovate or eventually replace them. The network's most critical pipes can be seen in Appendix E, Table E-1.

5.3. Proactive Intervention Plan

The proactive intervention plan for the selected portion of Porto's domestic wastewater drainage network is presented on Figure 65.

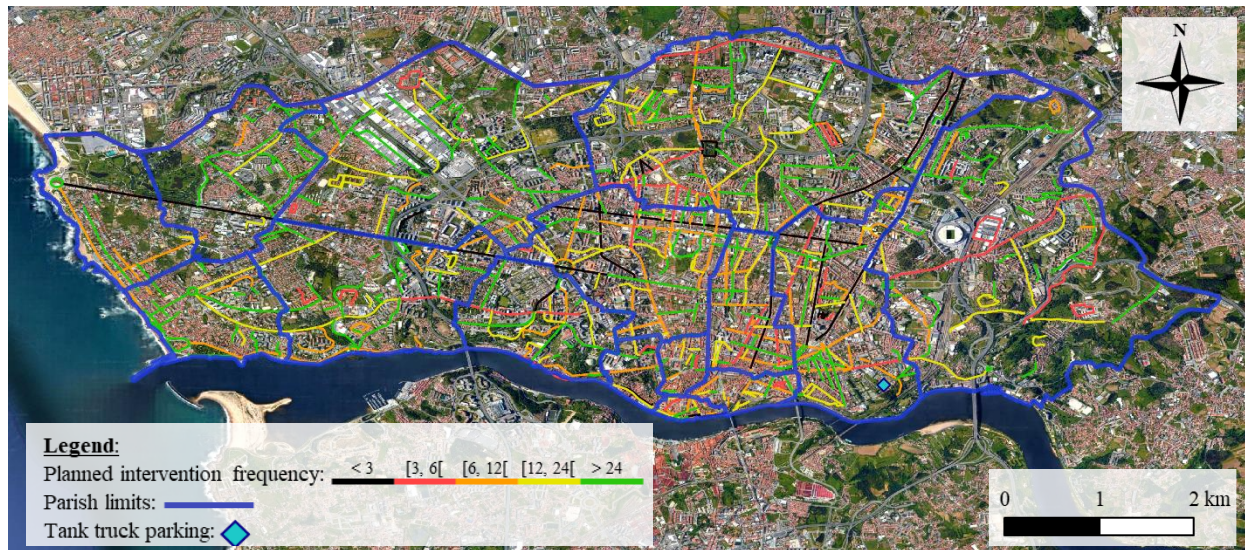


Figure 65: Proactive intervention frequency on street scale. Results based on Table F-1

As stated during the validation of this study's hypothesis, only streets with 3 or more interventions over the analysed 10-year period were considered for analysis. This implies that every street that has drainage pipes installed and wasn't analysed should be intervened every four years, an intervention frequency that was already considered adequate by (Rocha 2017) during the development of AdP's current PIP.

The proposed plan was developed with the aim of presenting an alternative as to how a PIP can be developed based on street criticality, ultimately resulting in each street being assigned an ideal intervention frequency.

While the presented PIP can be readily used, there are a few aspects which can be further analysed. Firstly, analysis was only made on street scale, meaning that critical sections within streets were not identified. When intervening proactively at a city-wide scale, with a considerable amount of streets requiring several interventions within a year, it is likely necessary that most streets are sectioned and that only the most critical sections are intervened regularly, in order to comply with the cleaning capacity of the company. Alternatively, CCTV inspections could be performed at the time of proactive intervention, if more convenient. Furthermore, the performance and impact analyses performed and the consequent classification methodology did not consider information involving specific knowledge regarding the streets conditions, which has certainly been obtained by the company throughout the years.

Summarizing, the presented results allow for the development of an adequate PIP for Porto's domestic wastewater drainage network, based on the characteristics of its structures and on its intervention history. The methodology developed can easily be adapted to any other domestic wastewater drainage network, if a statistical analysis is performed over that network's specific characteristics.

5.4.Developed Machine Learning Models

5.4.1. Classification Models

Two classification models were developed, using the RF and XGB algorithms. The heat map for the RF model is presented on Figure 66, representing the classes that the model predicted correctly and incorrectly.

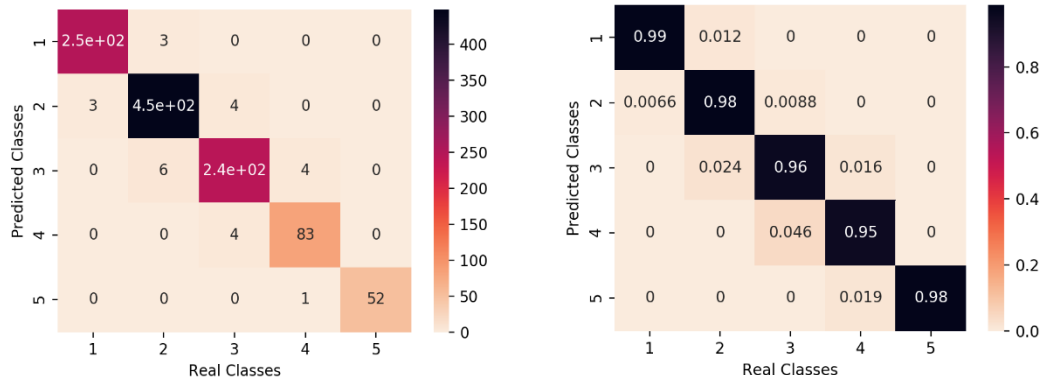


Figure 66: Heat map for the RF model, in absolute values (left) and normalized (right)

Analysis of the model's predicted results compared to the real results suggests the model performed fairly well, with the class that displayed the lowest accuracy still having had 95% (Class 4, Figure X, right) of its data predicted correctly. Evaluation metrics (Table X) also suggest a good performance from the model, having been 100% for the training set, which was reasonably expectable, but also significantly high for the test set (ranging from 97.4 to 97.7%).

Table 19: Evaluation metrics for the RF model, using the Holdout method

Parameter	Dataset	
	Train	Test
Accuracy	100.0	97.7
F1-Score	100.0	97.5
Precision	100.0	97.6
Recall	100.0	97.4

K-fold validation using the developed RF algorithm achieved a score of 89.17%, using 10 folds. This is a considerably lower result, when compared to the aforementioned metrics. It can mainly be explained by analysing Figure 66 and noting the poor representation of classes 4 and 5, when compared to the remaining classes. This problem had been previously addressed when discussing the development of the classification models, and it had been concluded that currently, it is not possible to further balance the data set whilst maintaining the representativeness of classes 4 and 5. Joining classes 4 and 5 might have solved the representation issues, but it would have led to the creation of a class that was not truly representative of the network's most critical streets.

The XGB model was tested with the same input and expected output data sets used for the RF model, in an effort to determine whether one of the models performed significantly better than the other and was, therefore, more adequate for future use in the implementation of the classification methodology.

Results for the developed model are depicted in Figure 67.

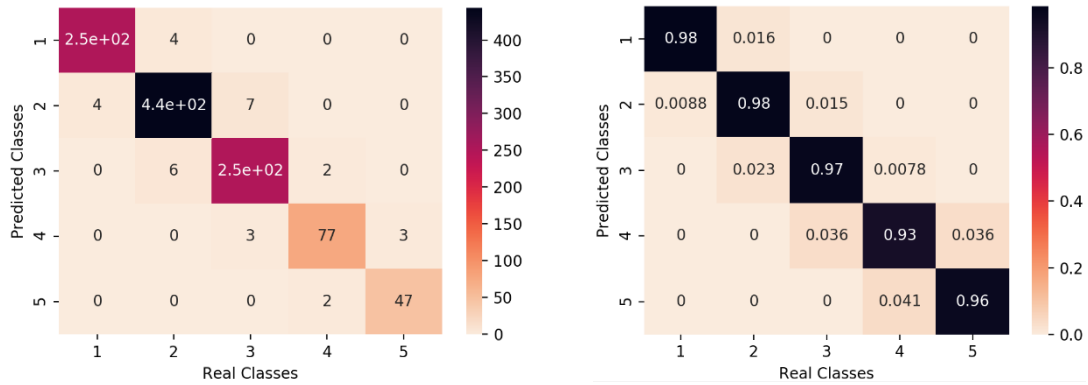


Figure 67: Heat map for the XGB model, in absolute values (left) and normalized (right)

Preliminary analysis of the results obtained suggested a similar performance of the XGB model, when compared to the previously analysed RF model. Results for the evaluation metrics for XGB (see Table 20) were observed to be just slightly lower than the ones observed for the RF model.

Table 20: Evaluation metrics for the XGB model, using the Holdout method

Parameter	Dataset	
	Train	Test
Accuracy	99.9	97.2
F1-Score	99.9	96.3
Precision	99.9	96.3
Recall	99.9	96.3

The developed XGB model obtained a result of 89.56% regarding K-Fold cross validation, using 10 folds. This was a slightly higher result than what the RF model had obtained.

In the context of this work, it can be concluded that the performance of both models could benefit from more data, due to the slightly lower results obtained when using K-Fold cross validation. The reason behind this conclusion can be pointed as being the under-representation of two of the classes used. There was no evidence suggesting eventual faults in the development of the models or in the treatment of data.

It can be concluded that, considering the low average of the Criticality impact on street scale and the classification methodology's objective of highlighting the most critical streets, the supervised classification algorithms used achieved satisfactory results. However, the most critical streets tended to display worse results. This was due to the under-represented classes being the ones that are the most critical and, therefore, had the most need of proper classification. Nevertheless, both models achieved similar results. However, the slightly higher K-Fold validation result of XGB means that this model can be considered instead of the RF model, in the case that the implementation of a classification model for estimating street criticality is desired.

5.4.2. Regression Model

Results for the ANN regression model (MLPRegressor) can be observed in Figure 68, under the form of the average difference between the real Criticality indicator and the value predicted by the model. Table 21 presents the average, maximum and minimum differences between real Criticality values and Criticality values predicted by the regression model.

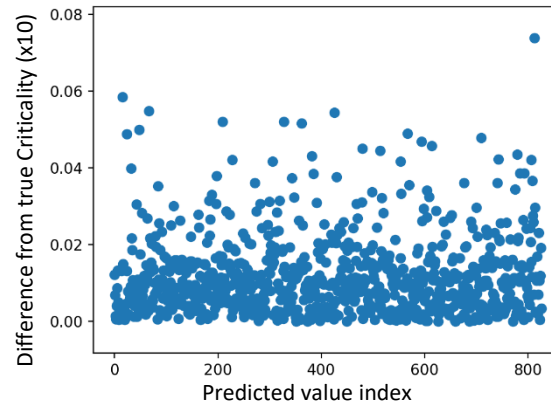


Figure 68: Difference from true Criticality for all predicted values

Table 21: Difference between predicted and real Criticality values, using MLPRegressor

Difference	
Average	0.10
Maximum	0.78
Minimum	0.00

On average, predicted Criticality values differed approximately 0.10 from real values. A 0.10 difference in street criticality would generally mean a 0.01 difference in the intervention frequency multiplier introduced in section 5.3. It is, by all means, a small difference. There were, however, considerably higher differences between real and predicted criticality. The maximum difference was 0.78, which is considerably high. It can be observed on Figure 68 that this maximum was an outlier, as no other differences above 0.6 were observed.

The model's performance was evaluated using the r^2 score metric. Results obtained for the metric were 0.995 for both train and test sets, suggesting the model is capable of obtaining results consistent to those it was trained with.

The r^2 score for K-Fold cross validation, using r^2 score and 10 folds, was 98.22%. It is considerably higher when compared to both classification models, suggesting the use of regression algorithms may be more adequate in the context of this work and for the accurate prediction of street criticality. Consequently, the eventual use of a ML model in the determination of street criticality or other variables used in the context of this work, such as the intervention frequency multiplier, may also benefit from the use of regression ML algorithms such as the one considered in this thesis.

Table F-1 in Appendix F shows the Criticality scores calculated using the aforementioned regression model, that can be used as guidelines for the development of a PIP, which is the most important objective of this work.

6. Conclusions and Future Perspectives

6.1. Conclusions

This work was performed in three stages. Firstly, information regarding characteristics of the network's pipes and streets considered to theoretically influence obstruction occurrence was collected and analysed. The analysed characteristics were used to develop indicators capable of estimating the actual and expected performance of pipes and streets, as well as their associated impact.

The indicators that statistically displayed an influence in street performance were average pipe age, average pipe diameter and restaurant presence (i.e. street extension per restaurant). On pipe scale, material was also influential. It was observed that pipe diameter and restaurant presence influence street performance the most. Geographical representations showed how the network's most critical areas regarding all performance indicators are essentially the same. These are the most central areas of the city, which were developed earlier than the more peripheral areas, as they were already established when the construction of Porto's domestic wastewater drainage network began. Therefore, the drainage pipes installed in these areas were dimensioned considering lower water consumption, in comparison to current values. Consequently, the average pipe diameter is lower in these areas and, therefore, more critical, while average pipe age logically displays the highest values in the whole network. In addition to this, a great percentage of the city's leisure activities and tourist attractions are located in these areas, which implies higher restaurant presence as well.

The impact indicators developed represented the equivalent consumers of streets per pipe extension, and whether streets were located in the historical centre of the city or referenced for having restricted intervention schedules. The parishes associated with the highest obstruction impacts were mostly the parishes that had previously displayed worse performance, and were, consequently, most critical parishes as well. The high obstruction impact associated with these parishes (namely Cedofeita, São Nicolau, Santo Ildefonso and Vitória) was concluded to be due to the high commercial activity and restaurant presence.

The development of this work's classification methodology allowed for street criticality to be estimated with convincing results, meaning that it can be used for making adjustments to the company's current proactive intervention plan. By doing so, every street in the network can be associated to its ideal proactive intervention frequency, therefore facilitating the planning of proactive interventions. The MS Excel spreadsheet in which the methodology was developed allows for indicators to be easily updated and interventions to be registered, meaning that priorities regarding pipe and street intervention can be defined in real time.

Regression algorithms were concluded to be the best option for estimating street criticality through Machine Learning models, with the regression model developed displaying good results, meaning it can be used in the implementation of the developed methodology and obtain immediate results.

6.2.Future Perspectives

Although the analysis of Porto's domestic wastewater drainage network's characteristics was considerably comprehensive, there are still additional indicators that can be developed in order to increase the complexity of the classification methodology, therefore increasing its ability to adapt to the network's reality.

Indicators such as the wastewater flow associated with each pipe, the likelihood of tree root infiltration and the cumulative effect of restaurant presence (i.e. the effects suffered by a certain street due to heavy restaurant presence in the streets directly upstream) all have the potential of being associated with a linear influence on the network's performance. Data regarding these indicators was not readily available and, even working with just half of the whole network's extension, obtaining representative information for every pipe or street was not considered to be feasible, due to the working limitations during the development of this work.

As previously mentioned, the proactive intervention plan presented was considered to have been adequately developed, and it is expectable that the implementation of such a plan would result in considerable reduction in obstruction occurrence. However, the presented plan lacked the influence of pipe scale analysis. That is, it is worth noting that the plan presented cannot currently be executed (due to resource limitations), unless further analysis is made regarding which street sections are most critical, so that proactive intervention is only performed regularly in such sections. Considering that the vast majority of the analysed pipes did not register a single obstruction over a five-year period, it is reasonable to assume that proactive intervention only on critical street sections can be implemented without significant loss of efficiency. In such case, streets would likely only require intervention on their full extension once every four years, as is already implemented by AdP.

Even though this work was developed in the context of the determination of an ideal proactive intervention frequency, some of the analyses are also important for the development of further work regarding the prediction of pipe collapses and the determination of ideal CCTV inspection frequencies.

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Appendices

Appendix A – Street Characteristics

Table A - 1: Street characteristics used in the development of Performance and Impact indicators

Street Identification		Street Characteristics					
ID	Code	Pipe extension (m)	Interventions per pipe km per year	Average age (y)	Average diameter (mm)	Pipe extension per restaurant (m)	Eq. Consumers per pipe extension
1	24 de Agosto, Campo	936.7	3.5	51.2	314.0	234.2	519.0
2	Abade de Faria, Rua	73.9	4.1	33.0	200.0	-	924.6
3	Abracos, Rua	122.1	32.0	58.0	175.0	-	544.6
4	Acacio Lino, Rua	100.4	10.0	70.0	181.4	-	24.4
5	Academico Futebol Clube, Rua	548.2	1.6	15.0	200.0	-	909.0
6	Actor Ferreira Silva, Rua	541.5	4.2	62.9	199.0	541.5	54.3
7	Adelaide Estrada, Rua	275.1	3.3	31.0	200.0	-	1534.9
8	Adolfo Casais Monteiro, Rua	307.8	1.3	76.3	191.1	76.9	685.4
9	Agra do Amial, Bairro	193.8	5.7	61.0	175.0	48.5	1463.1
10	Aguas, Travessa	199.4	6.5	70.0	195.7	-	311.0
11	Alcacer Ceguer, Rua	132.9	3.8	29.6	230.6	132.9	216.5
12	Alcantara, Rua	531.1	0.8	59.5	202.8	-	404.4
13	Aldoar, Bairro	1172.3	3.3	44.9	192.7	586.1	612.3
14	Alegria, Praca	783.6	1.4	70.1	199.6	783.6	279.4
15	Alegria, Rua	2090.7	2.7	81.6	175.0	160.8	1698.2
16	Aleixo da Mota, Rua	412.8	1.2	30.9	200.0	-	2289.7
17	Aleixo, Bairro	425.2	7.8	60.5	178.6	212.6	950.0
18	Alexandre Braga, Rua	198.8	5.0	19.0	360.9	39.8	638.8
19	Alexandre Herculano, Rua	442.1	5.0	89.3	175.0	44.2	1546.9
20	Alfredo Keil, Rua	718.1	3.1	70.0	200.0	-	1415.0
21	Aliados, Avenida	87.5	11.4	70.0	231.3	29.2	6833.3
22	Alianca, Rua	544.2	2.2	70.0	143.5	20.9	852.6
23	Almada, Rua	923.7	2.3	80.9	177.4	61.6	1509.9
24	Almirante Leote do Rego, Rua	306.2	8.5	67.6	133.6	153.1	2389.5
25	Alvaro Casteloes, Rua	814.9	0.7	55.2	202.3	135.8	898.3
26	Alvaro Ferreira Alves, Rua	129.1	3.1	23.0	200.0	-	694.8
27	Alves Redol, Rua	305.1	1.6	70.0	200.0	305.1	1791.9
28	Amial, Rua	1743.8	1.2	50.2	214.7	871.9	842.0
29	Amorim de Carvalho, Rua	424.7	0.7	13.3	208.4	-	5.8
30	Andrezas, Rua	222.3	2.2	31.8	183.3	222.3	3985.2
31	Anibal Cunha, Rua	645.5	3.7	66.8	287.8	215.2	483.6
32	Anselmo Braancamp, Rua	875.7	0.7	84.1	176.8	218.9	679.7
33	Antas, Rua	506.1	3.0	66.3	177.7	253.0	425.0
34	Antero De Quental, Rua	796.9	2.9	78.9	178.0	66.4	1844.2
35	Antero Quental, Travessa	402.8	0.7	80.0	162.4	80.6	1026.8
36	Antonio Calem, Largo	236.6	3.0	63.1	200.0	-	10.3
37	Antonio Candido, Rua	392.5	3.1	71.0	200.0	196.2	789.1
38	Antonio Correia Silva, Rua	119.0	8.4	55.5	200.0	-	360.3
39	Antonio Granjo, Rua	272.5	10.3	70.0	175.0	272.5	632.0
40	Arada, Rua	208.4	2.9	28.0	250.0	-	153.7
41	Areias, Rua	970.7	0.6	28.7	233.7	970.7	250.8
42	Argentina, Rua	733.9	3.8	63.1	200.0	-	759.3
43	Arq Julio de Brito, Rua	178.7	1.7	70.0	200.0	-	542.2
44	Arq Marques da Silva, Rua	200.4	5.5	70.0	187.2	100.2	2577.6
45	Artes Graficas, Rua	212.9	4.7	70.0	125.0	212.9	1118.4
46	Artur Bras, Rua	425.9	1.4	15.0	200.0	-	95.5
47	Asprela, Rua	479.4	1.7	34.2	200.0	-	215.3
48	Ateneu Comercial Porto, Rua	165.0	4.8	60.5	190.0	27.5	2798.3

Street Identification		Street Characteristics					
ID	Code	Pipe extension (m)	Interventions per pipe km per year	Average age (y)	Average diameter (mm)	Pipe extension per restaurant (m)	Eq. Consumers per pipe extension
49	Augusto Gil, Rua	466.1	0.6	70.0	158.1	-	449.6
50	Augusto Lessa, Rua	876.9	0.7	31.1	200.0	438.4	738.4
51	Augusto Rosa, Rua	288.6	9.0	82.6	183.6	48.1	696.3
52	Aurelia de Sousa, Rua	215.3	6.0	70.0	178.9	107.7	661.1
53	Aurelio Paz Reis, Rua	591.4	1.9	61.5	219.1	295.7	367.7
54	Aval de Cima, Rua	451.2	0.7	43.1	200.0	-	834.5
55	Avelino Ribeiro, Rua	404.8	4.2	47.9	224.8	-	191.9
56	Azaleas, Rua	105.3	15.2	70.0	200.0	-	245.2
57	Azenha, Rua	216.3	1.4	29.0	200.0	216.3	16.2
58	Azevedo, Rua	942.7	1.3	69.3	205.6	-	182.0
59	Bacelo, Rua	231.5	2.6	8.0	250.0	-	166.6
60	Bainharia, Rua	188.6	5.8	89.3	175.0	47.1	705.9
61	Bairro Bom Retiro, Rua	152.7	13.8	78.8	175.0	-	335.7
62	Barao Forrester, Rua	645.3	4.2	87.3	181.9	215.1	824.4
63	Barao Nova Sintra, Rua	283.9	7.0	86.5	172.6	283.9	8822.2
64	Barao S. Cosme, Rua	411.7	1.2	92.0	175.0	411.7	523.4
65	Barata Feyo, Rua	286.8	6.6	24.5	200.0	-	934.7
66	Barros Lima, Rua	355.0	2.8	56.0	179.7	177.5	804.6
67	Bartolomeu Velho, Rua	2090.3	0.2	67.5	204.0	2090.3	337.9
68	Basilio Teles, Alameda	270.2	17.8	70.0	184.1	67.5	1317.8
69	Batalha, Praca	221.1	7.7	76.3	176.6	36.9	3336.1
70	Beato Inacio Azevedo, Rua	489.6	1.0	48.2	200.0	163.2	739.1
71	Belem, Rua	645.7	3.6	25.0	210.8	645.7	368.4
72	Belomonte, Rua	193.4	5.7	83.2	183.8	17.6	1067.2
73	Belos Ares, Rua	279.0	4.7	38.0	242.1	279.0	849.5
74	Beneditina, Rua	251.2	6.4	27.0	200.0	-	466.6
75	Berlengas, Rua	423.2	0.7	50.6	203.5	423.2	5.8
76	Bica Velha, Travessa	70.9	9.9	92.0	175.0	70.9	1532.5
77	Boa Viagem, Rua	173.8	19.6	70.0	176.7	-	110.5
78	Boavista, Avenida	9648.2	1.3	41.6	278.6	344.6	647.5
79	Boavista, Rua	906.8	0.8	74.4	262.2	60.5	1732.7
80	Bolhao, Patio	111.3	35.9	70.0	154.5	18.6	34.6
81	Bolhao, Rua	241.9	16.9	92.0	175.0	30.2	1543.4
82	Bom Sucesso, Praca	310.5	1.3	76.0	186.2	155.2	1389.4
83	Bom Sucesso, Rua	271.7	8.1	92.0	175.0	90.6	666.1
84	Bonfim, Rua	926.3	2.8	78.6	175.5	185.3	900.7
85	Bonjardim, Rua	1992.9	1.0	61.9	187.3	90.6	904.6
86	Bonjoia, Rua	294.0	4.8	63.1	200.0	294.0	596.1
87	Bouca, Rua	356.4	2.0	75.3	186.3	-	363.1
88	Bragas, Rua	382.6	1.3	92.0	175.0	63.8	1363.2
89	Brasil, Avenida	997.3	2.8	60.5	198.1	83.1	854.7
90	Breiner, Rua	372.6	4.8	92.0	175.0	74.5	1659.6
91	Burgaes, Rua	417.6	4.8	89.3	175.0	417.6	317.7
92	Cadoucous, Rua	40.8	12.3	29.0	200.0	40.8	217.4
93	Camara Pestana, Rua	437.0	4.3	34.1	189.9	218.5	514.0
94	Camoes, Rua	843.9	2.3	86.1	175.0	105.5	1733.6
95	Campinas, Bairro	1272.0	1.4	57.3	196.3	-	956.8
96	Campo Alegre, Rua	2154.7	2.7	64.7	181.7	215.5	1436.7
97	Campo do Paiva, Travessa	85.8	25.6	70.0	175.0	-	69.4
98	Campo Lindo, Rua	378.9	3.4	64.0	193.4	378.9	857.7
99	Campolide, Rua	174.9	5.7	70.0	200.0	-	659.0
100	Canastreiros, Rua	44.6	24.6	70.0	156.6	8.9	3195.9
101	Candido dos Reis, Rua	154.0	2.6	92.0	175.0	14.0	1595.3
102	Capitao Pombeiro, Rua	406.2	0.7	54.5	191.3	101.6	759.5
103	Carlos Passos, Rua	286.8	1.7	65.3	195.6	-	8.5
104	Carlos Teixeira, Rua	41.7	7.2	22.0	200.0	-	4154.8

Street Identification		Street Characteristics					
ID	Code	Pipe extension (m)	Interventions per pipe km per year	Average age (y)	Average diameter (mm)	Pipe extension per restaurant (m)	Eq. Consumers per pipe extension
105	Carregal, Travessa	292.4	4.4	76.6	202.8	146.2	359.1
106	Carrical, Bairro	1290.2	1.8	50.1	184.2	-	302.1
107	Carrilho Videira, Jardim	16.2	18.5	92.0	175.0	8.1	150.7
108	Carvalhido, Bairro	638.1	3.9	70.0	171.8	-	658.5
109	Castelo, Esplanada	261.9	3.4	36.1	199.3	87.3	865.6
110	Cedofeita, Rua	665.0	3.6	85.9	176.5	30.2	1648.2
111	Cedofeita, Travessa	112.9	5.3	70.0	200.0	16.1	1062.2
112	Central do Viso, Rua	272.1	1.1	40.0	218.0	-	306.9
113	Central Francos, Rua	1104.1	0.5	32.5	232.4	552.1	270.8
114	Cerco do Porto, Bairro	1285.4	3.0	50.7	200.0	-	1067.7
115	Cerco do Porto, Rua	832.0	0.7	47.1	200.0	-	605.9
116	Cervantes, Rua	722.3	0.8	80.4	175.6	-	485.1
117	Ceuta, Rua	182.0	7.1	70.0	200.0	36.4	1363.4
118	Ciclames, Rua	112.4	3.6	70.0	200.0	-	209.9
119	Cidade do Recife, Rua	210.6	6.6	41.4	204.7	210.6	1009.4
120	Cinco de Outubro, Rua	512.2	2.5	48.0	196.1	170.7	1824.7
121	Circunvalacao, Estrada	7400.9	0.8	35.9	223.0	411.2	644.3
122	Clemente Meneres, Rua	235.5	18.3	58.7	222.9	58.9	686.2
123	Clerigos, Rua	114.8	6.1	92.0	175.0	19.1	1048.9
124	Codecal, Escadas	157.1	17.8	70.0	174.7	-	416.8
125	Coelho Neto, Rua	150.2	2.7	73.3	176.5	37.5	1280.2
126	Combatentes Grande Guerra, Avenida	1341.1	1.1	78.9	128.0	1341.1	212.1
127	Comercio do Porto, Rua	358.1	12.6	68.1	184.8	44.8	964.7
128	Conceicao, Rua	207.5	3.4	92.0	175.0	29.6	930.9
129	Conde da Covilha, Rua	287.6	2.4	43.4	200.0	95.9	287.1
130	Conde de Ferreira, Rua	324.8	1.8	77.3	190.0	108.3	475.5
131	Conde de Vizela, Rua	180.5	28.3	87.6	175.0	20.1	1235.0
132	Condominhas, Rua	1163.0	0.3	70.0	341.1	387.7	355.6
133	Congostas, Avenida	678.9	0.9	18.0	242.7	226.3	139.7
134	Constituicao, Rua	2737.4	5.5	76.5	175.3	109.5	1130.6
135	Contumil, Bairro	893.7	5.5	41.1	200.0	-	972.7
136	Contumil, Rua	1078.2	0.4	40.0	200.0	1078.2	300.4
137	Costa Barreto, Rua	245.1	6.5	64.0	204.5	-	334.0
138	Costa Cabral, Rua	3399.7	3.5	57.6	190.8	136.0	1045.1
139	Covelo, Rua	470.2	1.3	55.2	171.9	470.2	669.3
140	Covelo, Travessa	133.9	3.0	67.0	175.0	-	1166.1
141	Crasto, Rua	1021.4	2.1	46.1	199.7	510.7	641.4
142	Cruz, Rua	333.9	0.9	47.0	222.2	333.9	864.1
143	Cruzes, Rua	263.8	1.1	38.0	201.8	-	548.3
144	Cruzes, Travessa	111.6	3.6	25.8	217.8	-	1314.1
145	Cunha Junior, Rua	317.4	1.3	59.1	178.7	158.7	1362.1
146	Cunha, Rua	564.6	1.1	71.6	181.5	282.3	562.9
147	D. Agostinho Jesus Sousa, Rua	189.0	7.4	58.0	181.9	-	1022.1
148	D. Antonio Barroso, Rua	236.5	4.2	75.5	175.0	236.5	1442.0
149	D. Joao Coutinho, Rua	1107.4	1.3	42.0	244.2	-	174.3
150	D. Joao IV, Rua	1098.1	1.9	90.8	175.0	156.9	689.4
151	D. Joao Mascarenhas, Rua	147.4	4.1	53.0	200.0	-	244.6
152	D. Joao Peculiar, Rua	312.8	2.6	49.2	199.8	312.8	58.6
153	D. Lopo De Almeida, Rua	146.0	2.1	92.0	175.0	-	588.2
154	D. Manuel Ii, Rua	547.8	0.7	40.1	217.7	78.3	5483.6
155	D. Pedro V, Rua	1040.6	0.8	60.8	340.6	1040.6	28.0
156	Dalias, Rua	145.6	2.1	70.0	200.0	-	177.6
157	Damiao Gois, Rua	583.5	3.3	70.0	200.0	145.9	2375.8
158	Delfim Ferreira, Rua	918.7	0.5	52.3	200.0	-	245.5
159	Diogo Botelho, Rua	1835.2	0.9	54.5	200.0	1835.2	409.9

Street Identification		Street Characteristics					
ID	Code	Pipe extension (m)	Interventions per pipe km per year	Average age (y)	Average diameter (mm)	Pipe extension per restaurant (m)	Eq. Consumers per pipe extension
160	Diogo Brandao, Rua	59.5	18.5	44.0	200.0	29.8	1378.1
161	Diogo Cao, Rua	448.0	8.5	30.8	186.4	448.0	749.5
162	Direita Francos, Rua	940.9	0.9	21.3	245.0	-	263.6
163	Diu, Rua	614.2	1.3	58.3	186.9	307.1	413.7
164	Domingos Machado, Rua	449.3	0.7	26.7	189.3	449.3	458.5
165	Domingos Sequeira, Rua	211.8	2.4	70.0	179.5	-	1134.7
166	Domingues Alvarez, Rua	171.5	3.5	28.0	200.0	171.5	2000.8
167	Doze Casas, Rua	303.3	4.3	74.4	178.5	151.6	1096.2
168	Dr Alberto Sousa Costa, Rua	61.8	21.0	58.0	200.0	-	812.0
169	Dr Alfredo Magalhaes, Rua	154.6	2.6	70.0	175.0	77.3	1057.9
170	Dr Antonio Bernardino Almeida, Rua	576.2	3.1	42.1	266.6	576.2	528.2
171	Dr Antunes Guimaraes, Avenida	2307.5	1.4	49.2	203.4	256.4	405.6
172	Dr Eduardo Santos Silva, Rua	976.4	0.7	47.2	205.2	139.5	789.7
173	Dr Fernando Azeredo Antas, Alameda	411.7	0.7	28.1	200.0	-	914.3
174	Dr Francisco Sa Carneiro, Praça	598.1	5.7	59.9	176.7	199.4	665.0
175	Dr Manuel Pereira Silva, Rua	873.5	1.9	56.0	204.7	291.2	553.9
176	Dr Placido Costa, Rua	148.4	5.4	34.7	200.3	-	35270.6
177	Dr Roberto Frias, Rua	433.7	1.8	19.2	221.1	-	3748.6
178	Dr Sousa Rosa, Rua	330.1	2.7	54.0	200.0	165.0	884.3
179	Dr Vasco Valente, Rua	811.7	1.1	58.7	186.5	-	209.6
180	Duarte Barbosa, Rua	490.9	1.0	67.9	196.7	490.9	1136.3
181	Duque da Terceira, Rua	621.6	0.6	71.5	195.9	310.8	617.3
182	Duque de Loule, Rua	282.7	2.5	86.5	175.0	56.5	1473.5
183	Duque Saldanha, Bairro	192.4	1.6	14.0	200.0	96.2	2285.4
184	Eca de Queiros, Alameda	706.0	2.5	63.3	168.2	353.0	959.8
185	Egas Moniz, Rua	567.8	4.2	70.0	171.9	189.3	932.1
186	Eirinhas, Rua	437.0	1.8	72.9	182.3	-	224.1
187	Eng Carlos Amarante, Rua	410.1	1.7	61.5	177.8	-	367.1
188	Eng Ezequiel Campos, Rua	781.1	0.9	54.2	200.0	260.4	433.6
189	Eng Ferreira Dias, Rua	1108.0	0.8	50.0	200.0	1108.0	4701.0
190	Eng Machado Vaz, Bairro	580.0	3.3	58.1	200.0	-	283.0
191	Entre Campos, Rua	113.5	3.5	51.7	141.5	113.5	551.9
192	Entreparedes, Rua	190.2	3.7	73.7	180.1	47.5	938.4
193	Escura, Rua	51.4	11.7	70.0	175.0	25.7	469.4
194	Estacao, Rua	124.1	4.0	70.0	175.0	15.5	3181.8
195	Estiva, Cais	87.0	23.0	70.0	175.0	12.4	708.7
196	Eugenio de Castro, Rua	147.7	56.9	70.0	200.0	36.9	5822.0
197	Exercito Libertador, Praça	187.4	11.2	24.8	235.4	62.5	1076.9
198	Falcao, Bairro	307.5	1.6	70.0	200.0	-	1934.9
199	Falcao, Rua	927.4	1.4	28.2	243.4	463.7	583.1
200	Faria Guimaraes, Rua	1701.3	0.9	51.1	190.6	243.0	818.0
201	Feliciano Castilho, Rua	369.1	0.8	70.0	175.0	-	284.9
202	Fernandes Costa, Rua	279.2	3.9	70.0	175.0	139.6	1036.5
203	Fernandes Tomas, Rua	1259.9	2.8	66.8	205.8	74.1	758.7
204	Fernao Magalhaes, Avenida	4939.1	1.8	49.4	206.6	126.6	719.3
205	Fernao Magalhaes, Bairro	560.9	17.1	58.0	164.1	560.9	866.8
206	Ferreira Cardoso, Rua	252.6	5.9	87.6	175.0	63.1	1203.5
207	Ferreira De Castro, Rua	359.8	2.8	37.8	232.4	-	649.1
208	Fez, Rua	1377.3	0.5	41.7	192.9	1377.3	318.3
209	Figueira da Foz, Rua	236.3	3.0	70.0	175.0	118.2	255.0
210	Firmeza, Rua	703.3	1.4	79.2	215.0	63.9	950.0
211	Flor da Rosa, Avenida	500.8	0.8	70.0	200.0	-	110.4

Street Identification		Street Characteristics					
ID	Code	Pipe extension (m)	Interventions per pipe km per year	Average age (y)	Average diameter (mm)	Pipe extension per restaurant (m)	Eq. Consumers per pipe extension
212	Flores, Praca	476.4	1.9	26.8	191.6	-	556.3
213	Florinha Abrigada, Rua	307.9	2.6	70.0	200.0	-	222.7
214	Fonseca Cardoso, Rua	345.7	1.4	67.3	185.6	57.6	683.2
215	Fontainhas, Alameda	389.1	2.3	71.7	213.6	-	256.1
216	Fontainhas, Rua	325.7	2.8	74.4	196.8	108.6	617.7
217	Fonte da Moura, Bairro	466.7	7.7	58.8	181.8	466.7	2140.9
218	Fonte da Moura, Rua	971.8	1.0	55.6	200.0	323.9	284.9
219	Fonte de Contumil, Rua	293.8	1.7	23.3	200.0	-	727.8
220	Fonte de Contumil, Travessa	368.8	1.9	28.8	201.0	-	226.4
221	Fonte de Massarelos, Rua	242.1	5.4	62.3	194.0	242.1	146.5
222	Fonte do Outeiro, Rua	619.3	3.6	50.2	206.9	-	180.9
223	Fonte Taurina, Rua	152.7	41.9	70.0	175.0	11.7	2892.6
224	Formosa, Rua	824.2	0.8	55.5	222.3	103.0	770.5
225	Franca, Avenida	1552.4	2.2	62.7	187.6	388.1	462.4
226	Francos, Bairro	76.0	23.7	70.0	200.0	76.0	9569.1
227	Frei Heitor Pinto, Rua	154.6	1.9	70.0	175.0	-	556.7
228	Freixo, Rotunda	127.8	3.1	20.4	209.9	-	19.1
229	Freixo, Rua	1763.3	0.9	41.6	234.5	195.9	301.9
230	Galeria Paris, Rua	125.2	7.2	77.3	139.9	17.9	2024.8
231	Gloria, Rua	231.3	4.8	72.4	128.3	-	412.8
232	Gomes Freire, Rua	657.7	3.0	78.7	318.7	657.7	223.1
233	Gomes Leal, Rua	137.8	2.2	70.0	200.0	-	732.2
234	Goncalo Cristovao, Rua	835.3	3.5	65.7	181.3	104.4	945.3
235	Goncalo Sampaio, Rua	388.0	15.2	50.8	191.5	388.0	2346.3
236	Goncalves Zarco, Praca	718.5	1.1	70.0	200.0	239.5	74.6
237	Gondarem, Rua	1162.1	0.5	58.3	200.0	232.4	1002.1
238	Graciosa, Rua	235.9	2.1	70.0	175.0	-	698.7
239	Grijo, Rua	296.6	1.7	37.5	229.6	98.9	809.3
240	Guedes Azevedo, Rua	197.1	3.6	92.0	175.0	17.9	3244.9
241	Guerra Junqueiro, Rua	786.4	0.8	80.3	175.9	786.4	573.8
242	Guilherme Braga, Rua	222.4	2.2	70.0	175.0	-	390.9
243	Guilhermina Suggia, Rua	317.3	7.2	57.2	183.3	317.3	303.3
244	Guindais, Escadas	311.3	3.5	76.9	186.4	311.3	146.5
245	Gustavo Eiffel, Av. Eng.	539.7	5.0	70.0	203.8	269.8	555.8
246	Herculano, Bairro	141.6	30.4	70.0	175.0	-	62.0
247	Heroismo, Rua	513.3	6.2	82.2	175.0	46.7	1621.7
248	Igreja de Paranhos, Rua	672.7	2.4	24.1	213.6	672.7	279.3
249	Igreja de Ramalde, Rua	83.4	15.6	70.0	300.0	-	690.4
250	Imperio, Praca	337.4	1.8	70.0	200.0	-	353.9
251	Inacio Alberto Sousa, Rua	438.9	0.9	49.2	173.3	-	185.4
252	Infante D. Henrique, Rua	194.7	4.1	27.7	212.1	32.5	1330.4
253	Joao das Regras, Rua	309.9	1.9	92.0	175.0	77.5	818.6
254	Joao de Barros, Rua	375.9	1.1	70.0	188.8	75.2	1711.1
255	Joao de Deus, Rua	789.0	2.2	66.2	205.8	157.8	952.7
256	Joao Grave, Rua	371.6	8.6	67.8	197.6	185.8	573.2
257	Joao Pedro Ribeiro, Rua	374.4	1.3	75.5	181.2	53.5	1280.5
258	Joaquim Kopke, Rua	138.0	10.1	65.0	175.0	-	566.2
259	Joaquim Leitao, Rua	599.4	1.8	60.0	175.0	599.4	673.4
260	Jornal Noticias, Rua	673.4	1.8	44.5	200.0	673.4	602.9
261	Jose Silva Passos, Rua	199.3	4.0	70.0	200.0	-	111.9
262	Julio Dinis, Rua	1234.6	1.4	62.1	180.2	308.7	1141.3
263	Justino Teixeira, Rua	1121.4	2.4	53.6	227.0	160.2	587.0
264	La Couture, Rua	414.7	1.9	50.5	247.7	-	118.5
265	Lada, Rua	34.6	49.2	70.0	175.0	2.9	1979.0
266	Lagarteiro, Bairro	770.1	6.0	44.7	200.0	-	963.7
267	Laje, Travessa	63.3	6.3	92.0	175.0	-	207.1

Street Identification		Street Characteristics					
ID	Code	Pipe extension (m)	Interventions per pipe km per year	Average age (y)	Average diameter (mm)	Pipe extension per restaurant (m)	Eq. Consumers per pipe extension
268	Lapa, Rua	231.1	8.2	77.3	175.0	57.8	435.9
269	Latino Coelho, Rua	514.6	1.4	81.0	175.0	257.3	942.6
270	Leonardo Coimbra, Bairro	275.2	1.5	49.3	229.4	-	720.5
271	Liberdade, Praça	231.8	6.5	73.7	240.6	38.6	2310.7
272	Lidador, Rua	789.0	0.5	41.7	200.0	789.0	38.5
273	Lindo Vale, Rua	631.4	5.2	63.5	182.6	210.5	510.2
274	Linhas de Elvas, Rua	165.7	1.8	70.0	200.0	-	316.4
275	Loios, Largo	140.5	2.8	6.0	200.0	35.1	1250.2
276	Lordelo, Bairro	640.5	2.0	70.0	200.0	-	476.3
277	Luz Soriano, Rua	371.8	1.1	13.6	235.7	-	610.4
278	Macieirinha, Rua	307.5	1.6	59.4	191.3	-	61.3
279	Madeira, Rua	281.1	7.5	88.3	175.0	40.2	2216.0
280	Magnolias, Rua	382.6	9.9	66.5	184.5	-	134.4
281	Manuel Bandeira, Rua	703.6	1.6	70.0	200.0	-	480.8
282	Manuel Laranjeira, Col. Dr	574.4	1.7	50.8	200.0	574.4	631.5
283	Manuel Marques, Rua	58.3	8.6	35.0	200.0	-	762.2
284	Manuel Pinto Azevedo, Rua	1460.6	1.1	47.0	200.0	365.1	1003.2
285	Marechal Gomes Costa, Avenida	2683.7	0.5	68.8	196.4	894.6	222.7
286	Marechal Saldanha, Rua	1380.9	1.4	56.4	198.0	690.4	983.1
287	Margaridas, Rua	125.3	7.2	70.0	200.0	-	287.4
288	Maria Lamas, Rua	402.8	4.0	66.1	289.6	201.4	106.3
289	Marques de Pombal, Praça	368.2	1.4	92.0	175.0	122.7	1213.3
290	Marques Oliveira, Rua	156.2	6.4	32.0	200.0	156.2	377.5
291	Marracuene, Rua	56.5	7.1	70.0	125.0	-	694.9
292	Marta Mesquita da Camara, Rua	848.9	0.4	70.0	200.0	-	893.2
293	Martim Moniz, Rua	1368.1	0.5	51.1	200.9	456.0	524.1
294	Martires da Patria, Campo	706.7	2.5	49.1	188.4	78.5	4615.4
295	Martires Liberdade, Rua	543.7	1.3	92.0	175.0	68.0	961.3
296	Melo, Rua	636.2	0.8	92.0	161.4	-	272.7
297	Mestre Afonso Domingues, Rua	169.8	9.4	28.0	200.0	-	676.6
298	Miguel Bombarda, Rua	680.6	2.8	85.2	176.5	68.1	1094.5
299	Miosotis, Rua	342.5	3.2	58.6	200.0	-	498.8
300	Miradouro, Rua	130.4	9.2	92.0	175.0	65.2	529.5
301	Miragaia, Rua	532.4	21.6	87.6	177.8	76.1	422.6
302	Mocambique, Rua	887.8	0.3	54.1	194.6	-	234.4
303	Mocidade da Arrabida, Rua	401.8	9.7	70.0	186.8	-	141.6
304	Monchique, Rua	507.2	2.6	31.6	198.4	126.8	125.4
305	Monsanto, Rua	1068.2	1.2	51.6	202.3	267.0	750.2
306	Monte Alegre, Rua	344.4	10.2	70.0	144.5	57.4	1014.9
307	Monte Cativo, Rua	491.3	5.5	70.0	133.1	245.7	614.1
308	Monte da Bela, Bairro	522.8	3.3	70.0	200.0	-	185.4
309	Monte da Bela, Travessa	137.3	2.9	70.0	200.0	-	468.9
310	Monte da Estacao, Rua	390.7	0.8	41.4	189.0	-	699.0
311	Monte Louro, Travessa	104.5	7.7	70.0	125.0	104.5	1045.9
312	Montebelo, Rua	315.9	3.2	53.8	200.0	-	400.2
313	Montevideu, Avenida	1460.3	2.7	50.6	196.4	365.1	443.5
314	Morgado de Mateus, Rua	255.0	2.0	76.3	192.0	36.4	604.2
315	Mouteira, Bairro	25.0	20.0	8.0	250.0	-	258.6
316	Mouzinho Albuquerque, Praça	972.6	3.6	45.9	234.8	121.6	658.2
317	Mouzinho Silveira, Rua	679.2	2.8	11.2	261.6	37.7	1215.3
318	Nasc. Col. Dr. Manuel Laranjeira, Rua	95.5	14.7	43.3	200.0	-	903.1
319	Nau Vitoria, Rua	1146.2	0.4	38.5	254.3	573.1	492.4

Street Identification		Street Characteristics					
ID	Code	Pipe extension (m)	Interventions per pipe km per year	Average age (y)	Average diameter (mm)	Pipe extension per restaurant (m)	Eq. Consumers per pipe extension
320	Naulila, Rua	587.6	5.3	20.9	190.5	-	133.7
321	Nevala, Rua	208.5	5.3	92.0	125.0	-	206.5
322	Niassa, Rua	200.0	5.0	70.0	181.4	200.0	668.0
323	Nossa Senhora Calvario, Rua	659.1	2.0	58.1	200.0	659.1	146.3
324	Nossa Senhora de Fatima, Rua	538.5	2.0	70.0	175.0	107.7	1232.3
325	Nova Alfandega, Rua	198.9	5.5	45.2	184.1	28.4	1433.6
326	Nova das Areias, Rua	354.3	7.1	70.0	200.0	-	110.5
327	Nova de S. Crispim, Rua	483.0	1.4	70.0	165.1	80.5	1292.6
328	Nova do Regado, Rua	350.3	1.7	77.3	209.8	116.8	593.6
329	Nova do Rio, Rua	470.5	0.6	54.5	173.9	-	5.2
330	Nova Sintra, Calçada	128.3	3.1	9.0	250.0	-	279.1
331	Nova Sintra, Travessa	374.1	2.4	72.9	180.9	-	432.7
332	Nove de Abril, Praça	411.5	15.3	42.0	264.3	82.3	1109.4
333	Nove de Abril, Rua	1874.1	2.6	62.1	245.2	624.7	461.2
334	Nove de Julho, Rua	785.6	0.8	53.9	181.9	-	708.4
335	Nuno Pinheiro Torres, Bairro	1028.5	4.2	70.0	198.3	-	685.8
336	Oliveira Martins, Rua	424.2	7.1	70.0	186.5	212.1	484.4
337	Oliveira Monteiro, Rua	1110.9	6.2	75.3	180.1	185.1	1141.9
338	Oliveiras, Rua	141.7	9.2	87.6	175.0	14.2	1798.6
339	Oliveirinhas, Rua	128.0	2.3	70.0	175.0	128.0	374.9
340	Orfeao do Porto, Rua	440.3	1.1	29.1	200.0	-	1974.6
341	Oscar da Silva, Rua	319.1	1.6	49.0	200.0	319.1	855.8
342	Ourique, Rua	149.9	2.7	66.3	200.0	149.9	249.6
343	Ouro, Rua	1345.5	2.6	60.0	205.6	149.5	207.4
344	Outeirinho, Rua	26.0	23.1	81.0	175.0	13.0	10744.3
345	Outeirinho, Travessa	16.6	36.1	92.0	175.0	-	4040.4
346	Outeiro, Bairro	529.4	10.8	58.9	183.3	-	1069.5
347	Padre Alexandre, Rua	141.4	29.7	70.0	125.0	141.4	602.0
348	Padre Cruz, Rua	214.7	9.8	92.0	175.0	-	578.8
349	Padre Jose Pacheco Do Monte, Rua	497.2	12.5	70.0	188.9	124.3	774.3
350	Padre Manuel Nobrega, Rua	240.2	6.2	65.0	155.6	-	538.8
351	Paiol, Travessa	46.9	27.7	70.0	125.0	46.9	72.6
352	Panoramica, Via	566.7	2.1	50.7	195.3	566.7	308.8
353	Papoilas, Rua	211.4	1.4	70.0	200.0	-	89.2
354	Paraíso, Rua	285.6	8.4	75.5	207.5	57.1	977.9
355	Parque, Avenida	801.1	0.4	27.0	286.7	400.5	365.0
356	Part de Francos, Rua	326.9	0.9	31.7	208.5	81.7	194.8
357	Passeio Alegre, Jardim	220.5	2.3	34.0	200.0	110.2	316.1
358	Passeio Alegre, Rua	1024.4	2.0	66.8	202.1	93.1	932.6
359	Passos Manuel, Rua	506.9	6.7	35.8	192.1	23.0	1248.8
360	Pasteleira, Bairro	97.1	37.1	70.0	200.0	24.3	9983.7
361	Paulo da Gama, Rua	862.6	2.3	52.2	200.2	-	1427.8
362	Pedras, Cais	162.8	25.8	70.0	176.6	40.7	813.0
363	Pedro Hispano, Rua	1803.3	1.6	64.0	286.7	200.4	642.5
364	Pedro Homem de Melo, Rua	511.3	2.0	35.0	200.0	170.4	1441.5
365	Pedro Ivo, Rua	142.4	2.1	63.0	175.0	71.2	470.0
366	Pena, Rua	382.1	7.3	70.0	175.0	-	615.1
367	Pereiro, Bairro	406.3	1.2	21.8	200.0	-	409.8
368	Pio XII, Bairro	428.7	1.4	52.7	161.4	428.7	473.3
369	Platanos, Rua	240.9	2.1	38.0	200.0	-	711.9
370	Poen Col. Dr. Manuel Laranjeira, Rua	197.4	2.0	70.0	200.0	-	478.3
371	Poveiros, Praça	137.2	2.2	77.3	175.0	9.8	1780.4
372	Povoa, Rua	712.2	10.5	73.3	212.8	712.2	307.3
373	Povoa, Travessa	240.5	13.7	81.0	175.0	-	480.4

Street Identification		Street Characteristics					
ID	Code	Pipe extension (m)	Interventions per pipe km per year	Average age (y)	Average diameter (mm)	Pipe extension per restaurant (m)	Eq. Consumers per pipe extension
374	Praia, Rua	159.7	2.5	12.0	200.0	-	35.9
375	Preciosa, Rua	511.8	0.8	68.4	200.0	128.0	686.7
376	Priorado, Largo	101.7	8.8	77.3	175.0	33.9	602.3
377	Prof Abel Salazar, Largo	32.4	21.6	54.0	179.4	32.4	1662.3
378	Prof Agostinho Silva, Rua	721.4	1.7	62.9	200.0	721.4	727.4
379	Prof Alberto Saavedra, Rua	69.2	14.5	26.0	200.0	23.1	2609.8
380	Prof Bento Jesus Caraca, Rua	631.1	1.0	38.1	200.0	315.5	925.8
381	Prof Duarte Leite, Rua	415.3	0.7	57.5	200.0	207.6	1163.2
382	Prof Luis Costa, Rua	51.8	5.8	70.0	200.0	-	903.3
383	Prof Mendes Correia, Rua	257.1	1.6	30.3	200.0	-	662.0
384	Prof Ruy Luis Gomes, Alameda	416.9	1.2	36.0	200.0	416.9	821.2
385	Quanza, Rua	224.0	2.2	70.0	128.9	112.0	493.9
386	Rainha D. Estefania, Rua	389.7	3.1	53.9	222.2	129.9	320.7
387	Rainha D. Leonor, Bairro	1299.9	0.5	70.0	181.2	433.3	311.3
388	Regado, Bairro	1069.6	11.4	46.6	195.6	356.5	823.9
389	Reinaldo Oudinot, Rua	637.6	0.8	16.0	210.3	-	441.5
390	Restauracao, Rua	1663.7	1.4	43.6	199.9	208.0	258.0
391	Revilao, Rua	360.8	1.1	43.6	200.0	360.8	384.9
392	Ribeira, Cais	250.9	25.5	64.1	173.7	12.5	819.4
393	Ribeira, Praça	127.1	55.9	51.7	177.6	18.2	1732.3
394	Ribeiro de Sousa, Rua	491.4	2.0	70.0	191.6	491.4	424.5
395	Ricardo Severo, Rua	166.5	6.6	92.0	175.0	166.5	985.0
396	Rodrigues Freitas, Avenida	469.2	4.3	76.2	176.9	67.0	2053.0
397	Rodrigues Lobo, Rua	118.2	5.1	70.0	155.8	-	1155.2
398	Rodrigues Sampaio, Rua	110.3	10.9	56.8	176.8	13.8	832.0
399	Rosario, Rua	648.8	1.5	77.1	182.2	59.0	1267.2
400	Rovuma, Rua	223.6	2.2	92.0	125.0	-	193.9
401	Ruben A, Rua	267.5	3.0	41.3	200.0	-	1466.0
402	Rui Faleiro, Rua	170.6	2.9	70.0	175.0	-	628.4
403	S. Bartolomeu, Rua	273.8	1.5	47.7	200.0	54.8	150.8
404	S. Bras, Rua	742.1	1.1	82.0	179.1	185.5	632.6
405	S. Dinis, Rua	1687.9	3.3	75.3	185.3	140.7	602.7
406	S. Francisco, Rua	81.5	29.4	92.0	175.0	20.4	754.0
407	S. Joao Bosco, Rua	710.8	2.8	58.6	200.0	710.8	1372.3
408	S. Joao De Brito, Rua	682.3	1.5	35.6	200.0	113.7	1244.2
409	S. Joao De Deus, Bairro	234.1	11.1	70.0	169.7	234.1	181.0
410	S. Joao, Rua	524.3	2.9	35.9	178.0	52.4	821.3
411	S. Luis, Rua	191.4	9.9	92.0	175.0	-	171.3
412	S. Miguel, Rua	132.7	3.8	81.0	175.0	33.2	1646.8
413	S. Roque Lameira, Bairro	212.4	15.1	59.0	182.9	212.4	2814.3
414	S. Roque Lameira, Rua	2647.1	1.9	32.9	227.5	264.7	722.7
415	S. Tome, Rua	365.6	1.9	52.4	202.1	121.9	1923.2
416	S. Vitor, Rua	579.4	1.9	90.2	175.0	193.1	708.4
417	Sa Albergaria, Rua	230.8	1.3	25.2	200.0	-	300.9
418	Sa da Bandeira, Rua	940.2	4.7	71.0	236.9	40.9	1387.2
419	Sa de Miranda, Rua	388.1	4.6	29.6	200.0	-	973.1
420	Sa de Noronha, Rua	93.8	11.7	92.0	175.0	7.8	2840.6
421	Sacadura Cabral, Rua	90.9	8.8	32.0	175.0	90.9	856.4
422	Salado, Rua	231.1	3.5	67.8	200.0	-	125.9
423	Salazares, Rua	567.3	0.9	30.0	199.7	-	456.5
424	Salgueiro Maia, Rua	192.6	8.3	70.0	200.0	-	881.9
425	Salgueiros, Rua	377.8	2.9	70.0	125.0	-	159.2
426	Sampaio Bruno, Rua	188.2	4.3	77.3	220.3	26.9	1493.9
427	Santa Catarina, Rua	1931.6	4.0	81.8	179.0	62.3	1518.0
428	Santo Antonio Contumil, Rua	1026.4	0.7	29.0	203.9	-	412.2

Street Identification		Street Characteristics					
ID	Code	Pipe extension (m)	Interventions per pipe km per year	Average age (y)	Average diameter (mm)	Pipe extension per restaurant (m)	Eq. Consumers per pipe extension
429	Santo Ildefonso, Rua	610.0	3.4	84.7	177.1	55.5	1241.6
430	Santo Isidro, Rua	294.4	6.5	89.3	173.3	-	360.7
431	Santo Isidro, Travessa	150.4	4.0	84.7	175.0	150.4	707.3
432	Santos Pousada, Rua	1215.4	6.9	73.5	220.1	110.5	1476.6
433	Sarah Afonso, Rua	167.8	4.2	30.2	200.0	55.9	2238.8
434	Sarmiento Beires, Rua	470.0	4.5	46.0	273.9	156.7	3145.2
435	Seixal, Rua	159.5	2.5	70.0	185.0	-	1658.7
436	Senhora da Conceicao, Travessa	333.0	2.7	33.6	200.0	-	417.8
437	Senhora da Lapa, Rua	245.2	5.3	83.2	152.5	122.6	195.6
438	Senhora da Luz, Rua	364.4	2.5	36.7	200.6	72.9	1023.1
439	Senhora da Luz, Travessa	144.3	3.5	64.5	200.0	-	60.2
440	Senhora do Porto, Rua	750.2	1.5	39.6	200.0	750.2	1197.1
441	Serpa Pinto, Rua	877.2	6.0	53.4	172.9	79.7	1320.0
442	Sidonio Pais, Avenida	1035.5	0.9	48.1	223.2	1035.5	241.4
443	Silva Porto, Rua	581.4	2.4	44.3	164.4	-	1037.7
444	Silva Tapada, Rua	370.9	4.9	21.9	318.8	123.6	775.1
445	Soares dos Reis, Largo	179.4	15.0	92.0	175.0	179.4	2349.0
446	Sobreiras, Rua	421.9	5.9	70.0	200.0	140.6	751.0
447	Sobre-O-Douro, Calçada	185.8	1.6	70.0	191.8	92.9	62.0
448	Sol, Rua	292.7	4.4	92.0	175.0	146.3	1074.2
449	Tanger, Rua	483.8	1.2	55.1	175.0	161.3	963.9
450	Teatro, Rua	320.2	1.6	46.9	200.0	-	589.2
451	Tenente Valadim, Rua	904.3	0.7	66.6	185.7	226.1	1761.2
452	Teodoro Sousa Maldonado, Rua	189.9	1.6	16.7	200.0	-	710.0
453	Terreiro, Largo	29.2	10.3	70.0	175.0	7.3	768.0
454	Torrinha, Rua	720.6	1.2	47.1	237.1	102.9	1216.6
455	Vale Formoso, Rua	964.7	2.5	49.7	194.8	80.4	671.5
456	Valpacos, Rua	204.4	4.9	31.4	200.0	-	679.3
457	Vanzeleres, Rua	423.7	3.1	55.0	185.9	141.2	779.0
458	Vasco da Gama, Avenida	694.0	1.7	56.6	200.0	347.0	354.7
459	Venezuela, Rua	669.6	2.1	70.0	187.4	167.4	1538.6
460	Vieira da Silva, Rua	355.0	2.0	70.0	200.0	-	938.9
461	Vigorosa, Rua	490.2	5.5	41.7	152.7	163.4	575.3
462	Vilar, Rua	356.2	1.4	70.0	175.0	118.7	1487.4
463	Vilarinha, Rua	1440.1	0.6	64.7	198.3	288.0	434.9
464	Vimara Peres, Avenida	249.9	4.4	23.3	196.5	50.0	291.5
465	Visconde de Bobeda, Rua	175.4	1.7	92.0	175.0	175.4	578.5
466	Visconde de Setubal, Rua	349.5	1.1	67.0	175.0	58.2	1394.5
467	Viso, Bairro	668.9	6.4	43.7	200.0	668.9	1287.0
468	Vitorino Nemesio, Rua	154.1	1.9	39.4	200.0	154.1	2748.9

Appendix B – Statistical Analysis on Pipe Scale

Table B - 1: Information used in the determination of the influence of pipe age obstructions per km per year

Age (a, years)	Absolute Values			Percentages			Obs/km.y
	Interventions	Pipes	Total Length (km)	Interventions	Pipes	Total Length (km)	
60 < a	1,567	3,951	159.5	8.7	25.6	20.8	1.96
30 < a ≤ 60	360	1,150	44.6	17.1	16.8	17.3	1.61
a ≤ 30	183	1,756	53.8	74.3	57.6	61.9	0.68
totals	2,110	6,857	257.9	100.0	100.0	100.0	1.64

Table B - 2: Information used in the determination of the influence of pipe diameter in obstructions per km per year

Diameter (d, mm)	Absolute Values			Percentages			Obs/km.y
	Interventions	Pipes	Total Length (km)	Interventions	Pipes	Total Length (km)	
d < 175	226	276	11.8	10.7	4.0	4.6	3.83
d = 175	998	1,612	76.3	47.3	23.5	29.6	2.62
d = 200	791	4,036	137.0	37.5	58.9	53.1	1.15
200 < d ≤ 350	83	706	24.6	3.9	10.3	9.5	0.67
350 < d	12	227	8.2	0.6	3.3	3.2	0.29
Total	2,110	6,857	257.9	100.0	100.0	100.0	1.64

Table B - 3: Information used in the determination of the influence of pipe material in obstructions per km per year

Material	Absolute Values			Percentages			Obs/km.y	Avg. Diameter (mm)
	Interventions	Pipes	Total Length (km)	Interventions	Pipes	Total Length (km)		
Cast iron	11	175	4.2	0.5	2.6	1.6	0.52	280.6
HDPE/PP/PVC	49	461	15.0	2.3	6.7	5.8	0.65	237.1
Stoneware	2,049	6,194	238.2	97.1	90.3	92.4	1.72	199.5
Others	1	27	0.5	0.0	0.4	0.2	0.41	249.3
Total	2,110	6,857	257.9	100.0	100.0	100.0	1.64	201.4

Table B - 4: Information used in the determination of the influence of pipe inclination in obstructions per km per year

Inclination (i, %)	Absolute Values			Percentages			Obs/km.y
	Interventions	Pipes	Total Length (km)	Interventions	Pipes	Total Length (km)	
i ≤ 0.5	612	2,528	103.3	30.1	40.2	43.0	1.18
0.5 < i ≤ 1	399	977	41.6	19.6	15.5	17.3	1.92
1 < i ≤ 2	449	1,101	43.0	22.1	17.5	17.9	2.09
2 < i ≤ 5	379	1,009	34.9	18.6	16.0	14.5	2.17
5 < i	195	680	17.4	9.6	10.8	7.2	2.25
Total	2,034	6,295	240.2	100.0	100.0	100.0	1.69

Appendix C – Statistical Analysis on Street Scale

Table C - 1: Intervention amount per type and per year

Year	Interventions				Percentage of the year's total		
	Total	Clearances	Floods	Proactive	Clearances	Floods	Proactive
2010	967	602	188	177	62.3	19.4	18.3
2011	1,045	652	265	128	62.4	25.4	12.2
2012	964	645	206	113	66.9	21.4	11.7
2013	953	654	194	105	68.6	20.4	11.0
2014	798	514	173	111	64.4	21.7	13.9
2015	895	580	182	133	64.8	20.3	14.9
2016	826	544	158	124	65.9	19.1	15.0
2017	898	661	126	111	73.6	14.0	12.4
2018	912	505	186	221	55.4	20.4	24.2
2019	970	498	158	314	51.3	16.3	32.4
Total	9,228	5,855	1,836	1,537	100.0	100.0	100.0

Table C - 2: Information used in the determination of the influence of average pipe age interventions per pipe km per year

Age (a, years)	Absolute Values			Percentages			Int/km.y
	Interventions	Streets	Total Length (km)	Interventions	Pipes	Total Length (km)	
a ≤ 30	401	49	16.9	5.1	10.5	6.6	2.38
30 < a ≤ 60	2,543	147	113.7	32.5	31.4	44.2	2.24
60 < a	4,873	272	127.4	62.3	58.1	49.6	3.82
Total	7,817	468	257.0	100.0	100.0	100.0	3.03

Table C - 3: Information used in the determination of the influence of average pipe diameter in interventions per pipe km per year

Diameter (d, mm)	Absolute Values			Percentages			Int/km.y
	Interventions	Streets	Total Length (km)	Interventions	Pipes	Total Length (km)	
d < 175	756	41	15.1	9.7	8.8	5.9	5.00
175 ≤ d < 200	3,952	203	101.3	50.6	43.4	39.3	3.90
200 ≤ d < 205	1,532	142	67.2	19.6	30.3	26.1	2.28
205 ≤ d < 225	726	36	33.0	9.3	7.7	12.8	2.20
225 ≤ d	851	46	41.3	10.9	9.8	16.0	2.06
Total	7,817	468	257.9	100.0	100.0	100.0	3.03

Table C - 4: Information used in the determination of the influence of average pipe inclination in interventions per pipe km per year

Inclination (i, %)	Absolute Values			Percentages			Int/km.y
	Interventions	Pipes	Total Length (km)	Interventions	Pipes	Total Length (km)	
i ≤ 0.5	775	70	28.1	9.9	15.0	10.9	2.76
0.5 < i ≤ 1	1,749	101	76.3	22.4	21.6	29.6	2.29
1 < i ≤ 2	2,337	142	70.7	29.9	30.3	27.4	3.31
2 < i ≤ 5	1,775	104	43.7	22.7	22.2	16.9	4.06
5 < i	1,181	51	39.2	15.1	10.9	15.2	3.01
Totals	7,817	468	257.9	100.0	100.0	100.0	3.03

Table C - 5: Information used in the determination of the influence of pipe length per restaurant in interventions per pipe km per year

Pipe Length per Restaurant (r, m)	Absolute Values			Percentages			Int/km.y	Avg. Diameter (mm)
	Interventions	Streets	Total Length (km)	Interventions	Streets	Total Length (km)		
$r \leq 75$	1,689	94	27.7	21.6	20.1	10.8	6.09	190.9
$75 < r \leq 150$	1,482	69	43.6	19.0	14.7	16.9	3.40	196.1
$150 < r \leq 250$	1,129	60	37.8	14.4	12.8	14.7	2.99	200.6
$250 < r$	1,755	90	92.1	22.5	19.2	35.7	1.91	215.7
No Restaurants	1,762	155	56.7	22.5	33.1	22.0	3.11	196.1
Total	7,817	468	257.9	100	100	100	3.03	201.4

Table C - 6: Information used in the determination of pipe diameter influence on the results of Table C - 5

Diameter (d, mm)	Pipe Length per Restaurant (r, m)	Absolute Values			Percentages			Int/km.y
		Interventions	Streets	Total Length (km)	Interventions	Streets	Total Length (km)	
$d < 175$	$r \leq 75$	179	7	1.5	2.3	1.5	0.6	12.19
	$75 < r \leq 150$	135	8	2.6	1.7	1.7	1.0	5.21
	$150 < r \leq 250$	140	6	2.3	1.8	1.3	0.9	6.08
	$250 < r$	161	6	3.8	2.1	1.3	1.5	4.25
	No Restaurants	164	15	5.1	2.1	3.2	2.0	3.19
$175 \leq d < 200$	$r \leq 75$	1,067	63	18.5	13.8	13.5	7.2	5.76
	$75 < r \leq 150$	826	33	21.5	10.6	7.1	8.3	3.84
	$150 < r \leq 250$	684	33	22.0	8.8	7.1	8.5	3.11
	$250 < r$	689	34	26.9	8.9	7.3	10.4	2.56
	No Restaurants	671	44	16.5	8.7	9.4	6.4	4.06
$d = 200$	$r \leq 75$	180	10	1.3	2.3	2.1	0.5	13.94
	$75 < r \leq 150$	95	9	3.1	1.2	1.9	1.2	3.04
	$150 < r \leq 250$	75	11	4.7	1.0	2.4	1.8	1.59
	$250 < r$	245	22	16.7	3.2	4.7	6.5	1.47
	No Restaurants	679	68	23.2	8.8	14.5	9.0	2.93
$d > 200$	$r \leq 75$	263	14	6.5	3.4	3.0	2.5	4.07
	$75 < r \leq 150$	426	19	16.3	5.5	4.1	6.3	2.61
	$150 < r \leq 250$	203	10	8.8	2.6	2.1	3.4	2.30
	$250 < r$	641	28	44.6	8.3	6.0	17.3	1.44
	No Restaurants	234	28	20.2	3.0	6.0	7.8	1.16
Total		7,817	468	257.9	100.0	100.0	100.0	3.03

Table C - 7: Information used in the determination of the influence of equivalent consumers per pipe length in interventions per pipe km per year

Equivalent Consumers per Pipe Length	Absolute Values			Percentages			Int/km.y
	Interventions	Pipes	Total Length (km)	Interventions	Pipes	Total Length (km)	
$c < 50$	2,066	164	87.2	26.4	35.0	33.8	2.37
$50 \leq k < 85$	2,325	125	84.8	29.7	26.7	32.9	2.74
$85 \leq k < 120$	1,466	71	41.4	18.8	15.2	16.1	3.54
$120 \leq c$	1,960	108	44.5	25.1	23.1	17.3	4.40
Totals	7,817	468	257.9	100.0	100.0	100.0	3.03

Table C - 8: Information used in the determination of the influence of street characteristics in interventions per pipe km per year

Street Characteristic		Absolute Values			Percentages			Int/km.y
		Interventions	Streets	Total Length (km)	Interventions	Streets	Total Length (km)	
Historical centre	Yes	482	23	4.3	6.2	4.9	1.7	11.21
	No	7,335	445	253.6	93.8	95.1	98.3	2.89
Referenced	Yes	3,411	178	148.7	43.6	38.0	57.7	2.29
	No	4,406	290	109.2	56.4	62.0	42.3	4.04
Total		7,817	468	257.9	100.0	100.0	100.0	3.03

Appendix D – Statistical Analysis on Parish Scale

Table D - 1: City and network characteristics on parish scale

Parish	Description			Average Characteristics			
	Area (km ²)	Population (2011)	Population Density (Population/km ²)	Age	Performance Diameter	M/Rest.	Impact E.q. C./km
Aldoar	2.41	12843	5329.0	49.4	213.3	419.6	55.8
Bonfim	3.1	24265	7827.4	63.4	194.2	214.2	86.4
Campanhã	8.04	32659	4062.1	47.9	207.3	243.9	56.2
Cedofeita	2.66	22077	8299.6	65.4	190.9	145.4	97.8
Foz do Douro	1.83	10997	6009.3	60.9	197.9	609.3	59.9
Lordelo do Ouro	3.64	22270	6118.1	59.8	217.8	363.5	79.2
Massarelos	1.94	6789	3499.5	58.8	200.5	297.9	87.2
Miragaia	0.43	2067	4807.0	54.2	198.4	107.4	134.6
Nevogilde	1.84	5018	2727.2	48.1	231.8	413.8	65.9
Paranhos	7.17	44298	6178.2	53.4	199.1	282.6	82.6
Ramalde	5.83	38012	6520.1	49.2	208.9	338.3	94.1
Santo Ildefonso	1.24	9029	7281.5	62.5	192.6	83.3	123.2
São Nicolau	0.25	1906	7624.0	56.5	193.4	44.0	112.3
Sé	0.49	3460	7061.2	61.6	188.0	231.1	91.1
Vitória	0.33	1901	5760.6	62.3	181.3	45.2	206.4

Table D - 2: Performance, Impact and Criticality scores on parish scale

Parish	Average Indicators			Multiplier
	Performance	Impact	Criticality	
Aldoar	1.2	3.4	0.4	1.96
Bonfim	2.7	4.1	1.1	1.89
Campanhã	1.5	3.1	0.5	1.95
Cedofeita	2.9	5.1	1.5	1.85
Foz do Douro	1.7	3.8	0.6	1.94
Lordelo do Ouro	1.7	4.1	0.7	1.93
Massarelos	2.4	4.6	1.1	1.89
Miragaia	2.8	4.6	1.2	1.88
Nevogilde	1.2	4.2	0.5	1.95
Paranhos	2.0	4.0	0.8	1.92
Ramalde	1.5	4.1	0.6	1.94
Santo Ildefonso	2.8	5.7	1.6	1.84
São Nicolau	8.9	14.9	5.6	1.40
Sé	2.8	4.6	1.4	1.86
Vitória	3.6	6.9	2.4	1.72

Appendix E – Classification Results on Pipe Scale

Table E - 1: Most critical pipes in the network over the 2013-2017 period. Showing only pipes with at least 5 obstructions during the aforementioned 5-year period

Street Identification		Pipe Length	Obstructions	Obstruction Frequency (months)	Obs/km.y
Code	ID				
Bom Sucesso, Praça	82	30.7	31	1.94	201.8
Soares dos Reis, Largo	445	37.9	15	4.00	79.1
Fernao Magalhaes, Bairro	205	27.7	14	4.29	101.0
Povoa, Rua	372	56.5	13	4.62	46.0
Outeirinho, Travessa	345	16.6	12	5.00	144.3
Oliveira Martins, Rua	336	69.8	12	5.00	34.4
Miragaia, Rua	301	34.6	11	5.45	63.5
Constituicao, Rua	134	39.7	11	5.45	55.4
Ribeira, Cais	392	51.4	11	5.45	42.8
Miragaia, Rua	301	56.1	11	5.45	39.2
Fonte Taurina, Rua	223	19.9	10	6.00	100.4
Nossa Senhora de Fatima, Rua	324	22.4	10	6.00	89.3
Joao Grave, Rua	256	89.5	10	6.00	22.4
Padre Alexandre, Rua	347	20.2	9	6.67	89.3
Oliveira Monteiro, Rua	337	20.7	9	6.67	86.9
Fernao Magalhaes, Bairro	205	30.3	9	6.67	59.5
Conde De Vizela, Rua	131	55.1	9	6.67	32.7
Fonte De Massarelos, Rua	221	62.7	9	6.67	28.7
Lapa, Rua	268	84.3	9	6.67	21.4
Campo Alegre, Rua	96	87.2	9	6.67	20.7
Monte Alegre, Rua	306	89.0	9	6.67	20.2
Sobreiras, Rua	446	21.8	8	7.50	73.3
Montebelo, Rua	312	24.4	8	7.50	65.4
Outeiro, Bairro	346	41.6	8	7.50	38.4
Aldoar, Bairro	13	45.1	8	7.50	35.4
Bolhao, Patio	80	45.6	8	7.50	35.1
S Francisco, Rua	406	49.0	8	7.50	32.7
Anselmo Braancamp, Rua	32	57.4	8	7.50	27.9
Ferreira Cardoso, Rua	206	65.5	8	7.50	24.4
Padre Jose Pacheco do Monte, Rua	349	73.5	8	7.50	21.8
Amial, Rua	28	13.8	7	8.57	101.6
Ribeira, Praça	393	31.5	7	8.57	44.4
Augusto Rosa, Rua	51	33.4	7	8.57	41.9
Diogo Botelho, Rua	159	35.8	7	8.57	39.1
Batalha, Praça	69	37.6	7	8.57	37.2
Rainha D. Leonor, Bairro	387	42.2	7	8.57	33.2
Senhora da Lapa, Rua	437	53.2	7	8.57	26.3
Bairro Bom Retiro, Rua	61	59.2	7	8.57	23.6
Ribeiro de Sousa, Rua	394	59.4	7	8.57	23.6
Goncalo Cristovao, Rua	234	71.1	7	8.57	19.7
Miguel Bombarda, Rua	298	76.1	7	8.57	18.4
Gomes Freire, Rua	232	89.5	7	8.57	15.6
Dr Francisco Sa Carneiro, Praça	174	35.2	6	10.00	34.1
Eugenio de Castro, Rua	196	37.9	6	10.00	31.7
Nova das Areias, Rua	326	40.6	6	10.00	29.5
Constituicao, Rua	134	43.7	6	10.00	27.5
Argentina, Rua	42	48.2	6	10.00	24.9
Magnolias, Rua	280	49.7	6	10.00	24.1
Comercio do Porto, Rua	127	49.7	6	10.00	24.1
Circunvalacao, Estrada	121	59.4	6	10.00	20.2
Padre Jose Pacheco do Monte, Rua	349	60.6	6	10.00	19.8
Diogo Cao, Rua	161	64.7	6	10.00	18.5
Padre Alexandre, Rua	347	64.8	6	10.00	18.5

Street Identification		Pipe Length	Obstructions	Obstruction	Obs/km.y
Code	ID	(m)		Frequency (months)	
Santa Catarina, Rua	427	69.6	6	10.00	17.2
Constituicao, Rua	134	71.0	6	10.00	16.9
Mouzinho Albuquerque, Praça	316	71.8	6	10.00	16.7
Breiner, Rua	90	81.5	6	10.00	14.7
Naulila, Rua	320	86.8	6	10.00	13.8
Naulila, Rua	320	88.5	6	10.00	13.6
Outeirinho, Rua	344	11.3	5	12.00	88.5
Mocidade da Arrabida, Rua	303	16.5	5	12.00	60.5
Povoa, Rua	372	18.5	5	12.00	53.9
Acacio Lino, Rua	4	25.9	5	12.00	38.7
Ribeira, Cais	392	31.0	5	12.00	32.3
Bairro Bom Retiro, Rua	61	36.8	5	12.00	27.2
Salado, Rua	422	37.6	5	12.00	26.6
Franca, Avenida	225	37.7	5	12.00	26.6
Alianca, Rua	22	40.6	5	12.00	24.6
Sa de Miranda, Rua	419	43.2	5	12.00	23.1
Passeio Alegre, Rua	358	43.9	5	12.00	22.8
Belos Ares, Rua	73	46.2	5	12.00	21.7
Azaleas, Rua	56	46.6	5	12.00	21.5
Clemente Meneres, Rua	122	51.8	5	12.00	19.3
Joao de Deus, Rua	255	52.0	5	12.00	19.2
Nove de Abril, Rua	333	53.7	5	12.00	18.6
Marechal Saldanha, Rua	286	56.4	5	12.00	17.7
Padre Jose Pacheco do Monte, Rua	349	59.2	5	12.00	16.9
Dr Roberto Frias, Rua	177	59.4	5	12.00	16.8
Diogo Brandao, Rua	160	59.5	5	12.00	16.8
Abracos, Rua	3	60.0	5	12.00	16.7
Actor Ferreira Silva, Rua	6	60.1	5	12.00	16.6
Barao Forrester, Rua	62	61.9	5	12.00	16.2
Bom Sucesso, Rua	83	62.0	5	12.00	16.1
Joaquim Kopke, Rua	258	66.0	5	12.00	15.1
Regado, Bairro	388	66.5	5	12.00	15.0
Aurelia de Sousa, Rua	52	66.9	5	12.00	14.9
Alegria, Rua	15	69.8	5	12.00	14.3
Almirante Leote do Rego, Rua	24	71.9	5	12.00	13.9
Sampaio Bruno, Rua	426	72.1	5	12.00	13.9
S. Joao, Rua	410	72.9	5	12.00	13.7
Nevala, Rua	321	73.8	5	12.00	13.6
Vigorosa, Rua	461	75.1	5	12.00	13.3
Alexandre Herculano, Rua	19	83.3	5	12.00	12.0
Costa Cabral, Rua	138	84.6	5	12.00	11.8
Padre Cruz, Rua	348	95.5	5	12.00	10.5

Appendix F – Classification Results on Street Scale

Table F - 1: Classification results from intermediate indicators to Criticality and proactive intervention frequency. Streets associated with high Criticality (>6) and/or with ideal intervention frequencies under 6 months are highlighted

Street Identification		Indicators							Intervention Frequency (months)	
ID	Code	Performance			Impact	Criticality	ML Criticality	Multiplier	Real	Proactive
		Actual	Expected	Total						
1	24 de Agosto, Campo	3.52	1.79	2.92	4.08	1.19	1.16	1.88	3.90	7.33
2	Abade de Faria, Rua	4.06	2.83	3.63	3.70	1.34	1.40	1.87	42.85	79.96
3	Abracos, Rua	10.00	5.68	8.49	2.18	1.85	1.86	1.82	3.30	5.98
4	Acacio Lino, Rua	9.96	5.53	8.41	2.10	1.76	1.68	1.82	12.86	23.44
5	Academico Futebol Clube, Rua	1.64	2.70	2.01	3.64	0.73	0.86	1.93	14.28	27.52
6	Actor Ferreira Silva, Rua	4.25	3.77	4.08	0.22	0.09	0.05	1.99	5.59	11.13
7	Adelaide Estrada, Rua	3.27	2.81	3.11	6.14	1.91	2.05	1.81	14.28	25.84
8	Adolfo Casais Monteiro, Rua	1.30	6.99	3.29	4.74	1.56	1.39	1.84	32.14	59.26
9	Agra do Amial, Bairro	5.68	8.25	6.58	5.85	3.85	3.57	1.43	11.69	16.72
10	Aguas, Travessa	6.52	4.05	5.65	1.24	0.70	0.80	1.93	9.89	19.08
11	Alcacer Ceguer, Rua	3.76	3.84	3.79	0.87	0.33	0.20	1.97	25.71	50.58
12	Alcantara, Rua	0.75	3.05	1.56	1.62	0.25	0.09	1.97	32.14	63.47
13	Aldoar, Bairro	3.33	4.12	3.60	2.45	0.88	0.92	1.91	3.30	6.30
14	Alegria, Praca	1.40	3.99	2.31	1.12	0.26	0.10	1.97	11.69	23.07
15	Alegria, Rua	2.68	7.37	4.32	8.79	3.80	3.80	1.44	2.30	3.31
16	Aleixo da Mota, Rua	1.21	2.81	1.77	10.00	1.77	2.21	1.82	25.71	46.87
17	Aleixo, Bairro	7.76	6.13	7.19	3.80	2.73	2.74	1.65	3.90	6.44
18	Alexandre Braga, Rua	5.03	2.63	4.19	2.56	1.07	1.18	1.89	12.86	24.34
19	Alexandre Herculano, Rua	4.98	8.70	6.28	8.19	5.14	5.16	1.40	5.84	8.18
20	Alfredo Keil, Rua	3.06	3.60	3.25	7.66	2.49	3.26	1.70	5.84	9.95
21	Aliados, Avenida	10.00	5.59	8.46	10.00	8.46	7.72	1.15	12.86	14.84
22	Alianca, Rua	2.21	9.52	4.77	3.41	1.63	1.47	1.84	10.71	19.69
23	Almada, Rua	2.27	8.45	4.43	6.04	2.68	2.62	1.66	6.12	10.19
24	Almirante Leote do Rego, Rua	8.49	8.38	8.45	8.00	6.76	6.78	1.32	4.94	6.55
25	Alvaro Casteloes, Rua	0.74	4.50	2.05	5.59	1.15	1.34	1.89	21.43	40.39
26	Alvaro Ferreira Alves, Rua	3.10	2.75	2.98	2.78	0.83	0.95	1.92	32.14	61.62
27	Alves Redol, Rua	1.64	4.09	2.49	7.17	1.79	2.03	1.82	25.71	46.83
28	Amial, Rua	1.20	3.10	1.87	5.37	1.00	0.92	1.90	6.12	11.63
29	Amorim de Carvalho, Rua	0.71	2.55	1.35	0.02	0.00	-0.18	2.00	42.85	85.69
30	Andrezas, Rua	2.25	5.26	3.30	8.00	2.64	2.79	1.67	25.71	42.98
31	Anibal Cunha, Rua	3.72	2.78	3.39	3.93	1.33	1.22	1.87	5.36	10.00
32	Anselmo Braancamp, Rua	0.69	6.74	2.80	2.72	0.76	0.72	1.92	21.43	41.22
33	Antas, Rua	2.96	6.23	4.11	1.70	0.70	0.75	1.93	8.57	16.54
34	Antero De Quental, Rua	2.89	8.39	4.81	9.38	4.51	4.22	1.40	5.59	7.83
35	Antero Quental, Travessa	0.74	8.93	3.61	4.11	1.48	1.27	1.85	42.85	79.35
36	Antonio Calem, Largo	2.96	3.26	3.06	2.04	0.63	0.49	1.94	18.37	35.58
37	Antonio Candido, Rua	3.06	4.50	3.56	5.16	1.84	2.01	1.82	10.71	19.46
38	Antonio Correia Silva, Rua	8.40	3.06	6.53	1.44	0.94	0.79	1.91	12.86	24.50
39	Antonio Granjo, Rua	10.00	6.69	8.84	2.53	2.24	2.27	1.75	4.59	8.05
40	Arada, Rua	2.88	1.98	2.56	0.61	0.16	0.09	1.98	21.43	42.52
41	Areias, Rua	0.62	2.55	1.29	1.00	0.13	-0.11	1.99	21.43	42.57
42	Argentina, Rua	3.82	3.25	3.62	3.04	1.10	1.24	1.89	4.59	8.68
43	Arq Julio de Brito, Rua	1.68	3.60	2.35	2.17	0.51	0.57	1.95	42.85	83.52
44	Arq Marques da Silva, Rua	5.49	7.01	6.02	10.00	6.02	5.87	1.40	11.69	16.34
45	Artes Graficas, Rua	4.70	8.28	5.95	6.47	3.85	4.20	1.43	12.86	18.38
46	Artur Bras, Rua	1.41	2.70	1.86	0.38	0.07	-0.10	1.99	21.43	42.70
47	Asprela, Rua	1.67	2.84	2.08	0.86	0.18	0.08	1.98	16.07	31.85
48	Ateneu Comercial Porto, Rua	4.85	6.66	5.48	8.00	4.39	4.04	1.40	16.07	22.50
49	Augusto Gil, Rua	0.64	6.64	2.74	1.80	0.49	0.40	1.95	42.85	83.59
50	Augusto Lessa, Rua	0.68	3.26	1.59	4.95	0.79	0.71	1.92	21.43	41.17

Street Identification		Indicators							Intervention Frequency (months)	
ID	Code	Performance			Impact	Criticality	ML Criticality	Multiplier	Real	Proactive
		Actual	Expected	Total						
51	Augusto Rosa, Rua	9.01	7.81	8.59	4.79	4.11	4.03	1.40	4.94	6.92
52	Aurelia de Sousa, Rua	6.04	7.75	6.64	2.64	1.76	1.62	1.82	9.89	18.04
53	Aurelio Paz Reis, Rua	1.86	3.35	2.38	3.47	0.83	0.65	1.92	11.69	22.41
54	Aval de Cima, Rua	0.66	2.93	1.46	3.34	0.49	0.50	1.95	42.85	83.62
55	Avelino Ribeiro, Rua	4.20	2.58	3.63	0.77	0.28	0.10	1.97	7.56	14.91
56	Azaleas, Rua	10.00	3.60	7.76	0.98	0.76	0.73	1.92	8.03	15.46
57	Azenha, Rua	1.39	3.55	2.14	2.06	0.44	0.09	1.96	42.85	83.81
58	Azevedo, Rua	1.27	3.48	2.04	2.73	0.56	0.33	1.94	10.71	20.83
59	Bacelo, Rua	2.59	1.85	2.33	2.67	0.62	0.34	1.94	21.43	41.52
60	Bainharia, Rua	5.83	8.70	6.84	4.82	3.30	3.30	1.54	11.69	18.00
61	Bairro Bom Retiro, Rua	10.00	6.20	8.67	1.34	1.16	1.18	1.88	6.12	11.53
62	Barao Forrester, Rua	4.18	6.25	4.91	3.30	1.62	1.68	1.84	4.76	8.75
63	Barao Nova Sintra, Rua	7.05	6.75	6.94	8.00	5.55	5.56	1.40	6.43	9.00
64	Barao S. Cosme, Rua	1.21	6.66	3.12	2.09	0.65	0.56	1.93	25.71	49.74
65	Barata Feyo, Rua	6.62	2.76	5.27	3.74	1.97	1.99	1.80	6.77	12.20
66	Barros Lima, Rua	2.82	6.22	4.01	5.22	2.09	1.93	1.78	12.86	22.91
67	Bartolomeu Velho, Rua	0.19	3.41	1.32	3.35	0.44	0.44	1.96	32.14	62.86
68	Basilio Teles, Alameda	10.00	7.75	9.21	7.27	6.70	6.67	1.33	2.68	3.56
69	Batalha, Praca	7.69	8.53	7.98	10.00	7.98	7.75	1.20	7.56	9.09
70	Beato Inacio Azevedo, Rua	1.02	4.13	2.11	4.96	1.05	1.12	1.90	25.71	48.73
71	Belem, Rua	3.56	2.98	3.36	1.47	0.50	0.50	1.95	5.59	10.90
72	Belomonte, Rua	5.69	7.78	6.42	6.27	4.03	4.07	1.40	11.69	16.36
73	Belos Ares, Rua	4.66	2.69	3.97	3.40	1.35	1.31	1.87	9.89	18.44
74	Beneditina, Rua	6.37	2.78	5.11	1.87	0.95	1.00	1.90	8.03	15.30
75	Berlengas, Rua	0.71	3.40	1.65	0.02	0.00	-0.53	2.00	42.85	85.69
76	Bica Velha, Travessa	9.88	8.70	9.47	8.13	7.70	7.36	1.23	18.37	22.60
77	Boa Viagem, Rua	10.00	6.02	8.61	0.44	0.38	0.34	1.96	3.78	7.42
78	Boavista, Avenida	1.30	2.12	1.58	4.59	0.73	0.65	1.93	1.03	1.98
79	Boavista, Rua	0.77	5.10	2.29	8.93	2.04	1.62	1.79	18.37	32.91
80	Bolhao, Patio	10.00	9.23	9.73	0.14	0.13	0.25	1.99	3.21	6.38
81	Bolhao, Rua	10.00	8.70	9.55	6.17	5.89	5.79	1.40	3.14	4.39
82	Bom Sucesso, Praca	1.29	6.24	3.02	7.56	2.28	2.51	1.74	32.14	56.02
83	Bom Sucesso, Rua	8.10	8.44	8.22	4.66	3.83	3.85	1.43	5.84	8.38
84	Bonfim, Rua	2.81	7.14	4.32	5.60	2.42	2.38	1.72	4.94	8.48
85	Bonjardim, Rua	1.00	6.75	3.02	3.62	1.09	0.97	1.89	6.43	12.15
86	Bonjoia, Rua	4.76	3.74	4.41	2.38	1.05	1.15	1.89	9.18	17.40
87	Bouca, Rua	1.96	5.02	3.03	1.45	0.44	0.45	1.96	18.37	35.92
88	Bragas, Rua	1.31	8.70	3.89	5.45	2.12	2.18	1.78	25.71	45.65
89	Brasil, Avenida	2.81	5.69	3.82	5.42	2.07	2.03	1.79	4.59	8.20
90	Breiner, Rua	4.83	8.70	6.19	8.64	5.34	5.20	1.40	7.14	10.00
91	Burgaes, Rua	4.79	6.65	5.44	1.27	0.69	0.67	1.93	6.43	12.41
92	Caducos, Rua	10.00	5.29	8.35	0.87	0.73	0.67	1.93	25.71	49.56
93	Camara Pestana, Rua	4.35	4.63	4.45	2.06	0.91	0.93	1.91	6.77	12.91
94	Camoes, Rua	2.25	8.19	4.33	6.93	3.00	2.91	1.60	6.77	10.82
95	Campinas, Bairro	1.42	3.46	2.13	3.83	0.82	1.05	1.92	7.14	13.70
96	Campo Alegre, Rua	2.74	6.00	3.88	7.75	3.00	2.99	1.60	2.18	3.48
97	Campo do Paiva, Travessa	10.00	6.20	8.67	0.28	0.24	0.30	1.98	5.84	11.55
98	Campo Lindo, Rua	3.43	4.45	3.79	5.43	2.06	2.14	1.79	9.89	17.69
99	Campolide, Rua	5.72	3.60	4.98	2.64	1.31	1.40	1.87	12.86	24.03
100	Canasteiros, Rua	10.00	9.18	9.71	10.00	9.71	10.05	1.03	11.69	12.02
101	Candido dos Reis, Rua	2.60	8.70	4.73	6.38	3.02	3.06	1.60	32.14	51.29
102	Capitao Pombeiro, Rua	0.74	6.01	2.58	3.04	0.78	0.63	1.92	42.85	82.34
103	Carlos Passos, Rua	1.74	3.82	2.47	0.03	0.01	-0.27	2.00	25.71	51.40
104	Carlos Teixeira, Rua	7.19	2.75	5.64	8.00	4.51	4.74	1.40	42.85	59.99
105	Carregal, Travessa	4.45	4.87	4.59	1.44	0.66	0.79	1.93	9.89	19.13
106	Carrical, Bairro	1.78	4.65	2.79	1.21	0.34	0.18	1.97	5.59	10.99
107	Carrilho Videira, Jardim	10.00	8.70	9.55	2.60	2.48	2.64	1.70	42.85	72.98

Street Identification		Indicators							Intervention Frequency (months)	
ID	Code	Performance			Impact	Criticality	ML Criticality	Multiplier	Real	Proactive
		Actual	Expected	Total						
108	Carvalhido, Bairro	3.92	6.28	4.75	4.63	2.20	2.34	1.76	5.14	9.05
109	Castelo, Esplanada	3.44	5.23	4.06	5.46	2.22	2.16	1.76	14.28	25.08
110	Cedofeita, Rua	3.61	8.55	5.34	8.59	4.59	4.57	1.40	5.36	7.50
111	Cedofeita, Travessa	5.32	6.10	5.59	4.25	2.37	2.22	1.73	21.43	36.96
112	Central do Viso, Rua	1.10	2.61	1.63	1.23	0.20	-0.18	1.98	42.85	84.85
113	Central Francos, Rua	0.54	2.72	1.30	1.08	0.14	-0.33	1.99	21.43	42.55
114	Cerco do Porto, Bairro	3.03	3.01	3.02	4.27	1.29	1.44	1.87	3.30	6.17
115	Cerco do Porto, Rua	0.72	2.97	1.51	4.42	0.67	0.87	1.93	21.43	41.42
116	Cervantes, Rua	0.83	6.14	2.69	1.94	0.52	0.47	1.95	21.43	41.73
117	Ceuta, Rua	7.14	6.10	6.78	5.45	3.70	3.56	1.46	9.89	14.45
118	Ciclames, Rua	3.56	3.60	3.57	0.84	0.30	0.34	1.97	32.14	63.32
119	Cidade do Recife, Rua	6.65	3.63	5.59	4.04	2.26	2.33	1.75	9.18	16.06
120	Cinco de Outubro, Rua	2.54	4.48	3.22	9.30	2.99	3.08	1.60	9.89	15.84
121	Circunvalacao, Estrada	0.82	2.94	1.57	4.58	0.72	0.65	1.93	2.11	4.06
122	Clemente Meneres, Rua	10.00	5.22	8.33	4.74	3.95	3.68	1.41	2.99	4.22
123	Clerigos, Rua	6.10	8.70	7.01	6.20	4.34	4.36	1.40	18.37	25.71
124	Codecal, Escadas	10.00	6.21	8.67	3.67	3.18	3.49	1.56	4.59	7.18
125	Coelho Neto, Rua	2.66	8.54	4.72	7.12	3.36	3.25	1.53	32.14	49.10
126	Combatentes Grande Guerra, Avenida	1.12	7.63	3.40	2.85	0.97	1.01	1.90	8.57	16.31
127	Comercio do Porto, Rua	10.00	7.59	9.16	5.86	5.36	5.23	1.40	2.86	4.00
128	Conceicao, Rua	3.37	8.70	5.24	3.72	1.95	1.81	1.80	18.37	33.15
129	Conde da Covilha, Rua	2.43	5.09	3.36	1.15	0.39	0.17	1.96	18.37	36.02
130	Conde de Ferreira, Rua	1.85	6.59	3.51	1.90	0.67	0.59	1.93	21.43	41.42
131	Conde de Vizela, Rua	10.00	8.70	9.55	4.94	4.72	4.61	1.40	2.52	3.53
132	Condominhas, Rua	0.26	1.78	0.79	3.42	0.27	0.18	1.97	42.85	84.55
133	Congostas, Avenida	0.88	2.71	1.52	2.56	0.39	0.07	1.96	21.43	42.02
134	Constituicao, Rua	5.48	8.09	6.39	6.52	4.17	4.10	1.40	0.86	1.20
135	Contumil, Bairro	5.48	2.91	4.58	3.89	1.78	1.88	1.82	2.62	4.78
136	Contumil, Rua	0.37	3.17	1.35	3.20	0.43	0.23	1.96	32.14	62.89
137	Costa Barreto, Rua	6.53	3.23	5.37	1.34	0.72	0.77	1.93	8.03	15.49
138	Costa Cabral, Rua	3.53	5.51	4.22	6.18	2.61	2.58	1.68	1.07	1.80
139	Covelo, Rua	1.28	6.17	2.99	4.68	1.40	1.03	1.86	21.43	39.86
140	Covelo, Travessa	2.99	6.05	4.06	4.66	1.89	2.00	1.81	32.14	58.19
141	Crasto, Rua	2.06	3.42	2.53	4.57	1.16	1.10	1.88	6.12	11.54
142	Cruz, Rua	0.90	3.09	1.67	3.46	0.58	0.62	1.94	42.85	83.24
143	Cruzes, Rua	1.14	2.85	1.74	2.19	0.38	0.29	1.96	42.85	84.07
144	Cruzes, Travessa	3.58	2.48	3.20	5.26	1.68	1.84	1.83	32.14	58.87
145	Cunha Junior, Rua	1.26	6.49	3.09	5.45	1.68	1.68	1.83	32.14	58.86
146	Cunha, Rua	1.06	6.02	2.80	4.25	1.19	0.94	1.88	21.43	40.30
147	D. Agostinho Jesus Sousa, Rua	7.41	4.96	6.55	6.09	3.99	4.50	1.40	9.18	12.88
148	D. Antonio Barroso, Rua	4.23	6.80	5.13	7.77	3.98	4.07	1.40	12.86	18.04
149	D. Joao Coutinho, Rua	1.26	2.21	1.59	2.70	0.43	0.08	1.96	9.18	17.97
150	D. Joao IV, Rua	1.91	7.40	3.83	4.76	1.82	1.77	1.82	6.12	11.13
151	D. Joao Mascarenhas, Rua	4.07	3.03	3.71	2.98	1.10	1.30	1.89	21.43	40.49
152	D. Joao Peculiar, Rua	2.56	3.49	2.88	0.23	0.07	-0.11	1.99	16.07	32.03
153	D. Lopo De Almeida, Rua	2.06	6.20	3.51	2.35	0.82	0.88	1.92	42.85	82.17
154	D. Manuel II, Rua	0.73	5.06	2.25	10.00	2.25	2.48	1.75	32.14	56.27
155	D. Pedro V, Rua	0.77	1.15	0.90	2.11	0.19	0.16	1.98	16.07	31.83
156	Dalias, Rua	2.06	3.60	2.60	0.71	0.18	0.08	1.98	42.85	84.91
157	Damiao Gois, Rua	3.26	4.92	3.84	10.00	3.84	4.08	1.43	6.77	9.69
158	Delfim Ferreira, Rua	0.54	3.02	1.41	2.98	0.42	0.24	1.96	25.71	50.34
159	Diogo Botelho, Rua	0.93	3.11	1.69	3.64	0.62	0.52	1.94	7.56	14.66
160	Diogo Brandao, Rua	10.00	5.44	8.40	5.51	4.63	4.55	1.40	11.69	16.36
161	Diogo Cao, Rua	8.48	4.67	7.15	3.00	2.14	2.05	1.77	3.38	5.99
162	Direita Francos, Rua	0.85	2.01	1.26	3.05	0.38	-0.05	1.96	16.07	31.52
163	Diu, Rua	1.30	4.93	2.57	3.65	0.94	0.69	1.91	16.07	30.63

Street Identification		Indicators							Intervention Frequency (months)	
ID	Code	Performance			Impact	Criticality	ML Criticality	Multiplier	Real	Proactive
		Actual	Expected	Total						
164	Domingos Machado, Rua	0.67	4.34	1.95	1.83	0.36	0.04	1.96	42.85	84.17
165	Domingos Sequeira, Rua	2.36	5.74	3.54	6.54	2.32	2.71	1.74	25.71	44.65
166	Domingues Alvarez, Rua	3.50	3.88	3.63	8.00	2.90	2.83	1.62	21.43	34.69
167	Doze Casas, Rua	4.29	7.08	5.26	4.38	2.31	2.25	1.74	9.89	17.19
168	Dr Alberto Sousa Costa, Rua	10.00	3.08	7.58	3.25	2.46	2.62	1.71	9.89	16.89
169	Dr Alfredo Magalhaes, Rua	2.59	8.66	4.71	4.23	1.99	1.67	1.80	32.14	57.87
170	Dr Antonio Bernardino Almeida, Rua	3.12	2.26	2.82	4.11	1.16	1.16	1.88	7.14	13.46
171	Dr Antunes Guimaraes, Avenida	1.39	3.43	2.10	3.62	0.76	0.58	1.92	4.02	7.73
172	Dr Eduardo Santos Silva, Rua	0.72	4.31	1.98	5.16	1.02	1.10	1.90	18.37	34.86
173	Dr Fernando Azeredo Antas, Alameda	0.73	2.79	1.45	3.66	0.53	0.63	1.95	42.85	83.43
174	Dr Francisco Sa Carneiro, Praca	5.68	6.41	5.94	2.66	1.58	1.53	1.84	3.78	6.97
175	Dr Manuel Pereira Silva, Rua	1.95	3.47	2.48	4.22	1.05	1.07	1.90	7.56	14.33
176	Dr Placido Costa, Rua	5.39	2.84	4.50	10.00	4.50	3.29	1.40	16.07	22.50
177	Dr Roberto Frias, Rua	1.84	2.39	2.03	10.00	2.03	2.15	1.79	16.07	28.82
178	Dr Sousa Rosa, Rua	2.73	4.18	3.23	5.54	1.79	1.95	1.82	14.28	26.01
179	Dr Vasco Valente, Rua	1.11	4.50	2.29	2.84	0.65	0.45	1.93	14.28	27.64
180	Duarte Barbosa, Rua	1.02	4.27	2.16	4.55	0.98	1.27	1.90	25.71	48.90
181	Duque da Terceira, Rua	0.64	4.51	2.00	2.47	0.49	0.51	1.95	32.14	62.70
182	Duque de Loule, Rua	2.48	8.70	4.65	7.89	3.67	3.62	1.47	18.37	26.91
183	Duque Saldanha, Bairro	1.56	4.84	2.71	8.00	2.17	2.14	1.77	42.85	75.71
184	Eca de Queiros, Alameda	2.55	6.51	3.94	3.84	1.51	1.47	1.85	7.14	13.20
185	Egas Moniz, Rua	4.23	7.24	5.28	5.73	3.02	2.89	1.60	5.36	8.54
186	Eirinhas, Rua	1.83	5.45	3.10	0.90	0.28	0.22	1.97	16.07	31.69
187	Eng Carlos Amarante, Rua	1.71	5.49	3.03	3.47	1.05	0.97	1.89	18.37	34.80
188	Eng Ezequiel Campos, Rua	0.90	3.54	1.82	3.73	0.68	0.51	1.93	18.37	35.48
189	Eng Ferreira Dias, Rua	0.81	3.27	1.67	10.00	1.67	2.09	1.83	14.28	26.18
190	Eng Machado Vaz, Bairro	3.28	3.08	3.21	1.13	0.36	0.35	1.96	6.77	13.29
191	Entre Campos, Rua	3.52	8.35	5.21	4.21	2.19	2.22	1.76	32.14	56.61
192	Entreparedes, Rua	3.68	8.17	5.25	3.75	1.97	1.71	1.80	18.37	33.11
193	Escuro, Rua	10.00	8.70	9.55	3.88	3.70	3.48	1.46	21.43	31.28
194	Estacao, Rua	4.03	8.70	5.66	10.00	5.66	5.51	1.40	25.71	36.00
195	Estiva, Cais	10.00	8.70	9.55	4.83	4.61	4.66	1.40	6.43	9.00
196	Eugenio de Castro, Rua	10.00	6.10	8.64	8.00	6.91	6.87	1.31	1.53	2.00
197	Exercito Libertador, Praca	10.00	4.69	8.14	6.31	5.14	4.66	1.40	6.12	8.57
198	Falcao, Bairro	1.63	3.60	2.32	7.74	1.79	2.01	1.82	25.71	46.81
199	Falcao, Rua	1.40	2.53	1.80	4.33	0.78	0.62	1.92	9.89	19.01
200	Faria Guimaraes, Rua	0.94	4.54	2.20	5.27	1.16	1.19	1.88	8.03	15.14
201	Feliciano Castilho, Rua	0.81	6.20	2.70	1.14	0.31	0.14	1.97	42.85	84.39
202	Fernandes Costa, Rua	3.94	7.62	5.23	6.15	3.21	3.09	1.56	11.69	18.20
203	Fernandes Tomas, Rua	2.78	5.85	3.85	3.03	1.17	1.05	1.88	3.67	6.92
204	Fernao Magalhaes, Avenida	1.76	4.53	2.73	4.88	1.33	1.33	1.87	1.48	2.76
205	Fernao Magalhaes, Bairro	10.00	6.38	8.73	3.47	3.03	3.11	1.59	1.34	2.14
206	Ferreira Cardoso, Rua	5.94	8.70	6.91	4.81	3.32	3.35	1.54	8.57	13.16
207	Ferreira De Castro, Rua	2.78	2.35	2.63	4.60	1.21	1.20	1.88	12.86	24.16
208	Fez, Rua	0.51	3.85	1.68	3.27	0.55	0.33	1.95	18.37	35.72
209	Figueira da Foz, Rua	2.96	7.98	4.72	1.02	0.48	0.46	1.95	18.37	35.85
210	Firmeza, Rua	1.42	5.86	2.97	5.80	1.73	1.81	1.83	12.86	23.49
211	Flor da Rosa, Avenida	0.80	3.60	1.78	0.44	0.08	-0.28	1.99	32.14	64.03
212	Flores, Praca	1.89	3.65	2.51	4.23	1.06	1.06	1.89	14.28	27.06
213	Florinha Abrigada, Rua	2.60	3.60	2.95	0.89	0.26	0.24	1.97	16.07	31.72
214	Fonseca Cardoso, Rua	1.45	7.46	3.55	4.73	1.68	1.45	1.83	25.71	47.10
215	Fontainhas, Alameda	2.31	3.38	2.69	3.02	0.81	0.75	1.92	14.28	27.41

Street Identification		Indicators							Intervention Frequency (months)	
ID	Code	Performance			Impact	Criticality	ML Criticality	Multiplier	Real	Proactive
		Actual	Expected	Total						
216	Fontainhas, Rua	2.76	5.87	3.85	2.47	0.95	0.95	1.90	14.28	27.21
217	Fonte da Moura, Bairro	7.71	5.42	6.91	8.00	5.53	5.12	1.40	3.57	5.00
218	Fonte da Moura, Rua	1.03	3.54	1.91	1.14	0.22	-0.04	1.98	12.86	25.43
219	Fonte de Contumil, Rua	1.70	2.76	2.07	2.91	0.60	0.68	1.94	25.71	49.87
220	Fonte de Contumil, Travessa	1.90	2.78	2.21	0.91	0.20	0.12	1.98	18.37	36.36
221	Fonte de Massarelos, Rua	5.37	4.39	5.03	0.59	0.29	0.37	1.97	9.89	19.49
222	Fonte do Outeiro, Rua	3.55	2.89	3.32	0.72	0.24	0.08	1.98	5.84	11.55
223	Fonte Taurina, Rua	10.00	8.70	9.55	10.00	9.55	9.40	1.05	2.01	2.10
224	Formosa, Rua	0.85	4.73	2.21	5.08	1.12	1.09	1.89	18.37	34.67
225	Franca, Avenida	2.19	4.99	3.17	3.85	1.22	0.98	1.88	3.78	7.10
226	Franco, Bairro	10.00	6.08	8.63	8.00	6.90	7.02	1.31	7.14	9.35
227	Frei Heitor Pinto, Rua	1.94	6.20	3.43	2.23	0.76	0.78	1.92	42.85	82.43
228	Freixo, Rotunda	3.13	2.58	2.94	2.08	0.61	0.47	1.94	32.14	62.32
229	Freixo, Rua	0.91	3.26	1.73	3.21	0.56	0.11	1.94	8.03	15.62
230	Galeria Paris, Rua	7.19	9.61	8.04	8.00	6.43	6.06	1.36	14.28	19.39
231	Gloria, Rua	4.76	7.41	5.69	1.65	0.94	1.04	1.91	11.69	22.28
232	Gomes Freire, Rua	3.04	2.07	2.70	0.89	0.24	0.20	1.98	6.43	12.70
233	Gomes Leal, Rua	2.18	3.60	2.68	2.93	0.78	0.96	1.92	42.85	82.35
234	Goncalo Cristovao, Rua	3.47	7.34	4.82	5.78	2.79	2.61	1.64	4.43	7.28
235	Goncalo Sampaio, Rua	10.00	4.35	8.02	10.00	8.02	7.94	1.20	2.18	2.61
236	Goncalves Zarco, Praca	1.11	4.18	2.19	2.30	0.50	-0.06	1.95	16.07	31.33
237	Gondarem, Rua	0.52	3.72	1.64	6.01	0.98	1.34	1.90	21.43	40.75
238	Graciosa, Rua	2.12	6.20	3.55	2.79	0.99	1.03	1.90	25.71	48.87
239	Grijo, Rua	1.69	4.50	2.67	5.24	1.40	1.30	1.86	25.71	47.83
240	Guedes Azevedo, Rua	3.55	8.70	5.35	8.00	4.28	4.46	1.40	18.37	25.71
241	Guerra Junqueiro, Rua	0.76	6.46	2.76	4.30	1.18	1.17	1.88	21.43	40.32
242	Guilherme Braga, Rua	2.25	6.20	3.63	1.56	0.57	0.59	1.94	25.71	49.96
243	Guilhermina Suggia, Rua	7.25	5.29	6.56	1.21	0.80	0.77	1.92	5.59	10.73
244	Guindais, Escadas	3.53	5.49	4.22	0.59	0.25	0.25	1.98	11.69	23.09
245	Gustavo Eiffel, Av. Eng.	5.00	4.03	4.66	2.22	1.04	1.15	1.90	4.76	9.03
246	Herculano, Bairro	10.00	6.20	8.67	0.25	0.22	0.36	1.98	2.99	5.92
247	Heroismo, Rua	6.23	8.70	7.10	8.49	6.02	5.95	1.40	4.02	5.62
248	Igreja de Paranhos, Rua	2.38	2.93	2.57	3.12	0.80	0.47	1.92	8.03	15.43
249	Igreja de Ramalde, Rua	10.00	1.98	7.19	2.76	1.99	2.29	1.80	9.89	17.81
250	Imperio, Praca	1.78	3.60	2.42	3.42	0.83	0.86	1.92	21.43	41.08
251	Inacio Alberto Sousa, Rua	0.91	5.64	2.57	0.74	0.19	-0.12	1.98	32.14	63.67
252	Infante D. Henrique, Rua	4.11	5.09	4.45	7.32	3.26	3.14	1.55	16.07	24.88
253	Joao das Regras, Rua	1.94	8.66	4.29	3.27	1.40	1.21	1.86	21.43	39.84
254	Joao de Barros, Rua	1.06	7.27	3.23	8.84	2.86	2.54	1.63	32.14	52.32
255	Joao de Deus, Rua	2.15	4.51	2.98	3.81	1.14	1.19	1.89	7.56	14.27
256	Joao Grave, Rua	8.61	4.72	7.25	4.29	3.11	3.10	1.58	4.02	6.34
257	Joao Pedro Ribeiro, Rua	1.34	8.06	3.69	7.12	2.63	2.62	1.67	25.71	43.06
258	Joaquim Kopke, Rua	10.00	5.95	8.58	4.26	3.66	3.70	1.47	9.18	13.48
259	Joaquim Leitao, Rua	1.84	6.11	3.33	2.69	0.90	0.82	1.91	11.69	22.33
260	Jornal Noticias, Rua	1.78	3.33	2.32	4.41	1.03	0.96	1.90	10.71	20.33
261	Jose Silva Passos, Rua	4.01	3.60	3.87	0.45	0.17	0.21	1.98	16.07	31.86
262	Julio Dinis, Rua	1.38	5.75	2.91	6.57	1.91	1.87	1.81	7.56	13.68
263	Justino Teixeira, Rua	2.41	3.77	2.89	2.35	0.68	0.50	1.93	4.76	9.20
264	La Couture, Rua	1.93	2.23	2.04	2.47	0.50	0.23	1.95	16.07	31.33
265	Lada, Rua	10.00	8.70	9.55	9.92	9.46	8.51	1.05	7.56	7.97
266	Lagarteiro, Bairro	5.97	2.95	4.91	3.85	1.89	1.98	1.81	2.79	5.06
267	Laje, Travessa	6.32	6.20	6.28	0.83	0.52	0.60	1.95	32.14	62.61
268	Lapa, Rua	8.22	8.70	8.39	3.74	3.14	2.91	1.57	6.77	10.64
269	Latino Coelho, Rua	1.36	6.70	3.23	3.77	1.22	1.28	1.88	18.37	34.50
270	Leonardo Coimbra, Bairro	1.45	2.52	1.83	4.88	0.89	1.21	1.91	32.14	61.41
271	Liberdade, Praca	6.47	5.44	6.11	10.00	6.11	5.20	1.39	8.57	11.90

Street Identification		Indicators							Intervention Frequency (months)	
ID	Code	Performance			Impact	Criticality	ML Criticality	Multiplier	Real	Proactive
		Actual	Expected	Total						
272	Lidador, Rua	0.51	3.27	1.47	2.15	0.32	-0.33	1.97	32.14	63.26
273	Lindo Vale, Rua	5.23	5.88	5.46	2.04	1.11	1.14	1.89	3.90	7.36
274	Linhas de Elvas, Rua	1.81	3.60	2.44	1.27	0.31	0.24	1.97	42.85	84.38
275	Loios, Largo	2.85	5.14	3.65	7.00	2.56	2.88	1.69	32.14	54.28
276	Lordelo, Bairro	2.03	3.60	2.58	1.91	0.49	0.54	1.95	9.89	19.29
277	Luz Soriano, Rua	1.08	2.11	1.44	2.44	0.35	0.35	1.96	32.14	63.15
278	Macieirinha, Rua	1.63	4.00	2.46	0.25	0.06	-0.22	1.99	25.71	51.27
279	Madeira, Rua	7.47	8.70	7.90	10.00	7.90	7.47	1.21	6.12	7.41
280	Magnolias, Rua	9.93	5.03	8.22	0.54	0.44	0.53	1.96	3.38	6.62
281	Manuel Bandeira, Rua	1.56	3.60	2.28	1.92	0.44	0.45	1.96	11.69	22.86
282	Manuel Laranjeira, Col. Dr	1.74	3.42	2.33	4.53	1.05	1.06	1.89	12.86	24.36
283	Manuel Marques, Rua	8.57	2.85	6.57	3.05	2.00	2.01	1.80	25.71	46.27
284	Manuel Pinto Azevedo, Rua	1.10	3.44	1.92	6.01	1.15	1.24	1.88	8.03	15.14
285	Marechal Gomes Costa, Avenida	0.52	4.24	1.82	2.89	0.53	0.38	1.95	9.18	17.88
286	Marechal Saldanha, Rua	1.45	3.65	2.22	5.93	1.32	1.27	1.87	6.43	12.01
287	Margaridas, Rua	7.18	3.60	5.93	1.15	0.68	0.78	1.93	14.28	27.59
288	Maria Lamas, Rua	3.97	2.82	3.57	0.43	0.15	0.24	1.98	8.03	15.95
289	Marques de Pombal, Praca	1.36	7.90	3.65	4.85	1.77	1.82	1.82	25.71	46.87
290	Marques Oliveira, Rua	6.40	4.02	5.57	1.51	0.84	0.76	1.92	12.86	24.63
291	Marracuene, Rua	7.08	7.50	7.23	2.78	2.01	2.19	1.80	32.14	57.79
292	Marta Mesquita da Camara, Rua	0.35	3.60	1.49	3.57	0.53	0.84	1.95	42.85	83.42
293	Martim Moniz, Rua	0.51	3.44	1.54	4.10	0.63	0.49	1.94	18.37	35.57
294	Martires da Patria, Campo	2.55	6.64	3.98	10.00	3.98	4.14	1.40	7.14	10.03
295	Martires Liberdade, Rua	1.29	8.70	3.88	5.85	2.27	2.25	1.75	18.37	32.07
296	Melo, Rua	0.79	6.55	2.80	1.09	0.31	0.16	1.97	25.71	50.64
297	Mestre Afonso Domingues, Rua	9.42	2.79	7.10	2.71	1.92	1.88	1.81	8.03	14.53
298	Miguel Bombarda, Rua	2.79	8.54	4.80	4.38	2.10	1.90	1.78	6.77	12.04
299	Miosotis, Rua	3.21	3.09	3.17	4.00	1.27	1.56	1.87	11.69	21.90
300	Miradouro, Rua	9.20	8.70	9.03	2.12	1.91	1.97	1.81	10.71	19.38
301	Miragaia, Rua	10.00	8.39	9.44	1.69	1.59	1.60	1.84	1.12	2.06
302	Mocambique, Rua	0.34	3.60	1.48	0.94	0.14	-0.27	1.99	42.85	85.11
303	Mocidade da Arrabida, Rua	9.71	4.97	8.05	0.57	0.46	0.54	1.95	3.30	6.44
304	Monchique, Rua	2.56	4.62	3.28	2.50	0.82	0.65	1.92	9.89	18.97
305	Monsanto, Rua	1.22	3.47	2.01	5.00	1.00	1.15	1.90	9.89	18.79
306	Monte Alegre, Rua	10.00	9.49	9.82	4.06	3.99	3.77	1.40	3.67	5.15
307	Monte Cativo, Rua	5.50	7.82	6.31	2.46	1.55	1.68	1.85	4.76	8.78
308	Monte da Bela, Bairro	3.25	3.60	3.37	0.74	0.25	0.25	1.97	7.56	14.94
309	Monte da Bela, Travessa	2.91	3.60	3.15	1.88	0.59	0.70	1.94	32.14	62.38
310	Monte da Estacao, Rua	0.77	4.06	1.92	2.80	0.54	0.39	1.95	42.85	83.41
311	Monte Louro, Travessa	7.65	9.51	8.30	4.18	3.47	3.52	1.51	16.07	24.19
312	Montebelo, Rua	3.17	3.04	3.12	1.60	0.50	0.49	1.95	12.86	25.07
313	Montevideu, Avenida	2.67	3.85	3.08	1.77	0.55	0.51	1.95	3.30	6.41
314	Morgado de Mateus, Rua	1.96	6.93	3.70	4.42	1.63	1.43	1.84	25.71	47.22
315	Mouteira, Bairro	10.00	1.85	7.15	1.03	0.74	0.74	1.93	25.71	49.52
316	Mouzinho Albuquerque, Praca	3.60	4.12	3.78	4.63	1.75	1.68	1.82	3.67	6.70
317	Mouzinho Silveira, Rua	2.80	4.18	3.28	6.86	2.25	2.00	1.75	6.77	11.84
318	Nasc. Col. Dr. Manuel Laranjeira, Rua	10.00	2.93	7.53	3.61	2.72	2.90	1.66	9.18	15.21
319	Nau Vitoria, Rua	0.44	2.42	1.13	1.97	0.22	-0.09	1.98	25.71	50.85
320	Naulila, Rua	5.28	3.73	4.73	0.53	0.25	0.26	1.97	4.15	8.19
321	Nevala, Rua	5.28	7.50	6.05	0.83	0.50	0.58	1.95	11.69	22.79
322	Niassa, Rua	5.00	6.41	5.49	2.67	1.47	1.43	1.85	12.86	23.83
323	Nossa Senhora Calvario, Rua	1.97	3.47	2.50	2.59	0.65	0.25	1.94	9.89	19.14

Street Identification		Indicators							Intervention Frequency (months)	
ID	Code	Performance			Impact	Criticality	ML Criticality	Multiplier	Real	Proactive
		Actual	Expected	Total						
324	Nossa Senhora de Fatima, Rua	2.04	8.16	4.18	6.93	2.90	2.77	1.62	11.69	18.94
325	Nova Alfandega, Rua	5.53	7.11	6.08	7.73	4.70	4.78	1.40	11.69	16.36
326	Nova das Areias, Rua	7.06	3.60	5.85	0.44	0.26	0.37	1.97	5.14	10.15
327	Nova de S. Crispim, Rua	1.45	8.86	4.04	7.17	2.90	2.72	1.62	18.37	29.75
328	Nova do Regado, Rua	1.71	5.25	2.95	4.37	1.29	1.20	1.87	21.43	40.09
329	Nova do Rio, Rua	0.64	5.67	2.40	0.02	0.00	-0.13	2.00	42.85	85.68
330	Nova Sintra, Calcada	3.12	1.85	2.68	1.12	0.30	0.35	1.97	32.14	63.32
331	Nova Sintra, Travessa	2.41	5.58	3.52	1.73	0.61	0.67	1.94	14.28	27.70
332	Nove de Abril, Praça	10.00	4.26	7.99	6.44	5.14	4.92	1.40	2.04	2.86
333	Nove de Abril, Rua	2.61	2.87	2.70	3.84	1.04	1.05	1.90	2.62	4.97
334	Nove de Julho, Rua	0.76	4.92	2.22	2.83	0.63	0.59	1.94	21.43	41.51
335	Nuno Pinheiro Torres, Bairro	4.18	3.77	4.04	2.74	1.11	1.28	1.89	2.99	5.65
336	Oliveira Martins, Rua	7.07	5.79	6.62	1.94	1.28	1.30	1.87	4.29	8.02
337	Oliveira Monteiro, Rua	6.21	6.66	6.37	6.57	4.18	4.22	1.40	1.86	2.61
338	Oliveiras, Rua	9.18	8.70	9.01	9.19	8.28	7.92	1.17	9.89	11.59
339	Oliveirinhas, Rua	2.34	7.82	4.26	1.50	0.64	0.59	1.94	42.85	82.97
340	Orfeao do Porto, Rua	1.14	2.79	1.72	7.90	1.36	1.66	1.86	25.71	47.94
341	Oscar da Silva, Rua	1.57	3.47	2.23	5.42	1.21	1.41	1.88	25.71	48.31
342	Ourique, Rua	2.67	4.67	3.37	1.00	0.34	0.33	1.97	32.14	63.20
343	Ouro, Rua	2.60	4.27	3.18	2.83	0.90	0.69	1.91	3.67	7.02
344	Outeirinho, Rua	10.00	8.70	9.55	10.00	9.55	9.93	1.05	21.43	22.40
345	Outeirinho, Travessa	10.00	6.20	8.67	8.00	6.94	7.30	1.31	21.43	27.99
346	Outeiro, Bairro	10.00	4.83	8.19	4.28	3.50	3.53	1.50	2.26	3.38
347	Padre Alexandre, Rua	10.00	8.89	9.61	2.41	2.31	2.41	1.74	3.06	5.32
348	Padre Cruz, Rua	9.78	6.20	8.53	2.32	1.97	2.21	1.80	6.12	11.03
349	Padre Jose Pacheco Do Monte, Rua	10.00	6.43	8.75	3.10	2.71	2.70	1.66	2.07	3.44
350	Padre Manuel Nobrega, Rua	6.24	6.46	6.32	2.16	1.36	1.45	1.86	8.57	15.97
351	Paiol, Travessa	10.00	10.00	10.00	0.29	0.29	0.53	1.97	9.89	19.49
352	Panoramica, Via	2.12	3.91	2.74	3.24	0.89	0.60	1.91	10.71	20.48
353	Papoilas, Rua	1.42	3.60	2.18	0.36	0.08	-0.08	1.99	42.85	85.37
354	Paraiso, Rua	8.40	5.98	7.56	3.91	2.96	2.81	1.61	5.36	8.62
355	Parque, Avenida	0.37	1.84	0.89	1.46	0.13	0.01	1.99	42.85	85.15
356	Part de Francos, Rua	0.92	5.07	2.37	0.78	0.18	0.13	1.98	42.85	84.91
357	Passeio Alegre, Jardim	2.27	4.75	3.14	3.26	1.02	0.85	1.90	25.71	48.79
358	Passeio Alegre, Rua	1.95	5.60	3.23	5.73	1.85	1.95	1.81	6.43	11.67
359	Passos Manuel, Rua	6.71	6.18	6.52	5.00	3.26	2.84	1.55	3.78	5.85
360	Pasteleira, Bairro	10.00	6.10	8.64	8.00	6.91	7.19	1.31	3.57	4.68
361	Paulo da Gama, Rua	2.32	3.02	2.56	5.71	1.46	1.82	1.85	6.43	11.91
362	Pedras, Cais	10.00	8.53	9.49	5.25	4.98	4.96	1.40	3.06	4.29
363	Pedro Hispano, Rua	1.61	2.77	2.02	4.57	0.92	0.90	1.91	4.43	8.46
364	Pedro Homem de Melo, Rua	1.96	3.95	2.65	5.77	1.53	1.54	1.85	12.86	23.75
365	Pedro Ivo, Rua	2.11	8.35	4.29	1.88	0.81	0.67	1.92	42.85	82.25
366	Pena, Rua	7.33	6.20	6.93	2.46	1.71	1.72	1.83	4.59	8.40
367	Pereiro, Bairro	1.23	2.75	1.76	1.64	0.29	0.21	1.97	25.71	50.68
368	Pio XII, Bairro	1.40	6.43	3.16	1.89	0.60	0.46	1.94	21.43	41.57
369	Platanos, Rua	2.08	2.88	2.36	2.85	0.67	0.67	1.93	25.71	49.70
370	Poen Col. Dr. Manuel Laranjeira, Rua	2.03	3.60	2.58	1.91	0.49	0.54	1.95	32.14	62.69
371	Poveiros, Praça	2.19	8.70	4.47	7.12	3.18	2.81	1.56	42.85	67.02
372	Povoa, Rua	10.00	3.77	7.82	1.23	0.96	1.00	1.90	1.71	3.26
373	Povoa, Travessa	10.00	6.20	8.67	1.92	1.67	1.74	1.83	3.90	7.14
374	Praia, Rua	2.50	2.68	2.57	0.14	0.04	-0.07	2.00	32.14	64.16
375	Preciosa, Rua	0.78	5.14	2.31	2.75	0.63	0.60	1.94	32.14	62.24
376	Priorado, Largo	8.85	8.70	8.80	4.41	3.88	3.66	1.42	14.28	20.34
377	Prof Abel Salazar, Largo	10.00	7.68	9.19	6.65	6.11	5.54	1.39	18.37	25.51

Street Identification		Indicators							Intervention Frequency (months)	
ID	Code	Performance			Impact	Criticality	ML Criticality	Multiplier	Real	Proactive
		Actual	Expected	Total						
378	Prof Agostinho Silva, Rua	1.66	3.62	2.35	2.91	0.68	0.77	1.93	10.71	20.69
379	Prof Alberto Saavedra, Rua	10.00	5.27	8.35	8.00	6.68	6.62	1.33	12.86	17.13
380	Prof Bento Jesus Caraca, Rua	0.95	3.36	1.79	3.70	0.66	0.72	1.93	21.43	41.43
381	Prof Duarte Leite, Rua	0.72	3.89	1.83	4.65	0.85	1.13	1.91	42.85	82.05
382	Prof Luis Costa, Rua	5.79	3.60	5.02	3.61	1.81	1.95	1.82	42.85	77.93
383	Prof Mendes Correia, Rua	1.56	2.80	1.99	2.65	0.53	0.56	1.95	32.14	62.58
384	Prof Ruy Luis Gomes, Alameda	1.20	3.31	1.94	3.28	0.64	0.67	1.94	25.71	49.79
385	Quanza, Rua	2.23	9.28	4.70	1.98	0.93	0.90	1.91	25.71	49.04
386	Rainha D. Estefania, Rua	3.08	4.26	3.49	1.28	0.45	0.25	1.96	10.71	20.95
387	Rainha D. Leonor, Bairro	0.46	6.00	2.40	1.25	0.30	0.08	1.97	21.43	42.21
388	Regado, Bairro	10.00	3.89	7.86	3.30	2.59	2.85	1.68	1.05	1.77
389	Reinaldo Oudinot, Rua	0.78	2.54	1.40	1.77	0.25	0.10	1.98	25.71	50.79
390	Restauracao, Rua	1.38	3.77	2.22	3.03	0.67	0.33	1.93	5.59	10.80
391	Revilao, Rua	1.11	3.41	1.91	1.54	0.29	0.07	1.97	32.14	63.33
392	Ribeira, Cais	10.00	8.44	9.45	5.28	4.99	4.97	1.40	2.01	2.81
393	Ribeira, Praca	10.00	7.84	9.25	8.93	8.26	7.26	1.17	1.81	2.13
394	Ribeiro de Sousa, Rua	2.03	4.91	3.04	1.70	0.52	0.50	1.95	12.86	25.05
395	Ricardo Severo, Rua	6.61	7.33	6.86	5.94	4.07	4.19	1.40	11.69	16.36
396	Rodrigues Freitas, Avenida	4.26	8.50	5.75	10.00	5.75	5.27	1.40	6.43	9.00
397	Rodrigues Lobo, Rua	5.08	6.70	5.64	4.62	2.61	2.92	1.68	21.43	35.96
398	Rodrigues Sampaio, Rua	10.00	7.99	9.29	3.33	3.09	2.78	1.58	10.71	16.94
399	Rosario, Rua	1.54	7.95	3.79	7.07	2.68	2.74	1.66	12.86	21.40
400	Rovuma, Rua	2.24	7.50	4.08	0.78	0.32	0.34	1.97	25.71	50.61
401	Ruben A, Rua	2.99	2.91	2.96	5.86	1.74	1.97	1.83	16.07	29.35
402	Rui Faleiro, Rua	2.93	6.20	4.07	2.51	1.02	1.09	1.90	25.71	48.79
403	S. Bartolomeu, Rua	1.46	5.48	2.87	2.60	0.75	0.31	1.93	32.14	61.88
404	S. Bras, Rua	1.08	6.76	3.07	2.53	0.78	0.72	1.92	16.07	30.89
405	S. Dinis, Rua	3.32	6.53	4.44	4.41	1.96	1.83	1.80	2.30	4.14
406	S. Francisco, Rua	10.00	8.70	9.55	5.02	4.79	5.06	1.40	5.36	7.50
407	S. Joao Bosco, Rua	2.81	3.46	3.04	7.49	2.28	2.02	1.74	6.43	11.21
408	S. Joao De Brito, Rua	1.47	4.71	2.60	6.98	1.82	1.95	1.82	12.86	23.38
409	S. Joao De Deus, Bairro	10.00	6.96	8.94	2.72	2.43	2.27	1.71	4.94	8.47
410	S. Joao, Rua	2.86	7.65	4.54	5.29	2.40	2.01	1.72	8.57	14.75
411	S. Luis, Rua	9.93	6.20	8.62	0.69	0.59	0.76	1.94	6.77	13.13
412	S. Miguel, Rua	3.77	8.70	5.49	8.59	4.72	4.65	1.40	25.71	36.00
413	S. Roque Lameira, Bairro	10.00	5.65	8.48	8.00	6.78	6.95	1.32	4.02	5.31
414	S. Roque Lameira, Rua	1.89	2.88	2.24	4.89	1.09	1.09	1.89	2.57	4.86
415	S. Tome, Rua	1.91	4.71	2.89	9.69	2.80	2.82	1.64	18.37	30.11
416	S. Vitor, Rua	1.90	7.13	3.73	2.83	1.06	1.00	1.89	11.69	22.14
417	Sa Albergaria, Rua	1.30	2.77	1.81	1.20	0.22	0.10	1.98	42.85	84.77
418	Sa da Bandeira, Rua	4.68	5.50	4.97	7.55	3.75	3.53	1.45	2.92	4.24
419	Sa de Miranda, Rua	4.64	2.80	3.99	3.89	1.55	1.60	1.84	7.14	13.17
420	Sa de Noronha, Rua	10.00	8.70	9.55	10.00	9.55	9.48	1.05	11.69	12.22
421	Sacadura Cabral, Rua	8.81	7.66	8.40	5.43	4.56	4.32	1.40	16.07	22.50
422	Salado, Rua	3.46	3.49	3.47	0.50	0.17	0.15	1.98	16.07	31.86
423	Salazares, Rua	0.88	2.83	1.56	1.83	0.29	0.18	1.97	25.71	50.69
424	Salgueiro Maia, Rua	8.31	3.60	6.66	3.53	2.35	2.49	1.73	8.03	13.90
425	Salgueiros, Rua	2.91	7.50	4.52	0.64	0.29	0.30	1.97	11.69	23.04
426	Sampaio Bruno, Rua	4.25	5.77	4.78	5.98	2.86	2.52	1.63	16.07	26.17
427	Santa Catarina, Rua	4.04	8.28	5.52	8.07	4.46	4.46	1.40	1.65	2.31
428	Santo Antonio Contumil, Rua	0.68	2.73	1.40	1.65	0.23	0.07	1.98	18.37	36.31
429	Santo Ildefonso, Rua	3.44	8.48	5.21	6.97	3.63	3.62	1.47	6.12	9.03
430	Santo Isidro, Rua	6.45	6.24	6.38	1.44	0.92	1.00	1.91	6.77	12.91
431	Santo Isidro, Travessa	3.99	7.45	5.20	2.83	1.47	1.40	1.85	21.43	39.70
432	Santos Pousada, Rua	6.91	5.18	6.31	7.91	4.99	5.00	1.40	1.53	2.14

Street Identification		Indicators							Intervention Frequency (months)	
ID	Code	Performance			Impact	Criticality	ML Criticality	Multiplier	Real	Proactive
		Actual	Expected	Total						
433	Sarah Afonso, Rua	4.17	5.30	4.57	8.00	3.65	3.28	1.47	18.37	26.98
434	Sarmiento Beires, Rua	4.47	2.97	3.94	8.00	3.15	3.00	1.57	6.12	9.61
435	Seixal, Rua	2.51	5.16	3.44	6.63	2.28	2.60	1.74	32.14	56.05
436	Senhora da Conceicao, Travessa	2.70	2.84	2.75	1.67	0.46	0.50	1.95	14.28	27.91
437	Senhora da Lapa, Rua	5.30	8.49	6.42	0.78	0.50	0.40	1.95	9.89	19.28
438	Senhora da Luz, Rua	2.47	5.36	3.48	6.09	2.12	2.07	1.78	14.28	25.37
439	Senhora da Luz, Travessa	3.46	3.33	3.42	0.24	0.08	0.01	1.99	25.71	51.21
440	Senhora do Porto, Rua	1.47	3.26	2.09	4.79	1.00	1.32	1.90	11.69	22.20
441	Serpa Pinto, Rua	6.04	8.11	6.77	7.28	4.93	4.77	1.40	2.43	3.40
442	Sidonio Pais, Avenida	0.87	2.89	1.58	0.97	0.15	-0.10	1.98	14.28	28.35
443	Silva Porto, Rua	2.41	5.82	3.60	4.15	1.50	1.47	1.85	9.18	16.99
444	Silva Tapada, Rua	4.85	2.52	4.03	3.10	1.25	1.39	1.87	7.14	13.39
445	Soares dos Reis, Largo	10.00	7.23	9.03	8.00	7.22	7.17	1.28	4.76	6.08
446	Sobreiras, Rua	5.92	5.01	5.60	5.00	2.80	2.89	1.64	5.14	8.43
447	Sobre-O-Douro, Calçada	1.61	6.65	3.38	0.25	0.08	-0.12	1.99	42.85	85.35
448	Sol, Rua	4.44	7.51	5.52	4.30	2.37	2.51	1.73	9.89	17.07
449	Tanger, Rua	1.24	6.82	3.19	3.86	1.23	1.09	1.88	21.43	40.22
450	Teatro, Rua	1.56	2.97	2.05	4.36	0.89	1.13	1.91	25.71	49.12
451	Tenente Valadim, Rua	0.66	5.59	2.39	9.04	2.16	2.13	1.77	21.43	37.88
452	Teodoro Sousa Maldonado, Rua	1.58	2.71	1.98	2.84	0.56	0.62	1.94	42.85	83.30
453	Terreiro, Largo	10.00	8.70	9.55	5.07	4.84	4.56	1.40	42.85	59.99
454	Torrinha, Rua	1.25	4.41	2.35	6.87	1.62	1.58	1.84	14.28	26.26
455	Vale Formoso, Rua	2.49	5.95	3.70	4.69	1.73	1.56	1.83	5.36	9.78
456	Valpacos, Rua	4.89	2.81	4.17	2.72	1.13	1.19	1.89	12.86	24.26
457	Vanzeleres, Rua	3.07	5.91	4.06	5.12	2.08	1.95	1.78	9.89	17.64
458	Vasco da Gama, Avenida	1.73	3.54	2.36	3.42	0.81	0.63	1.92	10.71	20.56
459	Venezuela, Rua	2.09	6.03	3.47	6.15	2.14	2.21	1.77	9.18	16.28
460	Vieira da Silva, Rua	1.97	3.60	2.54	3.76	0.95	1.21	1.90	18.37	34.98
461	Vigorosa, Rua	5.51	7.25	6.12	2.30	1.41	1.43	1.86	4.76	8.85
462	Vilar, Rua	1.40	7.97	3.70	7.95	2.94	2.68	1.61	25.71	41.43
463	Vilarinha, Rua	0.56	4.01	1.76	3.74	0.66	0.48	1.93	16.07	31.08
464	Vimara Peres, Avenida	4.40	5.62	4.83	3.17	1.53	1.47	1.85	11.69	21.59
465	Visconde de Bobeda, Rua	1.71	7.26	3.65	2.31	0.85	0.74	1.92	42.85	82.08
466	Visconde de Setubal, Rua	1.14	8.55	3.74	5.58	2.08	1.79	1.78	32.14	57.31
467	Viso, Bairro	6.43	3.32	5.34	7.15	3.82	3.25	1.44	2.99	4.29
468	Vitorino Nemesio, Rua	1.95	4.11	2.71	8.00	2.16	2.26	1.77	42.85	75.73