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Management and Sustainability of Urban Drainage Systems within Smart Cities

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Management and Sustainability of Urban Drainage Systems within Smart Cities

Abstract

This work presents the Real Time Control (RTC) of Urban Drainage Systems (UDS) within smart cities. RTC requires to understand the system operation and to perform simulations on measured, forecasted, and synthetic events. Therefore, a Real Time Monitoring system (RTM) was implemented on the experimental site, and combined to a simulation model. A model auto-calibration process and hydraulic boundary conditions forecast system were developed in order to simulate the hydrologic-hydraulic response. Aiming to protect the citizens and mitigate flooding consequences, the RTC was composed of a flooding forecast system followed by a dynamic management strategy. The proposed concept and methodologies were applied and evaluated on the Lille 1 University Campus, within the SunRise project.

It was concluded through the applications, that visualizing the structural observations found during inspections, which are temporally and geographically localized within a GIS database, is an efficient technique in detecting structural critical zones. In parallel, RTM was found very helpful in understanding the system operation and calibrating the simulation model. Genetic Algorithm followed by Pattern Search formed an effective auto-calibration procedure for the simulation model. NARX Neural Network was developed and validated for forecasting the hydraulic boundary conditions required for conducting simulations on un-measured events. Once understanding the UDS operations, the RTC was developed. NARX Neural Network was found capable to forecast flooding events in critical areas, where flooding may appear, based on a weather forecast system. A dynamic management for increasing a tank retention capacity was studied based on calculating a Valve State Schedule, and results were satisfying by using Genetic Algorithm and a modified form of Artificial Bee Colony, as optimization methods. A qualitative management was also proposed and tested for verifying its potential in reducing flooding volumes, and good results were obtained.

Keywords

Smart Cities, Urban Drainage Systems, Real Time Monitoring, Auto-Calibration, Optimization Algorithms, Flooding Forecast, NARX Neural Networks, Dynamic Management

Gestion et Durabilité des Réseaux d'Assainissement dans le Cadre des Villes Intelligentes

Résumé

Ce travail présente le Contrôle en Temps Réel (CTR) des Réseaux d'Assainissement (RA) dans le cadre des villes intelligentes. Le CTR nécessite de comprendre le fonctionnement du système et d'effectuer des simulations sur des évènements mesurés, prévus et synthétiques. Par conséquent, un système de Surveillance en Temps Réel (STR) a été mis en œuvre sur le site expérimental, et combinée à un modèle de simulation. Une méthode d'auto-calage des modèles hydrauliques et un système de prévision des conditions aux limites, ont été développés, afin de simuler la réponse hydrologique-hydraulique des RA. Visant à protéger les citoyens et d'atténuer les conséquences des inondations, le CTR est composé d'un système de prévision des inondations suivi d'une stratégie de gestion dynamique. Le concept et les méthodes proposées ont été appliqués et évalués sur le campus de l'Université de Lille 1, au sein du projet SunRise.

Il a été conclu à travers les résultats, que la visualisation des observations constatées lors des inspections, qui ont été temporellement et géographiquement localisés au sein d'une base de données SIG, est une technique efficace pour la détection des zones structurellement critiques. En parallèle, STR a été trouvé très utile pour comprendre le fonctionnement du système et le calage du modèle de simulation. L'Algorithme Génétique suivi par Pattern Search a formé une procédure d'auto-calage efficace pour le modèle de simulation. NARX Neural Network a été développé et validé pour la prévision des conditions aux limites hydrauliques, nécessaires pour effectuer des simulations sur des événements non-mesurée. Une fois l'opération du RA est analysée, un CTR a été développé. NARX Neural Network est trouvé capable de prévoir les inondations dans les zones critiques, où elles tendent à apparaître, sur la base d'un système de prévision météorologique. Une gestion dynamique pour augmenter la capacité de rétention du réservoir, a été étudiée sur la base du calcul de la variation temporaire optimale de l'ouverture d'une vanne, et les résultats ont été satisfaisants en utilisant l'Algorithme Génétique et l'Algorithme des Abeilles, comme méthodes d'optimisation. Une gestion qualitative a également été examinée et testée pour vérifier son potentiel dans la réduction des volumes d'inondation, et des bons résultats ont été obtenus.

Mots Clés

Ville Intelligentes, Réseau d'Assainissement, Surveillance en Temps Réel, Auto-Calage, Algorithmes d'Optimisation, Prévision des Inondations, Réseau de Neurones NARX, Gestion Dynamique.

Acknowledgment

The greatest challenge to any thinker is stating the problem in a way that will allow a solution. ***Bertrand Russell***

Undertaking this PhD has been a truly challenge and experience for me and it would not have been possible without the support and guidance that I received from my surroundings.

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We should be taught not to wait for inspiration to start a thing. Action always generates inspiration. Inspiration seldom generates action. ***Frank Tibolt***

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- 1-D SVE: One-Dimensional Saint-Venant Equation
- ANN: Artificial Neural Network
- CIL: Consecutive Iterations Limit before abandoning the unimproved solution
- COD: Chemical Oxygen Demand
- CRI: Computer Resource Centre of Lille1 University
- EA: Evolutionary Algorithms
- FFS: Flooding Forecast System
- FNU: Formazin Nephelometric Unit
- GA: Genetic Algorithm
- GIS: Geographical Information System
- GPS: Global Positioning System
- IETD: Inter-Event Time Definition
- MEL: Métropole Européenne de Lille
- MLP: Multi-Layer Preceptor
- MNI: Maximum Number of Iterations
- MSE: Mean Squared Errors
- NARX: Nonlinear Autoregressive Network with Exogenous Inputs
- NI: Number of Individuals
- NS: Number of Solutions
- NSE: Nash–Sutcliffe Efficiency
- ORP: Oxidation-Reduction Potential
- PS: Pattern Search
- PSB: Parameters Space Boundaries
- RNN: Recurrent Neural Network
- RTC: Real Time Control
- RTM: Real Time Monitoring
- SunRise: Smart Urban Networks for Resilient Infrastructures and Sustainable Ecosystems
- SWMM: EPA's Stormwater Management Model
- TSS: Total Suspended Solids
- UDS: Urban Drainage Systems
- VSS: Valve State Schedule
- YRP: Year Return Period

General Introduction

The urban population was increasing continuously until reaching presently 50% of the world population. It is expected that this percentage will rise to 70% in 2050. The demographic boom over stresses the infrastructures of the cities. As a result, the utilities of urbanized cities are undergoing different types of failures during operations. In addition, cities are facing many other problems as water resources shortages and massive energy consumptions. Therefore, a new technological concept, based on real time monitoring and controlling the system operations, is recently appearing. This concept, called smart cities, is not limited to optimally operate the city components, but to integrate multi-objectives elements into an overall intelligent system. The present work concerns the Urban Drainage Systems (UDS). Urbanization led to increase impermeable surfaces, and thus induces higher runoff volumes and velocities. Age of these infrastructures is also a concern, since it limits their capacities and induces operation problems. In addition, climate changes, characterized by long dry periods followed by highly intense storms, is a major contributor to UDS malfunctions. Consequently, researches were conducted in order to improve the UDS operations and efficiency. Since replacing and enlarging the existing drainage systems is not feasible in most cases due to its high relative cost and required time, applications were more focusing on alternative techniques and Real Time Control (RTC) implementations.

The integration of the UDS into the smart city concept is proposed in this thesis. A structural assessment of the different branches of the system, followed by conditions priority ranking and critical area's localization, is the first step in this integration. Besides improving the system actual state, the construction of an updated log within a Geographical Information System (GIS), was proposed. Such GIS database assists managers in evaluating the structural state's evolution of the system. These evaluations improve the long term proactivity of the maintenance and rehabilitation actions. In parallel with the structural improvements, this work tends to present applications for strengthening UDS hydraulic operations. UDS Hydraulic response is monitored through Real Time Monitoring system (RTM). These systems consist of quantitative and qualitative sensors, implemented inline the network, and able to measure parameters during the events. A calibrated hydrologic-hydraulic model extends the monitoring zones to cover the operations of the entire system elements.

Due to UDS complexity and stochastic dynamic nature of their loadings, an effective evaluation of the system hydraulic operation, requires analysing the system response on multiple and different events. Conducting multiple scenarios simulations is an efficient technique for deeply analysing the UDS hydraulic operation. Moreover, simulating extreme weather scenarios helps in evaluating and applying RTC, which is manipulating online the system elements in the most proper way aiming some objectives. In this study, the objectives of a smart city were defined as protecting the citizens and the environment, recharging water resources, offering esthetical places for the citizens and respecting economical aspect.

This thesis includes 4 chapters. The first chapter is a literature review of the UDS and Smart City Concept. After defining the UDS shortages, alternative techniques applications, RTM characteristics and smart city principal, this chapter tends to represent the proposed concept for integrating UDS within the smart cities.

The second chapter of this thesis aims to present the experimental site, the structural assessment methodology and the real time monitoring system implementation. This work is part of the SunRise project, which consists of implementing a large-scale demonstrator of smart and sustainable city on the Lille 1 University Campus. Within this project, the stormwater system architecture, equipment and inspection data were collected, verified and digitized into a GIS database. The GIS analysis and visualization potential in assessing and predicting the structural state evolution of UDS are presented in this chapter. In addition, aiming to analyse the system's hydraulic response, the studied site was equipped by multiple quantitative and qualitative sensors. Characteristics, usefulness and installation procedures of the implemented sensors are also discussed in this chapter.

UDS simulation model is an essential element in analysing the real system's hydraulic response. Simulating an UDS operation requires a lot of parameters, which are highly interconnected and generally un-measured. A calibration process is necessary to identify these parameters, but it is a hard task to accomplish. Therefore, the third chapter is dedicated to develop an effective method for auto-calibrating a hydrologic-hydraulic model. Auto-calibration process was based on interacting EPA-SWMM with Matlab for applying Genetic Algorithm and Pattern Search optimization techniques. Once a calibrated model was constructed and verified on multiple storm events and through multi-point measurements, the objective was to enable simulations on synthetic and unmeasured storm events. Hydraulic boundary conditions are necessary in order to conduct such simulations. Consequently, a NARX neural network is presented and verified in this chapter, charged for forecasting the outfall water depth variation for the synthetic storm events.

Final chapter is the core element of this research, where a RTC is presented. Aiming the objectives of a smart city, the constructed RTC is composed of a flooding forecast system and a dynamic management strategy. The flooding forecast system is based on a NARX neural network for predicting water depth variations in different critical areas of the system. Combined to a weather forecast, this system is able to proactively alert the managers for possible inundations. The dynamic management strategy focuses on optimally benefiting the system and the tank retention capacities, by dynamically manipulating the tank-connecting valve. The objective of this management was to reduce the total flooding volume and duration. Genetic Algorithm and modified form of the Artificial Bee Colony optimization techniques were both tested and evaluated in calculating the Valve State Schedule. Evaluation of optimization techniques was based on final results and required calculation time. Finally a qualitative dynamic management was introduced at the end of this chapter, aiming to support the dynamic management in strengthening the system operation.

This work opened a lot of perspectives in this research field, which are presented at the end of the thesis.

Chapter 1

Urban Drainage Systems within Smart Cities: State of the Art & Emerging Challenges

1.1 Introduction

Several studies show that by the year 2050, the world's cities will host more than 70% of the world population, while they cover only 2% of the earth surface. To deal with this problem, caused by globalization and integration process, cities are facing the difficulty of combining efficiency and sustainability in its urban development. In addition, due to increasing urbanization, cities are already facing many problems of resources shortages and massive energy consumption (space, mobility, power, water etc.) (Bello 2014).

Consequently, a new concept was developed, called 'smart cities', represented by modern cities able to implement interconnected and sustainable infrastructures (water, electricity, gas, transportation, emergency services, public services, building, etc.) (Mattoni *et al.* 2015; Rathore *et al.* 2016). This concept has been developed to improve the comfort of the citizens and to be more effective in respecting the environment (Bello 2014). The present work concerns the Urban Drainage Systems (UDS) within smart cities. Urbanization has led to increase surface impermeability and therefore, increase runoff volumes, velocities and flow rates, generating pollution spills into the environment and flooding at the lowest areas (Yazdanfar & Sharma 2015; Zhou *et al.* 2016). In addition, climate change, characterized by long dry periods followed by severe storm events, is also a major contributor in aggravating UDS operations, resulting in floods and environmental pollutions (Jung *et al.* 2015; van der Pol *et al.* 2015). Consequently, in the last decades, researchers were focusing on how to optimize the existing capabilities of UDS, based on Real Time Control (RTC) systems taking into account inter- and intra- variability of volume and quality of runoff in a storm event (García *et al.* 2015; Yazdanfar & Sharma 2015). It has been noticed that a good management of a monitored UDS can ensure the operation continuity of the system and all its related structures, protect the environment, use energy efficiently, detect parasite flows, check and prioritize all problems and assure a better maintenance management (Veolia-eau 2013). As well, other studies show that Real Time Monitoring (RTM) data can be a useful tool to provide information that make the operators able to detect problems and pollution events that in conventional systems would go unnoticed (Pouet *et al.* 2006). Thus the efficiency and time response in taking actions, in order to protect the city considered at risk, will be improved. Moreover, received data, using these techniques, allow the implementation of pollution load reduction policies (Fleishmann 2007), and consequently decrease pollution spills, protect wastewater treatment plant and network facilities, and support a city to be smarter on all its objectives and potentials.

This work proposes a step-by-step methodology to reinforce an UDS to become more intelligent and suitable for a smart city concept. Firstly, a general presentation of weaknesses and pollution sources, within these utilities, is presented in order to define the undesirable incidents and determine the ultimate goals to achieve a successful transformation to a smart UDS. Moreover, smart city does not work on improving each utility to its optimum within its limited responsibilities. Therefore, the third section is a presentation of different techniques and structures used for strengthening UDS as well as reinforcing a smart city multi-objective behaviour. Since real time data offer a great potential for a city to be smarter, it is obvious that monitoring sensors will be the key elements in developing the UDS concept within smart cities project. Consequently, a detailed review on RTM systems is presented in section 4 of this chapter, showing the benefits of these systems as well as listing their different forms and characteristics.

After a general review on UDS, alternative structures and monitoring systems, section 5 introduces the smart city concept. At first, smart city concept with all its multi objectives were defined and combined to actual UDS conditions, to finally establish headlines for the construction of these utilities in the smart city structure. A prioritization and smart rehabilitation plan of UDS is firstly proposed. Secondly, a smart historical and updated information log with its usefulness study, which contributes to a long-term strategy and system future condition assessment, is defined. Finally a smart UDS, which participates in the enlargement of the city intelligence, is proposed as a combination between green city concept and smart monitoring system, based on sensors deployment, citizens' interaction, and effective central control station.

The last section presents the different types and benefits of a management strategy. This section shows that an optimal strategy could help the city on a multi-level, as for example the economic benefits, time saving, environmental protection, recharging resources, system sustainability, design and research fields, as well as progress in multiple other fields and domains.

1.2 Failures and Pollution sources

One of the degradation causes of the natural environment is UDS discharges during wet weather. Since 1970s, numerous studies have shown the importance of the pollution they cause and their harmful impact on aquatic environments (Saget *et al.* 1995; Gromaire *et al.* 2001; Brombach 2002; Diaz-Fierros T *et al.* 2002; Even *et al.* 2004). Since then, combined systems had been given more attention, and more studies focused on how managing overflows. On the other hand, some studies led to consider that separated stormwater runoff also generates significant pollution, higher than the daily flow discharged by treatment plants for many pollutants parameters, due to leaching urban surfaces (Gromaire-Mertz *et al.* 1998; Diaz-Fierros T *et al.* 2002; Kinoshita *et al.* 2002; Weyrauch *et al.* 2010). Therefore, the fact that only separating sewage from stormwater systems cannot solve the problem, and developing an ultimate strategy in order to optimally operate and manage the infrastructure networks is a must. Problems within UDS are not limited to pollution spills. Due to the urbanization process and climate change, floods are frequently appearing, generating serious economic consequences and casualties, and become one of the major challenges for cities' managers. Examples of flooding events are presented in the literature. Due to several consecutive storm events, the city of Dubrovnik in Croatia was inundated on 3 September 2014, and thus cars and trams movements were blocked for several hours (Figure 1-1). Boulogne-Sur-Mer in North of France in 26 August 2015, presented another example of flood occurrences due to severe storm events (Figure 1-2). Multiple other factors also led existing UDS to undergo structural failures combined to hydraulic insufficiencies. These multiple factors, had been developed in several studies, and defined as aging of the system, soil conditions surrounding the pipe, design defects, root intrusion and tectonic and seismic movements (ASCE 1994).

Figure 1-1: Inundation at Dubrovnik, (Croatia) - 03 September 2014 (Nature Alerte 2014)

Figure 1-2: Inundation at Boulogne-Sur-Mer, (France) - 26 August 2015 (La Voix du Nord 2015)

1.2.1 Wastewater Sources and Pollution

1.2.1.1 Surface Runoff

Water entering the UDS is derived from multiple sources studied and discussed in the literature. First, the surface runoff is collected by the UDS from urban areas. From rainfall to runoff, this water will be polluted through different steps. Before reaching the ground, the first stage of pollution is by leaching the atmosphere. Water represents at this stage, a low concentration of pollutants (Grange & Deutsch 1986; Becouze-Lareure 2010). Furthermore runoff pollution comes from leaching impervious surfaces, contaminated by air pollution deposit during dry weather and pollution associated with human activities (industry, traffic...). The characteristics of runoff from different urban areas have already been the subject of several studies (Gromaire-Mertz *et al.* 1999; Gnecco *et al.* 2005; Han *et al.* 2006; Lamprea 2009).

Types of pollution associated with human activities are classified into four categories (Gaber 1995). Firstly, there is the chronic pollution related to the condition of use of impervious surfaces (Movement of vehicles, corrosion of roof elements, pavement wear, etc.). The nature of the pollutants in this type is highly variable, and heavy metals and hydrocarbon oils can mainly pollute runoff. Secondly, the seasonal pollution, caused in principle by the maintenance of roads and infrastructures during winter, exists. The salt used for snow removal belongs to seasonal pollution type, which beyond a certain dose is toxic to aquatic organisms and plants. Thirdly, there is accidental pollution. An example of this type is discharges resulted from an accident while transporting hazardous materials, which could cause very serious consequences. The nature of this pollution is very diverse but the hydrocarbons are frequently involved (Griffond 1993). Lastly, temporary pollution related to the construction of roads, buildings and infrastructures (dust, vehicle discharges, etc.), occurs. Runoff from these platforms are primarily loaded with suspended material of mineral origin (Gaber 1993).

1.2.1.2 Dry Weather Flow

In combined UDS, water flow during dry weather is called sewage. In general, this water comes from human use and is divided in domestic and professional activities. Studies have been developed concerning the amount, temporal distribution and characteristics of domestic water (Verbanck 1990; Butler *et al.* 1995; Coghlan 1995; Piatyszek *et al.* 2002). Other studies were conducted to determine the pollutant flows of the domestic wastewater discharges (Rambaud *et al.*

1977; Besse *et al.* 1989; Pujol & Lienard 1990; Butler *et al.* 1995; Bécares *et al.* 2009), and found that fecal matter is the primary source of the presented suspended solids in this type of water (Vinnerås *et al.* 2003). On the other hand, for industrial and commercial water, a huge variety in the volume and nature of discharges exists, according to the type of occupation (Sörme & Lagerkvist 2002). Studies on the pollution generated by this water is also presented in the literature (Gromaire-Mertz 1998).

1.2.1.3 Road Washing

There are different wash methods that use chemical products, like manual sweeping, washing with pressure spraying and mechanical aspiration. Experiments were conducted on the watershed of Marais to evaluate the characteristics of the water induced by this application (Gromaire-Mertz *et al.* 1999). Comparing the concentration of suspended solids generated by this water and that brought by runoff, during rainfall, shows that median masses and median concentrations are generally comparable.

1.2.1.4 Infiltration

In addition, there is water infiltration that may increase the flow through the pipes. This water generally unpolluted, exist in the system due to defects in design, construction or operation of the networks (Davies *et al.* 2001). Infiltration influence is not negligible and may cause significant increases in water volumes (Bareš *et al.* 2012), and can also change the quality of effluent and causes a decrease in the effectiveness of treatment works (Wei *et al.* 2002). Infiltrated water into the network, and even water that reappear on the surface through springs and water sources that flows to enter the UDS, can be rich in nutrient elements as azote, especially for networks placed near agricultural areas, and can cause eutrophication phenomenon in the environment where overflows are discharged (Bobbink *et al.* 1992).

1.2.2 Pollution Types and Characteristics

1.2.2.1 Different Pollutants in UDS

No matter what the urbanization and the UDS types are, various studies show that most of the pollution of urban wet weather discharges is fixed to suspended solids materiel (Chebbo *et al.* 1995; Ashley *et al.* 2005; Zgheib *et al.* 2011) as shown in Table 1-1, taken from the technical guide of stormwater retention basins (STU 1994). In some cases, runoff overflows into the natural environment without any treatment. Pollutants in particulate form can then settle and participate in the degradation of sediment quality (Seidl *et al.* 1998; Servais *et al.* 1999).

Table 1-1: Proportion of Particulate Pollution Over Total Pollution

Pollutants	***COD***	***Hydrocarbons***	***BOD5***	***Metals***
(%)	*83-95*	*82-99*	*83-92*	*79-99*

In UDS, the main pollutants of runoff water are:

- Nutrients as phosphor and azote, which cause eutrophication and alter the whole environmental system balance
- Sediments or suspended matter that once deposited can have harmful effects on aquatic life in rivers, streams and lakes.
- Organic materials, which can cause a lack of oxygen during their decomposition.
- Pathogens measured in terms of fecal coliform concentration, sometimes exceed public health standards.
- Hydrocarbons resulted from vehicle operation. They are toxic even at low concentration to aquatic organisms.
- Metals generally found in runoff, which can be toxic even at low concentrations.
- Pesticides may be detected at concentrations that exceed the toxicity threshold to aquatic organisms.
- Chlorides involved in acid rain or salts used for snow removal applications.
- Trash and debris trained by sanitation flow.

1.2.2.2 Dry Time Deposit and Re-suspension

Researches on the Parisian sewer system have led to consider the three following components of solid deposits in pipe systems (Ahyerre 1999; Oms 2003):

- The coarse deposit with highly mineral nature.
- The organic layer easily mobilized and located at the surface of mineral coarse deposits. This layer is identified as the main source of pollutants in rainfall event and appears in areas where the slope of pipes is shallow ($j < 0.05$) and the flow velocity is low ($U < 0.1$ m/s). During dry weather, this layer tends to a stable height and fills the hollow of coarse deposit.
- The biofilms are consisted of micro-organisms, extracellular polymers and organic and inorganic substances. Polymers represent 90% of the organic content of this layer (Ahyerre 1999; Houhou 2009).

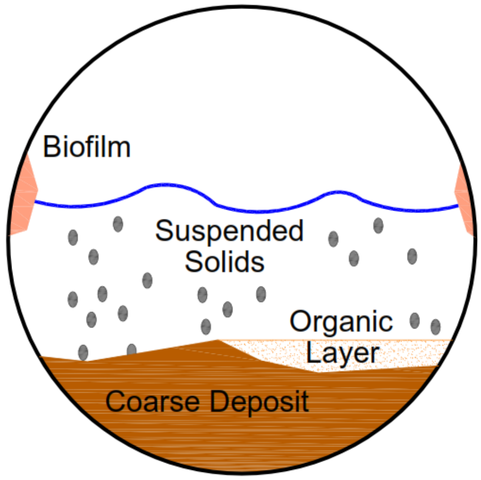

Figure 1-3: Different layers of solid deposits in networks

In the sedimentary layer, thick sludge accumulated in the bottom of pipes, as presented in Figure 1-3, results in an oxygen deprived areas allowing anaerobic sulphate-reducing bacteria to grow (US EPA 1974) excreting hydrogen sulphide H_2S (US EPA 1985) which is gasified later in the network. This gas considered as deadly gas may impact the pipe structure by reacting directly with the materials or by being transformed into sulphuric acid, which cause dissolution of the materials, and generates a toxic runoff.

1.3 Alternative Structure

Since the mid-1980s, municipal authorities and government policy makers have had a real awareness on sustainable management of rainwater in the natural environment. Thus, many cities in the world have worked to develop new practices for integrating stormwater management into urban planning and future development of their territories: Minneapolis (MSM 2006); Vancouver (Ngan 2005); Toronto (MOE 2003); Calgary (Jaska 2000); Paris (Certu 2003); London (Bettess 1996).

1.3.1 Principles of Alternative Techniques

Alternative techniques present an effective solution for stormwater management in urban areas (Liao *et al.* 2013). They are based on two principles: **Temporary storage** of water, which is used to regulate the flow in the downstream network, and the **Infiltration** of water, which reduces or eliminates the volumes flowing downstream in the network. Studies have shown that these techniques could also be good for water treatment objectives (Jia *et al.* 2014; Baek *et al.* 2015). Indeed, their use allows some degree of governing stormwater quality by treating runoff, either by decantation or filtration processes. In addition, adding to storage structures certain means of treatment or implementing some plants to enhance area landscaping, could have a great decontaminating capacity. In the literature, lots of discussions on optimal alternative practices and the criteria to be considered in choosing the specific type had been established (De Paola *et al.* 2015; Liu *et al.* 2016; Monteiro *et al.* 2016). In the following paragraphs, a brief description for most of these structures' types will be presented.

1.3.2 Types of Alternative Techniques

In the following paragraphs, a general review of the literature on optimal alternative practices has been established, and the criteria to be considered in choosing an alternative structure to a particular site practices have been discussed.

Storage or vegetated roofs, shown in Figure 1-4, are used to slow runoff and reduce the effect of ground waterproofing. The stored water is either directly used in residential applications, through storage barrels (Infraguide 2005), or directed in a regulated flow to the network. In case of a vegetated roof represented in Figure 1-5, in addition to the retention benefit, buildings thermal insulation, evapotranspiration for the runoff and water purification exist. Application of these alternatives requires a well-designed roof taking into account the load of these materials. Maintenance of these structures is difficult and it requires at least two visits per year.

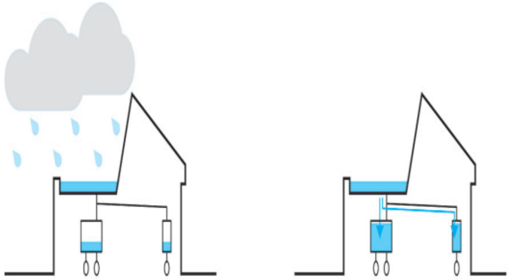

Figure 1-4: Storage roof (Ward 2014)

Figure 1-5: Vegetated roof (Fuamba et al. 2010)

Drainage trenches are linear surface structures, located downstream of the impervious area, collects runoff perpendicular to their length through a gully system or by infiltration using a draining surface layer, as shown in Figure 1-6 (Certu 2008). Water evacuation will be either through infiltration or returned as a regulated flow into a stream or a network.

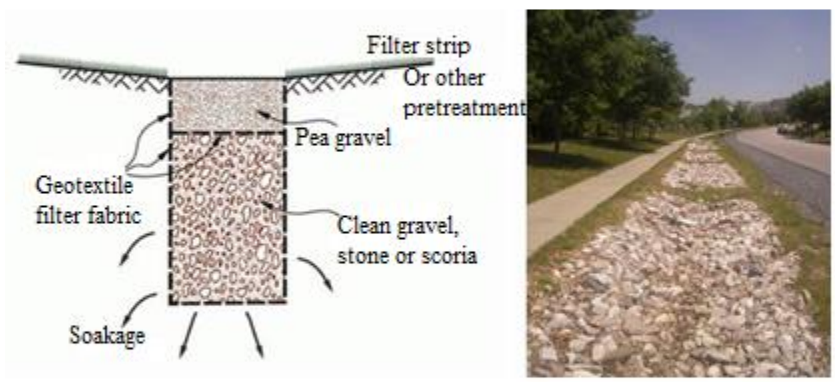

Figure 1-6: Drainage Trench (RiverSides ; Sustainable Stormwater Management 2007)

Porous pavements, where concrete layer and asphalt mixture are porous, are shown in Figure 1-7. In these techniques the stored water is evacuated either by infiltration if the ground permeability allows and accidental pollution is not possible, and hence the runoff volume will be reduced, or routed to an UDS and therefore peak flow will be dispersed (Azzout *et al.* 1994). This kind of alternative technique is sensitive to freezing and thawing phenomenon, and requires regular maintenance, by simple aspiration, in order to minimize clogging problems.

Figure 1-7: Porous pavement (Jen McDonnell 2014) & (Kris 2008)

Retention ponds and infiltration basins, shown in Figure 1-8 and Figure 1-9, are storage or infiltration structures, which essentially control the quantitative aspects of stormwater, and sometimes can provide sedimentation whether a water pollution control is required. For this type of structures, the concrete underground tanks and the excavated outside open basin, where evaporation process exist, are distinguished. Studies have examined the effectiveness of these basins by purifying the water using decantation phenomenon (Thirionet & Grégeois 2000).

Figure 1-8: Retention or detention pond (Strand Associates 2011)

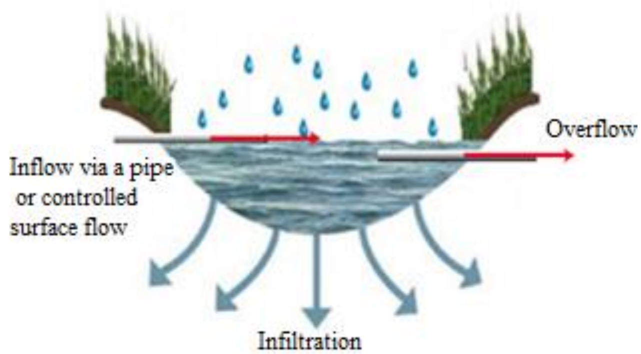

Figure 1-9: Infiltration basin (Vermont)

Swales and ditches shown in Figure 1-10 and Figure 1-11, are structures designed to collect water by pipes or runoff from adjacent surfaces, and evacuate it by outfall structure or by infiltration. In case of a steep longitudinal slope, dams can be implemented to increase the storage volume, reduce runoff speed, increase infiltration and activate the settling phenomenon. These structures require regular preventive maintenance and may not be applicable in areas with sensitive soils to erosion.

Designing these structures by dividing their total length allows managing incidents of accidental pollution by isolating the polluted section and pumping the stored water.

Figure 1-10: Vegetated swale (Copeland et al. 2012)

Figure 1-11: Ditch (The Carrs Wetland Project)

Infiltration wells, shown in Figure 1-12, are point structures with varying depths depending on inflow and geology of the site. This system has the advantage of being used in existing constructed areas where space is limited. This technique may be associated with a pumping system for removing water in case of damage or detection of polluted water. Maintenance is required at least twice a year.

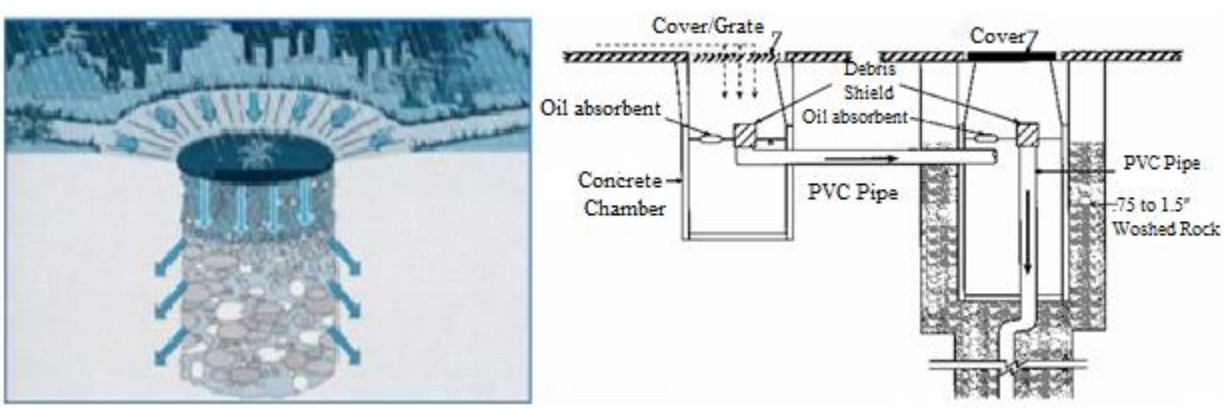

Figure 1-12: Infiltration well (US EPA 2013) & (GUIDEnR HQE)

Perforated pipes, shown in Figure 1-13, may be considered when soils have sufficient permeability and groundwater table level and rock are at a depth greater than 1 meter at any point in the system (WSDE 2005). This method is not suitable for industrial or commercial sites where the release of significant amounts of pollutants is possible.

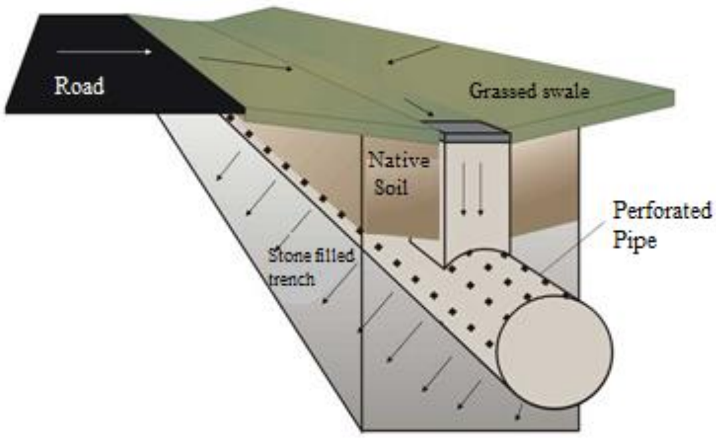

Figure 1-13: Drainage system using perforated pipes to increase soil infiltration (Jun 2010)

1.3.3 Pre-treatment for Alternative Structures

The design of alternative structures must absolutely support maintenance activities to ensure their best performance. The quality of water directed to these structures should be verified, before any contact with the environment, either by infiltration or spillage. For this purpose, sometimes, when water is directed to the alternative structure through a network, a pre-treatment is suggested to ensure the lifespan of these structures, their storage capabilities, their treatment potentials and the protection of the environment. Several types of pre-treatment are possible: vegetated filter strip, sediment trap, vortex separator, commercial filtration systems, oil and sediment separator, neutralization tank etc. (Bettess 1996). Two of these types are presented in Figure 1-14 and Figure 1-15.

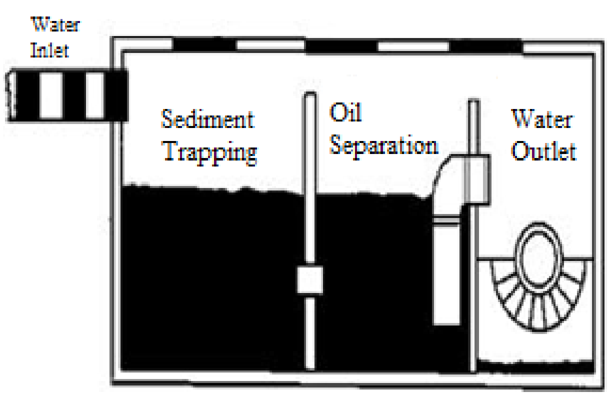

Figure 1-14: Oil and sediment separator (Schueler 1987)

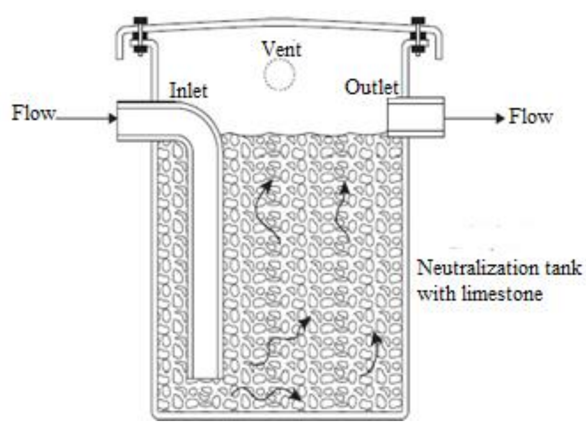

Figure 1-15: Neutralization tank (Michael Frankel 2012)

1.3.4 Example of Implemented Alternative Structures

The city of Greensburg, described as a green city, is a good example to show the different concepts and structures used in these types of projects. The system of stormwater management, in Greensburg city, uses green engineering practices to create the chain of natural treatment process throughout the city (Greensburg 2007). First, devices for rainwater harvesting, such as rain barrels, are installed for direct reuse of water collected from green roofs. Permeable pavements are used, in this city, to increase the power of soil infiltration. In addition, prairies with deep roots exist in order to reduce the volume of surface water flow using the infiltration and evapotranspiration phenomenon. Biological drainage basins and rain gardens, which have a high absorption capacity, are used to store rainwater. Moreover, conventional wetlands are installed to allow sedimentation and reduce soil erosion. Finally the rest of runoff is dispersed in local reservoirs or in ephemeral streams.

1.4 Real Time Monitoring Data

Traditionally, the operation and sustainability of a wastewater system is dependent on two different processes: design of the network and maintenance interventions (Laterasse *et al.* 1990). Besides that, a modern concept introduces a new strategy to benefit from our underground infrastructures. A continuous monitoring data, revealing the status of the system, leads to an improvement in UDS management, maintenance works, rehabilitation procedures and environmental protection. The dynamic management in infrastructure works may designate a variety of levels ranging, from local control over a particular structure (tank, valve, pump etc.) to a consideration of the overall automation of the entire system (Lemoine 2004). Controlling the operation of pumping stations, in order to ensure pumps optimum utilization, is a good example of managing a particular structure within the system (Schütze & Alex 2003).

Conventionally, monitoring a system operation is obtained through continuous sampling method. Even though valuable information for research and system operation had been provided (Brombach & Fuchs 2003), this approach suffers from many limitations. Short duration campaigns with high proportional costs, limited information obtained while using destructive testing method, heavy maintenance and errors due to sample preparation, transportation and conservation, are factors that may limit the profitability of this approach (Bertrand-Krajewski *et al.* 2003).

While water legislation requires more effective control of water bodies, technology introduces a new approach for water survey and control, based on dynamic acquisition of the system state. Continuous recordings of quality and flow data through RTM sensors is proposed instead of discontinuous sampling of biological quality elements (Fleishmann 2007). Runoff quality and RTM concept for efficient use of this methodology have been listed and defined by multiple articles and guidelines (Harmancioglu & Alpaslan 1994; Bertrand-Krajewski *et al.* 2000; Serramià 2004; Batle Ribas 2006; Schütze *et al.* 2006; Thomas & Pouet 2006; Llopart-Mascaró *et al.* 2008; Rieger & Vanrolleghem 2008).

1.4.1 Controlling UDS

Efficiently controlling UDS is operating actuators to influence the process, depending on monitored variables in the system using inline sensors. The whole strategy and control is applicable through data transmission networks communicating the different devices of the controlling system (Schütze *et al.* 2004). Management strategies can be based on rainfall and hydraulic forecasts in short term proactive strategy by modelling the process, or only reacting instantly to values and levels reached in the system and measured by sensors (Lemoine 2004). Similarly, management strategies can be set in advance and applied based on forecasts and conditions at any given time, or it could be adaptive and optimized in real time according to unexpected changing conditions in the system (Schütze *et al.* 2002; Schütze *et al.* 2004; Chocat 2005; Pleau *et al.* 2005).

The RTC appears to be a possible answer to regulate discharges of urban wet weather. Moreover, it lets operators to maximum benefit the system and evaluate its functioning and performance. A good example of an effective monitored wastewater system is the RTC system of Quebec Urban Community. It has been operating since 1999, and its main objectives are the minimization of overflow volumes and the maximization of the use of treatment plant capacity, by limiting accumulated volumes within tunnels and flow rates below pipes hydraulic capacities. Measures in Quebec system consist of flow and water level data, rainfall intensity, radar rainfall images and 2 hours of rain prediction model. These data are transmitted from different locations to a central station where, after analysing it, the system controls five moveable gates in order to apply the best protective management (Pleau *et al.* 2001). At first, this RTC system managed the western portion of Quebec Urban Community, and by optimizing the capacity of the wastewater treatment plant and with the use of only two tunnels, this system achieved a reduction of 70% in the overflow volumes in the year 2000.

Another example of RTM systems is the project of LEWAS laboratory (Learning Enhanced Watershed Assessment System), on the Virginia Tech campus. LEWAS Lab uses implemented sensors and computing technologies to capture continuous water and weather data in order to support watershed research and educational outreach. This monitoring project has shown not only progress in providing knowledge about watershed behaviours, but has also demonstrated benefits for hydrology education by increasing undergraduate student motivation in multiple courses (McDonald *et al.* 2014). However, the implementation of an RTC requires an effective and valuable continuous measurement system, as well as taking into account the measurements uncertainties (Chocat 2005). Thus, in the following paragraphs, discussions about uncertainties in the monitoring systems, as well as characteristics, process verification and programming rules are presented.

1.4.2 Real Time Measurement Uncertainties

Despite the importance and contribution of RTM sensors in UDS management, their use in these networks is limited for many reasons. Due to lack of reliability, operational difficulties, fast fouling and difficult access for maintenance, some researchers and UDS managers doubt the possibilities of setting up RTC systems especially those that are based on qualitative measurements (Duchesne *et al.* 2003; Gruber *et al.* 2005).

Regular maintenance interventions should not only enable the cleaning of the probes, but also check the possible drift of the measurements by verifying a high and a low point values. In addition, the acquisition and data filtering are essential steps to obtain continuous exploitable measurements. Noises can make the raw signal unusable; therefore a treatment is necessary to convert it into a final usable signal.

A guide to support management decision, as allowing the listing of the important elements to consider when developing an RTC system, is presented in the literature (Schütze *et al.* 2006). Furthermore, researches have been conducted to design, install, operate and test different technologies for measuring and estimating short time steps of flow characteristics and concentrations of the pollutant loads (Gruber *et al.* 2005; Llopart-Mascaró *et al.* 2008; Chowdhry *et al.* 2009; Sempere-Payá & Santonja-Climent 2012).

1.4.3 Monitoring System Architecture

Authors describe the architecture of each part which make up the monitoring system structure (Sempere-Payá & Santonja-Climent 2012). Sensors deployed in sites could be of different forms, depending on their use and the site conditions. First, fixed station sensors are used to capture environmental and water control data (Ritchie & Cooper 2001). These sensors are fixed in their locations and installed based on experience or modelling results in the system critical points. Management strategies that are set in advance, mainly depend on these sensors data, and control the system using this architecture form of activators. Second, mobile units similar to those of fixed station sensors but are not tied to only one measuring point. This type can be used either when temporal additional information or routine checks are necessary. Third form of sensor structures is the quick deployment network applicable without any previous monitoring plan and with less equipment and specialist personnel.

Every architecture form of sensors, after collecting information, send it to a central control station, which acts as monitoring and activity station and is charged for storing, managing and processing all the received data. In this station, server reads the memory space continuously, so that as new data arrives, system conditions and information are analysed, and depending on strategy plans, necessary actions are taken. Ordinary services to send and receive data over a network is not appropriate to be used for these types of applications, as they are designed for high transfer rates and mobility, and present frequent service quality problems (Artell *et al.* 2005). Products, which meet the specific requirements, have been designed and realized and Machine to Machine services have appeared, which have real advantages over the traditional lines (Sempere-Payá & Santonja-Climent 2012).

1.4.4 Parameters Measurement Types

For UDS management, examples of useful sensors measuring valuable data for controlling the networks are rain gauges, water level gauges, flow gauges and quality gauges. While the choice of actuators depends on the action to be taken and could be pumps, gates, weirs, valves, flow splitters, chemical dosing, aeration devices etc. (Schütze *et al.* 2004).

To establish an effective UDS qualitative management, which can meet the needs of a city, each type of pollution should be associated with the quality gauge, which can detect it. First of all, the suspended solids, which represent the important part of the pollution in wastewater flow, and may indicate the presence of other pollutants, can be detected according to the literature by the turbidity sensor probe. In the runoff, as in combined effluent during dry weather and wet weather, good correlations between suspended solids concentrations and turbidity measurements were obtained (Deletic & Maksimovic 1998; Ruban *et al.* 2001; Mels *et al.* 2004; Fletcher & Deletic 2007). In recent years, several laboratories have therefore implemented continuously measuring devices of turbidity in UDS to measure particulate pollution (Ruban 1995; Henckens *et al.* 2002; Schellart 2002; Aumond & Joannis 2005; Langeveld *et al.* 2005; Ruban *et al.* 2006). The organic part, measured as Chemical Oxygen Demand (COD), which can attack the environment through their oxygen consumption in times of their fermentation, and thus reduce the dissolved oxygen in receiving environment, indispensable for fish and algae, is also well correlated to the turbidity (Mels *et al.* 2004). Measures by s::can spectrometer probes allow working on several pollutants, including dissolved pollutants form as COD_{eq}, filtered COD_{eq}, TSS_{eq}, $nitrate_{eq}$ and hydrogen sulphide (H_2S) by scanning through different wave lengths from ultraviolet to infrared. Furthermore, there are other devices of continuous measurements that may be related to parameters of the pollutants. Probes for continuous measurements of ammonia, nitrogen or phosphorus, which discharged in large quantities into the environment, leads to eutrophication of aquatic environments, have also been developed in recent years. There are even sensors for continuous measurements of polycyclic aromatic hydrocarbons. For detecting the presence of minerals in the flow, the conductivity sensor probe is suitable. The presence of mineral salts in high concentration can cause regression and even disappearance of certain amphibians, affect the trees which capture it, accelerate the corrosion of certain metals, and beyond a certain amount, can be considered as toxic to aquatic organisms.

Moreover, Oxidation-Reduction Potential (ORP) used in wastewater systems is a measurement of the potential of occurrence of specific biological reactions in wastewater flows. Knowing the ORP values associated with specific reactions, allows the ORP probes measurements to be useful in monitoring the state of the wastewater systems and to indicate to the operators if unwanted biological activity is occurring (Gerardi 2007). An application of this management can be as following: the production of malodours can be indicated by an ORP value less than -100mV due to sulphide formation and fatty acid production, and then it is possible for the operators to increase the ORP value above -50 mV by adding sodium nitrate (Na_2NO_3) to a manhole, and thus prevent biological malodour production.

1.4.5 Vision Capabilities

Furthermore, the vision capabilities, which could be fixed or mobile station sensors, are an efficient tool to detect and prevent problems in the UDS. Through image capture and video recording it is possible to detect breaks, infiltrations, blockages, increases in flow, and dumped material (Sempere-Payá & Santonja-Climent 2012). Besides that, permanent video and camera surveillance are actually cheap and greatly facilitate maintenance, rehabilitation and evaluation of different branches of the UDS (Gruber *et al.* 2005). For information diagnosis, manual processing is not the best suitable method due to human fatigue, subjectivity, time and high cost. Therefore, several research projects have focused on automating the analysis of these images (Wirahadikusumah *et al.* 1998; McKim & Sinha 1999; Moselhi & Shehab-Eldeen 2000).

1.4.6 Measurement System Implementation

The measurement point must be easily accessible in order to make the maintenance and verifications for the measuring system (Lorentz *et al.* 2002). Quantitative measurements are done inline the system, while according to the experimental site conditions, qualitative measurements could be done directly inside the pipes, or by diverting a portion of the influent by an intake pipe to a protected channel structure, where sensors are installed.

1.4.6.1 Inline Real Time Measurement

The representativeness of the measurements taken by inline sensors depends heavily on hydraulic conditions of water flow in the chosen test section. Firstly, it is necessary that the measuring point guarantees a sufficient mixing of the effluent to reduce the risk of heterogeneity in the measuring section (Bertrand-Krajewski *et al.* 2000). Also, attention to the sensors location should be paid to avoid flow disturbances, such as a downstream of an elbow, a bend or a confluence area (Schellart 2002). On the other hand, the system installation must provide an acceptable protection of measurement probes from floating debris carried by the flow that could clog and damage the sensors (Schellart 2002). In case of qualitative measurements, the installation should be far enough from conduit or channel walls, to reduce the problem of fouling sensor probes. At the same time, the probes should always be sufficiently immersed, with a minimum depth of 10 to 30 cm below the water surface, to obtain good quality measurements (Lorentz *et al.* 2002). In addition, probes should be positioned in parallel with flow direction to prevent clogging and significant disruption measures (Ruban 1995; Henckens *et al.* 2002). The installation device must maintain the orientation of the probes, even in difficult hydraulic conditions (Lorentz *et al.* 2002). Conversely, in periods of low flows and water levels, the installation device must prevent sedimentation around the probes (Gruber *et al.* 2005). Figure 1-16 presents an inline flowmeter installed inside a drainage pipe. A turbidity meter installation shown in Figure 1-17, presents the rotation of a water holding device, insuring the submergence of the turbidity meter probe during low water depth.

Figure 1-16: Inline Flowmeter Installation

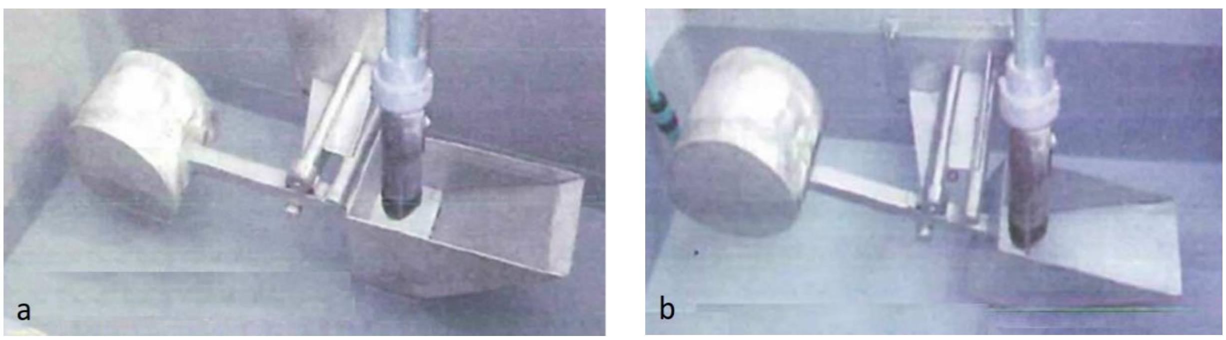

Figure 1-17: Inline Turbidity Meter Installation (a-Submerged Probe during Low Water Level b-Real Time Measurements during Rainfall Events)

1.4.6.2 Parallel By-Pass Real Time Measurement

Due to the difficulty of inline measurements, some devices had been developed to measure in parallel structure. As illustrated in Figure 1-18, the effluent are pumped and sent to a parallel channel provided with various measuring devices. The measurement channel should also be regularly cleaned. The installation of a water supply must meet certain technical hydraulic requirements as in the case of inline monitoring (Bertrand-Krajewski *et al.* 2000). At the same time, water level and flow speed in the measurement channel should properly represent the state of the flow in the system. For the question of pumping the effluent from the collector to the measuring channel, as for sampling, it must be ensured that the effluent does not undergo changes during transition process; therefore the use of peristaltic pumps is recommended.

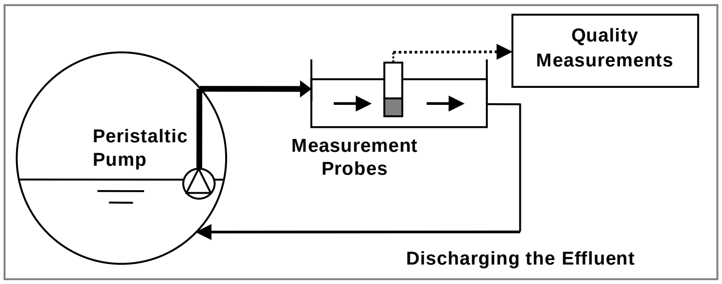

Figure 1-18: Illustration of Parallel Real Time Measurement By-Pass Chamber

1.4.7 Transmitting and Filtering Data

1.4.7.1 Data Transmission Types

Three different traditional types exist to present and control communications between the different types of sensors and the central acquisition station. First, the synchronous architecture; where the information signals are transmitted periodically from the sensor to the database at the central station. Second, the request by central architecture; where the sensors transmit observations and information about the system when the central station requests it. Finally, an asynchronous architecture based on transmitting the information when triggered by state changes. Changes in the captured information will generate the transmission of data between the sensor and the central station and initiate any action that may be necessary (Sempere-Payá & Santonja-Climent 2012).

As well as the importance of having periodic transmission of information, it is also important to have a non-periodic model that is able to transmit alarms, in case of having values beyond the acceptable ranges. In fact, a synchronous communication model, with a very small time step of sending data, would mean an overload of transmissions and could have high costs, while in increasing the time step, some anomalies could be undetected, hence the importance of combining the synchronous with the asynchronous architecture. However, it is important to be able, from the central station, to request information of current situation, independently of its value or the time; so that the operators can have the information they need at any time, as in case of requesting initial conditions required for starting model calculations.

1.4.7.2 Selecting the Transmitted Data

In areas where critical situations could happen or sensor data verification is needed, spatially dense sensor deployment is required. As a result, multiple sensor nodes that are close could have approximately the same data for the same event. In this case, only one of the nodes has to transmit its measurements instead of all the deployed sensors. Allowing only nodes with different information to send their data can effectively reduce energy consumption (Vuran *et al.* 2004; Vuran & Akyildiz 2006).

Some problems could arise when a lot of information, which could be avoided, are sent to the central station, as loss of packets, less computing capabilities, more memory spaces, slower transmission, and more energy consumption etc. Since transmission of data requires more energy than computation, algorithm of sending data had been established in the literature (Chowdhry *et al.* 2009). Before transmitting the data, an algorithm based on two factors runs, first consideration is based on filtering the information at each node, then the filtered data of each sensor is compared with other sensors, and only unique, valuable and representative data is sent to the central station.

1.4.8 Real Time Measured Data Verification

Multiple techniques exist, in order to limit the transmission of redundant values and reduce the energy consumption. For example, comparing each measured value with an average of already measured values, during the transmission time step, can detect the representativeness of this value and if it is allowed to participate in the calculation of the total average sent to the central station (Lacour 2009). Other techniques exist to reduce the corruption of the signal, as using a kernel smoother (Alferes *et al.* 2013), or by checking the measured data with predicted ones. In order to predict values, the rating curve model with the Kalman filter form an interesting methodology shown in several studies (Bennis & Bruneau 1993; Assabbane & Bennis 2000). This methodology has been successfully tested in sector I of Verdun city in Quebec (Temimi & Bennis 2002). Another proposed methodology based on values provided by autoregressive model combined with the Kalman filter was also successfully tested in the literature (Bennis *et al.* 2000).

1.4.9 Management Strategy Programming Rules

The control strategy is an optimized response to the objectives formulated during the implementation of the RTC (Schütze *et al.* 2001; Schütze *et al.* 2006). Defining strategies is not always obvious, because it is finding the best suitable response to management objectives that can be numerous and sometimes contradictory. Depending on the complexity of the situation, the tools developed are multiple. Lists of programming rules "if-then-else" exist for the simplest cases (Schütze *et al.* 2005; Polaskova *et al.* 2006), decision matrices, fuzzy logic, neural networks, or progression through trial/error are more potential tools when systems become more complex (Schütze *et al.* 2002; Schütze & Alex 2004). An extensive review on RTC exist in the literature (García *et al.* 2015). When the strategy is optimized in real time, computational steps must be compatible with the system management.

1.5 UDS within Smart Cities

A smart city is a successful city in six characteristics that represent its structures and functions. The effectiveness of a smart city is based on its intelligence by managing the economy of the city, mobility of the citizens, protection of the environment, lifestyle of the citizens, citizens participation in government management and cities' resources (Giffinger *et al.* 2007). A smart city is classified by comparing it to multiple standards, and the difference in intelligence between smart cities is based on education and culture of the people, system of cooperation and effectiveness of the equipped infrastructure with digital tools (Komninos 2002).

1.5.1 Smart City Concept

To achieve a smart city, the concept to follow is the overlap of several short-term improvements to achieve the ultimate long-term goal (Smart Cities Stakeholder Platform 2013). In addition, the interaction between all the components of a city and the impact of improving an entity on the rest of the system must be treated carefully. For example, the subject concerning the distance between the bus stations and the citizens' locations cannot be studied without considering the pollution produced by buses gas emissions, and the traffic jam caused by these buses movements.

In the past, management solves a single problem at a one time, without thinking of future needs (Carter 2013). This type of management focused on elements with one objective to exist, and it is based on reactive strategies. While in the concept of smart cities, management is based on multi-objective elements that are anticipatory and proactive at the same time, planned for short and long-term strategies and combined for the management to be truly sustainable. For example, garden plots in the community area may be useful as aesthetic value, social interaction area for the citizens, and a stormwater management system.

On the other hand, there is no a smart city prototype that can be adapted to any selected site. In studying smart cities, the area, the topography of the land, the needs of the society and their citizens, the culture, the catastrophic impact and the future projects should be considered (Carter 2013). For example the use of wind turbines for energy production instead of solar panels may be more useful in Northern Europe. Another example is the use of recycled grey water or rainwater to flush the toilet may be more useful in areas where water scarcity exists and is more important than in areas rich in water, where the change of all infrastructure systems and houses connections can be much more expensive.

The objective of smart cities is not to make the elements of a city more intelligent, but to run the whole system of a city intelligently ranging from intelligent production, through smart consumption and use of a metering system, then create an intelligent citizen-government interaction, to finally achieve intelligent storage systems and reserve.

1.5.2 Applications

Mentioning in this research some smart applications could be helpful to understand the smart city concept. Managing public transportation to respond to congestion, such as directing buses to where people gather and manage road lights signals based on traffic patterns and congestion, is applied in Songdo, South Korea. Other type of management in this city, is allocating electricity to meet demand, and therefore a huge power can be saved (Williamson 2013). In Rio de Janeiro, technological tools are used in areas where public safety is threatened by infrastructure failure as a building collapse or flooding of polluted water. Studies in the future may consider the flow of wastewater as a clean water resource. For example, in Silicon Valley in Southern California, wastewater were converted into drinking water, which are potentially cleaner than those produced from melting snow (Standen 2013). In Boston an application called StreetBup inform the city when the driver hit a hole on the road, and subsequently maintenance can be more effective (Carter 2013). Management in smart cities can consider natural disasters if they exist in the study area, such as cities where high waves can attack the shore, coastal structures equipped with suitable sensors can be used.

To properly study the UDS concept for a smart city and to develop effective management strategies useful to the network, city, citizens and environment, first understand the problems of managers and operators expectations is a must.

1.5.3 Smart UDS Concept

The objective of minimizing polluted effluent into the environment was expressed in most cases as an objective of minimizing the total amount released into the environment (Schütze & Alex 2004; Schütze *et al.* 2004). Specifically it comes in the form of using uniformly the retention capacity of the system and authorizing spills only after all the available storage capacities were used (Hochedlinger *et al.* 2006; Schütze *et al.* 2006). On the other hand, temporal and areal variations in rainfall intensities and water pollution concentrations, during a storm event, makes the strategy types based on weather forecasting and quality criteria for system management more interesting (Grüning & Orth 2002). This can help to make choices between different flows, and give destination to each flow, according to future conditions and pollution degrees, especially when the storage and treatment capacities are limited (Klepiszewski 2005). Therefore, the continuous measurement combined to multiple scenarios modelling, can be used to help in determining whether the effluent shall be treated in treatment plant, stored in storage basin or can be discharged directly into the environment if significant dilution phenomenon occurred, and thus optimally operate retention capacities and saving treatment cost.

Since urbanization decrease ground water recharge potential, the concept of returning rainwater to the natural environment, in order to recharge resources, is increasingly required in the case of smart city construction. Therefore, to obtain a durable and effective smart system, the stormwater management facilities must be integrated in the urban development sector. Having an effective

UDS is not limited to monitor its operation in order to protect the environment and support an optimized dynamic management strategy or recharge resources using alternative techniques. In addition, the sustainability of the system should be continuously evaluated, assured and enhanced.

During the transformation or the design of a new smart city, UDS must meet, as it is already shown in the preceding paragraphs, several expectations representing the success on all the characteristics level of the city. Since the multi objective concept must be respected during the transformation, the optimal method to proceed in improving the city elements must be found. Sometimes, choosing to invert the whole system already built may not meet the project economy objective. Therefore, the transformation plan for the intelligence of a city should be composed of several overlaps of short-term strategies to achieve the smart city long-term objective at a minimal cost. One way to accomplish this is by prioritizing and optimizing a long-term rehabilitation plan for existing systems. It remains to note that the RTM system, once installed, is widely involved in future optimal rehabilitation and prioritization of UDS.

1.5.4 Prioritization and Smart Rehabilitation of UDS

Network elements prioritization and rehabilitation process aims to accomplish several objectives, such as improving the structural, hydraulic and environmental behaviour of the system, as well as reducing the operating and maintenance costs and extending the useful life of the infrastructure. The optimization of interventions requires a realistic assessment of the service level and damages within the system.

Several studies have focused on the development of methodologies for evaluating UDS and how to combine the network characteristics to create a real assessment of its condition (Fenner 2000). This should allow prioritizing the interventions, in addition to, developing optimization procedures to determine the appropriate rehabilitation method for each section, and respecting budgetary constraints at the same time (Abraham 2003; Iyer & Sinha 2006; Kuhn & Madanat 2006). Among these researches, some are interested in the analysis of data collected following the inspection and modelling, to assess the hydraulic, structural and environmental performance of the UDS and prioritizing sections to be rehabilitated (Kurz *et al.* 1997; Kurz & Woodard 2000; Tagherouit *et al.* 2011). Additionally, there is a study on the risk assessment based on an evaluation of network floods using a geographic information system (GIS) as ArcGIS software (Schaedler 2005). This evaluation method, used by multiple municipalities, allowed them to prioritize the various pipes of the system, based on their location and harmful consequences in case of dysfunctions, and establish a short and long term rehabilitation plan.

Many models for forecasting the conditions of the systems have already been proposed in the literature (Abraham & Wirahadikusumah 1999; Mailhot *et al.* 2000; Kleiner & Rajani 2001; Rajani & Kleiner 2001; Dirksen & Clemens 2008; Tran & Ng 2010). An example of a prioritization system is the fuzzy logic, field of computer science that allows a computer system to reason with uncertainty (Castillo *et al.* 2007), applied with combined entries between structural, hydraulic and possible consequences of failure assessment. The fuzzy logic uses these entries to calculate an overall performance index for each pipe (Tagherouit *et al.* 2011). This methodology had been successfully applied to the system of Laval city in Canada.

It is important to mention that after any changes and decision on the rehabilitation of any part of the network, simulation and prioritization should be repeated, since rehabilitation could affect the hydraulic characteristics and performance index of the downstream pipes. These changes are due to the flow that will increase, following the changes in diameters or manning coefficients in the rehabilitated pipes. On the other hand, in some situations, one of the methods of controlling the flow is to create a delay of time by surcharging certain sections in the network. In this case, it is important to verify the hydraulic vulnerability of the site, soil surrounding the pipe and ground water protection in case of existence of an undesired pollution.

After rehabilitation procedure is accomplished, final simulation and prioritization results are used to detect critical parts of the system, where predicted problems could likely happen and have very harmful consequences on the environment, citizens and the system itself. These locations are used in the monitoring and management system planning and installation, where appropriate sensors and actuators, responsible for the sustainability of the system, should be implemented.

1.5.5 Smart Information Log within a Geographical Layer

Once critical pipes have been rehabilitated and safety is respected, and after that condition and importance of the rest of the system elements are prioritized, system state should be continuously numerated and recorded within a geographical layer, to provide a full dynamic vision of the system condition and its long term evolution. This layer could also help operators and managers in analysing the sensors measurements and modelling results. For example, anomalies in influent volumes, during wet periods in separated wastewater networks, could be analysed due to network structure information log, where the presence of cracks, indicating the significant parasite water infiltration is stored and archived.

This layer should contain in addition to the system actual state and branches priorities, all received climate information, maintenance works, interventions details and future rehabilitation plan. Intelligence of a smart city is not limited to a management strategy that reacts to a present situation or a short term estimated behaviour, it is also a long-term future evaluation of the infrastructure evolution. Information logs are capable to detect future climate change, which should be incorporated in future calculations and assessment of network state. Based on received data and historical logs, operators could better predict, analyse and be prepared for future situations and needs. Moreover, using these techniques, managers could better maintain their UDS, while designers could improve the conception and planning of new UDS. Many black box models were developed in order to forecast system future structural conditions and plan the long term rehabilitation and maintenance works (Tran *et al.* 2007).

In addition, a smart city could improve its intelligence by an experience process, using historical logs that contain all system problems and operators reactions. The management system itself could, progressively with time, propose already applied solutions, or even directly react to any similar situation in the future. In such case, the smart city is considered as self-improving city, and it is getting more and more intelligence to resolve any problem that could be repeated.

In the introduction to smart cities, it was mentioned that there is no a smart city prototype, since the concept is dependent on the needs and conditions of the city. It is also important to note that even the concept itself is not bounded, conversely it is flexible and its intelligence lies on its internal development potential. Therefore, an updated historical log could be useful even for researcher to improve smart cities design and to enhance the concept of intelligence.

1.5.6 Monitored UDS within Smart Cities

After this section, it may appear that UDS within smart cities concept, presented in Figure 1-19, after being safely smart rehabilitated and prioritized, are based on a RTM system combined to alternative structures and historical smart updated information log, offering sustainability and clear short and long term dynamic vision for all processes within these infrastructures, in addition to system states and conditions.

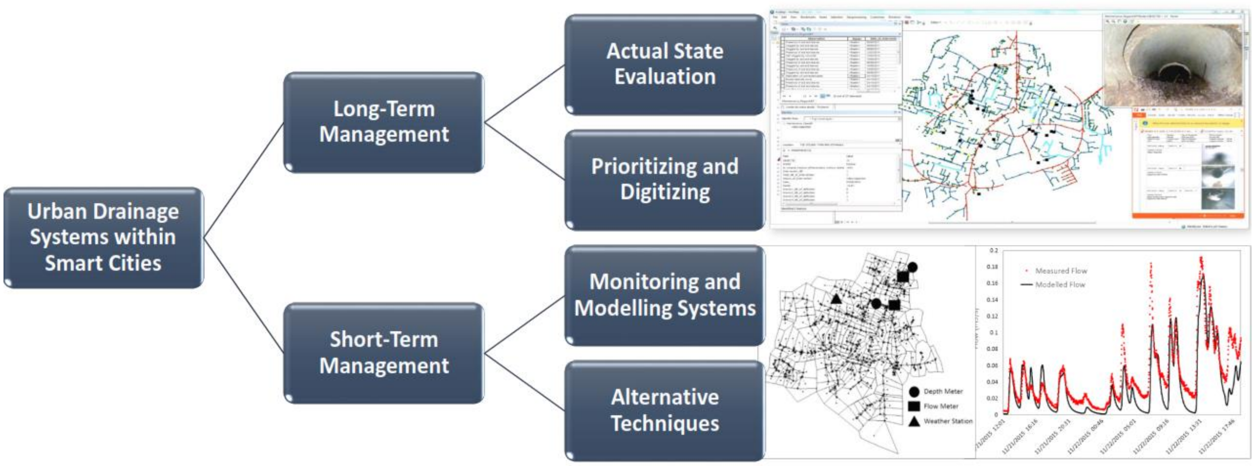

Figure 1-19: Urban Drainage Systems within Smart Cities Concept

The hierarchy presented in Figure 1-19 presents the combination of actual state evaluation with branches prioritization and information digitization in order to develop a long-term strategy for managing and planning maintenance and rehabilitation actions. Short-term management strategy is based on RTM data and modelling results to understand, analyse and optimally operate the underground infrastructure, through alternative techniques based on retention and infiltration potential.

Monitored systems, as seen in previous sections, are realized by the implementation of specific sensors at critical and significant locations within the infrastructures. In addition to this application, monitoring UDS, within smart cities, could be reinforced by citizens' participation. Smart city concept focuses on citizens' interaction with managers and operators, and works on improving their comfort through their participation and sharing their ideas in decision-making. Thus, smart city residents should be able to communicate with utility directors to report any problem or urgent situation within the system, as well as suggesting ideas and solutions or expressing frustrations concerning system condition or construction of alternative structures. Furthermore, management strategy should consider the danger surrounding residents, and should alert them in case of emergency situation and propose actions to be taken for the sake of protecting them. For example, in case of flooding, managers should warn people living near the flooded areas, and inform close drivers about the location of safer roads to avoid passing through the flooding zones.

After measurements are done, as mentioned in RTM data section, data is transferred to a central control station charged for storing received information and managing necessary actions to operate UDS. In smart city concept, in addition to these characteristics, central control station has to be general and unified for all monitored utilities. Utilities interaction must be studied and consequences of an accident should be reported for operators of other utilities. Therefore, central station should be connected to all operators from different fields offering them a simple interface with status information concerning all activities and actions taking place within the system. When accidents happened, it was either expected during management planning phase or not. In case of expected situation, already planned action should be practiced. Otherwise, comparing it to the most severe expected one, besides checking branches priorities and historical data logs, is necessary to assess the severity of danger. This is the reason behind having from central control station, an easy and quick access to all planned situation, historical log and branches priority record, so operators could save time and be more efficient in responding to any unexpected situation. Furthermore, received and stored data allow the establishment of an optimal dynamic management strategy, enabling operators and managers to understand and benefit the full system operations and resources at their ultimate multi objective potential within the city, as discussed in the following section.

1.6 Management Practices

In fact an online management can manipulate the system in changing the flow directions with remotely controlled actuators. The actions taken depend on a comprehensive control strategy, real time received data and forecasting results. The control procedure should be developed to meet the objectives of a smart city and to improve the operation of their UDS and natural environment condition. An example of these applications consists of developing a simulation model, which at every time step of receiving data, evaluates the impacts of different control actions and applies the most beneficial procedure.

1.6.1 Infiltration Process

In addition to the direct reuse of rainwater stored in rain barrels, in residential and agricultural applications, the structures that rely on infiltration to evacuate their content are encouraging the enrichment of water resources and enhance smart cities principles. First, these techniques respect the natural water cycle and contribute to the conservation of green spaces in the city. Furthermore, infiltration strategy solves the problem of flat surfaces where the drainage pipe system implementation requires expensive excavation and multiple lifting stations. On the other hand, some limitations exist for the application of infiltration structures, such as ground water level, site usage, and existence of nearby potable intake locations. Careful design is needed as well as regular maintenance to prevent clogging, risks and nuisances to residents. The risk of groundwater contamination in case of discharge of accidental pollution remains the critical problem in infiltration structures. In the concept of a smart city, which is based on a RTM system, this problem can be overcame, by installing a storage system equipped with necessary quality sensors and actuators before any structure that allows infiltration, to ensure influent quality and take immediate actions upon detection of contamination. Such protecting systems will be highly valuable, not only for ground water and environmental protection, but also for the alternative structure sustainability itself.

1.6.2 Smart Treatment Process

Besides infiltration process, intelligence of a city can improve the treatment phenomenon in storage reservoirs and alternative structures, by assisting operators in treatment decisions, reducing the time to release stored water into the environment and capturing danger substances, in need of pre-treatment before being mixed with other influents. In the following, an example showing the benefits of such system, in reducing time of treatment in sedimentation tanks in addition of ensuring the water quality of effluents is presented.

Once a sedimentation basin is partially or completely filled, the particles will gradually settle toward the bottom as a function of their falling speed. Traditionally, settling tanks design is based on a fixed retention time, which is determined to ensure adequate settling process but also to avoid the anaerobic process in the basins (Escaler *et al.* 2005). However, multiple studies had already noted a significant variability in the particle settlement velocity (Chebbo 1992; Gromaire *et al.* 2006), which shows that the expected settling efficiency is not necessarily effective with this temporal system. Therefore, the fact of knowing in real time the concentration of suspended particles through continuous measurements represents an interesting perspective for the management of settling tanks. Hence, in recent years, multiple studies focused on managing settling basins using continuous measurements of water quality (Grüning & Orth 2002; Aires *et al.* 2003; Jacopin L'Azou & Bourgogne 2003; Rabier *et al.* 2003). Similarly, in Paris, turbidity meters were installed to assess effluent discharges stored in collectors (Bouchet 2003). The importance of real time measurements is not limited to the reduction of retention time in settling tanks; they can also be used to control the discharge flow, based on detection of any particles re-suspension from the bottom. Even if the particles were sufficiently settled, the hydraulic conditions of the discharge can cause re-suspension of settled particles that may be discharged into the natural environment.

Turbidity meters allowing control of sedimentation process can be installed in settling basins in two different ways. The first is the installation on a pontoon that tracks the top layer quality in the tank in filling and emptying process. Whilst the second is the installation on a fixed depth, preferably near the bottom, which allows for example to monitor the progress of settlement at the limit between the layer that should be drained into the environment and the bottom layer that should be directed to the wastewater treatment plant.

1.6.3 Management Strategies

In addition to enhancing the infiltration and treatment phenomenon, management of UDS in smart cities is used to monitor the entire system and to protect its lower areas against any possible flood, discharge of pollution into the environment and even against any outside influence that can attack the quality of the flow and therefore, the performance of the UDS and its treatment plant. Thoroughly monitor the network from its higher branches to its outlet, can increase the ability to prevent emergency situations. For example, in case of a severe storm, where neither the network capacity and its treatment plant, nor the storage capacity of alternative structures can prevent flooding, situation can be predicted and a management implementation that shares floods at several low critical manholes in the system, without subjecting the citizens of the downstream zone to danger, and benefiting from the storage capacity of underground pipeline network, can be implemented. Another example is the detection of industrial or accidental influent before reaching the main branch of the UDS and being mixed with the total runoff, in order to direct or pump the flow to toxic pre-treatments.

The sensors responsible for flow and velocity measurements are used to direct the water, when the runoff-measured volume exceeds the capacity of the UDS, under an overall strategy set by managers. In parallel, sensors in charge of effluent quality seek to improve the management and make it more efficient either by spilling diluted volumes and increasing storage capacity, or by improving the management strategy applied according to the water qualitative readings. For example, if storage facilities show a high filling ratio, it may be decided to maintain the remaining capacity for heavily polluted flows and release water with lower levels of pollution in receiving environment (Grüning *et al.* 2002; Klepiszewski 2005). This strategy can be applied by forecasting the water quality that arrives at the system outlet as a function of time, through the installation of quality sensors on the whole length of the network. In case where the total capacity of the tank is used, a comparison between water arriving at the outlet and water in storage facilities is useful to decide which flow is better to be spilled in the receiving environment.

For large storage tanks, volumes are divided into compartments in order to reduce service and maintenance costs. It is common for this case in a smart city, that each compartment has its proper way of management. Depending on qualitative real time measurements, management can empty the least polluted portion in a low critical environment, in order to receive the inflows that are more polluted. Similarly, if a treatment plant is limited, by the volume to accept, and receives runoff from different watersheds, a strategy based on qualitative measurements can prioritize the treatment of the most polluted volume and the spilling of the rest into the environment, according to the quality measured on each watershed. Furthermore, if the influent water is slightly polluted, management strategy could direct the flow to a pre-treatment process in a storage tank, which might be enough before direct discharge into the environment and thus treatment plant potential could be saved for highly polluted flows.

RTC applications in smart cities could go beyond the UDS elements, and installation of sensors to monitor the environment and all that can be affected by a problem within the network, could be applied. Sometimes monitoring the environment is important to switch between different management strategies, as monitoring different lakes conditions, where an acceptable quality of stormwater spills could happen and the direction of the outflow depends on the lakes initial conditions. In these cases, management strategy is more complicated, and decisions are based on integrated modelling results and multiple factors combination as influent quality and multiple receiving areas initial condition.

Dynamic management strategy in UDS is not limited to periods of rainfall events, where the overload of the system, induced by the large amount of surface runoff, should be avoided. For example, RTM and dynamic management should be active and effective for a long period of time, in areas where snow exists. In these areas, monitoring system go beyond water quantity and quality data to include other climate variables as air temperature, intensity of the sun, wind speed, snow depth etc. Snowmelt process should be very well monitored and considered in management strategy, since it could produce huge water volumes and flows, especially when it is combined to rainfall events.

Dynamic management, as already seen in previous sections, can be local to a specific structure as it may be affecting the entire UDS. In case of a global strategy, or application of multiple local strategies in a network, it is important to ensure an interaction relationship between the different alternative structures of the same network, such as measuring the water height in all structures and direct the water to avoid an overload of an annex structure. On the other side, attention should be given to verify the emptying process of the retention structures, in order to be functional during successive rain events, and at the same time does not overload the downstream network, especially in case of emptying several structures together.

In addition, applying RTM system combined with an effective online strategy could result in a significant cost reduction for system improvement projects. Although the high cost of implementing RTC system, the use of such systems helps to prevent building new tanks and infrastructures, resulting in significant savings and encouraging the economic objective of the smart city (Schilling 1994; Lavallee *et al.* 2001). For example, the cost of implementing the first phase of RTC in Quebec Urban Community was US$ 2.6 million compared to an estimated US$ 15.5 million to attain an equivalent control level through conventional method and retention facilities (Lavallee *et al.* 2001).

Since accidents are not limited to pollution incidents, monitoring system designers should pay attention to the effect of any dysfunction at the level of sensors, operators, transmitters or even the entire smart system. A static backup plan or a proactive automatic strategy should always be ready for unexpected situations. For example, the central control system, at Quebec RTC system in 1999, was able to control proactively all its functions in order to prevent overflows for a power failure exceeding one hour at its water treatment plant (Pleau *et al.* 2005).

1.6.4 Real Time Monitoring Contribution in Researches and System Design

The sedimentation process, erosion and transportation of suspended matter in the UDS are some of many processes, which could significantly affect the performance of treatment plants and flows quality in the sanitation networks. Although many researchers have studied these processes taking place within the network and have developed computational models (Schlütter & Schaarup-Jensen 1998; Skipworth *et al.* 1999; Gamerith *et al.* 2009; Kim *et al.* 2010; Mannina & Viviani 2010; Carbone *et al.* 2012; Mannina *et al.* 2012), uncertainties in the results of these researches and models exist. Other authors have been working in order to identify the source of these uncertainties and found that the insufficient amount of data on water quality, in addition to knowledge gaps on these very complex processes, are the main sources of the unreliability of these models (Mannina *et al.* 2006; Willems 2008).

RTM system, through the amount of data collected, can largely contribute to the modelling improvements and understanding of phenomenon taking places within the infrastructures. Calibrating models, locating deposit accumulation places, identifying nature of mobilized sediments and understanding sedimentation and re-suspension processes during peak flows, are now possible due to real time measurements collected data (Gruber *et al.* 2005; Hannouche *et al.* 2011). Thereby in recent years, several studies have used this method to study some complex processes within the networks (Gamerith *et al.* 2009; Métadier & Bertrand-Krajewski 2012).

In addition, real time measurements can be a useful tool for monitoring the effect of a particular implementation on the system. Sometimes, the application of system management may affect the flow conditions and even create polluted water by increasing the pollution concentration for specific short periods of time. In the literature, researchers have used real time measurements to study the impact of (ON/OFF) pumping process on the flow quality upstream the treatment plant, and quality changes were noticed (Sharma *et al.* 2013).

The use of RTM and dynamic management in UDS, can go beyond water and wastewater projects and studies, and can participate in other fields' progress, either on practical or even research level. For example, directors of a project in New York City, based on analysing wastewater quality measurements, trying to uncover trend in infectious disease, are looking to sequence the microbiome of New York City, in order to develop a genetic map that would highlight the city's microbial diversity across different districts. As a result, they will be better able to identify dangerous outliers and even to determine if a public health campaign, started by city officials, is effective (Joshua 2014).

1.6.5 Implementation and Verification of a Management Study

A management strategy in a smart city concept, must respond to the request of the site and the UDS needs, in the most efficient and profitable manner. In order to achieve this objective, the site should be studied in details before the implementation of a management strategy, and the contribution of this management on UDS operation must be investigated for most storm events. For example, in order to study a management plan based on quality, firstly, a variation analysis of the pollution degree in runoff must be done for all the events, which often take place in this area (Inter-events). Secondly, for each event apart, the pollutants concentration variability should be studied (Intra-events). M(V) curves can be useful for this purpose (Lacour *et al.* 2009). The M(V) curves represent the cumulated mass of a pollutant, function of the cumulated volume from the beginning of the storm event (Bertrand-Krajewski *et al.* 1998). A comparison of the M(V) curve obtained, after applying a strategy, with the optimized M(V) curve can reflect the effectiveness of the strategy. The optimized M(V) curve is listing pollution measures in descending order and considering that the interception of flow begins with the UDS being overloaded.

1.7 Conclusion

Cities have progressively been overstressed, due to the demographic boom and the urbanization process, leading to the development of smart cities concept. This work is focusing on UDS within the urbanized cities. After listing UDS shortages and characteristics, a literature review on alternative structures, implemented to strengthen these utilities, is presented. These structures are based either on temporary storage or on improving management strategies by recharging resources or pre-treatment potential. On the other side, monitoring systems are increasingly used to support UDS operations, by optimizing their capacities to evacuate water, and to help operators in analysing and evaluating these infrastructures. Despite their wide contribution in improving management applications, UDS managers still doubt the applicability and efficiency of RTM systems. Hence, a general and detailed review concerning monitoring sensors is presented to offer researchers, engineers, managers and decision makers a sufficient knowledge to understand and evaluate the monitoring systems. Measurement uncertainties and filtration, data transmission procedure, types of monitoring system deployments and architectures, measurement capabilities and programming rules of these monitoring systems, are all issues discussed in this chapter.

The integration of UDS within smart cities is performed while considering many points to accomplish. Since smart cities concept is based on multi-objective elements, which are beneficial on all the aspects of the city, a combination of RTM systems with alternative structures constitutes a principal step in this integration. This combination offers the capacity of managing the UDS by controlling and directing flows to retention, infiltration or pre-treatment structures, in order to eliminate flooding, protect the environment, recharge ground water as well as presenting aesthetic and social areas for the citizens. According to the same concept of smart cities, a combination of smart rehabilitation and prioritization process with smart information log assists operators in forecasting and planning long-term management strategies. Based on these data, temporarily and geographically localized within layers, operators can evaluate the evolution of each sector state of the system, and plan interventions, maintenance and rehabilitation actions according to predicted future conditions. Thus, operators and managers can be more proactive in their management, assure the durability of infrastructures and maintain the economic benefits within smart city concept. In addition, these combinations are not limited to short and long-term infrastructure management, they are wider in their applications and offer the capacity for design improvements, model calibrations, research developments and complex phenomenon studies requiring a large amount of data in order to be understood and analysed.

This chapter intends to offer a wide knowledge on smart monitored UDS, and practical applications on how dynamic management can contribute in systems development and their multi-level benefits. It aims to assist researchers and engineers in understanding and applying these systems. However, since RTM and RTC systems are based on modern technology, this domain should be continuously followed up in order to expand our knowledge concerning the recent developed tools. In addition, taking into account that smart city concept depends on the area where to be implemented, and a generalized prototype that can meet the need of all the cities could not be developed, one should know that even if applications had been conducted and listed, researches and studies in these domains should continue to enrich the experiences in these fields.

After defining the concept for integrating UDS into the smart cities, this thesis aims to represent the methodologies and applications of this integration. Prioritizing the actual system states was found efficient by visualizing the interventions and the inspections on GIS layers. In addition, a GIS database including an updated log with successive digitized inspections was considered helpful in analysing and forecasting the structural state evolution of the UDS. GIS database construction and its potential in managing the rehabilitation and the maintenance of UDS, are presented in chapter 2. In addition, chapter 2 discusses the characteristics and implementation of RTM systems, which constitutes the key element for managing the UDS hydraulic operations. Combining RTM system to a simulation model, enables the system managers to extend the monitoring zones to cover the overall operations of the UDS, and thus increases their potential for further analysis and evaluations. A simulation model requires a calibration, which is a hard task to accomplish. Therefore, this work presents an efficient auto-calibration process in the third chapter. Moreover, chapter 3 presents boundary conditions forecast system, which enables the hydrologic-hydraulic model to perform simulations on unmeasured events. Thus, the evaluation potential required for the integration of the UDS within the smart cities was efficiently elaborated. As discussed in the literature, it remains for the integration into the smart cities, to optimally operate the UDS and to protect the citizens and the environment. For this purpose, chapter 4 was allocated to develop a RTC. The developed RTC consists of a flooding forecast system, which enhances the proactivity of the actions, and a dynamic management, able to increase the system capacity.

Finally, a qualitative dynamic management was also presented based on a RTM and alternative structures implementation, aiming to improve the system operation, to protect the citizens and the environment and to offer esthetical places for the city.

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Chapter 2

Site Description and Real Time Monitoring System Implementation

2.1 Introduction

This chapter describes the experimental site and provides an overview of the implemented Real Time Monitoring system (RTM). The Lille 1 University Campus serves as the experimentation site for this work, which is part of the SunRise project. SunRise project consists of implementing a "large-scale demonstrator of smart and sustainable city". Improving a utility within a city requires first an evaluation of its actual components and current states. Therefore, the first section of this chapter focuses on presenting the Campus, and describing the methodology of assessing its condition. Information concerning all the utilities of the studied site were collected, verified and introduced into Geographic Information System (GIS). Our work was concerning the collection and digitalization of stormwater system information. In addition to the system architecture, the monitoring data, maintenance actions and regular interventions were also digitized and introduced to GIS layers. The constructed GIS database helps in analysing the system structural conditions, and thus localizing the critical zones, where system components are more likely to undergo structural failure, and thus requires more priorities in maintenance and rehabilitation plans.

In parallel with system structural assessment, the analysis of the hydraulic capacity of the Urban Drainage System (UDS) was also conducted on a critical sector of the University Campus. An RTM system was implemented on this section, as discussed and described in this chapter. Quantitative and qualitative sensors were deployed in defined locations of the UDS, aiming to represent the system operation, to calibrate hydrologic-hydraulic simulation model and to participate in dynamic management strategies. Since dynamic management in smart cities enhance the infiltration of stormwater; an evaluation of the applicability of infiltration techniques on the Campus area is conducted at the end of this chapter.

2.2 Geographic Information System

GIS is a computer system for capturing, storing, checking, and displaying data related to positions on Earth’s surface. The GIS is widely used for storage and analysis of geo-localized information in various fields, such as geography, geology, transport, ecology, water, energy etc. It is increasingly used for urban data studies, since it enables patterns and relationships analysis. It allows to collect data and attributes on urban infrastructures and to perform analysis and spatial correlations combined to an easy and representative visualization. This system allows:

- To store the geographic information (maps, aerial photographs, satellite images) and metadata (names, timetables).
- To perform spatial and statistical data analysis
- Display the stored data as maps, reports and graphics

The first GIS was developed in 1962 in Ottawa, Canada. This led to the establishment of the urban information systems association. In 1967 a consumption and natural resource management system appeared in New York. In the 90s, governments and institutions showed a great interest for this system, especially for environmental, natural land and aquatic life protections. In addition, the development of computer technology and the emergence of Global Positioning System (GPS) enabled significant development of GIS.

Due to its high potential in data analysis and visualization, GIS database is able to enhance the proactivity of system managers and operators. The ArcGIS 10.2.2 software was used in this study for the database construction of the Lille 1 University Campus. Each utility on the Campus was identified and digitized into a layer within the ArcGIS database, offering the capability to analyse systems interactions and to evaluate performances and problems regarding many factors. The next paragraphs will describe the University Campus and the usefulness of the constructed GIS layers in maintaining the UDS and managing its operations.

2.3 Lille 1 University Campus

The Lille 1 University Campus was chosen to be the demonstrator site of smart and sustainable city within the "SunRise" European project. This thesis is part of this project, and concerns the management and durability of stormwater systems within smart cities. The University Campus represents a small town of about 25000 users, including 4000 students that reside on the Campus. It is located in Villeneuve d'Ascq in the southwest of Lille in northern France. Lille 1 University was built in 1960 on a plot of 110 hectares. It is served by different urban networks: drinking water, sewage and drainage evacuation systems, district heating, gas, average and low tension electricity and public lighting. Figure 2-1 presents the University Campus.

Figure 2-1: Google Earth Photo taken for Lille 1 University Campus

The Campus has a high density of constructed area, representing 320 000 m^2 of its total surface, and occupied by nearly 140 buildings. These buildings are classified and used for various purposes, including teaching, research, student residence, administration, catering, sport, cultural activities, and recreation. The Campus is organized academically into different major sectors: chemistry, physics, biology, social sciences, mathematics, engineering and technological institute.

Since 1960, Lille 1 University Campus is continuously expanded by the construction of new buildings. Figure 2-2 presents the year of construction of the University buildings. We noticed that a huge area was lately constructed, imitating the demographic boom, which occurs in urbanized cities.

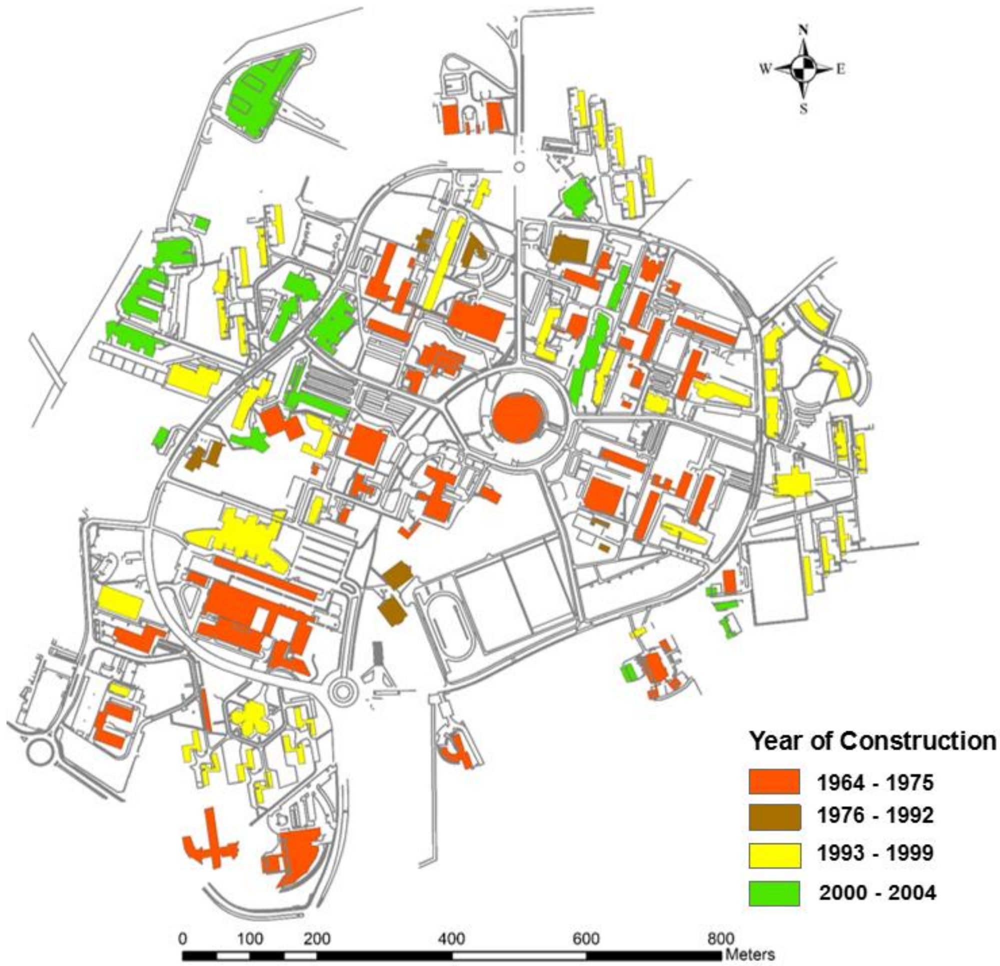

Figure 2-2: Year of Construction of Lille 1 University Buildings

For UDS operations, maps representing the year of buildings construction are very helpful in analysing the overstress of the infrastructure. Newly constructed areas are responsible of generating extra inflows to the UDS elements, which were not been considered in the design phase. In the next section, a detailed presentation of the UDS with all the existing elements is presented.

2.3.1 Urban Drainage System at Lille 1 University Campus

Water evacuation on the University Campus is conducted in two separated systems. Stormwater system, considered in this study and referred to it as the UDS, collects rainwater runoff, while wastewater system collects sewages from buildings. Both of the collecting systems release their contents, after exiting the Campus area, in a combined network managed by Métropole Européenne de Lille (MEL). The stormwater system in this area is composed of 31 km of pipelines with diameters ranging from 150 to 1200 mm. The system consists of secondary branches (24 km), managed by the University, spilling their flows into two main collectors (7 km) managed by MEL, as presented in Figure 2-3.

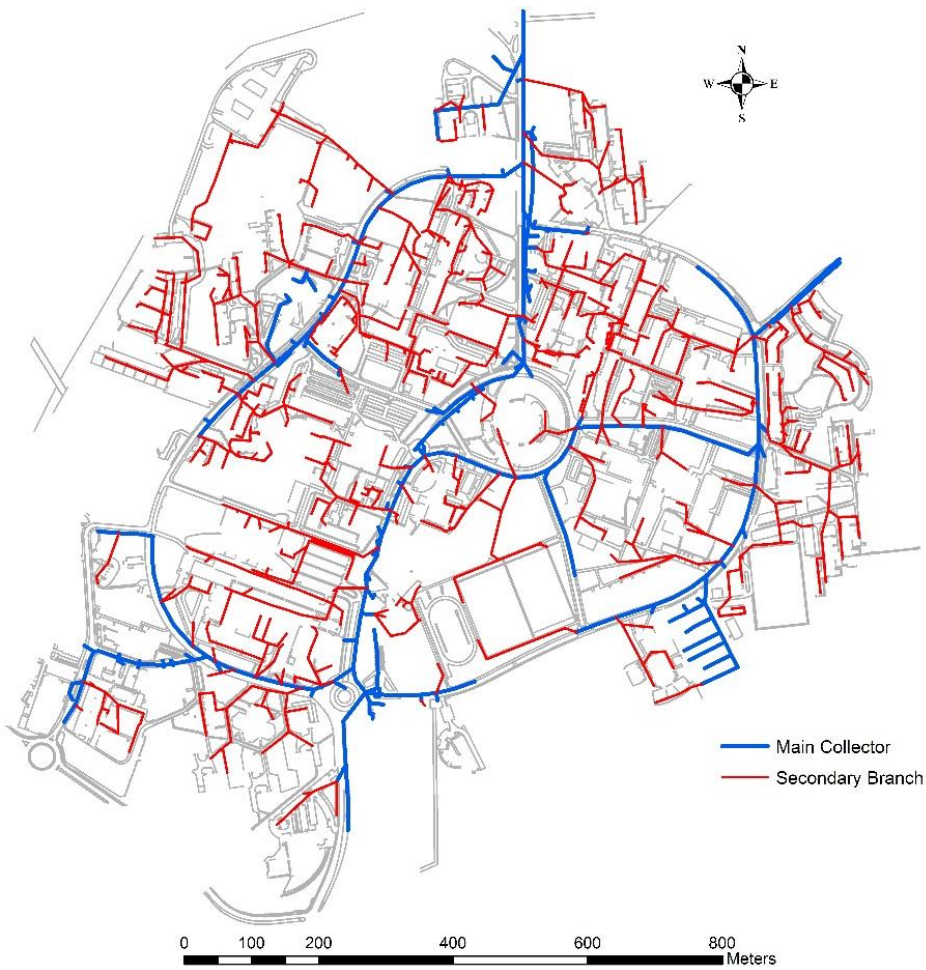

Figure 2-3: Stormwater System of Lille 1 University Campus

The first main collector evacuates water from a watershed basin, which have a surface of 50 ha and an impermeable coefficient of 0.4, and directs it to the north of the Campus. The second collector evacuates the runoff of the south watershed of the Campus, characterized by a surface of 80 ha and an impermeable coefficient of 0.3, and directs it in the northeast direction. Figure 2-4 presents the two watersheds of the Lille 1 University Campus. Figure 2-5 presents the diameters of the stormwater network pipes on the University Campus.

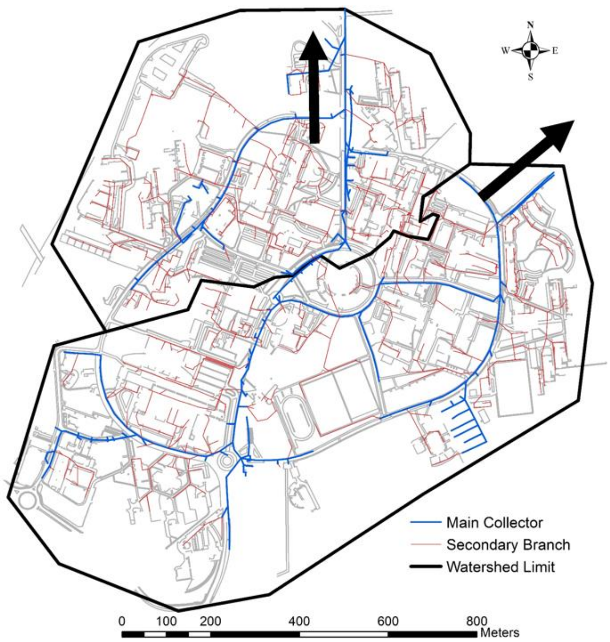

Figure 2-4: The Two Separated Watersheds on Lille 1 University Campus

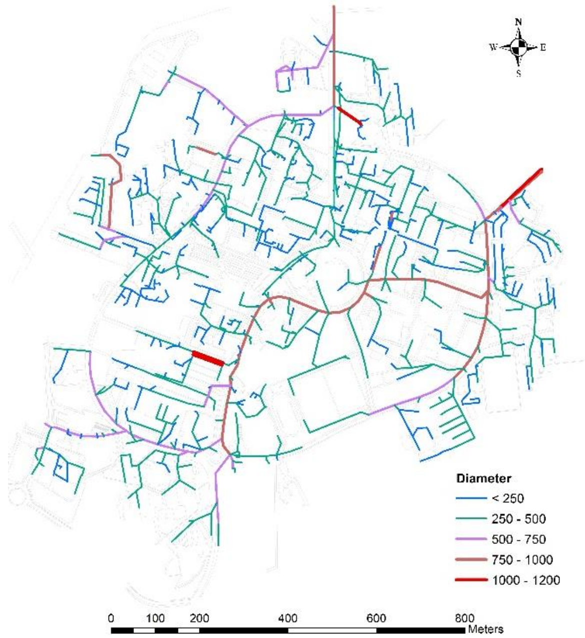

Figure 2-5: Diameter of Stormwater network pipes digitized within the GIS Layers

The system is equipped by multiple elements charged to direct, regulate and limit the water flows, and hence protect the upstream and downstream parts of the system, from being surcharged during severe storm events. Three retention tanks are located within the Campus and designed to store the excess water flowing from the upstream areas, especially those produced by the recent large constructions as parking and buildings. These retention tanks have a role of storing runoff volume during peak flows and regulate the out flow through flow regulators. We also note the presence of check valves that prevent backflow to retention tanks when the main network is overloaded, and thus allocate the storage capacity to upstream areas of the tanks. Two lifting stations exist on the Campus in order to evacuate the water from basements. The equipment installed on the University Campus, which can be dynamically managed, is presented in Figure 2-6.

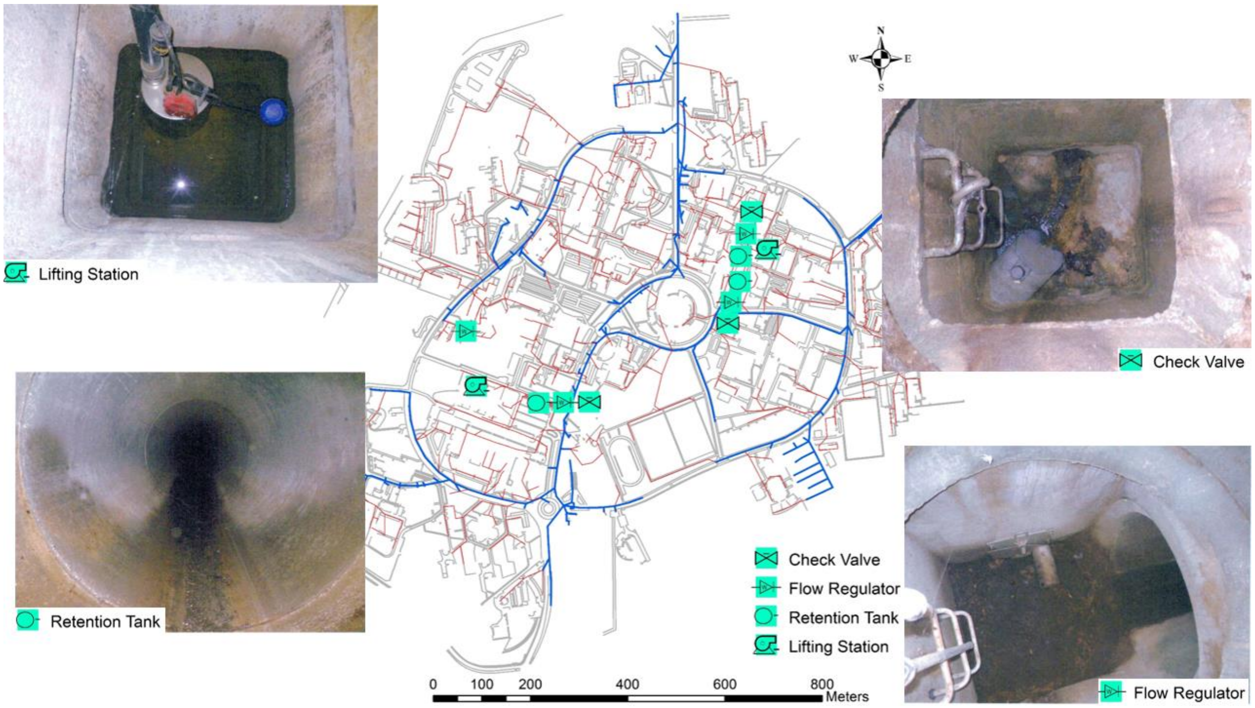

Figure 2-6: Existing Equipment on the UDS of Lille 1 University Campus

2.4 GIS Layers for Interventions and Actions

After digitizing the locations and characteristics of the UDS elements and equipment, this work focuses on collecting all useful archived information concerning the system. In this section, we describe the steps for creating the "Intervention Layer" within the GIS database. All the information concerning the UDS of Lille 1 University Campus, were collected, digitized, and introduced in this specific layer. 136 representative information concerning the pipes, manholes and equipment were collected and introduced on the intervention layer, covering almost all the Campus branches. This information was identified as observations, inspections, cleaning and maintenance actions and problems encountered. We determined for each section:

- Nature and number of performed interventions
- Date of the interventions
- Description of observed damage
- Images and video sequences for the observations
- Gravity factor indicating the disturbance and degradation of the observation
- Report of the inspecting company

A great effort was conducted in order to improve and construct a historical information log, giving the intervention layer high potentials in different management fields. Visualizing geographically the actual structural state of the UDS elements, helps in defining the structural critical zones, in need for extensive and frequent inspections. Moreover, the actual states information assists the UDS managers in planning next maintenance and rehabilitation actions. Since the intervention layer is continuously updated with new observations, which are dated and affected by gravity factors, besides planning the next rehabilitation actions, this layer assists managers in evaluating the structural state evolution of the system. Therefore, actions could be planned within a long-term management system.

Video inspection requires very specific conditions of use, which should meet NF EN 13 508-2 Standards, in order to properly classify the failures. The video inspection is a very important element in the management of UDS structural assessment, since it assists in detecting structural and functional defects. Visual inspections of the UDS pipes on the Lille 1 University Campus have detected anomalies on the following levels:

- Assemblies (dislocations, angular deviations, …)
- Geometry (slopes, roundness, …)
- Waterproofing
- Pipes and manholes connections
- Fractures and cracks
- Deformations and collapses
- Perforations and punctures
- Obstructions, obstacles and sediment depositions
- Connections of branches

During manholes inspections, observations generally concern sediment depositions and connection anomalies.

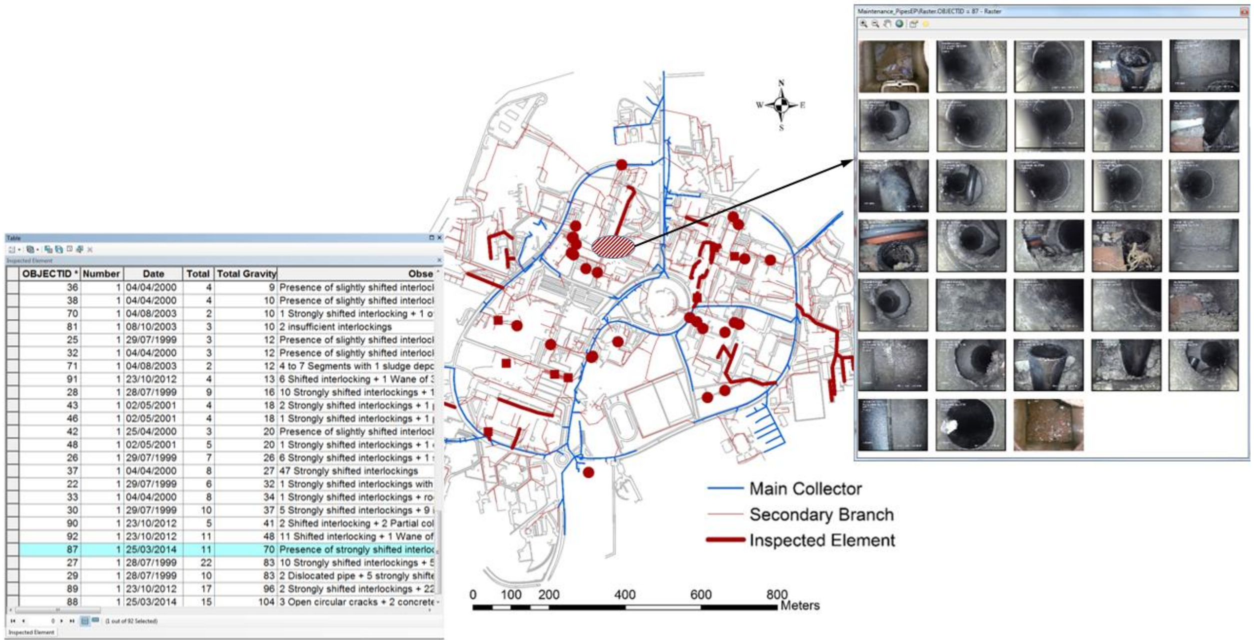

Figure 2-7: Inspection Layer within the GIS Database, with an Example of Observations taken from an Inspected Pipe

Figure 2-7 illustrates the intervention layer. An example of an inspected pipe is shown in this figure. Pipe ID 87, inspected in 25 March 2014, presents 11 shortcomings weighted by a total gravity factor equivalent to 70. The total gravity factor is calculated dependent on the numbers and gravities of observations. The numbers and levels of severity of the observations, made during the inspection of this pipe, are: 2 observations of gravity 2, 1 of gravity 3, 7 of gravity 4 and 1 of gravity 5. Major observations made in this pipe structure are: presence of strongly shifted interlocking and longitudinal cracks.

Anomalies and failures are classified in a gravity grid, which is a decision support for the UDS managers. The anomalies are classified into 6 levels of severity. According to NF EN 13 508-2, we recommended actions to be practiced for each level of gravity. Table 2-1 summarizes the different levels of severity with the definition of each level, the actions to take and illustrative examples. Each observation participates in the calculation of the total gravity factor according to its level of severity.

Table 2-1: Grid for Gravity Evaluations of Observations

Level of Severity	Risk Evaluation	Action Required	Examples	Total Gravity Factor
Gravity 1	Serious risk leading to network failure	Immediate recovery	- Complete collapse - Flow blocked	32
Gravity 2	Important risk may lead to network failure	Fast recovery (within 15 days)	- Partial collapse - Soil infiltration	16
Gravity 3	Important risk may disturb network operations	Recommended recovery (within 1 year)	- Fractures - Interlocking deviations - Presence of roots	8
Gravity 4	Potential risk may be developed into a more serious one	Advisable recovery (within 2 years)	- Small roots - Puncturing - Small obstructions	4
Gravity 5	Moderate risk	Recovery according to risk progression	- Punching - Small profile deviation	2
Gravity 6	Minor risk	No recovery is needed	- Waterproofing shortages	1

The distribution of anomaly observations, made during the inspections of the Campus' UDS between the years 1993 and 2014, is presented in Figure 2-8. Each inspected element was classified according to the total gravity factor calculated based on the observations.

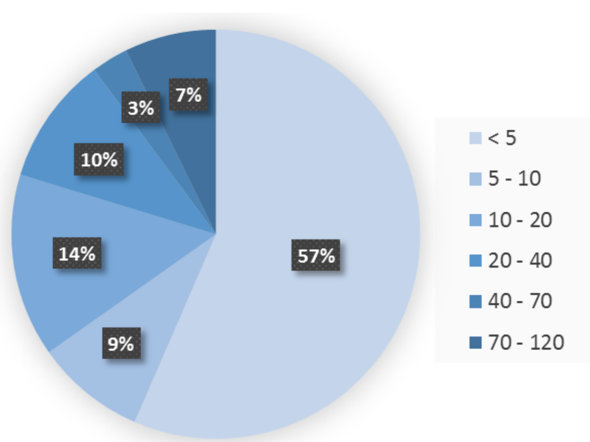

Figure 2-8: Distribution of Total Gravity Factor for Inspected Elements

Figure 2-8 indicates that 7% of inspected pipes are highly critical, since they present total gravity factors above 70. In addition, 3% were considered as critical elements, presented by total gravity factors between 40 and 70. Pipes with moderate structural conditions were those having a total gravity factor between 10 and 40, and consist of 24% of inspected elements. Finally, 66% of pipes were considered in good structural conditions, indicated by total gravity factors less than 10. Through these inspections and statistics, structural critical areas within the UDS were localized. Figure 2-9 presents the geographical locations of structural critical areas, where inspected pipes present calculated total gravity factors higher than 40. Characteristics and number of critical pipes within these locations are presented in Table 2-2.

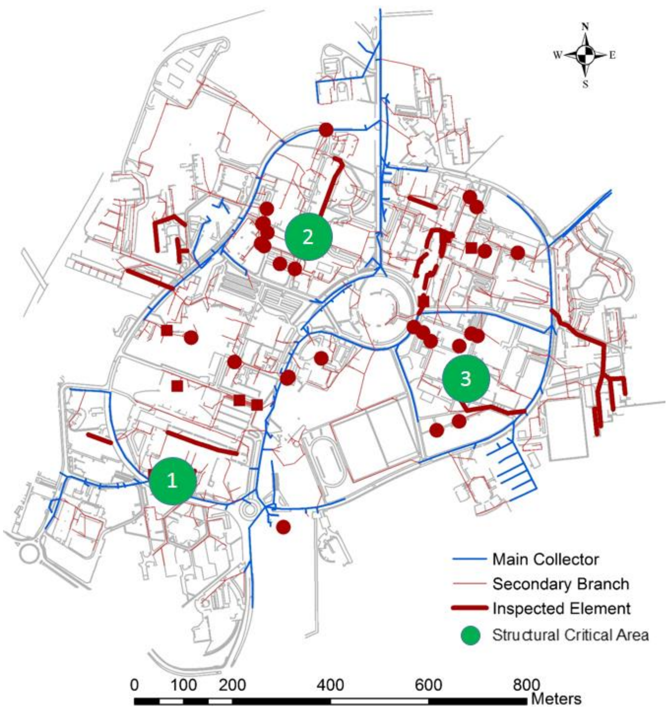

Figure 2-9: Structural Critical Areas within the UDS of the Campus

Table 2-2: Characteristics of Pipes within Critical Areas

Pipe within the Area	Total Gravity Factor
Zone 1	
P1	96
P2	48
P3	41
Zone 2	
P1	104
P2	70
Zone 3	
P1	83
P2	83

2.5 UDS Hydraulic Operation

It was mentioned that Lille 1 University surface is continuously expanding and waterproofed, through the construction of buildings, parking and roads (Figure 2-2). Nowadays, impermeable surfaces reach around 40% of the Campus total area, generating higher runoff volumes and overstressing the existing UDS. The studied site presents an average annual rainfall depth around 679 mm with highly intense storm in summer season and an annual temperature range between 0 and 23°C.

The vulnerability of the UDS on the Campus site is presented by appearances of floods during the yearly severest storms. Flooding zones are extremely dangerous due to their locations next to the University buildings, where underground laboratories exist and water entering the building threatens the equipment, students and researchers. Two main flooding locations were historically identified on the geographic map. Figure 2-10 presents these flooding locations with 3 photos taken during different storm events near Lille Engineering Central School (Flooding Area 1).

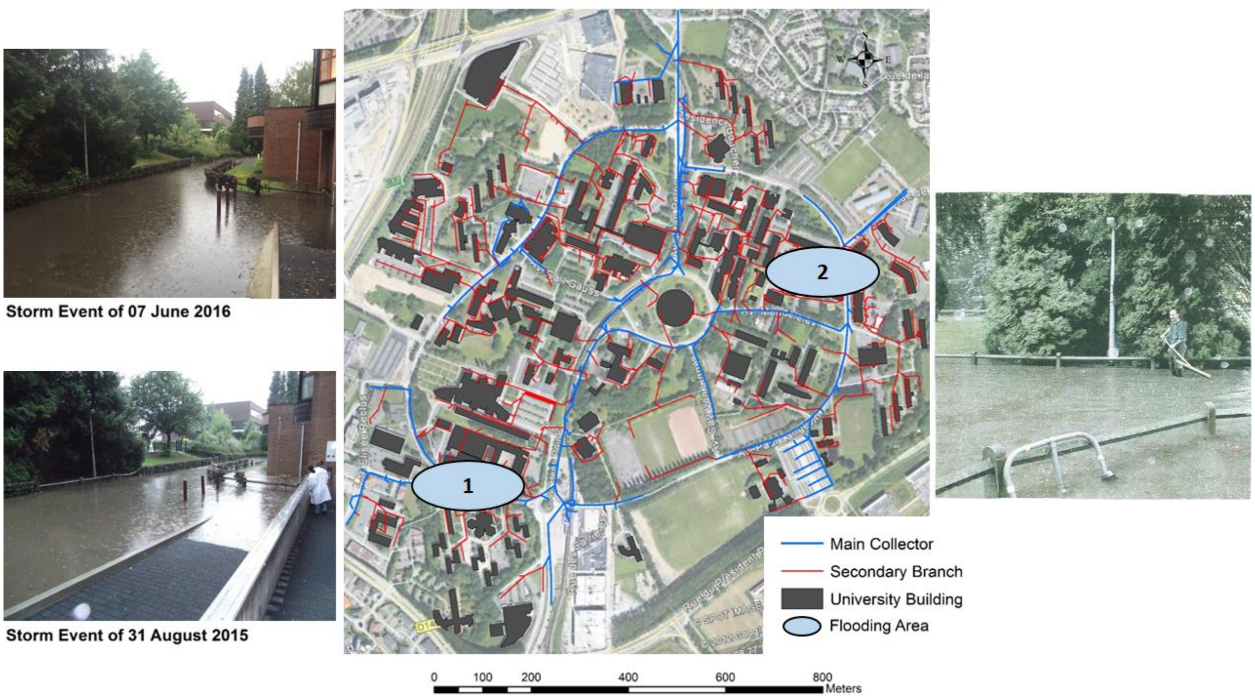

Figure 2-10: Flooding Areas on Lille 1 University Campus

The flooding area (1), presented in this figure, is located near Lille Engineering Central School, and was yearly observed since 30 years. Currently, floods in this area happened once to twice a year, during the severe storm events. Depth of flooding water is ranged between 30 and 50 cm. Site observations indicate the presence of the floods in a low topographical area (Figure 2-11), which could be explained by backwater coming from the main collector when it is surcharged to a level over the topographical level of the flooded manholes. These floods are affecting the security of the neighbourhood University building, since they percolate to inside the basements, where underground laboratories exist (Figure 2-12). The flooding area (2) is located in the University chemical sector, near the C7-a building, and appeared since 10 years. Occurring once to twice a year, this flooding event has generally a water depth from 10 to 15 cm.

Figure 2-11: Topographical Level Difference between the Main Street and the Flooding Area

Figure 2-12: Underground Laboratories at Lille Engineering Central School

This thesis aims to represent an effective methodology for strengthening the UDS and enlarging their capabilities, through understanding their operations and dynamically manipulate the installed equipment. Therefore, a sector of the UDS on the Campus, was chosen to be equipped by RTM system. Next sections of this chapter will describe the studied sector with the implemented sensors, used later in order to analyse and understand the operation of the system, calibrate the hydraulic simulation model and apply the proposed dynamic management strategies.

2.6 Monitored and Studied Sector of Lille 1 University Campus

The chosen sector of Lille 1 University Campus, used in this work for RTM system implementation, has an area of 30 hectares regrouping different types of surfaces and buildings (restaurant, residences, parking, one to four floors buildings, green areas, etc.). Figure 2-13 presents the studied sector, and Figure 2-14 presents the equipment able to be dynamically managed on this sector. The retention tank of this sector is composed of 4 big diameters pipes, around 1200 mm, offering a retention capacity of 280 m^3. The flow regulator is located downstream the retention tank, and it aims to regulate the outflow to 10 l/s. Two pumps equip the lifting station; each one is regulated to evacuate water from the basement level by 6.4 l/s and a lifting height of 12 m.

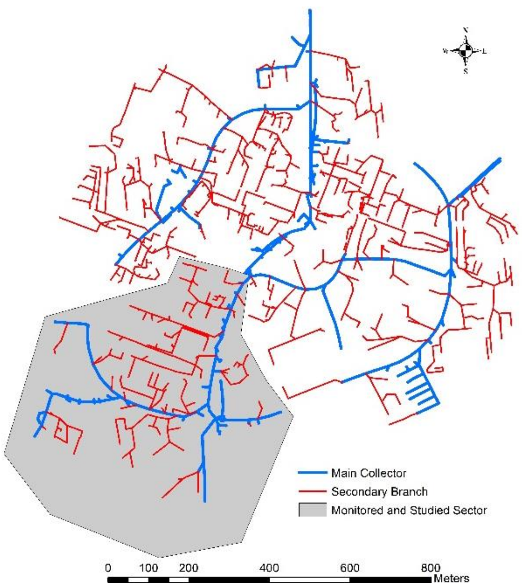

Figure 2-13: Monitored and Studied Sector of the UDS of Lille 1 University Campus

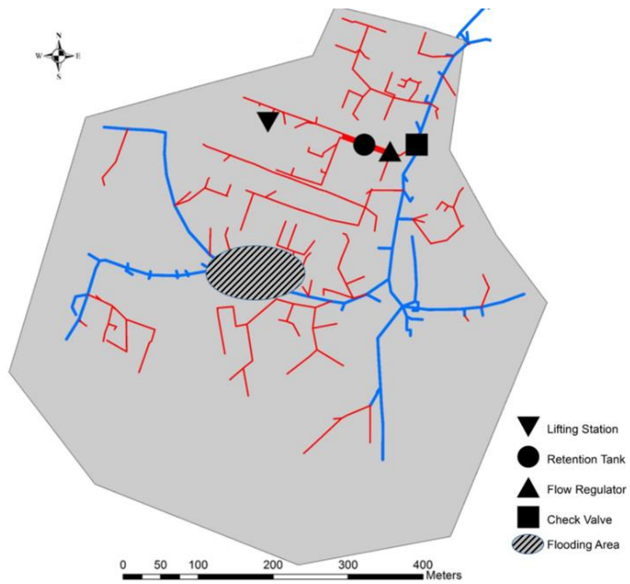

Figure 2-14: Existing Equipment on the Studied Sector of the Campus

The studied sector was equipped with different types of sensors in order to monitor its operation and evaluate its capacity. Firstly, the weather station (a) located on the centre of the sector at Polytech'Lille building, measuring weather parameters, as rain intensity, temperatures, wind speed etc. In parallel, the system was equipped with inline sensors useful for system operation analysis and model calibration. Two depth meters were installed in the network. The first was placed in the retention basin to measure the water-filling ratio during the rainfall events (b). The second depth meter was located at the outfall of the studied sector (c), and aims to measure the hydraulic downstream boundary condition. In addition, two flow meters were implemented to monitor the system operation. The first was installed at the outfall, and measures the runoff generated from all the studied sector area (d), while the second is located in the main collector downstream the retention basin (e), and is dedicated to measure runoff generated from a part of the studied sector. As discussed in chapter 1, runoff pollution in UDS is mostly fixed to suspended solids materiel. Since good correlations between suspended solids concentrations and turbidity measurements exist, a turbidity sensor was implemented inline the network (f), for measuring the pollution degree of the runoff during the rainfall events. The studied sector and the deployed sensors are presented in Figure 2-15.

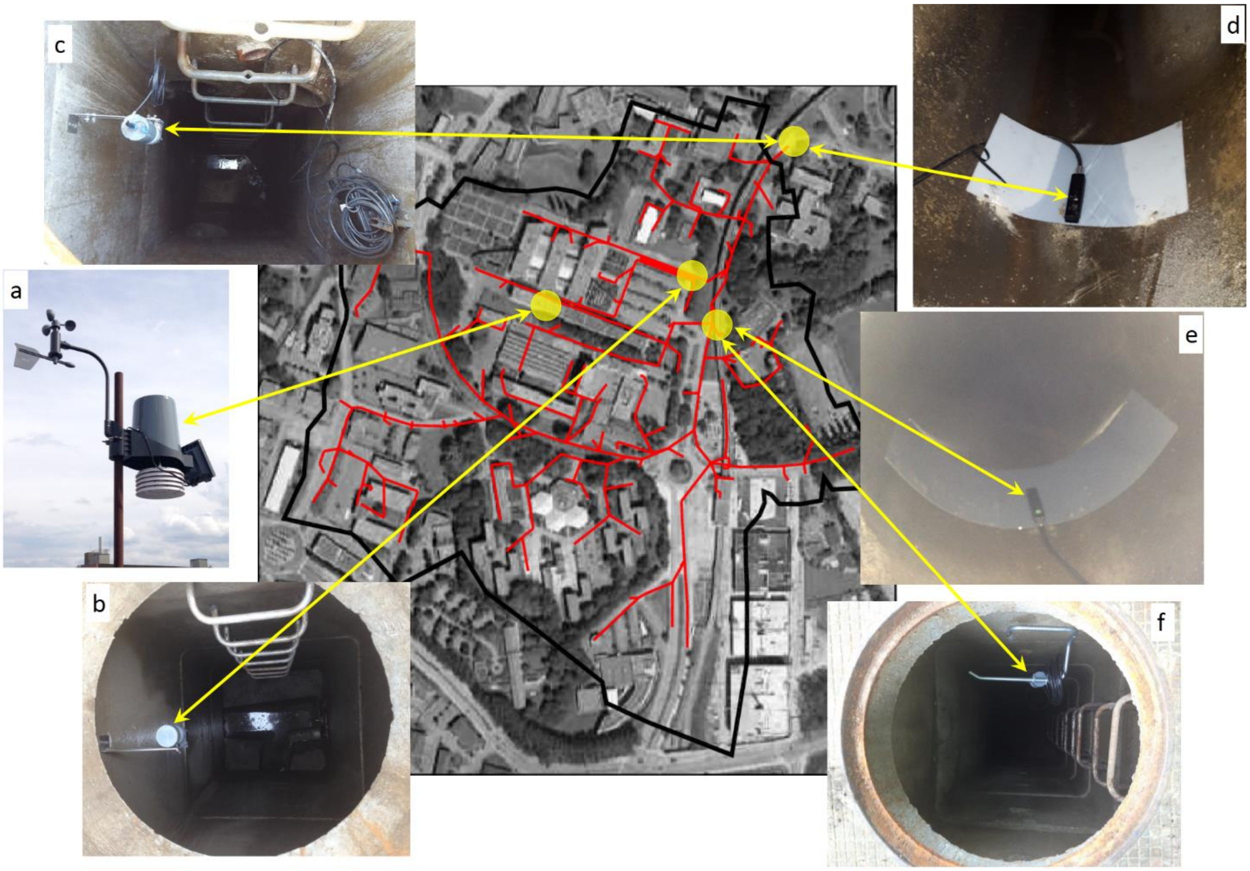

Figure 2-15: Monitoring System Installed on the Studied Sector of Lille 1 University Campus

All sensors types and characteristics are presented in the next section of this chapter. The monitoring system was scheduled to measure at a one minute time step, and sends each 1 hour the measurements to a server, where collected data is stored, filtered and analysed. Once the sensors were deployed on the Campus, we began to receive and manage the data through a GPRS system (Figure 2-16). Measurements accuracy and reliability were evaluated through comparison between multiple sensors data (e.g. water depth measured by depth meter and flow meter at the outfall).

Sensors implementation, done on April 2015, had measured multiple storm events, which were analysed and used in the next chapters of this thesis.

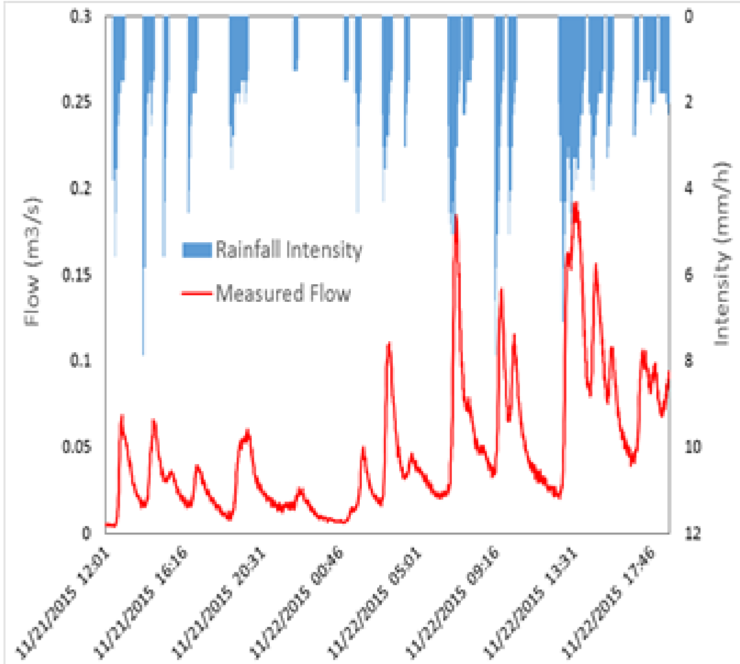

Figure 2-16: Rainfall Intensity and Flow Measurements in 22 November 2015 Storm Event

2.7 Types and Characteristics of Implemented Sensors

2.7.1 Weather Station

The weather station installed on the studied site is of type Oregon Scientific VMR300 (Figure 2-17). This ultra-precision weather station WMR300 automatically collects and transfers detailed meteorological data, allowing easy monitoring of weather parameters and patterns over medium & long term. Measurements are transmitted to a display/receiver console (Figure 2-18) with a distance up to 300m through a powerful 900MHz RF link.

Figure 2-17: Oregon Scientific VMR300 Weather Station

Figure 2-18: Display/Receiver Console

Parameters measured by this weather station and used in this study are rainfall intensity and external temperature. These measurements were used as input for hydrologic-hydraulic simulation model and neural networks in chapter 3 and 4 of this work.

The remaining implemented monitoring system was Ijinus sensors. Ijinus is a manufacturer of instrumentation, process control and metrology for wireless remote management and monitoring.

2.7.2 Water Depth Meter

The two depth meters installed on the Campus are battery powered ultrasonic sensors LNU. The first water depth meter LNU 300 X (Figure 2-19 and Figure 2-20) is installed in the retention tank and has a measuring range from 0.2 to 3m. Collected data from this sensor is transferred manually to a PC through the Avelour software connected to a connection Kit.

Figure 2-19: Water Depth Meter with a measuring range 0.2 to 3 m

Figure 2-20: Water Depth Meter installed in the Retention Basin of the Studied Sector

Since the last modelled manhole represent a total depth around 5.5 meters, the second depth meter LNU 600 X (Figure 2-21 and Figure 2-22) was chosen to be able to measure water level up to 6 m. In addition, this sensor was equipped by a GSM/GPRS transmission potential in order to transmit data to the Ijitrack website.

Figure 2-21: Water Depth Meter with a measuring range 0.3 to 6 m

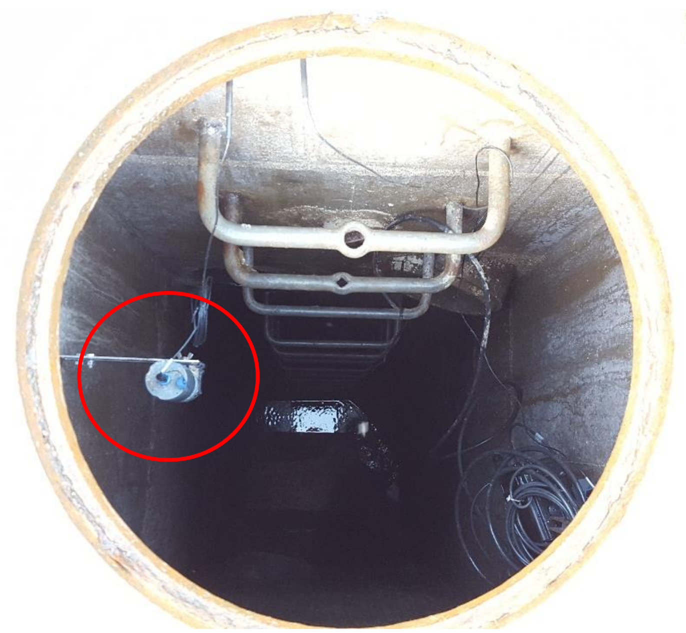

Figure 2-22: Water Depth Meter installed in the last manhole of the Studied Sector

2.7.3 Flowmeter

Equipped with a flat digital pressure sensor, it provides a measure of height from 2 mm of water. Compensated in temperature and pressure, it allows a level calibration according to the atmospheric pressure, and avoids potential measurement drift. It is also capable to measure water velocity after exceeding a 25 mm of depth. Having the depth-area relationship, this sensor is capable to measure the flow. This type of sensors is capable, through three quality indicators, to validate the quality of the measurement. These quality indicators are: necessary signal strength to measure velocity, discrimination of the received velocity spectrum and the quality of the measured flow (laminar or turbulent).

Figure 2-23: Different Parts of the Flowmeter Installed at the Outfall of the Sector (Probe, Battery, Transmitter)

Figure 2-24: Flowmeter with Lithium Battery Pack, Installed at the Outfall of the Studied Sector

The first flowmeter (Figure 2-23), installed at the last pipe in the studied sector, is equipped by a Lithium battery pack (Figure 2-24), non-rechargeable, but offering sufficient power for a long time use (6 months). The battery was fixed on the manhole wall as presented in Figure 2-25, while the probe of this sensor is fixed inside the monitored pipe, through a plastic plate, as seen in Figure 2-26.

Figure 2-25: Installation of the Battery Pack of Flowmeter at the Outfall of the Studied Sector

Figure 2-26: Installation of the Flowmeter Probe at the Pipe Existing the Outfall of the Studied Sector

Data transmission from this flowmeter was made through the logger/transmitter delivered with this sensor to the Ijitrack website.

On the other side, the same flowmeter type was installed in the main collector pipe downstream the retention tank, but equipped with a rechargeable battery (Figure 2-27 and Figure 2-28). With one-minute time step of measurements, this battery lasts for 20 days.

Figure 2-27: Flowmeter Installed Downstream the Retention Tank (Battery & Logger, Probe)

Figure 2-28: Flowmeter with Rechargeable Battery Pack Installed Downstream the Retention Tank

This sensor was delivered with a logger, not able to transmit the measurements to the Ijitrack website. Therefore, a transmitter was installed next to this flowmeter, charged for transmitting data by a GSM/GPRS system to the Ijitrack website. The battery pack was installed on the manhole wall as shown in Figure 2-29, and the probe inside the main collector pipe as presented in Figure 2-30.

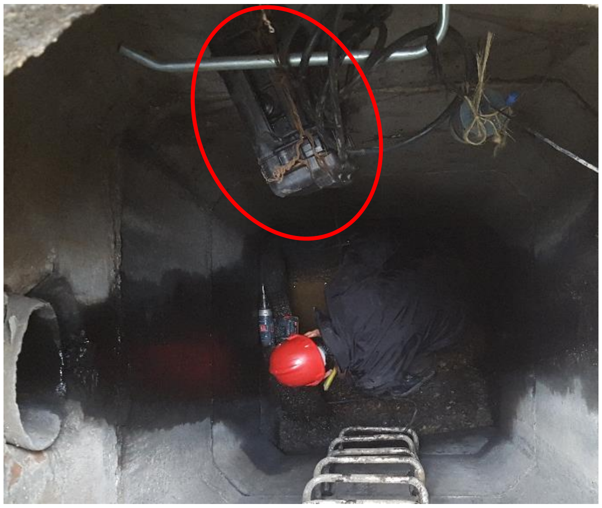

Figure 2-29: Installation of the Battery Pack of Flowmeter Downstream the Retention Tank

Figure 2-30: Installation of the Flowmeter Probe at the Main Collector Pipe Downstream the Retention Tank

2.7.4 Turbidity Meter

The installed turbidity meter (Figure 2-31), measure turbidity in Formazin Nephelometric Units (FNU) by optical technology IR fibre optic. This sensor is characterized by water tightness and low energy consumption. The probe was freely installed in the manhole, always submerged in a water depth, even in dry periods, and fixed to the manhole ladder for not touching the bottom. Cleaning of the probe was done before each rainfall event, in order to remove any depositions, which may affect the measurements.

Figure 2-31:Data Logger and Probe of the Turbidity Meter

Figure 2-32: Installation of the Turbidity Meter (1)

As for the flowmeter, installed in the same location of this sensor, data transmission was accomplished through a transmitter installed next to the logger of this sensor. Figure 2-32 and Figure 2-33 present the turbidity probe installation inside the manhole. Turbidity logger, which is also the energy provider to the probe, is presented in Figure 2-34.

Figure 2-33: Installation of the Turbidity Meter (2)

Figure 2-34: Installation of the Data Logger of the Turbidity Meter

2.7.5 Transmission

Ijilog records data up to 15 devices in his radio Ijinus field and sends them via GSM / GPRS to Ijitrack website. Ijilog transmitter was installed in the main collector manhole, downstream the retention tank, charged to transmit the flowmeter and turbidity meter measurements to the Ijitrack website. Figure 35 presents the transmitter, and the installation of this logger/transmitter is shown in Figure 36.

Figure 2-35: Data Logger and Transmitter

Figure 2-36: Installation of the Data Logger and Transmitter

2.7.6 Data management

Sensors initialization and configuration was done through a connection Kit presented in Figure 2-37. This connection Kit allows also manual data retrieval. In addition, data retrieval is done through the Ijitrack website. Ijitrack website gives the ability to manage, visualize and analyse the retrieved data, and thus plan interventions in case of detecting anomalies. Moreover, measurements thresholds and alarms could be planned in order to facilitate interventions and proactive control of the network. Figure 2-38 presents an example of data retrieval from the Ijitrack website.

Figure 2-37: Connection Kit

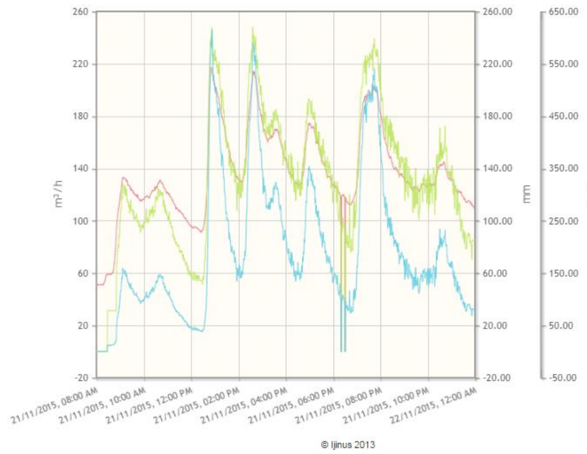

Figure 2-38: Example of Data Retrieved from Ijitrack Website

Characteristics of all the sensors, which constitute the monitoring system, implemented on Lille 1 University Campus, could be found on Ijinus website (http://www.ijinus.com).

2.8 Infiltration Potential

In Chapter 1, it was noticed that in smart cities, RTM and Dynamic Management Strategies are not limited to improve UDS operations and reduce flooding volumes. The multi-objectives nature of a smart city requires the use of multi-purposes elements in the design phase. Improving the UDS operations, recharging water resources, protecting the environment and providing esthetical areas for citizens are the main objectives for a smart city in managing UDS. Since these objectives depend on a qualitative management and infiltration structures implementations, it should be noted that practicing infiltration techniques in a specific region should be first verified regarding many criteria. Infiltration potential depends mainly on the supporting soil and groundwater level variations. In addition, regulatory constraints may limit sometimes the application of infiltration process, depending on the site locations. Thus, they should be checked in areas where a smart city is planned to be built. Infiltration potential of the supporting soil and groundwater level at the University Campus were checked through maps brought from Lille municipality. In addition, the area was verified concerning regulatory constraints and site vulnerability, through maps presenting the protection surface of intake potable water and underground cavities, which could be dangerous for infiltration applications. Figure 2-39 and Figure 2-40 present the University Campus and its ability for applying infiltration.

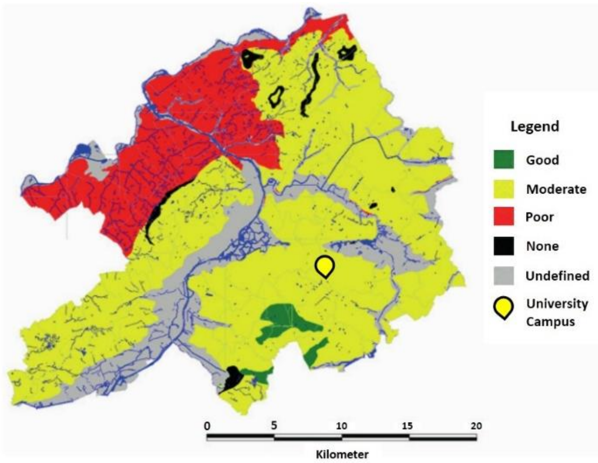

Figure 2-39: Infiltration Potential Based on Soil Type and Thickness of Unsaturated Layer

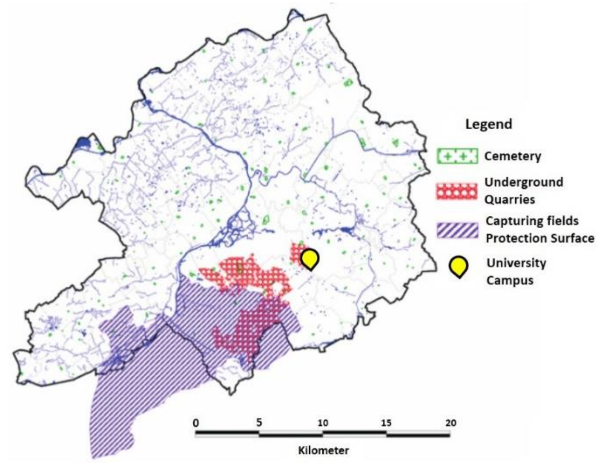

Figure 2-40: Regulatory Constraints Limiting the Infiltration Applicability

Applying infiltration on the University Campus is moderately favourable since the surface layer of the soil is sandy loam and the groundwater level is deeper than 3 m. In addition, as presented on Figure 2-40, no regulatory constraints prevent the infiltration application on the studied site.

2.9 Conclusion

This chapter presents the Lille 1 University Campus, which will be used in this study for evaluating the research. SunRise project use this site as big scale demonstrator of smart and sustainable city. All utilities information was collected and digitized into a GIS database. Combining the site information into a GIS layers enables deeper analysis of the systems interactions and consequences as recommended for smart cities. An example of these analyses is the building construction ages and the UDS operation shortages, which are different bur related data. ArcGIS software was used for constructing the Campus GIS database.

Beside the system architecture, components and equipment characteristics, GIS layers containing all maintenance and rehabilitation actions, historical problems and interventions, were constructed. Structural condition assessment was conducted based on these layers, allowing the determination of three critical areas. These layers are not limited to allow structural assessment for the actual conditions and plan short-term future rehabilitation and maintenance actions. Since they are dated, geographically localized and affected by gravity factors, at a certain level, the interventions layers will be used for forecasting future structural conditions for each section of the Campus.

Historically, the UDS of Lille 1 University Campus experienced flooding scenarios once to twice a year. Two major areas were identified in this chapter. In this context, a sector of the Campus was equipped by RTM system in order to conduct hydraulic analysis, as discussed in the following chapters. Implemented sensors with their characteristics were presented in this chapter. Finally, the Campus infiltration potential and permission was checked and turn to be allowed on the studied area.

Chapter 3

Auto-Calibration and Boundary Conditions Forecast of Urban Drainage Systems Models

3.1 Introduction

Urbanization processes, modifying land uses and site occupations, results in converting permeable to impermeable surfaces, and thus generates increases in surface runoff volumes and pollutions (Goonetilleke *et al.* 2005), leading to insufficiencies in Urban Drainage Systems (UDS). Stormwater considered, for a long time, as clean water turn to be a major environmental pollution contributor after considering the contaminants quantities transported by surface runoffs to receiving waters (Burton Jr & Pitt 2001; Desbordes *et al.* 1994; Huang *et al.* 2010; Lee *et al.* 2007). In addition, climate changes characterized by long dry periods followed by intense rains leads to rising flood damages and costs over the last two decades (Luechinger & Raschky 2009; Marsalek 2000; Ntelekos *et al.* 2010). This is the reason to be oriented toward monitoring and controlling UDS in order to increase their capabilities. Real Time Monitoring (RTM) is carried out through sensors implementation, while real time control is applied according to modelling results and evaluations. Several studies demonstrated that modelling approaches are suitable and effective for evaluating management strategies impacts and effectiveness (Elliott & Trowsdale 2007). Therefore, a calibrated model, reflecting the actual and real operation of the underground infrastructure, is required.

This chapter will present an approach for auto-calibrating UDS models based on a combination of two heuristic search algorithms (Genetic Algorithm (GA) and Pattern Search (PS)). This combination is applied in order to find the optimal combination of parameters for an UDS model to represent the real system response subjected to any storm event. After the calibration section, a NARX neural network able to predict the unknown downstream boundary conditions of a hydrologic-hydraulic simulation model under a forecasted or synthetic rain is presented. Having a calibrated simulation model and knowing the downstream boundary conditions, allow evaluating active and passive control strategies, UDS operations and equipment modifications, under any forecasted or unmeasured rainfall event.

The proposed two methods were evaluated on the already described sector of Lille 1 University Campus, under the SunRise project “Large Scale Demonstrator of a Smart and Sustainable City”, showing good results and efficiencies on calibration level as well as modelling accuracy.

3.2 Modelling

For modelling purposes, EPA's StormWater Management Model (SWMM) was chosen for its potential to plan, analyse and design UDS in urban and non-urban areas. The SWMM (version 5.1) has been applied, throughout the world, to simulate runoff, combined and separated systems, open regular and irregular channels, and other drainage systems (Guitierrez 2006). Considered as a dynamic rainfall-runoff model capable to simulate runoff quantity and quality for continuous and single event (Rossman 2010), in addition to its capacity to model hydrologic performance of specific types of low impact development controls, this software, once quantitatively calibrated, allows the extension of our project, as proposed in the next chapter, to model qualitatively the system operation. Using SWMM, surface runoff, routing model, infiltration and evaporation is computed respectively by Manning's equation, Dynamic wave, Horton model and daily min and max measured temperature record. Full dynamic wave flow routing method was used to take into account backwater effects, channel storage, pressurized flow, flow reversal, and considering outfall behaviour as final downstream boundary condition, instead of being considered as a simple junction. This routing method produces the most accurate results, since it solves the complete One-Dimensional Saint-Venant Equation (1-D SVE), by considering the continuity and momentum equations for conduits, and volume continuity equation at nodes.

3.3 Auto-Calibration Method

Modelling UDS is not limited to modelling the geography of its components by connecting pipes, with defined diameters, to manholes locations at precise levels. Lots of coefficients and parameters should be assumed, especially concerning the watersheds characteristics, in order to run calculations. Since UDS are very complex and the parameters impacts on the operation are highly interconnected, manual calibration does not allow the determination of the suitable parameters for an accurate UDS response simulation during any rainfall event. Calibrated model should be continuously verified due to parameters modifications associated with time and human activities (e.g. Surface Impermeability coefficient, Roughness, etc.). In this work, an auto-calibration process is presented, analysed and verified. A combination of two heuristic search algorithms with recent computer development makes possible the calibration of high complex phenomenon, without excluding the least sensitive parameters. The calibration process is based on an automated trial system and logical process to find the appropriate coefficients. In recent studies, sensitivity analysis provides a good option to reduce parameters in the calibration process. However, in this study, it was found that some parameters could be less sensitive during some storm events, while being more sensitive during others. Therefore, this work focused on calibration and algorithm efficiency, instead of reducing the number of parameters. The proposed calibration algorithm, presented in Figure 3-1 and discussed later in this chapter, is based firstly on a GA, searching the variables range space aiming to find the best parameters combination. Later, GA solution is directed to PS, in order to be tuned by applying a complete multidimensional search for each parameter apart. The next paragraphs briefly describe these two search algorithms, and their combination in this study, for an efficient hydrologic-hydraulic model calibration.

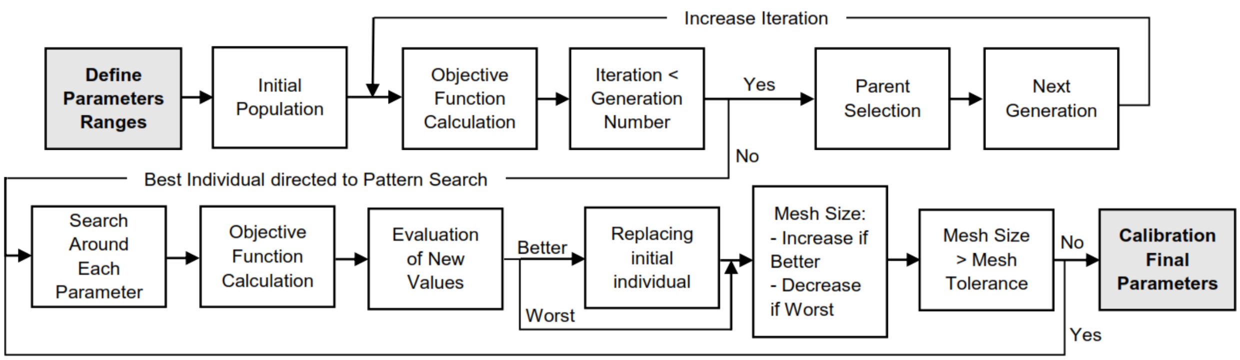

Figure 3-1: Auto-Calibration Process based on Genetic Algorithm and Pattern Search

3.3.1 Genetic Algorithm

Inspired by Darwin's theory about evolution "Survival of the fittest individual based on the biological process of survival and adaptation", GA developed in the 1970s, which is part of Evolutionary Computing, is largely used as a function optimizer (De Jong 1992; 1993). GA due to its stochastic nature, is more trustworthy to converge to global optimum by evolving a population toward a goal, than deterministic optimization methods (Davis 1987; De Jong 1975; Forrest 1993; Goldberg 1989; Holland 1975). In addition, these algorithms are based on optimizing a cost function and do not require gradient computation, therefore they could be applied on irregular and non-differentiable functions with solutions that belong to discrete search spaces (Ozkol & Komurgoz 2005; Weile & Michielssen 1997). Applied in several fields, as heat transfer problems (Gosselin *et al.* 2009), protein engineering (Rashid *et al.* 2016), banking and finance (Aguilar-Rivera *et al.* 2015; Varetto 1998), train and construction of neural networks (Kalderstam *et al.* 2013; Lazzús 2016), electromagnetics (Weile & Michielssen 1997), management (Paulo *et al.*

2016) in addition to many other fields as automotive, robotics, engineering, telecommunications, traffic and shipments etc. GA has shown high optimization performances.

GA process starts searching the parameters space by generating a set of random solutions, within user defined parameter ranges, called initial population. Once, initial population is generated, the algorithm enters in a calculation loop over the generations. Objective function, sought to be optimized, is calculated for each individual in the population followed by a fitness ranking that will drive the selection process. Best individuals among others, called parents, based on evaluating their objective function values, are selected to form a new generation. Multiple selection methods had been developed and could be found in the literature (Fraser & Burnell 1970; Goldberg & Deb 1991; Weile & Michielssen 1997). Examples of these methods are the Roulette Wheel, Boltzmann, Tournament, Ranking and Steady State Selection etc. Once parents are selected, next generation is produced by crossover and mutation genetic operations applied on parents' parameters. Crossover select parameters values from two parents and combine them into a new individual, called child, according to a user defined crossover operator such as single point, two points, intermediate, heuristic, arithmetic, ring crossover operator etc. (Abdoun & Abouchabaka 2011; Kaya & Uyar 2011). On the other hand, the mutation operator changes some parameter values of an individual randomly with a certain probability (Sharapov 2007). Crossover and mutation fraction should be well chosen, in order to efficiently apply the GA optimization search. Mutation operations prevent population conversion to a local optimum of the objective function, while crossover operations orient the algorithm towards the fittest solution and distinguish it from a random search. In order to prevent regression of the best fitted solution many authors use elitism, which is sometimes combined to a local search (De Jong 1975; Kim & Baek 2004; Kolen & Pesch 1994; Leblond & Gosselin 2008; Ulder *et al.* 1991; Villemure *et al.* 2008).

Some other important factors in GA efficiency are population size and generation number. Population size should be enough to allow the algorithm to search the space with sufficient individuals for covering the entire parameters ranges and not being stuck to local optimums. Population size proportional to individual length should be enough for practical applications (Goldberg *et al.* 1991). There is no problem of using a larger population except the increase of computation time. Generation number and generation number without improvement of the best objective function value, are defined as stopping criteria for GA iterations (Gosselin *et al.* 2009). Effectiveness and speed of optimization are mainly influenced by GA parameters. Discussion and references for some parameters and operations, which are not described above, as Elitism, Local search, Niching, Diversity level, Micro Genetic Algorithm and other evaluative algorithms, could be found in (Gosselin *et al.* 2009).

The most time consuming step in the GA application is the objective function calculation, since it should be calculated for each individual of the population at each iteration, especially in cases where objective function calculation is based on a simulation model, and thus not analytically treatable (Bäck *et al.* 1996; Schwefel 1979). In such cases, users could benefit from GA structure representing the feature of producing population of good solutions instead of just one optimal solution, allowing them to pre-optimize the problem with a simplified model, and then evaluate precisely the obtained good solutions with the real global model (Kim *et al.* 2007). Other method to benefit GA structure, is by parallelizing the objective function calculation on multiple processors, limited by the population size, since it could be applied independently on all individuals belonging to the same population (Hoffmeister 1991).

3.3.2 Pattern Search

Proposed firstly by (Hooke & Jeeves 1961), and presented later in a detailed formal definition by (Torczon 1997), the PS, considered as a numerical optimization approach, is applied in order to determine an optimal problem solution, through a systematic direct search method based on a multidimensional search direction (Findler *et al.* 1987). Similarly to GA, PS is accomplished through an iterative calculation process of objective function and solution evaluation, not requiring gradient calculation. Therefore, this method is suitable to optimize functions, not necessarily differentiable, stochastic, or even continuous, which standard optimization methods cannot handle (Sahu *et al.* 2015). Unlike GA that performs evaluations on a population of individuals, PS is a single-point search method based on investigating, at each iteration, the current solution neighbourhood points, searching the best move to take (Bao *et al.* 2013). Several applications of PS show the effectiveness of this optimization method especially in tuning solutions. Some of these applications are in electrical engineering field (Moazzami *et al.* 2016), hydrologic-hydraulic model calibration (Baek *et al.* 2015), antenna engineering (Güneş & Tokan 2010), radiation therapy (Rocha *et al.* 2013) etc.

At each iteration, PS algorithm searches within the solution space, which could be bounded and representing linear and nonlinear constraints, by computing the objective function at a sequence of current solution neighbourhood points, aiming to find a fitter solution. Modifying a single parameter within the current solution, while keeping other parameters unchanged, creates each neighbourhood point in the mesh. Practically, mesh points are generated at each iteration, by adding to the actual individual, the pattern vectors multiplied by the mesh actual size. Pattern vectors are defined in a manner to ensure the existence of mesh points representing each parameter modification alone (e.g. a problem with solution composed of two parameters, resolved using mesh points equal to two times parameter number, the pattern vectors will be as follow [1 0] [0 1] [-1 0] [0 -1]). PS algorithm polls the mesh, by computing objective function at each point. If a point of the mesh turn to be fitter then the current solution, it will form the current solution for the next iteration (Al-Othman *et al.* 2013), and the mesh size will be increased. Otherwise, if all neighbourhood points fail to provide optimization progress, the algorithm conserves the current solution for the next iteration, and decreases the mesh size. Increasing the mesh size, after each successful iteration, helps PS algorithm to escape local optimums in the neighbourhood environment, while decreasing the mesh size, following each unsuccessful iteration, ensure at the end of the algorithm the convergence to the best neighbourhood optimum by investigating all the nearest points. The minimum mesh size tolerance is generally used as the stopping criteria for the PS algorithm.

Even though PS algorithm is effective on a global search level and in fine tuning local search due to its flexible and balanced operator (Dolan *et al.* 2003), applications of this optimization method were limited principally to fine tuning local solutions. In other words, despite the dynamic nature of the mesh size, PS is considered as an efficient local optimizing methods, made to exploit local solutions and examines neighbourhood environments, rather than global ranges, the reason generally for not applying it alone for global optimization problems (Al-Othman *et al.* 2013; Bao *et al.* 2013; Mahapatra *et al.* 2014; Moazzami *et al.* 2016; Wen *et al.* 2013).

3.4 Calibration Process

As described earlier in this chapter, calibration of an UDS model is not an easy task, since it is based on finding many suitable interconnected parameters in order to enable a numerical model to simulate the real complex operation of a hydrologic-hydraulic phenomenon. In this study, a combination of GA and PS is used for the calibration process. As already discussed, firstly the GA, capable to search within wide parameter ranges through population guidance and iterations, is used to find the absolute optimal solution, which will be tuned later by the PS, characterized by its effectiveness in determining and identifying the best suitable and fitter solution in the neighbourhood of the provided initial one. The hybridized GA and PS calibration process was accomplished by a combination of SWMM hydrologic-hydraulic software and Matlab R 2015a. A Matlab script, allows running the calculation of SWMM, after modifying the input parameters for each individual at each iteration, and bringing back the results for objective function evaluation. "Patternsearch.m" function, combined to a precedent search option step using GA "searchga.m", was used to accomplish the calibration iteration work. The parameters for GA calculation were defined and selected based on trials. A population size of 100, with elite number, crossover and mutation fractions equal 5, 0.6 and 0.4 respectively, were found sufficient in fewer than 20 iterations, to provide an efficient initial point to be tuned by the PS. The GA parent selection function was chosen to be "Stochastic Uniform", while "Intermediate" and "Adaptive feasible" were selected to be respectively the crossover and mutation functions, in order to satisfy boundary conditions and linear constraints. Boundary conditions were defined as parameter ranges limits, while linear constraints were introduced to insure parameters logical combinations (e.g. minimum infiltration lower than maximum infiltration potential in Horton infiltration method). PS algorithm was designed to poll the variable space completely {"CompletePoll", "On"} at each iteration using the "GSSPositiveBasis2N" function, applying search in negative and positive directions for each parameter. The dynamicity nature of the mesh size was represented by a contraction factor of 0.5 and an expansion factor of 2, and calculations remain working until reaching a mesh size below 10^{-6}.

As stated before, parameters studied and calculated through the calibration process, have not been reduced by a sensitivity analysis, since we have considered the sensitivity variation, of each parameter, according to the situation and the storm event. Ranges of these parameters, used by GA and PS as variable search space, were found in the literature and extended to offer the optimization technique the wider possible choices to calibrate the model. In addition, the aim to construct a model capable to represent the UDS operations at all circumstances, requires a parallel calibration under multiple storm events with different characteristics. Therefore, 20 different rainfall events, presented later in this chapter, were divided in two halves. The first one is used in the parallel calibration process, while the other in the verification phase. The calibration and the verification have been accomplished based on different types of measurements taken from multiple sensors, implemented in several parts of the UDS, as already discussed in the "real time monitoring system" section. Measured water depth at the retention basin location, was used for verification purpose during intense storm event, while measured water depth at the outfall structure, was used as downstream boundary condition for the SWMM model simulation. Flowmeters' measurements during 10 storm events were used for the calibration process, while the verification phase was based on these sensors' measurements during 10 other rainfall events.

3.4.1 Objective Function

Firstly, calibration process was based on modelled and measured flow values comparison, showing very good results on flow levels, but limited efficiencies on velocity and depth levels, which could be due to parameters interactions and pipes' roughness errors. Therefore, in the following stage, measured and modelled flow, depth and velocity, within the monitored pipes, were compared using the SSE method and normalized to be introduced in the objective function according to $ObjFun1$, presented in Equation 3-1. In addition, due to the importance of calibrating a model for peaks evaluations and analysis, and since previous studies showed that SWMM models have a limitation in simulating peaks (Baek *et al.* 2015; Barco *et al.* 2008; Tsihrintzis & Hamid 1998), *ObjFun2*, presented in Equation 3-2 and responsible for calibrating a model capable to represent peak values, was added to total objective function $ObjFun$, used for the overall calibration purpose and presented in Equation 3-3.

$$ObjFun1 = \frac{\sum(q_m - q_o)^2}{(\sum q_m + \sum q_o)^2} + \frac{\sum(v_m - v_o)^2}{(\sum v_m + \sum v_o)^2} + \frac{\sum(h_m - h_o)^2}{(\sum h_m + \sum h_o)^2} \qquad \textit{Equation 3-1}$$

$$ObjFun2 = \frac{|\,max(q_m) - max(q_o)\,|}{max(q_m) + max(q_o)} + \frac{|\,max(v_m) - max(v_o)\,|}{max(v_m) + max(v_o)} + \frac{|\,max(h_m) - max(h_o)\,|}{max(h_m) + max(h_o)} \qquad \textit{Equation 3-2}$$

$$ObjFun = ObjFun1 + C * ObjFun2 \qquad \textit{Equation 3-3}$$

Where q, v, h, o and m refer to flow, velocity, depth, observed and modelled respectively. Coefficient C equal to 0.01 was determined through iterative work, in order to assign an equal importance factor for both functions participating in the total objective function. In other words, a matching of the results overall the storm period and at peak time were equally evaluated by the auto-calibration process.

3.4.2 Efficiency Criteria

One effective fundamental approach in evaluating the performance of a calibrated model is through visual inspection of the simulated and observed measurements. In addition, evaluation of hydrologic-hydraulic calibration process could be accomplished through different efficiency criteria, presented in the literature. An efficiency criteria is a mathematical measure of the similitude in model simulation results and real observed measurements (Beven 2011). The efficiency criteria calculations, which are most frequently used in hydrologic-hydraulic modelling studies, are the Bravais-Pearson coefficient or coefficient of determination "r2", Nash Sutcliffe efficiency "NSE" (Nash & Sutcliffe 1970), index of agreement "d" (Willmott 1981; 1984). A description and analysis of each of these criteria with other modified form of efficiency evaluation functions could be found in (Krause *et al.* 2005), which notices that none of the tested efficiency calculation performed ideally, and a combination of efficiency evaluations is better to be adopted. (Janssen & Heuberger 1995) found that the intended use of the hydrologic-hydraulic constructed model should affect the selection of the suitable efficiency calculation. In this study, once calibration process had been accomplished, SWMM model performance was evaluated graphically and statistically through Nash–Sutcliffe Efficiency (NSE) presented in Equation 3-4.

$$NSE = 1 - \frac{\sum_{i=1}^{n}(O_i - P_i)^2}{\sum_{i=1}^{n}(O_i - \bar{O})^2}$$ *Equation 3-4*

Where O and P referred to observed and predicted respectively.

As stated in NSE equation, the summation of the squared errors is used for the efficiency calculation. Therefore, larger errors, taking place at higher values, will affect more the calculated efficiency (Legates & McCabe 1999). In addition, it should be noted that normalization of the squared differences between the observed and modelled results, by the squared differences between the observed and the mean of observed measurements, generates higher possible values with higher dynamic events. NSE efficiency value varies between 1 and –infinity. E=1 reflect a perfect fit while negative E value indicates that the prediction based on the mean of observed values is better than modelled values. Values of NSE efficiency criteria calculated for the 20 storm events, used in the calibration as well as validation phases, have been calculated and presented in the following sections.

3.4.3 Rainfall Events Selection

Selecting and separating rainfall events is a critical work, especially for calibration purposes, since any fault at this phase could affect the model efficiency in representing the real operation of the UDS. The calibration algorithm in this study is based on calibrating the constructed model over 10 storm events, which ranges from low to high rainfall intensities and severities, in a parallel process. Calibrating the SWMM model on different rainfall intensities is a key element in the calibration process to ensure an efficient and complete calibration of permeable and impermeable surfaces. In order to reduce calculation time, each worker of the Matlab cluster have been charged to calculate the objective function, given in Equation 3-3, for a separate storm event. The total objective function indicating the fitness of the parameters combination was calculated by summing the objective function values calculated for all the rainfall events and returned by the cluster workers. Moreover, reducing the storm event period without affecting the model representativeness had been also a target in order to reduce calibration calculation time. When separating two interconnected rainfall events, the resulted model simulate a wrong unconnected behaviour of the UDS, leading to overestimated results, while matching modelled and observed behaviours. In other words, if the current and the precedent rainfall events affect the real UDS response, trying to match this response by a model subjected to the current storm event solely, generates an overestimation of the real UDS operation. In the literature, separating an individual rainfall event from continuous rainfall record is applied through an Inter-Event Time Definition (IETD), expressed as a minimum dry period for separation (Baek *et al.* 2015; Guo & Adams 1998; Kim & Han 2010; Palynchuk & Guo 2008; Restrepo-Posada & Eagleson 1982). For the calculation of IETD, autocorrelation analysis, average annual number of events analysis, and coefficient of variation analysis, are three traditional proposed methods, taking into account only the rainfall characteristics and excluding drainage basin characteristics. (Joo *et al.* 2014) discusses these three methods and propose a new method for IETD calculation based on basin characteristics and modelling results.

In this paper, due to the inefficient results of the already cited methods, a new approach has been used for the determination of IETD. The proposed approach is based, as in (Joo *et al.* 2014), on rainfall and basin characteristics, but not limited to separate rainfall events without runoff hydrographs overlaps. Since interaction, between two consecutive rainfall events, could go beyond hydrographs superposition, and affect permeable surface infiltration potential and depression storage capacity, even if Antecedent Dry Days parameter was respected in SWMM model, the used approach consists of the following steps. First, UDS operation subjected to the chosen rainfall event is modelled on SWMM combined to the precedent rainfall events, and resulted hydrograph for the chosen rainfall period is compared with the resulted hydrograph of modelling the UDS operation subjected to the chosen rainfall event solely, with modifying the Antecedent Dry Days parameter in the SWMM Model. The chosen rainfall event could be isolated from the continuous rainfall measurements, if and only if the two modelled hydrographs, during the chosen event period, were similar. Since watershed characteristics will be tuned during calibration, it should be noted that these procedures should be repeated and verified after calibration is finished, to ensure the selection procedure and assumptions made before the calibration.

3.5 Real Time Monitoring Data

The studied sector of the UDS of Lille 1 University Campus was equipped with multiple water quantity sensors, as described in chapter 2, in order to measure, model and analyse its operation. In this chapter, the quantitative sensors' measurements will be used for the hydrologic-hydraulic model calibration, and as training data set for the NARX neural network, designed to forecast the modelled UDS downstream boundary conditions. Figure 3-2 presents the constructed hydrologic-hydraulic model, with the implemented sensors used in this chapter. Locations of the sensors are numbered (Nb) in order to facilitate the referencing to this equipment. Firstly, the measurements of the weather station (Nb1) will be introduced as input to the hydrologic-hydraulic model simulation. The measurements of the two flowmeters, located inside the last modelled pipe before reaching the outlet (Nb2) and in the main collector, downstream the retention basin (Nb3), will be dedicated for calibration and verification purposes. In parallel, the measurements of the two depth meters, installed in the retention basin (Nb4) and at the outfall of the studied sector (Nb5), will be used for verifying the calibrated model and measuring the downstream boundary conditions, respectively.

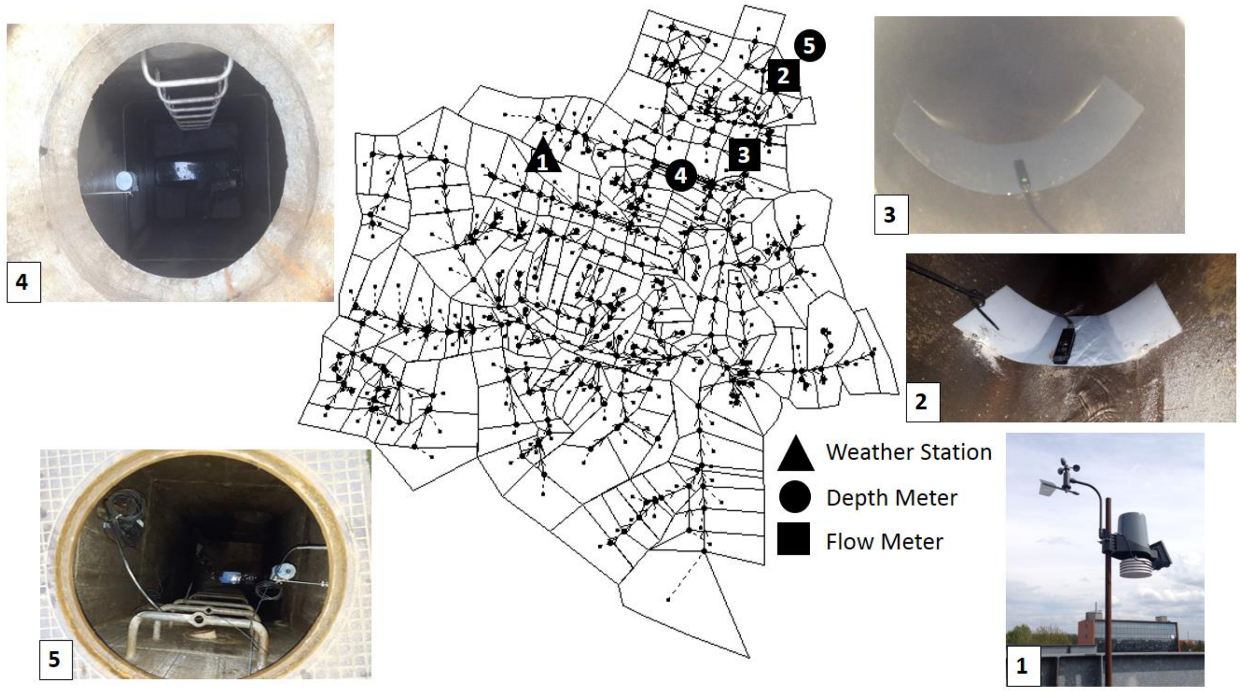

Figure 3-2: Urban Drainage System within the Studied Sector and the Implemented Quantitative Sensors

Infrastructure sensors equipment is useful also to continuously calibrate and verify the hydraulic model operation in the future. In chapter 2, measurements accuracy and reliability assessments was applied through comparison between multiple sensors data (e.g. depth measured by depth meter and flow meter at the outfall), while at the end of this chapter, once a calibrated model is obtained, modelled values could assist in sensors measurements filtrations and verifications. Sensors implementation, done on April 2015, had measured multiple storm events, which were analysed, separated and used in the calibration process, as shown and explained in the precedent sections.

3.6 Calibration Results and Discussions

Calibration process was automated through a matlab script capable to run iteratively the SWMM model, simultaneously on 10 different storm events by charging each worker in the local cluster to run the model on a specified event separately from others. The following Table 3-1 shows the hydrologic parameters reported as variables to be found for the calibration process. As noted in this chapter, calibration intervals were chosen to offer the SWMM model the wider space of parameters combinations possible, aiming to find the best parameter vector in matching modelling to real network operation. After calibration, calculated parameters were compared to ranges found by preceded researchers, showing very good correlations for the majority of the parameters.

Table 3-1: Calibrated Parameters of SWMM Model

Type	**Parameters**	**Description**[a]	**Calibration Interval**	**Range of Preceded**	**Value**	**Unit**
Catchment	Width	Catchment width	10 – 1000	___	19.09	Meters
Catchment	Slope	Catchment slope	0.2 – 1	___	0.992	Percent
Catchment	Imp	Impervious fraction	10 – 60	___	43.09	Percent
Catchment	N_{imp}	Impervious Manning's n	0.001 – 0.05	0.011 – 0.033[b]	0.035	
Catchment	DS_{imp}	Depression storage for	0 – 10	0.25 – 2.48[b]	1.849	mm
Catchment	N_{perm}	Pervious Manning's n	0.005 – 0.8	0.02 – 0.8[b]	0.08	
Catchment	DS_{perm}	Depression storage for	0 – 10	2.48 – 5.08[b]	0.852	mm
Catchment	%Zero	Percent of impervious area	10 – 80	___	16.17	Percent
Pipe	Rough	Roughness parameter	0.01 – 0.03	0.011 – 0.015[c]	0.012	
Horton Infiltration	Max_{inf}	Maximum infiltration	0 – 250	25 – 250[a,d]	28.93	mm/hr
Horton Infiltration	Min_{inf}	Minimum infiltration	0 – 120	0.25 – 120[a,d]	0.731	mm/hr
Horton Infiltration	Decay	Decay rate constant	0 – 10	2 – 7[a]	4.005	1/hr
Horton Infiltration	Dry Time	Time it takes for fully saturated soil	0 – 20	2 – 14[a]	2	days

[a] (Rossman 2010), [b] (Huber & Dickinson 1992), [c] (Glasgow 1982), [d] (Akan 1993)

Once calculated parameters fall into an acceptable and logical ranges, model efficiency was examined through visual inspection and NSE calculation for the 10 different rainfall events used in the calibration phase, as well as the 10 other rainfall events dedicated for the verification purpose. Table 3-2 presents the characteristics of the rainfall events used in this study, showing the intensity and severity range covered during the calibration and verification phases. This table presents the NSE coefficient calculated for each rainfall event according to Equation 3-4, based on flowmeters' measurements and EPA-SWMM' modelled results. Average NSE coefficients equivalent to 0.753 and 0.713 were calculated for calibration and validation phases respectively.

The majority of calculated NSE coefficients are greater than 0.5, and thus could be regarded as acceptable performance (Moriasi *et al.* 2007).

Table 3-2: Rainfall Events for Calibration and Verification Purposes

Date	Duration	Depth	Peak	Surface	Min-Max	Nash-
Calibration Purpose						
14/05/2015	678	8.331	6.86	2.320	7.3-14.4	0.636
25/07/2015[a]	320	13.04	16.76	5.935	12.6-20.2	0.822
30/07/2015[a]	30	5.545	59.95	1.585	11.1-17.6	0.844
04/08/2015[a]	51	6.651	86.36	2.075	15.6-21.7	0.735
24/08/2015	709	7.682	14.99	2.026	14.2-20.2	0.467
26/08/2015[a]	46	9.774	39.62	3.888	16.8-25.8	0.754
13/09/2015[a]	274	20.842	96.27	12.777	8.9-16.1	0.823
05/10/2015[a]	1026	12.028	7.87	3.973	12-20.7	0.637
28/10/2015	777	6.141	6.86	1.736	10.9-15.4	0.912
07/11/2015	45	2.358	19.05	0.282	14-19.9	0.902
Verification Purpose						
27/08/2015	428	7.776	15.49	2.442	13.8-19.6	0.619
31/08/2015[a]	164	24.354	217.18	17.514	16.7-27.1	0.725
19/11/2015[a]	430	17.287	22.61	8.721	10.5-14.1	0.520
21/11/2015	2011	29.487	7.87	14.762	0.8-7.2	0.595
26/11/2015	487	2.865	4.06	1.115	4.7-10.1	0.819
11/12/2015[a]	172	5.813	23.37	2.44	3.9-10.2	0.947
30/01/2016[a]	452	11.327	13.97	4.426	4.1-9.6	0.807
08/02/2016	415	7.378	11.68	2.388	5.4-9.8	0.786
09/02/2016	1404	18.237	11.43	9.229	3.5-7.5	0.527
04/03/2016	333	9.812	6.1	3.812	3.6-9.3	0.789

[a] Rainfall events used in the training process of the NARX network presented in section 8 of this work

Visual inspections, through plotting the modelled and observed variables, are very useful and helpful in affirming the calibration efficiency and the preceded attainments. Figure 3-3 to Figure 3-22 present the comparison between modelled and measured values for the 20 storm events used in this section.

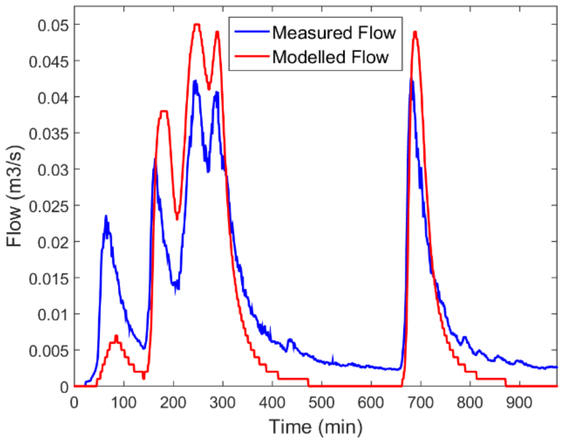

Figure 3-3: Measured and Modelled Flow Comparison for Rainfall Event 14/05/2015 (NSE=0.64)

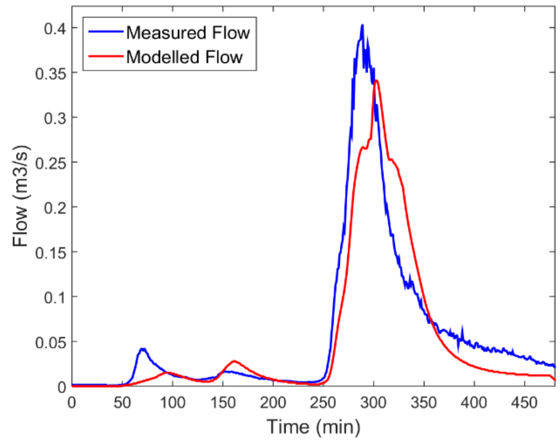

Figure 3-4: Measured and Modelled Flow Comparison for Rainfall Event 25/07/2015 (NSE=0.82)

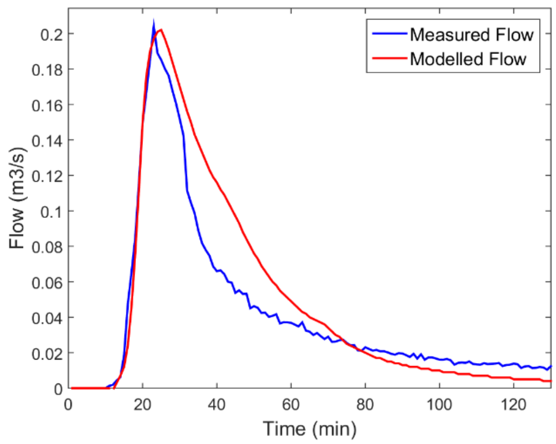

Figure 3-5: Measured and Modelled Flow Comparison for Rainfall Event 30/07/2015 (NSE=0.84)

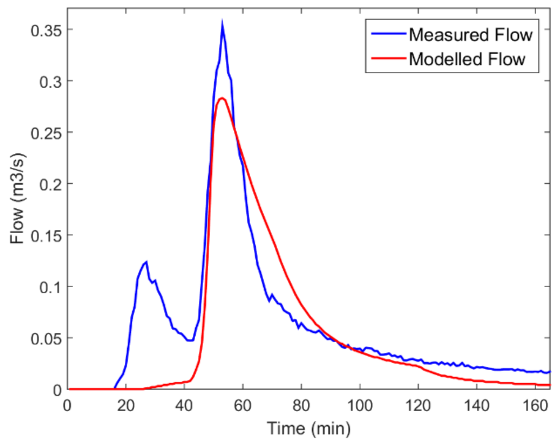

Figure 3-6: Measured and Modelled Flow Comparison for Rainfall Event 04/08/2015 (NSE=0.74)

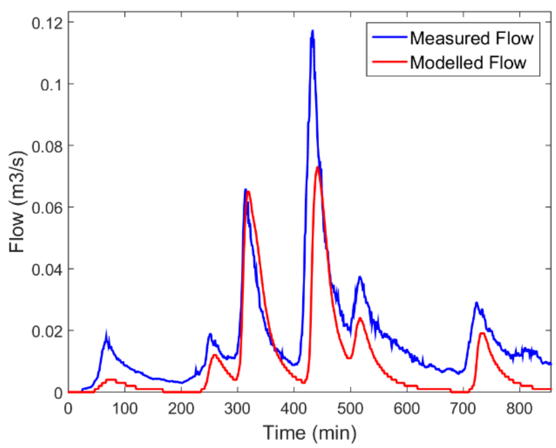

Figure 3-7: Measured and Modelled Flow Comparison for Rainfall Event 24/08/2015 (NSE=0.47)

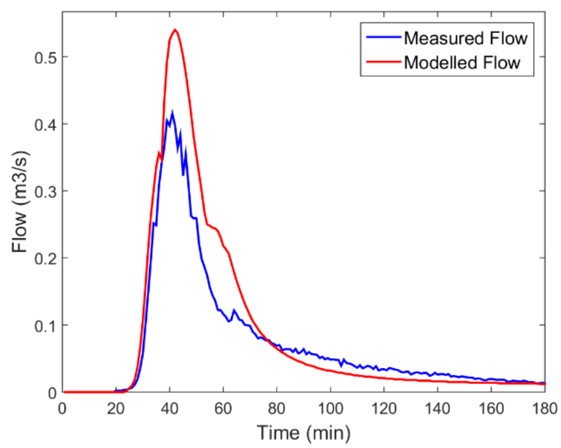

Figure 3-8: Measured and Modelled Flow Comparison for Rainfall Event 26/08/2015 (NSE=0.75)

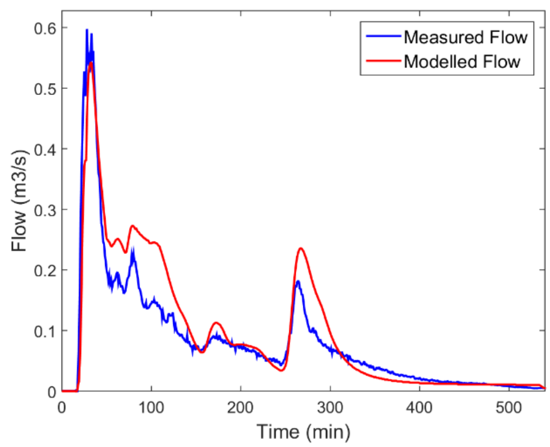

Figure 3-9: Measured and Modelled Flow Comparison for Rainfall Event 13/09/2015 (NSE=0.82)

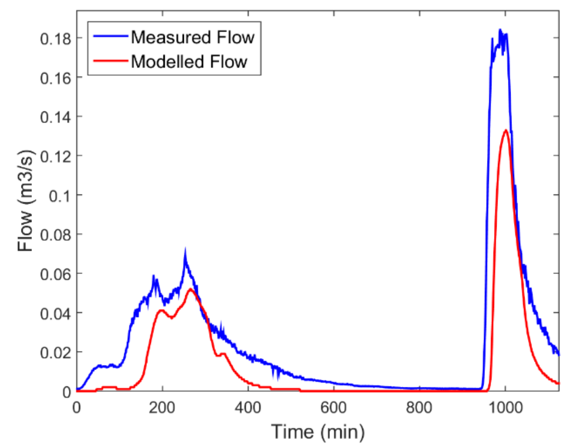

Figure 3-10: Measured and Modelled Flow Comparison for Rainfall Event 05/10/2015 (NSE=0.65)

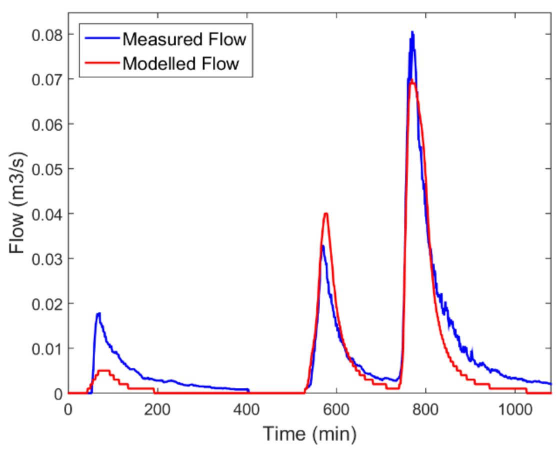

Figure 3-11: Measured and Modelled Flow Comparison for Rainfall Event 28/10/2015 (NSE=0.91)

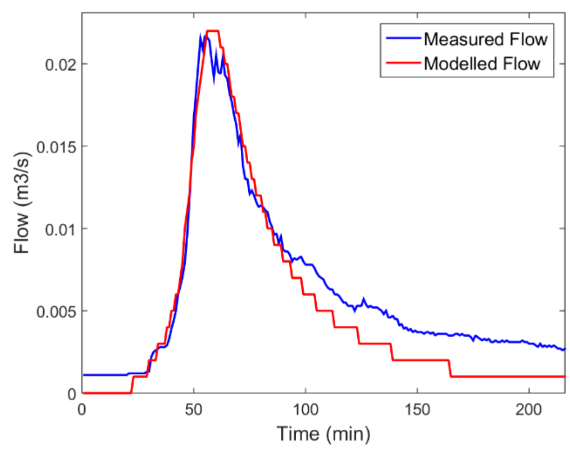

Figure 3-12: Measured and Modelled Flow Comparison for Rainfall Event 07/11/2015 (NSE=0.90)

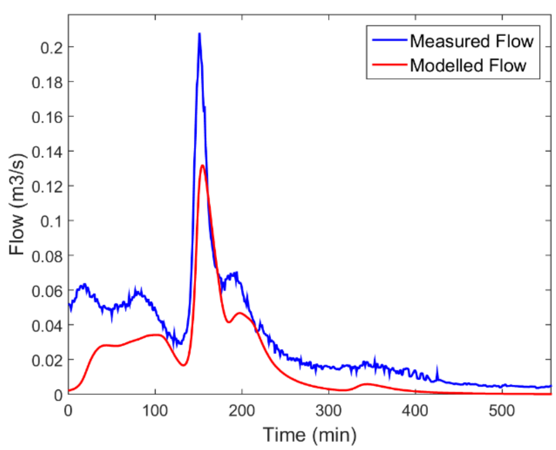

Figure 3-13: Measured and Modelled Flow Comparison for Rainfall Event 27/08/2015 (NSE=0.62)

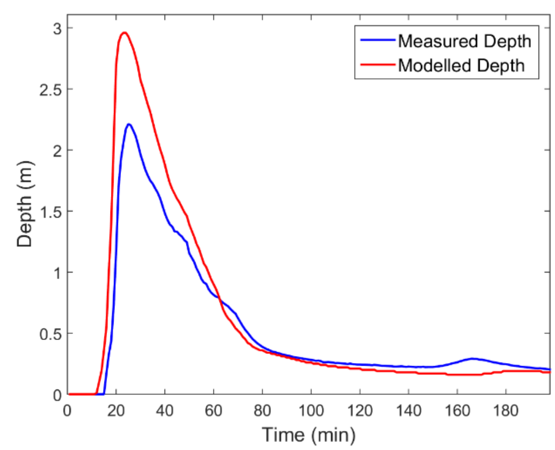

Figure 3-14: Measured and Modelled Flow Comparison for Rainfall Event 31/08/2015 (NSE=0.73)

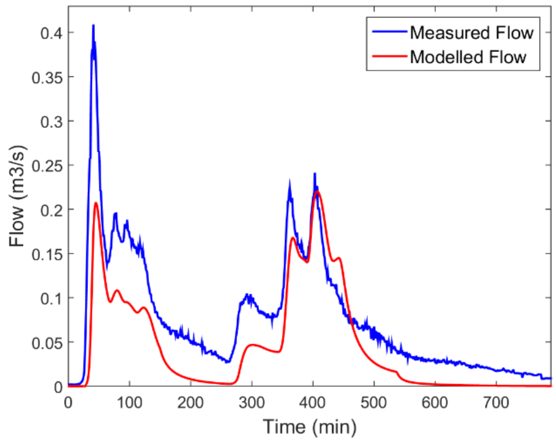

Figure 3-15: Measured and Modelled Flow Comparison for Rainfall Event 19/11/2015 (NSE=0.52)

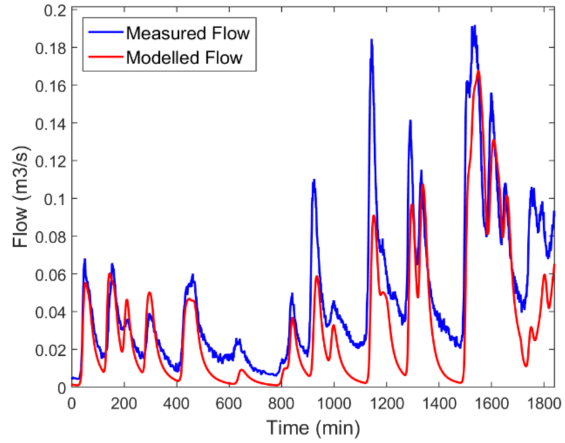

Figure 3-16: Measured and Modelled Flow Comparison for Rainfall Event 21/11/2015 (NSE=0.60)

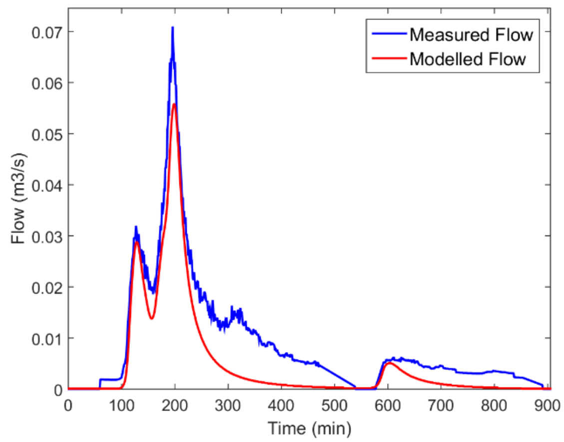

Figure 3-17: Measured and Modelled Flow Comparison for Rainfall Event 26/11/2015 (NSE=0.82)

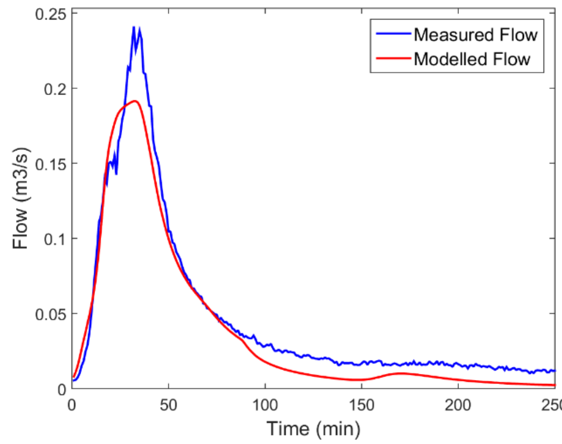

Figure 3-18: Measured and Modelled Flow Comparison for Rainfall Event 11/12/2015 (NSE=0.95)

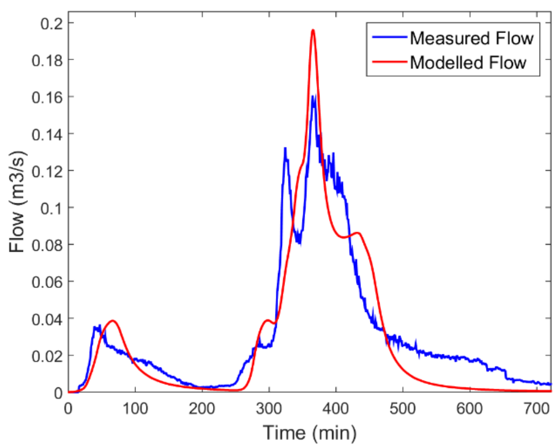

Figure 3-19: Measured and Modelled Flow Comparison for Rainfall Event 30/01/2016 (NSE=0.81)

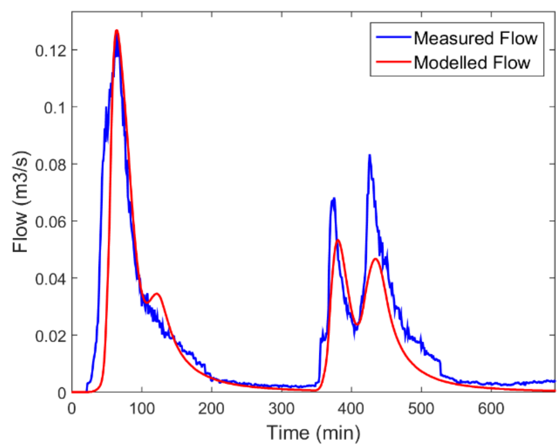

Figure 3-20: Measured and Modelled Flow Comparison for Rainfall Event 08/02/2016 (NSE=0.79)

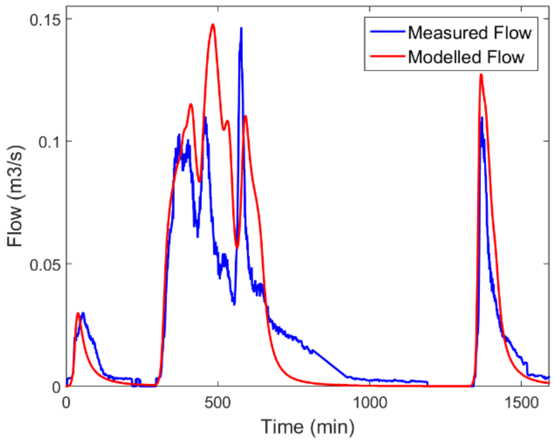

Figure 3-21: Measured and Modelled Flow Comparison for Rainfall Event 09/02/2016 (NSE=0.53)

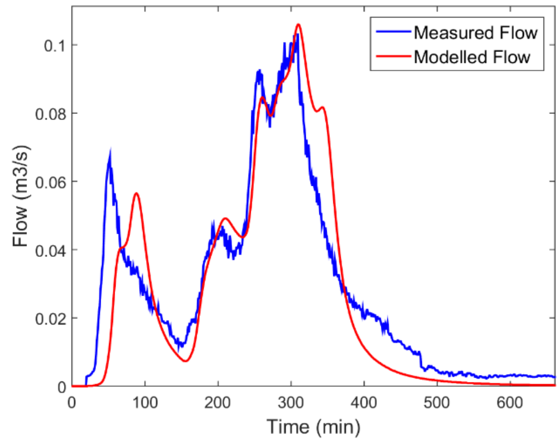

Figure 3-22: Measured and Modelled Flow Comparison for Rainfall Event 04/03/2016 (NSE=0.79)

Visual inspections based on the previous figures allow us to conclude that the calibrated model represents effectively the real UDS operations under different storm events. Furthermore, the peak flow is well represented in the hydrologic-hydraulic model, due to its participation in the objective function calculation, unlike previous researches results. After inspecting the model responses to all selected rainfall events, a similarity in flow, velocity and depth for measured and modelled values in different parts of the UDS, is presented. Therefore the hydrologic-hydraulic SWMM model is considered as an efficient tool to simulate, study, analyse and understand the real operation of Lille 1 University Campus UDS, subjected to forecast or synthetic rainfall events.

It should be noted that in case of having a difference in modelled and measured values, during a particular rainfall event, we cannot affirm definitively a calibration error or failure, because the observation could be explained, after visual inspection, by measurements errors at the weather station or sensors levels, or even in a temporary shift between input and output measurements at the implemented monitoring system. Hence, a calibrated model could be an effective tool to detect sensors malfunctions or problems at the global monitoring system level.

3.7 Forecasting Downstream Boundary Conditions

Once a calibrated model was built and verified, the evaluation of the network operation subjected to unmeasured and extreme events, in order to understand and localize weaknesses of the UDS, could be realized. The simulation of the real UDS operation requires the knowledge of the input data and the boundary conditions. The input data for a hydrologic-hydraulic model simulation are the weather data and the initial states of the operation, which could be found for an unmeasured event from a weather forecast system or synthetic storm events construction, and previous simulations results or sensors actual measurements, respectively. The boundary conditions of an UDS simulation model are values, which affect the model calculations and results and could not be simulated due to model limited capabilities and geographical coverage. The boundary conditions are used, in UDS models, for simulating the effect of the un-modelled downstream parts on the modelled upstream network. This information affect the model calculations and results especially when the UDS is surcharged and present backwater and limited flow effect, and while modelling is limited to a sector and do not cover the complete network and receiving water bodies. Therefore, forecasting the downstream boundary conditions, presented by the last modelled manhole water depth, is an essential step in the modelling procedure of the studied sector of Lille 1 University Campus.

3.7.1 Nonlinear Autoregressive Network with Exogenous Inputs

The water depth in a manhole is a complex hydrologic-hydraulic response of the system operation subjected to a rainfall event. Since struggling in the access to the complicated deterministic equations for forecasting these conditions is undesirable, the black box model is found to be more suitable to be used in this section. The outfall water depth variation depends on the rainfall intensities sequence for the duration of the studied catchment concentration time. In addition, the hydrologic modifications, occurring during the event period, affect and differentiate the outfall water depth variation of the modelled sector, depending on antecedent conditions. Therefore, a Nonlinear Autoregressive Network with Exogenous Inputs (NARX) model was used for the forecast of this response.

NARX model (Leontaritis & Billings 1985) is introduced as the nonlinear form of the ARX model, which represents a standard tool in linear black box model identification (Ljung 1999). NARX model is commonly used in time-series modelling and forecasting applications. Applied in different domains, NARX model was found able to represent a wide variety of nonlinear dynamic behaviours (Pisoni *et al.* 2009). Its potential for this study was expected due to its calculation nature, presented by connecting a precedent sequence of output values with a sequence of input values in order to calculate the actual output value. NARX model is defined through the Equation 3-5:

$$y(t) = f[\, u(t-1), \dots, u(t-n_u), y(t-1), \dots, y(t-n_y)\,]$$ *Equation 3-5*

Where y(t) and u(t) are the model output and input time series, n_u and n_y are the maximum time delays required for the model to effectively represent the dynamic behaviour of the studied phenomenon.

The exogenous inputs, within the NARX model, will account for the rainfall intensities involvement in the outfall water depth calculation, while the precedent series of the already calculated values, enable the model to understand the hydrological modifications and thus differentiate between the sequences of multiple consecutive events. The function defined in Equation 3-5, presenting the NARX model, could be resolve through multiple techniques as polynomial expansions or neural networks. In this study, the Artificial Neural Network is used to resolve the NARX function, as described in the following sections.

3.7.2 Artificial Neural Network to Resolve NARX Model

An Artificial Neural Network (ANN) is employed to resolve the NARX model described above. ANN models descriptions and applications are widely presented in the literature (Almási *et al.* 2016; Gardner & Dorling 1998; Qazi *et al.* 2015). Briefly described, an ANN is a group of interconnected computational units, which transmit their information in parallel and through unidirectional channels. Each computational unit represent an artificial neuron, where the input is the sum of received weighted information from the neurons of the precedent layer and a bias, and the output is the result of an activated function applied on the input. Multiple types of activated functions are presented in the literature: Hard-Limit, Linear, Log-Sigmoid, Hyperbolic Tangent Sigmoid, Exponential Transfer Functions are some examples of these functions. Each connecting channel is associated with a numerical weight reflecting its relative influence in the process calculation. The ANN structure, performance and capacity turn it to be evolved as an advanced data mining and analysis tool (Behrang *et al.* 2010; Journée & Bertrand 2010; Martí & Gasque 2011).

The Multi-Layer Preceptor (MLP), consisting of three interconnected parts, is the widely used type in ANN models. The first and last parts of the MLP consist of the input and output layer respectively, while the middle part is composed of one or several hidden layers. Numbers of neurons in the input and output layers are specified through the network geometry, while the number of embedded neurons within the hidden layers is a parameter to be defined through iterative work and performance evaluation. Feed-forward neural network is the most popular approach in ANN, represented by full connectivity between adjacent layers and a one directional propagation of the information from the input to the output layer. When a network exhibits loops within its structure, it is considered as a Recurrent Neural Network (RNN).

Training an ANN is tuning the weights of the neurons inter-connection channels and the biases, through an iterative work in order to match output data with target values. Learning and training is a data-driven mechanism for neural network, thus the training success and efficiency is related to the quality and size of the training data set. The choice of the training function is also a key element in the training process, where multiple and different techniques exist and are presented in the literature. Backpropagation method (Rumelhart *et al.* 1986), based on a gradient descent algorithm, is by far the most successful neural network learning algorithm. In backpropagation it is important to be able to calculate the derivatives of any transfer function used, because it should be able to process the derivatives from the last layer to the first one within the network. During the training process, network performance function, which is an indication of the differences between the output and target values, tend to be minimized through the iterative adjustment of the weights and biases of the network. Network performance function in the training process of ANN, defined as the cost function to be minimized, could be any comparison function as mean or sum of squared errors between target and output values.

3.7.3 Forecasting Application

In this section, Neural Network toolbox in Matlab R2015a was used for the resolution of the nonlinear NARX function “f” presented in Equation 3-5. Dynamic neural network based on NARX model was considered, in the literature, as a highly efficient tool especially for modelling nonlinear complex systems (Ljung 1991; Narendra & Parthasarathy 1990; Sastry *et al.* 1994). The NARX neural network was involved, in addition to modelling nonlinear dynamic systems, in different application types as predictor for the next values of input signal and nonlinear filter generating noise-free version of the input signal (Demuth *et al.* 2008). This network was recently applied in different domains as modelling gas turbines (Asgari *et al.* 2016), water distribution network (Zhe *et al.* 2015), automated engineering (Tijani *et al.* 2014), analysing chaotic time series (Goudarzi *et al.* 2016), wastewater treatment work (Çoruh *et al.* 2014), Environmental pollution field (Pisoni *et al.* 2009).

NARX neural network could be implemented within two different types of architecture. The first type, called series-parallel architecture, is defined as using the real measured sequence of output values with the input sequence in the calculation of the new actual output. The second type, known as parallel architecture, is based on using the sequence of the neural network output values, instead of the target values, in calculating the actual result. Since the output measurements are available during the training phase, it is common to apply the train procedure on a series-parallel architecture, then to transform the trained network to a parallel architecture in order to perform iterated prediction for multi time steps. The advantages of this method lie in the more accurate input for the model, during the training process, and thus the better performance results, and the less required calculation time due to the static backpropagation training function instead of the dynamic recurrent behaviour (Demuth *et al.* 2008). In this work, the procedure above was firstly applied, showing good results in the training phase, but a limited performance during a long time forecast of the outfall water depth. Therefore, the method adopted later was based on training from the beginning a parallel architecture network, since it is the form that will be used in the forecasting process.

One of the major challenges in building an efficient NARX neural network, for modelling a nonlinear dynamic system, is choosing the suitable architecture and characteristics for the network. Based on the Stone-Weierstrass theorem stating that a sufficient number of neurons within a two layer network can approximate any continuous function (Haykin 1998; Hornik *et al.* 1989), a network with one hidden and one output layers, was chosen for forecasting the outfall water depth. The hyperbolic tangent sigmoid and linear functions were selected to be the transfer functions of the hidden and output layers of the constructed network respectively. The number of previous values of the exogenous input signal, defined as the rain intensities in this network, was selected to be the time of concentration of the studied basin, equivalent to 15 time steps. This choice was made based on the fact that the actual rain intensity will affect the network operation for a duration equivalent to its time of concentration. The Levenberg-Marquardt backpropagation training function and the Mean Squared Errors (MSE) performance function were selected for the training process. The Levenberg-Marquardt function is considered as the fastest training function and has been very successfully applied for neural networks, while being limited for large networks, where it requires more memory space and computation time for networks presenting thousands of weights (Demuth *et al.* 2008; Hagan *et al.* 1996). The rest of the network parameters were defined according to the obtained results of several training iterations. The required number of previous neural network output values contributing to the calculation of the actual output value was found equal to 15, and 10 neurons within the hidden layer were sufficient for offering good results. The constructed model for forecasting the downstream boundary conditions for the hydrologic-hydraulic EPA-SWMM model is presented in Figure 3-23.

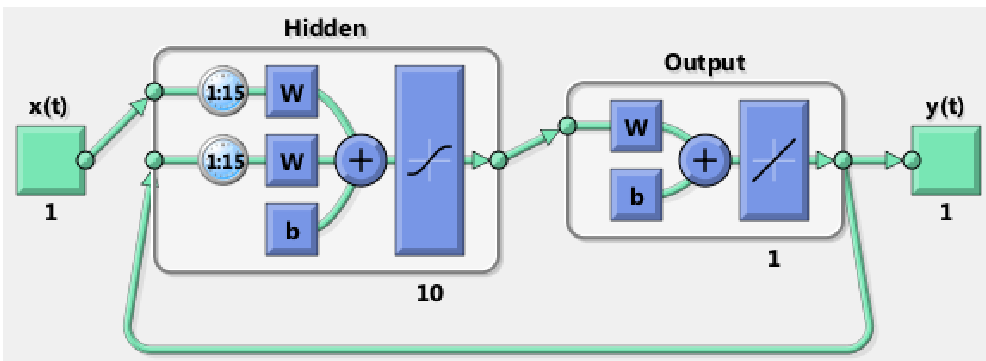

Figure 3-23: NARX Neural Network for Forecasting Downstream Boundary Conditions of the EPA-SWMM Model

Since neural network profitability is related to the form of the data set used during training and application phases, data processing functions exist in order to normalize and transform the input and output data, and thus increase the neural network efficiency. In the constructed NARX neural network, the default processing function “mapminmax” was used to rearrange its input and target values within the range of [-1 1]. This pre and post processing functions were necessary in the mentioned NARX neural network in order to avoid a high weighted input values for the hyperbolic tangent sigmoid transfer function in the neurons of the hidden layer, and thus avoid the saturation of these functions followed by slow gradients values and slow training process. The data used in the training process, was also divided into three different parts. The first one, provided by 65% of the data, was used as training data, where the result of the performance function was calculated through the comparison of the target and network output of this part. The second part, defined by

10% of the data set, was used as validation data, having the authority to stop the training process in order to protect the system from the over fitting behaviour. The final part, which is 25% of the measurements, was dedicated for testing the training process, and do not contribute in the training phase, neither in the results calculation nor in the stopping criteria.

The training process was applied on measured data of 10 different rainfall events, presented previously in Table 3-2, having different characteristics and measured water depth in the last modelled manhole. A minimal effect was considered for the boundary condition of the EPA-SWMM model during low rainfall events, where the highest water depth does not exceed 30 cm and could be modelled by a normal flow in the connecting conduit. Since the ANN performs better when it is designed to operate on a narrower range of values, the choice of the events was conducted based on the existence of a measured water depth in the outfall, exceeding a depth of 30 cm. Figure 3-24 shows the performance evaluation and changes through the epochs of the training phase. The regression results of the network output values and targets for the three parts of training process with an overall regression value are presented in Figure 3-25.

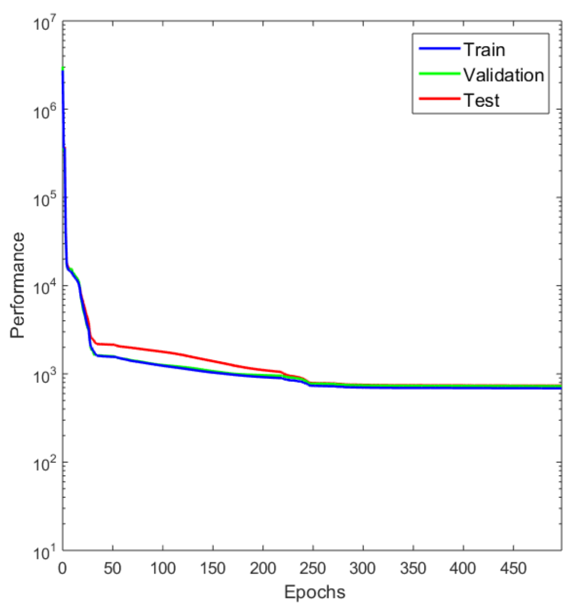

Figure 3-24: Performance Evaluation through the Training Process Epochs

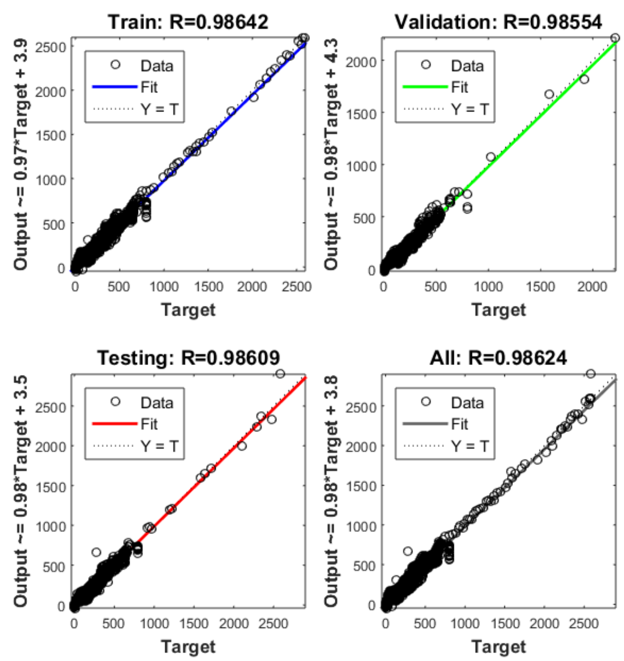

Figure 3-25: Regression Results of the Trained NARX Network

The performance plot, in Figure 3-24, presents the efficiency of the training process in reducing the MSE value form $3x10^6$ to 687 in 498 epochs. The efficiency of the network is presented in Figure 3-25, where a good regression value (R) is presented for all the parts of the training data set. An R value equivalent to 0.986 is presented for the training, validation and testing parts, indicating the potential of the constructed NARX neural network in forecasting the outfall water depth time series for the UDS, of Lille 1 University campus, subjected to an unmeasured rainfall event. The measurements of the severe storm event of 31 August 2015, inducing flooding in the studied sector, were very helpful in extending the NARX network capacity in forecasting the outfall water depth at high rainfall intensities where the UDS is surcharged, but it should be noted that measuring more similar severe events increase the efficiency and capacity of the system through the existence of more training values and data correlations.

3.8 Verification

In order to test and verify the calibrated model with the downstream boundary conditions forecast proposed in this work, we applied the described procedure on the rainfall events that occurred on the campus between 25 and 30 March 2016. Firstly, the rainfall intensities recorded during this period were introduced on the NARX neural network in order to forecast the outfall water depth. After comparing the NARX neural network results with the depth meter measurements, the forecasted depth was introduced, together with the measured rainfall intensities, as boundary conditions and input to the calibrated EPA-SWMM model, in order to simulate the UDS operation, and compare it to the measurements of the implemented sensors on the campus. Figure 3-26 presents a comparison between the depth meter measurements and the NARX neural network forecasted values for the verification period from 25 to 30 March 2016.

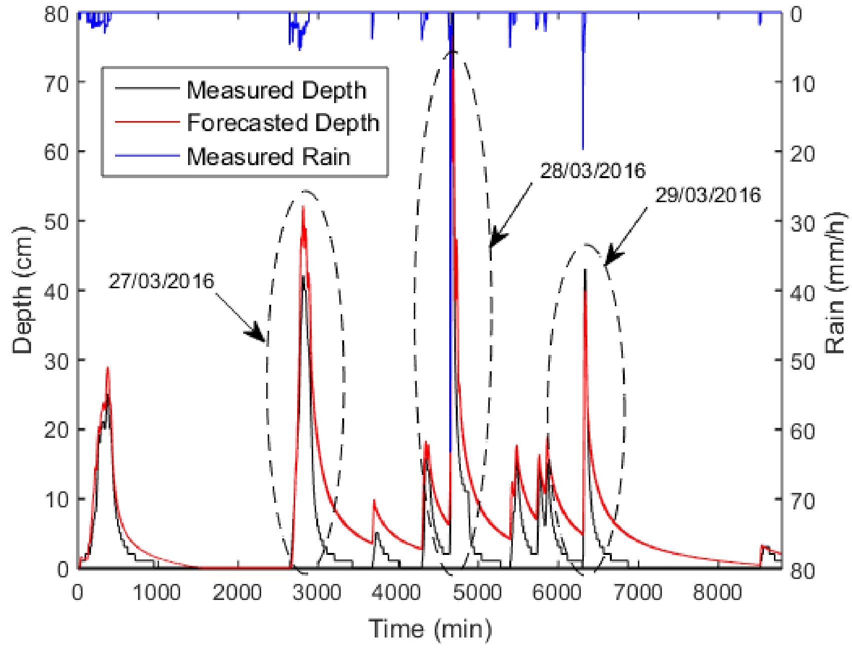

Figure 3-26: Comparison of Measured and Forecasted Outfall Water Depth for the Rainfall Events Occurring between 25 and 30 March 2016

A good correlation between measured and forecasted results, especially for the values exceeding 10 cm, highlight the efficiency of the NARX neural network in forecasting outfall water depth, even for a very long period of rainfall. Once the efficiency of the downstream boundary conditions forecast was evaluated and accepted, it remains to verify the hydrologic-hydraulic model capabilities to simulate the real operation of the existing UDS. Similarly to outfall water depth forecast, the modelling was done for the entire period between 25 and 30 March 2016. The results were compared through a visual inspection and Nash-Sutcliff coefficient calculation for the three highest events, presented in Figure 3-26 , and dated by 27, 28 and 29 March 2016.

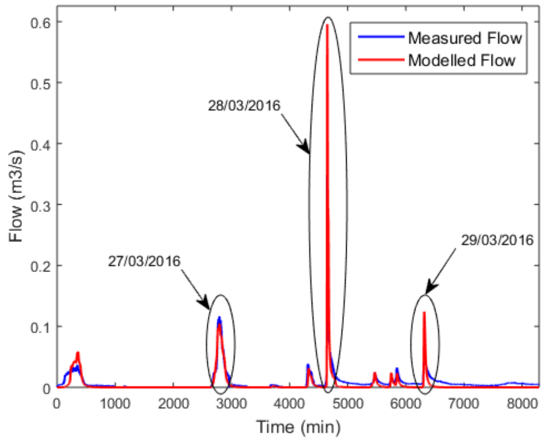

Figure 3-27: Measured and Modelled Flow Comparison (Rainfall Events 25-30/03/2016)

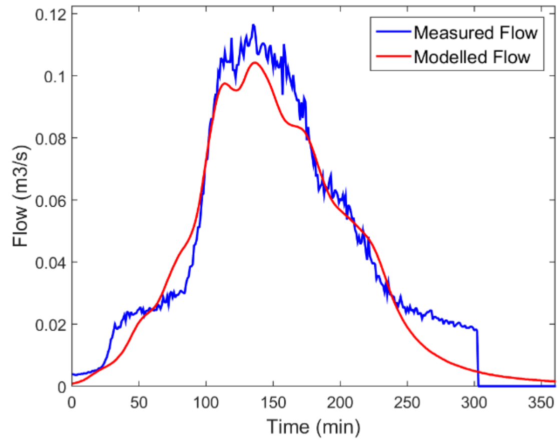

Figure 3-28: Measured and Modelled Flow Comparison for Rainfall Event 27/03/2016 (NSE=0.96)

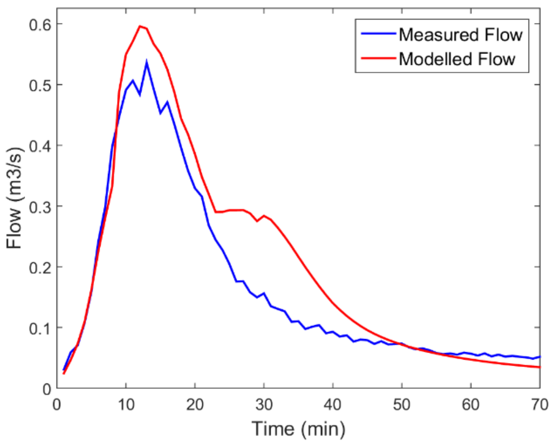

Figure 3-29: Measured and Modelled Flow Comparison for Rainfall Event 28/03/2016 (NSE=0.82)

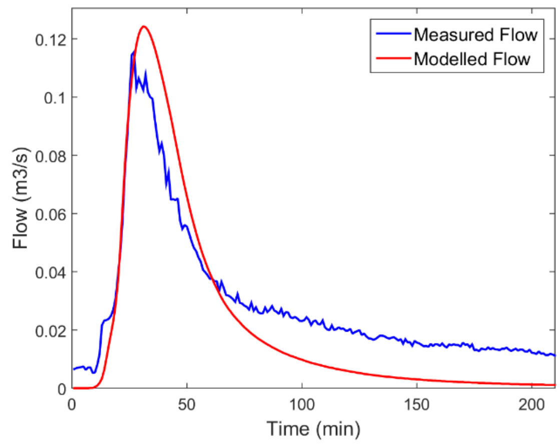

Figure 3-30: Measured and Modelled Flow Comparison for Rainfall Event 29/03/2016 (NSE=0.73)

Figure 3-27 to Figure 3-30, show the comparison between measured and modelled flow, presenting a good matching between the results, and thus affirming the efficiency of the methods described in this chapter. In addition, very good NSE coefficients, equivalent to 0.96, 0.82 and 0.73 were calculated for the 3 selected high rainfall events within this period.

3.9 Conclusion

The overstress of the existing UDS due to both aging and increasing urbanization requires the development of new management strategies of infrastructures, which could beneficiate from digital technology and numerical modelling. RTM is accomplished through sensors implementation in critical zones. Combining the sensors measurements to hydraulic-hydrologic model extends the monitoring system to cover the entire infrastructure operations. The hydrologic-hydraulic models represent complex phenomenon. They require the determination of multiple unmeasured and interconnected parameters. The manual calibration of these models constitutes a laborious task. This work aims at the development of an auto-calibrate method of the hydrologic-hydraulic models, through a hybrid optimization algorithm based on GA followed by a PS. This auto-calibration procedure is applied simultaneously on multiple rainfall events and based on measured and modelled values comparison from multiple elements of the UDS. It constitutes an effective method for modelling the real UDS response. The efficiency of this method was confirmed by through high Nash Sutcliffe Coefficients and good visual observations. Since modelling should not be limited to experienced events, extending the model ability to represent the UDS operation subjected to forecast or synthetic events is a target for this study. Weather inputs for the hydrologic-hydraulic model are forecasted or synthetic time series. Initial states necessary to start calculations are assumed for synthetic events, and actual sensors measurements for forecasted events. The downstream boundary conditions of the UDS, representing outfall water depth variations during the event period, are unknown values. In this context, the downstream boundary conditions forecast system, based on NARX model resolved by an artificial neural network, was developed in this chapter. The verification of the model on a long period of unseen rainfall events confirms the efficiency of the combination between the model calibration and downstream boundary conditions forecast. The efficiency of the proposed methods could be improved, through a wider calibration and training data, with extending the measurements database and duration. Sensors implementation should be conserved on studied sites, in order to measure initial states for model calculation, continuously verify and calibrate the constructed model, assess in dynamic management strategies based on real time measurements, and enlarge measurements data base for improving the two described methods in this chapter. In addition, temporal and seasonal variations of the hydrologic complex phenomenon parameters as well as, climate and surface impermeability changes, could be taken into account during the calibration processes.

3.10 References

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Chapter 4

Flooding Forecast System and Dynamic Management Strategy

4.1 Introduction

The disproportionate growth of the cities and the aging infrastructures are the main reasons behind overstressing Urban Drainage Systems (UDS). Cities expansion, not been accompanied by suitable drainage infrastructures upgrades, results in generating frequent floods events, environment degradation and less of groundwater recharge (Konrad & Booth 2002; Wang *et al.* 2003; Brandes *et al.* 2005). In the literature, runoff increases due to urbanization process, were noticed in various parts of the world (Bhaduri *et al.* 2000; Kim *et al.* 2002; Konrad 2003; Tang *et al.* 2005; Zhou *et al.* 2013). The demographic boom effect on UDS is mainly notable for small and moderate storm events, since large storms could balance the differences between pervious and impervious characteristics. Additionally, climate changes affecting rainfall amounts and patterns, and consequently runoff volumes (Ponce *et al.* 1997; May 2008), have induced a considerable impacts, leading to insufficient capabilities in the UDS of the cities (Berggren *et al.* 2012). Therefore, flood risks, resulting in serious economic consequences and casualties, had become a significant challenge for the cities and a major interest for researchers and practitioners.

Floods frequently occurring and difficult to be predicted, results in significant damages and loss of lives (Kenyon *et al.* 2008). Since floods are responsible of 40% of economic losses caused by all kinds of natural disasters (Feng & Lu 2010), flooding damage limitations is considered a major issue in many cities. Based on International Disaster Database, the number of flooding occurrences has more than doubled since 2000, to affect in 2010 more than 100 million people and generate around USD 40 billion of losses to societies worldwide (De Albornoz Portes & Valle 2014). Flooding in Europe, is as well a serious concern, presented by 11 flooding episodes each year, accounting for 26% of all natural disasters and generating 150 deaths and more than 400000 influenced persons (De Albornoz Portes & Valle 2014).

Having considerable social, economic and environmental impacts, an effective UDS capable to limit flooding and pollution is a must (Hammond *et al.* 2013). UDS responsible basically for flood protection (Ashley & Hopkinson 2002; Ellis *et al.* 2004; DeSilva *et al.* 2011), should be strengthen to optimally operate under climate conditions and volume loadings, bigger than what they were designed to support (Solomon *et al.* 2007; Milly *et al.* 2008; Karl *et al.* 2009). Three main alternatives exist in order to strengthen the UDS. The first evident solution is conducted by enlarging the existing UDS. Generally, this solution is not feasible due to its high relative cost and implementation time (García *et al.* 2014). The second solution seeks to mimic natural hydrologic cycle through the implementation of alternative techniques, known also as low impact development and presented in chapter 1 of this thesis. These techniques encourage the retention, infiltration, evaporation and recycle at source of the stormwater volume. The last solution consists of optimally operate the existing networks and structures, through an efficient Real Time Monitoring (RTM) and Control (RTC) systems, requiring none or minimal extensions. Dynamically control the UDS, is continuously operating actuators, based on real time measurements analysis and modelled results, in order to optimally benefit the system components (Schütze *et al.* 2003).

4.2 Real Time Control

RTC was found more appropriate than off-line control, for managing UDS, due to the dynamic and stochastic nature of these utilities and their loadings (Jacobson 2011). Analysing and managing UDS is a challenging task, due to their sizes, operations dynamicity and complexity, delays and disturbances (Ocampo-Martinez 2010). Therefore, the first step in mitigating flooding impacts consists in understanding the actual system operation during the flooding events. Afterwards, the second step consists in finding the convenient actions, which should be taken by active elements, in response to current states and future conditions. Description of some strategies for controlling active elements could be found in the literature (Villeneuve *et al.* 2000). Even though, multiple studies represent RTC as a cost effective solution for improving system operations and performances (Schütze *et al.* 2003; Jamieson *et al.* 2007; Beeneken *et al.* 2013), implementation of such system may be quite expensive in some cases. This is why a benefit and robustness evaluation should precede any RTC implementation.

Multiple classifications of RTC exist and depend on the UDS management complexity and objectives. RTC is classified into two major types. The first type is heuristic algorithm, purely based on experience without modelled results evaluation. The second type is optimization-based algorithm, which aims to optimize certain criteria based on RTM measurements and modelling results. Rule based control and fuzzy logic control are two examples of heuristic algorithms, while optimization-based algorithms could be one of the following examples: linear quadratic regulator, evolutionary strategies, model predictive control or population dynamics-based control. Control rules could be local to each actuator, related to measurements in the sensor location, as it could be global and centralized in a control station. A global management strategy is more likely to operate the infrastructure optimally and benefits the maximum of measurements taken from the system (Cembrano *et al.* 2004). In addition, reactive and predictive RTC systems exist to differentiate between management based on actual values, and those who try to adjust system operation depending on future conditions and forecasts. RTC could be implemented aiming one single objective, as reducing flooding volumes, or multi-objectives, as reducing flooding volumes, operational costs and sewer overflows etc. Multi-objectives functions are normally evaluated through weighted sum of several single-objective cost functions or a Pareto optima solution. An extensive review on simulation models and RTC of UDS, presenting in details all the characteristics and types mentioned above, could be found in (García *et al.* 2015).

Before any implementation, evaluating the actual state of the UDS and the efficiency of a management strategy should be accomplished on a wide range of climate conditions. Multiple scenarios analysis conducted on computer simulation models, were considered as a useful technique for this purpose (Carter *et al.* 2007). In addition of evaluating the flood protection level, modelling software assists in identifying critical zones and elements prone to be surcharged and flooded during sever storm events (Bennis *et al.* 2003; Jin & Mukherjee 2010). The EPA-SWMM model was developed and calibrated, in chapter 3, for these purposes.

Depending on how many details they offer, UDS simulation software are characterized and divided into two main categories. Simulation-oriented models are used for understanding, designing and evaluating the systems operations, and thus they should be able to represent UDS responses with sufficient details. Calculation engines of these models are based on resolving the full or simplified One-Dimensional Saint-Venant Equation (1-D SVE) as a dynamic wave, diffusive wave or kinematic wave. On the other hand, optimally operate a network through a model-base control procedure requires an evaluation of a large number of control actions and combinations within a short period. Hence, computation time in these applications is a critical factor to be considered. Therefore, control-oriented models exist, offering the possibility to model a network response within a very short relative time, based on hydrologic-hydraulic phenomenon simplifications.

Examples of the control-oriented models are: Linearization-based models, Data driven models and Conceptual Models (Muskingum model, Nash Model, Virtual tanks model etc.).

The purpose of this chapter is to propose, test and analyse a RTC system. The proposed RTC aims to predict flooding occurrences and dynamically manage the UDS operations. It is composed firstly of an alarm system, capable to forecast flooding occurrences in critical areas based on two hours ahead weather forecast. Secondly, an optimization algorithm starts to evaluate the Valve State Schedule (VSS) options for the valve of the retention tank, and through a population orientation procedure returns the best suitable solution. For this purpose, genetic algorithm and a modified artificial bee colony algorithm were both tested and evaluated based on their performances and required computation times. Finally, a qualitative management strategy aiming to recharge groundwater in addition to support the UDS in limiting flooding damages and occurrences was proposed and tested. The efficiency of the RTC system was tested on a sector of the stromwater network of Lille 1 University Campus, equipped with different types of sensors as presented in previous chapters.

4.3 Analysis of the Actual Urban Drainage System Operation

In this chapter the analysis of the system operation, Flooding Forecast System (FFS) and the dynamic management strategies will be based and evaluated on the EPA-SWMM modelled results. The working procedure for evaluating the UDS operations, presented in this section will be as follow. First the operation of the UDS, subjected to the severe storm event occurring on 31 August 2015 will be analysed. In addition, due to the stochastic nature of storm events, interpreted by spatial and temporal variability of rainfall intensities, the operation of the UDS will also be studied, while it is subjected to the synthetic events of 1, 2 and 5 Year Return Period (YRP). Finally, critical zones and manholes, where water depth should be monitored and predicted, will be localized based on the hydraulic model results.

4.3.1 Modelling Results on Storm Event of 31 August 2015

Due to RTM and modelling capabilities, the system operation, subjected to the severe storm event of 31 August 2015, was monitored and analysed at a small time step (1 minute). Weather station measurements and outfall water depth variations were both introduced to the model in order to start calculations. Due to modelled results, it was found that at time 14:09, floods start to appear. Figure 4-1 presents the system operation at the beginning of the flooding appearances. The analysis is based on two profile plots, the first represent the retention tank filling ratio at the moment of flooding appearance, while the second profile shows the major flooding zones presented on the campus, in order to understand their origins.

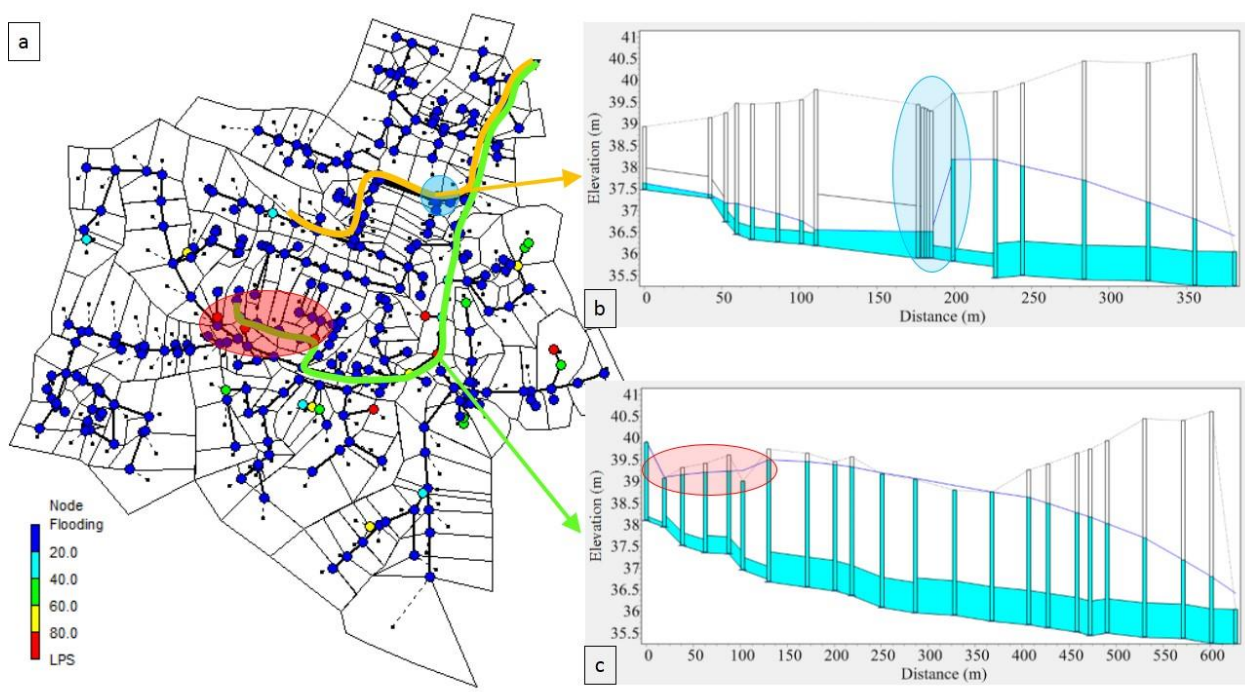

Figure 4-1: Model Results for the Storm Event of 31 August 2015 - 14:09 (a-Plan View Showing the Flooding Areas b-Profile Plot through the Retention Tank c-Profile Plot through the Flooding Areas)

The hydrologic-hydraulic model indicates the location of flooding areas at different locations of the system, especially in the neighbourhood area of Lille Engineering Central School. In this area, flooding appearances were mentioned historically, as described in chapter 2. During this event, a flooding depth around 40 to 50 cm was observed, as shown in Figure 4-2. Plotting two profiles through these locations, presented in the previous figure, helps us in analysing their origins. Profile (c), indicates the appearance of floods in the topographical lower areas, due to the surcharge of the entire principal collector and the backwater effect. Profile (b), indicates that the filling ratio of the retention tank, is less than 50%, and thus a representative volume of the retention tank was not been effectively used at the moment of flooding appearances. The non-efficient use of the retention tank capacity is due to its isolation from the downstream part of the system by the static implemented check valve, which was installed in order to allocate the storage capacity to the runoff generated from the upstream area of the tank.

Figure 4-2: Flooding near Lille Engineering Central School

On the other hand, after the end of this event, further observations were made, showing the tank fully surcharged, while the principal collector has the capacity to evacuate the stored water at a higher speed then the regulated flow (10 l/s). Figure 4-3 presents the system operation at 15:11, indicating the inefficiency of the emptying process due to the static regulator flow. The effects of the storm event of 31 August 2015 could be worst, causing large damages for the University campus, underground laboratories and even car drivers and passengers, if this event has been longer or was followed by another severe storm event. The static flow regulator was installed in order to protect the downstream parts of the UDS, from being surcharged during tank emptying process combined to surface runoff evacuation. Model results highlight the benefits of a dynamic management strategy, which is able to control the equipment of the system and manage their status schedule. The static equipment was installed in the system for an objective, which is not always helping the actual situation and operation of the network. Model results indicate a total flooding volume and duration, under the actual static operation of the existing equipment, equivalent to 869 m^3 (40.3h), distributed on all flooded manholes.

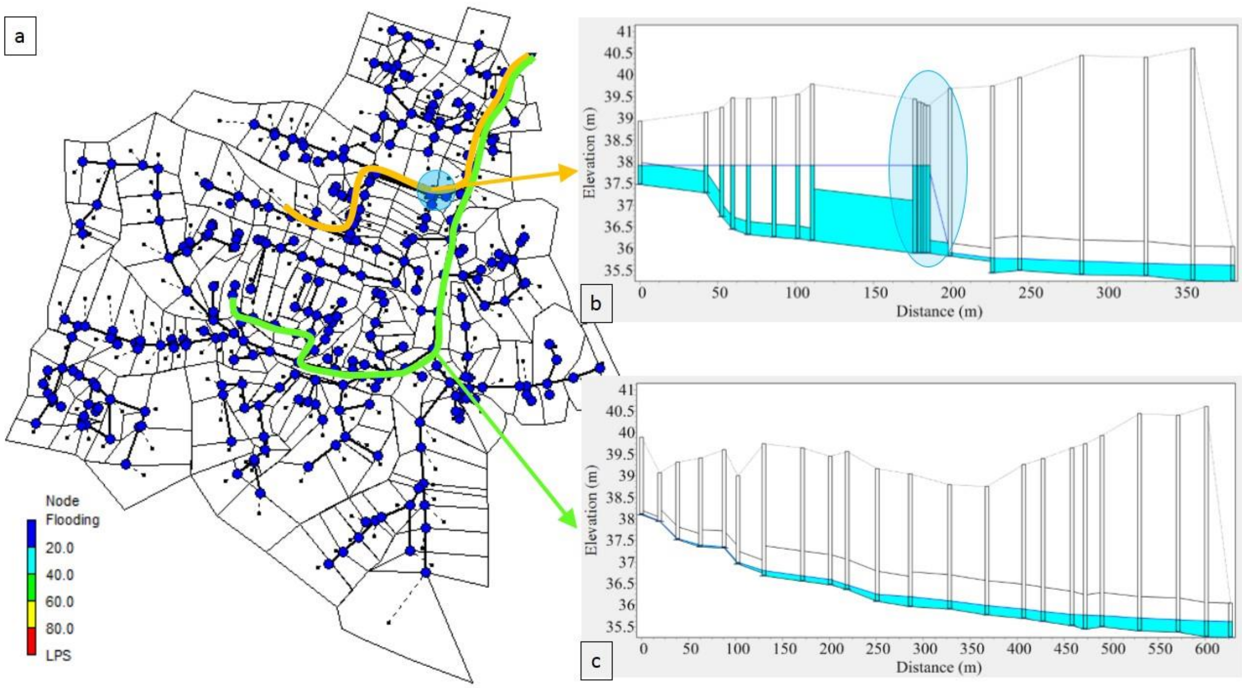

Figure 4-3: Model Results for the Storm Event of 31 August 2015 - 15:11 (a-Plan View of the System b-Profile Plot through the Retention Tank c-Profile Plot through the Principal Collector)

4.3.2 UDS Operation Subjected to Synthetic Storm Events

Due to the stochastic nature of storm events, and since UDS operations are complex nonlinear response to the temporal variability of rainfall intensities, the system operation was also studied under synthetic events. Different methods for constructing synthetic storm events exist in the literature. Among these methods, the Constant Intensity, mostly used for system design under peak flow calculation, the Chicago Type (Keifer & Chu 1957), based on reproducing the hyetograph directly from IDF curves, and the Double Triangular Type (Desbordes 1974), consisting of a relative short period of intense rain situated inside a rain sequence of few hours, are the most used in France. In this study, the Double Triangular synthetic rainfall event, providing a good representation of the actual structure of storm events (Hémain 1986), will be used for the analysis of the UDS.

4.3.2.1 Construction of the Synthetic Storm Events

The determination of the parameters (Duration and Rainfall depth) of the Desbordes hyetograph will be based on the watershed characteristics and the Montana coefficients, found for the region concerned. Since this work is conducted on a small watershed, the total duration of the synthetic event was chosen to be 2 hours including at its middle 15 minutes of severe rainfall intensities. The rainfall depths occurring during the synthetic events were calculated through the Montana equation, presented in Equation 4-1. Montana coefficients found for the North region of France and for a return period of 1, 2, 5 and 10 years, are presented in Table 4-1.

$$h(t,F) = a(F)\,.\;t^{(1-b(F))}$$ *Equation 4-1*

With *h(t, F)*: maximal rainfall depth *(mm)* for a duration of *t (min)* and a return period of *F*. *a(F)* and *b(F)* are the Montana coefficients.

Table 4-1: Montana Coefficient for Region 1 in France

Return Period	**a**	**b**
1 Year	3.1	0.64
2 Years	3.7	0.62
5 Years	5.0	0.61
10 Years	5.9	0.59

Once the Montana Coefficients and the rainfall duration are fixed, the hyetographs for the synthetic storm events for 1, 2 and 5 YRP were constructed and presented in Figure 4-4 to Figure 4-6. Characteristics of these storm events are presented in Table 4-2 to Table 4-4.

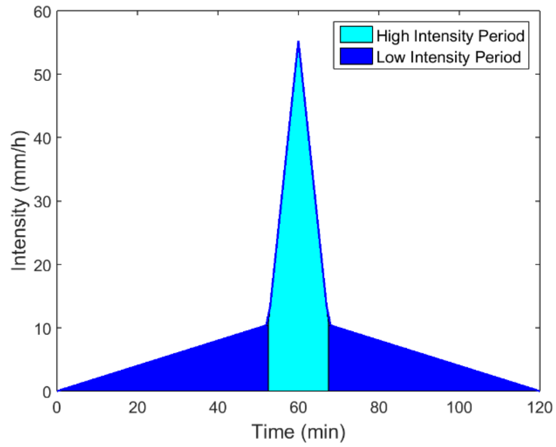

Figure 4-4: Synthetic Strom Event of 1 Year Return Period

Table 4-2: Synthetic Storm Event Characteristics

Return Period	1 Year
Total Storm Duration	2 Hours
High Intensity Duration	15 Minutes
Total Rainfall Depth	17.37 mm
High Intensity Period Rainfall Depth	8.22 mm
Maximum Rainfall Intensity	55.28 mm/h

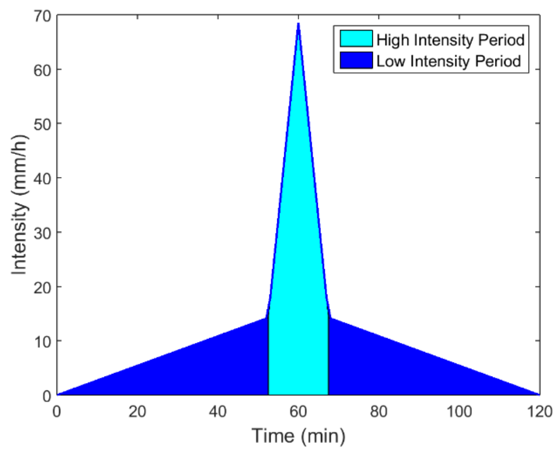

Figure 4-5: Synthetic Strom Event of 2 Year Return Period

Table 4-3: Synthetic Storm Event Characteristics

Return Period	2 Years
Total Storm Duration	2 Hours
High Intensity Duration	15 Minutes
Total Rainfall Depth	22.82 mm
High Intensity Period Rainfall Depth	10.35 mm
Maximum Rainfall Intensity	68.6 mm/h

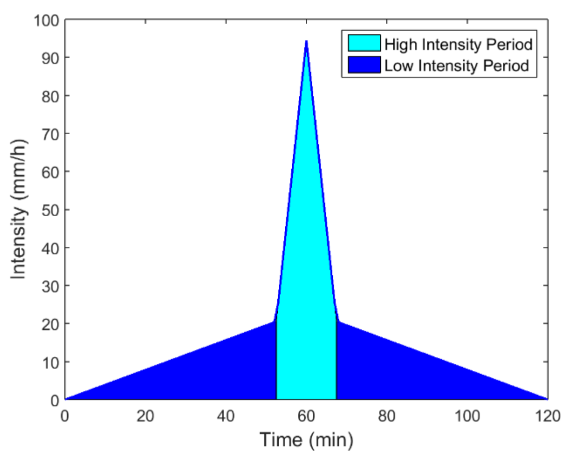

Figure 4-6: Synthetic Strom Event of 5 Year Return Period

Table 4-4: Synthetic Storm Event Characteristics

Return Period	5 Years
Total Storm Duration	2 Hours
High Intensity Duration	15 Minutes
Total Rainfall Depth	32.35 mm
High Intensity Period Rainfall Depth	14.38 mm
Maximum Rainfall Intensity	94.5 mm/h

It remains before starting the calculations of the EPA-SWMM model, to define the variations of the outfall water depth during the unmeasured synthetic storm events. Therefore, the constructed synthetic events were introduced on the NARX neural network, developed and presented in Chapter 3, in order to calculate the downstream boundary conditions, required to perform the simulations. Figure 4-7 to Figure 4-9 present the 3 synthetic rainfall events and their calculated outfall water depth variations.

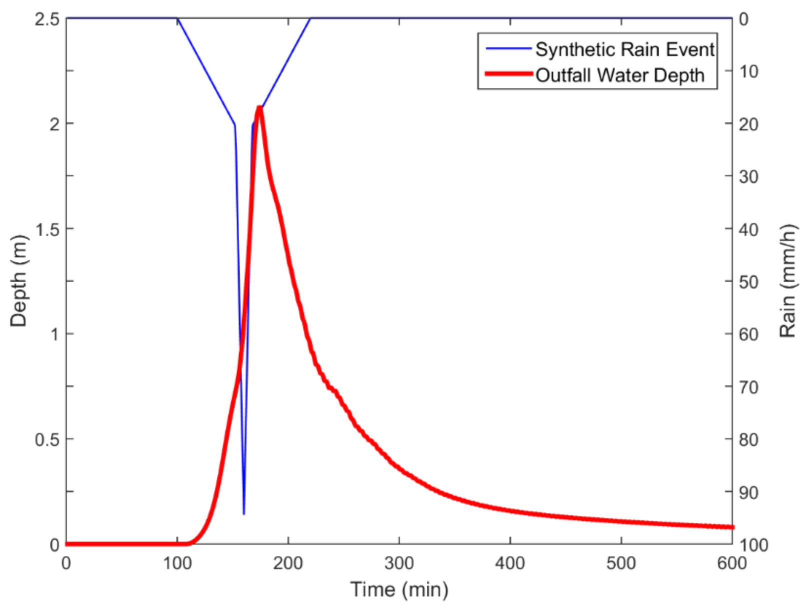

Figure 4-7: Outfall Water Depth for the Event of 5 Year Return Period, Calculated by NARX Neural Network

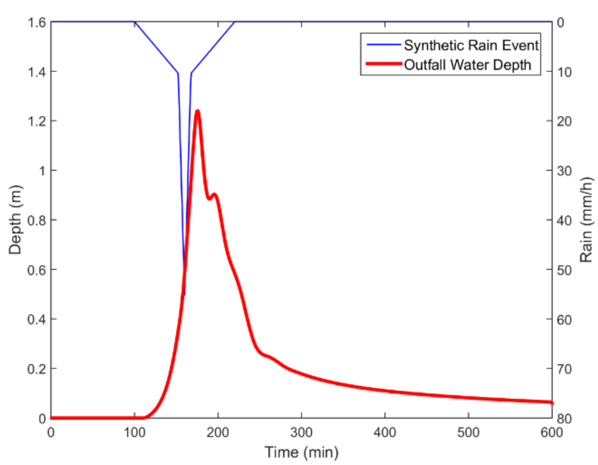

Figure 4-8: Outfall Water Depth for the Event of 1 Year Return Period

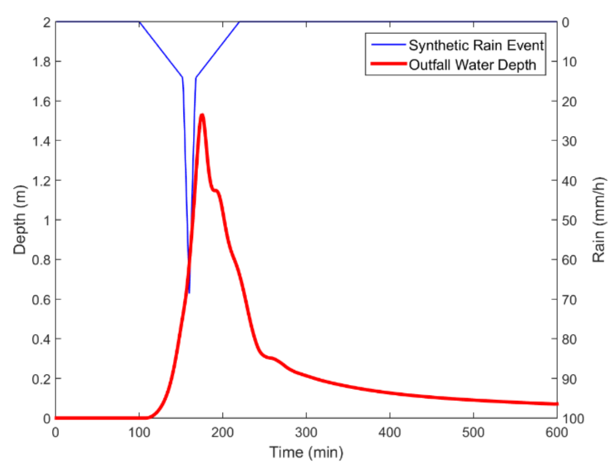

Figure 4-9: Outfall Water Depth for the Event of 2 Year Return Period

In order to study the system operation subjected to the synthetic storm events, the rainfall intensities were introduced as input to the simulation model, while the outfall water depth variation was considered as downstream boundary condition, introduced as a time series for the outfall water depth. The results found for the model subjected to 5 YRP, shows flooding appearances in different parts of the system. Minor floods were reported for the 2 YRP synthetic rain, while the 1 YRP event just surcharges the system. In the following paragraph, just the model results of the network subjected to the 5 YRP will be presented, while later in this chapter, all the three synthetic storm events will participate in verifying the constructed FFS.

4.3.2.2 UDS Modelled Results for the Storm Event of 5 Year Return Period

Modelled results on measured rainfall events had shown that evaporation, which was calculated based on minimum and maximum daily temperatures, mostly affect long rainfall events, where successive low intensity rainfall periods exist. This was explained by the main potential of evaporating water stored in the depression storages, during the dry hours separating successive low intensities rainfall events. Therefore, aiming to understand the system operation under the synthetic events, characterized by short periods and high rainfall intensities, the evaporation was considered not influential and will not be introduced in these calculations. After the calculations were completed, it was found that the 5 YRP storm event, characterized by 32.35 mm of rainfall depth, generates 25.84 mm of surface runoff, while 5.85 and 0.66 mm were respectively lost by infiltration and captured by the depression storages.

Analysing the obtained results, as done for the event of 31 August 2015, similar findings were noticed. Floods started to appear 1 hour 3 minutes after the storm had begun, which means 3 minutes after the peak rainfall intensity, in different parts of the UDS. Figure 4-10 presents the system operation by showing the flooding zones and the two profiles passing by the retention tank and the major flooding areas. These results affirm the inefficiency of the check valve placed downstream the retention tank, preventing the use of the remaining storage capacity. More than half of the total tank volume is unused, while floods are spread in several locations of the network.

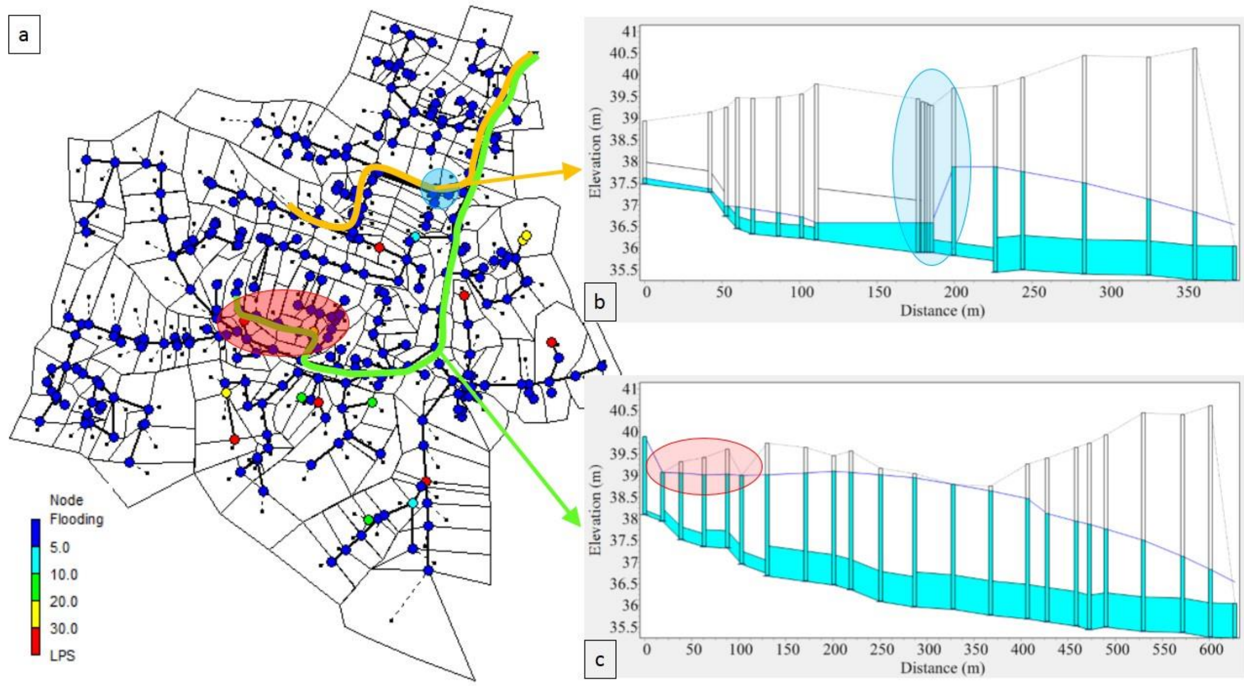

Figure 4-10: Model Results for the 5 Year Return Period Synthetic Storm Event – 1:03 (a-Plan View of the System b-Profile Plot through the Retention Tank c-Profile Plot through the Principal Collector)

During the synthetic rainfall event of 5 YRP, the observations made at the end of the storm were more critical and harmful than those found during the analysis of the 31 August 2015 event. This synthetic event generates 25.84 mm of surface runoff, exceeding the 17.51 mm generated during the event of 31 August 2015, by an amount of 8.33 mm. This excess was capable to overload the retention basin and to induce floods in the upstream area of the tank. Figure 4-11 presents the system operation state 2 hours after floods first appearance, which means 1 hour 3 minutes after the storm had finished.

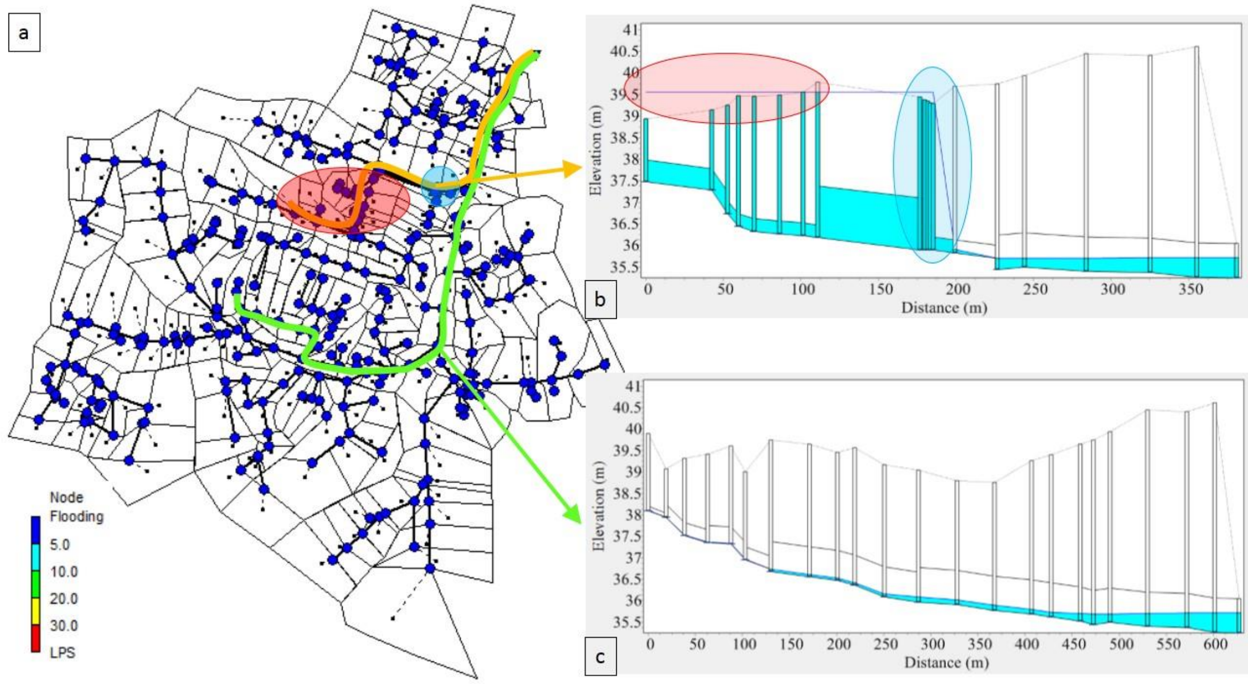

Figure 4-11: Model Results for the 5 Year Return Period Synthetic Storm Event – 3:03 (a-Plan View of the System b-Profile Plot through the Retention Tank c-Profile Plot through the Principal Collector)

Flooding in the upstream area of the retention tank lasts for about 6 hours. This long period was explained by the static flow regulator, which prevents an outflow that exceeds 10 l/s from the retention tank, without assessing the gravity of the situation. It should be noted that in this study no surface flow routing had been assumed or applied between the different manholes locations. Infiltration and evaporation were also excluded from the calculation and had not been considered for the ponded water. Modelling results indicate a total flooding volume and duration equivalent to 1013 m^3 (180.7h) distributed on all flooded manholes.

4.4 Localization of the Critical Zones

The localization of the critical manholes, in need for monitoring and forecasting their water depth variation, was accomplished through the evaluation of multiple criteria. Modelled results indicate that the entire floods are located in the lowest topographical areas, and are generated due to a backflow coming from the main system, when the network is surcharged. Hence, the critical manholes were chosen to be on the main collector, where branches of the lowest topographical areas are connected. This choice was made in order to reduce the number of critical manholes, by monitoring the water depth in the main manhole of the branch instead of monitoring it in each flooded manhole. In addition, monitoring the principal manhole water depth helps in avoiding an additional complexity for the FFS, to be constructed in the following paragraphs, expressed by backflow, generating sudden water depth variation after a certain level. It was also decided to not forecast water depth in two close manholes, since water depth takes a long distance to vary significantly. Therefore, it was decided that a minimal distance of 120 m including at least 3 principal manholes, should separate any two chosen critical manholes. This criterion should depend on the site characteristics and surface. It was defined relatively small in this case, due to the small size of the studied UDS. Finally, the number of critical manholes was defined to be 5, and located according to the aforementioned criteria, to their geographical location near sensitive areas (University buildings, metro station, student residence, roads), and to the total flooded volume induced from the connected braches to these structures. Some flooded manholes were ignored due to their relative small water volume flooding out, or to their locations in green spaces not threatening citizens or university buildings. Figure 4-12 presents the locations of the critical manholes.

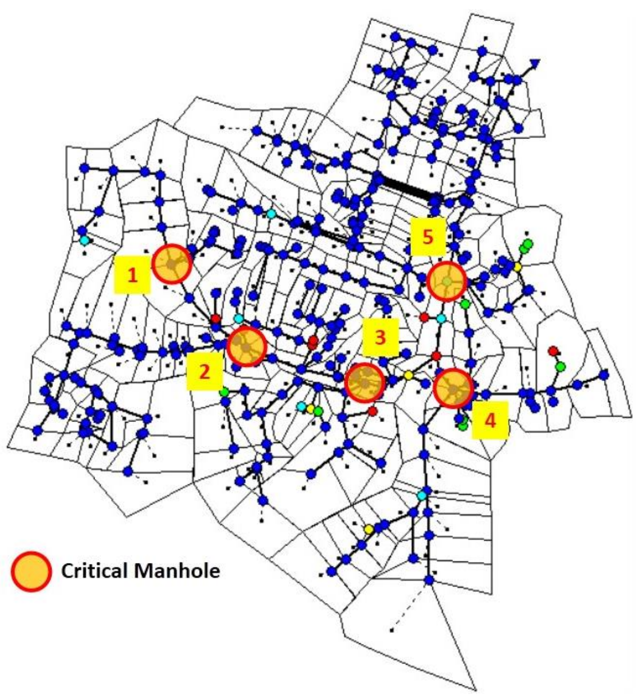

Figure 4-12: Locations of the Critical Manholes

The water depth in the critical manholes will be predicted through a FFS based on a NARX neural network, and a radar weather forecast system offering rainfall intensities for duration of 2 hours ahead. The characteristics, training and applications of the proposed FFS will be detailed and presented in the next paragraphs.

4.5 Flooding Forecast System

Offering sufficient lead-time to system operators and managers in order to take preventive measures and apply an optimal management strategy, a FFS is considered as an essential tool in mitigating flooding impacts. The complexity of UDS operations, together with temporal and spatial loading variability, make the construction of FFS a very demanding task, taking into consideration the time delays, constraints and nonlinearities. Traditionally, flooding forecasts are based on historical data and mathematical models or graphs dealing with pattern recognition (Rajendra Acharya *et al.* 2003). Recently, black box models, trained on historical data and combined to rainfall radar forecast, allows the prediction of urban flooding occurrences (Duncan *et al.* 2013). Applied largely for rivers analysis and protection, FFS shows a good efficiency and practicality (Elsafi 2014; Perera & Lahat 2015; Amarnath *et al.* 2016; Artinyan *et al.* 2016), while for urban drainage networks, such systems were limitedly developed and evaluated (Yen-Ming *et al.* 2010). The proposed FFS in this work will be based on forecasting the water depth at the already mentioned 5 critical manholes. Once the weather forecast detects the presence of rainfall events in the two hours period ahead, the FFS evaluates the water depth at the 5 critical manholes. If a forecasted water depth in any critical manhole exceeds a defined threshold, the FFS alerts the managers for a possible inundation. Responding to the alert, infrastructure managers evaluate the severity of the situation on the complete hydrologic-hydraulic EPA-SWMM model, localize areas likely to be inundated, take appropriate actions and precautions and launch the dynamic management strategy calculation, described later in this chapter. Actions and precautions could be as follows: informing specialist operators, warning underground basements inhabitants, changing road signs for car drivers, etc.

4.5.1 NARX Neural Network for Flooding Forecast System

Due to the efficiency of NARX neural network in forecasting outfall water depth variations, presented in Chapter 3, the same network and procedure was used for forecasting flooding events in this chapter. The difference in the network architecture was limited to the number of the output layer nodes. Since the new NARX neural network is designed to calculate water depth at 5 manholes simultaneously, 5 nodes in the output layer are needed, as shown in Figure 4-13. The FFS was trained on the same 10 storm events used for training the outfall water depth forecasting system, developed in chapter 3. Measured intensities and modelled water depth variations in the 5 critical manholes, were introduced as input and target values respectively, for the NARX neural network training process. The validation of the constructed system was evaluated through a comparison between the EPA-SWMM modelled results and NARX forecasted results, for the UDS operation subjected to synthetic rainfall events with 1, 2 and 5 YRP. The results of this comparison are presented in the next section. 2 and 5 YRP storm events were used to affirm the system capability in forecasting flooding events, while 1 YRP storm event was necessary for testing the system robustness in not generating erroneous alarms.

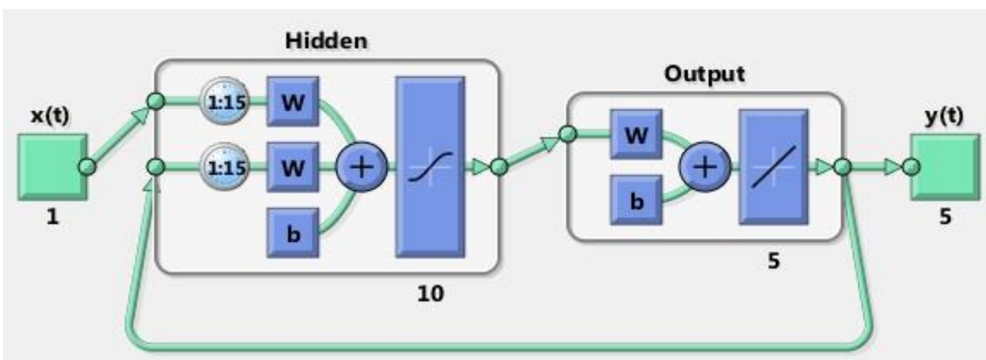

Figure 4-13: NARX Neural Network for Forecasting Flooding Events

The NARX neural network shows very good correlation and efficiency on the training data set, which was divided into training (70%), validation (15%) and testing (15%) sub-divisions. Figure 4-14 presents the performance of the NARX neural network train, while Figure 4-15 shows the regression results of the different sub-divisions after the training was completed.

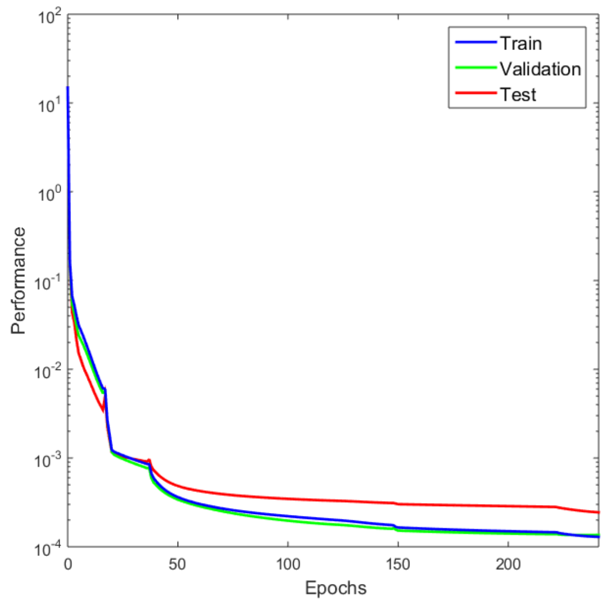

Figure 4-14: Performance Evaluation through the Training Process Epochs

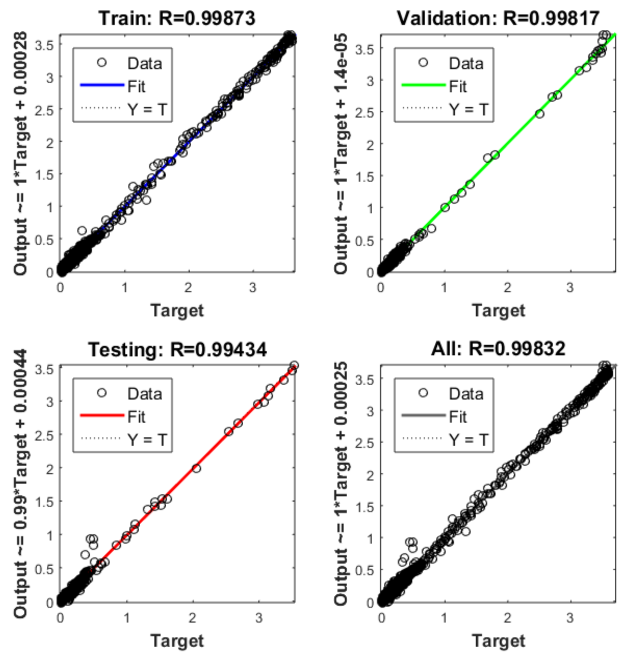

Figure 4-15: Regression Results of the Trained NARX Neural Network

The training process was able to reduce the MSE value from 14 to 1.3 x10^{-4} in 235 epochs. The efficiency of the trained network was evaluated, and very good regression values (R) were found. An R equal to 0.999 is presented for the training data set sub-division, while R-values equivalent to 0.998 and 0.994 were found for the validation and testing parts respectively. These results highlight the efficiency of the constructed Neural Network during the training process and in forecasting the water depth in the 5 critical manholes during the 10 measured rainfall events. The FFS was evaluated on the synthetic rainfall events of 1, 2 and 5 YRP. The rainfall intensities distributions and downstream boundary conditions of these synthetic events were calculated and presented earlier in this chapter (Section 4.3.2.1).

4.5.2 Verification of the NARX Neural Network as Flooding Forecast System

The synthetic rainfall events intensities and the downstream boundary conditions were both introduced on the calibrated EPA-SWMM hydrologic-hydraulic model, in order to run the calculations and obtain the water depth variations in the 5 critical manholes. On the other hand, the rainfall intensities of these 3 synthetic events were introduced to the flooding forecast NARX neural network, in order to compare the modelled to the forecasted results. Comparisons were made through visual inspections and calculated NSE coefficients. NSE coefficients for the water depth variation in the 5 critical manholes, during the 3 synthetic events, are presented in Table 4-5. In addition, due to the importance of simulating the peak water depth, which will be responsible for launching the flooding alarm, Table 4-6 presents the modelled over the forecasted peak value for the 5 critical manholes during the 3 synthetic events.

Table 4-5: Nash Sutcliffe Efficiency for the 5 Critical Manholes

Return Period	Manhole 1	Manhole 2	Manhole 3	Manhole 4	Manhole 5
One Year	0.39	0.86	0.95	0.82	0.94
Two Years	0.87	0.90	0.85	0.85	0.82
Five Years	0.93	0.95	0.95	0.92	0.89

Table 4-6: Modelled over Forecasted Peaks for the 5 Critical Manholes

Return Period	Manhole 1	Manhole 2	Manhole 3	Manhole 4	Manhole 5
One Year	0.52	0.78	1.22	1.49	1.00
Two Years	1.11	1.25	1.30	1.31	0.93
Five Years	0.97	0.96	0.95	0.91	0.87

Calculated NSE coefficients are relatively high values, affirming the capacity of the NARX neural network in representing the water depth variation during a rainfall event, especially for the intensive storms, as presented for the synthetic event of 5 YRP. Similarly, modelled over forecasted peaks ratio can be considered as a very good indicator of the FFS efficiency in alerting the UDS managers for dangerous events. After validating statistically the FFS, it remains to examine visually its operation. Defining the water level limit, where the floods began to appear in the adjacent areas of the critical manholes, was based on the results of the synthetic event of 2 YRP. During this event, water level in the flooding areas reach the limit of the total depth of the manholes, with some minor flooding, not exceeding a 1 cm depth. By inspecting the water depth in the critical manholes during this event, it was found that a water level limit equivalent to 1.3 meter is efficient in detecting flooding occurrences in the neighbourhood areas of the critical manholes. Figure 4-16 to Figure 4-30 present the modelled and forecasted water depth variations, during the 3 synthetic events, and compare them to the water depth threshold of 1.3 m.

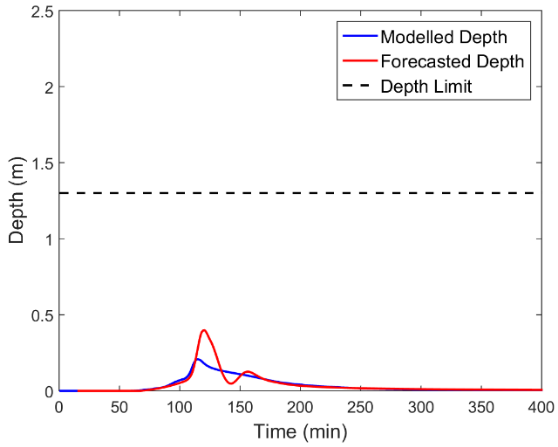

Figure 4-16: Modelled and Forecasted Water Depth at Critical Manhole 1 – 1 YRP Event

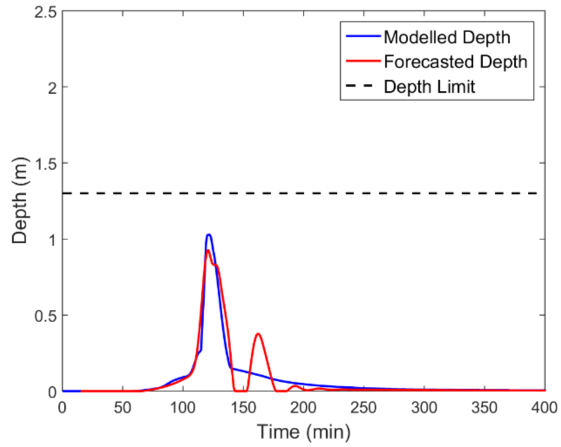

Figure 4-17: Modelled and Forecasted Water Depth at Critical Manhole 1 – 2 YRP Event

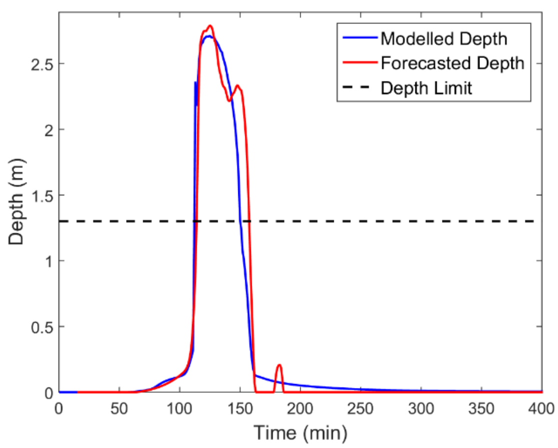

Figure 4-18: Modelled and Forecasted Water Depth at Critical Manhole 1 – 5 YRP Event

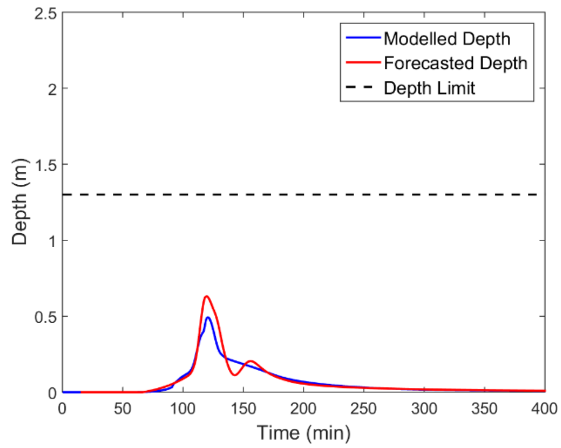

Figure 4-19: Modelled and Forecasted Water Depth at Critical Manhole 2 – 1 YRP Event

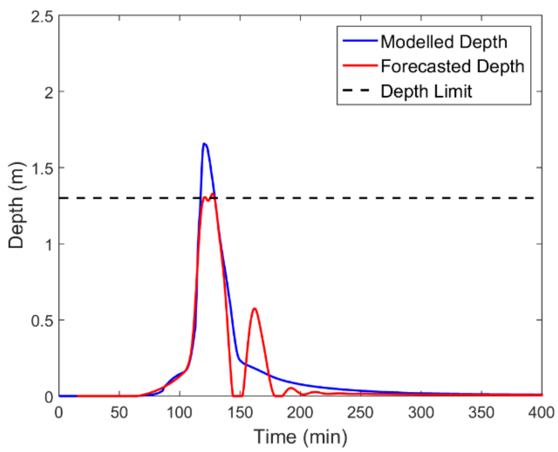

Figure 4-20: Modelled and Forecasted Water Depth at Critical Manhole 2 – 2 YRP Event

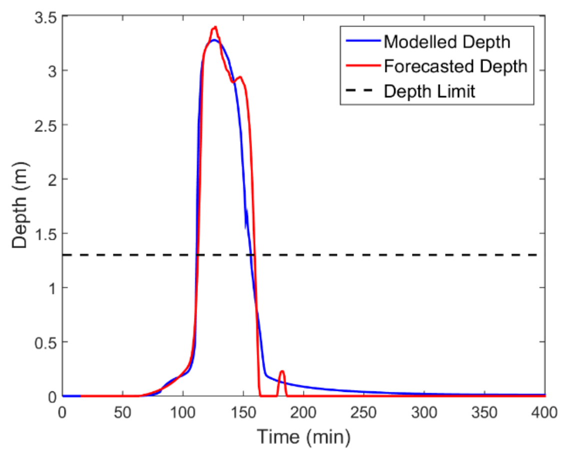

Figure 4-21: Modelled and Forecasted Water Depth at Critical Manhole 2 – 5 YRP Event

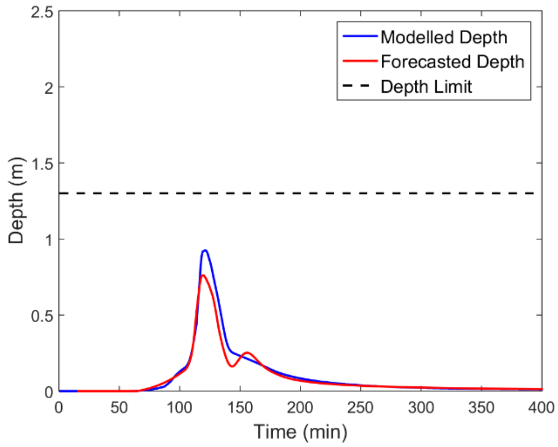

Figure 4-22: Modelled and Forecasted Water Depth at Critical Manhole 3 – 1 YRP Event

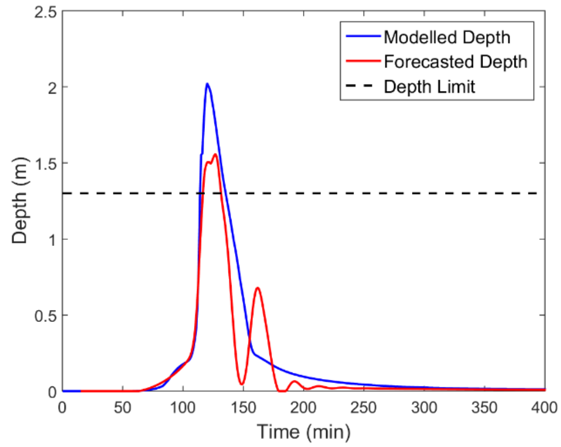

Figure 4-23: Modelled and Forecasted Water Depth at Critical Manhole 3 – 2 YRP Event

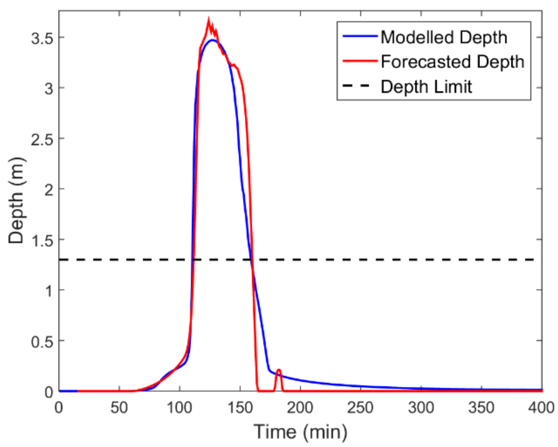

Figure 4-24: Modelled and Forecasted Water Depth at Critical Manhole 3 – 5 YRP Event

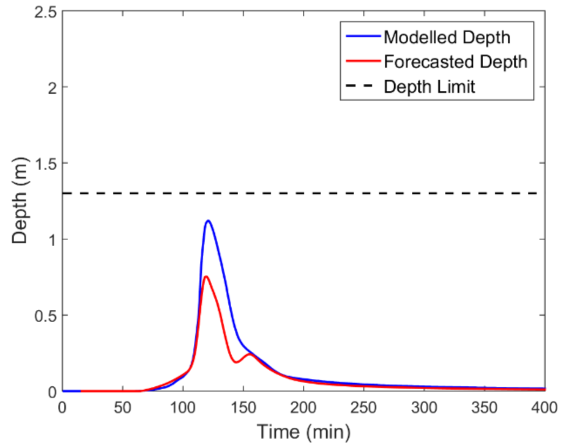

Figure 4-25: Modelled and Forecasted Water Depth at Critical Manhole 4 – 1 YRP Event

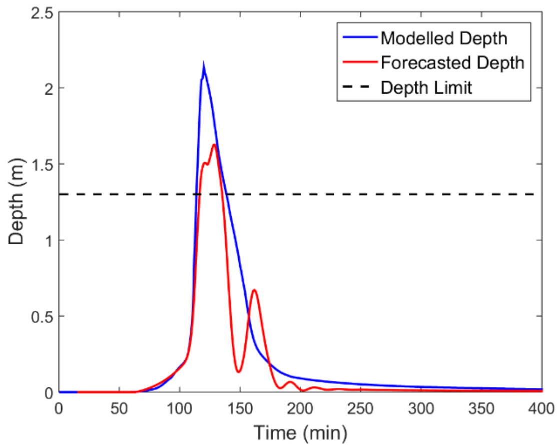

Figure 4-26: Modelled and Forecasted Water Depth at Critical Manhole 4 – 2 YRP Event

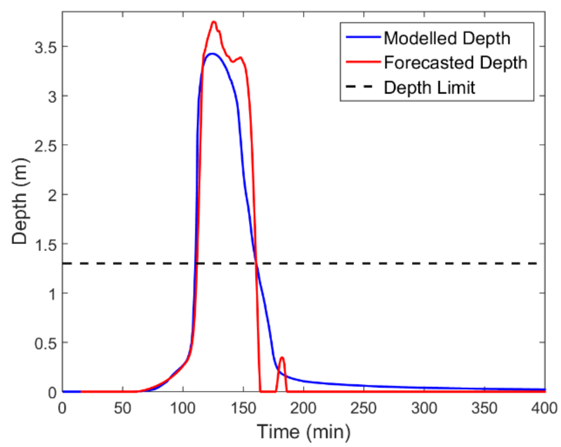

Figure 4-27: Modelled and Forecasted Water Depth at Critical Manhole 4 – 5 YRP Event

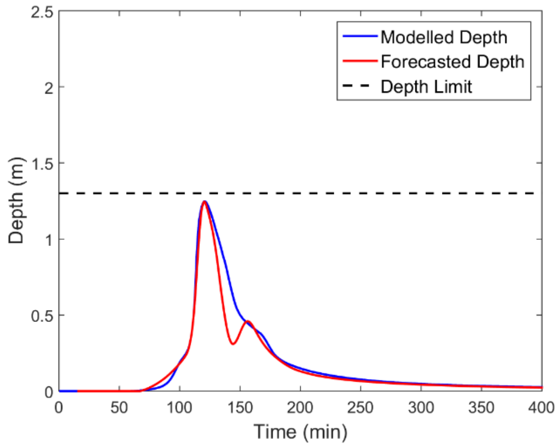

Figure 4-28: Modelled and Forecasted Water Depth at Critical Manhole 5 – 1 YRP Event

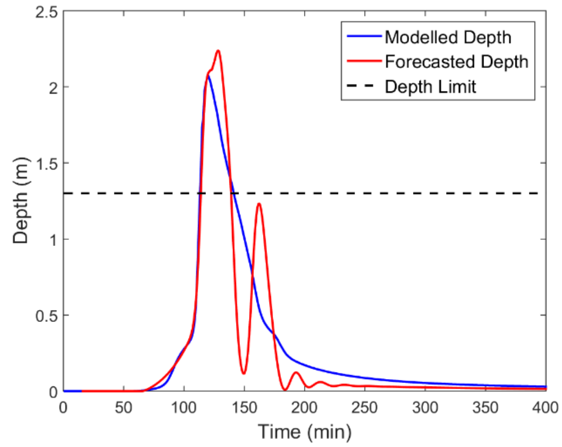

Figure 4-29: Modelled and Forecasted Water Depth at Critical Manhole 5 – 2 YRP Event

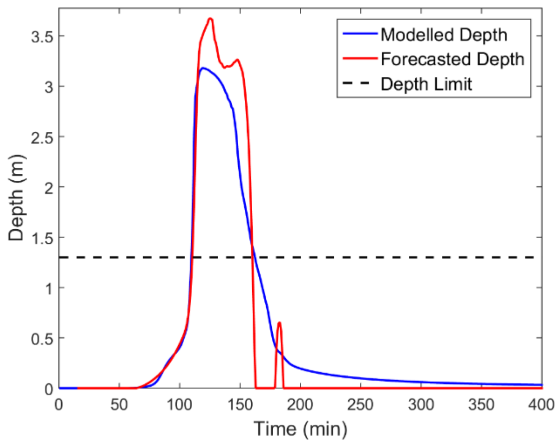

Figure 4-30: Modelled and Forecasted Water Depth at Critical Manhole 5 – 5 YRP Event

The previous figures represent good correlations between the modelled and the forecasted results, affirming the conclusion made in the statistical analysis. By comparing the water depth with the manhole depth limit, it is clear that an alarm will be activated under the storm event of 5 YRP, indicating an inundation in all the branches connected to the 5 critical manholes. For the event of 2 YRP, an alarm will be activated for all manholes except the critical manhole 1, and this result was examined in the EPA-SWMM model, where no floods were mentioned in the branches connected to this manhole. No alarms had been activated for the synthetic event of 1 YRP, which is a good observation, indicating the capacity of the system in generating representative and not erroneous alarms. It is better to define the threshold level to trigger alarms below 1.3 m in order to maintain a security factor. Modelled over forecasted peak values, which are presented in Table 4-6, could assist in defining the optimal security factor.

4.6 Dynamic Management Strategy

Studies have introduced dynamic management as a reliable, adaptable and cost effective solution in improving the performance of existing UDS. Management strategies consist of optimally operating the UDS elements; aiming to reduce flooding volumes, combine sewer overflows and energy consumption, in addition to increase water treatment plant and retention capacities (Schütze *et al.* 2003; Beeneken *et al.* 2013). The dynamic management strategy, in this work, is based on computing, ahead of time, the most feasible time-state schedule for the valve connecting the retention tank to the principal stormwater collector. Calculations are conducted for a fixed time horizon, in order to enable the best system performance regarding certain objectives. This management involves the retention tank with its associated valve, along with the installed monitoring sensors and a weather forecast system. The VSS calculation is aiming to increase the tank retention capacity through optimally manipulating its valve, based on iterative model calculations. Model calculations receive their initial states through sensors implemented on the site, while input data are weather forecasts and downstream boundary conditions are outfall water depth time series resulted from NARX neural network. The calculation process of the proposed dynamic management is presented in Figure 4-31.

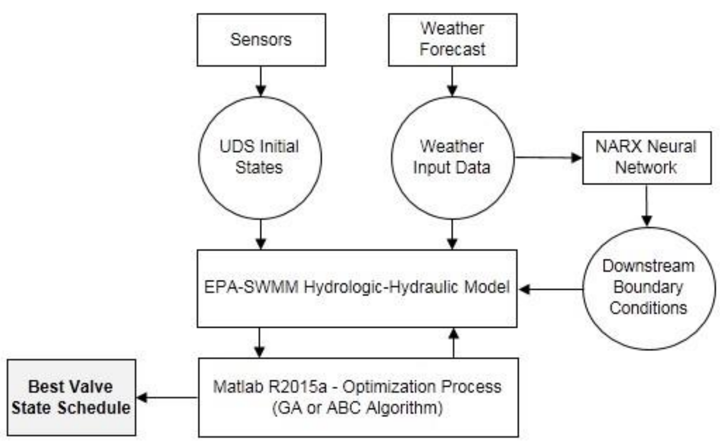

Figure 4-31: Valve State Schedule Optimization Process

Since the management strategy is based on weather forecast, the optimization horizon is bounded by the period of how long ahead in time, forecasts have acceptable degrees of confidence. In addition, computation time is a critical issue in the proposed management, since calculations start once weather forecast is received, and thus it consumes time from the optimization horizon. Furthermore, reducing calculation time enables to restart the VSS calculation periodically and hence, a model adjustment through updating sensors readings and weather forecasts. Despite the existence of control-oriented models, presented at the beginning of this chapter, in this work, the complete calibrated EPA-SWMM hydrologic-hydraulic model was used for the VSS evaluation, offering more details and phenomenon simulation. Reducing the computation time was more focusing on the calculation process and computation capabilities, instead of using reduced models and hydrologic-hydraulic phenomenon simplifications. The Genetic Algorithm and Artificial Bee Colony were selected as the optimization algorithms, based on their efficiency in performing simultaneously global and local searches, in addition to their population-orientation nature. Since these algorithms evaluate a population of individuals at each iteration, the cluster at the Computer Resource Centre of Lille1 University (CRI), was used to parallelize the objective function calculations simultaneously for all the population individuals. Reducing the required number of workers reserved to perform the calculations, which is equivalent to the number of individuals in a population, was also a concern. This concern was treated by performing the calculations several times on different population sizes, and evaluating the optimal number of individuals balancing between the representatively of the results and the computer requirements.

The objective of the work presented in this section, was defined as limiting the total flooding volume occurring on the campus. Therefore, it was based on a single objective management, concerning the total flooding volume, while treating all the network elements equally. On the other side, this study presents a lot of perspectives in the dynamic management of UDS. At the end of this thesis, a perspective concerning a multi-objective function taking into account, in addition to the flooding volumes, the flooding durations and the retention tank-filling ratio at the end of the storm event, will be proposed. Another perspective concerning a dynamic management strategy accounting for the importance of flooded manhole locations, through a GIS system and modelled results will be also proposed. Multiple structures of the VSS were evaluated and the adopted structure was a changing state occurring each 6 minutes for a horizon of 2 hours. This choice resulting in a vector of 20 consecutive values, describing the time-state sequence of the valve, was made due to its suitability for real life applications and to the balance found between the effectiveness in increasing the retention capacity and the required computation time. Valve state was discretized into 5 options, represented by completely closed (0%) to 25%, 50%, 75% and completely opened valve (100%). No constraints were imposed on two consecutive states, since a transition from fully closed to fully open valve each 6 minutes was considered applicable for a pipe with a diameter of 300 mm. The pipe (Diameter = 300 mm) connecting the retention tank to the main stormwater collector is relatively a small pipe and it was intended to evacuate the small unidirectional regulated flow (10 l/s). The purpose of this research is limited to present the profitability of applying a dynamic management, therefore the network elements were neither replaced nor improved, and the connection pipe was conserved in its actual state.

4.6.1 Optimization Algorithms

For optimization problems, lots of Evolutionary Algorithms (EA) types were developed, offering powerful search tools and optimization techniques. Besides their potential in searching wide spaces, these algorithms have the capacity of being applied with objective functions, which are not convex, continuous or differentiable, generalizing their effectiveness on all types of real life applications (Shi *et al.* 2016). Genetic Algorithm (GA) (Mitchell 1998), Particle Swarm Optimization (PSO) (Shi & Eberhart 1998), Ant Colony Optimization (ACO) (Dorigo & Birattari 2010), Artificial Bee Colony (ABC) (Karaboga 2005), are some of EA types that have been developed, applied and evaluated in different fields in the literature (Zhang *et al.* 2012; Ren *et al.* 2014; Gu *et al.* 2015; Juang *et al.* 2015; Li *et al.* 2015; Pan *et al.* 2015). Since the VSS calculation is limited by computation time, a hybrid optimization technique offering local and global search potential, similar to the GA-PS used in chapter 3 of this work, could not be applied. In the following, GA and a modified form of ABC will be separately used, compared and evaluated in order to find the optimal VSS aiming to increase the capacity of the retention tank, implemented at Lille 1 University Campus.

4.6.1.1 Genetic Algorithm

GA capable to search for the optimal solution within wide parameters ranges, through a guided population toward the fittest individuals, was used in this section due to its potential, effectiveness, and its population convergence nature. The GA optimization technique was already presented in chapter 3; therefore it will not be discussed again in this chapter. Stochastic uniform, scattered and adaptive feasible are the used functions for parent selection, crossover and mutation operators respectively. Only 1 elite solution was defined to move to the next iteration. Crossover fraction equal to 0.6 was chosen to orient the population toward the best valve dynamicity, while 0.4 as mutation fraction, ensuring a global coverage of the solution space. For the VSS optimization purpose, the objective function, requiring the EPA-SWMM model simulation results, will be calculated in a parallel way for all the individuals, which belong to the same population. GA in this section was applied within a discontinuous solutions environment. Each individual (X), of a population during an iteration, consists of 20 values limited between 0 and 1. Each value of the VSS vector could have 1 of the 5 valve opening options (0 0.25 0.5 0.75 1). The VSS vector is sent to the EPA-SWMM simulation model, in order to calculate the objective function of the individual. The objective function to minimize was defined as the total flooding volume occurring during the storm event. The reduction in flooding volumes as well as the required computation time, using GA optimization algorithm will be evaluated and compared to the results found through a modified ABC, presented in the next paragraph. The same procedure applied in GA optimization method, in order to transform an individual, composed of 20 consecutive integer values into a representative VSS, is applied during the modified ABC algorithm.

4.6.1.2 Artificial Bee Colony

Simulating the foraging behaviour of honey bees swarm, (Karaboga 2005) introduce a nature inspired algorithm capable to solve numerical optimization problems. As GA, ABC is a population based stochastic evolutionary algorithm. Its simplicity, interpreted by few control parameters and easy implementation, combined to its performance, efficiency and robustness, let it attracts researchers attention and turned it to be widely employed to solve many real world problems (Shi *et al.* 2016; Wu *et al.* 2016). In this study, ABC was applied due to its nature, which is balancing the exploitation and exploration processes. The different types of bees, explained in the following paragraphs and employed in this algorithm, offer a multi-local search potential with conserving a global search strategy.

Unlike GA, ABC differs between number of individuals and number of solutions, since in its iterative calculation, same solution could be checked for a possible improvement by multiple individuals spread in its neighbourhood. Therefore, the total number of individuals is categorized into three groups of bees, distinguished by their functionality (Karaboga *et al.* 2007). The first group, named employed bees, is responsible for exploiting the food sources in the whole search space. Food sources represent the population of solutions for a given problem. Employed bees bring back information of the food sources characteristics to the second bees group. The second group, known as onlooker bees and responsible for exploitative search, evaluates the received information and is recruited to examine the neighbourhood of the best food sources for a possible fitter solution. The whole bees colony, is double the solutions number, and is divided equally between employed and onlooker bees. A neighbourhood of a solution is inspected for a limited number of times, and is abandoned in case of no objective function improvement was observed after several consecutive iterations. The employed bee, which has abandoned its food source, turn into a scout bee, belonging to the third group, and starts searching randomly for a new food source, regardless of any information in the hive. The scout bees group is responsible for avoiding local optima during the optimization algorithm. The ABC algorithm perform its calculation through successive steps as described below:

Step1: User defines the algorithm parameters. Parameters Space Boundaries (PSB), Number of Solutions (NS), Number of Individuals (NI), Maximum Number of Iterations (MNI) and Consecutive Iterations Limit before abandoning the unimproved solution (CIL) are defined at this step.

Step2: Initialization of NS random solutions through Equation 4-2.

$$X_{i,j} = X_{i.j}^{min} + Rand[0,1]\,(X_{i.j}^{max} - X_{i.j}^{min}) \qquad \text{Equation 4-2}$$

Where $X_{i,j}$ is the j^{th} parameter in the i^{th} solution, *Rand[0,1]* generates a random number between 0 and 1, min and max are the user defined PSB for the j^{th} parameter in Step 1.

Step3: Fitness evaluation through the objective function calculation for the initial population. The objective function is calculated through the problem structure. Then the fitness of each solution is given through Equation 4-3.

$$Fitness_i = \begin{cases} 1/(1+f(X_i)) & if\ f(X_i) \geq 0 \\ 1+abs(f(X_i)) & if\ f(X_i) < 0 \end{cases} \qquad \text{Equation 4-3}$$

With $f(X_i)$ is the objective function calculated for the solution X_i.

Step4: Solution exploitation through NI/2=NS employed bees. One employee bee explores each solution neighbourhood according to Equation 4-4.

$$Y_{i,j} = X_{i,j} + Rand[-1,1]\,(X_{i,j} - X_{k,j})$$ *Equation 4-4*

Where K is a random selected solution. New solution will replace the initial one, if objective function improvement were found.

Step 5: After conserving the best solutions between the initial ones and theirs neighbourhoods explored by employed bees, each onlooker bee selects a solution, based on its profitability, through a "roulette wheel selection" (Goldberg 1989). Onlooker bee searches for a fitter solution in the neighbourhood of the selected solution through Equation 4-4. The probability of a solution to be selected is given in Equation 4-5.

$$P_i = \frac{Fitness_i}{\sum_{j=1}^{NS} Fitness_j}$$ *Equation 4-5*

As for an employee bee, if an onlooker bee found a fitter solution than the initial one, the new solution will be memorized for the next iteration.

Step 6: Once CIL is exceeded and no solution improvement was noticed, the solution is abandoned by its employee bee, which is transformed into scout bee and starts to explore randomly the space through Equation 4-2.

Step 7: Compare actual iteration number with the MNI. If MNI is attained, return the best solution found, if not go to **Step 4**.

Through these steps, it is well shown that ABC combines the local search, through solutions neighbourhood evaluation managed by employed and onlooker bees, with the global search, performed by the scouts trying to cover the whole parameters ranges. The ABC nature enabling it to perform simultaneously exploration and exploitation (Karaboga & Basturk 2007; Kong *et al.* 2013), is the main reason for being adopted for the VSS calculation. Researchers highlight weaknesses in this method, although the great performance of this algorithm. Some studies relate the shortages of this method to its exploitation ability (Zhu & Kwong 2010), while others consider the inefficiency in its exploration potential (Kong *et al.* 2013; Luo *et al.* 2013; Xiang & An 2013). In addition, (Wu *et al.* 2016) consider ABC algorithms as premature and improvements should be done to enhance its speed of convergence. Plenty of works had been conducted to improve ABC performance. Some of these works were focusing on applying changes to the ABC algorithm, while others on combining it to other optimization techniques. (Anuar *et al.* 2016; Shi *et al.* 2016) cited some of the researches conducted to improve the ABC performance.

The global exploration is related to the scout bee (Karaboga & Basturk 2008), which is executed only after trials number exceeds CIL, without noticing any improvement in a solution. CIL is an important control parameter in ABC (Karaboga & Gorkemli 2012). Reducing CIL will enhance the global search but limit the exploitation capacity, while raising it increase the probability of being stuck in local optima. Recent studies reveal the absence of scout bees in some applications, and as a result a lack in the global exploration (Bullinaria & AlYahya 2014a, b). In the standard ABC, a high MNI is required to enable the exploration process, which is a drawback for the application of the standard ABC in the VSS calculation. In this work, instead of applying major changes to the ABC algorithm, adaptation of the algorithm to meet the problem structure and perform ideally in responding to the system requirements, was made.

The principal modification applied to the standard ABC algorithm is in parallelizing the exploitation and exploration processes for all the iterations. The population was divided from the beginning into two groups (onlooker and scouts) conserving the same number of individuals throughout the process. The onlooker bees are distributed to discover solutions neighbourhood, according to results obtained in the precedent iteration, this is the reason for not adopting employed bees and considering all the exploitative bees as onlookers. The solutions or food sources are divided into 3 groups. The first one, composed of the fittest solutions, is called elite sites, and here were most of the onlookers will be directed. The second group, are also selected sites but not promising solutions as much as the elite ones. Fewer onlookers will be directed to the non-elite but selected sites. Finally, the worst solutions found in the actual iteration will be discarded in the next iteration, and scout bees will be randomly sent in the parameters environment to discover if better solutions exist. As for the Genetic Algorithm, the calculation was parallelized on the cluster composed of multiple workers. Thus, to benefit from all cluster workers overall the process, the same number of solutions are inspected by the same number of onlookers and scouts bees simultaneously, based on solution comparison and ranking process applied in the precedent iteration. Figure 4-32 presents the calculation procedure and the different steps of the modified ABC algorithm.

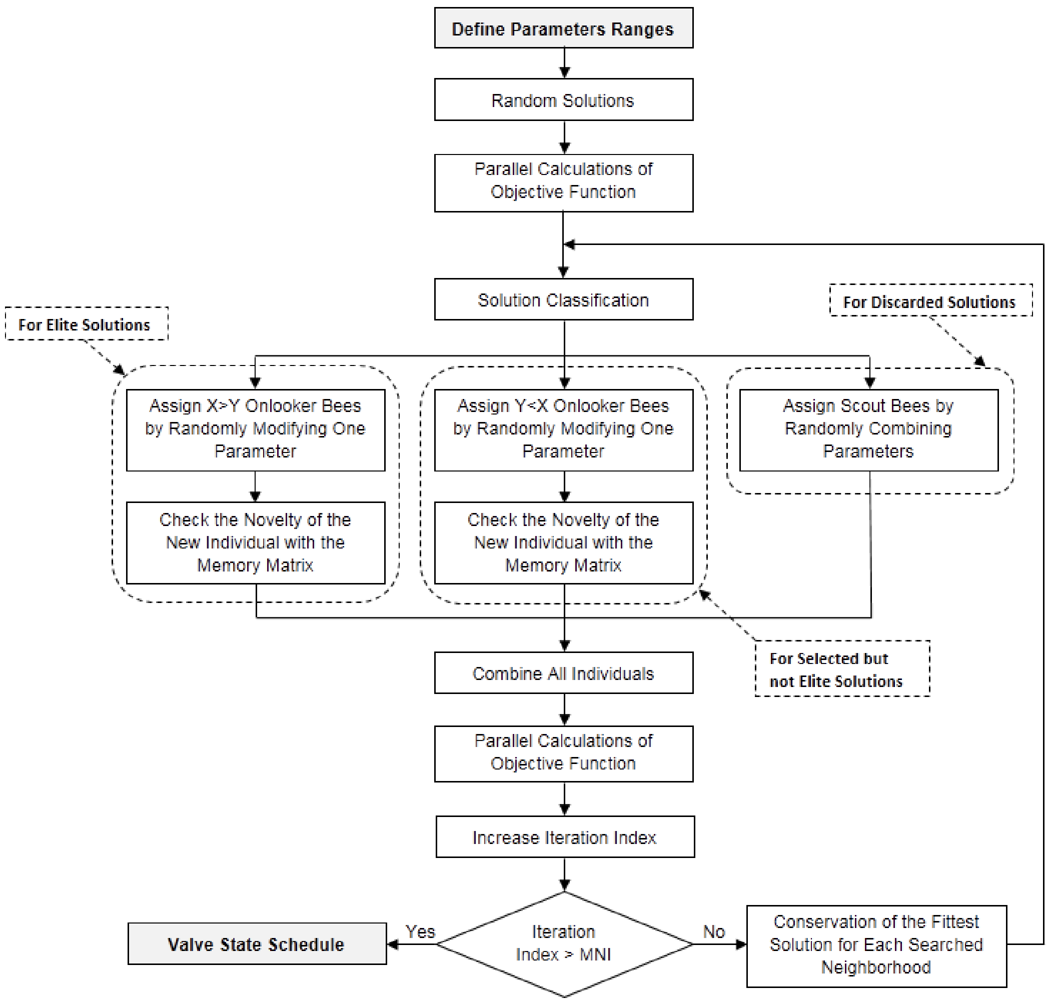

Figure 4-32: Calculation Steps of the Modified Artificial Bee Colony

First, user defines parameters ranges and starts the calculation. The modified ABC algorithm selects random solutions within the variables spaces, combines them into a matrix and calculates their objective functions in a parallel process. Once objective function value for each solution is calculated, the algorithm classifies and arranges the solutions within three different groups. Solutions having the lowest objective functions are elites among others, and more onlooker bees are sent to their neighbourhood, in order to inspect for better solutions. Selected but not elite solutions are also inspected but with fewer individuals. All onlooker bees are assigned by modifying randomly one arbitrary chosen parameter. Each new individual in the neighbourhood of a selected solution is compared to a matrix memorizing all already inspected locations, and thus avoiding wasting time by inspecting same solutions more than once. In each iteration, the same number of solutions is discarded and scouts are assigned to examine the variables spaces for better solutions. Once the new population is ready, simultaneously for all the individuals, they are sent to separate workers on the cluster of Lille 1 University Server, to calculate in parallel all individuals' objective function. If the iteration index exceeds the maximum allowed iteration number, defined by the user, the algorithm return the best calculated VSS. If not, modified ABC algorithm proceed for the next iteration after conserving the fittest solution of each inspected neighbourhood, and thus protecting the algorithm from converging, after several iterations, all onlooker bees to the same area. The parameters of the modified ABC algorithm were defined after several trials and efficiency evaluations. 10% and 20% of the inspected solutions in the precedent iteration will be considered, based on their objective function values, as elite and selected but not elite solutions, respectively. During the actual iteration, 4 individuals are sent to discover the neighbourhood of each elite solution, while 2 individuals are allocated to discover the neighbourhood of a selected but not elite solution. 70% of solutions are discarded each iteration to be replaced by another 70% of random solutions, each 1 discovered by 1 individual.

4.6.2 Results and Observations of the Dynamic Management

During the analysis of the UDS operation (Section 4.3), an anomaly in the system response to severe storm events was mentioned. This anomaly was explained by the separation of the branches of the UDS, through a check valve and a flow regulator, isolating the retention tank from the main UDS collector. Before applying the dynamic management, proposed in this section, the operation of the retention tank was simulated and evaluated without the already installed isolating equipment. Understanding the operation of the UDS enabled us, through a simple equipment modification, to improve its operation. Flooding volumes and durations were reduced from 869 m^3 (40.3h) to 853 m^3 (39.9h) and from 1013 m^3 (180.7h) to 889 m^3 (68.3h), for the 31 August 2015 and 5 YRP events, respectively. The obtained results highlight one of the benefits of understanding the UDS operation, through a RTM system combined to a simulation model. This section of this chapter aims to represent the benefits of applying a dynamic management. Therefore, the flooding volumes, which will result after dynamically operating the valve, will be compared to the results found after improving the UDS operation, by removing the check valve and the flow regulator. Before evaluating the dynamic management results, the robustness of the optimization algorithms was analysed.

4.6.2.1 Robustness Evaluation of the Optimization Algorithms

GA and the modified ABC are stochastic optimization algorithms based on orienting a population of individuals toward the optimal solution. Therefore, a work was allocated to evaluate their robustness in maintaining the same level of performance during their applications. For each population size, 10 optimizations were accomplished, in order to test the algorithm performance. Each optimization consists of running the algorithm over 50 iterations. The calculations were conducted on 5 different population sizes composed of 30, 60, 90, 120 and 150 individuals. The objective function to decrease during the optimization process is defined as the total flooding volume, simulated by the EPA-SWMM model. Figure 4-33 to Figure 4-42 show the resulted final optimal VSS and the GA performance during the iterations, for the 10 trials conducted on the synthetic event of 5 YRP. The 10 resulted optimal VSS are presented in these figures in a bar graph showing the opening ratio during each time step. Each VSS is presented by one of 10 different colours, ranging between cyan and blue. All VSS of the same population are superposed on the same graph, in order to compare the resulted valve-opening ratio at each time step. Flow presented by a red line in these figures, was simulated by considering a complete open valve, without applying the dynamic management. It is the flow inside the main collector pipe, downstream the retention tank, and is drawn on these figures, to help in analysing the VSS obtained values. One time step is equivalent to 6 minutes as indicated at the beginning of this section.

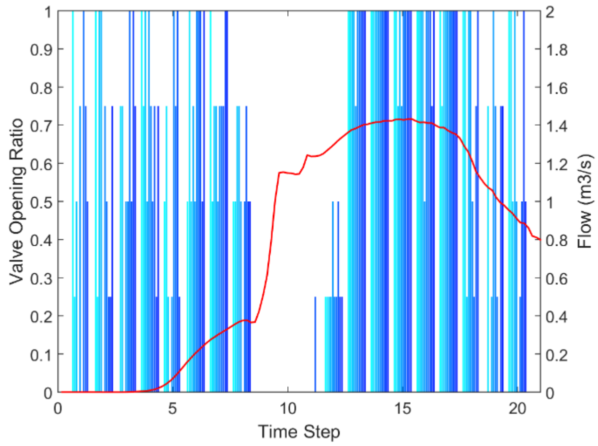

Figure 4-33: VSS Calculated for 10 Trials on 5 YRP Event by GA (Population=30)

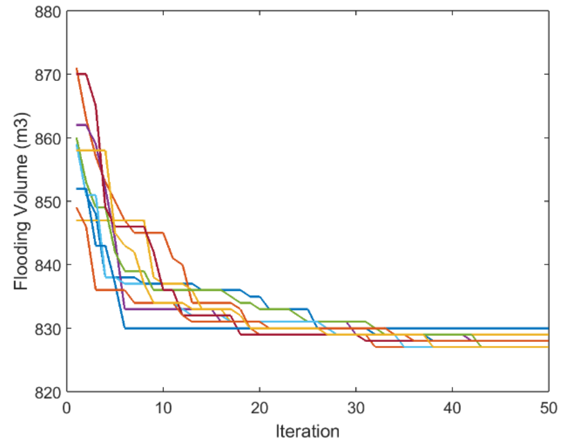

Figure 4-34: Performance of GA in Reducing Flooding Volume (Population=30 - 5 YRP)

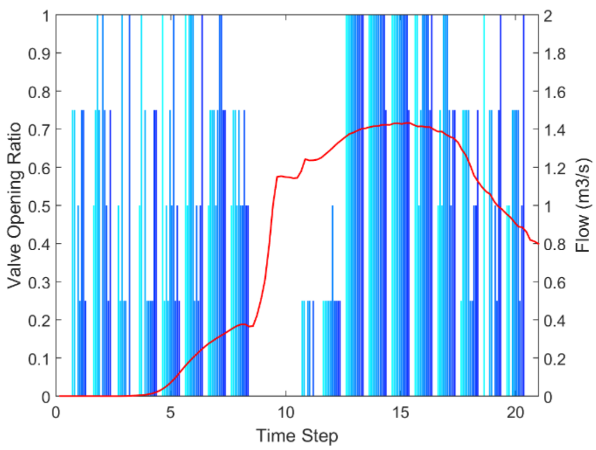

Figure 4-35: VSS Calculated for 10 Trials on 5 YRP Event by GA (Population=60)

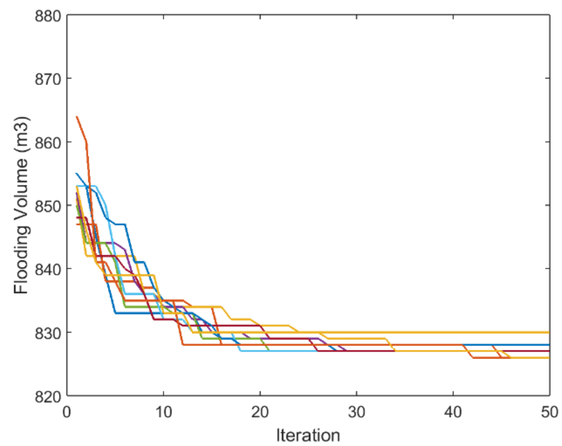

Figure 4-36: Performance of GA in Reducing Flooding Volume (Population=60 - 5 YRP)

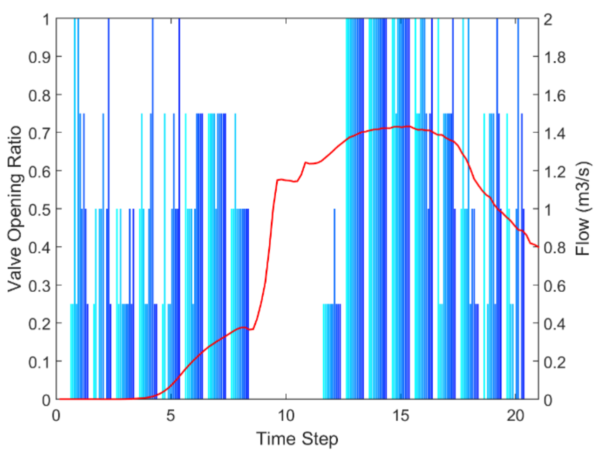

Figure 4-37: VSS Calculated for 10 Trials on 5 YRP Event by GA (Population=90)

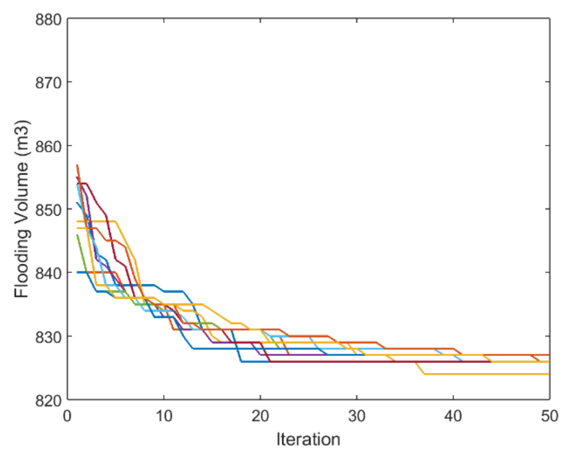

Figure 4-38: Performance of GA in Reducing Flooding Volume (Population=90 - 5 YRP)

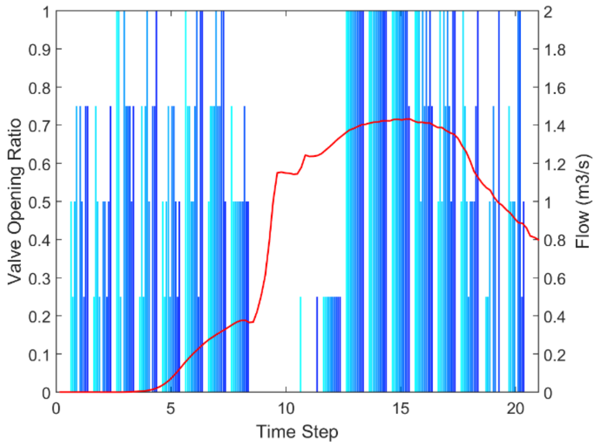

Figure 4-39: VSS Calculated for 10 Trials on 5 YRP Event by GA (Population=120)

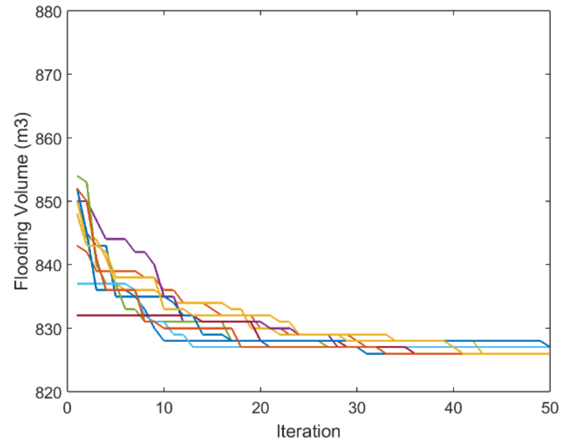

Figure 4-40: Performance of GA in Reducing Flooding Volume (Population=120 - 5 YRP)

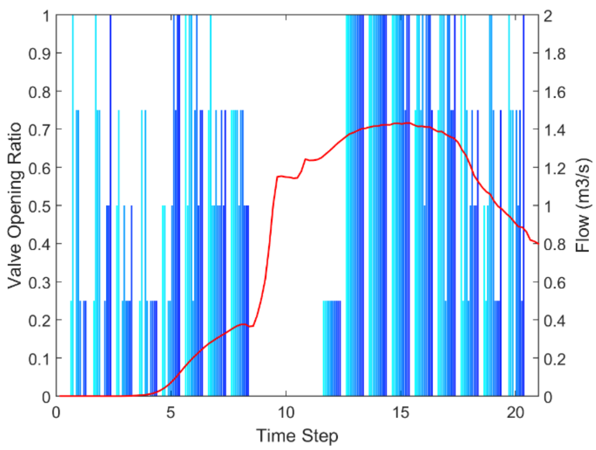

Figure 4-41: VSS Calculated for 10 Trials on 5 YRP Event by GA (Population=150)

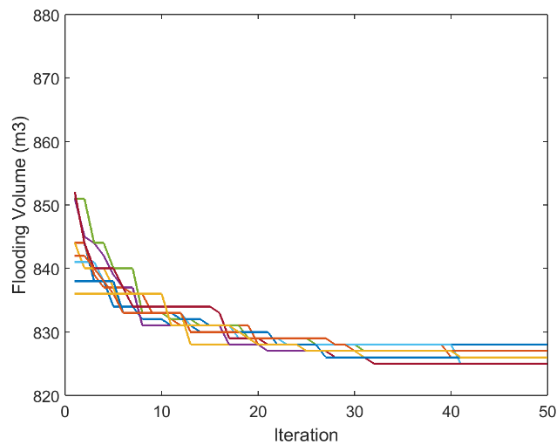

Figure 4-42: Performance of GA in Reducing Flooding Volume (Population=150 - 5 YRP)

Through the obtained results, we can notice the similarity between the 10 calculated optimal VSS for each population, especially between time step 8 and time step 17. This similarity exists also between the results of the different population sizes. At the beginning of the event, where the flow values are minors, the valve-opening ratio does not affect the total flooding volume. This explains why VSS values at the first time steps represent some differences between the different optimal solutions. At time step 8, high flows begin to appear and all optimal calculated VSS, present approximately the same opening ratio. These results affirm the robustness of the GA in converging to the same efficient VSS, after completing the 50 iterations. The performance of the GA during the iterations is also a very important factor, since it helps in reducing the total iterations number, which means a decrease of the computation time. For each population, the plotted performance results indicate a very close behaviour of the GA during the iterations for the 10 conducted trials. The convergence of the results becomes more highlighted after accomplishing 20 iterations. After evaluating the GA performance and results, the same procedure was applied on the modified ABC algorithm, and results are presented in Figure 4-43 to Figure 4-52.

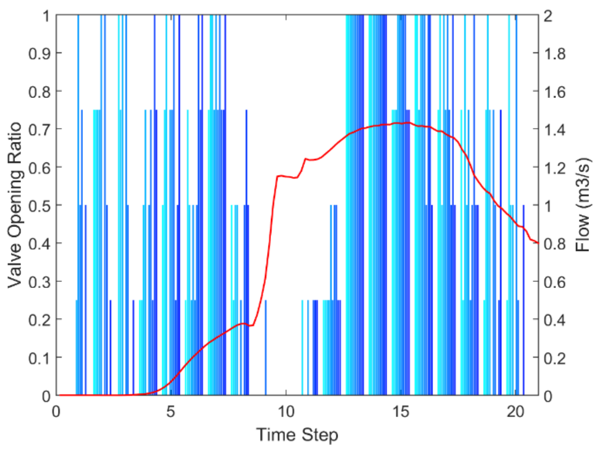

Figure 4-43: VSS Calculated for 10 Trials on 5 YRP Event by ABC (Population=30)

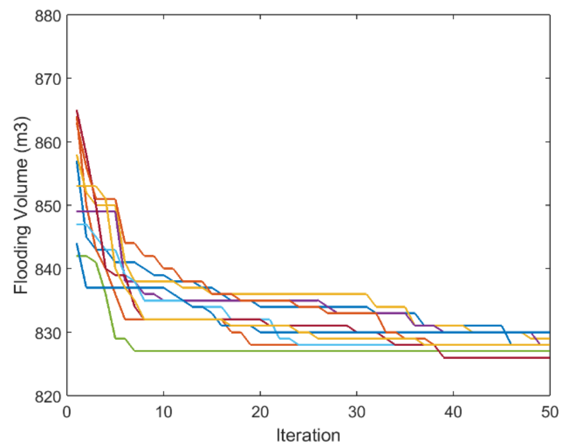

Figure 4-44: Performance of ABC in Reducing Flooding Volume (Population=30 - 5 YRP)

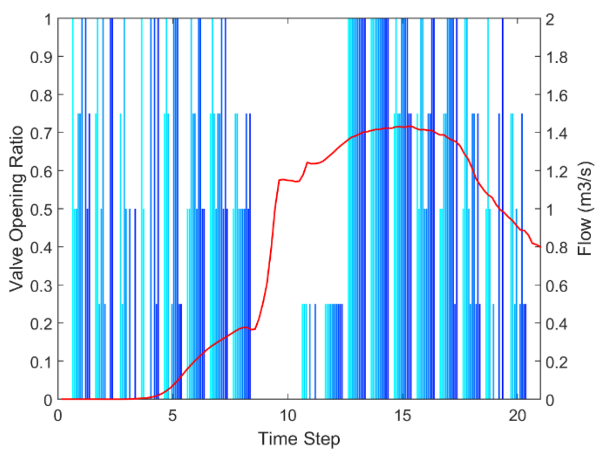

Figure 4-45: VSS Calculated for 10 Trials on 5 YRP Event by ABC (Population=60)

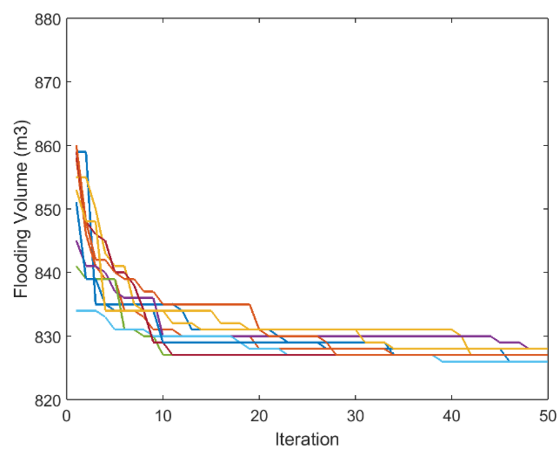

Figure 4-46: Performance of ABC in Reducing Flooding Volume (Population=60 - 5 YRP)

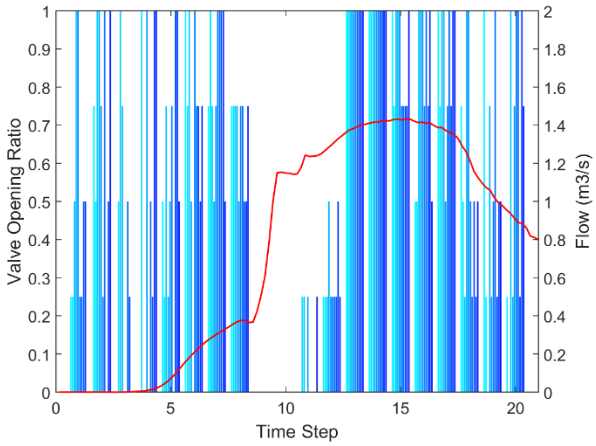

Figure 4-47: VSS Calculated for 10 Trials on 5 YRP Event by ABC (Population=90)

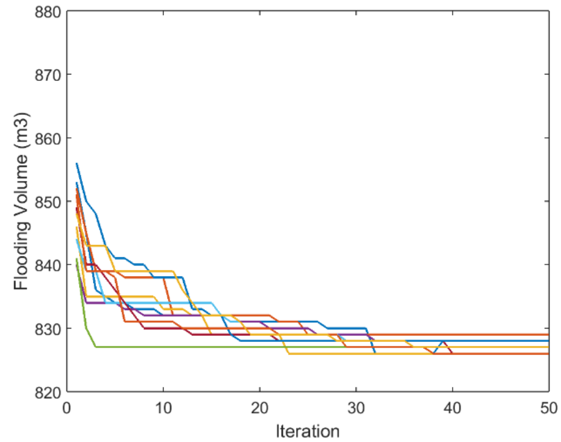

Figure 4-48: Performance of ABC in Reducing Flooding Volume (Population=90 - 5 YRP)

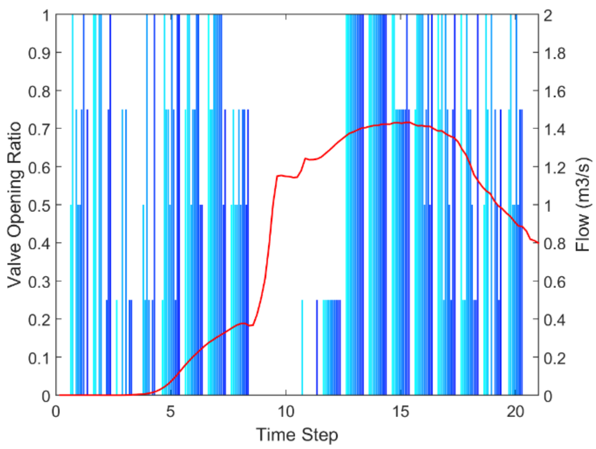

Figure 4-49: VSS Calculated for 10 Trials on 5 YRP Event by ABC (Population=120)

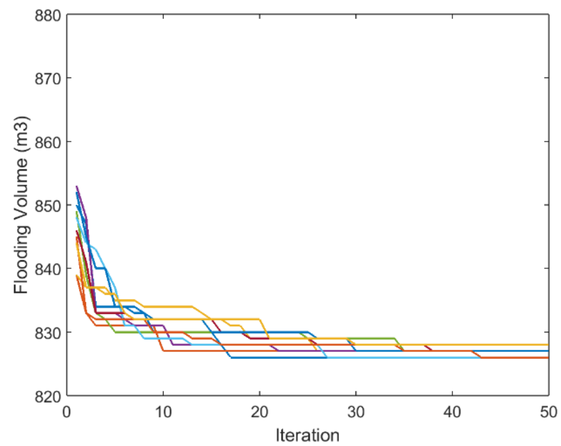

Figure 4-50: Performance of ABC in Reducing Flooding Volume (Population=120 - 5 YRP)

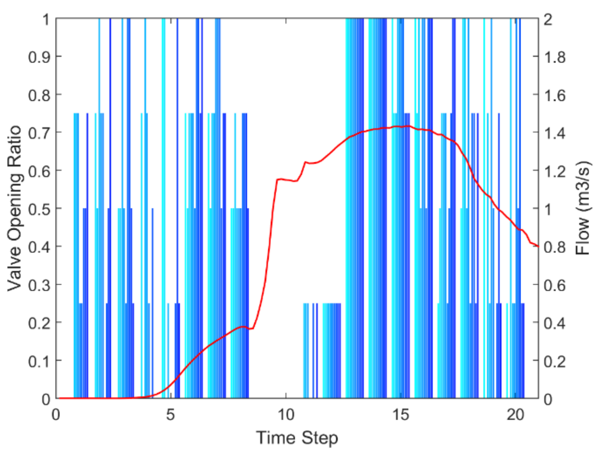

Figure 4-51: VSS Calculated for 10 Trials on 5 YRP Event by ABC (Population=150)

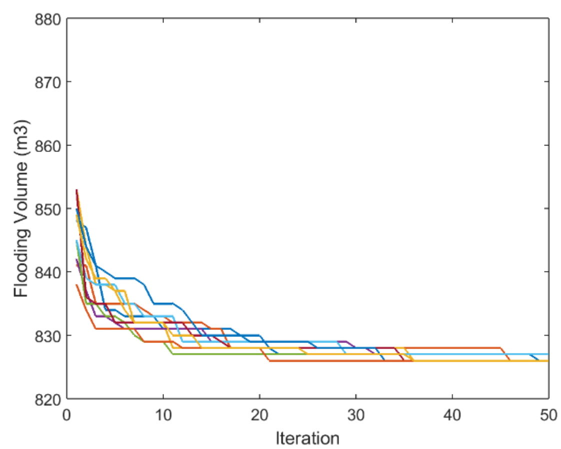

Figure 4-52: Performance of ABC in Reducing Flooding Volume (Population=150 - 5 YRP)

Same observations made for GA were also found for the modified ABC algorithm. In addition, we noticed approximately the same resulted optimal VSS for the two optimization techniques used in this study. These results affirm the efficiency of these optimization algorithms in converging to optimal solution after 50 iterations. For each population size, a comparison between the performances of GA and the modified ABC was made, in order to understand their progress in finding the optimal VSS. Performances plots, of the two optimization algorithms, are presented in Figure 4-53 to Figure 4-57. The performance, plotted for each optimization algorithm, is the average of the performance results found for the 10 conducted trials.

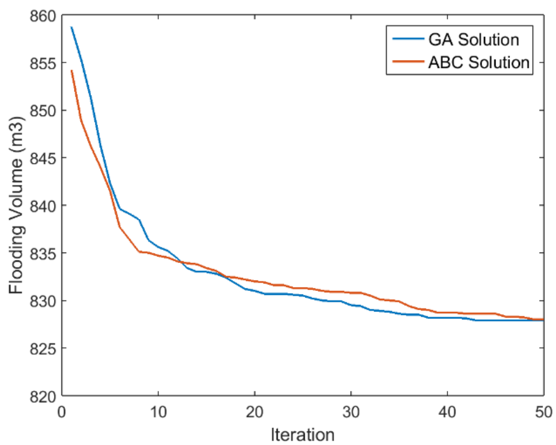

Figure 4-53: Comparison of GA and ABC Performances (Population=30 – 5 YRP)

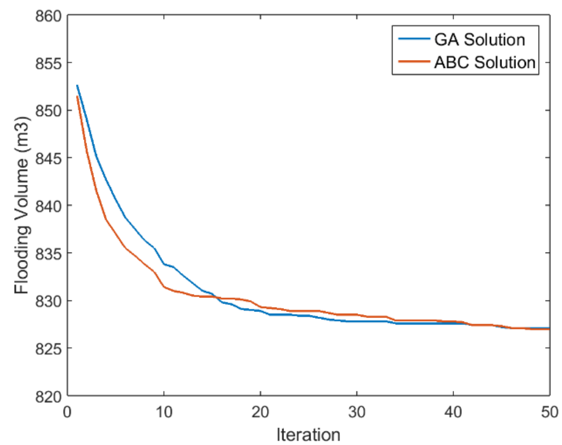

Figure 4-54: Comparison of GA and ABC Performances (Population=60 – 5 YRP)

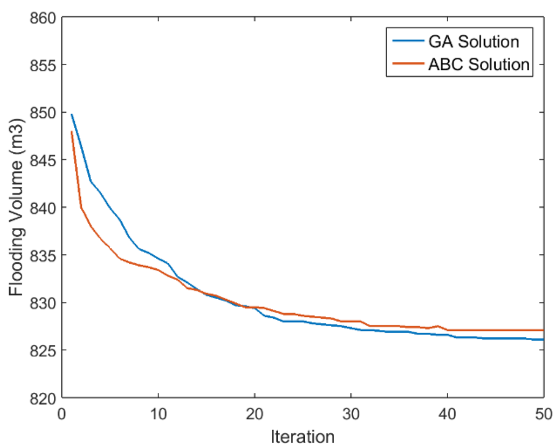

Figure 4-55: Comparison of GA and ABC Performances (Population=90 – 5 YRP)

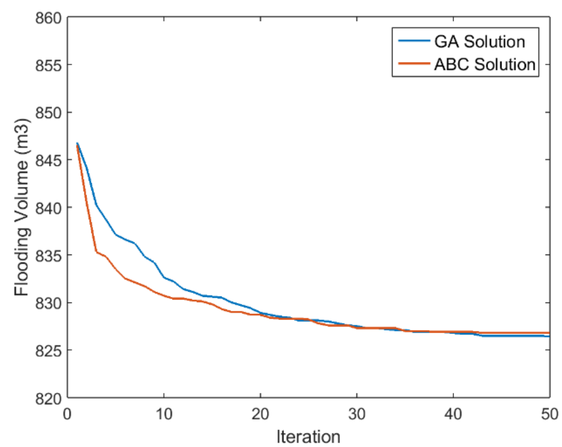

Figure 4-56: Comparison of GA and ABC Performances (Population=120 – 5 YRP)

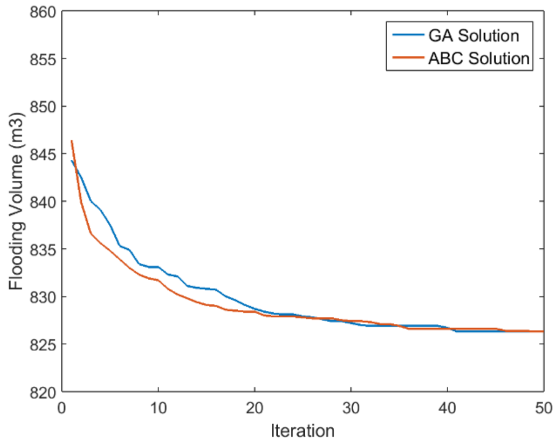

Figure 4-57: Comparison of GA and ABC Performances (Population=150 – 5 YRP)

A slight advantage for the modified ABC algorithm over the GA is presented in the previous figures. This better performance is limited before reaching the 15th iteration for all the tested population sizes. Consequently, we can consider the modified ABC better than GA for applications with short time horizon, where consecutive calculations are running during the same storm event. Such applications improve the optimization process through the reduction of uncertainties at the modelling and forecasting level, by updating the actual conditions through sensors readings. The same procedures were conducted on the GA and modified ABC for the storm event of 31 August 2015. Similarity between the resulted optimal VSS and the performances of the optimization algorithms were also noticed for this event. It was clear for all the trials that an improvement in the system operation and retention tank capacity is obtained directly after the first iteration, while after a certain number of iterations all trials converge to a constant result. This fact enables us to reduce the population size and the iteration number to meet the minimum calculation time and computer requirements, needed for conducting the optimization. Next section will discuss the optimal iteration number and population size, for efficiently calculating the VSS.

4.6.2.2 Required Population Size and Iteration Number

A comparison between the average performances during the trials for all tested population sizes helps us in defining the required population size and iteration number. Calculations are conducted in parallel, for all the population individuals, on a cluster worker. Thus, reducing the population size means reducing the required computer capabilities. At each iteration, the calculation is conducted for a new population of individuals. Hence, reducing the total iteration number is reducing the required computation time. Figure 4-58 and Figure 4-59 present the average performances calculated through the 10 trials of the 5 tested population, for GA and modified ABC optimization methods.

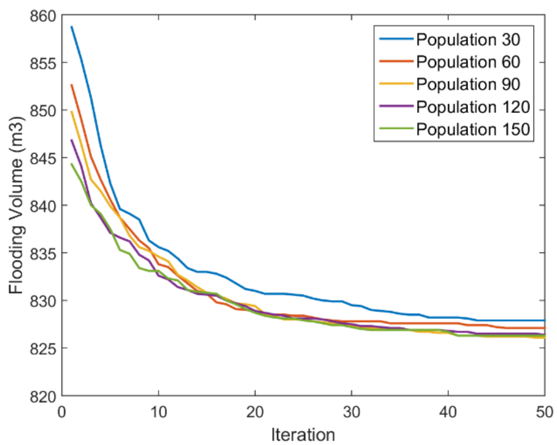

Figure 4-58: Average Performances for the 5 Population Sizes by GA (5YRP)

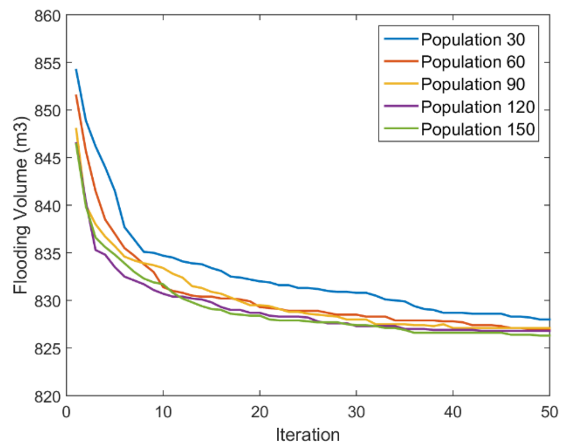

Figure 4-59: Average Performances for the 5 Population Sizes by ABC (5YRP)

The population sizes remain affecting the performance of the optimization process until completing 15 iterations. Once the algorithms exceed the 15th iteration, all population sizes except 30, show a very similar performances. Since the complexity of the storm event could affect the performance of the optimization process, and consequently the algorithms may require much more iterations to converge to the optimal VSS, this evaluation was also conducted on the storm event of 31 August 2015. Figure 4-60 and Figure 4-61 represent the average of flooding volumes decreases during the iterations, for the storm event of 31 August 2015, for the two optimization algorithms.

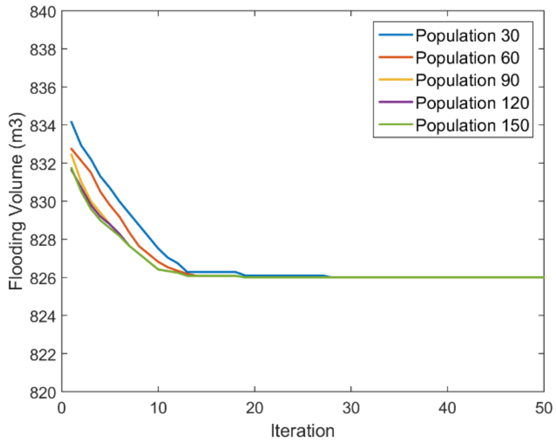

Figure 4-60: Average Performances for the 5 Population Sizes by GA (31 August 2015)

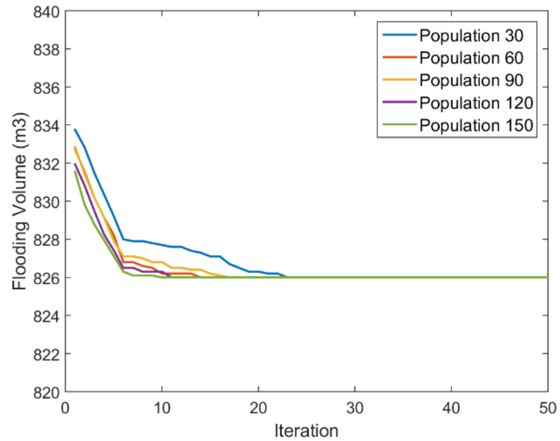

Figure 4-61: Average Performances for the 5 Population Sizes by ABC (31 August 2015)

Obtained results for the storm event of 31 August 2015, affirm the observations found for the synthetic event of 5 YRP. After exceeding 15 iterations, all population sizes above 30 show a convergence to the optimal solution. Results could be more improved and affirmed, by conducting similar analysis on additional events. In this case, a population of 60 individuals under 20 iterations was found able to converge to a good VSS solution. Hence, the required computer capability is a server of 60 processors capable to perform in parallel, the simulation for all the individuals of the population, at each iteration. Considering a simulation time of 4 hours is sufficient for the EPA-SWMM model to simulate the complete UDS response subjected to 2 hours storm event, the calculation of one iteration requires less than 30 seconds to finish. Therefore, all the optimization process requires less than 10 minutes to calculate an efficient VSS. As already noticed, a choice of fewer numbers of iterations could be practiced with multiple consecutive optimizations. Such applications are powerful in reducing the model and weather forecast uncertainties, through real time sensor measurements. In addition, it could be highly valuable for managing big UDS, where a single iteration requires a long computation time. After defining the ideal parameters and minimum computer requirements for our optimization process, it remains to evaluate the obtained results. Next section will discuss the potential of the dynamic management in enlarging the retention tank storage capacity.

4.6.2.3 Optimization Results

Under the defined parameters, both of the optimization algorithms show the capacity to reduce the flooding volume to be equal to 826 m^3 (38.9h) and smaller than 830 m^3 (63.7h) for the storm events of 31 August 2015 and 5 YRP, respectively. Comparing the reduced flooding volumes with the model results found after removing the check valve and flow regulator, we found 27 and 59 m^3 of flooding volume decreases. These results indicate an increase of the storage capacity of the 280 m^3 retention tank, by 9.6% and over 21.1% for the 31 August 2015 and 5 YRP storm events, respectively. The potential of the dynamic management strategy in increasing the retention tank capacity, is dependent on the characteristics of the storm event (Duration, total depth, rainfall intensity repartition, etc.). Plotting the rainfall intensity, the flow in the main collector and the resulted VSS, helps in understanding and evaluating the changes made in the system operation at each time step. Figure 4-62 to Figure 4-65 present the rainfall intensities, the modelled flow and the average VSS resulted from all trials, done on both of the optimization algorithms, function of the time steps, for the two studied events.

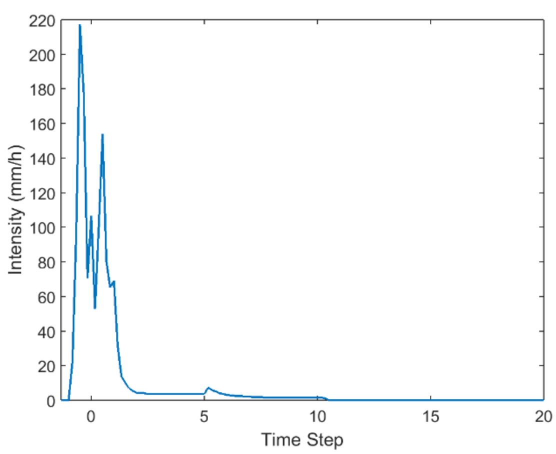

Figure 4-62: Rainfall Intensity During the Storm Event of 31 August 2015

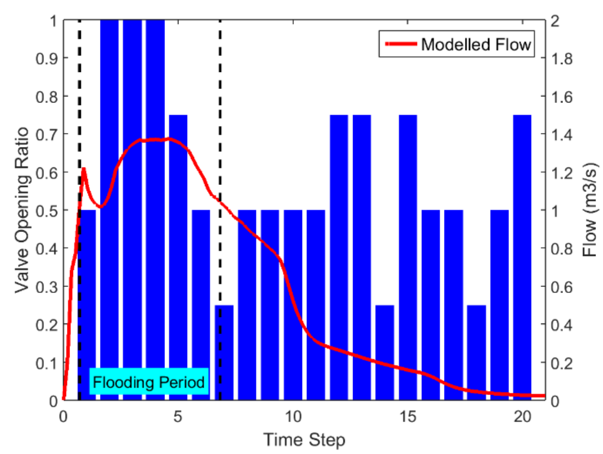

Figure 4-63: Flow in the Main Collector and Optimal VSS for the Event of 31 August 2015

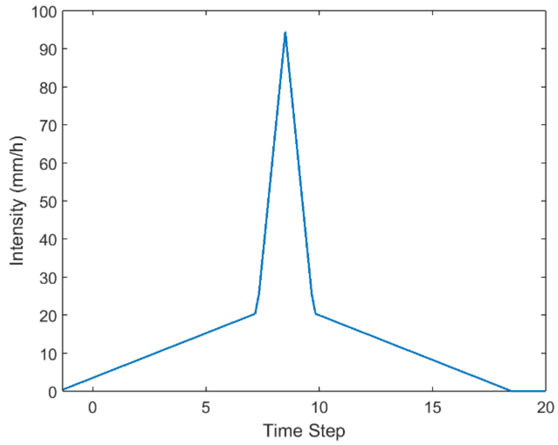

Figure 4-64: Rainfall Intensity During the Synthetic Storm Event of 5 YRP

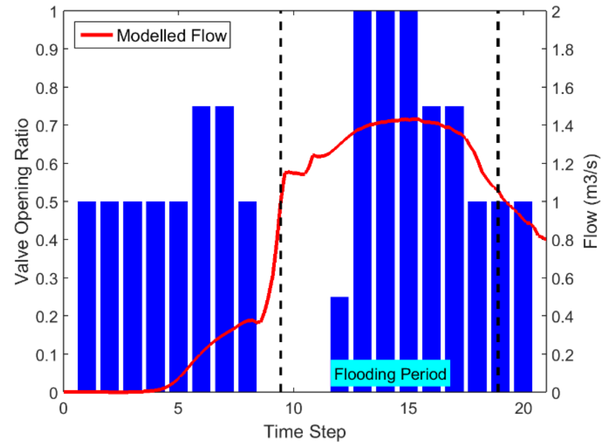

Figure 4-65: Flow in the Main Collector and Optimal VSS for the Synthetic Event of 5 YRP

The storm event of 31 August 2015 is characterized by very high rainfall intensities occurring in a short period at the beginning of the event, and followed by low intensity rainfalls. Such events require using the storage capacity of the retention tank at the beginning of the storm, instead of allocating it to a more critical time. Therefore, the dynamic management was not very efficient in enlarging the retention capacity compared to a simple open pipe. The optimal VSS for this event indicates an open valve during the first time steps, and thus the system with or without dynamic management will operate approximately the same. After time step 7, floods disappeared from the site, as shown in Figure 4-63, and thus valve opening ratios at the following time steps, are not affecting the total flooding volume. A multi-objective function including the retention tank emptying process, could benefit from such situation in opening the valve and accelerating the emptying process, especially if another storm is predicted by the weather forecast system. On the other hand, the synthetic storm of 5 YRP is more spread with 15 minutes of high intensity occurring at the middle of the event. Hence, the dynamic management was more effective during this event. Figure 4-65 shows that at the beginning of the event, before reaching high flow values, the valve was half opened. During these time steps, the retention tank was emptying its content coming from its upstream area. The valve is not fully opened because the flow does not represent high values, and a valve half opened allows the evacuation of the stored water. Once the flow increases rapidly, we noticed that the valve is totally closed. This observation was noticed in all optimal VSS calculated for this event, and presented earlier in this chapter. Even if the floods appear during these time steps, the optimization process found more appropriate to allocate the storage to a later flow. This is possible due to a weather forecast system, able to predict future rainfall intensities. Such observation could be explained by the high water depth in the system, which surcharges the pipes, and thus creates a pressurized flow. By closing the valve at that moment, we allocate the storage capacity to a more critical situation, while we benefit from higher flow induced by increasing the water depth. After a certain time, the valve is fully opened for 3 consecutive time steps, where water is directed to the retention tank in the most beneficial way. Later, the valve is half closed in order to limit the interaction between the two branches, and protect the system from being surcharged by the tank emptying process. Finally, after the flooding disappeared from the studied sector, the VSS calculated values are arbitrary, since they do not affect the resulted total flooding volume.

In addition to the dynamic management, a qualitative management is also studied and evaluated as described in the following sections.

4.7 Qualitative Dynamic Management Proposition

Qualitative dynamic managements are normally based on directing water flow within the UDS according to the measured pollution. As explained in chapter 1 of this thesis, stormwater evacuated by separated UDS could be a valuable water resource, either by direct reuse or by recharging the groundwater through infiltration structures. The main factor threatening the cities, which practice such management types, is runoff pollution. Other than leaching urban surfaces, the existence of an accidental pollution, which was not considered during design phases, induces high catastrophic impacts on groundwater quality. In a smart city, where monitoring sensors are a key element, this problem could be overcome. In this work, a qualitative management will be proposed aiming two objectives. The first objective is to support the quantitative management by allocating the tank retention volume to the polluted water, while the second objective is to recharge ground water, and thus fill the gap induced by surface waterproofing and urbanization. Figure 4-66 presents the flowmeter and the turbidity meter used in this section for evaluating the proposed management.

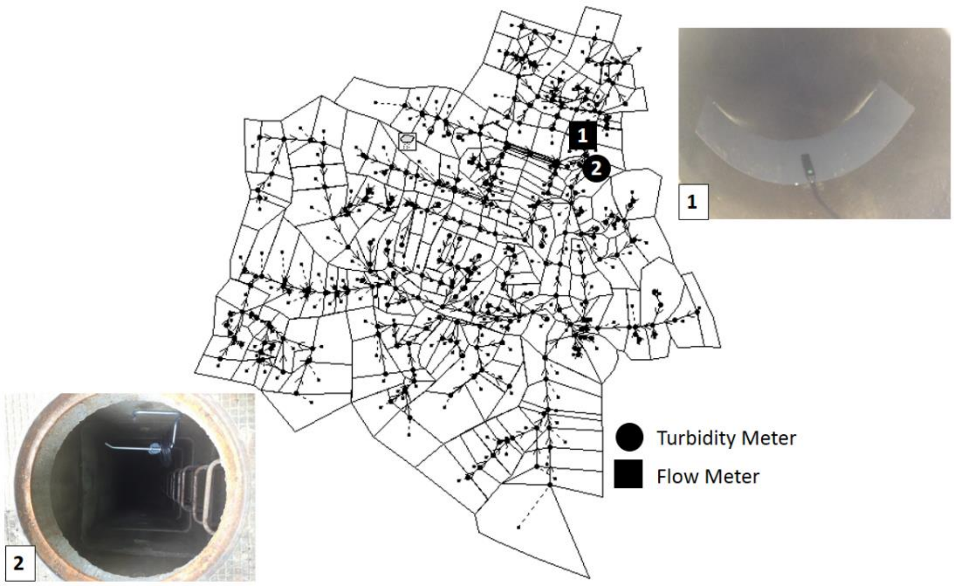

Figure 4-66: Flowmeter and Turbidity Meter Implemented on the Lille 1 University Campus

4.7.1 Turbidity and Flow Measurements

Once sensors were implemented, collected data was stored in a database, in order to be analysed and evaluated. Characteristics of the rainfall events, where the measured flow and turbidity are recorded and analysed in this section, are presented in Table 4-7.

Table 4-7: Characteristics of Rainfall Events

Date	Duration (min)	Total Depth (mm)	Peak Intensity (mm/h)
25/07/2015	320	13.04	16.76
30/07/2015	30	5.545	59.95
04/08/2015	51	6.651	86.36
26/08/2015	46	9.774	39.62
31/08/2015	164	24.354	217.18
19/11/2015	430	17.287	22.61

11/12/2015	172	5.813	23.37
30/01/2016	452	11.327	13.97

Figure 4-67 to Figure 4-74 present the measured turbidity and flows during the 8 different events monitored on the University Campus.

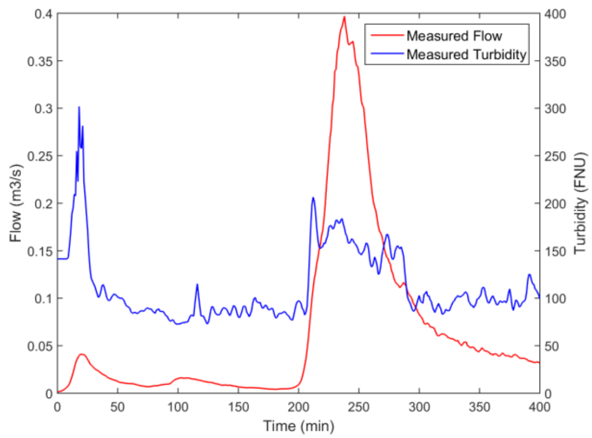

Figure 4-67: Measured Flow and Turbidity during the Rainfall Event of 25 September 2015

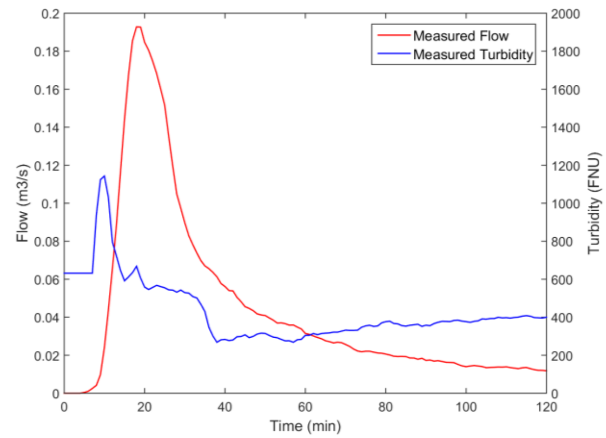

Figure 4-68: Measured Flow and Turbidity during the Rainfall Event of 30 September 2015

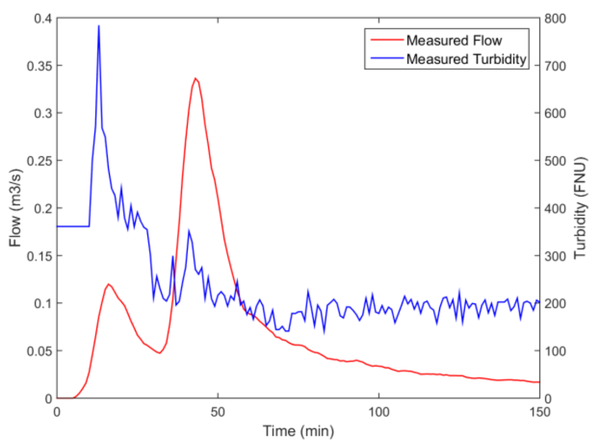

Figure 4-69: Measured Flow and Turbidity during the Rainfall Event of 4 August 2015

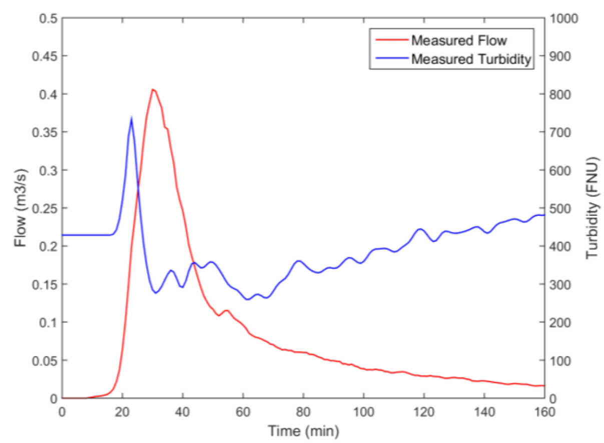

Figure 4-70: Measured Flow and Turbidity during the Rainfall Event of 26 August 2015

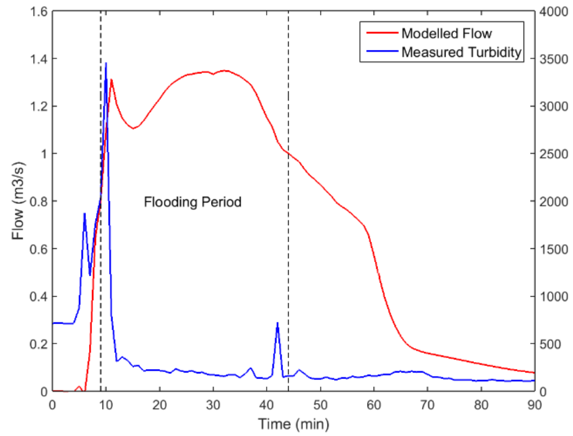

Figure 4-71: Measured Flow and Turbidity during the Rainfall Event of 31 August 2015

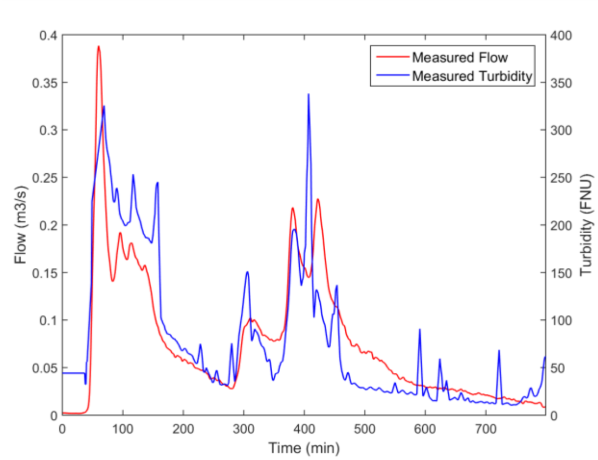

Figure 4-72: Measured Flow and Turbidity during the Rainfall Event of 19 November 2015

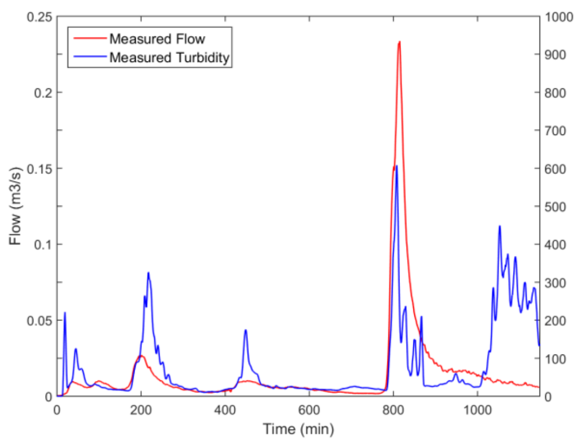

Figure 4-73: Measured Flow and Turbidity during the Rainfall Event of 11 December 2015

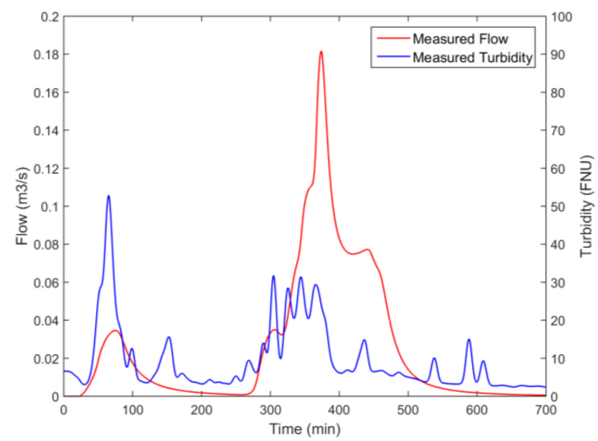

Figure 4-74: Measured Flow and Turbidity during the Rainfall Event of 30 January 2016

While analysing the received data, presented in the precedent figures, the variability of the pollution degree within the UDS flows is clearly indicated. Moreover, two relationships between turbidity and flow were noticed. Higher turbidity values come with higher flows, is the first relationship to observe. The second observation indicates that higher turbidity values are more likely to occur with the beginning of the runoff, if sufficient water volume was flowing in the system. These pollutions are majorly produced through leaching the surfaces. Since, high rainfall intensities have high leaching potential, higher turbidity are correlated to higher flows, which explains the first observation. In addition, first flows are leaching the biggest layer of depositions occurred during antecedent dry periods, and thus induce higher turbidity values, which explains the second observation.

The variability of pollution degree within the runoff, during the same event, could support the decision of recharging groundwater with clean water, when the flow represents a low measured pollution. In addition, the obtained results offer the possibility of proposing a dynamic qualitative management that could support and enhance the network capacity, during severe events. The proposed management in the preceding paragraph was based on calculating the best VSS in reducing the flooding volume, while considering the runoff equally polluted and without giving importance for a specified period of floods. In this section, the proposed management, is based on qualitative measurements, and by directing clean water to infiltration structures, more storage importance will be given for polluted flows during the first and highest volumes of runoff.

4.7.2 Qualitative Management Strategy

The qualitative management is based on directing a water volume from a principal manhole to an inspection manhole, where the quality of water is measured. Flow will be directed to infiltration structure, in case of an acceptable pollution was indicated. Otherwise, water will be returned to the UDS. The locations of principal and inspection manholes were chosen to be close to the flooding areas and near a green surface, where the infiltration structures could be implemented. Figure 4-75 presents the locations of manholes participating in the proposed qualitative management.

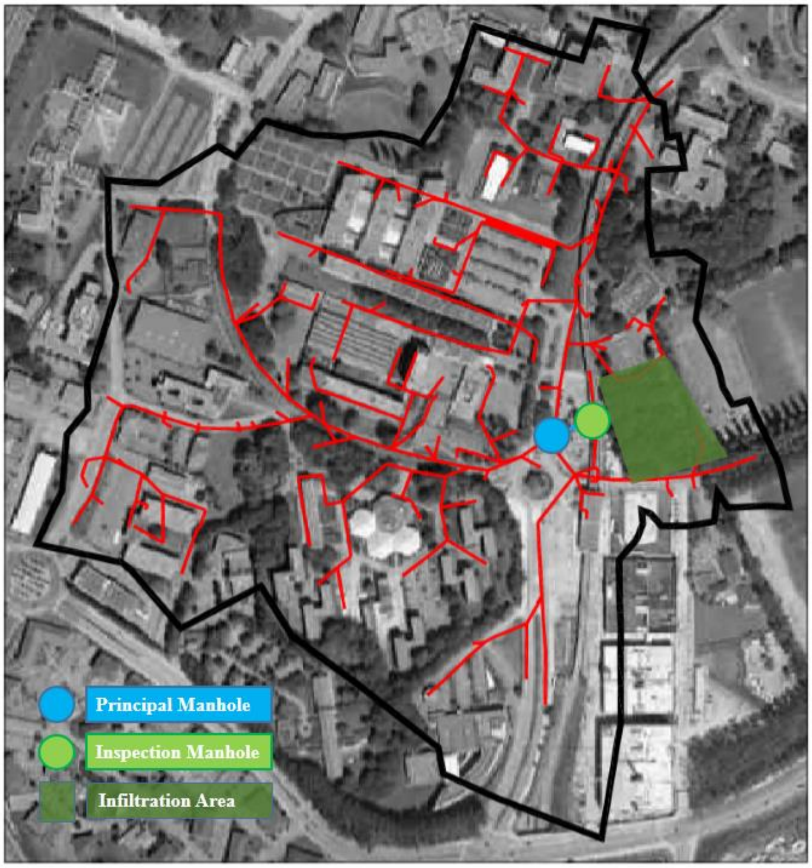

Figure 4-75: Locations of Manholes for Qualitative Management Application

Since turbidity is related to flow magnitude, the effectiveness of the proposed management in reducing flooding volume, occurring when high flows exist, should be verified. Therefore, the severe storm event of 31 August 2015 was used to test the efficiency of the proposed management. Few minutes after the beginning of this event, floods appear in different sections of the campus. Turbidity and flow measurements during this event, with the beginning and the end of the floods appearances, are presented in Figure 4-71. For testing the proposed qualitative management, simulations were conducted on the calibrated EPA-SWMM model, after adding a storage unit, having a volume of 200 m^3 and connected to the principal manhole by a pipe with a diameter of 300 mm. Storage unit was located in the infiltration area presented in Figure 4-75. Inflow to the infiltration structure begins after the turbidity measurements were dropped, and stops when water level in the structure is equivalent to 1 m.

4.7.3 Results and Discussions of the Qualitative Management

For evaluating the potential of such qualitative management, 4 different simulations were conducted. The first simulation present the system operation by conserving the static equipment of the UDS, and adding to the simulation model the storage unit, which represents the infiltration structure studied in this work. The second simulation aims to represent the network operation, while adding the storage unit and removing the static equipment downstream the retention tank. The third simulation differentiates from the second one, by adding a dynamic valve downstream the retention tank as presented in the precedent section. The fourth simulation is similar to the third one, but with adding a dynamic valve upstream the infiltration structure and thus optimally benefit from the storage capacity of the retention tank and the infiltration structure. The dynamic management of the valves connecting the retention tank and the added infiltration structure to the UDS, were both of them based on calculating a VSS as described in the dynamic management section (Section 4.6).

The first simulation shows the benefit provided by adding the infiltration structure to the actual system state, indicating a flooding volume and duration equal to 789 m^3 (34.6h), and thus a reduction of 80 m^3 (5.7h) compared to the current operation. The second simulation shows the benefit provided by understanding the system operation and the remove of the static equipment disturbing the UDS capacity. This benefit was interpreted by the decrease of the flooding volume and duration to achieve 767 m^3 (34.2h). The third simulation aims to represent the benefit of implementing an infiltration structure in focusing the retention tank storage capacity for the polluted runoff. Since the infiltration occur after turbidity drop, the retention capacity of the tank will be automatically focusing on storing the runoff at the beginning of the event. Compared to the second simulation, third simulation shows a decrease of flooding volume and duration by an amount of 30 m^3 (1.5h), to attain a total flooding volume and duration equal to 737 m^3 (32.7h). Finally, the fourth simulation had the objective of presenting the potential of dynamically operating the equipment of UDS, in enlarging the operation capacity and the retention and infiltration benefits. This simulation illustrates its benefit through a resulted flooding volume and duration of 718 m^3 (32.6h), indicating an increase in the infiltration structure benefit by 19 m^3 (0.14h), compared to the third simulation.

As previously discussed, the storm event of 31 August 2015 is characterized by short period of heavy rain, occurring at the beginning of the event. The short intense storms limit the benefits of infiltration structures, since they do not allow the reuse of the storage capacity of the structure, after the infiltration of the already stored water. The efficiency of a dynamic management is also limited during such events. For multiple trials, using a population of 60 individuals, the optimal solutions were found directly after few iterations, indicating a complete opening of the valve since the beginning of the event. The dynamic management, described in this chapter and applied for two different valves, consists of 40 different values. For complicated storm events or big UDS, algorithms could have difficulties in optimizing 2 VSS with 40 values. Therefore, a new type of management was proposed for the infiltration structure valve, consisting of calculating a constant optimal valve-opening ratio, during the entire event. After several iterations, the minimum flooding volume, equivalent to 724 m^3 (32.6h), was reached. Comparing the results to the third simulation results, presented earlier, a decrease of flooding volume and duration by an amount of 13 m^3 (0.12h) is found. The resulted optimal constant opening ratio of the valve is equal to “0.75”. In this management, high opening value is more suitable for events that start with high rainfall intensity, while low opening ratio could suit more the events, characterized by late high intensities.

In this section the turbidity measurements were directly used for indicating the pollution degree of the runoff, and an equation to relate the turbidity to suspended solids or chemical oxygen demand was not constructed. This proposition was based on considering the stormwater runoff as clean water when it is characterized by constant low turbidity measurements. Linking turbidity to pollution parameters could help in evaluating the need of a pre-treatment process, before the contact with the environment. In addition, knowing the pollution parameters concentration assists in modelling the pollution, and thus running studies and evaluations on unmeasured events. Black box model could also have a great potential in relating flow to turbidity variations.

4.8 Conclusion

Urbanization, old infrastructures and climate changes are the main factors in surcharging and overstressing UDS operations. Recent technologies, offering modelling potentials, communication systems, sensors and actuators, had been widely used in improving UDS operations. Despite their good feedbacks and results, mentioned in multiple studies, RTC systems remain limitedly developed and in need for further studies and deeper evaluations. In addition, since dynamic management depends on the site conditions, the UDS characteristics and the actual states, more studies could help in generalizing and understanding these types of projects.

This chapter presents an overall RTC, starting by a FFS and followed by a retention tank capacity optimization. NARX neural network to trigger danger situations was developed, offering an efficient tool to inform UDS managers for possible inundation. Based on two hours ahead weather forecast, the trained NARX neural network performs accurately on weak and severe storm events, showing a robustness and efficiency in flooding forecast fields.

Understanding the real operations of UDS, while it is subjected to multiple storm events, enabled us to reduce a large amount of flooding volumes and durations. These reductions were achieved through simple modification of the existing equipment. Afterwards, the second part of this work was focusing on developing and testing a dynamic management procedure. Once an alert is detected, besides taking appropriate actions, an automatic calculation of the optimal VSS, is activated. Since calculation time is a critical factor in dynamic management, two optimization algorithms were tested, evaluated and compared based on their final results and performances. Modified ABC shows faster convergence than the GA to the optimal solution, before reaching both the same results after 15 iterations. Both algorithms performed good after 20 iterations, by reducing flooding volumes by an amount of 27 and more than 59 m^3 in the storm event of 31 August 2015 and 5 YRP, respectively. Thus 9.6% of increasing retention tank capacity was mentioned for the event of 31 August 2015, while 21.1% for the event of 5 YRP. Optimization algorithms efficiencies were evaluated according to the obtained results and the population size, and it was found that 60 individuals within a population is an optimal choice concerning the optimization efficiency and speed, and the required computing capability.

The turbidity measurements taken from the UDS of Lille 1 University Campus highlight the variation of the pollution within the runoff. Beside groundwater recharge benefit, these variations could support the management strategies, through a qualitative dynamic management, dividing the total runoff in 2 sub-flows. Part of the clean water is directed to infiltration structures, and thus storage capacity of the retention tank will be more reserved for polluted runoff. The qualitative monitoring and management could support the VSS calculations by prioritizing the flows, which should be stored in the retention tank. A proactive qualitative management requires a calibrated qualitative model, able to forecast the pollution scenario for the two hours ahead weather forecast. The calibrated qualitative model, which could be developed on the same EPA-SWMM model, will also assist in the evaluation and the improvement of the proposed qualitative management strategy. Other solution in predicting turbidity variation during a storm event could be based on black box models.

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General Conclusion

Urbanization is leading infrastructures to overstress. Smart Cities concept based on technological and computer progress appeared as a promising solution for improving the components of the cities. Real time monitoring and controlling the operations of the infrastructures is the key element in optimally benefitting their capacities. Urban Drainage Systems (UDS) are facing a lot of difficulties in performing their functions in urbanized cities. The literature described the reasons and consequences of these operations shortages. Waterproofing the soil surfaces, infrastructure ages and climate changes are the main reasons in limiting UDS potentials in performing their duties. Major failures of these utilities are reflected by structural collapses, frequent flooding appearances and combined sewer overflows. Consequences of UDS limited performance are generally leading to threatening citizens' protection, polluting the environment, limiting the groundwater resources, in addition to serious economic losses and casualties.

Due to the important roles of UDS for the city operation and existence, multiple researches were conducted aiming to strengthen their capacities. This thesis has the objective of managing UDS and improving their sustainability by integrating them into the smart cities. The proposed concept for the integration was based on several overlaps of short-term improvements. Firstly, assessing the actual state of the utility for allowing a localization and prioritization of structural critical elements. It was found in this study that geographically defining the structural states, helps in planning maintenance actions based on priority levels. Once structural condition is rectified and verified, an updated log for the system condition form an essential element in maintaining the infrastructure. Successive observations digitized and stored into a Geographic Information System (GIS), allows the evaluation of the system structural evolution. Black box models and fuzzy logic are efficient in evaluating structural evolution. In this thesis, methodologies for constructing a GIS database, supporting the system branches prioritization and structural evolution evaluation, were presented. This work does not address the forecasting of structural evolution, due to the limited recurrent inspection for the same branches on the experimental site. Through the literature, a black box model was also found able to extend the existing system structural information, from limited inspected areas to cover the entire system branches. Such black box model was not studied in this work, since this research was oriented for improving hydraulic operations, leaving behind some perspectives in structural assessment and evaluation fields.

Hydraulic operation of UDS can be evaluated through a real time monitoring system. Implementing quantitative and qualitative sensors in different locations of the system helps in understanding the UDS operations and failures. Simulating the hydraulic operation of the utility enables to extend the monitoring potential, under a measured event, from local monitored areas to cover the entire system branches. Therefore, having a hydrologic-hydraulic simulation model is highly important for studying and analysing UDS operations. Since simulating a hydraulic operation of UDS requires the determination of multiple interconnected and unmeasured parameters, a calibration of simulation model is needed, which is a difficult task to accomplish. This work described, in its third chapter, an effective methodology for auto-calibrating simulation models. The auto-calibration process was based on hybrid optimization techniques, combining Genetic Algorithm and Pattern Search. The optimization was conducted through an iterative calculation work accomplished between Matlab and EPA-SWMM, and based on multi-points measurements and 10 different rainfall events. The efficiency of the calibration process on the UDS of the Lille 1 University Campus was reflected through good visual observations and high Nash-Sutcliff coefficients calculated for the 10 events participating in the process, as well as 10 other rainfall events.

The complexity of the UDS response and the stochastic nature of rainfall events require evaluating the system operation and flooding appearances on multiple severe storm events. Conducting multiple scenarios simulations and analysis is an efficient way to understand the UDS operation at the peaks. In order to simulate UDS operations, downstream hydraulic boundary conditions are necessary, which are unknown information for un-measured events. Consequently, this work presented a NARX Neural Network able to forecast these conditions. Calculations are based on an exogenous input representing the rain intensity variation over the catchment concentration time, and a recurrent behaviour allowing to account for hydrologic modifications during the event. Simulated results with the forecasted downstream hydraulic boundary conditions were compared to measured values for a long period of rainfall events, validating the calibration of the simulation model and the forecasting system efficiency. The calibration process was accomplished on a relative small watershed, but it should be noted that for larger ones, the system could be decomposed into multiple subsystems, and the calibration could be progressively accomplished from the upper watershed till reaching the bottom at the end. This methodology is proposed for not considering the same hydrologic parameters for all sub catchments of a large watershed.

Once a calibrated simulation model was built and found able to represent the real UDS operation under unmeasured events, the system response for synthetic storm events, was studied and analysed. A good improvement in the UDS operation was possible through a simple modification of the equipment, after understanding and analysing the system failures. Moreover, a work was dedicated in this section, to protect the citizens and to improve the system operation, through an optimal manipulation of the network elements. Since the simulation model was able to represent the UDS operation for forecasted storm event, a real time control (RTC) system was proposed, based on two hours ahead weather forecast. The RTC was composed of a Flooding Forecast System (FFS), able to alert the UDS managers for possible inundations, and a Valve State Schedule (VSS) calculation, able to optimally benefit the retention tank storage capacity. The proposed FFS was based on a NARX Neural Network capable to monitor the water depth in 5 critical manholes, chosen according to multiple criteria. The results of the flooding forecast system were satisfied on 1, 2 and 5 Year Return Period, showing the flooding forecast ability during severe events and the system robustness in not generating erroneous alarms during un-flooding events.

After an alarm is triggered, UDS managers evaluate the system operation through the simulation model, and areas likely to be flooded is defined and localised. Necessary actions should be taken in such situations. A dynamic management aiming to reduce flooding volumes was described and presented to be applied during severe storm events. The dynamic management consists of calculating the optimal VSS for the valve of the retention tank. The calculation is based on optimization algorithm, running iteratively the simulation of the EPA-SWMM model, in order to reduce the flooding volume. Two optimization algorithms were tested for this purpose in order to evaluate their performances. Genetic Algorithm (GA) and modified Artificial Bee Colony (ABC) showed both a good optimization performance. Slight advantage was mentioned for the modified ABC before reaching the 15th iteration. According to the retention tank storage capacity, the resulted reductions in the flooded volumes were noteworthy in this study, especially for the 5 Year Return Period synthetic event. The efficiency of the dynamic management depends on the storm event characteristics as duration and temporal intensity distribution, which explains the difference in resulted improvement between the two studied events. Since high turbidity values generally occur simultaneously with high flows, the efficiency of reducing flooding volumes through infiltrating clean water, is questionable. This work presents also a qualitative management, based on infiltrating clean water outside the high turbidity measurement values, in order to be tested.

Through the simulation results of the 31 August 2015 storm event, the proposed qualitative management was found able to effectively reduce the flooding volumes. It was also found that such managements support quantitative managements by allocating storage volumes to the highly polluted runoff. Qualitative management could be improved and deeply evaluated after relating turbidity to pollution parameters, and thus allowing qualitative simulations and forecasting for unmeasured events.

The dynamic management proposed in this work is limited to calculate an optimal VSS in order to reduce the total flooding volume. Total flooding volume is found through the simulation model, and is calculated by summing equally the flooded volumes of all manholes. Affecting each manhole by a consequence factor, allows differentiating the importance of each flooding volume, and thus the optimization techniques will search to decrease the objective function in another concept. More importance will be given to reduce floods of manholes in critical locations, as near buildings with underground basements or in the middle of principal roads. Even if the resulted total flooding volume is bigger, restricting these flooding in green areas or secondary roads could be more important. GIS database is a main contributor in developing the consequence factors of all manholes in a UDS, due to its layers representing all utilities and site information. The consequence factors could be also dynamic and the importance of flooding volume of each manhole could depend on daytime, season and actual activities presented in the city.

A mono-objective function was presented in this thesis aiming to reduce flooding volume. In real life applications, other objectives could have also importance, as reducing combined sewer overflow, required energy for pumping stations in addition to effectively using treatment plant capacity and emptying retention tanks. The dynamic management presented for the University Campus could be studied under a multi-objective function, which combines the flooding volume, duration and the retention tank emptying process. “gamultiobj” function in Matlab was tested for this purpose. This function generates a local Pareto set solutions of the objective functions to be calculated. VSS solutions in the Pareto set are equally optimal, since each solution is better than all other solutions by one objective function result. Depending on the actual situation and forecasting results, it is up to the manager to select the suitable solution to apply. For example, if 2 VSS solutions exist, the first one support the flooding volume decrease and the second favours the earlier emptying process, in case of forecasting a severe storm event in the next hours by the weather forecast system, choosing the second solution may be more efficient for the UDS operation.

Starting a VSS calculation from the beginning is sometimes highly time consuming technique, especially for large UDS. Thus, finding an initial point or population to start the optimization with, is important. Since these calculations are based on modelled results, a lot of storm scenarios could be conducted and recorded. For each scenario, a synthetic storm is constructed and then VSS optimization is carried to find the optimal solution. Once, having a large database of storm events and their optimal VSS, training a neural network with the storms as input and the VSS as output, could be realized. Having a trained neural network is useful for predicting an efficient VSS, which could be used as an initial solution for an optimization technique. In this case, Pattern Search could be more efficient than Genetic Algorithm or Artificial Bee Colony in performing the VSS calculation, since it is highly efficient in local searches near an initial individual.